

A Heuristic Approach to Flood Evacuation Planning

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ABSTRACT

Flood evacuation planning models are an important tool used in preparation for flooding events. Authorities use the plans generated by flood evacuation models to evacuate the population as quickly as possible. Contemporary models consider the whole solution space and use a stochastic search to explore and produce solutions. The one issue with stochastic approaches is that they cannot guarantee the optimality of the solution and it is important that the plans be of a high quality. We present a heuristically driven flood evacuation planning model; the proposed heuristic is deterministic, which allows the model to avoid this problem. The determinism of the model means that the optimality of solutions found can be readily verified.

Keywords

Flood Evacuation Planning, Heuristic, Deterministic, Multi-objective optimization

INTRODUCTION

Flooding is the most frequent and high-risk natural disaster to affect the UK (Defra 2012). There have been several severe flood events in the UK's recent history (Kelman 2001; Pitt 2008; Risk Management Solutions 2013). As the climate changes, more extreme weather is expected to occur – and more floods. Flooding has the potential to cause fatalities, the displacement of people and damage to the environment. The disruption caused by flooding compromises the economic development and economic activities of the community (Defra 2012). Although environmental agencies aim to reduce the likelihood of flooding by managing land, rivers, coastal systems and flood defences. However, it is a natural process that cannot be eliminated (Defra 2014).

Because floods cannot be prevented environmental agencies create flood evacuation plans, these are used by local authorities and emergency services to manage the evacuation of people in a flooded area or an area expected to flood (Environment Agency 2012; Defra 2014). The plans contain optimal or near-optimal routes to evacuate people from high-risk locations to safe locations. However, as flood waters rise some routes are no longer accessible, meaning alternative routes must be used to evacuate people. The plans are created using static maps, historical flood data for the area, and scenario-based studies predicting the extent of inundation (Defra 2014).

Flood evacuation models help environmental agencies create plans by providing them with routes to evacuate people. To meet this end, the flood evacuation models require knowledge of the road network and a set of safe locations. The safe locations, usually located on high ground, are safe from the rising flood waters and provide shelter, food, and medical assistance (Lumbroso et al. 2010). It is typical to use pre-existing buildings such as community hospitals, churches and schools as safe locations. However, areas with high population densities may, also, require temporary shelters (Cabinet Office 2014).

Flood evacuation planning models solve the problem of distributing evacuees to safe locations while minimising the evacuation time (or: distance travelled) and prevent over-allocating people to any given safe location. Minimising evacuation time is analogous to the shortest path problem and for which there exist well-established algorithms.

However, this is true for where there are no capacity constraints at safe locations, so the problem has two conflicting objectives 1) send evacuees to the closest safe location and 2) not to send too many to any single location. Contemporary models represent the problem as a Multi-Objective Problem (MOP) and solve them using evolutionary algorithms (Saadatseresht et al. 2009; Yang et al. 2015). This approach means such models inherit several disadvantages. Even with the use of evolutionary algorithms such as NSGA-II (Deb et al. 2002) that help to mitigate a fast convergence on a local optimal, the stochastic nature of evolutionary algorithm means the optimality of the solution cannot be guaranteed.

This paper proposes a new heuristically driven flood evacuation planning model. The model is a potential alternative to evolutionary (or: genetic) stochastically driven models and as a result, does not inherit the same disadvantages. The model is expected to yield high-quality solutions without performing an exhaustive exploration of the search space; this gives the model good runtime performance and scalability.

Current research (Yang et al. 2015) on flood evacuation planning identifies the flooding as a dynamic problem that needs responsive solutions. The proposed model as well as being deterministic also runs in polynomial time; the runtime characteristic means that this model may be used to find solutions in dynamic search spaces. In other words, as the search space changes, a new high-quality solution can be found by the proposed model quickly enough to satisfy the dynamic problem.

The paper is structured as follows. In the next section, there is a brief overview of the current approaches used to solve the problem of flood evacuation planning exploring the strengths and weaknesses of the different approaches and how the proposed model in this paper is expected to differ. The next section presents the proposed model alongside a numeric case study that serves to both explain and demonstrate the model. Finally, a discussion the future research interests and expectations.

FLOOD EVACUATION PLANNING RESEARCH

Evacuation planning is studied from several different perspectives ranging from models to predict evacuee behaviour, the development of methods to identify potential shelter sites, and route planning algorithms for evacuations. (Hamacher and Tjandra 2001) classified evacuation plans into two scopes, microscopic and macroscopic. Microscopic planning refers to perspectives that consider small-scale operations such as evacuee behaviour whereas macroscopic planning refers to perspectives that consider operations performed on a population. In this paper, we are concerned with models that work on the macroscopic level of evacuating an entire population.

