

SCHEDULING AND ROUTING OF CHRONIC DIALYSIS PATIENTS IN THE AFTERMATH OF A DISASTER

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To my family

ABSTRACT

Disasters have devastating effects on patients with chronic diseases who need regular treatments to preserve their health. In this thesis, we focus on developing effective, fast and joint solution methodologies to support the scheduling and routing decisions of chronic dialysis patients assigned to a dialysis center after a disaster. The problem involves determining whether a patient is served or transferred out of the dialysis center. The days, sessions and treatment types of patients for their visits must be assessed over the planning horizon. The vehicle routes must be constructed for each session. We formulate a multi-objective mathematical model in which the primary objective is to minimize the number of patients transferred. With their hierarchical order, the secondary objectives are minimizing the sum of the number of vehicles required each day, the number of short and normal treatments, and the total travel time. The secondary objectives increase the effectiveness of the solutions. The short treatment type is considered to decrease the number of patients transferred. Besides, visiting frequency of patients differs according to the treatment types provided. To solve this problem, we propose a constructive heuristic and two matheuristics. Within the heuristics, we apply various strategies to improve the solutions. A rapid approach for the matheuristics is proposed to obtain solutions in a shorter time. To evaluate the performance of heuristics, we provide several metrics and present insights on different problem characteristics. We perform a numerical study based on actual data of a dialysis center in Turkey. In the results, even if the same value of the primary objective is achieved under both matheuristics, in most instances, Matheuristic MO results in the best solutions. Our heuristics lead to effective solutions that can be applied in a post-disaster setting.

ÖZETÇE

Afetlerin, sađlıklarını korumak için düzenli tedavilere ihtiyaç duyan kronik hastalar üzerinde yıkıcı etkileri vardır. Bu çalışmada, bir afet sonrası diyaliz merkezine atanan kronik diyaliz hastalarının çizelgeleme ve rotalama kararlarını desteklemek için etkin, hızlı ve ortak çözüm metodolojileri geliştirilmektedir. Bu problem, bir hastaya servis yapılmasını veya diyaliz merkezinden transfer edilmesini belirlemeyi içerir. Planlama ufku süresince, hastaların ziyaret günleri, seansları ve tedavi yöntemi belirlenmelidir. Her seans için araç rotaları oluşturulmalıdır. Birincil amacın transfer edilen hasta sayısını en aza indirmek olduđu çok amaçlı bir matematiksel model formüle edilmiştir. Hiyerarşik sıralamalarına göre ikincil amaçlar, her gün gerekli araç sayısı toplamını, kısa ve normal tedavi sayısını ve toplam seyahat süresinin toplamını en aza indirmektir. İkincil amaçlar, çözümlerin etkinliğini arttırmaktadır. Kısa tedavi yöntemi transfer edilen hasta sayısını azaltmak için düşünülmektedir. Ayrıca hastaların ziyaret sıklığı uygulanan tedavi türlerine göre farklılık göstermektedir. Bu problemi çözmek için bir yapıcı sezgisel yöntem ve iki mat-sezgisel yöntem önerilmektedir. Sezgisel yöntemler içinde, çözümleri iyileştirmek için çeşitli stratejiler uygulanmaktadır. Mat-sezgisel yöntemlerle daha kısa sürede çözümler elde etmek için hızlı bir yaklaşım önerilmiştir. Sezgisel yöntemlerin performansını değerlendirmek için çeşitli performans göstergeleri sağlanmıştır ve farklı problem özelliklerine ilişkin içgörüler sunulmaktadır. Türkiye’deki bir diyaliz merkezinin gerçek verilerine dayalı sayısal bir çalışma yapılmıştır. Sonuçlarda, her iki mat-sezgisel yöntemde de birincil amaç için aynı değere ulaşılsa bile, çođu durumda Mat-sezgisel MO yöntemi en iyi çözümleri vermiştir. Sezgisel yöntemlerimiz, afet sonrası ortamda uygulanabilecek etkili çözümler sunmaktadır.

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CHAPTER I

INTRODUCTION

The number and magnitude of disasters increase rapidly each year. The Global Assessment Report on Disaster Risk Reduction 2022 states that between 350 and 500 medium to large-scale disasters happened between 2001 and 2020 [1]. It is projected that by 2030, the number of disasters will be 560 per year. These disasters have devastating effects on people's lives. The Centre for Research on the Epidemiology of Disasters announces that in 2021, 10492 deaths occurred and 101.8 million people were affected due to 432 natural disasters [2]. People having chronic illnesses such as cancer, diabetes, kidney failure and heart disease are among the most vulnerable group to a disaster and these patients are at high risk for the destructive effects of disasters. They need continual health care to sustain their well beings. However, in the post disaster setting, even sustaining regular operations is challenging. In the aftermath of a disaster, problems mostly encountered in the related literature for humanitarian operations are about the allocation of disaster relief supplies for nutrition or sheltering and emergency evacuations. Efficient methodologies are developed to provide solutions in a short time. However, we focus on a rare studied problem of providing health services to patients who are continually getting health services aftermath of a disaster.

In this thesis, we consider the end stage renal patients. These patients' kidneys are not functioning and they need regular dialysis treatments for the rest of their lives. In hemodialysis treatment, a machine filters wastes and fluids from the blood and then filtered blood returns to the patient's body. Usually, normal treatment (i.e., regular treatment) takes 4 hours and a patient visits the dialysis center three times a week [3]. The duration of treatment and frequency of visits can be adjusted by the doctors according to the patient's medical condition. Hemodialysis

treatment can take place at a hospital or a private dialysis center. The centers take the scheduling decisions and provide transportation services for dialysis patients. Even in normal conditions, deciding the scheduling and routing of the patients is challenging due to the revisits. In a post disaster setting, several factors make taking the decisions even harder.

In normal conditions, chronic dialysis patients usually prefer receiving treatments in dialysis centers and hospitals which are near to their houses. They visit their center for being treated several times a week to stay healthy. However, after an earthquake, resources become scarce due to various disaster related complications. A part of the resources can be lost due to damaged buildings and medical equipment. After the Marmara earthquake, five out of twelve hemodialysis centers were nonoperating [4]. During Hurricane Katrina, 94 dialysis centers were affected in that area and 48% of these clinics remained closed for 10 days or longer [5]. Besides, even undamaged machines may not work due to the affected infrastructure, power and water outages [6]. The number of available hemodialysis personnel can be decreased as a result of injuries and deaths [7]. In addition, roads to dialysis centers can be covered with debris. A dialysis center can be partially or entirely inaccessible. Hence, the number of available dialysis centers and hemodialysis machines may be reduced due to annihilating impact of the disaster. Patients with reduced capacitated or unavailable dialysis centers must be transferred to available dialysis centers.

Besides reduced capacity, the demand for dialysis treatment increases due to several factors. Kantarcı et al. [8] state that after the Marmara Earthquake, 18.3% of the patients assessed to Marmara University Hospital has the medical condition of kidney failure caused by the crush trauma. Crush syndrome is the trauma caused by staying under the rubble. To treat patients with crush syndrome, long dialysis sessions are needed. Crush trauma is among the leading cause of death after direct trauma [9]. In this study, we assume that hospitals are reserved for patients with crush syndrome. On the other hand, chronic dialysis patients

who receive weekly treatments in hospitals must be assigned to available dialysis centers. The dialysis centers are responsible for the transportation of patients. Therefore, vehicles of the dialysis center carry patients from their home locations to the dialysis center. At the end of the treatment session, vehicles bring patients to their locations.

There are discussions about the dosage and duration of hemodialysis treatments and their effects on the patient health [10]. In this thesis, normal treatment and short treatment types are considered. The short treatment type has half of the duration of normal treatment and patients who receive the short treatment type must revisit the dialysis center earlier. Even if it is not the healthier treatment option, in the aftermath of a disaster, it brings the benefit of serving more patients.

The long travel time spent on the transportation of patients to the dialysis center decreases the health-related quality of life [11]. Besides, patients having longer travel times may skip their dialysis sessions or may have shortened treatments [11] which may affect their overall health. In addition, long travel times may cause delays between sessions which can lead to a shorter treatment for the patients in the next session. Besides, in the aftermath of a disaster, long duration may cause more distress to patients and uncertainties related to road conditions can increase the route duration. In a post disaster setting in which there are scarce resources, giving less treatment because of the delay may worsen the conditions. While constructing a session's vehicle route, the time that a patient spends in the vehicle (i.e., ride time) and total travel time should be considered and minimized to increase service quality.

In the aftermath of a disaster, various operations must be handled effectively and rapidly to decrease the impacts in a complicated environment. The coordination in the dependent operations is crucial to creating functional real time responses [12]. We aim to provide scheduling and routing decisions for a dialysis center in which the chronic dialysis patients are assigned by the authorities

aftermath of a disaster. Since the decisions taken in the scheduling part have a direct effect on the routing decision, we address both decisions interdependently. We developed a mathematical model, a constructive heuristic and two variants of a matheuristic approach to provide effective treatments to as many end stage dialysis patients as we can fit into the dialysis center throughout a planning horizon aftermath of a disaster. We aim to provide solutions in a reasonable time. We evaluate the performance of the solution approaches with small test instances and a case study conducted in a dialysis center in Istanbul, Turkey with different service capacities, patient size, short treatment limit, ride time and travel time limits.

Our results show the benefit of providing short treatments in the dialysis center since it drastically lowers the number of patients transferred. Besides, higher capacity and higher short treatment limits decrease the number of transfers. However, a higher short treatment limit decreases the service quality in terms of the treatment types. In addition, restricted ride time and travel time limits may increase the number of routes constructed. However, it leads to an increase in the service quality in terms of the transportation of patients since the travel times decrease and patients spend less time on the vehicles. We find out that patients who are served in the dialysis center are patients who received their last treatments at a time close to the disaster since such patients create flexibility in the scheduling decisions. Our results also show that patients whose locations are close to each other can be assigned to the same sessions and vehicle routes over the planning horizon. Therefore, while determining the patients to be served and their scheduling decisions, we need to also encounter the routing decisions.

In Chapter 2, we review the related literature. In Chapter 3, we define the characteristics of the system and the problem studied. We present the mathematical model, the constructive heuristic and two variants of the matheuristic in Chapter 4. The performances of the solution methodologies are evaluated and the case study is included in Chapter 5. We present our conclusions in Chapter 6.

CHAPTER II

LITERATURE REVIEW

In normal conditions, operational decisions such as scheduling and/or routing may be challenging. In the aftermath of a disaster, the execution of operations and decision-making are much harder. This study aims to provide effective and fast solutions for the treatment scheduling and routing decisions of chronic dialysis patients in a dialysis center over a planning horizon aftermath of a disaster. There are various routing and scheduling studies in the literature, in which decisions on routing and scheduling have been made independently. Differently from the existing literature, in this thesis, the aim is to make interdependent decisions of scheduling and routing jointly to maximize the overall effectiveness of the decisions. Coordination is the key to achieving overall high-quality results, especially after a disaster. In this chapter, we mainly review the related scheduling and routing problems which are both well researched areas. In particular, literature on home healthcare routing and scheduling problems, which are similar problem types to ours and taking into account the periodicity of patient visits, is examined. In addition, we review the literature on disaster management. However, the problems mostly studied are about the allocation of disaster relief supplies for nutrition or sheltering and emergency evacuations.

2.1 Home Healthcare Routing and Scheduling Problems

Home healthcare is a rich and growing area including both scheduling and routing decisions of patients. Health services are delivered in the home of the patients in such problems [13]. In most of the studies, periodic visits to patients' locations are considered. Duque et al. [14] focus on the home care service planning in which assignment of patients to caregivers, scheduling and the order of patient visits are determined for a planning horizon (i.e., two months). The authors develop a

two stage solution methodology in which at the first stage the service level which is determined by patients' and caregivers' time availability and scores of their assignment to each other is maximized by a mathematical model. In the second stage, a randomized local search algorithm (RLS) is applied to find a solution with less total travel distance by allowing a low degradation from the service level achieved in the first stage. To reach the neighborhood solutions, two patients with different visits in the same week are swapped for improving the total travel distance. As a result of swap operations, new weekly schedules for the patients are generated. They conduct a case study to analyze the performance of their approach. Kandakoğlu et al. [15] study a daily home dialysis service planning problem in which routes for dialysis nurses are decided for serving patients of the day. They developed a mixed integer linear programming (MILP) model in which they minimize multiple criteria: total travel distance, the number of nurses needed, costs associated with travel and overtime of nurses and balance among workload of nurses. Shao et al. [16] consider the problem of weekly scheduling and routing of therapists for providing rehabilitative services to patients. The solution approach proposed is a two phase greedy randomized adaptive search procedure (GRASP). In the first stage, patients are assigned to patterns and the visit days for each patient are determined. Thus, daily routes are constructed and they form weekly schedules. In the second stage, inter-route and intra-route moves are applied to search the neighborhood solutions. Their goal is to minimize the costs of travel, treatment, administrative and mileage reimbursement. In our problem, improvement moves such as the swap operation among visits (e.g, [14], [16], [17]) cannot be considered due to the combination of some problem characteristics such as the short treatment type limit, the number of days passed after the last treatment of each patient, ride time and travel time limits. Firstly, the number of days passed after the last treatment of each patient diminishes the flexibility in the scheduling decisions because, regarding the previous treatment type, a patient must be served within certain days. Secondly, the changes among

the patients are also limited since the capacity allocated in a dialysis session is different for the treatment types and changing treatment types may be infeasible since there is a limit on the number of short treatments allocated to a patient over the planning horizon. Besides, changing a treatment type in a day may make the decisions taken for the rest of the planning horizon infeasible. Lastly, improvement moves between constructed routes may be also infeasible due to the total travel time and ride time constraints. Therefore, instead of the improvement methods applied to the initial result, we consider various strategies on the heuristics to obtain different results and select the best of them, which is explained in Chapter 5. Bard et al. [18] formulate a mixed integer programming (MIP) model to obtain the weekly schedules of therapists. For instances with realistic size, they develop a branch-and-price-and-cut algorithm. Bennett and Erera [13] focus on a rolling horizon planning approach for the home health nurse scheduling and routing problem. Two heuristics are proposed. The first heuristic is a distance based insertion heuristic. The second heuristic is a more complex capacity based insertion heuristic which aims to handle the capacity efficiently to increase the number of patients visited. Trautsamwieser et al. [19] work on the daily home healthcare service planning aftermath of natural disasters to provide routes for nurses. They develop a mathematical model and a heuristic based on variable neighborhood search (VNS) for the real size instances. Their model minimizes total travel and waiting times and the dissatisfaction degree of patients and nurses.

2.2 Related Routing and Scheduling Problems

A similar problem type to this study in terms of considering scheduling and routing decisions jointly is the Period Vehicle Routing Problem (PVRP). Overview of Francis et al. [20] provides extensions of the PVRP and modeling techniques. In the PVRP, there is a specified visiting frequency for each customer such as daily or two-day visits during a determined period. Similarly, in this problem, periodic visits are required for chronic dialysis patients who receive dialysis treatments

multiple times a week. Gulczynski et al. [17] develop an IP based heuristic for PVRP. In the first step, customers are assigned to service patterns with an assignment MIP model that minimizes the maximum amount of demand served in a day and all patients must be assigned to a pattern. Then, routes are constructed with Clarke and Wright savings algorithm. An improvement integer programming (IIP) model is proposed to reassign customers to schedules and move them to new routes to minimize the distance traveled. Besides, an enhanced record-to-record travel algorithm (ERTR) is utilized to improve the current solution. Peter Francis and Tzur [21] consider a variant of PVRP, which is PVRP with Service Choice (PVRPSC). In this problem, there is a lower limit on visiting frequency. Thus for PCRPS, visiting frequency is a decision. Peter Francis and Tzur [21], optimize travel times and service benefits which means providing frequent services to nodes by a function of frequency and demand-weighted service benefit. For large problem instances, they develop a heuristic approach in which routing subproblems are solved with an optimality gap determined by the time budget stopping rule. Francis and Smilowitz [22] develop a continuous approximation model for PVRPSC. Martinez-Puras and Pacheco [23] propose a bi-objective scheduling-routing model in which the aim is to minimize the total distance traveled and the changes in visit schedules in terms of the visit frequency (ex. every day, 1 day a week, 1 day a month) with respect to the current visit schedules. There are some limitations such as multiple types of services, technicians who are drivers of cars may not perform all the service types and weekly clients must be served on the same days each week. A solution method with tabu search and multiobjective adaptive memory programming (MOAMP) is developed. MOAMP-Tabu search method performs better compared to a common strategy: a non-dominated sorting genetic algorithm. With both PVRP and PVRPSC, a set of feasible schedules can be formed and customers can be assigned to a fixed schedule from the set of schedules. However, in this study, different from the existing literature, instead of a prespecified visiting frequency, the visiting frequency varies according

to the treatment types that patients receive in each treatment session. Choi et al. [24] propose a genetic algorithm (GA) to solve the weekly scheduling problem of hemodialysis patients. They also include alternative treatments with the duration of two, three and four hours. They consider the number of treatments applied during the week and the minimum total treatment time requirement. However, differently in our problem, according to the treatment type received, there is a limit for the last day to be treated in the following days. With different treatment types (i.e., normal or short treatment), the maximum number of consecutive days that a patient can wait without treatment is changing. Bozkır et al. [25] study the problem of assigning patients to dialysis centers and providing treatments for chronic dialysis patients over a planning horizon after a disaster. The authors consider a network level scheduling of patients. Whereas, we focus on the patients of a singular dialysis center for both scheduling and routing decisions. They develop a mathematical model in which the number of patients transferred out of the system, the number of visits of patients and providing short treatments are minimized. The authors develop a Logic Based Benders Decomposition (LBBD) method and a matheuristic to solve large sized problems.

There also exists a rich literature on routing decisions. The variants of VRP are reviewed. Kallehauge et al. [26], present modeling techniques and decomposition methods for vehicle routing problems with time windows (VRPTW). In VRPTW, there is the earliest time and the latest time defined for all customers and the depot. Similarly, in this study, a maximum travel time for each vehicle is specified to prevent delays. Pamukcu and Balcik [27] work on a multi-cover routing problem (MCRP) for post-disaster rapid needs assessments. They develop two alternative models with different objectives, which are minimizing the maximum route duration and minimizing the maximum arrival to a node. They develop two constructive heuristics based on cluster first route second methodology and tabu search algorithm. They indicate that the tabu search algorithm results in a high quality solution for the MCRP. Cordeau and Laporte [28] provide a review

of dial-a-ride problems (DARP). In DARP, both pickup and delivery options are available. Posada et al. [29] consider an integrated DARP, in which a fixed-route transportation system is included and a customer can make transfers between fixed-route transportation and a vehicle. Talarico et al. [30] develop two mathematical model implementations for the problem of the routing of patients with ambulances in a disaster. There are two types of patients. One of the patient types can be treated directly in the field and the other patient type has severe injuries and must be taken to the hospital. They minimize the time after the service of the last patient. They propose a large neighborhood search metaheuristic (LNS) to provide solutions in seconds since, in a post disaster setting, fast and effective solution approaches are required. Na and Banerjee [31], consider the routing of disaster evacuation vehicles between evacuation areas and the shelters. They propose a MIP model in which the evacuation cost is minimized and the number of people with different priority levels evacuated is maximized and apply branch-and-cut methods.

In summary, our contribution is to provide effective, fast and joint solution methodologies for the scheduling and routing decisions of the chronic dialysis patients of a dialysis center in a post disaster environment. We also consider varying visiting frequencies with respect to the treatment types selected during the planning horizon.

CHAPTER III

PROBLEM DEFINITION

Disasters impede the execution of regular operations. Chronic dialysis patients need continual treatments to preserve their health. In the aftermath of a disaster, providing effective service to chronic dialysis patients must be a key concern to decision-makers.

In the aftermath of a disaster, a number of chronic dialysis patients are assigned to a dialysis center throughout a planning horizon by the authorities. The planning horizon considered is the recovery period of one or two weeks after the disaster strikes. Chronic dialysis patients need regular dialysis treatment (i.e., normal treatment) to stay healthy. However, due to the scarce resources, an additional type of treatment is applied during the disaster period (i.e., short treatment). Short treatment has half of the duration of the normal treatment. In this thesis, given a set of patients to be served by a dialysis center, the problem is to decide (i) whether a patient will be served in that dialysis center or will be transferred to get treatments in another dialysis center and determine (ii) scheduling of that dialysis center by deciding the treatment types of chronic dialysis patients receive in each of their visits during the planning horizon and (iii) routing of patients to the dialysis center for each session of the center aftermath of a disaster. In the following, we explain the characteristics and assumptions of our problem.

- **Dialysis center.** We focus on an early stage of a disaster (i.e., 1 or 2 weeks). Similar to before the disaster period, there are two sessions of dialysis each day. Sessions last for regular hemodialysis treatment duration (i.e., 4 hours). Each session has a predetermined capacity formulated by the number of hemodialysis machines. However, due to the resource damages and decrease in the number of skilled personnel, a severe decrease in the service capacity

of the dialysis center may occur. Even some of the centers might become unserviceable. That leads to providing treatments to a number of patients with fewer resources.

- **Treatment types.** Typically, a patient is treated with a fixed length of four hours of dialysis treatment which is called normal treatment. After normal treatment, a patient must revisit the center in three days to get a new treatment (e.g., if a patient is treated with normal treatment on Monday, that patient must receive another treatment on Tuesday or Wednesday or Thursday at the latest). However, in the aftermath of a disaster, due to resource limitations, a short treatment type is offered by the authorities. The duration of the short treatment is two hours. This way, two patients can be treated in the same session by sharing the same dialysis machine. In a short treatment, since the blood is not filtered as much as needed, the patient must revisit the center in two days to get a new treatment (e.g., if a patient is treated with a short treatment on Monday, that patient must receive another treatment on Wednesday at the latest). In the routine, a short treatment option is not preferable for a patient. However, under the circumstance of a disaster, short treatment can be essential to serve as many patients as the dialysis center can serve. Since the short treatment is not the healthier choice, the number of short treatments that a patient can be treated during the planning horizon is restricted by the decision maker in this problem.

