RESPOND-OR

Modeling and Solving the assisted evacuation problem for natural disasters: A multi-objective programming approach

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Executive Summary

Large scale natural disasters, such as earthquakes, volcano eruptions, floods, inflict massive destruction, cause significant disruption of socio-economic activities of the affected communities, have devastating environmental impacts, and result to loss of human lives. Besides their heavy toll on human lives, natural disasters force people to leave the disaster hit areas causing population displacement. Evacuation planning is a key disaster response management activity aiming to optimize the movement of displaced population due to natural disasters. Evacuation operations involve relocation of people from the disaster affected areas to shelters. Evacuation operations include two different types of decisions, namely: self-evacuation, and assisted evacuation. In the case of self-evacuation, evacuees are using their own transportation means to leave the affected area and arrive to a safe place, i.e., shelters; while in the case of assisted evacuation competent authorities provide the transportation means and all required logistical support for moving the affected population to designated safe places, i.e., shelters. To deal effectively with the assisted evacuation problem, there is a need to develop decision support capabilities that will help decision-makers to optimize the allocation and use of scarce resources, while at the same time ensure the safe and efficient evacuation of the affected population.

This report summarizes the results of the RESPOND-OR project regarding the modelling and solution of the assisted evacuation problem. The assisted evacuation problem under consideration is defined as follows: in a disaster-affected area people need to be evacuated to candidate safe locations (shelters) of given location and capacity. The origin of the evacuation (assembly points) and the potential destination (shelters) are given. In addition, information regarding the risk and distance (travel-time) of the links of the underlying roadway network are also inputs to the optimization problem. A heterogeneous fleet of vehicles is used for the assisted evacuation operations. The evacuation vehicles start from their depot, then are traveling to the assembly point of an affected zone, to collect people and transport them directly to the shelters. The following questions usually arise in making assisted evacuation decisions:

- Which shelters should be used?
- How many vehicles are required for evacuation?
- How many trips between evacuation zones and shelters each vehicle should perform?
- Which routes should be used for the evacuation?
- What is the total risk of using proposed routes?
- What is the total time that the evacuation vehicles will be used to perform the evacuation operation?
- What is the maximum evacuation time?
- What are the trade-offs between evacuation efficiency, fairness, and risk objectives?

Depending on the assumptions made about the nature of the assisted evacuation problem parameters, two types of problems arise: i) the Deterministic Assisted Evacuation Problem (DAEP), and ii) the Assisted Evacuation Problem Under Uncertainty (AEPUU). Furthermore, based on the decision-making context two variants of the AEP are defined, namely: i) the Fleet Size Constrained Assisted Evacuation Problem (FSC-AEP), and ii) the Time Constrained Assisted Evacuation Problem (TC-AEP). The FSC-AEP arises when the size and composition of the evacuation fleet are given, and the maximum time needed to complete the evacuation operations should be determined. The TC-AEP problem arises when the maximum acceptable evacuation time is given, and the optimal fleet size and composition needs to be defined in order to complete the evacuation within the pre-established maximum evacuation time.

In the RESPOND-OR project we have introduced a novel multi-objective shelter-allocation and assisted evacuation routing model that considers efficiency, fairness and risk objectives and heterogeneous fleet of evacuation vehicles for both the DAEP and AEPUU. In order to address the AEPUU we have introduced a robust optimization approach.

The kernel of the proposed multi-objective assisted evacuation models and the associated solution algorithms are generic and can be used in any assisted evacuation planning context. The country specific variants of the proposed generic model are developed by incorporating in the generic model, specific operational requirements emerging in the context of Indonesian and Sudanese assisted evacuation operations. For the case of Indonesia, we are considering the coordination of the joint evacuation of people and livestock; while for the case of Sudan we have introduced the constraint that does not allow evacuees from rival tribes to be allocated to the same shelter. Furthermore, in selecting shelter locations in Sudan we have introduced an objective that seeks to minimize the number of gates associated with the shelters.

We have introduced a two-stage multi-objective programming framework to solve the assisted evacuation problem. At the first stage the proposed framework uses the risk and the travel time associated with the links of the underlying roadway network to define the efficient frontier of the complete graphs over which the evacuation routes will be optimized. At the second stage, the complete graphs are used to lexicographically optimize the efficiency, fairness, and safety objectives associated with the AEP. We have used different priority orderings for the optimization of the four objectives considered in our multi-objective formulation to generate the associated efficient frontier.

We developed a random sequence multi-objective hype heuristic which uses 14 low-level heuristics to solve larger instances of both variants, FSC-AEP, and TC-AEP of the DAEP. The proposed hyper-heuristic solves the multi-objective DAEP lexicographically to approximate the associated efficient frontier. The Multi-objective deterministic models developed in the context of the Indonesian assisted evacuation operations constitute the Assisted Evacuation Module of the RESPOND-OR Decision Support System. We have used a robust optimization framework for solving the AEPUU. The proposed framework uses the concept of recoverable robustness in conjunction to the random sequence multi-objective hyper-heuristic developed for the DAEP using a different set of lower-level heuristics.

The mathematical models and algorithms developed to address the AEP provide useful decision support to decision makers dealing with assisted evacuation operations in the aftermath of natural disasters. The proposed mathematical models incorporate the requirements of the decision-making environment emerging in real world assisted evacuation situations. The kernel of the proposed models reflects more generic assisted evacuation requirements. However, the customized versions of the models reflect the requirements emerging in assisted evacuation decisions in Indonesia and Sudan. The proposed models and the associated algorithms allow decision makers to examine the trade-offs existing between efficiency, fairness, and safety objectives. However, the final choice of the assisted evacuation solution that should be implemented lies with the decision makers themselves.

The remainder of this report is organised into 7 sections. Section 1 introduces the importance and need to provide decision support tools for addressing assisted evacuation decisions. Section 2 provides an overview of the literature associated with the deterministic assisted evacuation problem. Section 3 describes the assisted evacuation problem, while section 4 presents the Deterministic Multi-Objective Assisted Evacuation Models and the exact solution approach used along with the results emerging from the application of the models. Section 5 presents a hyper heuristic framework for solving the proposed models and the results emerging from its application. Section 6 presents the robust optimization variant of the problem and discusses the results of its application, while Concluding Remarks are provided in the end.

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1 Introduction

Large scale natural disasters, such as earthquakes, volcano eruptions, floods, inflict massive destruction, cause significant disruption of socio-economic activities of the affected communities, have devastating environmental impacts, and result to loss of human lives. According to (Ritchie, 2014), the annual average loss of human lives due to natural disasters for the period between 2009 and 2019 was 60 000 which accounts for 0.1% of the total number of deaths. Besides their heavy toll on human lives, natural disasters force people to leave the disaster hit areas causing massive population displacement. The Internal Displacement Monitoring Centre (IDMC) has reported that 24.8 million people around the world have been displaced in the results of disasters in 2019 only, which is almost triple of the corresponding value for conflicts and violence (8.5 million, Displacement Data[1]).

Evacuation planning is the key decision regarding the management of the movement of population displaced due to natural disasters. Evacuation operations involve relocation of people from the area affected by a disaster to shelters.

From a decision-making point of view evacuation operations include two different types of decisions, namely: self-evacuation, and assisted evacuation. In the case of self-evacuation, people are using their own transportation means to leave the affected area and arrive to a safe place, while in the case of assisted evacuation competent authorities provide the transportation means and all required logistical support for moving the affected population to designated safe places, i.e., shelters. Although, the self-evacuation problem has attracted considerable research attention, the assisted evacuation remains underrepresented in the literature. This issue has been highlighted by (Altay & Green, 2006) almost 14 years ago and remains largely untapped until now (Amideo, et al., 2019). Furthermore, most of the existing models are generic and are not based on decision-making requirements emerging in real-world settings (Amideo, et al., 2019). The research reported in this document reflects real-world operational requirements and is motivated by the assisted evacuation problems emerging in evacuation operations in Indonesia and Sudan. Based on Internal Displacement Data for 2019[2], Indonesia is ranked eighth in the world in terms of the average expected number of displacements per year for a sudden-onset hazards. The importance of the need to optimize evacuation decisions in Indonesia is underlined by the fact that in 2019, 378 000 people were displaced in Indonesia due to natural hazards. In Sudan the flooding of Nile requires the evacuation of the population of impacted areas to shelters. In 2019, 272 000 people were displaced due to the floods.

To deal effectively with the assisted evacuation problem, there is a need to develop decision support capabilities that will help decision-makers to optimize the allocation and use of scarce resources while at the same time ensure the safe and efficient evacuation of the affected communities.

The assisted evacuation problem can be modelled as a variant of the vehicle routing problem (VRP) where a set of vehicles, depots, pick-up locations (assembly points), and shelters are given; and the objective is to transport evacuees from pick-up locations to shelters minimising one or more

[1] Source: https://www.internal-displacement.org/database/displacement-data

[2] See 1

evacuation-performance criteria. It should be noted that the decision-making environment of the assisted-evacuation operations has some important characteristics that need to be taken into consideration in making assisted evacuation decisions. Specifically, due to the magnitude of damage inflicted by large-scale natural disasters on the transportation infrastructure, the risk associated with the use of the underlying transportation network becomes a decisive factor making the consideration of risk an important attribute of the problem. In addition, the fairness in the provision of the evacuation services to all impacted communities is an important modelling consideration with significant societal implications.

The objective of this report is to address the assisted evacuation problem by incorporating real world problem characteristics emerging in the context of assisted evacuation operations in Indonesia and Sudan. To this end we propose a multi-objective shelter-allocation and assisted evacuation routing model that considers efficiency, fairness and risk objectives and heterogeneous fleet of evacuation vehicles. The kernel of the proposed multi-objective assisted evacuation planning model and the associated solution algorithms are generic and can be used in any assisted evacuation planning context. The country specific variants of the proposed generic model are developed by incorporating in the generic model specific operational requirements emerging in the context of Indonesian and Sudanese assisted evacuation operations. In order to address the uncertainty associated with assisted evacuation operations for large scale natural disasters we introduce a robust optimization variant of the proposed multi-objective assisted evacuation problem.

The remainder of this report is organised into 6 sections. Section 2 provides an overview of the literature associated with the assisted evacuation problem. Section 3 describes the assisted evacuation problem, while section 4 presents the Deterministic Multi-Objective Assisted Evacuation Models and the exact solution approach used along with the results emerging from the application of the models to a case study. Section 5 presents a hyper heuristic framework for solving the proposed models and the results emerging from its application to a case study. Section 6 presents the robust optimization variant of the problem and discusses the results of its application, while section 9 provides concluding remarks.

2 Literature review for the deterministic assisted evacuation problem

Evacuation decisions relate to two major types of operations, namely self-evacuation, and assisted evacuation. In self-evacuation decisions authorities in charge of the evacuation provide instructions to population of an area that will be evacuated, and the evacuees use their own resources, i.e., vehicles, to evacuate the affected area. In assisted evacuation decisions authorities in charge of evacuation provide the transportation means and coordinate all activities in order to evacuate population to designated safe areas, i.e., shelters. The focus of this research is on assisted evacuation decisions and therefore our literature review is focused on assisted evacuation research. Depending on the assumptions made about the nature of the problem parameters, i.e., deterministic, stochastic, the literature is divided into two major research streams, namely deterministic and stochastic assisted evacuation models. In what follows we are providing an overview of the literature related to the deterministic assisted evacuation problem. The literature regarding the stochastic version of the problem is discussed in section 6 of this report, where we are dealing with the formulation and solution of the assisted evacuation problem (AEP) under uncertainty.

2.1 Deterministic assisted evacuation models

Introduced a MILP model seeking to maximise the number of people that can be evacuated from an affected area within a given timeframe using a fleet of buses and a predetermined number of trips. The assisted evacuation problem for transit dependent citizens in Fort Worth Texas was modelled in (Sayyady & Eksioglu, 2010). Their model considers non-capacitated shelters, homogeneous fleet, and pre-defined pick-up locations for the evacuees. The model uses a time-space network formulation and aims to minimise total evacuation time. A Tabu search algorithm was used for solving small to moderate instances of the proposed model. The assisted evacuation planning problem as a special case of vehicle routing problem (VRP) was modelled in (Bish, 2011). This approach considered for advance notice disasters and referred to as the bus evacuation problem (BEP). In BEP, a set of bus depots, pickup locations, and shelters are given. The objective is to transport evacuees from the pickup locations to the shelters minimising the evacuation time using a homogeneous fleet of buses, which are initially located at one or more depots. The duration of evacuation is defined as the time span between when the first bus leaves its depot until the last evacuee is sheltered. The number of evacuees at each location is known and can exceed the capacity of a single bus. Every shelter has a capacity limit representing the number of evacuees it can serve. Two mixed-integer linear programming (MILP) models were introduced Aiming to minimize the maximum evacuation time (min-max), and the total travel time of all vehicles respectively. A heuristic algorithm was also proposed for solving the proposed MILP models. The agent-based simulation system to model the real-world strategy for citizen-assisted evacuation planning within the context of hurricanes was developed in (Naghawi & Wolshon, 2012). Simulation was performed using a fleet of buses on a regional road network.

A bi-objective model for assisted evacuation planning for short-notice disasters was presented in (Shahparvari, et al., 2016). To the two objectives consider were maximisation of the number of evacuees and the minimisation of the required resources (shelters and vehicles). The problem was solved using the ε-constraint method using a small-size case study of bushfires in Australia. A dynamic single-objective version of the model and developed a genetic algorithm for solving it was presented in (Shahparvari, et al., 2019).

A model that considers fairness objectives was proposed in (Aalami & Kattan, 2020). Fairness is modelled in terms of the proportion of resources (vehicles) allocated for the evacuation of different areas. Randomly generated instances involving 30 and 50 pick-up locations, 10 and 25 shelters, and alternative fleet sizes, were used to test the proposed models and the associated solution algorithms.

The literature review revealed that currently available models do not adequately address important problem attributes characterizing real-world assisted-evacuation decisions. Specifically, currently available models do not consider:

- The risk associated with the links of the underlying transportation network in optimizing shelter-allocation and assisted- evacuation routing decisions.
- Multiple objectives such as fairness, efficiency, and risk of evacuation and shelter allocation decisions have not been incorporated in a single multi-objective optimization model that will allow the investigation of trade-offs between these objectives.

In the subsequent section of this report, we are presenting a deterministic multi-objective shelter-allocation and assisted evacuation routing and scheduling model that simultaneously considers efficiency, fairness, and risk objectives. We are also introducing two variants of the generic assisted evacuation problem which considers requirements emerging from the assisted evacuation context of rural Indonesia and Sudan respectively. For the case of Indonesia, we are considering the e coordination of the joint evacuation of people and livestock, while for the case of Sudan we are considering the requirement to ensure that evacuees from rival tribes are not evacuated to the same shelter, and that the selection of the shelter locations takes into account the number of the security forces personnel needed to guard the gates of the shelters.

