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A multi-objective rolling horizon personnel routing and scheduling approach for natural disasters

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ABSTRACT

The magnitude of the workload associated with the provision of emergency response services in the aftermath of natural disasters, coupled with limited availability of personnel for providing these services, leads to demand–supply imbalances with detrimental effects on the provision of the required services. In this context, personnel routing and scheduling decisions aim to meet the demand as fast as possible while at the same time they ensure fair provision of services among the impacted areas. Due to their excessive working hours, and their travel over unreliable transportation networks, personnel are prone to burnout effects and are exposed to risks derived from the unreliable condition of the disaster impacted transportation networks. To address these issues, we propose a novel Disaster Response Personnel Routing and Scheduling (DRPRS) model with efficiency, fairness and risk objectives, subject to working and resting related constraints. The proposed model can be applied to routing and scheduling decisions for different types of emergency response services, and takes into account the precedence relations among them. We solve the resulting multi-objective model lexicographically over a rolling horizon sequentially on a daily basis until the demand for all types of services considered is satisfied. We report results from the application of the proposed model for routing and scheduling personnel involved in the provision of evacuation and medical services in the context of 2018 Lombok Earthquake, Indonesia.

1. Introduction

The last two decades witnessed many severe disasters such as Boxing day tsunami in Indonesia (2004), Cyclone Nargis (2008), Kashmir earthquake (2005), Sichuan earthquake (2008), Port-au-Prince earthquake (2011), Japan earthquake and tsunami (2011), Nepal earthquake (2015) which are responsible for the deaths of almost one million people in total. A recent report of the United Nations Disaster Risk Reduction Office shows the number of natural disasters has doubled in the last 20 years (UN, 2020). The magnitude and frequency of these catastrophic events and their grave socio-economic and environmental consequences have drawn considerable research attention aiming to improve disaster management decisions.

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A key decision involved in disaster response services relates to the timely dispatching of the Disaster Response Personnel (DRP) needed to provide disaster relief services, e.g., medical care, evacuation support, and distribution of relief supplies, to the population of the areas affected by the disaster. In fact, the unavailability of the DRP at the right place at the right time may constitute a critical bottleneck affecting the overall performance of the disaster response services. For instance, in the case of Hurricane Katrina, Lei et al. (2015) and Wang et al. (2018) found that although adequate relief supplies were delivered on time at the disaster hit areas, the relief services could not be performed immediately due to the insufficient number of the DRP. Furthermore, personnel shortages may result in excessive working hours for the emergency responders, creating burnout conditions for the available personnel (Brooks et al., 2018). This endangers both the personnel's own safety and efficiency, and consequently the safety of the impacted population. However, the extant literature suggests that studies regarding personnel scheduling and/or routing tend to neglect the resting requirements of the DRP (Wex et al., 2014; Bodaghi and Palaneeswaran, 2016; Rodríguez-Espíndola et al., 2018; Rauchecker and Schryen, 2019). Another gap identified in the literature relates to the objectives used in the emerging optimization models. Existing studies consider mostly efficiency-related objectives. Efficiency of the disaster response services, which usually indicates the completion of the required services as quickly as possible, is essential considering the fatal consequences due to their delays. However, the classical utilitarian approach that vigorously pursues the efficiency can lead to disproportional response to the demands from different impacted areas and thereby the differential treatment of certain groups of people (Gutjahr and Nolz, 2016). On the other hand, the World Health Organization (WHO) suggests that the humanitarian response should be provided in proportion to the needs identified (Wisner and Adams, 2003). In this respect, consideration of the fairness objective can mitigate the adverse effects of sheer efficiency-oriented approaches. To date, the existing models do not provide adequate decision making support for examining trade-offs among efficiency and fairness objectives (Gutjahr and Nolz, 2016).

In terms of routing decisions, the existing efficiency-oriented approaches tend to neglect the risks associated with the condition of the transportation network. Disasters can render the transportation network unreliable so that it may necessitate to use longer yet less risky routes for the well-being of both the services and the personnel executing them. Therefore, it is crucial to develop models that incorporate efficiency, fairness and risk objectives and to support the decision makers to assess the trade-offs among these three important objectives.

The objective of this paper is to fill the identified gaps and enhance the existing disaster response personnel deployment decisions by formulating and solving a novel multi-objective Disaster Response Personnel Routing and Scheduling (DRPRS) problem, with working hours limitations and scheduled work breaks at specific resting points. The proposed multi-objective model incorporates efficiency, fairness, and risk objectives.

The remainder of the paper is organized as follows. The DRPRS problem is reviewed on the grounds of relevant literatures in Section 2. The problem environment is explained in more detail in Section 3. The proposed model and its extension to the multi-period environment by the rolling horizon approach are introduced in Section 4. Two-stage approach proposed to handle the multiple objectives is presented in Section 5. Computational analysis of the proposed solution approach is provided in Section 6. Finally, Section 7 summarizes the outputs of this study and discusses future research directions.

2. Literature review

The DRPRS problem has often been studied in the context of personnel offering specific disaster relief services. For example, Chen and Miller-Hooks (2012) propose a multi-stage stochastic programme for the deployment of the search-and-rescue teams where decisions are taken dynamically as the new information arrives. Zheng et al. (2014) study the deployment of search-and-rescue teams as a bi-objective problem. They develop a heuristic algorithm to minimize the weighted completion times of demands and the total operational risk, that the search-and-rescue teams are exposed. To this end, the disaster affected area is divided into sub-areas based on their environmental conditions and associated operational risks. The operational risk includes both the risks exposed during the services in these areas and the risks due to the travels between them. Moreno et al. (2020) study the routing and scheduling of network repair crews for the post-disaster road network restoration to minimize the weighted sum of the accessibility time to affected zones.

In addition to service specific DRPRS, generic DRPRS formulations have also been proposed in the literature. These formulations are applicable to different types of services and consider the dependencies between the different types of services offered. Rolland et al. (2010) consider different types of personnel and emergency services simultaneously. Each personnel is capable of a subset of the services, which are subject to precedence relations. The objective is to minimize the total cost including the processing and tardiness cost of services and the mismatching cost between personnel and services. The data sets generated for a different context, i.e., the audit scheduling (Dodin et al., 1998), are used for computational experiments. Thus, the test experiments do not address specific emergency services. Bodaghi and Palaneeswaran (2016) propose a mathematical model for a similar problem where the demand points require a set of different services and each personnel category is capable of offering different categories of services. This model considers distinct release times and seeks to minimize the weighted completion times. The proposed model is tested on a fire emergency scenario including both medical and fire fighter personnel. Nadi and Edrisi (2017) study the coordination of relief assessment and emergency response teams. The assessment teams evaluate demands for humanitarian supplies and search-and-rescue services, which are satisfied by the emergency response teams. A multi-agent assessment and response system is proposed to maximize the satisfaction of demand over diverse services. A hypothetical case study including the assessment and relief distribution services is used for test purposes. Wang et al. (2018) propose a single objective routing and scheduling model for both medical supplies and medical teams for a single period. The proposed model minimizes the total completion time and ensures that the provision of medical services at the hospitals can be initiated when both personnel and supplies are present. Bodaghi et al. (2018)

Table 1
Literature review summary.

	Decisions		Multi-depot	Time window	Service take over	Time limits		Specific break points	Planning horizon		Objectives		
	Routing	Scheduling				Work	Break		Single	Multiple	Efficiency	Fairness	Risk
Rolland et al. (2010)	✓	✓		✓		✓				✓	✓		
Bodaghi and Palaneeswaran (2016)	✓	✓							✓		✓		
Nadi and Edrisi (2017)	✓	✓							✓		✓		
Bodaghi et al. (2018)	✓	✓							✓		✓		
Wang et al. (2018)	✓	✓							✓		✓		
Zheng et al. (2014)	✓	✓	✓								✓		✓
Wex et al. (2014)	✓								✓		✓		
Rauchecker and Schryen (2019)	✓								✓		✓		
Rodríguez-Espíndola et al. (2018)		✓								✓	✓		
Doan and Shaw (2019)		✓				✓	✓			✓	✓		
This paper	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓

develop a bi-objective model for a similar problem with both renewable (i.e., response personnel) and non-renewable (i.e., relief supplies) resources. Services cannot be started before both types of resources are present at the demand points. The objectives of the proposed model are to minimize the makespan and the weighted sum of the completion times.

The models discussed in the preceding paragraph consider both routing and scheduling decisions for DRP. Two sub-categories of the generic DRPRS model emerge when only DRP Routing (Wex et al., 2014; Rauchecker and Schryen, 2019) or only DRP Scheduling (Doan and Shaw, 2019; Rodríguez-Espíndola et al., 2018) are considered. However, none of them consider DRP that route between different demand points subject to working time requirements. Table 1 summarizes the comparison of the generic DRPRS problem studied herein and similar DRP problems in the literature. We observe that single objective models seeking to improve the efficiency are dominant in the literature. Another gap in the literature is the lack of consideration of intermediate resting points and replacement of personnel due to excessive working hours. These are important modelling consideration in the context of the provision of disaster relief services, where due to long working hours under stressful conditions, DRP may need to take a resting break before completing the assigned task. In this case, another personnel should be assigned to complete the service. To ensure continuity of the service, the replacement personnel should arrive at the service location before the personnel to be replaced departs in order to be briefed on the status of the service. However, as shown in Table 1, existing studies do not include the personnel synchronization constraints associated with service hand-over.

In this paper, we introduce a generic DRPRS model for the personnel involved in a wide range of disaster response services. The proposed model can be employed both for routing and scheduling personnel involved in different types of services independently, and for routing and scheduling DRP offering different services which have precedence relationships. Possible precedence relations among them are incorporated as scheduling constraints in determining the execution times of the services, i.e., earliest start and latest finish times. Execution times can be further constrained due to other operational restrictions, e.g., a service may have to be executed only in daylight. However, Table 1 shows that studies addressing the DRPRS problem often neglect the time windows imposed for serving the demand and resting requirements for the personnel. Rolland et al. (2010) is the only study restricting starting and ending times of the services in the context of the DRPRS to the best of our knowledge. Moreover, resting time requirements are not addressed in the context of the DRPRS but of the DRP Scheduling (Doan and Shaw, 2019). The proposed DRPRS model incorporates both time windows and personnel resting requirements.

Another novel feature of our formulation is the simultaneous consideration of efficiency, fairness and risk objectives. All studies in Table 1 include 'efficiency' objectives such as the minimization of total cost, sum of completion times, makespan or unsatisfied demand. To the best of our knowledge, fairness has not been considered in the context of the DRPRS. Herein, we define the fairness in relation to the services and express fairness as the minimization of the sum of the unsatisfied demand differences between all demand points. The proposed fairness metric satisfies the property of analytical tractability and the principle of transfers (Marsh and Schilling, 1994).

Different fairness measures have been proposed in the context of humanitarian operations. These measures are defined in terms of the unmet demand at demand points, such as the minimization of maximum unmet demand (Vitoriano et al., 2011; Tzeng et al., 2007), the minimization of the range of the unmet demand (Lin et al., 2011), or the deviation of the unmet demand distribution from a targeted/goal value (Ferrer et al., 2018). However, these measures either do not satisfy the principle of transfers or the analytical tractability. Moreover, by applying the rolling horizon approach, fairness of the services in our study is evaluated over the entire planning horizon rather than myopic short term considerations. This enables to prioritize the demand points that have higher unsatisfied demand percent than others over time in line with the consideration of inter-temporal effects (Holguín-Veras et al., 2013).

In this study, we consider the transportation risk as in Nolz et al. (2011) and Hamedi et al. (2012) who use transportation risk in routing relief supplies. Our risk metric takes into account the transportation network unreliability and associated risks (i.e., failure risk of roads due to disaster-induced disruptions). The proposed model considers the efficient frontier of the complete graphs emerging from the bi-objective shortest paths on the road-network with respect to travel times and risks.

Contributions of this study:

The review of the extant literature reveals that existing DRPRS models do not (i) investigate the trade-offs between efficiency, risk, and fairness objectives addressed in our study, (ii) include multiple types of services with precedence relationship offered over a planning horizon, and (iii) consider scheduling constraints regarding the personnel resting and task hand-over requirements.

