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Doctoral Dissertation

Decision support for home health care services in urban regions

submitted by

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in partial fulfilment of the requirements for the academic degree

Doktor der Sozial- und Wirtschaftswissenschaften (Dr.rer.soc.oec.)

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Part I

Preface

Affidavit

I hereby declare that I have authored this dissertation independently, and that I have not used any assistance other than that which is permitted. The work contained herein is my own except where explicitly stated otherwise. All ideas taken in wording or in basic content from unpublished sources or from published literature are duly identified and cited, and the precise references included.

I further declare that this dissertation has not been submitted, in whole or in part, in the same or a similar form, to any other educational institution as part of the requirements for an academic degree.

I hereby confirm that I am familiar with the standards of Scientific Integrity and with the guidelines of Good Scientific Practice, and that this work fully complies with these standards and guidelines.

Vienna, Sept. 26, 2021 Klaus-Dieter REST (manu propria)

Acknowledgements

Without the support and advice of several people, I would not have been able to successfully complete this thesis. Thus, I would like to express my gratitude to the following:

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Ultimately, I am sincerely grateful to my family for supporting all of my decisions, for always believing in me, and thus making this possible for me in the first place.

- Klaus-Dieter Rest

Summary

Home health care (HHC) services allow elderly and frail people to live independently in their familiar environment. Due to current demographic and social developments, demand is expected to rise. Care-dependent people are in need of continuous support. Thus, HHC service providers are facing two challenges: an increased organizational effort due to the rising demand and the need for comprehensive risk management.

This cumulative dissertation consists of three publications in renowned scientific journals and one peer-reviewed extended abstract from an international conference. It focuses on the optimization of the routing and scheduling of HHC services, during both daily business and in times of disasters. While previous research is limited to rural areas, the focus of this thesis is on urban areas.

The first publication describes the situation of HHC and explains its different regional requirements. Based on literature research and the experiences of the Austrian Red Cross (ARC), the impacts of different disaster scenarios are shown. A Variable Neighborhood Search metaheuristic is applied to evaluate flood scenarios in predominantly rural regions.

The second publication, an extended abstract, presents a first version of the Tabu Search metaheuristic, developed for urban use. A sensitivity analysis was conducted to show the impacts of various disasters, including the effects of using different modes of transportation.

The third publication contains a model formulation in the form of a mixed integer linear program. The main focus is on planning with public transportation, considering time-dependent travel times. Three Tabu Search metaheuristics are developed. In addition to the implementation of the HHC specific requirements, the paper discusses different search strategies as well as the optimization of the start times. Comprehensive numerical computations with real-world data from the ARC show the potentials of the developed algorithms.

In the fourth publication, the complex interdependencies of the HHC system and the cascading effects of selected disasters are investigated using Causal-Loop diagrams. In a case study, the impacts of the COVID-19 pandemic on the working times of nurses is outlined. A further development of the previous algorithms is used for this.

Zusammenfassung

Mobile Pflegedienste ermöglichen älteren und gebrechlichen Menschen ein selbstbestimmtes Leben in ihrer gewohnten Umgebung. Aufgrund der aktuellen demografischen und gesellschaftlichen Entwicklungen ist ein weiter steigender Bedarf zu erwarten. Da pflegebedürftige Menschen auf eine kontinuierliche Betreuung angewiesen sind, stehen Anbieter mobiler Pflegedienste vor zwei Herausforderungen: einem erhöhten organisatorischen Aufwand aufgrund der steigenden Nachfrage und der Notwendigkeit eines umfassenden Risikomanagements.

Diese kumulative Dissertation besteht aus drei Publikationen in wissenschaftlichen Zeitschriften und einem erweiterten Abstract einer internationalen Konferenz. Sie beschäftigt sich mit der Optimierung der Einsatzplanung mobiler Pflegedienste, sowohl im Tagesgeschäft als auch im Katastrophenfall. Während sich bisherige Forschungen auf ländliche Regionen beschränken, liegt der Fokus der vorliegenden Arbeit im urbanen Bereich.

Die erste Publikation beschreibt die Situation der mobilen Pflege und erläutert deren unterschiedliche regionale Anforderungen. Basierend auf Literaturrecherchen und den Erfahrungen des Österreichischen Roten Kreuzes (ÖRK) werden die Auswirkungen verschiedener Katastrophenszenarien aufgezeigt. Eine Variable Neighborhood Search Metaheuristik wird angewendet, um konkrete Hochwasserszenarien in überwiegend ländlichen Regionen zu bewerten.

Die zweite Publikation, ein erweiterter Abstract, präsentiert eine erste Version, der für den urbanen Einsatz entwickelten Tabu Search Metaheuristik. Mittels einer Sensitivitätsanalyse wurden die Auswirkungen von Katastrophen, auch unter Verwendung verschiedener Verkehrsmittel, betrachtet.

Die dritte Publikation beinhaltet eine Modellformulierung in Form eines linearen Programms. Im Fokus steht dabei die Planung mit öffentlichen Verkehrsmitteln unter Verwendung tageszeitabhängiger Fahrzeiten. Drei Tabu Search Metaheuristiken werden vorgestellt. Neben den spezifischen Anforderungen der mobilen Pflege liegt der Fokus auf den verschiedenen Suchstrategien sowie der Optimierung der Startzeiten. Ausführliche numerische Analysen mit realen Daten des ÖRK zeigen das Optimierungspotential auf.

In der vierten Publikation werden die komplexen Abhängigkeiten des Systems der mobilen Pflege und die kaskadierenden Effekte einiger Katastrophen mittels Causal-Loop-Diagrammen untersucht. Im Rahmen einer Fallstudie werden die Auswirkungen der COVID-19 Pandemie auf die Einsatzzeiten der Pflegekräfte berechnet.

Part II

Framework Paper

1 Background and motivation

This cumulative dissertation consists of three publications in scientific journals and one peer-reviewed extended abstract from an international conference. It focuses on the optimization of the routing and scheduling of home health care (HHC) services, during both daily business and in times of disasters, and was motivated by the facts presented in the following subsections.

1.1 Increasing demand for home health care

A significant increase in demand for long-term care is expected and several reasons contribute to this increase. Although long-term care services are also received by younger people with disabilities, the main driver is the aging of the population. In OECD countries, decreasing birth rates combined with increasing life expectancy result in a growing share of elderly people in the total population. While the share of those aged 65+ years amounted to 9% in 1960, it already surpassed 17% in 2017 and is forecast to reach 27% by 2050. The increase is particularly rapid in the 80+ age group. On average across the OECD countries, this group will more than double between 2017 and 2050, from 4.6% to 10.1% (OECD, 2019). Despite medical achievements, an increase in life expectancy does not mean that these additional years will be spent in good health. The older people get, the higher the risk of developing disabilities and being dependent on support. As a result, across OECD countries, an average of 13% of the people over 65 years received long-term care in 2017, either directly through care providers or in form of cash services like care allowances. A total of 51% of all recipients were aged 80 or older (OECD, 2019).

By tradition, most care services are provided by family members or friends. According to OECD statistics, 61% of it by women. However, their emancipation and increased labor participation are steadily reducing this informal care potential. The decline in family size and increasing geographic mobility are also contributing factors (OECD, 2019). As a result, long-term care is increasingly delivered by professional service providers either in institutional care facilities (e.g., nursing homes), semi-institutional facilities (e.g., day-care centers) or by mobile care services.

Many care-dependent people want to live in their familiar environment for as long as possible. HHC services allow them to still receive professional care. As outlined in Rest et al. (2012), there are additional benefits of HHC, like enabling earlier discharges from in-patient care. HHC also provides support and relief for family members or other informal caregivers and allows to maintain social contacts in order to prevent social isolation. After all, the HHC system is also more cost efficient than institutional long-term care. Thus, in 2017, on average 68% of the long-term care recipients in OECD countries received HHC services whereas the governmental and compulsory insurance spending for HHC services amount only to 33% of the total spending for long-term care (OECD, 2019).

HHC services are a fundamental component of the health care system of many countries. In addition to the core service of providing professional medical care at the client's home, HHC service providers offer supplementary services like maintaining social contacts (e.g., visiting services), assisting in everyday life (e.g., housekeeping, shopping, accompanying visits to doctors or authorities), transportation services, equipment rental (e.g., nursing beds) and counseling. These additional services are often as important as medical care and impact both the physical and mental health of clients. Furthermore, these services are also used to monitor the health status of the clients, which allows to quickly adapt the provided services to the changing needs.

1.2 Increasing frequency and severity of disasters

Care-dependent people, and especially those with limited mobility or medical needs (e.g., diabetics, respirator dependents), rely on continuous care. Interruptions can cause a serious deterioration of their health. Therefore, HHC service providers must ensure business continuity. On top, the number of natural disaster and extreme weather events increased steadily in recent decades. According to the UN Office for Disaster Risk Reduction (UNDRR, 2020), 7,348 natural disasters (excluding biological events) have been recorded in the last twenty years. For comparison, between 1980 and 1999, 4,212 events were registered. The total number of persons affected increased from 3.25 to 4.03 billion and the number of fatalities from 1.19 to 1.23 million.

Figure 1 shows how much the incidence of each type of disaster has changed. In the last twenty years, climate-related disasters experienced the largest increase. Floods and storms were the most frequent events in terms of numbers, with the former increasing by 1,865 and the latter by 586. However, the number of extreme temperature events has more than tripled in the same period (UNDRR, 2020).

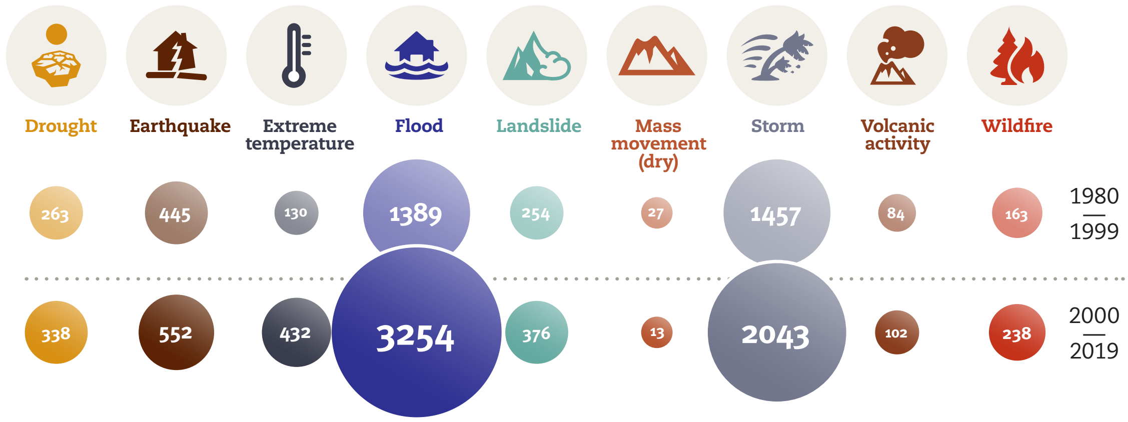

Figure 1: Total disaster events by type: 1980-1999 vs. 2000-2019 (UNDRR, 2020).

1.3 Increasing urbanization

Most of the existing HHC literature, both in terms of optimization and risk management, focuses either explicitly on rural areas or does not address the unique requirements of urban regions. However, according to a study from the OECD and European Commission (2020), the population living in cities with more than 50,000 inhabitants has more than doubled in the last 40 years. It went from 1.5 billion in 1975 to 3.5 billion in 2015 and is forecast to reach 5 billion by 2050. Global population growth has led to an increase in population in all regions. However, as shown by Figure 2, the population is moving more and more to urban areas. Compared to 1975, the share of the world's population living in cities increased from 37.3 % to 48.2 % in 2015. Although the increase is slowing down, a share of 54.5 % is predicted for the year 2050 (OECD and European Commission, 2020).

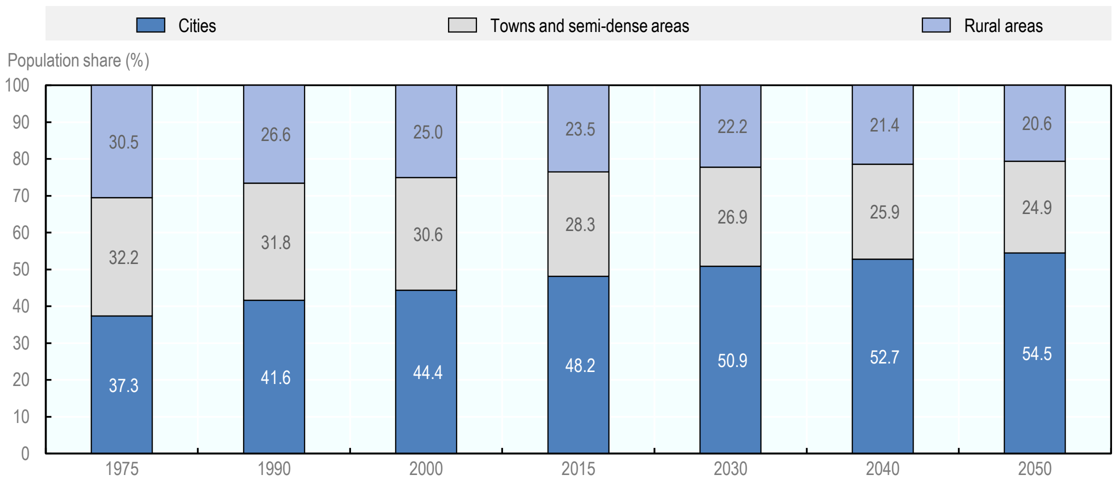

Figure 2: World population shares by degree of urbanization, 1975-2050 (OECD and European Commission, 2020)

In terms of disaster impacts, cities are particularly at risk due to their higher population density. On the other hand, civil protection usually receives more attention in urban regions. As a result, disasters in urban regions can be seen as high-impact, low-probability events, i.e., events that rarely occur but have serious consequences (e.g., failure of disaster protection systems).

In summary, HHC service providers face two challenges: an increased organizational burden due to rising demand and the need for comprehensive risk management. The publications of this cumulative dissertation aimed to fill the gap in research and support for HHC service providers in urban regions. The remainder of this thesis is structured as follows: Part II contains the framework paper of this cumulative dissertation and consists of the following sections. Section 2 describes the HHC problem that this research focuses on. A review of the relevant literature is given in Section 3. Section 4 presents the main contributions of the publications this thesis is based on, followed by a discussion of the results in Section 5. Conclusions and an outlook on future research paths are given in Section 6. In Part III, the journal articles constituting this cumulative dissertation are provided.

2 Problem description

The HHC problem considered in this thesis has a daily planning horizon and aims to address the specifics of urban HHC. It is based on the requirements of the Austrian Red Cross (ARC) in Vienna. In Rest and Hirsch (2021), the HHC problem was slightly adapted and customized for another large HHC service provider in Vienna, which used the decision support system (DSS) resulting from this thesis for several years.

Table 1: Differences between urban and rural HHC

	urban	rural
general demand	higher demand for HHC	lower demand for HHC
qualification	more assistance services	more medical services
avg. service time	longer service times	shorter service times
transportation	mainly public transportation, sometimes cars, bicycles or walking	exclusively cars
avg. distance between clients	shorter distance	longer distance

As outlined in Rest et al. (2012), there are several differences between rural and urban HHC, which have been summarized in Table 1. In general, the demand for HHC services is higher in urban regions, due to the less pronounced social structures resulting in a reduced potential of informal care (e.g., more solitary or childless people). Next, health care facilities are more easily accessible. On the one hand, because of the higher density of facilities and, on the other, because of the better transportation infrastructure. This results in reduced demand for qualified services (e.g., wound care), but an increased demand for support services (e.g., housekeeping), with the latter taking more time on average.

The most notable difference for the scheduling of HHC nurses arises from the superior transportation infrastructure. Combined with the usually shorter distances between clients, this allows nurses to use other modes of transportation. While in rural regions, cars are almost exclusively used, their use is discouraged in urban areas due to congestion and lack of parking. Thus, the majority of the HHC nurses in Vienna use public transportation. Some nurses also use bicycles or just walk if enough clients are located in their area of operation, like in apartment complexes.

Due to the planning with public transportation, multimodality and time-dependent travel times are taken into account. Several means of public transportation (e.g., a combination of buses and subways) are necessary to get from the point of departure to the destination, and each of them operates according to its own timetable. The varying departure intervals, as well as the occasionally divergent routing of public transportation, result in different travel times between two locations throughout the day.

From an operations research perspective, the underlying problem is considered a rich vehicle routing problem (VRP). The basis is a time-dependent VRP with time windows that has been extended by HHC specific constraints. In Rest and Hirsch (2016), a mixed integer linear program (MILP) of the problem is presented. It is defined on a complete graph $G = (V, A)$, where the vertex set V contains the depot of the HHC service provider as well as the home locations of the nurses and clients. Due to the multimodality and time-dependent travel times, each arc $(i, j) \in A$ is assigned a travel time for public transportation, cars, bicycles and walking. Only public transportation is considered to be time-dependent, making their travel times dependent on the departure time t. In the following, the HHC specifics are briefly described by the characteristics of the clients and the nurses.

Clients require one or more services (jobs) per day and each job...

- has to be carried out by a feasible and appropriately skilled nurse (i.e., qualification level, language skills).
- has to be carried out by a nurse that is not rejected by the client.

- has to be assigned either to a nurse included in the clients' team of preferred nurses or to the same nurse, all his/her other jobs of the day are assigned to (for each qualification level).
- has to start within its given time window.
- has a predefined service time, which may not be shortened.

Nurses are required to...

- carry out jobs that are at most one level below their qualification level.
- obey working time restrictions (i.e., earliest/latest and minimum/maximum working time).
- hold breaks when a certain working time is exceeded, and both the duration and location of the break are part of the optimization (i.e., 1x 30, 2x 15, or 3x 10 minutes).
- work at most two shifts a day.
- not exceed the given limit for waiting times, occurring due to early arrivals.
- use one of the available transportation modes (i.e., public transportation, cars, bicycles, walking).
- start/end their shift either at the depot or directly at the location of their first/last job.
- not exceed the total overtime limit defined for all nurses.

The objective of the HHC problem is to minimize the sum of the working times of the nurses and to maximize the satisfaction of the nurses and clients. The working time is defined as the sum of the travel and waiting times. To incorporate the satisfaction, a weighted objective function is used in combination with additional constraints. Thus, a surcharge for overtime, a compensation for working a second shift, and an artificial penalty for overqualification is added to the objective. The client's satisfaction is represented by additional constraints concerning the consistency of care in terms of the visiting times and nurses. These prefer solutions in which the jobs of a client are performed by the same nurse, and within a further tightened time window.

In Rest and Hirsch (2021), this problem definition is slightly adapted according to the requirements of another large HHC service provider in Vienna. This results in the following additions [$+$] and changes [$\rightleftharpoons$] to the previous problem definition.

$+$ Additional assignment constraints are added to allow exclusions based on the gender of the nurses and clients, their allergies, and the transportation mode used by the nurse (e.g., prohibit cars due to lack of parking).

+ Additional constraints allow to directly manage the workloads of the nurses, in order to achieve a similar workload of the nurses (relative to their target working time).
+ The concept of 'multiclient jobs' is introduced, which allows linking of two jobs from different clients. Linked jobs must be performed by the same nurse and in immediate succession.
+ Minimum and maximum time offsets between jobs are added to flexibly manage the time between two jobs (e.g., at least 3h between a morning and lunch job, guarantee a certain time between medical treatments).
+ For each nurse, a separate location can be defined to end the first shift and to start the second shift.
+ For each nurse, the length and position of the mandatory break can be predefined (e.g., 15 minutes before the last and second last job).

⇌ The previously hierarchical qualification structure is replaced with a set-based system, in which nurses have one main and several permitted qualifications. In order to carry out a job, its qualification must be covered by these. Overqualification occurs in this system when a job does not match the main qualification of the nurse.

3 Related work

This cumulative dissertation addresses two research areas in HHC: a) vulnerability assessments of the HHC system and b) decision support for HHC planning, as well as the combination of both areas.

3.1 Vulnerability assessments in the area of HHC

HHC services are an important component of the health care system in many countries. Inherently, they provide unique opportunities to assist in the management of disaster situations, both before and during a disaster. The US National Association for Home Care & Hospice (NAHC, 2008) emphasize the role of the HHC system for effective emergency planning and highlight, that its ability to deliver health services to individuals in non-structured environments makes them ideal as key responders in times of crisis.

On the other hand, HHC services are themselves susceptible to disruptions in their operation. They are complex systems whose functionality depends on the smooth interaction of their critical components. In order to meet the needs of their clients during disasters and emergency situations, HHC service providers need to adequately prepare themselves. Those participating in the US Medicare and Medicaid programs are even legally required to do so. An emergency preparedness program consisting of four elements is demanded: a) an all-hazards risk assessment and emergency planning, b) policies and procedures for successful execution of the emergency plan, c) a communication plan, d) a staff training and testing program (Centers for Medicare & Medicaid Services, 2016).

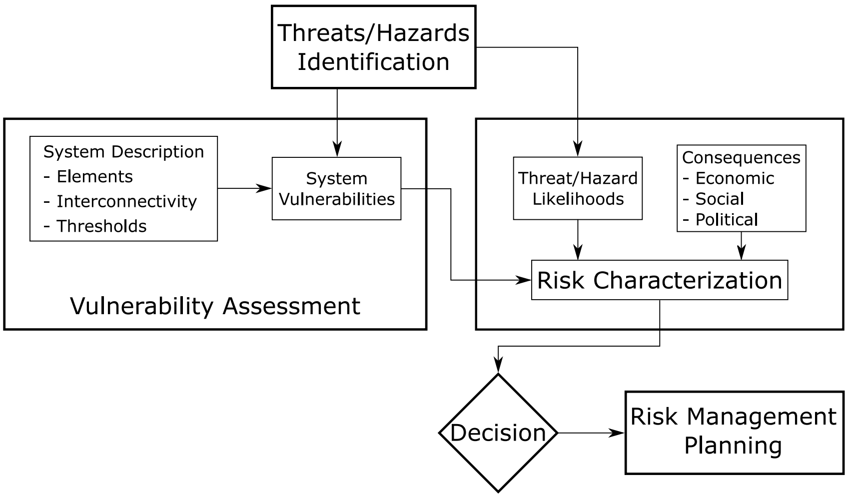

Figure 3: Risk assessment process according to Baker (2005)

Figure 3 shows the risk assessment process, as presented by Baker (2005). The process starts with the identification of the relevant threats and hazards that an organization is exposed to. Vulnerability assessments then examine whether and how a system is vulnerable to these threats. In risk characterization, risks are determined by assigning probabilities to each threat. The final step consists of managerial decision making.

In this thesis, only the first two steps of the risk assessment process are addressed. The relevant threats were identified through extensive literature reviews, the results of which were discussed with decision makers at the ARC. Regarding the vulnerability analyses, most of the scientific literature studies the lessons-learned from individual disasters. All-hazards risk assessments in the field of HHC are rare. Doherty (2004) highlights the importance of an all-hazards approach and proposes the standards of the Joint Commission on Accreditation for Healthcare Organizations (JCAHO) as blueprint. The all-inclusive emergency management plan of the JCAHO standard requires not only an all-hazards vulnerability assessment but also training and community participation. The author refers to various analysis models and raises questions that need to be addressed by the HHC service providers. Rodriguez and Long (2006) propose a spreadsheet-based tool to assess the probability of an event, the risk to the patient, and the level of preparedness. Furthermore, they list various possible

threats and provide suggestions on what to consider when preparing for disasters.
Since too little attention is paid to the complexity of the HHC system and the disasters, the concept of Causal-Loop diagrams (CLD) is applied in one of the publications of this thesis. CLDs are part of the System Dynamics toolset and are used to visualize cause-and-effect relationships and feedback processes. To my knowledge, they have not been used to model disaster impacts in the field of HHC. However, CLDs have been successfully used in the context of risk assessments, for example to analyze flood threat to an electricity substation Powell et al. (2016). Berariu et al. (2015) use CLDs to visualize the cascading effects of floods and heat waves on critical infrastructures.

3.2 Decision support for HHC planning

Due to the rising importance of HHC for today's society, optimization of HHC services is a quickly evolving research area. HHC service providers offer a variety of services and operate under different legal conditions. Accordingly, a large number of publications covering different aspects of HHC were published in the last decade. Hulshof et al. (2012) provides a literature review in which they categorized planning decisions in HHC as strategic, tactical, and operational, as shown by Table 2. The listed publications are also classified according to the applied methods (i.e., computer simulation, heuristics, markov processes, mathematical programming, and queuing theory).
The optimization of the routing of HHC nurses covered in this thesis, falls into the category of *offline operational planning* and solves primarily the *visit scheduling*. In addition, the *staff-to-shift assignment* as well as the *tactical* decision of *staff-shift scheduling* are solved implicitly. Several comprehensive literature reviews focus on this type of decision problem, the most notable among them being Cissé et al. (2017), Fikar and Hirsch (2017), Grieco et al. (2020), and Mascolo et al. (2021). They reveal various challenging routing problems with a wide range of constraints and objectives. Most publications focus on a few individual aspects of the problem (e.g., synchronization, continuity of care, or uncertainty) or attempt to develop better solution approaches, usually to tackle real-world sized instances with exact solution approaches.
However, research aimed at HHC routing in urban areas, considering public transportation and/or time-dependent travel times, is still scarce. To my knowledge, Rest and Hirsch (2016) is the first publication to fully cover these aspects. In Hiermann et al. (2015), nurses can use either public transportation or cars. Although travel time data are based on estimates from a public transportation ser-

vice provider and on floating car data, a single estimate is used for each mode. Thus, travel times are not dependent on the actual departure times. A combination of constraint programming with one of four implemented metaheuristics (Variable Neighborhood Search, Memetic Algorithm, Scatter Search, and Simulated Annealing) is used to solve real-world instances from an HHC service provider in Vienna. Szander et al. (2018) address sustainability aspects of urban HHC routing. They compare the efficiency of nurses using buses, e-bikes, and cars. The presented solution approach is based on Branch and Bound and the problem is partitioned into several stages (i.e., grouping of clients, calculating the load, assigning of nurses, calculating the costs, calculation the efficiency of each mode of transportation). Although the authors claim that the calculation of travel times for buses is based on their timetables and depends on the time of day, the paper does not discuss the modeling of the time-dependent travel times.

The use of operations research methods and techniques to support HHC service providers in times of disaster is still rather rare. There are few publications that aim to integrate the impacts of complex crisis and disaster scenarios into the optimization of HHC services.

Trautsamwieser et al. (2011) present a MILP and a Variable Neighborhood Search metaheuristic to support the routing of HHC nurses. It has a daily planning horizon and assumes that all nurses travel by car. The algorithm was tested with both artificial and real-world data provided by the ARC, covering several districts in Upper Austria. The impact of natural disasters is examined using a sensitivity analysis that adds incremental delays to the travel times. Furthermore, a real-world flood and official flood risk scenarios with a 30, 100, and 200 year return period are analyzed.

Guinet et al. (2017) present a MILP to decide which patients need evacuation during hydrological disasters, and which HHC resources must be assigned to the non-evacuated areas. This problem formulation is improved in Barkaoui et al. (2018). The previously predefined clustering of clients is replaced with a dynamic risk-based clustering. The enhanced model incorporates the geographic proximity of the clients and their individual risk ratings for each time period to form groups with similar risk behaviors. In addition to the allocation of HHC resources and the decision of which groups to evacuate, the evacuation destination (i.e., regular hospital or temporary shelter) is also determined. However, neither of the two publications addresses the routing of HHC nurses.

Table 2: Classification of planning decisions in HHC, based on Hulshof et al. (2012)

Level	Planning decision	Short description
Strategic	Placement policy	Determine which client types are eligible for HHC and which are eligible for inpatient facilities.
	Regional coverage	Determine the number, types and locations of HHC service providers.
	Service mix	Determine which services an HHC service provider should offer.
	Case mix	Determine the types and volumes of clients an HHC service provider should serve.
	Panel size	Determine the number of potential clients to ensure a minimum standard service.
	Districting	Partition the operational area into districts to limit travel times and improve coordination.
	Capacity dimensioning	Dimension the capacity of staff (e.g., nurses, therapists), equipment (e.g., medical, information technology), and fleet vehicles (means of transportation).
Tactical	Capacity allocation	Assign resources to districts and client groups.
	Admission control	Determine which clients on the waiting list should be served.
	Staff-shift scheduling	Determine how many nurses should work on a shift to meet the demand.
Operational (Offline)	Assessment and intake	Determine the care requirements of a client and assign him/her to a case manager.
	Staff-to-shift assignment	Assign nurses to shifts to meet the required staffing levels.
	Visit scheduling	Determine which visit will be performed, on which day and time, and by which nurse.
Operational (Online)	Visit rescheduling	Adjust the plan to unplanned events (e.g., absenteeism, urgent requests).

4 Methods and results

This thesis focuses on the optimization of the routing and scheduling of urban HHC services, during both daily business and in times of disasters. The differences between urban and rural HHC planning is discussed in Rest et al. (2012) and has already been summarized in the beginning of Section 2. Furthermore, the impacts of a broad variety of disasters have been analyzed. Again, the focus of this particular publication was to outline the differences of disasters striking urban and rural regions. First, the vulnerable factors, which are essential to maintain HHC, have been identified, followed by descriptions of the effects various disasters have on them. This study is based on extensive literature reviews as well as expert knowledge from the ARC, which is not only one of the major HHC service providers in Austria, but also has extensive expertise in health care and disaster management. Finally, a numerical study shows the impacts of floods on the scheduling of the nurses for three regions in Upper Austria. An existing solution approach has been adapted for the computation, which has been developed by Trautsamwieser et al. (2011). The results demonstrate the potential uses of DSSs in the event of a disaster. In addition to the efficient use of the available resources, it is possible to identify those clients who can no longer be reached due to the flood. However, the algorithm is not designed to use time-dependent travel times and is therefore not suitable for urban HHC.

To support the daily planning of HHC nurses in urban regions, a new MILP as well as three Tabu Search (TS) metaheuristics have been developed. They are published in Rest and Hirsch (2016), and to my knowledge, this is the first publication in the field of HHC optimization that explicitly incorporates the specifics of urban regions. In addition to the various HHC-related requirements, the main focus of this work is on planning with public transportation. For this reason, a whole section of the paper is dedicated to the modeling of the travel times. In order to properly represent a public transportation network, the modeling must consider the different modes of public transportation (i.e., bus, subway, train, streetcar) and allow transfers between the different lines. The departure times of the vehicles are based on the timetables of the individual lines and vary throughout the day, resulting in time-dependent travel times. These are modeled with a discrete time approach that uses a granularity of one minute, which is also the smallest unit in the timetables of the public transportation service providers. A dynamic programming algorithm is presented. It is inspired by the Decreasing Order of Time algorithm of Chabini and Dean (1999) and allows to efficiently process timetables and compute the required travel time matrices. It works on a complete directed graph and allows waiting for later departures at the same node, as well as walking to other nodes. The resulting travel times satisfy the first-in, first-out principle. It is also known as non-passing property and states that traversing the same arc at a later time, results in a later, or at best the same arrival, compared to the arrival of an earlier departure. In addition to public transportation, nurses can also use cars, bicycles, or walk. Their travel times are assumed to be independent of the time of day and are based on publicly available OpenStreetMap data.

Three TS algorithms have been developed, based on the ideas of the Unified TS of Cordeau et al. (2001). They were tailored to the time-dependent HHC routing problem. One of the biggest challenges in time-dependent routing is the optimization of the start times of the routes. Due to its complexity, it is usually performed in a post-optimization phase by varying the start times in small steps. In contrast, a binary search approach is presented and applied at each evaluation of a solution. Another feature of the algorithms is the handling of the mandatory breaks, which can be partitioned in order to replace waiting times. For this task, a heuristic approach is applied that makes use of the forward time slack. The three TS variants differ in the neighborhood structures and were developed to combat the high computational effort. While the first variant (*TS*) searches the whole neighborhood in each iteration, the second (*TSAS*) uses a restricted neighborhood of fixed size and the third (*TSDYN*), a dynamically adjusted neighborhood. An estimate of the objective value is used to search only promising regions of the neighborhood, which requires less computational resources to calculate.

Comprehensive numerical studies with real-world data from the ARC in Vienna are conducted to show the potentials of the developed algorithms. 20 instances with up to 202 jobs and 46 nurses were used and two operational scenarios are considered. The first comply with the predefined rosters of the nurses, which were provided by the ARC and specify the start and end times they are expected to work. However, this significantly limits the search. Therefore, flexible working times are used in the second scenario, which are determined by each nurse's working hours.

The comparison of the algorithms in Figure 4 shows that the *TS* is clearly superior in the roster scenario. In case of flexible working times, the *TSDYN* outperforms the others. It can be deduced that further limiting the neighborhood in an already sparse solution space is too short-sighted and thus yields worse solutions. On the other hand, for large solution spaces, it provides additional guidance to direct the search to promising regions. If comparing with the actual planning at the ARC, it is revealed that the developed algorithms can significantly improve the routing of the nurses. With predefined rosters, average savings of 41.53% (*TS*) are achievable and without them, even higher savings of 51.08%

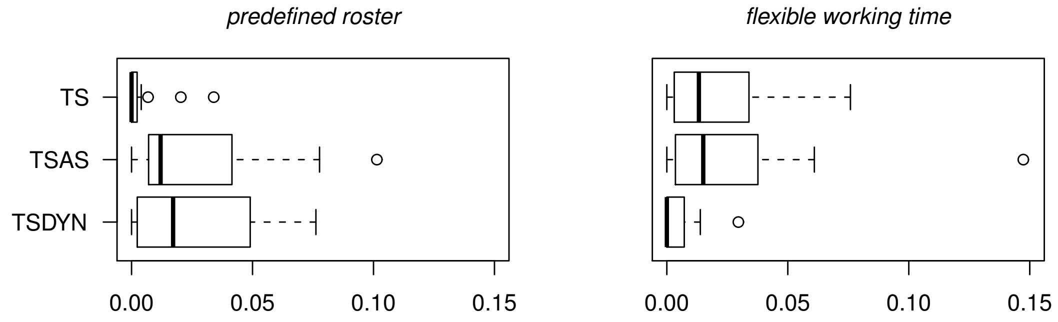

Figure 4: Variation of deviations from the BFS for each TS version and for each operational scenario after a computation time of 600 sec. (Rest and Hirsch, 2016)

(*TSDYN*). The detailed results are given in Table 3. Part of the savings can be attributed to the reduction in the number of second shifts, which were significantly reduced and, in some instances, even avoided altogether.

Table 3: Deviation from actual planning at ARC for each TS version and for each operational scenario after a computation time of 600 sec. [in %] (Rest and Hirsch, 2016)

	predefined roster			flexible working time		
	TS	*TSAS*	*TSDYN*	*TS*	*TSAS*	*TSDYN*
I08	-37.78	-37.04	-34.67	-50.94	-50.74	-51.09
I09	-29.82	-29.13	-28.71	-46.19	-46.82	-46.19
I10	-40.68	-38.20	-40.85	-56.15	-55.94	-57.37
I11	-51.46	-51.10	-47.76	-59.22	-58.22	-59.91
I12	-40.79	-34.78	-38.00	-52.03	-52.58	-52.49
I13	-49.25	-48.83	-48.88	-54.16	-53.93	-54.49
I14	-48.85	-47.49	-48.47	-57.79	-56.30	-57.87
I15	-61.06	-60.81	-59.61	-65.31	-64.02	-65.18
I16	-37.66	-34.61	-37.40	-40.59	-39.86	-39.95
I17	-45.72	-41.74	-45.94	-51.85	-51.67	-52.54
I18	-34.85	-33.51	-34.81	-38.70	-37.60	-38.70
I19	-35.31	-35.25	-34.12	-43.99	-42.04	-44.16
I20	-26.63	-23.84	-22.97	-39.96	-43.55	-44.06
mean	-41.53	-39.72	-40.17	-50.53	-50.25	-51.08
stdv	9.50	10.02	9.79	8.20	7.83	8.04

In Rest and Hirsch (2015), the algorithms have been applied to analyze the impacts of various disasters. A scenario analysis has been conducted to identify the operational limits of the different groups of nurses. In addition, the effects of using different transportation modes (i.e., public transportation, public transportation during blackout, bicycles, walking) are outlined. Based on real-world instances, additional instances are generated by gradually increasing the number of jobs and the service times of all jobs in steps of 5%. The jobs were randomly taken from a pool of jobs that would be served by the same group of nurses, but on another day of the week. This guarantees that the chosen jobs are in the same operational area. Because of the randomness, 10 instances have been generated for each data set.

jobs \ time		+ 0 %				+ 5 %				+ 10 %				+ 15 %				+ 20 %			
		public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking
G_1	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
G_2	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9	8	8	10	6
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	8	9	9	10	8	1	1	10	0
G_3	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	9	10	9	0	0	10	0
	+ 10 %	10	10	10	10	10	10	10	10	5	5	10	2	0	0	10	0	0	0	3	0
	+ 15 %	9	8	10	8	2	1	10	1	0	0	10	0	0	0	1	0	0	0	0	0
	+ 20 %	2	1	10	1	0	0	9	0	0	0	1	0	0	0	0	0	0	0	0	0
G_4	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	9	9	10	6	0	0	10	0
G_5	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
G_6	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	9	10	10	10	8	10	10	10	7	10	9	10	7
G_7	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
G_8	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	8

public transport blackout bicycle walking

Figure 5: Number of solvable instances for each scenario of increasing number of jobs and service times, using various transportation modes (extended results from Rest and Hirsch (2015))

Figure 5 shows the results of this scenario analysis, which are an unpublished extension of those in Rest and Hirsch (2015). The numbers indicate how many of the 10 instances of each setting are solvable within a computation time of 5 minutes. The color coding is used to highlight the identified bottlenecks. Groups G_1, G_5 and G_7 can completely handle a 20% increase in jobs and service times, independent of the considered transportation modes. The other groups except G_3 only show a bottleneck when there is a high increase of both factors. Only group G_3 struggles at an earlier stage. This group serves the 3rd and 11th district of Vienna. The latter extends to the city border, has an industrial character and a below-average age structure. This results in a lower density of clients and thus, in longer travel times. In addition, this group has slightly less spare capacities than other groups in normal business. It is also shown that the use of bicycles is superior to the other modes of transportation. Except for group G_3, this transportation mode allows to find feasible schedules for all instances.