- **Last treatment before the disaster.** The last treatment day of a patient before the disaster is an important parameter to determine whether the patient will be served in the dialysis center or transferred to a new center. As stated above, after a normal treatment, patients must be treated in three days. Therefore, in this problem, the number of days passed since the last treatment received by patients before the disaster can be one, two or three

days. If it is three days, then whether the patient must receive treatment on the first day of the planning horizon or must be transferred to a different dialysis center. We assume that all patients are treated with a normal treatment before the disaster since the normal treatment type is applied during a regular dialysis session.

- Routes.** We assume that the dialysis center has a fleet of vehicles. In the aftermath of a disaster, the dialysis center must have constructed the vehicle routes utilizing the minimum number of vehicles each day. For simplicity, we assume uniformity of vehicles in the fleet. Since the speeds of the vehicles are the same due to uniformity, travel time between two stops in the road network will be the same for each vehicle. Likewise, the passenger capacities of the vehicles are identical. For each session, vehicles perform routes by leaving the center and visiting patients who are waiting to be picked up. After picking up all patients, vehicles return to the center and patients start their treatments. Similarly, at the end of a session, vehicles bring patients to their locations and return to the dialysis center. Vehicles can serve multiple sessions in a day. Therefore, to prevent delays in treatment sessions, each vehicle's route duration for a session is limited with a prespecified time called T_{max}^2 . Each treatment session has a starting time. Therefore route of the vehicle assigned to a session must be completed before the starting time of the next session. Accordingly, we assume that each vehicle starts its route T_{max}^2 time before the session starts. In addition, we aim to enable safer and faster transportation for the patients. The reason is if the patients spend a long time in a vehicle, this may cause discomfort which can affect their health condition. Thus, we enforce a time limit to restrict the time spent in a vehicle, called T_{max}^1 . That is, when the first patient of a route gets on, the vehicle should finish its route at most in T_{max}^1 time.

- Performance Metrics.** There are four objectives to be considered in the

decision making of this problem. However, the main objective is to minimize the number of patients transferred. As mentioned, patients are assigned to dialysis centers by the authorities. However, due to the disaster, dialysis centers and dialysis equipment may be damaged and the road to the dialysis center may become unreachable because of the rubble. Health personnel may be affected by the disaster. Due to such internal and external limitations, some of the patients can be transferred to nearby cities to be treated. In this problem, the transfer of a patient to a new center must be the last option since it can cause additional adjustments and discomfort for the patient itself and also for the overall network of dialysis centers.

The remaining objectives are the secondary objectives that increase the effectiveness of the solutions. Secondary objectives are explained in their hierarchical order of importance. The first secondary objective is minimizing the sum of the number of vehicles utilized each day over the planning horizon. This is an important factor for the dialysis center's resource management and to occupy the road network as little as possible which will create a space for the mobility of the vehicles of primary importance such as ambulances and fire trucks aftermath of the disaster. The second secondary objective is minimizing the treatment numbers to avoid giving excessive service to a patient. The number of treatments must be controlled to serve as many as patients. Ideally, normal treatment is preferred since it is the healthier treatment option for a patient. Therefore, providing the short treatment type is penalized more than the normal treatment type. This objective increases the service quality in terms of treatment types. Lastly, the total travel time is minimized to prevent long route duration which can create difficulties for patients and the network. This increases the service quality in terms of the transportation of the patients. A hierarchical solution strategy is applied among the objectives by strongly differentiating their penalization weight values. The first secondary objective has a network-level effect, therefore

it is considered as a highly prioritized secondary objective among the secondary objectives. The second secondary objective which is minimizing the number of short and normal treatments affects the service quality in terms of the treatments of patients. Lastly, the total travel time of vehicle routes is minimized since it affects the service quality in terms of the transportation of patients.

In Figure 1, a small network of 25 patients and the scheduling and routing decisions for a planning horizon of seven days aftermath of a disaster is illustrated (i.e., Instance 2). In this example solution, only patient 19 is transferred. In the left part of the figure, there is the schedule of patients with respective treatment types. For instance; in the second session of the second day, five patients are served with patient numbers 2, 5, 16, 17 and 20. Patient 16 receives normal treatment and the rest of the patients receive short treatment. In the right part of the figure, there is the route constructed for the second session of the second day. The values of objectives for this solution with their hierarchical order are described next. Firstly, one patient is transferred. Secondly, the sum of the number of vehicles required each day over the planning horizon is 7 vehicles since each day at most 1 vehicle is utilized. Thirdly, the number of short treatments provided equals 68 and the number of normal treatments provided equals 8 over seven days. Lastly, the total travel time is 991.7 minutes.

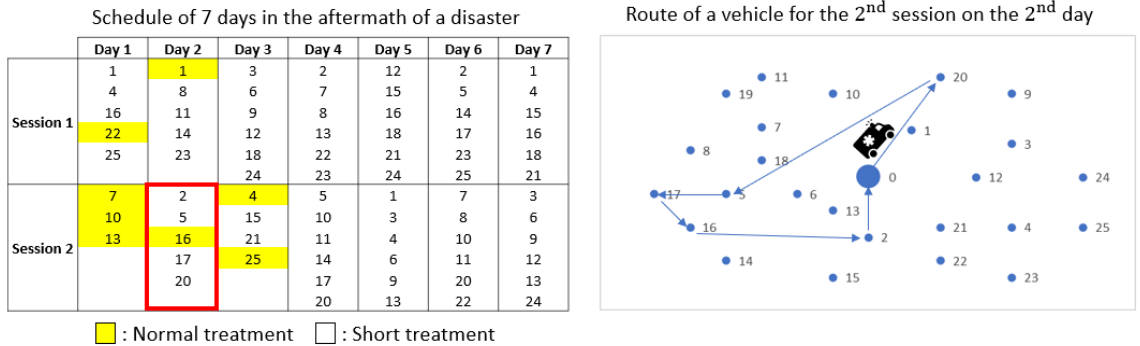


Figure 1: Scheduling and routing decisions in the aftermath of a disaster on a small network

Consequently, the main objective is to serve as many patients as it can be served in the dialysis center with the consideration of the preferences of the decision maker (e.g., short treatment limit, T_{max}^1 , T_{max}^2) and also maximize the service quality with the secondary objectives. Therefore, scheduling and routing decisions must be taken jointly to balance the aforementioned aspects.



CHAPTER IV

MATHEMATICAL MODEL

We formulate a mixed-integer linear programming (MILP) model for the integrated scheduling and routing problem described above. The formulation is as follows.

Sets

P set of patients; $p \in P = \{1, \dots, p\}$

N set of nodes; $n \in N = \{1, \dots, p, p+1\}$ ($p+1$: dialysis center)

D set of treatment types; $d \in D$ ($d=1$ for normal and $d=2$ for short treatment types)

B set of sessions in a day; $b \in B$

T set of days in a period; $t \in T$

V set of vehicles; $v \in V$

Parameters

S_p Number of days passed after the last treatment of patient p

α_{pd} Number of days that patient p can wait after treatment type d

C_{tb} Maximum number of patients that can be treated with normal treatment on session b of day t

z_d Capacity needed for treatment type d ($z_1 = 1$ for normal treatment, $z_2 = 0.5$ for short treatment)

L Maximum number of short treatment that a patient can be treated (i.e., short treatment limit)

R_{ij} Travel time of arc (i, j)

W_v Maximum number of people that can be assigned to vehicle v

T_{max}^1 Maximum time that a patient can spend in a vehicle

T_{max}^2 Maximum travel time of a vehicle

F' Bound for scaling the sum of the vehicles required each day

X'_1 Bound for scaling the total number of normal treatments

X'_2 Bound for scaling the total number of short treatments

R' Bound for scaling the total route duration over the planning horizon

f_p Penalty of transfer of patient p

γ Penalty of usage of a vehicle

β_{pd} Penalty of applying treatment type d to patient p

λ Penalty of unit travel time

Decision Variables

$X_{pbt d}$ 1 if patient p is scheduled to a session b on day t for treatment type d

U_{pd} 1 if patient p is treated with treatment type d in its first treatment

Y_p 1 if patient p is transferred

V_{ptd} 1 if patient p is covered with treatment type d at day t

Z_{vbtij} 1 if vehicle v travels arc (i, j) for session b on day t

$S_{vbt p}$ 1 if vehicle v serves patient p for session b on day t

A_{vbt} 1 if vehicle v is used for session b on day t

$H_{vbt p}$ Auxiliary integer variable for subtour elimination

F_t Maximum number of vehicles used for serving sessions of day t

$$\begin{aligned} \min \quad & \sum_p^P f_p \frac{Y_p}{p} + \sum_t^T \gamma \frac{F_t}{F'} + \sum_p^P \sum_b^B \sum_t^T \beta_{p2} \frac{X_{pbt2}}{X'_2} + \sum_p^P \sum_b^B \sum_t^T \beta_{p1} \frac{X_{pbt1}}{X'_1} \\ & + \sum_v^V \sum_b^B \sum_t^T \sum_i^N \sum_j^N \lambda \frac{R_{ij} Z_{vbtij}}{R'} \end{aligned} \quad (1)$$

$$\text{s.t.} \quad \sum_b^B \sum_{t=0}^{\alpha_{p1}-S_p} X_{pbt d} \geq U_{pd} \quad \forall p \in \mathcal{P}, d \in \mathcal{D} \quad (2)$$

$$\sum_d^D U_{pd} = 1 - Y_p \quad \forall p \in \mathcal{P} \quad (3)$$

$$\sum_{\tau=t-\alpha_{pd}+1}^t \sum_b^B X_{pb\tau d} \geq V_{ptd} \quad \forall p \in \mathcal{P}, d \in \mathcal{D}, t = \alpha_{pd} - 1, \dots, T \quad (4)$$

$$\sum_d^D V_{ptd} = 1 - Y_p \quad \forall p \in \mathcal{P} \quad (5)$$

$$\sum_b^B \sum_t^T X_{pbt2} \leq L \quad \forall p \in \mathcal{P} \quad (6)$$

$$\sum_p^P \sum_d^D z_d X_{pbt d} \leq C_{tb} \quad \forall t \in \mathcal{T}, b \in \mathcal{B} \quad (7)$$

$$\sum_b^B \sum_d^D X_{pbt d} \leq 1 - Y_p \quad \forall p \in \mathcal{P}, t \in \mathcal{T} \quad (8)$$

$$\sum_d^D X_{pbt d} = \sum_v^V S_{vbt p} \quad \forall p \in \mathcal{P}, b \in \mathcal{B}, t \in \mathcal{T} \quad (9)$$

$$\sum_p^P S_{vbt p} \leq W_v \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (10)$$

$$\sum_j^N Z_{vbt ji} = \sum_j^N Z_{vbt ij} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, i \in \mathcal{P}, i \neq j \quad (11)$$

$$H_{vbt i} - H_{vbt j} + |P| Z_{vbt ij} \leq |P| - 1 \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, i \in \mathcal{P}, j \in \mathcal{P}, i \neq j \quad (12)$$

$$\sum_i^P \sum_j^N R_{ij} Z_{vbt ij} \leq T_{max}^1 \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (13)$$

$$\sum_i^N \sum_j^N R_{ij} Z_{vbt ij} \leq T_{max}^2 \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (14)$$

$$\sum_i^P S_{vbt i} \leq |P| A_{vbt} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (15)$$

$$\sum_v^V A_{vbt} \leq F_t \quad \forall b \in \mathcal{B}, t \in \mathcal{T} \quad (16)$$

$$\sum_j^P Z_{vbt(p+1)j} = A_{vbt} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (17)$$

$$Z_{vbtij} + Z_{vbtji} = 0 \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, i \in \mathcal{N}, j \in \mathcal{N}, i = j \quad (18)$$

$$2S_{vbt p} = \sum_j^N Z_{vbt p j} + \sum_j^N Z_{vbt j p} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, p \in \mathcal{P} \quad (19)$$

$$F_t \geq 0 \text{ and integer} \quad \forall t \in \mathcal{T} \quad (20)$$

$$Y_p \in \{0, 1\} \quad \forall p \in \mathcal{P} \quad (21)$$

$$U_{pd} \in \{0, 1\} \quad \forall p \in \mathcal{P}, d \in \mathcal{D} \quad (22)$$

$$V_{ptd} \in \{0, 1\} \quad \forall p \in \mathcal{P}, t \in \mathcal{T}, d \in \mathcal{D} \quad (23)$$

$$A_{vbt} \in \{0, 1\} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T} \quad (24)$$

$$X_{pbtd} \in \{0, 1\} \quad \forall p \in \mathcal{P}, b \in \mathcal{B}, t \in \mathcal{T}, d \in \mathcal{D} \quad (25)$$

$$S_{vbt p} \in \{0, 1\} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, p \in \mathcal{P} \quad (26)$$

$$H_{vbt p} \geq 0 \text{ and integer} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, p \in \mathcal{P} \quad (27)$$

$$Z_{vbtij} \in \{0, 1\} \quad \forall v \in \mathcal{V}, b \in \mathcal{B}, t \in \mathcal{T}, i \in \mathcal{N}, j \in \mathcal{N} \quad (28)$$

This model has multi-objectives. The objective function (1) minimizes weighted sum of the ratio of transferred patients, the sum of the vehicles required each day, the number of short treatments, the number of normal treatments and the total travel time respectively in decreasing hierarchical order. Therefore, the primary objective is minimizing the number of transferred patients, whereas secondary

objectives maximize the effectiveness of solutions in the hierarchical order stated above. The weighted sum method is a frequent approach applied in multi-objective optimization due to its simplicity. Weights of objectives are determined according to the importance of each objective to the decision maker. In this study, the weighted sum method is selected to distinguish the hierarchy among objectives. However, objectives are on various scales. A methodology that is applied to scale each objective function's value between 0 and 2, is explained in Section 4.1. For the primary objective of the mathematical model, no bound for scaling is necessary. The reason is that the primary objective results in a value between 0 and 1 since it is the rate of patients transferred. Then, scaled values of each objective function are multiplied with the respective weights decided according to the preference of the decision maker.

Constraints (2) and (3) are for the scheduling of the first treatment of patients after the disaster. Constraints (2) enable the assignment of the first treatment regarding the number of days passed after the last treatment of a patient. Constraints (3) ensure that if patients are not transferred then they have to be assigned to treatment after the disaster. Constraints (4) and (5) are for the scheduling of treatments except for the first treatments of patients. Constraints (4) are utilized to provide a treatment type to patients during the period. Constraints (5) specify that if patients are not transferred then each day, patients must be covered with a treatment type. Constraints (6) limit the number of short treatments that a patient can receive over the planning horizon. Constraints (7) define the capacity limitation of a session in terms of the maximum number of patients that can be treated with a normal treatment type. Constraints (8) prevent transferred patients to be included in the schedule of the dialysis center. Constraints (9) ensure that if a patient is treated in a session, then a vehicle must bring that patient for that session. Constraints (10) limit the number of patients that can travel in a vehicle. Constraints (11) are node balance constraints. Constraints (12) are subtour elimination constraints. Constraints (13) restrict the maximum time spent in a vehicle

for a patient. Constraints (14) restrict the maximum travel time of vehicles. Constraints (15) specify that if no patient is served with a vehicle then that vehicle will not be used. Constraints (16) define the number of vehicles required each day for serving sessions of the day. Constraints (17) specify if a vehicle travels from the dialysis center to a patient, then the vehicle is used. Constraints (18) prevent a node to travel to itself. Constraints (19) specify if a patient is served, a vehicle must travel to that node and also must leave from that node. Lastly, constraints (20)-(28) define the domains of variables.

4.1 The Scalarization of the Objectives in the Objective Function

Each objective results in different scales and without pre-processing, the value of each objective cannot be known. Therefore to reflect and preserve the hierarchical order of penalty weights, each objective value is scaled between 0 and 2 as follows. For the scalarization, good enough scaling values of the objectives for the problem are found by applying three sub-models that have the same constraints as the mathematical model, but different objective functions. Therefore, three sub-models that have hierarchical orders between each of their terms in the objective functions are developed. The penalty weights of the main mathematical model are the same as the sub-models. With respective hierarchical order of objectives, the penalty values of f_p , γ , β_{p2} , β_{p1} and λ are 100,000, 1,000, 100, 50 and 1. After, solving the three sub-models, we use the values resulting from the sub-models to scale the objectives of the main mathematical model by dividing each objective by the respective scaling value. We limit the computation time of each sub-model to 5 minutes. Since the sub-models may not find the maximum values for the objectives, the objectives of the main mathematical model are scaled between 0 and 2 and then multiplied with the penalty weights. Below, the objective function of each sub-model is presented.

$$\min \quad \sum_p^P f_p \frac{Y_p}{p} + \sum_t^T \gamma F_t \quad (29)$$

$$\min \quad \sum_p^P f_p \frac{Y_p}{p} + \sum_p^P \sum_b^B \sum_t^T \beta_{p2} X_{pbt2} + \sum_p^P \sum_b^B \sum_t^T \beta_{p1} X_{pbt1} \quad (30)$$

$$\min \quad \sum_p^P f_p \frac{Y_p}{p} + \sum_v^V \sum_b^B \sum_t^T \sum_i^N \sum_j^N \lambda R_{ij} Z_{vbtij} \quad (31)$$

The first sub-model is solved with the objective function in equation (29). Since the first and second objectives of the mathematical model are minimized, the candidate scaling values for the third, fourth and fifth objectives are denoted. Then, the second sub-model is solved with the objective function in equation (30). Since the first, third and fourth objectives of the mathematical model are minimized, the candidate scaling values for the second and fifth objectives are denoted. Lastly, the third sub-model is solved with the objective function in equation (31). Then, since the first and fifth objectives of the mathematical model are minimized, the candidate scaling values for the second, third and fourth objectives are denoted.

Finally, after solving the three sub-models, two candidate scaling values for the second, third, fourth and fifth objectives of the mathematical model are obtained. Then, the maximum of two candidate scaling values is determined to be used in the mathematical model as the scaling value of the respective objectives in the objective function (i.e., F' , X'_2 , X'_1 , R'). An example of the scalarization and the weighted sum of the objectives are presented in Appendix.

CHAPTER V

SOLUTION METHODOLOGY

In this chapter, we present three heuristics which are the constructive heuristic explained in Section 5.1 and the matheuristics SO and MO explained in Section 5.2.

5.1 Constructive Heuristic

In this section, a constructive heuristic for the specified problem is described. In the aftermath of a disaster, fast decision-making is important. Therefore we develop a heuristic that provides a feasible solution in a short time considering the characteristics of the problem. The constructive heuristic is decomposed into three main phases. In Figure 2, the flow of the phases is represented. In the first phase, the patients who will be served in a day are decided. In the second phase, the assignment of the day's patients into one of two sessions and the decision of assigning which treatment type to patients are made. Phases 1 and 2 are executed for each day of the planning horizon and treatment schedules are formed. Lastly, in the third phase, the vehicle routes of each session are constructed.

There are various interrelated decisions to be taken about the scheduling of the dialysis center and the routing of patients served in the dialysis center. Therefore, the strategic insights observed from the results of the mathematical model are considered while developing the constructive heuristic. For instance, the selection of patients to be served during the planning horizon directly affects the number of vehicles used each day and the travel time of the vehicles. The reason is if the patients selected to be served are located in distinct areas, due to the travel and ride time limits, the length and size of the routes increase sharply. Besides, the same patient pairs or more patients are observed to be in the same vehicle routes. Since the locations of those patients are close to each other, they are assigned to

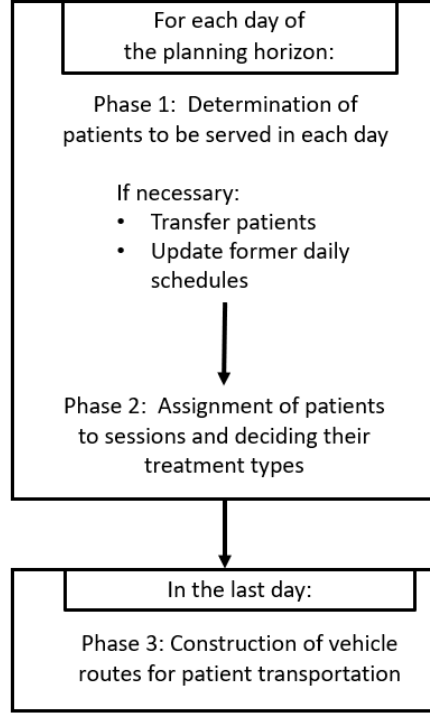


Figure 2: Flowchart of the constructive heuristic

the same sessions and vehicle routes over the planning horizon. In addition, when the number of short treatments provided during the planning horizon and the short treatment limit increase, the number of patients transferred decreases. The selection of patients to be served each day and the vehicle routes constructed over the planning horizon are affected by the treatment type decision of the patients. Hence, within the constructive heuristic, we develop several strategies to expand the solution space in the selection of the daily patients to be served (i.e., in Phase 1) for a wide exploration. Moreover, different capacity allocation options to decide on how many normal and short treatment types to allocate in a session (i.e., given as parameters at the start of the heuristic), are applied during the decision-making to improve the solution quality. In our heuristic, we assume that the patients will be treated on the last day of the treatment duration when they get a new treatment on the planning horizon. For instance, a patient receiving a short treatment on the first day must revisit the dialysis center exactly on the third day to receive treatment. Therefore, if the last treatment of a patient is short treatment and the value of S_p equals two, or if the last treatment of a patient is normal treatment and

the value of S_p equals three, that patient must be either served in that specific day or must be transferred. Due to this assumption, more patients may be transferred compared to the optimal solution, but it simplifies the problem being dealt with. Also, we assume there are at most two sessions in a day.

In this problem, the total service capacity of a session is equal to the number of machines, and it is known. However, the capacity allocation among normal and short treatment types is unknown. In Figure 3, five representative capacity allocation options for a dialysis center with four machines are illustrated. In a dialysis center with a session capacity of four machines (i.e., four normal treatments), from four to eight patients can be treated without exceeding the session capacity with the multiple treatment types considered.