Yamada (Yamada 1996), created two models to optimise a cities emergency evacuation plan, both models represent a city as a graph with vertices representing Places of Refuge (PR) and Residential Areas (RA). The first model considers the trivial case where there are no capacity constraints at PRs; this problem is analogous to the shortest path problem and is solved using well-established algorithms. This model is of interest, even though the problem it solves is simple, the model is used to gauge the quality of the solutions produced by his second model that considers capacity constraints at PRs. The second model treated the problem as a minimal-cost network flow problem, by creating a second graph with an addition source and sink node connected to all RAs and PRs respectively and applied known methods (Ford Jr et al. 1963). This approach has several advantages; it is a high-performance model and therefore is scalable to large problems and by the measure of the first model produces high-quality solutions. However, unlike contemporary methods (Kongsomsaksakul et al. 2005; Saadatseresht et al. 2009; Yang et al. 2015) it does not consider the evacuee allocations simultaneously, leading to potentially unfair evacuation plans.

Lu et al. (Lu et al. 2005) present a heuristic algorithm that produces sub-optimal solutions for flood evacuation planning with capacity constraints at safe locations. Their heuristic approach discovers high-quality solutions at considerably reduced computation cost, and when applied to large-scale problems found in urban areas is still performs quickly. Lu et al.'s model addresses the limitations found with linear programming approaches that can find optimal solutions, by producing time expanded graphs whereas their solution works on a single graph representation of the flooded area. Lu et al.'s model demonstrates that heuristics can generate high-quality sub-optimal answers for and their performance characteristics are desirable for large scale problems. However, their heuristic does not consider evacuee allocations simultaneously.

Kongsomsaksakul et al. (Kongsomsaksakul et al. 2005) presented flood evacuation planning as a Stackelberg game with the local authority as the (leader) determining shelter locations and evacuees as the (follower) choosing a shelter and route. Formulating the problem as a bi-level programming problem with the upper level modelling the shelter locations and a Combined Distribution and Assignment (CDA) model for the evacuees' decision as the lower problem. The bi-level programming problem is solved using a Genetic Algorithm (GA). Kongsomsaksakul et al.'s model performs a simultaneous stochastic search for solutions; this approach addresses that flood evacuation planning has multiple objectives, as modelled in the Stackelberg game, with both objectives considered at the same

time. However, the GA used in this model limits the model to small-to-medium sized problems as the GA dominates the total runtime. The stochastic search also does not provide any guarantee of the discovered solution's optimality.

To create effective evacuation plans, it is important that models have access to geospatial data. A Geographic Information System (GIS) can provide this data as well as methods for route planning, and flood modelling (Mansourian et al. 2006; Chen et al. 2009; Saadatseresht et al. 2009) utilise GIS in their work on emergency management and evacuation planning. Although using GIS-assisted models is a relatively recent development, there were geospatial components in older models too.

Saadatseresht et al. (Saadatseresht et al. 2009) use a GIS in conjunction with a multi-objective evolutionary algorithm to create a GIS-assisted evacuation planning model. Saadatseresht et al.'s model simultaneously considers two objective functions, 1) population assigned to the each safe area is less than or equal to its capacity. 2) Buildings with the largest populations have priority over those with smaller populations. The first objective is common sense as we cannot assign more evacuees to safe areas than there is available space. The second objective reduces the cumulative time of evacuation for the population. In other words, the greatest number of people reach safe areas in the shortest time. It can be seen that the two objectives conflict with one another. Saadatseresht et al. treat the problem as a multi-objective optimisation problem while considering two objectives simultaneously. An evolutionary approach is used namely, NSGA-II (Deb et al. 2002) which helps to prevent an early convergence on a local optimal and provides mild performance improvements over other evolutionary approaches (Deb et al. 2002; Saadatseresht et al. 2009). The model considers all allocations simultaneously and uses an evolutionary approach that mitigates some of the associated disadvantages. However, the stochastic search does not guarantee the optimality of the discovered solution.

