Risk-based Optimization of Adaptable Protection Measures Against Natural Hazards

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ABSTRACT: Risk protection measures against natural hazards are typically costly structures with a long lifespan. Their design should therefore take into account possible future changes in risk, e.g. due to socio-economic development and climate change. These future changes are uncertain, and one possibility for coping with these uncertainties is building adaptable risk protection systems, which allow later alterations with low cost. The challenge is to quantitatively evaluate how cost-effective such systems are. This paper proposes a formal quantitative measure of adaptability and it introduces a general decision model using Bayesian decision analysis for quantification and optimization of the risk protection systems taking into account their adaptability. The decision model is applied on a numerical example of risk-based optimization of flood protection measures under different scenarios of climate change. The numerical investigations show that for non-adaptable measures, a conservative design is recommendable, while for adaptable systems, the optimal initial capacity is lower because their potential future adjustments are not costly. Furthermore, the value of adaptability is evaluated, and it is found that building adaptable measures is not significantly more cost-effective. It is concluded that in most situations, a conservative design is preferable, as the additional risk reduction due to the conservative design is beneficial under all possible future scenarios.

1. INTRODUCTION

Risk mitigation measures, such as flood and landslide protection infrastructure, hazard zonation of built areas and hazard proofing of individual structures, reduce the probability and consequences of natural and man-made hazards. These measures often have a life-span of many decades. Their design and planning thus should take into account the possible future change in risk that is associated with uncertain future climate, socioeconomic development and societal preferences and needs (Mokrech et al., 2012; Garré and Friis-Hansen, 2013).

Research in developing methods for designing robust and/or adaptable risk mitigation measures and infrastructures is an active field (Vrijling et al., 2009; Voortman and Veendorp, 2011; Hall et al., 2012; Georgakakos et al., 2012; Kasprzyk et al., 2013; Haasnoot et al., 2013). In this paper, adaptability is understood as the ability of a system to be adjusted to new needs and requirements in the future without excessive costs.

Adaptable systems can be associated with higher initial costs than classical non-adaptable systems. For example, adaptable dikes for flood protection require a reserved space (i.e. land buyout and building restrictions) along the dike to allow future extension and heightening of the dike (Vrijling et al., 2009). Likewise, building an adaptable sewage system may require higher initial investments to central elements of the system to ensure sufficient capacity for future

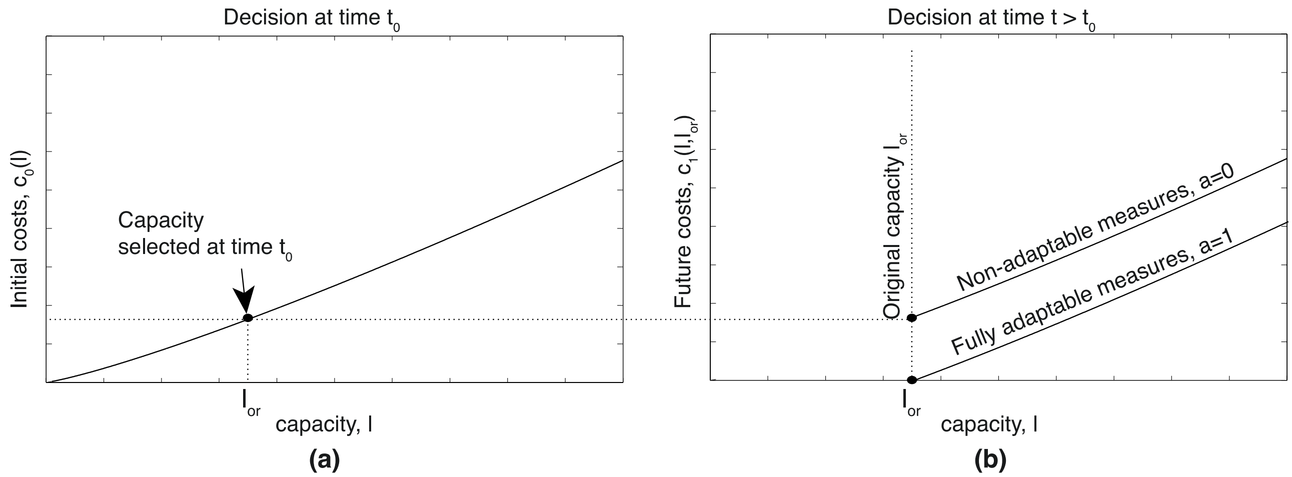

Figure 1: Illustration of the costs for fully adaptable vs. non-adaptable measures: (a) initial costs when the system is first implemented, (b) adjustment costs for adjustment of the system to new needs in the future.

extensions. In the long term, building an adaptable system may be considerably cheaper than a conservative design for a worst-case scenario or for a wide range of possible scenarios.