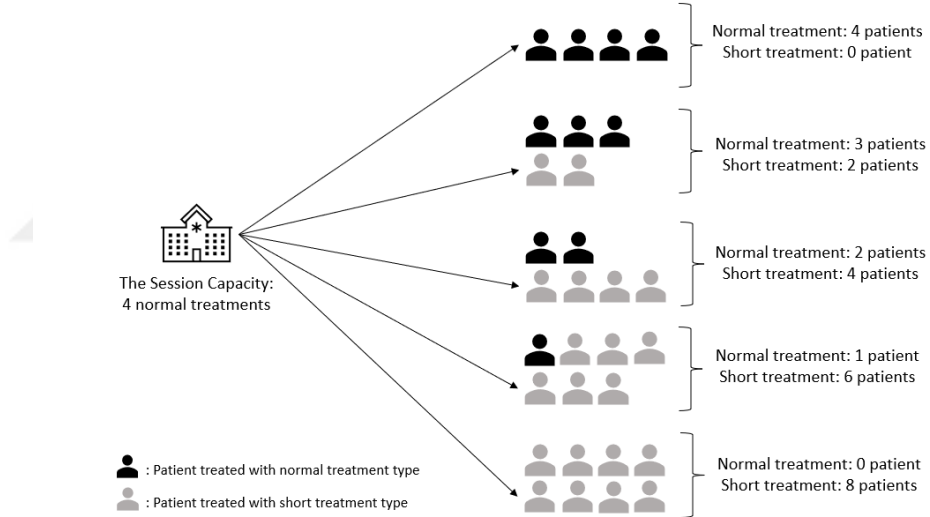


Figure 3: An example capacity allocation in a session with 4 machines

Before starting Phase 1, the capacity allocation decisions among normal and short treatment types are declared as parameters. θ_s is the capacity allocation parameter that declares the number of patients planned to receive short treatment in a session, whereas, θ_n is the capacity allocation parameter that declares the number of patients planned to receive normal treatment in a session. Assigning two patients with short treatment and three patients with normal treatment is

an example of the capacity allocation decisions taken for the dialysis center presented in Figure 3 (e.g., $\theta_n = 3$, $\theta_s = 2$). The constructive heuristic arranges the schedules according to the declaration of the capacity allocation parameters by the decision maker. However, setting daily capacity allocation parameters is not straightforward. Therefore, within the constructive heuristic, all capacity allocation options are applied and the best resulting solution is selected. In addition, over the planning horizon, there might be infeasible capacity allocation given to a day due to the short treatment limit of the patients or accumulation of the patients on the same day. For such cases, in Phase 1, the constructive heuristic may deviate from the capacity allocation parameters and assign more or less normal treatment capacity than the capacity allocation decision taken before starting Phase 1, to serve patients of the day. Therefore, the constructive heuristic assimilates the scheduling of the patients to the capacity allocation parameters stated. For simplicity, we take the same capacity allocation parameters (i.e., θ_n , θ_s) for each day of the planning horizon. If the capacity allocation parameters are two for the normal treatment and four for the short treatment, then we expect to have the same or a similar number of patients and treatment types to see in daily schedules over the planning horizon. The constructive heuristic runs iteratively for all capacity allocation parameters. The first combination of the capacity allocation is assigning only normal treatments as much as the session capacity and we continue to solve the constructive heuristic by decreasing 1 patient from the capacity allocated to normal treatment and adding 2 patients to the capacity allocated to short treatment until we reach the option with assigning only short treatments. For instance, for the dialysis center in Figure 3, the constructive heuristic runs five times since it considers five different capacity allocations as represented in the figure and reports the best solution.

5.1.1 Phase 1: Determination of daily patients to be served

In this problem, times of the patients' last dialysis sessions (i.e., S_p) can be one, two or three days before the disaster. Therefore, in the first three days of the

planning horizon, the patients selected to be served in the dialysis center are decided. On the fourth day of the planning horizon, if a patient does not get any treatment, the patient is decided to be transferred. Apart from the first treatment after the disaster, if the previous treatment of a patient is normal treatment, then the patient must revisit the dialysis center on the third day after the previous treatment. If the previous treatment of a patient is short treatment, then the patient must revisit the dialysis center on the second day after the previous treatment. In Figure 4, the days and types of treatments received by a patient over seven days of a planning horizon are represented. Since the value of S_p equals three, the patient is treated on the first day with normal treatment. Then, the patient receives a short treatment on the fourth day (i.e., three days passed after the previous normal treatment). Finally, on the sixth day, the patient receives a short treatment (i.e., it has been two days after the previous short treatment was received). To sum up, the most important part is to decide on the days of the first treatments of patients since the days of future treatments are decided according to the previous treatment type of patients. For deciding the days of the first treatments, the constructive heuristic regards the S_p values of the patients. At the beginning of each day, a daily candidate patients list is formed according to four variants of the candidate patient selection rule which we call the S_p strategies described next.

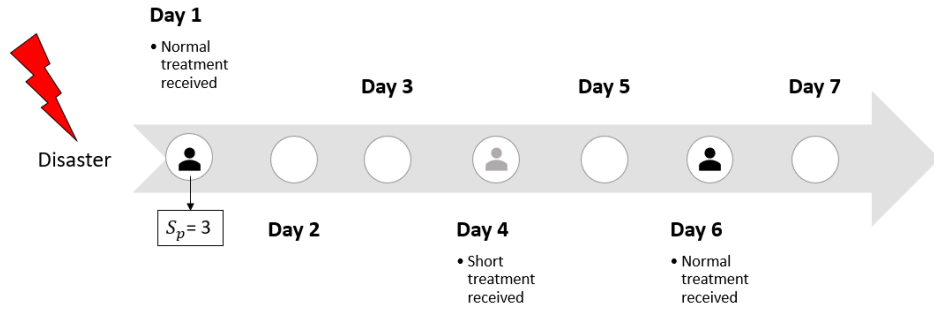
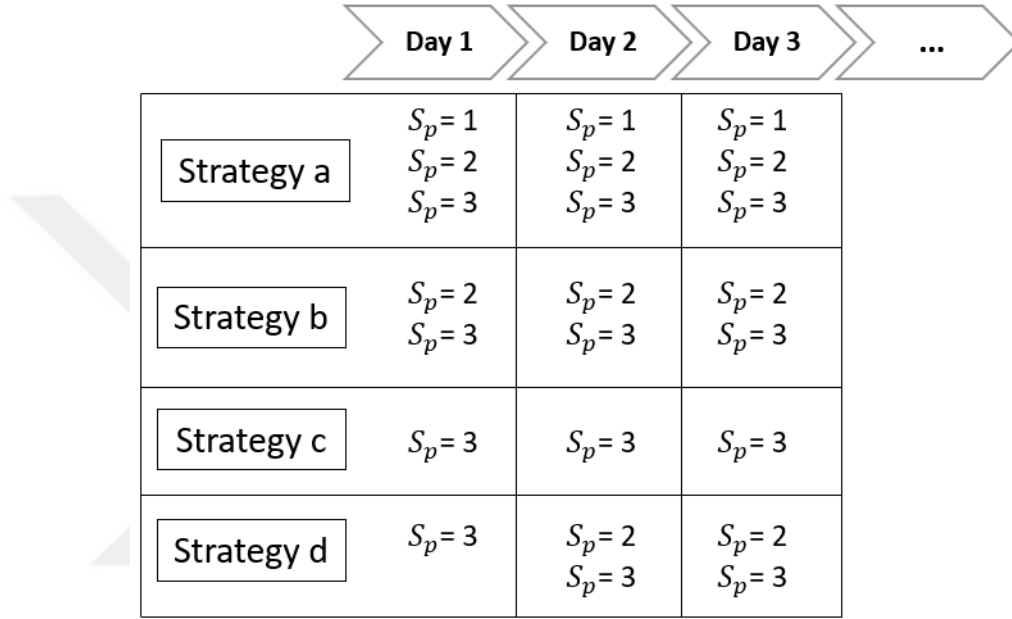


Figure 4: An example schedule of a patient for a seven days of planning horizon

S_p Strategies While determining the daily patients to serve after the disaster, all patients who must revisit the center due to their previous treatments provided

in the dialysis center, are added directly to the daily candidate patient list of the respective day. In addition to current patients, for deciding which patients to add to the list of the first three days, we define four S_p strategies. In Figure 5, for receiving their first treatments, patients who are eligible to be included in the daily candidate list under different S_p strategies are represented for the first three days of the planning horizon.



	Day 1	Day 2	Day 3	...
Strategy a	$S_p = 1$ $S_p = 2$ $S_p = 3$	$S_p = 1$ $S_p = 2$ $S_p = 3$	$S_p = 1$ $S_p = 2$ $S_p = 3$	
Strategy b	$S_p = 2$ $S_p = 3$	$S_p = 2$ $S_p = 3$	$S_p = 2$ $S_p = 3$	
Strategy c	$S_p = 3$	$S_p = 3$	$S_p = 3$	
Strategy d	$S_p = 3$	$S_p = 2$ $S_p = 3$	$S_p = 2$ $S_p = 3$	

Figure 5: Candidate patient lists of S_p strategies on the first three days

- **Strategy a:** In this strategy, all patients are candidates to be served in the first three days to receive their first treatments.
- **Strategy b:** In this strategy, only the patients with S_p values of two or three are considered candidate patients to be served in the first three days to receive their first treatments. In Figure 5, a patient whose last treatment is a day before the disaster (i.e., $S_p = 1$ on Day 1), can be selected as a candidate patient on the second or third day to receive her/his first treatment.
- **Strategy c:** In this strategy, only the patients with S_p values of three are considered candidate patients to be served in the first three days to receive their first treatments. In Figure 5, a patient whose last treatment is a day

before the disaster (i.e., $S_p = 1$ on Day 1), can be selected as a candidate patient on the third day to receive her/his first treatment.

- **Strategy d:** In this strategy, on the first day, only the patients with S_p values of three are considered as candidate patients to receive their first treatments. On the second and third days, only the patients with S_p values of two or three are considered candidate patients to be served to receive their first treatments. In Figure 5, a patient whose last treatment is two days before the disaster (i.e., $S_p = 2$ on Day 1), can be selected as a candidate patient on the second day to receive her/his first treatment.

By applying various S_p strategies (i.e., multi start with different strategies), we can achieve different scheduling and routing solutions. In the end, the solution of the best resulting strategy is selected considering the primary and secondary objectives. As declared, the decisions of scheduling and routing are interdependent and the decisions taken for the scheduling part have a direct effect on the routing decisions. Therefore locations of patients selected to be served are also important in terms of minimizing the sum of the vehicles required each day and the total travel time (i.e., secondary objectives) which are explained next.

Location Strategies While deciding on the patients to be served, we develop two strategies, which we call location strategies, to decrease the number of daily candidate patients. For instance; if the capacity allocation parameters are two for the normal treatment and four for the short treatment for the dialysis center represented in Figure 3, the number of daily patients served is six. Therefore, six patients must be selected from the daily candidate patient list. Location strategies 1 and 2 choose among the candidate patient list defined via S_p strategy by considering the travel times between the nodes in the network.

- **Strategy 1:** In this strategy, among the candidate patients selected according to their S_p values, the patients who will be served on a day are selected

according to their proximity to the dialysis center. Therefore, since there are two sessions in a day, candidate patients who have the shortest travel times to the dialysis center are selected as much as the capacity allocation parameters $2\theta_s$ and $2\theta_n$ if a feasible allocation exists with such parameters considering the patient characteristics in the candidate list (e.g., their remaining short limits). Patients who have already received treatment on previous days are prioritized in the selection of daily patients compared to the patients who do not receive any treatment over the planning horizon.

- **Strategy 2:** In this strategy, the average value of the three smallest travel times from a patient to three other patients in the candidate list is calculated for each patient on the candidate list. Then, candidate patients who have the shortest average times are selected to be served on that day, as much as the capacity allocation parameters $2\theta_s$ and $2\theta_n$ if a feasible allocation exists with such parameters considering the patient characteristics in the candidate list (e.g., their remaining short limits). Patients who have already received treatment on previous days are prioritized in the selection of daily patients compared to the patients who do not receive any treatment over the planning horizon.

Transfer mechanism

After the selection of daily patients, due to the limited capacity, some patients served in the previous days may be unserved on the day they must get treatment. For such patients, since the dialysis center cannot provide treatment on time, they must be transferred. Therefore, a transfer operation is applied according to location strategy 1 or 2. The minimum capacity for serving all patients that must receive treatment on that day is calculated (i.e., allocating short treatment to patients who can receive it). If this minimum capacity is greater than the session capacity, transfers occur. The number of transfers is calculated according to the minimum capacity, and transfers are realized for the patients who cannot receive

short treatment due to the short treatment limit. The reason for transferring such patients is that in the next treatments since they can receive the short treatment type, they will consume less capacity on a session. Among the patients who cannot receive short treatment, according to the location strategy, the patients are transferred. For Strategy 1, transferred patients are selected among the patients who cannot receive short treatment and who are farthest from the dialysis center. For Strategy 2, transferred patients are selected among the patients who cannot receive short treatment and who have the largest average times. If there have to be more transfers than the number of patients who cannot receive short treatment, after transferring the patients who cannot receive short treatment, then the rest of the transfers will be decided among the patients who can receive short treatment according to the respective location strategy. After deciding on the patients who will be transferred, the daily schedules in which transferred patients receive treatments are updated.

5.1.2 Phase 2: Assignment of patients to sessions and deciding their treatment types

In the first phase, the patients served in a day are determined. In the second phase, patients are assigned to the first or second session of the day and the aim is to assign patients who are close to each other in the same session because while assigning the patients to the sessions, their treatment types are also decided concurrently. While selecting the daily patients in the first phase, the algorithm ensures to include patients who can get a short treatment as the same or a similar number to the daily short capacity ($2\theta_s$). If there are fewer patients than the value of $2\theta_s$, all of the patients who can get short treatments are considered to be served as decided in the first phase. Firstly, in the second phase of the constructive heuristic, the patients who can receive short treatments are assigned to one of two sessions. After the assignment of the short patients, patients who receive normal treatment are assigned. Short patients must be assigned as pairs since they share the same machine. Below, the assignment of sessions and treatment types are

explained under various conditions that may arise during the assignment process.

Terminology

m : The number of patient who can receive a short treatment in the daily patient list

u : The number of patients in the daily patient list

θ_s : The capacity allocation parameter of a session for short treatment (i.e., the number of patients planned to receive short treatment in a session)

θ_n : The capacity allocation parameter of a session for normal treatment (i.e., the number of patients planned to receive normal treatment in a session)

θ_t : The daily treatment capacity ($\theta_s + 2\theta_n$)

Methodology

- If the number of patients served in a day is one or two, patients are assigned to the first session of the day with a normal treatment assignment. We assume that there are at least 2 machines in the dialysis center.
- If $m < 4$ or $2\theta_s < 4$: That means two short patients for each session cannot be assigned or $2\theta_s$ is less than four patients.
 - If $m < 2$: In such a case, the constructive heuristic finds the farthest two patients and assign them to the 1st and 2nd sessions respectively. If they can receive short treatment, short treatment will be assigned to them. Otherwise, normal treatment will be assigned.
 - If $m \geq 2$: The heuristic finds the closest patients who can both receive short treatment and assign them to the first session as the short treatment patients. Then, the farthest node to the nodes in the first session is assigned to the second session and allocated with short treatment if it is eligible.

After that point, for both conditions $m < 2$ and $m \geq 2$, until all of the daily patients will be served, the heuristic finds the closest patient pairs and tries to assign them in the same session. If the session capacity is not sufficient, heuristic finds the next closest patient pair. If both of the nodes in the pair are not assigned to any sessions, they will be assigned to the session in which the nearest node exists to one of the nodes in the pair if there is sufficient capacity. They will get short treatments if they are eligible to get a short treatment.

- If $m \geq 4$ or $2\theta_s \geq 4$: The heuristic finds the closest patients who can both receive short treatment and assign them to the first session as the short treatment patients. Then, the farthest short node (i.e., a patient who can receive short treatment) to the nodes in the first session is assigned to the second session and allocated with short treatment. Then, the closest short node to the node in the second session is assigned to the second session with a short treatment. Therefore, two short patients are assigned to both sessions.
- Else: That means, the number of patients who can receive short treatment can be greater than two in a session. Then, until we serve as much as the value of θ_s or short patients as much as the value of m is added to the sessions, the heuristic finds the closest short patients pairs and tries to assign them in the same session. If both of the nodes in the pair are not assigned to any sessions, they will be assigned to the session in which the nearest node exists to one of the nodes in the pair. They will get short treatments.
 - If $\frac{m}{2} + (u - m) = \theta_t$ or $\theta_s + (u - 2\theta_s) > \theta_t$: In this condition, assigning short treatment to all patients who can receive short treatment and assigning normal treatment to the rest of the daily patients will be equal to the daily treatment capacity. Also, in this condition, assigning short treatment as much as the $2\theta_s$ and assigning normal treatment to

the rest of the daily patients exceeds the daily treatment capacity. If one of the conditions exists, until all of the daily patients will be served, the heuristic finds the closest patients pairs and tries to assign them in the same session. If both of the nodes in the pair are not assigned to any sessions, they will be assigned to the session in which the nearest node exists to one of the nodes in the pair. They will get short treatments if they are eligible to get a short treatment. During the assignment, if one normal patient is not added to any session and the remaining capacity for both sessions is 0.5, the patient will be transferred.

- Else: Short patients are assigned to sessions. Until all of the daily patients will be served, the heuristic finds the closest patient pairs and tries to assign them in the same session. If the session capacity is not sufficient, the heuristic finds the next closest patient pair. If both of the nodes in the pair are not assigned to any sessions, they will be assigned to the session in which the nearest node exists to one of the nodes in the pair if there is sufficient capacity. Normal treatment is provided to patients.

At the end of the phase 2, the patients of each session and their treatment types are decided.

5.1.3 Phase 3: Construction of vehicle routes for patient transportation

Lastly, after the decision of which patients to serve (i.e., decided in phase 1), their treatment types and their schedules during the planning horizon (i.e., decided in phase 2), the transportation of patients must be considered. We use a two-phase method, which is the route first cluster second method to construct the routes. Since the patients of each session are known, a giant route that involves all the patients served in a session is constructed. We use a TSP heuristic developed by Google OR-Tools to construct giant routes for each session [32]. Then, the giant

route is partitioned into clusters (i.e., vehicle routes). While constructing the vehicle routes of a session, the giant route is traversed by the order and divided into vehicles by regarding the vehicle capacity, travel time (T_{max}^2) and ride time (T_{max}^1) limits.

5.2 *Matheuristics*

The second heuristic is decomposed into two phases. In the first phase, an integer programming model is solved to take the scheduling decisions of the dialysis center. In the second phase, routing decisions are considered. Even though routing of the patients is not included in the scheduling part, a problem characteristic that impacts the routing decisions is considered. In our problem, the patients who are served in the same session are mostly close to each other to have lower values on the sum of the vehicles required each day and the total travel time which are minimized in the objective function of the mathematical model. Therefore, given this consideration, to improve the service quality in terms of the transportation of patients, we impose a travel time limit (K) between the patients who will be served in the same session. By imposing that, we aim to schedule patients which are close to each other in the same session.

In the first phase, the scheduling model decides on either assigning a patient to a schedule among the set of prespecified schedules or transferring that patient. The schedules are consisting of the days of treatments and the capacity allocated to the treatment (i.e., the treatment type). Since there are extensive schedule options, we form the set of schedules with the assumption that the patients receive treatment on the last day of the treatment duration. For instance; if a patient is treated with a normal treatment type, then the patient must revisit the dialysis center after 3 days passed. Similarly, if a patient is treated with a short treatment type, then the patient must revisit the dialysis center after 2 days passed. The set of schedules are changing depending on the number of days on the planning horizon and the short treatment limit assigned to the planning horizon. In Figure

6, the set of schedules is formed for seven days when the short treatment limit is two. There are 17 schedules formed for such a problem. In the schedules between 1 and 4, patients are treated on the third day since their S_p values equal to one. Therefore, patients with S_p value of 1 are allowed to be assigned to a schedule from 1 to 4. Similarly, patients with S_p value of 2 are allowed to be assigned to a schedule from 5 to 10 and patients with S_p value of 3 are allowed to be assigned to a schedule from 11 to 17. For instance, a patient assigned to the first schedule receives normal treatments on the third and sixth days. When the number of days and value of the short limit increase, the size of the set increases. We develop two alternatives for the scheduling model. Below, we present the mathematical model that decides transferred patients, the treatment types, treatment days and the sessions in which patients are treated during the planning horizon.