The last publication that is part of this thesis is Rest and Hirsch (2021) and focuses on decision support in times of disasters. First, CLDs are used to model the effects of epidemics, blackouts, heatwaves, and floods on the HHC system. It aims to provide insights into the complex system of HHC and the cascading effects of these disasters. Next, a case study of the COVID-19 pandemic is presented. It describes both, the effects of the pandemic in Austria and the actions taken to combat it. HHC service providers and their nurses were especially challenged by the pandemic. Elderly people and those with chronic diseases are particularly at risk of getting very sick. Lockdowns, border and school closures, as well as illnesses of HHC nurses and dispatchers, have led to a reduction in available nurses. At the beginning, in spring 2020, there were also no vaccines available and personal protection equipment (e.g., face masks) was scarce. A DSS is presented and applied to real-world data from a large HHC service provider in Vienna, in order to numerically analyze the impacts of the pandemic. For the DSS, the algorithms developed for Rest and Hirsch (2016) were further developed into a commercial product. While the previous TS algorithms were implemented in C++ as a command line application, the further development has been implemented as a Java-based web service. Its structure is shown by Figure 6.

The DSS was used by a large HHC service provider in Vienna for several years and due to the sensitivity of personal data, high priority was given to data protection. Thus, the structure of the DSS shows a 2-stage process. The geographical data is independently processed into time-dependent and time-independent travel time matrices. Only the final travel time matrices are stored, which prevents direct geographic traceability. In the second stage, the extended TS algorithm is used to compute schedules for the anonymized instance data, submitted on-demand by the HHC service provider. In addition to the extensions of the HHC routing problem described in Section 2, the most significant algorithmic change concerns the optimization of the start time. A new approach is presented, which

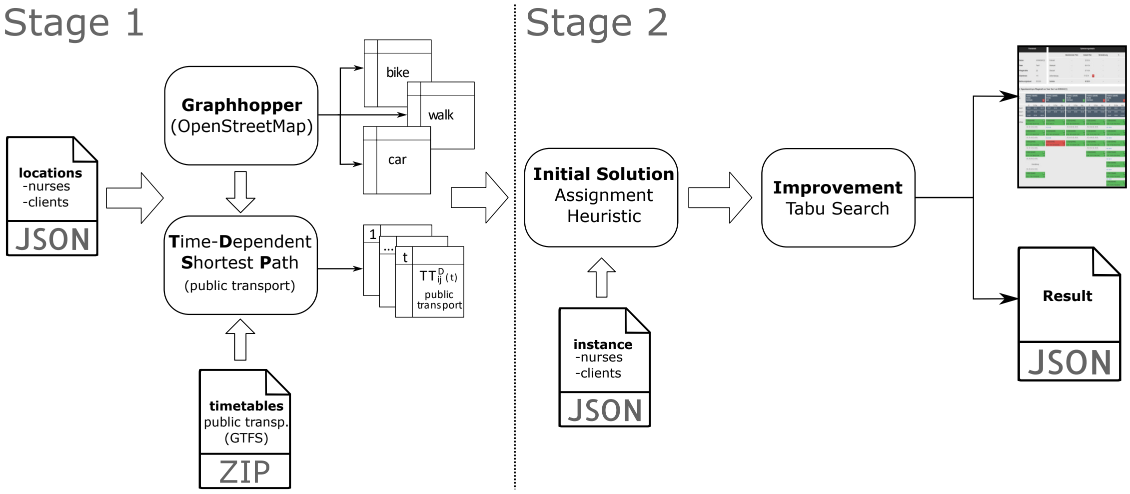

Figure 6: Structure of the DSS (Rest and Hirsch, 2021)

does not postpone the start time too much in order to have more leeway in case of delays. The DSS is used for numerical studies with 16 real-world instances. The scheduling before and during COVID-19 is compared, as public transportation was scaled back during the lockdown. This resulted in an average increase of the travel times (incl. waiting) and overtime of 6.6%. However, those instances with a low share of cars in their modal split showed increases of up to 18%. Furthermore, computations were made to compare the average overtime and tardiness of the nurses when using the current modal split (i.e., mix of public transportation and cars), only cars, bicycles, or walking.

5 Discussion

Facing an increase in demand of HHC services and in climate-related disasters, HHC service providers are in need of support to tackle these two challenges. The elderly and those in need of care are particularly affected by disasters. As outlined in Rest and Hirsch (2021), the COVID-19 pandemic revealed the dependencies and vulnerabilities of modern societies. The vulnerability analyses provide insights into the complex system of HHC and show how it is affected by different disasters. The presented DSS and its enhancement can make a significant contribution to support HHC service providers in increasing their disaster resilience. It can be used during multiple phases of the disaster management cycle. By optimizing the daily scheduling of HHC nurses, it can be used for capacity analysis and planning (preparedness phase), as well as to guarantee that the available staff is scheduled as efficient as possible in times of disasters (response phase).

However, increasing the dependency on the IT infrastructure is potentially doubleedged in its consequences, as shown in the vulnerability analysis of blackouts. In addition, the accuracy of the decision support depends on the quality of the underlying data. In times of disasters, data availability and quality might be insufficient. The DSS currently use freely available data, provided by Google, or gathered by the OpenStreetMaps community. The benefits of community gathered data has been shown for example during the Haiti earthquake in 2010, where data has been collected by people in the field or by analyzing satellite and aerial images (Soden and Palen, 2014). The use of such data increases the chances that routable maps will be available in the event of a disaster. In addition, remote sensing technologies can be used to automatically collect data. For example, the co-authored research of Reyes-Rubiano et al. (2021) analyzes the deployment of unmanned aerial vehicles to explore the accessibility of a road network.

Although HHC service providers already rely heavily on public transportation, especially in regions with a sufficiently developed public transportation network, it is hardly considered in the scientific community. The entire sector of long-term care is experiencing a shortage of nurses and HHC is particularly affected. HHC work is physically and mentally demanding, which is further exacerbated by the traveling and irregular working hours. Through the developed DSS, HHC service providers are supported in their daily planning activities. Its flexible design allows to balance the often conflicting objectives according to the individual needs of the HHC service provider, caregivers, and clients. This results not only in a more efficient scheduling of the nurses, it also further speeds up the planning process itself. It is also revealed that the DSS can significantly reduce the number of required second shifts, which means a considerable improvement of the working conditions of the nurses.

The consideration of various alternative modes of transportation can also contribute to sustainability. As outlined by Haghshenas and Vaziri (2012), transportation is an important aspect of urban sustainability, which has significant and long-lasting economic, social, and environmental impacts. In addition, more and more cities are banning cars and introducing car-free zones. Public transportation is one of the most efficient modes of transportation in urban regions. This thesis outlines the impacts of using different modes of transportation and shows that careful planning even allows to cover many distances by foot or (electric) bicycles. A transportation service, as proposed by Fikar and Hirsch (2015), might be an interesting alternative for regions with longer distances or a less developed public transportation network.

6 Conclusion and future research paths

This thesis presents solution approaches to tackle the increasing demand for HHC services and to support them in times of disasters. Vulnerability analyses were conducted to provide insights into the complex system of HHC and how it is impacted by various disasters. CLDs were used to visualize selected disasters to identify their cascading effects and feedback loops.

The published DSS for the HHC routing problem can be seen as one of the most comprehensive in its field. It is based on the requirements of two major HHC service providers in Austria and covers a wide range of aspects of the daily routing of HHC nurses. It contains several working time regulations, flexible breaks, constraints regarding consistency of care (i.e, nurses and visiting times), workload distribution, and synchronization (i.e., time offsets, order of jobs). The use of time-dependent public transportation is still a unique feature. The DSS is highly flexible regarding its constraints and objective function, which allows to adjust the planning according to the needs and preferences of the dispatchers. The DSS is able to solve real-world sized instances within a few minutes. It has been applied to various real-world instances from HHC service providers in Vienna. The enhanced version of the DSS, presented in Rest and Hirsch (2021) has been in use by a large HHC service provider for several years.

Nevertheless, there are numerous interesting ways to extend the presented research. For example, future work should cover the stochastic and dynamic aspects of HHC. The current work assumes that the service times of the jobs have a fixed length that is neither exceeded nor undercut. In fact, the service time depends on the situation on site, especially on the client's state of health. In addition, due to the time-dependent travel times, small deviations in service or travel times can cause major disruptions in the scheduling of the nurses. Due to the short computation times, the DSS can be used for rescheduling. However, it is usually preferred to adapt to the new situation with as few changes as possible, but this cannot be guaranteed with the current algorithms. Two research directions can be envisioned: a) computing robust schedules by incorporating uncertainties, and b) developing algorithms for rapid rescheduling.

In terms of disaster support, it must be noted that all presented solution approaches operate on the assumption that all jobs must be executed. While the algorithms in Rest and Hirsch (2016) do not provide a solution if constraints are violated, those in Rest and Hirsch (2021) return the best infeasible solution. However, in case the operational limits are exceeded, the computed schedules show massive violations of time windows and working times and are practically useless. In such cases, triage is inevitable to maintain an orderly operation. This involves prioritizing the most critical jobs and postponing or, if possible, outsourcing others. Cinar et al. (2021) address the provision of medical nutrition services at the client's home, however, with a predefined assignment of clients to nurses. The number of clients exceeds each nurse's daily capacity, resulting in prioritization based on several factors, including the last visit time and severity of the client's condition. They present a MILP, a matheuristic called Successive Single Period Heuristic, and an Adaptive Large Neighborhood Search metaheuristic. Others, like Manerba and Mansini (2016) and Gobbi et al. (2019), work on a very simplified version of the HHC problem even ignoring skill requirements. Integrating triage not only further complicates the HHC problem, but also raises ethical questions about prioritizing visits.

References

Baker, G. H. (2005). A vulnerability assessment methodology for critical infrastructure facilities. In *DHS Symposium: R&D Partnerships in Homeland Security*, pages 1–13.

Barkaoui, H., Guinet, A., and Wang, T. (2018). Securing Home Health Care structures facing forecastable natural disasters: A new tool to regulate between evacuation and adaptive home support services. *IFAC-PapersOnLine*, 51(11):986–991, DOI: 10.1016/j.ifacol.2018.08.479.

Berariu, R., Fikar, C., Gronalt, M., and Hirsch, P. (2015). Understanding the impact of cascade effects of natural disasters on disaster relief operations. *Int. J. Disaster Risk Reduct.*, 12:350–356, DOI: 10.1016/j.ijdrr.2015.03.005.

Centers for Medicare & Medicaid Services (2016). Emergency preparedness requirementsfor medicare and medicaid participating providers and suppliers. https://www.federalregister.gov/d/2016-21404. (accessed Sept. 10, 2021).

Chabini, I. and Dean, B. (1999). Shortest path problems in discrete-time dynamic networks: Complexity, algorithms, and implementations. Technical report, Massachusetts Institute of Technology, Cambridge, MA.

Cinar, A., Salman, F. S., and Bozkaya, B. (2021). Prioritized single nurse routing and scheduling for home healthcare services. *Eur. J. Oper. Res.*, 289(3):867–878, DOI: 10.1016/j.ejor.2019.07.009.

Cissé, M., Yalçındağ, S., Kergosien, Y., Şahin, E., Lenté, C., and Matta, A. (2017). OR problems related to home health care: A review of relevant routing and scheduling problems. *Oper. Res. Health Care*, 13-14:1–22, DOI: 10.1016/j.orhc.2017.06.001.

Cordeau, J.-F., Laporte, G., and Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *J. Oper. Res. Soc.*, 52(8):928–936, DOI: 10.1057/palgrave.jors.2601163.

Doherty, M. (2004). An emergency management model for home health care organizations. *Home Health Care Manag. & Practice*, 16(5):374–382, DOI: 10.1177/1084822304264610.

Fikar, C. and Hirsch, P. (2015). A matheuristic for routing real-world home service transport systems facilitating walking. *J. Clean. Prod.*, 105:300–310, DOI: 10.1016/j.jclepro.2014.07.013.

Fikar, C. and Hirsch, P. (2017). Home health care routing and scheduling: A review. *Comp. & Oper. Res.*, 77:86–95, ISSN: 0305-0548, DOI: 10.1016/j.cor.2016.07.019.

Gobbi, A., Manerba, D., Mansini, R., and Zanotti, R. (2019). A kernel search for a patient satisfaction-oriented nurse routing problem with time-windows. *IFAC-PapersOnLine*, 52(13):1669–1674, DOI: 10.1016/j.ifacol.2019.11.440.

Grieco, L., Utley, M., and Crowe, S. (2020). Operational research applied to decisions in home health care: A systematic literature review. *J. Oper. Res. Soc.*, pages 1–32, DOI: 10.1080/01605682.2020.1750311.

Guinet, A., Barkaoui, H., Wang, T., and Dubost, E. (2017). A mitigation tool to protect a home health care structure facing a hydrological disaster. *IFAC-PapersOnLine*, 50(1):4630–4635, DOI: 10.1016/j.ifacol.2017.08.658.

Haghshenas, H. and Vaziri, M. (2012). Urban sustainable transportation indicators for global comparison. *Ecological Indicators*, 15(1):115–121, DOI: 10.1016/j.ecolind.2011.09.010.

Hiermann, G., Prandtstetter, M., Rendl, A., Puchinger, J., and Raidl, G. R. (2015). Metaheuristics for solving a multimodal home-healthcare scheduling problem. *Cent. Eur. J. Oper. Res.*, 23(1):89–113, DOI: 10.1007/s10100-013-0305-8.

Hulshof, P. J. H., Kortbeek, N., Boucherie, R. J., Hans, E. W., and Bakker, P. J. M. (2012). Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. *Health Syst.*, 1(2):129–175, DOI: 10.1057/hs.2012.18.

Manerba, D. and Mansini, R. (2016). The nurse routing problem with workload constraints and incompatible services. *IFAC-PapersOnLine*, 49(12):1192–1197, DOI: 10.1016/j.ifacol.2016.07.670.

Mascolo, M. D., Martinez, C., and Espinouse, M.-L. (2021). Routing and scheduling in home health care: A literature survey and bibliometric analysis. *Comp. & Ind. Eng.*, 158:107255, DOI: 10.1016/j.cie.2021.107255.

NAHC (2008). Emergency preparedness packet for home health agencies. Technical report, The National Association for Home Care & Hospice, Washington.

OECD (2019). Health at a Glance 2019: OECD Indicators. OECD Publishing, Paris, DOI: 10.1787/4dd50c09-en.

OECD and European Commission (2020). Cities in the World: A New Perspective on Urbanisation. OECD Urban Studies, OECDPublishing, Paris, DOI: 10.1787/d0efcbda-en.

Powell, J. H., Mustafee, N., Chen, A. S., and Hammond, M. (2016). System-focused risk identification and assessment for disaster preparedness: Dynamic threat analysis. *Eur. J. Oper. Res.*, 254(2):550–564, DOI: 10.1016/j.ejor.2016.04.037.

Rest, K.-D. and Hirsch, P. (2015). Supporting urban home health care in daily business and times of disasters. *IFAC-PapersOnLine*, 48(3):686–691, DOI: 10.1016/j.ifacol.2015.06.162.

Rest, K.-D. and Hirsch, P. (2016). Daily scheduling of home health care services using time-dependent public transport. *Flex. Serv. Manuf. J.*, 28(3):495–525, DOI: 10.1007/s10696-015-9227-1.

Rest, K.-D. and Hirsch, P. (2021). Insights and decision support for home health care services in times of disasters. *Cent. Eur. J. Oper. Res.*, pages 1–25, DOI: 10.1007/s10100-021-00770-5.

Rest, K.-D., Trautsamwieser, A., and Hirsch, P. (2012). Trends and risks in home health care. *J. Humanit. Logist. Supply Chain Manag.*, 2(1):34–53, DOI: 10.1108/20426741211225993.

Reyes-Rubiano, L., Voegl, J., Rest, K.-D., Faulin, J., and Hirsch, P. (2021). Exploration of a disrupted road network after a disaster with an online routing algorithm. *OR Spectrum*, 43(1):289–326, DOI: 10.1007/s00291-020-00613-w.

Rodriguez, D. and Long, C. O. (2006). Emergency preparedness for the home healthcare nurse. *Home Healthc. Nurse*, 24(1):20–27.

Soden, R. and Palen, L. (2014). From Crowdsourced Mapping to Community Mapping: The Post-earthquake Work of OpenStreetMap Haiti. In Rossitto, C., Ciolfi, L., Martin, D., and Conein, B., editors, *COOP 2014 - Proceedings of the 11th International Conference on the Design of Cooperative Systems, 27-30 May 2014, Nice (France)*, pages 311–326. Springer, Cham, DOI: 10.1007/978-3-319-06498-7_19.

Szander, N., Ros-McDonnell, L., De-la-Fuente-Aragón, M., and Vodopivec, R. (2018). Sustainable urban homecare delivery with different means of transport. *Sustainability*, 10(2):398, DOI: 10.3390/su10020398.

Trautsamwieser, A., Gronalt, M., and Hirsch, P. (2011). Securing home health care in times of natural disasters. *OR Spectr.*, 33(3):787–813, DOI: 10.1007/s00291-011-0253-4.

UNDRR (2020). The human cost of disasters: an overview of the last 20 years (2000-2019). UN Office for Disaster Risk Reduction, Geneva, https://www.undrr.org/publication/human-cost-disasters-2000-2019.

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Part III

Journal Publications

This cumulative dissertation consists of three journal publications and one peer-reviewed extended abstract from an international conference. All of these articles were accepted for publication in international scientific journals:

- Rest K.-D., Trautsamwieser A., Hirsch P. (2012): Trends and risks in home health care. *Journal of Humanitarian Logistics and Supply Chain Management*, 2(1):34-53, doi:10.1108/20426741211225993.
  Citations:[1] Web of Science: 22; Scopus: 25; Google Scholar: 48
  Rankings: Impact Factor 2020: -; 5-Year Impact Factor 2020: -; Scimago Journal & Country Rank 2020: 0.695

- Rest K.-D., Hirsch P. (2015): Supporting Urban Home Health Care in Daily Business and Times of Disasters. *IFAC-PapersOnLine*, 48(3):686-691, doi:10.1016/j.ifacol.2015.06.162.
  Citations:[1] Web of Science: 15; Scopus: 15; Google Scholar: 20
  Rankings: Impact Factor 2020: -; 5-Year Impact Factor 2020: -; Scimago Journal & Country Rank 2020: 0.308

- Rest K.-D., Hirsch P. (2016): Daily scheduling of home health care services using time-dependent public transport. *Flexible Services and Manufacturing Journal*, 28:495-525, doi:10.1007/s10696-015-9227-1.
  Citations:[1] Web of Science: 38; Scopus: 44; Google Scholar: 71
  Rankings: Impact Factor 2020: 2.603; 5-Year Impact Factor 2020: 3.132; Scimago Journal & Country Rank 2020: 0.934

- Rest K.-D., Hirsch P. (2021): Insights and decision support for home health care services in times of disasters. *Central European Journal of Operations Research*, 1-25, doi:10.1007/s10100-021-00770-5.
  Citations:[1] Web of Science: -; Scopus: -; Google Scholar: -
  Rankings: Impact Factor 2020: 2.345; 5-Year Impact Factor 2020: 2.035; Scimago Journal & Country Rank 2020: 0.706

The following section provides the final of these publications.

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Trends and risks in home health care

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Abstract

Purpose – The number of care-dependent people will rise in future. Therefore, it is important to support home health care (HHC) providers with suitable methods and information, especially in times of disasters. The purpose of this paper is to reveal potential threats that influence HHC and propose an option to incorporate these threats into the planning and scheduling of HHC services.

Design/methodology/approach – This paper reveals the different conditions and potential threats for HHC in rural and urban areas. Additionally, the authors made a disaster vulnerability analysis, based on literature research and the experience of the Austrian Red Cross (ARC), one of the leading HHC providers in Austria. An optimization approach is applied for rural HHC that also improves the satisfaction levels of clients and nurses. A numerical study with real life data shows the impacts of different flood scenarios.

Findings – It can be concluded that HHC service providers will be faced with two challenges in the future: an increased organizational effort and the need for an anticipatory risk management. Hence, the development and use of powerful decision support systems are necessary.

Research limitations/implications – For an application in urban regions new methods have to be developed due to the use of different modes of transport by the nurses. Additionally, an extension of the planning horizon and triage rules will be part of future research.

Practical implications – The presented information on developments and potential threats for HHC are very useful for service providers. The introduced software prototype has proven to be a good choice to optimize and secure HHC; it is going to be tested in the daily business of the ARC.

Social implications – Even in the case of disasters, HHC services must be sustained to avoid health implications. This paper makes a contribution to securing HHC, also with respect to future demographic trends.

Originality/value – To the best of the authors' knowledge there are no comprehensive studies that focus on disaster management in the field of HHC. Additionally, the combination with optimization techniques provides useful insights for decision makers in that area.

Keywords Austria, Health care, Risk management, Rural areas, Urban areas, Home health care, Disaster vulnerability, Decision support, Routing

Paper type Research paper

1. Introduction

Based on the current demographic and social developments in industrialized countries a significant increase in the demand for home health care (HHC) can be expected in the future. At the same time, however, the potential for family care reduces due to prolonged employment and changes in family structures. HHC services allow frail people to stay at home as long as possible and to receive professional help. Furthermore, HHC implies lower costs for the social insurance system if compared to

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intramural health care (e.g. nursing homes, hospitals) (see e.g. Kaye *et al.*, 2009; Biringer *et al.*, 2010).

This paper describes the situation of HHC in industrialized countries and explains the different requirements in organizing and planning of these services in rural and urban areas exemplarily for Austria. Based on literature reviews and the experience of the service providers, it is also shown how different disasters influence HHC. In most studies the effects of disasters are analyzed after their occurrences. Thus, they show the "lessons learned" from a concrete event. Preventive comprehensive studies on this subject hardly exist. In this context, in Trautsamwieser *et al.* (2011) a software prototype has been developed in cooperation with the Austrian Red Cross (ARC), one of the main HHC service providers in Austria. It serves as a decision support system (DSS) and is able to optimize the daily scheduling of HHC services, as well as to depict the effects of disasters. Therefore, the decision maker(s) can anticipate possible adverse effects and take measures well in advance.

The main contribution of this paper is to reveal potential threats that influence HHC. Based on the work in Trautsamwieser *et al.* (2011), an option to incorporate these threats into the planning and scheduling of HHC services is proposed. The presented approach was applied to carry out some additional numerical studies with flood data and the results will be discussed with respect to practicability. Furthermore, this paper describes the importance of HHC for industrialized countries and outlines the differences between urban and rural HHC.

This paper is structured as follows. The HHC services and their relevance for today's society are described in Section 2. Additionally, we outline the differences between urban and rural HHC. Section 3 contains the risk assessment and shows the critical factors and vulnerability of HHC services. In Section 4, we apply a DSS from Trautsamwieser *et al.* (2011). We also present results of some numerical studies with real-life data that show the applicability of the software prototype on different flood scenarios in Upper Austria. Section 5 concludes the paper and gives an outlook on future research on this topic.

2. The HHC system

HHC providers cover a wide range of services, reaching from qualified home nursing to assistance in leading the household and maintenance of social contacts. These tasks are performed by qualified health care and nursing staff, nursing assistants, geriatric nurses, and home helpers. The stated core services are supplemented by additional services, such as visiting services, meals on wheels, transport services, emergency call systems, or equipment rental and consulting.

The main advantages of HHC services are (see e.g. Schaffenberger and Pochobradsky, 2004):

- Facilitation of care-dependent people to stay at home as long as possible.
- Prevention or delay of admission to hospitals or nursing homes.
- Enabling earlier discharge from in-patient care.
- Support and relief for relatives or other informal caregivers.
- Maintenance of social contacts and prevention of social isolation.

In Austria, according to Statistics Austria (2011), a total of 433,880 people, representing 5.2 percent of the whole population received care allowance in 2009. A current report

(Biringer *et al.*, 2010) states that 58 percent of them are informally cared for at home by their own families or friends. The remaining percentage counts to the formal sector of care. This includes traditional elderly or nursing homes as a form of institutional care and day-care facilities (together 16 percent), as well as HHC services (24 percent). The remaining 2 percent are receiving fulltime care, 24 hours per day. Furthermore, there are alternative concepts in development that are situated between HHC and institutional care, such as the system of "assisted living" (Schneider *et al.*, 2006). Currently, these services count either to institutional care or HHC. Since all the presented numbers include only those people who are reported to national subsidies, the actual number of care-dependent people is estimated to be significantly higher.

Besides the social aspects, there are also monetary reasons to promote the expansion of HHC services. In Austria, health care is within responsibility of the federal states and therefore there is no homogeneous data available that is up to date. Thus, we present only data of the two regions we consider more detailed in the subsequent sections of this paper, namely Upper Austria (rural) and Vienna (urban). According to Biringer *et al.* (2010) in Upper Austria the total expenses for intramural care for the elderly (18,059 persons) reached about €123 million in 2009; while in the HHC sector only €50 million (27,923 persons) were recorded. Thus, intramural care of one person costs on average €6,816 while these costs amount only to €1,716 for HHC. In Vienna the situation is similar; intramural health care counts to €435 million (13,950 persons) and HHC to €138 million (26,880 persons). This leads to average costs per capita of €46,438 for intramural care and €5,126 for HHC. The high differences in costs per capita are due to different cost structures in the provinces. Furthermore, the average costs also depend on the quality and amount of services the clients have received. The costs of informal care, however, are not well known, there are only rough scientific estimates, which move in the range of €2 to €3 billion per year for whole Austria (Schneider *et al.*, 2006).

Similar results have been reported by Kitchener *et al.* (2006) and Kaye *et al.* (2009), who compared the expenditures for institutional and non-institutional long-term care in the US Medicaid system. They found out that states, which are offering extensive HHC services, were able to reduce their spending significantly. On average, total expenditures per capita were $43,947 less per year.

2.1 Current and expected development of HHC

Although the organization of HHC systems differs from country to country, many industrialized countries have reported an increased demand for HHC services in recent years. A study of the OECD states, that per capita spending for long-term care has increased in the past decade by an annual average of 6.5 percent across 24 OECD countries (Fujisawa and Colombo, 2009). In this time the usage of health services has also changed significantly. Elderly people want to remain in their familiar environment as long as possible. Thus, the traditional retirement homes for people without great care needs were less demanded. A look at the history of hours worked in HHC from 2000 to 2008 shows a change of +29.4 percent for Austria (Bednar *et al.*, 2010) and thus supports this assumption for our test region. Given the current demographic and social developments, not only a significantly increased demand for HHC, but also a drastic reduction in informal care must be expected in future. Starting with around 15 percent in 2006, the share of the population aged 65 and above is estimated to reach 26 percent of the total OECD population until 2050. The group of aged 80 and above is expected to increase its share by 2.5 times between 2008 and 2050 (Fujisawa and

Colombo, 2009). Together with increased life expectancy, decreasing birth rates lead to a shift in the age structure. Hence, those demographic groups with the highest probability of being in need of care will grow disproportionately. Additionally, changes in family structures, like the trends to more single households, childless families, and rising divorce rates will also reduce family care potential as well as prolonged employment (Schneider *et al.*, 2006). Woodward *et al.* (2004) identified three trends for the rapid growth in HHC expenditures in Canada. First, Canadian hospitals faced financial constraints, which led to more aggressive discharge planning and shorter stays. More people recovering from surgery or acute illnesses entered the HHC system. Second, they mention demographic changes, which lead to more frail elderly people. Third, they state that a growing segment of the population has chronic illnesses and physical disabilities. These people also have a longer life expectancy and often want to stay at home as long as possible.

There exist several models to predict the further demand for long-term care and its expenditures. However, all of them predict a remarkable increase, even under favorable assumptions. Oliveira Martins and de la Maisonneuve (2006) use both demographic and non-demographic factors to determine future expenditures for 30 OECD countries. They point out that expenditures are highly related to the shares of formal and informal care. As labor force participation is expected to rise in future, informal care has to be supplemented with formal care. One major driver are labor costs of staff, which are given by 85 percent in the UK and between 70 and 90 percent in Germany. Based on the considered scenario, the average spending on long-term care would rise from 1.1 percent of gross domestic product (GDP) in 2005 up to 1.9 to 3.9 percent of GDP by 2050. Hancock *et al.* (2007) combined a micro- and a macrosimulation model to predict future trends in the key drivers of demand for long-term care in the UK. Starting with a central base case, they evaluate different funding regimes and care strategies (e.g. free personal care and different charging systems). Besides the demographic development, their model incorporates some key factors like household structures, home-ownership rates, and marital status. Three factors seem the most important exogenous drivers of demand for and expenditure on long-term care: life expectancy, disability, and unit costs. Results for the base case show an increase in demand of 156 percent for residential care, 135 percent for local authority HHC, 119 percent for private HHC, and 111 percent for informal care until 2051. In addition to this base case, also a low and a high expenditure scenario is presented, which differ in the assumptions for the exogenous factors. A recent study by the Austrian Institute of Economic Research (Mühlberger *et al.*, 2008) includes similar factors as the study by Oliveira Martins and de la Maisonneuve (2006). Besides the demographic changes and the change in health condition, they also take the rising employment of women and increases in the cost of care into account. Currently, about 80 percent of informal care is still carried out by women. The authors predict the number of people receiving care allowance to be 536,041 in the lower-bound and 623,083 in the average and upper-bound scenario in 2030. The average scenario is subject to the same assumptions on the number of recipients as the upper-bound scenario but differs on the assumptions for cost trend and demand for formal care. The forecast of health care expenditures shows a total increase of approximately 160 percent for the average scenario. According to this forecast the share of nursing expenses on real GDP will hence increase from 1.13 to 1.96 percent between 2006 and 2030 (Mühlberger *et al.*, 2008).

In summary, it can be stated that within the next decades a massive increase in demand for care services has to be expected in industrialized countries. As HHC services are both more cost-effective and usually preferred by care-dependent people, this will lead to a further expansion of HHC services and their importance for the society.

2.2 Scheduling and routing of HHC services

The task of scheduling nurses is quite complex and there are numerous factors that must be considered to obtain a feasible solution. Especially HHC service providers that are still planning manually need a lot of time for this task and the outcome is presumably non-optimal. This shows itself particularly in the case of vacation or illness of the experienced dispatchers. Another case in which planning time and quality of solutions play an important role is in times of disasters. In such cases it is necessary to adapt the routing accordingly as fast as possible and to use the limited resources as efficiently as possible.

Looking at the published literature in the field of HHC reveals that the requirements for planning and scheduling are rather similar in industrialized countries, and that they mainly differ in the prevailing regulatory restrictions. Cheng and Rich (1998) present a mathematical problem formulation for HHC scheduling in the USA. They consider different types of nurses (part- and full-time) with varying qualification levels that have to serve clients within a given time window. Nurses are starting their duty at home. Their objective is to minimize the amount of overtime and part-time worked. Eveborn *et al.* (2006) developed a DSS called Laps Care to aid the planners of HHC services in Sweden. Beside the medical skills, language knowledge, and the gender of the nurses, they also consider that clients have preferred nurses and that some visits require more than one nurse. Furthermore, nurses can use several modes of transport, namely walking, bicycles, and cars. Bredström and Rönnqvist (2008) also take temporal constraints that impose pairwise synchronization and pairwise temporal precedence between visits into account. Nickel *et al.* (2009) presents an optimization model for HHC in Germany. Within their model nurses are starting from a single depot and the objective function consists of four objectives (patient-nurse loyalty, number of unscheduled tasks, overtime costs, and traveling distance) that are combined within a weighted objective function. Similar problem descriptions have also been published for example by Akjiratikarl *et al.* (2007) for the UK, Rasmussen *et al.* (2010) for Denmark, or Trautsamwieser *et al.* (2011) for Austria.

Summarizing, the task of scheduling nurses consists of assigning visits to nurses and to determine the optimal order in which they should be performed. Thereby, assignment constraints (e.g. qualification levels, language skills, and gender), temporal constraints (e.g. time windows and temporal dependencies), and working time regulations (e.g. maximum working time, shift work, and mandatory breaks) must not be violated. In addition, nurses could start their paid duty at different locations (depot, at home, or at the first client) and may use various modes of transport, even in combination. The objectives range from reducing traveling times (distances, or costs) to increasing the quality of service. One of the major challenges in HHC scheduling is that there are service peaks in the morning, at lunchtime, and in the evening. Therefore, nurses are often employed part-time or work several shifts a day.

2.3 Differences between urban and rural HHC

The processes of scheduling and routing of HHC services show some differences between urban regions and rural regions. The social structures are usually less pronounced in urban areas. Additionally, the number of solitary or childless people is much higher. This leads to a reduced potential of informal care. A study of the American Medicare system (Kenny, 1993) shows that, due to social structures, the general demand for HHC is larger in urban regions. However, due to the better infrastructure, the demand for qualified services is far smaller than in rural areas. On the other hand, people living in rural regions receive not only more qualified services; they also have a higher visitation frequency. In Austria, Schaffenberger and Pochobradsky (2004) show that a notable difference can be observed in the demanded qualification between Vienna and the remaining provinces. According to them, in Vienna about 81 percent of the employed HHC staff were home helpers, 9 percent assistant nurses, and only 10 percent qualified nurses in 2002. In the other provinces the share of qualified nurses is between 22 and 36 percent.

There are also differences in organizational issues that occur mainly because of two reasons. First, the internal structures of the HHC service providers differ from region to region and second, HHC may be subject to various areas of responsibility. Both apply to Austria, but also to the American Medicare system.

For example, in Upper Austria care-dependent people or their relatives are asking for services at their next ARC base or at other HHC organizations. The scope of services depends on the level of care dependency and is individually adapted to the client. Depending on the address of the client, he/she is forwarded to the team leader, who is responsible for this region. The team leader assigns the new visits to a nurse who is organizing his/her route by himself/herself, manually. In contrary, in Vienna the municipality-funded HHC is organized through an organization called "Fonds Soziales Wien". It collects all service demands and spreads them among all registered organizations that are offering HHC services. This is done according to frame contracts, which are negotiated at regular intervals. The organizations get a detailed offer for a service which has to be performed. This offer includes type and service time, and the number of visits. If known in advance, special requirements like language skills are also given. When the ARC accepts the offer it is given to the team leader of the corresponding district. He/she is then updating the scheduling and route planning. This is done within a scheduling program that is also used for accounting. The nurses are then able to view their schedule at any time with their personal digital assistants. With these mobile devices they are also logging their activities.

If one directly compares the specifications of the previously described rural HHC model with the requirements for an urban model, the most important differences show up at the transport infrastructure. In urban areas like Vienna, access to institutional care is easier because of a bigger density of facilities and a better transport infrastructure. There is also a denser network with different modes of transport. Due to the bigger traffic density, planning with cars will be though considerably more difficult (e.g. traffic jams and searching for parking lots). At the ARC in Vienna about 90 percent of the nurses use public transport to get to their clients whereas in the rural province of Upper Austria all nurses are using cars. Moreover, the distances between the single clients are usually smaller in cities so that nurses can also use bicycles or just walk. As a consequence for routing, one has to consider multiple modes of transport for the nurses on one tour as well as time-dependent travel times. The latter not only addresses car traffic but also public transport. During rush hours for example, trains and buses have significantly shorter intervals than during the rest of the day. At the outskirts, those intervals are generally larger than at the city center. Time-dependent travel times are needed on a detailed level without much aggregation to avoid larger waiting periods at the stations. However, to service clients, who are hard to reach with public transport the ARC in Vienna also has a couple of cars, which may only be used by qualified nurses.

3. Disaster vulnerability analysis

People with limited mobility or relying on medical supply (e.g. diabetics) do often need consistent health care. Thus, regular treatments are also necessary in case of disasters. HHC services must be prepared for such situations. Projections of the Intergovernmental Panel on Climate Change (IPCC) (2007) imply that there will be an increase in climate variability, changes in frequency, intensity, and duration of extreme events. Thus, one should be prepared for an increased number of natural disasters. The following assessment analyzes the potential threats and their impacts on HHC and is based on literature reviews, complemented by previous experience of the ARC. As many Red Cross organizations, the ARC is also one of the leading emergency organizations in case of disasters. We highlight different consequences on urban and rural regions, if they are significant. Due to the higher population density, potential impacts are much higher in urban regions than in rural regions.

To the best of our knowledge, there are limited studies that focus on risk assessment in the field of HHC, especially in a comprehensive manner. In general, the effects of individual major disasters are analyzed for all aspects of life, or for the entire health sector. One of the most extensive studies is that of Johnson and Galea (2009) which focusses on the effects of disasters on population health, health systems, and their infrastructure. Their study is based on nearly 200 articles and covers many different types of disasters such as earthquakes, storms, floods, mass fires, terrorism, infectious diseases, and technological disasters like the Enschede Fireworks Disaster of May 2000, and the Chernobyl Disaster of April 1986. A detailed risk assessment for natural disasters is also provided by Melching and Pilon (2006). Besides the general effects, they present background information regarding cause and incurrence of various disasters. A good manual to develop an all-encompassing Hazards Emergency Preparedness Plan for HHC and hospice has been given by the US National Association for Home Care and Hospice (NAHC) (2008). It lists potential threats as well as the vulnerable infrastructure.

3.1 Vulnerable factors in HHC

According to the description of HHC in Section 2, one can identify the following important factors that are essential to maintain HHC:

- *Staff*. The greatest asset of HHC service providers are their employees, both nurses and administrative staff. Absence of the regular dispatchers often leads to suboptimal schedules. Usually, deputies do not have enough experience for such complex scheduling tasks where extensive knowledge of clients, services, and nurses is required. On the other hand, if nurses are absent, other nurses with appropriate qualification have to fill in for them. If there are no more nurses available, the services must be limited or postponed. The reasons for unexpected absence of employees are diverse, ranging from sickness of individual employees up to a massive absence in the event of disasters. Additionally, motivation of the employees is an important topic.
- *Clients*. Situations that lead to an increase in the number of clients or of the service time require a particularly efficient planning to service all clients. If this is no longer possible they must either be cared for by other organizations,

leave their homes for temporary residential care, or stay with relatives or friends. The latter is very uncommon in urban areas because of weaker social networks.