The challenge tackled in this paper is the quantitative evaluation of the cost-effectiveness of different risk mitigation measures, taking into account their (non-)adaptability. Classical static approaches for evaluating costs and benefits of alternatives do not take into account the future change in uncertainty and the value of adaptability thus cannot be quantified. First attempts to compare adaptable with non-adaptable strategies in a quantitative way were made only recently (e.g. Woodward et al., 2014; Yzer et al., 2014).

It is the aim of this paper to propose a formal quantitative measure of adaptability (Section 2) and to introduce a general decision framework for quantification and optimization of the systems taking into account their adaptability (Section 3). The proposed framework uses Bayesian decision analysis (BDA). BDA provides a flexible probabilistic framework for modeling a wide range of decision problems in a rigorous way, without putting restrictions on the probabilistic models to be used; it has been widely used, e.g., in inspection planning for structures and infrastructure (Corotis et al., 2005; Straub and Faber, 2005) or in health risk management (Graham et al., 2002). In Section 4, an application of the proposed decision framework is demonstrated on the example of risk-based optimization for flood protection measures.

2. ADAPTABILITY OF RISK MITIGATION SYSTEMS

A measure of adaptability should express how costly it is to adjust the capacity l of a system at a future time t, relative to the initial investment at time t_0. The capacity can be, e.g., the height of a flood protection dike in [m], the total area of a hazard zone in [km^2], or the capacity of sewage system in [m^3/day]. The capacity can be a scalar or vector value and can be defined on a continuous or discrete scale.

We propose to define the adaptability a of a system as a function of its original capacity l_{or} and the adjusted capacity l_{ad}:

$$a(l_{or}, l_{ad}) = \frac{c_0(l_{ad}) - c_1(l_{or}, l_{ad})}{c_0(l_{or})} \quad (1)$$

where $c_0(l)$ is the cost of building the system to capacity l initially, i.e. when the system is first implemented; $c_1(l_{or}, l_{ad})$ is the cost of a future adjustment of the system capacity from l_{or} to l_{ad}. For most systems, the adaptability a takes a value between 0 and 1, where 0 corresponds to a non-adaptable system and 1 to a fully adaptable system[1]. For systems with zero adaptability, the cost of increasing the capacity to l_{ad} is identical to an entirely new measure with this capacity. For measures with adaptability 1 (fully adaptable measures), the cost of increasing the protection to l_{ad} equals the difference in cost between building to l_{ad} initially and building to l_{or} initially, i.e. no additional costs are incurred by building in two steps.

For systems with a fixed value a, it is possible to express the costs of adjusting the capacity from l_{or} to l_{ad} as a function of adaptability based on Eq. (1):

$$c_1(l_{or}, l_{ad}, a) = c_0(l_{ad}) - a \cdot c_0(l_{or}) \qquad (2)$$

Initial and adjustment costs for different degrees of adaptability are illustrated in Figure 1, assuming that the capacity can only be increased, i.e. $l_{or} < l_{ad}$.

3. BAYESIAN DECISION MODEL FOR ADAPTABLE SYSTEMS

A Bayesian decision model is proposed for evaluation and optimization of infrastructure and risk mitigation measures, taking into account their adaptability. A scheme of the decision framework is shown in Figure 2. For ease of presentation, we restrict ourselves to uncertainty in future demand, and do not consider uncertainty in exposure to the hazard.

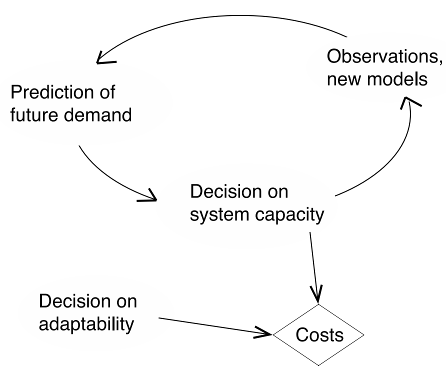

Figure 2: Scheme of the decision framework.

[1] Adaptability can be negative when adjusting the system to capacity l_{ad} is more expensive than building to this level initially, this can occur when the original system must be fully replaced and additional removal costs are thus invoked.

The capacity l of the system is selected based on a probabilistic prediction of future demand $\boldsymbol{\Theta}$. The optimal capacity is the one minimizing the Net Present Value (NPV) of costs c over the entire planning period. Potential benefits b, and risk r, i.e. expected damage, can be included as well, as will be demonstrated later in Sec. 3.3.In the future, observations $\boldsymbol{Z}$ will be made and new (improved) prediction models may become available. These will be used to update the prediction of the demand. If the new information indicates a change in the demand, an adjustment of the system capacity may be optimal. The cost of such an adjustment depend on the adaptability of the system a, which is included as a parameter in the model. It influences the costs of both the initial implementation and of future adjustments. The adaptability is here considered as constant for the entire life time of the system; it is considered to be an inherent feature of the system.

