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# Covering Vehicle Routing Problem: Application for Mobile Child Friendly Spaces for Refugees

**Elfe Buluc · Meltem Peker · Bahar Y. Kara · Manoj Dora**

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**Abstract** The world is facing a large-scale refugee crisis because of the ongoing war in Syria, and it is important to improve refugees' life conditions from a humanitarian point of view. In order to analyse the living conditions of refugees, we conduct fieldwork in a district in Ankara, Turkey, and interview refugees, the local population and humanitarian practitioners from several organizations. Among the many challenges refugees face, we observe that addressing the problems of refugee children is critical. Thus, in this study, we focus on increasing the efficiency of the education services provided to refugee children. We investigate a service provided via mobile trucks that supply informal education and psychological support to children. By analysing the operational dynamics of these trucks, we introduce two problems to the logistics literature, which we refer to as the Covering Vehicle Routing Problem and the Covering Vehicle Routing Problem with Integrated Tours. In the first problem, we either visit or cover all nodes, such that every node not in one of the tours is within a predetermined distance of any visited node. In the second problem, we generate smaller tours for covered (or unvisited) nodes originated at the visited ones. We first propose mathematical models for the problems and then introduce heuristic methods to overcome the computational challenge of the second problem. In the computational study, we compare the optimal solutions obtained using the models with a solution of real life application. We then test the models and heuristics on medium and large real data sets gathered from Turkey and conduct sensitivity analysis on the model parameters.

**Keywords** Humanitarian Logistics · Refugee Services · Covering Vehicle Routing Problem · Integrated Tours

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## 1 Introduction

The world is facing a large-scale refugee crisis because of the ongoing war in Syria. As of 2017, Syrian refugees are contributing almost one-third of the world's refugee population and 5.6 million refugees are registered outside of Syria (UNHCR, 2018). Most of them live in Middle Eastern and North African countries, Turkey, Lebanon, Jordan, Iraq, and Egypt, and around 10% of them are in European countries. The end of the war is still not imminent: hence, the integration of refugees in the host countries becomes an important aspect of the refugee crisis from a humanitarian point of view.

Children constitute more than half of the Syrian refugee population and 1.7 million of these children are school-aged (UNICEF, 2017): 57% of them are enrolled in formal education and 3% are enrolled in informal education (NLG, 2017). However, 43% of Syrian refugee children are unable to attend any kind of education because of challenges such as funding, resources, and their families' income (UNICEF, 2017).

### 1.1 Refugees' Children in Turkey and their Needs

Turkey is the largest host of refugees in the world, with over 3.7 million registered refugees, according to the estimates of the Ministry of Interior (ECHO, 2018). Only 6% of the Syrian refugees live in one of 20 camps in Turkey that meet their basic needs, such as shelter, health services, food and education. The remaining Syrians prefer not to live in these camps, even though meeting their basic needs can be much more challenging outside of the camps (ECHO, 2018). Most of the refugees who live outside of the camps are in the southeast region of Turkey and in some major cities such as Istanbul, Ankara, and Izmir.

In order to analyse the conditions of the Syrian refugees through first-hand observations, the first author conducts a fieldwork study in an area where a considerable number of Syrian refugees have settled. The main focus of the fieldwork is to listen to people who are faced with a change in their life because of the war, and get a sense of the real situation in order to give a solid and practical background to the theoretical work. Syrian refugee children in Turkey constitute 52.5% of Syrians in the camps and 43.3% of Syrians outside of the camps (AFAD, 2018). Enrolment in formal education is high in the camps, since education services are provided free of charge by volunteer Syrian teachers. On the other hand, enrolment in formal education by Syrian children who live outside of the camps is very low (Alpaydın, 2017). We interviewed Syrians and officers from organizations such as Ministry of the Interior Directorate General of Migration Management, the Civil Registry Office, Social Assistance and Solidarity Foundations, the Turkish Red Crescent and temporary education centres. Using these interviews, we deduct that another important reason for not enrolling in formal education is due to economic challenges. Although there are schools in the district that offer education to Syrian children with Syrian teachers, most of the children have to work to meet their and their families' basic human needs. We also observe that, even though there are Turkish schools which provide education services for Syrian children, the number of these schools is inadequate to meet the demand. There are also private schools that are supported by some Syrians and NGOs. However, enrolment in these schools is also low (Sonmez, 2014). The language barrier is another important factor, since it is considered that Syrians will live in Turkey for a short period of time and then go back to Syria after the war is over. Thus, teaching Turkish to Syrian children is undervalued and families disregard their children's education (Seydi, 2014).

### 1.2 Child-Friendly Spaces

In Turkey, it is estimated that around 380,000 Syrian children are not attending school, which makes them vulnerable because of the risk of isolation, discrimination, economic and sexual exploitation, and child marriage (UNICEF, 2017). Thus, increasing educational services for refugee children is an important problem to prevent a lost generation and increase their adaptation to the host country.

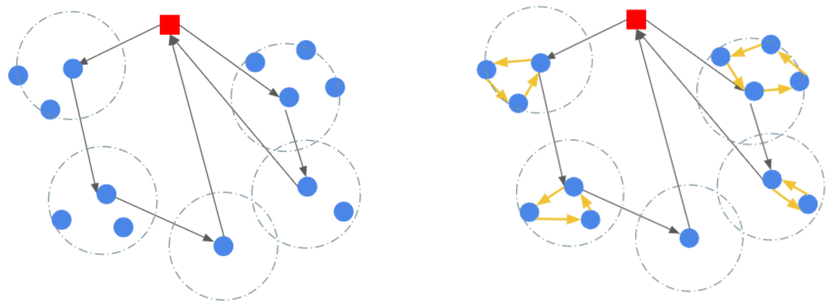
There are some services in Turkey that provide either formal or informal education to refugee children. They are mainly operated by the Turkish Red Crescent and UNICEF. For informal education, child-friendly spaces (CFS) are used to ensure children's protection and well-being. They provide opportunities for children to play, acquire skills, receive social support and become aware of their rights (UNICEF, 2011). In Turkey, as of 2017, there are 28 CFS and two mobile CFS (MCFS) that are used to reach vulnerable children. These MCFS are large trucks which provide informal education and support services through a team of teachers and psychologists who travel within the trucks. The MCFS trucks travel to reach refugee children, especially in areas where the Syrian refugee population is high. The trucks generally park near schools that have large numbers of Syrian students, and it is estimated that around 400 students visit these trucks in a month (Lorch, 2017).

### 1.3 Problem Definition

Upon investigating the situation explained above and the real data for the trucks, taken from Turkish Red Crescent, we realize that the number of areas visited and the number of refugee children served by the MCFS trucks can be improved drastically using optimization methods. By minimizing the distance travelled by the MCFS trucks and guaranteeing the accessibility of the MCFS service for children, we aim to increase the efficiency of the service. We consider that the MCFS trucks travel to certain areas and stay there for a while to provide psychological support and educational activities to the children in the area. Once the truck has stopped in a particular area, children from "close enough" neighbouring areas are assumed to travel to MCFS. Thus, children residing in neighbouring areas are also assumed to be reached.