- *Communication*. An increasing number of organizations are relying on mobile communication technologies for controlling their HHC services. At the ARC in Vienna for example, the dispatchers are creating schedules within their operational software. Nurses are then able to view their plans through mobile devices. As a consequence they are rarely at the base. Since time and activity recording are also done electronically, information and communication technologies are essential for almost all organizational activities, but this leads to new vulnerabilities, especially in case of power outages.
- *Transport*. Nurses rely on various modes of transport. Due to the lack of public transport, nurses in rural regions almost always use cars. Whereas in urban regions many, alternative and comprehensive modes are accessible, including public transport. Furthermore, average distances between clients are much lower in urban regions and thereby many routes are being covered by foot or by bike. Cars are mostly used in the suburbs, where the intervals and driving times of public transport are too large.

3.2 Effects of disasters on HHC

There are many possible disasters that are likely to influence the mentioned factors in subsection 3.1. Disasters can be classified in man-made and natural disasters. The former are of human origin and range from technical and/or human error to intentional damage like terrorism. However, natural disasters are outside the direct human sphere of influence. Table I summarizes the effects of disasters in the fields of transport, nurses, clients, and communication and is the result of a literature review and the practical experience of decision makers at the ARC; it extends the findings presented in Trautsamwieser *et al.* (2011) significantly. The selection is based on the classification of the International Disaster Database (EM-DAT, 2011), which lists the following groups of natural disasters: geophysical (earthquake, volcano, mass movement), meteorological (storm), hydrological (flood), climatological (extreme temperature), and biological (epidemic). Furthermore, it is complemented with blackouts as technological disaster.

Earthquakes lead to building damages and other infrastructure failure in wide areas and as they are usually not predictable they are latent threats, especially in densely built-up areas. Depending on the magnitude, earthquakes are caused from minor

Influence disaster	Nurses	Clients		Transport		Communication
	Number	Number	Service time	Driving times	Trafficability	Availability
Earthquake	↓	↑	↑	↑	↓	↓
Volcano	↓	↑	↑	↑	↓	↓
Mass movement	↓	↑	↑	↑	↓	↓
Storm	↓	↑	↑	↑	↓	↓
Flood	↓	↑	↑	↑	↓	↓
Heat wave	↓	↑	↑	↔	↔	↔
Cold wave	↔	↑	↑	↔	↔	↔
Epidemic	↓	↑	↑	↔	↔	↔
Blackout	↓	↑	↑	↑	↓	↓

Notes: ↑, increment; ↓, decrement; ↔, constancy

Table I.
Influences of disasters

structural damage (e.g. falling objects) up to severe destruction of a whole region. Mori *et al.* (2007) studied the health needs of people with chronic diseases during an earthquake in Japan. They state that natural disasters have a large physical and mental impact on people with chronic diseases. To minimize exacerbation of symptoms one should pay attention to medication availability and appropriate food (e.g. diabetics), but also for stress management or support for activities of daily living.

Current technology allows monitoring of volcanoes and as eruptions do not occur without warnings, they can be predicted very well. Hence, there should be enough time to prepare for the eruption. Consequently, the International Disaster Database (EM-DAT, 2011) lists no volcanic disasters in industrialized countries with harm of people. As the usual action is evacuation, volcanic eruptions do not influence HHC significantly. Therefore, the classification in Table I must be seen as potential influence only, if early warnings are failing.

Mass movements like landslides or avalanches mostly occur in alpine regions and have a huge damage potential if directly hitting areas of settlement. Otherwise, they may easily lead to isolation of certain regions, without infliction of major damage or harm. Therefore, the number of clients is likely to increase and if nurses are not able to get to work, their number is also decreasing. As transport and communication infrastructure in alpine regions is usually sparse, failures lead to significant impairments.

Storm disasters may be classified into several sub-types, but the effects of each type are more or less the same and mostly differ in the affected area. In particular the most common local/convective storm will lead to prolonged driving times and to a reduced trafficability. Roads could be blocked or closed, and power lines could break. Beem *et al.* (2008) analyze the storm risk in Germany and present a comparison of gust speed and landscape topology. They conclude that the impacts at open fields are much larger than at built areas and therefore, rural regions are more vulnerable. At the same time, the number of available nurses will reduce because some of them may not be able to get to work, while both the number of clients and the service times will increase, since more people would need assistance. Winter storms, which come along with heavy snowfall, will lead to similar effects, due to restricted visibility or slippery roads (see e.g. Changnon, 2007; Norrman *et al.*, 2000). The impact of this type of disaster is much bigger in rural- than in urban regions, due to the longer driving distances. Since most power lines in rural areas are overhead transmission lines, snow breakage-induced blackouts could lead to impairments in communication. Tornados and tropical storms have a particularly high potential for destruction. While the former are highly localized and therefore easier to manage, the second affects huge areas and thus requires a comprehensive disaster management.

Floods can occur in different ways, river floods, coastal floods, and flash floods. Nowadays, river floods are more predictable and therefore provide time to prepare for disaster response. In contrary, flash floods (e.g. caused by heavy rain) or coastal floods (e.g. tsunamis), are hardly predictable, but lead to significant damage. Urban regions are exposed to greater risks because they show large areas of sealed surfaces. The flood risk analysis by Compton *et al.* (2008) for Vienna reveals that failure of protection measures would lead to substantial damage of transport infrastructure, especially due to possible flooding of underground lines. Thereby, they refer to similar events in Boston, Seoul, Taipei, and Prague. Furthermore, floods often lead to power outages within the flooded area, such that communication will be affected. Clients may need additional services during such events, but limitations in the availability of nurses, however, are only likely to be expected in individual cases, if the nurses are affected themselves or are hindered to get to work.

Extreme temperature events like heat and cold waves affecting primarily the health situation of the clients. However, recent experiences of the ARC revealed that there is reduced availability of nurses during extreme heat events. The main reason for this are cardiovascular diseases. Investigations of past heat waves (see e.g. Diaz *et al.*, 2002; PROCLIM, 2005; Moshammer *et al.*, 2006, 2009) show that especially elderly and single people are vulnerable to heat waves. Palecki *et al.* (2001) further point out that there is a more significant increase in mortality in urban areas, due to the social structure and the urban-heat-island effect. The latter is responsible for the fact that temperature within the city center is higher by up to 8°C and also does not drop significantly during night. Transport infrastructure may be affected by extreme temperatures as road surface could melt or crack and rails could deform. But usually this is only the case to a very limited extent, therefore we do not take this into account.

The main problem of epidemics is the huge increase in the number of clients and service times, paired with a significant decrease in nurse availability. During influenza epidemics, Knebel and Phillips (2008) revealed that more care-dependent people would be discharged from hospitals earlier, due to short capacities, and that about a quarter of nurses will be sick themselves. Another problem arises from the fact that not all nurses will appear at work, especially if no protective measures are taken (e.g. vaccines). Ehrenstein *et al.* (2006), Mackler *et al.* (2007), and Irvin *et al.* (2008) analyze this circumstance for different diseases like avian influenza and pox. They state that only 20 percent of the nurses are willing to work in the worst case. In this case no protective measures are available. Furthermore, they mention that the willingness to work increases with the qualification level of staff. Gershon *et al.* (2007) state that the incidence of new diseases seems to increase, and that climate change leads to a shift in vector ranges, such that tropical diseases may occur in temperate regions. Globalization also helps to spread diseases. Theoretically, epidemics may also influence transport or communication infrastructure, but as this only happens if social life totally collapses, we assume that they will not be influenced much.

As technological disaster, blackouts take up a special role since they are often the result of other disasters or man-made and technical failures. In most cases, however, external events such as extreme weather conditions or other disasters lead to disturbances in the power supply. Pirker and Wiesinger (2005) give an overview of impacts of storms, mass movements, or geographically large events like floods or droughts. Power outages are affecting virtually every area of daily life. Schrümpf (2008) exemplarily describes the impact of a blackout on normal daily routine. A recent and more detailed study about the effects of large-scale and long-lasting blackouts was carried out by the "Committee on Education, Research and Technology Assessment" of the German Bundestag (Burchardt *et al.*, 2011). They analyze the effects on several critical infrastructures like telecommunication, transport (road, rail, water, and air), supply of goods (e.g. water, food), and waste disposal, as well as on the financial and health care sector. The authors conclude that after a few days the adequate supply of the population is no longer ensured in affected areas. Freese *et al.* (2006) analyze the impacts on New York's emergency call system in August 2003, caused by a heat-induced blackout. They reveal that cardiovascular- and respiratory problems, as well as gastro-intestinal disorders have increased, due to the high temperature, increased physical exertion, and failure of food-cooling systems. Therefore, increases in number of clients and service times are most likely. Especially in urban areas, it will also come to prolonged driving times and reduced trafficability, due to the collapse of electricity-based modes of transport like underground, train, and tram. Using buses or cars instead is also not a good alternative because of failure of traffic management systems (e.g. traffic lights). Fickert and Malleck (2008) describe the impact on telecommunication infrastructure. While the old-fashioned fixed phone line can often be maintained for days, the supply of the new mobile and broadband technologies is only possible for a few hours, at maximum. This hits especially those organizations, which use mobile devices for managing their nurses.

Besides the described singular events, one should also consider that several disasters could occur at the same time or that one disaster might trigger another one. This could lead to multiplier effects and to larger impacts. An example of this can be seen in the earthquake off the coast of Japan in March 2011, which led to a tsunami, which itself triggered a nuclear disaster.

4. Real-life application for assisting HHC

We studied the HHC services of the ARC in detail for the two provinces: Upper Austria and Vienna. In both regions the task of routing the nurses is done manually or only with limited computational assistance. There is no DSS which computes and suggests possible schedules. Together with the ARC we developed a mathematical model and a software prototype to optimize the daily scheduling of rural HHC services. The main requirements for the software prototype are as follows:

- to find good and feasible solutions;
- in short computation time; and
- with the possibility to incorporate the different effects of disasters.

4.1 Solution approach

The developed model is based on a vehicle-routing problem (VRP) and takes all the requirements of HHC in rural areas into account. The aim of the optimization is to assign all service tasks a client needs to nurses and to determine the most efficient visiting order, so that the sum of driving times and waiting times of nurses is minimized. At the same time the satisfaction level of both clients and nurses should be maximized. Several factors that may be considered as indicators of satisfaction were incorporated into a weighted objective function. For the clients, the compliance of the preferred nurses and treatment times are measured. On the side of the nurses, overtime and overqualification, as well as the violation of the preferred working times and break times are considered. Constraints that must not be violated are working time regulations (maximum working hours, mandatory breaks, and shift work) and treatment times, if they are time-critical (e.g. insulin shots). Furthermore, a nurse may also medicate a client only if he/she has the necessary qualification level and shares at least one common language with the client. It is also possible that a client rejects the treatment of a specific nurse due to previous incidents; this is also possible for the nurse. Moreover, there are also various employment contracts; nurses may start their paid duty at home, at the ARC base, or at the first client's home.

Small test instances of the problem can be solved exactly with the solver software Xpress 7.0. However, for real-life instances it is not possible to find exact or even feasible solutions within finite computing time. Therefore, we developed an algorithm based on variable neighborhood search (VNS). We have chosen this metaheuristic, because it has proven to be a good choice for solving VRPs. A detailed description of the mathematical model formulation and the adapted VNS algorithm can be found in Trautsamwieser *et al.* (2011).

To enable use of the algorithm in case of a disaster we followed a two-step approach. In the first step the required data are processed for the second step, the optimization itself. This allows more flexibility since the optimization is independent from disaster modeling. Although most of the scenarios presented in Table I are quite likely to influence the test regions in Upper Austria, it is hard to predict the consequences on HHC in quantitative measures without the corresponding data. Driving times, for example, will increase in most cases but on which roads and by how much are not easily answered questions. Various disasters are locally limited in their impact and both intensity and the affected area cannot be accurately predicted, even with latest forecast models. One just has to think of storm damage or flooding caused by heavy rain. Therefore, we present results for disaster scenarios for which plausible data are available. In the case of Upper Austria data for various flood scenarios are on hand.

The developed software prototype is quite flexible and easy to handle. The team leader or any other person in charge can compute various scenarios. Typically, the overall aim is a minimization of driving times and waiting times. Nevertheless, the team leader can also account to the other attributes which lead to a higher satisfaction level of nurses and clients. These attributes lose their attractiveness in case of disasters, in which decision makers are mainly interested to find feasible schedules. Those can be found by concentrating on a reduction of driving times and waiting times. Hence, the other objectives like overtime have been neglected in the following computations. Additionally, computing time often plays a vital role in case of disasters. Therefore, the user of the software prototype can specify how much time she/he has at disposal to compute a solution.

4.2 Numerical studies

The software prototype was tested for three different regions in Upper Austria. These regions are affected by floods regularly. Region r_1 is a small urban region, whereas regions r_2 and r_3 are bigger in size and rural. For these three regions we obtained real-life data from the ARC. Tables III-V give an overview on the problem sizes in these regions. For example, in region r_2 there are 39 nurses employed to serve 196 clients. Some of these clients have to be visited several times a day for different treatments. Hence, in total 223 home visits are required. In region r_1 the number of clients equals the number of visits, whereas in region r_3 283 clients need 324 visits. Each visit is characterized by a certain qualification level according to the nurses abilities needed for this visit. A nurse is only allowed to visit a client if the qualification level of the nurse is at least as high as the qualification level required for this visit. A visit with a qualification level of 1 might be a simple aid in the household and is done by home helpers, whereas a visit with a qualification level of 3 requires a qualified nurse.

The provided data contains the performed visits, the addresses of the participants, the qualification level of both nurses and visits, and the daily contract working times of the single nurses. The data of the duration of the visits as well as the time windows of the visits, in which the treatment has to happen, are not yet recorded in an electronic form. Sometimes the operative staff decides during the day if it is necessary to visit a client in a specific time window. This is often based on information gathered in an informal way (e.g. phone calls from colleagues or the client). Additionally, the service times for the treatments are not standardized and depend on individual factors. Nevertheless, we know that the duration of the visits is normally distributed with a mean dependent on the qualification level. The following times in minutes are needed on average to perform a visit with a certain qualification level: 1 (46.69 minutes), 2 (39.71 minutes), and 3 (28.81 minutes). The standard deviation is set to 15 minutes. Each visit has to be covered within a time horizon of 720 minutes. Some of the visits are assumed to be time-critical and have to be covered within a time frame of 120 minutes. They are spread over the day randomly. Visits with a qualification level of 1 are usually not time-critical, because they are not life-threatening. Some visits with a qualification level of 2 or 3, as for example the change of bandages or an insulin shot, are however time-critical. The concrete numbers of assumed time-critical visits for each region (depicted in Table II) were generated through estimates of the decision makers and evaluation of historical data.

According to the decision makers language skills are not relevant in these regions, at the moment. This also holds for preferences of clients and nurses with respect to their preferred working times and treatment times. According to the different work contracts, nurses start their shift at home, at the ARC base, or at the first client's home.

In the following we compare results for a normal day (i.e. a day without any disturbances), a recent flood scenario of the year 2002 (HW 2002), and three flood predictions, estimated by "Hochwasserrisikozonierung Austria" (HORA). HORA is a project funded by the Austrian Government to estimate future potential risks of flood scenarios. Therefore, flood scenarios of the past have been analyzed to estimate 30-, 100-, and 200-year return flood discharges (HQ 30, HQ 100, and HQ 200). We have used these estimations on the current data set to show the consequences of floods on HHC in the corresponding regions. This was done within the geographic information system (GIS) Arc GIS 9.3. The flood zones were used to identify impassable road segments. Based on the remaining roads, shortest travel times were computed between all locations (nurses, clients, and base). The shortest travel time calculation itself was done by the "Department of Geoinformation and Property" of the federal government of Upper Austria, since we did not have access to all required data. In order to calculate travel times that largely correspond to reality, average travel speeds based on floating car data were used therefore. For each scenario, the corresponding travel times were stored in driving time matrices. After this first step of data preparation the optimization starts.

To make suitable comparisons all results are based on the same data set, but with different underlying driving time matrices. The solution values equal the sum of driving times and waiting times for the whole schedule, measured in seconds. As the VNS algorithm includes some randomness in its search procedure, the averages of ten runs are reported. In general, we assume that in case of disasters the results will be worse compared to a normal day. This means that the solution values will increase or no feasible solution can be obtained. However, this is not always the case as shown later. The number of available nurses usually decreases because some of them cannot start their shifts, whereas the number of clients increases. In these computations the number of clients does not increase, because we do not have any information about clients who will only need treatment under such circumstances. Currently, there exists

Table II.
Time-critical visits for each region

Attribute region	Qualification level 1	2	3	Time window (minutes)
r_1	–	–	17	120
r_2	–	26	19	120
r_3	–	25	31	120

no reliable data about that; it can be assumed that this information is highly dynamic in disaster situations. Therefore, we rely on the number of clients under normal conditions for our computations. Some of the current clients may not be reached via the road network in case of floods. A part of these clients might need to be evacuated and brought to intramural facilities, whereas some treatments might be postponed to a later time if they are not life-threatening. The decision rests with the person in charge.

As shown in Table III floods do not really have an effect on the results for region r_1. If an HW 2002 repeats, the flood neither leads to a reduction in the number of available stuff, nor to a reduction in the number of clients. Moreover, no essential parts of the road network are affected. Hence, the same solution value as under normal conditions is obtained. For an HQ 30, the number of nurses decreases by two and the number of clients that cannot be reached equals 28. In case of an HQ 100 and HQ 200 these numbers change only slightly compared to an HQ 30. We obtain smaller solution values for these scenarios compared to a normal day, because the problem size is smaller and there exist a lot of short ways from one client to another, as region r_1 is a small urban region. In Tables III-V the qualification level of the nurses and the required qualification levels for the single visits are written in parentheses.

Attribute scenario	# nurses (1)	# nurses (2)	# nurses (3)	# clients	# visits (1)	# visits (2)	# visits (3)	Solution value (average of ten runs) (seconds)
Normal day	0	0	13	84	0	0	84	5,022
HW 2002	0	0	13	84	0	0	84	5,022
HQ 30	0	0	11	56	0	0	56	4,110
HQ 100	0	0	10	56	0	0	56	4,092
HQ 200	0	0	10	55	0	0	55	4,086

Table III.
Data and results for region r_1 – mean value of ten test runs with 10^6 iterations

Attribute scenario	# nurses (1)	# nurses (2)	# nurses (3)	# clients	# visits (1)	# visits (2)	# visits (3)	Solution value (average of ten runs) (seconds)
Normal day	0	24	15	196	0	129	94	43,866
HW 2002	0	23	13	165	0	107	79	36,126
HQ 30	0	20	13	149	0	103	66	44,640
HQ 100	0	20	13	147	0	103	64	45,960
HQ 200	0	20	13	147	0	103	64	45,972

Table IV.
Data and results for region r_2 – mean value of ten test runs with 10^6 iterations

Attribute scenario	# nurses (1)	# nurses (2)	# nurses (3)	# clients	# visits (1)	# visits (2)	# visits (3)	Solution value (average of ten runs) (seconds)
Normal day	16	34	25	283	42	126	156	57,996
HW 2002	16	32	24	278	42	124	153	63,906
HQ 30	15	29	22	224	27	108	124	70,680
HQ 100	15	29	21	215	23	102	121	64,656
HQ 200	15	29	20	208	22	97	116	61,212

Table V.
Data and results for region r_3 – mean value of ten test runs with 10^6 iterations

In region r_2 it can be observed that in case of the floods 2002 a smaller solution value can be obtained. There are two reasons for this result. First, the number of nurses and visits decreases in relation to a normal day. Second, the driving times do not increase a lot between the clients in reach. An HQ 30, HQ 100, or HQ 200 in contrast leads to a higher solution value, although the number of nurses and clients reduces even more. However, in this region the driving times increase significantly and so more time is required to visit all clients.

In region r_3 the solution value increases for all disaster scenarios. The number of nurses and the number of clients decreases in all cases. However, feasible schedules can be found for all scenarios.

Figure 1 shows exemplary a part of the solution of region r_3. On a normal day there are 75 nurses available who have to handle 324 visits at 283 different clients. Since 21 nurses have to visit the ARC base first, many routes start and end there. The clients are marked with circles and show the client ID, the nurses are marked with rectangles and their ID, and the ARC base is symbolized through a rectangle with a cross. Figure 2 shows the same area as Figure 1, but in case of an HQ 200 flood. The flooded area is shaded and all locations that are affected by the flood are crossed out in Figure 2. If a client is not located directly within the flooded area but is surrounded by water and therefore not reachable anymore, she/he is also crossed out if there is no suitable nurse nearby. In the HQ 200 scenario the number of available nurses is reduced by 11 but also the number of visits decreases significantly. The ARC base will also not be reachable in

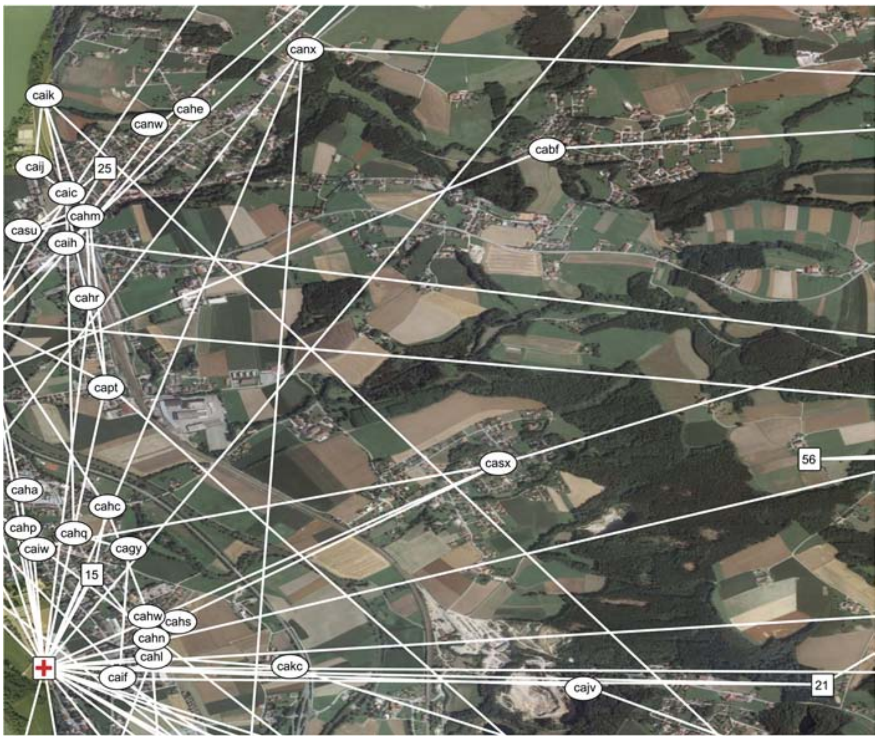

Figure 1.
Extract of tours in region r_3 for a normal day

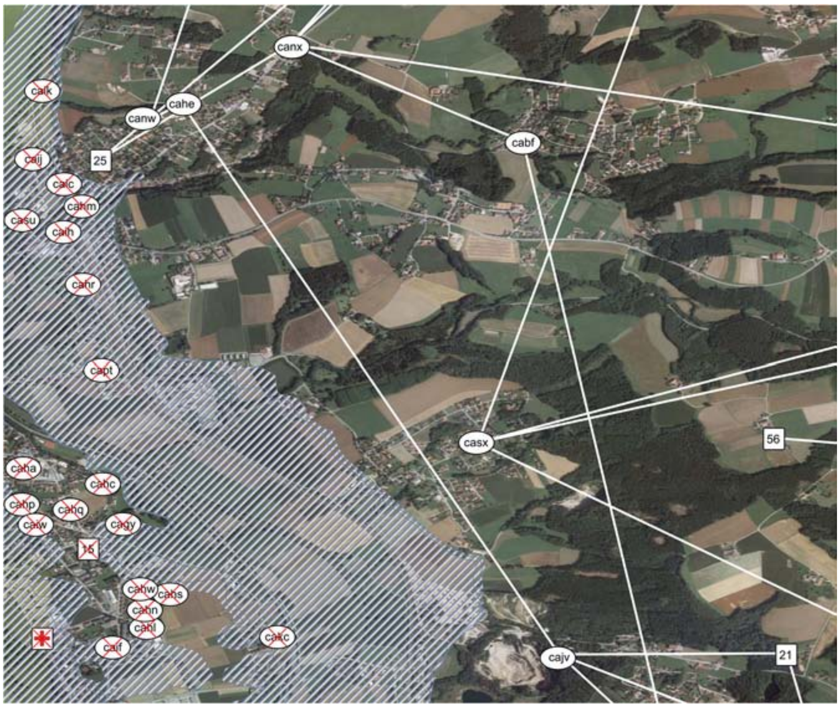

Figure 2.
Extract of tours in region r_3 in case of HQ 200 floods

case of such enormous floods. Although, only those nurses who drive directly to their first clients are scheduled in the computed solution, other disaster scenarios may require all nurses to obtain feasible solutions. For such situations all nurses should be able to drive directly to their first clients, independent of their contract.

We presented results for a normal day and various flood scenarios. The consequences of other disasters might be investigated by sensitivity analysis, since no quantitative data are available for these disasters. Typically, the driving times increase for many disasters as depicted in Table I. A possible scenario might be a reduction of the travel speed such that driving times increase by a certain factor for a certain number of roads. We also mentioned that both the number of clients and the service times will increase. This may not hold for all clients because nurses could try to tighten the service time at unaffected clients, if this is possible. Furthermore, there are currently no data available about clients who only need treatment during disasters. Hence, the number of clients and their service times are hard to predict and thus are best modeled by a sensitivity analysis. The presented computations show that there is still a buffer for new clients and extended service times even in case of an HQ 200. Therefore, the ARC is prepared for a certain level of uncertainty in the tested areas.

5. Final remarks

Several studies indicate that industrialized countries will be confronted with an increased demand for HHC in the future. Furthermore, it can be expected that the number of natural disasters increase. Therefore, HHC service providers will be faced with two challenges: an increased organizational effort due to the increased demand

and the need for an anticipatory risk management. As shown in Section 3 there are many potential disasters that may influence HHC. We showed exemplary how potential floods affect HHC in three regions in Upper Austria. To tackle the above-mentioned challenges we presented a solution approach from Trautsamwieser *et al.* (2011) that has been developed in cooperation with the ARC. The algorithm ensures that resources are used as efficient as possible and the chosen design of the software prototype also allows disaster modeling within GIS. This also opens up the possibility to use real-time data, such as available at the public authorities. As disaster modeling is done independently from optimization, various disaster types can be incorporated.

For further evaluation, the software prototype is going to be tested in the daily business at the ARC in Upper Austria. Together with the ARC in Vienna, a software prototype for optimization of HHC in urban regions is currently in development. Due to the different requirements mentioned in Section 2, the developed software prototype for rural regions is not suitable for urban regions. Especially the different modes of transport and the usage of time-dependent travel times require different data structures and algorithmic procedures. Additionally, an inclusion of sequenced visits and divisible mandatory breaks further complicates the model.

For all presented flood scenarios feasible solutions could be found. Nevertheless, still with optimization methods, disasters may occur that make it impossible to sustain the care for all clients. Therefore, some kind of triage should be implemented in future. At the ARC triage is based on the profound knowledge of the nurses and team leaders. To build up a comprehensive and staff independent triage system, sufficient data about the clients and their relatives are needed. These data are currently not available. Furthermore, it is intended to enlarge the planning horizon from a single day to one week. This gives decision makers more flexibility, as it offers the possibility to postpone non life-threatening services to a later day in the week. Indeed, this leads to a more complex model because one has to consider additional constraints like mandatory rest periods or constancy of the servicing nurses.

The presented DSS was intentionally designed and developed to help HHC service providers in industrialized countries like Austria to cope with the increasing demand and to support them during times of disaster. As this DSS relay on modern information technologies, its applicability in developing countries may be limited at the moment.

References

Akjiratikarl, C., Yenradee, P. and Drake, P.R. (2007), "PSO-based algorithm for home care worker scheduling in the UK", *Computers & Industrial Engineering*, Vol. 53 No. 4, pp. 559-83.

Bednar, M., Biringer, E., Floh, S., Grasser, M., Nagy, V., Ostermeyer, E., Rubisch, M., Rudolf, L. and Weinert, R. (2010), *Österreichischer Pflegevorsorgebericht 2008*, Federal Ministry of Social Affairs and Consumer Protection, Vienna.

Beem, H., Fendler, R. and Krätzig, W. (2008), "Impact of storms and earthquakes on industrial installations – new risk control approaches required?", *Natural Hazards*, Vol. 46 No. 2, pp. 243-56.

Biringer, E., Dorn, M., Floh, S., Grasser, M., Krispl, M., Nagy, V., Ostermeyer, E. and Weinert, R. (2010), *Österreichischer Pflegevorsorgebericht 2009*, Federal Ministry of Social Affairs and Consumer Protection, Vienna.

Bredström, D. and Rönnqvist, M. (2008), "Combined vehicle routing and scheduling with temporal precedence and synchronization constraints", *European Journal of Operational Research*, Vol. 191 No. 1, pp. 19-31.

Burchardt, U., Feist, T., Neumann, N., Fell, H.-J., Röspel, R. and Sitte, P. (2011), "Gefährdung und Verletzbarkeit moderner Gesellschaften – am Beispiel eines großräumigen und langandauernden Ausfalls der Stromversorgung", Technology Assessment Project, Committee on Education, Research and Technology Assessment of the German Bundestag, Berlin.

Changnon, S.A. (2007), "Catastrophic winter storms: an escalating problem", *Climatic Change*, Vol. 84 No. 2, pp. 131-9.

Cheng, E. and Rich, J.L. (1998), "A home health care routing and scheduling problem", Technical Report No. TR98-04, Department of CAAM, Rice University, Houston, TX.

Compton, K.L., Faber, R., Ermolieva, T., Linnerooth-Bayer, J. and Nachtnebel, H.P. (2008), "Development of a catastrophe model for managing the risks of urban flash flooding in Vienna", Interim Report IR-08-001, International Institute for Applied Systems Analysis, Laxenburg.

Diaz, J., Jordán, A., Garcia, R., López, C., Alberdi, J.C., Hernández, E. and Otero, A. (2002), "Heat waves in Madrid 1986-1997: effects on the health of the elderly", *International Archives of Occupational Environmental Health*, Vol. 75 No. 3, pp. 163-70.

Ehrenstein, B.P., Hanses, F. and Salzberger, B. (2006), "Influenza pandemic and professional duty: family or patients first? A survey of hospital employees", *BMC Public Health*, Vol. 6, p. 311.

EM-DAT (2011), "The International Disaster Database", available at: www.emdat.be/ (accessed November 21, 2011).

Eveborn, P., Flisberg, P. and Rönnqvist, M. (2006), "Laps care – an operational system for staff planning of home care", *European Journal of Operational Research*, Vol. 171 No. 3, pp. 962-76.

Fickert, L. and Malleck, H. (2008), "Herausforderungen durch Abhängigkeiten der Telekommunikationsinfrastruktur vom öffentlichen Stromnetz", *Elektrotechnik & Informationstechnik*, Vol. 125 Nos 7-8, pp. 274-7.

Freese, J., Richmond, N.J., Silverman, R.A., Braun, J., Kaufman, B.J. and Clair, J. (2006), "Impact of a citywide blackout on an urban emergency medical services system", *Prehospital and Disaster Medicine*, Vol. 21 No. 6, pp. 372-8.

Fujisawa, R. and Colombo, F. (2009), "The long-term care workforce: overview and strategies to adapt supply to a growing demand", OECD Health Working Papers No. 44, OECD, Paris.

Gershon, R.R.M., Qureshi, K.A., Stone, P.W., Pogorzelska, M., Silver, A., Damsky, M.R., Burdette, C., Gebbie, K.M. and Raveis, V.H. (2007), "Home health care challenges and avian influenza", *Home Health Care Management & Practice*, Vol. 20 No. 1, pp. 58-69.

Hancock, R., Wittenberg, R., Pickard, L., Comas-Herrera, A., Juarez-Garcia, A., King, D. and Malley, J. (2007), "Paying for long-term care for older people in the UK: modelling the costs and distributional effects of a range of options", PSSRU Discussion Paper 2336/2, Personal Social Services Research Unit, London.

Intergovernmental Panel on Climate Change (IPCC) (2007), "Summary for policymakers", in Parry, M.L., Canziani, O.F., Palutikof, J.P., Van der Linden, P.J. and Hanson, C.E. (Eds), *Climate Change 2007: Impacts, Adaptation and Vulnerability*, Cambridge University Press, Cambridge, pp. 7-22.

Irvin, C.B., Cindrich, L., Patterson, W. and Southall, A. (2008), "Survey of hospital healthcare personnel response during a potential avian influenza pandemic: will they come to work?", *Prehospital and Disaster Medicine*, Vol. 23 No. 4, pp. 328-35.

Johnson, J. and Galea, S. (2009), "Disasters and population health", in Cherry, K.E. (Ed.), *Lifespan Perspectives on Natural Disasters*, Springer, New York, NY, pp. 281-326.

Kaye, H.S., LaPlante, M.P. and Harrington, C. (2009), "Do noninstitutional long-term care services reduce Medicaid spending?", *Health Affairs*, Vol. 28 No. 1, pp. 262-72.

Kenny, G.M. (1993), "Rural and urban differentials in medicare home health use", *Health Care Financing Review*, Vol. 14 No. 4, pp. 39-57.

Kitchener, M., Ng, T., Miller, N. and Harrington, C. (2006), "Institutional and community-based long-term care", *Journal of Health & Social Policy*, Vol. 22 No. 2, pp. 31-50.

Knebel, A. and Phillips, S.J. (Eds) (2008), *Home Health Care during an Influenza Pandemic: Issues and Resources*, AHRQ Publication No. 08-0018 Agency for Healthcare Research and Quality, Rockville, MD.

Mackler, N., Wilkerson, W. and Cinti, S. (2007), "Will first-responders show up for work during a pandemic? Lessons from a smallpox vaccination survey of paramedics", *Disaster Manage Response*, Vol. 5 No. 2, pp. 45-8.

Melching, C.S. and Pilon, P.J. (Eds) (2006), *Comprehensive Risk Assessment for Natural Hazards*, WMO/TD No. 955 World Meteorological Organization, Geneva.

Mori, K., Ugai, K., Nonami, Y., Kirimura, T., Kondo, C., Nakamura, T., Motoki, E. and Kaji, H. (2007), "Health needs of patients with chronic diseases who lived through the great Hanshin earthquake", *Disaster Management & Response*, Vol. 5 No. 1, pp. 8-13.

Moshammer, H., Hutter, H.P. and Gerersdorfer, T. (2009), "Einfluss von Adaptationsmaßnahmen auf das akute Sterberisiko in Wien durch Temperaturextreme", Sub-project of StartClim2008, available at: www.austroclim.at/index.php?id=startclim2008 (accessed June 9, 2011).

Moshammer, H., Hutter, H.P., Frank, A., Gerersdorfer, T., Hlava, A., Sprinzl, G. and Leitner, B. (2006), "Einflüsse der Temperatur auf Mortalität und Morbidität in Wien", Sub-project of StartClim2005, available at: www.austroclim.at/index.php?id=startclim2005 (accessed June 9, 2011).

Mühlberger, U., Knittler, K. and Guger, A. (2008), *Mittel- und langfristige Finanzierung der Pflegevorsorge*, Austrian Institute of Economic Research, Vienna.

National Association for Home Care and Hospice (NAHC) (2008), *Emergency Preparedness Packet for Home Health Agencies*, The National Association for Home Care & Hospice, Washington, DC.

Nickel, S., Schröder, M. and Steeg, J. (2009), "Planning for home health care services", Technische Berichte des Fraunhofer ITWM, No. 173, Fraunhofer-Institut für Techno- und Wirtschaftsmathematik, Kaiserslautern.

Norrman, J., Eriksson, M. and Lindqvist, S. (2000), "Relationships between road slipperiness, traffic accident risk and winter road maintenance activity", *Climate Research*, Vol. 15 No. 3, pp. 185-93.

Oliveira Martins, M.J. and de la Maisonneuve, C. (2006), "The drivers of public expenditure on health and long-term care: an integrated approach", *OECD Economic Studies*, No. 43, pp. 115-54.

Palecki, M.A., Changnon, S.A. and Kunkel, K.E. (2001), "The nature and impacts of the July 1999 heat wave in the Midwestern United States: learning from the lessons of 1995", *Bulletin of the American Meteorological Society*, Vol. 82 No. 7, pp. 1353-67.

Pirker, O. and Wiesinger, E.E. (2005), "Energie und Wasser: Sicherung der Versorgung", in Steininger, K.W., Steinreiber, C. and Ritz, C. (Eds), *Extreme Wetterereignisse und ihre wirtschaftlichen Folgen*, Springer, Berlin, pp. 177-89.

PROCLIM. (Eds) (2005), *Hitzesommer 2003*, Synthesis, Bern, available at: www.proclim.ch/4dcgi/proclim/fr/Media?137 (accessed June 9, 2011).

Rasmussen, M.S., Justesen, T., Dohn, A. and Larsen, J. (2010), "The home care scheduling problem: preference-based visit clustering and temporal dependencies", Report 11.2010, DTU Management Engineering, Technical University of Denmark, Kgs. Lyngby.

Schaffenberger, E. and Pochobradsky, E. (2004), *Ausbau der Dienste und Einrichtungen für pflegebedürftige Menschen in Österreich – Zwischenbilanz*, Österreichisches Bundesinstitut für Gesundheitswesen, Vienna.

Schneider, U., Österle, A., Schober, D. and Schober, C. (2006), *Die Kosten der Pflege in Österreich. Ausgabenstrukturen und Finanzierung*, Institute for Social Policy, Vienna University of Economics and Business, Vienna.

Schrümpf, E.G. (2008), "Stromausfall – und danach?", *Elektrotechnik & Informationstechnik*, Vol. 125 No. 5, pp. 218-20.