Schedule	S_p	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	1	-	-	normal	-	-	normal	-
2		-	-	normal	-	-	short	-
3		-	-	short	-	normal	-	-
4		-	-	short	-	short	-	normal
5	2	-	normal	-	-	normal	-	-
6		-	normal	-	-	short	-	normal
7		-	normal	-	-	short	-	short
8		-	short	-	normal	-	-	normal
9		-	short	-	normal	-	-	short
10		-	short	-	short	-	normal	-
11	3	normal	-	-	normal	-	-	normal
12		normal	-	-	normal	-	-	short
13		normal	-	-	short	-	normal	-
14		normal	-	-	short	-	short	-
15		short	-	normal	-	-	normal	-
16		short	-	normal	-	-	short	-
17		short	-	short	-	normal	-	-

Figure 6: A set of schedules for 7 days with short treatment limit of 2

Sets

P set of patients; $p \in P$

B set of sessions in a day; $b \in B$

T set of days in a period; $t \in T$

S set of schedules; $s \in S$

Parameters

C_{tb} Maximum number of patients that can be treated with normal treatment type on session b of day t

h_{st} Capacity needed for a patient who served in day t of schedule s (1 for normal treatment, 0.5 for short treatment)

R_{ij} Travel time of arc (i,j)

K Maximum travel time limit between two patients in the same session

a_{st} 1 if day t is in schedule s

w_{ps} 1 if patient p is allowable to be assigned to schedule s

f_p A large penalty value for the transfer of patient p

Decision Variables

Y_p 1 if patient p is transferred

Z_{ps} 1 if schedule s is assigned to patient p

X_{pbt} 1 if patient p is served in session b of day t of schedule s

5.2.0.1 Alternative 1: Single Objective Model (SO)

In the Single Objective Model (SO), the objective function (29) includes only the primary objective which is minimizing the number of transferred patients.

$$\min \sum_p^P Y_p \quad (29)$$

5.2.0.2 Alternative 2: Multi Objective Model (MO)

In the Multi Objective Model (MO), the objection function (30) includes multiple objectives. The primary objective is minimizing the number of transferred patients and secondary objectives are minimizing the number of short treatments and the

number of normal treatments. Providing a short treatment is penalized twice as providing a normal treatment.

$$\min \quad \sum_p^P f_p Y_p + \sum_p^P \sum_b^B \sum_t^T 2X_{pbt2} + \sum_p^P \sum_b^B \sum_t^T X_{pbt1} \quad (30)$$

$$\text{s.t.} \quad \sum_s^S Z_{ps} = 1 - Y_p \quad \forall p \in \mathcal{P} \quad (31)$$

$$a_{st} Z_{ps} = \sum_b^B X_{pbt s} \quad \forall p \in \mathcal{P}, t \in \mathcal{T}, s \in \mathcal{S} \quad (32)$$

$$\sum_p^P \sum_s^S h_{st} X_{pbt s} \leq C_{tb} \quad \forall t \in \mathcal{T}, b \in \mathcal{B} \quad (33)$$

$$R_{ij} \sum_s^S X_{ibts} \leq K \sum_s^S X_{jbts} + R_{ij} (2 - \sum_s^S X_{ibts} - \sum_s^S X_{jbts}) \quad (34)$$

$$\forall i \in \mathcal{P}, j \in \mathcal{P}, b \in \mathcal{B}, t \in \mathcal{T}, i \neq j$$

$$Z_{ps} \leq w_{ps} \quad \forall p \in \mathcal{P}, s \in \mathcal{S} \quad (35)$$

$$Y_p \in \{0, 1\} \quad \forall p \in \mathcal{P} \quad (36)$$

$$Z_{ps} \in \{0, 1\} \quad \forall p \in \mathcal{P}, s \in \mathcal{S} \quad (37)$$

$$X_{pbt s} \in \{0, 1\} \quad \forall p \in \mathcal{P}, b \in \mathcal{B}, t \in \mathcal{T}, s \in \mathcal{S} \quad (38)$$

Constraints (31) prevent assignments of transferred patients to the schedules and ensure that a patient can be assigned to at most one schedule. Constraints (32) ensure if a day is included in the schedule assigned to a patient, that patient must be served in one of the sessions of that day. Constraints (33) are for the service capacity limitation of sessions. Constraints (34) limit the travel time between

two patients served in the same session. Constraints (35) define the allowance of a patient to be assigned to a schedule among the set of schedules. Constraints (36)-(38) define the domains of variables.

In the first phase, patients who get treatments during a session are decided. Therefore, in the second phase, the routing decisions are taken regarding the scheduling decisions determined in the first phase. The same methodology considered in phase 3 of the constructive heuristic is applied to construct the vehicle routes for all sessions.



CHAPTER VI

NUMERICAL STUDY

In this chapter, we evaluate the performance of the solution methodologies with multiple network sizes and under different parameter settings. Firstly, we present our key performance indicators (KPIs) for evaluating the performance of a solution (Section 6.1). Secondly, we describe our test instances and evaluate the solutions obtained from the mathematical model, the constructive heuristic and the matheuristics SO and MO for the test instances (Section 6.2). Lastly, we present a case study and evaluate the performance of the solution methodologies in the case study (Section 6.3).

6.1 Key performance indicators (KPIs)

We propose several KPIs to decision makers to evaluate the quality of the scheduling and routing solutions. In Table 1, the list and descriptions of KPIs are provided. In our mathematical model, each objective has a different scale than others. For each problem instance, to scale criteria in the objective function, each criterion is divided by the values obtained by the sub-models of that instance. Thus, instances have their own scalarization values. Therefore to compare the results of the solution methodologies among various problem instances, instead of the objective function, we define a metric called performance score (i.e., KPI 1). The performance score is the weighted objective function without scalarization and its calculation is declared in equation (39). Performance score consists of the weighted values of objectives in their hierarchical order. A low value for the performance score is better than the higher values since the objectives are to be minimized. The primary KPIs which are included in the objective function of the mathematical model and in the performance score are the number of transferred patients, the sum of the vehicles required each day, treatment score and the total travel time (i.e.,

KPIs 2-5). Treatment score (i.e., KPI 4) is a combined metric for the treatment types provided. Since providing a short treatment is penalized twice as providing a normal treatment, the treatment score is equal to the sum of the number of normal treatments (i.e., KPI 12) and twice the number of short treatments (i.e., KPI 11). The calculation of the treatment score is shown in the equation (40). A low valued treatment score is preferred and indicates a high quality of service in terms of the treatment type. In addition to the primal metrics, we evaluate the effectiveness of solutions by the maximum travel time, the maximum time spent in a vehicle, the maximum average time spent in the vehicle, the number of vehicles required, the number of routes, the number of patients who receive one, two, three or four short treatments during the planning horizon and the capacity utilization. These metrics show the service quality in terms of the treatment types (e.g., KPIs 4,11-17) and in terms of the transportation of the patients (e.g., KPIs 3,5-10) and overall effectiveness of the scheduling and routing decisions of the dialysis center (e.g. KPIs 1,2).

$$\begin{aligned}
\text{KPI 1: } & \sum_p^P f_p Y_p + \sum_t^T \gamma F_t + \sum_p^P \sum_b^B \sum_t^T \beta_{p2} X_{pbt2} + \sum_p^P \sum_b^B \sum_t^T \beta_{p1} X_{pbt1} \\
& + \sum_v^V \sum_b^B \sum_t^T \sum_i^N \sum_j^N \lambda R_{ij} Z_{vbtij}
\end{aligned} \tag{39}$$

$$\text{KPI 4: } \sum_p^P \sum_b^B \sum_t^T 2X_{pbt2} + \sum_p^P \sum_b^B \sum_t^T X_{pbt1} \tag{40}$$

Table 1: KPIs for evaluating the solutions

KPI No.	KPI	KPI Description
KPI 1	Performance score	Weighted score of hierarchical objectives stated as KPIs 2, 3, 4 and 5
KPI 2	Transfer number	Number of patients transferred
KPI 3	Sum of the vehicles required each day	Sum of the number of vehicles required each day over the planning horizon
KPI 4	Treatment score	Sum of the number of normal treatments and twice the number of short treatments
KPI 5	Total travel time	Total travel time of vehicles over the planning horizon
KPI 6	Maximum travel time	Maximum travel time of a route over the planning horizon
KPI 7	Maximum time spent	Maximum time spent in a vehicle over the planning horizon
KPI 8	Maximum of average time spent	Maximum of average time spent of a patient in the vehicles over the planning horizon
KPI 9	Number of vehicles	Minimum number of vehicles required to perform routing over the planning horizon
KPI 10	Number of routes	Total number of vehicle routes over the planning horizon
KPI 11	Number of short treatments	Number of short treatments provided over the planning horizon
KPI 12	Number of normal treatments	Number of normal treatments provided over the planning horizon
KPI 13	Number of patients with 1 short treatment	Number of patients who receive short treatment 1 time over the planning horizon
KPI 14	Number of patients with 2 short treatments	Number of patients who receive short treatment 2 time over the planning horizon
KPI 15	Number of patients with 3 short treatments	Number of patients who receive short treatment 3 time over the planning horizon
KPI 16	Number of patients with 4 short treatments	Number of patients who receive short treatment 4 time over the planning horizon
KPI 17	Capacity Utilization	Capacity needed for provided treatments divided by the total capacity of the planning horizon

6.2 Test instances

In this section, we describe our test instances and evaluate the performance of the mathematical model, the constructive heuristic and the matheuristics SO and MO. In Table 2, characteristics of the instances such as the patient size, days on the planning horizon, capacity of each session, short treatment limit, travel and ride time limits are provided for both test and case study instances as an overview. In our experiments, we use CPLEX with default solver parameters. Our mathematical model is coded with Java and solved on a computer with Intel Core i9-10920X CPU 3.5 GHz and 128 GB of RAM.

6.2.1 Test instances' description

We develop a small test instance to evaluate the performance of the mathematical model and proposed solution methodologies on a small problem network. A random network is selected from the Solomon instances to conduct analysis [33]. The network N1 is presented in Figure 7. In network N1, there are 25 patients assigned to a dialysis center and the dialysis center has 2 sessions during the day. In the test

Table 2: Instance details

Instance	# Patients	# Days	Capacity	L	T_{max}^2	T_{max}^1
1	25	7	3	3	244	244
2	25	7	3	3	90	72
3	25	7	3	3	60	48
4	25	7	3	2	244	244
5	25	7	3	2	90	72
6	25	7	3	2	60	48
7	25	7	2	3	244	244
8	25	7	2	3	90	72
9	25	7	2	3	60	48
10	25	7	2	2	244	244
11	25	7	2	2	90	72
12	25	7	2	2	60	48
13	42	14	10	3	210	210
14	42	14	10	3	90	72
15	42	14	10	3	60	48
16	42	14	7	4	90	72
17	42	14	7	4	60	48
18	42	14	7	3	90	72
19	42	14	7	3	60	48
20	42	14	4	3	90	72
21	42	14	4	3	60	48
22	42	14	4	3	90	72
23	42	14	4	3	60	48
24	64	14	10	4	210	210
25	64	14	10	4	90	72
26	64	14	10	4	60	48
27	64	14	10	3	210	210
28	64	14	10	3	90	72
29	64	14	10	3	60	48
30	64	14	7	4	90	72
31	64	14	7	4	60	48
32	64	14	7	3	90	72
33	64	14	7	3	60	48
34	64	14	7	4	90	72
35	64	14	7	4	60	48
36	64	14	7	3	90	72
37	64	14	7	3	60	48

instances, we consider a planning horizon of 7 days for the scheduling and routing decisions of chronic dialysis patients after an earthquake. In the dialysis center, there are 3 machines. Therefore, 3 normal treatments can be provided in each session. At most 6 people can be treated in a session if all of them receive short

treatments. The severity of an earthquake is considered via treatment capacity in a session. Due to the effects of the disaster, capacity can be lowered. The dialysis center has 6 vehicles with a capacity of carrying 6 passengers. Therefore, a large number of vehicles are available and vehicle capacity permits to transport all patients of a session in the same vehicle. In the results, the effects of different (i) session capacities, (ii) short treatment limits, (iii) travel time limits and maximum time spent in a vehicle limit are compared.

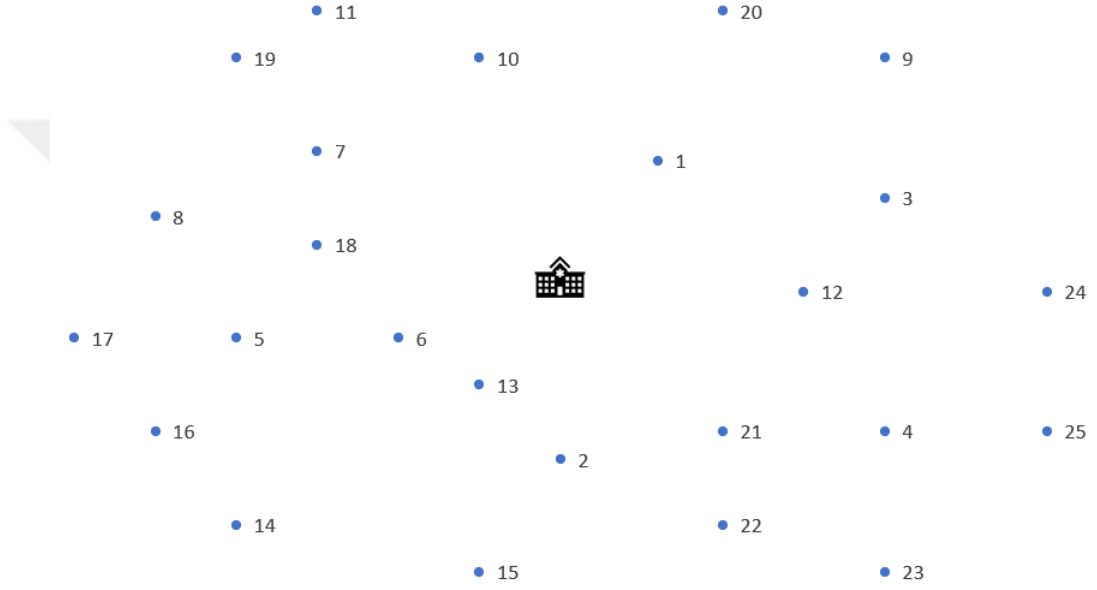


Figure 7: Network N1 with 25 patients

Euclidean distances are calculated using the latitude and longitude data of nodes. Euclidean distances divided by two are taken as the travel times. Travel times in minutes are rounded up to two decimals. T_{max}^1 and T_{max}^2 parameters are assigned according to the network characteristics as follows. In normal conditions, patients are regularly treated in their dialysis center which is close to their location. In the aftermath of a disaster, travel times may increase due to road conditions or farther patients can be assigned to the dialysis center. Each vehicle picks up the patients from their locations. At the end of the session, patients are carried back to their locations and vehicles return to the dialysis center. Therefore, the total travel time must be at most one and a half hours to avoid delays in the next

session. In addition, spending a long duration on a vehicle can affect the health of chronic dialysis patients. Therefore, we analyze several values for the total travel time limit T_{max}^2 , which are 60 minutes as a low T_{max}^2 value, 90 minutes as a high T_{max}^2 value and 244 minutes is determined as a large T_{max}^2 value decided for relaxation of T_{max}^2 and T_{max}^1 constraints. The maximum travel time between two nodes is multiplied by seven to achieve a large value for the network. The reason is that since the vehicle capacity is six and the vehicles depart from the dialysis center and return to the dialysis center, at most seven arcs are formed in a vehicle route. Their respective maximum time that a patient can spent in a vehicle T_{max}^1 values are set to 80% of the T_{max}^2 for the low and high T_{max}^2 values (i.e, 48 minutes of T_{max}^1 for 60 minutes of T_{max}^2 and 72 minutes of T_{max}^1 for 90 minutes of T_{max}^2). For the relaxation case, T_{max}^1 and T_{max}^2 are set to a large value (i.e, 244 minutes).

The number of days passed after the last treatment of patients (i.e., S_p) are changing among 1, 2 and 3 each having a probability of 32%, 32% and 36%. In Figure 8, the dispersion of the S_p values throughout the network is presented. The maximum number of short treatments is assumed to be changing between 2 per week for the low value of L and 3 per week for the high value of L .

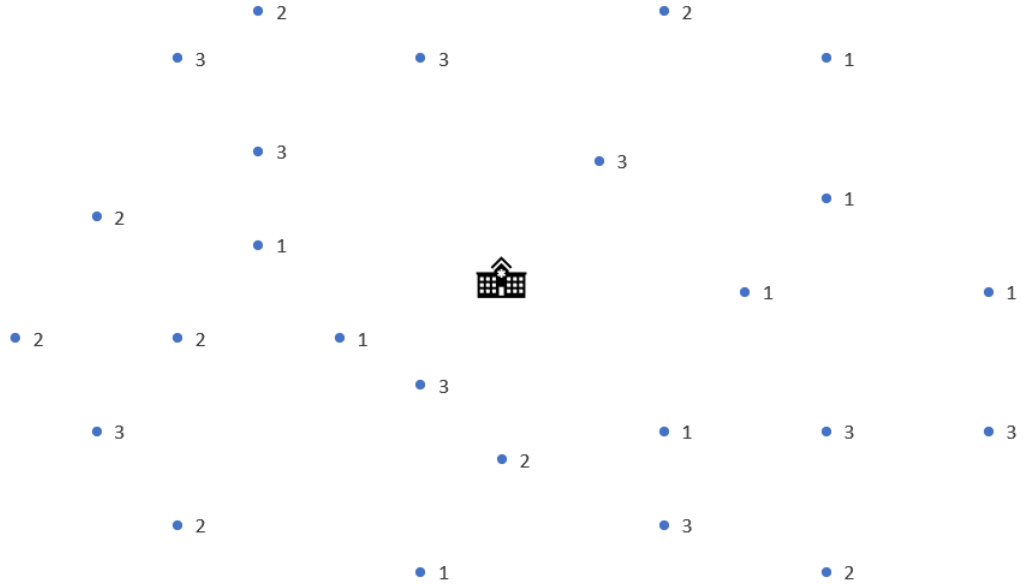


Figure 8: S_p of patients in the network N1

6.2.2 Results on test instances

Mathematical Model (CPLEX) Results We first evaluate the solution obtained from the mathematical model for small network N1. Table 3 represents the CPLEX results and metrics for the network with 25 patients. There are 12 instances with different characteristics such as different capacity levels (i.e., the severity of disaster), short treatment limits, T_{max}^1 and T_{max}^2 limits. Parameters of the mathematical model to penalize the objectives are determined according to the hierarchy among the objectives. Their values are applied in all of the instances of this thesis. With the hierarchical order of objectives, their penalty values of f_p , γ , β_{p2} , β_{p1} and λ are 100,000, 1,000, 100, 50 and 1 respectively. The computation time limit on CPLEX is two hours for the mathematical model and 5 minutes for each sub-model (i.e., 15 minutes in total for three sub-models). In four of the instances with higher short treatment limits and higher T_{max}^1 and T_{max}^2 limits, optimal solutions are obtained (e.g., Instances 1, 2, 7, 8). In Instance 6, a high optimality gap is achieved (i.e, 31.9%). For the rest of the instances, the optimality gaps are less than 10%.

Firstly, as our finding, due to the severity of the disaster when the capacity gets lower, the number of transferred patients increases. In the instances with higher capacity and higher short limits, the number of patients transferred is one (e.g., Instances 1-3). However, when the capacity is decreased by one unit, the number of transfers increases to nine patients (e.g., Instances 7-9). Similarly, with a lower short limit and higher capacity level, the number of transfers is three or four patients (e.g., Instances 4-6). However, with one unit lower capacity, the number of transfers increases to eleven patients (e.g., Instances 10-12).

Secondly, when the short treatment limit over the planning horizon is increased, the number of transferred patients decreases. In the high capacitated instances with a low value of short treatment limit under different T_{max}^1 and T_{max}^2 values, the transfer number is three or four patients (e.g., Instances 4-6). However, when

Table 3: KPIs of the mathematical model solution for Network N1

KPI No.	KPI	Instance	1	2	3	4	5	6	7	8	9	10	11	12
-	Objective value		4,359.8	4,358.0	4,519.5	12,422.7	12,403.4	16,450.8	36,370.8	36,364.9	36,398.4	44,566.5	44,538.3	44,464.7
1	Performance score		115,179.6	115,191.7	118,081.1	312,484.5	312,565.5	413,744.4	911,613.1	911,518.7	912,266.1	1,110,127.4	1,110,115.4	1,110,179.7
2	Transfer number		1	1	1	3	3	4	9	9	9	11	11	11
3	Sum of the vehicles required each day		7	7	10	7	7	9	6	6	7	7	7	7
4	Treatment score		144	144	144	96	96	81	96	96	94	52	52	52
5	Total travel time		979.6	991.7	881.1	684.5	765.5	694.4	813.1	718.7	566.1	527.4	515.4	579.7
6	Maximum travel time		96.2	87.9	58.8	62.6	80.4	53.3	101.4	80.1	53.5	60.3	47	53.3
7	Maximum time spent		81.7	71.7	47.7	50.3	71.4	45.8	83.3	64.3	40.8	53.0	39.5	40.0
8	Maximum of average time spent		54.0	56.5	35.1	37.9	45.4	35.8	73.2	49.3	29.0	31.5	25.9	32.2
9	Number of vehicles		1	1	2	1	1	2	1	1	1	1	1	1
10	Number of routes		14	14	19	14	14	16	12	12	13	14	14	14
11	Total number of short treatments		68	68	68	36	36	26	48	48	46	16	16	16
12	Total number of normal treatments		8	8	8	24	24	29	0	0	2	20	20	20
13	Number of patients with 1 short treatment		0	0	0	6	6	8	0	0	0	8	6	6
14	Number of patients with 2 short treatments		4	4	4	15	15	9	0	0	2	4	5	5
15	Number of patients with 3 short treatments		20	20	20	0	0	0	16	16	14	0	0	0
16	Number of patients with 4 short treatments		0	0	0	0	0	0	0	0	0	0	0	0
17	Capacity utilization (%)		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	85.7%	85.7%	89.3%	100.0%	100.0%	100.0%
-	Optimality Gap (%)		0.0%	0.0%	2.5%	6.6%	6.9%	31.9%	0.0%	0.0%	0.1%	9.5%	8.8%	8.8%
-	Solution Time (s)		1,300.8	1,725.0	8,104.8	8,103.0	8,107.8	8,103.6	749.4	1,363.8	7,810.2	8,103.0	8,107.8	8,103.0

one more short treatment becomes eligible for all the patients, the transfer number decreases to one person (e.g., Instances 1-3). A similar outcome is observed with the low capacitated instances, as the transfer number decreases to nine from eleven when one more short treatment is permitted over the planning horizon. In addition, increasing the value of the short limit affects other KPIs related to treatment quality. In the high capacitated instances (e.g., Instances 2 and 5), when the short limit increases by one treatment, the number of short treatments provided during two weeks increases by 189%. With the lower short limit (i.e., Instance 5), 6 patients receive 1 short treatment and 15 patients receive 2 short treatments. However, with the higher short limit (i.e., Instance 2), 20 patients receive 3 short treatments and 4 patients receive 2 short treatments. Therefore, when the number of short treatment type limit increases, it can cause fewer transfers from the dialysis center (i.e., 1 transfer for Instance 2 and 3 transfers for Instance 5), but it also causes a low service quality in terms of the treatment types offered since short treatment number grows rapidly and the short treatment type is not the healthier treatment option.