In 2015, Yang et al. proposed the first dynamic flood evacuation planning model. Their model is dynamic because it considers the extent of inundation. In other words, during a flood event, their model is aware that some routes will become inaccessible due to the rising flood waters and provide an updated evacuation plan. Yang et al.'s model must update the evacuation plan at regular intervals to maintain its dynamic property. The problem is encoded as a binary optimisation problem, and the model uses a Genetic Algorithm (GA) to solve it, this encoding gives the model high performance as the GA only needs to modify a decision variable. Yang et al.'s model has a time-critical constraint and presents the need for efficient models that produce high-quality solutions. Similar to (Saadatseresht et al. 2009) the fitness function used to evaluate the population simultaneously considers all allocations and the binary optimisation encoding allows this model to perform much quicker. However, the stochastic search does not guarantee the optimality of the discovered solution.

The model proposed in this paper uses a heuristic to find high-quality non-optimal solutions for the problem of distributing evacuees to safe locations during a flooding event. The model considers all allocations simultaneously and prioritises them based on a heuristic. The heuristic considers the relative distances of evacuation locations and safe locations, as well as the capacity constraints at safe locations. The model can be briefly described in the following steps. First, initialise all possible evacuation to safe locations allocations. Order the allocations based on the heuristic function, select the current 'best' allocation and add it to the flood evacuation plan. Apply the heuristic to the remaining allocations and repeat the selection process until all evacuation locations have been assigned. It can be seen that after each selection the model considers all remaining allocations simultaneously.

The proposed model assesses the multi-objective problem in a similar fashion to that of the evolutionary/genetic approaches already discussed in this section except there is not a stochastic exploration of the search space, which is the reason they cannot guarantee the optimality of the discovered solutions. The model proposed avoids the search and therefore does not inherit the same disadvantage. It should also be easier to verify the quality of solutions as the approach is deterministic. Similar to (Lu et al. 2005) the approach should have a relatively high performance and scale to large problem sets, due to the heuristic approach. The proposed model uses normalised relative distances, this allows the model to distribute evacuees fairly, but that loss of information can result in non-optimal solutions.

HEURISTIC FLOOD EVACUATION PLANNING MODEL

The present section describes the new heuristic model alongside a numeric case study which is used to describe and demonstrate the model. The model solves the problem of allocating evacuees located at evacuation locations to different safe locations while minimising evacuation time (or: distance traveled) while considering the capacity constraints at safe locations.

The first part of the model requires that a set of evacuation and safe locations be known, in this paper it is assumed that local authorities have taken such measures in preparation for a flood event. The chosen safe locations should be secure from the effects of inundation and have enough space to accommodate evacuees.

