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

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1 Introduction

In the aftermath of disasters, disaster-affected areas demand different types of emergency response services, e.g., medical, evacuation support for temporary shelter provision, which are typically provided by Disaster Response Personnel (DRP). The imbalance between the considerable and urgent workload associated with the provision of these services and the DRP available to provide the required services usually results to excessive working hours for the available personnel [1]. This may compromise the safety and efficiency of the services offered by the DRP. Therefore, the resting requirements of the DRP should be explicitly considered in DRP scheduling. Furthermore, when DRP travel to provide their services, they are encountering risks associated with the network they travel. Therefore, risk should be considered in making DRP routing and scheduling decisions. Moreover, routing and scheduling decisions for DRP should consider fairness criteria. However, these requirements are often neglected [2]. This can lead to i) unfair treatment to different disaster-affected areas and ii) choosing highly risky transportation routes for the sake of more efficient solutions [3].

To the best of our knowledge, [3] is the only study addressing the identified gaps by proposing a multi-objective Disaster Response Personnel Routing and Scheduling (DR-PRS) model. A lexicographic optimization approach was used in [3] for solving the proposed model. However, the proposed approach cannot cope with large-scale instances of the proposed model. Therefore, there is a need to develop efficient heuristics to solve in reasonable computational time large-scale problem instances. In this study, we are presenting a heuristic algorithm that approximates the set of Pareto optimal solutions over a rolling horizon for different types of disaster relief services with precedence relations.

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2 Modelling and Solution Framework

The multi-objective DRPRS [3] considers the following four objectives: i) total unsatisfied demand, ii) total service completion time of the demand satisfied, iii) fairness and iv) total transportation risk. The inputs, objectives, constraints and outputs of the DRPRS model are shown in Figure 1.

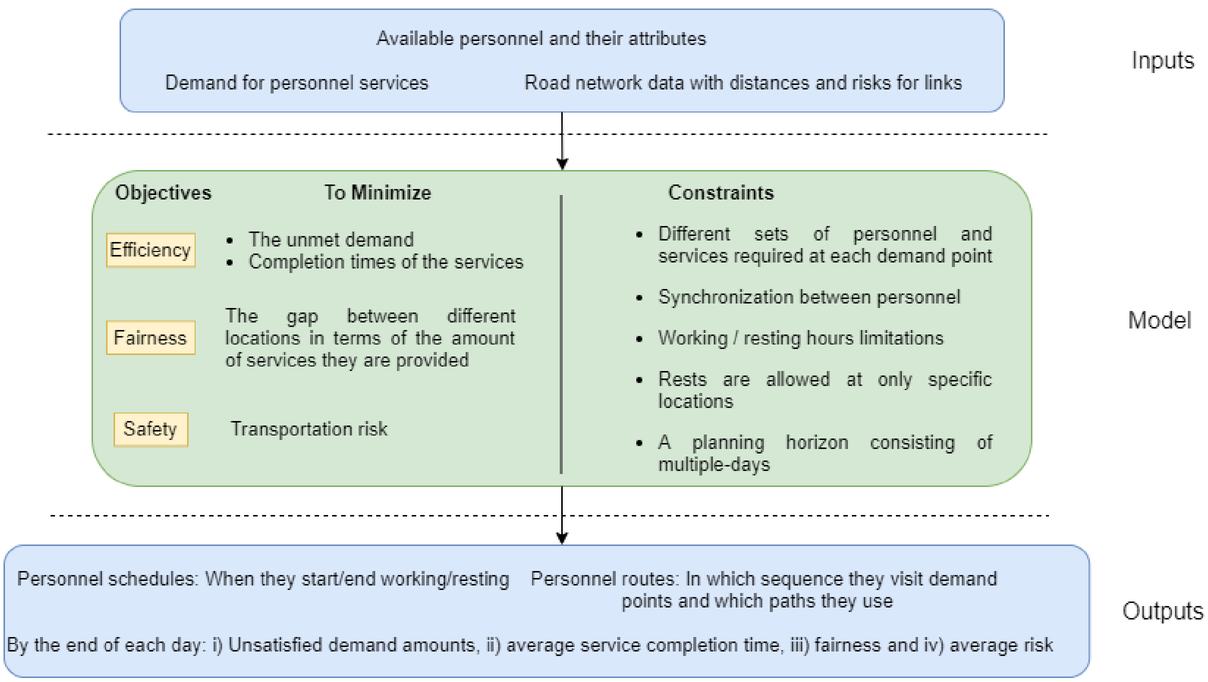

Figure 1: Inputs, objectives, constraints and outputs of the DRPRS model

We are considering a rolling horizon over which the DRPRS problem is solved iteratively day by day until the entire demand is satisfied. Among the four objectives listed in Figure 1, the unmet demand minimization has the highest priority. Therefore, for each day of the rolling horizon, we first find the minimum value of the unmet demand and then convert it to a constraint. In the following, we solve the resulting tri-objective single period (3O1P) model. Consequently, the rolling horizon approach (RHA) comprises of solving tri-objective single period (3O1P) models sequentially.