This paper aims to close the identified gaps in the disaster response personnel routing and scheduling literature by introducing a novel model which considers: (i) efficiency, fairness and risk objectives, (ii) personnel involved in different types of disaster response services and precedence relationships between different services, (iii) a rolling horizon for satisfying the demand for the provision of different types of services, and (iv) spatial and temporal personnel scheduling constraints related to their resting breaks and task hand-over requirements. We are introducing a two-stage multi-objective programming framework in order to study the trade-offs between efficiency, risk, and fairness objectives. At the first stage we are using a bi-objective (travel time, risk) shortest path formulation to generate the efficient frontier of the complete graphs that are used to solve the second stage multi-objective disaster response personnel routing and scheduling problem. The second stage DRPRS problem is solved lexicographically by generating scenarios reflecting different priorities for the optimization of the efficiency and fairness objectives. We apply the proposed model for routing and scheduling the personnel involved in the provision of evacuation and medical services in Indonesia. Evacuation service corresponds to the setting-up tents, i.e., temporary shelters, at demand points. Medical service is preceded by the evacuation such that there has to be at least one tent at a demand point to be provided medical services. In implementing the proposed DRPRS model, we are considering two alternative strategies for satisfying the demand for evacuation and medical services. In the first strategy, the evacuation personnel fulfil the entire demand they are assigned to. On the other hand, in the second strategy, there has to be at least one tent at each demand point to proceed with the set-up of the rest of the tents.

3. Problem definition

The DRPRS problem is motivated by the disaster response services, in the aftermath of large-scale disasters, to satisfy the demand for services offered by different personnel types. Our work is motivated from the disaster response services in Indonesia. In this context, various organizations are involved in response services of natural disasters including the Indonesian National Board for Disaster Management (BNPB), Regional Disaster Management Agency (BPBD), police, army and non-governmental organizations, e.g., Indonesian Red Cross. BNPB coordinates different organizations offering emergency response services such as search-and-rescue, evacuation, medical and logistics among many others. These services are often provided by multi-member personnel teams which are referred to as personnel hereafter. Disaster response personnel routing and scheduling decisions are made on a daily basis to determine personnel schedules and routes for the next day. The demand for the different types of required services is known at the beginning of the planning horizon. Depending on the nature of the services under consideration, the demand can be discrete, e.g., number of tents to be set to accommodate the evacuated population at a given location, or continuous, e.g., number of medical personnel hours needed at a given location. From the emergency response operations point of view, the two types of demand differ on how the demand has been covered. In the case of discrete demand, the provision of service for one unit of demand is considered completed when the work required to satisfy the single unit of demand has been provided in its entirety, i.e., a tent is either set or not set. In the case of continuous demand, this restriction is not applicable and the number of hours that services have been provided is counted towards the completion of the required number of hours.

In this problem setting, we are given a set of demand points that require specific types of emergency services offered by different personnel types. Each demand should be served within a pre-defined time window defined by operational requirements (e.g., services should be performed in day-light or when lighting equipment is available) or due to the precedence relations among different types of services. The term personnel refers to teams of individuals that can perform the tasks involved in the provision of a given type of service. Services are provided in their entirety by the corresponding personnel teams. Therefore, the precedence relations between different tasks required by a given type of service are handled implicitly. Furthermore, there is no precedence relation in terms of services provided at different locations, stated otherwise the provision of a service at a particular location is independent of its provision at other locations.

Personnel depart from designated depots. The deployed personnel teams do not necessarily return to their depot in the same day that their deployment started. There is a limit on the maximum number of continuous working hours, that the DRP can offer their services. Therefore, the DRP should be provided with a resting break when the threshold of continuous allowable working hours is reached. The resting breaks correspond to the end of the DRP's shifts which are mandatory considering the fact that the disaster response operations can last for days which renders non-stop working of the DRP implausible. Breaks are provided only at specific locations and should have a minimum pre-defined duration. If the personnel should halt an ongoing service due to the working hours limitation, another personnel should take-over the service (task hand-over) such that the new personnel can continue the corresponding service after they are briefed by the personnel they will replace.

Due to the excessive workload associated with the provision of emergency response services, it is unlikely that the entire demand for the required services will be fulfilled in a single day. Therefore, the DRPRS problem is solved over a rolling horizon aiming to minimize the unmet demand on a daily basis. The ultimate goal is to satisfy the entire demand over the rolling horizon as soon and as fairly as possible and to minimize the risks exposed to the personnel providing emergency services. Based on the requirements and characteristics discussed so far, the DRPRS problem is modelled as a multi-depot multi-objective routing problem with time windows, and scheduling constraints, and is formulated as a Mixed Integer Linear Programming (MILP) model. The resulting MILP model has four objectives, which are the minimization of the unsatisfied demand, completion times of the demand served, unfair distribution of the unsatisfied demand among different demand locations and minimization of the transportation risks for personnel. We are using a two-stage solution approach for solving the proposed model. In the first stage, we generate the efficient frontier of the complete graphs by solving a bi-objective shortest path model, which considers both travel time and risk for all links of the underlying roadway network. In the second stage, we are using the efficient frontier of the complete graphs generated in the first stage to formulate the tri-objective MILP model, which considers the amount of unmet demand, service completion times and the fairness among the demand points. The proposed two-stage approach is explained in more detail in Section 5.

4. Mathematical model and rolling horizon approach

The proposed MILP model is generic and can take into account the personnel scheduling and routing requirements involved in different types of services. In this section, we are introducing first the generic formulation of the proposed MILP (Section 4.1). We then customize the generic formulation to reflect the demand characteristics, i.e., discrete and continuous demand units of services (Sections 4.1.2 and 4.1.3). Finally, the rolling horizon approach, which renders the single period MILP model applicable for longer horizon, is described (Section 4.2).

4.1. The MILP model

Sets
P: Personnel
V_D: Set of $v_p, p \in P$, where v_p is the depot of personnel p
V_B: Set of $\bar{v}_p, p \in P$, where $\bar{v}_p$ is the resting point of personnel p
V_I: Demand points
V_{IB} : $V_I \cup V_B$
V : $V_{IB} \cup V_D \cup \{v_e\}$ where v_e is a dummy ending node each working personnel visits at the end of the period
A: Set of arcs $a_{i,j}, i, j \in V$
$G(V, A)$: Complete graph comprising the nodes in V and the arcs in A (see Section 5 for its definition and generation)
Parameters
$t_{i,j}$: Travel time of arc $a_{i,j}$; $i, j \in V$
W_p: Maximum working hours of personnel p without resting; $p \in P$
B_p: Minimum resting hours of personnel p before restart working; $p \in P$
d_i: Amount of the demand required by demand point i; $i \in V_I$
h: Duration required to satisfy a unit of demand
e_i: Earliest allowable start time of the services at demand point i; $i \in V_I$
l_i: Latest allowable completion time of the services at demand point i; $i \in V_I$
q_i: Briefing time required before taking over a service at demand point i; $i \in V_I$
*e_i and l_i are set to 0 and L, $\forall i \in V \backslash V_I$, respectively, for the modelling purposes where L is the length of the period and equal to 24 hours.
*Travel time to dummy ending node v_e is zero.
Decision variables
$y_{p,i,j}$: 1 if personnel p uses arc $a_{i,j}$, 0 otherwise; $i, j \in V, i \neq j, p \in P$
$z_{p,\bar{p},i}$: : 1 if personnel $\bar{p}$ takes over service from personnel p at demand point i, 0 otherwise; $i \in V_I, p, \bar{p} \in P$
s_i: Satisfied demand amount at demand point i; $i \in V_I$
u_i: Unsatisfied demand amount at demand point i; $i \in V_I$
$x_{p,i}$: Amount of time spent by personnel p at demand point i; $i \in V_I, p \in P$
$g_{p,i,j}$: Service completion time of personnel p at node i if it uses arc $a_{i,j}$ afterwards, 0 otherwise; $i, j \in V, i \neq j, p \in P$
$\bar{g}_i$: Service completion time at demand point i ; $i \in V_I$

4.1.1. Generic formulation

Regardless of the demand type, the MILP model can be formulated generically as follows:

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

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

$$\text{Minimize} \quad f_3 = \frac{\sum_{i,j \in V_I : i<j} |\frac{u_i}{d_i} - \frac{u_j}{d_j}|}{\lceil |V_I|/2 \rceil \lfloor |V_I|/2 \rfloor} \tag{3}$$

s.t.

$$\sum_{p \in P, j \in V} y_{p,i,j} \leq 1 + \sum_{p,\bar{p} \in P} z_{p,\bar{p},i} \qquad \forall i \in V_I \tag{4}$$

$$\sum_{\bar{p} \in P} z_{p,\bar{p},i} \leq \sum_{j \in V} y_{p,i,j} \qquad \forall i \in V_I, p \in P \tag{5}$$

$$\sum_{\bar{p} \in P} z_{\bar{p},p,i} \leq \sum_{j \in V} y_{p,i,j} \qquad \forall i \in V_I, p \in P \tag{6}$$

$$\sum_{p \in P} x_{p,i} = s_i h \qquad \forall i \in V_I \tag{7}$$

$$x_{p,i} \leq \sum_{j \in V} y_{p,i,j} d_i h \qquad \forall i \in V_I, p \in P \tag{8}$$

$$\sum_{j \in V} y_{p,v_p,j} = \sum_{j \in V} y_{p,j,v_e} \leq 1 \qquad \forall p \in P \tag{9}$$

$$\sum_{j \in V} y_{p,i,j} = \sum_{j \in V} y_{p,j,i} \leq 1 \qquad \forall i \in V_{IB}, p \in P \tag{10}$$

$$\sum_{j \in V} (g_{p,i,j} - g_{p,j,i} - y_{p,j,i} t_{j,i}) \geq x_{p,i} + \sum_{\bar{p} \in P} (z_{p,\bar{p},i} + z_{\bar{p},p,i}) q_i \qquad \forall i \in V_I, p \in P \tag{11}$$

$$\sum_{j \in V} (g_{p,i,j} - g_{p,j,i}) \geq \sum_{j \in V} y_{p,j,i}(t_{j,i} + B_p) - y_{p,i,v_e} B_p \qquad \forall i \in V_B, p \in P \tag{12}$$

$$\sum_{j \in V} (g_{p,j,i} + y_{p,j,i} t_{j,i} - g_{\bar{p},i,j}) \leq (1 - z_{\bar{p},p,i})L - z_{\bar{p},p,i} q_i \qquad \forall i \in V_I, p, \bar{p} \in P \tag{13}$$

$$\sum_{j \in V} (g_{p,i,j} - g_{\bar{p},i,j}) \geq x_{p,i} + \sum_{\bar{\bar{p}} \in P} z_{p,\bar{\bar{p}},i} q_i - (1 - z_{\bar{p},p,i})L \qquad \forall i \in V_I, p, \bar{p} \in P \tag{14}$$

$$\sum_{j \in V} (g_{p,j,v_e} - g_{p,v_p,j}) \leq W_p + \sum_{j \in V} y_{p,j,\bar{v}_p}(L - W_p) \qquad \forall p \in P \tag{15}$$

$$\sum_{j \in V} ((g_{p,j,\bar{v}_p} + y_{p,j,\bar{v}_p} t_{j,\bar{v}_p}) - g_{p,v_p,j}) \leq \sum_{j \in V} y_{p,j,\bar{v}_p} W_p \qquad \forall p \in P \tag{16}$$

$$\sum_{j \in V} g_{p,i,j} \geq \sum_{j \in V} y_{p,i,j} e_i + x_{p,i} + \sum_{\bar{p} \in P} z_{p,\bar{p},i} q_i \qquad \forall i \in V_I, p \in P \tag{17}$$

$$g_{p,i,j} \leq y_{p,i,j} \min\{l_i, l_j - t_{i,j}\} \qquad \forall i, j \in V, p \in P \tag{18}$$

$$\bar{g}_i \geq \sum_{j \in V} g_{p,i,j} \qquad \forall i \in V_I, p \in P \tag{19}$$

$$u_i + s_i = d_i \qquad \forall i \in V_I \tag{20}$$

$$y_{p,i,j}, z_{p,\bar{p},i} \in \{0,1\}, g_{p,i,j}, \bar{g}_i, x_{p,i}, s_i, u_i \in R^+ \qquad \forall i, j \in V, p, \bar{p} \in P \tag{21}$$

Eqs. (1), (2) and (3) represent the three objective functions considered in the optimization of the DRPRS problem. Objectives (1) and (2) seek to minimize the total unsatisfied demand and the completion times of the satisfied demand, respectively, while Objective (3) expresses the fairness objective. Given the fact that the workload for the provision of different types of services might exceed the available resources, the allocation of the scarce available resources should not only be based on the efficiency objective, i.e., minimization of the service completion times, but it should also consider how the demand for services at different demand points (communities) is met. Thus, in our formulation, we are introducing a criterion to measure the fairness associated with the provision of services at each demand point. In our formulation, we define fairness as the difference of the unmet demand among the different points requiring services. Following this definition, the fairness metric is expressed in our model as the normalized sum of the unsatisfied demand percent differences among all demand points.