Numeric Case Study

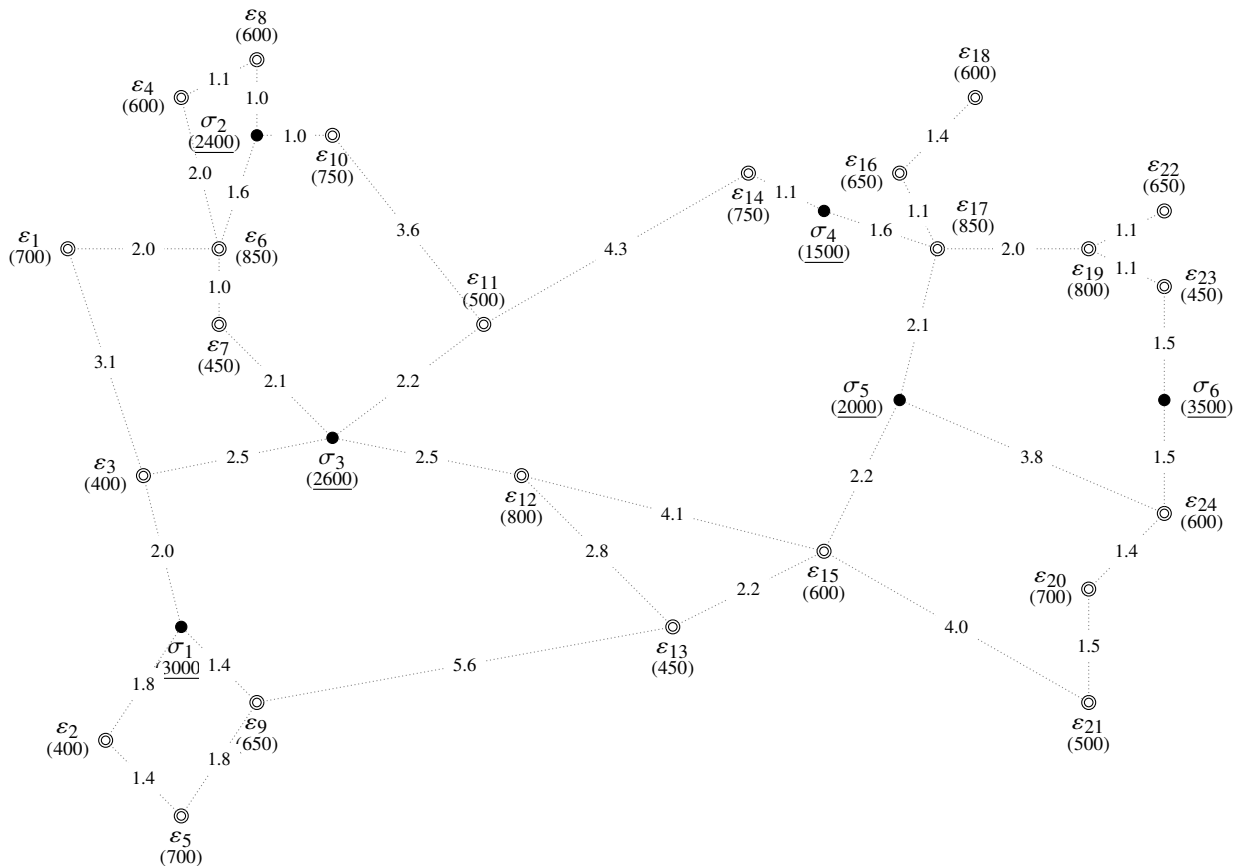


Figure 1. Numeric Case Study

Figure 1 is the numeric case study examined in this paper; the figure shows a graph with safe locations as filled vertices labelled with σ 's and evacuation locations as unfilled doubled bordered vertices labelled with ϵ 's. The line (or: edge) between any two vertices represents a route between them, and the distance is labelled at the midpoint. The distance between vertices that are not adjacent to one another is calculated as the sum of all edges visited on the path between the respective vertices. The population at each evacuation location and the capacity at each safe location is shown in brackets at each node label. In the numeric case study, there is a total of 15 000 evacuees and 15 000 available spaces at the safe locations.

Shortest Path Trees

The first step in the model is to calculate the shortest paths for all evacuation locations to each safe location. In this model shortest path trees are used to answer these queries. For each safe location, the model creates a shortest path tree as shown in Figure 2 with the respective safe locations as the roots of the trees. Well established algorithms such as Dijkstra's algorithm can be used to create the shortest path trees.

