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A quadrant shrinking heuristic for solving the dynamic multi-objective disaster response personnel routing and scheduling problem

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ABSTRACT

In the aftermath of natural disasters there is a need to provide disaster relief services. These services are offered by diverse disaster relief personnel teams that are specialized in the provision of the required services, e.g., teams that set up temporary shelters, teams that are providing medical services. These services are provided during a rolling horizon and the demand and supply characteristics of the disaster relief system evolve dynamically over time. In this paper we are presenting a dynamic variant of the multi-objective disaster relief personnel routing and scheduling (DDRPRS) problem, which considers efficiency, fairness and transportation risk objectives. We introduce a Quadrant Shrinking Method (QSM) based heuristic algorithm to approximate the Pareto Optimal Solutions of the DDRPRS problem under consideration. The proposed algorithm considers the performance of the solutions over the entire planning horizon and their robustness over time in terms of their efficiency, fairness and transportation risk. We apply the proposed heuristic for routing and scheduling personnel involved in evacuation and medical operations using data from the 2018 Lombok Earthquake in Indonesia. Our heuristic implementation covers both the dynamic and static variants of the disaster relief personnel routing and scheduling problem. Computational results show that the proposed heuristic can generate in a short time sufficiently large number of Pareto Optimal Solutions which cover the entire Pareto frontier as indicated by the diverging behaviours of the Pareto Optimal Solutions and the associated hypervolume metrics.

1. Introduction

As reported by the United Nations Disaster Risk Reduction Office, the number of natural disasters has increased significantly in the last 20 years (UNODR, 2020), including severe disasters such as the Boxing day tsunami in Indonesia (2004), the Port-au-Prince earthquake (2011) and the Nepal earthquake (2015). In 2015, the United Nations presented the Sendai Framework for Disaster Risk Reduction 20152030 which points to the need for focused action in four priority areas: i) understanding the disaster risk, ii) strengthening the disaster risk governance, iii) investing in disaster risk reduction and iv) enhancing disaster preparedness for disaster response. These priorities require to reinforce the disaster response resources to promote policies assisting public services (UNDRR, 2015). As the emergency management divisions are often underfunded, as well as understaffed (Oostlander, Bournival, & O'Sullivan, 2020), the necessary investments to foster the disaster response personnel (DRP) units are hardly made which results in lack of DRP and imbalance between the available personnel and demand for disaster relief services. These conditions underline the importance to efficiently manage the available DRP.

An implication of the personnel shortages is the excessive working hours of the DRP which risk both the safety of the personnel and the operations they carry out. This necessitates to consider resting requirements of the DRP in their scheduling. Furthermore, the routing and scheduling of the DRP should consider the efficiency and fairness of the disaster response services while taking into account the risks on the transportation network due to the disasters. While the demand for the disaster response services should be satisfied as quickly as possible (i.e, efficiently), it is also vital to provide a fair provision of these services among different disaster-affected zones (i.e., fairness). Considering the possible damages on the transportation network in the aftermath of disasters, it is also crucial to consider the corresponding transportation

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risks along with the efficiency and fairness associated with the provision of the disaster relief services.

Due to the nature of disasters, disaster response services are carried out in an environment that is highly dynamic. Therefore, the routing and scheduling decisions of the DRP should be able to be efficiently adapted to the possible changes realized after the onset of disasters. Specifically, the magnitude and spatial distribution of demand and/or the condition of the transportation network might change over time (e.g., emergence of new demand and changes of the characteristics of the underlying transportation network such as travel time, connectivity and risk) due to post-disaster effects of the disaster. Consequently, the dynamic changes over the horizon of the provision of the disaster response services should be considered. Although there are models incorporating the resting requirements of the DRP and the efficiency, fairness and risk objectives in a static environment (Tarhan, Zografos, Sutanto, Kheiri, & Suhartanto, 2023), there are no models incorporating the dynamic aspects of the DRP routing and scheduling (DRPRS) problem. Furthermore, there are no efficient heuristics available for solving both the static and dynamic variants of the multi-objective disaster relief personnel routing and scheduling problem.

In this paper, we are introducing the Dynamic Multi-Objective Disaster Response Personnel Routing and Scheduling (DDRPRS) model by extending the multi-objective model proposed for the static DRPRS problem in Tarhan et al. (2023). Furthermore, we are introducing a heuristic algorithm to solve larger instances of both variants, i.e., static and dynamic, of the DRPRS problem. The proposed heuristic approximates the entire Pareto-optimal frontier and in the case of the DDRPRS problem incorporates the dynamic changes of the problem parameters, namely magnitude and location of the demand and condition of the transportation network.

The proposed solution methodology is tested by using historical data for the 2018 Lombok Earthquake. The proposed approach is first applied to a small-size test instance which considers part of the affected area by the relevant earthquake. Subsequently, we are using the proposed heuristic approach to solve a larger-size instance considering a wider area (and a larger number of personnel). Finally, different scenarios, reflecting the dynamic characteristics of the problem stemming from possible transportation network failures and the evolution of demand for the provision of services over time, are generated and solved to demonstrate the applicability of the proposed solution methodology. While our case study and the associated computational experiments relate to the routing and scheduling of personnel offering evacuation and medical services at the onset of 2018 Lombok Earthquake, the proposed methodology is applicable for different types of disasters (and types of response personnel) in which personnel are deployed at the onset of the disaster and are routed between disaster-affected zones over a sufficiently long period that requires them to take resting/sleeping breaks (such as earthquakes and floods).

In a nutshell, the contributions of this paper are as follows:

- The dynamic extension of the Multi-Objective Dynamic Disaster Response Personnel Routing and Scheduling Problem (DDRPRS) is introduced. The proposed model incorporates the resting requirements and synchronization of personnel and considers efficiency, fairness and risk objectives. We also introduce a new fairness metric that takes into account the dynamic nature of demand. A mixed-integer linear programming (MILP) model is proposed for the DDRPRS problem.
- A Quadrant Shrinking Method (QSM) based heuristic (QSH) algorithm is developed that can be used to solve any tri-objective integer programming model.
- The static (DRPRS) and dynamic (DDRPRS) variants of the proposed model are solved by the QSH. A construction heuristic and a tabu search algorithm are developed to be employed within the QSH. A new set-partitioning model, including a dynamic programming approach in its pre-processing, is introduced to optimize the path selection decisions on a multi-graph transportation network.
- The proposed solution methodology is applied on a test instance using historical data for 2018 Lombok Earthquake, to gain further insights regarding the optimization of the static and dynamic DRPRS.

The remainder of the paper is organized as follows. The literature pertaining to the DDRPRS problem is reviewed in Section 2. The problem is formally defined in Section 3. The proposed MILP model is presented in Section 4. The proposed solution methodology is explained in Section 5. Results of the computational experiments considering both static and dynamic problem environments are shared in Section 6. Finally, outputs of this study and promising future research directions are summarized in Section 7.

2. Literature review

The focus of this paper is to twofold: i) to incorporate the dynamic aspects of the DRPRS problem and ii) to develop a heuristic algorithm that will be able to address both the dynamic and static variants of the DRPRS problem. For completeness, we first review solution approaches proposed in studies addressing the static version of the DRPRS problem and then discuss studies regarding the dynamic version of the DRPRS problem. Subsequently, we briefly review the multi-objective approaches applied to the DDRPRS or similar problems in the literature. We conclude this section by stating our contributions. We note that personnel routing and scheduling problems for disaster response operations have often been studied in the context of personnel involved in operations offering specific services such as disaster assessment, network restoration, search-and-rescue, evacuation and medical operations (Amideo, Scaparra, & Kotiadis, 2019; Balcik & Yanıkoğlu, 2020; Chen & Miller-Hooks, 2012; Duque, Dolinskaya, & Sörensen, 2016; Karabuk & Manzour, 2019; Liu, Li, Liu, & Patel, 2016; Talarico, Meisel, & Sörensen, 2015). Each of these studies addresses specific properties of the corresponding services such as the transportation reliability, survival likelihood and triage of the disaster victims. Herein, we focus our review on more generic (not disaster specific) studies that are more closely related to the research reported in this paper.

2.1. Literature related to the DRPRS problem

Rolland, Patterson, Ward, & Dodin (2010) developed an adaptive reasoning technique heuristic to solve the routing and scheduling problem including multiple types of emergency services and multiple types of personnel each with a distinct skill set. It is shown that the proposed heuristic can find the best solution known for many instances generated by Dodin, Elimam, & Rolland (1998). Bodaghi & Palaneeswaran (2016) proposed a MILP model for the routing and scheduling of the personnel to serve different types of services with distinct release times. Nadi & Edrisi (2017) developed a Markov decision process considering a multi-agent assessment and response system which coordinates relief assessment and emergency response teams. Wang, Liu, Lian, Hong, & Chen (2018) developed a two-stage heuristic for dispatching both medical supplies and medical personnel. In the first stage, they apply an artificial bee colony algorithm to solve the reduced problem without medical supply distribution constraints. In the second stage, a rolling horizon heuristic is applied to generate a feasible solution in terms of medical supply distribution. Bodaghi, Palaneeswaran, & Abbasi (2018) developed an MILP model to be used within a two-phase method (Ulungu & Teghem, 1995) to solve the bi-objective (i.e., minimization of the makespan and weighted sum of the completion times) routing and scheduling of relief supply and personnel. The proposed method was tested on a hypothetical dataset and on a data set case study for the Melbourne metropolitan area. Tarhan et al. (2023) proposed a lexicographic optimization approach applied over a rolling horizon to optimize the efficiency, fairness and transportation risk of the DRP routing and scheduling. The proposed approach was tested by using historical data for 2018 Lombok Earthquake.

To the best of our knowledge, Tarhan et al. (2023) is the only study addressing the fairness and transportation risk objectives in the context of the DRPRS problem. On the other hand, there exist studies considering the corresponding objectives in similar contexts such as disaster relief supply distribution. For example, Ortuño, Tirado, & Vitoriano (2011) and Vitoriano, Ortuño, Tirado, & Montero (2011) consider the fair distribution of relief supplies along with total transportation risk exposure associated with their distribution of supplies. In these two studies, a single path between two given locations is considered. Nolz, Semet, & Doerner (2011) and Wan, Ye, & Peng (2023) take into account different paths between two nodes having different travel time and transportation risk trade-off. They propose different models such that in the pre-processing of each model, one of these alternative paths is selected based on a distinct criterion (such as the minimal travel time and the maximum reachability probability). Tikani & Setak (2019), on the other hand, minimize the total service completion times of distributing relief supplies to disaster-affected zones while using a multi-graph transportation network. They impose a risk-oriented constraint that is bounding the maximum total risk of the paths traversed by vehicles.

