Provision of En-Route Relief Aid to Forcibly Displaced Persons

Bachelor Thesis

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Economics and Business Economics

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Abstract

Forcibly displaced persons need periodic relief aid along their routes to safe places. To this end, continuation of service is crucial to alleviate their mental and physical burden, and humanitarian organizations must coordinate mobile facilities to provide relief aid en route. This thesis extends existing $\mathcal{NP}$-hard multi-period mobile facility location problems with mobile demand to model reality more closely, and investigates the impact of capacity and length constraints to provide valuable insights for humanitarian organizations. The Adaptive Large Neighborhood Search previously employed to solve large problem instances is augmented by additional destroy and repair operators to diversify and intensify the search. A hybridization with the Tabu Search meta-heuristic did not yield an increase in performance. The impact of capacity constraints on the cost was more than twice the impact of length constraints. Often, these constraints led to a higher utilization of already deployed mobile facilities instead of the addition of mobile facilities.

Keywords: Humanitarian Logistics, Operations Research, Facility Location, Vehicle Routing, Adaptive Large Neighborhood Search, Tabu Search

Contents

1 Introduction

82.4 million individuals were forcibly displaced worldwide by the end of 2020 (UNHCR, 2021). This is more than five times the number of forcibly displaced persons at the end of 2003 (UNHCR, n.d.). Unfortunately, this number is expected to grow even further in the future, with as many as 216 million individuals forced to migrate due to climate change alone by 2050 (Clement et al., 2021). Besides losing their homes, forced migrants may endure day-long, uncertain journeys until they arrive at a safe place, making them vulnerable to mental as well as physical distress (Fazel, Reed, Panter-Brick, & Stein, 2012; Borho, Morawa, Schmitt, & Erim, 2021). Although meeting medical needs of forcibly displaced persons en route is difficult (Shortall, Glazik, Sornum, & Pritchard, 2017), the provision of relief aid is a humanitarian imperative. A key goal in the effort to provide relief aid en route is the continuity of care (Abbara, Jarman, Isreb, Gunst, & Sahloul, 2016; Chiesa, Chiarenza, Mosca, & Rechel, 2019). The benefits of continuity of care are also of economic nature, as hospital admissions and visits to an emergency apartment are reduced and medical costs lowered (World Health Organization, 2018).

A recent trend for forcibly displaced persons is to migrate as a caravan to acquire group safety and leverage shared resources (Brigida, 2018). This trend facilitates the schematic planning to provide relief aid en route. To this end, Bayraktar, Günneç, Salman, and Yücel (2022) have introduced an operations research problem to the academic literature which captures the mobile nature of both demand and supply over a planning horizon of several periods: the multi-period mobile facility location problem with mobile demand (MM-FLP-MD) aims to schedule mobile facilities for the provision of relief aid en route. Due to the very recent development, the initial version of this problem remains uncapacitated. As practically all resources are scarce, especially in humanitarian support, this paper asks

How does limited capacity impact the cost of optimal schedules of mobile facilities to provide relief aid to forcibly displaced persons en route?

Particularly, the MM-FLP-MD is enhanced by (a) constraints on the number of forcibly displaced persons a mobile facility can serve in any period (period capacity constraints), (b) constraints on the number of forcibly displaced persons a mobile facility can serve in one duty trip without restocking at the depot (duty capacity constraints), and (c) constraints on the number of consecutive periods a mobile facility can be in duty without visiting the depot (duty length constraints). The MM-FLP-MD can be solved as a Mixed Integer Linear Programming (MILP) model or in an Adaptive Large Neighborhood Search (ALNS). In a quest to provide results faster, the ALNS algorithm proposed by Bayraktar et al. (2022) is augmented by additional destroy and repair operators and a Tabu Search hybridization.

Overall, the proposed capacitated version of the MM-FLP-MD depicts reality more closely and can be the starting point to develop further models in academia. The Tabu Search hybridization joins attempts of other researchers to advance the performance of ALNS algorithms by enriching the framework with different types of meta-heuristics. Humanitarian organizations can draw on valuable insights from the impact analysis of capacity and length constraints. They can readily identify bottlenecks in the cost-efficient provision of en-route relief aid and can potentially increase the number of forcibly displaced persons served or reduce operating costs.

The paper begins with a review of relevant literature in Section 2. The MM-FLP-MD is restated and defined in more detail in Section 3. Section 4 contains the methodology of the MILP model and ALNS algorithm which is applied in a case study in Section 5. The paper concludes with Section 6.

2 Literature Review

In this section, we provide a twofold literature review. The literature review in economics shows ample motivation for the provision of relief aid en route with continuity of care, whereas the literature review in operations research (OR) embeds the MM-FLP-MD into well-known OR problems and discusses possible solution approaches.

2.1 Economics

Providing relief aid to forcibly displaced persons is a crucial sign of humanity. However, providing a continuity of care to forcibly displaced persons may also be in the self-interest of hosting communities and countries.

If forcibly displaced persons must be hosted, e.g., due to the right of asylum, or are deliberately chosen to be hosted, healthy forcibly displaced persons reduce the burden on the hosting community. The health spending on displaced persons can be an indicator of the economic burden on the country, and several direct and indirect effects of displacement on health are inevitable. Especially men suffer from direct effects such as injury, disability, or death when fleeing from violent conflicts (Biswas et al., 2016; Cakmak et al., 2021). Indirect effects from worse nutrition and less hygiene while migrating as well as psychological issues also accrue costs in health care. Ultimately, limiting the access of asylum seekers and refugees to health care imposes higher costs than providing them with a continuity of care (Bozorgmehr & Razum, 2015). Furthermore, an advantage of periodic relief aid can be the early detection of diseases. This can reduce the number of infections and, thus, lead to cost savings in the medium and long term (see Wingate et al., 2015, for a cost-benefit analysis in the case of tuberculosis).

The provision of continuous relief aid cannot only reduce the economic burden in the health care sector. The arrival of forcibly displaced persons who are healthy and integrated into the hosting communities has a positive aggregate effect (Alix-Garcia, Artuc, & Onder, 2017). For instance, Burundian and Rwandan refugees in the 1990s sparked a persistent increase in welfare in Tanzanian hosting communities—even after their return to Burundi and Rwanda (Maystadt & Duranton, 2019). More recently, the European Union expected a GDP increase of 0.2 % upon the migration wave in 2015 (European Commission, 2016), and Syrian refugees in Jordan and Lebanon led to an increase in GDP of 0.9 percentage points due to increased aggregate demand and labor supply (World Bank, 2020). On the contrary, isolating forcibly displaced persons such as refugees can lead to bad reputation and economic loss (see Ivanov & Stavrinoudis, 2018, for an example in the Greek hotel industry). Additionally, insecurities about the permanent status in the host country can cause economic and social costs for the displaced persons as well as the host country (Ukrayinchuk & Havrylchyk, 2020).

One of the channels through which welfare can be enhanced is the labor market. Labor market frictions from the inclusion of displaced persons in the labor market can be reduced by job search assistance and mentor programs (Battisti, Giesing, & Laurentsyeva, 2019; Bagnoli & Estache, 2022). Preliminary results from inclusive sports projects also show a positive positive impact on the social and labor market integration (Lange, Pfeiffer, & van den Berg, 2017). More labor market research has been performed on the impact of Syrian refugees on the labor market in southeastern Turkey. The impact of Syrian refugees on the Turkish labor market itself was limited (Ceritoglu, Yunculer, Torun, & Tumen, 2017). Only informal employment, which has a relatively large share in hosting communities, among the native population decreased because refugees were not allowed to work or not qualified for formal employment. However, wages remained unchanged and the cost advantage in informal labor-intensive markets by the substitution of native informal labor with refugees led to lower consumer prices (Balkan & Tumen, 2016).

Another channel which can increase welfare is trade, as migrants increase the trade between their home and host countries, e.g., due to reduced bilateral trade costs and knowledge diffusion (Steingress, 2018; Bahar & Rapoport, 2018). However, this effect is smaller for refugee immigrants (White & Tadesse, 2010).

To conclude, forcibly displaced persons as well as hosting communities can benefit from the immigration of forcibly displaced persons. Although practically untested, the overall welfare can theoretically be maximized by forming a market of tradable immigration quotas (Fernández-Huertas Moraga & Rapoport, 2014, 2015a, 2015b). Nevertheless, common causes for the increase in welfare are the health and integration of displaced persons, with health a driver for successful integration. Hence, providing continuous relief aid en route improves the probability that the arrival of displaced persons can be a blessing rather than a curse.

2.2 Operations Research

The multi-period mobile facility location problem with mobile demand (MM-FLP-MD) was first introduced by Bayraktar et al. (2022). The problem entails the coordination, i.e. location and travel, of mobile facilities to provide relief aid en route to a caravan of forcibly displaced persons on a regular basis. Despite mobile demand, Bayraktar et al. (2022) assume the location of caravans in every period to be deterministic and known beforehand. Moreover, mobile facilities do not experience capacity issues; it suffices that a mobile facility and a caravan are at the same location in the same period to provide sufficient service. Besides constraints to model facility usage and travel for the objective function, service constraints constitute the most important constraints in the model: every caravan of forcibly displaced persons must be served at least once in a specified number of consecutive periods.

As Bayraktar et al. (2022) provide an extensive literature review to differentiate the MM-FLP-MD from other well-known problems in OR, we focus on similarities and develop links. To that end, it is useful to recognize the MM-FLP-MD as an integrated location and routing problem: while the location of the mobile facilities must be determined, they must route certain parts of caravan paths to regularly provide relief aid. Hence, we explore mainly two different strands of OR literature—facility location problems and vehicle routing problems—, which also serve as starting points to develop a more general and extended MM-FLP-MD model.

The facility location problem (FLP) is a strategic problem for decision makers which affects other decisions on a tactical and operational level. Facilities must be located according to an objective, usually to minimize costs, while allowing the fulfillment of ordinary operations, such as meeting customers' demand within limits of capacity, over multiple periods. Likewise in the MM-FLP-MD, a selection of mobile facilities must be made. However, this decision is operational, as facilities travel to provide relief aid. The classical FLP—and also the MM-FLP-MD of Bayraktar et al. (2022)—is static and deterministic. That is, model parameters are known beforehand and with certainty. In dynamic formulations, not all model parameters are known immediately but become available successively over the time horizon; stochastic models have stochastic model parameters. FLPs are often extended to incorporate scarce capacities in decision-making. A review of different models to solve an FLP can be found in Owen and Daskin (1998).

The vehicle routing problem (VRP) is a tactical or operational problem for decision makers. Starting from a depot, a fleet of vehicles must route a set of nodes and arcs, e.g., to deliver or collect packages, at minimal cost. This optimization is usually constrained due to scarce resources. For instance, a vehicle has a finite loading capacity and a route may further be limited by the vehicle's fuel consumption and the driver's maximum working hours. A variant of this problem, the vehicle routing and scheduling problem with time windows, respects that certain nodes and arcs must be visited within a specified time window (Solomon, 1987; Ropke & Pisinger, 2006). This task is similar to the service requirement of the MM-FLP-MD: to serve a caravan of forcibly displaced persons at least once in a specified interval, a mobile facility must be at the same location in the same period, or time window.

Both FLPs and VRPs are $\mathcal{NP}$-hard problems which cannot be solved to optimality in reasonable time. The first attempts to solve these intractable problems heuristically employed local search techniques, in which solutions were slightly altered through "move operators" for improvements. However, local search techniques may quickly be trapped in a local optimum without opportunity to improve further towards a global optimum. For this reason, so-called meta-heuristics apply minima-escaping procedures in the hope to reach global optima (Shaw, 1997). Some well-studied meta-heuristics include Simulated Annealing (SA) (Kirkpatrick, Gelatt Jr, & Vecchi, 1983) and Tabu Search (TS) (Glover, 1986). In SA, an iterated solution may be replaced by a worse-performing solution which may escape the local optimum; in TS, a previous solution or parts of it should not be repeated within a given number of move operators to reduce redundant cycling and intensify the neighborhood search.