Statistics Austria (2011), "Social statistics", available at: www.statistik.at/web_en/statistics/social_statistics/index.html (accessed May 19, 2011).

Trautsamwieser, A., Gronalt, M. and Hirsch, P. (2011), "Securing home health care in times of natural disasters", *OR Spectrum*, Vol. 33 No. 3, pp. 787-813.

Woodward, C.A., Abelson, J., Tedford, S. and Hutchison, B. (2004), "What is important to continuity in home care? Perspectives of key stakeholders", *Social Science & Medicine*, Vol. 58 No. 1, pp. 177-92.

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Supporting Urban Home Health Care in Daily Business and Times of Disasters

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Abstract: Home health care (HHC) services are of vital importance for today's society. They allow old and frail people a self-determined living in their familiar environment. Due to the current demographic and social developments further increases in demand for HHC must be expected. Additionally, people with limited mobility or relying on medical supply usually need consistent care. Thus, HHC service providers will be faced with two challenges: an increased organizational effort due to the rising demand and the need for an anticipatory risk management. Previous research combining optimization and risk management in the field of HHC limits itself to rural regions, where nurses are solely using cars. The presented work specifically aims to deal with the peculiarities of urban regions. Together with the Austrian Red Cross (ARC), a vulnerability analysis has been conducted in order to identify the critical success factors and processes of HHC as well as potential threats. To support the daily scheduling, a Tabu Search (TS) based metaheuristic has been implemented. As nurses can choose between different transport modes (public transport, car, bike, and walking), time-dependent multimodal transport has been considered. The TS has been tested with real-world data from the ARC in Vienna to support both, daily business and scheduling in times of disasters. Significant reductions of travel and waiting times can be obtained, such that more time remains for serving the clients. Through sensitivity analysis the effects of disasters (esp. blackout, pandemics, and heat waves) are visualized and the operational limits during such events are shown.

Keywords: Home health care, decision support systems, risk management, disaster vulnerability, routing algorithms, time-dependent travel times

1. INTRODUCTION

Home health care (HHC) services are of vital importance for today's society. Their services are ranging from qualified home nursing to assistance in leading the household and maintenance of social contacts. By this means, they allow old and frail people a self-determined living in their familiar environment but still receive professional help. Many countries are already facing a significant increase in demand for HHC services and due to the current demographic and social developments further rises must be expected. In addition, people with limited mobility or relying on medical supply (e.g. diabetics) do often need consistent care. Hence, HHC services must be sustained by all means in order to avoid health implications. Thus, HHC service providers will be faced with two challenges: an increased organizational effort due to the rising demand and the need for an anticipatory risk management. Additionally, they are exposed to high cost pressure and are thus, highly interested in suitable decision support systems (DSS). Such systems lead not only to better solutions, but also to a reduced planning effort; especially if one bears in mind that the planning of the nurses is quite complex but usually done manually at the moment.

Even though it can be assumed that the number of (natural) disasters increases, the impacts of complex crisis and disaster scenarios on HHC services have been hardly discussed scientifically. Previous research combining optimization and risk management in the field of HHC limits itself to DSS's for rural regions, where nurses are solely using cars. The presented work specifically aims to deal with the peculiarities of urban regions. It is based on a collaborative project with the Austrian Red Cross (ARC), which is not only a main player in times of disasters, but also one of the leading HHC service providers in Austria. The considered HHC problem has a daily planning horizon and as nurses can choose between different transport modes (public transport, car, bike, and walk), time-dependent multimodal transport has been considered. A risk analysis has been carried out to identify the critical success factors of HHC as well as potential threats. In times of disasters the efficient usage of the limited resources is crucial. To be able to compute efficient schedules within short computation time a Tabu Search (TS) based metaheuristic has been developed and implemented. The TS algorithm is able to support the daily scheduling of nurses in both, daily business and in times of disasters. Comparisons with

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daily business show that significant reductions of travel and waiting times can be obtained, such that more time remains for serving the clients. Through sensitivity analysis the effects of disasters (esp. blackout, pandemics, and heat waves) are visualized and the operational limits during such events are shown.

This paper is structured as follows. Section 2 contains a problem description, followed by a brief literature review on daily HHC scheduling in Section 3. In Section 4 the vulnerability analysis is exemplarily shown for the disasters that are of greatest importance for the ARC in Vienna. Section 5 presents the designed and implemented solution approach, followed by numerical results with real-world data in Section 6. Finally, conclusions and an outlook on future research are given in Section 7.

2. PROBLEM DESCRIPTION

From a modeling point of view, the considered problem can be seen as a rich Vehicle Routing Problem with time-dependent travel times, multimodal transport and HHC related constraints. It is based on the demands of the ARC in Vienna and can be described by the following characteristics of clients and nurses.

Clients: Clients need one or more services (jobs) per day and depending on the task that has to be carried out, a certain minimal qualification level is needed. For example, if the job consists of cleaning or preparing lunch it is carried out by home helpers, whereas for medical treatments (e.g. medication, wound treatment, etc.) a qualified nurse is needed. As it was not the intention of this work to address the subject of triage in times of disasters, it is essential that all jobs have to be carried out by appropriately qualified nurses. However, it is assumed that nurses are allowed to carry out jobs that require a qualification level that is one level below their qualification. However, this overqualification not only leads to dissatisfaction, but also to increased costs for the HHC service provider and thus, should be avoided. The type of service as well as the duration of the service times are stated in a contract between the client and the HHC service provider and thus are also not a subject of change. Each job must start within a given hard time window, whilst taking into account that clients have some preferred visiting times. A smooth communication and mutual trust between nurses and clients are crucial for successful care. Therefore, the language skills of the nurses and clients are required to match and clients may have some preferred and/or rejected nurses (e.g. due to personal dislike or previous incidents).

Nurses: Nurses are mainly characterized by their qualification level, language skills, and working times. No central base is used in the underlying test region and thus, the working times of the nurses start at the first and end at the last clients. Due to various contracts, nurses have different contracted hours, earliest and latest as well as maximum working times. The actual working time of a nurse is stated by a roster that has been drawn up a few weeks ago. The roster shows the working and resting days and defines begin and end of duty for each nurse. Depending on the scope of application, the optimization is either based on the predefined roster or on flexible working times. For the latter, only the scheduled daily working hours are taken into account. This setting not only increases the flexibility in times of disasters but may also be used for deriving a roster in mid-term. As the majority of the jobs are piling up at certain peak times (morning, noon, and evening) nurses often have to work two shifts a day. These second shifts are not very popular with the nurses and thus, they should be limited to the minimum. In case a nurse is scheduled to work a shift, his/her working time must exceed a certain minimum working time, dependent on whether the shift is a morning or an evening shift. If the working time exceeds a certain amount of time, a break has to be scheduled. To substitute waiting time, it is possible to split the break into smaller parts. Thus, leading to a state-dependent problem where the optimal break positions and durations have to be determined.

The main objective is to minimize the sum of all tour lengths, resulting in a minimization of travel and waiting times as the durations of the jobs are fixed. To ensure the satisfaction of clients and nurses a dual strategy is followed. In this way, the problem can be easily relaxed in order to increase the flexibility in times of disasters. Factors with easily determinable impacts to the objective (e.g. overtime, second shifts, and overqualification) are integrated by using a weighted objective function and are therefore measured in minutes. Other factors are implemented through aspiration levels by introducing additional hard constraints with user-defined parameters. Especially aged people need consistency with respect to visiting times and nurses. The first is implemented by an artificial reduction of the time windows, based on the actual visiting times in the past. For the latter, the concept of "care teams" has been introduced. Thus, for each client, a team of nurses with whom he/she is already familiar is considered. These teams may only be expanded by a limited number of unfamiliar nurses. Finally, the dispatcher may also set a limit to the total amount of overtime; but as overtime is also part of the weighted objective function, it is used only where it is beneficial for the whole solution.

What mainly distinguishes our problem from previous work on HHC routing is that nurses may choose between different individual transport modes (car, bike, walk) and public transport. In urban regions with a well developed public transport infrastructure the shorter distances between the clients encourage nurses to use public transport, especially if traffic and parking conditions are taken into account. In Vienna, for example, more then 90 % of the HHC nurses use public transport. Within the public transport system they have to switch between different lines of buses, trams, subways, and trains to reach their destinations. These are operating on timetables and as there are severe fluctuations in the driving intervals, time-dependent travel times must be considered in addition to the multimodality, in order to obtain viable solutions. However, routing with public transport is still hardly considered in literature and we are not aware of any published work in this field, taking time-dependent travel times into account; with the exception of conference presentations of our working group (e.g. Rest and Hirsch (2013)).

3. LITERATURE REVIEW

Optimizing the scheduling of HHC services is a rather young but quickly evolving research area. A recent comprehensive literature review on both daily and periodic HHC scheduling can be found in Trautsamwieser and Hirsch (2014). For the daily scheduling many different approaches have been published in the last 10 years. Besides the varying legal and organizational requirements the points of focus are diverse: Bertels and Fahle (2006) list several relevant factors for an allocation of clients to nurses. A a combination of Constraint Programming (CP) and the metaheuristics Simulated Annealing and TS are used to solve instances with up to 50 nurses and 326 jobs. Akjiratikarl et al. (2007) use a Particle Swarm Optimization based metaheuristic to compare themselves with real world schedules from a local government authority in UK as well as with a proprietary routing software. Eveborn et al. (2006, 2009) developed a DSS called Laps Care for Swedish HHC service providers. The problem is treated as a set partitioning problem and solved by a solution approach based on repeated matching. Considered modes of transport are car, bicycle, and walking, but without any combinations of them. They present results for real-world instances, including an urban region, but because of the short distances all trips are made by foot. Dohn et al. (2008) use a Branch-and-Price approach to solve real-world instances with up to 150 jobs and 15 nurses. Elbenani et al. (2008) present a TS algorithm to solve a real-world HHC problem in Canada. A unique feature of this work is that nurses have to collect blood samples from some clients and deliver them to the hospital within a given time window. Bräysy et al. (2009) use a commercial VRP solver to optimize several communal services in Finland (HHC, transportation of the elderly, and home meal delivery). For HHC, the authors claim that nurses can use different modes of transport (walking, car, bicycle, and bus); however, a single average travel speed over all modes is taken. Bredström and Rönnqvist (2007, 2008), Rasmussen et al. (2012), and Mankowska et al. (2013) focused their work on interdependent services, taking into account synchronization and temporal precedence. Bredström and Rönnqvist (2007) and Rasmussen et al. (2012) use Branch-and-Price algorithms, but to reduce the computational effort Rasmussen et al. (2012) further analyze different clustering schemes. Bredström and Rönnqvist (2008) and Mankowska et al. (2013) use metaheuristic solution approaches to achieve short computation times. Trautsamwieser et al. (2011) present a Variable Neighborhood Search approach and a model formulation for HHC in Austria, considering many legal constraints as well as the satisfaction of nurses and clients. The authors also analyze the possible impacts of some natural disasters (esp. floodings) on the scheduling. However, this work is based on time-independent travel times and is focused on rural areas, where nurses only use cars. In Rest et al. (2012) the vulnerability analysis is extended to urban regions. The works of Trautsamwieser et al. (2011) and Rest et al. (2012) provide the basis for the time-dependent, multimodal TS based solution approach presented in this paper. Another recent work on urban HHC has been published by Hiermann et al. (2013). The authors present a two-stage approach combining CP with different metaheuristics to solve real-world instances of an HHC service provider in Vienna. Nurses are able to use either public transport or cars. Their travel time data is based on estimates from a public transport service provider and on floating car data. However, a single estimate is used for each mode for the whole day and thus, they do not rely on the actual time of departure. In Fikar and Hirsch (2014) an alternative mobility concept is proposed, in which a transport service is used to transport nurses from one operational area to another. Discussions with decision makers at the ARC revealed that such a concept might also be useful in times of disasters, as it relies only on a small number of cars to sustain the mobility of all nurses.

4. VULNERABILITY ANALYSIS

For direct applicability in times of disasters, the solution approach must be capable of finding good and feasible solutions in short computation time and requires the possibility to incorporate the different effects of various types of disasters. Relevant disaster events and their respective impacts on HHC have been identified by combining the thorough expertise of the ARC with findings in scientific literature. Manuals for developing an hazards emergency preparedness plan, as published by the United States National Association for Home Care and Hospice (NAHC, 2008) are used to identify potential threats as well as the critical success factors and processes. Most studies however, aim to reveal the “lessons learned” after occurrence of a certain event and analyze its impact on all aspects of life. Preventive comprehensive studies focusing on HHC still hardly exists. A detailed risk assessment for natural disasters is provided by Melching and Pilon (2006). Besides the general impacts, they present background information regarding cause and incurrence of various disasters. Johnson and Galea (2009) are focusing on the effects of many different types of disasters such as earthquakes, storms, floods, mass fires, terrorism, infectious diseases, and technological disasters on population health, health systems, and their infrastructure. Table 1 summarizes the identified critical success factors for planning and execution of HHC services, the relevant disaster events as well as their expected impacts on the respective critical factors ($\uparrow$ suggests increment, $\downarrow$ implies decrement, and $\leftrightarrow$ assumes constancy). For the ARC in Vienna, blackouts, epidemics, and heat-waves are among the most important disaster types. These are briefly described in the following; for a comprehensive description it is refered to Rest et al. (2012).

Blackouts are often the result of other disasters or man-made- and technical failures. Large scale power failures are affecting virtually every area of daily life. Burchardt et al. (2011) study the effects of long-lasting blackouts on several critical infrastructures like telecommunication, transport (road, rail, water, and air), supply of goods (e.g. fresh water, food), and waste disposal, as well as on the financial and health care sector. It can be concluded that the number of available nurses will decrease, while the number of clients and service times will increase. Especially in urban areas, blackouts will lead to prolonged driving times and reduced trafficability due to the collapse of electric-powered vehicles (e.g. trains, trams, subways) and to failure of traffic management systems (e.g. traffic lights). The operability of the telecommunication infrastructure heavily depends on the availability of backup systems and batteries. Current mobile and broadband technologies, for

Table 1. Influences of disasters (Rest et al., 2012)

	nurses	clients		transport		communication
	number	number	service time	driving times	trafficability	availability
earthquake	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
volcano	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
mass movement	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
storm	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
flood	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$
heat-wave	$\downarrow$	$\uparrow$	$\uparrow$	$\leftrightarrow$	$\leftrightarrow$	$\leftrightarrow$
cold-wave	$\leftrightarrow$	$\uparrow$	$\uparrow$	$\leftrightarrow$	$\leftrightarrow$	$\leftrightarrow$
epidemic	$\downarrow$	$\uparrow$	$\uparrow$	$\leftrightarrow$	$\leftrightarrow$	$\leftrightarrow$
blackout	$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\downarrow$	$\downarrow$

example, can be usually sustained only for a few hours, at maximum.

Epidemics are characterized by a huge increase in the number of clients and service times, paired with a significant decrease in the available nurses. According to Knebel and Phillips (2008) it is expected that more care dependent people would be discharged earlier from hospitals due to short capacities in times of influenza epidemics. In addition he assumes that about a quarter of the nurses will be sick themselves. Another major problem arises from the fact that not all nurses will appear at work. This effect has been analyzed by Ehrenstein et al. (2006), Mackler et al. (2007), and Irvin et al. (2008) for different diseases like avian influenza and pox. The willingness to work mainly depends on the available protective measures (e.g. vaccines) and the nurse's qualification and level of information. Adverse effects on the transport or communication infrastructure can be expected only if social life totally collapses.

Heat waves primarily affect the health situation of the clients because of cardiovascular diseases. Therefore, increases in number of clients and service times are most likely. Investigations of past heat waves as done by Palecki et al. (2001) or Diaz et al. (2002) showed that especially elderly and solitary people are vulnerable to heat waves and that there is a significant increase in mortality in urban areas. The latter is attributed to the urban-heat-island effect which leads to temperatures within city centers that are significantly higher than in the surroundings. In addition, the ARC experienced that there is also a reduced availability of nurses during extreme heat events. Impacts on the communication and the transport infrastructure (e.g. cracked or melted road surfaces, deformed rails) are negligible, as these are usually locally limited.

5. SOLUTION APPROACH

The planning of HHC services is characterized by an initial planning a few days in advance, and some short term changes during the operated day. While the initial planning is usually not time-sensitive, disruptions may occur several times a day and require rapid rescheduling, especially in times of disasters. To solve real world sized instances within reasonable time a time-dependent TS based solution approach has been developed and implemented in the programming language c++. The algorithm is based on the ideas of the unified TS, as used in time-independent routing problems by Cordeau et al. (2001) or Hirsch (2011). Thus, infeasible solutions are temporarily allowed and a dynamically adapted weighted objective function is used to guide the search process.

To speed up the search the developed TS dynamically changes the size of its neighborhood. Starting with a restricted neighborhood, its size is either increased or decreased, dependent on the feasibility and quality of the current solution at the end of each iteration. Particular attention was also paid to the optimization of the starting times of the routes. Due to the time-dependency this is very time consuming, because small changes at the beginning of a route can cause substantial increases in subsequent travel times. However, the objective function and data structure allow to speed up this task by applying a binary search between a certain time interval. Thus, for correct evaluation of the routes, their optimal start times are always computed.

The underlying network of the algorithm is based on timetable data from the public transport system as well as time-independent travel times, extracted from OpenStreetMap (OSM). OSM data has been taken as they are not only available under a creative commons license, but because they are usually of high quality in urban regions. In addition, the OSM community has been actively engaged in providing up-to-date geographical data during past disaster events (e.g. during the 2010 earthquake in Haiti) by digitizing aerial imageries or on-site data collection. For the modeling of the time-dependency, a discrete time approach has been chosen. However, setting the time intervals to the smallest considered time unit, lets the travel time function behave like a discontinuous piecewise linear function. Thus, it complies with the first-in first-out principle. To efficiently compute time-dependent travel time matrices out of the timetables, a dynamic programming approach has been developed and implemented. It is based on the ideas of the algorithm DOT (Decreasing Order of Time) introduced by Chabini and Dean (1999). Starting at the latest possible, it iterates through all time intervals and at each step all possible combinations of public transport modes (bus, tram, train, subway) are checked for shorter travel times. Besides waiting at a station, walking to nearby stations is also taken into account in order to cope with the multimodality.

6. NUMERICAL STUDIES

To show the applicability of the presented solution approach several computational experiments with real-world data from the ARC in Vienna have been carried out. For daily business, instances with up to 202 jobs and 46 nurses are used to compare the approach with the actual planning at the ARC. For this computations it has been assumed that all nurses use public transport to visit their clients.

For the operational scenario with a predefined roster significant improvements can be obtained, with average savings of about 41 % and up to 60 % for individual instances. For the scenario without predefined working times, the average savings increases by additional 10 percentage points. While the first scenario represents daily business, where the dispatcher is legally bounded by the rosters that have been given to the nurses a few weeks before, the second is intended to be used for deriving a roster in mid-term. Therefore, the total working time is only limited by the contracted working times of the nurses. In addition, it is possible to vastly reduce the number of second shifts for both scenarios.

A sensitivity analysis has been carried out in order to depict the effects of various disasters. It is also based on real-world data from the ARC in Vienna. However, in the absence of data of historical events the ARC data has been stochastically modified. Given a real instance of a certain day, both the number of jobs as well as the service times of all jobs are increased in steps of 5 %. The added jobs were randomly taken from a pool of jobs that are located in the same area, but would usually be severed on another day of the week. For each setting 10 instances have been generated. To identify the operational limits during times of disasters, they were solved with a relaxed version of the TS algorithm. The prime principle during such events is to maintain the care for all clients. Therefore, the unrestricted time windows of the jobs are considered and the overtime and care team limitations are neglected. It is further assumed that nurses are able to use either public transport, bicycles or just walking. Going by car has not been considered for two reasons. First, in times of major disasters it is very likely that traffic will collapse. But of even greater importance for HHC service providers, also for daily business, is the fact that more and more nurses in urban regions do not have a driver's license. In order to model blackouts, another set of time-dependent travel time matrices has been computed in which electric-powered vehicles (e.g. trams, trains, subways) are excluded. The results of this analysis are exemplarily shown in Figure 1 for four data sets $A - D$. It shows how many of these 10 instances can be solved within a computation time of 5 minutes.

While data set A seems to be insensitive to the considered increases, B and D start to struggle with increases between 15 and 20 %. Data set D is the most vulnerable. Only a few instances can be solved at a simultaneous increase of 10 %. It also revealed that a sole increase in service time is easier to cope with than an increase in the number of jobs. Regarding the different transport modes it can be stated that the care can be sustained the longest if bicycles were used. Because of the short distances between the clients, cycling is usually the most efficient transport mode in urban regions, also for daily business, especially if traffic and parking conditions are taken into account. In the case that the rostered working times can be neglected, all HHC teams of the analyzed instances are able to cope with increases in jobs and service times of 20 %, independent of the considered transport modes.

predefined roster

	time / jobs	+ 0 %				+ 5 %				+ 10 %				+ 15 %				+ 20 %			
		public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking	public transport	blackout	bicycle	walking
A	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
B	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	9	7	8	10	6
	+ 20 %	10	10	10	10	10	9	10	10	10	10	10	8	9	9	10	8	1	1	10	0
C	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	9	10	9	0	0	10	0
	+ 10 %	10	10	10	10	9	10	10	10	3	5	10	2	0	0	10	0	0	0	3	0
	+ 15 %	9	8	10	8	2	1	10	1	0	0	10	0	0	0	1	0	0	0	0	0
	+ 20 %	2	1	10	1	0	0	9	0	0	0	1	0	0	0	0	0	0	0	0	0
D	+ 0 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 5 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 10 %	10	10	10	10	10	10	10	10	10	10	10	10	9	10	10	10	10	10	10	10
	+ 15 %	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
	+ 20 %	10	10	10	10	10	10	10	10	10	9	10	10	9	9	10	6	0	0	10	0

public transport blackout bicycle walking

Fig. 1. Number of solvable instances for each data set at increasing number of jobs and service times, using different transport modes

7. CONCLUSION

The demand for HHC services is rising and there are many potential threats that may influence them. To tackle these challenges, a time-dependent TS based solution approach has been developed and implemented. It ensures that the available resources are used as efficient as possible. By design, the disaster modeling is done independently from the optimization. This allows to deal with various disaster types and to incorporate real-time data, as available at public authorities.

Disaster situations are usually highly dynamic events that require repeated adjustments throughout a day. Even if good schedules can be computed within seconds, the presented DSS is currently only capable of computing schedules from scratch. Rescheduling requires an adjustment of the input data and may lead to entirely different schedules for the nurses. However, it might be preferable to adapt to the new situation with as few changes as possible, especially if communication is limited. Hence, its most appropriate area of application is to support scheduling in the day-to-day business as well as to raise awareness and preparedness for disaster situations. Nevertheless, a new solution approach that is operational in dynamic environments, and thus able to overcome this limitations, is currently in development.

REFERENCES

Akjiratikarl, C., Yenradee, P., and Drake, P.R. (2007). Pso-based algorithm for home care worker scheduling in the UK. *Comput Ind Eng*, 53(4), 559 – 583. doi: 10.1016/j.cie.2007.06.002.

Bertels, S. and Fahle, T. (2006). A hybrid setup for a hybrid scenario: Combining heuristics for the home health care problem. *Comput Oper Res*, 33(10), 2866–2890. doi:10.1016/j.cor.2005.01.015.

Bräysy, O., Dullaert, W., and Nakari, P. (2009). The potential of optimization in communal routing problems: case studies from Finland. *J Transp Geogr*, 17(6), 484–490. doi:10.1016/j.jtrangeo.2008.10.003.

Bredström, D. and Rönnqvist, M. (2007). A branch and price algorithm for the combined vehicle routing and scheduling problem with synchronization constraints. Discussion Paper No. 2007/7, NHH Dept. of Finance & Management Science, Norwegian School of Economics, Norway. doi:10.2139/ssrn.971726.

Bredström, D. and Rönnqvist, M. (2008). Combined vehicle routing and scheduling with temporal precedence and synchronization constraints. *Eur J Oper Res*, 191(1), 19–31. doi:10.1016/j.ejor.2007.07.033.

Burchardt, U., Feist, T., Neumann, N., Fell, H.J., Röspel, R., and Sitte, P. (2011). Gefährdung und Verletzbarkeit moderner Gesellschaften am Beispiel eines grossräumigen und langandauernden Ausfalls der Stromversorgung. Technology assessment project, Committee on Education, Research and Technology Assessment of the German Bundestag, Berlin.

Chabini, I. and Dean, B. (1999). Shortest path problems in discrete-time dynamic networks: Complexity, algorithms, and implementations. Technical report, Massachusetts Institute of Technology, Cambridge, MA.

Cordeau, J.F., Laporte, G., and Mercier, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *J Oper Res Soc*, 52(8), 928–936.

Diaz, J., Jordan, A., Garcia, R., Lopez, C., Alberdi, J., Hernandez, E., and Otero, A. (2002). Heat waves in Madrid 1986-1997: effects on the health of the elderly. *Int Arch Occup Environ Health*, 75(3), 163–170.

Dohn, A., Rasmussen, M.S., Justesen, T., and Larsen, J. (2008). The home care crew scheduling problem. In K. Sheibani (ed.), *Proceedings of the 1st International Conference on Applied Operational Research (ICAOR'08)*, volume 1 of *Lecture Notes in Management Science*, 1–8. Yerevan, Armenia.

Ehrenstein, B., Hanses, F., and Salzberger, B. (2006). Influenza pandemic and professional duty: family or patients first? A survey of hospital employees. *BMC Public Health*, 6(311).

Elbenani, B., Ferland, J., and Gascon, V. (2008). Mathematical programming approach for routing home care nurses. In *Proceedings of Industrial Engineering and Engineering Management 2008 (IEEM08)*, 107–111. Singapore. doi:10.1109/IEEM.2008.4737841.

Eveborn, P., Flisberg, P., and Rönnqvist, M. (2006). Laps care–an operational system for staff planning of home care. *Eur J Oper Res*, 171(3), 962–976. doi: 10.1016/j.ejor.2005.01.011.

Eveborn, P., Rönnqvist, M., Einarsdóttir, H., Eklund, M., Lidén, K., and Almroth, M. (2009). Operations research improves quality and efficiency in home care. *Interfaces*, 39(1), 18–34. doi:10.1287/inte.1080.0411.

Fikar, C. and Hirsch, P. (2014). A matheuristic for routing real-world home service transport systems facilitating walking. *J Clean Prod.* doi: 10.1016/j.jclepro.2014.07.013.

Hiermann, G., Prandtstetter, M., Rendl, A., Puchinger, J., and Raidl, G.R. (2013). Metaheuristics for solving a multimodal home-healthcare scheduling problem. *Cent Eur J Oper Res*, 1–25. doi:10.1007/s10100-013-0305-8.

Hirsch, P. (2011). Minimizing empty truck loads in round timber transport with tabu search strategies. *Int J Inf Syst Supply Chain Manag*, 4(2), 15–41. doi: 10.4018/jisscm.2011040102.

Irvin, C., Cindrich, L., Patterson, W., and Southall, A. (2008). Survey of Hospital Healthcare Personnel Response during a Potential Avian Influenza Pandemic: Will They Come to Work? *Prehosp Disaster Med*, 23(4), 328–335.

Johnson, J. and Galea, S. (2009). Lifespan perspectives on natural disasters. In K. Cherry (ed.), *Disasters and Population Health*, 281–326. Springer, New York.

Knebel, A. and Phillips, S. (2008). Home health care during an influenza pandemic: Issues and resources. AHRQ Publication No. 08-0018, Agency for Healthcare Research and Quality, Rockville.

Mackler, N., Wilkerson, W., and Cinti, S. (2007). Will First Responders Show Up for Work During a Pandemic? Lessons from a Smallpox Vaccination Survey of Paramedics. *Disaster Manag Response*, 5(2), 45–48.

Mankowska, D.S., Meisel, F., and Bierwirth, C. (2013). The home health care routing and scheduling problem with interdependent services. *Health Care Manag Sci*, 17(1), 15–30. doi:10.1007/s10729-013-9243-1.

Melching, C. and Pilon, P. (2006). Comprehensive risk assessment for natural hazards. Technical Report WMO/TD No. 955, World Meteorological Organization, Geneva.

NAHC (2008). Emergency preparedness packet for home health agencies. Technical report, The National Association for Home Care & Hospice, Washington.

Palecki, M., Changnon, S., and Kunkel, K. (2001). The nature and impacts of the july 1999 heat wave in the midwestern United States: learning from the lessons of 1995. *Bull Am Meteorol Soc*, 82(7), 1353–1367.

Rasmussen, M.S., Justesen, T., Dohn, A., and Larsen, J. (2012). The home care crew scheduling problem: Preference-based visit clustering and temporal dependencies. *Eur J Oper Res*, 219(3), 598–610. doi: 10.1016/j.ejor.2011.10.048.

Rest, K.D. and Hirsch, P. (2013). Time-dependent travel times and multi-modal transport for daily home health care planning. In C. Cortés, M. Gendreau, P. Rey, and D. Sáez (eds.), *Proceedings of TRISTAN VIII - The Eight Triennial Symposium on Transportation Analysis*. San Pedro de Atacama, CHILE. Http://www.isci.cl/tristan/.

Rest, K.D., Trautsamwieser, A., and Hirsch, P. (2012). Trends and risks in home health care. *J Humanit Logist Supply Chain Manag*, 2(1), 34–53. doi: 10.1108/20426741211225993.

Trautsamwieser, A., Gronalt, M., and Hirsch, P. (2011). Securing home health care in times of natural disasters. *OR Spectr*, 33(3), 787–813. doi:10.1007/s00291-011-0253-4.

Trautsamwieser, A. and Hirsch, P. (2014). A branch-price-and-cut approach for solving the medium-term home health care planning problem. *Networks*, 64(3), 143–159. doi:10.1002/net.21566.

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Daily scheduling of home health care services using time-dependent public transport

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Abstract This paper presents a real-world optimization problem in home health care that is solved on a daily basis. It can be described as follows: care staff members with different qualification levels have to visit certain clients at least once per day. Assignment constraints and hard time windows at the clients have to be observed. The staff members have a maximum working time and their workday can be separated into two shifts. A mandatory break that can also be partitioned needs to be scheduled if the consecutive working time exceeds a certain threshold. The objective is to minimize the total travel- and waiting times of the care staff. Additionally, factors influencing the satisfaction of the clients or the care staff are considered. Most of the care staff members from the Austrian Red Cross (ARC) in Vienna use a combination of public transport modes (bus, tram, train, and metro) and walking. We present a novel model formulation for this problem, followed by an efficient exact solution approach to compute the time-dependent travel times out of the timetables from public transport service providers on a minute-basis. These travel time matrices are then used as input for three Tabu Search based solution methods for the scheduling problem. Extensive numerical studies with real-world data from the ARC show that the current planning can be improved significantly when these methods are applied.

Keywords Home health care · Multimodal routing · Time-dependent travel times · Tabu search

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1 Introduction

Home health care (HHC) services are ranging from assistance in leading the household and maintenance of social contacts to qualified home nursing. They allow old and frail people a self-determined living in their familiar environment as long as possible. Demographic (e.g., rising life expectancy) and social (e.g., more childless families and prolonged employment) changes are leading to more care dependent people and to a reduced potential of family care. As a result, many industrialized countries are facing a significant increase in demand for HHC services and further rises must be expected. Additionally, HHC service providers are exposed to high cost pressure and are thus, highly interested in suitable decision support systems (DSS). Due to various constraints the planning of the care staff's schedules is quite complex. Matta et al. (2014) depict the main processes and management decisions after analyzing several HHC service providers in France and Italy. In Austria, the planning process is usually still done manually. Hence, DSSs lead presumably not only to better solutions, but also to a reduced planning effort.

The daily HHC scheduling problem can be summarized as follows: A certain number of care staff members with different qualification levels has to visit a set of clients at least once during a day. Assignment constraints and hard time windows of these visits as well as maximum working times per day and mandatory break times have to be observed. The mandatory break times can also be splitted. The objective is to minimize the total travel- and waiting times of the care staff. Additionally, factors influencing the satisfaction of the clients or the staff members are either considered within the objective function or through hard constraints. A detailed formal explanation of the problem can be found in Sect. 3.

The presented research is based on a collaborative project with the Austrian Red Cross (ARC), one of the leading HHC service providers in Austria. According to them, the majority of care staff in urban areas uses public transport (bus, tram, subway, and train) to visit their clients, if there is a well-developed public transport system. In the case of Vienna, more than 90 % of the ARC care staff uses exclusively public transport. As public transport operates on timetables with varying intervals and travel times during the day, time-dependent travel times are considered to model real travel times the best possible way. Public transport also implies multi-modality as different lines of the public transport system could be necessary to reach the homes of the clients (e.g., the combination bus-subway-tram). Existing research in the field of HHC usually considers just the use of a single mode of transport for the staff and to the best of our knowledge, also none of these approaches are based on time-dependent travel times. From a modeling point of view, the presented problem can be seen as a time-dependent vehicle routing problem (TDVRP) with additional HHC-related constraints.

The main contribution of this paper is to present solution approaches to solve the introduced real-world HHC problem with time-dependencies and multi-modality. In a first step we develop an efficient exact solution approach to compute time-dependent travel times out of the timetables from the public transport service providers. Time intervals of 1 min are used. The generated travel time matrices are then used as input for metaheuristic solution approaches. We have designed and implemented three Tabu Search (TS) approaches and compare their solutions against each other as well as with the actual planning of the ARC. The numerical studies are based on real-world data and deal with problem sizes of up to 46 care staff members and 202 visits. The results show that the solution approaches are capable to provide solutions of good quality in short computation times. The presented methods are tailored to the requirements of HHC in urban areas. Nevertheless, it is worth mentioning that the introduced ideas can also be used with adapted constraints in other application areas like for example service technician routing.

Our research on the time-dependent HHC problem differs from the published work by combining both research areas. Thus, we link a complex real-world problem in the field of HHC with the complexity of time-dependent routing. The contributions to the individual areas are as follows. For optimization of daily HHC services, we extend the published work by considering additional constraints related to working time restrictions (e.g., split breaks, minimal working times). In the area of time-dependent routing, we present an efficient way to compute time-dependent travel times out of timetable data as well as an approach to determine the optimal start time of time-dependent routes.

The organization of the paper is as follows: Sect. 2 contains a literature review on HHC as well as on time-dependent routing. In Sect. 3 a problem description is given, including a linear programming formulation. Section 4 explains the modeling aspects of the time-dependency, followed by our TS based solution approaches in Sect. 5. To show the applicability of our approaches, numerical studies with real-world data from the region of Vienna are presented in Sect. 6. Finally, conclusions and an outlook on future research are given in Sect. 7.

2 Literature review

In the following we present an overview on literature about HHC scheduling and time-dependent routing.

2.1 Home health care

The problem we are dealing with is usually addressed in literature as HHC problem. Optimization in the field of HHC is a rather young but quickly evolving research area, due to the rising importance of HHC for today's society. Thus, many different approaches have been published in the recent years. Besides the varying legal and organizational requirements the points of focus are diverse: The first paper in this field we are aware of, comes from Begur et al. (1997). The authors present a sequential savings algorithm to solve a HHC problem in the USA. Cheng and Rich (1998) introduce a model formulation for the HHC problem. They give both, a two- and a three-index formulation and solve them with a construction heuristic as well as with CPLEX as a MIP solver. Bertels and Fahle (2006) list several factors that are relevant for an allocation of clients to care staff members. For solving their HHC problem they have developed a software called PARPAP, a combination of Constraint Programming (CP) with the metaheuristics Simulated Annealing and TS, which is able to solve instances with up to 50 staff members and 326 jobs. Eveborn et al. (2006) developed a DSS called Laps Care for Swedish HHC service providers. They treated the problem as a set partitioning problem and use a solution approach based on repeated matching. Considered modes of transport are car, bicycle, and walking. Nevertheless, these modes of transport are not combined during the trip of a staff member. They present results for real-world instances, including an urban region, where all journeys are made by foot due to the high density of clients. Their recent work on this topic has been published in Eveborn et al. (2009). Akjiratikarl et al. (2007) compare solutions obtained by a Particle Swarm Optimization based metaheuristic with schedules from a local government authority in UK using its existing manual processes and with a proprietary routing software. Elbenani et al. (2008) present a TS algorithm to solve a real-world HHC problem in Canada. A unique feature of this work is that nurses have to collect blood samples from some clients and deliver them to the hospital within a given time window. To facilitate continuity of care for clients requiring several visits a day, penalty costs are introduced if the follow-ups are carried out by different nurses. Bräysy et al. (2009) present some case studies, which aim to optimize several communal services (HHC, transportation of the elderly, and home meal delivery) in Finland by using a commercial VRP solver. For HHC, the authors claim that care staff members can use different modes of transport (walking, car, bicycle, and bus); however, a single average travel speed over all modes is taken. Dohn et al. (2008) use a Branch-and-Price approach to solve real-world instances with up to 150 jobs and 15 staff members. Bredström and Rönnqvist (2007), Bredström and Rönnqvist (2008), Rasmussen et al. (2012), and Mankowska et al. (2013) focused their work on interdependent services, taking into account pairwise synchronization as well as pairwise temporal precedence between jobs. Like Dohn et al. (2008), Bredström and Rönnqvist (2007) and Rasmussen et al. (2012) also present a Branch-and-Price algorithm. To reduce the computational effort, Rasmussen et al. (2012) further analyze different clustering schemes. Bredström and Rönnqvist (2008) and Mankowska et al. (2013) use metaheuristic solution approaches to achieve this goal. Trautsamwieser et al. (2011) present a model formulation for HHC in Austria considering many legal constraints as well as the satisfaction of clients and care staff members through several factors within a weighted objective function. Mandatory breaks are also included if the working time of a staff member exceeds a certain amount of time, however, breaks are always of fixed length and can not be partitioned into smaller parts. Trautsamwieser et al. (2011) also analyze the effects of some natural disasters on the planning. While the focus of their work is on rural areas, Rest et al. (2012) review trends and risks in HHC with a focus on urban regions. Another recent work with a focus on urban regions has been published by Hiermann et al. (2013). The authors present a two-stage approach that uses CP to generate a feasible initial solution that is further improved with one of four implemented metaheuristics (Variable Neighborhood Search, Memetic Algorithm, Scatter Search, and Simulated Annealing). Care staff members are able to use either public transport or cars. Their travel time data is based on estimates from a public transport service provider as well as on floating car data for the road network. However, a single estimate is used for each mode and thus, they do not rely on the actual time of departure. Real-world instances of an HHC service provider in Vienna are used to evaluate their solution approach.