2.2. Literature related to the DDRPRS problem

Fiedrich, Gehbauer, & Rickers (2000) dynamically optimize the allocation of both rescue personnel and rescue equipment to minimize the expected number of fatalities. Simulated annealing and tabu search algorithms were developed and applied for a set of damage-and-loss scenarios. Yi & Özdamar (2007) proposed a two-stage approach that first determines the aggregate vehicle flows and then constructs feasible routes along with the allocation of the resources to the vehicles in a multi-period setting (in order to include dynamic changes over time). The proposed approach, that minimizes the weighted sum of the unsatisfied demand, was tested on a possible Istanbul earthquake expected to take place in the next decades. Al Theeb & Murray (2017) consider transfer of commodities and workers from distribution centers to affected zones to carry out emergency services such as evacuation, medical and repair of damaged infrastructure. They proposed a multi-period routing and scheduling problem to minimize the total unsatisfied demand and a set of heuristic algorithms that can solve problems of practical size in reasonable time. Xu, Gai, & Salhi (2021) and Fitrianie & Rothkrantz (2015) proposed modified Dijkstra algorithms to evacuate victims from affected zones to safe locations. While the former study considers evacuation following a chemical accident and the resulting risks, e.g., heat radiation changing over time, the latter study considers the possibility of arcs' becoming inaccessible over time. Mills, Argon, & Ziya (2018) developed Markov-decision based heuristic algorithms to dynamically dispatch ambulances to patient locations and decide where to carry them for treatment. The proposed heuristics were tested on a case study for a hypothetical earthquake. Kim, Shin, Lee, & Moon (2018) consider rescue operations in a multi-period setting in order to incorporate the varying risk (e.g., due to fire spread or gas leak), arc capacity and processing times over the planning horizon. They proposed a greedy algorithm to maximize the weighted satisfied demand. Although there are studies addressing the transportation risk in different dynamic disaster-related contexts (e.g., Zhou, Liu, Zhang, & Gan, 2017), they do not consider multiple paths between two nodes and do not incorporate a fairness objective. For more detailed literature review, readers can refer to the recent systematic review of operations research and management science in humanitarian operations by Farahani, Lotfi, Baghaian, Ruiz, & Rezapour (2020) and Baxter, Lagerman, & Keskinocak (2019).

2.3. Multi-objective considerations related to the DRPRS and DDRPRS problems

There are various exact approaches that have been proposed for solving multi-objective integer programming problems (Ehrgott, 2006; Romero, Tamiz, & Jones, 1998). Vitoriano et al. (2011) and Ortuño et al. (2011) apply goal programming and lexicographic goal programming optimization, respectively, which are defined for any number of objectives. These algorithms require to solve a set of single-objective problems which are handled by MILP solvers in the corresponding studies. Another exact multi-objective algorithm used in our problem context (Bodaghi et al., 2018) is the two-phase approach by Ulungu & Teghem (1995) that is specifically designed for bi-objective problems, where again each single-objective subproblem is solved by a MILP model.

Performance of the exact approaches can deteriorate as the number of integer variables increases. This motivates the development of heuristic algorithms addressing the multi-objective problems. Particularly, there have been many metaheuristic algorithms specifically designed for the multi-objective problems (Jones, Mirrazavi, & Tamiz, 2002). Most of these metaheuristics involve a dominance-based (mostly Pareto dominance) selection mechanism to be able to approximate the Pareto frontier (Liu, Li, Liu, & Guo, 2020). Among those studies, population-based algorithms such as genetic algorithm and particle swarm optimization are shown to produce satisfactory results for diverse class of problems. Accordingly, in our problem context, Wan et al. (2023) developed a population-based multi-objective hybrid salp swarm and sine cosine algorithm and Zhou et al. (2017) proposed a multi-objective evolutionary algorithm.

While there are generic population-based algorithms such as genetic (e.g., Deb, Pratap, Agarwal, & Meyarivan, 2002) and particle swarm optimization (e.g., Alaya, Solnon, & Ghedira, 2007) algorithms, they need to be fine-tuned with respect to the problem specifics for an improved performance. Ehrgott & Gandibleux (2000) specify this pitfall as underlining that each problem has its own specifics and a general multi-objective metaheuristic cannot cope with all of these. In a recent study, Liu et al. (2020) share the following two findings after their review on multi-objective discrete optimization algorithms: i) most of the existing studies propose algorithms to solve specific optimization problems and ii) it is promising to introduce the optimum-seeking capability of analytical/exact techniques into multi-objective metaheuristics. In this line, we reviewed the exact approaches that are applicable for our problem. As shown in Section 5, the DDRPRS problem we are studying reduces to a tri-objective problem. To the best of our knowledge, the Quadrant Shrinking Method (Boland, Charkhgard, & Savelsbergh, 2017) is the state-of-the-art algorithm for tri-objective integer problems. The Quadrant Shrinking Method (QSM) requires to solve a set of single-objective problems. Tabu search (Fiedrich et al., 2000) or adaptive reasoning technique (Rolland et al., 2010) which is inspired by the tabu search algorithm of Dodin et al. (1998) are used effectively in our problem context. Tabu search algorithm is also shown to be competitive for both routing and scheduling problems (Mathlouthi, Gendreau, & Potvin, 2021). Although an improved version of the QSM method exists for binary problems that avoids generating duplicate solutions (Boland, Charkhgard, & Savelsbergh, 2019), our DDRPRS problem is not necessarily binary and can be integer depending on the disaster response service to be considered (as explained in Section 4). Thus, our heuristic is developed based on the QSM for integer problems.

2.4. Contributions of this study

Tarhan et al. (2023) optimize the fairness and transportation risk objectives in the DRPRS context. They consider a static environment and propose a solution approach in which different paths between two given locations are not considered simultaneously. On the other hand, the majority of the DDRPRS studies reviewed in Section 2.2 consider a single objective and seek to optimize the efficiency of the disaster response services, e.g., minimization of expected fatalities and unsatisfied demand, and to the best of our knowledge, the fairness and transportation risk objectives are not addressed in the DDRPRS context. Another gap in the literature is the absence of heuristic algorithms taking into account the properties of the DRPRS problem (such as personnel resting requirements, personnel synchronization due to service take-overs, and different types of demand explained in Section 3). While the dynamic DRP routing and scheduling (DDRPRS) problems mostly address evacuation and/or rescue operations, they do not take into account the personnel resting requirements, inherently assuming that the relevant operations can be completed in a short horizon. In consideration of the dynamic changes such as aftershock effects and secondary disasters, personnel rests can be inevitable due to the extended horizon of operations.

In this paper, we address the identified gaps and propose a dynamic multi-objective mathematical model that optimizes simultaneously and dynamically the fairness and transportation risk of the disaster response operations along with their efficiency subject to the constraints such as personnel rests. A multi-graph transportation network is used to better represent the trade-off between travel time and risk of the paths to traverse. We also propose a new fairness measure considering the temporal evolution of demand, which is differentiating it from the static fairness measures.

In terms of the solution approach, we develop a heuristic algorithm exploiting the capability of exact approaches as suggested in Liu et al. (2020). Specifically, we propose a heuristic adaptation of the state-of-the art algorithm QSM for tri-objective integer problems. The heuristic adaptation is defined at a higher level and it is applicable to any tri-objective integer problem. It requires a solution algorithm to tackle the successive single-objective subproblems resulting from the QSM. To this end, we also develop a tabu search algorithm for the single-objective version of the DDRPRS problem that can handle the specific attributes of the DRPRS (and DDRPRS) problem. The proposed heuristic applies the rolling horizon approach so that it can update the changing problem parameters such as the transportation risks of paths and/or demand locations and magnitudes on a daily basis. While the single-objective version of the DDRPRS problem is NP-Hard and difficult to be solved per se, the proposed heuristic can generate efficient solutions that approximate the Pareto frontier of the DDRPRS problem in a short time.

3. Problem definition

The DDRPRS problem differs from its static counterpart DRPRS in three aspects. First of all, the DDRPRS problem incorporates dynamic changes of the problem parameters over the disaster response period. Secondly, it considers unequal priorities of demand at different locations unlike its static version. Demand priorities can change over time as well. Lastly, the fairness measures takes into account the changes on demand over time (i.e., emergence of new demand locations and/or changing demand magnitudes at existing demand locations).

For completeness and in order to highlight the elements differentiating the static and dynamic variants of the problem, we are presenting in this section a brief description of the static DRPRS problem, as well as the additional features of the dynamic (DDRPRS) problem.

The DRPRS problem is motivated by the disaster response services provided in the aftermath of large-scale disasters in Indonesia. In this context, Disaster Response Personnel (DRP) teams specialized in the provision of different types of services are dispatched to disaster impacted areas, to satisfy the demand for their services. An example, that has motivated the research reported in this paper, refers to the dispatching of DRP teams that are dedicated to provide either evacuation or medical services. More details regarding this example can be found in Section 6.

In this context, personnel teams are deployed in the aftermath of a disaster and travel between affected zones to provide the services corresponding to their specialization. Evacuation personnel set-up tents, i.e., temporary housing, to accommodate the evacuees while medical personnel provide medical assistance. A personnel team might involve a single person or a group of people working as a team which are qualified to execute their dedicated service (e.g., a medical team comprising from doctors and nurses).

We are making some assumptions relevant to the context of the DRPRS problem that has motivated our work. Each demand point requires a set of services each of which should be provided during daylight unless there exists lighting equipment at the service site. This assumption results in service time-windows defined by their earliest start and latest completion time during the day. Due to the lack of personnel, it might not be possible to dedicate personnel to each demand location and thus personnel are routed through the demand points to serve the demand. They need to take sleeping breaks after reaching the maximum allowable number of continuously working hours. Sleeping facilities are assumed to be provided to DRP at designated locations such as a shelter or a hotel. When personnel need to stop an ongoing service to have a rest, another personnel can continue the provision of the services. In this case, the relevant personnel should be synchronized such that the personnel taking-over the service should arrive to the demand point before the previous personnel leaving it in order to be briefed on the status of the service.

In the DRPRS problem, starting from the onset of the disaster, decision makers make DRP routing and scheduling decisions on a daily basis so as to provide the emergency services required by the disaster-affected areas. In case of precedence relations between different types of services, decision makers consider the routing and scheduling of the personnel involved in the corresponding services in tandem. Disaster response personnel routing and scheduling decisions are made on a daily basis until all demand for emergency services is satisfied.

Unlike the DRPRS problem for which the problem parameters are known at the beginning of the planning horizon and remain the same throughout the planning horizon, the parameters of the DDRPRS problem can change over the planning horizon due to various reasons such as secondary disasters, after-shock impacts, transportation network failures etc. When the problem parameters change, the DDRPRS problem is solved with the updated values of the parameters. Given that the demand for the provision of services changes over time with respect to both location and magnitude, the DDRPRS problem should take into account the time that the demand for services is manifested in order to differentiate between demand that has been awaiting for long time to be satisfied and demand that has been recently arrived.

The DDRPRS problem has four objectives which are the minimization of i) the total unsatisfied demand, ii) the total completion time of the demand satisfied, iii) unfair distribution of the unsatisfied demand among different demand locations and iv) the total transportation risk. The DDRPRS problem is solved over a rolling horizon and the multi-objective routing and scheduling problem is solved on a daily basis sequentially throughout the planning horizon. Objective functions of the mixed-integer linear programming (MILP) model proposed to solve the multi-objective routing and scheduling problem are presented in Section 4. The rolling horizon approach (RHA) and the heuristic algorithm proposed to solve its sub-problems (for each day) are presented in Section 5. We note that the proposed MILP model and heuristic algorithm address the assumptions specific to our problem context by introducing the respective constraints. However, the proposed modelling and solution framework can be applied to different contexts as well in which some of these assumptions are not present, by dropping the corresponding constraints.