The idea of a Large Neighborhood Search (LNS) is to remove a larger part of the current solution through a destroy operator and construct a feasible solution again through a repair operator (Shaw, 1998). This idea is extended by Ropke and Pisinger (2006) in an Adaptive Large Neighborhood Search (ALNS). This LNS is adaptive in the sense that a destroy and a repair operator are iteratively selected from a set of operators with changing probabilities, and experiences a greater diversification of iterated solutions. Which destroy and repair operators are used is determined in a roulette-wheel fashion in which the probability depends on the past performance. The ALNS as proposed by Ropke and Pisinger (2006) includes SA in its framework, but recent advances attempted to develop a TS hybridization (Butsch, Kalcsics, &

Laporte, 2014), which eventually yielded the so-called ALNS/TS framework (Žulj, Kramer, & Schneider, 2018). Not all meta-heuristics work equally well in any setting (Gent, 1998; Fahimnia, Davarzani, & Eshragh, 2018), but the ALNS and ALNS/TS have proven to be particularly useful for vehicle routing and scheduling problems (Ropke & Pisinger, 2006; Pan, Zhang, & Lim, 2021).

3 Problem Definition

This thesis aims to solve the problem of providing relief aid from mobile facilities to forcibly displaced persons en route at minimal cost. According to the International Organization of Migration (IOM), the migration agency of the United Nations, displaced persons *"have been forced or obliged to flee or to leave their homes or places of habitual residence, either across an international border or within a State, in particular as a result of or in order to avoid the effects of armed conflict, situations of generalized violence, violations of human rights or natural or human-made disasters"* (IOM, 2019, p. 55). Although the forced nature is included in the definition of a displaced person (DP), the term "forcibly displaced person" is used where a more expressive statement is warranted. The most commonly known subgroup of DPs are refugees, who are forced to migrate across borders due to violations of human rights, as defined in the *Convention and Protocol Relating to the Status of Refugees* (1951). However, also internally displaced persons within a country's borders and persons forced to migrate due to natural or other human-made disasters require relief aid en route and are included in the definition of DPs.

The provision of relief aid en route is determined for the directed network $G = (V, A)$, where V is a set of nodes and A a set of arcs. Mobile facilities and DPs each use a subgraph of the network. On the one hand, DPs use the network $G_\rho = (V, A_\rho)$. They can use all nodes of the original network but may not be able to use all arcs due to limitations in their mode of travel. Hence, DPs can travel along arcs in $A_\rho \subseteq A$. On the other hand, mobile facilities are also limited in their daily travel distance or are able to use different routes, as they operate on behalf of internationally acknowledged humanitarian organizations, and, thus, may use arcs $A_\nu \subseteq A$. Furthermore, only a subset of nodes $V_\nu \subseteq V$, called primary nodes, may be suitable for mobile facilities to provide service. Hence, the original network for mobile facilities is $G_\nu = (V_\nu, A_\nu)$. In deviation from Bayraktar et al. (2022), an additional node 0 corresponds to the depot where mobile facilities commence and can restock any utilities required for providing relief aid. The set of all nodes where a mobile facility can be located, called facility nodes, is, thus, $V_{\nu'} \subseteq V_\nu \cup \{0\}$, and the set of arcs connecting facility nodes is $A_{\nu'} = A \cup \{(0, i) : i \in V_\nu\} \cup \{(i, 0) : i \in V_\nu\}$.

The planning horizon for the MM-FLP-MD is the set of periods T, where each period corresponds to one day. The day the first DP enters the network is 1, and the day the last DP leaves the network is $|T|$. When including the travel of mobile facilities from the depot, the extended planning horizon $T' = T \cup \{0\}$ with additional period 0 is used.

The set of mobile facilities M is assumed to contain at least as many mobile facilities as required to solve the MM-FLP-MD. A mobile facility is in duty when it is not located at the depot, and l_m is the maximum number of consecutive periods a mobile facility $m \in M$ can be in duty without a visit to the depot. A mobile facility conducts a service act $\sigma = (n, t)$ if it provides service to at least one DP at node $n \in V_\nu$ in period $t \in T$. Meanwhile, it is limited to serve at most k_m adult DPs in every period, e.g., due to limited capacity of relief aid workers, and can serve at most K_m adult DPs without restocking at the depot, e.g., due to limited storage capacity in the mobile facility. The usage of a mobile facility $m \in M$ comes at a certain cost. The preparation cost f_m is incurred to ready a mobile facility for deployment, e.g., the cost to lease a vehicle and converting it into a mobile facility for relief aid. The duty cost g_m accrues every period the mobile facility is not located at the depot, e.g., to cover personnel costs of drivers and relief aid workers. Lastly, the travel cost c_{ij} to move a mobile facility between two facility nodes $i, j \in V_{\nu'}$ can include fuel cost, potentially costs for crossing borders, or other facility-related costs.

The set of possible paths which caravans of DPs may use in the network is described by P. Any path $p \in P$ is a sequence of node-time pairs which represent the location of the caravan at the end of a day. For instance, the location of the caravan on path $p \in P$ in period $t \in T$ is $n_{pt} \in V$. The time indexation allows to establish a one-to-one relationship between paths and caravans of DPs, such that these terms can be used interchangeably.[1] The period in which a caravan enters the network is given by a_p, and the set of all periods in which a caravan $p \in P$ is in the network is denoted by T_p. Consequently, the total number of periods a caravan is in the network is $|T_p|$. In addition to the notation defined in Bayraktar et al. (2022), the size of each caravan $p \in P$ is given by d_p and used to determine the amount of relief aid needed. For this purpose, equivalence scales can be used for children to determine their needs relative to adults, e.g., as used by the OECD (n.d.) for its income distribution database.

The effectiveness of providing relief aid en route is critically dependent on the continuity of care. Therefore, DPs should be provided relief aid en route at least once every τ consecutive periods when possible. To determine whether this service requirement is feasible, we let $I_\tau(p,t)$ denote the probability that caravan $p \in P$ visits at least one primary node in periods $t, ..., \max(t+\tau-1, |T|)$, i.e. the probability that it can receive relief aid in these periods. The MM-FLP-MD considered in this thesis is static and deterministic and, hence, $I_\tau(p,t)$ is an indicator function assuming values 0 and 1.

4 Methodology

Bayraktar et al. (2022) were the first to propose a Mixed Integer Linear Programming (MILP) model to solve the MM-FLP-MD. We provide another MILP model in Section 4.1 to solve the problem for more general, i.e. capacitated, cases. However, Bayraktar et al. (2022) also showed that the MM-FLP-MD is $\mathcal{NP}$-hard. Hence, an Adaptive Large Neighborhood Search (ALNS) algorithm can be used to solve problem heuristically. The ALNS algorithm and its advancements from the one used in Bayraktar et al. (2022) are described in Section 4.2.

4.1 Model Formulation

The MILP model comprises several decision variables to schedule mobile facilities for the provision relief aid en route. The facility usage variable Z_m determine whether a mobile facility $m \in M$ is used during the planning horizon, $Z_m = 1$, or not, $Z_m = 0$. The location of a mobile

[1] Contrary, Bayraktar et al. (2022) do not use paths and refugee groups interchangeably. In their sense, a path is a sequence of nodes independent of time, while a refugee group traverses a path in certain periods, making the path time-indexed.

facility $m \in M$ is modeled by the facility location variable Y_{imt}, which assume a value of 1 if m is located at node i in period t, and is 0 otherwise. The travel of a mobile facility $m \in M$ during the planning horizon is modeled by the travel variable X_{ijmt}, which is 1 if $m \in M$ travels from facility node $i \in V_{\nu'}$ to a different facility node $j \in V_{\nu'}, j \neq i$, at the end of period $t \in T \setminus \{|T|\}$ and 0 otherwise. Similarly defined are the travel variables for any mobile facility $m \in M$ which travels from the depot node 0 to any primary node $i \in V_\nu$ in the inaugural period 0 and from any primary node $i \in V_\nu$ to the depot node 0 at the end of the planning horizon in period $|T|$, X_{0im0} and $X_{i0m|T|}$, respectively. The service act variable y_{pimt} indicates whether the caravan on path $p \in P$ is served by mobile facility $m \in M$ at node $i \in V_\nu$ in period $t \in T$, $y_{pimt} = 1$, or not, $y_{pimt} = 0$. The capacitated nature of a mobile facility $m \in M$ is captured by the inventory variable I_{mt}, which counts the available capacity in period $t \in T$, and the restock variable s_{mt}, which determines how much additional capacity is available at the start of period $t \in T \setminus \{1\}$. An overview of all notation is provided in Table 1.

The MILP model to solve the MM-FLP-MD is then as follows.

$$\min \quad o(\boldsymbol{Z}, \boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{y}, \boldsymbol{I}, \boldsymbol{s}) \tag{1a}$$

s.t. **Location and travel constraints**

$$\sum_{i \in V_\nu} Y_{imt} \leq Z_m, \qquad \forall m \in M, \forall t \in T, \tag{1b}$$

$$\sum_{i \in V_{\nu'}} Y_{imt} = 1, \qquad \forall m \in M, \forall t \in T, \tag{1c}$$

$$Y_{imt} + Y_{jm(t+1)} - X_{ijmt} \leq 1, \qquad \forall (i,j) \in A_{\nu'}, \forall m \in M, \forall t \in T \setminus \{|T|\}, \tag{1d}$$

$$X_{i0mt} \leq Y_{imt}, \qquad \forall i \in V_\nu, \forall m \in M, \forall t \in T \setminus \{|T|\}, \tag{1e}$$

$$X_{i0mt} \leq Y_{0m(t+1)}, \qquad \forall i \in V_\nu, \forall m \in M, \forall t \in T \setminus \{|T|\}, \tag{1f}$$

$$Y_{im1} = X_{0im0}, \qquad \forall i \in V_\nu, \forall m \in M, \tag{1g}$$

$$Y_{0m1} = 1 - \sum_{i \in V_\nu} X_{0im0}, \qquad \forall m \in M, \tag{1h}$$

$$Y_{im|T|} = X_{i0m|T|}, \qquad \forall i \in V_\nu, \forall m \in M, \tag{1i}$$

Service constraints

$$\sum_{m \in M} \sum_{t=a_p+k}^{a_p+k+\tau-1} y_{pn_{pt}mt} \geq I_\tau(p, a_p + k), \qquad \forall p \in P, 0 \leq k \leq l_p - \tau, \tag{1j}$$

Inventory constraints

$$I_{m1} = K_m, \qquad \forall m \in M, \tag{1k}$$

$$I_{mt} = I_{m(t-1)} - \sum_{i \in V_\nu} \sum_{\substack{p \in P: \\ i = n_{pt}}} d_p y_{pim(t-1)} + s_{mt}, \qquad \forall m \in M, \forall t \in T \setminus \{1\}, \tag{1l}$$

$$s_{mt} \leq \sum_{i \in V_\nu} K_m X_{i0m(t-1)}, \qquad \forall m \in M, \forall t \in T \setminus \{1\}, \tag{1m}$$

$$s_{mt} \leq K_m - I_{m(t-1)} + \sum_{i \in V_\nu} \sum_{\substack{p \in P: \\ i = n_{pt}}} d_p y_{pim(t-1)}, \qquad \forall m \in M, \forall t \in T \setminus \{1\}, \tag{1n}$$