3 Problem definition

In this section we are presenting the context of assisted evacuation in rural Indonesia and Sudan and we define the associated assisted evacuation problems.

3.1 Assisted evacuation operations in rural Indonesia

We consider the assisted evacuation problem as a part of disaster response operations aimed to relocate population from affected zones to shelters. The context of the problem includes large-scale disasters in Indonesia. According to the data from Indonesian National Board for Disaster Management (BNPB) and Regional Disaster Management Agency (BPBD), assisted evacuation usually may be required in the following situations:

- massive evacuation in a short time after volcano eruptions;
- evacuation following early warning of floods and during floods;
- secondary evacuation after earthquakes and aftershocks.

These are three general situations; however, it also depends on a practice of local authorities for other types of disaster. Thus, in case of volcano eruptions, there are three levels of warning. During the first or second level, authorities may decide to proceed with self-evacuation of population because of the lack of immediate threat. During the third level or even no-notice eruption they require everyone to leave the affected area in short time, and assisted evacuation becomes necessary. Another important aspect of assisted-evacuation decisions in rural Indonesia is the need to evacuate livestock in parallel to the evacuation of people. The importance of this problem attribute is two-fold. From a practical point of view the simultaneous coordinated evacuation of people along with their livestock is important since people may refuse to be evacuated with grave consequences for their lives if their livestock which represents a significant asset for their live hood is not securely evacuated with them. Furthermore, in order for the civil protection authorities to ensure the livestock owners that their livestock is safe and secure, the livestock should be allocated to shelters in close proximity to the shelters where their owners will be evacuated.

3.2 Assisted Evacuation Operations in Sudan

Assisted evacuation operations in Sudan are associated with the displacement of people due to the flooding of Nile. The population of flooded areas is evacuated with the help of the pertinent authorities which provide the required transport means for the evacuation. The evacuees are taken to designated safe places, i.e., shelters. Due to conflicts existing between rival tribes' evacuees that belong to rival tribes should be evacuated to different shelters. Furthermore, in order to control violent behaviour at the shelters, security forces are assigned to guard the shelters and control the access and egress to/from the shelters. Therefore, an important aspect of the assisted evacuation problem in Sudan is the selection of shelters that minimize the number of gates that should be guarded, and consequently the number of the security forces personnel needed to ensure orderly conduct in the shelters.

3.3 Generic definition of assisted evacuation problem

The assisted evacuation problem under consideration is defined as follows: in a disaster-affected area people need to be evacuated to candidate safe locations (shelters) of given location and capacity. The origin of the evacuation (assembly points) and the potential destination (Shelters) are represented as nodes of a network. In addition, the underlying transportation network is geocoded and information regarding the risk and distance (travel-time) of the links of the underlying roadway network are also inputs to the optimization problem. A heterogeneous fleet of vehicles is used for the assisted evacuation operations. The evacuation vehicles start from their depot, then are traveling to the assembly point of an affected zone, to collect people and transport them directly to the shelters. The vehicles may make as many trips as needed to evacuate all people and livestock. The vehicles are travelling directly from assembly points to shelters, in order to reduce evacuation time and risk and they are not visiting multiple locations to maximize the use of their capacity (An, et al., 2013).

Using the inputs described above, the following questions associated with assisted-evacuation decisions should be addressed:

1. Which shelters should be used?
2. How many vehicles are required for evacuation?
3. How many trips between evacuation zones and shelters each vehicle should perform?
4. Which routes should be used for the evacuation?
5. What is the total risk of using proposed routes?
6. What is the total time that the evacuation vehicles will be used to perform the evacuation operation?
7. What is the maximum evacuation time?
8. What are the trade-offs between evacuation efficiency, fairness, and risk objectives?

Depending on the decision-making requirements two types of models can be formulated to address the assisted evacuation problem. The first model represents the case when the number of available vehicles is given, and the maximum evacuation time should be determined. The second model considers as input the maximum acceptable evacuation time and seeks to determine the optimal fleet size needed to complete the evacuation. In the remainder of the paper, we are referring to them as Fleet Size Constrained Evacuation Problem FSC-AEP and Time Constrained Evacuation Problem TC-AEP, respectively.

The solution of FSC-AEP optimises safety, fairness and efficiency objectives as well as satisfies constraints on fleet cost (size), vehicle capacities, available place in shelters, and allocation of people. Fairness is determined as the minimisation of maximal evacuation time among all Evacuation vehicles. For each evacuation vehicle the travel time includes the time needed to travel from its depot to the assembly pick-up point of a zone, the travel time from the pickup point to the shelter and back from the shelter to the pick-up point. The Safety objective is expressed through the minimisation of the transportation risk. Two Efficiency objectives are used. The first efficiency objective seeks to minimise the number of shelters to be used, while the second efficiency objective minimises the total travel time (the travel time of all evacuation vehicles) between all affected zones and the open shelters.

The TC-AEP model seeks to optimise the same safety, shelter use and total travel time related efficiency objectives, while the optimum number of vehicles needed to evacuate people and livestock, within a predetermined travel time is introduced in this model as an additional objective.

4 The proposed multi-objective deterministic assisted evacuation models

In this section we are presenting first the two variants of the generic multi-objective deterministic assisted evacuation model, namely the FSC-AEP and the TC-AEP models. Then we proceed with the modelling of the additional evacuation requirements in rural Indonesia and Sudan.

4.1 The Fleet Size Constraint Assisted Evacuation Problem FSC-AEP

Notation:

Table 4-1. Notation for sets

Symbol	Description	Associated index
V	set of zones	$v = 1, \dots, \lvert V \rvert$
J	set of shelters	$j = 1, \dots, \lvert J \rvert$
T	set of runs (trips)	$t = 1, \dots, \lvert T \rvert$
G	set of vehicle types	$g = 1, \dots, \lvert G \rvert$
F_g	set of vehicles of the type g	$f = 1, \dots, \lvert F_g \rvert$

Table 4-2. Parameters for AEP

Symbol	Description
H_v	expected number of people at the zone v
Z_j	people capacity of the shelter j
Q_g	people capacity of a vehicle of type g
$d_{v,j}$	time of the route from zone $v$to shelter j
$\bar{d}_{v,j}$	time of the route from shelter $j$to zone v(necessary to calculate the transportation time between two runs)
$d_{g,f,v}^{IN}$	time that vehicle $f$needs to arrive to the zone $v$in the beginning of evacuation
$r_{v,j}$	risk of transportation from zone $v$to shelter j
$\bar{r}_{v,j}$	risk of transportation from shelter $j$to zone v(necessary to calculate the transportation risk between two runs)

Table 4-3. Decision variables for AEP

Symbol	Description
y_j	1 if shelter j is open, 0, otherwise
$P_{v,j,g,f,t}$	the number of people that are going to be evacuated by the vehicle f of type g from the zone $v$to the shelter j during its run t
$\delta_{v,j,g,f,t}$	1 if vehicle f of type g moves from zone v to shelter $j$in run t, 0, otherwise
$\delta_{g,f,v}^{IN}$	1 if vehicle f of type g starts evacuation from zone v, 0, otherwise
$\bar{\delta}_{v,j,g,f,t}$	1 if vehicle f of type g moves from shelter j to zone v after run t in order to perform evacuation for the next run, 0, otherwise
$\Omega_{g,f}$	evacuation time of the vehicle f of type g
T_{evac}	maximum evacuation time among all vehicles

Constraints:

Constraints (1) require that all people in a given zone v should be evacuated to available shelters using the available evacuation vehicles.

$$\sum_{j\in J}\sum_{g\in G}\sum_{f\in F_g}\sum_{t\in T} P_{v,j,g,f,t} = H_v, \forall v \in V \tag{1}$$

Constraints (2) ensure that the number of people allocated to each shelter j should not exceed the corresponding shelter capacity.

$$\sum_{j\in J}\sum_{g\in G}\sum_{f\in F_g}\sum_{t\in T} P_{v,j,g,f,t} \leq Z_j, \forall j \in J \tag{2}$$

Constraints (3) postulate that the number of evacuees per vehicle trip should not exceed the corresponding evacuation vehicle capacity.

$$P_{v,j,g,f,t} \leq Q_g \delta_{v,j,g,f,t}, \forall\, v \in\, V, j \in\, J, g \in\, G, f \in\, F_g, t \in\, T \tag{3}$$

Constraints (4) ensure that from any zone v, vehicle f can be routed only to shelters j that have been selected to be used for the evacuation.

$$\sum_{v\in V} \delta_{v,j,g,f,t} \leq y_j, j \in\, J, g \in G, f \in\, F_g, t \in T \tag{4}$$

Constraints (5) require that each evacuation vehicle travels to only one zone or remain in their depot.

$$\sum_{v\in V} \delta^{IN}_{g,f,v} \leq\, 1, \forall\, g \in\, G, f \in F_g \tag{5}$$

Constraints (6) and (7) ensure that a vehicle f cannot be routed from a node that it has not visited.

$$\sum_{v\in V} \bar{\delta}_{v,j,g,f,t} \leq \sum_{v\in V} \delta_{v,j,g,f,t}\,, \forall\, j \in\, J, g \in G, f \in\, F_g, t \in\, T \setminus |T| \tag{6}$$

$$\sum_{j\in J} \delta_{v,j,g,f,t} \leq \sum_{j\in J} \bar{\delta}_{v,j,g,f,t}\,, \forall\, v \in V, g \in G, f \in F_g, t \in\, T \setminus |T| \tag{7}$$

At the start of evacuation, vehicles can be dispatched to a zone only if they will be used to transport evacuees. Constraints (8)–(9), along with constraints (6) and (*7*) prevent vehicles from visiting zones without collecting population. Constraints (6)–(*7*), ensure that succeeding vehicle runs cannot include more vehicles than the preceding runs i.e., the fleet size is estimated at the beginning of evacuation. Constraint (9) requires that the number of vehicles that will be used in the first run is equal to the number of vehicles that will be dispatched from the depot.

$$\sum_{j\in J} \delta_{v,j,g,f,1} \leq \delta^{IN}_{g,f,v}, \forall g \in G, f \in F_g, v \in V \tag{8}$$

$$\delta^{IN}_{g,f,v} \leq \sum_{j\in J} \delta_{v,j,g,f,1}\,, \forall g \in G, f \in F_g, v \in V \tag{9}$$

Equation (10) defines the total evacuation time as the sum of the travel times from the depots to the assembly point of the zones and the travel time between the assembly points of the zones to shelters and back.

	$$\Omega_{g,f} = \sum_{v\in V} d^{IN}_{g,f,v}\,\delta^{IN}_{g,f,v} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T} d_{v,j}\delta_{v,j,g,f,t} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T\setminus\|T\|} \bar{d}_{v,j}\bar{\delta}_{v,j,g,f,t}$$	(10)

Constraint (11), requires that the evacuation time of each vehicle is less than or equal to the maximum evacuation time.

	$\Omega_{g,f} \leq T_{evac}, \forall g \in G, f \in F_g$	(11)

Objectives:

The FSC-AEP model involves four objective functions. The minimisation of the number of shelters needed to accommodate all evacuees (12), the minimisation of the maximum evacuation time (13), the minimisation of total evacuation risk (14), and the minimisation of the total transportation time (15).

	$$\min \sum_{j\in J} y_j$$	(12)
	$\min T_{evac}$	(13)
	$$\min \sum_{g\in G}\sum_{f\in F_g}\Big(\sum_{v\in V}\sum_{j\in J}\sum_{t\in T} r_{v,j}\delta_{v,j,g,f,t} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T\setminus\|T\|} \bar{r}_{v,j}\bar{\delta}_{v,j,g,f,t}\Big)$$	(14)
	$$\min \sum_{g\in G}\sum_{f\in F_g}\Big(\sum_{v\in V}\sum_{j\in J}\sum_{t\in T} d_{v,j}\delta_{v,j,g,f,t} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T\setminus\|T\|} \bar{d}_{v,j}\bar{\delta}_{v,j,g,f,t}\Big)$$	(15)

4.2 The Time Constraint Assisted Evacuation Problem TC-AEP

For the description of the time constraint assisted evacuation problem TC-AEP, we are using the same notation as in the case of the FSC-AEP introduced in section 4.1. In what follows we are introducing additional notation needed for the formulation of TC-AEP.

Table 4-4. Additional notation for TC-AEP

Symbol	Description
T_{UB}	the maximum acceptable evacuation time
C_g	the cost associated with the use of a vehicle of type g

- **Property 1:** the upper bound of the vehicles needed to evacuate people and livestock is calculated based on available data for all evacuation zones and according to the procedure in section 4.5.
- **Property 2:** all vehicles assume that are initially located at the same depot.

The TC-AEP model involves constraints (1)-(10) defined for the case of the FSC-AEP. In addition, constraint (16) is used to ensure that the evacuation time of any vehicle used for the evacuation does not exceed the maximum allowable evacuation time.

	$\Omega_{g,f} \leq T_{UB}, \forall g \in G, f \in F_g$	(16)

In addition to objectives (12), (14), and (15) defined for the FSC-AEP, for the TC-AEP objective (17) is also considered. This objective seeks to minimize the total cost of the vehicles that will be used for the evacuation.

	$\min \sum_{g\in G} \sum_{f\in F_g} \sum_{v\in V} C_g \delta^{IN}_{g,f,v}$	(17)

4.3 Extending models to include livestock evacuation

As discussed in section 3.1 an important attribute of the assisted evacuation problem in rural Indonesia is the coordination of the evacuation of people with the evacuation of their livestock. Therefore, the models presented in sections 4.1 and 4.2 can be extended to incorporate this decision-making requirement. To do so in every zone v we introduce the parameter H^L_v representing the expected number of animals that need to be evacuated from this zone. Respectively, every shelter j has a capacity Z^L_j for livestock. Shelters for people and their livestock are located close to each other as people need to take care of their animals. Therefore, in our model (without loss of generality) we assume that the two different types of shelters are located at the same node of the network under consideration each one of them with different capacities for people and animals respectively.

For each vehicle of type g we introduce the parameter Q^L_g expressing its capacity. Since every vehicle type is either for people or livestock, $Q^L_g = 0$ if vehicles of type g are used for people and $Q_g = 0$, when the vehicles are used for livestock. Furthermore, we introduce the variables $P^L_{v,j,g,f,t}$ to represent the number of livestock to be evacuated by vehicle $f$from zone $v$to shelter j in run t.

Constraints (18) ensure that livestock of every zone will be fully evacuated, while constraints (19) suggest that the livestock allocated to a shelter cannot exceed its livestock capacity. Constraints (20) ensure that the maximum number of animals that will be transported by a given vehicle and a given run will does not exceed the vehicle's livestock carrying capacity.