4. Mathematical model

The proposed MILP model is considering the provision of the disaster response services on a given day t^*. The adaptation of the single-period

MILP model to a multi-period setting to cover the entire disaster response horizon is explained in Section 5. Let T be the set of days/periods until and including day t^*, i.e., $T = \{1, \ldots, t^*\}$. Set V_I includes the set of demand points each having an unsatisfied demand at the beginning of period t^*. Demands of different locations in V_I do not necessarily emerge in the same period of the time horizon T. Therefore, $\widehat{d}_{i,t}$ denotes the amount of demand that is emerged at demand point $i \in V_I$ in period t yet not satisfied by period t^*, $t \in T : t \le t^*$. λ_i, $i \in V_I$, is the priority of the demand required by demand point i: the higher the priority of a demand, the more urgently it needs to be satisfied. We also define set V which includes the points of interest in our problem that are i) demand points (V_I), ii) resting points and iii) base/starting locations of the personnel where P is the set of personnel. Considering the transportation network spanning the locations in set V, $A_{i,j}$ includes the set of paths/arcs between locations i and j each representing a distinct trade-off between travel time and transportation risk. $r_{i,j,k}$ denotes the transportation risk of the kth arc between i and j where $k \in A_{i,j}$. Alongside these parameters, we have three types of variables: u_i, $\bar{g}_i$ and $y_{p,i,j,k}$. u_i is the unsatisfied demand of demand point i at the end of period t^* whereas $\bar{g}_i$ is the completion time of the services at demand point i. On the other hand, $y_{p,i,j,k}$ is a binary variable which takes value of one if personnel p travels between i and j by using the kth arc between these locations and zero otherwise. We note that depending on the type of the disaster response service, $u_i, i \in V_I$, can be continuous or integer and accordingly, the MILP becomes either binary or integer. In this model, we have the following four objectives:

$$\text{Minimize} \quad f_1 = \sum_{i \in V_I} u_i \lambda_i \tag{1}$$

$$\text{Minimize} \quad f_2 = \sum_{i \in V_I} \bar{g}_i \lambda_i \tag{2}$$

$$\text{Minimize } f_3 = \frac{\sum\limits_{i,j \in V_I : argmin\left\{t \middle| \hat{d}_{i,t} > 0\right\} \le argmin\left\{t \middle| \hat{d}_{j,t} > 0\right\}} \max\left\{\frac{u_i}{\sum_{t \in T} \widehat{d}_{i,t}} - \frac{u_j}{\sum_{t \in T} \widehat{d}_{j,t}}, 0\right\}}{\lceil |V_I|/2 \rceil \lfloor |V_I|/2 \rfloor} \tag{3}$$

$$\text{Minimize} \quad f_4 = \sum_{p \in P, i,j \in V, k \in A_{i,j}} y_{p,i,j,k} r_{i,j,k} \tag{4}$$

The objective functions of the DDRPRS problem (Eqs. (1)–(4)) minimize the weighted total unsatisfied demand, the weighted completion times of the satisfied demand, unfair distribution of the services among demand points and the total transportation risk, respectively. Given that the urgency to satisfy the demand at different locations varies, priorities for satisfying the demand according to its urgency need to be assigned (Hick, Hanfling, & Cantrill, 2012; Tofighi, Torabi, & Mansouri, 2016; Yi & Özdamar, 2007). Accordingly, the first two objectives (Eqs. (1) and (2)) consider the priority associated with the satisfaction of the different types of demand and seek to minimize the unsatisfied demand and the service completion times for the urgent demands accordingly. Priorities for the satisfaction of demand can change over time as new demands may emerge over the planning horizon or the severity of existing demands may increase as awaiting to be satisfied.

The fairness objective (Eq. (3)) seeks to minimize the deviation of unsatisfied demand among demand points. Tarhan et al. (2023) show that this fairness measure takes value in [0,1] in the static version: The fairness would be equal to 0 if all demand points have equal services in proportion to their demands, which is deemed as the fairest case, and it would be equal to 1 if the demand of the half of the demand points is fully served yet the other half is not served at all. This disparate case is deemed as the most unfair scenario by this fairness measure. As all demand emerges on the first day (i.e., day 1) in the static case, $\bar{d}_{i,1}$ will be greater than 0 and $\bar{d}_{i,t}$ will be 0 for each i in V_I and t in $T \backslash \{1\}$. Therefore, in this case, the numerator in Eq. (3) will be equal to the sum of the absolute differences of the unsatisfied demand percentages between the demand points. On the other hand, in the dynamic version, Eq. (3) prioritizes the satisfaction of the demand that emerged earlier in line with first-come first-serve discipline which is deemed to be an egalitarian service policy (Persad, Wertheimer, & Emanuel, 2009). Therefore, in the dynamic version, the unsatisfied demand percentage difference between two demand points i and j will be considered in the numerator only if one of these demand points has a smaller demand satisfaction percentage although its demand did not emerge later than the other demand point. As we are imposing additional conditions in the dynamic case to sum the terms in the numerator of the fairness objective, it will still take a value in [0,1]. The fairness in the dynamic case becomes zero when demand points do not have higher unsatisfied demand percentages than other demand points of which demand emerged in the same period or later. This represents the most fair scenario according to the proposed fairness measure.

The risk objective (Eq. (4)) is to minimize the total transportation risk of the roads/arcs travelled by the DRP. To this end, a risk index is assigned to each arc of the transportation risk. The risk index can be defined in different terms depending on the decision makers such as the vulnerability and accessibility of the corresponding arcs (Cantillo, Macea, & Jaller, 2019). Once the risk definition is made, risk indices can be determined by using historical data and topographical GIS maps (Hamedi, Haghani, & Yang, 2012) or if possible, by using the real-time information after the disaster. The entire MILP model with its constraint sets is presented in the supplementary material to this paper.

The proposed MILP model can incorporate the dynamic changes of the problem parameters unlike its static version proposed by Tarhan et al. (2023). In their solution approach, Tarhan et al. (2023) convert a given road-network into a set of complete graphs by solving a bi-objective shortest path problem minimizing the total travel times and transportation risks. This is achieved by using the weighted sum method for a set of weights and for each pair of points of interest (i.e., depots, resting points and demand points) on the network. Subsequently, they apply a lexicographic optimization, independently to each complete graph, considering the tri-objective problem excluding the total transportation risk objective. Underlying assumption is that each complete graph represents a different transportation risk level and the transportation risk objective does not need to be included explicitly.

In the model presented in this paper, we implement the same conversion of the road-network into a set of complete graphs. However, instead of handling each complete graph independently, we are considering all complete graphs simultaneously by uniting all complete graphs into a single multi-graph. In this multi-graph, there is not necessarily a single path/arc between points of interest (the terms path and arc are used interchangeably hereafter as each arc in multi-graph corresponds to a path between its nodes). The proposed model defines the transportation risk objective explicitly and by using multi-graph, it takes into account the impacts of choosing paths to travel between nodes not only in terms of the transportation risk but the efficiency and fairness of the services as well. Consequently, it enables to cover a wider spectrum of solutions. In short, the proposed MILP model extends the static MILP model for the DRPRS problem by introducing i) the transportation risk objective, ii) the path selection decisions between the nodes visited by personnel and iii) dynamic changes of the problem parameters.

5. Solution methodology

The MILP model presented in Section 4 is defined for a single-period DDRPRS problem. On the other hand, DRP routing and scheduling decisions are made on a daily basis until all demand for emergency services is satisfied as explained in Section 3. Therefore, in our solution methodology, we use a rolling horizon approach that solves a single-period DDRPRS problem for each period/day of the disaster response horizon sequentially until all disaster response services are completed. A brief flow chart of the proposed rolling horizon approach (RHA) is provided in Fig. 1.

As shown in Fig. 1, the RHA involves the solution of the single-period DDRPR problem for periods/days $t = \{1, \ldots, T\}$ sequentially where $t = 1$ is the beginning of the disaster response period (i.e., no disaster response service demand has been served yet) and $t = T$ defines the end of the period that the entire demand for disaster response services is satisfied. The single-period DDRPR problem for period t is solved using the 3O1P (t) model which is presented in Section 5.1. Hereafter, 3O1P, instead of 3O1P(t), is used when we do not address a particular period yet explain how the 3O1P model works for any given period.

At the end of period t, the RHA generates a set of solutions for the routing and scheduling of the DRP in period t. Subsequently, for each of these solutions, the RHA applies the 3O1P($t+1$) model, after updating the problem parameters (i.e., status of demand, personnel and transportation network), which generates a new set of solutions for period $t+1$. This process continues until we reach period T such that there is no unmet demand at the end of any solution generated by the 3O1P(T) model. Since we apply the 3O1P model in a given day for all solutions of the previous day, the number of solutions is non-decreasing over the periods. We note that period T is not pre-specified and depends on the problem parameters.

5.1. The 3O1P model

The 3O1P model is used to solve the single-period DDRPRS problems. It reduces the originally quad-objective problem (see Section 4) into a tri-objective problem. Subsequently, we solve the resulting tri-objective problem heuristically as explained in the following.

Considering the fact that unsatisfied demand minimization has a higher priority than the other objectives discussed in Section 4, the 3O1P (t) model first finds the minimum possible total unsatisfied demand at the end of period t. Then, it converts this minimum value to a constraint such that the total unsatisfied demand should not exceed the corresponding minimum value plus a tolerance term representing how much decision makers are willing to deviate from the minimum total unsatisfied demand for the sake of other objectives. The resulting tri-objective problem is solved at the end of the 3O1P(t) model.

The MILP model presented in Section 4 is NP-Hard. Moreover, Tarhan et al. (2023) show that solving the static MILP model for even small-size instances is computationally difficult. Therefore, we propose a heuristic quadrant shrinking algorithm, QSH, to solve the tri-objective problems in the 3O1P models. QSH is a heuristic adaptation of the exact quadrant shrinking method (QSM) proposed by Boland et al. (2017), the state-of-the-art algorithm for the tri-objective integer problems. The proposed heuristic that is applying the QSH over a rolling horizon is denoted as QSH RHA.

The solution approach of the 3O1P model is provided in Algorithm 1. The proposed algorithm first generates a solution by using a constructive heuristic (CH). This solution is set as the initial solution of a tabu search (TS) that seeks to minimize the total unmet demand at the end of the given day. Then, given the minimum possible total unmet demand, the Quadrant Shrinking Heuristic (QSH) is applied to generate a set of efficient solutions for the resulting tri-objective single-period DDRPRS problem.

In Section 5.2, we provide an overview of the exact QSM and discuss the characteristics of our heuristic adaptation QSH while in Sections 5.3 and 5.4, we present respectively the CH and TS algorithms used in Algorithm 1.