Table 1: Notation

Sets	
P	Set of caravans of forcibly displaced persons, or, interchangeably, their paths
V	Set of network nodes excluding the depot for mobile facilities
V_ν	Set of primary nodes where a mobile facility can conduct a service act, $V_\nu \subseteq V$
$V_{\nu'}$	Set of facility nodes where a mobile facility can be located at, $V_{\nu'} = V_\nu \cup \{0\}$, where 0 is the depot
A	Set of arcs
A_ν	Set of arcs mobile facilities can travel
A_ρ	Set of arcs forcibly displaced persons can travel
M	Set of mobile facilities
T	Set of periods, planning horizon
T'	Extended planning horizon, $T' = T \cup \{0\}$, where 0 is the inaugural period
T_p	Set of periods in path $p \in P$, $T_p \subseteq T$
Parameters	
k_m	Maximum number of forcibly displaced persons mobile facility $m \in M$ can serve in one period
K_m	Maximum number of forcibly displaced persons mobile facility $m \in M$ can serve in one duty trip without restocking at the depot
l_m	Maximum number of consecutive periods mobile facility $m \in M$ can be in duty
f_m	One-time preparation cost to ready mobile facility $m \in M$ for deployment
g_m	Deployment cost for every period mobile facility $m \in M$ is in duty
c_{ij}	Travel cost from node $i \in V_{\nu'}$ to node $j \in V_{\nu'}$
a_p	First period of path $p \in P$ in the network
n_{pt}	Node of path $p \in P$ in period $t \in T$
d_p	Number of adult-equivalent forcibly displaced persons on path $p \in P$
s	Cost to provide service to one adult forcibly displaced person
τ	Number of periods in which each forcibly displaced person should be served at least once if possible
$I_\tau(p,t)$	Probability that path $p \in P$ visits a primary node in period $t \in T$ and the succeeding $\tau - 1$ periods
Decision Variables	
Z_m	1 if mobile facility $m \in M$ is used; 0 otherwise
Y_{imt}	1 if mobile facility $m \in M$ is located at node $i \in V_\nu$ in period $t \in T$
X_{ijmt}	1 if mobile facility $m \in M$ travels from node $i \in V_{\nu'}$ to node $j \in V_{\nu'}$ in period $t \in T$; 0 otherwise
X_{0im0}	1 if mobile facility $m \in M$ travels from the depot to node $i \in V_\nu$ in period 0; 0 otherwise
$X_{i0m\lvert T\rvert}$	1 if mobile facility $m \in M$ travels from node $i \in V_\nu$ to the depot in period $\lvert T\rvert$; 0 otherwise
y_{pimt}	1 if forcibly displaced persons on path $p \in P$ are served by mobile facility $m \in M$ at node $i \in V_\nu$ in period $t \in T$; 0 otherwise
I_{mt}	Inventory level of mobile facility $m \in M$ at the start of period $t \in T$
s_{mt}	Restocking of mobile facility $m \in M$ at the start of period $t = 2, ..., \lvert T\rvert$

Capacity constraints

$$\sum_{\substack{p \in P: \\ i = n_{pt}}} d_p y_{pimt} \leq k_m Y_{imt}, \qquad \forall i \in V_\nu, \forall m \in M, \forall t \in T, \tag{1o}$$

$$\sum_{i \in V_\nu} \sum_{\substack{p \in P: \\ i = n_{pt}}} d_p y_{pimt} \leq I_{mt}, \qquad \forall i \in V_\nu, \forall m \in M, \forall t \in T, \tag{1p}$$

Length constraints

$$\sum_{t'=t}^{t+l_m} \sum_{i \in V_\nu} Y_{imt'} \leq l_m, \qquad \forall m \in M, t = 1, \ldots, |T| - l_m, \tag{1q}$$

Domain constraints

$$Z_m \in \{0,1\}, \qquad \forall m \in M, \tag{1r}$$

$$X_{ijmt} \in \{0,1\}, \qquad \forall (i,j) \in A_{\nu'}, \forall m \in M, \forall t \in T \setminus \{|T|\}, \tag{1s}$$

$$X_{0im0} \in \{0,1\}, \qquad \forall i \in V_\nu, \forall m \in M, \tag{1t}$$

$$X_{i0m|T|} \in \{0,1\}, \qquad \forall i \in V_\nu, \forall m \in M, \tag{1u}$$

$$Y_{imt} \in \{0,1\}, \qquad \forall i \in V_{\nu'}, \forall m \in M, \forall t \in T, \tag{1v}$$

$$y_{pimt} \in \{0,1\}, \qquad \forall p \in P, \forall m \in M, \forall t \in T_p, i = n_{pt} \in V_\nu, \tag{1w}$$

$$I_{mt} \geq 0, \qquad \forall m \in M, \forall t \in T, \tag{1x}$$

$$s_{mt} \geq 0, \qquad \forall m \in M, \forall t \in T \setminus \{1\}. \tag{1y}$$

The objective (1a) is to minimize a cost function o of the decision variable vectors $\boldsymbol{Z}$, $\boldsymbol{X}$, $\boldsymbol{Y}$, $\boldsymbol{y}$, $\boldsymbol{I}$, and $\boldsymbol{s}$. In particular, we use the objective function

$$\begin{aligned} o(\boldsymbol{Z}, \boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{y}, \boldsymbol{I}, \boldsymbol{s}) = o(\boldsymbol{Z}, \boldsymbol{X}, \boldsymbol{Y}) = \sum_{m \in M} f_m Z_m + \sum_{i \in A_\nu} \sum_{m \in M} \sum_{t \in T} g_m Y_{imt} \\ + \sum_{(i,j) \in A_{\nu'}} \sum_{m \in M} \sum_{t=1}^{|T|-1} c_{ij} X_{ijmt} + \sum_{i \in V_{\nu'}} \sum_{m \in M} c_{0i} X_{0im0} + \sum_{i \in V_{\nu'}} \sum_{m \in M} c_{i0} X_{i0m|T|}, \end{aligned} \tag{2}$$

which consists of three parts. These are, by their occurrence in (2), preparation costs to ready mobile facilities for deployment, duty costs for every period a mobile facility is in duty, and travel costs for moving mobile facilities between facility nodes.

Constraints (1b) and (1c) are facility usage and location constraints. (1b) implies that a mobile facility m can only be located at a primary node i if it is deployed, $Z_m = 1$. Furthermore, (1c) ensure that a mobile facility m is located at exactly one facility node in every period of the planning horizon.

Constraints (1d) to (1i) are travel constraints which relate the location variables $\boldsymbol{Y}$ to the travel variables $\boldsymbol{X}$. (1d) enforce that if a mobile facility changes location in two consecutive periods, then the corresponding travel variable assumes a value of 1. Otherwise, the default value of X_{ijmt} is generally 0, as travel costs are positive and the objective is to minimize total costs. An exception are the travel variables corresponding to travels to the depot because of their occurence in constraints (1m). Hence, constraints (1e) and (1f) ascertain that the depot travel variable X_{i0mt} is 1 if and only if mobile facility m is located at the primary node i in period t and at the depot in the succeeding period. Constraints (1g) and (1h) initialize the starting location of mobile facilities: if a mobile facility is deployed in the first period, then it must be transported from the depot to this location in period 0; otherwise, the mobile facility remains at the depot, $Y_{0m1} = 1$. The last location and travel constraints (1i) ensure that every mobile facility ends at the depot after the planning horizon.

The heart of the MM-FLP-MD lies in constraints (1j). These constraints require that a caravan is fully served at least once every τ periods if possible. The feasibility of this requirement is determined by the indicator function $I_\tau(p,t)$, which is equal to 1 when the caravan on path $p \in P$ visits at least one primary node in period t and the succeeding $\tau - 1$ periods, and 0 otherwise.[2]

Constraints (1k) to (1n) establish the limited capacity feature of the displayed model. Constraints (1k) initialize the starting inventory and constraints (1l) balance the inventory level over all periods. Constraints (1m) and (1n) cap the restocking such that a mobile facility can only have additional capacity if it travels to the depot in the previous period and can restock at most its maximum duty capacity K_m, respectively.

Constraints (1o) and (1p) are capacity constraints. (1o) imply that if a mobile facility m is not used at a node i in period t, $Y_{imt} = 0$, then it cannot provide relief aid to any caravan at that node-time pair, $y_{pimt} = 0$. However, if a mobile facility m is present at node i in period t, $Y_{imt} = 1$, then it can serve at most k_m DPs at that node-time pair. (1p) in conjunction with the inventory constraints imply that a mobile facility m can serve at most its current inventory level, or, alternatively, K_m DPs in one duty trip without restocking at the depot.

Constraints (1q) are length constraints, which limit the number of periods a mobile facility m can be consecutively in duty without visit to the depot to l_m.

Constraints (1r) to (1y) are domain constraints which render the facility usage, travel, and location variables as well as the service act variables binary, and the inventory level and restocking variables to non-negative values.

The original, uncapacitated model of Bayraktar et al. (2022) can be recovered from the proposed model (1a) to (1y) as follows. The inventory, capacity, and length constraints (1k) to (1q) are removed and with them the then useless inventory and restocking variables $\boldsymbol{I}$ and $\boldsymbol{s}$. Furthermore, the depot is not included in the set of facility nodes and the corresponding location and travel variables can be removed as well. Due to the uncapacitated nature, the service act variables $\boldsymbol{y}$ are not needed and replaced by the location variables $\boldsymbol{Y}$ in the service constraints. The right-hand side of the service constraints is changed to 1, which also requires that τ is sufficiently large to find a feasible solution. The original model with the notation of this thesis is then

$$\min \quad o(\boldsymbol{Z}, \boldsymbol{X}, \boldsymbol{Y}) \tag{3a}$$

s.t. **Location and travel constraints**

$$\sum_{i \in V_\nu} Y_{imt} = Z_m, \qquad \forall m \in M, \forall t \in T, \tag{3b}$$

$$Y_{imt} + Y_{j,m,t+1} - X_{ijmt} \leq 1, \quad \forall (i,j) \in A_\nu, m \in M, t \in T \setminus \{|T|\}, \tag{3c}$$

[2] This definition of the service requirement is convenient for the case in which a caravan can be served partly in a period or in which the future locations of the caravan cannot be forecast with certainty, i.e. in a stochastic MM-FLP-MD. However, the model at hand disincentivizes the division of relief aid provided to a caravan over several mobile facilities or periods due to the binary domain of service act variables $\boldsymbol{y}$ and the MM-FLP-MD is assumed to be static and deterministic. The relaxation of these constraints and assumptions is beyond the scope of this thesis and subject for future research.

Service constraints

$$\sum_{m\in M}\sum_{\substack{t=a_p+k:\\ n_{pt}\in V_\nu}}^{a_p+k+\tau-1} Y_{n_{pt}mt} \geq 1, \qquad \forall p \in P, 0 \leq k \leq l_p - \tau, \tag{3d}$$

Domain constraints

$$Z_m \in \{0,1\}, \qquad \forall m \in M, \tag{3e}$$
$$X_{ijmt} \in \{0,1\}, \qquad \forall (i,j) \in A_\nu, m \in M, t \in T \setminus \{|T|\}, \tag{3f}$$
$$Y_{imt} \in \{0,1\}, \qquad \forall i \in V_\nu, m \in M, t \in T, \tag{3g}$$

where the objective

$$o(\boldsymbol{Z},\boldsymbol{X},\boldsymbol{Y}) = o(\boldsymbol{Z},\boldsymbol{X}) = \sum_{m\in M} f_m Z_m + \sum_{(i,j)\in A_\nu}\sum_{m\in M}\sum_{t=1}^{|T|-1} c_{ij}X_{ijmt} \tag{4}$$

is used in Bayraktar et al. (2022).

It is to note that the integrality constraints of the facility usage and travel variables can be relaxed. This is because the facility usage variables are set equal to the sum of the binary facility location variables in (1b) and, thus, assume either the value of 1 or 0. Similarly, the value of facility travel constraints assumes a value of 0 by default, as the objective is to minimize total cost and travel costs are positive, or through constraints (1e) and (1f). However, only if the location variables Y_{imt} and $Y_{j,m,t+1}$ obtain a value of 1, then also X_{ijmt} must be equal to 1 by constraints (1d). Hence, model solutions remain feasible and optimal when replacing domain constraints (1r) to (1u) by the domain constraints

Relaxed domain constraints

$$0 \leq Z_m \leq 1, \qquad \forall m \in M, \tag{5a}$$
$$0 \leq X_{ijmt} \leq 1, \qquad \forall (i,j) \in A_{\nu'}, m \in M, t \in T \setminus \{|T|\}, \tag{5b}$$
$$0 \leq X_{0im0} \leq 1, \qquad \forall i \in V_\nu, m \in M, \tag{5c}$$
$$0 \leq X_{i0m|T|} \leq 1, \qquad \forall i \in V_\nu, m \in M. \tag{5d}$$

Another opportunity to reduce the complexity of the model lies in the application of symmetry-breaking constraints. For example, Bayraktar et al. (2022) sort the list of mobile facilities such that the cost of deploying a mobile facility is non-decreasing. This gives rise to the symmetry-breaking constraints

Symmetry-breaking constraints

$$Z_{m+1} \leq Z_m, \qquad \forall m = 1, \ldots, |M| - 1, \tag{6a}$$
$$\sum_{t'=1}^{t'=t}\sum_{i\in V_\nu} Y_{imt'} \geq \sum_{i\in V_\nu} Y_{i(m+1)t}, \quad \forall m = 1, \ldots, |M| - 1, \forall t \in T. \tag{6b}$$

Constraints (6a) enforce that a mobile facility can only be deployed if cheaper mobile facilities are already deployed. Constraints (6b) reduce the number of solutions, as a mobile facility can only leave the depot once cheaper mobile facilities have left the depot. These symmetry-breaking constraints are possible because Bayraktar et al. (2022) only include fixed costs in their objective function. Unfortunately, this does not hold in general for the objective (2) with more than one cost parameter dependent on the mobile facility. Hence, the symmetry-breaking constraints (6a) and (6b) can only be used if the fleet of mobile facilities can be ordered in a non-decreasing order in all cost parameters.