In addition to the daily scheduling of HHC services, there is also an increasing research interest in the periodic/mid-term HHC problem. This problem is characterized by a prolonged planning horizon of a week or more, which induces additional constraints (e.g., rest periods, visiting frequencies, continuity of care) and requires different modeling and solution approaches. Therefore, those who are interested in this type of HHC problem are referred to the recent publications of Cappanera and Scutellà (2014), Liu et al. (2014), or Trautsamwieser and Hirsch (2014) as these already contain comprehensive literature reviews.

2.2 Time-dependent routing

Using time-dependent travel times leads to schedules that are more viable, especially in urban regions. Because of this main benefit, there were still some early efforts to incorporate varying travel times into models and algorithms. Nevertheless, not all of them satisfy the First-In First Out (FIFO) principle, although it is a natural assumption. FIFO, also referred to as non-passing property, implies that a vehicle departing from node i to node j using arc (i, j) at time t will always arrive before or at the same time as a vehicle using the same arc but departing at a later time: $A_{ij}(t_0) \leq A_{ij}(t_1)$ as long as $t_1 > t_0$. Hence, the arrival time function A_{ij} will be a non-decreasing function of time. Malandraki and Daskin (1992) were among the first who stated a mixed integer linear programming formulation of the TDVRP. A stepwise travel time function is assumed, but as waiting at nodes is permitted, the actual travel time function (after computing the shortest paths) behaves like a continuous function, as long as the travel time is not increasing. FIFO is achieved because in times of decreasing travel times, travel time will be substituted with waiting time. However, one will arrive at the same time which does not represent reality. To solve the model formulation, a nearest neighbor and a cutting plane heuristic are presented. Hill and Benton (1992) present a modeling approach, where the time-dependent information is assigned to the nodes instead of the edges. This can be interpreted as the average speed for the area around a node. In this way they wanted to simplify data collection and to reduce the computational effort. Their usage of different speed levels for discrete time periods leads to piecewise constant speed functions. As a result, the travel time function is also piecewise constant and does not satisfy the FIFO property. To validate their approach the authors are mentioning the implementation of a greedy heuristic for a TDVRP in a city with 210 locations and time-dependent travel speeds for 96 time periods. Ichoua et al. (2003) also use piecewise constant speed, but in contrary to Hill and Benton (1992), they do not assume constant speed over the entire length of the link. The travel speed is adjusted when the vehicle crosses the boundaries of the time periods. Hence, the travel time is computed by summing up the time used for each part of the link. This approach results in a travel time function, that is piecewise continuous over the time and thus satisfies FIFO. Fleischmann et al. (2004) provide a modeling approach that is based on linear smoothing of the travel time function. The underlying travel speeds are considered to be piecewise constant, as given by traffic information systems. Smoothing is used to comply with the FIFO property, as such speed data usually leads to travel time functions with jumps between two time intervals. For solving a VRP with customer and route time windows, where waiting is not allowed, they have implemented various heuristics, based on combinations of a savings heuristic, sequential insertion heuristic, and a 2-opt algorithm. Their approach is tested on real data from logistics service providers in Berlin with up to 786 orders and 84 vehicles. The results are also analyzed with respect to different numbers of time slots. More recent work on this topic has been done for example by Kritzinger et al. (2011). The authors are tackling a TDVRP with soft time windows by using a Variable Neighborhood Search procedure. Ehmke et al. (2012) are presenting an optimization framework to solve the time-dependent traveling salesman problem (TDTSP) and the TDVRP. The framework is based on several simple heuristics, as well as on a TS based metaheuristic. In addition to optimization, their work also focuses on data collection and preparation.

Optimizing the start time of a route has a major impact on the objective function, due to the tradeoff between the travel time and the tardiness from time windows. Even though, this is rarely discussed within current work which is based on heuristic or metaheuristic solution approaches. Dabia et al. (2013) claim to be the first, solving the TDVRP with time windows exactly, using a Branch-and-cut-and-price algorithm. Time-dependency is modeled in the same way as in Ichoua et al. (2003), stepwise speed functions are translated into stepwise linear travel time functions to satisfy the FIFO principle.

3 Problem description

The HHC problem we are dealing with is based on the demands of the ARC and has a daily planning horizon. It specifically aims to deal with the peculiarities of urban regions and can be described by a given set of care staff members $\mathcal{N}$ and a given set of clients $\mathcal{C}$. Each client $c \in \mathcal{C}$ needs one or more services per day, while each service is modeled as a single job $j \in \mathcal{J}$. Depending on the task that has to be carried out, a certain minimal qualification level q_j is needed. For example, if the job consists of cleaning or preparing lunch it is carried out by home helpers, whereas for medical treatments a nurse is needed. It is assumed that staff members are allowed to carry out jobs that require a qualification level that is one level below their qualification. The duration d_j of a job j is of fixed length and the job must start within a given hard time window bounded by $[a_j, b_j]$. A smooth communication and mutual trust are crucial for successful care. Therefore, the language skills of the staff members and clients, as well as the preferred or rejected (e.g., due to previous incidents or personal dislike) care staff members of the clients have to be considered. Along with the qualification, this information limits the assignment of jobs to staff members. Rather than taking care of each restriction individually, we

Table 1 Notations for the model formulation

Data	
N	Number of care staff members
S	Number of shifts (tours)
C	Number of clients
J	Number of jobs
L	Number of qualification levels
T	Number of discrete time values during the working day
P	Number of lengths in which the break can be partitioned
$\mathcal{N} = \{1, \ldots, N\}$	Set of care staff members
$\mathcal{N}_j^F \subseteq \mathcal{N}$	Set storing the feasible care staff member for each job j
$\mathcal{S} = \{1, \ldots, S\}$	Set of shifts
$\mathcal{C} = \{1, \ldots, C\}$	Set of clients
$\mathcal{J} = \{1, \ldots, J\}$	Set of jobs
$\mathcal{J}_0 = \{1, \ldots, J+1\}$	Set of jobs including the artificial depot
$\mathcal{L} = \{1, \ldots, L\}$	Set of qualification levels
$\mathcal{T} = \{1, \ldots, T\}$	Set of discrete time values
$\mathcal{P} = \{p_r : r \in \{1, \ldots, P\}\}$	Indexed set of break lengths
W_n	Contracted working time of care staff member n
$\bar{W}_n$	Maximum daily working time of care staff member n
ST	Time after which a waiting time leads to a second shift
SC	Compensation for working a second shift
OC	Compensation for overtime
D	Point of time marking the start of evening shifts
MS	Minimum working time for morning shifts
ES	Minimum working time for evening shifts
PT	Working time after which a break is mandatory
PR_k	Required break time if the care staff member of shift k needs to make a break
O	Maximum amount of overtime over all care staff members
q_j	Qualification level of job j
Q_n	Qualification level of care staff member n
d_j	Service time for a job j
a_j, b_j	Lower and upper bound of the time window of job j
A_k, B_k	Lower and upper bound of the working time window of a care staff member's shift k according to the roster
$\bar{A}_k, \bar{B}_k$	Lower and upper bound of the working time window of a care staff member's shift k according to legal restrictions
tt_{ijt}	Travel time from job i to job j departing at time t
$\vartheta : \mathcal{S} \rightarrow \mathcal{N}$	Function matching shifts with corresponding staff members

Decision variables	
x_{ijtk}	Binary, 1 if the care staff member departs from job i at time t in order to visit job j on tour k, 0 otherwise
y_{jrk}	Binary, 1 if a break of length r is made before job j on tour k, 0 otherwise

Table 1 continued

Decision variables	
Y_k	Binary, 1 if there is a break on tour k, 0 otherwise
z_n	Binary, 1 if care staff member n works a second shift, 0 otherwise
$v_k, \bar{v}_k$	Binary, 1 if shift k is used as an morning shift (v_k) or evening shift ($\bar{v}_k$), 0 otherwise
u_j, s_j	Arrival time (u_j) and starting time (s_j) of job j
S_k, E_k	Starting (S_k) and ending time (E_k) of shift k
$o_n, \bar{o}_k$	Overtime of care staff member n (o_n) and at shift k ($\bar{o}_k$)

aggregate them into single sets $\mathcal{N}_j^F$, storing the feasible care staff member for each job j.

Each staff member $n \in \mathcal{N}$ is mainly characterized by his/her qualification level Q_n and working times. In Austria, HHC service providers are legally obliged to inform their employees some weeks in advance of their upcoming working times by handing over a roster. The roster states the begin A_k and end of each shift B_k and deviations from the rosters imply overtime. The working time of each staff member starts at the first and ends at the last client of his/her tour. As the majority of the jobs are piling up in the morning, at noon, and in the evening, they often have to work two shifts a day. Working a second shift is not very popular with the staff members because in general, they are not able to make good use of the interruption. From a modeling point of view we treat each shift $k \in \mathcal{V}$ as a single tour, using a matching function $\vartheta(k)$ to identify the corresponding staff member. Due to various contracts, staff members have not only different contracted hours W_n, but also different legal claims regarding working times (earliest working time $\bar{A}_k$, latest working time $\bar{B}_k$, minimum working time for morning shifts MS and evening shifts ES, as well as maximum total working times $\bar{W}_n$), and break times PR_k. To substitute waiting time, it is possible to split the break into smaller parts. The possible break lengths are given in the indexed set $\mathcal{P}$. What mainly distinguishes our problem from previous work in HHC is that care staff members use public transport. In urban regions like Vienna, the denser public transport infrastructure together with shorter distances between the clients encourage them to use public transport. This makes sense especially when the traffic and parking situation are taken into account. Within the public transport system staff members have to switch between different lines of buses, trams, subways, and trains to reach their destinations. These are operating on timetables and as there are severe fluctuations in the driving intervals, time-dependent travel times are considered to obtain viable solutions. Especially in the suburbs, there are severe fluctuations of travel times between rush hours and off-peak times. The travel time between two jobs i and j at a certain departure time t is given by tt_{ijt}.

The following model formulation is presented in order to give a precise problem description. We tried solving small instances with 6 staff members and 30 jobs with the solver software FICO Xpress 7.0, but due to the large number of time intervals ($T = 960$) we are not able to get a solution with an acceptable gap within several days of computation time. To solve real-world sized instances, we therefore propose solution approaches based on the metaheuristic TS as introduced in Sect. 5. Table 1 gives an overview on the notation. The binary decision variable $x_{ijtk} = 1$ if the care staff member of shift k departs from job i at time t to carry out job j, 0 otherwise. The starting times of the jobs are denoted by s_j and take discrete values from set $\mathcal{T}$. Similarly, u_j represents the starting time of a break at job j and the length of the breaks is encoded in the binary variable y_{jrk}. $y_{jrk} = 1$ if the staff member of shift k makes a break of length r before serving the client of job j. S_k (resp. E_k) represents the starting (resp. ending) time of shift k. The overtime of a staff member is counted by o_n. If a staff member works a second shift the binary variable $z_n = 1$. The starting time of a shift indicates if it has to be treated as a morning or an evening shift. If the binary variable $v_k = 1$ the staff member is working a morning shift, whereas $\bar{v}_k = 1$ indicates an evening shift, which has a larger minimum working time requirement. In case $v_k = \bar{v}_k = 0$, the shift is not performed at all.

$$\min \sum_{k \in \mathcal{S}} (E_k - S_k - PR_k \cdot Y_k) \tag{1}$$

$$+ OC \sum_{n \in \mathcal{N}} o_n \tag{2}$$

$$+ SC \sum_{n \in \mathcal{N}} z_n \tag{3}$$

$$+ \sum_{i \in \mathcal{J}_0} \sum_{j \in \mathcal{J}} \sum_{t \in \mathcal{T}} \sum_{k \in \mathcal{S}: q_j < Q_{\vartheta(k)}} d_j \cdot x_{ijtk} \tag{4}$$

The main objective is to minimize the sum of all shift lengths (1), resulting in a minimization of travel and waiting times as the durations of the jobs are fixed. To ensure the satisfaction of clients and staff members a dual strategy is applied. Factors with easily determinable impacts to the objective are integrated by using a weighted objective function. Overtime (2), the number of second shifts (3), and overqualification (4) are taken into account this way. All of these are not only costly for the HHC service providers, they also have a negative impact on the satisfaction of the staff members. To comply with the objective function, those factors are also measured in minutes. Overtime is measured by the time exceeding the daily working hours or, if the optimization is based on a given roster, by the deviations from the roster. It is penalized with an overtime surcharge OC. The number of second shifts gets multiplied with the time SC a staff member gets as compensation for the double journey, while overqualification counts the time a staff member with a higher qualification level performs a job that only requires a lower qualification. Other factors are implemented through aspiration levels. This is either done by adding constraints or by tightening given hard constraints. The given time windows for jobs are quite long for HHC providers in reality. But especially aged people require consistency with respect to visiting times. Therefore, dispatchers could decide to tighten some time windows based on former visiting data in order to satisfy these demands.

$$\sum_{i\in\mathcal{J}_0}\sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{S}} x_{ijtk} = 1 \quad \forall j \in \mathcal{J} \tag{5}$$

$$\sum_{j\in\mathcal{J}_0}\sum_{t\in\mathcal{T}} x_{0jtk} = 1 \quad \forall k \in \mathcal{S} \tag{6}$$

$$\sum_{i\in\mathcal{J}_0}\sum_{t\in\mathcal{T}} x_{i0tk} = 1 \quad \forall k \in \mathcal{S} \tag{7}$$

$$\sum_{i\in\mathcal{J}_0}\sum_{t\in\mathcal{T}} x_{ijtk} = \sum_{h\in\mathcal{J}_0}\sum_{t\in\mathcal{T}} x_{jhtk} \quad \forall j \in \mathcal{J}, \forall k \in \mathcal{S} \tag{8}$$

$$\sum_{i\in\mathcal{J}_0}\sum_{t\in\mathcal{T}} x_{ijtk} = 0 \quad \forall j \in \mathcal{J}, k \in \mathcal{S} : \vartheta(k) \notin \mathcal{N}_j^F \tag{9}$$

(5) guarantee that each job is covered exactly once. Even if the computed schedule may not need all care staff members, all of them leave the depot exactly once (6)–(7). However, those who are not working, finish their tour immediately at the depot ($x_{00tk} = 1$). To identify the start and end of a tour an artificial depot is used. The flow conservation constraints are given by (8), while (9) allow only those staff members to execute a job, who are feasible with respect to the qualification level, language skills, and acceptance (no rejection by the client and/or staff member).

$$s_i = \sum_{t\in\mathcal{T}}(t - d_i)\sum_{j\in\mathcal{J}_0}\sum_{k\in\mathcal{S}} x_{ijtk} \quad \forall i \in \mathcal{J} \tag{10}$$

$$s_i \geq a_i \quad \forall i \in \mathcal{J} \tag{11}$$

$$s_i \leq b_i \quad \forall i \in \mathcal{J} \tag{12}$$

$$s_i + \sum_{t\in\mathcal{T}}(d_i + tt_{ijt})\sum_{k\in\mathcal{S}} x_{ijtk} \leq u_j + b_i(1 - \sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{S}} x_{ijtk}) \quad \forall i,j \in \mathcal{J} \tag{13}$$

$$s_i + \sum_{t\in\mathcal{T}}(d_i + tt_{ijt})\sum_{k\in\mathcal{S}} x_{ijtk} \geq u_j - b_j(1 - \sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{S}} x_{ijtk}) \quad \forall i,j \in \mathcal{J} \tag{14}$$

$$u_i + \sum_{r\in\{1,\ldots,P\}} p_r \sum_{k\in\mathcal{S}} y_{irk} \leq s_i \quad \forall i \in \mathcal{J} \tag{15}$$

$$s_i - u_i - \sum_{r\in\{1,\ldots,P\}} p_r \sum_{k\in\mathcal{S}} y_{irk} \leq ST - 1 \quad \forall i \in \mathcal{J} \tag{16}$$

(10) link the start time of each job with the departure time t encoded in the binary variables x_{ijtk}, and (11) and (12) force it to be within the time window of the job. Equations (13)–(15) are responsible for setting the correct starting times of the jobs and breaks. Equation (16) limit the waiting time before each job to less than ST minutes. Waiting times of ST minutes or longer would otherwise interrupt the working time and impose another shift.

$$S_k = \sum_{t \in \mathcal{T}} t \sum_{i \in \mathcal{J}_0} x_{0itk} \quad \forall k \in \mathcal{S} \tag{17}$$

$$E_k = \sum_{t \in \mathcal{T}} t \sum_{i \in \mathcal{J}_0} x_{i0tk} \quad \forall k \in \mathcal{S} \tag{18}$$

$$S_k \geq \bar{A}_k \quad \forall k \in \mathcal{S} \tag{19}$$

$$S_k \leq E_k \quad \forall k \in \mathcal{S} \tag{20}$$

$$E_k \leq \bar{B}_k \quad \forall k \in \mathcal{S} \tag{21}$$

$$\bar{W}_n \geq \sum_{k \in \mathcal{S}:\vartheta(k)=n} (E_k - S_k - PR_k \cdot Y_k) \quad \forall n \in \mathcal{N} \tag{22}$$

$$v_k = \sum_{t \in \mathcal{T}:t<D} \sum_{i \in \mathcal{J}} x_{0itk} \quad \forall k \in \mathcal{S} \tag{23}$$

$$\bar{v}_k = \sum_{t \in \mathcal{T}:t \geq D} \sum_{i \in \mathcal{J}} x_{0itk} \quad \forall k \in \mathcal{S} \tag{24}$$

$$MS \cdot v_k + ES \cdot \bar{v}_k \leq E_k - S_k - PR_k \cdot Y_k \quad \forall k \in \mathcal{S} \tag{25}$$

(17) and (18) set the starting and ending times of the shifts. The compliance with the earliest and latest working times is ensured by (19)–(21), while observance of the maximum daily working time restriction is guaranteed by (22). Equation (23)–(24) identify if the shift is a morning or an evening shift, depending on whether the shift starts before time D or not. Subsequently, constraints (25) force that the right minimal working time is taken into account, but only if the staff member actually works that shift.

$$\begin{aligned} \bar{o}_k &\geq E_k - B_k && \forall k \in \mathcal{S} \\ o_n &= \sum_{k \in \mathcal{S}:\vartheta(k)=n} \bar{o}_k && \forall n \in \mathcal{N} \end{aligned} \tag{26a}$$

$$o_n \geq \sum_{k \in \mathcal{S}:\vartheta(k)=n} (E_k - S_k - PR_k \cdot Y_k) - W_n \qquad \forall n \in \mathcal{N} \tag{26b}$$

$$\sum_{n \in \mathcal{N}} o_n \leq O \tag{27}$$

The overtime is computed either by (26a) or (26b), depending on the desired operative scenario. Equation (26a) is used if a predefined roster is given, otherwise (26b) is applied. In the first case, overtime occurs immediately if a staff member works outside of his/her roster. A staff member may exceed his/her planned end of shift B_k, while starting earlier is not permitted. Without a given roster, only the contracted working time for each staff member W_n is considered (26b). Equation (27) restricts the total amount of overtime for the day over all care staff by the parameter O.

$$z_n \geq \sum_{k \in \mathcal{S}: \vartheta(k)=n} (v_k + \bar{v}_k) - 1 \quad \forall n \in \mathcal{N} \tag{28}$$

$$S_h \geq E_k + ST \qquad \forall k, h \in \mathcal{S} : k < h \wedge \vartheta(k) = \vartheta(h) \tag{29}$$

$$\begin{aligned} & S_h \geq E_k + tt_{ijt}(x_{i0tk} + \sum_{l \in \mathcal{T}} x_{0jlh} - 1) \\ & \quad \forall i, j \in \mathcal{J}, t \in \mathcal{T}, k, h \in \mathcal{S} : k < h \wedge \vartheta(k) = \vartheta(h) \end{aligned} \tag{30}$$

In order to count the second shifts, the binary variable z_n is set to 1 if a staff member works two shifts (28). In such a case, it has to be ensured that the time between the two shifts exceeds at least ST minutes (29), otherwise it counts as waiting time from a legal point of view. Furthermore, the time between the two shifts must be sufficient to travel from the last job of the first shift to the first job of the second shift (30).

$$Y_k \geq (E_k - S_k - PT - PR_k \cdot Y_k)/PT - 1 \quad \forall k \in \mathcal{S} \tag{31}$$

$$Y_k \leq (E_k - S_k - PR_k \cdot Y_k)/PT \quad \forall k \in \mathcal{S} \tag{32}$$

$$u_i \leq PT + S_k + b_i(1 - \sum_{r \in \{1,\ldots,P\}} y_{irk}) \quad \forall i \in \mathcal{J}, k \in \mathcal{S} \tag{33}$$

$$\sum_{r \in \{1,\ldots,P\}} y_{irk} \leq 1 - \sum_{t \in \mathcal{T}} x_{0itk} \quad \forall i \in \mathcal{J}, k \in \mathcal{S} \tag{34}$$

$$\sum_{i \in \mathcal{J}} \sum_{r \in \{1,\ldots,P\}} y_{irk} \cdot p_r = PR_k \cdot Y_k \quad \forall k \in \mathcal{S} \tag{35}$$

$$\sum_{r \in \{1,\ldots,P\}} y_{jrk} \leq \sum_{i \in \mathcal{J}} \sum_{t \in \mathcal{T}} x_{ijtk} \quad \forall j \in \mathcal{J}, k \in \mathcal{S} \tag{36}$$

$$x_{ijtk} \in \{0, 1\} \quad \forall i, j \in \mathcal{J}_0, t \in \mathcal{T}, k \in \mathcal{S} \tag{37}$$

$$y_{irk} \in \{0, 1\} \quad \forall i \in \mathcal{J}, r \in \{1, \ldots, P\}, k \in \mathcal{S} \tag{38}$$

$$v_k, \bar{v}_k \in \{0, 1\} \quad \forall k \in \mathcal{S} \tag{39}$$

$$Y_k \in \{0, 1\} \quad \forall k \in \mathcal{S} \tag{40}$$

$$z_n \in \{0, 1\} \quad \forall n \in \mathcal{N} \tag{41}$$

$$s_i, u_i \geq 0 \quad \forall i \in \mathcal{J} \tag{42}$$

$$S_k, E_k \geq 0 \quad \forall k \in \mathcal{S} \tag{43}$$

$$o_n, \bar{o}_k \geq 0 \quad \forall n \in \mathcal{N} \tag{44}$$

A break has to be scheduled if the working time of a staff member exceeds a given amount of time PT (31)–(32). Furthermore, the break must start no later than PT minutes after the start of the shift (33). Equation (34) limit the number of breaks before each job to at most one and prevent that a break is made before the first job. Equation (35) guarantee that the single parts of the break sum up to the required break time PR_k of the staff member, if a break is required. To ensure that a staff member only makes a break at the jobs on his/her tour, (36) link the corresponding decision variables. The model is completed by the binary and non-negativity constraints (37)–(44).

4 Travel time modeling

The calculation of (time-dependent) shortest paths is a field of research that has been well researched. Given the time-dependent travel times for each arc, one can apply modified versions of standard algorithms for the Shortest Path Problem (SPP). Such algorithms are for example based on label setting or label correcting (e.g., Dijkstra or A*). A huge compression and classification of different algorithms for the SPP is given in Klunder and Post (2006); they implemented a total of 168 versions. Chabini and Dean (1999) compare different algorithms for the time-dependent SPP, each tested with FIFO and non-FIFO data. They also describe an algorithm called DOT (decreasing order of time), which is based on dynamic programming.

The idea behind DOT is used to efficiently compute time-dependent travel times out of the timetables of public transport service providers. Additionally, time-independent walking times TT_{ij} between clients and stations are computed out of OpenStreetMap data using geographic information systems (ArcGIS 10). This source has been chosen because the data usually contains more informal paths (e.g., through residential blocks) than commercial data and thus, it is more suitable for urban regions. The dynamic programming approach works as follows:

Let $G = (V, A)$ be a complete directed graph with a set of vertices $V = \{0, 1, \ldots, m\}$ and a set of arcs $A = \{(i,j) | i,j \in V, i \neq j\}$. $A_{it} \subseteq A$ contains all outgoing arcs from node i at time $t \in T$, and $|(i,j)|$ denotes the travel (ride) time needed to traverse the arc from vertex i to j. At different times $t \in T$, the arcs between the same vertices might have different lengths. While for the routing of the care staff only the vertices of the clients are needed, V contains both, the locations of the clients as well as the locations of the stations of the public transport system. The shortest travel time tt_{ijt} from node i to node j departing at time t can be computed by Algorithm 1.

Algorithm 1 Time-dependent travel time computation

$tt_{ijt} = TT_{ij} \quad \forall\, i,j \in V, t \in T$
for t = T-1 $\rightarrow$ 0 **do**
  for all $i \in V$ **do**
    for all $(i,j) \in A_{it}$ **do**
      for all $k \in V$ **do**
        $tt_{ikt} = \min(tt_{ikt}, |(i,j)| + tt_{jk,t+|(i,j)|})$
      end for
    end for
  end for
end for

The idea is as simple as efficient. First, all travel times are initialized with the time-independent travel times for walking. Afterwards, as in Chabini and Dean (1999), Algorithm 1 iterates through all time intervals, starting at the latest possible. At each time t and for each vertex i all outgoing arcs (i, j) are checked if using them leads to a shorter travel time in order to reach vertex k, compared to the shortest travel time from i to k that is already known at this time. Using this approach allows to compute a travel time matrix for each minute of the day. Thus, our modeling of the time-dependent travel times is based on a discrete time approach, but using 1 min as smallest unit, lets the travel time function behave like a discontinuous piecewise linear function.

Figure 1 shows a typical travel time function for public transport, together with the corresponding arrival time function. In this example a first service (e.g., a bus) leaves the station at a departure time $dt = 5$ and needs 5 min to reach its destination. If one arrives earlier at this station, waiting time occurs at the station. Thus, the total travel time consists of the waiting time plus the ride time. For example, leaving at $dt = 6$ generates 4 min waiting time and 5 min ride time. After $dt = 10$ the service interval is extended from 5 to 10 min while at $dt = 30$ it is shortened again to 6 min. Also the ride time is reduced to 3 min. While most of the time-dependency in public transport is caused by the varying intervals of the services, there might also be some fluctuations in ride times as well. For example, at certain times of the day it may happen that buses drive different routes between two stations in order to avoid traffic. The resulting arrival time function shows that our approach complies with the FIFO condition; hence, passing is not an issue. For several modes of the public transport system passing is also impossible by nature (e.g., trains, trams).

5 Solution approach

The planning of HHC services is characterized by an initial planning, usually a few days in advance, and some short term changes during the day of operation. While the initial planning is usually not time-sensitive, disruptions may occur several

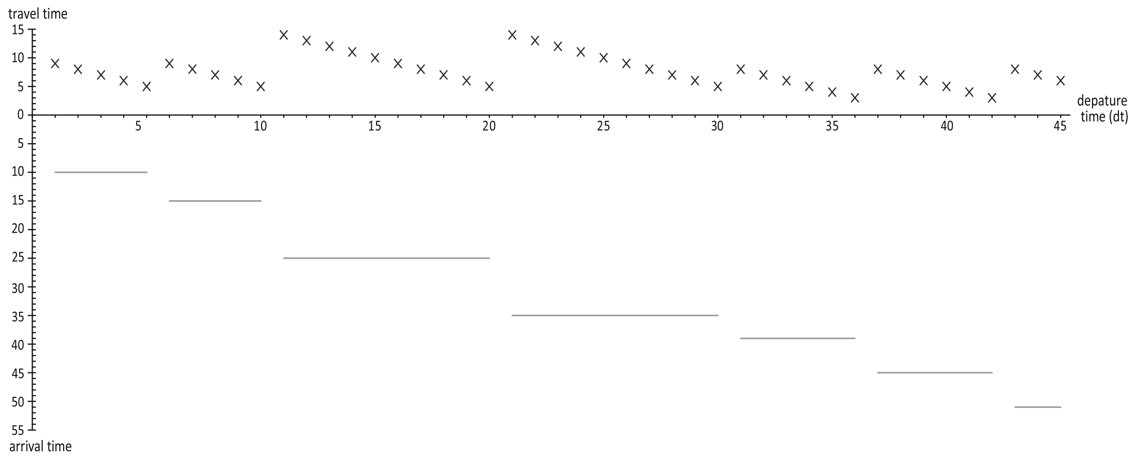

Fig. 1 Example for a typical travel and arrival time function for public transport

times a day and require rapid rescheduling. For example, if a care staff member reports sick in the morning all of his/her jobs have to be reallocated to the remaining staff. On the other hand, it is also possible that a client no longer has to be visited this day (e.g., due to hospitalization or family care), or that a new client enters the HHC system (e.g., hospital discharge). To achieve short computation times and good solution quality for real-world sized instances, we have developed three TS based solution approaches. TS was first introduced by Glover (1986) and has since been efficiently applied to various routing problems. A more recent publication about the structure of TS based metaheuristics can be found in Glover et al. (2007), together with an overview of innovative design strategies.

Algorithm 2 TS/TSAS/TSDYN: General structure

```
currentSolution s = initialSolution()
if s == feasible then
   bestSolution s* = s
   σ_jk = f(s) ∀ (j,k) ∈ s
end if
while !terminate do
   bestNeighbor s° = ∞
   bestMoves M = s.estimateMoves()
   for all j ∈ M do
      for all k ∈ S do
         for i = 0 → route[k].end() do
            build new solution s′
            move j to s′.route[k][i]
            s′.route[k].optimizeStart()
            while s′.route[k].length > PT ∧ s′.route[k].break < PR_k do
               s′.route[k].insertBreak()
               s′.route[k].optimizeStart()
            end while
            s′.evaluate()
            s′.checkTabu()
            if s′ == tabu then
               s′.checkAspiration()
            end if
            if s′.objective < s°.objective then
               s°.objective = s′.objective
            end if
         end for
      end for
   end for
   s = s°
   if s == feasible ∧ s.objective < s*.objective then
      s* = s
   end if
end while
return s*
```

The main principle of TS consists of a local search combined with memory structures to guide the search and to avoid getting stuck in local optima. Starting with an initial solution, in each iteration TS switches to the best solution within a neighborhood as long as it is not flagged as ’tabu’ and therefore prohibited, if it does not meet the aspiration criteria. Our algorithms are based on the ideas of the unified TS as used in time-independent routing problems (Cordeau et al. 2001; Hirsch 2011). Thus, infeasible solutions are temporarily allowed and a dynamically adapted weighted objective function is used to guide the search process. In total, we designed and implemented three different versions of time-dependent TS algorithms, which differ in the size of the neighborhood and are completely deterministic by design. Their general structure is roughly the same and outlined in Algorithm 2. The first version, simply named TS, searches the whole neighborhood in each iteration, the second uses an alternating strategy (TSAS), while the third dynamically adjusts the size of the neighborhood (TSDYN). The reason for developing different versions is the computational complexity of the evaluation of a solution and the intention to reduce the computation time. The starting time of a route not only influences the total amount of waiting time but also the travel times, due to the time-dependency. Thus, the optimal starting time is calculated immediately after composing a new route. In the next steps, breaks are inserted if necessary and the resulting solution is evaluated. Finally, the current and/or best solution, as well as all affected parameters are updated. This process is repeated until one of the termination criteria, the number of iterations or the maximum computation time, is reached. The important parts of our algorithms are outlined in the following.

5.1 Solution representation and initial solution

In our solution approaches a solution is represented by a set of routes, whereas each route represents a shift of a care staff member. Thus, if a staff member works two shifts a day each shift corresponds to a separate route. The routes itself are permutations of the assigned jobs and state the order in which they are carried out by the corresponding staff member. They start at the first client and end at the last client. The initial solution is based on an insertion heuristic. First, the jobs are ordered according to their centered time windows. Beginning with the earliest, the algorithm searches for the best assignments. The jobs of clients who have preferred care staff members are given preferential treatment. Following the best insertion principle, we try to insert them to every position of all preferred care staff members. If the insertion leads to a feasible solution, the assignment with the lowest objective value is accepted, otherwise the insertion of the job is postponed. In the next step the postponed jobs are inserted into the schedules of staff members who are not rejected by the client and who also have the appropriate skills and qualification level to carry out the job. Again only feasible solutions are accepted. At the end, all unassigned jobs are inserted according to the lowest objective value, which may lead to an infeasible initial solution.

5.2 Neighborhood

The neighborhood of a solution is composed by applying a relocate move operator. It extracts a job from its current route and re-inserts it into a different route. The insertion in the new route is based on best insertion. Our TS approach searches the whole neighborhood for the best neighbor solution. All jobs are therefore relocated and inserted at any position of all other routes. This also includes shifting jobs from the first to the second shift of a care staff member. The TSAS and the TSDYN, however, make use of a restricted neighborhood containing only a certain number of promising moves, sorted according to the length of the travel time required to serve a job. For example, moves affecting jobs at the beginning or at the end of a route are only weighted with the travel time for the arrival or the departure. For jobs in between, both the travel time for the arrival and for the departure are taken into account. Thus, moves that will remove long travel times are favored in the search process. The size of the restricted neighborhood is given by R_S, marking a percentage of the most promising moves. While the TSAS uses a restricted neighborhood of fixed size, the TSDYN adapts its size dynamically during the search process. Starting with a small restricted neighborhood, its size is increased in predefined steps R_Δ if there was no improvement of the best found solution for a certain number of iterations R_T. On the other side, its size is reset to its base value if a new best solution is found. However, to avoid being too myopic, both algorithms search the whole neighborhood after a certain number of iterations F_T. In order to escape local optima the algorithms make use of different memory structures. The most common is the tabu list, representing a short term memory. In our algorithms, τ_{jk} stores the iteration until a move containing a certain attribute (j, k) is not permitted. Here, j represents the job that has been moved and k is the shift, the job was assigned to, before executing the move. This prevents previously executed moves to be reversed for a certain number of iterations. The duration a move is considered tabu depends on the size of the instance. It is given by $\theta = \left\lceil (log_{10}(J \cdot S))^3 \right\rceil$, where J is the total number of jobs and S the number of shifts of an instance. The slope of this function ensures that the length of the tabu list is not too large to choke off the search process of small problem instances, but increases according to the size of the neighborhood to provide adequate durations for large problem instances. In addition to the tabu list a long term memory is used. The objective value of the best feasible solution containing the attribute (j, k) is stored in σ_{jk}. It is used as aspiration criteria for good neighbor solutions that are marked as tabu, in order to not reject promising solutions.

5.3 Evaluation and search guidance

A solution is evaluated according to the objective function given in Sect. 3. However, all of our algorithms allow infeasible solutions during the search process because of the sparse solution space. Therefore, an evaluation function $f(s) = c(s) + \sum \alpha_i \cdot d_i(s)$ is used to determine the quality of a solution s. $c(s)$ denotes the objective value as stated in the model formulation, which is extended by the sum of all kinds of weighted violations, denoted by $d_i(s)$ (e.g., violations of time windows, overtime, minimum and maximum working times, latest working time). To quantify these violations and to take into account the degrees of the violations, they are measured by the amount of time the limits or time windows are deviated. To force the search back to feasible solutions after exploring infeasible regions for a certain time, a dynamically adjusted weight α_i is assigned to each of these violations. At the end of each iteration the weights are increased or decreased, depending if the selected neighbor solution s' shows any of the violations. If $d_i(s') > 0$ then $\alpha_i = \alpha_i \cdot (1 + \delta)$, else $\alpha_i = \alpha_i/(1 + \delta)$, with δ as a positive input parameter. To diversify the search a penalty factor $p(s') = \lambda \cdot c(s') \cdot \sqrt{J \cdot S} \cdot \sum_{(j,k) \in s'} \rho_{jk}$ is added to the evaluation function $f(s')$ if the neighbor solution is worse than the current solution. As described in Cordeau et al. (2001) the penalty factor is composed of a scaling factor $c(s') \cdot \sqrt{J \cdot S}$ which depends on the size of the instance. The frequency based memory ρ_{jk} counts how often the attribute (j, k) was already part of a current solution in order to penalize solutions with frequently recurring attributes. Finally, a control parameter λ is used to set the intensity of the diversification.

5.4 Optimal starting times

Starting at the earliest possible starting time, which is given by the lower time window of the first job in the route, is optimal with respect to the time window violations. However, this is obviously suboptimal as it results in unnecessary waiting times at the jobs as well as for public transport and it might also generate overtime. In addition, because of the working time constraints, solutions without optimized starting times might also be infeasible. In case of time-independent travel times the optimal starting time can be efficiently determined by applying the concept of the forward time slack (45) as described in Cordeau and Laporte (2003), which is an extension of Savelsbergh (1992) in such a way that it also allows to delay the start of the route even if there are already time window violations at some jobs.

$$F_i = \min_{i \leq j \leq l} \left(\sum_{i < p \leq j} w_p + \max(0, b_j - s_j) \right) \tag{45}$$

Given a route with a fixed order of l jobs, the slack at each job j can be computed by summing up the waiting times w_p up to job j and the positive difference between the end of the time window and the beginning of job j. The forward time slack F_i for a job i is then obtained by taking the minimum of the slacks of all following jobs j. Computing the forward time slack can be done with a complexity of $\mathcal{O}(n)$ as a whole iteration through the route is required, determining the optimal starting time can be done afterwards in $\mathcal{O}(1)$.