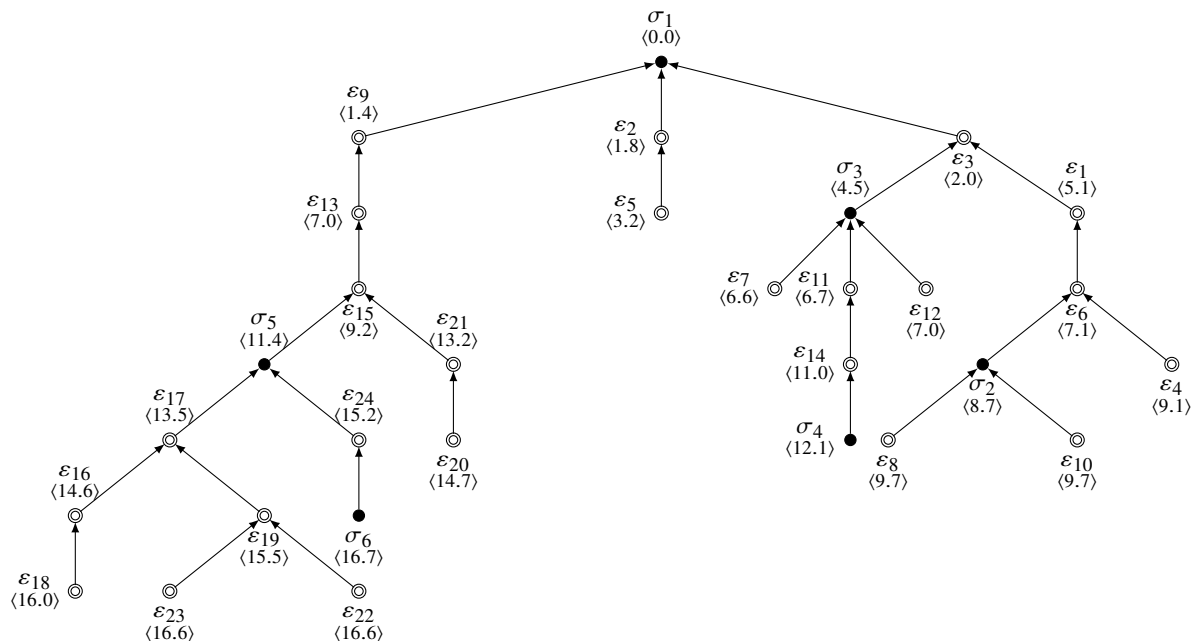


Figure 2. σ_1 Shortest Path Tree

Figure 2 shows the shortest path tree for the safe location σ_1 . It can be seen that the tree contains more than just the shortest path distances for each location and σ_1 , it also contains all of the shortest paths too. This is confirmed by taking any child node in the tree and repeatedly following the parent edge until the root node is reached.

When the shortest path trees are constructed the shortest path for each evacuation location to any safe location is answered by querying the respective shortest path tree. The set of shortest paths can be represented as a shortest path matrix as shown in Figure 3. Note, the shortest path distances between safe locations are intentionally left out.

The model considers the relative distances of evacuation locations and safe locations over a given shortest path tree this is important as it allows a fair distribution over relative distance between trees (or: safe locations). The values in the shortest path matrix are normalised between 0.25 and 0.75 as shown in Figure 4. Note, the values are normalised so that the lower bound is greater than 0, this is important as a normalisation that allows a relative distance value of 0 would effectively delete the distance component of the heuristic, leading to unfair assignments.

	σ_1	σ_2	σ_3	σ_4	σ_5	σ_6
ε_1	5.1	3.6	5.1	12.7	13.9	18.9
ε_2	1.8	10.5	6.3	13.9	13.2	18.5
ε_3	2.0	6.7	2.5	10.1	11.3	16.3
ε_4	9.1	2.1	5.1	12.1	13.9	18.3
ε_5	3.2	11.9	7.7	15.3	11.8	17.1
ε_6	7.1	1.6	3.1	10.7	11.9	16.9
ε_7	6.6	2.6	2.1	9.7	10.9	15.9
ε_8	9.7	1.0	5.7	11.0	14.5	17.2
ε_9	1.4	10.1	5.9	13.5	10.0	15.3
ε_{10}	9.7	1.0	5.7	9.0	12.7	15.2
ε_{11}	6.7	4.6	2.2	5.4	9.1	11.6
ε_{12}	7.0	7.2	2.5	10.0	6.3	11.6
ε_{13}	7.0	10.0	5.3	8.1	4.4	9.7
ε_{14}	11.0	8.9	6.5	1.1	4.8	7.3
ε_{15}	9.2	11.3	6.6	5.9	2.2	7.5
ε_{16}	14.6	12.7	10.3	2.7	3.2	5.7
ε_{17}	13.5	11.6	9.2	1.6	2.1	4.6
ε_{18}	16.0	14.1	11.7	4.1	4.6	7.1
ε_{19}	15.5	13.6	11.2	3.6	4.1	2.6
ε_{20}	14.7	16.8	12.1	8.9	5.2	2.9
ε_{21}	13.2	15.3	10.6	9.9	6.2	4.4
ε_{22}	16.6	14.7	12.3	4.7	5.2	3.7
ε_{23}	16.6	14.7	12.3	4.7	5.2	1.5
ε_{24}	15.2	17.3	12.6	7.5	3.8	1.5