In this paper, we define the Covering Vehicle Routing Problem (CVRP) as designing the routes of the MCFS trucks that either visit or cover all nodes, such that every node that is not in one of the tours is within a predetermined distance of any visited nodes (Fig. 1a). The aim of the problem is to minimize the total distance travelled by the trucks.

To remedy the possible decrease in accessibility or awareness of the MCFS trucks by the children in the nodes that are only covered (not visited), a variation of the CVRP is then proposed. In this variation, which is referred to as the CVRP with Integrated Tours (CVRPwIT), we generate smaller tours for the covered nodes originated at a visited node (Fig. 1b). We consider that the team, which consists of teachers and psychologists who travel within the trucks, visit the covered nodes on foot to increase awareness of the trucks, gather the children, observe and analyse the situation of the children's living conditions, and provide psychological support to the children who are not able to visit the trucks. The aim of the second problem is also to minimize the total distance travelled by the trucks and the team while ensuring that all nodes are visited by either trucks or teams.



(a) Covering Vehicle Routing Problem (CVRP)

(b) CVRP with Integrated Tours (CVRPwIT)

**Fig. 1** Illustrations of the proposed problems.

The paper continues as follows: In Section 2, we discuss the related literature. In Section 3, we provide mathematical programming models for the problems CVRP and CVRPwIT. We also provide solution approaches to handle the computational burden of the second model in the same section. In Section 4, we present the results of our computational study. We conclude with some final remarks in Section 5.

## 2 Literature Review

Given the increasing demand for humanitarian relief operations and the importance of logistics in such cases, and the direct consequences of both natural and man-made disasters, it can be argued that studying humanitarian logistics is of utmost importance. Various literature reviews have been conducted on humanitarian logistics and disaster management. Bayram (2016) conducts a literature review on emergency evacuation, while Behl and Dutta (2018) classify humanitarian supply chain management literature according to a scope of research such as resilience-based, disaster phases etc. Altay and Green (2006), Kovács and Spens (2007), Cozzolino (2012) and Galindo and Batta (2013) categorize articles in terms of their stance on the disaster management cycle, whereas Ozdamar and Ertem (2015) focus on the response and recovery phases of the disaster management cycle. Kara and Savaser (2017) and Gulczynski et al. (2006) categorize humanitarian logistics as relief logistics and development logistics.

In a recent review, Goldschmidt and Kumar (2016) argue that researchers have been primarily focused on establishing supply chain methodologies to improve disaster response rather than humanitarian development, such as relief distribution and network design (Habib et al., 2016; Bealt and Mansouri, 2018). For humanitarian supply chain management in the case of refugees, Seifert et al. (2018) argue that there are more theoretical works than empirical ones, and that recent studies focus more on disaster relief than on development aid operations. Thus, it can be observed that even though there are many studies on humanitarian logistics, many of them focus on disaster preparedness and relief rather than humanitarian development.

We now provide a summary of the routing literature, due to its close relation with the proposed problem in this study.

## 2.1 Related Routing Problems

In the classical Travelling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP), the routes of the vehicle(s) are determined while minimizing travelling costs and visiting all of the demand points in a network. However, there are some variations of the problems where not all of the points in the network are visited: rather, the most profitable ones are selected. Feillet et al. (2005) classify such problems as Travelling Salesman Problems with Profits (TSPs with Profits), and define three classes of such problems, namely the Selective Travelling Salesman Problem (STSP), the Quota Travelling Salesman Problem (Quota TSP), and the Profitable Tour Problem (PTP).

A general version of the selective routing problems is referred to as the Covering Salesman Problem (CSP), where a minimum cost tour is identified such that any node not included in the tour is within some predetermined covering distance of a node in the tour (Current and Schilling, 1989). In the CSP, every node must be either visited or covered and the decision as to which nodes to cover and which nodes to visit is considered by minimizing the travel costs. Another related problem is the Covering Tour Problem (CTP), in which a set of vertices $V$ that can be visited, a set of vertices $T \subseteq V$ that must be visited, and a set of vertices $W$ that must be covered are defined, and the aim is to find a minimum length tour over a subset of $V$ such that it contains all vertices of $T$ and lies within a prespecified distance from every vertex of $W$ (Gendreau et al., 1997). Hachicha et al. (2000) propose a multi-vehicle version of the CTP. An example of the application of the CTP is health care teams travelling in rural areas of developing countries to deliver medical care, where they visit a subset of villages and the residents of unvisited villages travel to the nearest node on the tour to obtain medical care (Current and Schilling, 1994). Furthermore, Hodgson et al. (1998) implement CTP for planning mobile health care facilities in Ghana, which are expected to increase the accessibility of the equipment, staff, and health care facilities supplied. Another CTP application in humanitarian aid is the location of satellite distribution centres to deliver aid to affected people in disaster areas, as studied by Naji-Azimi et al. (2012). People in disaster-affected regions are expected to go to these distribution centres, which are close to their homes, to supply their needs, and the distribution centres are supplied from a central depot through capacitated vehicles.

Other related routing problems are the Generalized Travelling Salesman Problem (GTSP) and the Generalized Vehicle Routing Problem (GVRP). Baldacci et al. (2010) define the GVRP as an extension of the VRP where each set of vertices is partitioned into clusters, and the routes of the vehicles are determined considering minimizing the total cost. Bektas et al. (2011) introduce application areas for GVRP such as health care logistics, where each district consists of several municipalities and the medical distribution team delivers pharmaceutical products into one municipality within each district. Another area of application of the GVRP is the urban waste collection problem, where the routes used by vehicles to collect urban waste and deliver it to the dump, incinerator, or recycling plant is determined considering minimum transportation costs (Bautista et al., 2008; Bektas et al., 2011). Other variants of covering-routing problems and their properties can be seen in Table 1.