4.2 Adaptive Large Neighborhood Search Heuristic

The MM-FLP-MD is proven to be $\mathcal{NP}$-hard (Bayraktar et al., 2022). Hence, solutions for sufficiently large instances cannot be solved within reasonable time by the MILP model introduced in Section 4.1. Instead, solutions can be obtained heuristically. For this reason, Bayraktar et al. (2022) developed an Adaptive Large Neighborhood Search (ALNS) algorithm. This thesis uses a similar ALNS algorithm for the case study in Section 5 but hybridizes it with a Tabu Search (TS) feature.

Before discussing the ALNS framework, the solution representation and some preliminaries are described in Section 4.2.1. The set of destroy and repair operators are defined in Section 4.2.2 and Section 4.2.3, respectively, and their selection in Section 4.2.4. The Simulated Annealing (SA) and TS features in the ALNS/TS algorithm are shown in Section 4.2.5. A refinement of the current ALNS/TS solution is done every ζ iterations in form of a local search (LS), whose algorithm is presented in Section 4.2.6. The ALNS/TS algorithm is concluded with the solution initialization and stopping criteria in Section 4.2.7. The algorithm of the ALNS/TS framework is shown in Algorithm 1.

4.2.1 Solution Representation and Preliminaries

A solution to the MM-FLP-MD can be represented by the set of all service act variables

Generic solution

$$s = \{y_{pimt} : p \in P, m \in M, t \in T_p, i = n_{pt} \in V_\nu\}. \tag{7}$$

This generic solution representation can be altered to represent partial solutions for caravans and mobile facilities, respectively.

For caravans, the mobile facility which provides the service does not matter. So, for each caravan $p \in P$, the service act variables of concern can be aggregated to $\hat{y}_{pit} = \sum_{m\in M} d_p y_{pimt}$. The partial solution from the perspective of a caravan p can then be represented as

Caravan, or path, solution

$$s_p = \{\hat{y}_{pit} : t \in T_p, i = n_{pt} \in V_\nu\}. \tag{8}$$

Similarly, mobile facilities must know how many DPs they serve every period; their path is of no interest. Hence, for every mobile facility $m \in M$, the service act variables can be aggregated to $\hat{y}_{mit} = \sum_{p\in P: i=n_{pt}} d_p y_{pimt}$. The partial solution from the perspective of a mobile facility is

Algorithm 1: ALNS/TS Framework

Input : Initial solution s_0

$s \leftarrow s_0$
$s_{best} \leftarrow s_0$
$w_h \leftarrow 1/|D|, \quad \forall h \in R$ `// Set initial weights of destroy operators`
$w_h \leftarrow 1/|R|, \quad \forall h \in R$ `// Set initial weights of repair operators`
$iter \leftarrow 0$
while `Stopping criteria not satisfied` **do**
  $iter \leftarrow iter + 1$
  if $iter \% \eta = 0$ **then** `// Weight adjustment once in` η `iterations`
    $w_R \leftarrow$ `Adjust(`w_R`)`
    $w_D \leftarrow$ `Adjust(`w_D`)`
  end
  if $iter \% \zeta = 0$ **then** `// Local search once in` ζ `iterations`
    $s \leftarrow$ `LocalSearch(`s`)`
    if $o(s) \leq o(s_{best})$ **then** $s_{best} \leftarrow s$
  end
  $h_{destroy} \leftarrow$ `SelectTS(`w_D`)`
  $h_{repair} \leftarrow$ `SelectTS(`w_R`)`
  `Update Tabu Search attributes`
  $s' \leftarrow h_{repair}(h_{destroy}(s))$
  if $o(s') \leq o(s_{best})$ **then** $s_{best} \leftarrow s'$
  if `AcceptSA(`s', s`)` **then** $s \leftarrow s'$
end
$s_{best} \leftarrow$ `LocalSearch(`s_{best}`)`

Output: s_{best}

then

Mobile facility solution

$$s_m = \{\hat{y}_{mit} : i \in V_\nu, t \in T\}. \tag{9}$$

For each partial solution, the value of the concerned aggregated service act variables at node-time pair (n, t) can be accessed by $s_p(n, t)$ and $s_m(n, t)$, respectively. The following two properties provide conditions for feasible partial solutions.

Property 4.1: Identification of a Feasible Partial Solution for a Caravan of Forcibly Displaced Persons

For every caravan of forcibly displaced persons $p \in P$, the following condition identifies a feasible solution s_p.

1. *p is fully served at least once every τ periods if possible:*

$$\sum_{t=a_p+k}^{a_p+k+\tau-1} s_p(n_{pt}, t) \geq d_p I_\tau(p, a_p + k), \quad 0 \leq k \leq l_p - \tau. \tag{10}$$

Corollary 4.1.1: Necessary Relief Aid for a Caravan of Forcibly Displaced Persons

Let $p \in P$ be a caravan which is located at non-primary nodes for τ or more consecutive periods *and the last node-time pair before and the first node-time pair after are* (n_1, t_1) *and* (n_2, t_2)*, respectively. A direct implication of Property 4.1 is that all forcibly displaced persons in* p *must be fully served at these two node-time pairs,* $\hat{y}_{pn_1t_1} = \hat{y}_{pn_2t_2} = d_p$*.*

Property 4.2: Identification of a Feasible Partial Solution for a Mobile Facility
For every mobile facility $m \in M$*, let* T_m *be the set of sets of consecutive periods* m *is in duty. Then the following conditions identify a feasible solution* s_m*.*

1. *m is located at at most one primary node in every period:*

$$|\{i \in V_\nu : s_m(i,t) > 0\}| \leq 1, \quad \forall t \in T. \tag{11}$$

The location of m *can be retrieved by* n_{mt}*. If* $s_m(i,t) = 0$ *for all primary nodes* $i \in V_\nu$*, then* m *is assumed to be at the depot,* $n_{mt} = 0$*.*

2. *m can serve at most k_m forcibly displaced persons in any one period:*

$$s_m(i,t) \leq k_m, \quad \forall i \in V_\nu, \forall t \in T. \tag{12}$$

3. *m can serve at most K_m forcibly displaced persons for any consecutive periods m is in duty:*

$$\sum_{t \in \vartheta} \sum_{i \in V_\nu} s^m(i,t) \leq K_m, \quad \forall \vartheta \in T_m. \tag{13}$$

4. *m can be in duty at most l_m consecutive periods:*

$$|\vartheta| \leq l_m, \quad \forall \vartheta \in T_m. \tag{14}$$

The costs in the objectives (2) and (4) are completely incident to mobile facilities. The relevant decision variable vectors $\boldsymbol{Z}$, $\boldsymbol{X}$, and $\boldsymbol{Y}$ can, thus, be recovered from a generic solution through all facility solutions by

$$Z_m = \begin{cases} 1, & \exists i \in V_\nu, \exists t \in T : 0 < \hat{y}_{mit} \in s_m \\ 0, & \text{otherwise} \end{cases}, \quad \forall m \in M, \tag{15a}$$

$$Y_{imt} = \begin{cases} 1, & 0 < \hat{y}_{mit} \in s_m \\ 0, & \text{otherwise} \end{cases}, \quad \forall i \in V_\nu, \forall m \in M, \forall t \in T, \tag{15b}$$

$$Y_{0mt} = \begin{cases} 1, & 0 = \hat{y}_{mit} \in s_m, \forall i \in V_\nu \\ 0, & \text{otherwise} \end{cases}, \quad \forall m \in M, \forall t \in T, \tag{15c}$$

$$X_{ijmt} = \begin{cases} 1, & Y_{imt} = Y_{jm(t+1)} = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \forall (i,j) \in A_{\nu'}, \forall m \in M, \forall t \in T \setminus \{|T|\}, \tag{15d}$$

$$X_{0im0} = \begin{cases} 1, & Y_{im1} = 1 \\ 0, & \text{otherwise} \end{cases}, \qquad \forall i \in V_\nu, \forall m \in M, \tag{15e}$$

$$X_{i0m|T|} = \begin{cases} 1, & Y_{im|T|} = 1 \\ 0, & \text{otherwise} \end{cases}, \qquad \forall i \in V_\nu, \forall m \in M. \tag{15f}$$

This allows to represent the objective value from a solution from the ALNS algorithm as $o(s) = \sum_{m \in M} o(s_m)$.

Similar to Bayraktar et al. (2022), it is possible to define the concept of dominated solutions.

Definition 4.1: Dominated Solutions

A solution s is dominated by another solution s' if any service act variable in s is at least as large as the corresponding service act variable in s',

$$y'_{pimt} \leq y_{pimt}, \quad \forall p \in P, \forall m \in M, \forall t \in T_p, i = n_{pt} \in V_\nu. \tag{16}$$

That is, s' provides a tighter service act schedule than s without higher total cost.

Similarly, a partial solution $s_h, h \in M \cup P$, is dominated by another solution s'_h, if any partial service act variable in s_h is at least as large as the corresponding partial service act variable in s'_h,

$$\hat{y}'_{hit} \leq \hat{y}_{hit}, \quad i \in V_\nu, t \in T. \tag{17}$$

With Definition 4.1, a set of minimal, i.e. non-dominated, feasible path solutions can be constructed, as outlined in Algorithm 1 in Bayraktar et al. (2022), with an additional check for Corollary 4.1.1. Minimal feasible path solutions are then used for the repair operators in Section 4.2.3.

4.2.2 Destroy Operators

Destroy operators remove parts of the current solution to diversify the set of candidate solutions. The larger the destruction of the current solution, the larger is the neighborhood of new candidate solutions. In the context at hand, a solution is destroyed by removing one or more service acts. Mathematically, a service act is a positive service act variable, and a service act is removed by setting the corresponding service act variable to 0. Like Bayraktar et al. (2022), at least κ service acts should be removed in each iteration, for which κ is drawn from a discrete uniform distribution with bounds $\underline{\kappa}$ and $\bar{\kappa}$. The bounds of the discrete uniform distribution are obtained by rounding $b_1|s|$ and $b_2|s|$, respectively, where b_1 and b_2 are lower and upper destroy degree parameters between 0 and 1, and $|s|$ the number of positive service act variables in the current solution s. The following set of destroy operators D is employed.

Random removal (RR) removes κ service acts at random. This type of operator diversifies the search (Pisinger & Ropke, 2007).

Random path removal (RPR) and *random mobile facility removal* (RMFR) iteratively remove all service acts of a path and mobile facility, respectively, until at least κ service acts are removed (see Bayraktar et al., 2022, for RMFR). This allows to explore a new set of feasible service acts for the stripped paths upon reparation in case of RPR, and to explore other mobile facilities in case of RMFR.

Worst removal (WR) iteratively removes the most expensive service act until κ service acts are removed. The expense of a service act y_{pimt} is determined by calculating the difference in the objective values of the current solution, and the solution after setting $y_{pimt} = 0$ and possibly rescheduling the location and travel of mobile facility m. The idea is that more expensive service acts can be rescheduled to obtain a cheaper solution (Pisinger & Ropke, 2007).