Proposition 1. *$\lceil |V_I|/2 \rceil \lfloor |V_I|/2 \rfloor$ is the maximum possible value of $\sum_{i,j \in V_I : i<j} |\frac{u_i}{d_i} - \frac{u_j}{d_j}|$ in Objective (3) and it is attained when the demand of half of the demand points is completely satisfied, and the demand of the remaining half is not satisfied at all.*

Proof. Let n be the number of demand points which are sorted in descending order of their unsatisfied demand percent without loss of generality such that $\frac{u_1}{d_1} \geq \frac{u_2}{d_2} \geq \cdots \geq \frac{u_n}{d_n}$. Then, $\sum_{i,j \in V_I : i<j} |\frac{u_i}{d_i} - \frac{u_j}{d_j}|$ is equal to: $(n-1)(\frac{u_1}{d_1} - \frac{u_n}{d_n}) + (n-3)(\frac{u_2}{d_2} - \frac{u_{n-1}}{d_{n-1}}) + \cdots + (\frac{u_{\lfloor n/2 \rfloor}}{d_{\lfloor n/2 \rfloor}} - \frac{u_{\lceil n/2 \rceil}}{d_{\lceil n/2 \rceil}})(1 + (n \bmod 2))$.

This expression is maximized when first $\lfloor n/2 \rfloor$ demand points are not served at all while the remaining demand points are fully served. In case of even number of demand points, its maximum value is equal to $\sum_{i=1}^{n/2}(2i-1)$. In case of odd number of demand points, its maximum value is equal to $\sum_{i=1}^{\lfloor n/2 \rfloor} 2i$. In both cases, the maximum value would be equal to $\lceil n/2 \rceil \lfloor n/2 \rfloor$. □

Normalization of Objective (3) is achieved by dividing the pairwise differences by $\lceil |V_I|/2 \rceil \lfloor |V_I|/2 \rfloor$ which renders the interpretation of Objective (3) clearer. f_3 is equal to zero if all demand points have the same percentage of unsatisfied demand. On the other hand, its maximum value is equal to one when a half of the demand points is completely served whereas the remaining half is not served at all.

Constraint (4) ensures that service provision is handed-over from the personnel that currently offers services at a demand location to the personnel that arrives at the demand point to replace the response team that has completed its maximum allowable hours of continuous working. Constraints (5) and (6) imply that the personnel can take-over a service only at the demand points they visit. Constraint (7) ensures that the total service time at a demand point should be equal to the time needed to provide the required service, while Constraint (8) requires to visit the demand points in order to serve them. Since the personnel do not necessarily return to their depots at the end of the period, a dummy ending node is designated as the final destination of the working personnel. Constraint (9) ensures that if personnel leave their depot, they should visit the dummy ending node. Constraint (10) maintains the flow-balance. Constraints (11) and (12) are the sub-tour elimination constraints for demand and resting points, respectively. Constraints (13) and (14) ensure that if task hand-over will take place due to the completion of the maximum allowable continuous working hours, the personnel that will take-over the task should arrive at the demand point in time to be briefed by the personnel handing-over the task. Constraints (15) and (16) enforce the requirements of the personnel resting break, and ensure that the resting break takes place before their working hours limitations are exceeded. Constraint (17) ensures that services cannot be started before their earliest start time, which can be due to operational restrictions and/or precedence relations. Constraint (18) enables to complete services before their latest finish times. It also ensures that if a personnel does not traverse a particular arc, the service completion time variable (g) associated with the corresponding personnel and arc should be equal to zero. Constraints (19) and (20) compute the service completion time and unsatisfied demand amount for each demand point, respectively. Constraint (21) defines the integrality and non-negativity of the decision variables.

Valid inequalities can be added to strengthen the MILP model. Demand points i and j are called 'incompatible' if it is not possible to serve demand point j after demand point i due to their time windows. Thus, the following constraints can be added in the pre-processing of the model:

$$y_{p,i,j} = 0 \quad \forall i,j \in V_I, p \in P : e_i + \bar{h} + t_{i,j} + \bar{h} > l_j \tag{22}$$

where $\bar{h}$ is the minimum service duration to provide if a demand point is served.

In a similar vein to Constraint (22), if a demand point cannot be visited after having a resting break due to its latest completion time constraint, the associated variables should be set to zero in the pre-processing:

$$y_{p,\bar{v}_p,j} = 0 \quad \forall j \in V_I, p \in P : B_p + t_{\bar{v}_p,j} + \bar{h} > l_j \tag{23}$$

A demand point is visited by multiple personnel only if its service is left incomplete by a personnel and needs to be taken-over by another personnel (see Constraint (4)). Since the preceding personnel should go to the resting point due to the working hours limitation (otherwise, the service would not be left incomplete), there cannot be two personnel visiting the same two demand points in a row. Consequently, arcs between demand points cannot be visited by multiple personnel and the following constraint holds:

$$\sum_{p\in P} y_{p,i,j} \le 1 \quad \forall i,j \in V_I \tag{24}$$

The following constraint is added to strengthen the computation of $\bar{g}$ values in Constraint (19):

$$\bar{g}_i \ge \sum_{p\in P, j\in V} g_{p,i,j} - \sum_{p,\bar{p}\in P} z_{p,\bar{p},i}(l_i - q_i) \quad \forall i \in V_I \tag{25}$$

Valid inequalities generated for the VRP with split delivery by Dror et al. (1994) are also valid for the DRPRS problem:

$$y_{p,i,j} \le \sum_{k\in V : k\neq j} y_{p,j,k} \quad \forall i,j \in V_{IB}, p \in P \tag{26}$$

Two personnel are called 'identical' if their starting locations, resting points and working and resting hours' limitations are the same and so lead to symmetric solutions. To break the corresponding symmetries, if there is any, the inequality proposed by Coelho and Laporte (2014) is adapted to the DRPRS problem as follows:

$$\sum_{k\in V} y_{p',k,i} \le \sum_{k\in V, j\in V_I : j\le i} y_{p'-1,k,j} \quad \forall i \in V_I, p' \in P' \backslash \{1\} \tag{27}$$

where P' denotes the set of identical personnel. Since there can be multiple identical personnel sets, Constraint (27) should be defined for each of them.

If the MILP model is used with only Objectives (1) and/or (2), a personnel moves between two demand points only if demand of the first point is fully served. Similarly, if a personnel leaves a demand point to go to its resting point, it means either the demand is fully served or the personnel has to leave due to working hours. Therefore, Constraints (28) and (29) should be satisfied.

$$g_{p,i,j} \ge (e_i + d_i h) y_{p,i,j} \quad \forall i,j \in V_I, p \in P \tag{28}$$

$$g_{p,i,\bar{v}_p} \ge min(e_i + d_i h, W_p - t_{i,\bar{v}_p}) y_{p,i,\bar{v}_p} \quad \forall i \in V_I, p \in P \tag{29}$$

4.1.2. Discrete demand

In the context of the DRPRS problem, discrete type of demand corresponds to the demand that is measured in integer numbers (e.g., number of tents to set-up) and a pre-determined service duration is required for each unit of demand (e.g., duration required to set-up a tent). In this respect, in order to adapt the generic model to discrete demand type, Constraint (30) should be added to restrict the satisfied demand amounts to integer values:

$$s_i \in Z^+ \quad \forall i \in V_I \tag{30}$$

$\bar{h}$ denotes the minimum service duration to be provided when a demand point is served. In case of the discrete demand, at least one unit of demand should be served when a demand point is visited. Therefore, $\bar{h}$ is equal to the service duration required for unit demand, h. Accordingly, $\bar{h}$ should be set equal to h.

4.1.3. Continuous demand

Continuous type of demand corresponds to the demand that is not necessarily integer and is often defined in units of time in the context of the DRPRS problem (e.g., number of hours required for medical services). By this definition, the duration required to satisfy a unit of demand is one (i.e., $h = 1$). Similarly, $\bar{h}$ should be equal to zero since the minimum service duration to be provided is not limited, unless such a restriction is explicitly defined, when demand is continuous.

4.2. Rolling horizon approach

The MILP proposed in Section 4.1 is a single period/day model. However, the number of periods/days required to serve all demand for services, i.e., the length of the planning horizon for the DRPRS problem, is not known in advance since it is dependent on the available personnel resources, the magnitude of the demand, the transportation network condition etc. (i.e., it is parameter-dependent). Therefore, the MILP model is applied in a rolling horizon fashion and is solved for each period sequentially until there is no unmet demand left. Hereafter, the MILP model refers to its application over a rolling horizon unless otherwise specified. It should be noted that while the rolling horizon approach ensures the satisfaction of the entire demand at the end of the planning horizon, the minimization of the unmet demand is retained as one of the objective functions of the single period MILP model to be able to minimize the length of the planning horizon by serving as much demand as possible in each period/day.

Before solving the proposed model for a particular period within the rolling horizon approach, demand and supply parameters should be updated based on the results for the previous periods. In each period, the proposed model only considers the demand not met yet and thereby $d_i, i \in V_I$, is updated in all constraints accordingly. On the other hand, Objective (3) measures the overall fairness, rather than a local fairness regarding only the current period. Therefore, original demand values are used in Objective (3) and not updated over the horizon.

To update the supply parameters, the state of personnel at the end of the previous period (i.e., for how long personnel have been working or resting) should be taken into account. To this end, based on their last location ll_p, working start time ws_p and finish time wf_p in the previous period, personnel $p \in P$ is assigned to one of two groups P_b and P_w: P_b is the set of personnel at their resting-break points at the beginning of the current period to take a rest due to the working hours limitation, while P_w includes the rest of the personnel (i.e., they have not reached their maximum working hours limitation yet). For the latter group, the model decides whether the corresponding personnel should have a break or continue working at the beginning of the current period. Accordingly, a new variable $\bar{y}_{p,i}, p \in P_w, i \in V_I$, is defined as follows:

$\bar{y}_{p,i}$: 1 if personnel p has a resting break at the beginning of the period and visits demand point i immediately after the break, 0 otherwise; $i \in V_I, p \in P_w$.

It should be noted that personnel have open routes since they do not return to their depots at the end of the scheduling periods. In this respect, when personnel p has a break at the beginning of the new period (i.e., $\bar{y}_{p,i} = 1$ for some $i \in V_I$), it actually means that upon its completion of services in the previous period, personnel p moves to its resting point. Therefore, it is not necessarily starting its movement at the beginning of the new period. In other words, this movement is backward-looking and determines how to 'close' the open route of personnel p. In the same respect, while assigning personnel to one of the sets P_w and P_b, their state in the previous period should be considered as shown in Algorithm 1. Along with determining the sets of personnel, Algorithm 1 generates two parameters $\bar{e}_p$ and $\bar{l}_p$: $\bar{e}_p$ is the earliest starting time to work if personnel $p \in P$ is on break at the beginning of the current period and $\bar{l}_p$ is the maximum allowable working time until having a break if it is not already on a break at the beginning. To compute parameters $\bar{e}_p$ and $\bar{l}_p$, parameter ab_p is defined for the personnel for which the last location does not coincide with their resting point. Parameter ab_p represents the earliest time personnel p can complete the resting time requirements before assigned to a new task. Therefore, it is equal to the arrival time to its resting point (i.e., the working completion time of personnel p in the previous period plus the travel time between its last location and its resting point) plus the minimum resting duration required.

As shown in Algorithm 1, working start and finish times of personnel in previous period should be taken into account to determine their status at the beginning of the current period. This algorithm also updates the last location of personnel $p \in P$ that is not yet at its break point at the end of the previous period. If personnel p would exceed maximum working hours limit by the beginning of the current period (i.e., $ll_p \neq \bar{v}_b$ and $L - ws_p \geq W_p$), then it requires a resting break before the beginning of current period. Then, its last position is changed to $\bar{v}_b$ and its earliest starting time to work $\bar{e}_p$ is determined accordingly.