Multiple capacity levels and short limits are analyzed in different T_{max}^1 and T_{max}^2 pairs. Another finding is that restricted T_{max}^1 and T_{max}^2 limits may cause an increase in the vehicle numbers and the number of routes (i.e., KPIs 9, 10) but the service quality in terms of transportation of patients improves since patients spend less time on the vehicles and the travel times decreases (i.e., KPIs 6, 7). In Table 3, the first three instances have the same capacity and short treatment type limit. However, their T_{max}^2 and T_{max}^1 differ. Although they have the same transfer number and the same treatment score, in Instance 3 with the restricted T_{max}^1 and T_{max}^2 values, the sum of the vehicles required each day increases, the number of vehicles needed is increased by one and the number of routes increases (e.g., see KPIs 3, 9, 10). Since more routes are constructed, service quality in terms of transportation improves (e.g., see KPIs 5-8). For instance, the maximum time spent in a vehicle decreases by 58% and total travel times decreases by 10%

compared to the relaxed setting.

While capacity is low and a high short treatment limit is permitted (e.g., Instances 7-9), the model assigns mostly short treatments to serve more patients. In Instances 7 and 8, only short treatments are provided and in Instance 9, two normal treatments are provided. Besides, if the capacity is low but also the short treatment type limit is lowered (e.g., Instances 10-12), the number of transfers is increased by 2 patients. However, the treatment types of the patients are more balanced (e.g., see KPIs 4, 13-15). Sessions' capacities are fully utilized and more normal treatments are provided.

The number of days passed after the last treatment of patients (S_p) is important for the scheduling of the dialysis center. Having more patients with ($S_p = 3$) diminishes the flexibility of scheduling decisions since either they must be treated on the first day of the planning horizon or they must be transferred. Apart from three instances having a low capacity and high short treatment limit (i.e., Instances 7-9), the capacity is fully utilized over the planning horizon. In Instances 7 and 8, all patients with $S_p = 3$ are transferred and to minimize KPIs 2 and 3, the model does not assign any normal treatment type to patients since it spends more capacity than the short treatment type and the sessions in the first and second days remain empty that leads to no usage of vehicles on both days. In the overall instances, all or most of the patients transferred have a S_p value of three.

To sum up, since the primary objective is to minimize the number of transfers, the model serves as many patients as it could in the dialysis center. The secondary objectives serve to improve the service quality in terms of treatment type and transportation of the patients in their hierarchical order.

Comparison of Mathematical Model and Heuristics We next evaluate the performance of the proposed heuristics. For the results of the constructive heuristic, we applied four S_p and two location strategies in the candidate patient selection phase of the heuristic. In total, 8 solution sets are obtained from the

constructive heuristic with the combination of S_p and location strategies. In the solution sets, within the heuristic, different capacity allocation decisions are taken as described in Section 5.1 to apply over the planning horizon. The best solution is selected regarding the hierarchy of objectives and the performance scores among the 8 solution sets for each instance. Table 4, shows the results of different capacity allocations applied within the constructive heuristic for Instance 3 with Strategy 2c. The best solution found is with the option of 2 normal treatments. The worst solution is obtained under no normal treatment capacity allocation option, and the primary objective worsens by 100% compared to the best one. Varying performance scores under different capacity allocation options show the necessity of solving the heuristic under multiple capacity schemes. Also, the results of the best capacity allocation for each of the 8 strategies are presented in Table 5 for the same instance (i.e., Instance 3). As it is shown, the least number of transfers are in Strategy 2c in which the location strategy 2 and the S_p strategy c are selected. As a result, since the constructive heuristic results in seconds, to improve the performance score, multiple capacity allocations, S_p and location strategies in the candidate patient selection phase are applied. The heuristic is solved iteratively starting from the capacity of the session and goes on by decreasing 1 unit from the normal capacity until it reaches no normal treatment capacity option. Besides, the solution with the best performance score is selected among 8 S_p and location strategy pairs.

While taking results from the matheuristics SO and MO, we develop a strategy in which starting from an upper limit for the value of K (i.e, the maximum travel time limit between two patients in the same session), we solve the scheduling model and then the routing heuristic iteratively by decreasing value of parameter K by 1 unit until the primary objective gets worse. Solving SO and MO with different K limits enables us to choose the solution with the best secondary objectives among the alternative solutions with the best primary objective. The upper limit of K is determined by rounding up the maximum travel time between two patients in the

Table 4: KPIs of the constructive heuristic solution for Instance 3 under Strategy 2c with varying normal capacity allocation options

KPI No.	KPI	$\theta_n = 3$	$\theta_n = 2$	$\theta_n = 1$	$\theta_n = 0$
KPI 1	Performance score	709,700.9	514,931.0	817,779.7	1,015,389.6
KPI 2	Transfer number	7	5	8	10
KPI 3	Sum of the vehicles required each day	7	10	12	10
KPI 4	Treatment score	42	84	100	94
KPI 5	Total travel time	600.9	731.0	779.7	689.6
KPI 6	Maximum travel time	51.1	58.0	53.5	53.5
KPI 7	Maximum time spent	40.8	42.1	42.0	41.3
KPI 8	Maximum of average time spent	40.8	41.0	30.6	37.7
KPI 9	Number of vehicles	1	2	2	2
KPI 10	Number of routes	14	17	20	17
KPI 11	Total number of short treatments	0	28	45	45
KPI 12	Total number of normal treatments	42	28	10	4
KPI 13	Number of patients with 1 short treatment	0	2	1	0
KPI 14	Number of patients with 2 short treatments	0	7	4	0
KPI 15	Number of patients with 3 short treatments	0	4	12	15
KPI 16	Number of patients with 4 short treatments	0	0	0	0
KPI 17	Capacity utilization (%)	100.0%	100.0%	77.4%	63.1%
-	Solution Time (s)	1.1	0.3	0.2	0.2

network. The maximum time between two patients in the studied networks and upper K limits are provided in Appendix.

The computation time of the matheuristic MO is higher than the matheuristic SO due to its multi objective structure. In the test instance network N1, since the number of patients is small, all instances of N1 result in a short time without an optimality gap in the matheuristic SO. However, in the matheuristic MO, three instances with low capacity and low short limit (i.e., Instances 10-12) result in long duration. Therefore, for those instances, we put a time limit of five minutes for the scheduling model and we apply three K limits which are 26, 18 and 15 which are calculated as i) half of the sum of the maximum time and the average time between two patients in the network, ii) the average time between two patients and iii) the average time between two patients subtracted by a low value respectively. As the

Table 5: KPIs of the constructive heuristic solutions for the Instance 3 with different S_p and Location strategies

KPI No.	Strategy 1a	Strategy 1b	Strategy 1c	Strategy 1d	Strategy 2a	Strategy 2b	Strategy 2c	Strategy 2d
KPI 1	914,463.6	813,445.0	516,981.7	613,733.2	914,280.7	809,541.6	514,931.0	614,854.0
KPI 2	9	8	5	6	9	8	5	6
KPI 3	10	8	12	9	9	7	10	9
KPI 4	76	96	84	82	93	40	84	103
KPI 5	663.6	645.0	781.7	633.2	630.7	541.6	731.0	704.0
KPI 6	58.7	53.3	55.1	54.2	54.4	49.7	58.0	59.4
KPI 7	45.3	47.3	44.7	42.0	43.5	40.7	42.1	47.6
KPI 8	35.2	37.7	32.3	29.4	34.3	40.7	41.0	31.4
KPI 9	2	2	2	2	2	1	2	2
KPI 10	18	16	19	16	16	14	17	16
KPI 11	28	42	28	28	41	0	28	44
KPI 12	20	12	28	26	11	40	28	15
KPI 13	4	0	3	4	1	0	2	2
KPI 14	6	6	8	6	2	0	7	3
KPI 15	4	10	3	4	12	0	4	12
KPI 16	0	0	0	0	0	0	0	0
KPI 17	81.0%	78.6%	100.0%	95.2%	75.0%	95.2%	100.0%	88.1%
S. Time (s)	2.7	2.6	2.8	2.7	2.6	2.9	2.6	2.6

best result, we compare three solutions according to the hierarchical objectives and report the best solution among them. In Appendix, we also provide the solutions of Instances 10, 11 and 12 obtained by different K values for five minutes of computation time limit for each scheduling model until the primary objective gets worse. However, applying different K values takes more than an hour and it improves only the last objective (see Appendix). In Section 6.3.2, we provide a rapid approach to apply on any network to obtain fast and effective solutions with different values of K limit.

In Table 6, KPI values related to objectives obtained from the results of CPLEX, constructive heuristic and matheuristics SO and MO are presented whose

detailed results are in Tables 3, 7, 8 and 9 respectively. CPLEX results are considered as benchmark solutions for the small network N1. However, out of 12 instances, only 4 instances result in the optimal solution. The rest of the instances have an average of 9.4% optimality gap. In the instances with high capacity (i.e., Instances 1-6), CPLEX performs better than the other methods except Instance 6 in which the model solution has a high optimality gap 31.9%.

For the instances with lower capacity (i.e., Instances 7-12), except for Instances 7 and 8, the matheuristic MO results in the best. KPIs 2 and 3 of matheuristic MO are the same as the results of the mathematical model and the matheuristic SO. However, in the matheuristic MO, KPI 4 and/or 5 are better than their results. Therefore, in all of the instances, matheuristics SO and MO transfer the same number of patients or one more patient than the mathematical model, which indicates a good performance for both matheuristics. In all of the instances, the constructive heuristic performs the worst.

Even though the mathematical performs the best, the computation time is higher than the other methodologies. The constructive heuristic has an average of 21.89 seconds of computation time. The matheuristic SO has an average of 34.60 seconds of computation time under various K limits. Except for Instances 10-12, the matheuristic MO results on an average of 4.24 minutes. However, the instances with lower capacity and lower short limit (i.e., Instances 10-12) result in 82.5, 132.6 and 83.6 minutes with the approach of decreasing the upper bound by 1 unit and trial of all K limits until the primary objective worsens. Therefore, for the instances with restricted capacity and short limit, we suggest applying a few numbers of K limit to obtain a quick solution such as we applied only three values for K limit in Table 6 for Instances 10,11 and 12. To sum up, since disasters happen suddenly, fast but also effective decision-making is crucial for the scheduling and routing of the patients to their assigned dialysis center aftermath of the disaster. The matheuristics SO and MO can be utilized for a similar network to obtain a fast but also effective solution.

Table 6: KPIs of the solution of Network N1 with 25 patients

Instance	Method	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5	S. Time (s)
1	CPLEX	115,179.6	1	7	144	979.6	1300.8
	Constructive	511,917.1	5	7	84	717.1	21.9
	SO	214,469.1	2	7	131	919.1	7.0
	MO	213,771.4	2	7	119	821.4	12.0
2	CPLEX	115,191.7	1	7	144	991.7	1725.0
	Constructive	511,917.1	5	7	84	717.1	23.1
	SO	214,469.1	2	7	131	919.1	7.1
	MO	213,771.4	2	7	119	821.4	11.9
3	CPLEX	118,081.1	1	10	144	881.1	8104.8
	Constructive	514,931.0	5	10	84	731.0	21.5
	SO	220,588.9	2	13	131	1038.9	7.2
	MO	218,901.0	2	12	119	951.0	11.6
4	CPLEX	312,484.5	3	7	96	684.5	8103.0
	Constructive	511,949.2	5	7	84	749.2	22.8
	SO	412,240.4	4	7	91	690.4	80.0
	MO	411,771.1	4	7	82	671.1	696.3
5	CPLEX	312,565.5	3	7	96	765.5	8107.8
	Constructive	511,949.9	5	7	84	749.9	24.5
	SO	412,240.4	4	7	91	690.4	79.3
	MO	411,771.1	4	7	82	671.1	695.7
6	CPLEX	413,744.4	4	9	81	694.4	8103.6
	Constructive	515,967.3	5	11	84	767.3	23.5
	SO	412,240.4	4	7	91	690.4	78.7
	MO	411,781.5	4	7	82	681.5	720.5
7	CPLEX	911,613.1	9	6	96	813.1	749.4
	Constructive	1,110,958.2	11	7	70	458.2	23.9
	SO	911,922.5	9	7	87	572.5	17.2
	MO	911,910.6	9	7	87	560.6	46.2
8	CPLEX	911,518.7	9	6	96	718.7	1363.8
	Constructive	1,110,958.2	11	7	70	458.2	21.0
	SO	911,922.5	9	7	87	572.5	17.1
	MO	911,910.6	9	7	87	560.6	46.9
9	CPLEX	912,266.1	9	7	94	566.1	7810.2
	Constructive	1,110,958.2	11	7	70	458.2	21.9
	SO	911,922.5	9	7	87	572.5	16.3
	MO	911,910.6	9	7	87	560.6	46.6
10	CPLEX	1,110,127.4	11	7	52	527.4	8103.0
	Constructive	1,210,501.4	12	7	61	451.4	20.6
	SO	1,110,392.7	11	7	57	542.7	35.3
	MO	1,110,111.7	11	7	52	511.7	461.7
11	CPLEX	1,110,115.4	11	7	52	515.4	8107.8
	Constructive	1,210,501.4	12	7	61	451.4	21.5
	SO	1,110,392.7	11	7	57	542.7	34.9
	MO	1,110,111.7	11	7	52	511.7	462.9
12	CPLEX	1,110,179.7	11	7	52	579.7	8103.0
	Constructive	1,210,501.4	12	7	61	451.4	21.4
	SO	1,110,392.7	11	7	57	542.7	35.1
	MO	1,110,111.7	11	7	52	511.7	457.0

Table 7: KPIs of the constructive heuristic solutions for Network N1

KPI No.	KPI	Instance	1	2	3	4	5	6	7	8	9	10	11	12
1	Performance score		511,917.1	511,917.1	514,931.0	511,949.2	511,949.9	515,967.3	1,110,958.2	1,110,958.2	1,110,958.2	1,210,501.4	1,210,501.4	1,210,501.4
2	Transfer number		5	5	5	5	5	5	11	11	11	12	12	12
3	Sum of the vehicles required each day		7	7	10	7	7	11	7	7	7	7	7	7
4	Treatment score		84	84	84	84	84	84	70	70	70	61	61	61
5	Total travel time		717.1	717.1	731.0	749.2	749.9	767.3	458.2	458.2	458.2	451.4	451.4	451.4
6	Maximum travel time		82.1	82.1	58.0	82.6	82.1	58.0	44.6	44.6	44.6	48.8	48.8	48.8
7	Maximum time spent		71.4	71.4	42.1	73.6	71.4	42.1	32.8	32.8	32.8	36.3	36.3	36.3
8	Maximum of average time spent		47.8	47.8	41.0	47.4	46.2	41.0	24.1	24.1	24.1	24.3	24.3	24.3
9	Number of vehicles		1	1	2	1	1	2	1	1	1	1	1	1
10	Number of routes		14	14	17	14	14	18	14	14	14	14	14	14
11	Total number of short treatments		28	28	28	28	28	28	28	28	28	24	24	24
12	Total number of normal treatments		28	28	28	28	28	28	14	14	14	13	13	13
13	Number of patients with 1 short treatment		2	2	2	4	10	10	3	3	3	2	2	2
14	Number of patients with 2 short treatments		7	7	7	12	9	9	8	8	8	11	11	11
15	Number of patients with 3 short treatments		4	4	4	0	0	0	3	3	3	0	0	0
16	Number of patients with 4 short treatments		0	0	0	0	0	0	0	0	0	0	0	0
17	Capacity utilization (%)		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	89.3%	89.3%	89.3%
-	Solution Time (s)		21.9	23.1	21.5	22.8	24.5	23.5	23.9	21.0	21.9	20.6	21.5	21.4

Table 8: KPIs of the mathuristic SO solutions for Network N1

KPI No.	KPI	Instance	1	2	3	4	5	6	7	8	9	10	11	12
1	Performance score	Sum of the vehicles required each day	214,469.1	214,469.1	220,588.9	412,240.4	412,240.4	412,240.4	911,922.5	911,922.5	911,922.5	1,110,392.7	1,110,392.7	1,110,392.7
2	Transfer number		2	2	2	4	4	4	9	9	9	11	11	11
3	Sum of the vehicles required each day		7	7	13	7	7	7	7	7	7	7	7	7
4	Treatment score		131	131	131	91	91	91	87	87	87	57	57	57
5	Total travel time		919.1	919.1	1038.9	690.4	690.4	690.4	572.5	572.5	572.5	542.7	542.7	542.7
6	Maximum travel time		73.3	73.3	59.7	54.7	54.7	54.7	46.4	46.4	46.4	46.1	46.1	46.1
7	Maximum time spent		65.7	65.7	47.6	45.7	45.7	45.7	40.8	40.8	40.8	37.6	37.6	37.6
8	Maximum of average time spent		62.9	62.9	44.2	41.1	41.1	41.1	38.1	38.1	38.1	32.8	32.8	32.8
9	Number of vehicles	Sum of the vehicles required each day	1	1	2	1	1	1	1	1	1	1	1	1
10	Number of routes		14	14	25	14	14	14	14	14	14	14	14	14
11	Total number of short treatments		61	61	61	34	34	34	40	40	40	21	21	21
12	Total number of normal treatments		9	9	9	23	23	23	7	7	7	15	15	15
13	Number of patients with 1 short treatment		1	1	1	8	8	8	1	1	1	5	5	5
14	Number of patients with 2 short treatments		6	6	6	13	13	13	6	6	6	8	8	8
15	Number of patients with 3 short treatments		16	16	16	0	0	0	9	9	9	0	0	0
16	Number of patients with 4 short treatments		0	0	0	0	0	0	0	0	0	0	0	0
17	Capacity utilization (%)	Sum of the vehicles required each day	94.0%	94.0%	94.0%	95.2%	95.2%	95.2%	96.4%	96.4%	96.4%	91.1%	91.1%	91.1%
-	Number of trials on K limit		10	10	10	18	18	18	23	23	23	25	25	25
-	Best K limit		27	27	27	21	21	21	18	18	18	17	17	17
-	Gap of scheduling model on best K limit (%)		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-	Solution Time (s)		7.0	7.1	7.2	80.0	79.3	78.7	17.2	17.1	16.3	35.3	34.9	35.1

Table 9: KPIs of the matheuristic MO solutions for Network N1

KPI No.	KPI \ Instance	1	2	3	4	5	6	7	8	9	10	11	12
1	Performance score	213,771.4	213,771.4	218,901.0	411,771.1	411,771.1	411,781.5	911,910.6	911,910.6	911,910.6	1,110,111.7	1,110,111.7	1,110,111.7
2	Transfer number	2	2	2	4	4	4	9	9	9	11	11	11
3	Sum of the vehicles required each day	7	7	12	7	7	7	7	7	7	7	7	7
4	Treatment score	119	119	119	82	82	82	87	87	87	52	52	52
5	Total travel time	821.4	821.4	951.0	671.1	671.1	681.5	560.6	560.6	560.6	511.7	511.7	511.7
6	Maximum travel time	76.4	76.4	54.8	57.5	57.5	56.3	45.6	45.6	45.6	45.6	45.6	45.6
7	Maximum time spent	67.0	67.0	46.4	51.9	51.9	43.9	38.1	38.1	38.1	39.1	39.1	39.1
8	Maximum of average time spent	54.3	54.3	32.7	42.2	42.2	42.6	38.1	38.1	38.1	31.4	31.4	31.4
9	Number of vehicles	1	1	2	1	1	1	1	1	1	1	1	1
10	Number of routes	14	14	22	14	14	14	14	14	14	14	14	14
11	Total number of short treatments	52	52	52	27	27	27	40	40	40	16	16	16
12	Total number of normal treatments	15	15	15	28	28	28	7	7	7	20	20	20
13	Number of patients with 1 short treatment	4	4	4	9	9	9	1	1	1	6	6	6
14	Number of patients with 2 short treatments	6	6	6	9	9	9	6	6	6	5	5	5
15	Number of patients with 3 short treatments	12	12	12	0	0	0	9	9	9	0	0	0
16	Number of patients with 4 short treatments	0	0	0	0	0	0	0	0	0	0	0	0
17	Capacity utilization (%)	97.6%	97.6%	97.6%	0.0%	0.0%	0.0%	64.3%	64.3%	64.3%	66.7%	66.7%	66.7%
-	Number of trials on K limit	10	10	10	18	18	18	23	23	23	3	3	3
-	Best K limit	27	27	27	23	23	21	15	15	15	15	15	15
-	Gap of scheduling model on best K limit (%)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-	Solution Time (s)	12.0	11.9	11.6	696.3	695.7	720.5	46.2	46.9	46.6	461.7	462.9	457.0

6.3 Case Study

6.3.1 Case Description

We develop a real life case study and solve the scheduling and routing problem of chronic dialysis patients assigned to a dialysis center aftermath of an earthquake. The planning horizon is assumed as the first two weeks after an earthquake. Bozkır et al. [25] develop a case study including the dialysis center network in Istanbul. Among the network of dialysis centers, we focus on a representative dialysis center from that network to evaluate our solution methodologies on a real life network.

The Dialysis Center

The dialysis center selected for the case study is Çamlıca Erdem Dialysis Center which is located in Uskudar district of Istanbul. In normal conditions, the dialysis center operates with 20 machines. The dialysis center provides normal treatments for its patients with a duration of four hours. There are two sessions which are realized between 06.00-10.00 am and 10.30-14.30 pm. However, aftermath of a risk analysis conducted in the scope of the study of Bozkır et al. [25], under a disaster scenario depending on factors such as the age of the dialysis center building, the number of expected highly damaged buildings in Uskudar district and the population size of the district, the half of the machines are expected to be damaged severely. Therefore, after the disaster, the dialysis center will operate with 10 machines in 2 sessions in each day of the week. In addition, aftermath of the disaster, short treatment type is considered to serve more patients with scarce resources. We assume that a patient can receive the short treatment at most 3 times during two weeks. We also assume that the size of dialysis patient transport vehicles are sufficient and we assign a relaxed number to determine the number of vehicles required. Therefore, the number of vehicles are assumed to be 20 vehicles, which is equal to the maximum number of patients that can be treated during a session. We assume that the vehicles can transport up to 10 patients.

