Adaptive short-term flood defence deployment planning

Mengke Ni[a], Tohid Erfani[a,*]

[a] *Department of Civil, Environmental and Geomatic Engineering, University College London, London, UK*

Abstract

Temporary flood defences constitute a supplementary approach to permanent engineering solutions for flood management. However, its deployment strategy is a challenge as it depends on uncertain short term weather conditions. The strategies that later prove insufficient or underused can have high social and environmental costs. Real Options Analysis (ROA) provides a mechanism to include flexibility in decision making to adapt the deployment strategies to future conditions and handle the above challenge in temporary flood defences planning. To apply ROA principles, we combine multistage stochastic programming and scenario tree. The methodology provides adaptive and flexible deployment decisions as uncertain future weather condition resolves. The proposed formulation is applied to nine flood-affected locations in Carlisle, Northwest England and the implication of the results are investigated. The results show that there is a value achieved by building ROA in design of temporary defence deployment planning under uncertainty.

1. Introduction

Flooding has always been one of the most natural disaster in the world. It has the potential to cause environment damage, severely compromise social-economic development, displace people and even lead to fatalities (Directive, 2007; Marsh et al., 2016). Flood risk management strategies implement long- and short-term flood risk management measures to reduce flood damages. Most common practices for the long-term measures are hard-engineering defences, including dams, levees and dykes (Hall et al., 2003). The majority of these long-term measures have high upfront investment and long construction time (Pitt, 2008; Abhas et al., 2008) as well as negative environment impact (Cartwright et al., 2018). In addition, they cannot always be implemented due to location specific barriers and budget constraints. Short-term measures are temporary flood defences, including metal or plastic barriers, and water or sand-filled containers (Fola Ogunyoye, 2011) that

*Corresponding author
Email address: t.erfani@ucl.ac.uk (Tohid Erfani)

are used to hold back flood water to provide flood protection for a certain period of time and removed completely when water levels have receded. Temporary flood defences are necessary and supplementary tools to the permanent long-term strategies to reduce the risks of floods (Cartwright et al., 2018). They are usually deployed where there is no protective defences or where the existing defensive measures do not provide adequate protection (Government, 2016; Rachel Brisley, 2018). In the UK, temporary defences are often used especially for economies and communities that depend on access to the river (such as river front bars and restaurants) or communities that currently cannot make large capital investment scheme at the occurrence of flooding (Cartwright et al., 2018; E.A., 2018). Given that many different locations are threatened at the same time by a single flood as well as there are usually limited availabilities of the temporary protective resource, identifying the most appropriate deployment strategy is a challenging important task.

The current temporary flood deployment strategies are developed so as to optimally deploy the resources in the UK. The strategies are based on scenarios of hydrological predictions (Pilling et al., 2016). Questions normally arise as to what deployment strategy is robust enough while adaptable to the changing future conditions. Robustness (Savic, 2005) seeks strategy that performs well in most of the circumstances and the adaptable one (Fricke and Schulz, 2005) is flexible enough to switch its course of direction as new information becomes available.

Various metrics are used to quantify robustness (Lempert et al., 2006). Robustness trades optimal performance in the sensitivity to problem's data and assumptions, however, it may become out of date as new information is gained. Unlike robustness, which does not pro-actively the strategies, the adaptable approach considers the uncertain future and responds to its conditions by adjusting the intervention schedule as future unfolds (Maestu and Gómez, 2012); including changing environment, market, regulation and technology (Fricke and Schulz, 2005). In literature, Adaptive Policy Pathway (DAPP) and Real Options Analysis (ROA) allows this.

DAPP (Haasnoot et al., 2013) combines the concepts of adaptive policy making (Kwakkel et al., 2016) and adaptation pathway (Haasnoot et al., 2013). It uses adaptation tipping point to specify conditions under which will fail when it no longer meets the specified goal (Kwadijk et al., 2010). The challenges of DAPP in flood management lies in timely detecting adaptation tipping points under high natural variability and monitoring changes of floods due to the lack of observations under extreme climates (Bloemen et al., 2018).

ROA is the right, but not the obligation to perform an action for a cost over a period of time

(De Neufville and Scholtes, 2011). ROA allows both delaying and modifying the planning strategy until they are really required. This brings a flexibility in planning that allows incorporating adaptation to future change when uncertainty is the key feature of decision problem (Dixit and Pindyck, 1994). This is through staged decision making by which costly and (on occasions) irreversible decisions are delayed until more information is available. This waiting for more information flexibility is of value in ROA where in the meantime alternative less costly and modular intervention strategies are available (Linquiti and Vonortas, 2012; Hino and Hall, 2017; Erfani et al., 2018, 2020). ROA has been implemented in different infrastructure systems planning, such as oil properties and developments (Smith and McCardle, 1998; Lazo et al., 2003), petroleum investment (Chorn and Shokhor, 2006), energy generation (Ceseña et al., 2016), maritime security (Zhang et al., 2009) and water resource system (Erfani et al., 2018). Various techniques are used to implement ROA in engineering systems design, such as Monte Carlo analysis (Chow and Regan, 2011; De Neufville and Scholtes, 2011), binomial and trinomial decision trees (Lander and Pinches, 1998; Brandão et al., 2005; Topal, 2008) and multistage stochastic programming (De Weck et al., 2004; Kapelan et al., 2005; Basupi and Kapelan, 2015; Erfani et al., 2018).