Algorithm 1 Determination of personnel status

$P_w, P_b = \emptyset$
for $p \in P : ll_p = \bar{v}_p$ **do**
  if $L - ws_p \geq W_p$ **then**
    $P_b = P_b \cup \{p\}$ and $\bar{e}_p = \max\{0, B_p - (L - wf_p)\}$
  else
    $P_w = P_w \cup \{p\}$, $\bar{e}_p = \max\{0, B_p - (L - wf_p)\}$ and $\bar{l}_p = W_p - (L - ws_p)$
  end if
end for
for $p \in P : ll_p \neq \bar{v}_p$ **do**
  $ab_p = wf_p + t_{ll_p,\bar{v}_p} + B_p$
  if $L - ws_p \geq W_p$ **then**
    $P_b = P_b \cup \{p\}$, $ll_p = \bar{v}_p$ and $\bar{e}_p = \max\{0, ab_p - L\}$
  else
    $P_w = P_w \cup \{p\}$, $\bar{e}_p = \max\{0, ab_p - L\}$ and $\bar{l}_p = W_p - (L - ws_p)$
  end if
end for

Since the starting points of personnel are not necessarily their depots after the first period, $t_{v_p,i}$ should be set to $t_{ll_p,i}$ $\forall p \in P, i \in V$. Moreover, the model needs to decide whether personnel wait at their last location to continue working in the current period or if they should have a break before the beginning of the current period. In the latter case, personnel would start working from their resting point in the current period rather than the last demand point they visited in the previous period. Consequently, $t_{v_p,i}$ should be equal to $t_{\bar{v}_p,i}$, instead of $t_{ll_p,i}$, to be able to set the resting points of the relevant personnel as their starting location at the beginning of the current period. To this end, we define $\bar{t}_{p,i}$ that is equal to $t_{\bar{v}_p} - t_{ll_p,i}$ and replace $y_{p,v_p,i} t_{v_p,i}$ with $(y_{p,v_p,i} t_{v_p,i} + \bar{t}_{p,i} \bar{y}_{p,i})$, $\forall p \in P, i \in V$, in all constraints . Thus, when $\bar{y}_{p,i}$ is equal to one for a demand point $i \in V_I$, the model requires personnel p to start working from its resting point. Otherwise, personnel p starts working from its last location ll_p.

Since personnel $p \in P_w$ has to take a break before $\bar{l}_p$ if it does not have a break at the beginning of the current period, Constraints (31) and (32) should be added to the model. Constraint (33) is required to link $\bar{y}_{p,i}$ and $y_{p,v_p,i}, p \in P_w, i \in V_I$ as they should be equal when personnel p has a break at the beginning of the period.

$$\sum_{i \in V} (\bar{y}_{p,i} + y_{p,i,\bar{v}_p}) \geq 1 \qquad \forall p \in P_w \tag{31}$$

$$\sum_{i \in V} (g_{p,i,\bar{v}_p} + y_{p,i,\bar{v}_p} t_{i,\bar{v}_p}) \leq \bar{l}_p + \sum_{i \in V_I} \bar{y}_{p,i} (L - \bar{l}_p) \qquad \forall p \in P_w \tag{32}$$

$$\bar{y}_{p,i} \leq y_{p,v_p,i} \qquad \forall i \in V_I, p \in P_w \tag{33}$$

Since personnel may not be able to immediately start working due to their work and resting hours' limitations, a new constraint should be added as follows:

$$\sum_{i \in V} g_{p,v_p,i} \geq \bar{e}_p \sum_{i \in V} (I_{p \in P_b} y_{p,v_p,i} + I_{p \in P_w} \bar{y}_{p,i}) \qquad \forall p \in P \tag{34}$$

For the same reasoning, Constraints (22) and (23) can be replaced with Constraints (35) and (36).

$$y_{p,i,j} = 0 \qquad \forall i, j \in V_I, p \in P : \max\{e_i, \bar{e}_p\} + \bar{h} + t_{i,j} + \bar{h} > l_j \tag{35}$$

$$y_{p,\bar{v}_p,j} = 0 \qquad \forall j \in V_I, p \in P : \bar{e}_p + B_p + t_{\bar{v}_p,j} + \bar{h} > l_j \tag{36}$$

As the earliest time the personnel can start working may change dynamically, Constraint (29) is updated accordingly by using the following two constraints :

$$g_{p,i,\bar{v}_p} \geq min(e_i + d_i h, \bar{e}_p + W_p - t_{i,\bar{v}_p}) y_{p,i,\bar{v}_p} \qquad \forall i \in V_I, p \in P_b \tag{37}$$

$$g_{p,i,\bar{v}_p} \geq min(e_i + d_i h, \bar{l}_p - t_{i,\bar{v}_p}) y_{p,i,\bar{v}_p} \qquad \forall i \in V_I, p \in P_w \tag{38}$$

The status of personnel changes over the rolling horizon. Therefore, sets of identical personnel with respect to their starting location and earliest starting time to work are dynamic. Therefore, at the end of each period, identical personnel sets for Constraint (27) need to be updated accordingly.

5. The proposed solution approach

As discussed in Section 3, the proposed DRPRS model considers the following four objectives: (i) the minimization of the unsatisfied demand, (ii) completion times of the demand met, (iii) unfair distribution of the unsatisfied demand among demand

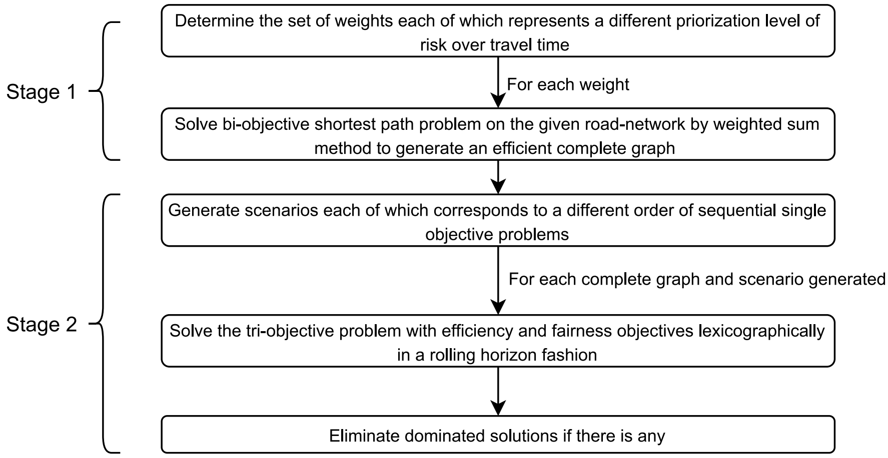

Fig. 1. Two-stage approach.

points, and (iv) minimization of the transportation risks. A two-stage approach is used to address the DRPRS problem. The first stage considers the risk and the travel time associated with the links of the underlying roadway network and solves the bi-objective shortest path problem among all pairs of nodes to generate the efficient frontier of the complete graphs over which the MILP formulation presented in Section 4 will be defined. The proposed two-stage approach is illustrated in Fig. 1.

The complete graphs are generated from the road-network graph by considering travel time and risk link attributes by solving the bi-objective shortest path problem using the following approach proposed in Zografos and Androutsopoulos (2008).

Let $G'(V',A')$ be the road-network graph where V' is the union of V_D, V_{IB} and junction points among them and A' is the associated arcs. Each arc $a'_{i,j}, i,j \in A'$, has risk measure $r'_{i,j}$ that represents the failure probability of the arc and travel time $t'_{i,j}$. $r'_{i,j}$ can be calculated as $P(DisasterIn_{i,j})P(ArcOut_{i,j}|DisasterIn_{i,j})$ where $P(DisasterIn_{i,j})$ is the probability of observing impacts of the disaster realized, or a new secondary disaster, on arc $a'_{i,j}$ and $P(ArcOut_{i,j}|DisasterIn_{i,j})$ is the probability of this arc's being unserviceable after the corresponding impact. We can turn graph $G'(V',A')$ into complete graph $G(V,A)$ by solving a bi-objective shortest path problem, for each pair of nodes in set V, minimizing both travel times and risks. Then, each arc $a_{i,j}, i,j \in V$, in set A corresponds to the shortest path with respect to the two objectives between nodes i and j and $t_{i,j}$ becomes the travel time of this shortest path. To this end, for a given weight w, each arc $a'_{i,j} \in A'$ is assigned cost $c_{i,j}$ such that:

$$c(i,j) = wr''_{i,j} + (1-w)t''_{i,j}$$

where $r''_{i,j} = \dfrac{r'_{i,j}}{\max_{a'_{i,j}\in A'} r'_{i,j}}$ and $t''_{i,j} = \dfrac{t'_{i,j}}{\max_{a'_{i,j}\in A'} t'_{i,j}}$.

By using arc costs, the bi-objective shortest path problem can be reduced to a single objective problem, which can be solved by any of conventional shortest path algorithms to generate the complete graph $G(V,A)$. The resulting non-inferior paths that define the edges of the complete graph depend on the value of weight w. Therefore, for each element of a given risk weight set W^r, we generate a complete graph over which we need to solve a tri-objective problem.

In the second stage of the proposed solution approach, the tri-objective problem is solved lexicographically for each complete graph generated in the first stage. Each lexicographic order of the objective functions produces a different efficient solution. Thus, the efficient frontier is approximated by using different lexicographic ordering combinations. Among the three objectives considered, minimization of the unsatisfied demand receives the highest importance by the decision makers considered in this study (i.e., BNPB). Hence, Objective (1) is prioritized over Objectives (2) and (3). There is no strong preference regarding the order of the optimization of the remaining two objectives. Therefore, we are proceeding with the consideration of two different lexicographic orderings. In the first lexicographic ordering, Objective (2) is given higher priority than Objective (3) while their priority ranking is the opposite in the second lexicographic ordering. Algorithm 2 describes the implementation of the lexicographic optimization.

As the cardinality of set W^r increases, Algorithm 2 approximates the non-dominated solutions more accurately, yet at the expense of excessive computational time. Therefore, set W^r is limited to $\{0, 0.25, 0.5, 0.75, 1\}$ herein which provides reasonably wide spectrum of travel time-risk prioritization without increasing the computation times significantly.

6. Model application

6.1. Implementation of the proposed solution framework to the test instance

The generic DRPRS model was used for routing and scheduling the personnel involved in two types of disaster response services, namely evacuation and medical assistance. The evacuation personnel considered in this application provide services of temporary

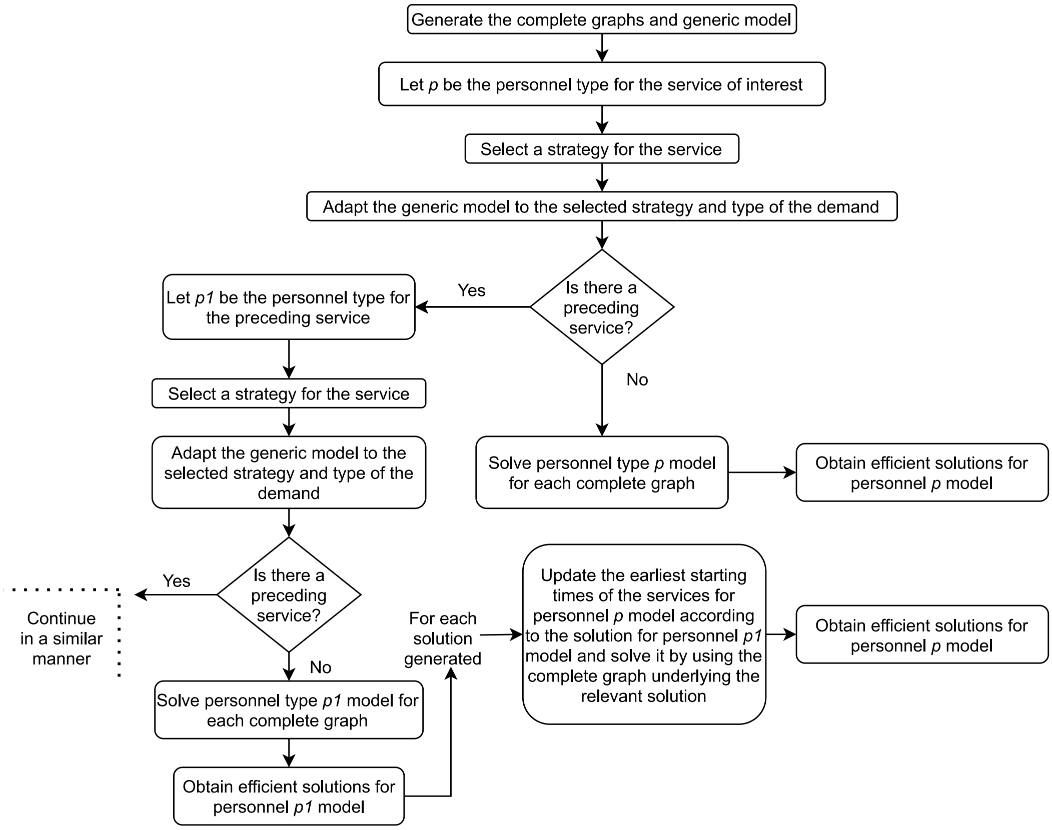

Fig. 2. Framework of the customization and implementation of the proposed model.