	$\sum_{j\in J} \sum_{g\in G} \sum_{f\in F_g} \sum_{t\in T} P^L_{v,j,g,f,t} = H^L_v, \forall v \in V$	(18)
	$\sum_{j\in J} \sum_{g\in G} \sum_{f\in F_g} \sum_{t\in T} P^L_{v,j,g,f,t} \leq Z^L_j, \forall j \in J$	(19)
	$P^L_{v,j,g,f,t} \leq Q^L_g \delta_{v,j,g,f,t}, \forall v \in V, j \in J, g \in G, f \in F_g, t \in T$	(20)

A key consideration in livestock evacuation is to ensure that people and their livestock are allocated to shelters that are close to each other. Constraints (21) assign at least one vehicle with evacuees to the same route that a vehicle with livestock is assigned. Thus, people and their livestock are assigned to shelters that are located in the same node.

	$\gamma_{v,j} \leq \sum_{g \in G^P} \sum_{f \in F_g} \delta_{v,j,g,f,t}$,$\forall\, v \in V, j \in J, t \in T$	(21)

Constraints (22) and (23) indicate that if no vehicles with evacuees were sent from zone v to shelter j in any run then no vehicles carrying livestock should be dispatched (i.e., $\gamma_{v,j} = 0$). A large number M ensures $\gamma_{v,j} = 1$ if there is at least one $\delta_{v,j,g,f,t} = 1$. It is clearly seen that constraints (21)-(23) do not directly affect the zones without livestock, i.e., people from there could be evacuated to any shelter with available places.

	$\gamma_{v,j} \leq \sum_{g \in G^L} \sum_{f \in F_g} \delta_{v,j,g,f,t}$,$\forall\, v \in V, j \in J, t \in T$	(22)
	$\sum_{g \in G^L} \sum_{f \in F_g} \delta_{v,j,g,f,t} \leq M\gamma_{v,j}$,$\forall\, v \in V, j \in J, t \in T$	(23)

4.4 The Assisted Evacuation Model for Sudan

In this section we present the assisted evacuation model for Sudan. Although the kernel of the assisted evacuation problem presented in section 4.1 is applicable for Sudan, there are additional operational requirements that should be incorporated in the model. These requirements were presented in section 3.2 and relate to the fact that due to potential conflict among rival tribes for security purposes, evacuees from rival tribes cannot be allocated to the same shelter. Furthermore, in selecting the shelter locations the number of gates associated with the selected shelters should be minimized.

The requirement to minimize the number of gates associated with the selected shelters is related to the need to minimize the security personnel required for guarding the shelters and it affects the subsequent security personnel rostering decisions.

Table 4-5. Additional notation for the case of evacuation in Sudan

Symbol	**Description**
b_j	the number of gates (barriers) at shelter j
$Exc(v_1, v_2)$	list of pair of indexes determining which zones cannot evacuated to the same shelter ($v_1, v_2 \in V$)
$Asgmt(v, j)$	list of pre-assignment for zones and shelters

$\gamma_{v,j}$ is an indicator if people from zone v have been evacuated to shelter j, 0, if not.

The assisted evacuation model for Sudan involves constraints (1)-(11) defined for the case of the FSC-AEP model in section 4.1 with the addition of constraints (24)-(27). Constraint (24) ensures that if zone vc cannot be evacuated to shelter j ($Asgmt(v,j) = 0$) then there is no vehicle that can use the corresponding route in every trip during the evacuation.

	$\delta_{v,j,g,f,t} \leq Asgmt(v,j), \forall\, g \in G, f \in F_g, t \in T, v \in V, j \in J$	(24)

Constraint (25) determines if there was an evacuation from zone v to shelter j (M – relatively big number).

$$\sum_{g\in G}\sum_{f\in F_g}\sum_{t\in T}\delta_{v,j,g,f,t} \le M\,\gamma_{v,j}, \forall\, v \in V, j \in J \tag{25}$$

Constraint (26) does not allow two rival tribes to be assigned to the same shelter. If $Exc(v_1, v_2) = 1$ then it means that we cannot simultaneously allocate people from v_1 and v_2 to the same shelter j.

$$\gamma_{v_1,j} + \gamma_{v_2,j} \le 2 - Exc(v_1, v_2), \forall\, j \in J, v_1, v_2 \in V, v_1 \ne v_2 \tag{26}$$

In addition to objectives (13)-(15) defined for the FSC-AEP, objective (27) seeks to minimise the number of gates of the selected shelters.

$$\min \sum_{j\in J} b_j y_j \tag{27}$$

The variant of TC-AEP for the case of Sudan can be formulated following the process described in section 4.2 with taking into account constraints (24)-(26) and objective (27).

4.5 Determining the number of runs for FSC-AEP and TC-AEP

One crucial decision regarding the FSC-AEP and TC-AEP models is the definition of the number of runs that each vehicle should perform during the evacuation. Therefore, an estimation of the initial value of this parameter is necessary. We use the approach of (Bansal, et al., 2007); (Clautiaux, et al., 2014), to determine the number of runs as the sum of the fractional bound for a bin-packing problem *for every affected zone* as per equation (28)

$$N^g_{runs} = \sum_{v\in V}\left\lceil\frac{H_v}{Q_g}\right\rceil, if\ Q_g > 0$$
$$N^g_{runs} = \sum_{v\in V}\left\lceil\frac{H^L_v}{Q^L_g}\right\rceil, if\ Q^L_g > 0 \tag{28}$$

N^g_{runs} also represents the ***number of vehicles*** of type $g$needed to simultaneously evacuate all people and can be used as ***an upper bound for TC-AEP***: $|F_g| = N^g_{runs}$.

In the **FSC-AEP** the number of vehicles is given, and the number of runs of each vehicle:

$$|T| = \max_{g\in G}\left\lceil\frac{N^g_{runs}}{|F_g|}\right\rceil \tag{29}$$

Equation (29) determines the maximum number of runs among all vehicle types.

In the **TC-AEP** for each vehicle the number of runs between zones and shelters should be within the allowable time limits. The best case is when this vehicle always moves between the zone and the shelter with the minimum total travel time.

$$|T| = \left\lceil\frac{T_{UB} + \bar{d}_{v^*,j^*}}{d_{v^*,j^*} + \bar{d}_{v^*,j^*}}\right\rceil,$$
$$d_{v^*,j^*} + \bar{d}_{v^*,j^*} = \min_{v\in V, j\in J}(d_{v,j} + \bar{d}_{v,j}) \tag{30}$$

4.6 The proposed solution approach

To solve both variants, i.e., FSC-AEP and TC-AEP, of the deterministic multi-objective assisted evacuation problem we introduce a two-stage multi-objective programming framework illustrated in Figure 4-1. In the first stage we use risk and the travel time associated with the links of the underlying roadway network to define the efficient frontier of the complete graphs over which the evacuation routes will be optimized.

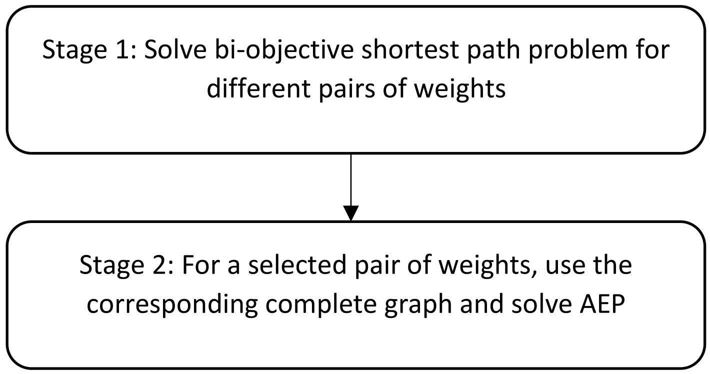

Figure 4-1. Solution approach

In the second stage, the complete graphs are used to solve the Assisted Evacuation Problem. The complete efficient frontier of complete graphs is generated by solving the bi-objective shortest path problem using the approach proposed in (Zografos & Androutsopoulos, 2008).

Let $G^0 = (V^0, A^0)$ be the underlying road-network where V^0 is the union of depot locations, candidate shelter locations, affected zones and junction points among them, and A^0 are the associated arcs. Each arc $a^0_{i,j}$, $i, j \in V^0$, has risk measure $r^0_{i,j}$ that represents the risk associated with the arc and travel time $t^0_{i,j}$. If the travel time is not given initially, it can be calculated as

$$t^0_{i,j} = \frac{l^0_{i,j}}{\min(MAS^0_{i,j}, ES)} \tag{31}$$

where $l^0_{i,j}$ is the length of the link, $MAS^0_{i,j}$ is the maximum allowed speed of the link, $ES$is average evacuation speed. Risk $r^0_{i,j}$ 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 realised, or a new secondary disaster, on arc $a^0_{i,j}$ and $P(ArcOut_{i,j}|DisasterIn_{i,j})$ is the probability of this arc's being unavailable for use after the corresponding impact.

We transform the graph $G^0 = (V^0, A^0)$ into the complete graph $G(V, A)$ by solving a bi-objective shortest path problem for every pair of nodes among zones, candidate shelter locations and depots, minimising both travel times and risks. As the result, each arc $a_{i,j}$, $i, j \in V$, in set A corresponds to the bi-objective shortest path between nodes $i$and j . To this end, for a given weight α, each arc$a^0_{i,j}$ is assigned cost $c_{i,j}$ such that:

$$c_{i,j} = (1-\alpha)t''_{i,j} + \alpha r''_{i,j} \tag{32}$$

where $r''_{i,j} = \frac{r^0_{i,j}}{\max_{a^0_{i,j} \in A'} r^0_{i,j}}$ and $t''_{i,j} = \frac{t^0_{i,j}}{\max_{a^0_{i,j} \in A'} t^0_{i,j}}$.

By using arc costs, the bi-objective shortest path problem is transformed into a single-objective problem which can be solved by any standard shortest path algorithm to generate the complete $G(V, A)$. The efficient frontier of the complete graphs is generated by varying the value ofα that expresses the importance assigned to the time minimization objective. Please note that αtakes values between zero and one.

At the second stage we lexicographically optimise the multi-objective problem (1)-(15), (18)-(23) or (1)-(10), (12), (14)-(23) for each generated graph. Each lexicographic order potentially delivers a different solution. Thus, an efficient Pareto frontier can be approximated by using different combinations of the ordering of the objectives. For a given objective function f_i, and for two solutions A and B that belong to the Pareto frontier the following condition holds: $f_i(A) < f_i(B), f_j(A) \leq f_j(B), \forall j \neq i$.

4.7 Model Application and Computational results

We applied the proposed deterministic multi-objective assisted evacuation models and the associated solution approach described in section 4.6 using real-world data of Jakarta Floods between November 2012 and January 2013. The OpenStreetMap (https://openstreetmap.org) was used to extract information regarding the attributes of the underlying roadway network. This network includes all zones, potential shelters, and depots. A zone is represented by its centroid or a pick-up point (assembly point). Nodes are connected by links representing existing roads (primary, secondary, service, residential, etc. as defined by the OpenStreetMap). Every link has a source node, a target node, length (distance between source node and target node), maximum allowed speed, and an indicator if the link is unidirectional or bidirectional. The risk associated with the nodes of the underlying roadway network were obtained from the InaRISK (https://inarisk.bnpb.go.id) portal. The values provided by InaRisk are continuous values in the interval $[0, 1]$ where 0 indicates no risk and 1 indicates highest risk. The risk level of a link that connects two nodes is the maximum value of the risks of the nodes[3]. The approach developed in (Gultom, et al., 2021) was used to extract the network data used in the computational experiments of the Indonesian problem instances.

In our data, every affected zone is represented by a single node. The number of people to be evacuated is proportional to the population of the zone. This number was also adjusted according to the information provided by BNPB that they usually provide assisted evacuation to 40% of all evacuees. Accordingly, instead of using the full shelter capacity, we use 40% of each shelter capacity as the number of available places for assisted evacuees. There is no livestock evacuation in the data of Jakarta Floods. A fleet for assisted evacuation consists of military trucks and rescue cars with a maximum capacity of 30 people for each vehicle, and a maximum speed of 40 kilometres per hour. For the application of the proposed models, i.e., FSC-AEP and TC-AEP and the associated exact solution approach we have used the following data (see Table 4-6). Please note that for the Jakarta flood case there was no need to consider livestock evacuation.

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[3] The data regarding describing the underlying network have been provided by Prof. Heru Suhartanto, Dr. Toto Haryanto, and Muhamad Fathurahman (Universitas Indonesia)

Table 4-6. Case study data

Parameter	Value
Number of zones	8
People per zone needing assisted evacuation	28–62
Number of potential shelters	7
Shelter capacity for assisted evacuation	75–276
Number of depots	5
Vehicle capacity	30
Number of vehicles (for FSC-AEP)	13

4.7.1 Computational experiments and results for the FSC-AEP model

The computational experiments were performed on a laptop, equipped with a 2.3 GHz Intel Core i5 (8 processors) with8 GB RAM. GUROBI 9.02 was used as a MIP solver for addressing the MILP formulations. The computation time has been limited to 1200 seconds per instance, i.e., the total time that the solver uses for optimisation of all four objectives should not exceed this limit. If the solver reaches the time limit, it returns the last found (stored) solution.

Distances and risks between zones, shelters and depots were calculated using the pre-processing procedure presented in Section 4.6. They correspond to the respective values of bi-objective shortest paths between every pair, i.e., for every zone $v$and every shelter j. The bio-objective shortest path problem was solved using travel time and risks in a bi-objective shortest path is determined by the parameter $\alpha \in [0,1]$. For our tests, we set$\alpha$to 0.3, i.e., the travel time has 0.7 or $(1-\alpha)$weight for bi-objective shortest path, while the risk has 0.3 weight.

Table 4-7. Results for FSC-AEP

		Absolute values of objective functions			
		1	2	3	4
Lexicographic Optimization Order	CPU (sec)	Number of Shelters	Max Evacuation Time	Risks	Total Travel Time
4,3,1,2	3.61	6	1 h 34 min	235.65	7 h 56 min
3,4,1,2	3.39	5	1 h 34 min	203.90	8 h 00 min
2,1,4,3	5.48	4	1 h 34 min	226.31	8 h 13 min
2,1,3,4	4.55	4	1 h 34 min	207.49	8 h 43 min
1,4,3,2	143.53	2	1 h 46 min	265.11	10 h 37 min
1,3,2,4	265.05	2	2 h 2 min	235.23	11 h 36 min

Table 4-7 summarizes the results from the application of the FSC-AEP model using the data of the case study under consideration. The table presents the results of all six non-inferior solutions that were generated using the proposed lexicographic optimization approach. The first column of the table represents the order used to lexicographically optimize the four model objectives. For instance, the row “3,4,1,2” indicates that the first objective that was optimized was objective 3 which stands for the minimization of the total risk ; the second optimized objective was objective 4 which represents the minimization of the total travel time; the third objective that was optimized was objective 2 which corresponds to the minimization of the maximum evacuation time , while the fourth optimized objective was objective 1 which represents the minimization of the total number of shelters.