Patients of the Dialysis Center

In the case study of Bozkır et al. [25], there are 12 dialysis centers and 7 hospitals in the five districts of Istanbul. They calculate the number of patients in the overall network according to the session number, machine number, group number (i.e., a group for patients served on Monday, Wednesday, Friday (MWF) and another group for Tuesday, Thursday, Saturday (TTS)) and the occupancy rate. Thus, the total patient number is 1540 for such a network. Patients are generated randomly around of the dialysis centers and hospitals within a 2 km circle. As a result of their model, 64 patients are assigned to Çamlıca Erdem Dialysis Center. Therefore, in this case study, we evaluate the scheduling and routing decisions of two networks which are network N2 with 42 patients and network N3 with 64 patients. In Figures 9 and 10, the location of patients and the location of the dialysis center are shown. Network N3 is the base network in which the dialysis center has 64 patients. The medium sized network N2 is derived from eliminating mostly the closest patients from the network N3. Thus, in the medium sized network, we assume that dialysis center has 42 patients to serve aftermath of the earthquake.

The S_p dispersion is similar for three of the values in the network with 1540 patients. Among the patients assigned to the dialysis center, the S_p values of patients are distributed as 15 patients with $S_p = 1$, 25 patients with $S_p = 2$ and 24 patients with $S_p = 3$ for network N3. Whereas, for network N2, there are 10 patients with $S_p = 1$, 16 patients with $S_p = 2$ and 16 patients with $S_p = 3$.

Travel Times

The travel time between the arcs are determined by using the Geographic Information System (GIS). The speed of the vehicles are assumed to be 30 km per hour. We assume that for each patient who picked up, vehicles spent 5 minutes in the location of the patient for various reasons such as searching for a parking stop, waiting the patient and time that patient getting into the vehicle. This fixed time is considered within the travel times between the nodes. There are patients



Figure 9: Network N2 with 42 patients

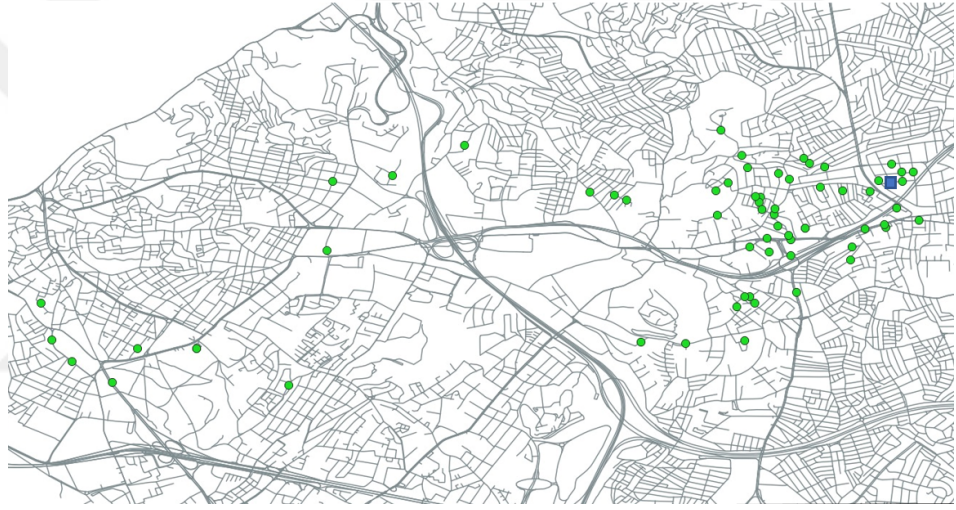


Figure 10: Network N3 with 64 patients

whose location is very close to the dialysis center. They are also included in the routing decisions. After the scheduling and routing decisions, by also considering their time spent in the vehicles and if their health conditions are not severe, they may prefer to walk by their selves to the dialysis center. However, even the closest patients, whose traveling times with vehicles are under a minute, must be included in the routing decision of the center. While constructing network N2, we eliminate the patients mostly among the patients who are closest to the dialysis center.

Under such conditions, we aim to take the scheduling and routing decisions of the dialysis center jointly by considering the hierarchical objectives. Different capacity levels, short treatment number limits, T_{max}^1 and T_{max}^2 levels and different

S_p dispersion among patients are considered. We conduct analysis for various capacity levels in which the capacity is decreased to 7 and 4 machines from 10 machines due to the additional hazards such as the lack of personnel, additional machine malfunctions or planned electricity shortages. We evaluate the effects of short treatment limit by increasing the short treatment limit by 1 (i.e., from 3 to 4). We evaluate low, medium and high settings of the restrictions on T_{max}^1 and T_{max}^2 . Similar to the test instances, due to problem characteristics mentioned, 60 minutes, 90 minutes and 210 minutes (i.e., relaxed value calculated by multiplying the maximum value between two nodes by the number eleven coming from the maximum of eleven arcs in a vehicle route) are considered for T_{max}^2 . Value of T_{max}^1 is taken as 80% of the value of T_{max}^2 except the T_{max}^2 of 210 minutes. In that relaxed limit, both T_{max}^1 and T_{max}^2 are considered as 210 minutes. Lastly, in Instances 22, 23 of network N2, S_p dispersion is changed as follows: 15 patients with $S_p = 1$, 25 patients with $S_p = 2$ and 24 patients with $S_p = 3$.

6.3.2 Results on case instances

The results of medium sized network N2 and the large sized real life case network N3 are evaluated in this section. For the scaling of the objectives of the mathematical model, we use the values obtained by the constructive heuristic. The reason is that even under a time limit of one hour, which is a large time limit for the sub models, in some cases, we could not get results. Since we can get the results of the constructive heuristic in a short time, the respective values from the results of the constructive heuristic are selected as the scaling values for both of the networks instead of applying the sub models. The limit for the solution time of the mathematical model solved by CPLEX is two hours. In the matheuristics SO and MO, increase in the number of patients affect the performance of scheduling model. In Figure 11, the computation time versus the respective optimality gaps are shown for the scheduling model of matheuristic MO with an hour time limit for the instances 18 from the network N2 and 32 from the network N3. The matheuristic MO achieves low optimality gaps in minutes. Therefore, we impose a

time limit of five minutes on the scheduling models of matheuristics SO and MO. For each instance, we run the matheuristics SO and MO multiple times with decreasing values of K parameters by 1 unit until the number of patients transferred is increased (i.e., until the primary objective worsens). Since the allowance on the maximum travel time between two patients in the same session becomes restricted (i.e., K limit), at a value of K , the number of transferred patients increases.

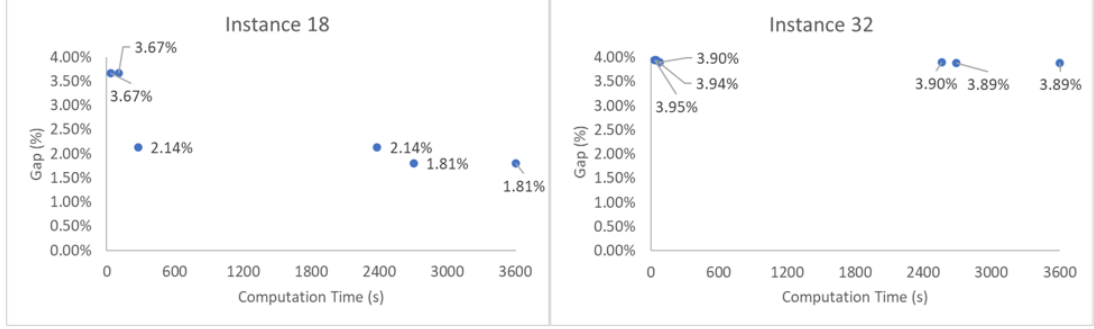


Figure 11: Gap (%) of the matheuristic MO in 1 hour time limit for Instances 18 and 32

Network N2 with 42 patients The KPIs related to primary and secondary objectives, obtained from the results of the mathematical model, the constructive heuristic, the matheuristics SO and MO are represented in Table 10 for the medium sized network N2. All KPI values of each solution methodology can be found in Tables 11, 12, 13 and 14. The mathematical model results on large optimality gaps within two hour limit in all instances. Results obtained from the mathematical model have the worst performance scores in all instances. This indicates the necessity of developing effective methodologies with a reasonable computation time.

In the instances of N2, we achieve the best results for seven of the instances with the matheuristic MO, for two of the instances with the constructive heuristic and two of the instances with the matheuristic SO. In all of the instances, matheuristics SO and MO result in the same primary objective but the secondary objectives differ. Except for the instances with low capacity (i.e., Instances 20-23), the constructive heuristic also achieves the same primary objective as the

matheuristics and does not transfer any patients out of the dialysis center. In the instances with the low capacity, constructive heuristic transferred only 1 more patient than the matheuristics SO and MO.

Table 10: KPIs of the solution of Network N2 with 42 patients

Instance	Method	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5	S. Time (s)
13	CPLEX	634,289.7	6	23	186	1989.7	7,294.7
	Constructive	25,600.2	0	14	200	1600.2	71.7
	SO	32,393.8	0	18	253	1743.8	40.7
	MO	25,603.4	0	14	200	1603.4	45.0
14	CPLEX	1,335,553.9	13	27	141	1503.9	7,216.6
	Constructive	25,600.2	0	14	200	1600.2	70.2
	SO	32,921.5	0	19	245	1671.5	41.4
	MO	25,603.4	0	14	200	1603.4	43.6
15	CPLEX	457,335.5	4	44	217	2485.5	7,224.6
	Constructive	39,896.6	0	28	200	1896.6	70.0
	SO	41,547.7	0	27	253	1897.7	40.6
	MO	37,969.1	0	26	200	1969.1	43.4
16	CPLEX	2,133,892.0	21	25	152	1292.0	7,213.1
	Constructive	29,318.8	0	14	272	1718.8	56.1
	SO	32,161.7	0	16	288	1761.7	470.6
	MO	27,398.0	0	14	233	1748.0	1,520.4
17	CPLEX	1,347,432.4	13	35	211	1882.4	7,209.4
	Constructive	43,661.9	0	28	272	2061.9	56.3
	SO	44,409.0	0	28	288	2009.0	468.6
	MO	41,674.9	0	28	233	2024.9	1,520.7
18	CPLEX	1,057,420.4	10	44	224	2220.4	7,212.5
	Constructive	29,298.9	0	14	272	1698.9	56.3
	SO	33,672.6	0	16	317	1822.6	749.0
	MO	27,433.4	0	14	233	1783.4	1,516.3
19	CPLEX	1,251,736.4	12	40	195	1986.4	7,213.8
	Constructive	43,656.4	0	28	272	2056.4	56.2
	SO	45,218.1	0	28	301	2168.1	778.2
	MO	41,190.6	0	27	245	1940.6	1,516.1
20	CPLEX	2,340,827.9	23	32	156	1027.9	7,214.6
	Constructive	1,624,772.1	16	14	196	972.1	42.7
	SO	1,526,336.2	15	14	223	1186.2	686.5
	MO	1,526,172.1	15	14	216	1372.1	2,425.5
21	CPLEX	2,531,117.1	25	24	125	867.1	7,216.6
	Constructive	1,624,772.1	16	14	196	972.1	43.6
	SO	1,528,486.9	15	16	226	1186.9	682.1
	MO	1,530,093.7	15	18	218	1193.7	2,427.6
22	CPLEX	2,146,744.9	21	37	166	1444.9	7,209.9
	Constructive	1,624,771.7	16	14	196	971.7	42.3
	SO	1,526,564.4	15	14	224	1364.4	389.1
	MO	1,526,248.0	15	14	216	1448.0	1,518.0
23	CPLEX	1,951,242.6	19	40	195	1492.6	7,212.0
	Constructive	1,624,771.7	16	14	196	971.7	42.8
	SO	1,532,636.2	15	20	226	1336.2	393.5
	MO	1,536,411.0	15	24	217	1561.0	1,517.6

Specifically, in Instances 13 and 14, the constructive heuristic is the best resulting solution methodology. The closest method for Instances 13 and 14 is the

matheuristic MO. Performance scores of these two methods are alike since the matheuristic MO performs worse on the last secondary objective KPI 5. In Instances 21 and 23, the matheuristic SO outperforms. The second best method is the matheuristic MO and their performances differ on KPI 3, in which two and four more vehicle routes are constructed. For the rest of the instances, we obtain the best results by applying the matheuristic MO. In Instances 15, 17, 20 and 22 the second best methodology is the matheuristic SO which results in worse performance on the KPIs 3, 4, 4 and 3 respectively. In Instances 16, 18 and 19, the second best methodology is the constructive heuristic which results in worse performance on KPIs 4, 4 and 3 respectively.

Similar observations exist with the results of the mathematical model for small network N1. When the capacity is low, the number of transfer increase rapidly from transferring no patient to 15 or 16 patients under all solution methodologies except the mathematical model with the large optimality gap. In the matheuristic MO, while T_{max}^1 and T_{max}^2 are decreasing in Instances 14 and 15, the sum of the vehicles required each day (i.e., KPI 3) increases by 86%. Instead of 1 vehicle, the number of vehicles required (i.e., KPI 9) increases to 2 vehicles. However, the maximum time spent in a vehicle (i.e., KPI 7) decreases by 15 minutes. When the capacity is high, all patients receive only the normal treatment type and the capacity utilization (KPI 17) is 71.4%. When the capacity is on the medium level, KPI 17 increases to 98.2%.

In Instances 22 and 23, the same network but with different S_p dispersion is examined. The same number of transfers (i.e., KPI 2) is realized with both S_p settings. In the new S_p setting, more patients have a S_p value of 1 in the network. For instance; in Instance 20, with the former S_p dispersion, all the patients transferred are among S_p values of 2 and 3 with 7 and 8 transfers respectively. However, with the new S_p dispersion in Instance 22, there are 2 patients transferred with S_p value of 3 and 1 patient transferred with S_p value of 2. Therefore, due to the flexibility that patients with S_p value of 1 enable, only 20% of the patients having

S_p value of 3 are transferred compared to the former S_p dispersion that 50% of the patients transferred have S_p value of 3.

In the medium sized network, the constructive heuristic results in less than one and a half minutes and the primary objectives are the same or one more transfer than the matheuristics SO and MO. The matheuristic SO provides solutions under 13 minutes in all of the instances for different K limits (i.e., on average 7 K limits applied, see Table 13) and its scheduling model results in no gap. In the instances with high capacity, the matheuristic SO results fast under the same number of trials on K limit (e.g., see Instances 13-19). Lastly, the matheuristic MO results are well compared to other methods in most instances. In the instances with a high capacity level, the matheuristic MO results in seconds. However, in the restricted capacity settings (i.e., Instances 20, 21), the computation time of matheuristic MO increases up to 41 minutes. Gaps in the scheduling model of the matheuristic MO are less than 6.95% in the best resulting solutions. The rapid version explained in Section 6.3.2 can be applied for having a faster solution but with lower performance on the secondary objectives.

Network N3 with 64 patients

In Table 17, the main KPIs related to primary and secondary objectives, obtained from the results of the solution methodologies to compare their performances are shown for the network N3 with 64 patients. Among fourteen instances of N3, the mathematical model provides solutions to four of the instances, but with large optimality gaps within two hour time limit and the results are much worse than the results in other solution methodologies. Therefore, for a real life sized network, the mathematical model cannot provide effective solutions in a short time. Therefore, the results of constructive heuristic, matheuristics SO and MO are evaluated.

In general, the matheuristic MO outperforms other solution methodologies for the large sized network N3. In eleven of the instances out of fourteen, matheuristic MO provides the best result. Whereas, in three of the instances, matheuristic SO

Table 11: KPIs of the mathematical model solutions for Network N2

KPI No.	KPI	Instance	13	14	15	16	17	18	19	20	21	22	23
-	Objective value		15,577.3	32,363.9	11,189.5	51,868.8	32,301.7	27,069.0	30,094.4	57,166.5	61,330.7	52,769.3	48,247.4
1	Performance score		634,289.7	1,335,553.9	457,335.5	2,133,892.0	1,347,432.4	1,057,420.4	1,251,736.4	2,340,827.9	2,531,117.1	2,146,744.9	1,951,242.6
2	Transfer number		6	13	4	21	13	10	12	23	25	21	19
3	Sum of the vehicles required each day		23	27	44	25	35	44	40	32	24	37	40
4	Treatment score		186	141	217	152	211	224	195	156	125	166	195
5	Total travel time		1989.7	1503.9	2485.5	1292.0	1882.4	2220.4	1986.4	1027.9	867.1	1444.9	1492.6
6	Maximum travel time		103.6	71.8	56.1	60.8	54.1	67.1	50.1	43.4	42.2	51.0	49.4
7	Maximum time spent		98.8	68.1	47.8	57.1	45.6	64.1	46.9	38.8	40.0	48.7	46.6
8	Maximum of average time spent		46.3	34.6	28.4	26.9	31.6	37.2	28.5	22.1	18.0	23.0	21.9
9	Number of vehicles		4	4	4	3	3	5	4	4	3	4	4
10	Number of routes		45	48	84	46	64	83	74	56	42	67	70
11	Total number of short treatments		2	0	6	30	28	39	28	42	29	44	58
12	Total number of normal treatments		182	141	205	92	155	146	139	72	67	78	79
13	Number of patients with 1 short treatment		2	0	6	5	8	7	12	5	1	1	1
14	Number of patients with 2 short treatments		0	0	0	6	7	13	8	5	8	8	9
15	Number of patients with 3 short treatments		0	0	0	3	2	2	0	9	4	9	13
16	Number of patients with 4 short treatments		0	0	0	1	0	0	0	0	0	0	0
17	Capacity utilization (%)		65.4%	50.4%	74.3%	54.6%	86.2%	84.4%	78.1%	83.0%	72.8%	89.3%	96.4%
18	Optimality Gap (%)		96.0%	98.2%	95.9%	98.0%	98.3%	96.2%	98.1%	39.1%	43.3%	34.3%	28.2%
-	Solution Time (s)		7,294.7	7,216.6	7,224.6	7,213.1	7,209.4	7,212.5	7,213.8	7,214.6	7,216.6	7,209.9	7,212.0

Table 12: KPIs of the constructive heuristic solutions for Network N2

KPI No.	KPI	Instance	13	14	15	16	17	18	19	20	21	22	23
1	Performance score	Instance	25,600.2	25,600.2	39,896.6	29,318.8	43,661.9	29,298.9	43,656.4	1,624,772.1	1,624,772.1	1,624,771.7	1,624,771.7
2	Transfer number		0	0	0	0	0	0	0	16	16	16	16
3	Sum of the vehicles required each day		14	14	28	14	28	14	28	14	14	14	14
4	Treatment score		200	200	200	272	272	272	272	196	196	196	196
5	Total travel time		1600.2	1600.2	1896.6	1718.8	2061.9	1698.9	2056.4	972.1	972.1	971.7	971.7
6	Maximum travel time		64.4	64.4	55.0	74.5	50.6	74.5	51.9	39.0	39.0	40.3	40.3
7	Maximum time spent		62.1	62.1	47.7	71.6	47.3	71.6	47.3	36.7	36.7	38.3	38.3
8	Maximum of average time spent		62.1	62.1	47.7	68.8	46.0	70.0	45.5	35.0	35.0	36.6	36.6
9	Number of vehicles		1	1	2	1	2	1	2	1	1	1	1
10	Number of routes		28	28	52	28	54	28	54	28	28	28	28
11	Total number of short treatments		0	0	0	56	56	56	56	56	56	56	56
12	Total number of normal treatments		200	200	200	160	160	160	160	84	84	84	84
13	Number of patients with 1 short treatment		0	0	0	6	6	4	4	7	7	4	4
14	Number of patients with 2 short treatments		0	0	0	5	5	5	5	5	5	2	2
15	Number of patients with 3 short treatments		0	0	0	4	4	14	14	13	13	16	16
16	Number of patients with 4 short treatments		0	0	0	7	7	0	0	0	0	0	0
17	Capacity utilization (%)		71.4%	71.4%	71.4%	95.9%	95.9%	95.9%	95.9%	100.0%	100.0%	100.0%	100.0%
-	Best resulted strategies		1c	2c	2c	2c	2c	2c	1c	1c	1c	2b	2b
-	Capacity parameter		10	10	10	6	6	6	6	3	3	3	3
-	Solution Time (s)		71.7	70.2	70.0	56.1	56.3	56.3	56.2	42.7	43.6	42.3	42.8

Table 13: KPIs of the matheuristic SO solutions for Network N2

KPI No.	KPI	Instance	13	14	15	16	17	18	19	20	21	22	23
1	Performance score		32,393.8	32,921.5	41,547.7	32,161.7	44,409.0	33,672.6	45,218.1	1,526,336.2	1,528,486.9	1,526,564.4	1,532,636.2
2	Transfer number		0	0	0	0	0	0	0	15	15	15	15
3	Sum of the vehicles required each day		18	19	27	16	28	16	28	14	16	14	20
4	Treatment score		253	245	253	288	288	317	301	223	226	224	226
5	Total travel time		1743.8	1671.5	1897.7	1761.7	2009.0	1822.6	2168.1	1186.2	1186.9	1364.4	1336.2
6	Maximum travel time		76.8	73.4	56.4	77.1	55.0	77.7	58.4	63.9	50.5	61.9	54.4
7	Maximum time spent		74.5	71.4	47.7	69.3	47.7	69.5	48.0	61.9	46.7	55.9	47.9
8	Maximum of average time spent		65.5	69.1	45.1	58.2	42.6	56.6	45.2	39.9	39.7	40.8	35.0
9	Number of vehicles		2	2	2	2	2	2	2	1	2	1	2
10	Number of routes		33	33	47	30	52	30	54	28	30	28	34
11	Total number of short treatments		40	37	40	69	69	91	80	75	77	76	78
12	Total number of normal treatments		173	171	173	150	150	135	141	73	72	72	70
13	Number of patients with 1 short treatment		8	7	8	5	5	5	4	0	0	1	0
14	Number of patients with 2 short treatments		10	6	10	12	12	13	14	3	4	3	3
15	Number of patients with 3 short treatments		4	6	4	4	4	20	16	23	23	23	24
16	Number of patients with 4 short treatments		0	0	0	7	7	0	0	0	0	0	0
17	Capacity utilization (%)		68.9%	67.7%	68.9%	94.1%	94.1%	92.1%	92.3%	98.7%	98.7%	98.2%	97.3%
-	Number of trials on K limit		7	7	7	7	7	7	7	8	8	6	6
-	Best K limit		14	13	14	15	15	15	16	14	12	14	15
-	Gap of scheduling model on best K limit (%)		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
-	Solution Time (s)		40.7	41.4	40.6	470.6	468.6	749.0	778.2	686.5	682.1	389.1	393.5