In flood risk management, combination of staged decision making and ROA are generally used (de Bruin, 2011; Linquiti and Vonortas, 2012; Woodward et al., 2014). In staged decision making, investment strategies are delayed, changed or abandoned over multiple stages; the number of decision stages defines how often the strategies are modified during the planning horizon. Most of the work in application of ROA in flood management systems focuses on large-scale infrastructure systems including evaluating flexibility in the design of flood dykes, which have demonstrated the benefits of incorporating staged decision making for long term system performance. For example, Woodward et al. (2014) designed flood protection embankments for widening or heightening over 100 years. Linquiti and Vonortas (2012) made decisions for coastal defence with a 100-year time period. Typically, those work lacks efforts in analysing flood risk management for temporary defences, especially for short-term deployment planning. This is a challenging task considering the short response time and high variability of weather conditions.

To account for this, this paper employs a multistage stochastic programming method that applies ROA principles for an optimised deployment planning for temporary flood management. We use an optimal scenario tree to represent the uncertainty space and incorporate it in the multistage decision problem plans to allow staged decisions that can be delayed, and/or modified as future unfolds.

The rest of the paper is organised as follows. The scenario tree generation method is discussed and a multistage stochastic mathematical model for temporary flood management under future river discharge uncertainty is formulated in the next section. The formulation is then applied to a case study in Carlisle in the UK and the results are discussed.

2. Staged decision making for temporary flood management

The main consideration in short term flood planning is to, on a regular basis (e.g. everyday), identify an optimal strategy to deploy the resources (e.g. temporary flood barriers) to the flood affected sites in a timely manner (e.g. for next day). The deployment plan is made with the information about the current weather condition as well as future (e.g. next 10 days) prediction. Given that the flood can affect many different sites with different degrees and that the resources are limited, identifying a strategy for short term deployment is a challenge. In practice, insufficient or underused resources deployed to the wrong flood affected site can results social, financial and environmental loss. Below we apply ROA based mechanism to tackle this challenge which allows optimally delaying and modifying the temporary flood defence strategies as future unfolds. We take two steps. In the first step, a scenario tree is optimally generated to evaluate the uncertainty space of the river discharge in the short-term planning horizon. In the second step, a multistage stochastic program is formulated on the scenario tree to obtain the optimal deployment solutions over the range of future conditions dictated by the scenario tree.

2.1. ***Scenario tree approach***

Scenario tree method is helpful as it represents the uncertainty space in form of decision stages using decomposition, reduction and clustering techniques (Heitsch and Römisch, 2003; Housh et al., 2013). The scenario stages are then become the representatives of the decision stages implied by ROA implementation. A scenario tree consists of both tree nodes and paths (Figure 1). Each node has a unique predecessor (parent node) and may have multiple successors (children node), indicating a possible realisation of the uncertain stochastic process. The paths in the scenario tree represents the relations between the nodes and are constructed to represent the uncertain future evolution in order to facilitate adaptive decisions making.

For practical purpose, identifying the number of leaves, nodes and transition probability information for each node requires accurate calculation and manually generating the above scenario

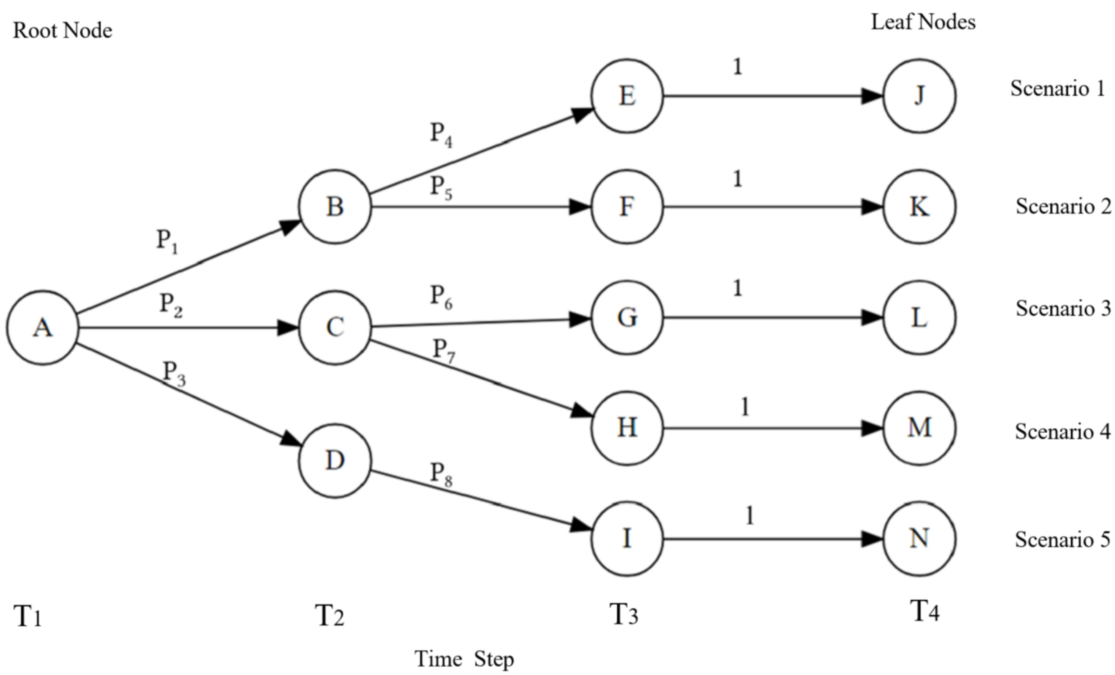

Figure 1: *A simple scenario tree with 14 nodes, represented with node as the root A , and J ,K ,L , M, N as leaf nodes. It contains four decision stages T_1 , T_2 , T_3 and T_4 as well as five scenarios with P_i the transition probabilities for each branch outcome.*

tree will result in high computational burden. Since the scenario tree will expand rapidly, this will be a major problem to implement ROA in decision-making.