The Column "CPU, provides the computational time associated with each generated non-inferior solution. We observe that the computational time for the generation of the non-dominated solutions depends on the order that the objective functions are optimized. Thus, whenever the number of opened shelters is optimised first the computational time is significantly increased in comparison to the cases that the remainder of the objectives are optimized with the highest priority.

The values of the objective functions considered in the FSC-AEP model are presented in each of the remaining table columns which have been labelled accordingly. The values in these columns represent the value achieved by each objective in the corresponding solution.

Figure 4-2 illustrates the value-paths of the solutions presented in Table 4-7. The vertical axes in Figure 4-2 represent the percentage deviation of each of the four objectives that were lexicographically optimised, from their corresponding optimal value. Each solution in Figure 4-2, is represented by a path connecting the values that each solution has achieved in relation to each objective.

Solutions "2,1,4,3" and "2,1,3,4" coincide for the number of shelters and max evacuation time. This is why we can see only 5 segments between corresponding columns while six are expected.

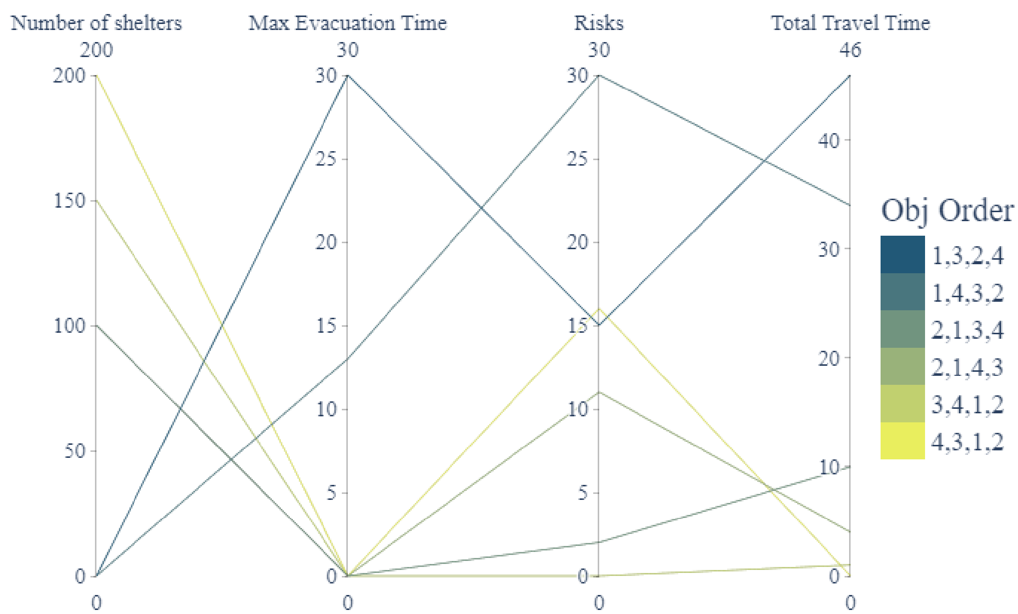

Figure 4-2. Value paths for the non-dominated solutions generated by the lexicographic optimization of the FSC-AEP Model

As expected, we observe that, when each objective receives the highest priority in the lexicographic optimization process the percentage deviation from its corresponding optimal value is equal to zero. The information provided by the generated efficient solutions can help decision makers to understand the trade-off existing between the alternatives objectives and can help them to rationalize their decisions. Computational experiments and results for the TC-AEP Model.

We also applied the TC-AEP model using the same data we used for the FSC-AEP model. Please recall that in the case of the TC-EPP model the maximum allowable time is an input while the number of vehicles needed to complete the evacuation within the maximum allowable time is a predefined parameter. In these experiments we set the maximum allowable evacuation time to 3 h. The non-dominated solutions generated by the lexicographic optimization of the TC-AEP model for different ordering arrangements regarding the prioritization of the optimization objectives are summarized in Table 4-8, and are graphically illustrated in the form of value paths in Figure 4-3.

Table 4-8. Results for TC-AEP

		Absolute values of objective functions			
		1	2	3	4
Lexicographic Optimization Order	CPU, s	Number of Shelters	Vehicles (Fleet Cost)	Risks	Total Travel Time
4,3,2,1	4.41	6	16	219.07	7 h 32 min
3,2,4,1	4.16	5	16	193.16	7 h 36 min
2,4,1,3	58.92	5	6	334.27	11 h 15 min
2,3,1,4	17.69	4	6	304.39	11 h56 min
2,1,4,3	37.28	3	6	318.44	11 h 45 min
2,1,3,4	47.34	3	6	309.46	12 h 43 min
1,4,3,2	190.56	2	16	248.86	10 h 9 min
1,3,4,2	44.39	2	16	224.49	11 h 11 min
1,2,4,3	352.33	2	7	371.86	13 h 58 min
1,2,3,4	109.16	2	7	324.16	14 h 58 min

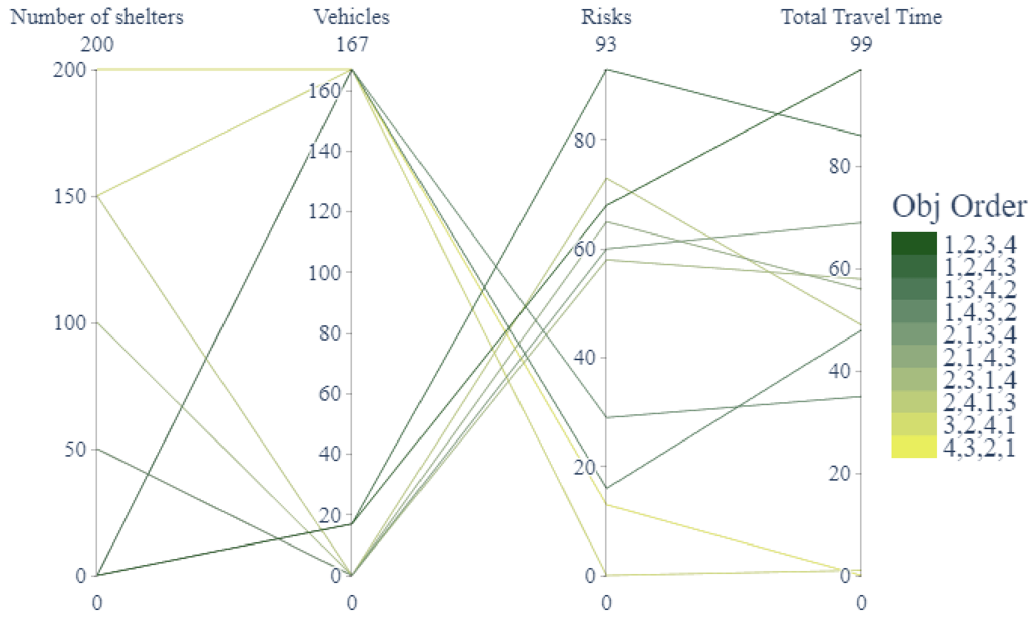

Figure 4-3. Value paths for non-dominated solutions of TC-AEP

5 A Hyper-Heuristic Framework for solving the deterministic multi-objective Assisted Evacuation Problem

Solving the multi-objective deterministic assisted problem variants introduced in section 4 of this report with exact methods may not be possible for larger problem instances. This defines the necessity in heuristic approaches delivering nearly optimal (or sub-optimal) solution in reasonable amount of time. In the current literature we can find examples of genetic algorithms (Shahparvari, et al., 2019), dynamic programming algorithms (Li, et al., 2019), memetic algorithms (Sabouhi, et al., 2018), Tabu-search (Sayyady & Eksioglu, 2010), and other heuristics based on the problem structure (Bish, 2011), (Wang & Wang, 2019), (Lakshay & Bolia, 2020).The recent work of (Niyomubyeyi, et al., 2020) provides a comparative study for classic versions of simulated annealing, artificial bee colony, standard particle swarm optimisation, genetic algorithm as well as for their multi-objective variants.

The major drawback of these approaches is that they are tailored for a particular problem domain. Such systems are generally costly to build, and they are custom-made, it is almost impossible to reuse them in another problem domain. Even a slight change in the problem definition (for example, changing the objective) may require expert intervention. There is a growing interest towards more general, cheaper, and intelligent systems that can automate the heuristic design process.

Hyper-heuristics (Carvalho, et al., 2021) are such automated search methodologies and can be broadly categorised into selection hyper-heuristics, also known as 'heuristics to choose heuristics', or generation hyper-heuristics. The solution approach used in this work is based on the selection type of hyper-heuristics that aims to improve an initially created candidate solution by controlling a set of pre-defined low-level heuristics under an iterative framework. The proposed approach aims to exploit fourteen low level heuristics, each that attempt to enhance an aspect of the quality of the current solution during the optimisation process. These heuristics are fairly simple moves such as swap and insert operators. Selection hyper-heuristics consists of two key elements: a selection method (to select a suitable heuristic and apply it to the candidate solution) and move acceptance (to decide whether to accept or reject the newly generated solution). The sequence-based selection hyper-heuristic replaces the first element of the traditional selection hyper-heuristic framework in order to select sequences of heuristics. These are then applied sequentially to the current solution.

5.1 Random Sequence Multi-objective Hyper-heuristic

The proposed hyper-heuristic solution framework is illustrated in Figure 5-1.

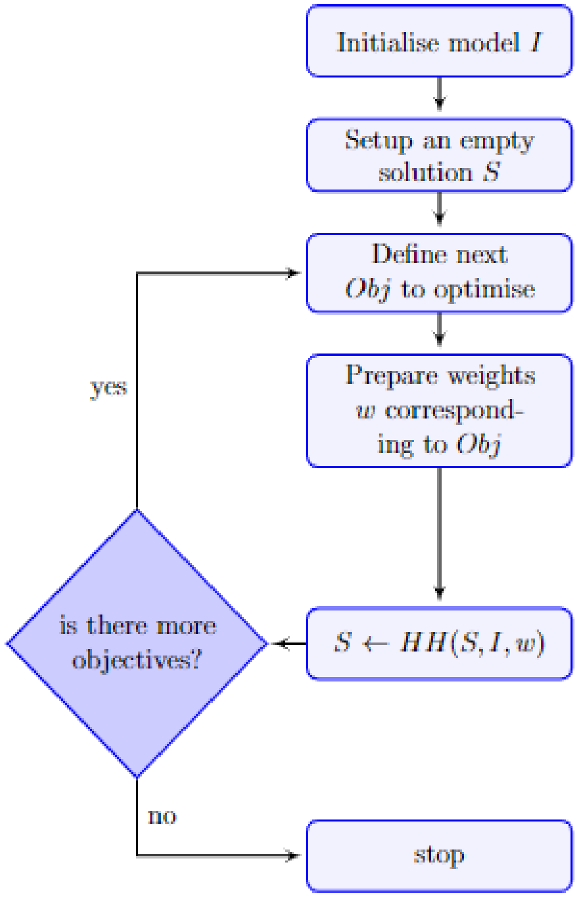

Figure 5-1. The proposed hyper-heuristic solution framework

The algorithm starts with an empty solution S corresponding to the given instance data I. A given order of objective functions determines the sequence that the objectives under consideration will be optimized. Once the objective Obj that will be optimized at the current iteration of the algorithm is defined, a list of weights w corresponding to the objective under consideration is defined. Thus, if at the current step we optimise the objective function Obj_i, then $w_i = 1$ and $w_j = 0$ for any $i \neq j$. There could be other functions supporting each objective. For any of these functions $w_s \in (0,1)$, i.e., they simply guide the search process without impact on the main objective value. This list indicates what objective will be optimised, which functions are used for guidance, and for which functions cannot degrade their previous values due to the optimisation in recent steps.

Then hyper-heuristic HH re-writes solution S with the best found one, and the entire process is repeated until there is a non-optimised objective function. In case of multiple objective orders, the process presented in Figure 5-1 needs to be repeated for each of them. Once all solutions are obtained, the dominance check must be performed. Remaining solutions form the Pareto frontier.

The pseudo-code of the proposed hyper-heuristic is presented below. It can be observed that Algorithm 1 operates with three solutions: S – current working solution, S_{prev} – previous solution,

Algorithm 1: Random Sequence Multi-objective Hyper-heuristic

```
   Let H = {h_0, ..., h_{k-1}} represent the set of low-level heuristics;
   Let Iter represent the number of iterations;
   Input: S – initial solution, I – instance data, w – vector of weights for
          objective functions
   Output: S_best
1  cost_prev ← TotalCost(S, I, w), cost_best ← cost_prev;
2  S_prev ← Copy(S), S_best ← Copy(S);
3  Check Feasibility and initial Objective Values (FOV);
4  iterations ← 1;
5  MaxSeqSize ← 2;
6  threshold ← 0.0001;
7  while True do
8      if iterations = Iter/2 then
9          MaxSeqSize ← 5;
10         threshold ← 0.05;
11     end
12     for i ← 1, ..., Rand(1, MaxSeqSize) do
13         Apply random LLH from H to S
14     end
15     if S violates at least one FOV then
16         S ← Copy(S_prev);
17         Continue
18     else
19         cost_new ← TotalCost(S, I, w);
20         if cost_new ≤ cost_prev or cost_new ≤ (1 + threshold) * cost_best
            then
21             if cost_new ≤ cost_best then
22                 cost_best ← cost_new;
23                 S_best ← Copy(S);
24             end
25             cost_prev ← cost_new;
26             S_prev ← Copy(S);
27         else
28             S ← Copy(S_prev);
29         end
30     end
31     iterations ← iterations + 1;
32     if iterations = Iter then
33         Break
34     end
35 end
36 return S_best
```

S_{best} – best found solution. Line 36 explicitly states that we return the later one when the algorithm finishes. The function $TotalCost$ includes the components representing all necessary objective functions but return only the value of the objective function optimised at the current iteration of the algorithm. For each solution we store the current value of the objective function, and we perform a feasibility check and verification of all objective values that have been optimised earlier.

Parameter $MaxSeqSize$ shows the maximum sequence size, i.e., the number of low-level heuristics that can be applied to S in one iteration (see lines 12-14). The level of degradation for the current objective value is limited by parameter $threshold$. Both parameters are increased once the algorithm has performed half of the number of specified iterations (lines 8-11).