Algorithm 2 $Lexico(W^r)$: Lexicographic method for the tri-objective model for a given personnel type and a set of weights W^r

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MILP(f_o, ub', ub'') is the MILP model minimizing f_o, o = {1,2,3}, subject to upper bounds ub' and ub'' for the remaining objectives in order and returns the optimal value for Objective o.
W^r : Set of risk weights, E: Set of non-dominated solutions
for k = 1; k ≤ |W^r|; k++ do
    Generate graph V by using kth weight in set W^r
    f_1^* ← MILP(f_1, ∞, ∞)
    for o = 2; o ≤ 3; o++ do
        ō ∈ {2,3} and ō ≠ o
        f_o^* ← MILP(f_o, f_1^*, ∞)
        f_ō^* ← MILP(f_ō, f_1^*, f_o^*)
        Compute the transportation risk of the last generated solution (i.e., sum of the risk values on graph
        V of the arcs traversed) and add it to set E
    end for
end for
Eliminate solutions in set E that are dominated by another solution in this set
Output: Set E
```

shelter facilities (tents) to the evacuated population. The evacuation personnel are located at predetermined locations (origin nodes) and travel to predetermined locations (demand nodes) to set-up a predefined number of tents. The population that will be evacuated to the temporary shelters will also require medical services. Therefore, medical personnel should be also dispatched, i.e., routed and scheduled, to provide their services to the evacuees staying at the temporary shelters. The demand for medical services is continuous and expressed in terms of the number of hours that the medical personnel should provide their services at each shelter location.

Based on the information obtained through interviews with BNPB Emergency Management experts, evacuation services (i.e., setting-up the shelter tents) precede the dispatching of medical personnel. Therefore, the routing and scheduling of the evacuation and medical personnel should be coordinated and should take into account this precedence relationship. Fig. 2 illustrates how the generic DRPRS model is customized to reflect the operational requirements of disaster response management in Indonesia and how it is integrated within the proposed solution framework.

The proposed solution framework starts with the generation of the complete graphs representing the trade-off between risks and travel times (see Section 5) and the generic mathematical model (see Section 4.1.1) both of which are independent of the personnel type of interest. In what follows, we are presenting the customization of the proposed model with respect to the: (i) personnel types (i.e., type of demand), (ii) precedence relations between them and (iii) strategies used for fulling the demand for services allocated to them. In our test instance, the scheduling of the evacuation personnel precedes the scheduling of the medical personnel such that medical services cannot be started at a demand point if no-tent has been set-up there yet. Therefore, the earliest starting time to work of the medical personnel at the corresponding demand points, i.e., location where they should offer their services, are constrained by the evacuation personnel schedule. To reduce the computational complexity resulting from the consideration of different types of DRP, we solve the DRPRS problem sequentially taking into account the precedence relationship between the different types of services offered, i.e., we first solve the problem for the evacuation personnel and then for the medical personnel, as shown in Fig. 2. In order to model the precedence relationship between the evacuation and medical services, we consider two alternative strategies. The first strategy assumes that the evacuation personnel fulfils all the demand at each point to which it is assigned, regardless of the number of tents that need to be set at each demand point. We call this full demand fulfilment strategy. The second strategy assumes that evacuation personnel should set at least one tent at each demand point. After providing one tent at each demand point, the evacuation personnel can proceed with the set-up of the rest of the tents to fulfil the entire demand of all demand points. We call this partial fulfilment strategy.

In order to adapt the generic model to the partial demand fulfilment strategy, we are introducing the following additional variable and associated constraints.

$\bar{s}$: 1 if there is at least one tent set-up at each demand point, 0 otherwise.

$$\bar{s} \leq s_i \qquad \forall i \in V_I \tag{39}$$

$$s_i \leq 1 + (d_i - 1)\bar{s} \qquad \forall i \in V_I \tag{40}$$

$$\bar{s} \in [0, 1] \tag{41}$$

Constraint (39) forces $\bar{s}$ to be zero if there is a demand point not served and if this is the case, Constraint (40) ensures that at most one tent can be set-up in other demand points. Constraint (41) restricts $\bar{s}$ to [0,1] range.

6.2. Case study description

The proposed model is tested by using historical data for Lombok Timur (East Lombok Regency) regarding the evacuation and medical services provided in the aftermath of the earthquake struck the island of Lombok on 29 July 2018. 10 people died and 20 people got injured in Lombok Timur in this earthquake. Moreover, 195 houses were destroyed which necessitated the displacement of the households (BNPB, 2018). In our computational experiments, we are using data referring to a part of the impacted area. The road-network within the impacted area consists of 18405 nodes and 20104 links. The network considered in our computational experiments includes 14 demand points distributed across different villages in Lombok Timur Regency (i.e., 14 nodes out of 18405 are the demand points). In the test instances, we are assuming that we have 5 teams for each type of service, i.e., evacuation and medical.

Each personnel has the same working and resting hours' limitations such that they are not allowed to work longer than 12 h without a resting break. The minimum duration of each resting break according to the Indonesian Disaster Response Services Procedures is set to be at least 12 h which is deemed sufficient for sleeping and other essential needs of personnel. The number of tents required by the corresponding demand points ranges between 1 and 4. In total, 26 tents are required to be set-up to accommodate the displaced people. Lighting equipment at shelters impact the length of the provision of the evacuation and medical services. Note that if lighting equipment is not available, the provision of services is stopped after sunset and the services resume the next day at sunrise. In our computational experiments, we assume that lighting equipment is available at all locations and that the earliest start and latest finish times for evacuation demands are set to 0 and 24, respectively. We note that this assumption is without loss of generality since the impacts of the lighting equipment are modelled in a parametric way and so can be addressed by modifying the relevant parameters of the proposed model. While the latest finish times for the provision of medical services are set to 24, their earliest start times are set in accordance with the set-up time that the first tent has been set at the corresponding demand point.

The data regarding the: (i) personnel resting locations, (ii) time needed to address the demand for medical services at each demand point, and (iii) briefing time required for the hand-over of tasks, were obtained through interviews with Indonesian National Board for Disaster Management (BNPB). The briefing time is assumed to be 0.5 h for all demand points and both types of services. We assume that the time needed to provide medical services at each demand point was 8 h per tent (and consequently, the total duration of the medical services to be provided at the tents is 208 h). Table 2 summarizes the values of the parameters used in our computational experiments.

In the context of our problem, the demand at all locations is assumed to have equal priority/urgency. However, in case of demands with different priorities, the proposed solution approach will be still applicable after adjusting the proposed MILP model

Table 2
Test instance parameters.

Parameter \Personnel		Evacuation	Medical	
$\|P\|$	=	5	5	
$\|V_I\|$	=	14	14	
$\|V_B\|$	=	2	2	
$\|V_D\|$	=	2	2	
h	=	3 h	n\a	
B_p	=	12 h	12 h	$\forall p \in P$
W_p	=	12 h	12 h	$\forall i \in V_I$
d_i	∈	[1, 4]	[8 h, 32 h]	$\forall i \in V_I$
e_i	=	0	Depends on the evacuation personnel solutions	$\forall i \in V_I$
l_i	=	24	24	$\forall i \in V_I$
q_i	=	0.5 h	0.5 h	$\forall i \in V_I$

accordingly. Specifically, we can modify the MILP model in Section 4.1 by assigning objective coefficients to Objective (1) and Objective (2) (minimization of the total unmet demand and the total service completion time) representing priorities for serving the demand at different locations for the respective objectives.

For the case study under consideration, the coordinates of the demand point locations and the initial/base locations of the disaster response personnel can be found *here*. The risk indices of the nodes, the length of each network link and the associated maximum vehicle speed were extracted from the *InaRisk* data (BNPB) and Gemsa (2017), respectively, using the approach proposed in Gultom et al. (2021)[2]. For each link of the roadway network of the case study, the risk index was calculated as the average of the risk indices of the nodes defining the corresponding link (Gultom et al., 2021). The travel time of each link was calculated using its length and the associated maximum vehicle speed. The calculated risk indices and the travel times associated with links of the roadway network constitute the inputs of the bi-objective shortest path problem solved in the first stage of the proposed approach (see Section 5). The solution of the resulting bi-objective (risk, travel time) shortest path problem determines the efficient frontier of the complete graphs used to solve the second stage MILP model.

Each run of the MILP model for a single objective and a single period was limited to 1800s. All model runs were performed on a workstation with an Intel Xeon E5-2640 processor, 2.60 GHz speed, and 32 GB of RAM, through Visual Studio 2019 and ILOG CPLEX 12.10.

6.3. Analysis of the test instance solutions

The solution of the DRPRS under consideration requires the generation of the complete graphs in the geographical area of our case study (Lombok Timur). This step provides the basis for the modelling and solution of the evacuation and medical personnel routing and scheduling problems in the corresponding geographical area. The complete graphs are generated by solving the bi-objective shortest path problem for five different values of w as described in Section 5. Following which, the models for each respective personnel are solved lexicographically for each complete graph over a rolling horizon subject to different evacuation strategies.

The metrics to evaluate the resulting solutions are presented in Section 6.3.1. Determination of their dominance status is explained in Section 6.3.2. An example solution is provided for illustration purposes in Section 6.3.3. Impacts of different demand fulfilment strategies on the solution characteristics regarding the routing and scheduling of both evacuation and medical personnel are examined in Sections 6.3.4–6.3.6.

6.3.1. Solution evaluation metrics

Solutions generated by the proposed model and the associated solution approach comprise of personnel routes and schedules over a multi-period horizon. Performance of the solutions can vary with respect to efficiency, fairness and risk objectives throughout the planning horizon. Decision makers can review the solutions not only by the end of the entire planning horizon but also by the end of certain time stamps, e.g., days. For example, they can be interested in the solutions that perform better at the beginning of the planning horizon (i.e., better solutions in terms of their immediate impacts) or in the solutions with better worst-case performances over the planning horizon (e.g., solutions that can maintain fairness throughout the planning horizon). Thus, we evaluate solutions with respect to their efficiency, fairness and transportation risk performance by the end of each period/day of the planning horizon. Hereafter, 'day' and 'period' are used interchangeably.