To account for this, the scenario tree construction algorithm is applied. It uses the original uncertainty space to build a tree with probabilistic weights assigned to each node used in the optimisation model. We assume that the scenarios are finitely defined. ξ_i, $\xi^{\hat{j}}$ be scenarios of n-dimensional stochastic processes ξ_i,$\widetilde{\xi}$, p_i, q_j is scenario probabilities (probability distribution of the processes ξ and $\widetilde{\xi}$ respectively). Given a stochastic programming problem with a discrete initial probability distribution, the optimal scenario reduction follows this rule: a scenario subset of prescribed cardinality and a probability measure is determined based on the set which is the closest to the initial distribution in terms of a natural (or canonical) probability metric.

Let S be number of scenarios in the initial scenario set, J be index set of deleted scenarios, cJ is cardinality of the index set J; i.e., the number of deleted scenarios. s = S-cJ is number of preserved scenarios, ϵ is tolerance for the relative probability distance, and $c_t(\xi^i, \xi^j)$ is distance between scenario ξ^i, ξ^j. Let P be the set of original scenarios, Q be scenario set based on original scenarios. The algorithm works as follows:

Step 1: Calculate the minimal Kantorovich distance D_k to P calculated as follows:

$$D_k(P, Q) = \sum_{i \in J} p_i \min_{j \notin J} c_T(\xi^i, \xi^j)$$

Step 2: Calculate the probability q_j of the preserved scenarios as follows:

$$q_j = p_j + \sum_{i \in J(j)} p_i$$

Choose

$$J(j) := \{i \in J : j = j(i)\}, j(i) \in \arg\min_{j \notin J} c_T(\xi^i, \xi^j), \forall i \in J$$

Step 3: Bundling similar scenarios and reduce the number of nodes to produce a smaller, computationally accessible scenario tree through:

$$\min \left\{ \sum_{i \in J} p_i \min_{j \in J} C_T(\xi^i, \xi^j) : J \subset \{1, ..., S\}, cJ = S - s \right\}$$

Subject to

$$D_k(P, Q) < \epsilon$$

The algorithm optimally keeps the probability information of the constructed scenario tree as close to the original stochastic process as possible by bundling tree nodes into separate sets to create the most informative scenario tree. The core of the algorithm is to minimise the distance between the original uncertain space and the scenario tree so as to reduce the information loss.

2.2. ***Mathematical model establishment***

With the constructed scenario tree, in this step, we develop a multistage stochastic program to represent the staged decisions for optimal deployment strategies at each node of the scenario tree. Let N be the set of nodes in the scenario tree $N = \{1, 2, ..., n\}$, I be the set of high-risk locations and discrete time horizon T in which decisions are made at each stage $t \in T$. We define $n-1$, the predecessor nodes and $n+1$, the successor nodes for a node on each path of the scenario tree. $P(n)$ represents the probability that node n is realised derived from the scenario construction algorithm. The stochastic parameter, Q represents random discharge in the river at the upstream boundary of the flood location site for node n, where $Q \in \{Q^1, ...Q^n\}$.

We denote the current decision making stage as t,and, as Figure 2(a) shows for an example of $T = 5$, only information up to t is available. Given the data available up until t, and the prediction of next T periods, the plan at stage t is optimal for the next T periods. As time progresses to the next decision making stage (as Figure 2(b) and Figure 2(c) show two consecutive stages), the future discharge Q prediction is updated, and new deployment strategy is made. This will continue on a rolling basis to accommodate into optimal deployment planning until new information becomes available. As can be seen in Figure 2, the plan is not based on a single prediction scenario but an ensemble of them. That is, the current plan is adaptive as it sees a set of possible future scenarios that are T periods ahead and deployment decisions are made considering all future possibilities. This way, the solution is not tied to a single possibility and can be modified as future unfolds. This reduces the risk of insufficient (as in deterministic single average scenario planning) or underused (as in worst-case scenario planning) deployments plans.

This results in the following multistage stochastic model that is solved for time period t with the available information on Q, and a scenario tree for the next T time period prediction of Q:

$$min \qquad f = f_2 - f_1 \tag{1}$$

$$f_1 = \sum_{n \in N_t} \sum_{i \in I} P(n) \times CC_i \times (dB_i^n - dB_i^{n-1}) - (RC_i + MC_i) \times dB_i^n \tag{2}$$

$$f_2 = \sum_{n \in N_t} \sum_{i \in I} P(n) \times D_i(Q^n) \times dB_i^n \tag{3}$$

$$CC_i = FC_i + BD_i \times (PC + OC_i) + TC_i \tag{4}$$

$$s.t \qquad \sum_{i \in I} y_{i,n} \le \sum_{t \in T} S_t \ , \forall\ n \in \mathcal{N}_t \tag{5}$$

$$\sum_i y_{i,n} \le \sum_i BD_i, \forall\ i \in \mathcal{I}, n \in \mathcal{N}_t, \mathcal{I} \in \Omega_n \tag{6}$$

$$\sum_{i \in \mathcal{I}} dB_i^n \times BD_i \ge 1, \forall\ i \in \mathcal{I}, n \in N_t \tag{7}$$

$$dB_i^n \le dB_i^{n+1}, \forall\ n \in \mathcal{N}, i \in \mathcal{I} \tag{8}$$

$$dB_i^n \le dB_k^{n-1}, \forall n \in N, i \in I_d, k \in I_p \tag{9}$$

$$y_{i,n} = BD_i \times dB_{i,}^n, \forall\ i \in \mathcal{I}, n \in \mathcal{N}_t, \mathcal{I} \in \Omega_n \tag{10}$$