**Table 1** Covering-Routing Problems

| Problem | Introduced By | Objective | Vehicle | Dynamics |
|---|---|---|---|---|
| Covering Salesman Problem | Current and Schilling (1989) | minimize cost | single | Each node can be covered or visited |
| Generalized Covering Salesman Problem | Golden et al. (2012) | minimize cost | single | Cost of visiting each node, Nodes can be visited more than once |
| Geometric Covering Salesman Problem | Arkin and Hassin (1994) | minimize cost | single | Covering intersection of the neighbourhoods |
| Covering Tour Problem | Gendreau et al. (1997) | minimize cost | single | Set of vertices to cover and set of vertices to visit |
| Multi-vehicle Covering Tour Problem | Hachicha et al. (2000) | minimize cost | multi | Set of vertices to cover and set of vertices to visit |
| Maximal Covering Tour Problem | Current and Schilling (1994) | minimize length maximize access | single | Visit only $p$ nodes of the network, Access - maximize demand |
| Median Tour Problem | Current and Schilling (1994) | minimize length maximize access | single | Visit only $p$ nodes of the network, Access - minimize access distance |
| Generalized Travelling Salesman Problem | Henrylab (1969) | minimize cost | single | Vertices are partitioned into clusters |
| Generalized Vehicle Routing Problem | Ghiani and Improta (2000) | minimize cost | multi | Vertices are partitioned into clusters |
| Close Enough Travelling Salesman Problem | Gulczynski et al. (2006) | minimize length | single | Visiting the intersection of coverage areas |
| Close Enough Vehicle Routing Problem | Mennell (2009) | minimize length | multi | Visiting the intersection of coverage areas |

Routing problems in humanitarian logistics also garner great interest in the light of the increasing demand for humanitarian relief operations. As discussed above, Current and Schilling (1994), Hodgson et al. (1998) and Naji-Azimi et al. (2012) study for the application of CTP to humanitarian logistics, and Bektas et al. (2011) introduce application areas for GVRP such as health care logistics. Hemmelmayr et al. (2009) study the problem of the delivery of blood products to hospitals and develop two routing strategies. The first strategy has fixed routes with flexible days and the second strategy has flexible routes with repeating delivery patterns. Huang et al. (2012) discuss the vehicle routing problem in relief operations and define metrics for equity, efficiency and efficacy. The authors analyse the effect of these metrics on routing decisions. Examples of routing problems in humanitarian logistics include home healthcare systems (An et al., 2012), assigning teaching assistants to disabled people and routing them (Maya et al., 2012), post-disaster logistics (Sheu, 2014), and routing ambulances after an earthquake (Mills et al., 2018).

A comparison of our problems to the most relevant literature can be seen in Table 2. Our problem can be classified as a generalization of the CSP with multiple vehicles, as each node can be covered or visited. It is also very similar to the mCTP; however, the common characteristic of the CTP and its variations is that the set of vertices to cover and the set of vertices to visit are different. Thus, rather than classifying the problem introduced as a variation of the CTP, we will refer to it as the Covering Vehicle Routing Problem (CVRP) as a generalization of the CSP.

Moreover, Semet and Taillard (1993) solve a similar problem to ours in which some customers can get services only via specified ways of transportation; and a truck covers a route, unloads its trailer to reach some specified customers through a subtour, turns back and loads its trailer again and continues its main tour. The problem is introduced as a real-life VRP and a tabu search-based method is used to find solutions. Even though our problem is similar, in this type of problem, the subsets are defined considering the characteristics of the ways of transportation through which the customers are served. Since we approach our problem as a covering-routing problem in terms of deciding on the subtours by means of coverage range rather than transportation type, we will refer to our problem as the Covering Vehicle Routing Problem with Integrated Tours (CVRPwIT). To the best of the authors' knowledge, this version of the problem has not previously been defined in the literature. We also note that the problem setting can be easily applied to the problems in the categories of CSP, CTP and CVRP. For example, for the travelling circus problem (ReVelle and Laporte, 1993), a presenter may visit cities near to the city where the circus is located to increase people's awareness of the circus.

**Table 2** Comparison of the Proposed Problems to the Related Literature

| Problem | Introduced By | Objective | Vehicle | Dynamics |
|---|---|---|---|---|
| Routing Problems with Profits | various | various | various | Most profitable nodes are selected to visit |
| Generalized Vehicle Routing Problem | Ghiani and Improta (2000) | minimize cost | multi | Set of clusters to visit |
| Multi-vehicle Covering Tour Problem | Hachicha et al. (2000) | minimize cost | multi | Set of vertices to cover and set of vertices to visit |
| Covering Salesman Problem | Current and Schilling (1989) | minimize cost | single | Each node should be covered or visited |
| Covering Vehicle Routing Problem (CVRP) | This study | minimize cost | multi | Each node should be covered or visited |
| Covering VRP with Integrated Tours (CVRPwIT) | This study | minimize cost | multi | Integrated tours from the visited nodes to the covered nodes |

## 3 Model Development

### 3.1 Covering Vehicle Routing Problem

The covering Vehicle Routing Problem (CVRP) determines the routes of the trucks that either visit or cover all nodes and minimizes the total distance travelled by the trucks. As customarily done in VRP literature, we assume that we have a limited number of trucks which should start and end their tours at the depot. We also assume that each node can be either visited or covered at most once.

Let $G = (V, A)$ be a graph such that $V = \{0, 1, ..., n\}$ is the set of nodes and $A = \{(i, j) : i, j \in V\}$ is the set of arcs. Node 0 denotes the depot. There is a symmetric distance matrix $D = \{d_{ij} : (i, j) \in A\}$ associated with each arc in the set $A$. $N_i$ denotes a set of nodes such that the distance between them and node $i$ is less than or equal to a threshold value, $\gamma$ (i.e. $N_i = \{j : d_{ij} \leq \gamma, j \in V\}$). The number of vehicles is denoted by $m$ and the maximum distance a vehicle can travel is denoted by $C$.

The binary decision variable $x_{ij}$ is 1 if node $j$ is visited immediately after node $i$ and 0 otherwise. The other binary decision variable $z_i$ is 1 if node $i$ is visited and 0 otherwise. Finally, for each arc in the set $A$, $u_{ij}$ is a continuous variable representing the total distance from the depot to node $j$ which is visited immediately after node $i$.

The model for CVRP ($M_C$) is given below:

$$
\begin{aligned}
(M_C) \quad & \min \quad \sum_{i\in V}\sum_{j\in V} d_{ij}x_{ij} && && (1)\\
\text{s.t.} \quad & \sum_{j\in V} x_{0j} = m && && (2)\\
& \sum_{i\in V} x_{i0} = m && && (3)\\
& \sum_{j\in V} x_{ij} = z_i && \forall i \in V \quad i \neq 0 && (4)\\
& \sum_{j\in V} x_{ji} = z_i && \forall i \in V \quad i \neq 0 && (5)\\
& (1 - z_i) \leq \sum_{k\in N_i} z_k && \forall i \in V && (6)\\
& \sum_{i\in V} x_{ii} = 0 && && (7)\\
& \sum_{\substack{j\in V\\ j\neq i}} u_{ij} - \sum_{\substack{j\in V\\ j\neq i}} u_{ji} - \sum_{j\in V} d_{ij}x_{ij} = 0 && \forall i \in V \quad i \neq 0 && (8)\\
& u_{0i} = d_{0i}x_{0i} && \forall i \in V \quad i \neq 0 && (9)\\
& u_{ij} \leq (C - d_{j0})x_{ij} && \forall i \in V \quad \forall j \in V \quad j \neq 0 && (10)\\
& u_{i0} \leq Cx_{i0} && \forall i \in V \quad i \neq 0 && (11)\\
& u_{ij} \geq (d_{0i} + d_{ij})x_{ij} && \forall i \in V \quad i \neq 0 \quad \forall j \in V && (12)\\
& x_{ij} \in \{0,1\} && \forall i \in V \quad \forall j \in V && (13)\\
& z_i \in \{0,1\} && \forall i \in V && (14)
\end{aligned}
$$

Objective function (1) minimizes the total distance travelled by trucks. Constraints (2) and (3) ensure that the tours start and end at the depot and $m$ vehicles are conducting the tours. Constraints (4) and (5) guarantee that a node cannot be visited more than once. Constraint (6) ensures that every node should be either visited or covered, and if a node is not visited (i.e. $z_i = 0$), then another node which is in the set $N_i$ must be visited. Constraint (7) eliminates visits from a node to itself. Constraints (8) - (12) are subtour elimination constraints, which are proposed in Kara (2011). Constraints (13) and (14) are domain restrictions.