5.2. Exact and heuristic quadrant shrinking methods (QSM and QSH)

5.2.1. The exact version of QSM

The QSM introduced by Boland et al. (2017) works in a projected 2-dimensional criterion space: It optimizes one of the objective functions chosen arbitrarily and converts the other two objective functions to constraints. Then, in each iteration of the QSM, two integer models are

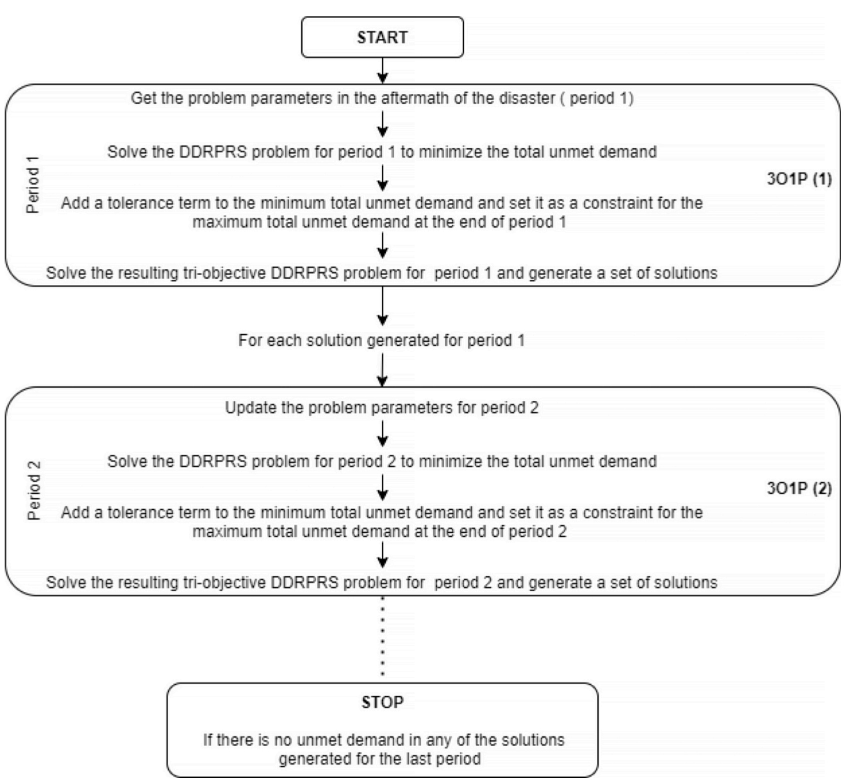


Fig. 1. The rolling horizon approach.

Algorithm 1
Outline of the solution of the 3O1P model.

```
Initialize the problem parameters for the period of interest
Set solution x to be null
Generate the initial solution: x ← ConstructionHeuristic(x, P, V_I, f_1)
Find the minimum unmet demand amount: x ← Tabu(x, 1, (∞, ∞))
Set the maximum allowable unmet demand amount to u_0 = f_1(x)(1 + ε_1)
Apply the QSH for the given u_0
```

solved sequentially for a given $u = (u_1, u_2)$ value (that is denoted as 2D-NDP-Search(u)) where u_1 and u_2 are set as the upper limits/bounds of the first and second objective functions converted to constraints, respectively. The first integer model of 2D-NDP-Search(u) optimizes the objective function (that is retained as an objective and not converted to a constraint) subject to the constraints such that the values of the remaining two objective functions that are converted to constraints do not exceed u_1 and u_2, respectively. Given the optimal solution to the first integer solution x, the second integer model of 2D-NDP-Search(u) minimizes the sum of the all three objective function values subject to the constraints such that none of the three objective function values is worse than that of solution x. The QSM systematically updates u and solves 2D-NDP-Search(u) for different u values iteratively so that it guarantees to find all Pareto-optimal solutions.

5.2.2. The QSH

The QSM guarantees to find all Pareto-optimal solutions only if both integer models in 2D-NDP-Search(u) are solved to optimality for different values of u that are determined over the course of the QSM. In the case of the DDRPRS problem, 2D-NDP-Search(u), i.e, the sub-problem of the QSM, requires to solve two integer models related to the single-objective single-period DDRPRS problem. Due to the NP-Hard nature of the relevant problems, it is not possible to use exact methods for solving the two integer models of 2D-NDP-Search(u) repetitively for different u values within the QSM in reasonable computational time in real world settings. Therefore, we have developed a tabu search (TS) algorithm to solve the corresponding integer models of 2D-NDP-Search. The TS algorithm enables the simultaneous handling of the two models and generates the approximate set of efficient solutions in much shorter time. Since we are solving the QSM sub-problems heuristically, we may not find the optimal solution for particular sub-problems which require the adaptation of the QSM accordingly. In the following, we explain our heuristic implementation of the QSM for the tri-objective DDRPRS problem which can be adapted to any tri-objective integer problem.

Without loss of generality, in our implementation of QSH, we consider the minimization of the total service completion time as the objective function and convert the other two objective functions (i.e., minimization of unfairness and total transportation risk) to constraints. In Algorithm 2, we provide detailed descriptions of both the QSM and the QSH in a single framework to show their differences clearly. The black font lines in this algorithm are applied to both the original exact QSM and its heuristic implementation QSH. On the other hand, the blue and red font lines are applied only to the QSM and QSH, respectively. For details of the original algorithm, the reader is referred to Boland et al. (2017).

In Algorithm 2, $z_1(x^n)$ and $z_2(x^n)$ are the values of the first and second objective functions, that are converted to constraints, of solution x^n, respectively. In our implementation, they correspond to $f_3(x^n)$ and $f_4(x^n)$, respectively. D is the list storing u values each for which a sub-problem of the QSM needs to be solved. D is sorted such that $u_1^f > \ldots > u_1^b$ and $u_2^f < \ldots < u_2^b$ where u^f and u^b are the front and back elements of list D, respectively. The QSM systematically solves the sub-problems for the elements of list D. Whenever a new solution x^n, which is guaranteed to be efficient, is generated during this process, new sub-problems (i.e., new u values) are added to list D so that new sub-problems are aiming to improve one of the objective function values $f_3(x^n)$ or $f_4(x^n)$ of solution x^n.

Differences between the QSM and QSH:

The heuristic implementation of the QSM (QSH) differs from the QSM in three aspects. First, the QSH uses the tabu search (TS) algorithm to solve the sub-problems, instead of solving two sequential integer optimization models (2D-NDP-Search) of the QSM (see lines 9–10 and 29–30 where $Tabu(x, 2, u)$ refers to the TS algorithm initiating from solution x and optimizing f_2 subject to $f_3 \leq u_1$ and $f_4 \leq u_2$). Second, the QSM seeks a slight improvement in one of the objective functions in producing new sub-problems after generating solution x^n by extracting small ϵ value from either $f_3(x^n)$ or $f_4(x^n)$. On the other hand, the QSH produces new sub-problems after generating solution x^n by extracting $f_3(x^n)\epsilon$ from $f_3(x^n)$ or extracting $f_4(x^n)\epsilon$ from $f_4(x^n)$ in order not to obtain very similar solutions to x^n in terms of f_3 and f_4 (see lines 15–20 and 35–40). The third differentiating aspect of the QSH is regarding its possibility of not being able to find optimal solutions of the sub-problems. Due to the heuristic implementation, it is possible that the QSH may not find the optimal solution of a sub-problem and this sub-optimality can be realized when a better solution than the best solution previously found is discovered for the relevant sub-problem in succeeding sub-problems. In such a case, the sub-problems to be solved in the succeeding iterations of the QSH should be adapted so as to take into account the new best solution (of the relevant sub-problem solved in preceding iterations). Therefore, whenever a new best solution x^{new} is found for a preceding sub-problem $u = (u_1, u_2)$ during the QSH, two new candidate sub-problems denoted by $u^{new}_{front} = (f_3(x^{new})(1-\epsilon), u_2)$ and $u^{new}_{back} = (u_1, f_4(x^{new})(1-\epsilon))$ are created. Then, these two candidate sub-problems are compared with the existing sub-problems to be solved as follows.

Let $u^{new} = (u_1^{new}, u_2^{new})$ be one of the sub-problems created for the new best solution x^{new}. u^{new} is not added to list D if one of the following two conditions holds:

i) If there is another sub-problem u^h in list $D_{history}$, that stores the previously solved sub-problems, such that $u_1^h \leq u_1^{new}$ and $u_2^h \leq u_2^{new}$

ii) If there is another sub-problem u^f in list D such that $u_1^f \geq u_1^{new}$ and $u_2^f \geq u_2^{new}$

The first condition means that we have already solved a sub-problem u^h whose feasible region is a subset of the feasible region of u^{new}. Thus, solving u^{new} would entail considering feasible regions of the sub-problems previously solved which can lead to repetitively solving sub-problems for similar feasible regions. On the other hand, the second condition means that we do not need to solve sub-problem u^{new} since we have another sub-problem u^f in list D that covers sub-problem u^{new}. If none of the two conditions holds, u^{new} is added to list D. Then, it should be checked if there is any sub-problem u^f in list D that is covered by u^{new} such that $u_1^f \leq u_1^{new}$ and $u_2^f \leq u_2^{new}$. If so, such sub-problems should be removed from list D.

Algorithm 2
Quadrant Shrinking Method (QSM) and Its Heuristic Adaptation (QSH).

1: Initialize the list of efficient solutions L to be empty
2: Initialize the double-ended linked list D with $u = (+\infty, -\infty)$ (Assume that u is generated after the solution minimizing the unmet demand (see Algorithm1))
3: Let $D^{history}$ and $L^{history}$ be empty sets
4: **while** D *is not empty* **do**
5: Let u^{front} be the front element of D
6: $Right\_boundary\_not\_treated \leftarrow True$
7: **while** $Right\_boundary\_not\_treated = True$ **do**
8: Pop the front element of D and denote it by u
9: $x^n \leftarrow$ 2D-NDP-Search(u)
10: $x^n \leftarrow Tabu(x, 2, u)$ where x is the solution after which generation u is added to D, and add u to $D^{history}$
11: **if** $x^n = Null$ **then**
12: $Right\_boundary\_not\_treated = False$
13: **else**
14: Add x^n to the list of efficient solutions L
15: **if** $u_1^f < z_1(x^n) - \epsilon$ or D *is empty* **then**
16: Add $(z_1(x^n) - \epsilon, u_2)$ to the front of D
17: Add $(u_1, z_2(x^n) - \epsilon)$ to the front of D
18: **if** $u_1^f < z_1(x^n)(1 - \epsilon)$ or D *is empty* **then**
19: Add $(z_1(x^n)(1 - \epsilon), u_2)$ to the front of D
20: Add $(u_1, z_2(x^n)(1 - \epsilon))$ to the front of D
21: Update $D^{history}$, $L^{history}$ and L by considering all solutions generated during $Tabu(x, 2, u)$ and add new elements to D accordingly
22: Let u^{new_front} be the front element of D
23: **if** $x^n = Null$ **and** $u_1^{new\_front} > u_1^{front}$ **then** Go to line 5
24: **if** $x^n = Null$ **then**
25: $Right\_boundary\_not\_treated = False$
26: $Top\_boundary\_not\_treated \leftarrow True$
27: **while** $Top\_boundary\_not\_treated = True$ **do**
28: Pop the back element of D and denote it by u
29: $x^n \leftarrow$ 2D-NDP-Search(u)
30: $x^n \leftarrow Tabu(x, 2, u)$ where x is the solution after which u is added to D, and add u to $D^{history}$
31: **if** $x^n = Null$ **then**
32: $Top\_boundary\_not\_treated = False$
33: **else**
34: Add x^n to the list of efficient solutions L
35: **if** $u_1^f < z_1(x^n) - \epsilon$ or D *is empty* **then**
36: Add $(u_1, z_2(x^n) - \epsilon)$ to the back of D
37: Add $(z_1(x^n) - \epsilon, u_2)$ to the back of D
38: **if** $u_1^f < z_1(x^n)(1 - \epsilon)$ or D *is empty* **then**
39: Add $(u_1, z_2(x^n)(1 - \epsilon))$ to the front of D
40: Add $(z_1(x^n)(1 - \epsilon), u_2)$ to the front of D
41: Update $D^{history}$, $L^{history}$ and L by considering all solutions generated during $Tabu(x, 2, u)$ and add new elements to D accordingly
42: Let u^{new_front} be the front element of D
43: **if** $u_1^{new\_front} > u_1^{front}$ **then** Go to line 5
44: **if** $x^n = Null$ **then**
45: $Top\_boundary\_not\_treated = False$
return L

5.3. Construction heuristic (CH)

Considering the efficiency objectives, i.e., Eqs. (1)-(2), it is crucial to be able to satisfy as much demand as soon as possible. Therefore, we propose a construction heuristic (CH) algorithm that starts with empty routes and produces new solutions by inserting demand points with unsatisfied demand into each possible position on each existing route, chooses the best solution in terms of the satisfied demand per unit time, and repeats this process until the chosen solution does not improve the total unsatisfied amount of the previous best solution. Thus, in each iteration, a new location is added/inserted to one of the routes until none of the possible insertions of the locations to the existing routes can improve the average amount of satisfied demand per unit time.