Two situations may arise: (1) The adaptability is given and the aim is to optimize the initial capacity of the system taking into account the system adaptability, i.e. the costs associated with possible future adjustments of the system. (2) The aim is to optimize both the adaptability and the initial capacity of the system. Such a situation arises when one can select from a number of systems with different adaptabilities or when the adaptability of the system can be influenced.

As illustrated in Figure 3, the time axis is discretized into N time steps (e.g. years) denoted as $i = 1, \dots. N$. In Figure 3, the decisions are made at the end of each time step (i.e. every year), but in many applications this is often not the case. The time of making the initial decision is thus denoted as t_0 and future decisions about possible adjustments of the capacity are made at discrete time instances $t_I, t_{II}, \dots t_M$.

3.1. Modeling of demand

The demand is modeled as a stochastic process. The definition and the modeling of demand are dependent on the type of system to be optimized. The demand can, e.g., correspond to the maximum annual discharge in case of designing a flood protection dike or to the maximum annual hourly rainfall in case of designing a rainwater sewage system.

Let Θ_i denote the demand in the ith time step with corresponding marginal prior Probability Density Function (PDF) $f_{\Theta_i}(\theta_i)$. We restrict ourselves to a Markov model of the demand, as is illustrated in Figure 3, hence it is necessary to define the conditional PDF $f_{\Theta_i|\Theta_{i-1}}(\theta_i|\theta_{i-1})$ of demand Θ_i in the ith time step given a demand θ_{i-1} in the previous time step.

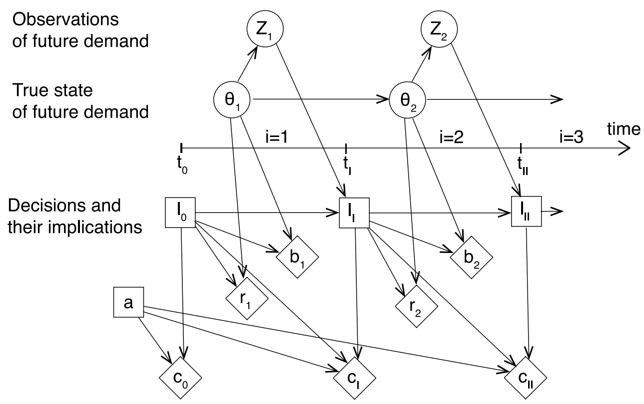

Figure 3: Decision process in time, illustrated as an influence diagram.

In many real applications, direct modeling of the demand as a Markov process is not possible. However, even non-Markovian processes can be transformed to Markovian ones through augmentation of the state space with additional variables (Rachelson et al., 2008). This can allow using existing algorithms for solving partially observable Markov decision processes POMDP (Lovejoy, 1991; Ellis et al., 1995) for evaluating the proposed model.

3.2. Observations and updating of demand

Direct or indirect observations of the system demand are made throughout the life-time of the system. When designing measures against natural hazards, the random process $\{\mathbf{\Theta}\}$ is typically only indirectly or partially observable. For example rainfall measurements, even if the measurement error is negligible, can only reduce but not eliminate the uncertainty on the parameters describing the rainfall extreme value statistics.

Let Z_i denote the observation(s) in the ith time step and $f_{Z_i|\Theta_i}(z_i|\theta_i)$ the conditional PDF of making an observation z_i for given true demand θ_i. The observations can be used to update the prediction about the true state of the demand in time step i using Bayes' rule:

$$f_{\Theta_i|Z_1,..Z_i}(\theta_i|z_1,\dots,z_i) \propto$$
$$\propto \int f_{Z_i|\Theta_i}(z_i|\theta_i)\, f_{\Theta_i|\Theta_{i-1}}(\theta_i|\theta_{i-1}) \cdot$$
$$\cdot\, f_{\Theta_{i-1}|Z_1,..Z_{i-1}}(\theta_i|z_1,\dots,z_{i-1})d\theta_{i-1} \tag{3}$$

3.3. Benefits, costs and risk

The decisions on the system capacity together with the system demand $\{\Theta\}$ determine the benefits (expected gains) and risks (expected losses) throughout the lifetime of the system. Let $b(\Theta_i, l_j)$ denote the benefits and $r(\Theta_i, l_j)$ the risk in the ith time step. They are functions of the demand Θ_i in the ith time step and the capacity l_j, which was selected at the last preceding decision time $t_j < i$. In Figure 3, the benefits and risk in ith time step are denoted as b_i and r_i. c_j is the cost of implementing capacity l_j at time t_j.