Figure 3. Shortest Path Matrix

	σ_1	σ_2	σ_3	σ_4	σ_5	σ_6		σ_1	σ_2	σ_3	σ_4	σ_5	σ_6	
ε_1	5.1	3.6	5.1	12.7	13.9	18.9		ε_1	0.372	0.330	0.393	0.658	0.726	0.750
ε_2	1.8	10.5	6.3	13.9	13.2	18.5		ε_2	0.263	0.541	0.450	0.701	0.698	0.739
ε_3	2.0	6.7	2.5	10.1	11.3	16.3		ε_3	0.270	0.425	0.269	0.567	0.621	0.675
ε_4	9.1	2.1	5.1	12.1	13.9	18.3		ε_4	0.503	0.284	0.393	0.637	0.726	0.733
ε_5	3.2	11.9	7.7	15.3	11.8	17.1		ε_5	0.309	0.584	0.517	0.750	0.641	0.698
ε_6	7.1	1.6	3.1	10.7	11.9	16.9		ε_6	0.438	0.268	0.298	0.588	0.645	0.693
ε_7	6.6	2.6	2.1	9.7	10.9	15.9		ε_7	0.421	0.299	0.250	0.553	0.605	0.664
ε_8	9.7	1.0	5.7	11.0	14.5	17.2		ε_8	0.523	0.250	0.421	0.599	0.750	0.701
ε_9	1.4	10.1	5.9	13.5	10.0	15.3		ε_9	0.250	0.529	0.431	0.687	0.569	0.647
ε_{10}	9.7	1.0	5.7	9.0	12.7	15.2		ε_{10}	0.523	0.250	0.421	0.528	0.677	0.644
ε_{11}	6.7	4.6	2.2	5.4	9.1	11.6		ε_{11}	0.424	0.360	0.255	0.401	0.532	0.540
ε_{12}	7.0	7.2	2.5	10.0	6.3	11.6	\Rightarrow	ε_{12}	0.434	0.440	0.269	0.563	0.419	0.540
ε_{13}	7.0	10.0	5.3	8.1	4.4	9.7		ε_{13}	0.434	0.526	0.402	0.496	0.343	0.486
ε_{14}	11.0	8.9	6.5	1.1	4.8	7.3		ε_{14}	0.566	0.492	0.460	0.250	0.359	0.417
ε_{15}	9.2	11.3	6.6	5.9	2.2	7.5		ε_{15}	0.507	0.566	0.464	0.419	0.254	0.422
ε_{16}	14.6	12.7	10.3	2.7	3.2	5.7		ε_{16}	0.684	0.609	0.640	0.306	0.294	0.371
ε_{17}	13.5	11.6	9.2	1.6	2.1	4.6		ε_{17}	0.648	0.575	0.588	0.268	0.250	0.339
ε_{18}	16.0	14.1	11.7	4.1	4.6	7.1		ε_{18}	0.730	0.652	0.707	0.356	0.351	0.411
ε_{19}	15.5	13.6	11.2	3.6	4.1	2.6		ε_{19}	0.714	0.637	0.683	0.338	0.331	0.282
ε_{20}	14.7	16.8	12.1	8.9	5.2	2.9		ε_{20}	0.688	0.735	0.726	0.525	0.375	0.290
ε_{21}	13.2	15.3	10.6	9.9	6.2	4.4		ε_{21}	0.638	0.689	0.655	0.560	0.415	0.333
ε_{22}	16.6	14.7	12.3	4.7	5.2	3.7		ε_{22}	0.750	0.670	0.736	0.377	0.375	0.313
ε_{23}	16.6	14.7	12.3	4.7	5.2	1.5		ε_{23}	0.750	0.670	0.736	0.377	0.375	0.250
ε_{24}	15.2	17.3	12.6	7.5	3.8	1.5		ε_{24}	0.704	0.750	0.750	0.475	0.319	0.250

Figure 4. Shortest Path Matrix Normalisation

The Heuristic

The model considers all possible allocations simultaneously, corresponding to the unique row, column pairs in the shortest path matrix. A heuristic is used to sort the possible allocations so that the current best allocation is included in the flood evacuation plan.

We introduce the following notation to describe the new heuristic. Let ε_i represent the i^{th} evacuation location and let σ_j represent the j^{th} safe location. Let an allocation between ε_i and σ_j be represented by $\varepsilon_i \mapsto \sigma_j$. The capacity component weight for a given allocation is represented as $C_{\varepsilon_i \mapsto \sigma_j}$. The distance component weight for a given allocation is represented as $\mathcal{D}_{\varepsilon_i \mapsto \sigma_j}$. The sort weight for a given allocation is represented as $\mathcal{W}_{\varepsilon_i \mapsto \sigma_j}$. The normalised distance of an allocation is denoted by $NormDist_{\varepsilon_i \mapsto \sigma_j}$. The population at a given evacuation location ε_i is denoted by Pop_{ε_i} . The capacity of a given safe location σ_j is denoted by Cap_{σ_j} and the vacancies at a given safe location σ_j is denoted by Vac_{σ_j} .