Due to the multi-graph transportation network considered in the DDRPRS problem, the routing decisions include not only the sequence of nodes/locations to be visited but also the roads/paths to travel between the relevant nodes. Therefore, in this paper, solutions are presented as the set of routes (i.e., sequence of demand points visited by each personnel), the set of arcs/paths selected to be travelled among the nodes visited and the working start time of personnel. It should be noted that solution encodings do not include resting times of the personnel. However, for a given personnel, by starting from its working start time and following the sequence of demand points it visits and travelling over the selected paths, we can determine when the given personnel reaches its working hours limitation and should go to its resting location accordingly.

When we insert a new node between two nodes of an existing route, we need to decide which arcs/paths to use between the inserted location and the preceding and succeeding locations on its route. To this end, we develop a set-partitioning model that can optimize path selection decisions for all routes/personnel simultaneously for given routes, i.e., the sequence of visited locations. Since it requires considerable computational time to apply the proposed set-partitioning model for each new solution generated over the course of the proposed heuristic approach, we only use it for promising solutions as explained in Section 5.4. For the remaining solutions, we develop a path selection (PS) algorithm. When two nodes become adjacent after a neighbourhood move applied on a solution, the PS algorithm determines the path to be selected between the corresponding nodes probabilistically by considering the total transportation risk of the corresponding solution. As the solutions violate the upper bound on the total transportation risk more, less risky paths are chosen and vice versa.

Another element of our solution encoding (besides the demand points visited and the paths used) is the working start time of personnel. Personnel are initially set to start to work as early as possible. When a new demand point, already served by another personnel, is inserted into the route of personnel $p \in P$ to generate new solutions, the proposed heuristic sets personnel $p \in P$ as the last personnel serving the corresponding demand point. Therefore, it ensures that the schedules of personnel p and personnel $\bar{p}$ who is the last personnel among the ones that have been already serving the corresponding demand point are synchronized so that personnel p can take-over the service from personnel $\bar{p}$. To this end, following the insertion move, the arrival time of personnel p to the corresponding location and the departure time of personnel $\bar{p}$ are compared. If personnel p arrives after personnel $\bar{p}$ leaves, the working start time of personnel $\bar{p}$, $s_{\bar{p}}$, is shifted so as to ensure that personnel p arrives before personnel $\bar{p}$ leaves. If this shift violates any constraints, the corresponding insertion move is discarded. Similarly, if personnel p arrives before personnel $\bar{p}$ starting to serve at the corresponding location, s_p is shifted so that personnel p does not arrive early. Again, if this shift violates any constraints, the corresponding insertion move is discarded.

The CH and PS algorithms are provided in more detail in the supplementary material to this paper.

5.4. Tabu search algorithm (TS)

The TS algorithm, which is shown to be competitive for both routing and scheduling problems (Mathlouthi et al., 2021), is used to improve the solutions generated by the CH algorithm. In the latter algorithm, only one move is executed to generate new solutions which is denoted as *InsertionOfNewDemand* move. In the TS algorithm, we are using two more moves to be able to search a wider space: *InterRouteSwapOfExistingDemands* and *ChangeRouteOfExistingDemand*. In *InterRouteSwapOfExistingDemands* move, two demand points, each from a different route of the current solution, are chosen and swapped so that the personnel serving these demand points change. In *ChangeRouteOfExistingDemand* move, a demand point is chosen from a route of the current solution, it is removed from the corresponding route and inserted into a new one. When the position of a demand point changes in an iteration, the moves that would change that demand point's position again are set as tabu and discarded during the tabu tenure unless the aspiration criteria holds. In our implementation, the aspiration criteria is the improvement of the best solution. Therefore, a tabu move can be performed if it generates a solution better than the best one previously found.

The moves used in the TS algorithm can result in slack (available) times at the end of the personnel's schedules. To exploit the relevant times, the CH algorithm is employed at the end of each move by considering only the personnel affected by that move and having available time at the end of their schedule. Call for the CH algorithm at the end of each move is illustrated for an example move presented in the supplementary material to this paper.

The TS algorithm is called to minimize objective function f_1 before applying the QSH in the 3OP1 model as shown in Algorithm 1. In this case, u is simply equal to (∞, ∞) which means that no boundary for objective functions f_3 and f_4 is considered, i.e., the fairness and transportation risk of the solutions are disregarded. On the other hand, when the TS algorithm is called within the QSH, by its definition, u is regularly updated. Thus, the TS algorithm should ensure that $f_3(x)$ and $f_4(x)$ are less than or equal to u_1 and u_2, respectively, where x is the solution to be returned by the TS algorithm. Let X denote the search space spanned by the original constraints, i.e., the ones included in the MILP models. We do not allow the infeasibility of the original constraints, i.e., do not go beyond the boundaries of X during the TS. On the other hand, infeasibility of the constraints regarding the boundaries for the objective functions is allowed. Accordingly, when the TS algorithm has f_2 as the objective of interest, it solves the following problem:

Minimize$_{x \in X}\bar{f}(x)$ where

$\bar{f}(x) = f_2(x) + \mu_1 \max(u_0 - f_1(x), 0) + \mu_2 \max(u_1 - f_3(x), 0) + \mu_3 \max(u_2 - f_4(x), 0)$ and μ_1, μ_2 and μ_3 are the coefficients to penalize the violations of the boundaries u_0, u_1 and u_2 for objective functions f_1, f_3 and f_4, respectively. In a similar way to Vidal, Crainic, Gendreau, Lahrichi, & Rei (2012), we allow the infeasibility of particular constraints by penalizing the relevant constraint violations on the objective function $\bar{f}(x)$ and continuously adjust the penalty values. Whenever a boundary u is violated, its associated μ value is multiplied by 1.05% and whenever u is satisfied, μ is multiplied by 0.95%.

Tabu search algorithms aggressively search for local optima and thereby they are prone to get stuck in a local optimum (Pirim, Eksioglu, & Bayraktar, 2008). Hence, diversification mechanisms enabling to escape local optima can improve the performance of the tabu search algorithms (Tarhan & Oğuz, 2022). To this end, $\bar{f}$ is updated so as to consider the search history in iteration *it* of the TS as the following:

$\bar{f} = f_2(x) + \mu_1 \max(u_0 - f_1(x), 0) + \mu_2 \max(u_1 - f_3(x), 0) + \mu_3 \max(u_2 - f_4(x), 0) + \sum_{i \in V_I} p_d f_d(i) I_{iaffectedinit}$

$f_d(i)$ is the number of previous iterations that has changed the position of demand point i. p_d is a pre-determined coefficient to penalize the highly frequent moves and guide the search to unexplored regions whereas $I_{iaffectedinit}$ is equal to one if the position of demand point i

changes in iteration *it*, 0 otherwise. $f_d(i), i \in V_I$, is set to 0 in each 50 iterations to limit the diversification with the recent search history.

The TS algorithm first generates solutions by randomly applying one of the three moves and updates the current solution even if the new solution is slightly worse than the current solution. When it fails to update the current solution for a pre-determined number of iterations, it produces all possible solutions that can be generated by applying the all three moves on the current solution and sets the best of them, in terms of function $\bar{f}$, as the current solution. A set partitioning model, which is presented in the supplementary material to this paper, is solved for the new current solution. This model enables to optimize the path selections between the nodes visited in the given current solution. Particularly, it does not only consider the arcs established by the PS algorithm but it considers all possible arcs between all nodes of the routes of the given current solution and finds the optimal path selections. When the best solution cannot be further improved for a given number of iterations, the TS algorithm terminates. The pseudocode of the proposed TS algorithm is provided in the supplementary material to this paper.

6. Computational results

The static version of the DDRPRS problem (DRPRS) was solved for routing and scheduling the personnel involved in two types of disaster response services, namely evacuation and medical assistance, in the aftermath of the 2018 Lombok Earthquake by Tarhan et al. (2023). The evacuation service in this problem instance is to provide temporary shelter facilities (tents) to the evacuated population which will be provided medical service at the temporary shelter locations. There is a precedence relation between the two services such that the provision of the medical services at a temporary shelter location cannot be started before at least a single tent is set-up there. Considering this relationship, Tarhan et al. (2023) proposed two strategies for the provision of services: Full and partial demand fulfilment strategy. In the partial demand fulfilment strategy, evacuation personnel first set-up a single tent at each location and then can proceed with the rest of the set-up of the additional required tents. In the full demand fulfilment strategy, there is no such a restriction. To be able to consider the precedence relationship between the services, Tarhan et al. (2023) implemented the sequential optimization approach so that they first solved the DRPRS problem for the evacuation personnel and thereafter, they solved it for the medical personnel given the solutions for the evacuation personnel. Since their solution approach cannot cope with the large-size problems, they considered a part of the impacted Lombok area and a subset of the available DRP teams (i.e., a smaller version of the original 2018 Lombok Earthquake instance).

In this paper, we apply the proposed QSH RHA approach for both evacuation service, for which demand is discrete, i.e., the number of tents to set-up, and medical service, for which demand is continuous, i.e., the number of service hours required. To be able to make QSH RHA applicable for both types of demands, we convert the discrete demand to continuous by multiplying the discrete demand with the time required to set-up a single tent and design QSH RHA in consideration of only continuous demands. Yet, whenever a new solution is generated for the service with discrete demands, i.e., evacuation, the services times are trimmed if necessary to guarantee that the demands satisfied are not fractional but discrete.

Performance of the solutions generated by the QSH RHA can vary over the planning horizon. Accordingly, decision makers might be interested not only in the performance of the solutions by the end of the planning horizon but also on a daily basis, i.e., at the end of each day. Therefore, we are implementing a temporal Pareto optimality (Coughlin & Howe, 1989) to compare the generated solutions. We define $UnsatisfiedDemand_t, AverageCompletionTime_t, Fairness_t$ and $AverageRisk_t$, $t \in T$ (where T is the set of periods in the planning horizon), as solution evaluation metrics. $UnsatisfiedDemand_t$ and $Fairness_t$ metrics of solution x, that is generated for period t, correspond to $f_1(x)$ and $f_3(x)$, respectively. On the other hand, $AverageCompletionTime_t$ and $AverageRisk_t$, $t \in T$, metrics are the summation of $f_2(x)$ and $f_4(x)$, respectively, for all the periods up to period t (inclusive) divided by the total amount of satisfied demand by the end of period t. We are using the corresponding average values for the purpose of a fair comparison since different solutions can have different amounts of demands satisfied by the end of each day.