$$dB_i^n \in \{0, 1\}\ , \forall\ i \in \mathcal{I}, n \in N_t \tag{11}$$

where FC_i denotes the capital cost of deployments at flood-risk site i, BD_i is the length of temporary barrier for flood-risk site i, PC is the unit purchase cost of temporary barrier, OC_i is the unit installation cost of deploying temporary defence at flood-risk site i. TC_i is the transportation cost from storage depot to flood-risk site i; RC_i is the fixed operational cost of temporary defence for flood-risk site i; MC_i is the fixed maintenance cost for flood-risk site i. $y_{i,n}$ is amount of temporary barriers transported from storage depot to flood risk site i at node n, S is the amount of total available barriers.

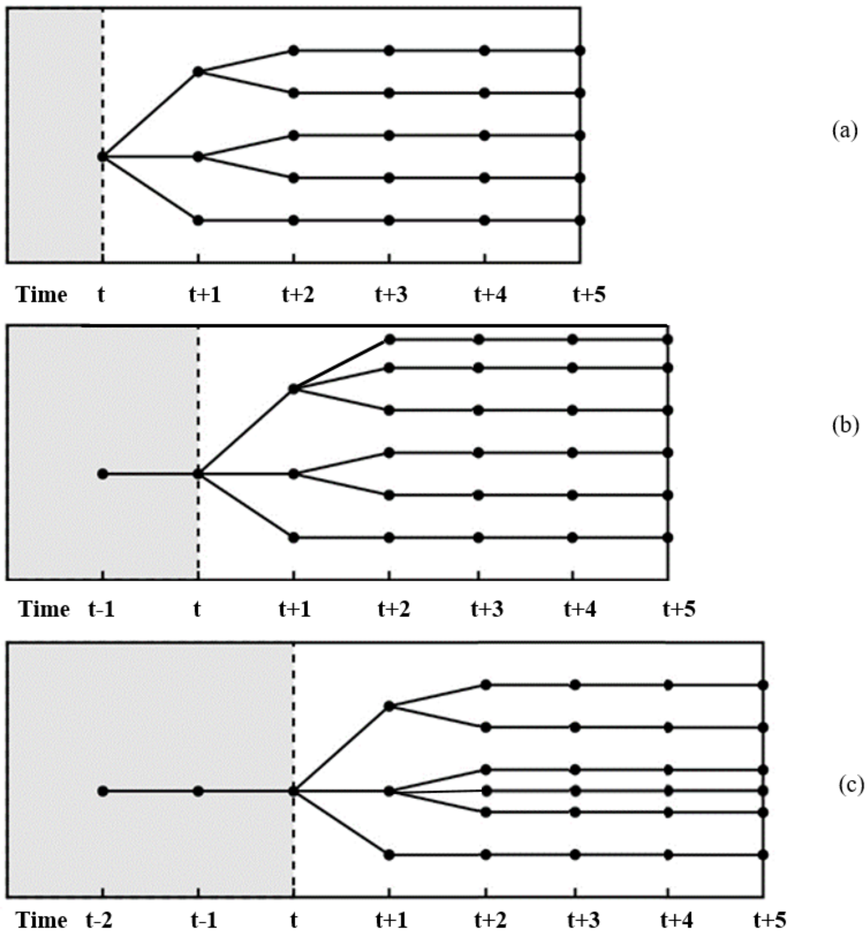

Figure 2: *Scenario tree for daily time step decision making. New decisions are made every day at stage t for the next $T = 5$ days based on available information on discharge Q (shadow area) and the prediction for the next $T = 5$ days (the scenario tree). This procedure is done on a rolling basis and new planning decision is required at each time stage t. Panel (a), (b) and (c) show three consecutive days scenario tree update for a rolling basis optimal decision making.*

In the above mathematical formulation, Constraint(3) balances storage with transported amount. Constraint(4) states that no over-shipment is allowed. Constraint (5) ensures that at least one site is chosen for deployment. Constraint(6) forces a situation that once a site deployed by defence, benefits received at the site to remain active at later stages of the scenario tree. Constraint(7) ensures that barriers can only be deployed as long as the prerequisite sites are already served shown by I_p, where I_p denotes the set of prerequisite sites, I_d indicates the set of dependent sites, deployed after I_p. Prerequisite sites are those that need to be protected before other sites as defined by EA because of political, economic, military and geographical factors. Deployment of barriers at different sites with different scenarios are non-anticipative meaning that each nodes decision in the scenario tree only depends on prior information up to time period t . Because there are a few subsequent nodes, the optimal decisions predict futures and would not exploit hindsight. Constraint(8) is the amount of barrier received at each site. Constraint(9) ensures that a site can be chosen no more than once in any period in the scenario tree.