We define $UnsatisfiedDemand_k$, $AverageCompletionTime_k$, $Fairness_k$ and $AverageRisk_k$, $k \in K$, where K is the set of periods (i.e., $|K|$ is the number of periods in the planning horizon) to be used as solution evaluation metrics. For a given solution, the values of the $UnsatisfiedDemand_k$ and $Fairness_k$ metrics are equal to the value of objective functions f_1 and f_3, respectively, of the MILP model solved for period k as the relevant objective function values do not only take into account period k but all periods until and including period k. On the other hand, the objectives of service completion time and transportation risk minimization (i.e., $ServiceCompletionTime$ and $TransportationRisk$) consider only the period of interest of the corresponding MILP

[2] The data regarding the risk index, the length and the maximum vehicle speed of the links of the case study network were provided by Y. Gultom, T. Haryanto and H. Suhartanto.

model. Therefore, we define $AverageCompletionTime_k$ and $AverageRisk_k$, $k \in K$, metrics to evaluate the solution performances with respect to service completion times and transportation risks considering all services provided up until period k.

For the discrete type of demands, $AverageCompletionTime_k$ is the average service completion time of a single unit of demand (i.e., a tent) by the end of period k and is computed as follows:

$$\frac{\sum_{\bar{k}=1}^{k} \sum_{\bar{s}=1}^{s'_{\bar{k}}} g'_{\bar{s},\bar{k}}}{\sum_{\bar{k}=1}^{k} s'_{\bar{k}}}$$

where s'_k is the number of tents set-up in period $k \in K$ and $g'_{\bar{s},k}$ is the set-up completion time of the $\bar{s}$th tent.

We use average service completion times per unit demand in the comparison of different solutions. Distribution of the amount of services among periods can vary among the solutions. Therefore, comparison of the sum, instead of the average, of the service completion times would be unfair if the amounts of services subject to the comparison (i.e., number of tents that has been set-up or number of hours medical services provided by the end of period $k \in K$) are not equal.

The proposed metric for the average service completion times is valid for discrete type of demands only. Therefore, continuous demand for medical services is discretized in the post-processing for the solution evaluations. Each 10 min demand for medical services is defined as a single unit of demand.

Following the same reasoning, transportation risks of different solutions are compared based on the risks exposed per unit of demand satisfied. Accordingly, $AverageRisk_k$ is the transportation risk per a single unit of demand by the end of period k and is computed as follows:

$$\frac{\sum_{\bar{k}=1}^{k} \sum_{i,j \in A_{\bar{k}}} r_{i,j}}{\sum_{\bar{k}=1}^{k} s'_{\bar{k}}}$$

where $r_{i,j}$ is the transportation risk of arc $a_{i,j}, i, j \in V$, and A_k is the set of arcs traversed in period $k \in K$.

6.3.2. Dominance check of the solutions

We use temporal Pareto optimality (Coughlin and Howe, 1989) to consider the solution performances throughout the planning horizon instead of considering the performances at a single time instant, i.e., end of the planning horizon. In the temporal Pareto optimality, dominance check is conducted by considering the objective function values in each period.

In our dominance check, a solution s is dominated only if (i) there exists another solution s' that does not have higher values for any of the metrics $UnsatisfiedDemand_k$, $AverageCompletionTime_k$, $Fairness_k$ and $AverageRisk_k$ than those of solution s, $\forall k \in K$, and (ii) solution s' has a lower value for at least one of the metrics by the end of at least one period.

In line with the solution framework presented in Fig. 2, we first apply the proposed two-stage approach for the evacuation personnel. For each non-dominated evacuation personnel solution, the proposed approach generates non-inferior solutions for the medical personnel routing and scheduling by considering the complete graph associated with the corresponding evacuation personnel solution. The dominance check for medical personnel solutions takes into account the associated evacuations personnel solutions. Therefore, the medical personnel solutions are compared only with the solutions that are associated with the same evacuation personnel solution for the dominance check.

6.3.3. Example solution

An example illustrating the performance of a solution for the evacuation personnel at the end of the first period is provided in Fig. 3 to demonstrate the type of output delivered by the proposed model. This solution (which is denoted as E_9 in later sections) uses the complete graph generated by setting w to 0.75 (i.e., this is a solution that assigns 0.25 importance to travel time and 0.75 importance to transportation risk) and it is subject to the partial demand fulfilment strategy. At the end of the first period of this solution, 15 tents have been set-up and there are 11 tents that could not be set-up yet ($UnsatisfiedDemand_1 = 11$). Tents that could be set-up on average are completed 8.33 h after the beginning of the planning horizon ($AverageCompletionTime_1 = 8.33$). Fairness index is 0.60 ($Fairness_1 = 0.60$) and the average transportation risk exposed per each tent set-up is 43.95 at the end of the first period ($AverageRisk_1 = 43.95$).

Black, grey and blue circles in Fig. 3 denote the depots, resting points and demand points, respectively. Red line represents the route of a given personnel type. Please note that the model generates routes and schedules for all personnel teams of each personnel type over a multi-period horizon. However, in this figure we are presenting indicatively (for illustration purposes) only one route used in the first period. A solution includes personnel routes along with the attributes of the route arcs, i.e., their travel time and risk index, and the performance indicators per demand point/location. In the boxes next to each demand point $i \in V_I$, we first show the total demand at the corresponding location and then display three measures associated with the relevant demand in Fig. 3. These measures, in order, are: (i) the demand satisfaction percent, s_i/d_i, (ii) the completion time of the service, $\bar{g}_i$, and (iii) the degree of unfair treatment towards demand point i in comparison to other demand points which is equal to $\sum_{j \in V_I} \max\{\frac{\frac{u_i}{d_i} - \frac{u_j}{d_j}}{\lceil |V_I|/2 \rceil \lfloor |V_I|/2 \rfloor}, 0\}$. This unfairness measure, for each demand point, assesses the percent of unsatisfied demand in relation to other demand points. Therefore, the sum of this unfairness measure over all demand points would be equal to the value of the fairness objective f_3.

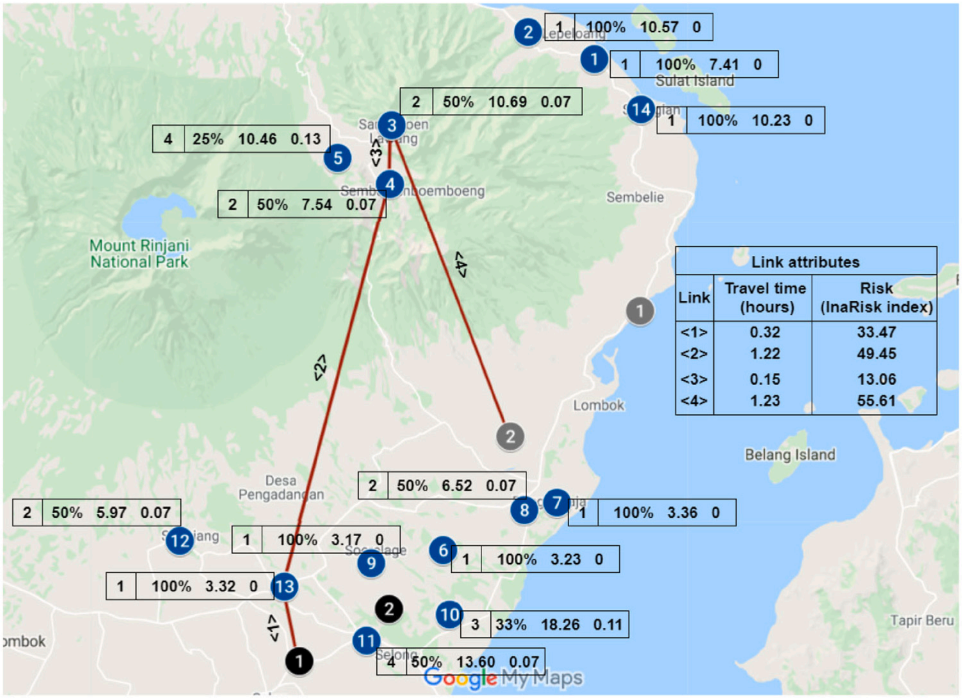

Fig. 3. Illustration of the example evacuation personnel solution E_9 by the end of the first period.

Table 3
Non-dominated solutions for the evacuation personnel under the full demand fulfilment strategy.

Solution	*Unsatisfied Demand* (number of tents)		*Average CompletionTime* (h)		*Fairness*[a]		*Average Risk* (*InaRisk* index[b])	
	Up to period		Up to period		Up to period		Up to period	
	1	2	1	2	1	2	1	2
E_1	10	0	8.06	17.18	1.00	0.00	30.96	32.36
E_2	10	0	8.09	17.11	1.00	0.00	22.58	27.19
E_3	9	0	10.69	18.17	0.98	0.00	28.94	30.01
E_4	9	0	9.31	17.21	1.00	0.00	31.17	35.45
E_5	9	0	12.53	19.97	0.65	0.00	37.42	34.52
E_6	9	0	12.08	19.66	0.81	0.00	30.32	30.65
E_7	9	0	12.55	19.93	0.65	0.00	37.42	32.99
E_8	9	0	12.54	20.24	0.62	0.00	42.07	41.29

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

6.3.4. *Full demand fulfilment strategy*

The non-dominated solutions for the routing and scheduling of the evacuation personnel under the full demand fulfilment strategy are summarized in Table 3. For each non-dominated solution, the solution evaluation metric values, up to the end of each period of the planning horizon, are provided. Since the direction of all optimization objectives is minimization, the lower values for the associated solution evaluation metrics indicate better performances in terms of the corresponding objectives.

All solutions in Table 3 meet the entire demand within two days. Since all demand should be satisfied at the end of the planning horizon, *UnsatisfiedDemand* and *Fairness* metrics should be by definition zero in the last period. All solutions, except solutions E_1 and E_2, in Table 3 have nine tents that could not be set-up at the end of the first day. This indicates that there are alternative optimal solutions for the $UnsatisfiedDemand$ metric so that each of them has distinct qualities in terms of the other metrics. For solutions $E_3 - E_8$ all of which achieve the optimal value for the $UnsatisfiedDemand$ metric in the first period, the $Fairness$ value ranges between 0.62 and 1. Better fairness values lead to less efficient and higher risk solutions. Solutions E_2 and E_8 exhibit the conflicting behaviour between the fair distribution of the unsatisfied demand and the transportation risk: Solution E_1 achieves the least transportation risk yet having the highest possible fairness value (i.e., $Fairness = 1$) whereas solution E_8 performs the best in

Table 4
Non-dominated solutions for the medical personnel under the full demand fulfilment strategy.

Medical personnel solution	Associated evacuation personnel solution	*Unsatisfied Demand* (h)				*Average CompletionTime* (h)				*Fairness*[a]				*Average Risk* (*InaRisk* index[b])			
		Up to period				Up to period				Up to period				Up to period			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
M_1	E_1	153	92	36	0	12	26	38	46	0.70	0.84	0.35	0.00	9	20	25	20
M_2	E_1	153	92	44	0	13	26	36	46	0.72	0.78	0.51	0.00	12	19	27	22
M_3	E_2	152	93	36	0	12	26	38	46	0.70	0.83	0.35	0.00	4	6	10	12
M_4	E_2	152	96	41	0	13	26	37	46	0.60	0.73	0.48	0.00	4	7	12	11
M_5	E_3	152	92	35	0	12	25	36	44	0.71	0.73	0.33	0.00	3	11	14	18
M_6	E_3	152	93	35	0	13	26	37	45	0.66	0.67	0.28	0.00	3	11	15	14
M_7	E_4	151	92	35	0	13	25	37	45	0.62	0.81	0.43	0.00	4	7	12	17
M_8	E_4	151	92	34	0	13	25	37	45	0.62	0.77	0.43	0.00	4	7	13	16
M_9	E_5	149	90	35	0	15	26	37	45	0.89	0.77	0.30	0.00	13	13	13	14
M_{10}	E_5	149	89	37	0	15	28	39	47	0.83	0.76	0.51	0.00	13	14	17	18
M_{11}	E_6	150	92	38	0	14	27	37	45	0.80	0.78	0.32	0.00	9	9	10	14
M_{12}	E_6	150	92	36	0	15	28	39	46	0.69	0.64	0.30	0.00	9	15	17	17
M_{13}	E_7	149	90	35	0	14	25	36	44	0.89	0.77	0.30	0.00	13	13	13	14
M_{14}	E_7	149	89	33	0	15	27	39	46	0.83	0.76	0.28	0.00	13	14	14	20
M_{15}	E_8	149	89	34	0	16	27	38	45	0.89	0.77	0.29	0.00	14	14	15	17
M_{16}	E_8	149	89	33	0	17	28	39	45	0.82	0.76	0.29	0.00	14	12	15	18

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

terms of fairness yet bears the highest transportation risk at the end of each period under the full demand fulfilment strategy. The value of the $Fairness$ metric at the end of the first period in solutions E_1, E_2 and E_4 is equal to 1 which is the maximum/worst possible $Fairness$ value for a single period.

For each evacuation personnel solution, the model generates routes and schedules for the medical personnel. The earliest possible starting times for the provision of the medical services are set according to the set-up time of the first tent at each location. The resulting solutions for the medical personnel are summarized in Table 4.[3] Table 4 suggests that the time needed to satisfy the demand for the provision of medical services is longer (4 days) as compared to the time needed to fulfil the demand for the provision of the evacuation services (2 days, see Table 3).

The provision of the medical services requires the medical personnel to stay longer at the same location as compared to the evacuation personnel that needs to be moving from one location to another in order to set-up the temporary shelter tents, therefore the medical personnel tends to travel less between locations as compared to the evacuation personnel. This characteristic is reflected in the total transportation risk and the total travel time of the medical personnel, which are comparable to that of the corresponding values of the evacuation personnel although the length of the planning horizon for the medical services is twice as much the planning horizon required for the provision of the evacuation services. As a result, the $UnsatisfiedDemand$ values of the medical personnel solutions in Table 4 are not widely spread. On the other hand, the performance of the solutions in terms of the demand completion times, fairness among different demand points, and transportation risk are more diverse.