For time-dependent travel times the forward time slack cannot be computed that easily because the effect of a delay cannot be predicted efficiently. In contrast to the time-independent case, a delayed starting time of Δ minutes at the first job does not always result in a delay at the following jobs of $\leq \Delta$ minutes but can also be $> \Delta$ if the travel time increases in the meantime. However, it is possible to compute the latest arrival time b_i^{max} that will not cause any further time window violations for each job within $\mathcal{O}(n)$.

$$b_i^{max} = \max(0, b_i - s_i) \tag{46}$$

$$b_i^{max} = \max(a_i, \min(b_i, b_{i+1}^{max} - tt^A_{i,i+1,b^{max}_{i+1}} - d_i)) \tag{47}$$

$$F_i = \max(0, b_i^{max} - (s_i - w_i)) \tag{48}$$

By iterating through the routes backwards, (46) determines the latest arrival time for the jobs at the end of the route and (47) for all other jobs. For the last job, this corresponds to the slack between the upper time window and the current starting time of the last job. For all other jobs in the route, according to (47), the time window of job i is compared with the previously computed latest arrival time of its immediate successor, denoted by $i+1$. Prerequisite is an additional set of time-dependent travel time matrices tt^A_{ijt}, storing the shortest travel time from job i to j if arrival should be at time t, which can be computed out of tt_{ijt}. The forward time slack is then given by (48). Due to its complexity of $\mathcal{O}(n \cdot T)$, determination of the optimal starting time by varying the starting time in small steps is usually done as a post optimization, as proposed for example by Fleischmann et al. (2004). However, it is possible to reduce the computational effort to $\mathcal{O}(n \cdot log\ T)$ by applying a binary search in the interval $[a_0, b_0^{max}]$ if the following conditions are met. First, the arrival time function has to be a monotonically increasing function, which is ensured by the FIFO-property, if it is satisfied. Thus, as long as postponing the start of the route does not change the end time of the route, the search is continued in the second half of the interval, otherwise in the first. Second, the evaluation function needs to be monotonic as well and directly proportional to the route lengths. This guarantees that minimizing the routes' length also minimizes the other factors in the evaluation function, if they are influenced by the start time of the route. Whereas the first condition is met, the second holds with one exception. While all other parts of the evaluation function are either not influenced by this procedure (e.g., overqualification, number of second shifts, time window violations) or directly proportional (e.g., overtime, maximum working time), only the minimum working time constraints are conflicting. However, it is debatable whether this exception is a limitation or a desired behavior from the dispatchers perspective. As the route length reduces, it might happen that the minimum working time gets violated and the previously feasible solution is now marked as infeasible. On the other hand, it would mean that a solution only satisfies the minimum working time constraint because of the insertions of waiting times and such solutions are usually rejected by the dispatchers.

Insertion of breaks If a staff member works more than a certain amount of time she/he has to make a mandatory break. In our approach breaks are inserted iteratively using the following rule. Within sequential order we try to insert the largest break type $p \in \mathcal{P}$ before job i…

1. …with largest waiting time, where $p \leq w_i$.
2. …with largest waiting time, where $p \leq F_i$.
3. …with largest forward time slack, where $p \leq F_i$.

First we try to find a position where the waiting time covers the break at whole (1). If the waiting time is not sufficient, we are looking for the largest waiting time where an insertion is still feasible, according to the forward time slack (2). In this way we are still able to reduce the waiting time. If this is not possible either, we only try to find a feasible position (3), otherwise we add the break in the middle of the route. As it is possible to partition the break in smaller parts, we have to evaluate the route after each insertion and check if further parts are required.

6 Numerical studies

To show the applicability of the proposed solution approaches several computational experiments with real-world data from the ARC in Vienna have been carried out. For privacy reasons, it must be mentioned that the data were made available to us encoded, such that no direct reference to individuals is possible. In this paper two operative planning scenarios were analyzed. The first is based on predefined rosters and might be used for short term rescheduling. In this scenario care staff members are scheduled according to their rosters, which define their actual working times as well as possible second shifts. The second is based on flexible working times and is intended to be used for deriving a roster in mid-term. Therefore, the total working time is only limited by the contracted working time of the staff members and it is assumed that each staff member is able to work a second shift. Thus, it is up to the optimization to determine the most suitable working times for the care staff.

6.1 Real-world data sets

Two different data sets have been used for these computations. Both sets are taken from actual planning data spanning a whole week and ordered by working groups. For each day and group, the data include both, the rosters of the staff members, as well as a list of jobs that must be performed by a staff member of this group. The first data sets ($I_1 - I_7$) were collected earlier in time and cover only one geographical test area in the south of Vienna. Due to the fact that the service areas of the groups are not congruent in their entirety with the test area, not all relevant information about the whole working day of the staff members are available. It happens that staff members serve clients who are located outside the test region, or that jobs have to be scheduled which are usually carried out by staff members from another group that is not included in the data. Therefore, this data set is not used for the real-world comparison of our results with the actual planning at the ARC. To overcome this shortcoming, data for whole Vienna has been collected later on. However, this second provided data set ($I_8 - I_{20}$) contains only one qualification level. In total, three qualification levels ($Q_1 - Q_3$) are considered. The lowest level Q_1 comprises assistance in housekeeping, while the highest level Q_3 includes medical services of nurses. The service times strongly depend on the qualification level. As shown in Table 2, a job of level Q_1 ranges from 15 to 165 min, with a mean of 51.1 min, while a Q_3 job requires only 23.9 min on average. Nevertheless, the service times of the jobs are well known in advance as they are

Table 2 Data characteristics of the service times per qualification level

	Q_1	Q_2	Q_3
Min.	15	15	10
Max.	165	90	40
Mean	51.1	47.9	23.9
SD.	24.5	12.7	9.3

defined in service contracts with the clients, depending on the clients' needs. The available working time of the staff members, however, is almost independent of the qualification of the staff member. On average, a care staff member is available for about 390 min a day.

Table 3 shows the characteristics of each instance with respect to the total number of jobs, clients, and care staff members, as well as their distribution by qualification level. On the part of the staff members, also the number of second shifts is given according to their rosters. For the first data set this number is only an approximation because of the gaps in the given schedules. Usually, a staff member of level Q_1 carries out 4 to 6 jobs per day, depending on the service time of the jobs. For higher qualified staff members this ratio is usually significantly higher. The number of services requiring a higher qualification is generally lower in urban regions, due to a denser medical infrastructure. Therefore, those staff members have a much larger service area. Unfortunately, their service area is not completely covered by our test area, resulting in a surplus of staff members of level Q_2 and Q_3 in our data. However, as overqualification is permitted, these staff members are able to carry out jobs that are one level below their qualification.

In the numerical studies, an overtime surcharge of $OC = 0.5$ for each minute of overtime and a compensation of $SC = 30$ min for each second shift is presumed. The total amount of overtime over the whole care staff is limited to $O = 300$ min. In Austria, if a continuous working time of 360 min is exceeded, a break has to be scheduled. Staff members of level Q_1 need a total break time of 30 min and members of level Q_2 and Q_3 are entitled to an additional 15 min. The maximum working time of a staff member is limited to either 8 or 9 h, depending on his/her contract. The same applies to the start (6 am) and end times of a day (8 or 10 pm), which leads to a planning horizon of 960 min. Thus, 960 asymmetric travel time matrices have been computed, using the algorithm presented in Sect. 4. A total of 1,595 stations of the public transport system was taken into account during the computation of the shortest paths between all clients, resulting in a dataset of about 27 GB. As these stations are not used during the scheduling, only the travel times between the clients are needed, and because of the rather small number of clients only a few MB of travel time data is stored in memory.

6.2 Parameter tuning

The algorithms have been implemented with C++, using MS Visual Studio 2012. For the computation of the time-dependent travel times the parallel programming API OpenMP has been used to take advantage of modern multi-core processors. On

Table 3 Data characteristics of the real-world instances

	Jobs				Clients	HHC staff				
	#	Q_1	Q_2	Q_3	#	#	Q_1	Q_2	Q_3	2nd shifts
I01	106	86	20	0	50	16	10	6	0	12
I02	115	95	20	0	57	21	14	7	0	12
I03	180	152	22	6	115	34	24	7	3	9
I04	188	162	21	5	116	42	33	6	3	5
I05	193	165	22	6	127	44	34	7	3	7
I06	193	169	21	3	119	45	33	9	3	10
I07	202	177	22	3	120	46	35	9	2	14
I08	112	112	0	0	76	28	28	0	0	11
I09	114	114	0	0	78	29	29	0	0	7
I10	122	122	0	0	85	38	38	0	0	10
I11	123	123	0	0	75	29	29	0	0	8
I12	123	123	0	0	82	37	37	0	0	12
I13	126	126	0	0	75	28	28	0	0	6
I14	131	131	0	0	81	28	28	0	0	6
I05	155	155	0	0	114	34	34	0	0	0
I16	155	155	0	0	102	35	35	0	0	4
I17	157	157	0	0	103	36	36	0	0	6
I18	166	166	0	0	112	35	35	0	0	4
I19	167	167	0	0	108	34	34	0	0	5
I20	173	173	0	0	118	35	35	0	0	8

the contrary, the TS metaheuristics were implemented as single-core applications. Depending on the TS algorithms different input parameters are needed. While the TS only needs values for $\delta \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and $\lambda \in \{0.01, 0.015, 0.02, 0.025\}$, the other versions also need parameters for the size of the restricted neighborhood $R_S \in \{0.2, 0.4, 0.6\}$, and the number of iterations after which a full neighborhood search is carried out $F_T \in \{2, 4, 6, 8, 10\}$. The TSDYN additionally requires values for R_T, the time after which the restricted neighborhood is adapted, as well as the increment $R_\Delta = 0.2$. R_T depends on the size of the instance and is given by $R_T = \lceil (log_{10}(J \cdot S)) \cdot 1.5 \rceil$, where J is the total number of jobs and S the number of shifts of an instance. The length of the tabu list is determined by $\theta = \left\lceil (log_{10}(J \cdot S))^3 \right\rceil$ for all TS variants. In order to choose the best parameter settings, all possible combinations of these values have been used to solve at least two different instances, leading to a total of 600 individual solutions. Furthermore, individual parameters were identified for each operational scenario as the solution space at given rosters contains significantly less feasible solutions. The weights for temporary violations α_i were initialized with 1.0 and capped with 10^{50}. Table 4

Table 4 Parameter selection for each TS version and for each operational scenario

	Predefined roster			Flexible working time		
	TS	TSAS	TSDYN	TS	TSAS	TSDYN
δ	0.3	0.1	0.5	0.5	0.1	0.5
λ	0.020	0.010	0.010	0.025	0.015	0.020
R_S	–	0.4	0.2	–	0.4	0.2
F_T	–	2	6	–	2	10

summarizes the chosen input parameters for each TS version and for each operational scenario.

6.3 Method comparison

In this section, the algorithms are compared with each other and with the current planning at the ARC by solving the presented instances. Comparisons with exact solutions or with benchmark instances from the literature cannot be given because of the complexity of the presented HHC problem and the absence of similar VRP instances with time-dependent travel times. As stated previously, we are currently not able to solve even small instances with 6 care staff members and 30 jobs up to optimality with the solver software FICO Xpress 7.0. However, this clearly outlines interesting future research activities in order to improve the presented model formulation.

The algorithms have been executed under Windows 7 on an Intel Core i7-4930K with 64 GB memory. Even though the CPU provides six cores, the algorithms only make use of a single core, and with respect to the memory capacity it can be denoted, that the average memory requirements are around 1 GB. Due to the different neighborhood sizes of the three TS versions, a fixed runtime of 600 seconds has been chosen to achieve a fair comparison of their performances. Furthermore, real-world applicability requires short processing times in order to cope with the rescheduling in daily business. As the design and implementation of the algorithms do not contain any stochasticity, they have been executed only once. Table 5 summarizes the results for all 20 instances for each operational scenario. It shows the deviation from the objective value of the best found solution (BFS). As the static service times at the clients count for about 85 % of the objective values in our data, they are subtracted to obtain a clear picture of the real differences between the algorithms.

With a given roster the TS clearly outperforms the other versions. It is able to find the BFS 14 out of 20 times and shows only an average deviation of 0.35 % from the objective values of the BFSs. The TSDYN performs second best, but by a considerable distance. In case of flexible working times the results are contrary. In this case, the TSDYN performs best followed by the TS. In the short term, limiting the neighborhood increases the chance of missing good solutions, but in the mid- or long term it may provide additional guidance to limit the search to promising regions of the solution space. The TSAS is the worst performing algorithm in both

Table 5 Deviation from the BFS for each TS version and for each operational scenario after a computation time of 600 s [in %]

	Predefined roster			Flexible working time		
	TS	TSAS	TSDYN	TS	TSAS	TSDYN
I01	0.16	0.00	0.73	2.91	14.73	0.00
I02	2.04	3.81	0.00	5.30	0.00	2.96
I03	0.00	1.21	4.82	3.88	0.00	1.32
I04	3.40	0.13	0.00	0.41	0.95	0.00
I05	0.00	6.82	5.19	3.80	6.10	0.00
I06	0.68	0.00	5.82	7.59	0.00	1.38
I07	0.00	1.13	3.61	2.99	4.90	0.00
I08	0.00	1.19	5.01	0.30	0.71	0.00
I09	0.00	0.98	1.58	1.20	0.00	1.20
I10	0.30	4.49	0.00	2.87	3.36	0.00
I11	0.00	0.75	7.62	1.71	4.21	0.00
I12	0.00	10.14	4.71	1.16	0.00	0.18
I13	0.00	0.83	0.74	0.72	1.23	0.00
I14	0.00	2.66	0.75	0.20	3.74	0.00
I15	0.00	0.66	3.74	0.00	3.71	0.37
I16	0.00	4.90	0.41	0.00	1.21	1.07
I17	0.40	7.77	0.00	1.45	1.83	0.00
I18	0.00	2.05	0.06	0.00	1.78	0.00
I19	0.00	0.11	1.85	0.31	3.79	0.00
I20	0.00	3.80	4.99	7.32	0.91	0.00
Mean	0.35	2.67	2.58	2.21	2.66	0.42
SD	0.86	2.89	2.47	2.36	3.40	0.78
#bfs	14	2	4	3	5	13

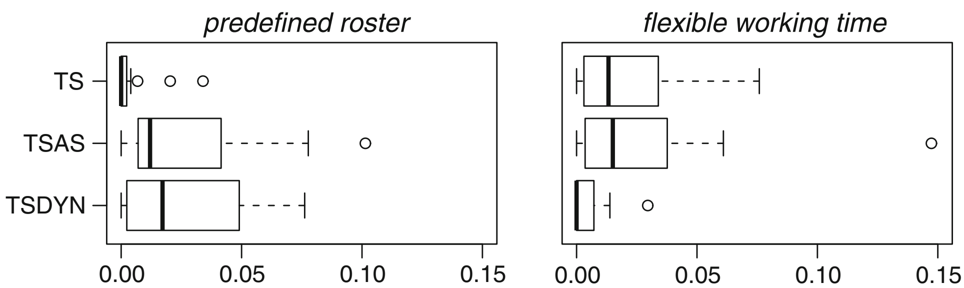

Fig. 2 Variation of deviations from the BFS for each TS version and for each operational scenario after a computation time of 600 s

scenarios, if looking at all instances. Although it finds the BFS for a few instances, the difference to the second-best solution is quite small. The TSAS needs to find a tradeoff between the computation time and the possible loss of good solutions, while dynamically adapting the size of the neighborhood allows to overcome this burden. However, the results suggest that further restricting the neighborhood within an already sparse solution space seems too myopic. With exception of the TSAS, the

Table 6 Deviation from the FFS for each TS version and for each operational scenario after a computation time of 600 s and 10 h [in %]

	Predefined roster						Flexible working time					
	TS		TSAS		TSDYN		TS		TSAS		TSDYN	
	10 min	10 h	10 min	10 h	10 min	10 h	10 min	10 h	10 min	10 h	10 min	10 h
I01	−34.50	−34.50	−27.91	−28.25	−19.13	−19.13	−53.34	−53.34	−44.10	−44.10	−49.52	−49.52
I02	−18.07	−18.07	−28.16	−28.16	−38.26	−38.44	−50.80	−51.92	−53.90	−53.90	−46.33	−46.94
I03	−33.10	−33.10	−40.08	−40.08	−38.97	−41.06	−46.63	−46.63	−46.25	−47.11	−61.05	−61.21
I04	−22.98	−22.98	−23.74	−23.74	−20.80	−20.80	−55.66	−56.37	−41.56	−41.98	−41.69	−41.84
I05	−35.96	−35.96	−31.59	−31.59	−30.62	−30.62	−48.05	−48.80	−48.36	−49.22	−38.71	−38.71
I06	−24.97	−24.97	−21.86	−21.86	−33.91	−33.91	−53.49	−54.76	−50.82	−51.44	−40.58	−40.58
I07	−48.68	−48.68	−39.90	−39.90	−44.10	−44.10	−52.60	−52.60	−41.46	−42.69	−50.13	−50.13
I08	−37.07	−37.07	−43.60	−43.60	−45.70	−45.70	−44.46	−44.78	−45.24	−45.53	−45.33	−45.56
I09	−31.74	−31.74	−37.39	−37.39	−32.60	−32.60	−56.67	−56.99	−46.77	−46.94	−39.45	−39.72
I10	−44.84	−44.84	−39.55	−39.55	−34.75	−34.75	−59.17	−59.17	−38.97	−39.21	−47.93	−47.93
I11	−52.71	−53.03	−54.44	−54.79	−37.00	−37.98	−55.31	−55.66	−51.69	−52.11	−68.34	−68.52
I12	−46.18	−46.18	−43.79	−43.79	−46.81	−46.81	−58.13	−58.31	−63.83	−63.97	−47.03	−47.09
I13	−57.48	−57.70	−30.91	−31.03	−39.36	−39.36	−59.36	−59.76	−55.76	−56.12	−44.85	−45.26
I14	−53.82	−53.82	−53.50	−53.98	−46.75	−46.83	−56.94	−57.25	−58.49	−58.88	−51.87	−52.10
I15	−61.93	−62.29	−61.29	−61.54	−51.09	−51.51	−62.80	−63.03	−62.09	−62.37	−44.12	−44.36
I16	−57.62	−57.69	−51.40	−51.81	−49.26	−49.55	−54.31	−54.72	−53.86	−54.17	−44.69	−45.11
I17	−54.47	−55.25	−54.54	−55.60	−52.38	−52.90	−43.83	−44.33	−59.86	−60.15	−48.20	−48.54
I18	−54.61	−54.92	−53.76	−54.11	−47.61	−48.16	−59.22	−59.70	−60.18	−60.75	−38.55	−38.92
I19	−48.48	−49.28	−48.66	−49.53	−46.09	−47.35	−50.39	−51.26	−46.65	−47.36	−55.39	−56.21
I20	−50.68	−51.76	−44.30	−45.77	−44.20	−45.66	−61.77	−62.80	−52.02	−52.61	−48.21	−48.80
max Δ	1.08		1.47		2.09		1.28		1.23		0.82	
mean Δ	0.20		0.28		0.39		0.46		0.44		0.26	
SD Δ	0.32		0.40		0.59		0.37		0.30		0.23	

deviations from the BFS are quite small for the TS and the TSDYN in their respective beneficial scenario. The variations of the results are also visualized in Fig. 2.

Prolonging the computation time does not improve the results considerably. In this regard, Table 6 shows the improvements of the first feasible solutions (FFS) after 10 min and after 10 h. It implies a strong relationship between the applied TS version and the operational scenario. If the algorithm performs well in the operational scenario, only marginal savings can be achieved. At the predefined roster scenario, for example, increasing the computation time of the TS to 10 h allows to increase the reported objective values by 0.20 percentage points on average and by 1.08 at most. Figure 3 exemplarily visualizes the convergence of the search for both operational scenarios for a single instance. For imaging reasons, the x-axis is scaled logarithmically and cut at 10^6 iterations, as no improvements have been achieved afterwards. However, the total number of iterations each algorithm performed within the 10 h limit is given in square brackets in the chart legend.

6.4 Real-world comparison

Table 7 shows the deviations of the objective values of our algorithms from the actual planned routes at the ARC. For this purpose, the schedules we received from the ARC are evaluated according to our objective function given in Sect. 3. The scheduled end of each job is taken as departure time for the time-dependent travel times. Any time window or working time violations that occur during the evaluation of the ARC schedule are neglected.

Although it is evident which algorithm is suitable for which operational scenario, significant savings can be achieved with all of them, if compared with the actual

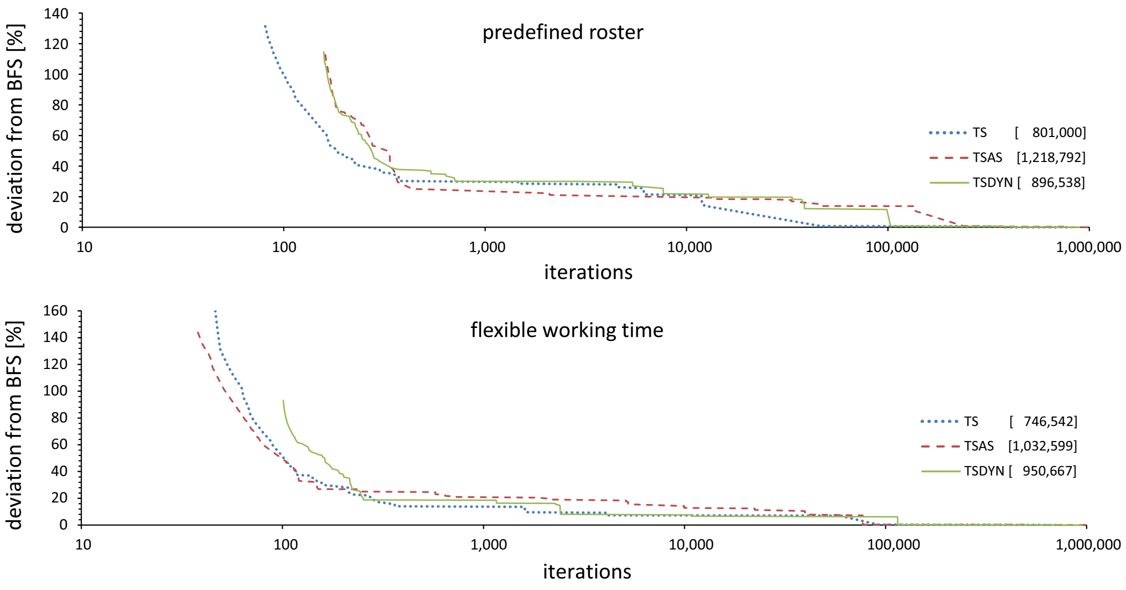

Fig. 3 Search convergence for each operational scenario of instance I13: deviation of the objective value from the BFS at all iterations achieved with a computation time of 10 h [in %]

Table 7 Deviation from actual planning at ARC for each TS version and for each operational scenario after a computation time of 600 s [in %]

	Predefined roster			Flexible working time		
	TS	TSAS	TSDYN	TS	TSAS	TSDYN
I08	−37.78	−37.04	−34.67	−50.94	−50.74	−51.09
I09	−29.82	−29.13	−28.71	−46.19	−46.82	−46.19
I10	−40.68	−38.20	−40.85	−56.15	−55.94	−57.37
I11	−51.46	−51.10	−47.76	−59.22	−58.22	−59.91
I12	−40.79	−34.78	−38.00	−52.03	−52.58	−52.49
I13	−49.25	−48.83	−48.88	−54.16	−53.93	−54.49
I14	−48.85	−47.49	−48.47	−57.79	−56.30	−57.87
I15	−61.06	−60.81	−59.61	−65.31	−64.02	−65.18
I16	−37.66	−34.61	−37.40	−40.59	−39.86	−39.95
I17	−45.72	−41.74	−45.94	−51.85	−51.67	−52.54
I18	−34.85	−33.51	−34.81	−38.70	−37.60	−38.70
I19	−35.31	−35.25	−34.12	−43.99	−42.04	−44.16
I20	−26.63	−23.84	−22.97	−39.96	−43.55	−44.06
mean	−41.53	−39.72	−40.17	−50.53	−50.25	−51.08
SD	9.50	10.02	9.79	8.20	7.83	8.04

planning of the ARC. This is explained by the short travel times in urban regions combined with the fact that a compensation in the amount of 30 min working time is accounted for a second shift. In almost each instance, it was possible to significantly reduce the number of second shifts or even to avoid them entirely. As those shifts are quite uncomfortable for most staff members, this result has a major impact on their satisfaction. If using the TS, savings between 26.63 % and 61.06 % are achievable, with a mean of 41.53 %. If not limited by a given roster, it is possible to further increase the savings by an additional 10 percentage points, on average.

7 Conclusion and outlook

We present a mathematical model for the daily scheduling of HHC services, where care staff members are using public transport with time-dependent travel times. The time-dependent travel times are computed by a dynamic programming approach, which is able to compute travel time matrices for each minute of the day out of timetable data. Although this leads to the most accurate travel times, it also revealed a drawback of our modeling approach of using minute-based travel times. Due to the large number of time intervals, it was not possible to get an exact solution with an acceptable gap within reasonable time for a small test instance with 6 staff members and 30 jobs, using the solver software FICO Xpress 7.0. Nevertheless, minute-based travel times are necessary for scheduling with public transport, especially for services in sub-urban regions or during off-peak times.

To solve real-world sized instances within reasonable computation time we developed three TS based metaheuristics. The TS always searches the whole neighborhood, the TSAS uses a restricted neighborhood of fixed size, and the TSDYN adapts the neighborhood dynamically. In case of time-independent travel times, optimizing the starting times of the routes is usually straightforward, but with time-dependent travel times, this task requires a lot of computational effort. To tackle this challenge, we use a binary search to identify the optimal time.

The approach has been tested with real-world data from the ARC in Vienna. Two data sets with a total number of 20 instances of different sizes are used to compare the algorithms with each other, as well as the actual planning at the ARC. The largest instance consists of 202 jobs and 46 staff members. Two operational scenarios are analyzed. The first is based on a predefined roster and represents daily business, where the dispatcher is legally bounded by the rosters that have been given to the care staff members a few weeks before. The second scenario assumes flexible working times for the staff members and is intended to show the full potential savings, if not limited by a given roster. It might be used to derive an optimized roster in future. However, additional constraints dealing with rest periods and overtime during a certain period would be needed in such a model. Furthermore, one has to cope with the uncertainties in the data, which arise due to the temporal distance between the drawing up of the rosters and the daily scheduling of the care staff. These must also be kept in mind at the comparison of the results of the second scenario with the planning at the ARC.

In the first scenario, the TS algorithm outperforms the other versions by almost two percentage points. In the second scenario the results are contrary, with the TSDYN outperforming the others. This behavior is explained by the sparse solution space in the first scenario. A given roster already limits the solution space in a way that an additional reduction of the neighborhood leads to unfavorable solutions. With flexible working times, however, the restricted neighborhood acts as an additional guidance into promising parts of the solution space. The dynamic adjustment of the size of the neighborhood allows to overcome the tradeoff between the computation time and the possible loss of good solutions.

If compared with the planning of the ARC, average savings of 41.53 % with a given roster, and 51.08 % without a roster are achievable through optimization. As for most real-world comparisons one has to bear in mind that the schedules with which we compared our results may not be based only on the rosters of the care staff members but also on undocumented knowledge we are not aware of. For example, it is conceivably that staff members are available throughout the day according to their rosters, but are scheduled only on the morning because of some private appointments. The same might apply in the other direction when a staff member has no duty but has to stand in for somebody who calls in sick.

In summary, it can be stated that there is a significant savings potential compared to the current routing and using time-dependent travel times result in more reliable schedules.

Day-to-day business in HHC is usually subject to stochastic and dynamic events that require repeated adjustments throughout a day. For example, the actual service time at a client depends on his/her health condition and thus, the scheduled service time might be exceeded easily. In addition, it might happen that the client has been hospitalized on short notice and the scheduled visit is canceled. Even if good schedules can be computed within seconds, the presented solution approach is currently only capable of computing schedules from scratch. Rescheduling requires an adjustment of the input data and may lead to entirely different schedules. However, it might be preferable to adapt to the new situation with as few changes as possible. Therefore, future research focuses on a new solution approach that is operational in dynamic environments, and thus able to overcome this limitations. In the mid-term, it is also planned to integrate additional independent transport modes like cycling, car driving, or pickup services (see, e.g., Fikar and Hirsch 2014). Allowing combinations of these moves the modal choice into optimization. This facilitates the consideration of user-dependent requirements (e.g., maximum cycling distance).

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References

Akjiratikarl C, Yenradee P, Drake PR (2007) Pso-based algorithm for home care worker scheduling in the UK. Comput Ind Eng 53(4):559–583. doi:10.1016/j.cie.2007.06.002

Begur SV, Miller DM, Weaver JR (1997) An integrated spatial dss for scheduling and routing home-health-care nurses. Interfaces 27(4):35–48. doi:10.1287/inte.27.4.35

Bertels S, Fahle T (2006) A hybrid setup for a hybrid scenario: combining heuristics for the home health care problem. Comput Oper Res 33(10):2866–2890. doi:10.1016/j.cor.2005.01.015

Bräysy O, Dullaert W, Nakari P (2009) The potential of optimization in communal routing problems: case studies from Finland. J Transp Geogr 17(6):484–490. doi:10.1016/j.jtrangeo.2008.10.003

Bredström D, Rönnqvist M (2007) A branch and price algorithm for the combined vehicle routing and scheduling problem with synchronization constraints. Discussion Paper No. 2007/7, NHH Department of Finance and Management Science, Norwegian School of Economics, Norway, doi:10.2139/ssrn.971726

Bredström D, Rönnqvist M (2008) Combined vehicle routing and scheduling with temporal precedence and synchronization constraints. Eur J Oper Res 191(1):19–31. doi:10.1016/j.ejor.2007.07.033

Cappanera P, Scutellà MG (2014) Joint assignment, scheduling and routing models to home care optimization: a pattern based approach. Transp Sci 1–23. doi:10.1287/trsc.2014.0548

Chabini I, Dean B (1999) Shortest path problems in discrete-time dynamic networks: Complexity, algorithms, and implementations. Tech. rep, Massachusetts Institute of Technology, Cambridge, MA

Cheng E, Rich JL (1998) A home health care routing and scheduling problem. Tech. rep. tr98-04, Department of CAAM, Rice University, Houston Texas, USA

Cordeau JF, Laporte G (2003) A tabu search heuristic for the static multi-vehicle dial-a-ride problem. Transp Res B 37(6):579–594. doi:10.1016/S0191-2615(02)00045-0

Cordeau JF, Laporte G, Mercier A (2001) A unified tabu search heuristic for vehicle routing problems with time windows. J Oper Res Soc 52(8):928–936

Dabia S, Ropke S, Van Woensel T, De Kok T (2013) Branch and price for the time-dependent vehicle routing problem with time windows. Transp Sci 47(3):380–396. doi:10.1287/trsc.1120.0445

Dohn A, Rasmussen MS, Justesen T, Larsen J (2008) The home care crew scheduling problem. In: Sheibani K (ed) Proceedings of the 1st international conference on applied operational (ICAOR'08), Yerevan, Armenia, Lecture Notes in Management Science, vol 1, pp 1–8

Ehmke JF, Steinert A, Mattfeld DC (2012) Advanced routing for city logistics service providers based on time-dependent travel times. J Comput Sci 3(4):193–205. doi:10.1016/j.jocs.2012.01.006

Elbenani B, Ferland J, Gascon V (2008) Mathematical programming approach for routing home care nurses. In: Proceedings of industrial engineering and engineering management 2008 (IEEM08), Singapore, pp 107–111, doi:10.1109/IEEM.2008.4737841
Eveborn P, Flisberg P, Rönnqvist M (2006) Laps care-an operational system for staff planning of home care. Eur J Oper Res 171(3):962–976. doi:10.1016/j.ejor.2005.01.011
Eveborn P, Rönnqvist M, Einarsdóttir H, Eklund M, Lidén K, Almroth M (2009) Operations research improves quality and efficiency in home care. Interfaces 39(1):18–34. doi:10.1287/inte.1080.0411
Fikar C, Hirsch P (2014) A matheuristic for routing real-world home service transport systems facilitating walking. J Clean Prod. doi:10.1016/j.jclepro.2014.07.013
Fleischmann B, Gietz M, Gnutzmann S (2004) Time-varying travel times in vehicle routing. Transp Sci 38(2):160–173. doi:10.1287/trsc.1030.0062
Glover F (1986) Future paths for integer programming and links to artificial intelligence. Comput Oper Res 13(5):533–549. doi:10.1016/0305-0548(86)90048-1
Glover F, Laguna M, Marti R (2007) Principles of tabu search. In: Gonzalez TF (ed) Handbook of approximation algorithms and metaheuristics. Chapman & Hall/CRC, Boca Raton, pp 23-1–23-11. doi:10.1201/9781420010749
Hiermann G, Prandtstetter M, Rendl A, Puchinger J, Raidl GR (2013) Metaheuristics for solving a multimodal home-healthcare scheduling problem. Cent Eur J Oper Res 23:1–25. doi:10.1007/s10100-013-0305-8
Hill AV, Benton WC (1992) Modelling intra-city time-dependent travel speeds for vehicle scheduling problems. J Oper Res Soc 43(4):343–351. doi:10.2307/2583157
Hirsch P (2011) Minimizing empty truck loads in round timber transport with tabu search strategies. Int J Inf Syst Supply Chain Manag 4(2):15–41. doi:10.4018/jisscm.2011040102
Ichoua S, Gendreau M, Potvin JY (2003) Vehicle dispatching with time-dependent travel times. Eur J Oper Res 144(2):379–396. doi:10.1016/S0377-2217(02)00147-9
Klunder G, Post H (2006) The shortest path problem on large-scale real-road networks. Networks 48(4):182–194. doi:10.1002/net.20131
Kritzinger S, Tricoire F, Dörner KF, Hartl RF (2011) Variable neighborhood search for the time-dependent vehicle routing problem with soft time windows. In: Coello CAC (ed) Proceedings of the 5th international conference on learning and intelligent optimization (LION'05), Rome, Italy, Lecture Notes in Computer Science, vol 6683, pp 61–75
Liu R, Xie X, Garaix T (2014) Hybridization of tabu search with feasible and infeasible local searches for periodic home health care logistics. Omega 47:17–32. doi:10.1016/j.omega.2014.03.003
Malandraki C, Daskin MS (1992) Time dependent vehicle routing problems: formulations, properties and heuristic algorithms. Transp Sci 26(3):185–200. doi:10.1287/trsc.26.3.185
Mankowska DS, Meisel F, Bierwirth C (2013) The home health care routing and scheduling problem with interdependent services. Health Care Manag Sci 17(1):15–30. doi:10.1007/s10729-013-9243-1
Matta A, Chahed S, Sahin E, Dallery Y (2014) Modelling home care organisations from an operations management perspective. Flex Serv Manuf J 26(3):295–319. doi:10.1007/s10696-012-9157-0
Rasmussen MS, Justesen T, Dohn A, Larsen J (2012) The home care crew scheduling problem: preference-based visit clustering and temporal dependencies. Eur J Oper Res 219(3):598–610. doi:10.1016/j.ejor.2011.10.048
Rest KD, Trautsamwieser A, Hirsch P (2012) Trends and risks in home health care. J Humanit Logist Supply Chain Manag 2(1):34–53. doi:10.1108/20426741211225993
Savelsbergh MWP (1992) The vehicle routing problem with time windows: minimizing route duration. ORSA J Comput 4(2):146–154. doi:10.1287/ijoc.4.2.146
Trautsamwieser A, Hirsch P (2014) A branch-price-and-cut approach for solving the medium-term home health care planning problem. Networks 64(3):143–159. doi:10.1002/net.21566
Trautsamwieser A, Gronalt M, Hirsch P (2011) Securing home health care in times of natural disasters. OR Spectr 33(3):787–813. doi:10.1007/s00291-011-0253-4

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Insights and decision support for home health care services in times of disasters

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Abstract

Home health care (HHC) services are of vital importance for the health care system of many countries. Further increases in their demand must be expected and with it grows the need to sustain these services in times of disasters. Existing risk assessment tools and guides support HHC service providers to secure their services. However, they do not provide insights on interdependencies of complex systems like HHC. Causal-Loop-Diagrams (CLDs) are generated to visualize the impacts of epidemics, blackouts, heatwaves, and floods on the HHC system. CLDs help to understand the system design as well as cascading effects. Additionally, they simplify the process of identifying points of action in order to mitigate the impacts of disasters. In a case study, the course of the COVID-19 pandemic and its effects on HHC in Austria in spring 2020 are shown. A decision support system (DSS) to support the daily scheduling of HHC nurses is presented and applied to numerically analyze the impacts of the COVID-19 pandemic, using real-world data from a HHC service provider in Vienna. The DSS is based on a Tabu Search metaheuristic that specifically aims to deal with the peculiarities of urban regions. Various transport modes are considered, including time-dependent public transport.

Keywords Home health care · Disaster management · Causal-Loop-Diagrams · Decision support system · COVID-19 case study

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1 Introduction

Many countries are experiencing a significant increase in demand for long-term care. The average share of the population aged 65+ years in OECD countries increased from about 9% in 1960 to 17% in 2015, and is forecast to reach 28% in 2050. The share of those aged 80+ years is expected to grow even stronger. An increase in life expectancy does not mean that the extra years are lived in good health. In fact, the risk to develop disabilities and to need assistance also increases. On average across the OECD countries, 13% of people over 65 receive long-term care and more than half of them are 80+ years old (OECD 2017). Many care-dependent people are cared for by friends or relatives. Others receive professional help either in nursing homes, day-care centers, or their own homes through home health care (HHC) services. As outlined in Rest et al. (2012), HHC services allow old and frail people to stay as long as possible in their familiar environment but still receive professional care. Furthermore, the HHC system is also more cost efficient than institutional long-term care.

HHC service providers offer a wide range of services, ranging from assisting in daily life to qualified medical services. People with limited mobility or medical needs (e.g., diabetics) require consistent services to avoid a deterioration of their health. But even seemingly less important tasks like assisting in daily life are of vital importance. These activities deal not only with personal hygiene or preparing meals, they are also used to monitor the health of the people. This information is crucial to adapt the services to the changing needs. Expecting an increase in demand and being a vital part of the health care system, HHC services must be sustained by all means in order to avoid health implications. To maintain business continuity, and thus continuity of care, HHC service providers must prepare for a variety of disaster situations.