2.3. Integration of environmental, economical and social damage

f_1 is the cost objective. It is a staged function of capital, operational and transportation cost. The transportation cost can be assessed after determining the amount of shipments, presented as $TC_i = UC_i \times \left\lceil \frac{y_{i,n}}{c_i} \right\rceil, \forall\ i \in \mathcal{I}, n \in N_t$. In the equation, TC_i presents transportation cost, UC_i is unit shipment cost and $\left\lceil \frac{y_{i,n}}{c_i} \right\rceil$ is number of shipments.

f_2 is the amount of economic loss that occurs in the absence of temporary flood defences. We estimate the loss based on Hino and Hall (2017)'s study of more than twelve estimation suggestions. We build a function that relates discharge Q^n, to function e. The function $e(Q^n) = (Q^n - Q_0)^2/(Q_{500} - Q_0)^2$ is calculated as flood damage rate, with a maximum possible damage of 1. Before reaching a certain threshold discharge Q_0, no damage will occur (no flooding, or the flood will not affect the properties), while damage increases when the discharge rate exceeds Q_0. A damage rate of 1 is assigned to the corresponding 1:500 year river discharge Q_{500}. The impact of a flood event is computed as

$$D_i(Q^n) = \sum_{ty} NB_{ty,i} \times PP_{ty,i} \times e(Q^n) \tag{12}$$

where $D_i(Q^n)$ denotes the exposed vulnerability (property damage) of river discharge amount Q at node n. ty is building type, $NB_{ty,i}$ is number of building type ty at site i and $PP_{ty,i}$ is presented as price per building type at site i.

This study evaluates the 500-year return period of flood using log-Pearson Type 3 (LP3) distribution, which is widely used in flood frequency analysis as described in (Griffis and Stedinger, 2007; Farooq et al., 2018; Bhat et al., 2019; England Jr et al., 2019). Following this, $Q_{500} = g^{-1}(500)$, where $g_X(x) = \frac{1}{\alpha x \Gamma(\beta)}(\frac{\ln x - \varepsilon}{\alpha})^{\beta-1} e^{-(\frac{\ln x - \varepsilon}{\alpha})}$, $\beta > 0, \varepsilon \leq \ln x < +\infty$, and that $\Gamma(\beta)$ is a Gamma function of β with $\alpha = \sigma_x/\sqrt{\beta}$, $\beta = (2/\gamma_x)^2$ and $\varepsilon = \mu_x\sqrt{\beta}$, with μ_x, σ_x and γ_x representing mean, standard deviation and skewness coefficient of X, which presents event of return periods in the model.

3. Application to a short-term flood management in the UK

In the UK, the Environment Agency of England and Wales (EA) has set up the Supporting Communities Remaining at Risk (SCRR) project in 2016 to reduce the impact of flooding with communities that do not currently have a permanent flood defence (E.A, 2016). Temporary flood protective barriers work by creating an artificial wall to block the discharge of water across the floodplain, preventing it reaching properties at risk without increasing the impact of flooding elsewhere (Fola Ogunyoye, 2011). These barriers, stored at depot to provide national support, are in the form of 1m-high metal frame. They are not applicable to all affected sites, potential locations have been identified with deployable length and initial barrier adjustments were designed with site walkover (E.A., 2018).

To account for the issues, EA is considering to incorporate adaptation mechanism to flexible plan for their temporary barrier deployment strategy. That said, they need to decide where to allocate their limited resources under changing discharge condition, so as to allow better use of their resources under downside conditions while providing contingencies if upside opportunities arise to reduce the risk of insufficient and underused resources.

3.1. ***UK Case Study Background***

The model built in Section 2.2 is applied to Carlisle city, located in Eden catchment, Northwest England. It is one of the most prone cities to flood risk in the UK (HMA, 2011). Disastrous flood events are historically relevant in this city with year of 1999, 2005, 2015 at the greatest disaster (Parkes and Demeritt, 2016). Flood risk management projects have been carried out during the last 50 years (Fewtrell et al., 2011; Parkes and Demeritt, 2016).Recently, EA has investigated sites with viable conditions for deploying temporary barriers making it a suitable case study for the use of the proposed flexible approach (E.A., 2018), showed in Figure 3.

3.2. ***Adaptive temporary flood management planning***

In this case study, a scenario tree is constructed to forecast the uncertain river discharge. We draw 100 uniformly distributed scenarios out of this set to represent an equiprobable scenarios stating that each scenario is not favourable over another. We use the scenario generation explained in Section 2.1 to construct an optimal scenario tree shown in Figure 4. In the scenario tree that represents the uncertain space, each scenario is a river discharge forecast, and the probability of each node and the threshold from one node to another is optimally calculated using the fast