In certain decision problems, benefits or risk can be disregarded. For example, in risk-based optimization of flood mitigation systems, other benefits than the risk reduction itself are typically not taken into account (Špačková and Straub, 2014). If legal requirements necessitate that risk mitigation measures are designed for a certain return period of the hazard (e.g. for a 100-year flood), the optimization reduces to a minimization of costs (Špačková et al., 2014; Dittes et al., 2014).

3.4. Optimal capacity

The optimal capacity $l_{j,opt}$ at time t_j, for $j = 0, I, II, \dots, M$, can be found by maximizing the difference between expected benefits and expected costs plus risk for the remaining life time of the system. The objective function is:

$$\max_{l_j}\left(B_{j+1}(l_j) - c_1(l_j, l_{j-1}, a) - R_{j+1}(l_j) + \Omega_{j+1}(l_j, a)\right) \quad (4)$$

where $c_1(l_j, l_{j-1}, a)$ is the NPV of the costs of increasing the capacity from l_{j-1} to l_j for given adaptability a. $B_{j+1}(l_j)$ and $R_{j+1}(l_j)$ are the NPVs of benefits and risk in time interval $j+1$ (i.e. the time until the next decision) for given capacity l_j:

$$B_{j+1}(l_j) = \int f_{\Theta_{t_j}|Z_1,\dots,Z_{t_j}}(\theta_{t_j}|z_1,\dots,z_{t_j}) \cdot \sum_{i=t_j+1}^{t_{j+1}} \left[\int b(\theta_i, l_j) f_{\Theta_i|\Theta_{t_j}}\left(\theta_i|\theta_{t_j}\right) \mathrm{d}\theta_i\right] \, \mathrm{d}\theta_{t_j} \quad (5)$$

and

$$R_{j+1}(l_j) = \int f_{\Theta_{t_j}|Z_1,\dots,Z_{t_j}}\left(\theta_{t_j}\middle|z_1,\dots,z_{t_j}\right) \cdot \sum_{i=t_j+1}^{t_{j+1}} \left[\int r(\theta_i, l_j) f_{\Theta_i|\Theta_{t_j}}\left(\theta_i|\theta_{t_j}\right) \mathrm{d}\theta_i\right] \, \mathrm{d}\theta_{t_j} \quad (6)$$

where $b(\theta_i, l_j)$ and $r(\theta_i, l_j)$ are the benefits and risk in the ith year for given capacity l_j and demand Θ_i. $f_{\Theta_i|\Theta_{t_j}}\left(\theta_i|\theta_{t_j}\right)$ is the conditional probability of demand Θ_i for given Θ_{t_j} and $f_{\Theta_{t_j}|Z_1,\dots,Z_{t_j}}(\theta_{t_j}|z_1,\dots,z_{t_j})$ is the PDF of the demand Θ_{t_j} given observations $Z_1,\dots,Z_{t_j}$ calculated using Eq. 3.

$\Omega_{j+1}(l_j, a)$ is the expected value of benefits minus risk and costs in the time period after the next decision l_{j+1}, for given capacity l_j:

$$\Omega_{j+1}(l_j, a) = B_{j+2}(l_{j+1,opt}) - R_{j+2}(l_{j+1,opt}) - c_1(l_{j+1,opt}, l_j, a) + \Omega_{j+2}(l_{j+1,opt}, a) \quad (7)$$

where $B_{j+2}(l_{j+1,opt})$ and $R_{j+2}(l_{j+1,opt})$ are the NPVs of benefits and risk, respectively, in time interval $j+2$ for the optimal capacity selected at time t_{j+1}, calculated analogously to Eqs. 5 and 6. $c_1(l_{j+1,opt}, l_j, a)$ is the NPV of the costs of increasing the capacity from l_j to $l_{j+1,opt}$ for given adaptability a. $\Omega_{j+2}(l_{j+1,opt}, a)$ is the expected value of benefits minus risk and costs in the time period after the decision at time t_{j+2} for given capacity $l_{j+1,opt}$ selected at time at time t_{j+1} and adaptability a, calculated analogously to Eq. 7.

Note that for the initial decision, i.e. for $j=0$, the term $c_1(l_j, l_{j-1}, a)$ in Eq. 4 is replaced with the initial costs $c_0(l_j, a)$. For the last decision, i.e. for $j=M$, it is $\Omega_{j+1}(l_j, a) = 0$.

This optimization problem can be solved recursively, starting from the last decision. The problem can be interpreted as a special case of a POMDP, where the state of nature θ_i does not depend on the actions taken. The optimal solution strategy in the general case is not presented here, for the sake of brevity. Instead, a numerical example is presented in the following, which is simple enough to not require a sophisticated solution strategy.