If an updated solution S violates feasibility constraints or values of objective functions from previous optimisation steps, then we restore the previous solution S_{prev} and trying again without increasing the number of iterations performed (lines 15-17). If there is no violation, we update S_{prev} and S_{best} (if possible) as it shown with straightforward comparison in lines 18-30, and then increase the number of passed iterations. Finally, we stop the execution when the number of iterations reaches the limit $Iter$.

5.1.1 Low-level heuristics

As we noted above, every low-level heuristic (LLH) is a fairly simple move such as swap and insert operators. In this subsection we provide a description for each of fourteen developed procedures. They are numbered from 0 to 13 in order to do not create discrepancies between the description and their inclusion in the framework.

[LLH0]: Add random trip to a random vehicle. Hereafter, a random trip determines both locations (zone and shelter) at random.

[LLH1]: Delete a trip from random position of a random vehicle. Includes a trigger that may force to delete a trip from the vehicle with maximum evacuation time.

[LLH2]: Insert a random trip from randomly selected vehicle to another random vehicle of the same evacuation type. The trip is removed from the first vehicle. Includes a trigger that may force to select (and delete) a trip from the vehicle with maximum evacuation time.

[LLH3]: Change a random trip of a random vehicle. With equivalent probability changes either zone or shelter of the trip. With probability of 33% changes both.

[LLH4]: Swap random trips of two random vehicles (one trip from each) of the same evacuation type. Includes a trigger that may force one of the vehicles be the vehicle with maximum evacuation time.

[LLH5]: Swap positions of two random trips in a random vehicle. Includes a trigger that may force to select the vehicle with maximum evacuation time.

[LLH6]: Insert a random trip in to a different position of the same random vehicle. Includes a trigger that may force to select the vehicle with maximum evacuation time.

[LLH7]: Change zone in a random trip of a random vehicle. Similar to LLH3, but explicitly changes the zone and only it.

[LLH8]: Change shelter in a random trip of a random vehicle. Similar to LLH3, but explicitly changes the shelter and only it.

[LLH9]: Distribute all trips of a random vehicle between random vehicles of the same evacuation type. Inserts each trip in to a potentially different vehicle. Effectively excludes the original vehicle from evacuation. Includes a trigger that may force to select the vehicle with maximum evacuation time as the original one.

[LLH10]: Insert a block of trips of a random vehicle to another vehicle of the same evacuation type. Includes a trigger that may force to select the vehicle with maximum evacuation time as the original one.

[LH11]: Re-insert a block of trips of a random vehicle. Includes a trigger that may force to select the vehicle with maximum evacuation time.

[LLH12]: Swap blocks of trips of two random vehicles. Ensures that blocks are of the same size. Includes a trigger that may force one of the vehicles be the vehicle with maximum evacuation time.

[LLH13]: Swap blocks of trips within a random vehicle. Ensures that blocks are of the same size. Includes a trigger that may force to select the vehicle with maximum evacuation time.

It can be seen that 10 out of 14 LLHs have a following line in the description: "Includes a trigger that may force to select the vehicle with maximum evacuation time". This is due to an observation widely discussed in (Bish, 2011). It refers to the fact that an evacuation with multiple vehicles can be easily represented by the evacuation with a single vehicle. While the latter is usually inappropriate in real-life cases, heuristics tend to construct a solution of similar structure (one vehicle performs many trips while others 0 or 1) during their first iterations. Thus, we are simply maximising the chance of equally distributed trips already in early solution stages. As a secondary effect, this approach helps to find better solutions for objectives related to travel times on the network (maximum evacuation time, total travel time).

The proposed framework was developed using Python 3.9. The tests were performed on a laptop, equipped with a 2.3 GHz Intel Core i5 (8 processors) and having 8 GB RAM.

5.2 Computational Results

In this section we are presenting computational results from the application of the proposed hyper-heuristic framework in two problem instances from Indonesian[4] (section 5.2.1) and Sudan[5] (section 5.2.2). The network data used in the Indonesian case study were extracted using the approach presented in (Gultom, et al., 2021); while the network data used in the Sudanese case study were extracted using the approach presented in (Abushama, Hisham; M. Ali, Hiba H. S.; Elbadawi, Khalid; Salih, Salih, 2022).

5.2.1 Computational results of the Indonesian case study

The case study in Indonesia is motivated from the Mount Merapi eruption between November 2020 and January 2021. While such disaster may affect multiple zones around the volcano, in the case under consideration only one zone required assisted evacuation of 71 people and 165 animals. In total there were three emergency depots able to provide 28 vehicles of six types. 12 of the available vehicles were for people and 16 for livestock. Five shelters with sufficient total capacity were presented for potential allocation. Two of the available shelters had facilities to accommodate both people and livestock, while the remaining three had only facilities for accommodating people. We modelled both the FSC-AEP and the TC-AEP of the problem, and we use the proposed random

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[4] The data used in the Indonesian case study were provided by Prof. Heru Suhartanto, Dr. Toto Haryanto, and Muhamad Fathurahman (Universitas Indonesia)

[5] The network used in the Sudanese case study were provided by Hisham Abushama, Hiba H. S. M. Ali, and Khalid Elbadawi (University of Khartoum)

sequence heuristic to solve the resulting multi-objective models. We set the number of allowable iterations per objective to 40000, and we generated all the efficient solutions associated with all 24 alternative ordering sequences of the four objectives considered in the FSC-AEP and TC-AEP models. It is worth noting that the exact algorithm used in section 4.7.1 to generate the efficient frontiers was not able to solve the FSC-AEP and TC-AEP models of the case study under consideration when the computational time limit was up to 30 minutes.

Table 5-1. Results of hyper-heuristic for FSC-AEP

		Absolute values of objective functions			
		1	2	3	4
Lexicographic Optimization Order	CPU (sec)	Number of shelters	Max Evacuation Time	Risks	Total Travel Time
1,2,3,4	416.0	2	1 h 2 min	1796.07	13 h 57 min
1,2,4,3	282.4	2	58 min	1855.12	14 h 24 min
1,4,3,2	257.2	2	1 h 3 min	1673.78	12 h 50 min
2,1,3,4	330.8	3	58 min	1850.91	14 h 23 min
3,1,4,2	344.8	3	1 h 3 min	1671.25	12 h 49 min
4,1,2,3	363.2	3	1 h 3 min	1671.25	12 h 49 min

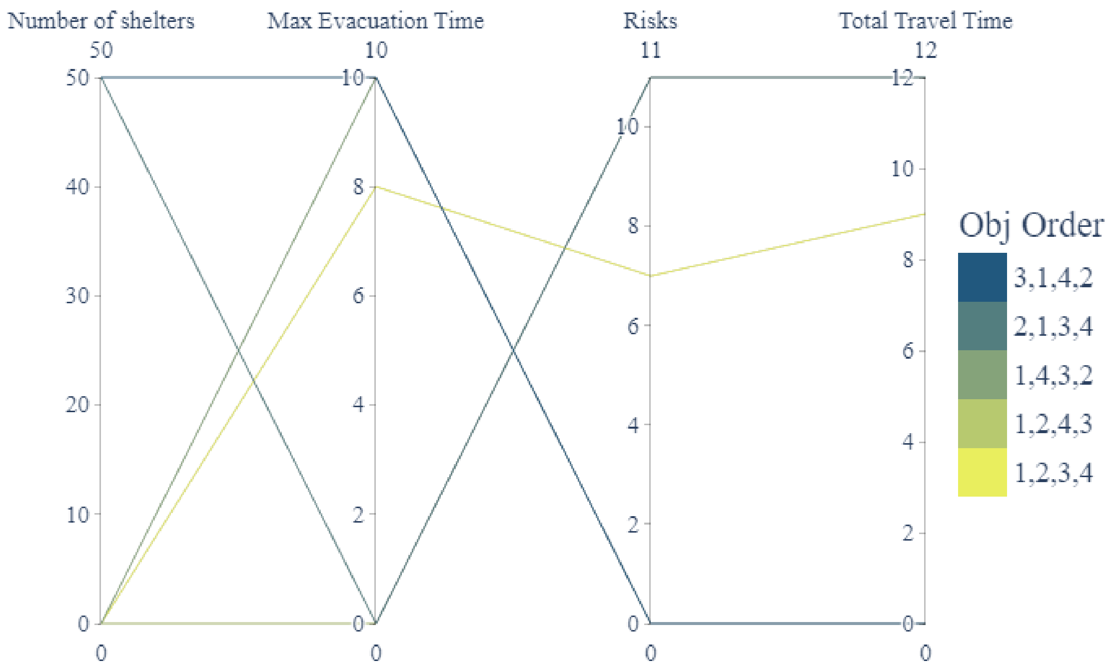

Figure 5-2. Value-Path diagram with non-dominated solutions for FSC-AEP

The values of the objective functions for the generated non-dominated solutions for the solution of the FSC-AEP variant of the assisted evacuation problem for the instance under consideration are summarized in Table 5-1. The Value-Paths representation of the generated non-dominated solutions are illustrated in Figure 5-2. Please recall that the values of the vertical axes of the value-path diagram indicate the percentage deviation of the value of the objective function of a given solution from the corresponding optimal value. In practice the value paths indicate to the decision makers how much they should sacrifice from the achievement of one objective in order to improve the performance of the other objectives.

Using OOP for the development of the implementation of the solution algorithm provides an advantage with regards to the parallel execution of several processes, which usually are limited for complex models in commercial solvers. Simply stated, we may run in parallel as many objective orderings as the number of cores in the machine used. The CPU reported for the solution of the assisted evacuation problem reflects the time needed to obtain all solutions[6].

The values of the objective functions for the generated non-dominated solutions for the solution of the TC-AEP variant of the assisted evacuation problem are summarized in Table 5-2. The Value-Paths representation of the generated non-dominated solutions are illustrated in Figure 5-3. Please recall that the values of the vertical axes of the value-path diagram indicate the percentage deviation of the value of the objective function of a given solution from the corresponding optimal value.

Table 5-2. Results of hyper-heuristic for TC-AEP

		Absolute values of objective functions			
		1	2	3	4
Lexicographic Optimization Order	CPU (sec)	Number of shelters	Fleet Cost (for people, for livestock)	Risks	Total Travel Time
1,2,3,4	376.5	2	18.9 (5, 14)	1614.73	12 h 23 min
1,3,2,4	1286.7	2	36.82 (9, 28)	1138.14	8 h 33 min
2,3,1,4	257.8	3	18.9 (5, 14)	1612.2	12 h 22 min
3,1,2,4	1669.8	3	36.82 (9, 28)	1136.87	8 h 33 min

For example, the risks for solution “1,2,3,4” is 42% more than the optimum risk value which is achieved by solution “3,1,2,4” which achieves the minimum possible risk value. We can also observe that although two solutions such as solutions “1,2,3,4” and “2,3,1,4” may be both efficient in practice the difference of their performance for the fleet cost size objective, the risk, and total travel time objectives is negligible and that their only significant difference relates to the number of shelters. In this case, the decision maker may opt to select solution “1,2,3,4” which minimizes the total number of shelters, i.e., 2 shelters, while does not significantly deteriorate the rest of the objectives under consideration.

[6] It is important to note that the program must be run without having any unnecessary windows open, no OS background processes going on (e.g. backup), no remote users on the computer, no CPU sharing processes running, and no other program running simultaneously. This will allow the program to effectively exploit the power of multiple threads

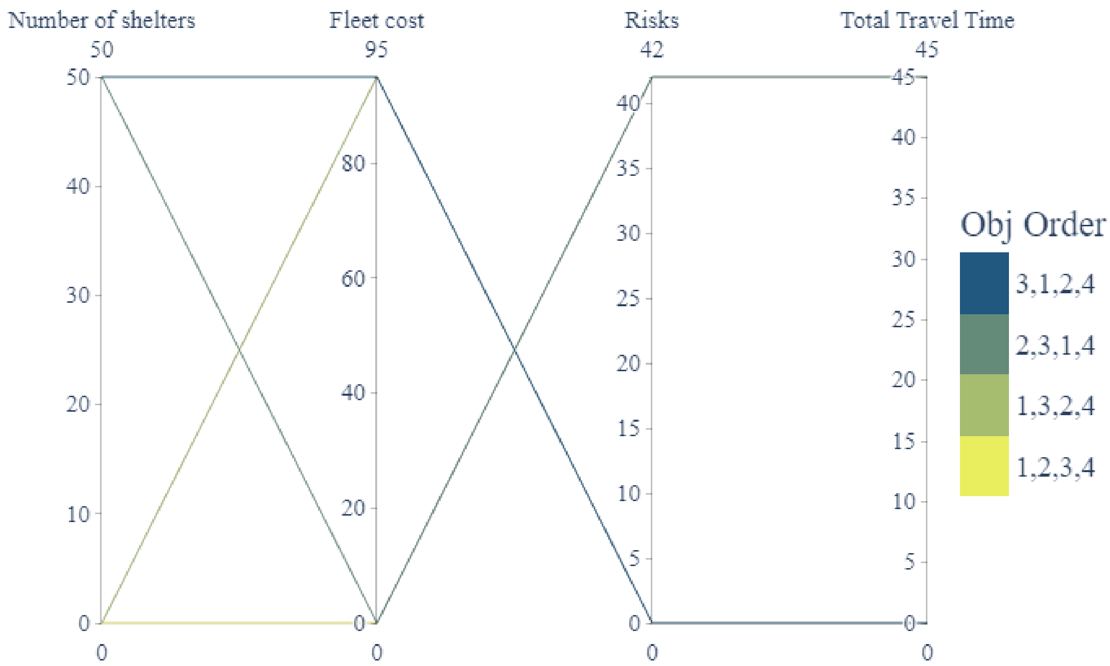

Figure 5-3. Value-Path diagram with non-dominated solutions for TC-AEP

5.2.2 Computational results for the case of Sudan

For the case of Sudan, we have used the synthetic data presented in Table 5-3.

Table 5-3. Data instance for Sudan

Parameters	Zone A	Zone B
Number of people to be evacuated	1290	630
Available shelters	(1, 2)	(2, 3)
Shelter capacities	(1300, 650)	(650, 650)
Number of gates per shelter	3, 2	2, 1

The evacuation fleet was presented in the form convoys (each convoy involves different number of vehicles of different capacity) of three types (by capacity): 84, 78, and 70 people in a trip per convoy. In total there are 17 convoys. People from Zone A and Zone B cannot be allocated to the same shelter. Thus, while the shelter 2 is available for both of them, they cannot use it simultaneously.