The 3O1P model is solved by the quadrant shrinking method (QSM) [4]. The QSM requires to solve single-objective sub-problems of the tri-objective problem sequentially. If each sub-problem is solved to optimality, it guarantees to find all efficient solutions. Considering the NP-Hardness of the single-objective version of the 3O1P model, we solve the single-objective sub-problems by applying tabu search algorithm (which includes a dynamic programming and a mixed-integer linear programming model). Thus, the proposed approach (QSH RHA) is applying the QSM heuristically within the RHA. As sub-problems of the QSM are solved heuristically in the QSH RHA, it is possible that we may not find the optimal solution for particular sub-problems. To address this issue, we adapt the QSM accordingly. Specifically, whenever a new candidate solution is generated, it is compared with the existing set of efficient solutions. If the new solution is not dominated by any of the current efficient solutions, the set of efficient solutions is updated and the subsequent iterations for solving the sub-problems consider the updated set of efficient solutions.

3 Preliminary Results and Conclusions

The proposed approach is tested for routing and scheduling evacuation and medical personnel using historical data from the 2018 Lombok Earthquake. The instance under consideration involves 26 demand zones, 10 personnel for each service category, i.e., evacuation and medical, 2 depots and 2 resting points. The network data of the test instance is generated using the network generation approach in [5].

Table 1: Deviations of the efficient unified solutions from the best values for each solution evaluation metric by the end of each day over the planning horizon

Unified solution	*Unsatisfied Demand*				*Average Completion Time*				*Fairness*				*Average Transportation Risk*			
	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
U_1	0.01	0.00	0.00	0.00	0.13	0.07	0.04	0.01	0.22	0.14	0.00	0.00	0.00	0.00	0.00	0.00
U_8	0.02	0.01	0.19	0.00	0.08	0.03	0.03	0.01	0.04	0.08	0.09	0.00	0.49	0.42	0.09	0.05
U_9	0.03	0.01	0.39	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.30	0.00	0.62	0.43	0.14	0.18

Demand/affected zones require both evacuation and medical services and completion times of the evacuation services affect the starting times of the medical services at the corresponding locations. QSH RHA considers one service at a time. Considering the precedence relationship between the evacuation and medical services, we first apply the QSH RHA for the deployment of the evacuation personnel, i.e., evacuation operations for establishing temporary shelters. Subsequently, we apply QSH RHA for the medical service personnel for each efficient evacuation solution. In our computational experiments, we are considering two strategies, i.e., partial and full demand fulfilment, for providing the required services. The partial demand fulfilment strategy requires that one temporarily shelter (tent) is set-up at each demand zone first before proceeding with the remaining demands for tents. The full demand fulfilment strategy does not impose this constraint and the evacuation teams can fulfil the entire demand at one zone before moving to their next assignment.

In the solution dominance check, we use four solution evaluation metrics: i) unsatisfied demand, ii) average service completion time (per unit demand), iii) fairness and iv) average transportation risk (per unit demand). To take into account the temporal performance of the solutions, the relevant metrics are evaluated not only for the end of the planning horizon but for the end of each period/day of the horizon. In the post-processing, we unify the medical solutions and their associated evacuation solutions by aggregating the corresponding demands at each demand point and computing the solution evaluation metric values by considering the aggregate demand values. The QSH RHA generates 10 efficient unified solutions. Out of 10, 7 solutions relate to the full demand fulfilment strategy, while remaining 3 refer to the partial demand fulfilment strategy. All generated solutions satisfy the entire demand, for both the evacuation and medical services, in four days.

Table 1 summarizes the results for three out of the ten solutions, U_1, U_8, U_9. Solution U_1 is related to the full demand fulfilment strategy, while U_8 and U_9 relate to the partial demand fulfilment strategy. Solution U_1 performs satisfactorily for the unsatisfied demand and transportation risk metrics at the expense of high unfairness. On the other hand, solution U_9 can provide fairer solutions with small service completion times yet with higher risks. The other partial demand fulfilment solution U_8 can achieve smaller risk whereas it is inferior to solution U_9 in all other metrics by the end of all days, except for fairness at the end of the third day. This indicates the significance of temporal performance comparisons as solutions can have fluctuating performances over the horizon.

Acknowledgements

The work to be presented has been funded by the UK's Engineering and Physical Sciences Research Council (EPSRC) through the project EP/T003979/1 "Resilient emergency preparedness for natural disaster response through operational research (RESPOND-OR)". Prof.Heru Suhartanto, Dr.Toto Haryanto and Mr.Yohanes Gultom provided the data used in the computational tests of the Indonesian case studies. The network data for the Indonesian case studies were generated by using the network extraction data procedure presented in [5].

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