In Section 6.1, we apply the proposed heuristic algorithm QSH RHA for the small Lombok test instance (that involves a smaller representation of the original 2018 Lombok Earthquake instance) to test its performance. Then, QSH RHA is applied for the original 2018 Lombok Earthquake to evaluate its performance on a larger-size test instance in a static environment in Section 6.2. Subsequently, QSH RHA is used to analyze the impacts of the dynamic parameter changes on the routing and scheduling decisions for the evacuation and medical personnel in Section 6.3.

After preliminary tests, ϵ is set to 0.05 for the evacuation service. On the other hand, it is 0.10 for the medical service as the number of solutions generated for the corresponding personnel is observed to be significantly increasing for smaller ϵ values. ϵ_1 is set to 0.20 and 0.05, respectively, for the evacuation and medical service. ϵ_1 is set higher for the evacuation service since increasing the minimum allowable unmet demand by a small ϵ_1 value may not increase the corresponding solution space due to the discrete evacuation demand. To scale the penalty coefficients for the objective functions f_1, f_3 and f_4 in proportion to f_2, we consider solution x which minimizes the unmet demand (see Algorithm 1). Specifically, μ_1, μ_2 and μ_3 are set equal to $f_2(x)/f_1(x), f_2(x)/f_3(x)$ and $f_2(x)/f_4(x)$, respectively. Lastly, $Max\_UnimprovedIteration\_Sub$, $Max\_UnimprovedIteration\_Total$ and p_d are 100, 100 and 2, respectively. The proposed heuristic algorithm is tested on a workstation with an Intel Core i7-8565U processor, 1.80 GHz speed, and 16 GB of RAM, through Visual Studio 2019 and the CBC 2.10.5 solver (which was also used to solve the set partitioning model).

For the case study under consideration, the coordinates of the demand point locations and the personnel base locations can be found in https://doi.org/10.17635/lancaster/researchdata/636. Risks of the regions surrounding the transportation network are provided via the InaRisk data (where InaRisk is a risk assessment portal launched by the Indonesian National Board for Disaster Management) found in https://inarisk.bnpb.go.id:6443/arcgis/rest/services/inaRISK/layer_bahaya_gempabumi_2015/ImageServer. We use the route generation procedure proposed by Gultom, Haryanto, & Suhartanto (2021) to derive risk indices for the transportation network links given the regional risks. In short, Gultom et al. (2021) assign a risk index to each link considering the average of the risk indices of the nodes defining the corresponding link which are extracted from the InaRisk data.

6.1. Testing the QSH RHA

In this section, we test the performance of the QSH RHA in terms of the solution quality and time, by comparing it with the QSM RHA (which is the exact version of the QSH RHA where the 3O1P model is solved exactly by using the MILP model in Section 4). Our original 2018 Lombok Earthquake instance includes 10 personnel teams, 26 demand points, 2 depots and 2 resting points. Since this instance cannot be solved exactly by the QSM RHA, we consider a sub-instance including 2 personnel, 12 demand points, 2 depots and 2 resting points that can be solved exactly by the QSM RHA.

Due to the precedence relation between the provision of evacuation and medical services, the medical personnel solutions are not independent of the evacuation personnel solutions. Moreover, the performance of the evacuation solutions after the first day of the planning horizon depends on their first day performance, which varies in each solution. Therefore, for a fair comparison, we applied the QSH RHA and QSM RHA algorithms for only the evacuation service and for only the first day. As specified in Section 6, in our computational experiments, we use i) different metrics (derived from their objective function values) to evaluate solutions and ii) use ϵ values 0.05 and 0.10 for the evacuation and medical services, respectively. On the other hand, specifically for this section, we consider the objective function values of the solutions instead of the relevant metrics and set ϵ value to 0.001 to be able to generate the entire Pareto-frontier defined over the objective function values of the solutions.

In Table 1, we compare the QSM RHA and QSH RHA algorithms in terms of the number of the (Pareto-optimal) solutions they generate, time required to generate these solutions and the ratio of their respective hypervolumes HV-QSM RHA and HV-QSH RHA. Hypervolume evaluates sets of efficient solutions by taking into account the proximity of the solutions to the Pareto front, diversity, and spread (Guerreiro, Fonseca, & Paquete, 2020). We use Leb Measure algorithm (Fleischer, 2003) to calculate the hypervolumes. A higher hypervolume means a better representation of the Pareto-optimal solution set.

By the definition of the QSM RHA, it generates the entire Pareto frontier. Therefore, there are 36 and 84 Pareto-optimal solutions under the full and partial demand fulfilment strategies, respectively. The QSH RHA enables to find 15 and 12 of the corresponding solutions under each strategy. On the other hand, the total number of solutions generated by the QSH RHA is 32 and 45, respectively, for each strategy. Comparing the hypervolume of these heuristic solutions (HV-QSH RHA) and that for the exact solutions (HV-QSM RHA), their ratio is 81% for the full demand fulfilment strategy whereas it is 69% for the partial demand fulfilment strategy. This implies a reasonable approximation of the Pareto frontier by the QSH RHA for both strategies. Moreover, the QSH RHA requires much less time in comparison to the QSM RHA.

Fig. 2 demonstrates the Pareto-optimal solutions over mesh surface plots for each algorithm and demand fulfilment strategy. Pareto-optimal solutions in this figure are marked in red. These solutions are generated through the 3O1P model in which the first objective (i.e., the unsatisfied demand minimization) is converted to a constraint. Accordingly, values for only three objectives (i.e., f_2, f_3 and f_4 of the MILP model in Section 4) are shown in Fig. 2. In line with the hypervolumes of the solutions sets, the surface plot for the solutions of the QSH RHA reasonably approximates the plot for those of the QSM RHA under the full demand fulfilment strategy. However, the higher the height of the QSH RHA solutions plot (see Fig. 2b) expresses the higher the transportation risk of the corresponding solutions. As seen in Figure 2d, the QSH RHA solutions lead to higher transportation risks under the partial demand fulfilment strategy as well. On the other hand, fairness of the solutions ranges within similar intervals in the solutions sets of both the QSM RHA and QSH RHA algorithm.

6.2. 2018 Lombok Earthquake instance: Static environment

In this section, we evaluate the solutions generated by the QSH RHA for our original Lombok instance in a static environment where no problem parameters change over time. To facilitate the decision-making process of the problem owners, we generate a representative subset of solutions from the solutions generated by the QSH RHA. To this end, we apply the smart Pareto filter (SPF) (Mattson, Mullur, & Messac, 2004) which chooses a single representative solution among similar solutions in terms of their solution evaluation metrics. The SPF starts from solution S that is on the top of the list of the solutions generated, removes the solutions in the remaining list for which solution S does not perform worse by more than 0.05 percent (which is a parameter set by us) in terms of any solution evaluation metric. Then, it moves to the second solution in the remaining list and applies the same filtering and so on until it reaches the last solution in the list.

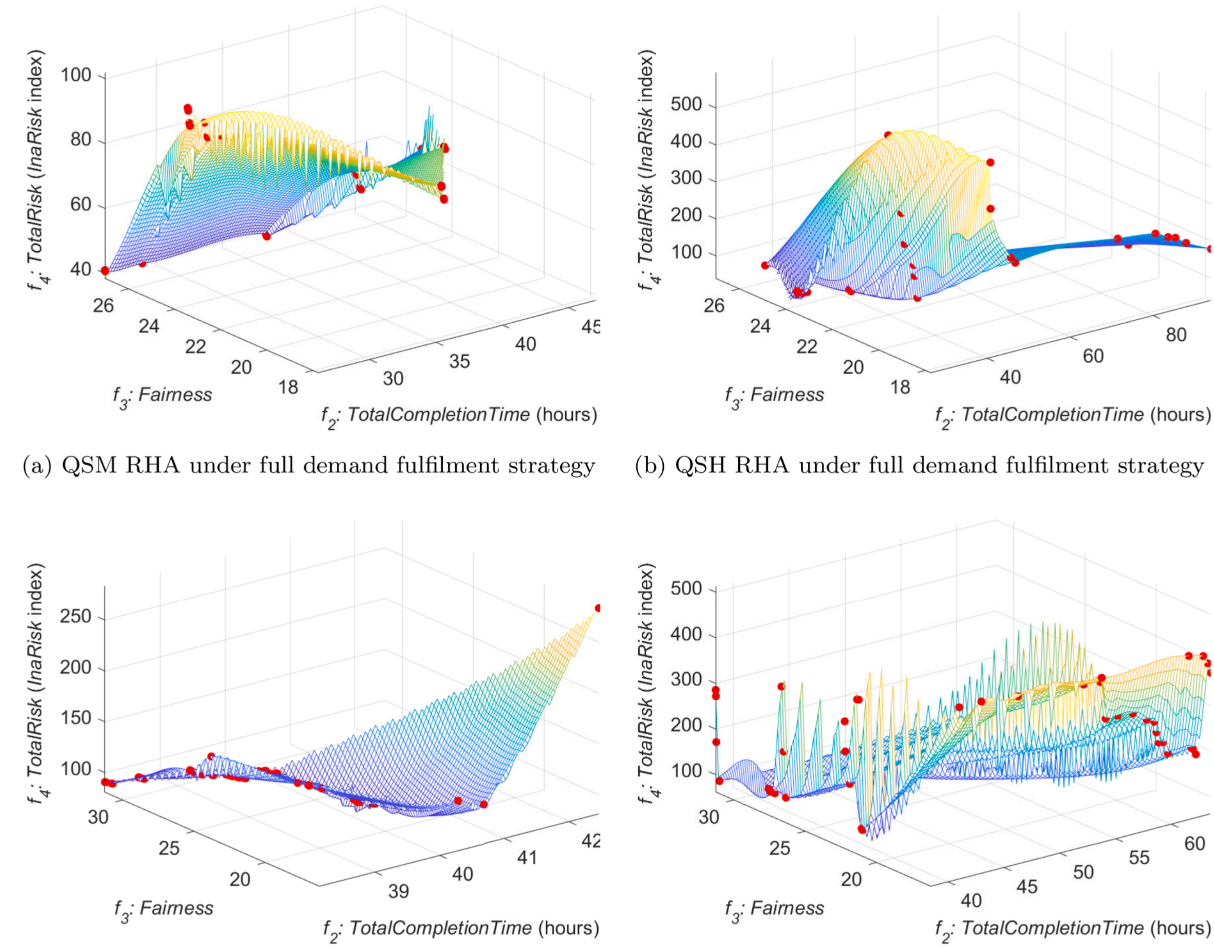
Table 1
Performances of the QSH RHA and QSM RHA algorithms.