The results of hyper-heuristic application are shown in Table 5-4. It worth mentioning that original model uses as input individual vehicles, while in this example the input has been provided in terms of convoys of vehicles. This means that the time and the risk associated with each evacuation trip should be multiplied by the number of vehicles composing in each convoy. Thus, for more accurate results the objective functions (14)-(15) of the model (1)-(11), (13)-(15), (24)-(27) presented in section 4 should be replaced by objective functions (33)-(34).

	$$\min \sum_{g\in G} \sum_{f\in F_g} \Big(\sum_{v\in V} \sum_{j\in J} \sum_{t\in T} w_{g,f} r_{v,j} \delta_{v,j,g,f,t} + \sum_{v\in V} \sum_{j\in J} \sum_{t\in T\setminus\lvert T\rvert} w_{g,f} \bar{r}_{v,j} \bar{\delta}_{v,j,g,f,t}\Big)$$	(33)
	$$\min \sum_{g\in G} \sum_{f\in F_g} \Big(\sum_{v\in V} \sum_{j\in J} \sum_{t\in T} w_{g,f} d_{v,j} \delta_{v,j,g,f,t} + \sum_{v\in V} \sum_{j\in J} \sum_{t\in T\setminus\lvert T\rvert} w_{g,f} \bar{d}_{v,j} \bar{\delta}_{v,j,g,f,t}\Big)$$	(34)

Where $w_{g,f}$ is the number of vehicles in the convoy f of the type g.

The converted values for vehicles are given in Table 5-4 for comparison. Thus, solutions for optimisation orders “1,2,3,4” and “4,1,3,2” are the same in terms of objective functions for convoys, but different, when we recalculate them for vehicles as original model supposed to do.

Table 5-4. Non-dominated solutions for the case study of Sudan

		Absolute values of objective functions				Converted values	
		1	2	3	4		
Lexicographic Optimization Order	CPU (sec)	Number of gates (shelters)	Max Evacuation Time	Risks for convoys	Total Travel Time for convoys	Risks	Total Travel Time
1,2,3,4	203.6	4 (2)	32 min	67.2	4 h 50 min	239.4	17 h 18 min
2,3,4,1	271.0	6 (3)	32 min	65.1	5 h 7 min	226.2	18 h 6 min
3,4,1,2	282.4	6 (3)	37 min	64.2	5 h 14 min	211.8	17 h 24 min
4,1,2,3	199.2	4 (2)	32 min	67.2	4 h 50 min	234.6	16 h 59 min

The Value-Path representation of the generated non-dominated solutions are illustrated in Figure 5-4.

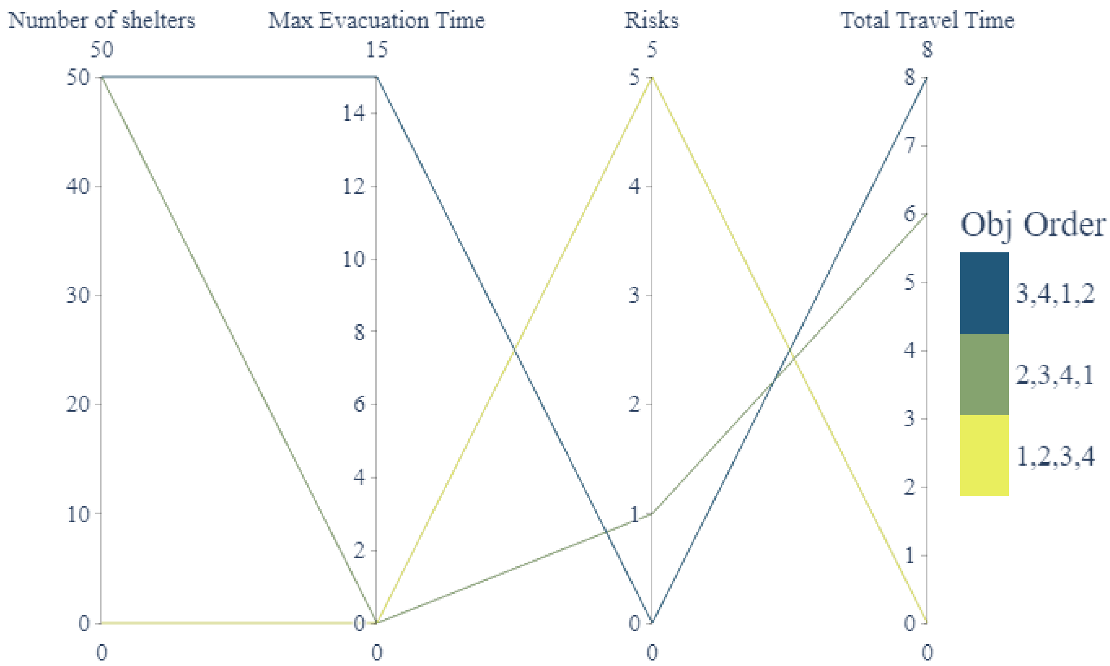

Figure 5-4. Unique non-dominated solutions for "Sudan"

6 Incorporating uncertainty in the assisted evacuation problem

In this section we are introducing the assisted evacuation problem under uncertainty. Following the presentation of the literature related to the Assisted Evacuation Problem Under Uncertainty (AEPUU). We proceed with a robust optimization formulation and solution of the multi-objective assisted evacuation problem, and we conclude with the presentation of the computational experiments and results.

An assisted evacuation planning with demand uncertainty was considered by (Kulshrestha, et al., 2012). The population of every location to be evacuated is given as an interval within which the number of evacuees may vary. The goal is to find an evacuation plan with minimum total travel time satisfying the worst-case scenario. The evacuation is performed using a fleet of heterogeneous buses, where each bus is assigned to only one particular pick-up point. Thus, it can serve different shelters but should always return to the same location to collect evacuees. A cutting plane scheme for the MILP model was introduced and tested on the dataset based on the Sioux Falls network and additionally generated parameters.

An example of transit-based model for predictable long-notice disasters was proposed by (An, et al., 2013). A set of identical vehicles (buses) is used for evacuation, and their number is supposed to be sufficient to perform evacuation at a fixed service rate for every pick-up location. A Single non-capacitated shelter represents the final destination for all evacuees. Every pick-up location has a fixed cost to be selected for evacuation; moreover, it is assumed that some of pick up locations can be damaged in the event of a disaster and, consequently, cannot be used in afterwards. The goal is to select pick-up locations for all groups of evacuees minimising the total cost of evacuation composed of three components: pick-up locations set-up, vehicle travel cost, and vehicles and evacuees’ cost. A scenario-based approach was used to represent potential service disruptions.

A two-stage robust optimisation approach for assisted evacuation problem that considers the evacuation time and the schedule vulnerability to changing evacuation circumstances was proposed in (Goerigk, et al., 2015). Initially, this approach computes a nominal solution which is robust with respect to alternative possible scenarios. Subsequently the nominal solution is adjusted to get a feasible solution for a given scenario. The experiments were carried for small-size real-world example in an urban area, and Pareto front regarding the trade-off between evacuation time and robustness was generated.

A short-notice bus-based evacuation planning represented by MILP model over time-space network diagram was considered by (Qazi, et al., 2017). The single objective minimises the total travel time of all buses. The performance of the model was tested on the small-size real-world example with different demand scenarios.

A robust optimization model for evacuation planning and distribution of relief supplies aiming to optimize the total cost of all response operations was presented in (Yahyaei & Bozorgi-Amiri, 2018). The number of affected people at each location has been modelled as uncertain parameters with symmetric distribution.

Single-source-multiple-destination evacuation planning was studied by (Wang & Wang, 2019). The mathematical formulation corresponds to a contraflow problem where the goal is to minimise evacuation time. A two-layer reconfiguration strategy was used to determine the number of buses or cars that need to be used under uncertain traffic conditions. The algorithm was tested on the real traffic network of moderate size.

A robust approach to solve the Bus Evacuation Problem with uncertain demand was proposed in (Lakshay & Bolia, 2020). It consists of three mathematical models. The first one determines the minimum number of buses that must be available in order to evacuate transit dependent population. The second uses the number of buses to find an evacuation plan with minimum evacuation time. Finally, the third model minimises the number of modification strategies among all possible scenarios of demand. Every stage resolves its own single-objective mathematical model. A heuristic algorithm was proposed for every model and tested with the moderate-size case study of radiological incident within urban area. The results showed that for certain scenarios heuristics may take up to 8 minutes to deliver a solution.

The literature review suggests that Robust optimization (Ben-Tal & Nemirovski, 2002), (Bukhtoyarov & Emelichev, 2019) can be used to cope with the uncertainty associated with certain parameters of the assisted evacuation problem such as the number of people that need to be evacuated, and the attributes of the links of the underlying roadway network used by the evacuation vehicles. The basic idea underpinning the robust optimization approach is that the problem parameters are not defined by single values and that scenarios describing the problem emerge from the combination of values of the different parameters. Thus, the solution of the robust optimisation problem performs “well” for all.

We consider a robust approach based on recoverable robustness initially described for simplified version of assisted evacuation planning in (Goerigk, et al., 2015). In this work we focus on the construction of a plan for multi-objective assisted evacuation planning problem. The proposed approach is general enough to be applied during both preparedness and response stages of the disaster management operations. The evacuation is assumed to be performed by a heterogeneous fleet to relocate evacuees and livestock from endangered areas, represented by a set of affected zones, to a selected set of candidate shelters. The evacuation is subject to capacity constraints for both vehicles and shelters.

The rest of this section is organised as follows. The detailed problem description and the associated mixed-integer linear programming (MILP) formulation are presented in Section 6.1. The uncertainty set is defined in Section 6.2. Section 6.3 presents the solution recovery, scenario generation, and the overall robust optimization algorithm of the AEPUU, while section 6.4 presents computational results from the application of the proposed robust optimization approach.

6.1 The assisted evacuation model with uncertainty $Stoch(\Xi)$.

Let V be the set of affected zones, J the set of potential shelter locations. The number F of the evacuation vehicles is given. For each $v \in V$ the numbers H_v of people and the number L_v of livestock to be evacuated are defined, while for each shelter $j \in J$ there are capacities Z_j^H and Z_j^L respectively for people and livestock. Similarly, every vehicle also provided with two capacities: Q_f^H and Q_f^L respectively for people and livestock; however, only one of them could be non-zero due to the strict separation of the fleet into two groups (for people and for livestock).

Each vehicle is originally located in one of available depots. All locations form the set of nodes in the problem network. Then, a link $e = (a, b)$ represents the route between locations a and b. A vehicle during the evacuation follows the sequence of activities:

[Step 1.] Travel from a depot to an affected zone

[Step 2.] Pick-up people or livestock to be transported from the evacuation zone to a shelter

[Step 3.] Travel to a shelter

[Step 4.] If evacuation has not been completed, vehicles travel to non-evacuated zones and repeat the evacuation process (Step 2)

After evacuation, vehicles are not obliged to return to depots since the later may be unavailable.

Ξ is a given set of scenarios, and $\xi \in \Xi$ is a single scenario from the set.

Notation:

Table 6-1. Decision variables for original model in stochastic formulation

Symbol	Description
y_j	1 if shelter $j$is open, 0, otherwise
$\delta_{v,j,f,t}$	1 if vehicle f moves from zone $v$to shelter $j$in run t, 0, otherwise
$\delta_{f,v}^{IN}$	1 if vehicle f starts evacuation from zone v, 0, otherwise
$\overline{\delta}_{v,j,f,t}$	1 if vehicle f moves from shelter $j$to zone $v$after run $t$in order to perform evacuation for the next run, 0, otherwise
Ω_f	evacuation time of the vehicle f
T_{evac}	maximum evacuation time among all vehicles

Constraints:

Constraints (35) and (36) require that all people and livestock in a given zone v should be evacuated to available shelters using available evacuation vehicles in every possible scenario ξ

$$\sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^H \delta_{v,j,f,t} \geq H_v^\xi, \forall v \in V, \xi \in \Xi \tag{35}$$

$$\sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^L \delta_{v,j,f,t} \geq L_v^\xi, \forall v \in V, \xi \in \Xi \tag{36}$$

Constraints (37) and (38) ensure that the number of people and livestock allocated to each shelter $j$should not exceed the corresponding shelter capacity.

$$\sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^H \delta_{v,j,f,t} \leq Z_j^H, \forall j \in J \tag{37}$$

$$\sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^L \delta_{v,j,f,t} \leq Z_j^L, \forall j \in J \tag{38}$$

Constraints (39) ensure that from any zone v, vehicle $f$can be routed only to shelters j that have been selected to be used for the evacuation.

$$\sum_{v \in V} \delta_{v,j,f,t} \leq y_j, j \in J, f \in F, t \in T \tag{39}$$

Constraints (40) require that each evacuation vehicle travels to only one zone or remain in their depot.

$$\sum_{v\in V} \delta_{f,v}^{IN} \leq 1, \forall f \in F \quad (40)$$

Constraints (41) and (42) ensure that a vehicle f cannot be routed from a node that it has not visited.

$$\sum_{v\in V} \bar{\delta}_{v,j,f,t} \leq \sum_{v\in V} \delta_{v,j,f,t}, \forall j \in J, f \in F, t \in T \setminus |T| \quad (41)$$

$$\sum_{j\in J} \delta_{v,j,f,t} \leq \sum_{j\in J} \bar{\delta}_{v,j,f,t}, \forall v \in V, f \in F, t \in T \setminus |T| \quad (42)$$

At the start of the evacuation operations, vehicles can be dispatched to a zone only if they will be used to transport evacuees. Constraints (41)–(42), ensure that succeeding vehicle runs cannot include more vehicles than preceding runs i.e., the fleet size is estimated at the beginning of evacuation. Constraint (43) requires that the number of vehicles that will be used in the first run is equal to the number of vehicles that will be dispatched from the depot. Constraints (43)–(44), along with constraints (41) and (42) prevent vehicles from visiting zones without collecting population.

$$\sum_{j\in J} \delta_{v,j,f,1} \leq \delta_{f,v}^{IN}, \forall f \in F, v \in V \quad (43)$$

$$\delta_{f,v}^{IN} \leq \sum_{j\in J} \delta_{v,j,f,1}, \forall f \in F, v \in V \quad (44)$$

Equation (45) defines the evacuation time for each vehicle as the sum of the travel time from the depot to the affected area, the time needed to travel from each evacuation zone to the shelter and return back to the evacuation zone. The value of the travel time of the evacuation vehicles could be different in each scenario:

$$\Omega_f^{\xi} = \sum_{v\in V} d_{f,v}^{IN,\xi} \delta_{f,v}^{IN} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T} d_{v,j}^{\xi} \delta_{v,j,f,t} + \sum_{v\in V}\sum_{j\in J}\sum_{t\in T\setminus|T|} \bar{d}_{v,j}^{\xi} \bar{\delta}_{v,j,f,t} \quad (45)$$

Constraints (46) ensure that the total evacuation time is not less than the evacuation time of any vehicle in each scenario:

$$\Omega_f^{\xi} \leq T_{evac}, \forall f \in F, \xi \in \Xi \quad (46)$$

Constraints (47) assign at least one vehicle with evacuees to the same route that a vehicle with livestock is assigned. Thus, people and their livestock are assigned to shelters that are located in the same node.

$$\gamma_{v,j} \leq \sum_{f\in F^H} \delta_{v,j,f,t}, \forall v \in V, j \in J, t \in T \quad (47)$$

Constraints (48) and (49) indicate that if no vehicles with evacuees were sent from zone $v$to shelter $j$in any run then no vehicles carrying livestock should be dispatched (i.e.,.$\gamma_{v,j} = 0$). A large number M ensures that $\gamma_{v,j} = 1$ if there is at least one relocation of livestock from zone v to shelter j. It is clearly seen that constraints (47)-(49) do not directly affect the zones without livestock, i.e., people from there could be evacuated to any shelter with available places.