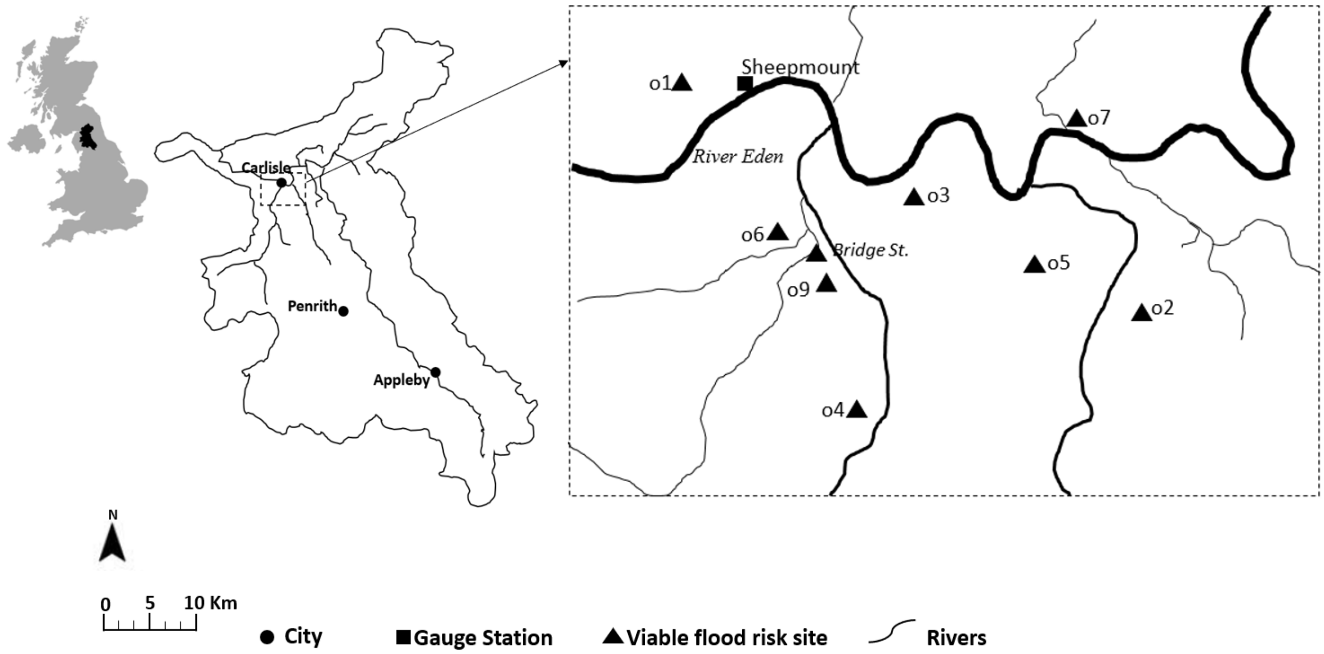

Figure 3: *Map of Carlisle, UK, showing viable flood risk sites for deploying temporary defences.*

forward algorithm explained in Appendix A. The planning horizon T is a ten discrete time periods showing a rolling 10-day ahead daily planning period. We consider nine flood-risk sites in Carlisle (named O_1 to O_9 in Table 1 and Figure 3). Those sites differ in barrier length, number of properties protected, exposed assets value, as presented in Table 1 as well as various capital, deployment and transportation costs. Some sites such as Willow Holme are industrial area, while the city centre (Corporation Rd), has more residential and commercial properties. The type of the properties in each site as well as value of assets are presented in Table 2 based on property-value tables in Multi-Coloured Manual for 2019-2020 (Penning-Rowsell et al., 2019).

4. Results and Discussion

4.1. ***Solving the temporary adaptive flood intervention planning problem over time***

We apply the multistage optimisation model described in Section 2.2 on the optimal scenario tree derived in last section. While the plan should be optimised considering the 10-day ahead flood condition, the main focus of EA is to determine proper locations to deploy protective defences in the short term, that is, to plan the optimal deployment portfolio of risky sites for the next day. Therefore, the results that are important for EA is to know the deployment plan on t_1. From the scenario tree, the discharge at t_1 is 687.35 m^3/s and for this the optimal temporary deployment

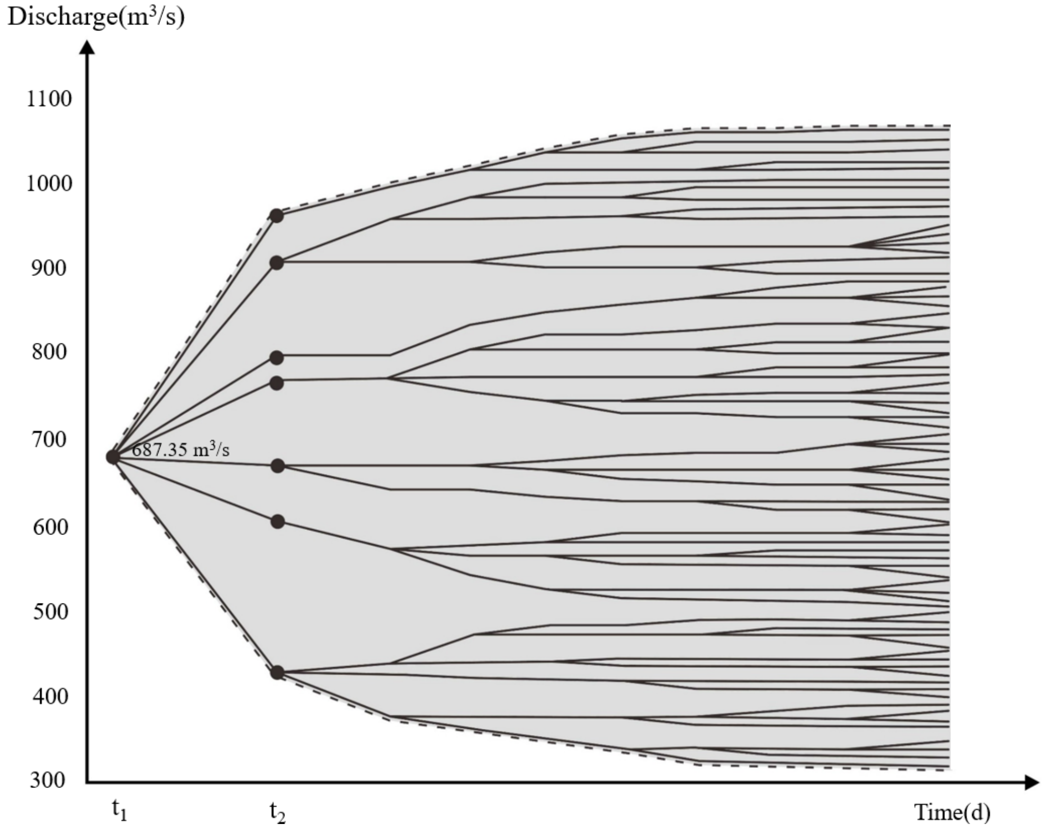

Figure 4: *Uncertain discharge range during the next 10-day planning period at Sheepmount station (grey shaded) with clustering of scenarios optimised for the planning decision for t_1.*

strategy is to send the barriers to O_2, O_3 and O_6. As discussed, this optimal plan at t_1 is re-optimised each day for the next day implementation knowing the next 10-day updated prediction at the time of decision and the past available information. This allows earlier decisions to be modified in later stages to compensates the impact of early decisions based on less accurate prediction. The scenario tree approach avoids locking the solutions to one possibility and therefore enables EA to review the plan at different decision stages. This flexibility allows EA to modify deployment plans, delay sending barriers at particular sites, or accelerate deploying them to another site and change the course of current plan as the future unfolds differently. The flexibility to deploy temporary protective defences incrementally at viable flood risk sites allows EA for increased defence supply and improved discharge scenario estimates before committing to deploy to additional locations.