	Full demand fulfilment strategy		Partial demand fulfilment strategy	
	QSM RHA	QSH RHA	QSM RHA	QSH RHA
Number of solutions generated	36	32	84	45
Number of Pareto-optimal solutions generated	36	15	84	12
Time per unit solution generated (in sec)	121.80	16.20	160.20	9.00
HV - QSH RHA / HV - QSM RHA	81%		69%	

After the SPF, 7 and 3 solutions remain for the evacuation and medical personnel in the full and partial demand fulfilment strategy, respectively. In both strategies, it takes 2 and 4 days (periods) to serve the entire demand for the evacuation and medical personnel, respectively. The evacuation personnel solutions under the full demand fulfilment strategy can serve the demand faster. On the other hand, under the partial demand fulfilment strategy, the evacuation personnel solutions in general can provide a fairer distribution of the evacuation services among the demand points. We observe a positive correlation between *UnsatisfiedDemand* and *Fairness* metrics regardless of the type of service considered. On the other hand, the best *Fairness* values are achieved at the expense of higher *AverageRisk* values. Regarding the medical service, medical personnel solutions initially serve the demand points with high demand volume. Thus, initially, the medical personnel are not travelling between demand points to offer their services since they can hardly meet the demand of a single demand point. However, as the remaining demand at currently served demand points decreases over time, the medical personnel is moving to visit additional demand points. Due to the movement of personnel to visit additional locations to provide their services, the travel time component of the corresponding solutions is changing and therefore, solutions become more diverse. As a consequence, the trade-offs get stronger as the routing component of the DRPRS problem is more involved in the decision-making process.

We observe that solutions having satisfactory performance in terms of *Fairness*, *AverageCompletionTime* or *AverageRisk* by the end of a period do not necessarily perform well in terms of the respective metrics by the end of the succeeding periods. This behaviour can be observed in the value path graph presented in Fig. 3. In this graph, we consider unified solutions which are generated as follows: We convert the discrete demand for evacuation services to continuous (by defining the demand as the number of hours required to set-up the tents rather than the number of tents), aggregate the evacuation and medical service demand at each demand point and compute the solution evaluation metrics by considering the aggregated demand values. As a result, we obtain a single unified solution for each medical personnel solution and its associated evacuation personnel solution (e.g., solution $E_1 - M_1$ in Fig. 3 corresponds to the unification of the first medical personnel solution M_1 and the associated evacuation personnel solution E_1). In the value path graph, solid and dash lines represent the unified solutions subject to the full and partial demand fulfilment strategy, respectively. Each solution is represented by connecting 16 values each of which shows its % deviation from the best/minimum value of a particular solution evaluation metric by the end of a particular day. Steeper slopes of the lines/solutions between adjacent metrics indicate stronger trade-off for the relevant metrics.

In terms of *Fairness*, while solutions $E_1 - M_1$ and $E_2 - M_2$ ($E_7 - M_7$ and $E_{10} - M_{10}$) are two of the worst (best) solutions at the end of the first day, they are the best (worst) at the end of the third day. Considering solution $E_5 - M_5$ in terms of *Fairness*, it is one of the best solutions at the end of the first day, worst solution at the end of the second day and it has an average performance at the end of the third day. Similar observations can be made for other metrics as well. For instance, in terms of *AverageRisk*, solution $E_2 - M_2$ is the second best solution at the end of the first day while it is the second worst solution at the end of the fourth and last day. This suggests that considering a longer horizon can be more insightful than a myopic approach that considers only the next day of the planning horizon.



(a) QSM RHA under full demand fulfilment strategy (b) QSH RHA under full demand fulfilment strategy

(c) QSM RHA under partial demand fulfilment strategy (d) QSH RHA under partial demand fulfilment strategy

Fig. 2. Mesh surface plots of the Pareto-optimal solutions.

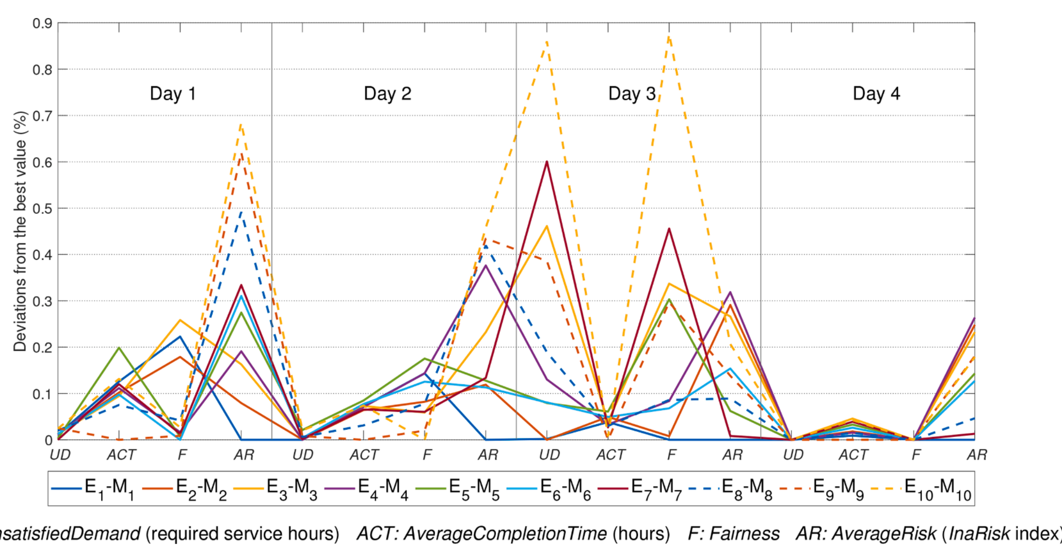


Fig. 3. Value path for the unified solutions to the large-size static Lombok instance.

We also observe that the performance of each demand fulfilment strategy varies over time. Specifically, the partial demand fulfilment strategy tends to produce fairer, yet riskier, solutions at the beginning of the planning horizon. On the other hand, the full demand fulfilment strategy produces both the fairest and riskiest solutions towards the end of the planning horizon. The partial demand fulfilment strategy provides better solutions in terms of average service completion times and fairness at the beginning of the planning horizon. However, considering the entire horizon, they are not as robust as they can deviate more than 50% from the minimum value of particular metrics by the end of particular periods. On the other hand, solutions of the full demand fulfilment strategy are more robust (e.g., solution $E_1 - M_1$ achieves less than 1% deviation for most of the metrics and periods). Therefore, for the case under consideration, if decision-makers do not prioritize any metrics or any periods, they might opt to use the full demand fulfilment strategy since it provides better solutions overall. On the other hand, decision makers may opt for the partial demand fulfilment strategy if they aim for fair demand satisfaction and short service completion times, particularly at the beginning of the planning horizon.

6.3. 2018 Lombok Earthquake instance: Dynamic environment

In this section, we consider the DDRPRS problem and accordingly evaluate the solutions generated by the QSH RHA for our original Lombok instance in a dynamic environment where certain parameters change over time.

The DDRPRS problem has mainly three categories of inputs: Supply (i.e., available personnel), demand for services and transportation network characteristics. The relevant inputs are prone to dynamic changes over the planning horizon due to the potential impacts of a disaster. To show the applicability of the proposed heuristic QSH RHA to the dynamic environment of the DDRPRS problem, we generate two sets of scenarios. The first set of scenarios pertains to the impacts of disasters on the transportation network and it is analysed in Section 6.3.1. The second set of scenarios pertains to the emergence of new demands over time and it is analysed in Section 6.3.2. We note that the QSH RHA can address the changes in supply availabilities as well. However, as the availability of professional DRP is more static in comparison to the demand and transportation network, we keep the available personnel constant in all scenarios.

6.3.1. Transportation network disruptions

Transportation network disruptions due to disasters often obstruct the DRP operations and therefore should be taken into account in their routing and scheduling decisions. The transportation network can be disrupted either in the immediate aftermath of disasters or over time (particularly due to their after-effects/after-shocks). Salman & Yücel (2015) proposed a distance-based dependency (DBD) model to generate scenarios in each of which a different set of links is destroyed in the immediate aftermath of a disaster. We apply a modified version of the proposed approach to generate scenarios each corresponding to a different transportation network. In our application, without loss of generality, we assume that the transportation networks failures occur at the end of the first day after the disaster. The generated scenarios are tested for the large-size Lombok instance and only for the full demand fulfilment strategy (not to prolong the discussion).

The DBD model initially receives a survival probability for each link on the network and sets a distance threshold β. Then, iteratively generates a random number between 0 and 1 for each link. If the random number is greater than the survival probability of the relevant link, all the weaker links (i.e., having smaller survival probability than the relevant link) within the distance β are destroyed, if they are not already destroyed in the previous iterations. The distance between two links is equal to the minimum distance between the four nodes at the end of the corresponding links.

In our DBD implementation, survival probabilities are generated by normalizing the risk indices of the links. We assume the connectivity of the transportation network, i.e., there is at least one undestroyed link between each pair of nodes. Therefore, whenever the last and only available link between two nodes should be destroyed according to the original DBD model, unlike the original DBD model we do not destroy it but we increase its travel time. Specifically, at each time the last link between two nodes needs to be destroyed, its travel time is increased by 10%. To keep the travel times in reasonable limits, we stop increasing the travel time of a link if it already exceeded a threshold value defined as three times of its original travel time. The underlying assumption in increasing the travel times is that in real-world cases, network disruptions result to an increase of travel time and not necessarily to a discontinuity in the network connectivity. Therefore, we assume that the connectivity of the transportation network is preserved while the travel times may change depending on the severity of the disruption.

In practice, decision-makers will know which links are damaged in the aftermath of the disaster and make their decisions accordingly. However, it would be useful for an effective disaster response to study in advance (i.e., in the preparedness phase) different scenarios exemplifying possible disaster-induced network infrastructure damages. To this end, we assess the impacts of network failures by applying the modified DBD model for three different distance threshold values $\beta \in \{5\,\text{km}, 10\,\text{km}, 20\,\text{km}\}$. As Salman & Yücel (2015) set β equal to 15 km, we use a range of β values to consider varying degrees of the network disruption. For each β value, we apply the modified DBD model for 20 times and hence generate 60 scenarios in total. In Table 2, for each β value, we provide the range, in the corresponding scenarios, of i) the number of efficient solutions generated, ii) the total number of days/periods of the planning horizon and iii) the number of nodes that would be disconnected by the original DBD model.

We made two key observations in relation to the impacts of the transportation network failures on the DRP routing and scheduling decisions. First of all, out of total 30 nodes in the large-size Lombok instance, 12 nodes can be disconnected from the rest of the nodes in case of a high-impact disaster (which represented by the case setting β to 20 km) according to the original DBD model. More importantly, one of the resting points is disconnected from the transportation network in all of the 60 scenarios generated. This demonstrates possible improvement areas regarding the nodes bearing high risk of becoming disconnected. If the node with high risk of becoming disconnected is a resting point, decision makers may prefer to choose a safer resting point in terms of accessibility. If the node with high risk of becoming disconnected is a demand point or a depot, then the transportation infrastructure around the corresponding locations can be strengthened in order to mitigate the disconnectivity risks.

The second key observation pertains to the length of the planning horizon for the medical services. The number of periods required to meet the entire medical service demand can be up to 19 days (which is 4 days in the static case). This is due to the increasing travelling times between particular demand points and resting points. Due to high travel times and resting requirements, personnel can stay at demand points a limited time and have to go back to their resting points after a short serving time. This necessitates to go back and forth between the same resting point and demand point which consequently extends the planning horizon. A potential action to mitigate the corresponding adverse outcomes could be the use of temporary resting points at appropriate locations so that personnel do not lose significant time on the road to/from resting points.