	$\gamma_{v,j} \leq \sum_{f\in F^L} \delta_{v,j,f,t}$, $\forall\, v \in V, j \in J, t \in T$	(48)
	$\sum_{f\in F^L} \delta_{v,j,f,t} \leq M\gamma_{v,j}$, $\forall\, v \in V, j \in J, t \in T$	(49)

where F^L is a subset of F including only vehicles for livestock transportation.

For the assisted evacuation problem under uncertainty, any Solution satisfying constraints (35)-(49) is called a feasible solution. To shorten the description and to do not repeat all constraints several times we will use the notation $S \in \mathcal{F}(I)$, where I identifies the instance of the problem.

Objectives:

The FSC-AEP model under uncertainty involves two objective functions. The minimisation of the number of shelters needed to accommodate all evacuees (50), the minimisation of the maximum evacuation time (51)

	$\min \sum_{j\in J} y_j$	(50)
	$\min T_{evac}$	(51)

We optimize the assisted evacuation problem under uncertainty (35)-(51) lexicographically for the two different orderings of the objective functions (50), (51), i.e., Hereafter, we call a solution of this problem a nominal solution.

6.2 Defining the uncertainty set

The mathematical model presented above has the following uncertain elements:

- number of people and livestock to be evacuated per zone;
- travel time associated with the links in the underlying roadway network.

The uncertainty associated with these two problem parameters is defined through the definition of an interval within which the values of the corresponding parameters vary. These intervals are exogenously defined, and they constitute input to the robust optimization problem under consideration.

6.3 Solution approach

In order to solve the assisted evacuation problem under uncertainty, we consider an algorithm based on the two-stage approach proposed by (Goerigk, et al., 2015). The difference is that in our case we solve a multi-objective problem whenever we need to generate a nominal solution instead of a single objective problem solved in (Goerigk, et al., 2015). In what follows we are presenting the formulations used in applying the proposed algorithm along with the pseudocode associated with its implementation.

6.3.1 Recovery solution generation model $SRM(S, \xi)$

In this section we are describing the process for identifying recovery solutions. A recovery solution is defined as the feasible solution with the smallest recovery distance from the nominal solution. The recovery solutions are generated by solving the optimization problem (52)-(59). Let scenario ξ

and nominal solution S be fixed. Then, among all feasible solutions for scenario ξ, we seek to find solution S^{ξ} that minimises the recovery distance from the nominal solution S.

	$\min \tau^{\xi} + \sum_{j \in J} Y_j^{\xi} + \sum_{v \in V, j \in J, f \in F, t \in T} \Delta_{v,j,f,t}^{\xi}$	(52)
	$S^{\xi} \in \mathcal{F}(I^{\xi})$	(53)

Subject to constraints (53)-(57). Constraints (54) defines the number of the deviations in evacuation routes. Constraints (55) define the number of deviations in the opened shelters, while

	$-\Delta_{v,j,f,t}^{\xi} \leq \delta_{v,j,f,t} - \delta_{v,j,f,t}^{\xi} \leq \Delta_{v,j,f,t}^{\xi}$	(54)

and the deviation of the number of opened shelters:

	$-Y_j^{\xi} \leq y_j - y_j^{\xi} \leq Y_j^{\xi}$	(55)

Constraint (56) expresses the intensity of the deviation of the recovery solution from the nominal solution in terms of the maximum evacuation time. For example, if $T_{evac}^{\xi} > T_{evac}$, then the recovery solution violates the maximum evacuation time of the nominal solution. τ^{ξ} characterises this deviation for the recovery solution. To differentiate two recovery solutions, we define an interval step of λ minutes. For each interval step the value of τ^{ξ} increases by 1.

	$\frac{60}{\lambda} * \left(T_{evac}^{\xi} - T_{evac}\right) \leq \tau^{\xi}$	(56)
	$\tau^{\xi} \in \mathbb{N} \cup 0$	(57)

The objective function (52) of the solution recovery model (52)-(57) generates non-zero distance whenever at least one of the following holds: i) there are differences in vehicle evacuation routes; ii) there is a change in opened/closed shelters; iii) the maximum evacuation time of recovery solution is larger than the nominal one.

A recovery solution can be constructed from the current nominal solution by solving the optimization problem (52)-(57). Please note that the objective functions (50), (51) are not considered at this stage. This renders any heuristic appropriate for the static model, such as the hyper heuristic presented in section 5, applicable for solving the recovery solution generation model with minor adjustments.

To shorten the description and simplify the notation we will refer to model (52)-(57) as $SRM(S, \xi)$.

6.3.2 Scenario generation model $WC\left(\left(S, S^{\xi}\right)_{\xi \in \Xi}\right)$.

Another key component of the assisted evacuation problem under uncertainty is the model used to generate scenarios for which all given candidate solutions are infeasible. A scenario ξ includes the following variables:

h_v – number of people at zone v;

l_v – number of livestock at zone v;

$d_{v,j}$ – distance of the path between zone v and shelter j;

$\bar{d}_{v,j}$ – distance of the path between shelter j and zone v.

Let $S = (y, \delta^*, T_{evac})$ be the nominal solution, and $k \in K$ be the index for the case of multiple solutions. We call S^k the k-th candidate solution. δ^* shows that we may access all delta variables (δ^{IN}, δ, and $\bar{\delta}$) if necessary.

The scenario generation idea consists in a finding a scenario for which all given candidate solutions are infeasible.

Constraints (40)-(44) need to be repeated for this model because they ensure that all vehicles have proper routes in any solution. Other objectives and constraints are listed below.

The objective function of this optimization problem is to maximise the infeasibility z of the scenario for all solutions. The objective Function (58) is non-linear and reaches its maximum for some value of z only when the denominator is as small as possible, i.e., we seek to construct a worst-case scenario that minimizes the number of deviations from the values of the scenario generation parameters of the base line scenario.

	$\max z + \frac{1}{\sum_{v \in V}(c_{k,v}^{H} + c_{k,v}^{L}) + \sum_{f \in F} c_{k,f}^{T}}$	(58)

Subject to the following constraints:

	$h_v \in \bar{H}_v$	(59)
	$l_v \in \bar{L}_v$	(60)
	$d_{v,j}, \bar{d}_{v,j} \in d_{i,j}$	(61)

The infeasibility of a scenario is measured by the infeasibility value $\mathcal{Z}_k$ of each solution S^k:

	$z \leq \mathcal{Z}_k, \forall\, k \in K$	(62)

The Solution infeasibility is modelled using the following constraints:

	$\mathcal{Z}_k \leq h_v - \sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^H \delta_{v,j,f,t}^k + M\,(1 - c_{k,v}^H)$	(63)
	$\mathcal{Z}_k \leq l_v - \sum_{j \in J} \sum_{f \in F} \sum_{t \in T} Q_f^L \delta_{v,j,f,t}^k + M\,(1 - c_{k,v}^L)$	(64)
	$\Omega_f = \sum_{v \in V} d_{f,v}^{IN}\, \delta_{f,v}^{IN,k} + \sum_{v \in V} \sum_{j \in J} \sum_{t \in T} d_{v,j} \delta_{v,j,f,t}^k + \sum_{v \in V} \sum_{j \in J} \sum_{t \in T \setminus \lvert T \rvert} \bar{d}_{v,j} \bar{\delta}_{v,j,f,t}^k$	(65)
	$\mathcal{Z}_k \leq \Omega_f - T_{evac}^k + M(1 - c_{k,f}^T)$	(66)

Constraints (63) and (64) require that the infeasibility $\mathcal{Z}_k$ is bounded by the number of people and livestock (respectively) that cannot be evacuated by the routes of the solution S^k under the worst-case scenario. Equations (65) express the vehicle evacuation time under the worst-case scenario while the difference between the calculated and maximum evacuation time of any candidate solution creates a bound for infeasibility in (66). For every solution s at least one constraint among (63)-(66) should be violated to ensure that the scenario is infeasible for all of them. Due to non-linearity the original formulation (Goerigk, et al., 2015) explicitly required that exactly one of these constraints is violated. However, in our case the expressions of uncertainty are linear, and the associated constraints have the following form:

	$\sum_{v\in V}(c^H_{k,v} + c^L_{k,v}) + \sum_{f\in F} c^T_{k,f} \geq 1, \forall\, k \in K$	(67)
	$c^H_{k,v}, c^L_{k,v}, c^T_{k,f} \in \{0,1\}$	(68)

Variables $c^H_{k,v}, c^L_{k,v}, c^T_{k,f}$ indicate which constraint has been violated in each candidate solution under the worst scenario.

We introduce a hyper-heuristic algorithm for solving the problem (58)-(68). The proposed hyper heuristic is similar to the hyper heuristic algorithm presented in Section 5.1. However, in this hyper-heuristic we are using the set of low-level heuristics described below:

[LLHWC0]: increase number of people at one random zone.

[LLHWC1]: increase number of livestock at one random zone.

[LLHWC2]: increase the distance of the path between random zone and shelter.

[LLHWC3]: increase the return distance of the path between random zone and shelter.

All increments are happening within the initially given limits. Thus, if an increment is impossible, other location(s) will be chosen.

6.3.3 The proposed robust optimization algorithm

The pseudo code of the proposed algorithm is presented under Algorithm 2. The algorithm starts by solving the deterministic FSC-AEP for the base line scenario and designates the generated solution as the nominal solution. Then, in a loop, it generates a worst-case scenario $WC((S,S^{\xi})_{\xi\in\Xi})$ using the model described in section 6.3.2. If the worst case scenario has been found, the algorithm looks for the recovery solution with minimum recovery distance (we call this secondary solution) using the model described in section 6.3.1. Otherwise, it stops and returns the set of solutions identified so far.

The nominal solution is updated if the recovery distance of the last recovery solution is larger than the current maximum value. In this case all previously found secondary solutions are discarded since the new nominal solution is feasible for all scenarios known so far.

Algorithm 2: Robust optimization algorithm

Input: Instance data
Output: $(S, S^{\xi})_{\xi \in \Xi}$ – robust solution and secondary candidates

$\Xi \leftarrow \xi_0$;
$D_{\max} = 0$;
Solve deterministic problem for nominal scenario: $S \leftarrow Stoch(\Xi)$;
$(S, S^{\xi})_{\xi \in \Xi} \leftarrow (S, \emptyset)$;
while $\xi^* \leftarrow WC((S, S^{\xi})_{\xi \in \Xi})$ **do**
  $S^{\xi^*} \leftarrow SRM(S, \xi^*)$;
  $D = ObjectiveFunction(S^{\xi^*})$;
  if $D > D_{\max}$ **then**
    $D_{\max} = D$;
    $S \leftarrow Stoch(\Xi \cup \xi^*)$;
    $(S, S^{\xi})_{\xi \in \Xi} \leftarrow (S, \emptyset)$;
  else
    $(S, S^{\xi})_{\xi \in \Xi} \leftarrow (S, S^{\xi})_{\xi \in \Xi} \cup (S, S^{\xi^*})$;
  end
  $\Xi \leftarrow \Xi \cup \xi^*$;
end
return $(S, S^{\xi})_{\xi \in \Xi}$

6.3.3.1 Mapping nominal solutions to scenarios

Algorithm 2 returns the result in the form $(S, S^{\xi})_{\xi \in \Xi}$. Where S indicates the nominal solution. S^{ξ} shows that there is a list of secondary solutions corresponding to different evacuation scenarios examined, . It should be noted that the total number of returned solutions is not greater than the number of generated scenarios Ξ : $\left|(S, S^{\xi})_{\xi \in \Xi}\right| \leq |\Xi|$. Figure 6-1 illustrates the correspondence between returned solutions and scenarios.

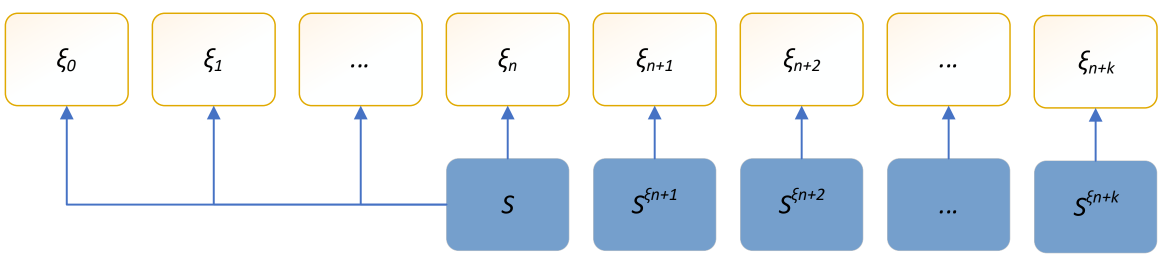

Figure 6-1. Solution-scenario compatibility

6.4 Computational results

The proposed framework was developed using Python 3.9. The tests were performed on a laptop, equipped with a 2.3 GHz Intel Core i5 (8 processors) and having 8 GB RAM.

We consider the case study of Mount Merapi eruption that has been presented in section 5.2.1 of this report. We run this instance for two alternative orderings of the objective functions: “1,2” and “2,1”, where 1 corresponds to the objective function (50), and 2 – (51). Due to the lack of data regarding the definition of the uncertainty intervals, we have used the procedure described in Appendix to define the uncertainty intervals for the case under consideration.

For the instance under consideration for each of the two optimization orderings examined we have one nominal solution and not secondary solutions. Table 6-2 and Table 6-3 present the details regarding the scenario generation part of the proposed solution approach. They include the original values for the number of people and livestock to be evacuated and travel time from the evacuation zone to every shelter, values for the last generated scenario, and worst possible case. “Last scenario” represents the selected values of corresponding parameters after which any new scenario can be solved by at least one candidate solution (in our case the nominal one).