$$C_{\varepsilon_i \mapsto \sigma_j} = \begin{cases} Pop_{\varepsilon_i} & \text{if } Vac_{\sigma_j} < Pop_{\varepsilon_i}, \\ Pop_{\varepsilon_i} / Vac_{\sigma_j} & \text{otherwise.} \end{cases} \quad (1)$$

$$\mathcal{D}_{\varepsilon_i \mapsto \sigma_j} = Pop_{\varepsilon_i} \cdot NormDist_{\varepsilon_i \mapsto \sigma_j} \quad (2)$$

$$\mathcal{W}_{\varepsilon_i \mapsto \sigma_j} = (\mathcal{D}_{\varepsilon_i \mapsto \sigma_j} + C_{\varepsilon_i \mapsto \sigma_j})^2 \quad (3)$$

The model considers all allocations simultaneously and sorts them on the sort weight $\mathcal{W}_{\varepsilon_i \mapsto \sigma_j}$. The current minimal allocation $\varepsilon_i \mapsto \sigma_j$ is added to the flood evacuation plan. Allocations that remain and contain ε_i are destroyed as the mapping has been satisfied. The process repeats until there are no more allocations to consider.

The capacity component in Equation 1 increases the selection pressure on allocations that map to safe locations with more vacancies. The distance component in Equation 2 increases the selection pressure on allocations that map to nearer safe locations. Finally, the sort weight is used to combine the pressures. This explains the heuristic and its use in the selection process of generating a flood evacuation plan. The model must employ a new technique to distribute evacuees from a single evacuation location to several different safe locations.

Population Division

In Figure 1 the population at each evacuation location is given in brackets below its label, this value is potentially large and without a way to divide the population between different safe locations it can be difficult to distribute the population to safe areas that are nearby. To solve this problem, the model employs a novel approach, at each evacuation location create new incident vertices with an edge distance of 0.0 and move the population from the evacuation location into the new vertices, as shown in Figure 5. The smallest population of all evacuation locations provides an upper bound for the size of the divided off populations. Then apply the model as described, the new vertices can be allocated to different safe locations.

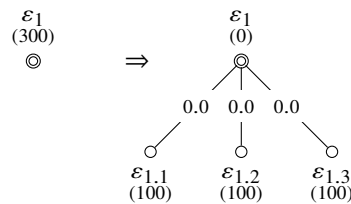


Figure 5. Population Splitting

The model as applied to the case study creates the evacuation plan as shown in Figure 6. Note, some populations are split between different safe locations.

$\varepsilon_1 \Rightarrow \sigma_1\langle 700.0 \rangle$	$\varepsilon_{13} \Rightarrow \sigma_1\langle 200.0 \rangle \sigma_3\langle 200.0 \rangle \sigma_5\langle 50.0 \rangle$
$\varepsilon_2 \Rightarrow \sigma_1\langle 400.0 \rangle$	$\varepsilon_{14} \Rightarrow \sigma_4\langle 750.0 \rangle$
$\varepsilon_3 \Rightarrow \sigma_1\langle 150.0 \rangle \sigma_3\langle 250.0 \rangle$	$\varepsilon_{15} \Rightarrow \sigma_5\langle 600.0 \rangle$
$\varepsilon_4 \Rightarrow \sigma_2\langle 200.0 \rangle \sigma_3\langle 400.0 \rangle$	$\varepsilon_{16} \Rightarrow \sigma_4\langle 150.0 \rangle \sigma_5\langle 500.0 \rangle$
$\varepsilon_5 \Rightarrow \sigma_1\langle 700.0 \rangle$	$\varepsilon_{17} \Rightarrow \sigma_5\langle 850.0 \rangle$
$\varepsilon_6 \Rightarrow \sigma_2\langle 850.0 \rangle$	$\varepsilon_{18} \Rightarrow \sigma_4\langle 600.0 \rangle$
$\varepsilon_7 \Rightarrow \sigma_3\langle 450.0 \rangle$	$\varepsilon_{19} \Rightarrow \sigma_6\langle 800.0 \rangle$
$\varepsilon_8 \Rightarrow \sigma_2\langle 600.0 \rangle$	$\varepsilon_{20} \Rightarrow \sigma_6\langle 700.0 \rangle$
$\varepsilon_9 \Rightarrow \sigma_1\langle 650.0 \rangle$	$\varepsilon_{21} \Rightarrow \sigma_1\langle 200.0 \rangle \sigma_6\langle 300.0 \rangle$
$\varepsilon_{10} \Rightarrow \sigma_2\langle 750.0 \rangle$	$\varepsilon_{22} \Rightarrow \sigma_6\langle 650.0 \rangle$
$\varepsilon_{11} \Rightarrow \sigma_3\langle 500.0 \rangle$	$\varepsilon_{23} \Rightarrow \sigma_6\langle 450.0 \rangle$
$\varepsilon_{12} \Rightarrow \sigma_3\langle 800.0 \rangle$	$\varepsilon_{24} \Rightarrow \sigma_6\langle 600.0 \rangle$

Figure 6. Flood Evacuation Plan

DISCUSSION

The optimality of solutions generated by evacuation planning models is necessary, due to the direct impact it has on emergency evacuation plans. Models that offer a guarantee of optimality are desirable as they help to reduce evacuation times. In this paper, a new heuristic evacuation model is proposed as an alternative to stochastic approaches to help mitigate some of their associated disadvantages.