Shaw, or related, removal (SR) was developed by Shaw (1997, 1998) with the idea that unrelated service acts which are jointly removed have a higher chance to be repaired in the same way, as the probability that they can be jointly optimized is relatively low compared to related service acts. The relatedness of two positive service act variables $y_{p_1 i_1 m_1 t_1}$ and $y_{p_2 i_2 m_2 t_2}$ is given by the score

$$\begin{aligned} R(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2}) = w_1 \frac{\min c_{i_1 i_2}}{\max_{(i,j)\in A_\nu} c_{ij}} + w_2 \frac{|t_1 - t_2|}{|T|} + w_3 \left(1 - \frac{2h_P(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}{H_P(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}\right) \\ + w_4 \left(1 - \frac{2h_M(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}{H_M(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}\right), \end{aligned} \tag{18}$$

where the first term is the normalized distance between the nodes, proxied by the minimal travel cost, the second term the normalized difference in time, the third term a measure of common path service acts, and the fourth term a measure of common facility service acts. For the last two terms, h_P and h_M count the number of node-time pairs at which p_1 and p_2 receive relief aid and at which m_1 and m_2 provide relief aid, respectively, and H_P and H_M count the total number of node-time pairs at which p_1 and p_2 receive relief aid and at which m_1 and m_2 provide relief aid, respectively. All terms are weighted by the coefficients w_1, w_2, w_3, and w_4. SR begins with the removal of a random service act variable and continues to remove the $\kappa - 1$ most related service act variables. Service act variables with a relatedness score close to 0 are more related than service act variables with a relatedness score close to 1.

From each term in (18), a separate destroy operator can be derived (Pisinger & Ropke, 2007). Each of the following variants of the SR begins with the removal of a random service act and continues to remove $\kappa - 1$ service acts with the lowest corresponding score.

Cluster removal (CR) removes κ service acts which belong to a node cluster. The affiliation to a node cluster is determined by the score

$$R_V(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2}) = \frac{\min c_{i_1 i_2}}{\max_{(i,j)\in A_\nu} c_{ij}}. \tag{19}$$

Time-oriented removal (TR) removes κ service acts which occur at roughly the same time. This property is given by the score

$$R_T(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2}) = \frac{|t_1 - t_2|}{|T|}. \tag{20}$$

Path-oriented removal (PR) and *facility-oriented removal* (FR) remove κ service acts which have the highest fraction of caravans served at the same node-time pairs and mobile facilities providing relief aid at the same node-time pair, respectively, given by the scores

$$R_P(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2}) = 1 - \frac{2h_P(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}{H_P(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})} \tag{21}$$

and

$$R_M(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2}) = 1 - \frac{2h_M(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}{H_M(y_{p_1 i_1 m_1 t_1}, y_{p_2 i_2 m_2 t_2})}. \tag{22}$$

4.2.3 Repair Operators

Repair operators repair previously destroyed solutions until they are feasible for both caravans of DPs and mobile facilities. Contrary to removal, inserting a service act corresponds to setting a service act variable y_{pimt} to 1. Due to the representation of a solution for paths and mobile facilities, the insertion of a service act can be done in two stages. As the service requirement is the heart of the MM-FLP-MD, the first stage is to insert path service act variables $\hat{y}_{pit}$ until all paths are feasible in terms of Property 4.1. In the second stage, the service acts are allocated to mobile facilities through the facility service act variables $\hat{y}_{mit}$, while respecting the feasibility conditions in Property 4.2.

The first stage repair operators are as follows. For each infeasible path, *random insertion* (RI) inserts service acts from a random minimal feasible path solution, and *worst insertion* (WI) inserts a service act at every primary node. These first stage repair operators diversify the search through randomness and excessive insertion, respectively. The last first stage repair operator is *common service act insertion* (CSI). CSI inserts for each infeasible path the service acts from the minimal feasible path solution which has the most service acts in common with already existing service acts on the path. Contrary to RI and WI, CSI intensifies the search for the current solution.

Each first stage operator can be combined with one of the following second stage allocation operators. *Random allocation* (RA) randomly allocates the service act to deployed mobile facilities, which diversifies the search. If the mobile facilities deployed cannot conduct the service acts feasibly, new mobile facilities can be deployed. *Least-cost allocation* (LCA) allocates service acts to mobile facilities such that the cost increase is minimal and, thus, intensifies the search.

Both stages are combined in the *least-cost insertion and allocation* (LCIA), and *n-regret insertion and least-cost allocation* (RI-n/LCA) repair operators. The LCIA iteratively inserts and allocates a service act at minimal cost increase. For the RI-n/LCA, let $\Delta o_{s_k^p}$ be the change in the objective function after inserting missing service acts of the kth cheapest feasible path solution for p based on LCIA. Then, the service acts of the cheapest feasible path solution are inserted for the path p^* which maximizes the regret of its n cheapest feasible solutions,

$$p^* = \underset{\substack{p \in P: \\ p \text{ infeasible}}}{\arg\max} \left\{ \sum_{k=2}^{n} (\Delta o_{s_k^p} - \Delta o_{s_1^p}) \right\}. \tag{23}$$

All first stage insertion operators can be combined with any second stage allocation operator, such that the set of repair operators R contains in total 8 operators.

4.2.4 Selection of Operators

Destroy and repair operators are selected in a roulette-wheel fashion. In the beginning, all destroy and repair operators $h \in D \cup R$ have the same probability, or weight ω_h, of being selected. That is, every destroy operator is selected with probability $1/|D|$, and every repair operator is selected with probability $1/|R|$.

The probabilities are updated every η iterations, called segments, based on past performance of the operators. For this, every operator $h \in D \cup R$ has a counter ν_h counting the number of selections in the current segment, and a score β_h which is increased if the recovered solution s' is accepted. The score is increased by ϵ_1 if s' improves the incumbent solution s_{best}, by ϵ_2 if s' only improves the current solution s, and by ϵ_3 if s' not improving but accepted due to SA (see Section 4.2.5). In the first two cases, the probability of a well-performing operator is intensified, whereas the latter case retains some diversification (Bayraktar et al., 2022). The probabilities are updated by

$$\omega_h = (1 - \rho)\omega_h + \rho\frac{\beta_h}{\nu_h}, \tag{24}$$

where ρ is a reaction factor which determines the momentum or recall of past performance (Pisinger & Ropke, 2007). The weights are smoothened for $\rho < 1$, whereas $\rho = 1$ only considers the performance of the last segment. After updating, the weights are normalized such that all destroy weights and repair weights sum to 1, and the counters and scores are reset.

4.2.5 Simulated Annealing and Tabu Search Hybridization

The ALNS framework proposed by Ropke and Pisinger (2006) includes the SA meta-heuristic by Kirkpatrick et al. (1983) to accept solutions. Recovered solutions s' which improve the current solution s are always accepted, while a non-improving recovered solution is accepted with probability

$$\exp\left(\frac{o(s) - o(s')}{T_{iter}}\right), \tag{25}$$

where $T_{iter} > 0$ is the temperature for the current iteration. For higher temperatures, the probability to accept a non-improving solution and to diversify the search is higher. In advanced iterations, intensification is more important than diversification, such that the temperature is updated based on the cooling rate $0 < \alpha < 1$, $T_{iter} = \alpha T_{iter-1}$. The temperature is initialized to $T_0 = \frac{o(s_0)}{\ln(2)}$ to allow for sufficient diversification in early iterations (Bayraktar et al., 2022).

The ALNS framework can also include a TS feature (Butsch et al., 2014; Žulj et al., 2018). For each destruction, the same combination of removed service acts cannot be removed again in the next ϑ iterations. Likewise, for each reparation, the same combination of inserted service acts cannot be inserted again in the next ϑ iterations. Similar to the number of service acts removed, ϑ is drawn from a discrete uniform distribution with bounds $\underline{\vartheta}$ and $\bar{\vartheta}$, which are parameters of the ALNS/TS framework.

4.2.6 Local Search

The current solution is intensified in an LS every ζ iterations. LS entails (1) a removal of redundant service acts, (2) optimization of service act allocations.

Redundant service acts are service acts which can be removed and all paths remain feasible. The remaining path solutions are then minimally feasible.

The allocation of service acts to mobile facilities is optimized through swaps and transfers of service acts (Bayraktar et al., 2022). That is, two mobile facilities can swap a service act each to the other mobile facility, or a service act can be transferred from one mobile facility to another. When a depot exists, the combination of service acts into duties and the consequent travels to the depot can be optimized. After optimization of facility schedules, mobile facilities can be swapped between schedules. Mobile facilities can be swapped either strategically when symmetry-breaking constraints such as (6a) and (6b) are applicable or by brute force when no natural ordering of mobile facilities is possible.

4.2.7 Solution Initialization and Stopping Criteria

The ALNS/TS algorithm in Algorithm 1 requires an initial solution s_0 as input. The initial solution is constructed by iterating randomly over all infeasible paths and applying the LCIA repair operator described in Section 4.2.3. After this iteration, all paths and mobile facilities are feasible with respect to Property 4.1 and Property 4.2. Finally, a local search described in Section 4.2.6 completes the construction of s_0.

The ALNS/TS algorithm terminates after a maximum number of iterations χ_1, after a maximum number of non-improving iterations χ_2, or after θ seconds.

5 Case Study

To compare the results from the ALNS/TS algorithm with the results of the ALNS algorithm of Bayraktar et al. (2022), the same case study is used, namely the Honduras Migration Caravan Crisis from 2018. In October that year, up to 4,000 Hondurans decided to leave their country towards Mexico and the United States due to a polarized government, corruption, poverty, and violence (Semple, 2018; International Crisis Group, 2019). Bayraktar, Günneç, Salman, and Yücel (2020) analyzed the migration route and provide a publicly available dataset. The data and further assumptions to the case study warranted for the application of the proposed MM-FLP-MD model are described in Section 5.1. The results of the comparison of ALNS algorithms and the extended MM-FLP-MD model are displayed in Section 5.2.

5.1 Data

The original network $G = (V, A)$ contains $|V| = 30$ nodes of which $|V_\nu| = 21$ are primary, i.e. accessible for mobile facilities, as shown in Figure 4 of Bayraktar et al. (2022). The $|A_\rho| = 42$ path arcs are chosen in accordance to different travel modes, such as by foot and by car. Particularly short are arcs which cross borders, due to bureaucracy or additional effort for illegal crossings. In total, 13 different paths through the network are recognized. All of them start at the first node in San Pedro Sula, but some of them stop before the last node. Mobile facilities can travel between any two primary nodes, leading to $|A_\nu| = 420$ primary arcs.

For the extended MM-FLP-MD model, the network has an additional node in form of the depot. It is assumed that the depot is located at Tuxtla Gutiérrez which lies in southern Mexico about halfway between the first and last node in the network. It is the biggest city in southern Mexico, which promises to offer a sufficient number of vehicles which can be leased and deployed as mobile facilities. The extended network, thus, has $|V_{\nu'}| = 22$ facility nodes and $|A_{\nu'}| = 480$ facility arcs. A map of all nodes and the migration route is shown in Figure 1.

Bayraktar et al. (2022) calculate the cost in the objective in terms of distance. The travel cost is, therefore, the shortest distance between the two nodes traveled. The fixed cost is estimated to be 600 km, roughly the ratio between the fixed cost of €784 and the average unit traveling cost of €1.31/km.

The objective for the extended MM-FLP-MD model calculates the cost in monetary terms. The preparation cost f_m consists of the lease cost of a vehicle and the cost to convert the vehicle into a mobile facility to provide relief aid. Bayraktar et al. (2022) estimated the monthly lease cost at €1,600. The exact lease cost is calculated by multiplying the monthly lease cost by the fraction of the month the leased vehicle is used, namely $(|T| + 3)/30$, where $|T|$ is the number of days in the planning horizon, plus three additional days for conversion into a mobile facility and back into a regular vehicle. The conversion cost in turn is assumed to be €200. The duty cost g_m consists of the salaries for the relief aid personnel. During the European migration wave in 2015, Tsiamis, Terzidis, Kakalou, Riza, and Rosenberg (2016) proposed the formation of so-called refugees' health units consisting of a physician, nurse, translator or cultural mediator, and an administrative assistant. As all Latin American countries along the route of the Honduras Migration Caravan Crisis are Spanish-speaking, a translator or cultural mediator is not necessarily needed. An administrative assistant can be hired at the Mexican minimum wage per day of 88.36 pesos in 2018. The medical care needed during the European migration wave comprised mostly basic first aid (Gulland, 2015). Barring any differences, two general practitioners at the average hourly salary of 403 Mexican pesos in 2022 can be hired to provide relief aid. Assuming a lengthy twelve-hour work day in view of the humanitarian necessity and adjusting for inflation and an exchange rate of 21.56 pesos for €1, the duty cost for employing two general practitioners and an administrative assistant is roughly €385 per period. The last cost term, the travel cost, is the product of the shortest distance between two facility nodes and the unit travel cost per kilometer. The unit travel cost comprises cost for fuel, crossing borders, and a driver, which is estimated by Bayraktar et al. (2022) at €1.31 per kilometer.