### 3.2 Covering Vehicle Routing Problem with Integrated Tours

CVRP with Integrated Tours (CVRPwIT) is an extension of the CVRP and generates smaller tours for the covered nodes that are originated at the visited ones. We consider that a team which consists of teachers and psychologists who travel within the trucks visits the covered nodes by foot. The goal is to minimize the total weighted distance travelled by the trucks and the team in the smaller tours, where $\alpha$ denotes the weight of the total distance travelled by trucks and $\beta$ is the weight of the total distance travelled by the team. In CVRPwIT, we assume that each small tour conducted by the team starts and ends at the same node. Each node in the small tours is also visited by the team exactly once.

In addition to the decision variables above, three new decision variables are defined for the model of CVRPwIT. $y_k^i$ is 1 if node $k$ is visited within the small tour originated at node $i$ and 0 otherwise. $w_{jl}^i$ is 1 if node $l$ is visited immediately after $j$ and visited within the small tour originated at node $i$, and 0 otherwise. $v_j^i$ is a continuous variable that is used to order the nodes in the small tour originated at node $i$.

The model for CVRPwIT ($M_{\text{C\_wIT}}$) is given below:

$$(M_{\text{C\_wIT}}) \quad \min \quad \sum_{i \in V} \sum_{j \in V} \Big( \alpha\, d_{ij} x_{ij} + \sum_{l \in V} \beta\, d_{jl} w_{jl}^i \Big) \tag{15}$$

$$\text{s.t.} \quad (2) - (14)$$

$$y_k^i \leq z_i \qquad \forall i \in V \quad \forall k \in V \tag{16}$$

$$\sum_{\substack{i \in N_k \\ i \neq k}} y_k^i = (1 - z_k) \qquad \forall k \in V \tag{17}$$

$$\sum_{\substack{j \in N_i \\ j \neq k}} w_{kj}^i = y_k^i \qquad \forall i \in V \quad \forall k \in N_i \quad k \neq i \tag{18}$$

$$\sum_{\substack{j \in N_i \\ j \neq k}} w_{jk}^i = y_k^i \qquad \forall i \in V \quad \forall k \in N_i \quad k \neq i \tag{19}$$

$$v_j^i - v_l^i + n\, w_{jl}^i \leq n - 1 \qquad \forall i \in V \quad \forall j \in N_i \quad \forall l \in N_i \quad l \neq i \tag{20}$$

$$y_k^i \in \{0, 1\} \qquad \forall i \in V \quad \forall k \in V \tag{21}$$

$$w_{jl}^i \in \{0, 1\} \qquad \forall i \in V \quad \forall j \in V \quad \forall l \in V \tag{22}$$

Objective function (15) is the weighted sum of the total distance travelled by the trucks and the team in the small tours, respectively. Constraints (2) - (12) are the same as in the first model and determine the main tour. Constraint (16) prevents any small tour from starting from a node that is not visited by the trucks. Constraint (17) ensures that a node that is not visited by the trucks should be in exactly one of the small tours. Constraint (17) also guarantees that the nodes visited by the trucks cannot be in the small tours. Constraints (18) and (19) guarantee that a node in a small tour can be visited by the team exactly once. Constraint (20) is the subtour elimination constraint and orders the nodes in the small tours. Constraints (21) and (22) are domain restrictions.

We also note that the following constraint can be added to the model ($M_{\text{C\_wIT}}$) to limit the distance of the smaller tours.

$$\sum_{j \in V} \sum_{l \in V} d_{jl} w_{jl}^i \leq \kappa \qquad \forall i \in V \tag{23}$$

where $\kappa$ is the threshold value for the walking tours.

### 3.3 Solution Approaches

During our preliminary study, we encounter instances whose optimality for the second problem (CVRPwIT) cannot be verified within a predetermined time limit for the medium-size data set, which will be discussed in detail in Section 4.2. Thus, to overcome the computational burden and avoid memory problems, we propose three heuristic solution methodologies for CVRPwIT. The heuristics consist of several steps that are evaluated sequentially. In the heuristics, we first identify nodes that are visited and covered (or unvisited) by the trucks. Using the outputs, we then determine the integrated tours.

In the first heuristic, we construct the main tour using the model $M_C$ and optimally solve it with a solver. We then use an assignment model and cluster the nodes by minimizing the distance of each unvisited node from the visited nodes. Finally, we utilize the mathematical programming model for the well-known travelling salesman problem (TSP) proposed in Miller et al. (1960) to find out the optimal tours within each cluster.

In the second heuristic, similar to the first one, we again first find the main tour optimally by running the model $M_C$ with a solver and identify the nodes visited by trucks and the main tour. After obtaining the main tour, we fix it in $M_{\mathrm{C\_wIT}}$ and run the model $M_{\mathrm{C\_wIT}}$ to find the integrated tours.

In the third heuristic, we first determine the number of visited nodes, $\tau$, and identify a set of candidate nodes, $S$, to be visited by the trucks in the main tour by solving the set covering model proposed in Toregas and Revelle (1973). We then run the model $M_C$ by adding the following constraints to the model, $(1-\delta)\tau \leq \sum_{k\in S} z_k$ and $\sum_{k\in V} z_k \leq (1+\delta)\tau$ where $0 \leq \delta \leq 1$. After obtaining the main tour, similar to the previous heuristic, we fix it in the model $M_{\mathrm{C\_wIT}}$ and obtain the integrated tours. In the computational analysis, we test the third heuristic with two different $\delta$ values, 0.10 and 0.25, and compare the solutions.

## 4 Computational Analysis

In this section, we first discuss the real routes of the trucks taken from Turkish Red Crescent data and the optimal routes obtained by the proposed models. We then test the models and solution approaches on medium and large size real data sets and provide a sensitivity analysis on the problem parameters. All experiments are implemented in a Java platform using Cplex 12.7.1 on a Linux OS environment with Dual Intel Xeon E5-2690 v4 14 Core 2.6 GHz processors with 128 GB of RAM.

### 4.1 Real Life Application

Data regarding the past activities of the two trucks for 2016 and 2017 is collected from the Turkish Red Crescent. Data shows that during this time period, the trucks travel 5552.9 km and visit 20 points, namely eleven temporary education centres, three schools, two camps for seasonal agricultural workers, one temporary shelter centre, one student residence, one repatriation centre, and one maintenance area. The representation of the visited points can be seen in Fig. 2.