4. NUMERICAL EXAMPLE

The proposed model is applied to a hypothetical example of optimizing the capacity of flood defense under climate change uncertainty. We consider the implementation of a new flood defense at time $t_0 = 0$, whose capacity may be adjusted at time $t_I = 15$ years. An influence diagram for the example decision problem is shown in Figure 4. The time is discretized into yearly time steps, the total planning horizon is 100 years, therefore $i = 1,2,\dots,100$. The annual discount rate is 0.02.

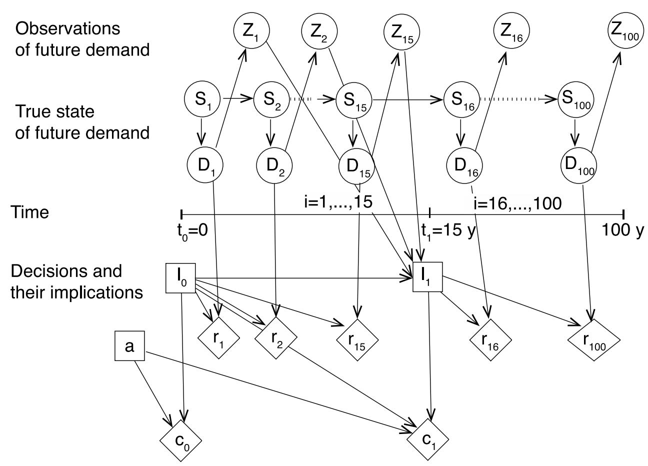

Figure 4: Influence diagram for the example decision problem.

The uncertainty in the future demand is modeled using two random variables: scenario S_i and annual maximum rainfall D_i . S_i is a discrete random variable representing the uncertainty in future climate. Three scenarios are considered: (A) no change in the future extreme precipitation, (B) moderate increase and (C) significant increase. Hence, scenario S_i consists of three states and its transition probability matrix is the 3x3 unit matrix. All scenarios are a-priori considered to be equally probable, $\Pr(S_1 = A) = \Pr(S_1 = B) = \Pr(S_1 = C) = 1/3$.

D_i is the annual maximum hourly rainfall in [mm/hour] and is described by a Weibull distribution with mean $\mu(i)$ and standard deviation $\sigma(i)$ conditional on the climate scenario as shown in Table 1. The mean and st.dev. are assumed to be linearly increasing with time, the c.o.v. is equal to 2/3 and is assumed to be constant over time.

For simplicity, the capacity of the flood protection system l is expressed in the same units as demand, i.e. in mm of rainfall per hour. Such a modeling approach is representative for the design of a sewage system as a protection against flash floods. For optimization of classical flood protection measures against river floods, the rainfall would be translated to discharge or water level using hydrologic and hydraulic modeling.

Table 1: Mean and st.dev. of annual maximum rainfall D_i [mm/h] for different climate scenarios.

Scenario S	*Mean $\mu(i)$*	*St.dev.$\sigma(i)$*
(A) no change	*15*	*10*
(B) moderate incr.	*15+0.02*i*	*10+0.013*i*
(C) significant incr.	*15+0.05*i*	*10+0.033*i*

Risk (expected damage) in the ith time step for given scenario S_i and for given capacity l_j equals:

$$r(S_i, l_j) = \int e \cdot V^{l_j}(d) \cdot f_{D_i|S_i}(d) dd \tag{8}$$

where $e = 6 \times 10^6$ Euro is exposure, $f_{D_i|S_i}(d)$ is the conditional Weibull PDF of annual maximum rainfall (demand) for given scenario and $V^{l_j}(d)$ is the vulnerability for given capacity of the protection system l_j:

$$V^{l_j}(d) = \begin{cases} 0 \; for \; d \le l_j \\ 0.01 \cdot d \; for \; l_j < d < 100 \\ 1 \; for \; d \ge 100 \end{cases} \tag{9}$$

Three different levels of adaptability are considered: full adaptability $a = 1$, intermediate adaptability $a = 0.5$ and zero adaptability $a = 0$. The initial and adjustment costs for the different capacities are shown in Figure 5, they are defined as follows:

$$c_0(l_0, a) = \gamma(a) \cdot b \cdot \sqrt{l_0} \tag{10}$$

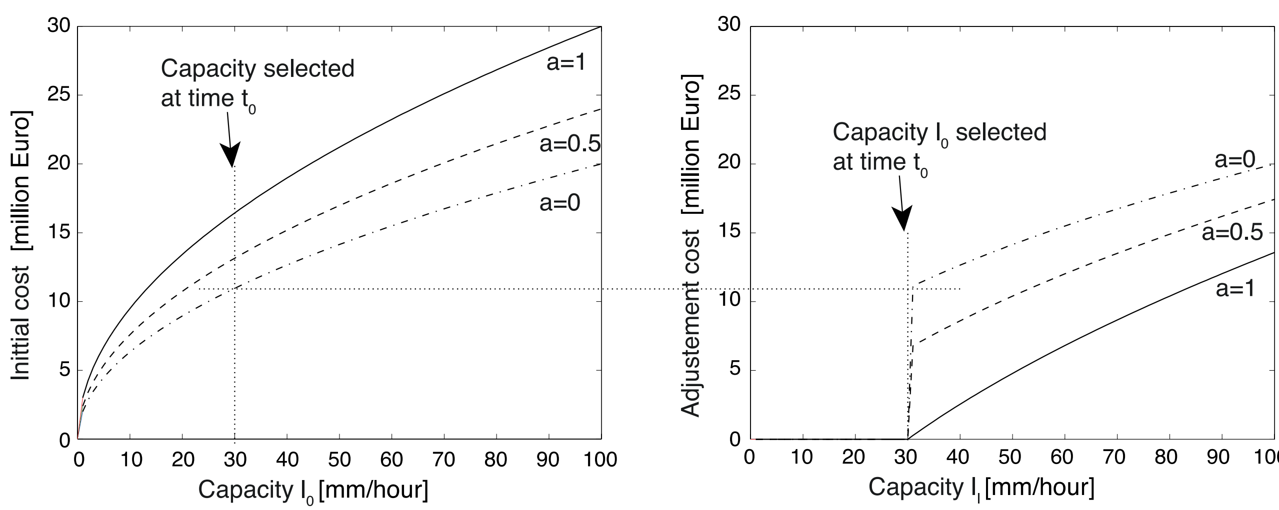

Figure 5: Costs of flood protection systems with different adaptabilities a as a function of the capacity of the system: (a) initial costs $c_0(l_0, a)$ at time $t_0 = 0$, (b) adjustment costs $c_1(l_I, l_0, a)$ at time $t_1 = 15$ years assuming that the original capacity selected at time t_0 is $l_0 = 30$ mm/h.

$$c_1(l_I, l_0, a) = \gamma(a) \cdot b \cdot \left[\sqrt{l_I} - a\sqrt{l_0}\right] \quad (11)$$

where $b = 2 \times 10^6$ Euro and $\gamma(a)$ is a coefficient representing the price of the adaptability, it is: $\gamma(0) = 1$, $\gamma(0.5) = 1.2$ and $\gamma(1) = 1.5$.

Observations of annual maximum rainfall will be made before the next decision at time $t_I = 15$ years, they are denoted as $z_1, \dots, z_{15}$. The error in measurement of the annual maximum rainfall is considered to be negligible. The observations will be used to update the probability of scenarios S_i:

$$\Pr(S_i | z_1, \dots z_{15}) \propto L(S_i | z_1, \dots z_{15}) \cdot \Pr(S_i) \quad (12)$$

wherein the likelihood of the observations is

$$L(S_i | z_1, \dots z_{15}) = \prod_{i=1}^{i=15} f_{D_i|S_i}(z_i) \quad (13)$$

Based on the updated probability of scenarios, the future decision on possible adjustment of the capacity of the flood protection system will be made at time $t_I = 15$ years. The benefits are assumed to be constant with capacity l and the objective function can thus be formulated as the minimization of the sum of risk and costs. The optimal capacity $l_{I,opt}$ for given adaptability a, observations $z, \dots, z_{15}$, and an existing capacity l_0, is obtained by (compare with Eq. 4):

$$\min_{l_I}(c_1(l_I, l_0, a) + R_{II}(l_I)) \quad (14)$$

where $c_1(l_I, l_{or}, a)$ are the costs of increasing the capacity from l_0 to l_I for given a, calculated using Eq. 11, and $R_{II}(l_I)$ is the NPV of future risk for given capacity l_I (compare with Eq. 6):

$$R_{II}(l_I) = \sum_{k=1}^{k=3} \Pr(S_i = k | z_1, \dots z_{15}) \cdot \sum_{i=16}^{i=100} r(D_i, S_i = k, l_I) \quad (15)$$

where $r(D_i, S_i = k, l_I)$ is the risk in the ith year computed using Eq. 8.

Finally, the optimal capacity $l_{0,opt}$ at time t_0 for given adaptability a can be found by (compare with Eq. 4):

$$\min_{l_0}\{c_0(l_0, a) + R_I(l_0) + \Omega_I(l_0, a)\} \quad (16)$$

where $c_0(l_0, a)$ are the costs of building to the capacity l_0 initially for given a, calculated using Eq. 10. $R_I(l_0)$ is the NPV of risk in the interval (t_0, t_I) for given capacity l_0 (compare with Eq. 6:

$$R_I(l_0) = \sum_{k=1}^{k=3} \Pr(S_i = k) \cdot \sum_{i=2}^{i=15} r(D_i, S_i = k, l_0) \quad (17)$$

and $\Omega_I(l_0, a)$ is the expected value of the sum of risk and costs from time interval II after the next decision is made (compare with Eq. 7):

$$\Omega_I(l_0, a) = R_{II}(l_{I,opt}) + c_1(l_{I,opt}, l_0, a) \quad (18)$$

To calculate the expected value of risk and costs over the future observations $Z_1, \dots, Z_{15}$ in Eq. 18, Monte Carlo simulation is applied.