The aim of this paper is to analyze the effects of natural and technical disasters on HHC services in urban regions. Based on information from the Austrian Red Cross (ARC), one of the major HHC service providers in Austria, epidemics, heat waves, floods, and blackouts have been defined as most important. Initial analysis and results have been published in Rest et al. (2012) and in the conference proceedings of Rest and Hirsch (2015). These findings are extended in two ways. First, the concepts of System Dynamics (SD), especially Causal-Loop-Diagrams (CLDs), are used to visualize and identify influential factors and vulnerabilities of HHC services. Second, in a case study the impacts of the pandemic of the coronavirus disease 2019 (COVID-19) on HHC in Austria in spring 2020 are analyzed. A decision support system (DSS) for the daily scheduling of HHC nurses is presented and applied to analyze the impacts of the COVID-19 pandemic. The DSS is a commercially available advancement of the previously developed algorithms, published in Rest and Hirsch (2016). In contrast to existing work, the DSS focuses on urban regions and allows planning with public transport and with time-dependent travel times. It is applied to real-world data from a Viennese HHC service provider to show the effects of the strict COVID-19 actions. As different transport modes are considered, their impact on the planning is outlined as well. The main findings of this work aim to raise the awareness of HHC service providers regarding their vulnerabilities. The DSS itself can be used for the daily scheduling as well as for training and capacity analysis and planning. During a disaster, it guarantees that the available staff is scheduled as efficient as possible.

The remainder of the paper is organized as follows: Sect. 2 discusses emergency preparedness of HHC services and relevant literature in this field. Section 3 assess the vulnerability of critical assets of HHC to the four mentioned disasters and plots them in CLDs. In Sect. 4, the COVID-19 case study is presented, including the presentation and application of the DSS using real-world data from a Viennese HHC service provider. Final remarks and an outlook on future research are given in Sect. 5.

2 Emergency preparedness of HHC services

HHC provides unique capabilities to manage disaster situations, both before and during the event. The ability to deliver health services in non-structured environments makes them ideal as key responders in times of crisis (NAHC 2008). Identifying and addressing the needs of vulnerable people has been the focus of several studies (e.g., Aldrich and Benson 2008; Khorram-Manesh et al. 2017). HHC services are tailored to the needs of care-dependent people, a group mainly consisting of frail older adults and people with disabilities. Exactly this group is disproportionately affected by emergencies. According to Aldrich and Benson (2008), about 80% of older adults have at least one chronic condition that makes them more vulnerable during a disaster. They point out that, for example, 71% of the fatalities of the hurricane Katrina in 2005 were over the age of 65 and that the median age of the heat-related deaths during the heat wave in Chicago 1995 was 75 years. Thus, HHC services already have direct access to one of the most vulnerable groups, which provides in-depth knowledge of their medical needs, impairments, resources, as well as their home environments. In addition, it enables targeted dissemination of public health (e.g., about vaccinations) and disaster preparedness information.

A manual for developing an all-hazards emergency preparedness plan is provided by the NAHC (2008). It lists potential hazardous events that should be rated based on probability, vulnerability and preparedness. Furthermore, a variety of recommended actions are given to increase the resilience of HHC services. In scientific literature, different approaches are proposed to increase the emergency preparedness of HHC services. Wyte-Lake et al. (2015) present the results of a literature review examining HHC organization policies and procedures, lessons learned in the field, and expert recommendations. Most of the literature discusses only individual actions (e.g., patient classification systems) or actions to tackle individual disasters (e.g., avian influenza). All-hazards risk assessments are only addressed by Doherty (2004) and Rodriguez and Long (2006). They provide advice on how to carry out risk assessments, particularly by raising questions that need to be addressed by the HHC service providers. However, the HHC system as well as various disaster events are complex systems that involve numerous interdependencies. In our opinion, these interdependencies have received little attention in the existing literature and risk assessment tools, but can be tackle by applying SD methods.

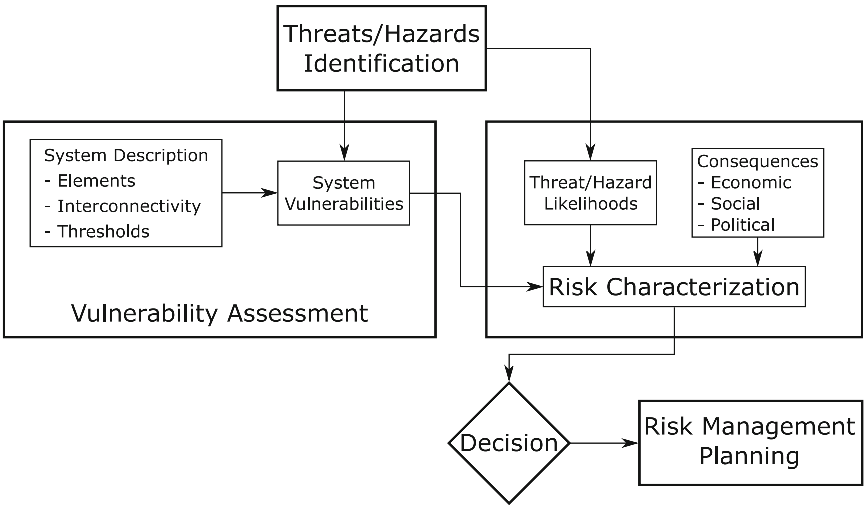

Fig. 1 Risk assessment process according to Baker (2005)

3 Vulnerability assessment and systems thinking

Risk assessments are an important part of the risk management procedure and a precondition for the subsequent phases of the crisis management cycle (Pursiainen 2017). As shown in Fig. 1, the first step of a risk assessment and management process is to identify relevant threats and hazards. In the next step, vulnerability assessments are used to evaluate the weaknesses of a system regarding these threats. Afterward, the risks are determined by assigning likelihoods to each threat. The final step consists of managerial decision making, heavily influenced by the resulting risk characterizations and the financial possibilities of an organization. The focus of this paper lies on the vulnerability assessments as we think that the existing HHC literature and risk assessment tools are deficient in this area. While they provide great guidelines for the remaining steps, they offer little help in terms of insights into interdependencies. According to Baker (2005), the main objectives of vulnerability assessments are to...

- understand the organization's mission and mission-supporting systems.
- identify mission-threatening vulnerabilities of critical systems.
- understand system design and operation to determine failure modes.
- identify consequences of failures and cascading effects on other systems.

Understanding complex systems is the main goal of the SD methodology. To the best of our knowledge SD methods have not been applied yet to model the HHC system. SD has been described first by Forrester (1997) to model the behavior of complex systems that are characterized by interdependencies of the influencing variables. CLDs are one of the main concepts in the SD toolset and used to visualize cause-and-effect relationships and feedback processes. A system is modeled as a network consisting of nodes representing variables and links representing an interaction between two variables. A link of a positive (resp. negative) interaction means a change in the same (resp. opposite) direction, i.e., if the cause increases then the effect increases (resp. decreases). Powell et al. (2016) show the advantages of using CLDs during the risk assessment process and use them to analyze flood threat to an electricity substation. CLDs are also well suited to visualize cascading effects of disasters, as shown by

Berariu et al. (2015). They analyze cascade effects of floods and heatwaves and their impact on critical infrastructures.

Expert interviews with decision makers of the ARC identified epidemics, blackouts, heatwaves, and floods as their most significant disaster events. The ARC is not only one of the largest HHC service providers in Austria, but also has extensive expertise in health care and disaster management. The effects of these disasters have been analyzed on the basis of scientific publications, addressing general disaster impacts on critical infrastructure and lessons learned from specific events. The findings were modeled in the form of CLDs and discussed and refined again with the ARC. In the following, the CLDs for each of these disasters are presented.

3.1 Epidemics

Infectious diseases repeatedly affected large parts of the population within a short period of time. Regionally confined outbreaks are classified as epidemics while the term pandemic describes a worldwide spread. Gershon et al. (2007) state that more than 30 novel pathogens have been identified in the past 2 decades and that the incidence of emerging pathogens is increasing. Globalization, with its increase in international travel, fosters the spread of diseases and areas of high population density are particularly at risk. For example, the 2002 SARS outbreak started in China and spread rapidly to Toronto, London, and New York. The US Centers for Disease Control and Prevention estimates that the 2009 H1N1 (swine flu) outbreak resulted in about 60 million cases, 270,000 hospitalizations, and 12,500 deaths in the United States (CDC 2019). At the time of writing, the ongoing COVID-19 pandemic has already caused massive economic damage and social restrictions worldwide. As of March 20, 2021, the COVID-19 Dashboard of the Johns Hopkins University reports more than 122 million infections and more than 2.7 million deaths across 192 countries and territories (Johns Hopkins University 2021). The pandemic is described in detail in the COVID-19 case study in Sect. 4.

The CLD in Fig. 2 shows the impact of epidemics. The intensity of an epidemic directly affects the variable *human health*, which expresses the health of the population and thus, the health of the nurses, the care-dependent people and their relatives. When affected by the disaster, the overall health of the population decreases. This decreases the number of *available nurses*. At the same time, people in poor health require more care and those whose health condition previously allowed for a self-sufficient life may now need care. The relation of vulnerable groups requiring additional care during times of disasters is emphasized by several studies (e.g., Fernandez et al. 2002; Khorram-Manesh et al. 2017). In addition, Knebel and Phillips (2008) point out that the number of care-dependent people will also increase because more people are discharged earlier from hospitals, due to short capacities. This is depicted in the CLD by *early dehospitalization*. Thus, it can be concluded that the better the *human health*, the lower the number of *care-dependent people* and the lower the *average care time*. The *human health* is also an influential factor of the *care efficiency*. Both, the physical and psychological health highly influences the efficiency of the conducted care.

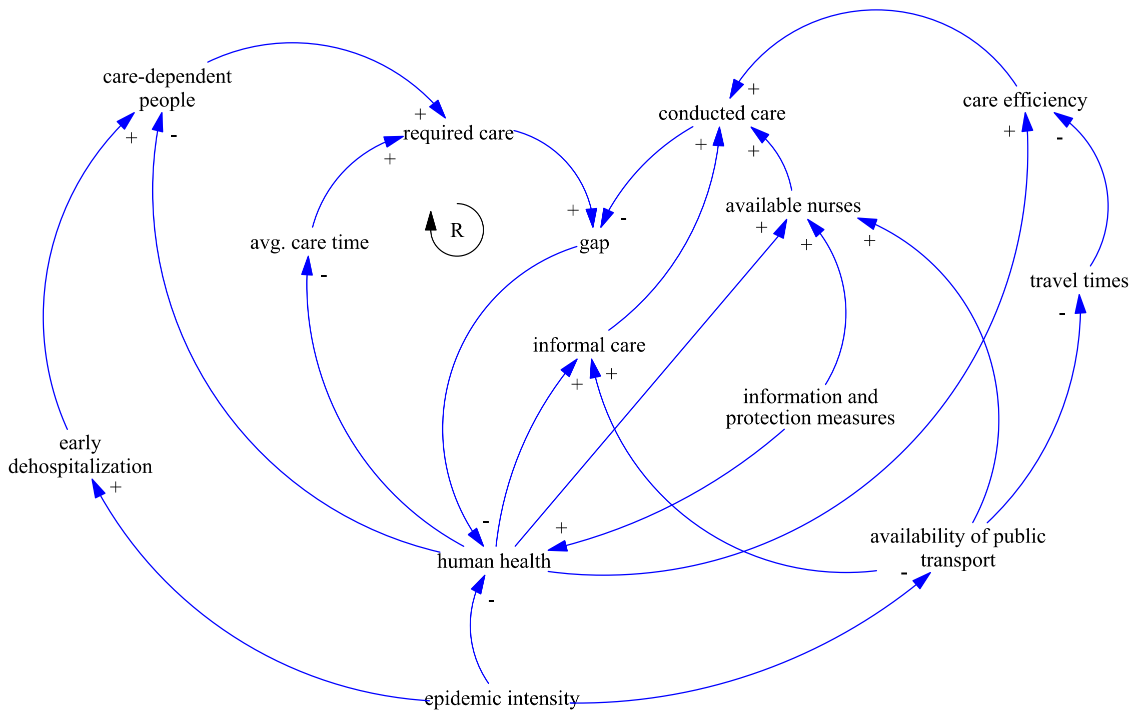

Fig. 2 CLD of the disaster impacts of epidemics on HHC

Another major problem arises from the nurses' ability and willingness to work. They might be sick themselves or have to care for other family members like children (e.g. due to the closure of schools and day-care centers). Knebel and Phillips (2008) estimate that about a quarter of the nurses will be sick themselves during an influenza epidemic. The willingness of healthcare personnel to work during different disease outbreaks (e.g., avian influenza and pox) has been addressed by several studies (e.g., Mackler et al. 2007; Irvin et al. 2008). They conclude that without protective equipment or vaccinations, few are willing to show up for duty, and even fewer if they fear that they might spread the disease to their own family members. However, the willingness to work increases with the staff's qualification and level of information about the disease. Thus, the variable *information and protection measures* directly affects not only *human health* by preventing infections, but also the *available nurses*. The availability of transportation also affect the nurses' ability to work. Fuel supplies and public transport might be limited because of high absenteeism or shut downs in order to limit the spread of the disease (Knebel and Phillips 2008). The higher the *availability of public transport*, the lower the *travel times*. The *travel times* are inversely proportional to the *care efficiency* because the more time is spent for traveling, the less is available for caring. A significant portion of care is still conducted by relatives and denoted by the variable *informal care*. It is directly proportional to *human health*. The worse the *human health*, the lower the amount of *informal care*. Relatives are unable to carry out care activities for the same reasons as the nurses. However, they are more affected as they might not have access to protective equipment or vaccinations to protect themselves from infection.

The main challenge of epidemics can be summarized by a huge increase in the number of care-dependent people and service times, paired with a significant decrease of the availability of nurses and informal care. The efficiency of the conducted care services is also expected to decrease. A higher demand for HHC services (*required care*) is thus offset by a reduced care potential (*conducted care*). The resulting *gap* creates a reinforcing feedback loop as unsatisfied demand decreases the *human health* of the care-dependent people. As a consequence, additional care is needed, which again increases the gap.

3.2 Blackout

Blackouts refer to large-scale power outages that last for several days or even weeks. However, even short-time interruptions of the electricity supply might result in cascading failures of critical systems. They are often the cascading result of other events (e.g., floods or winter storms) or of man-made- and technical failures. Alhelou et al. (2019) published a survey on blackouts around the globe and their cascading events. Europe in general, and Austria in particular, experience a very high level of electricity supply security. The single European electricity market imposes both, threats and benefits to supply security. Local shortages or disruptions might be compensated transnationally to avoid serious incidents, but in the worst case, they have ripple effects on their surrounding area, leading to large-scale power outages. For example, in September 2003, a tree flashover at a high-voltage line in Switzerland triggered a sequence of events that led to a separation of Italy from the European grid. Italy suffered a nationwide blackout that took about 19 h to re-energize all regions (Alhelou et al. 2019). According to Marston (2018), the US power supply suffers from its aging infrastructure and by the diverse set of infrastructure owners and operators, making the US power system even more susceptible to blackouts. The author also describes the impacts of various environmental and human-related threats, like physical sabotage and cyberattacks on the different electric system components (e.g., generation, transmission, or distribution). The significant growth of electricity generation from renewable energy sources results in an increasing supply volatility, thereby putting pressure on transmission and distribution systems (Reichl et al. 2013). The flourishing demand for electric vehicles will additionally stress the electricity supply. The frequency and scale of blackouts might therefore increase. Figure 3 visualizes the impacts of a blackout on the HHC system.

Blackouts affect nearly every aspect of daily life. Alhelou et al. (2019) describe the social, economic, and political impacts of blackouts on modern societies. For HHC, the most important impacts are on telecommunications, transport, and the health care sector. Most HHC service providers rely heavily on their IT and communication systems. Schedules are usually sent electronically to mobile devices of the nurses. These devices are also used to track and monitor the conducted care services directly at the clients' locations. Cowie et al. (2004) examine the impact of two widespread blackouts on the internet communication. Only the internet backbones were unaffected and thousands of institutional networks and millions of internet users where offline for hours or days, including banks, companies, hospitals and government institutions. Without IT systems and with limited ways of communication (modeled by *availability of ICT*) the *available nurses* are expected to decrease. Furthermore, the scheduling of the staff is less efficient, resulting in longer *travel times* and a reduced *care efficiency*. A

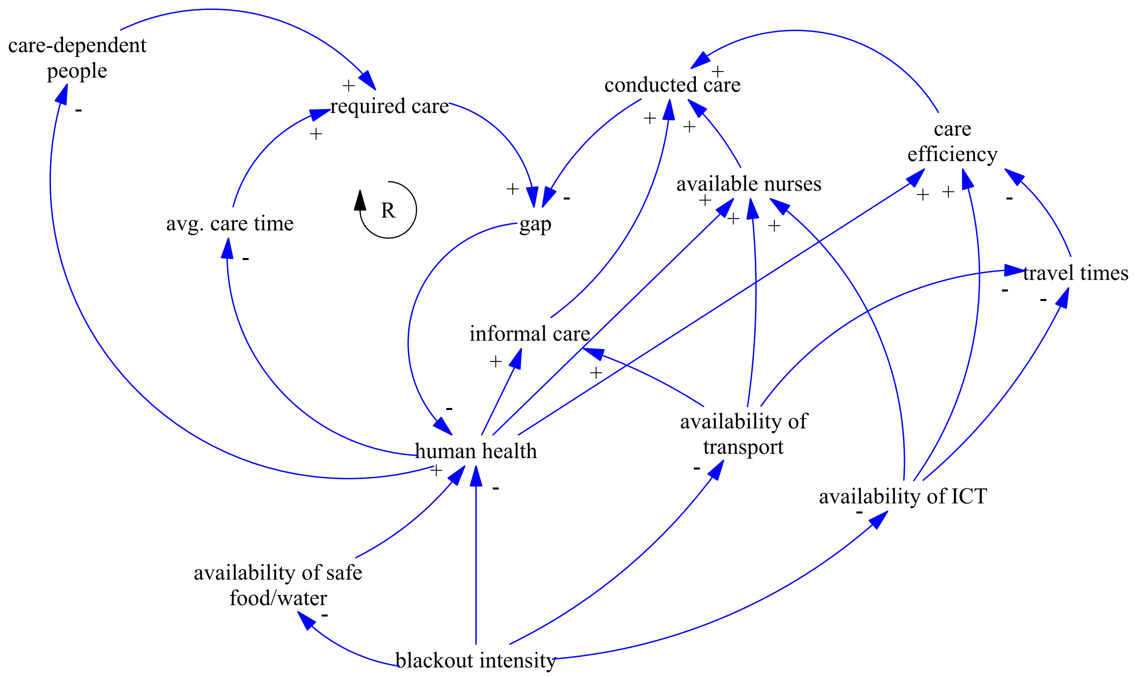

Fig. 3 CLD of the disaster impacts of blackouts on HHC

blackout also directly affects the *availability of transport*. Electricity-based transport (e.g., underground, train, and tram) will be inoperable and buses and cars suffer from lack of fuel and the failure of traffic management systems (e.g., traffic lights). A lack of *availability of transport* leads to longer *travel times* and to a reduction of *available nurses* and *informal care*.

The impacts on the health care sector are well documented by previous incidents. For example, the blackout that hit the northeast of the United States and the Canadian province of Ontario in August 2003 lasted for several days. Freese et al. (2006) reveal that the number of emergency calls increased by 103% in New York during this time. As the blackout happened in summer, most medical emergencies were related to cardiac and respiratory complaints. Beatty et al. (2006) emphasize the critical situation of those people, relying on electric equipment (e.g., lifting or oxygen devices) or medicines that require constant refrigeration. The authors also address an increase of foodborne diseases as well as contamination with untreated sewage. Klein et al. (2005) present the lessons learned from hospitals' perspectives. Compared to HHC, hospitals are well controlled environments and well prepared for disasters. Nevertheless, serious problems were encountered, including lighting, water supply, sanitation, hygiene, heating, ventilation, and air conditioning. Most of these issues were related to failing generators and city-wide loss of tap water supply and sewage disposal. The authors also identified staffing problems due to lack of communication, transportation, and childcare.

It can be concluded, that blackouts decrease *human health* in various ways, but most harm is done by the loss of electrically powered (medical) equipment or by the occurrence of diseases. The *availability of safe food/water* decreases without electricity, which further reduces *human health*. Especially cities with many high-rise buildings are at risk and depending on the season, the lack of heating or air conditioning further

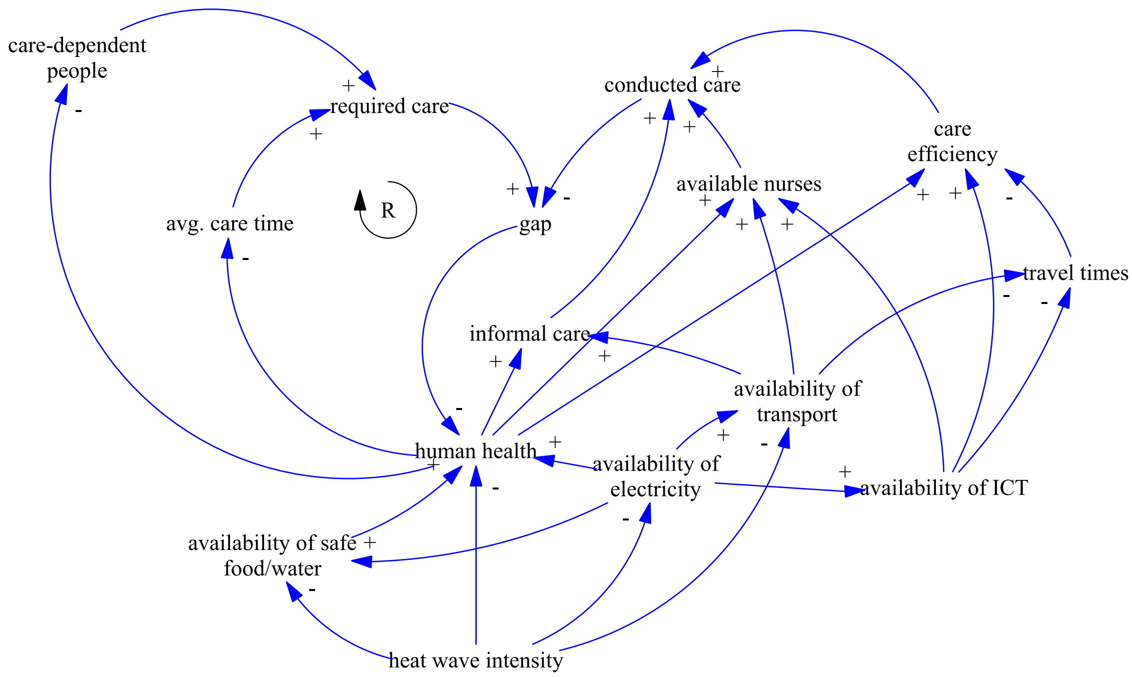

Fig. 4 CLD of the disaster impacts of heatwaves on HHC

aggravates these adverse health effects. The lower *human health*, the higher the number of *care-dependent people* and the higher the *avg. care time*. On the other hand, the *informal care* potential, the number of *available nurses* and the *care efficiency* are reduced. The top part of the CLD shows the same reinforcing feedback loop as during epidemics. Unsatisfied demand for care decreases the health of the care-dependent people, leading to an even higher demand.

3.3 Heatwave

Heatwaves refer to continuous periods with high temperature that last for weeks. Because of climate change and global warming, the frequency and intensity of heatwaves is expected to increase. Chapman et al. (2013) outline that urban regions are particularly affected by heatwaves, due to the urban heat island effect, which describes that temperatures in city centers are up to 10 °C higher than in the surroundings. Cities not only produce and absorb more heat, they also store it longer and therefore, they cool off more slowly. The CLD for heatwaves, shown in Fig. 4, resembles the CLD of blackouts in Fig. 3. The effects of both disasters are not only similar, but blackouts are often the cascading result of heatwaves. The main difference is therefore, that the CLD for heatwaves has been extended by an additional variable modeling the *availability of electricity*. This variable corresponds to the previous *blackout intensity*.

The impacts of heatwaves on *human health* are well documented and several studies outline the causal relation of increased mortality and morbidity during heatwaves. Mayrhuber et al. (2018) recently published a review on this topic in order to assess the vulnerability across societies. They emphasize that elderly and chronically ill people are among the most susceptible groups at risk. Being confined to bed, not leaving home daily, and being unable to care for oneself result in the highest risk of death.

The most common health implications are heatstroke, dehydration, cardiovascular, and respiratory diseases (Haines et al. 2006). Heatwaves might result in water shortages and thus, in an increase of infectious diseases. Zander et al. (2018) describe the effects of heat stress and relief measures on the workforce. Without relief measures (e.g., cooling, resting, or hydration) high temperatures result in fatigue, headaches and in reduced cognitive abilities and decision quality. The productivity of staff is significantly reduced and the risk of work place accidents increases, thus impacting the *care efficiency* and the *available nurses*.

In addition to the health effects, heat waves also affect the physical infrastructure. McEvoy et al. (2012) studied the impacts of a heatwave on Melbourne's critical infrastructure. They discovered severe impacts on the road, rail, and electricity infrastructure. The electricity generation is reduced during heatwaves. Hydro power stations suffer from low water levels and the efficiency of steam turbines depend on the temperature difference of the cooling water. However, the demand for electricity increases significantly because of air conditioning. As a consequence, the heatwave resulted in blackouts. More than a third of the train services were canceled because of the electrical faults, buckling rails, and failing air conditioning of the trains. Road traffic was affected by failing traffic management systems and by road bleeding (McEvoy et al. 2012). Similar findings have been reported by Arkell and Darch (2006) for London's transport network. It can be concluded, that heatwaves decreases both, the *availability of transport* and the *availability of ICT*.

3.4 Flood

Different types of floods must be distinguished. River floods are usually slow-rising and more predictable, providing time to prepare preventive actions. The predictability of coastal floods depends on the cause. Heavy storms or hurricanes are well monitored and allow for several days of preparation. Tsunamis however, are caused by spontaneous events like earthquakes and provide only a few hours of preparation, at best. The least predictable are flash floods, usually caused by heavy rain. Alpine and urban regions are especially at risk as they have large areas of sealed surfaces. Figure 5 shows the CLD of flood impacts on HHC. Again, this CLD has many similarities with the CLD of blackouts, because floods often cause widespread blackouts by flooding electrical equipment. However, *evacuations* have been included in the CLD. Usually, residents are not permitted to stay in their homes if they are flooded or even threatened to be flooded in near future. They often stay with relatives or at emergency shelters and thus, might not need HHC services during this time. The more people evacuated, the lower the number of *care-dependent people* in HHC.

The main impacts of floods are on *human health*, *availability of transport*, and *availability of ICT*. The health impacts of floods have been analyzed by Jakubicka et al. (2010). They distinguish short-term effects (e.g., injuries, or an increase in waterborne diseases) and long-term effects (e.g., chronic disease, or mental health issues). The disruption of sewage disposal and water treatment infrastructures has been identified as one reason for disease outbreaks. Mental health impacts are based on the destruction of property, loss of life, geographic displacement, or anxiety about event recurrence.

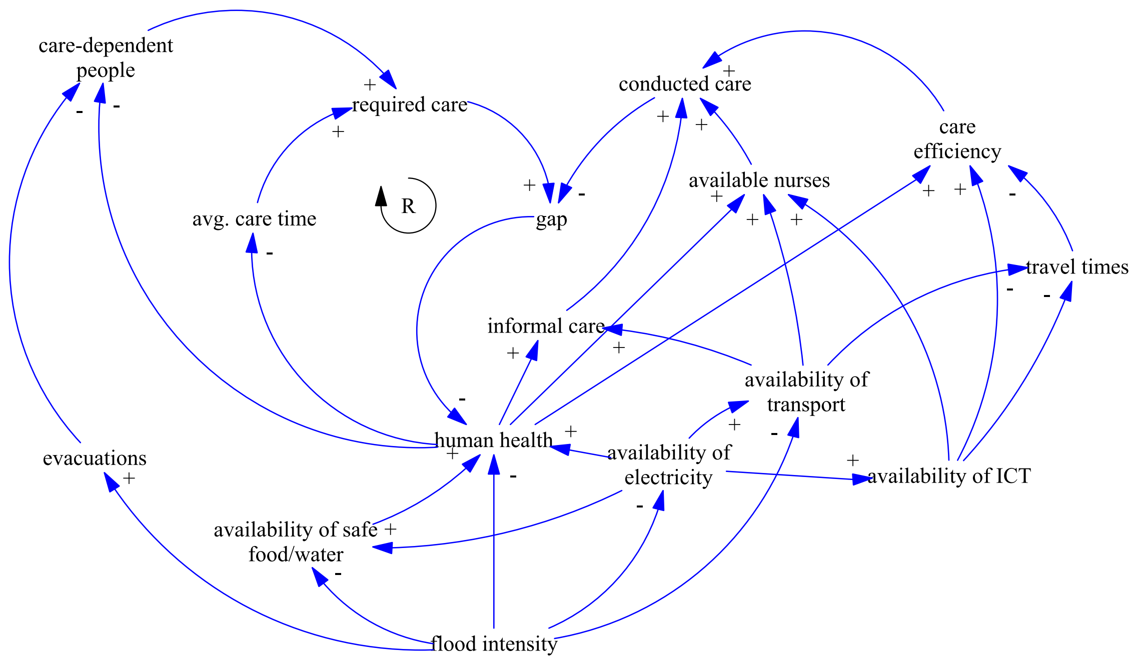

Fig. 5 CLD of the disaster impacts of floods on HHC

Suk et al. (2019) published a literature review to show how cascade effects of floods results in outbreaks of infectious diseases. According to Haines et al. (2006), large parts of the city of Dresden lost electricity and fresh water for several days during the flood that hit Europe in 2002. For the city of Vienna, floods are a high-impact low-probability risk because of large-scale flood protections (e.g., Danube Island). However, if these protections fail the effects are catastrophic, as outlined by the flood risk analysis of Compton et al. (2009). The transport infrastructure would be heavily damaged because of possible flooding of subway lines. The authors refer to subway floodings in Boston, Seoul, Taipei, and Prague, which took them out of service for several months. Road traffic concentrates itself on the remaining, non-flooded roads, leading to congestion and prolonged *travel times*.

4 Decision support in times of disasters: a COVID-19 case study in Austria

In late 2019, a novel coronavirus infection rapidly developed into an ongoing worldwide pandemic. The main transmission takes place from person to person, either through respiratory droplets (e.g., breathing, sneezing, coughing) or (in)direct contact with an infected person. The infection mostly affects the respiratory tract, with symptoms ranging from those of a common cold to very severe respiratory infections. While most infected people show only mild symptoms, older people and those with pre-existing conditions are particularly at risk. As a result, more than half of all COVID-19-related deaths in most EU countries are attributable to elderly residents of long term care facilities and nursing homes (ECDC 2020). The World Health Organization declared the outbreak as a pandemic on March 11, 2020 (Kreidl et al. 2020). As of March 20, 2021, the COVID-19 Dashboard of the Johns Hopkins University reports more than 122 million infections and more than 2.7 million deaths across 192 countries and territories (Johns Hopkins University 2021). In this section, the course of the COVID-19 pandemic in Austria in spring 2020 is described as well as the actions taken by the government and their effects on HHC. Subsequently, a DSS is presented that aims to support HHC services by optimizing the daily scheduling of HHC nurses. Based on the variables identified in Sect. 3, a case study with real-world data analyzes the impacts of the COVID-19 pandemic on the scheduling of the nurses.

4.1 COVID-19 pandemic and measures in Austria

In spring 2020, there were no specific treatments or approved vaccines for COVID-19. The measures and recommended actions focused on the treatment of the symptoms as well as preventing the further spread of the disease. The first diagnosed infections in Europe (January 24) were associated with travels from or to areas in south-east Asia. At that time, the European countries relied on screening and isolating symptomatic people coming from such an area or who had direct contact with a confirmed case. The first major outbreak in Europe was in Lombardy, northern Italy and thus, in the immediate vicinity of Austria (Moshammer et al. 2020). According to Kreidl et al. (2020), the first diagnosed cases in Austria (February 25) were an Italian couple working in Innsbruck but returning from Lombardy. Two days later, the first infected Austrian residents where diagnosed in Vienna. In retrospect, it became apparent that there were already large clusters of infections in skiing areas in the federal state of Tyrol. Between March 7 and 17 a total of 145 infections were diagnosed and attributed to a ski resort. It is assumed that the crowding conditions in aprés ski bars with infected staff members with mild symptoms during the influenza season resulted in an uncontrolled spread of the virus. On March 12 Austria recorded the first COVID-19 fatality (Kreidl et al. 2020).

Desson et al. (2020) compare the policy responses of Austria, Germany and Swiss in the early stage of the pandemic. With steadily increasing numbers of diagnosed infections and hospitalizations, one of the first actions in Austria was the introduction of selective border controls with health checks on March 6, especially on the Italian border. On March 10, people were encouraged to practice social distancing and to work from home, if possible. Public events like the upcoming Vienna City Marathon have been canceled and public facilities (e.g., museums, federal gardens) were closed (Desson et al. 2020). Universities were announced to close and switch to distance learning by March 16, at the latest. Further measures for schools and limits on the number of people attending events (incl. restaurants) have been promised. On March 12, the day of the first COVID-19 fatality, visits to hospitals were banned and actions were taken to increase hospital capacities (e.g., postpone/cancel elective surgeries) and to establish dedicated COVID-19 treatment centers (Pollak et al. 2020). In addition, about 10,000 citizens completing their mandatory civil service were also moved into health-care support roles as social care workers and paramedics (Desson et al. 2020). As a result of the ski resort clusters, some Tyrolean communities were quarantined for 14 days on March 13. In anticipation of a nationwide curfew, panic purchases took place, overloading the supply chains of certain products. In addition, a ban on visits to nursing homes was announced (Pollak et al. 2020). On March 16, the Austrian government declared a national state of emergency and initiated a strict nationwide lockdown (Desson et al. 2020). Borders were closed, air traffic was largely suspended, shops (apart from basic supply), restaurants, and bars were closed the following day (Pollak et al. 2020). Strict contact regulations and curfews demanded that people leave their home only for four reasons: (1) covering their basic needs (e.g., supermarkets, pharmacies), (2) essential work, (3) assisting other people, and (4) taking walks alone or with people from the same household. As a result of the lockdown, schools and kindergartens were closed and public transportation reduced its operation significantly. HHC nurses who are dependent on public transportation suffered from longer travel times. On March 30, it was announced that a mouth nose protection must be worn when shopping. The lockdown was gradually lifted on April 14, due to the successful containment and its economic impacts. Smaller shops were allowed to reopen and the requirement to wear a face mask was extended to public transport. On May 1, the curfews ended and the remaining shops and body-related service providers (e.g. hairdressers) reopened. Two weeks later, restaurants, bars, and cafes opened with restricted numbers of visitors. Schools opened nationwide on May 18 (Pollak et al. 2020).

Schmidt et al. (2020) analyzed the impact of COVID-19 on users and providers of long-term care services in Austria. On May 15, Austria had a total of 16,068 confirmed COVID-19 cases and 628 attributed fatalities. 788 residents of nursing homes and 448 staff were tested positive as of May 6. While 28% of the infected residents died, the number of cases in nursing homes is estimated to be low in comparison with other countries. It is outlined that the Austrian long-term care system significantly relies on migrant carers from Eastern European countries, who were heavily affected by travel restrictions and border closures. To prevent staff shortages, staffing regulations have been loosened to allow people with limited (e.g., in training) or no qualifications to provide basic care. To avoid infections of the nurses and transmissions to clients, recommendations for preventive and protective measures were published. However, it was difficult to provide sufficient amounts protective gear during the first weeks of the pandemic. In order to sustain the informal care potential, telephone hotlines providing psychological counseling and self-help through online support networks (e.g., online courses for unpaid carers) were provided (Schmidt et al. 2020). With reference to the CLD for epidemics presented in Sect. 3.1, the mitigation measures and their consequences are well locatable in the CLD. They mainly relate to *human health*, *available nurses*, *care-dependent people*, and *availability of public transport*.

4.2 Decision support system

A DSS can support multiple phases of the disaster management cycle (mitigation, preparedness, response, and recovery). For example, it allows HHC service providers to determine their operational limits and to adjust their processes and capacity planning, in order to enhance the resilience of their organization. Furthermore, a DSS can be used for the training of the dispatchers and nurses to prepare for various disaster events. During the response phase of a disaster, it guarantees that the available resources are used as efficiently as possible. By speeding up the planning process, a DSS also frees time of the dispatchers for other important activities.

Applying operations research methods and techniques to support HHC received a lot of attention in the recent years. The organization and processes of HHC service providers differ even within a single country, resulting in a wide range of publications, addressing different aspects of HHC. The literature review of Hulshof et al. (2012) lists various decision problems in HHC on the strategic (e.g., districting, capacity dimensioning), tactical (e.g., capacity allocation, staff-shift scheduling), and operational level (e.g., staff-to-visit assignment, route creation). Optimizing the routing of HHC services, which is in the main focus of this section, is addressed in the comprehensive literature reviews of Fikar and Hirsch (2017) and Grieco et al. (2020). They reveal various challenging routing problems with a wide range of regulative and operational constraints as well as diverse objectives. Despite the large number of works, the impacts of disaster scenarios on HHC services have been hardly discussed. To the best of our knowledge, there is only a limited number of publications to support HHC in such times. Barkaoui et al. (2018) developed a mixed integer linear program with a dynamic risk-based clustering. The model considers the geographical proximity of the clients and each client's predefined risk rating for each period. It is decided which groups are evacuated and which HHC resources are assigned to the groups of clients staying at home during forecastable natural disasters such as floods. The routing of the nurses is not considered. Trautsamwieser et al. (2011) present a mixed integer linear program as well as a Variable Neighborhood Search-based metaheuristic to support the daily routing of HHC nurses in the rural area of Upper Austria. A sensitivity analysis is carried out to show the impacts of natural disasters on the planning. A real-world flood is analyzed as well as official flood risk scenarios with a 30, 100, and 200 year return period.