Since Adapazari is visited once during this time period for maintenance, it is taken as the depot for the mathematical models. The predetermined distance to cover nodes, $\gamma$, is assumed to be 2 km so as not to exceed the walking distance considering the real-life application and not to decrease the accessibility of the MCFS.

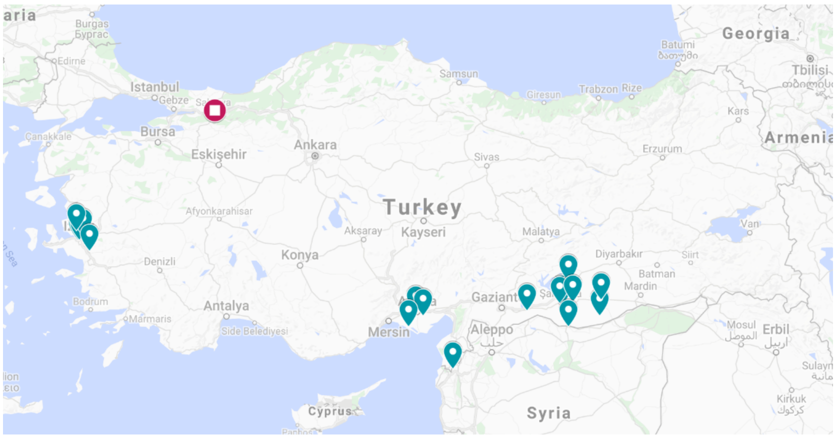



**Fig. 2** Points visited by the MCFS trucks in 2016 and 2017.

In the optimal solution of the first model ($M_C$), the trucks visit 19 points. The total travel distance of the trucks turns out to be 4147.2 km: thus, the optimization model decreases the total travel distance by 25.32%. The tour obtained for the first truck can be seen in Fig. 3. In this figure, the trails starting from the depot and ending at the depot are not fully shown. It can be observed that one point which is very close to a visited point is not included in the main tour, but rather covered. For the second model, $M_{\text{C\_wIT}}$, we first estimate the weights $\alpha$ and $\beta$ which denote the weights of the total distance travelled by trucks and by the team, respectively. Since trucks are scarce sources for the Turkish Red Crescent, we utilise reciprocal proportion of the speed of trucks and walking speed considering the real-life application which are assumed to be 80km/h (Demir et al., 2012) and 5 km/h (Azmi et al., 2012), and determine the weights as $\alpha = 1$ and $\beta = 0.0625$. With the estimated weights, the main tour remains the same and only one small tour, with a total travel distance of 3.2 km, is generated for the covered one. We note that we do not use Constraint (23) and only solve the model $M_{\text{C\_wIT}}$ since the distances are already small.

This result indicates that it is possible to decrease the travelled distance of the trucks by optimizing the routes and by not visiting all points; hence, we are able to cover more points, reach more children or increase service time for each visit in a given time period. This is a valuable improvement, considering the restricted number of vehicles and the fact that optimizing the routes would be much more cost efficient than renting/purchasing new vehicles, especially with budget restrictions. There may be still possible real-life implications during the decision-making process regarding the routes: for example, some schools may not be able to provide parking during certain time periods, or some vehicles may require maintenance at

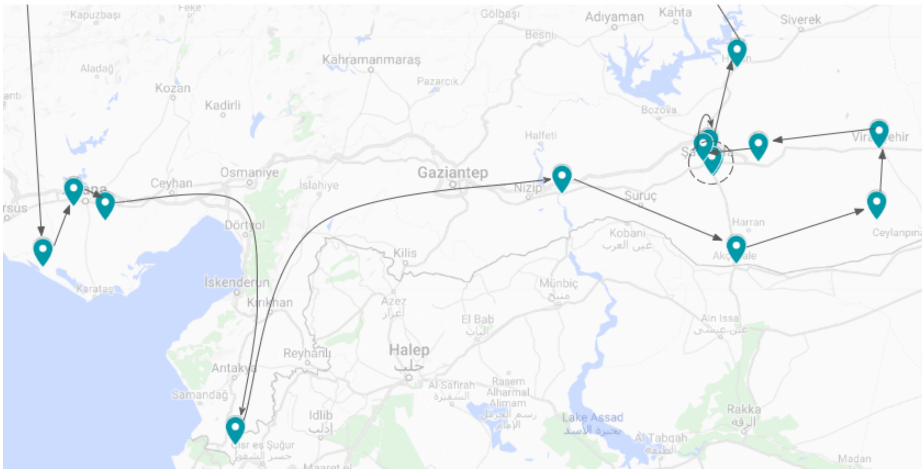



**Fig. 3** A part of the tour obtained by model $M_C$.

unpredicted times. However, it can be assumed that making use of the optimization methods would still be more efficient, considering that the improvement is quite significant.

### 4.2 Computational Results on a Medium-Size Real Data Set

The models are further tested with a medium-size data set that is also for a real-life application. The data set considers one of the cities in Turkey, Burdur, which includes a population of 45 villages with distances between them (Kara and Savaser, 2018). In this section, we first discuss the optimal solutions of models $M_{\mathrm{C}}$ and $M_{\mathrm{C\_wIT}}$. We then perform a sensitivity analysis on the weights $\alpha$ and $\beta$ assigned to distance travelled by the trucks and the team, respectively that are used in the second model.

#### *4.2.1 Solutions of the Models*

In this section, we discuss and analyse the results with different parameter settings. We vary the number of trucks, $m$, by 2, 3 and 4. The maximum time that each truck can travel, $C$, is decided by considering the number of trucks and the average time of the tours. Experiments are conducted with the values of 1200, 1500, and 2000 minutes for $m = 2$ and 1000, 1200, and 1500 minutes for $m = 3$ and $m = 4$. Using our results in preliminary studies, we set the coverage range, $\gamma$, to 90 minutes, and the weights of the objective function of the second model ($M_{\mathrm{C\_wIT}}$), $\alpha$ and $\beta$, are equal to 1 and 0.0625, respectively, as used for the real-life application in Section 4.1. The models are tested for a time limit of six hours.