5. RESULTS AND DISCUSSION

Table 2 shows the updated probability of scenarios using the 15 years of maximum rainfall observations following Eq. 12. It indicates that since the scenarios are not substantially different (the trends in mean and st.dev. are quite low), updating of their probability with only 15 years of annual maximum rainfall observations is not very informative.

Table 2: Mean updated probabilities of scenarios $Pr(S_i | Z_1, \dots Z_{15})$, given that a certain scenario is the true one.

True scenario:	*A*	*B*	*C*
$Pr(S_i = A \| Z_1, \dots Z_{15})$	*0.3357*	*0.3339*	*0.3304*
$Pr(S_i = B \| Z_1, \dots Z_{15})$	*0.3337*	*0.3334*	*0.3329*
$Pr(S_i = C \| Z_1, \dots Z_{15})$	*0.3306*	*0.3326*	*0.3367*

Figure 6 shows the results of the optimization of the initial capacity l_0 for all three evaluated adaptabilities, assuming that the adaptive measures have higher initial costs than non-adaptive ones, i.e. $\gamma(0) = 1$, $\gamma(0.5) = 1.2$ and $\gamma(1) = 1.5$ (see Eq. 10 and Figure 5). For a non-adaptable flood protection system with $a = 0$, a higher capacity $l_{0,opt} = 50$ mm/h (corresponding to a 200-year rainfall event based on the current state of the climate) is optimal because the future changes are costly and it thus makes sense to make a conservative design. For a fully adaptable system with $a = 1$, a lower capacity $l_{0,opt} = 45$ mm/h (corresponding to a 100-year rainfall event based on the current state of the climate) is optimal because the capacity can be adjusted in the future with relatively low costs (see Figure 5b). From the sum of expected costs and risks of the optimal solutions that are indicated with the solid line and black dots in Figure 6, it can be concluded for this example that adaptability is costly and that it is more economical to select non-adaptable systems together with a conservative design (higher initial capacity) of the flood protection system.

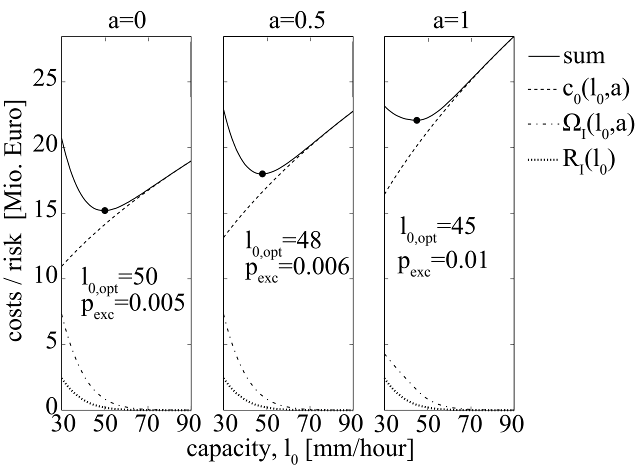

Figure 6: Results of the optimization in Eq. 16 for different adaptabilities. $l_{0,opt}$ is the optimal initial capacity in mm/h and p_{exc} is the exceedance probability of the capacity based on the current PDF of maximum annual rainfall.

Figure 7 shows alternative results of the optimization when assuming that the initial costs of adaptable and non-adaptable measures are identical, i.e. where $\gamma(0) = \gamma(0.5) = \gamma(1) = 1$ (see Eqs. 10-11). In this case, it is obviously more advantageous to choose a fully adaptable flood protection system, the sum of expected costs and risks corresponding to the optimum is lowest in the case of $a = 1$. However, the difference in sum of risk and cost for the three alternatives is low, indicating that the adaptability is not worth has little value.

Why is the benefit of adaptability low? One possible reason in the investigated example is that the effect of learning from the observations is low (Table 2), therefore the decision maker clearly has little incentives to adapt the system. To investigate this effect, we evaluate the example assuming unrealistically strong trends for scenarios B and C, as presented in Table 3 (compare with the original model from Table 1). In Table 4, the updated probability of scenarios using the 15 years of maximum rainfall observations is shown. With more pronounced differences among the scenarios, more can be learned in the first 15 years compared to the previous case (compare with Table 2).