$UnsatisfiedDemand$ and $AverageCompletionTime$ metrics are decreasing and increasing over time, respectively. On the other hand, the behaviour of $Fairness$ and $AverageRisk$ metrics is not monotonic. Particularly, in the second period of solutions $M_1 - M_8$, personnel continue serving demand points (having high amount of demands) that have been also served in the first period. Thus, the difference of the amount of services provided to these demand points and the rest increases and so is $Fairness$. Similarly, when the personnel first serve the locations with higher demands and then serve the locations with lower demands, they are able to visit a larger number of demand points over time. Therefore, in many of the medical personnel solutions, the transportation risk that the personnel are exposed increases throughout the planning horizon due to the larger number of demand points visited by the medical personnel.

Given the fact that routing and scheduling decisions for the evacuation personnel are affecting the medical personnel routing and scheduling, decision makers may opt to sacrifice the efficiency of the provision of the evacuation personnel service in order to improve the efficiency of the provision of the medical personnel service or vice versa. Evacuation personnel solutions performing better in terms of the $UnsatisfiedDemand$ and $AverageCompletionTime$ metrics yield the worst $Fairness$ performance indicating uneven distribution of the unsatisfied demand among demand points. Due to the delay encountered for setting-up all the tents at each visited location in the full demand fulfilment solutions, medical services may not be provided on time at the locations where none of the required tents has been set, leading to higher unsatisfied medical service demand. On the other hand, evacuation

[3] For the purpose of readability, decimals of the solution evaluation metric values, except for $Fairness$, are not presented in the tables for the medical personnel as they are negligible.

Table 5
Non-dominated solutions for the evacuation personnel under the partial demand fulfilment strategy.

Solution	*Unsatisfied Demand* (number of tents)		*Average CompletionTime* (h)		*Fairness*[a]		*Average Risk* (*InaRisk* index[b])	
	Up to period		Up to period		Up to period		Up to period	
	1	2	1	2	1	2	1	2
E_9	11	0	8.33	18.47	0.60	0.00	43.95	38.39
E_{10}	10	0	8.17	17.30	0.56	0.00	47.24	42.14
E_{11}	11	0	8.66	19.02	0.60	0.00	40.70	36.50
E_{12}	10	0	7.96	17.15	0.59	0.00	46.43	43.38

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

Table 6
Non-dominated solutions for the medical personnel under the partial demand fulfilment strategy.

Medical personnel solution	Associated evacuation personnel solution	*Unsatisfied Demand* (h)				*Average CompletionTime* (h)				*Fairness*[a]				*Average Risk* (*InaRisk* index[b])			
		Up to period				Up to period				Up to period				Up to period			
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
M_{17}	E_9	149	92	37	0	14	25	36	44	0.89	0.78	0.37	0.00	13	13	12	15
M_{18}	E_9	149	93	37	0	15	27	38	46	0.75	0.75	0.33	0.00	13	14	16	19
M_{19}	E_{10}	149	91	36	0	12	24	35	43	0.89	0.77	0.32	0.00	14	14	14	17
M_{20}	E_{10}	149	91	33	0	15	26	37	45	0.67	0.81	0.31	0.00	14	14	13	15
M_{21}	E_{11}	149	92	37	0	15	26	36	44	0.83	0.82	0.36	0.00	13	12	9	9
M_{22}	E_{11}	149	91	35	0	16	27	37	44	0.66	0.49	0.25	0.00	17	15	21	23
M_{23}	E_{12}	149	91	36	0	13	24	35	43	0.89	0.77	0.32	0.00	14	14	14	17
M_{24}	E_{12}	149	90	33	0	16	27	38	45	0.57	0.80	0.47	0.00	17	16	14	13

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

personnel solutions performing better in terms of the $Fairness$ metric mitigate the corresponding adverse affects and enable more efficient medical personnel solutions accordingly. Particularly, M_{14} and M_{16} are the best medical personnel solutions in terms of the $UnsatisfiedDemand$ metric (by the end of each period) and their associated evacuation personnel solutions E_7 and E_8, respectively, provide the best $Fairness$ metric values. This signifies that while fairness of a service is an eminent objective on its own right, it can also be very vital for the efficiency of the other services related to it in terms of their unsatisfied demand.

6.3.5. Partial demand fulfilment strategy

The non-dominated solutions for the routing and scheduling of the evacuation personnel under the full demand fulfilment strategy are summarized in Table 5. Due to the additional constraints imposed, the solution space of the partial demand fulfilment strategy and the number of non-dominated solutions are more limited as compared to the solution space of the full demand fulfilment strategy. In the partial demand fulfilment strategy, efficiency (i.e., $UnsatisfiedDemand$ and $AverageCompletionTime$) and fairness metrics are not in conflict therefore efficiency of the medical services is not compromised for the sake of fairness. Table 5 shows that solutions E_{10} and E_{12} perform better than the other two solutions (E_9 and E_{11}) in terms of all metrics except the transportation risk. This indicates that by visiting each demand point through short, yet riskier, paths and serving them partially, solutions E_{10} and E_{12} can simultaneously achieve lower unsatisfied demand and shorter demand completion times in a more equitable manner than solutions E_9 and E_{11}. Since all demand points are visited by the evacuation personnel in the first period due to the definition of the partial demand fulfilment strategy, the corresponding solutions do not face the dilemma of whether to visit only particular demand points to increase the efficiency of the services by limiting the travel times or visiting all demand points for fairer albeit less efficient solutions.

Medical personnel, on the other hand, are not subject to the partial demand fulfilment strategy constraints. Therefore, in this case, we observe a trade-off between the service completion times and the fairness of the service provision. This is illustrated in Solutions M_{21} and M_{22}, which are two medical personnel solutions associated with the same evacuation personnel solution as shown in Table 6. Solution M_{22} performs considerably better than solution M_{21} in terms of fairness on the expense of service completion times and transportation risks.

6.3.6. Comparison of the full and partial demand fulfilment strategies

Evacuation personnel solutions under the full demand fulfilment strategy provide better coverage of the demand, at the expense of fairness. Therefore, the partial demand fulfilment strategy provides fairer evacuation personnel solutions. However, since the partial fulfilment of the demand requires evacuation personnel to visit first all demand points to set-up a single tent at each demand location, this strategy results in larger total travel time for evacuation personnel. Consequently, the partial demand fulfilment strategy leads to higher transportation risk, less available time for providing services (due to higher total travel time) and thereby higher unsatisfied demand for evacuation personnel.

Given that in the case under consideration 7 out of 14 demand locations require a single tent, their demand for the provision of evacuation services is fully addressed in the partial demand fulfilment strategy by its definition. On the other hand, there are 2 demand locations that require four tents, and at most half of their demand is met by the partial demand fulfilment strategy. In contrast, only three evacuation personnel solutions of the full demand fulfilment strategy (which are also the most fair solutions in this strategy, i.e., E_5, E_6 and E_8) can serve all 7 demand locations requiring a single tent. This is due to the fact that the full demand fulfilment strategy is inclined to serve the locations with high demand first. As a consequence, half of the evacuation personnel solutions for the full demand fulfilment strategy can satisfy the entire demand of the locations with the highest demand (i.e., four tents). The contrasting behaviour of these strategies in terms of the evacuation service distribution among different demand locations results in their contrasting performance in terms of the fairness associated with the provision of evacuation services.

To analyse the impact of the fairness measure incorporated in the model under consideration, we apply the proposed lexicographic optimization approach by excluding the fairness objective (i.e., by considering the $UnsatisfiedDemand$ and $ServiceCompletionTime$ objectives only). We observe that when the fairness objective is not optimized, evacuation personnel solutions $E_1 - E_4$ still can be generated. However, when the fairness objective is ignored, solutions $E_5 - E_8$ cannot be generated. Considering the poor performances of evacuation personnel solutions $E_1 - E_4$ in terms of the fairness objective ($Fairness$ ranges between 0.98 and 1 in these solutions where 1 represents the worst performance in terms of fairness), it is necessary to introduce the fairness objective in order to be able to mitigate the unfairness resulting from the consideration of the full demand fulfilment strategy. On the other hand, evacuation personnel solutions E_9, E_{11} and E_{12} under the partial demand fulfilment strategy can be still generated in the absence of the fairness objective. The $Fairness$ value of these solutions ranges between 0.59 and 0.60. This indicates that while the partial demand fulfilment strategy can inherently improve the fairness objective even if we do not introduce it explicitly, the full demand fulfilment strategy can result in unfair solutions if the fairness objective is ignored.

Evacuation personnel solutions under the full demand fulfilment strategy, except solution E_8, have lower transportation risk than those under the partial demand fulfilment strategy, which shows the direct impact of the different strategies on the transportation risk. On the other hand, their comparison in terms of $AverageCompletionTime$ depends on the number of tents set-up. Regardless of the demand fulfilment strategy, the solutions setting-up fewer tents in the first period produce shorter average completion time per tent.

Unification of the evacuation and medical personnel solutions:

To be able to analyse the behaviours of the solutions evaluation metrics by considering the evacuation and medical services simultaneously, we unify the medical personnel and their associated evacuation personnel solution as described in the following.

Discrete demands for the evacuation service are converted to continuous demands by redefining the demand for a single tent as a demand for three hours service since it takes that long to set-up a tent. Then, the demand for the evacuation and medical services at each location are aggregated which yields a new demand definition in terms of the total/cumulative number of service hours required by the demand points (without the distinction of the service type). In the following, for each medical personnel and its associated evacuation personnel solution, solution evaluation metrics are computed by using aggregated demand values following the approach presented in Section 6.3.1. The resulting unified solutions for the routing and scheduling of the personnel providing evacuation and medical services are provided in Appendix A. We observe that there are unified solutions that are very similar in terms of all solution evaluation metrics throughout the planning horizon. Solutions with high degree of similarity offer limited insights regarding the trade-offs existing among different objectives/metrics. Therefore, in order to facilitate the decision makers to better understand the existing trade-offs, we apply a smart Pareto filter (Mattson et al., 2004) to filter out solutions with high degree of similarity and generate a Pareto frontier with a reduced number of representative solutions describing the trade-offs among the different objectives/metrics. This filtering ensures that for each resulting efficient solution, there is at least one solution evaluation metric that performs better than all other efficient solutions by at least Δ percent (which is a pre-determined parameter). In our implementation, we set Δ equal to five. Details of the implementation of the smart Pareto filter are provided in Appendix B.