The capacity and length constraints of the extended MM-FLP-MD model require additional assumptions regarding the capacity parameters k_m and K_m, length parameter l_m, and caravan size parameter d_p. As reported by newspapers (Lind, 2018), the initial caravan which left San Pedro Sula counted about 160 DPs. Due to the lack of knowledge of the caravan sizes in the data at hand, we consider $d_p = 160$ the size of all caravans in the network. The two general practitioners in the relief aid staff can cover all DPs in one caravan in a twelve hour work shift with an average service time of nine minutes per DP. The number of patients served may be more than appropriate on a permanent basis (Campbell, 2019), but humanitarian necessities vindicate short-term deviations and five percent of U.S. primary care physicians spend less time per patient on average on a permanent basis (Statista, 2019). Therefore, a mobile facility can serve only $k_m = 160$ DPs per period. Due to a twelve-hour workday when a mobile facility provides service to a caravan, it is acceptable for general practitioners to serve up to $K_m = 640$ DPs in one duty

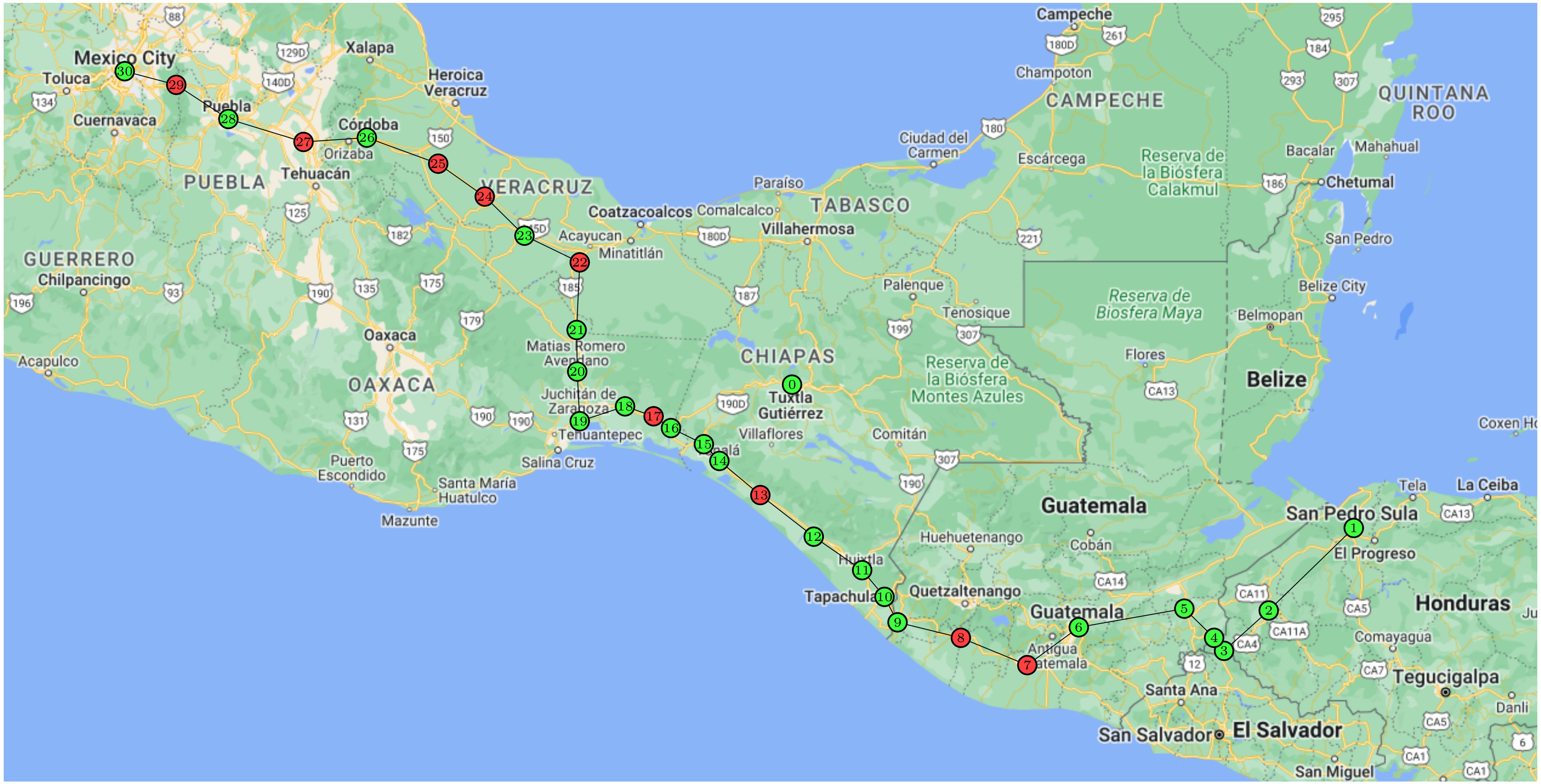


Figure 1: Route map

Note. Nodes 1 through 30 are path nodes and represent the nodes of the longest path in this order. Green nodes are facility nodes, with 0 being the depot. Red nodes cannot be visited by mobile facilities.

trip, corresponding to 48 hours of work in one duty trip, which is the weekly maximum working hours in Mexico. The maximum duty capacity can also be due to limited storage capacity in the mobile facility, about which no assumptions are made here. The maximum length of a duty trip is chosen to be $l_m = 7$ periods. After this duration of extraordinary service, the personnel must return for rest. Other reasons for this maximum length can be to restock first aid utensils, such as medicine and food.

The service frequency is set to $\tau = 3$ as in Bayraktar et al. (2022). Consequently, the probability of a caravan to visit a primary node in τ consecutive periods is always $I_\tau(p,t) = 1$. The heuristics and models are analyzed on a subset of 25 problem instances from all 75 problem instances in the dataset. 5 of these instances use the entire network; 10 instances each use the first 10 and 20 nodes of the network, respectively. Hence, a distinction between problem instances is made based on the number of nodes in its network. Instances with 10, 20, and 30 nodes are referred to as small-, medium-, and large-sized, respectively. The instances are named like P6E13N30_1, where P stands for the number of unique routes, i.e. sequence of nodes, E for the number of paths, and N for the number of nodes in the network. The number after the underscore indicates the instance version for instances with the same characteristics. Hence, the instance P6E13N30_1 is the first instance with 6 unique routes, 13 paths, and 30 nodes.

5.2 Results

The methods described in Section 4 are implemented in Java 17 using the IntelliJ IDEA 2022.1.1 integrated development platform and tested on the subset of 25 problem instances on a laptop with a 2.3 GHz Intel i7 processor with 8 cores and 16 GB of internal memory. The results for the additional ALNS operators and TS hybridization in the ALNS algorithm are provided in Section 5.2.1 and the results for the extended MM-FLP-MD model in Section 5.2.2.

5.2.1 Heuristic Results

In this subsection, the performances of three different ALNS algorithms are compared. The base heuristic $\mathcal{B}$ is the first ALNS algorithm proposed to solve the MM-FLP-MD and has the exact same parameter values as provided in Bayraktar et al. (2022), i.e. $\chi_1 = 25,000$, $\chi_2 = 1,000$ for small-sized instances and $\chi_2 = 3,000$ for medium- and large-sized instances, $w_1 = w_2 = w_3 = 1$, $w_4 = 0$, $n = 4$, $\alpha = 0.999$, $\epsilon_1 = 50$, $\epsilon_2 = 20$, $\epsilon_3 = 12$, $\rho = 0.1$, $\eta = 50$, $\zeta = 25$, $b_1 = 0.2$, and $b_2 = 0.8$. This algorithm uses the destroy operators RR, RMFR, and SR, and repair operators RI/LCA, WI/LCA, LCIA, and RI-4/LCA.[3] The first alternative algorithm $\mathcal{P}(0,0)$ employs additional operators proposed in Section 4.2.2 and Section 4.2.3, i.e. RPR, WR, CR, TR, PR, FR, and RI/RA, WI/RA, CSI/RA, CSI/LCA, respectively. Due to the larger number of ALNS operators, the segment length is increased to $\eta = 100$ accordingly to allow every operator a fair chance to be drawn in a roulette wheel selection. Besides the changes in the first alternative algorithm, the second alternative algorithm $\mathcal{P}(5,10)$ also has a TS feature with lower and upper tabu parameters $\underline{\vartheta} = 5$ and $\bar{\vartheta} = 10$. The time limit to solve the instances is set to one hour, i.e. $\theta = 3,600$, and each instance is solved in eight replications.

[3] Without the depot, the allocation of service acts in the repair operators of Bayraktar et al. (2022) is effectively the same as the least cost allocation in this paper.

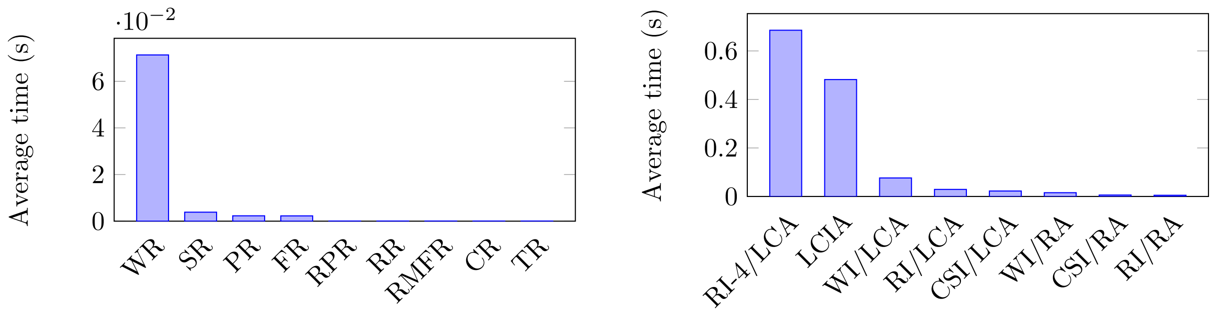
Table 2: Computational results of three different ALNS algorithms

	Gap (%)			Avg. iterations			Avg. running time (s)		
Instance	$\mathcal{B}$	$\mathcal{P}(0,0)$	$\mathcal{P}(5,10)$	$\mathcal{B}$	$\mathcal{P}(0,0)$	$\mathcal{P}(5,10)$	$\mathcal{B}$	$\mathcal{P}(0,0)$	$\mathcal{P}(5,10)$
P01E01N10_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	1,000	1,000	1,000	1	1	2
P01E02N10_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	1,000	1,000	1,000	2	2	2
P02E04N10_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	1,041	1,069	1,040	7	4	4
P02E04N10_2	*0.00*^{7}	*0.00*^{8}	*0.00*^{8}	1,314	1,178	1,209	31	18	18
P03E06N10_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	1,093	1,184	1,104	59	27	36
P03E06N10_2	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	1,021	1,081	1,088	71	31	35
P04E08N10_3	*0.00*^{6}	*0.00*^{6}	*0.00*^{3}	1,524	1,720	1,451	166	73	71
P04E08N10_4	*0.00*^{2}	*0.00*^{7}	*0.00*^{3}	1,433	1,837	1,640	226	128	127
P06E10N10_1	*0.00*^{7}	*0.00*^{8}	*0.00*^{8}	1,391	1,602	1,380	479	223	270
P06E10N10_2	*0.00*^{2}	*0.00*^{1}	*0.00*^{2}	1,892	1,750	2,334	786	340	511
P01E01N20_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,000	3,000	3,000	10	7	13
P01E02N20_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,013	3,018	3,018	84	43	54
P02E04N20_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,080	3,189	3,204	263	153	164
P02E04N20_2	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	4,068	5,010	3,922	386	294	252
P03E06N20_1	*0.00*^{8}	*0.00*^{7}	*0.00*^{8}	6,340	6,492	7,305	1,881	970	1,670
P03E06N20_2	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,718	4,227	4,289	1,151	1,006	600
P04E08N20_3	1.60^{2}	1.39^{1}	*0.24*^{1}	4,735	5,297	5,738	3,537	2,245	2,437
P04E08N20_4	*1.29*^{1}	*1.29*^{1}	1.33^{1}	3,598	5,117	5,402	3,488	2,999	2,754
P06E10N20_1	2.92^{2}	*2.12*^{1}	2.18^{1}	1,624	4,051	2,702	3,602	3,601	3,602
P06E10N20_2	4.10^{2}	*0.00*^{1}	0.15^{1}	1,572	2,591	2,829	3,601	3,601	3,570
P01E01N30_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,000	3,000	3,000	29	20	26
P01E02N30_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,010	3,045	3,050	186	112	103
P02E04N30_1	*0.00*^{8}	*0.00*^{8}	*0.00*^{8}	3,500	3,522	3,801	790	295	519
P02E04N30_2	*0.00*^{3}	*0.00*^{2}	*0.00*^{4}	5,459	6,140	7,349	1,489	1,297	1,345
P06E13N30_1	*10.45*^{1}	13.00^{1}	13.00^{1}	274	496	445	3,615	3,605	3,610
Total	1.43	1.36	1.32	62,699	71,613	72,300	25,939	21,091	21,795

Note. The gap is calculated in comparison to the best found solution in the Online Appendix of Bayraktar et al. (2022). Italicized gaps indicate the best gap among all three ALNS algorithms. Superscripts state the number of replications in which the gap occurred. $\mathcal{B}$ is the ALNS algorithm proposed by Bayraktar et al. (2022); $\mathcal{P}(x,y)$ the ALNS/TS algorithm proposed in this paper with lower and upper tabu parameters x and y, respectively.