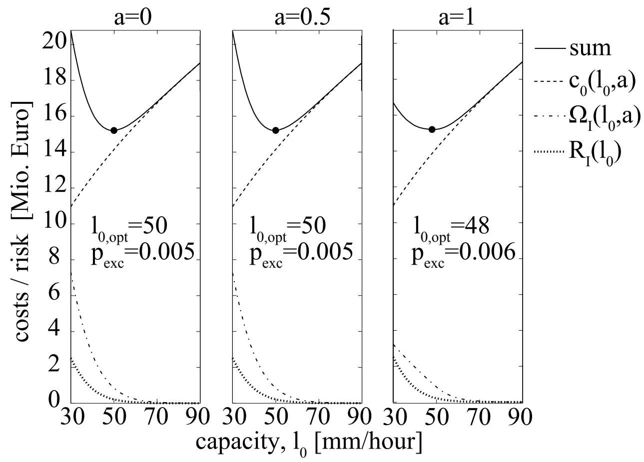

Figure 7: Alternative results of the optimization in Eq. 16 for different adaptabilities assuming that the adaptability has zero costs, i.e. $\gamma(0) = \gamma(0.5) = \gamma(1) = 1$.

Table 3: Mean and st.dev. of annual maximum rainfall D_i [mm/h] for different climate scenarios – unrealistically high increase of rainfall extremes.

Scenario S	*Mean $\mu(i)$*	*St.dev. $\sigma(i)$*
(A) no change	*15*	*10*
(B) moderate incr.	*15+0.1*i*	*10+0.067*i*
(C) significant incr.	*15+0.2*i*	*10+0.133*i*

Table 4:Mean updated probabilities of scenarios $Pr(S_i|Z_1, \dots Z_{15})$, given that a certain scenario is the true one – assuming an inflated trend in rainfall extremes following Table 3.

True scenario:	*A*	*B*	*C*
$Pr(S_i = A\|Z_1, \dots Z_{15})$	*0.3697*	*0.3353*	*0.2981*
$Pr(S_i = B\|Z_1, \dots Z_{15})$	*0.3330*	*0.3342*	*0.3326*
$Pr(S_i = C\|Z_1, \dots Z_{15})$	*0.2973*	*0.3305*	*0.3693*

The results of optimization of the initial capacity l_0 assuming the increase of rainfall extremes as shown in Table 3 and assuming that the adaptability has zero costs, i.e. that $\gamma(0) = \gamma(0.5) = \gamma(1) = 1$, are presented in Figure 8.

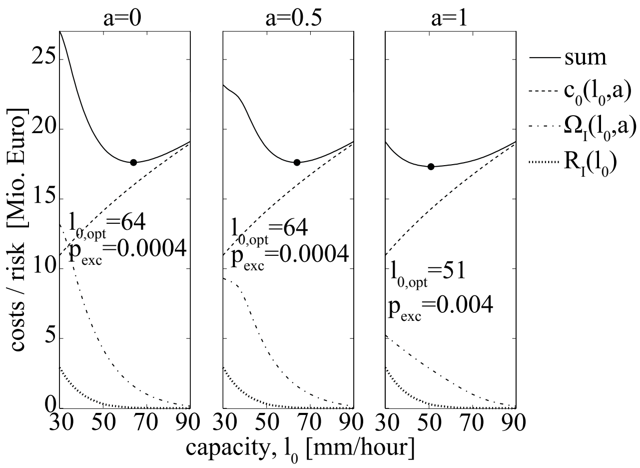

Figure 8: Alternative results of the optimization in Eq. 16 for different adaptabilities assuming that the adaptability has zero costs, i.e. $\gamma(0) = \gamma(0.5) = \gamma(1) = 1$, *and assuming artificially enhanced differences among scenarios following Table 3.*

In spite of the increased learning effect (Table 3), the value of the adaptability is low. A conservative design in case of non-adaptable (or partly-adaptable) measures is associated with similar sum of lifetime costs and risk as implementing an adaptable system (similarly to the results in Figure 7). The reason for the low value of adaptability is the fact that the amount saved when implementing an adaptable system is countervailed by the reduction of risk in case of the conservative design of a non-adabtable system.

6. CONCLUDING REMARKS

A quantitative decision model for optimization of risk mitigation measures taking into account their adaptability has been introduced, together with a formal measure of adaptability. The model is using Bayesian decision analysis and allows to probabilistically model the uncertainty in future risk (or hazard).

Application of the model is demonstrated on a hypothetical example of risk-based optimization of flood protection under three different scenarios of climate development and related changes in precipitation extremes. The numerical example demonstrates the optimization of the initial capacity of the flood risk protection as a function of the adaptability. In the example, the value of adaptability is found to be low, because the future costs saved when implementing an adaptable system are countervailed with the additional risk reduction in case of conservative design of non-adaptable systems.

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