To show the conflicting behaviours of the evaluation metrics of the relevant solutions, value path graphs are illustrated in Figs. 4 and 5 for the unified solutions emerging from the consideration of full and partial demand fulfilment strategies, respectively. To ensure comparability of the solution evaluation metrics, we use % deviations from the best/minimum value of the corresponding metrics, instead of their absolute values.

Solutions are represented by different coloured paths connecting 16 values along the vertical lines each of which corresponds to a particular solution evaluation metric and a particular period. The values on the vertical axes represent how much each solution differs from the best value for the corresponding solution evaluation metric value by the end of the corresponding period. Since each path corresponds to a non-dominated solution, there exists no pair of paths that do not intersect (since the one lying below would dominate the other otherwise). Slopes of the lines composing the paths indicate how strong the trade-off between the consecutive solution evaluation metrics is. Steep slopes of the lines connecting $Fairness$ with $AverageCompletionTime$ and $AverageRisk$ indicate the strong trade-offs between these metrics.

In comparing the full and partial demand fulfilment strategies with respect to fairness, unified solutions are evaluated in terms of deviations from the absolute $Fairness$ metric value by the end of each period. As illustrated in Fig. 4, for all full demand fulfilment strategy solutions, the value of $Fairness$ metric deviates by almost 20% from the absolute value by the end of the first three periods.

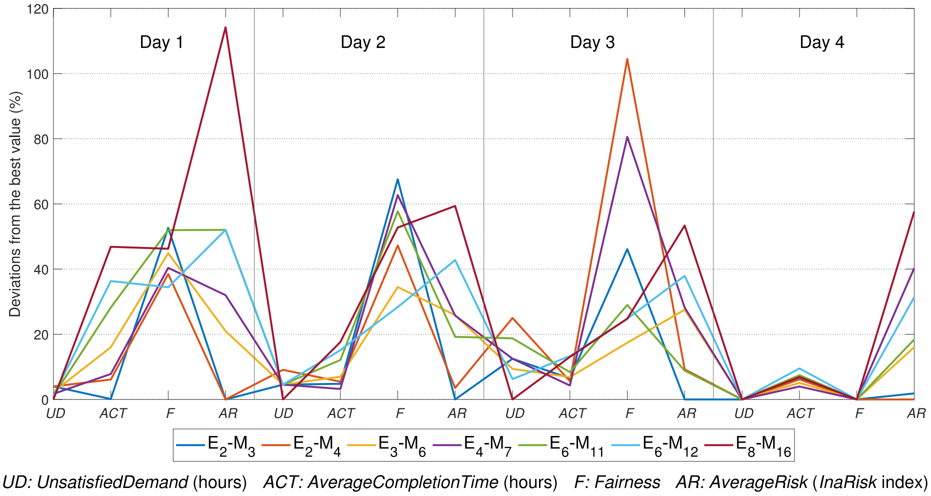

Fig. 4. Value paths of smart Pareto unified solutions under the full demand fulfilment strategy.

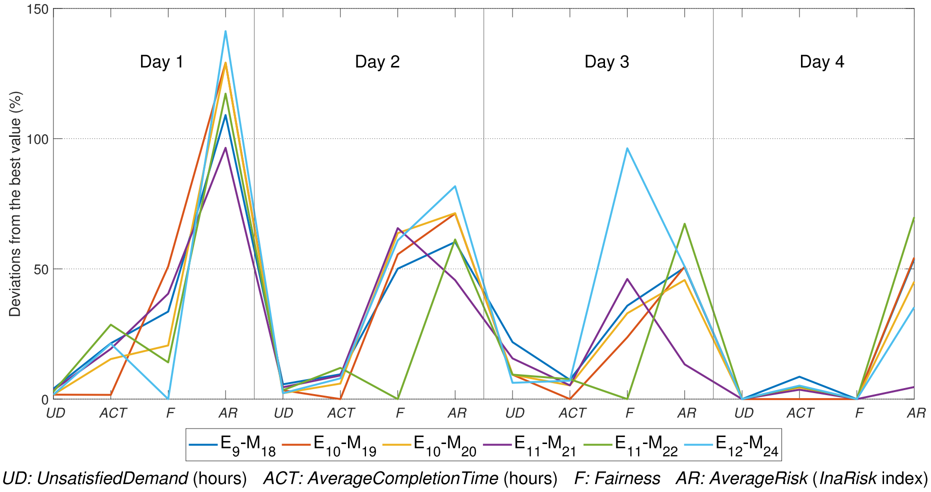

Fig. 5. Value paths of smart Pareto unified solutions under the partial demand fulfilment strategy.

On the other hand, there exists one partial demand fulfilment strategy solution that can achieve the absolute minimum $Fairness$ metric value by the end of each period as shown in Fig. 5. This indicates that partial demand fulfilment strategy produces fairer solutions not only for the evacuation service per se but for the unified services as well.

In terms of the $AverageRisk$ metric, we observe an opposite situation such that the $AverageRisk$ deviation is greater than 50% for almost all of the partial demand fulfilment strategy solutions by the end of any period except the last period. On the other hand, variance of the $AverageRisk$ deviation among the full demand fulfilment strategy solutions is considerable. Therefore, as the relevant strategy can produce the least risky solutions (e.g., unified solution $E_2 - M_4$ by the end of the first period), it can also lead to the solutions with high transportation risk (e.g., unified solution $E_8 - M_{16}$ by the end of the first period).

For both of the demand fulfilment strategies, the differences between the $UnsatisfiedDemand$ metric deviations of the unified solutions are relatively limited. Nonetheless, unified solution $E_8 - M_{16}$ performs best in terms of the $UnsatisfiedDemand$ metric by the end of any period. To recall, E_8 is the fairest evacuation personnel solution among the ones producing the least $UnsatisfiedDemand$ value (by the end of the first period).

Similar to the $UnsatisfiedDemand$ metric, deviations of the $AverageCompletionTime$ metric do not vary as much as those for the $Fairness$ and $AverageRisk$ metrics. To filter out more solutions in order to identify stronger trade-offs, we have also used Δ value equal to 15 in the smart Pareto filtering. This leads to four unified non-dominated solutions: $E_2 - M_3$, $E_3 - M_6$, $E_{11} - M_{22}$ and $E_{12} - M_{24}$. The first two are related to the full demand fulfilment strategy and they are the least risky ones among all the unified solutions. On the other hand, the last two are related to the partial demand fulfilment strategy and they perform best in terms of the fairness among all the unified solutions. Therefore, given that both strategies produce comparable solutions in terms of the $UnSatisfiedDemand$ and $AverageCompletionTime$ metrics, decision maker can choose full or partial demand fulfilment strategy based on the priorities of the fairness and transportation risk objectives.

7. Conclusion

In this paper, we study a disaster response personnel routing and scheduling problem which requires the consideration of different emergency services subject to precedence relations in a multi-objective setting including the efficiency, fairness and transportation risk of the services. To this end, a generic mixed integer linear programming model is proposed, which can be used for different types of disaster response services and includes properties that are often neglected in routing and scheduling personnel for providing different types of disaster relief services, such as personnel synchronization, working/resting hours' limitations and specific locations designated for resting. We have also introduced a solution framework integrating the proposed model within the rolling horizon approach and we use a lexicographic optimization approach to generate non-inferior solutions. The proposed model and solution framework are tested considering the evacuation and medical services provided in the aftermath of 2018 Lombok earthquake.

Two different strategies for the evacuation service, full and partial demand fulfilment are considered in the test experiments. Computational results show that the efficiency and fairness objectives of the evacuation personnel solutions show conflicting behaviours in the former strategy whereas they are agreeable in the latter one due to the additional constraints to pursue fairness at the expense of less efficient solutions. With respect to the aggregate efficiency of the evacuation and medical services, the best results are attained by the most fair evacuation personnel solutions under the full demand fulfilment strategy, which suggests that fairness of a service can be critical for the efficiency of its succeeding service. While both strategies produce comparably efficient solutions, they have distinctive characteristics in terms of the fairness and transportation risk objectives. While full demand fulfilment strategy leads to less risky solutions, partial demand fulfilment strategy achieves fairer solutions. Therefore, our computational experiments show the benefits of analysing the impacts of different strategies/policies for different types of disaster response services and the trade-offs between different objectives in the preparedness phase. Particularly, these analysis can help decision makers to understand the consequences of different policies on the provision of disaster response services before they decide which policy should be implemented. The outcome of the analysis of alternative disaster response policies provides decision support capabilities that enhances disaster preparedness for effective response which is deemed a key priority for disaster risk reduction by the UN Sendai framework for disaster risk reduction 2015–2030 (Pearson and Pelling, 2015).

It is shown that there can be alternative optimal solutions minimizing the unsatisfied demands; each of which provides a different spectrum for the fairness and risk objectives. This indicates that multi-objective approaches can help to improve the corresponding objectives, and not necessarily with the loss of efficiency, by considering different non-inferior personnel routes.

We have reported results from the implementation of the proposed model involving 5 personnel teams for each service type (i.e., evacuation and medical) and 14 demand points representing the disaster affected areas. Work under way includes: (i) the development of efficient heuristics for solving larger instances of the DRPRS problem, and (ii) the development a single stage multi-objective optimization approach that enables to handle all the complete graphs generated simultaneously (and thereby consider a multi-graph transportation network). Another possible extension of the proposed model is the consideration of the dynamic aspects of the demand and supply characteristics of disaster response services, and the performance of sensitivity analysis with relation to key problem parameters such as the availability of lighting equipment and available time windows for the services accordingly.

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Appendix A. Unified evacuation and medical personnel solutions

See Table A.1.

Table A.1
Unified solutions comprising of the medical personnel and their associated evacuation solutions.

Unified solution	*Unsatisfied Demand* (h)				*Average CompletionTime* (h)				*Fairness*[a]				*Average Risk* (*InaRisk* index[b])			
	Up to period				Up to period				Up to period				Up to period			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
$E_1 - M_1$	182	92	36	0	10	22	31	38	0.78	0.61	0.26	0.00	5	6	6	6
$E_1 - M_2$	183	92	43	0	10	22	30	37	0.80	0.57	0.37	0.00	6	6	6	6
$E_2 - M_3$	182	92	36	0	10	22	31	38	0.78	0.61	0.26	0.00	4	5	5	5
$E_2 - M_4$	182	96	40	0	10	22	31	38	0.71	0.53	0.36	0.00	4	5	6	5
$E_3 - M_5$	178	92	36	0	11	22	30	37	0.79	0.53	0.25	0.00	5	6	6	7
$E_3 - M_6$	179	92	35	0	11	22	31	37	0.74	0.49	0.21	0.00	5	6	6	6
$E_4 - M_7$	178	92	36	0	10	21	30	37	0.72	0.59	0.32	0.00	6	6	7	7
$E_4 - M_8$	178	92	36	0	10	22	30	37	0.72	0.57	0.33	0.00	6	6	7	7
$E_5 - M_9$	175	89	34	0	13	23	31	37	0.81	0.56	0.21	0.00	8	7	6	6
$E_5 - M_{10}$	175	89	36	0	13	24	33	39	0.79	0.56	0.37	0.00	8	7	7	7
$E_6 - M_{11}$	177	92	38	0	12	23	31	38	0.78	0.57	0.23	0.00	6	6	6	6
$E_6 - M_{12}$	177	92	34	0	13	24	33	39	0.69	0.47	0.22	0.00	6	7	7	7
$E_7 - M_{13}$	175	89	34	0	13	23	31	37	0.81	0.56	0.21	0.00	8	7	7	7
$E_7 - M_{14}$	175	89	35	0	13	24	32	39	0.79	0.56	0.21	0.00	8	7	7	8
$E_8 - M_{15}$	175	89	34	0	14	24	32	38	0.80	0.56	0.21	0.00	9	8	8	8
$E_8 - M_{16}$	175	88	32	0	14	24	33	38	0.75	0.55	0.22	0.00	9	8	8	8
$E_9 - M_{17}$	181	92	37	0	11	22	30	37	0.79	0.57	0.27	0.00	9	8	7	7
$E_9 - M_{18}$	182	93	39	0	12	23	31	38	0.69	0.54	0.24	0.00	9	8	8	8
$E_{10} - M_{19}$	178	91	35	0	10	21	29	35	0.78	0.56	0.22	0.00	10	8	8	8
$E_{10} - M_{20}$	178	90	35	0	11	22	30	37	0.62	0.59	0.23	0.00	10	8	7	8
$E_{11} - M_{21}$	181	92	37	0	11	23	30	37	0.72	0.60	0.26	0.00	8	7	6	5
$E_{11} - M_{22}$	180	91	35	0	12	23	31	37	0.59	0.36	0.18	0.00	9	8	9	9
$E_{12} - M_{23}$	178	91	35	0	10	21	29	35	0.77	0.56	0.22	0.00	9	9	8	8
$E_{12} - M_{24}$	178	90	34	0	12	22	31	37	0.51	0.58	0.35	0.00	10	9	8	7

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

Algorithm 3 Smart Pareto filter of the unified solutions for the DRPRS problem

Sort unified solutions with respect to the $AverageCompletionTime$ values (by starting from the latest period and considering previous periods in case of ties)
Let L be the list of the sorted unified solutions, $i = 1$
while $i < |L|$ **do**
  Set of dominated solutions $D = \emptyset$
  for $j = i + 1 : |L|$ **do**
    if Solution L_i is not inferior to solution L_j:
      i) for none of the solution evaluation metrics and
      ii) up to any period by Δ percent **then**
      Solution L_i dominates solution L_j: Add solution L_j to set D
    end if
  end for
  Remove solutions in set D from list L
  $i{+}{+}$
end while

Appendix B. Solution filtering

In the smart Pareto filter, solutions are initially sorted in ascending order (for minimization problems) of a given objective function. Herein, we sort the unified solutions in ascending order in terms of the $AverageCompletionTime$ metric such that solutions with shorter $AverageCompletionTime$ values by the end of the last period precedes others. In case of ties, $AverageCompletionTime$ values by the end of the previous period are compared. Subsequently, the smart Pareto filter considers the sorted solutions and compares the solution at the top of the list with all succeeding solutions and checks if the solution at the top dominates any of the succeeding solutions. Dominated solutions are removed from the list. Then, the next solution in the list is chosen and the process is repeated until the last solution in the list has been evaluated (see Algorithm 3).

We have implemented Algorithm 3 using Δ value equal to five. After applying the smart Pareto filter, 7 out of 16 and 6 out of 8 unified solutions of the full and partial demand fulfilment strategy respectively, are included in the final set of non-dominated solutions.

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