*4.2. **Quantifying adaptability in the planning***

We adopt two metrics to measure how adaptable decisions are valuable by applying multistage model that incorporate ROA. They are value of stochastic solutions (VSS) and expected value of perfect information (EVPI) (Birge, 1982; Escudero et al., 2007). VSS is defined as the difference

Table 1: Possible flood-risk sites to deploy temporary barrier

Site	Site Name	Watercourses	Barrier Length(m)	Number of Properties
O_1	Etterby, Carlisle	Eden, Caldew	120	80
O_2	Botcherby,Carlisle	Eden, Petteril	400	568
O_3	Corporat Rd, Carlisle	Eden	145	136
O_4	Denton Holme,Carlisle	Eden	110	57
O_5	Warwick Rd, Carlisle	Eden	70	42
O_6	Willow Holme,Carlisle	Eden, Caldew	95	57
O_7	Rickerby,Carlisle	Eden	90	72
O_8	Bridge Street, Carlisle	Eden, Caldew	150	104
O_9	Milbourne St, Holme Terrace	Eden, Caldew	90	78

between the expected objective value of applying single scenario expected value solution and the objective function value of the stochastic problem with considering all the possible scenarios. EVPI denotes the value of information in plans under uncertainty; it measures the maximum amount of economic value that the decision maker is willing to pay in exchange for the accurate, complete and perfect information about the future. In our case, VSS presents the cost of ignoring uncertainty in making the deployment planning decision. EVPI is a measure of the flexibility to delay sending barrier to a location and take early conditional actions until more information is available.

The mathematical detail on the calculations of VSS and EVPI are presented here. Set WS as the expected value of the objective function obtained by replacing all random variables by their expected values. AP denotes the optimal solution value to the adaptive multistage stochastic problem presented in this paper. EV denotes the expected result of expected value problem and measures how the optimal solution of the expected value problem performs allowing the other stages decisions to be chosen optimally as functions of different scenarios. For EVPI, nonanticipativity constraints are relaxed at each time step so that decisions are made with perfect information about the future. In the work of Escudero et al. (2007) those parameters are generalized to the multistage case. Let the expected result in t of using the expected value solution, denoted by EV_t for $t = 2, , T$, be the optimal value of the AP model, where the decision variables until stage $t-1$, $(x_1, ...x_{t-1})$, are fixed at the optimal values obtained in the solution of the average scenario model. This sequence of nonnegative values represents the cost of ignoring uncertainty and not providing adaptive solution to future condition in the decision making of multistage models. The metrics

Table 2: Number of Properties Protected and Property Value for each site. Prices are from MCM 2019-2020 price base (Penning-Rowsell et al., 2019)

Pro	MCM Code	Building Type	Properties Protected									Price
			O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	(k£/pro.)
Resi.	111	Detached	10	100	20	14	5	13	17	18	14	375
Prop.	115	Semi	15	68	40	8	6	7	11	9	12	228
	121	Terrace	20	63	5	0	2	6	6	16	5	196
	128	Bungalow	10	24	2	4	1	3	5	7	4	233
Non-	2	Retail	5	35	36	0	2	1	6	15	5	542
Resi.	3	Offices	0	71	22	5	6	2	4	10	9	490
Prop.	4	Warehouses	0	3	0	3	2	4	6	2	2	6257
	6	Public buildings	0	5	1	3	2	0	0	1	2	1012
	8	Industry	10	22	0	10	15	16	8	15	14	929

EVPI and VSS are calculated as follows:

Step 1: Calculate the VSS and EVPI by:

$$EVPI = AP - WS \tag{13}$$

$$VSS = EV - AP \tag{14}$$

Choose

$$WS \leq AP \leq EV$$

Step 2: Calculate VSS defined in stage t

$$VSS_t = AP - EV_t, \forall t \in T \tag{15}$$

Set

$$EV_{t+1} \leq EV_t, \forall t = 1, ...T-1,$$

$$0 \leq VSS_t \leq VSS_{t+1}, \forall t = 1, ...T-1$$

Step 3: Calculate VSS and EVPI in multistage problems as:

$$VSS = \sum_{t \in T} VSS_t \tag{16}$$

and

$$EVPI = \sum_{t \in T} EVPI_t \tag{17}$$

For the Carlisle case study, VSS is £372,145 over the 10-day planning period, which accounts for almost 12% of the total cost-related and damage reduction benefit. This high VSS indicates that uncertain discharge is a significant factor in the temporary defence deployment planning for short-term flood protection, where adaptive solutions can mitigate its consequence. EVPI corresponds to about 6% of the total cost-related and damage reduction return indicating that the value of waiting for accurate information.

4.3. ***Sensitivity analysis***

Analysis is performed to assess how the deployment planning results obtained respond to changes in the underlying assumptions. This step can be treated as a way to test the robustness of deployment plan. Two assumptions are tested in this paper.