Computational results of the three algorithms can be found in Table 2. For small-sized instances and instances with at most six caravans, all three algorithms terminate with the best solution found in Bayraktar et al. (2022). For these instances, there is no clear indication that one of the algorithms requires less iterations on average to terminate, but the base algorithm $\mathcal{B}$ proposed by Bayraktar et al. (2022) experiences a longer running time.

Out of the remaining five instances, $\mathcal{P}(0,0)$ provides the best solution in three instances, and $\mathcal{B}$ and $\mathcal{P}(5,10)$ find the best solution each once. What stands out is that, on average, $\mathcal{B}$ terminates with less iterations and after a longer running time for instances for which the other two algorithms do not reach the time limit of an hour. The reason for this lies in the time the operators need to destroy and repair a solution. Figure 2 shows the average time an operator needs to destroy and repair a solution, respectively. The average time is calculated across all ALNS algorithms and problem instances, because the task to destroy or repair remains the same. Figure 2a shows that the WR destroy operator is computationally more than 18 times as expensive as the other destroy operators. Still, all destroy operators perform reasonably fast in less



(a) Destroy operators

(b) Repair operators

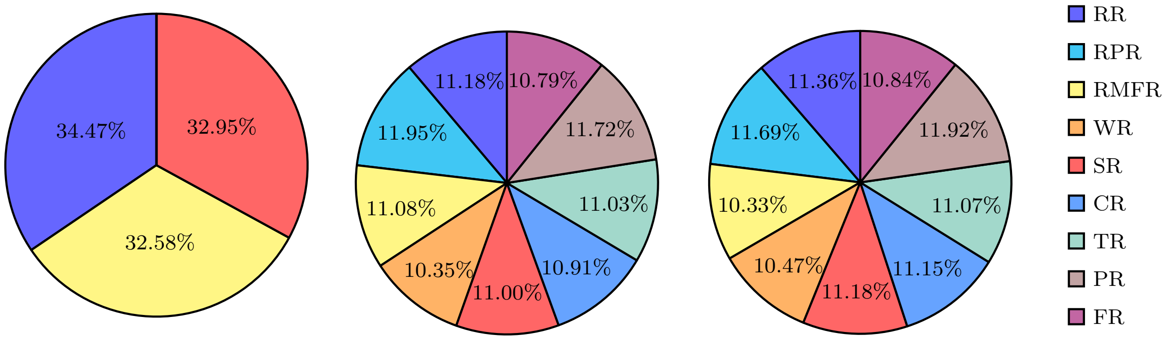
Figure 2: Average running times of operators across all ALNS algorithms and problem instances

than a tenth of a second. The task to repair an infeasible solution, however, is more challenging. This is reflected by longer running times for the repair operators in Figure 2b. Particularly RI-4/LCA and LCIA are expensive repair operators which take longer than half a second, on average. The four computationally most expensive repair operators jointly form the set of repair operators employed in algorithm $\mathcal{B}$. In comparison, $\mathcal{P}(0,0)$ and $\mathcal{P}(5,10)$ also employ a variety of "suboptimal" repair operators. The additional repair operators are suboptimal in the sense that they allocate service acts randomly and not cost-efficiently to mobile facilities. However, the random allocation is computationally easy and offers faster running times. Consequently, the alternative algorithms $\mathcal{P}(0,0)$ and $\mathcal{P}(5,10)$ perform, on average, 30% more iterations than $\mathcal{B}$ for instances which terminate due to the time limit.

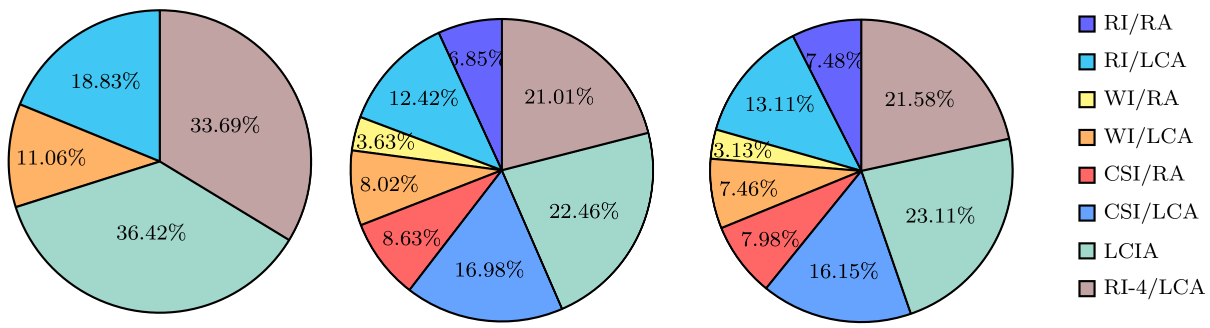
The dependency of the ALNS algorithm proposed by Bayraktar et al. (2022) on the computationally expensive repair operators LCIA and RI-4/LCA is reflected in the usage distribution shown in Figure 3b. The roulette wheel selection draws these two repair operators in more than two out of three cases, on average. For higher number of iterations, the probability that a non-improving solution is accepted due to SA shrinks, and consequently the probability of selection is based on the ability to recover an improving solution. The joint dominance of LCIA and RI-4/LCA is, thus, due to the lack of other repair operators which can recover an improving solution at low computational cost. For the two algorithms proposed in this paper, CSI proves to be such a repair operator, as it is drawn by the roulette wheel selection in almost every fourth iteration. Hence, inserting the minimal feasible path solution which has the most service acts in common with service acts already existing on the path is a computationally cheap shortcut to finding cost-efficient service acts for insertion exactly. Unsurprisingly, Figure 3b also shows that operators with LCA in the second stage comprise a larger share of the roulette wheel than operators with RA. Intuitively, LCA leads to a lower objective value and, thus, an improving solution more often than RA, which increases the probability of LCA operators to be selected in the next segment.

The usage distribution of destroy operators in Figure 3a is much more balanced than the usage distribution of repair operators. As all destroy operators are almost equally likely to be drawn in a roulette wheel selection, their impact on the recovered solution is minor. Hence, repair operators play a larger role to recover an improving solution.

The usage distributions of both destroy and repair operators in Figure 3 in $\mathcal{P}(0,0)$ and



(a) Destroy operators: $\mathcal{B}$, $\mathcal{P}(0,0)$, and $\mathcal{P}(5,10)$ (from left to right)



(b) Repair operators: $\mathcal{B}$, $\mathcal{P}(0,0)$, and $\mathcal{P}(5,10)$ (from left to right)

Figure 3: Usage of operators in ALNS algorithms

Note. $\mathcal{B}$ is the ALNS algorithm proposed by Bayraktar et al. (2022); $\mathcal{P}(x, y)$ the ALNS/TS algorithm proposed in this paper with lower and upper tabu parameters x and y, respectively.

$\mathcal{P}(5,10)$ are nearly identical. This is in line with the total gap, average iterations, and average running times in Table 2, which are all within a 3% margin. The algorithm with TS hybridization, thus, fails to intensify the neighborhood search sufficiently to boost performance.

5.2.2 Model Results

The extended MM-FLP-MD model in Section 4.1 has three capacity and length constraints. To analyze the impact of each constraint on the objective, four different models are solved. The first three models contain each one of the three capacity and length constraints, while the last model implements all of them simultaneously. The four models are solved by a Mixed Integer Linear Program (MILP) and the best-performing ALNS algorithm from Section 5.2.1. The MILP is solved using CPLEX 20.1, and the best-performing ALNS algorithm is $\mathcal{P}(0,0)$ due to the deficiency of the TS hybridization to distinguish its performance. Again, both solution methods have a running time limit of an hour.

Computational results for the four models can be found in Table 3 and Table 4. Table 3 shows the optimality gap of the best found solution and the running times for the two solution methods, ALNS and MILP. Table 4 shows the differences in the objective and number of mobile facilities of the four models in comparison to the basic model without any capacity and length constraints.

Table 3: ALNS and MILP results under capacity and length constraints

Constraints	PC				DC				DL				all			
	Gap (%)		Time (s)		Gap (%)		Time (s)		Gap (%)		Time (s)		Gap (%)		Time (s)	
Instance	ALNS	MILP	ALNS	MILP	ALNS	MILP	ALNS	MILP	ALNS	MILP	ALNS	MILP	ALNS	MILP	ALNS	MILP
P01E01N10_1	0.00	0.00	2	0	0.00	0.00	2	0	0.00	0.00	2	0	0.00	0.00	4	0
P01E02N10_1	0.00	0.00	6	0	0.00	0.00	5	0	0.00	0.00	5	0	0.00	0.00	6	0
P02E04N10_1	0.00	0.00	9	0	0.00	0.00	8	2	0.00	0.00	7	1	0.00	0.00	17	1
P02E04N10_2	0.00	0.00	28	2	0.00	0.00	18	7	0.00	0.00	18	3	0.00	0.00	44	6
P03E06N10_1	0.00	0.00	76	13	0.00	0.00	57	132	0.00	0.00	42	65	0.00	0.00	75	153
P03E06N10_2	0.00	0.00	88	10	0.00	0.00	42	29	0.00	0.00	38	2	0.00	0.00	48	82
P04E08N10_3	0.18	0.00	229	122	0.00	0.00	104	2,823	0.00	0.00	123	208	0.01	0.00	127	3,601
P04E08N10_4	0.00	0.00	164	74	0.00	0.00	161	3,601	0.00	0.00	104	198	0.00	0.00	129	2,210
P06E10N10_1	0.01	0.00	477	662	0.00	5.40	557	3,602	0.00	0.00	512	109	0.00	0.71	302	3,602
P06E10N10_2	3.02	0.00	356	30	0.00	6.16	504	3,601	0.00	0.00	485	488	1.60	0.00	465	3,601
P01E01N20_1	0.00	0.00	18	1	0.00	0.00	8	1	0.00	0.00	10	0	0.00	0.00	28	0
P01E02N20_1	0.00	0.00	87	3	0.00	0.00	64	5	0.00	0.00	58	4	0.00	0.00	96	4
P02E04N20_1	0.00	0.00	217	247	0.00	0.00	190	221	0.00	0.00	164	377	0.00	0.00	243	185
P02E04N20_2	0.00	0.00	253	363	0.00	0.00	196	626	0.00	0.00	213	98	0.00	0.00	405	1,013
P03E06N20_1	0.00	0.00	1,836	3,049	0.00	5.20	1,355	3,605	0.00	8.15	1,474	3,630	0.00	18.22	1,657	3,602
P03E06N20_2	0.00	11.67	2,360	3,604	0.00	2.02	1,242	3,615	0.00	4.14	1,258	3,611	0.00	12.62	1,765	3,609
P04E08N20_3	0.00	5.36	2,811	3,618	0.00	36.53	2,490	3,605	0.00	57.06	2,351	3,655	0.00	21.30	2,449	3,602
P04E08N20_4	0.00	3.80	2,643	3,620	0.00	6.66	2,709	3,608	0.00	4.18	2,864	3,642	0.00	20.03	3,106	3,602
P06E10N20_1	0.00	7.54	3,603	3,628	0.00	14.91	3,602	3,604	0.00	11.68	3,602	3,621	0.00	17.45	3,601	3,602
P06E10N20_2	0.00	11.93	3,602	3,605	0.00	17.71	3,602	3,602	0.00	58.75	3,601	3,614	0.00	7.25	3,601	3,604
P01E01N30_1	0.00	0.00	62	22	0.00	0.00	14	6	0.00	0.00	21	4	0.00	0.00	82	2
P01E02N30_1	0.00	0.00	197	63	0.00	0.00	107	60	0.00	0.00	135	41	0.00	0.00	259	32
P02E04N30_1	0.00	9.20	811	3,605	0.00	0.00	565	3,608	0.00	1.63	636	3,643	0.00	16.63	947	3,601
P02E04N30_2	0.00	1.98	1,465	3,924	0.00	0.75	1,124	3,601	0.00	3.14	687	3,633	0.00	3.24	1,923	3,604
P06E13N30_1	0.00	40.22	3,633	3,643	0.00	763.86	3,624	3,609	0.00	32.94	3,954	3,604	0.00	30.78	3,627	3,610
Total	0.13	6.40	25,030	33,908	0.00	102.22	22,346	47,173	0.00	8.70	22,360	34,251	0.07	10.24	25,005	46,928

Note. The gap is calculated in comparison to the best found solution of the ALNS or MILP.