Table 3 shows that for the same $C$ value, the distance of the main tours increases as the number of vehicles, $m$, also increases, which is due to the fact that all vehicles should start and end their tours at the depot (Fig. 2). On the other hand, for any $m$, the distance of the main tours increases while $C$ decreases. This result

**Table 3** Solutions of the Models on a Medium-Size Data Set with Different Parameters

| | | $(M_C)$ | | $(M_{\mathbf{C\_wIT}})$ | | |
|---|---|---|---|---|---|---|
| $m$ | $C$ | Total Time of Main Tours | Solution Time (sec.) | Total Time of Main Tours | Total Time of Small Tours | Solution Time (sec.) |
| 2 | 1200 | 2089.58 | 225.89 | 2095.16 | 1966.40 | 19979.78 |
| | 1500 | 1866.38 | 27.95 | 1872.49 | 2156.00 | 201.67 |
| | 2000 | 1811.42 | 24.17 | 1813.78 | 2263.19 | 109.75 |
| 3 | 1000 | 2532.66 | 178.28 | 2546.20 | 1951.25 | 9846.72 |
| | 1200 | 2166.86 | 129.82 | 2175.47 | 1841.56 | 6094.20 |
| | 1500 | 1943.66 | 26.60 | 1949.77 | 2106.38 | 138.22 |
| 4 | 1000 | 2609.93 | 165.74 | 2623.48 | 1901.63 | 1498.42 |
| | 1200 | 2251.95 | 299.57 | 2257.52 | 1841.56 | 980.52 |
| | 1500 | 2028.75 | 23.12 | 2031.94 | 2106.38 | 70.19 |

indicates that the more a vehicle's capacity to travel increases, the less distance is travelled to cover all the nodes. From Table 3, we also observe the importance of adding integrated tours since total time of main tours in the model $M_{\mathrm{C\_wIT}}$ are always higher than the total time of the main tours in the model $M_C$.

#### *4.2.2 Sensitivity Analysis on Weights $\alpha$ and $\beta$*

We further test and perform a sensitivity analysis on the weights $\alpha$ and $\beta$ in the second model. Table 4 shows the solutions obtained with $\alpha = 1$ and three different $\beta$ values where the weights demonstrate the relative importance of the distance travelled by the truck and the team. In any of the cases, main tours are valued over small tours because of the problem structure, however, the solutions still differ by the variations in $\beta$ and the decision maker can choose the value they give for smaller tours. For example, the scenario with $\alpha = 1$, $\beta = 0.01$ corresponds to the case where utilising the trucks has the utmost importance compared to utilizing the team. In Table 4, we again provide the solutions given in Table 3 obtained with the estimated $\alpha = 1$ and $\beta = 0.0625$ values for readability. The model is tested for a time limit of six hours.

Table 4 shows that similar to the discussions in Section 4.2.1, for all combinations of $\alpha$ and $\beta$ values, for the same $C$ value, the total time of the main tours increases as the number of vehicles, $m$, also increases and for any $m$, the total time of the main tours increases while $C$ decreases. However, there is no general trend for the the total time of the small tours as the trends highly depends on $\alpha$ and $\beta$ values. For example, when $m = 2$, for the scenario with $\beta = 0.0625$, total time of the small tours always increases as $C$ increases. On the other hand, total time of small tours first increases then decreases as $C$ increases with other weights. We finally note that, as expected, the objective value of the model increases as $\beta$ increases.

**Table 4** Comparison of the Solutions of Model $M_{\text{C\_wIT}}$ with Different Weights

| | $m$ | $C$ | Total Time of Main Tours | Total Time of Small Tours | Objective Value | Optimality Gap (%) | Solution Time (sec.) |
|---|---|---|---|---|---|---|---|
| $\alpha = 1$ $\beta = 0.01$ | 2 | 1200 | 2090.65 | 2101.96 | 2111.67 | 0 | 1345.45 |
| | | 1500 | 1866.38 | 2403.09 | 1890.41 | 0 | 53.86 |
| | | 2000 | 1811.42 | 2366.77 | 1835.09 | 0 | 42.80 |
| | 3 | 1000 | 2532.66 | 2354.96 | 2556.21 | 0 | 956.80 |
| | | 1200 | 2167.93 | 2065.64 | 2188.59 | 0 | 2239.54 |
| | | 1500 | 1943.66 | 2366.77 | 1967.33 | 0 | 69.96 |
| | 4 | 1000 | 2609.93 | 2325.22 | 2633.18 | 0.86 | 21600 |
| | | 1200 | 2253.02 | 2004.77 | 2273.07 | 0 | 11587.83 |
| | | 1500 | 2028.75 | 2305.90 | 2051.81 | 0 | 72.89 |
| $\alpha = 1$ $\beta = 0.0625$ | 2 | 1200 | 2095.16 | 1966.40 | 2218.06 | 0 | 19979.78 |
| | | 1500 | 1872.49 | 2156.00 | 2007.24 | 0 | 201.67 |
| | | 2000 | 1813.78 | 2263.19 | 1955.23 | 0 | 109.75 |
| | 3 | 1000 | 2546.20 | 1951.25 | 2668.15 | 0 | 9846.72 |
| | | 1200 | 2175.47 | 1841.56 | 2290.56 | 0 | 6094.20 |
| | | 1500 | 1949.77 | 2106.38 | 2081.42 | 0 | 138.22 |
| | 4 | 1000 | 2623.48 | 1901.63 | 2742.33 | 0 | 1498.42 |
| | | 1200 | 2257.52 | 1841.56 | 2372.62 | 0 | 980.52 |
| | | 1500 | 2031.94 | 2106.38 | 2163.59 | 0 | 70.19 |
| $\alpha = 1$ $\beta = 0.1$ | 2 | 1200 | 2104.83 | 1837.82 | 2288.61 | 0 | 2237.93 |
| | | 1500 | 1880.45 | 2068.00 | 2087.25 | 0 | 510.38 |
| | | 2000 | 1821.74 | 2175.20 | 2039.26 | 0 | 193.64 |
| | 3 | 1000 | 2546.20 | 1951.25 | 2741.33 | 0.94 | 21600 |
| | | 1200 | 2182.11 | 1760.54 | 2358.16 | 0 | 956.62 |
| | | 1500 | 1957.73 | 2018.39 | 2159.57 | 0 | 194.26 |
| | 4 | 1000 | 2623.48 | 1901.63 | 2813.64 | 0 | 401.02 |
| | | 1200 | 2264.17 | 1760.54 | 2440.22 | 0 | 14039.24 |
| | | 1500 | 2042.82 | 1975.12 | 2240.33 | 0 | 168.89 |

### 4.3 Comparison of Heuristic Solution Methodologies

Table 4 shows that at two instances for the second model $M_{\text{C\_wIT}}$, optimality is not guaranteed within the predetermined time limit and concludes with a 0.86% gap and 0.94% between the lower bounds and the best known solutions for the scenarios with $m = 4$, $C = 1000$ and $m = 3$, $C = 1000$, respectively. These result verify the need to use heuristics in order to obtain good solutions for larger instances. For the same instances used in Table 3, we test the three heuristics explained in Section 3.3. Table 5 shows the results obtained by the model $M_{\text{C\_wIT}}$, Heuristic 1, Heuristic 2 and two versions of Heuristic 3 with $\delta$ is equal to 0.10 and 0.25. We run the model and heuristics with the estimated real-life $\alpha$ and $\beta$ values in Section 4.1.