Table 2
Impacts of the transportation network failures.

β (km)	Evacuation personnel		Medical personnel		Range of the number of disconnected nodes*
	Range of the number of		Range of the number of		
	efficient solutions	days of the planning horizon	efficient solutions	days of the planning horizon	
5	[2–8]	[2–3]	[2–8]	[11–16]	[1–5]
10	[1–11]	[2–3]	[1–11]	[6–17]	[1–7]
20	[1–3]	[2–3]	[1–9]	[5–19]	[1–12]

* This columns shows the range of the number of nodes that would be disconnected from the network if the original DBD model would have been applied.

6.3.2. Emergence of new demand

Eshghi & Larson (2008) categorize disasters in six groups based on the number of fatal and affected victims: emergency situation, crisis situation, minor disaster, moderate disaster, major disaster and catastrophe. According to their categorization, Lombok Earthquake lies in the 'emergency situation' group for which the range of the number of fatal (affected) victims is between 10 and 100 (between 100 and 1000). Alem, Clark, & Moreno (2016) consider a stochastic network model for disaster relief and use the transition probabilities among different disaster types. Particularly, 'emergency situation' transits to 'emergency situation' with probability 0.75 and transits to 'crisis situation' with probability 0.25. The number of fatal (affected) victims is between 100 and 1000 (between 1000 and 10000) for the crisis situation. We assume that the demand for the evacuation and medical personnel is positively correlated with the number of victims and the demand in a crisis situation is ten times of the demand in an emergency situation on average considering the range for the number of fatal and affected victims for them. Then, in line with the transition probabilities, we assume that in case of a secondary disaster (or an aftershock) following an emergency situation (or simply the evolution of the initial emergency situation), the new demand can have a similar magnitude to that of the initial demand by probability 0.75 and it can be around ten times of the initial demand by probability 0.25.

To consider the dynamic changes in demands, we assume that new demands emerge at the end of the first day at the same locations affected by the initial disaster without loss of generality. Let $\bar{d}_i$ be equal to $[0.75d_i + 0.25d_i 10]$ where d_i is the initial evacuation or medical personnel demand of the demand point i depending on the service of interest. The amount of the new demand for demand point $i, \forall i \in V_I$, is assumed to be in $[0.75\bar{d}_i, 1.25\bar{d}_i]$. 30 different scenarios are produced by randomly generating new demands in the relevant ranges to assess the impacts of the demand changes on the DRPRS problem. In the first period, the priority of each demand point is assumed to be equal to one. At the subsequent periods, a random priority within the range [1,3] (representing increasing urgency) is set for each demand point with unsatisfied demand at the end of the first period. The underlying assumption is that it is reasonably sufficient to consider scenarios where a demand can be three times more urgent than another demand.

For each of the evacuation and medical service, we present results for a representative scenario for convenience. In Table 3, eleven efficient evacuation solutions for the representative scenario are presented.

Due to the emergence of new demand at the end of first day, evacuation demand can be satisfied in three periods (unlike two periods for the static case presented in Section 6.2). Therefore, we have more efficient evacuation personnel solutions for this dynamic case since the number of efficient solutions tends to increase with the number of periods. The average service completion times and average risks of the solutions after the first period are higher than those for the static case due to the higher amount of demand and higher priority of demands. The ranges of the average service completion time and average risk are wider than those for the static case. For example, Solution ED_8 has higher average service completion time than its maximum value for the static case yet has smaller average risk than its maximum value for the static case. This indicates stronger trade-offs for the relevant solution evaluation metrics.

The efficient medical personnel solutions for the representative scenario are shared in Table 4. We note that due to the limited space, the solution evaluation metric values are only provided for the first three and the last period of the planning horizon. While the medical personnel solutions for the static large-size instance have comparable *UnsatisfiedDemand* and *AverageCompletionTime* metric values by the end of the second and third days, the relevant metrics are getting more diverged after the arrival of new demands. On the other hand, *AverageRisk* metric is less affected by the new demand arrivals. In terms of *Fairness*, the emergence of new demands at the end of the first day results in less fair solutions by the end of the second and third days in comparison to corresponding *Fairness* values for the static case.

7. Concluding remarks

In this paper, we have extended the disaster response personnel routing and scheduling problem (Tarhan et al., 2023) by considering the dynamic effects of natural disasters. To this end, we have developed a MILP model and a heuristic algorithm for solving large-size problem instances. The proposed heuristic (QSH) is based on the quadrant shrinking method and is applied over a rolling horizon to generate efficient solutions for each day (with respect to the minimization of i) total unmet demand, ii) the total service completion time, iii) unfair distribution of the unsatisfied demand among different demand points and iv) the total transportation risk) until all demand is satisfied. We first tested the QSH by using a static small-size instance and showed that the proposed heuristic can approximate its Pareto frontier successfully. Subsequently, we applied the QSH to a larger-size static Lombok instance and analyzed two different demand satisfaction strategies: full and partial demand fulfilment.

We used the proposed DDRPRS model and the associated solution algorithm QSH to study the behavior of partial and full demand fulfilment strategies. We found that the full demand fulfilment strategy leads to smaller unsatisfied demand and generates more robust solutions over the planning horizon in comparison to the partial demand fulfilment strategy. On the other hand, while the performance of the partial demand fulfilment strategy solutions fluctuate more over the planning

Table 3
Non-dominated solutions for the evacuation personnel under the full demand fulfilment strategy in dynamic demand large-size Lombok instance.

Evacuation personnel solution	*Unsatisfied Demand* (number of tents)			*Average CompletionTime* (hours)			*Fairness**			*Average Risk* (*InaRisk* index**)		
	Up to period			Up to period			Up to period			Up to period		
	1	2	3	1	2	3	1	2	3	1	2	3
ED_1	8	18	0	8.42	22.33	35.72	0.32	0.26	0.00	20.13	58.45	175.37
ED_2	8	18	0	10.32	29.14	46.62	0.32	0.21	0.00	20.13	57.92	174.70
ED_3	8	15	0	9.76	20.71	33.14	0.32	0.17	0.00	20.13	60.96	177.40
ED_4	8	14	0	8.06	21.67	34.67	0.32	0.14	0.00	20.13	66.21	189.28
ED_5	9	14	0	8.92	34.85	55.75	0.35	0.15	0.00	17.24	58.38	177.26
ED_6	9	12	0	10.99	38.94	62.31	0.51	0.18	0.00	17.94	61.58	182.41
ED_7	9	14	0	8.75	26.68	42.68	0.51	0.16	0.00	17.94	60.73	179.55
ED_8	9	15	0	9.37	29.32	47.70	0.60	0.25	0.00	13.17	46.98	145.47
ED_9	9	13	0	10.74	21.85	48.48	0.60	0.32	0.00	13.17	48.07	148.04
ED_{10}	9	14	0	8.06	24.77	59.69	0.60	0.17	0.00	13.17	52.85	151.70
ED_{11}	9	15	0	10.06	20.45	39.83	0.60	0.51	0.00	13.17	58.95	168.63

* *Fairness* is ranged between zero and one where lower values indicate fairer solutions.
** *InaRisk* index of a single arc ranges between 0.38 and 247.20 where lower values indicate lower risk.

Table 4
Non-dominated solutions for the medical personnel under the full demand fulfilment strategy in dynamic demand large-size Lombok instance.

Medical and associated evacuation personnel solution	*Unsatisfied Demand* (required service hours)					*Average CompletionTime*(hours)					*Fairness**					*Average Risk* (*InaRisk* index**)				
	Up to period					Up to period					Up to period					Up to period				
	1	2	3	...	8	1	2	3	...	8	1	2	3	...	8	1	2	3	...	8
$MD_1 - ED_1$	222	681	418	...	0	13	92	124	...	320	0.92	0.72	0.77	...	0.00	2	3	4	...	7
$MD_2 - ED_2$	221	675	414	...	0	12	45	64	...	155	0.88	0.80	0.82	...	0.00	3	3	4	...	7
$MD_3 - ED_3$	221	662	420	...	0	12	75	101	...	260	0.88	0.82	0.78	...	0.00	3	3	4	...	8
$MD_4 - ED_3$	222	655	414	...	0	13	65	87	...	223	0.86	0.81	0.75	...	0.00	3	3	4	...	7
$MD_5 - ED_4$	221	654	405	...	0	12	75	100	...	258	0.86	0.82	0.76	...	0.00	3	3	4	...	7
$MD_6 - ED_5$	222	681	423	...	0	12	69	93	...	240	0.92	0.77	0.75	...	0.00	2	3	4	...	7
$MD_7 - ED_5$	222	670	416	...	0	12	83	112	...	288	0.86	0.75	0.76	...	0.00	3	3	4	...	7
$MD_8 - ED_6$	221	670	409	...	0	12	68	92	...	236	0.86	0.76	0.75	...	0.00	3	3	4	...	7
$MD_9 - ED_7$	222	681	422	...	0	13	80	99	...	231	0.92	0.77	0.75	...	0.00	2	3	4	...	6
$MD_{10} - ED_7$	222	681	419	...	0	12	50	62	...	145	0.92	0.77	0.75	...	0.00	2	3	4	...	7
$MD_{11} - ED_8$	222	668	413	...	0	13	69	85	...	199	0.86	0.76	0.74	...	0.00	3	3	4	...	6
$MD_{12} - ED_9$	221	670	409	...	0	12	87	109	...	253	0.86	0.73	0.76	...	0.00	2	3	4	...	6
$MD_{13} - ED_{10}$	222	657	403	...	0	13	48	60	...	140	0.88	0.82	0.80	...	0.00	2	3	4	...	7
$MD_{14} - ED_{10}$	222	646	405	...	0	12	60	75	...	174	0.86	0.85	0.77	...	0.00	3	3	4	...	7
$MD_{15} - ED_{11}$	222	655	411	...	0	12	72	89	...	208	0.86	0.83	0.74	...	0.00	3	3	4	...	6

* *Fairness* is ranged between zero and one where lower values indicate fairer solutions.
** *InaRisk* index of a single arc ranges between 0.38 and 247.20 where lower values indicate lower risk.

horizon, they can provide fairer solutions at the beginning of the decision-making horizon, at the expense of higher transportation risks. Regardless of the strategy used, the performances of generated solutions fluctuates over time. This behaviour underlines the advantage of considering sufficiently long planning horizon instead of a myopic approach focusing on a shorter horizon.

To consider the dynamic changes on problem parameters, particularly on the demand and transportation network attributes, we analyzed two types of scenarios using the static large-size Lombok instance. We first analyzed a set of scenarios in which the transportation network is damaged to a different extent after the onset of the disaster. Computational experiments show that certain nodes can bear high risk of inaccessibility. This type of analysis can provide useful information regarding the identification of the components of transportation network infrastructure that should be strengthened. In the second type of scenarios, we considered the emergence of new demand over time. Computational results show that the arrival of new demand can prolong significantly the planning horizon. The dynamic consideration of the demand over an extended planning horizon provides useful information to the decision-makers regarding the evolution of the trade-off between conflicting objectives.

Promising directions for future research that will enhance the proposed DDRPRS model include the endogenous consideration of the location decisions of the resting points of the DRP, and the investigation of the potential benefits emerging from the relocation of the resting points and/or the introduction of additional resting points as a proactive disaster preparedness measure in the anticipation of transportation network damages.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2023.09.002.

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