Table 4: Optimality results for capacity and length constraints

	Best found objective (€)				Cost increase (%)				Additional facilities			
Instance	PC	DC	DL	all	PC	DC	DL	all	PC	DC	DL	all
P01E01N10_1	5,769	5,769	5,769	5,769	0.00	0.00	0.00	0.00	0	0	0	0
P01E02N10_1	6,207	6,691	6,691	6,691	0.00	7.81	7.81	7.81	0	0	0	0
P02E04N10_1	7,342	8,309	7,827	8,309	0.00	13.17	6.60	13.17	0	0	0	0
P02E04N10_2	16,234	9,998	9,316	17,401	84.67	13.73	5.98	97.94	1	0	0	1
P03E06N10_1	13,917	13,360	11,983	15,794	22.58	17.67	5.55	39.12	1	1	0	1
P03E06N10_2	11,558	10,426	7,827	13,180	57.42	42.00	6.60	79.51	1	1	0	1
P04E08N10_3	14,814	14,509	12,499	18,307	42.04	39.11	19.84	75.53	1	1	1	1
P04E08N10_4	14,815	15,381	13,431	17,071	14.74	19.12	4.02	32.21	0	0	0	0
P06E10N10_1	19,918	20,789	15,055	25,297	41.39	47.57	6.86	79.57	1	1	0	1
P06E10N10_2	19,943	19,867	14,558	25,096	44.24	43.69	5.29	81.51	1	1	0	2
P01E01N20_1	9,018	9,018	9,018	9,018	0.00	0.00	0.00	0.00	0	0	0	0
P01E02N20_1	10,318	10,803	10,803	10,803	0.00	4.70	4.70	4.70	0	0	0	0
P02E04N20_1	13,618	14,103	14,103	14,103	0.00	3.56	3.56	3.56	0	0	0	0
P02E04N20_2	21,311	14,661	13,961	22,597	59.82	9.95	4.70	69.46	1	0	0	1
P03E06N20_1	21,861	22,535	21,482	24,088	6.80	10.09	4.95	17.68	0	0	0	0
P03E06N20_2	19,251	18,722	17,131	21,885	15.11	11.95	2.44	30.86	0	0	0	0
P04E08N20_3	22,787	22,085	20,090	27,477	15.31	11.76	1.66	39.05	0	0	0	1
P04E08N20_4	21,974	22,820	20,797	25,203	7.32	11.46	1.58	23.10	0	0	0	0
P06E10N20_1	33,637	28,369	22,101	38,975	56.27	31.80	2.68	81.07	1	1	0	2
P06E10N20_2	30,095	31,796	25,583	37,966	31.63	39.07	11.90	66.06	1	1	1	2
P01E01N30_1	14,666	14,666	14,733	14,733	0.00	0.00	0.46	0.46	0	0	0	0
P01E02N30_1	16,197	17,405	16,902	17,405	0.00	7.46	4.35	7.46	0	0	0	0
P02E04N30_1	20,792	22,776	21,497	22,776	0.00	9.54	3.39	9.54	0	0	0	0
P02E04N30_2	31,642	27,643	25,985	34,497	36.79	19.50	12.34	49.13	1	1	1	0
P06E13N30_1	62,535	58,623	42,919	64,847	58.18	48.28	8.56	64.02	3	2	1	4
Total	480,218	461,122	402,062	551,775	26.21	21.19	5.67	45.02	13	10	4	17

Note. The best found objective is taken from the ALNS and MILP solution methods. The cost increase and additional mobile facilities are compared to the results of the model without any capacity and length constraints. PC stands for period capacity, DC for duty capacity, and DL for duty length constraints.

The results in Table 3 show that the ALNS consistently outperforms the MILP. The dominating performance is even more outstanding for larger-sized instances for which the MILP does not obtain a single smaller gap than the ALNS.

The running time of the ALNS is similar across the four different models. Only for the three to four largest instances does the ALNS consistently reach the running time limit. For the MILP, the running times of the models with period capacity and duty length constraints are comparable but more than a third longer than the running times of the ALNS. Solving models with duty capacity and all constraints takes the MILP particularly long. For these models, the MILP takes more than twice the time of the ALNS until it terminates, often due to the running time limit.

The impact of capacity and length constraints on the cost can be interpreted from Table 4. Individually, the capacity constraints for the number of DPs which can be served in one period and in one duty trip cause a sharp cost increase of more than 25% and 20%, respectively, on average. The cost increase is, however, not evenly distributed across instances. Whereas the cost increase in smaller instances is moderate, restricting the capacity of mobile facilities in larger instances of more than four caravans can increase the cost by 50% or more. Nonetheless, constraints on the duty length do not lead to a sharp increase in costs. Even the worst cost increase for an instance constrained by a duty length of a week is less than the average increase due to capacity constraints. When all constraints are superimposed, the cost increase is not additive but some cost savings are possible. Still, the average cost increase for models with all constraints is about 45% higher than without any constraints. Except for small instances with one or two caravans, a cost increase by more than 60% is not seldom.

The cost increase due to capacity and length constraints cannot be equated with the use of additional mobile facilities. For most of the constrained instances, the same number of mobile facilities can be used. Only for instances with ten or more caravans are additional facilities almost inevitable. This implies that the capacity and length constraints usually lead to a higher utilization of the existing fleet of mobile facilities. For the largest instances, the utilization is probably already at a high level such that additional mobile facilities must be deployed.

6 Conclusions

This thesis explored advancements of the basic multi-period mobile facility location problem with mobile demand (MM-FLP-MD) by Bayraktar et al. (2022). The MM-FLP-MD can, for instance, be used for migration caravans whose forcibly displaced persons (DPs) must receive periodic relief aid. The continuation of service is crucial to alleviate mental and physical distress of DPs. Humanitarian organizations can rely on MM-FLP-MD models and solution methods to cost-effectively coordinate mobile facilities to provide relief aid en route.

The Adaptive Large Neighborhood Search (ALNS) proposed in previous literature (Bayraktar et al., 2022) was augmented by additional destroy and repair operators as well as a Tabu Search (TS) feature. The additional operators improved the performance of the ALNS algorithm through more diversification as well as intensification. Specifically, a variety of repair operators which can recover reasonably good, i.e. improving, solutions at low computational cost allowed the intensification in more iterations within the running time limit. This often led to smaller gaps for instances for which the running time was restrictive. However, the TS hybridization did not yield a significant increase in performance. The usage of operators as well as results in terms of the gap, number of iterations, and running time were all very similar to the algorithm without the TS feature.

Furthermore, the MM-FLP-MD model was extended by capacity and length constraints. For the case study of the Honduras migration caravan crisis, capacity constraints on the number of DPs which can be served in one period or in one duty trip were the most restrictive and led to an average cost increase of more than 25% and 20%, respectively. Constraints on the duty length had a moderate impact on costs with an increase of less than 6%, on average. When all constraints were imposed jointly, cost increases of more than 50% were often achieved for instances with four or more caravans. However, the increase in costs was mostly not due to the deployment of additional mobile facilities but led to an increase in utilization instead. Only for instances with at least ten caravans was the deployment of additional mobile facilities inevitable.

Despite the extensions proposed in this thesis, the MM-FLP-MD remains novel and the trend towards and projections for increased migration commands further research. The most intriguing suggestion for further research based on this thesis is the relaxation of the service act variable domain such that service acts provided to caravans can be divided over several mobile facilities or periods. When caravans are larger than the period capacity of a mobile facility, this relaxation is in fact required for a feasible solution. Division of service acts may also lead to lower costs when less mobile facilities must be deployed or deployed mobile facilities must travel less. The MM-FLP-MD model of this thesis can also be extended for a multi-depot case in which mobile facilities originate from different depots and can restock at any depot in the network. Moreover, the fleet of mobile facilities is likely non-homogeneous in practice. A heterogeneous fleet, especially without natural ordering in costs, poses a challenge for further research. A more advanced suggestion is to consider facility- and time-dependent travel costs to discriminate efficiency of mobile facilities in a heterogeneous fleet and eliminate certain arcs if they become unavailable over the planning horizon, e.g., due to war combats or natural disasters. This suggestion highlights the vehicle routing feature of the MM-FLP-MD. Lastly, the greatest progress towards application in practice is to solve the MM-FLP-MD in a dynamic and stochastic context.

The success of the above-mentioned suggestions is, however, dependent on research in other fields. This includes the stocktaking of the location of current DPs (Sarzin, 2017) and an examination of possible future origins. Beginnings are under way to forecast migration routes (Groen, 2016; Suleimenova, Bell, & Groen, 2017) which can be input in MM-FLP-MD models. Cost-benefit analyses can stress the importance and advantages of periodic relief aid en route to sponsors and decision-makers. The urgency of this research is undoubted, as new caravans of unprecedented size begin to form (Perlmutter, 2022).

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A Programming Code

The programming code for this thesis along with other resources can be found in the accompanying zip-file. In the root-level folder "Bachelor-Thesis" are three folders.

- Java: In the "Java" folder is the Java code, in which most of the program has been written. The folder inside called "thesis" can be loaded into IntelliJ IDEA or a different programming environment. Required dependencies include the libraries for CPLEX and Apache's POI and Commons Math. Once the project in the programming environment of choice is created, the working directory should be set to the "Java/thesis" folder and the entry point for the program is the `main.java` file in "src/io/" folder. In the run configurations, command line arguments can be added. Alternatively, the program can be started immediately from the command line with the compiled `main.class` file in the "out/production/thesis/io" folder.
  For the heuristic results, a subset of 25 instances is solved for three different configurations. These three configurations are

  ```
  -mb -alns -ob [list of instances]
  -mp -alns -ob [list of intances]
  -mp -alns -ob -ts=5,10 [list of instances]
  ```

  where the list of instances can be, e.g., `P01E01N01_1 P01E02N01_1`.
  For the model results, the constraints are added by `-pc=160`, `-dc=640`, and/or `-dl=7`. The solution method is chosen by the flag `-alns` or `-milp`. As the extended model requires additional information, the instances are prefixed by `Pasler_`. Exemplatory commands are

  ```
  -mb -milp -op -pc=160 [list of instances]
  -mp -alns -op -dc=640 [list of intances]
  -mp -alns -op -pc=160 -dc=640 -dl=7 [list of instances]
  ```

  where the list of instances can be, e.g., `Pasler_P01E01N01_1 Pasler_P01E02N01_1`.
  Additional commands are described in the `main.java` file. The Excel files with the instance data can be found in "Java/thesis/out/production/thesis/io/data/instances".

- Python: A small Python script to calculate the ALNS operator statistics is located in the "Python folder". The working directory should be set to the root level folder "Bachelor-Thesis".

- results: This folder contains all files which are obtained as results. The Excel file of the same name bundles all data together and provides an easier overview. The text files can be opened in an environment which recognizes ANSI escape codes for better visualization.