The solution approach of the presented DSS and the underlying HHC routing problem are based on those published in Rest and Hirsch (2016). They have been further developed by the same authors into a commercially used software that has been marketed by the *ingentus decision support KG*, a spin-off of the Institute of Production and Logistics of the University of Natural Resources and Life Sciences Vienna. The DSS is used by a major HHC service provider in Vienna for their daily planning. In total this service provider has about 750 nurses and over 3000 clients. The HHC routing problem has a daily planning horizon and can be briefly described by the characteristics of the clients and nurses.

Clients require one or more services (jobs) per day and each job...

- must be executed by a feasible and appropriately skilled nurse (i.e., qualification level, language skills, sex, not excluded nurse or transport mode).
- has to start within its given (hard) time window.
- has a fixed duration that must not be shortened.
- should be assigned to the clients' team of preferred nurses and all of his/her jobs should be assigned to the same nurse (for each qualification level).
- should be planned so that the minimum and maximum time offsets between jobs are fulfilled (e.g., 2h between a morning and lunch job).

- that is marked as ’multiclient job’ has to be carried out together with its counterpart (i.e., same time and nurse).

Nurses are required to...

- carry out jobs that correspond to their primary qualification or that require a qualification level that is included in their set of allowed qualifications (results in over-qualification).
- obey working time restrictions (i.e., earliest/latest and minimum/maximum working time).
- hold breaks if the working time exceeds a certain time.
- work at most two shifts a day.
- use one of the available transport modes (i.e., public transport, cars, bicycles, walking).
- start/end their shift either at a depot or directly at the location of their first/last job and return to a predefined location if working two shifts.
- not exceed the total overtime limit defined for all nurses.
- have a similar workload compared to the other nurses (relative to their target working time).

A weighted objective function balances the opposing goals of minimizing the route lengths and maximizing the satisfaction of the clients and nurses. The client’s satisfaction is mainly determined by the consistency of care regarding the visiting times and nurses. For the nurses, overtime and over-qualification are crucial indicators for their satisfaction. A total of 11 soft constraints are used to configure the tradeoffs between the individual factors of the objective function. The actual weights have been set together with the dispatchers and the managerial decision makers of the the HHC service provider. In contrast to the algorithms published in Rest and Hirsch (2016), the DSS must always present a schedule to the dispatcher. For this reason, only a few hard constraints are considered. These consist of assignment constraints that can be evaluated before the actual optimization. If the preliminary checks detect unassignable jobs, the reasons for the infeasibilities are reported. In addition, the time windows of jobs, the start and end times of a nurse’s shift as well as his/her total working time limit can be marked as a hard constraint by the dispatcher. However, if no satisfying solution is found, the best infeasible solution is reported.

The presented HHC routing problem mainly distinguishes itself from other work by the fact that public transport is considered. Public transport operates on timetables that have different departure intervals and travel times during the day. Thus, their time-dependent travel times are modeled using a travel time matrix for each minute of the day. The DSS is able to process timetable data from public transport service providers in the General Transit Feed Specification (GTFS) format, developed by Google. Another unique feature are the mandatory breaks, which in contrast to previous work, can be split into smaller parts. To the best of our knowledge, there are still no other publications except for Rest and Hirsch (2016) in the field of HHC routing, addressing one of these features. The routing itself is based on OpenStreetMap (OSM) data, which is a viable alternative data source, especially in urban regions. The benefits of community gathered data also ensures a better availability of routable maps in the event of a disaster.

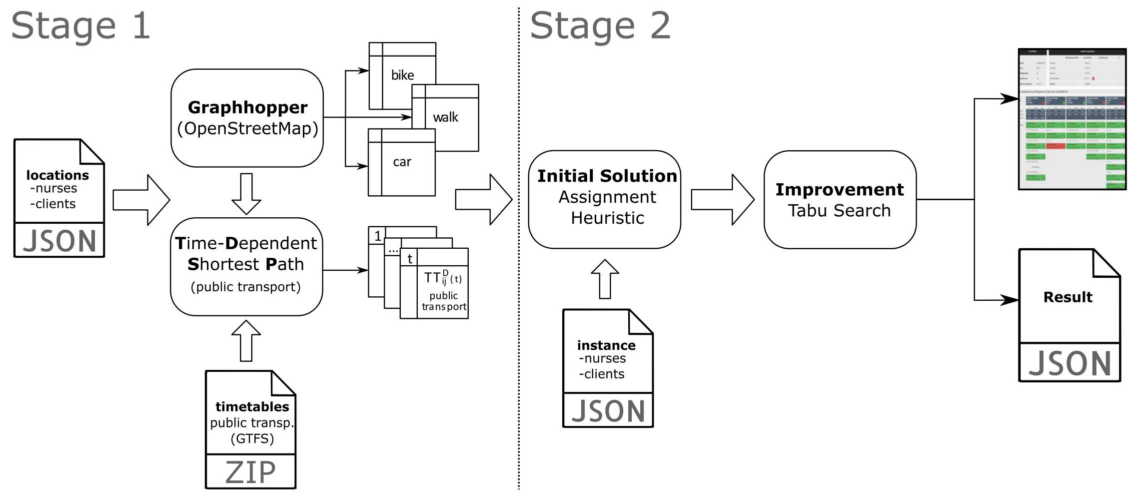

Fig. 6 Structure of the DSS

Time and efficiency are crucial for practical applications. Due to the complexity of the routing problem, the DSS uses a Tabu Search metaheuristic. The algorithm is explained in detail in Rest and Hirsch (2016). Its process can be summarized as follows: First, an initial solution is generated with an insertion heuristic, based on the centered time windows of the jobs. Afterward, neighbor solutions are generated by moving individual jobs from one nurse to the routes of all other nurses. The insertion into the new routes are based on the 'best insertion' principle. During the evaluation of the new routes, their starting times are optimized and breaks are inserted, if needed. The route with the best objective value updates the current solution and the cycle of generating new neighbor solutions continues until a termination criteria (i.e., elapsed time, number of iterations without improvements) is met. The best found solution is tracked during the search and returned at the end. The search process temporarily allows infeasible solutions and uses a 'tabu list' to prevent the reversal of moves for a certain amount of iterations. To further guide the search, dynamically adapted penalties are added to the weighted objective function.

The presented algorithm is based on the same concepts used in Rest and Hirsch (2016). However, several problem specific elements have been changed. The main difference is the optimization of the start time of the nurses. In Rest and Hirsch (2016) the aim was to determine the start time that results in the shortest working time of the nurse. However, this might lead to considerably postponed start times, which leave hardly any leeway for complications. Therefore, the algorithm of the DSS first calculates the earliest possible end of the tour and then determines the latest start for this end. Additional constraints have been implemented to cover the new requirements regarding the multiclient jobs and the minimum and maximum time offsets between jobs. A non-linear constraint was added to seek a balanced workload of the nurses.

For easy integration in existing systems, the DSS has been developed as a web service using Java 8. This way, it is highly scalable to manage heavy workloads as well as highly customizable and expandable with regard to constraints and objective functions. It is able to solve real-world sized instances with about 250 jobs and 40 nurses within a few minutes. The DSS can be used to evaluate or improve the manual planning of the dispatchers or to compute schedules from scratch. The structure of the DSS is shown in Fig. 6. For data protection reasons, a 2-stage process is followed. In the first stage, geographical data is processed into time-dependent (i.e., public transport) and time-independent (i.e., car, bike, walking) travel time matrices. Following the principle of data minimization, only the final travel time matrices are stored, preventing direct geographical traceability. In the second stage, the travel time matrices and the submitted anonymized instance data are used to compute the schedule. The results are returned as a report (Html format) and as raw data (Json format) in order to display and further process the schedules in the existing software systems of the HHC service provider.

4.3 Numerical studies

Based on the findings in Sects. 3.1 and 4.1, several strategies were followed to numerically assess the impact of the COVID-19 pandemic on HHC in Vienna. The focus was laid on two areas, the transport infrastructure (travel times, availability of transport modes) and the clients (duration of care). The DSS was adapted so that changes in these areas can be done directly through input data modifications. Due to the sensitivity of the real-world data, artificial manipulations such as adding and removing clients, jobs or nurses were avoided. Unfavorable decisions can quickly lead to useless instances whose results may even lead to wrong conclusions. For example, it is easy to overburden some nurses while others hardly work at all because of exclusions. In practice, dispatchers would then deploy nurses in or from different areas, but such decisions are based on the expertise of the dispatchers. The specific settings of each scenario are described below, together with their results.

The DSS is applied to real-world data from a major HHC service provider in Vienna. A total of 16 instances ($I_1 - I_{16}$) from regular weekdays are available. For data protection reasons, the instances originate from a corresponding period in 2019. Geographically, the clients are spread across all districts of Vienna. Each instance represents a group of nurses working in a certain area. The zoning has been done by the HHC service provider, primarily based on public transport hubs. The working times of the nurses are given by their contracts and the rosters of the corresponding weekday. Table 1 shows for each instance the number of jobs, nurses, total shifts as well as how many nurses use public transport or cars. The average walking time between all clients is given as indicator for their geographical distribution. The walking speed is based on 5 km/h, for cycling a speed of 18 km/h was assumed and for cars, the speed is based on the OSM road types but set slightly below their limits. However, all speeds are reduced by the actual speed limits on the streets. The qualification level of all nurses and jobs correspond to those of home helpers. The service times of the jobs vary between 15 and 165 min, averaging 49 min. The average length of the jobs' time windows is just under 2.5 h, but with a minimum length of 15 min and a maximum of 6.75 h for less time critical jobs.

The weight setting used for the computations of this paper are the same that the dispatchers at the HHC service provider use in practice. In times of disasters, priorities are usually shifting to ensuring the delivery of care. However, the DSS was designed

Table 1 Data characteristics of the real-world instances

	Jobs (#)	Nurses (#)	Shifts (#)	Pub. transp. (#)	Cars (#)	Avg. walking (min)
I_1	139	28	34	21	7	32
I_2	140	20	26	20	0	20
I_3	138	18	27	18	0	19
I_4	123	20	24	15	5	26
I_5	134	18	24	15	3	33
I_6	109	18	22	7	11	60
I_7	133	24	33	20	4	34
I_8	136	27	35	23	4	22
I_9	135	21	29	18	3	22
I_{10}	129	21	25	14	7	26
I_{11}	154	26	33	20	6	47
I_{12}	163	21	29	17	4	48
I_{13}	121	17	21	16	1	33
I_{14}	140	25	32	18	7	32
I_{15}	122	26	31	26	0	22
I_{16}	134	20	25	17	3	34

to always report a solution and its constraints have been configured so that the focus is shifting in case of larger violations. For example, at low workloads, the focus is on meeting the preferences of the clients (i.e., preferred nurses, consistency of care). On the other hand, at high workloads, meeting the mandatory working time restrictions is more important. Furthermore, using the real-world setting allows for a good comparability of the results from before and during the pandemic. All computations have been carried out locally on a Lenovo ThinkPad T490 with an Intel Core i7-8565U processor, 16 GB of RAM and running Windows 10 Pro. The computation time limit has been set to 600 seconds per instance.

The first scenario analyzes transport infrastructure impacts. As outlined in Sect. 4.1, only public transport was affected during the pandemic in Austria. In this scenario, each instance is solved using the timetable data from before and during the lockdown. As reference for a timetable without restrictions the day of January 13, was chosen, a normal weekday without COVID-19 measures. For the second date, March 23 was chosen, the same weekday but 1 week after the curfew came into effect. Just looking at the raw GTFS data, it can be seen that there are substantially less connections on this day. The modal split of the nurses, shown in Table 1, remains unchanged in this scenario. Table 2 compares the resulting schedules for all instances before and during the lockdown. As key performance indicators for the travel impacts the total travel times (incl. waiting) as well as the total overtime of each instance are reported. Additionally, these values were summarized to an objective value to show a percentage increase. Overtime is defined as the time that a nurse works outside his/her defined working time window (e.g., 7 a.m. to 2 p.m.). In addition, dispatchers define a target total working time for each shift of the nurse (e.g., 4 h) and exceeding these targets also counts to overtime. This is done to balance the accumulated over- and undertime of a nurse in order to reach his/her contracted working time. As a consequence, the pre corona results already show a considerable overtime for those instances that were submitted with minimum target working times (e.g., I_8, I_9, I_{12}).

It can be seen that the restrictions on public transport result only in small increases in travel (incl. waiting) times and overtime, amounting to an average increase of the objective value of 6.6%. However, individual instances like I_1, I_4, I_7, and I_{15} show increases from 10% up to 18%, which might be deemed already infeasible by dispatchers. The biggest impact is caused by the share of cars in the modal split, in combination with the average distances between clients. As car travels were not affected by the COVID-19 actions, instances with a high share of car users (e.g., I_6, I_{14}) are less affected as long distances are then covered by nurses using cars. On the other hand, nurses relying on public transport suffer even more from its reduced availability the longer the walking distances between the clients are.

The second scenario aims to analyze the operational limits of the different instances during the COVID-19 pandemic. In the CLD for epidemics in Sect. 3.1 it is outlined that clients require more care in such disaster situations. Thus, it should be analyzed how much the service times can be prolonged before capacity problems occur. Therefore, the service times of all jobs are gradually increased in steps of 10%. Determining the feasibility of an instance is difficult to generalize. From the perspective of a dispatcher, even a minor delay at a single job might render the schedule infeasible, if he/she considers it time critical. On the other hand, a slight violation of the maximum working time can still be acceptable in order to guarantee care for all clients. Therefore, the average overtime per nurse and the average time window violation per job are reported as key performance indicators of the schedules. It has already been shown in the previous scenario that the modal split has a large impact on the scheduling. Thus, all computations are carried out also with additional transport modes. The current mix of public transport and cars is used as reference and in case no changes to the modal split are possible. Under the assumption that already existing cars are still available, calculations were made in which all nurses, who previously used public transport, use cars, bicycles or walking. The use of walking can be seen as a worst case scenario, if public transport is shut down completely or if the dispatcher wants to minimize the risk of infections. The calculations with public transport are again based on the timetable data at the time of the lockdown.

Table 3 shows the impacts of the considered transport modes and the prolonged service times on the average overtime and tardiness. Regarding the prolonged service times, both the average overtime per nurse as well as the average tardiness indicate an even increase for each transport mode. At first glance, the numbers seem to be manageable by the HHC provider. At the current modal split the average tardiness increases from about 5 min without prolonged service times up to 31 min at +50%. Being late by 5 min is negligible and by half an hour is also most likely acceptable in times of a pandemic, as long as the jobs are not time critical. On the other hand, the average overtime of each nurse increases from 53 min to slightly more than 3 h. The ability to work additional 3 h every day depends on the nurses' contracted working times. It is most likely not recommended for longer-lasting events like pandemics.

Table 2 Real-world scheduling results for each instance before and during COVID-19

	Pre corona			Corona			
	Travel + wait (min)	Overtime (min)	Objective (min)	Travel + wait (min)	Overtime (min)	Objective (min)	Increase (%)
I_1	1730	231	1961	1957	294	2251	14.8
I_2	1937	164	2101	1989	299	2288	8.9
I_3	1838	1320	3158	1887	1321	3208	1.6
I_4	1231	701	1932	1325	808	2133	10.4
I_5	1400	222	1622	1438	282	1720	6.0
I_6	1276	323	1599	1299	328	1627	1.8
I_7	2033	564	2597	2423	643	3066	18.1
I_8	1344	2751	4095	1383	2772	4155	1.5
I_9	1292	3632	4924	1340	3684	5024	2.0
I_{10}	1340	1291	2631	1461	1333	2794	6.2
I_{11}	1851	880	2731	1882	932	2814	3.0
I_{12}	1747	2883	4630	1817	2960	4777	3.2
I_{13}	1159	1326	2485	1227	1392	2619	5.4
I_{14}	1854	429	2283	1886	442	2328	2.0
I_{15}	1739	230	1969	1839	369	2208	12.1
I_{16}	1360	364	1724	1429	438	1867	8.3
Mean	1571	1082	2653	1661	1144	2805	6.6

Table 3 Impacts of transport modes and service times on overtime and tardiness (in min)

	Prolonged service time + 0%	+ 10%	+ 20%	+ 30%	+ 40%	+ 50%
Current mix						
Avg. overtime	53.4	77.4	101.0	131.1	157.2	189.1
Avg. tardiness	5.3	7.7	11.6	17.3	23.2	31.3
Car						
Avg. overtime	32.8	54.1	77.6	107.7	134.4	165.4
Avg. tardiness	2.3	5.3	8.6	13.6	19.0	26.9
Bike						
Avg. overtime	39.7	62.3	85.7	115.8	143.2	175.0
Avg. tardiness	3.1	6.6	9.7	14.3	20.4	28.4
Foot						
Avg. overtime	55.3	79.3	103.4	132.7	159.5	191.3
Avg. tardiness	5.5	7.9	12.1	17.7	23.5	31.6

Considering the average instance size of 22 nurses and 134 jobs, even without prolonged service times, the COVID-19 situation results in a total overtime of about 19.5 h and a total tardiness of almost 12 h, on average across all instances. Thus, each instance would need 2.5 additional full-term nurses, working 8 h a day, to compensate the additional workload. The advantage of using cars was already apparent in the previous scenario. In comparison with the current modal split, the overtime can be reduced by 23% if all nurses have access to cars. The use of bicycles is inferior to cars due to the lower average speed. Although the DSS is able to explicitly consider times for parking, this feature is not used by the HHC service provider, because the considered speed limits already result in realistic driving times. However, the bicycle results are still significantly better then the current modal split. Furthermore, they are an economically and ecologically viable alternative, and also usable by nurses who do not have a driver's license. Avoiding public transport only leads to a slight increase of the average overtime by 2% across all scenarios.

5 Discussion and outlook

HHC services are rising in importance in the health care systems of many countries and with it grows the need to sustain these services in times of disasters. Risk assessment tools and guides support HHC service providers to secure their services. However, they do not provide insights on interdependencies of complex systems like HHC. CLDs have been used to visualize the impacts of epidemics, blackouts, heatwaves, and floods on the HHC system. They help to understand the system design as well as cascading effects. Additionally, SD simplifies the process of identifying points of action in order to mitigate the impacts of disasters. For example, during an epidemic, protective equipment is crucial as it prevents not only infection of HHC staff and transmission of the disease to clients, but increases their willingness to work. The CLDs also show the importance of informal care, provided by friends and relatives. This outlines the need for a close coordination with them. In case of their unavailability, HHC services need to step in immediately to prevent health issues. On the other hand, relatives might be able to reduce the pressure of HHC services if they are able to take over some tasks.

In a case study, real-world data from a HHC service provider in Vienna was used to show the impacts of the COVID-19 pandemic on HHC in spring 2020. Furthermore, it shows the applicability of the presented DSS in times of disasters, which can be used for the daily scheduling of the nurses to ensure that the limited resources are used as efficient as possible. By speeding up the planning process, it frees time of the dispatchers for other important activities. It also allows HHC service providers to better prepare for disasters and helps to determine the operational limits of the nursing teams, operating in different areas with different characteristics (i.e., distance between clients, availability of public transport). The DSS also shows the effects of using various transport modes. In urban regions, careful planning allows to cover many distances by foot or (electric) bicycles.

While the DSS was used to analyze the impacts of the COVID-19 pandemic in Vienna, it can also be applied to analyze other disaster scenarios, such as those presented in Sect. 3 of the paper. The applicability of the DSS in other regions and countries depends on the organizational requirements of the respective HHC system. However, as the DSS was developed as a commercial software, much attention was paid to flexibility and customizability. Both, the objective function and the constraints can be easily extended and adjusted to the new requirements. Most of the analysis can be done by varying the input data, making the availability of reliable data one of the biggest challenges.

However, the presented DSS has limitations. While supporting HHC service providers, it further increases their dependency on IT systems, which are especially vulnerable during disasters with limited availability of electricity. While it is designed to run on low-powered hardware like notebooks, continuous local backups of the relevant data are required. Furthermore, in its current stage of development, it is assumed that all jobs have to be carried out. At some point during major disasters the operational limits are reached. For these cases, a computer assisted triage system is needed to prioritize the most critical jobs and to carry out as many jobs as possible. Future work should also cover the dynamics of the HHC routing problem. The short computation times of the DSS allows for rapid re-scheduling, but the generated schedules might be entirely different each time. Especially with limited means of communications, it is usually preferable to adapt to the new situation with as few changes as possible.

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Declaration

Conflict of interest The authors declare that they have no conflict of interest.

References

Aldrich N, Benson WF (2008) Disaster preparedness and the chronic disease needs of vulnerable older adults. Prev Chronic Dis 5(1):1–7

Alhelou HH, Hamedani-Golshan M, Njenda T, Siano P (2019) A survey on power system blackout and cascading events: research motivations and challenges. Energies 12(4):682. https://doi.org/10.3390/en12040682

Arkell BP, Darch GJC (2006) Impact of climate change on Londons transport network. Proc Inst Civ Eng Municipal Eng 159(4):231–237. https://doi.org/10.1680/muen.2006.159.4.231

Baker GH (2005) A vulnerability assessment methodology for critical infrastructure facilities. In: DHS symposium: R&D partnerships in homeland security, pp 1–13

Barkaoui H, Guinet A, Wang T (2018) Securing home health care structures facing forecastable natural disasters: a new tool to regulate between evacuation and adaptive home support services. IFAC-PapersOnLine 51(11):986–991. https://doi.org/10.1016/j.ifacol.2018.08.479

Beatty ME, Phelps S, Rohner C, Weisfuse I (2006) Blackout of 2003: public health effects and emergency response. Public Health Rep 121(1):36–44. https://doi.org/10.1177/003335490612100109

Berariu R, Fikar C, Gronalt M, Hirsch P (2015) Understanding the impact of cascade effects of natural disasters on disaster relief operations. Int J Disaster Risk Reduct 12:350–356. https://doi.org/10.1016/j.ijdrr.2015.03.005

CDC (2019) Centers for disease control and prevention: 2009 H1N1 pandemic. https://www.cdc.gov/flu/pandemic-resources/2009-h1n1-pandemic.html. Accessed 27 Sept 2020

Chapman L, Azevedo JA, Prieto-Lopez T (2013) Urban heat and critical infrastructure networks: a viewpoint. Urban Clim 3:7–12. https://doi.org/10.1016/j.uclim.2013.04.001

Compton KL, Faber R, Ermolieva TY, Linnerooth-Bayer J, Nachtnebel HP (2009) Uncertainty and disaster risk management: modeling the flash flood risk to Vienna and its subway system. Tech. Rep. RR-09-002, International Institute for Applied Systems Analysis, Laxenburg, Austria

Cowie JH, Ogielski AT, Premore B, Smith EA, Underwood T (2004) Impact of the 2003 blackouts on internet communications. Preliminary Report, Renesys Corporation

Desson Z, Lambertz L, Peters JW, Falkenbach M, Kauer L (2020) Europe's Covid-19 outliers: German, Austrian and Swiss policy responses during the early stages of the 2020 pandemic. Health Policy and Technology, pp 1–14. https://doi.org/10.1016/j.hlpt.2020.09.003

Doherty M (2004) An emergency management model for home health care organizations. Home Health Care Manag Pract 16(5):374–382. https://doi.org/10.1177/1084822304264610

ECDC (2020) European centre for disease prevention and control: latest evidence on COVID-19. https://www.ecdc.europa.eu/en/covid-19/latest-evidence. Accessed 27 Sept 2020

Fernandez LS, Byard D, Lin CC, Benson S, Barbera JA (2002) Frail elderly as disaster victims: emergency management strategies. Prehospital Disaster Med 17(2):67–74. https://doi.org/10.1017/S1049023X00000200

Fikar C, Hirsch P (2017) Home health care routing and scheduling: a review. Comput Oper Res 77:86–95. https://doi.org/10.1016/j.cor.2016.07.019

Forrester JW (1997) Industrial dynamics. J Oper Res Soc 48(10):1037–1041. https://doi.org/10.1057/palgrave.jors.2600946

Freese J, Richmond NJ, Silverman RA, Braun J, Kaufman BJ, Clair J (2006) Impact of a citywide blackout on an urban emergency medical services system. Prehospital Disaster Med 21(6):372–378

Gershon RRM, Qureshi KA, Stone PW, Pogorzelska M, Silver A, Damsky MR, Burdette C, Gebbie KM, Raveis VH (2007) Home health care challenges and avian influenza. Home Health Care Manag Pract 20(1):58–69. https://doi.org/10.1177/1084822307305908

Grieco L, Utley M, Crowe S (2020) Operational research applied to decisions in home health care: a systematic literature review. J Oper Res Soc. https://doi.org/10.1080/01605682.2020.1750311

Haines A, Kovats RS, Campbell-Lendrum D, Corvalan C (2006) Climate change and human health: impacts, vulnerability and public health. Public Health 120(7):585–596. https://doi.org/10.1016/j.puhe.2006.01.002

Hulshof PJH, Kortbeek N, Boucherie RJ, Hans EW, Bakker PJM (2012) Taxonomic classification of planning decisions in health care: a structured review of the state of the art in OR/MS. Health Syst 1(2):129–175. https://doi.org/10.1057/hs.2012.18

Irvin CB, Cindrich L, Patterson W, Southall A (2008) Survey of hospital healthcare personnel response during a potential avian influenza pandemic: will they come to work? Prehospital Disaster Med 23(4):328–335

Jakubicka T, Vos F, Phalkey R, Marx M, Guha-Sapir D (2010) Health impacts of floods in Europe: data gaps and information needs from a spatial perspective. MICRODIS report, Centre for Research on the Epidemiology of Disasters, Brussels, Belgium

Johns Hopkins University (2021) COVID-19 dashboard by the center for systems science and engineering (CSSE) at Johns Hopkins University. https://coronavirus.jhu.edu/map.html. Accessed 20 Mar 2021

Khorram-Manesh A, Yttermyr J, Sörensson J, Carlström E (2017) The impact of disasters and major incidents on vulnerable groups: risk and medical assessment of Swedish patients with advanced care at home. Home Health Care Manag Pract 29(3):183–190. https://doi.org/10.1177/1084822317699156

Klein KR, Rosenthal MS, Klausner HA (2005) Blackout 2003: preparedness and lessons learned from the perspectives of four hospitals. Prehospital Disaster Med 20:343–349

Knebel A, Phillips SJ (2008) Home health care during an influenza pandemic: issues and resources. AHRQ Publication No. 08-0018, Agency for Healthcare Research and Quality, Rockville

Kreidl P, Schmid D, Maritschnik S, Richter L, Borena W, Genger JW, Popa A, Penz T, Bock C, Bergthaler A, Allerberger F (2020) Emergence of coronavirus disease 2019 (COVID-19) in Austria. Wien Klin Wochenschr, pp 1–8. https://doi.org/10.1007/s00508-020-01723-9

Mackler N, Wilkerson W, Cinti S (2007) Will first responders show up for work during a pandemic? Lessons from a smallpox vaccination survey of paramedics. Disaster Manag Response 5(2):45–48

Marston TU (2018) The US electric power system infrastructure and its vulnerabilities. Bridge 48(2):31–39

Mayrhuber EAS, Dückers MLA, Wallner P, Arnberger A, Allex B, Wiesböck L, Wanka A, Kolland F, Eder R, Hutter HP, Kutalek R (2018) Vulnerability to heatwaves and implications for public health interventions—a scoping review. Environ Res 166:42–54. https://doi.org/10.1016/j.envres.2018.05.021

McEvoy D, Ahmed I, Mullett J (2012) The impact of the 2009 heat wave on Melbournes critical infrastructure. Local Environ 17(8):783–796. https://doi.org/10.1080/13549839.2012.678320

Moshammer H, Poteser M, Lemmerer K, Wallner P, Hutter HP (2020) Time course of COVID-19 cases in Austria. Int J Environ Res Public Health 17(9):3270. https://doi.org/10.3390/ijerph17093270

NAHC (2008) Emergency preparedness packet for home health agencies. Technical report, The National Association for Home Care & Hospice, Washington

OECD (2017) Health at a glance 2017: OECD Indicators. OECD Publishing, Paris. https://doi.org/10.1787/health_glance-2017-en

Pollak M, Kowarz N, Partheymüller J (2020) Chronology of the corona crisis in Austria. https://viecer.univie.ac.at/en/projects-and-cooperations/austrian-corona-panel-project/corona-blog/overview/. Accessed 27 Sept 2020

Powell JH, Mustafee N, Chen AS, Hammond M (2016) System-focused risk identification and assessment for disaster preparedness: dynamic threat analysis. Eur J Oper Res 254(2):550–564. https://doi.org/10.1016/j.ejor.2016.04.037

Pursiainen C (2017) The crisis management cycle. Routledge, London. https://doi.org/10.4324/9781315629179

Reichl J, Schmidthaler M, Schneider F (2013) The value of supply security: the costs of power outages to Austrian households, firms and the public sector. Energy Econ 36:256–261. https://doi.org/10.1016/j.eneco.2012.08.044

Rest KD, Hirsch P (2015) Supporting urban home health care in daily business and times of disasters. IFAC-PapersOnLine 48(3):686–691. https://doi.org/10.1016/j.ifacol.2015.06.162

Rest KD, Hirsch P (2016) Daily scheduling of home health care services using time-dependent public transport. Flex Serv Manuf J 28(3):495–525. https://doi.org/10.1007/s10696-015-9227-1

Rest KD, Trautsamwieser A, Hirsch P (2012) Trends and risks in home health care. J Humanit Logist Supply Chain Manag 2(1):34–53. https://doi.org/10.1108/20426741211225993

Rodriguez D, Long CO (2006) Emergency preparedness for the home healthcare nurse. Home Healthc Nurse 24(1):20–27

Schmidt AE, Leichsenring K, Staflinger H, Litwin C, Bauer A (2020) The impact of COVID-19 on users and providers of long-term care services in Austria. Technical report, International Long-Term Care Policy Network, CPEC-LSE, 15 May 2020

Suk JE, Vaughan EC, Cook RG, Semenza JC (2019) Natural disasters and infectious disease in Europe: a literature review to identify cascading risk pathways. Eur J Public Health. https://doi.org/10.1093/eurpub/ckz111

Trautsamwieser A, Gronalt M, Hirsch P (2011) Securing home health care in times of natural disasters. OR Spectr 33(3):787–813. https://doi.org/10.1007/s00291-011-0253-4

Wyte-Lake T, Claver M, Dalton S, Dobalian A (2015) Disaster planning for home health patients and providers: a literature review of best practices. Home Health Care Manag Pract 27(4):247–255. https://doi.org/10.1177/1084822314567536

Zander K, Mathew S, Garnett S (2018) Exploring heat stress relief measures among the Australian labour force. Int J Environ Res Public Health 15(3):401. https://doi.org/10.3390/ijerph15030401

Appendices

A Curriculum Vitae

Mag. Klaus-Dieter Rest

Education

05/2013 **VRP2013 – European Spring School on Vehicle Routing**, *Université Catholique de l'Ouest*, *Angers, France*

09/2010 – present **Doctorate in Social and Economic Sciences**, *University of Natural Resources and Life Sciences*, *Vienna, Austria*, Institute of Production and Logistics

03/2009 **Strategic simulation 'TOPSIM - Macro Economics'**, *Vienna University of Economics and Business*

09/2005 – 08/2009 **Degree program in Business and Economics**, *Vienna University of Economics and Business*, *Vienna, Austria*
- Specialist Area: Management Science
- Diplom thesis: „Comparison of optimization techniques for planning deliveries for the Upper Austrian municipality Suben“
  Supervisor: Werner Jammernegg
  Grade: excellent(1)

11/2004 **MarketTrack Basis Seminar**, *ACNielsen Ges.m.b.H*, *Vienna*

2003 – 2004 **Military service as scout**, *Bolfras-Kaserne, Mistelbach, Austria*

2000 – 2003 **Commercial high school**, *International Business College Hetzendorf*, *Vienna, Austria*

1997 – 2000 **Commercial school**, *Mistelbach, Austria*

Experience

Academic

04/2009 – 07/2016 & 10/2019 – 11/2020 **Research Assistant**, *University of Natural Resources and Life Sciences*, *Vienna, Austria*, Institute of Production and Logistics
- Implementation of distributed ledger technology in a food supply chain project
- Development of meta- and matheurstics for home health care projects
- Development of meta- and matheurstics for urban freight transport projects
- Drafting of project proposals

Teaching

03/2010 – 07/2016 & 03/2019 – 07/2020 **Graduate Teaching Assistant**, *University of Natural Resources and Life Sciences*, *Vienna, Austria*, Institute of Production and Logistics
Course titel: Unternehmensnetzwerke (Logistik)
- Leading a seminar group of up to 30 students
- Preparation of homework, evaluation of student performances during the semester, and grading of written exams

Industry

10/2016 – present **ingentus decision support KG**, *Vienna, Austria*
- Software development (system architecture, backend, database)
- Development of optimization algorithms
- Process analysis

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2016 **Freelance work for h2 projekt.beratung KG**, *Vienna, Austria*
- Algorithmic design of a decision support tool

07/2004 – 08/2005 **ACNielsen Ges.m.b.H**, *Vienna, Austria*
- Creating databases and customer analysis for food retail market research

11/2001 – 08/2002 **Walter Dr. u. Mostbeck Dr. GnbR**, *Vienna, Austria*
- Administrative activities (part-time worker)

Reviewer

since 2016 Journal of Computational Science

since 2014 European Journal of Operational Research

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Skills

Language skills

German	native language	French	basic knowledge
English	fluent	Russian	basic knowledge

Computer skills

Typography	LaTeX, Microsoft Office (incl. VBA)	Imaging	Gimp, Inkscape
Programming	C++, Java	Scientific	Xpress, Gecode, R, ArcGIS

Additional qualifications

08/2001 Austrian driving licence cat. B

12/2011 Fire warden acc. AStVO and TRVB O 117

Awards

07/2006 Medal of the Province of Lower Austria for Disaster Response

Interests

research transportation logistics, health care logistics, disaster management, metaheuristics, exact methods, linear programming

private traveling, archery, photography

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Publications

Scientific Journal publications

Rest K.-D., Hirsch P. (2021): Insights and decision support for home health care services in times of disasters. *Central European Journal of Operations Research*, 1-25, doi:10.1007/s10100-021-00770-5

Reyes-Rubiano L., Vögl J., Rest K.-D., Faulin J., Hirsch P. (2021): Exploration of a disrupted road network after a disaster with an online routing algorithm. *OR Spectrum*, 43:289-326, doi:10.1007/s00291-020-00613-w.

Rest K.-D., Hirsch P. (2016): Daily scheduling of home health care services using time-dependent public transport. *Flexible Services and Manufacturing Journal*, 28:495-525, doi:10.1007/s10696-015-9227-1.

Rest K.-D., Trautsamwieser A., Hirsch P. (2012): Trends and risks in home health care. *Journal of Humanitarian Logistics and Supply Chain Management*, 2(1): 34-53, doi:10.1108/20426741211225993.

Conference proceedings (peer-reviewed)

Rest K.-D., Hirsch P. (2015): Robust scheduling of urban home health care services using time-dependent public transport. In: Campbell, A.M., Cleophas, C., Ehmke, J.F. (Eds.), *2015 TSL Workshop - Recent Advances in Urban Transportation through Optimization and Analytics*, 83-84, JUL 6-8, Berlin, Germany.

Rest K.-D., Hirsch P. (2015): Tabu Search strategies for daily scheduling of urban home health care services considering individual and public transport. *Odysseus 2015, Sixth International Workshop on Freight Transportation and Logistics - Extended Abstracts*, 193-196, MAY 31-JUN 5, Ajaccio, France.

Rest K.-D., Hirsch P. (2015): Supporting Urban Home Health Care in Daily Business and Times of Disasters. *IFAC-PapersOnLine. 15th IFAC Symposium on Information Control Problems in Manufacturing*, 48(3), 686-691, MAY 11-13, Ottawa, Canada, doi:10.1016/j.ifacol.2015.06.162

Rest K.-D., Hirsch P. (2013): Time-dependent travel times and multi-modal transport for daily home health care planning. In: Cortés C., Gendreau M., Rey P.A., Sáez D. (Eds.), *TRISTAN VIII - The Eight Triennial Symposium on Transportation Analysis*, JUN 9-14, San Pedro de Atacama, Chile, .

Rest K.-D., Hirsch P. (2012): A Tabu Search Approach for Daily Scheduling of Home Health Care Services using Multi-Modal Transport. In: Tarantilis C., et al. (Eds.), *Odysseus 2012, 5th International Workshop on Freight Transportation and Logistics - Extended Abstracts*, 373-377, MAY 21-25, Mykonos, Greece.

Conference presentations without proceedings (as presenter)

Rest K.-D., Zazgornik J., Hirsch P. (2019): Challenges of the practical implementation of solution algorithms for routing and scheduling home health care staff using public transport at a Viennese service provider. *Tagung der ÖGOR-Arbeitsgruppe 'Operations Research in Health Care & Disaster Management'*, OCT 25, Vienna, Austria.

Rest K.-D., Zazgornik J., Hirsch P. (2018): Time dependent routing and scheduling of home health care staff using public transport: Practical implementation at a Viennese service provider. *Joint EURO/ALIO International Conference 2018 on Applied Combinatorial Optimization*, JUN 25-27, Bologna, Italy.

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Rest K.-D., Hirsch P. (2013): Optimierte Touren- und Einsatzplanung von mobilen Pflegekräften bei Verwendung öffentlicher Verkehrsmittel. *Tagung der ÖGOR Arbeitsgruppe Operations Research im Gesundheitswesen*, MAY 13, Vienna, Austria.

Rest K.-D., Hirsch P. (2012): Scheduling of home health care services using time-dependent multi-modal transport. *EURO - 25th European Conference on Operational Research*, JUL 8-11, Vilnius, Lithuania.

Hirsch P., Trautsamwieser A., Rest K.-D. (2010): Unterstützung der Touren- und Einsatzplanung in der Hauskrankenpflege durch computergestützte Planungsverfahren, *team up! - 2. e-Health Day Salzburg*, JUN 16, Salzburg, Austria.

Rest K.-D., Trautsamwieser A., Hirsch P. (2010): Einsatz von GIS zur Simulation der Auswirkungen von Naturkatastrophen auf die Touren- und Einsatzplanung in der extramuralen Pflege. *Entscheidungsunterstützung in der Logistik: Geographische Informationssysteme und Optimierung*, APR 9-10, Salzburg, Austria.