Table 5 shows that the solution times of the proposed heuristics are significantly shorter than the solution times of the model. Table 5 also presents the gap between the optimal solution values of the model and the results obtained with the heuristics, and the proposed heuristics find solutions all less than 4% gap. Heuristic 2 and Heuristic 3 ($\delta = 0.25$) are the best among the alternatives in terms of solution quality since the average optimality gaps are 0.66%, 0.58%, 1.61% and 0.58% for Heuristic 1, Heuristic 2, Heuristic 3 ($\delta = 0.10$) and Heuristic 3 ($\delta = 0.25$), respectively. We note here that all solutions obtained by Heuristic 2 and Heuristic 3 ($\delta = 0.25$) are the same. The maximum gaps for the best two heuristics are 0.98% whereas it is equal to 1.13% for Heuristic 1 and 3.85% for Heuristic 3 ($\delta = 0.10$). On the other hand, Heuristic 3 ($\delta = 0.10$) considerably outperforms other heuristics in terms of solution time since Heuristic 1, Heuristic 2 and Heuristic 3 ($\delta = 0.25$) find the solutions within five minutes whereas Heuristic 3 ($\delta = 0.10$) finds the solutions within 20 seconds. We also observe that as we enlarge the feasible region by increasing $\delta$ in Heuristic 3, we find better solutions while sacrificing from the computation time.

**Table 5** Comparison of the Heuristics on a Medium-Size Data Set

| | $m$ | $C$ | Total Time of Main Tours | Total Time of Small Tours | Objective Value | Optimality Gap (%) | Solution Time (sec.) |
|---|---|---|---|---|---|---|---|
| $M_{\text{C\_wIT}}$ | 2 | 1200 | 2095.16 | 1966.40 | 2218.06 | 0 | 19979.78 |
| | | 1500 | 1872.49 | 2156.00 | 2007.24 | 0 | 201.67 |
| | | 2000 | 1813.78 | 2263.19 | 1955.23 | 0 | 109.75 |
| | 3 | 1000 | 2546.20 | 1951.25 | 2668.15 | 0 | 9846.72 |
| | | 1200 | 2175.47 | 1841.56 | 2290.56 | 0 | 6094.20 |
| | | 1500 | 1949.77 | 2106.38 | 2081.42 | 0 | 138.22 |
| | 4 | 1000 | 2623.48 | 1901.63 | 2742.33 | 0 | 1498.42 |
| | | 1200 | 2257.52 | 1841.56 | 2372.62 | 0 | 980.52 |
| | | 1500 | 2031.94 | 2106.38 | 2163.59 | 0 | 70.19 |
| Heuristic 1 | 2 | 1200 | 2089.58 | 2427.60 | 2241.31 | 1.05 | 235.92 |
| | | 1500 | 1866.38 | 2403.09 | 2016.57 | 0.47 | 28.82 |
| | | 2000 | 1811.42 | 2421.60 | 1962.77 | 0.39 | 25.22 |
| | 3 | 1000 | 2532.66 | 2355.47 | 2679.87 | 0.44 | 185.17 |
| | | 1200 | 2166.86 | 2391.28 | 2316.32 | 1.13 | 135.66 |
| | | 1500 | 1943.66 | 2366.77 | 2091.58 | 0.49 | 28.15 |
| | 4 | 1000 | 2609.93 | 2319.16 | 2754.88 | 0.46 | 174.34 |
| | | 1200 | 2251.95 | 2330.41 | 2397.60 | 1.05 | 311.86 |
| | | 1500 | 2028.75 | 2305.90 | 2172.87 | 0.43 | 23.87 |
| Heuristic 2 | 2 | 1200 | 2089.58 | 2372.77 | 2237.88 | 0.89 | 226.81 |
| | | 1500 | 1866.38 | 2403.09 | 2016.57 | 0.47 | 28.87 |
| | | 2000 | 1811.42 | 2366.77 | 1959.35 | 0.21 | 24.99 |
| | 3 | 1000 | 2532.66 | 2354.96 | 2679.84 | 0.44 | 179.24 |
| | | 1200 | 2166.86 | 2336.45 | 2312.89 | 0.98 | 130.65 |
| | | 1500 | 1943.66 | 2366.77 | 2091.58 | 0.49 | 27.49 |
| | 4 | 1000 | 2609.93 | 2305.35 | 2754.02 | 0.43 | 166.60 |
| | | 1200 | 2251.95 | 2275.59 | 2394.17 | 0.91 | 300.54 |
| | | 1500 | 2028.75 | 2305.90 | 2172.87 | 0.43 | 23.98 |
| Heuristic 3 ($\delta = 0.10$) | 2 | 1200 | 2089.58 | 2372.77 | 2237.88 | 0.89 | 13.92 |
| | | 1500 | 1905.62 | 2372.77 | 2053.92 | 2.33 | 9.65 |
| | | 2000 | 1811.42 | 2366.77 | 1959.35 | 0.21 | 5.25 |
| | 3 | 1000 | 2537.30 | 2369.59 | 2685.4 | 0.65 | 17.6 |
| | | 1200 | 2166.86 | 2336.45 | 2312.89 | 0.98 | 10.58 |
| | | 1500 | 1982.90 | 2336.45 | 2128.92 | 2.28 | 4.38 |
| | 4 | 1000 | 2614.66 | 2369.59 | 2762.76 | 0.75 | 11.62 |
| | | 1200 | 2287.50 | 2336.45 | 2433.53 | 2.57 | 7.13 |
| | | 1500 | 2100.77 | 2336.45 | 2246.80 | 3.85 | 2.67 |
| Heuristic 3 ($\delta = 0.25$) | 2 | 1200 | 2089.58 | 2372.77 | 2237.88 | 0.89 | 192.77 |
| | | 1500 | 1866.38 | 2403.09 | 2016.57 | 0.47 | 39.71 |
| | | 2000 | 1811.42 | 2366.77 | 1959.35 | 0.21 | 23.80 |
| | 3 | 1000 | 2532.66 | 2354.96 | 2679.84 | 0.44 | 191.03 |
| | | 1200 | 2166.86 | 2336.45 | 2312.89 | 0.98 | 64.48 |
| | | 1500 | 1943.66 | 2366.77 | 2091.58 | 0.49 | 20.84 |
| | 4 | 1000 | 2609.93 | 2305.35 | 2754.02 | 0.43 | 59.46 |
| | | 1200 | 2251.96 | 2275.59 | 2394.17 | 0.91 | 45.12 |
| | | 1500 | 2028.75 | 2305.90 | 2172.87 | 0.43 | 8.55 |

## 4.4 Computational Results on a Large-Size Real Data Set

In order to further test the proposed heuristics, we utilise a large-size data set that is collected from the southeast region of Turkey where the refugee population is high due to the geographic region being close to the border with Syria. The data set includes 74 points which are scattered between 10 cities that near the border or in the neighbouring area. Among the 74 points, 19 of which are existing refugee camps and 55 are potential camp locations (Yontucu and Demir, 2018).