Table 14: KPIs of the matheuristic MO solutions for Network N2

KPI No.	KPI	Instance	13	14	15	16	17	18	19	20	21	22	23
1	Performance score	Performance score	25,603.4	25,603.4	37,969.1	27,398.0	41,674.9	27,433.4	41,190.6	1,526,172.1	1,530,093.7	1,526,248.0	1,536,411.0
2	Transfer number		0	0	0	0	0	0	0	15	15	15	15
3	Sum of the vehicles required each day		14	14	26	14	28	14	27	14	18	14	24
4	Treatment score		200	200	200	233	233	233	245	216	218	216	217
5	Total travel time	Total travel time	1603.4	1603.4	1969.1	1748.0	2024.9	1783.4	1940.6	1372.1	1193.7	1448.0	1561.0
6	Maximum travel time		64.7	64.7	59.4	74.1	51.6	73.5	55	61.3	49.7	64.2	50.0
7	Maximum time spent		62.4	62.4	47.3	71.0	47.8	71.3	47.9	59.3	47.7	59.4	48.0
8	Maximum of average time spent		62.4	62.4	42.8	63.7	45.1	59.9	37.5	49.3	37.5	45.8	45.3
9	Number of vehicles	Number of vehicles	1	1	2	1	2	1	2	1	2	1	2
10	Number of routes		28	28	48	28	55	28	53	28	32	28	44
11	Total number of short treatments		0	0	0	27	27	27	36	70	71	70	71
12	Total number of normal treatments		200	200	200	179	179	179	173	76	76	76	75
13	Number of patients with 1 short treatment	Number of patients with 1 short treatment	0	0	0	8	8	10	19	3	1	2	3
14	Number of patients with 2 short treatments		0	0	0	5	5	7	7	5	8	7	4
15	Number of patients with 3 short treatments		0	0	0	3	3	1	1	19	18	18	20
16	Number of patients with 4 short treatments		0	0	0	0	0	0	0	0	0	0	0
17	Capacity utilization (%)	Capacity utilization (%)	71.4%	71.4%	71.4%	98.2%	98.2%	98.2%	97.4%	99.1%	99.6%	99.1%	98.7%
-	Number of trials on K limit		7	7	7	5	5	5	5	8	8	5	5
-	Best K limit		14	14	16	16	16	16	15	18	12	18	17
-	Gap of scheduling model on best K limit (%)		0.0%	0.0%	0.0%	2.7%	2.7%	2.1%	6.9%	0.7%	2.4%	1.7%	2.2%
-	Solution Time (s)	Solution Time (s)	45.0	43.6	43.4	1,520.4	1,520.7	1,516.3	1,516.1	2,425.5	2,427.6	1,518.0	1,517.6

outperforms. The primary objective of the matheuristics SO and MO are the same (i.e., KPI2). However, the performance of the matheuristics differs on KPIs 3, 4 and 5. For the high capacity setting in six of the instances (i.e., Instances 24-29), the constructive heuristic results in transferring 1 more patient than the matheuristics. Thus, the constructive heuristic provides promising solutions. For the instances with lower capacity (i.e., Instances 30-37), transfer numbers are 2, 3 or 4 more patients than the results of the matheuristics. However, the constructive heuristic gives the solution in under two minutes.

The matheuristic SO results in an average of 14.46 minutes. Except for Instances 36 and 37, the best resulting solution of the scheduling model of matheuristic SO has no gaps. The gap is 7.1% for Instances 36 and 37. In the matheuristic SO, the number of K limit trials changes between 5 and 10 values. On the other hand, the best results among different K limits obtained by the matheuristic MO have a minimum of 1.13% and a maximum of 6.87% gaps. The matheuristic MO has an average of 30.7 minutes of computation time for various K limits. In the matheuristic MO, the number of K limit trials is 4, 6 or 8. In a general sense, in the instances having high capacity, the best K limit examined is closer to the upper limit, whereas, in the low capacity settings, it is much lower than the upper limit. However, there are contra examples such as Instances 33, 34 with the matheuristic MO and Instance 35 with the matheuristic SO. In both matheuristics SO and MO, the trial of multi K limits provides higher quality solutions. Instead of the trials with multi K values, longer computation time limits can be forced. However, we find that applying various K limits is more effective since it results in multiple solutions with the same value for the primary objective but different values for the secondary objectives are achieved and low gap values are obtained for the scheduling models. In Table 20, the values of K in the best solutions obtained are shown for the matheuristic MO and the best resulting value of K differs on instances. In Tables 15 and 16, weighted performance scores KPI 1 and KPIs 2-5 are represented for the matheuristics SO and MO with various K limits.

Even KPI 2 has the same value for all K limits except for the lowest K limit, the secondary objectives differ. The best of the KPI 1 is determined as the best resulting solution. The best K limit selected is 13 for both matheuristics for Instance 32. However, it may cause a long computation time such as in Instances 36 and 37. Therefore, at the end of this section, we provide an approach (i.e., rapid approach) in which two K limits are applied for the matheuristics SO and MO and the performance of the rapid approach is evaluated compared to the current approach.

Table 15: KPIs of the solutions of matheuristic SO for Instance 32 with various K limits

K limit	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5
12	1,837,592.7	18	17	378	1692.7
13	1,740,348.1	17	19	391	1798.1
14	1,744,580.5	17	23	395	1830.5
15	1,741,550.6	17	20	394	1850.6
16	1,743,587.1	17	22	394	1887.1
17	1,744,666.9	17	23	394	1966.9
18	1,746,781.1	17	25	394	2081.1
19	1,745,629.9	17	24	390	2129.9

Table 16: KPIs of the solutions of matheuristic MO for Instance 32 with various K limits

K limit	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5
12	1,838,816.8	18	18	382	1716.8
13	1,739,032.7	17	18	385	1782.7
14	1,741,077.7	17	20	385	1827.7
15	1,741,150.2	17	20	385	1900.2
16	1,743,220.0	17	22	385	1970.0
17	1,746,132.5	17	25	382	2032.5
18	1,746,129.0	17	25	382	2029.0
19	1,748,301.6	17	27	384	2101.6

In the high capacity settings (i.e., Instances 24-29), all patients are served as a result of matheuristics and one patient is transferred as a result of the constructive heuristic. While T_{max}^1 and T_{max}^2 become restricted, KPI3 increases drastically. When more vehicle routes are constructed, the service quality in terms of the transportation of patients increases (e.g., see KPIs 6-8). In the lower capacity setting, between 14 and 19 patients are transferred depending on the instances

and the solution methods. The decrease in capacity highly affects the number of patients served in the dialysis center. The capacity utilization is higher than 94.6% in the constructive heuristic and the matheuristics. Matheuristic MO allocates more normal treatments to patients. Therefore, the service quality in terms of the treatment types increases. In instances 27 and 28, the best K limit is 19 for both matheuristics SO and MO. In the unrestricted T_{max}^1 and T_{max}^2 setting (i.e., Instance 27), matheuristic MO constructs two vehicle routes fewer than the solution of matheuristic SO. In the restricted setting (i.e., Instance 28), the treatment score is improved with matheuristic MO. In the solution of matheuristic SO, patients are frequently allocated with short treatments. The numbers of patients who get short treatments 1, 2 or 3 times during two weeks are 7, 23 and 28 respectively. In matheuristic MO, the treatment score is much better and the allocation of treatments is more balanced (e.g., KPIs 13-17 are 14, 27 and 19 in matheuristic MO). As a result, even though the primary objectives are the same for matheuristics, matheuristic MO provides a higher quality of solutions in most instances.

Table 17: KPIs of the solution of Network N3 with 64 patients

Instance	Method	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5	S. Time (s)
24	CPLEX	-	-	-	-	-	7228.1
	Constructive	152,609.6	1	28	444	2409.5	106.2
	SO	54,786.0	0	27	503	2636.0	646.9
	MO	52,618.6	0	27	460	2618.6	1,231.4
25	CPLEX	5,819,185.4	58	17	40	185.4	7224.7
	Constructive	152,746.9	1	28	444	2546.9	107.5
	SO	55,911.3	0	28	503	2761.3	647.1
	MO	53,714.4	0	28	460	2714.4	1,231.9
26	CPLEX	5,819,235.4	58	17	41	185.4	7220.7
	Constructive	167,571.7	1	39	517	2721.7	104.7
	SO	68,252.0	0	39	528	2852.0	635.9
	MO	62,937.7	0	37	463	2787.7	1,230.9
27	CPLEX	5,817,874.4	58	16	34	174.4	7217.5
	Constructive	152,656.6	1	28	444	2456.6	102.1
	SO	54,653.2	0	28	480	2653.2	375.6
	MO	52,797.8	0	27	463	2647.8	1,224.5
28	CPLEX	-	-	-	-	-	7216.6
	Constructive	152,784.3	1	28	444	2584.3	104.1
	SO	54,768.4	0	28	480	2768.4	376.0
	MO	53,871.0	0	28	463	2721.0	1,224.1
29	CPLEX	-	-	-	-	-	7228.3
	Constructive	165,828.6	1	41	444	2628.6	105.2
	SO	65,104.2	0	38	486	2804.2	372.2
	MO	64,063.7	0	38	465	2813.7	1,224.3
30	CPLEX	-	-	-	-	-	7215.9
	Constructive	1,833,774.8	18	14	364	1574.8	80.4
	SO	1,550,662.0	15	25	474	1962.0	1,116.3
	MO	1,546,168.5	15	21	464	1968.5	2,458.6
31	CPLEX	-	-	-	-	-	7214.6
	Constructive	1,847,855.2	18	28	364	1655.2	82.7
	SO	1,553,796.6	15	28	474	2096.6	1,110.9
	MO	1,553,298.8	15	28	464	2098.8	2,459.8
32	CPLEX	-	-	-	-	-	7215.6
	Constructive	1,933,243.7	19	14	354	1543.7	79.8
	SO	1,740,348.1	17	19	391	1798.1	445.1
	MO	1,739,032.7	17	18	385	1782.7	2,444.8
33	CPLEX	-	-	-	-	-	7226.7
	Constructive	1,947,319.5	19	28	354	1619.5	80.4
	SO	1,749,484.0	17	28	391	1933.9	447.7
	MO	1,749,326.0	17	28	382	2226.0	2,445.4
34	CPLEX	-	-	-	-	-	7223.2
	Constructive	1,833,843.8	18	14	364	1643.8	80.6
	SO	1,450,698.4	14	25	473	2048.4	540.5
	MO	1,450,751.3	14	25	471	2201.3	1846.5
35	CPLEX	-	-	-	-	-	7218.3
	Constructive	1,847,947.4	18	28	364	1747.4	80.4
	SO	1,454,114.9	14	28	476	2314.9	543.1
	MO	1,456,019.6	14	30	473	2369.6	1849.4
36	CPLEX	5,915,647.7	59	14	30	147.7	7221.3
	Constructive	1,833,853.9	18	14	364	1653.9	81.1
	SO	1,737,686.0	17	17	379	1735.9	2,443.2
	MO	1,740,226.9	17	19	389	1776.9	2,444.0
37	CPLEX	-	-	-	-	-	7227.0
	Constructive	1,847,954.5	18	28	364	1754.5	80.3
	SO	1,748,807.6	17	28	379	1857.6	2443.0
	MO	1,748,644.0	17	28	374	1944.0	2456.4

Table 18: KPIs of the constructive heuristic solutions for Network N3

KPI No.	KPI	Instance	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	Performance score		152,609.6	152,746.9	167,571.7	152,656.6	152,784.3	165,828.6	1,833,774.8	1,847,855.2	1,933,243.7	1,947,319.5	1,833,843.8	1,847,947.4	1833853.9	1847954.5
2	Transfer number		1	1	1	1	1	1	18	18	19	19	18	18	18	18
3	Sum of the vehicles required each day		28	28	39	28	28	41	14	28	14	28	14	28	14	28
4	Treatment score		444	444	517	444	444	444	364	364	354	354	364	364	364	364
5	Total travel time		2409.5	2546.9	2721.7	2456.6	2584.3	2628.6	1574.8	1655.2	1543.7	1619.5	1643.8	1747.4	1653.9	1754.5
6	Maximum travel time		85.2	73.0	60.0	85.2	73.7	58.5	61.4	49.5	61.6	50.3	68.1	49.5	70.0	49.3
7	Maximum time spent		85.1	71.8	48.0	85.1	71.7	47.7	59.7	47.9	59.9	47.7	67.6	48.0	69.8	47.8
8	Maximum of average time spent		60.9	55.3	43.2	70.8	65.1	42.2	56.6	41.3	45.4	39.1	61.7	39.0	60.2	36.8
9	Number of vehicles		2	2	3	2	2	3	1	2	1	2	1	2	1	2
10	Number of routes		56	56	67	56	56	71	28	56	28	54	28	56	28	56
11	Total number of short treatments		112	112	168	112	112	112	112	112	108	108	112	112	112	112
12	Total number of normal treatments		220	220	181	220	220	220	140	140	138	138	140	140	140	140
13	Number of patients with 1 short treatment		9	9	12	11	11	11	5	5	4	4	7	6	6	6
14	Number of patients with 2 short treatments		11	11	9	7	7	7	12	12	10	10	7	10	11	11
15	Number of patients with 3 short treatments		7	7	10	29	29	29	5	5	28	28	5	6	28	28
16	Number of patients with 4 short treatments		15	15	27	0	0	0	17	17	0	0	19	17	0.0%	0.0%
17	Capacity utilization (%)		98.6%	98.6%	94.6%	98.6%	98.6%	98.6%	100.0%	100.0%	98.0%	98.0%	100.0%	100.0%	100.0%	100.0%
-	Best resulted strategies		1c	2c	2c	2c	1c	2c	2c	2c	1c	1c	1d	1c	1c	1c
-	Capacity parameter		8	8	7	8	8	8	5	5	5	5	5	5	5	5
-	Solution Time (s)		106.2	107.5	104.7	102.1	104.1	105.2	80.4	82.7	79.8	80.4	80.6	80.4	81.1	80.3

Table 19: KPIs of the matheuristic SO solutions for Network N3

KPI No.	KPI	Instance	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	Performance score		54,786.0	55,911.3	68,252.0	54,653.2	54,768.4	65,104.2	1,550,662.0	1,553,796.6	1,740,348.1	1,749,484.0	1,450,698.4	1,454,114.9	1,737,686.0	1,748,807.6
2	Transfer number		0	0	0	0	0	0	15	15	17	17	14	14	17	17
3	Sum of the vehicles required each day		27	28	39	28	28	38	25	28	19	28	25	28	17	28
4	Treatment score		503	503	528	480	480	486	474	474	391	391	473	476	379	379
5	Total travel time		2636.0	2761.3	2852.0	2653.2	2768.4	2804.2	1962.0	2096.6	1798.1	1933.9	2048.4	2314.9	1735.9	1857.6
6	Maximum travel time		86.3	74.3	59.7	84.9	72.3	59.9	72.1	49.6	74.7	49.4	74.1	58.2	70.8	50.1
7	Maximum time spent		83.8	71.9	47.6	84.5	72.0	47.9	71.9	47.8	71.8	47.9	71.8	47.7	70.6	48.0
8	Maximum of average time spent		70.5	66.1	43.2	76.4	68.8	43.6	52.5	36.6	60.8	39.1	59.1	43.2	62.7	42.7
9	Number of vehicles		2	2	3	2	2	3	2	2	2	2	2	3	2	2
10	Number of routes		52	54	70	51	55	67	40	55	33	56	45	54	31	54
11	Total number of short treatments		156	156	175	137	137	142	188	188	132	132	186	188	124	124
12	Total number of normal treatments		191	191	178	206	206	202	98	98	127	127	101	100	131	131
13	Number of patients with 1 short treatment		9	9	6	7	7	8	0	0	0	0	0	0	2	2
14	Number of patients with 2 short treatments		18	18	9	23	23	16	0	0	9	9	0	0	7	7
15	Number of patients with 3 short treatments		9	9	17	28	28	34	8	8	38	38	14	12	36	36
16	Number of patients with 4 short treatments		21	21	25	0	0	0	41	41	0	0	36	38	0	0
17	Capacity utilization (%)		96.1%	96.1%	94.8%	98.0%	98.0%	97.5%	98.0%	98.0%	98.5%	98.5%	99.0%	99.0%	98.5%	98.5%
-	Number of trials on K limit		6	6	6	5	5	5	10	10	8	8	7	7	9	9
-	Best K limit		17	17	16	19	19	16	14	14	13	13	14	18	13	13
-	Gap of scheduling model on best K limit (%)		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	7.1%	7.1%
-	Solution Time (s)		646.9	647.1	635.9	375.6	376.0	372.2	1,116.3	1,110.9	445.1	447.7	540.5	543.1	2,443.2	2,443.0

Table 20: KPIs of the matheuristic MO solutions for Network N3

KPI No.	KPI	Instance	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	Performance score		52,618.6	53,714.4	62,937.7	52,797.8	53,871.0	64,063.7	1,546,168.5	1,553,298.8	1,739,032.7	1,749,326.0	1,450,751.3	1,456,019.6	1,740,226.9	1,748,644.0
2	Transfer number		0	0	0	0	0	0	15	15	17	17	14	14	17	17
3	Sum of the vehicles required each day		27	28	37	27	28	38	21	28	18	28	25	30	19	28
4	Treatment score		460	460	463	463	463	465	464	464	385	382	471	473	389	374
5	Total travel time		2618.6	2714.4	2787.7	2647.8	2721.0	2813.7	1968.5	2098.8	1782.7	2226.0	2201.3	2369.6	1776.9	1944.0
6	Maximum travel time		85.0	73.7	59.8	85.6	73.4	59.9	74.0	51.7	73.9	59.1	72.6	56.7	73.1	51.9
7	Maximum time spent		83.6	71.9	48.0	85.0	71.5	47.9	71.5	47.8	71.8	47.9	71.9	47.3	70.7	47.6
8	Maximum of average time spent		81.2	68.7	41.9	78.9	69.1	43.2	49.6	31.4	59.6	38.0	64.5	40.4	62.7	42.2
9	Number of vehicles		2	2	3	2	2	3	2	2	2	2	2	3	2	2
10	Number of routes		51	55	67	53	55	68	39	56	32	56	47	57	33	54
11	Total number of short treatments		124	124	125	125	125	125	181	181	127	125	184	186	131	120
12	Total number of normal treatments		212	212	213	213	213	215	102	102	131	132	103	101	127	134
13	Number of patients with 1 short treatment		15	15	14	14	14	14	0	0	0	2	0	0	0	0
14	Number of patients with 2 short treatments		19	19	16	27	27	21	2	2	8	12	2	1	7	6
15	Number of patients with 3 short treatments		17	17	17	19	19	23	11	11	37	33	12	12	39	36
16	Number of patients with 4 short treatments		5	5	7	0	0	0	36	36	0	0	36	37	0	0
17	Capacity utilization (%)		97.9%	97.9%	98.4%	98.4%	98.4%	99.1%	98.2%	98.2%	99.2%	99.2%	99.5%	99.0%	98.2%	99.0%
-	Number of trials on K limit		4	4	4	4	4	4	8	8	8	8	6	6	8	8
-	Best K limit		18	18	17	19	19	17	13	13	13	17	17	16	13	14
-	Gap of scheduling model on best K limit (%)		2.1%	2.1%	2.7%	2.8%	2.8%	1.9%	6.0%	6.0%	3.9%	3.9%	1.1%	1.1%	6.9%	5.9%
-	Solution Time (s)		1,231.4	1,231.9	1,230.9	1,224.5	1,224.1	1,224.3	2,458.6	2,459.8	2,444.8	2,445.4	1,846.5	1,849.4	2,444.0	2,456.4

Rapid Approach for Matheuristics SO and MO

The number of trials on K limit changes among different instances by various factors such as the capacity level, the short limit, the proximity of locations in the network, S_p dispersion of patients, and the number of schedules. The minimum value of the K limit, in which the primary objective get worse cannot be known beforehand and the search until that value is reached can take a long time. For the settings in which an immediate solution is necessary, the decision-maker can prefer to use a quick version of the matheuristic MO in which the highest primary objective will be achieved but the secondary objectives may be deteriorated compared to the results of Section 6.3, which we call multi K trial. Instead of applying various K limits, a limited number of K limits can be applied. Since high values of K limits provide the best primary objective and after a K limit the primary objective worsens, for generalization, the trial on the higher values of K limits would be preferred for all instances. For the quick version of the matheuristics, we apply two K limits with high values such as 95% and 85% of the upper limit (i.e., rounded to 16 and 18), which is the maximum time between two patient locations. We call this approach the rapid approach of matheuristics SO and MO. We analyze the solutions obtained by the rapid approach on the network N3. Since two K limits are applied and there is a five minutes time limit on the scheduling model of matheuristics, the overall result is achieved in ten and a half minutes. In Tables 23 and 24, all KPIs are presented for the solutions of matheuristics SO and MO. We compare KPIs obtained by the multi K trial and rapid approaches and present changes that occurred on KPIs in Table 21. In the rapid approach, either a solution has a worse performance score (see KPI 1) or the same performance score with the multi K trial approach. The number of patients transferred is the same in both approaches, therefore the change is 0.0%. Since the computation time decreases with the rapid approach, all the rates are negative indicating decreasing value on the solution time. To give an example, in Instance 24 with the matheuristic SO, the performance score increases by 2.2% since KPI

3 is increased in the rapid approach compared to the multi K trial approach.