The optimality of a solution is difficult to measure, one theme which is common in all literature is that evacuation plans should minimise the evacuation time. In other words, minimising the total distance that each evacuee has to travel during an evacuation. This measure does not take into account outside pressures that compete for the same resources. As a result, the plans generated may also be suboptimal. At this moment in time this limitation is not exclusive to this model, and it is believed that the impact may be reduced as this model can produce updated plans during the flooding event.

This work is part of an ongoing UK research project, and more is expected to come from this research shortly. The next step is to develop the model and test it under many different conditions, to evaluate the current design. It is also planned to test the model on large-scale real-world data to investigate the model further.

REFERENCES

- Cabinet Office (2014). *Evacuation and shelter guidance*.
- Chen, J., Hill, A. A., and Urbano, L. D. (2009). "A GIS-based model for urban flood inundation". In: *Journal of Hydrology* 373.1–2, pp. 184–192.
- Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). "A fast and elitist multiobjective genetic algorithm: NSGA-II". In: *IEEE transactions on evolutionary computation* 6.2, pp. 182–197.
- Defra (2012). *UK Climate Change Risk Assessment: Government Report*.
- Defra (2014). *The National Flood Emergency Framework for England*.
- Environment Agency (2012). *flooding-minimising the risk*.
- Ford Jr, L. R., Fulkerson, D. R., and Ziffer, A. (1963). *Flows in networks*.
- Hamacher, H. W. and Tjandra, S. A. (2001). *Mathematical modelling of evacuation problems: A state of art*. Fraunhofer-Institut für Techno-und Wirtschaftsmathematik, Fraunhofer (ITWM).
- Kelman, I. (2001). "The autumn 2000 floods in England and flood management". In: *Weather* 56.10, pp. 346–360.
- Kongsomsaksakul, S., Yang, C., and Chen, A. (2005). "Shelter location-allocation model for flood evacuation planning". In: *Journal of the Eastern Asia Society for Transportation Studies* 6, pp. 4237–4252.
- Lu, Q., George, B., and Shekhar, S. (2005). "Capacity constrained routing algorithms for evacuation planning: A summary of results". In: *International Symposium on Spatial and Temporal Databases*. Springer, pp. 291–307.
- Lumbroso, D., Johnstone, W., De Bruijn, K., Di Mauro, M., and Tagg, A. (2010). "Modelling mass evacuations to improve the emergency planning for floods in the UK, the Netherlands and North America". In: *International Conference on Emergency Preparedness (InterCEPT), the Challenges of Mass Evacuation, 21 to 23, September 2010, University of Birmingham, UK*.
- Mansourian, A., Rajabifard, A., Zoj, M. V., and Williamson, I. (2006). "Using {SDI} and web-based system to facilitate disaster management". In: *Computers & Geosciences* 32.3, pp. 303–315.
- Pitt, M. (2008). "The Pitt Review: Learning lessons from the 2007 floods". In: *Cabinet Office, London, UK*.
- Risk Management Solutions (2013). "The 2012 UK Floods". In: *RMS White Paper*.
- Saadatseresht, M., Mansourian, A., and Taleai, M. (2009). "Evacuation planning using multiobjective evolutionary optimization approach". In: *European Journal of Operational Research* 198.1, pp. 305–314.
- Yamada, T. (1996). "A network flow approach to a city emergency evacuation planning". In: *Int. J. Systems Science* 27.10, pp. 931–936.
- Yang, L., Liu, Q., Yang, S., and Yu, D. (2015). "Evacuation Planning with Flood Inundation as Inputs". In: *12th Proceedings of the International Conference on Information Systems for Crisis Response and Management, Krystiansand, Norway, May 24-27, 2015*. Ed. by L. Palen, M. Büscher, T. Comes, and A. L. Hughes. ISCRAM Association.