Table 5 demonstrates that Heuristic 1, Heuristic 2, and Heuristic 3 ($\delta = 0.25$) achieve good results with the medium-size data set, however, their computation times are relatively high compared to Heuristic 3 ($\delta = 0.10$). In our preliminary results for the large-size data set, we observe that for more than half of the instances (4 out of 7 feasible solutions), the optimality of the model $M_C$, which is the first step of Heuristic 1 and Heuristic 2, could not be verified within 6-hour time limit. Therefore, we only provide the solutions for Heuristic 3 ($\delta = 0.10$) for the large-size data set which is proven to find the best solutions in terms of solution time with acceptable solution quality for the medium-size data as seen in Table 5.

Table 6 shows the solutions obtained with Heuristic 3 ($\delta = 0.10$) for the large-size data set with the same parameters used in Section 4.2.1. It can be observed that Heuristic 3 ($\delta = 0.10$) finds the results under one hour except for one instance, and under 5 minutes except for three instances. Thus, it can be argued that for large data sets, Heuristic 3 ($\delta = 0.10$) is the only solution among proposed alternatives to achieve results within reasonable solution times.

From Table 6, we also observe similar trends as in Section 4.2 and for any $m$, the total distance of the main tours increases while $C$ decreases. For the large-size data set, we find out that $C$ turns out to be an important parameter since we could not find any feasible solutions for the two instances that we find optimal results with the medium-size data set ($m$=2, $C$=1200 and $m = 3$, $C$=1000).

**Table 6** Solution of Heuristic 3 ($\delta = 0.10$) on a Large-Size Data Set

| | $m$ | $C$ | Total Time of Main Tours | Total Time of Small Tours | Objective Value | Solution Time (sec.) |
|---|---|---|---|---|---|---|
| Heuristic 3 ($\delta = 0.10$) | 2 | 1200 | infeasible | | | |
| | | 1500 | 2619.49 | 3710.17 | 2851.37 | 372.32 |
| | | 2000 | 2610.00 | 3537.69 | 2831.11 | 2031.89 |
| | 3 | 1000 | infeasible | | | |
| | | 1200 | 2912.12 | 3537.69 | 3133.22 | 2992.76 |
| | | 1500 | 2635.89 | 3696.34 | 2866.91 | 180.29 |
| | 4 | 1000 | 3362.84 | 3710.17 | 3594.72 | 5433.79 |
| | | 1200 | 2928.51 | 3523.87 | 3148.75 | 508.57 |
| | | 1500 | 2662.15 | 3690.84 | 2892.83 | 417.54 |

## 4.5 Insights for the Organization of Refugee Aid

The results obtained during the computational analysis with different data sets and different weights all imply that the solutions are sensitive to both the number, m, and the capacity, C, of the trucks and decision makers should carefully analyze the trade-offs between the results obtained with different parameters. For example, as seen on Table 4, we found out that for the same C value, increasing the number of the trucks increases the total distance travelled by trucks by 3%-4.4%, but decreases the total distance travelled by the team within small tours up to 6%. This result indicates that by increasing the number of trucks, more points are visited and less points are covered. This may enhance the awareness and accessibility to the MCFS as the trucks visit more points, however, the operational costs such as driver, fuel, and maintenance costs would increase in addition to the cost of acquiring trucks. Hence, there is a trade-off between accessibility and costs, and decision makers should carry out both a qualitative and a quantitative analysis to assess their solutions in order to deliver an effective strategy considering their budget restrictions and the aim of providing MCFS to children of need.

We also observed that the capacity of the trucks is an important factor especially on the large data set where we achieved infeasible results with restricted number of trucks with smaller capacities. Even if one does not have the data or means to conduct the proposed models and heuristics to find optimal routes, it would be beneficial to carry out a feasibility analysis in the planning phase. If the refugee aid organization has a scarce source of trucks, they may not complete their routes considering different restrictions related to the travelling capacity of the trucks such as time limits or the maintenance scheduling. In this case, decision makers should consider increasing the number of trucks or decreasing the number of nodes that are planned to be visited. Thus, conducting such analyses in the planning phase could be beneficial for the operation to achieve a more effective strategy.

It is also beneficial to use qualitative research approaches such as conducting fieldworks, interviews or surveys to assess the needs and to construct the execution plan according to the local specifications and restrictions. The decision whether to apply CVRP or CVRPwIT setting can also be given considering this information. To illustrate, if the area is well-connected, CVRP can be applied assuming the children can come easily to the location of the trucks, on the other hand, if there are isolated places within the area, CVRPwIT can be applied so that the team can help raise the awareness to the MCFS. The implementation setting may also change according to the strategy of the refugee aid organization. If decision makers would like to combine several humanitarian operations such as providing MCFS and conducting household visits to analyse the living conditions of refugees, they may decide to apply CVRPwIT setting.

## 5 Conclusion

The ongoing refugee situation has caused Turkey to become the largest host of refugees in the world, with over 3.7 million registered refugees. Children constitute almost half of the refugee population in Turkey, and more than 40% of them are not enrolled in formal education. In order to understand the situation through first-hand observation, fieldwork is conducted in Ankara, Turkey, and it is observed that children remain vulnerable in these changing conditions. Therefore, increasing refugees' integration with the community and improving their living conditions, especially for the development of children, is highly important to prevent a lost generation. The focus of this work is on the routing of the Mobile Child Friendly Space (MCFS) trucks in order to increase refugee children's access to psychological support and informal education.

For the routing of the MCFS trucks, two cases are taken into account, which are covering all demand points but not visiting all, and covering all demand points and visiting the nodes that are not included in the tour through smaller tours. Two problems are introduced for these cases, namely the Covering Vehicle Routing Problem (CVRP) and the Covering Vehicle Routing Problem with Integrated Tours (CVRPwIT), respectively.

Computational analysis is conducted using data generated from the real-life activities of the trucks, which is obtained from the Turkish Red Crescent. The comparison of the optimal solution with the real-life activities shows that it is possible to decrease the total travel distance by 25.32% using the proposed models. The models and proposed heuristics are tested with different parameter settings on a medium-size real data set that considers one of the cities in Turkey, Burdur to solve the model for CVRPwIT in shorter times. The solutions obtained with the best heuristic among alternatives in terms of solution time are also provided and discussed on a large-size data set that considers locations of refugee camps in Turkey. We note here that the notion in our problem setting in CVRPwIT (i.e. generating smaller tours from visited nodes) can be used in many problems related to selective routing. Similarly, the proposed solution approaches can be easily adapted to the extended versions of the problems.

In future research, one could develop a multi-objective version of the problem by taking other objectives into account. To illustrate, balanced coverage according to the demand of the nodes might be added as an objective: i.e. each coverage cluster could have an approximately equal demand to obtain a more balanced service. In addition, the nodes' demand could be taken into account in the decision as to whether visiting or covering a node is preferable, such that a node with higher demand would be visited rather than covered, while nodes with lower demands are covered rather than visited. Service times during visiting nodes could also be included in the problem if time is also an important restriction.

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