In Table 22, the main KPIs of all solution methodologies are shown. Similar to the multi K trial approach, the best resulting solution methodology is the matheuristic MO for eleven of the instances out of fourteen. In Instances 34 and 35, similar to the multi K approach, matheuristic SO performs the best. Differently, in Instance 29, the solution of matheuristic SO is the same as the multi K approach since the selected K limit is the same, but the matheuristic MO performs worse than the multi K trial approach. For that instance, the matheuristic SO outperforms.

To sum up, with both multi K trials and rapid approaches, the matheuristic MO performs the best in most of the instances even if the performance of secondary objectives slightly gets worse on the rapid approach. However, the computation time is short which is an important aspect required for the solution methodologies in post disaster conditions.

Table 21: Change percentages of KPIs among the solutions of multi K limits and 2 K limits

Instance	Method	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5	S. Time (s)
24	SO	2.2%	0.0%	3.7%	0.6%	2.5%	-66.7%
	MO	0.0%	0.0%	0.0%	0.0%	0.0%	-50.0%
25	SO	0.3%	0.0%	0.0%	0.6%	0.3%	-66.7%
	MO	0.0%	0.0%	0.0%	0.0%	0.0%	-50.0%
26	SO	0.0%	0.0%	0.0%	0.0%	0.0%	-66.7%
	MO	3.1%	0.0%	5.4%	-0.6%	2.7%	-50.0%
27	SO	0.3%	0.0%	0.0%	1.3%	-4.6%	-60.0%
	MO	2.0%	0.0%	3.7%	0.4%	-0.8%	-50.0%
28	SO	0.3%	0.0%	0.0%	1.3%	-5.6%	-60.0%
	MO	0.2%	0.0%	0.0%	0.4%	0.6%	-50.0%
29	SO	0.0%	0.0%	0.0%	0.0%	0.0%	-60.0%
	MO	4.7%	0.0%	7.9%	0.0%	-0.3%	-50.0%
30	SO	0.1%	0.0%	8.0%	0.0%	4.4%	-80.0%
	MO	0.2%	0.0%	14.3%	0.2%	7.6%	-75.0%
31	SO	0.1%	0.0%	3.6%	0.0%	3.4%	-80.0%
	MO	0.1%	0.0%	3.6%	0.2%	8.0%	-75.0%
32	SO	0.2%	0.0%	15.8%	0.8%	5.0%	-75.0%
	MO	0.2%	0.0%	22.2%	0.0%	10.5%	-75.0%
33	SO	0.0%	0.0%	0.0%	0.8%	5.0%	-75.0%
	MO	0.0%	0.0%	0.0%	0.5%	-2.1%	-75.0%
34	SO	0.0%	0.0%	0.0%	0.0%	6.2%	-71.4%
	MO	0.1%	0.0%	4.0%	0.4%	-0.3%	-66.7%
35	SO	0.0%	0.0%	0.0%	0.0%	0.0%	-71.4%
	MO	0.0%	0.0%	0.0%	0.0%	0.0%	-66.7%
36	SO	0.4%	0.0%	35.3%	2.9%	8.9%	-74.8%
	MO	0.2%	0.0%	21.1%	-1.3%	9.8%	-75.0%
37	SO	0.0%	0.0%	0.0%	2.9%	8.3%	-74.9%
	MO	0.0%	0.0%	0.0%	1.1%	15.5%	-75.0%

Table 22: KPIs of the solution of Network N3 with 64 patients with 2 K Limits

Instance	Method	KPI 1	KPI 2	KPI 3	KPI 4	KPI 5	S. Time (s)
24	CPLEX	-	-	-	-	-	7228.1
	Constructive	152,609.6	1	28	444	2409.5	106.2
	SO	56,002.6	0	28	506	2702.6	215.6
	MO	52,618.6	0	27	460	2618.6	615.7
25	CPLEX	5,819,185.4	58	17	40	185.4	7224.7
	Constructive	152,746.9	1	28	444	2546.9	107.5
	SO	56,068.9	0	28	506	2768.9	215.7
	MO	53,714.4	0	28	460	2714.4	616.0
26	CPLEX	5,819,235.4	58	17	41	185.4	7220.7
	Constructive	167,571.7	1	39	517	2721.7	104.7
	SO	68,252.0	0	39	528	2852.0	212.0
	MO	64,863.4	0	39	460	2863.4	615.5
27	CPLEX	5,817,874.4	58	16	34	174.4	7217.5
	Constructive	152,656.6	1	28	444	2456.6	102.1
	SO	54,831.3	0	28	486	2531.3	150.2
	MO	53,876.6	0	28	465	2626.6	612.3
28	CPLEX	-	-	-	-	-	7216.6
	Constructive	152,784.3	1	28	444	2584.3	104.1
	SO	54,914.1	0	28	486	2614.1	150.4
	MO	53,987.3	0	28	465	2737.3	612.1
29	CPLEX	-	-	-	-	-	7228.3
	Constructive	165,828.6	1	41	444	2628.6	105.2
	SO	65,104.2	0	38	486	2804.2	148.9
	MO	67,056.6	0	41	465	2806.6	612.2
30	CPLEX	-	-	-	-	-	7215.9
	Constructive	1,833,774.8	18	14	364	1574.8	80.4
	SO	1,552,747.4	15	27	474	2047.4	223.3
	MO	1,549,367.6	15	24	465	2117.6	614.7
31	CPLEX	-	-	-	-	-	7214.6
	Constructive	1,847,855.2	18	28	364	1655.2	82.7
	SO	1,554,867.1	15	29	474	2167.1	222.2
	MO	1,554,517.5	15	29	465	2267.5	615.0
32	CPLEX	-	-	-	-	-	7215.6
	Constructive	1,933,243.7	19	14	354	1543.7	79.8
	SO	1,743,587.1	17	22	394	1887.1	111.3
	MO	1,743,220.0	17	22	385	1970.0	611.2
33	CPLEX	-	-	-	-	-	7226.7
	Constructive	1,947,319.5	19	28	354	1619.5	80.4
	SO	1,749,730.6	17	28	394	2030.6	111.9
	MO	1,749,378.2	17	28	384	2178.2	611.4
34	CPLEX	-	-	-	-	-	7223.2
	Constructive	1,833,843.8	18	14	364	1643.8	80.6
	SO	1,450,824.5	14	25	473	2174.5	154.4
	MO	1,451,844.9	14	26	473	2194.9	614.0
35	CPLEX	-	-	-	-	-	7218.3
	Constructive	1,847,947.4	18	28	364	1747.4	80.4
	SO	1,454,114.9	14	28	476	2314.9	155.2
	MO	1,456,019.6	14	30	473	2369.6	616.5
36	CPLEX	5,915,647.7	59	14	30	147.7	7221.3
	Constructive	1,833,853.9	18	14	364	1653.9	81.1
	SO	1,744,390.8	17	23	390	1890.8	615.0
	MO	1,744,151.4	17	23	384	1951.4	611.0
37	CPLEX	-	-	-	-	-	7227.0
	Constructive	1,847,954.5	18	28	364	1754.5	80.3
	SO	1,749,512.0	17	28	390	2012.0	613.8
	MO	1,749,145.3	17	28	378	2245.3	614.1

Table 23: KPIs of the matheuristic SO solutions for Network N3 with 2 K limits

KPI No.	KPI	Instance	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	Performance score		56,002.6	56,068.9	68,252.0	54,831.3	54,914.1	65,104.2	1,552,747.4	1,554,867.1	1,743,587.1	1,749,730.6	1,450,824.5	1,454,114.9	1,744,390.8	1,749,512.0
2	Transfer number		0	0	0	0	0	0	15	15	17	17	14	14	17	17
3	Sum of the vehicles required each day		28	28	39	28	28	38	27	29	22	28	25	28	23	28
4	Treatment score		506	506	528	486	486	486	474	474	394	394	473	476	390	390
5	Total travel time		2702.6	2708.9	2852.0	2531.3	2614.1	2804.2	2047.4	2167.1	1887.1	2030.6	2174.5	2314.9	1890.8	2012.0
6	Maximum travel time		86.2	73.6	59.7	85.0	77.3	59.9	74.3	53.7	72.2	52.7	74.5	58.2	73.6	56.9
7	Maximum time spent		84.2	71.6	47.6	82.1	71.8	47.9	71.5	47.9	71.8	47.5	71.7	47.7	72.0	47.9
8	Maximum of average time spent		70.9	67.8	43.2	73.4	66.4	43.6	65.4	43.4	64.3	44.4	61.0	43.2	54.8	37.9
9	Number of vehicles		2	2	3	2	2	3	2	3	2	2	2	3	2	3
10	Number of routes		53	55	70	55	56	67	44	56	36	56	47	54	38	54
11	Total number of short treatments		158	158	175	142	142	142	188	188	134	134	186	188	132	132
12	Total number of normal treatments		190	190	178	202	202	202	98	98	126	126	101	100	126	126
13	Number of patients with 1 short treatment		8	8	6	8	8	8	0	0	0	0	0	0	0	0
14	Number of patients with 2 short treatments		10	10	9	16	16	16	0	0	7	7	0	0	6	6
15	Number of patients with 3 short treatments		18	18	17	34	34	34	8	8	40	40	14	12	40	40
16	Number of patients with 4 short treatments		19	19	25	0	0	0	41	41	0	0	36	38	0	0
17	Capacity utilization (%)		96.1%	96.1%	94.8%	97.5%	97.5%	97.5%	98.0%	98.0%	98.5%	98.5%	99.0%	99.0%	98.0%	98.0%
-	Number of trials on K limit		2	2	2	2	2	2	2	2	2	2	2	2	2	2
-	Best K limit		18	18	16	16	16	16	16	16	16	16	16	18	16	16
-	Gap of scheduling model on best K limit (%)		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	6.4%	6.4%
-	Solution Time (s)		215.6	215.7	212.0	150.2	150.4	148.9	223.3	222.2	111.3	111.9	154.4	155.2	615.0	613.8

Table 24: KPIs of the matheuristic MO solutions for Network N3 with 2 K limits

KPI No.	KPI	Instance	24	25	26	27	28	29	30	31	32	33	34	35	36	37
1	Performance score		52,618.6	53,714.4	64,863.4	53,876.6	53,987.3	67,056.6	1,549,367.6	1,554,517.5	1,743,220.0	1,749,378.2	1,451,844.9	1,456,019.6	1,744,151.4	1,749,145.3
2	Transfer number		0	0	0	0	0	0	15	15	17	17	14	14	17	17
3	Sum of the vehicles required each day		27	28	39	28	28	41	24	29	22	28	26	30	23	28
4	Treatment score		460	460	460	465	465	465	465	465	385	384	473	473	384	378
5	Total travel time		2618.6	2714.4	2863.4	2626.6	2737.3	2806.6	2117.6	2267.5	1970.0	2178.2	2194.9	2369.6	1951.4	2245.3
6	Maximum travel time		85.0	73.7	59.7	85.6	73.4	59.9	74.4	55.8	71.8	59.2	73.5	56.7	73.9	59.1
7	Maximum time spent		83.6	71.9	47.9	84.2	72.0	47.7	71.9	47.8	71.3	47.4	72.0	47.3	71.6	47.6
8	Maximum of average time spent		81.2	68.7	43.9	65.6	58.4	44.5	61.7	38.8	65.2	35.3	58.0	40.4	55.0	37.3
9	Number of vehicles		2	2	3	2	2	3	2	3	2	2	2	3	2	3
10	Number of routes		51	55	73	53	55	72	44	57	37	56	47	57	38	55
11	Total number of short treatments		124	124	124	125	125	125	182	182	127	126	186	186	127	123
12	Total number of normal treatments		212	212	212	215	215	215	101	101	131	132	101	101	130	132
13	Number of patients with 1 short treatment		15	15	15	20	20	20	1	1	0	3	0	0	0	4
14	Number of patients with 2 short treatments		19	19	19	21	21	21	1	1	8	9	1	1	8	10
15	Number of patients with 3 short treatments		17	17	17	21	21	21	9	9	37	35	12	12	37	33
16	Number of patients with 4 short treatments		5	5	5	0	0	0	38	38	0	0	37	37	0	0
17	Capacity utilization (%)		97.9%	97.9%	97.9%	99.1%	99.1%	99.1%	98.0%	98.0%	99.2%	99.5%	99.0%	99.0%	98.7%	98.7%
-	Number of trials on K limit		2	2	2	2	2	2	2	2	2	2	2	2	2	2
-	Best K limit		18	18	18	18	18	18	16	16	16	16	16	16	16	18
-	Gap of scheduling model on best K limit (%)		2.1%	2.1%	2.1%	3.1%	3.1%	3.1%	5.2%	5.2%	3.9%	3.9%	1.1%	1.1%	6.3%	5.9%
-	Solution Time (s)		615.7	616.0	615.5	612.3	612.1	612.2	614.7	615.0	611.2	611.4	614.0	616.5	611.0	614.1

CHAPTER VII

CONCLUSION

The focus of this thesis is to provide an effective and fast solution methodology to construct interdependent scheduling and routing decisions for a dialysis center aftermath of a disaster. In the post disaster setting, chronic dialysis patients are assigned to a dialysis center by a central authority. In the scope of the problem, we need to determine whether a patient receives treatments during the planning horizon in the dialysis center or is transferred out of the dialysis center. For the patients who get treatments, the days, sessions and treatment types of patients for each of their visits must be assessed. The dialysis center must construct vehicle routes for each session during the planning horizon. Decisions are taken regarding the primary and secondary objectives of the problem. The primary aim is to minimize (i) the number of patients transferred out of the dialysis center. The secondary objectives serve to increase the overall effectiveness of decisions. With their hierarchical order, the aim is to minimize (ii) the number of vehicles used each day during the planning horizon, (iii) treatment numbers and (iv) total travel time. Secondary objectives improve the service quality in terms of treatments applied and the transportation of the patients. The short treatment type is offered in the post disaster setting and it has half of the duration of the normal treatment. The normal treatment type is the healthier option and there is an upper limit for receiving short treatments during the planning horizon. A mathematical model is developed for taking decisions interdependently with the objectives stated. However, it is complex and we cannot obtain results for the real life problem sizes. Therefore, we develop a constructive heuristic and two matheuristics with different objective functions in the scheduling models, specifically matheuristic SO and matheuristic MO. After the development of constructive heuristic, to

improve the solutions, we define improvement strategies which are called S_p and location strategies. Besides, we propose an approach in which various capacity allocation parameters are applied iteratively. For the matheuristics SO and MO, to improve the solutions, we apply an approach in which the scheduling models within the matheuristics are solved with multiple K limits iteratively. We propose a rapid approach to obtain the solutions in a short time. We specify metrics to evaluate quality of the solutions. To test the solution methodologies, we analyze various instances on low, medium and large patient sized networks. Medium and large sized networks are derived from real data. Lastly, we compare the solutions obtained from the methodologies.

In the small test instances, the best results are achieved in CPLEX and the matheuristic MO. The primary objectives of matheuristics are the same. However, secondary objectives achieved by the matheuristic MO are the better than the results of the matheuristic SO. The constructive heuristic has the worst performance. In the case study, for the medium and large sized networks, CPLEX results are the worst due to large optimality gaps. The constructive heuristic performs better in the medium and large sized instances. In general, the matheuristic MO performs the best. Even if the same value of the primary objective is achieved under both matheuristics, higher quality solutions in terms of the secondary objectives are mostly achieved by applying various K limits on the matheuristic MO. However, the number of trials on the K limit is uncertain and varies by multiple factors. In a post disaster setting, all operations must be realized quickly and the decision must have been taken in a short time. Therefore, for an effective and fast response, the rapid approach is proposed.

Constructive heuristic results in under two minutes for all instances. Although, it provides less effective solutions compared to matheuristics. The matheuristic SO performs faster than the matheuristic MO. However, the computation time of both matheuristics may be affected by the low capacity and the dispersion of the last treatment days of patients before the disaster. Therefore, within the rapid

approach, the solutions of the matheuristics are achieved within 10 minutes and effective solutions can be applied for the decision making in the aftermath of a disaster.

The biggest contribution of this thesis is to provide effective and fast solution methodologies by considering the scheduling and routing problems jointly in the aftermath of a disaster. The consideration of the routing components in the scheduling decisions enables the achievement of overall effectiveness in operational decision making. Moreover, taking the decisions of scheduling and routing separately can lead to uncoordinated responses and complicate the application in both of the operations in a post disaster setting. Besides, multiple treatment options with varying visiting frequencies allow flexibility in the scheduling decisions while minimizing the number of patients transferred out of the dialysis center. We maintain service quality in terms of treatments and transportation of patients by features such as short treatment limit, travel time and ride time limit for patients. Future research can be considering the uncertainty on travel times that can be encountered due to the road conditions in the aftermath of a disaster.

CHAPTER VIII

APPENDIX

8.1 *An example of the scalarization of the objectives in the objective function*

The scalarization of the objectives is presented in Figure 12 for Instance 2 in which 25 patients are assigned to a dialysis center to get treatments. The maximum values among the outputs of sub-models are selected to be considered as the bounds for scaling for the respective objectives. Then, in Figure 13, the scaled values of objectives that are achieved from the solution of the mathematical model are presented. All of the scaled objectives are between 0 and 2 as described in Section 4.1. The penalty-weighted objectives are obtained by multiplying the scaled objectives by the respective penalty weights. The hierarchical order of the objectives is noticed by comparing the values of the weighted objectives. Lastly, the sum of weighted objectives is equal to the objective value of the mathematical model.

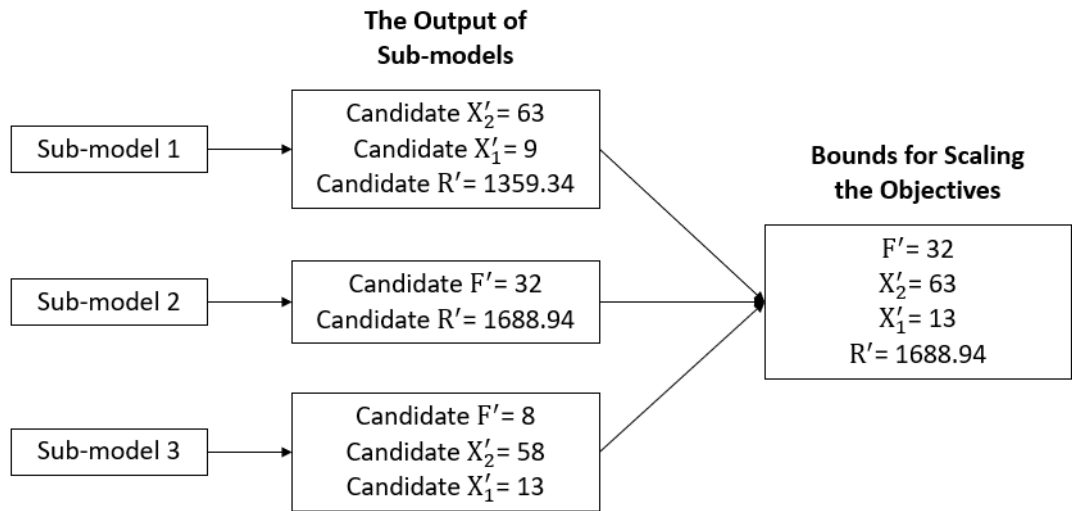


Figure 12: Scheme of scalarization of objectives

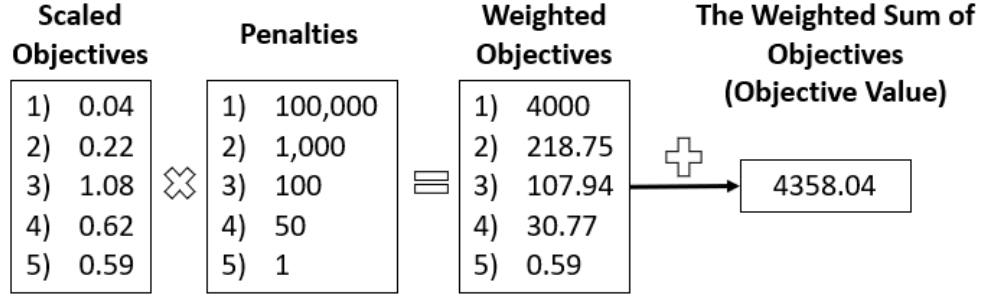


Figure 13: Scheme of the weighted sum of the objectives

8.2 Upper K limits on the networks

The maximum time between two patients in minutes and respective upper K limit are presented for Networks N1, N2 and N3 below.

Table 25: Upper K limits on Networks N1, N2 and N3

	Network N1	Network N2	Network N3
Maximum travel time	34.74	17.45	18.47
Upper K limit	35	18	19

8.3 The best results of matheuristic MO on Instances 10, 11 and 12 under different K limits

Table 26: KPIs of the matheuristic MO solutions for Instances 10, 11 and 12 of Network N1

KPI No.	KPI	Instance	10	11	12
1	Performance score		1,110,096.4	1,110,096.4	1,110,096.4
2	Transfer number		11	11	11
3	Sum of the vehicles required each day		7	7	7
4	Treatment score		52	52	52
5	Total travel time		496.4	496.4	496.4
6	Maximum travel time		42.6	42.6	42.6
7	Maximum time spent		33.6	33.6	33.6
8	Maximum of average time spent		31.8	31.8	31.8
9	Number of vehicles		1	1	1
10	Number of routes		14	14	14
11	Total number of short treatments		16	16	16
12	Total number of normal treatments		20	20	20
13	Number of patients with 1 short treatments		8	8	8
14	Number of patients with 2 short treatments		4	4	4
15	Number of patients with 3 short treatments		0	0	0
16	Number of patients with 4 short treatments		0	0	0
17	Capacity utilization (%)		100.0%	100.0%	100.0%
-	Number of trials on K limit		25	25	25
-	Best K limit		14	14	14
-	Gap of scheduling model on best K limit (%)		1.4%	3.6%	1.7%
-	Solution Time (s)		4950.0	7956.4	5015.8

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VITA

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