It should be stressed here that the “Worst possible” scenario is presented only for comparison with the last scenario and that this scenario is not generated by the algorithm. Orange coloured values correspond to values that reached the upper bound of the proposed uncertainty interval. Yellow highlighted values indicate values between the defined bounds. Green colour indicates values that are still original (unchanged).

Table 6-2. Generated scenario for objective order "1,2"

	People	Livestock		Shelter 1	Shelter 2	Shelter 3	Shelter 4	Shelter 5
Original	171	165	**Distance[7]**	0.27	0.27	0.28	0.27	0.33
			Distance (return)	0.27	0.27	0.27	0.27	0.27
Last scenario	181	169	**Distance**	0.30	0.27	0.28	0.32	0.38
			Distance (return)	0.27	0.27	0.27	0.27	0.27
Worst possible	181	169	**Distance**	0.32	0.32	0.33	0.32	0.38
			Distance (return)	0.32	0.32	0.32	0.32	0.32

We observe that the scenario generation model varies according to the order that the objectives under consideration are optimized. This can be explained with the help of Table 6-4. In the deterministic case, when the order for optimizing the objectives is “1,2”, i.e., we first minimize the number of shelters and the maximum evacuation time, the optimum number of required shelters is 2. However, when the order of optimizing the objectives is reversed, i.e., “2,1” , the optimum number of required shelters is 3. . For every generated scenario the options for recovery solution are different. Consequently, when running the objective order “2,1” the values of the travel time of the links of underlying transportation network changes significantly. These changes affect the value of the Max Evacuation Time. Since the Max Evacuation Time is increased, there is no need to introduce a third shelter. This is due to the fact that even with three shelters we cannot achieve a better (lower) Max Evacuation Time.

[7] All distances in Table 6-2 and Table 6-3 are expressed in hours

Table 6-3. Generated scenario for objective order "2,1"

	People	**Livestock**		**Shelter 1**	**Shelter 2**	**Shelter 3**	**Shelter 4**	**Shelter 5**
Original	171	165	**Distance**	0.27	0.27	0.28	0.27	0.33
			Distance (return)	0.27	0.27	0.27	0.27	0.27
Last scenario	181	169	**Distance**	0.27	0.30	0.28	0.30	0.38
			Distance (return)	0.30	0.30	0.30	0.30	0.30
Worst possible	181	169	**Distance**	0.32	0.32	0.33	0.32	0.38
			Distance (return)	0.32	0.32	0.32	0.32	0.32

The comparison between the deterministic and robust optimization solutions for the two alternative orderings of the optimization of the two objectives under consideration, i.e., minimization of number of shelters and minimization of maximum time are summarized in Table 6-4. We observe that the number of dispatched vehicles is larger for the robust optimization models which is reasonable because any additional vehicle can be used to keep down the maximum evacuation time. Remaining capacity shows how many available places are in all vehicles, i.e., the number of people and livestock that can be added to the instance, while the solution remains feasible.

Table 6-4. Difference in objectives values and characteristics

		Absolute values of objectives			Remaining capacity	
Order that the objectives are optimized	Model	Number of shelters	Max Evacuation Time	Number of dispatched vehicles	People	Livestock
1,2	Deterministic	2	1 h 27 min	25	4	1
	Robust optimization	2	1 h 29 min	27	4	1
2,1	Deterministic	3	1 h 26 min	25	4	1
	Robust optimization	2	1 h 28 min	26	4	1

For the case under consideration the solution of the robust optimization model when the order for optimizing the objectives is “2,1” the resulting solution dominates the solution when the order for optimizing the objectives is reversed, i.e., “1,2”. Therefore, the non-dominated solution “1,2” could be recommended to the decision makers for possible implementation.

Concluding Remarks

In the RESPOND-OR project we have developed mathematical models and algorithms to address the deterministic assisted evacuation problem (DEAP) and the assisted evacuation problem under uncertainty (AEPUU). To this end, we have introduced a novel multi-objective shelter-allocation and assisted evacuation routing models that considers efficiency, fairness and risk objectives and heterogeneous fleet of evacuation vehicles. The kernel of the proposed multi-objective assisted evacuation models and the associated solution algorithms are generic and can be used in any assisted evacuation planning context. The country specific variants of the proposed generic model were developed by incorporating in the generic model, specific operational requirements emerging in the context of Indonesian and Sudanese assisted evacuation operations. For the case of Indonesia we have considered the coordination of the joint evacuation of people and livestock, while for the case of Sudan we have considered the constraint that evacuees from rival tribes should not be evacuated to the same shelter, and the objective that the shelters should be selected in such a way as to minimize the number of the security forces personnel needed to guard the gates of the shelters.

We have introduced exact and heuristic algorithms for solving the DAEP. For solving the FSC-AEP and TC-AEP variants of the deterministic multi-objective assisted evacuation problem we have introduced a two-stage multi-objective programming framework. At the first stage we use the risk and the travel time associated with the links of the underlying roadway network to define the efficient frontier of the complete graphs over which the evacuation routes will be optimized. At the second stage, the complete graphs are used to lexicographically optimize the efficiency, fairness, and safety objectives associated with the AEP. We have used different priority orderings for the optimization of the four objectives considered in our multi-objective formulation to generate the associated efficient frontier.

We developed a random sequence multi-objective hyper-heuristic which uses 14 lower-level heuristics to solve larger instances of both variants, FSC-AEP, and TC-AEP of the DAEP. The proposed hyper-heuristic solves the multi-objective DAEP lexicographically to approximate the associated efficient frontier. We developed a robust optimization framework for solving the AEPUU using the concept of recoverable robustness in conjunction to the random sequence multi-objective hyper-heuristic developed for the DAEP using a different set of 4 lower level heuristics.

The Multi-objective deterministic models developed in the context of the Indonesian assisted evacuation operations constitute the Assisted Evacuation Module of the RESPOND-OR Decision Support System. The mathematical models and algorithms developed to address the AEP within the framework of the RESPOND-OR project provide useful support to decision makers dealing with assisted evacuation operations in the aftermath of natural disasters. The proposed mathematical models incorporate the requirements of the decision making environment emerging in real world assisted evacuation situations. The kernel of the proposed models reflects more generic assisted evacuation requirements and as such can be use in a variety of assisted evacuation decision making settings, while the customized versions of the models reflect the requirements emerging in assisted evacuation decisions in Indonesia and Sudan. The proposed models and the associated algorithms allow decision makers to examine the trade-offs existing between efficiency, fairness, and safety objectives. However, the final choice of the assisted evacuation solution that should be implemented lies with the decision makers themselves.

References

Aalami, S. & Kattan, L., 2020. Fair transit trip planning in emergency evacuations: A combinatorial approach. *Transportation Research Part C: Emerging Technologies,* 11.p. 102760.

Abushama, Hisham; M. Ali, Hiba H. S.; Elbadawi, Khalid; Salih, Salih, 2022. *Risk Estimation and Network Generation,* -: RESPOND-OR.

Altay, N. & Green, W. G., 2006. OR/MS research in disaster operations management. *European Journal of Operational Research,* 11, Volume 175, pp. 475-493.

Amideo, A. E., Scaparra, M. P. & Kotiadis, K., 2019. Optimising shelter location and evacuation routing operations: The critical issues. *European Journal of Operational Research,* 12, Volume 279, pp. 279-295.

An, S., Cui, N., Li, X. & Ouyang, Y., 2013. Location planning for transit-based evacuation under the risk of service disruptions. *Transportation Research Part B: Methodological,* 8, Volume 54, pp. 1-16.

Bansal, N., Liu, Z. & Sankar, A., 2007. Bin-packing with fragile objects and frequency allocation in cellular networks. *Wireless Networks,* 11, Volume 15, pp. 821-830.

Ben-Tal, A. & Nemirovski, A., 2002. Robust optimization—methodology and applications. *Mathematical Programming,* 5, Volume 92, pp. 453-480.

Bish, D. R., 2011. Planning for a bus-based evacuation. *OR Spectrum,* 5, Volume 33, pp. 629-654.

Bukhtoyarov, S. E. & Emelichev, V. A., 2019. Stability Aspects of Multicriteria Integer Linear Programming Problems. *Journal of Applied and Industrial Mathematics,* 1, Volume 13, pp. 22-29.

Carvalho, V. R., Özcan, E. & Sichman, J. S., 2021. Comparative Analysis of Selection Hyper-Heuristics for Real-World Multi-Objective Optimization Problems. *Applied Sciences,* 10, Volume 11, p. 9153.

Clautiaux, F., Dell'Amico, M., Iori, M. & Khanafer, A., 2014. Lower and upper bounds for the Bin Packing Problem with Fragile Objects. *Discrete Applied Mathematics,* 1, Volume 163, pp. 73-86.

Goerigk, M., Deghdak, K. & T'Kindt, V., 2015. A two-stage robustness approach to evacuation planning with buses. *Transportation Research Part B: Methodological,* 8, Volume 78, pp. 66-82.

Gultom, Y., Haryanto, T. & Suhartanto, H., 2021. Route Subnetwork Generation using OpenStreetMap Data for Emergency Response Problem Modeling in Indonesia. *Proceedings of the International Conference on Advanced Computer Science and Information Systems (ICACSIS),* pp. 1-6, doi: 10.1109/ICACSIS53237.2021.9631340.

Kulshrestha, A., Lou, Y. & Yin, Y., 2012. Pick-up locations and bus allocation for transit-based evacuation planning with demand uncertainty. *Journal of Advanced Transportation,* 12, Volume 48, pp. 721-733.

Lakshay & Bolia, N. B., 2020. Robust scheduling for large scale evacuation planning. *Socio-Economic Planning Sciences,* 9, Volume 71, p. 100756.

Li, M. et al., 2019. Modeling a Risk-Based Dynamic Bus Schedule Problem under No-Notice Evacuation Incorporated with Dynamics of Disaster, Supply, and Demand Conditions. *Journal of Advanced Transportation,* 1, Volume 2019, pp. 1-17.

Naghawi, H. & Wolshon, B., 2012. Performance of Traffic Networks during Multimodal Evacuations: Simulation-Based Assessment. *Natural Hazards Review,* Volume 13, pp. 196-204.

Niyomubyeyi, O. et al., 2020. A Comparative Study of Four Metaheuristic Algorithms, AMOSA, MOABC, MSPSO, and NSGA-II for Evacuation Planning. *Algorithms,* 1, Volume 13, p. 16.

Qazi, A.-N., Nara, Y., Okubo, K. & Kubota, H., 2017. Demand variations and evacuation route flexibility in short-notice bus-based evacuation planning. *IATSS Research,* Volume 41, pp. 147-152.

Ritchie, H., 2014. Natural Disasters. *Our World in Data.*

Sabouhi, F., Bozorgi-Amiri, A., Moshref-Javadi, M. & Heydari, M., 2018. An integrated routing and scheduling model for evacuation and commodity distribution in large-scale disaster relief operations: a case study. *Annals of Operations Research,* 3, Volume 283, pp. 643-677.

Sayyady, F. & Eksioglu, S. D., 2010. Optimizing the use of public transit system during no-notice evacuation of urban areas. *Computers & Industrial Engineering,* 11, Volume 59, pp. 488-495.

Shahparvari, S., Abbasi, B., Chhetri, P. & Abareshi, A., 2019. Fleet routing and scheduling in bushfire emergency evacuation: A regional case study of the Black Saturday bushfires in Australia. *Transportation Research Part D: Transport and Environment,* 2, Volume 67, pp. 703-722.

Shahparvari, S., Chhetri, P., Abbasi, B. & Abareshi, A., 2016. Enhancing emergency evacuation response of late evacuees: Revisiting the case of Australian Black Saturday bushfire. *Transportation Research Part E: Logistics and Transportation Review,* 9, Volume 93, pp. 148-176.

Wang, Y. & Wang, J., 2019. Integrated reconfiguration of both supply and demand for evacuation planning. *Transportation Research Part E: Logistics and Transportation Review,* 10, Volume 130, pp. 82-94.

Yahyaei, M. & Bozorgi-Amiri, A., 2018. Robust reliable humanitarian relief network design: an integration of shelter and supply facility location. *Annals of Operations Research,* 1, Volume 283, pp. 897-916.

Zografos, K. G. & Androutsopoulos, K. N., 2008. A decision support system for integrated hazardous materials routing and emergency response decisions. *Transportation Research Part C: Emerging Technologies,* 12, Volume 16, pp. 684-703.

Appendix

Number of people and livestock

In the assisted evacuation problem formulation (1)-(15), (18)-(23), described in section 4, for each zone v there are two parameters H_v and L_v expressing the number of people and livestock that need to be evacuated. Although in the deterministic version of the assisted evacuation problem these parameters are expressed through the use of point estimates due to the uncertainty associated with the magnitude of the damages inflicted by a natural disaster the values of these two parameters vary within an interval. In order to define the interval within which H_v and L_v vary we are using the capacities of the vehicles Q_f^H for people and Q_f^L for livestock respectively. We are using the vehicle capacities to express the range of the values of these parameters. Let say the vehicle f has two capacities Q_f^H for people and Q_f^L for livestock (only one of them is non-zero). Then we define two values representing minimum non-zero capacities for the entire fleet:

	$Q_{min}^H = \min_{f\in F, Q_f^H \neq 0} Q_f^H ,$	(69)
	$Q_{min}^L = \min_{f\in F, Q_f^L \neq 0} Q_f^L .,$	(70)

These values will represent the potential underestimation of the values of people and animals that will be evacuated. Then for each evacuation zone the interval within which the number of people and livestock that will evacuated varies is defined as follows:

	$\bar{H}_v = [H_v, H_v + Q_{min}^H]$	(71)
	$\bar{L}_v = [L_v, L_v + Q_{min}^L]$	(72)

Equations (69)-(72) suggest that for each zone at most one additional evacuation trip of the vehicle with the smallest capacity will be required to accommodate the underestimated demand.

Travel time of links

The travel time associated with the links of the underlying road network used to evacuate people and livestock from evacuation zones to shelters also may be affected by the uncertainty associated with the damages caused on the road network by the natural disasters. Therefore, the travel time associated with the links of the network may take values within an interval. The attributes of the network links are expressed through such parameters as length, maximum allowed speed, and risk.

Thus, every link e will have a nominal time d_e and a worst-case time $d_e + d_e * r_e$. The model that incorporates uncertainty assumes that for each link of the roadway network the value of travel time varies within this interval:

	$\bar{d}_e = [d_e, (1 + r_e)d_e]$	(73)

Using the interval estimation of travel time, the path between nodes i and j can be any since we are going to consider it as a standard path whose travel time equals to the sum of intervals of all links in it:

	$d_{i,j} = \left[\sum_{e\in Path(i,j)} d_e , \sum_{e\in Path(i,j)} (1 + r_e)d_e \right].$	(74)

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