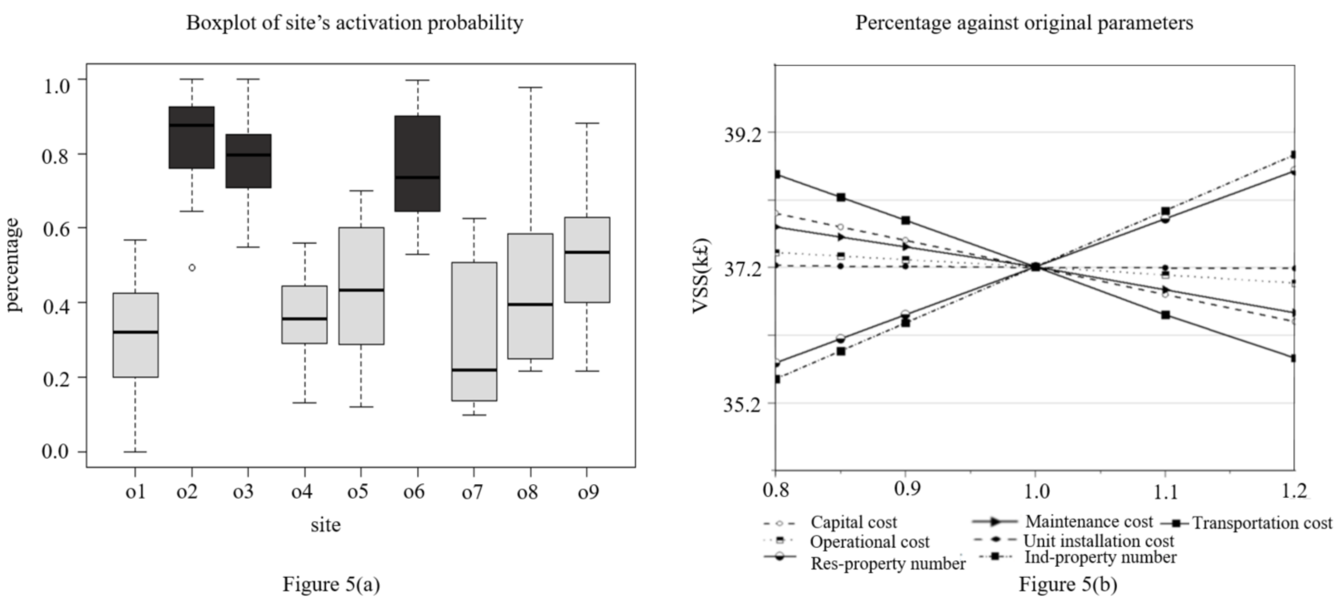

Figure 5: *(a) The probability of installing temporary barriers in each location under different structure of scenario trees at t_1. (b) Sensitivity analysis of Value of Stochastic Solution (VSS).*

Firstly, we explore the sensitivity of solutions on t_1 to change of scenario tree structures. Nine different scenario trees were generated out of the uncertain set. The results of the sensitivity analysis, shown as box-plots in Figure 5(a), presents the probability of each flood-risk site (O_1 to O_9) to deploy temporary barriers at t_1. It can be seen from the sensitivity analysis that with a high probability (more than 70%) temporary barriers are deployed at site O_2, O_3 and O_6, demonstrating the robustness of the deployment solution and indicating the influence of scenario tree structure to deployment strategy is limited for t_1. This directly follows the fact that the scenario tree is optimally driven from the uncertainty set and therefore encourage its utilisation.

Another type of sensitivity analysis is carried out to investigate the performance of VSS of changing major assumptions. Capital cost, unit installation cost, operational cost, transportation cost, maintenance cost and number of residential/industrial properties are assumed to be major influence on the performance of VSS. One-factor-at a time method (OFAT) is applied in the sensitivity analysis (Czitrom, 1999). The values of the above factors are varied by $\pm 20\%$ and 5% at each time, and VSS is re-evaluated accordingly. According to Figure 5(b), the variation of unit installation costs imposes almost no influence on the VSS. Besides, the total transportation cost is shown to affect the performance of VSS most (much stronger than the set up cost of the flood-risk sites), which indicates reduction of transportation cost will significantly increase VSS. Figure 5(b) also presents the number of industrial properties at risky sites is the most critical factor on the VSS for temporary defence deployment. The result concludes that a higher percentage of industrial properties at flood-risk sites contributes to a higher VSS; explaining the need for considering the uncertainty in deployment planning through scenario tree approach and not ignoring it.

5. Conclusion

Short term flood management is a challenge due to unknown future. Decision on deployment strategies for flood affected sites should be made on short term intervals with current information as well as future prediction that are mostly with high variability. The planning decision has high social and economical cost if the deployment strategy is insufficient or underused. This paper proposed a framework to apply ROA principles to tackle this and used multistage stochastic programming accompanied with scenario tree to apply it. The staged decision making provides the decision maker with an adaptive to river condition deployment plan that can be delayed and modified as new information of uncertain weather condition becomes available in future. The approach was applied on a case study in Carlisle, UK to assess its applicability. In the appraisal process, nine flood-risk sites with different barrier length, value of assets exposed to damage as well as various deployment costs are evaluated. The results show the benefits of ROA implementation to facilitate adaptable and flexible decision making in temporary defence planning. Specifically, ignoring uncertainty accounts for increasing the total deployment cost of 12% while incorporating flexibility has a value of 6% of the total cost. The sensitivity of solutions is analysed by varying scenario tree structures as well as evaluating the assumptions on major components in uncertainty consideration.

Data availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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