Robby Caspeele · Luc Taerwe
Dirk Proske *Editors*

# 14th International Probabilistic Workshop

Springer

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# Preface

Probabilistic methods are currently of crucial importance for research and developments in the field of engineering, which is challenged by new materials and technologies and rapidly changing societal needs and values. Hence, the societal importance of risk and safety has significantly increased in the last decades. Contemporary needs related to, for example, performance-based design, service-life design, life cycle analysis, product optimization, assessment of existing structures, structural robustness, etc., still give rise to new developments in order to establish accurate and practically applicable probabilistic and statistical engineering methods to support these developments.

In 2003, a series of annual symposia or workshops has been established to provide a multidisciplinary forum for the exchange of knowledge and expertise in probabilistic methods, uncertainty quantification, safety and risk management, focusing on theory as well as practice and stimulating discussions on developments, and needs in this fascinating field of expertise.

Originally, the series started as the 1st and 2nd Dresdner Probabilistic Symposium in 2003 and 2004, respectively, which were launched to present research and applications that mainly dealt with at Dresden University of Technology. Since then, the series has grown to an internationally recognised conference dealing with research and applications of probabilistic techniques, mainly in the field of structural engineering.

After Dresden in 2003 and 2004, the International Probabilistic Workshop was organised in Vienna (2005), Berlin (2006), Ghent (2007), Darmstadt (2008), Delft (2009), Szczecin (2010), Braunschweig (2011), Stuttgart (2012), Brno (2013), Weimar (2014) and Liverpool (2015). For the first time, the workshop is now returning to a former location. From 5 to 7 December 2016, Ghent University will host the 14th edition of the International Probabilistic Workshop (IPW2016) once more in the beautiful city of Ghent, Belgium.

The proceedings of this 14th edition of the International Probabilistic Workshop include 36 papers, of which 2 are keynote papers, representing contributions from 14 countries. Overall, the papers relate to the following topics:

- Structural reliability methods and statistical approaches
- Probability and statistics
- Uncertainty quantification
- Uncertainty modelling
- Applied structural reliability analysis
- Risk analysis and optimization
- Probabilistic assessment of new and existing structures

The editors are grateful to all the contributing authors for their efforts and enthusiasm as well as to the Scientific Committee and the reviewers for safeguarding the quality of the Workshop's contributions.

We hope that this booklet can stimulate the research activities and interests into probabilistic applications and foster international cooperation in the field.

Ghent, Belgium — Robby Caspeele
Ghent, Belgium — Luc Taerwe
Döttingen, Switzerland — Dirk Proske
December 2016

# Organization

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# Optimizing Adaptable Systems for Future Uncertainty

**D. Straub and O. Špačková**

**Abstract** Demands on structures and infrastructures change over their service life and cannot be predicted with certainty. Adaptable (or flexible) infrastructure designs are thus potentially beneficial, enabling easier adjustments of the systems at a later stage. However, systematic quantitative investigations and corresponding recommendations are missing. In Špačková and Straub (Bayesian models for long-term adaptation decisions. Working paper, ERA Group, TU München, Germany) (2016), we present a framework for such an analysis, which is based on sequential decision processes. In this contribution, we summarize the approach and focus on the interpretation of flexibility. We show that the framework enables quantification of the *value of flexibility*, to answer the question: what is the maximum amount that should be spent additionally to ensure system flexibility? Two case studies illustrate that this value is strongly dependent on a number of factors, in particular on the types of uncertainty present and the amount of future information collected in the future.

**Keywords** Planning · Infrastructure · Risk · POMDP · Decision making · Sustainability · Adaptability

## 1 Introduction

Most structures and infrastructure are built to last, with projected service life times of 50 years or more. However, these systems are subject to changing demands from environment and users over their service life. Bridges are deteriorating and are subject to possibly increasing traffic loads, demands on dwater infrastructure are

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affected by changing climates and population development and industrial facilities undergo changes in user requirements (Hall et al. 2014; Yzer et al. 2014). If these systems cannot be adapted to the new demands, they may become inefficient or obsolete. On the other hand, increasing the flexibility or adaptability of engineering systems is typically associated with additional costs, and it may turn out to be unnecessary in the long run if demands are not changing. To further complicate the matter, safety margins against future changes in demand may be built into systems as an alternative to building adaptable systems. These margins also come at a cost though, and it is necessary to find a trade-off among safety, adaptability and risk.

Such an optimization problem can be formalized by sequential decision analysis, which was first developed by economists and was later enhanced in the field of artificial intelligence (Raiffa and Schlaifer 1961; Kochenderfer et al. 2015). In Špačková and Straub (2016), we show that the theory and the available mathematical tools are ideally suited to model infrastructure systems under uncertain future demands. The approach can account for the fact that adaptable systems may be adjusted when demands are changing or when new information is available in the future. In contrast to alternative approaches, most of which are based on real-options analysis (e.g. Neufville et al. 2006), sequential decision analysis allows to consistently address all uncertainty and decision alternatives in the process, and also can account for partial observability of the relevant processes. To facilitate the modeling process and communication, the decision process is represented by an influence diagram, similar to the proposal of Nishijima (2016).

A special focus of this contribution is on investigating the effect of a system's flexibility. It has been pointed out in the literature that flexible system designs can be advantageous under future uncertainties, such as climate change uncertainty or demand uncertainty (Hallegate 2009). Intuitively, this appears reasonable, as flexible systems can be adapted in the future with limited cost. However, formal quantitative investigations of the effect of flexibility in the context of infrastructure planning are missing. To enable such analysis, we propose a measure of flexibility in Špačková and Straub (2016). Through sequential decision analysis, one can then derive a value of flexibility and make recommendations on optimal strategies for dealing with future uncertainty. In particular, the relation between a system's flexibility and the initial safety margin can be derived. As we show, this relation depends on a number of factors, not least the amount of information that can be obtained in the future.

The generic concepts are illustrated by application to infrastructure subject to demand uncertainty and to flood management systems under climate change uncertainty.

## 2 Adaptable or Flexible Engineering Systems

Adaptable or flexible systems are designed such that they are easily adjusted to changing demands (Ross et al. 2008; Saleh et al. 2009). Examples include pipes with additional capacity for future transmission cables, buildings with structural

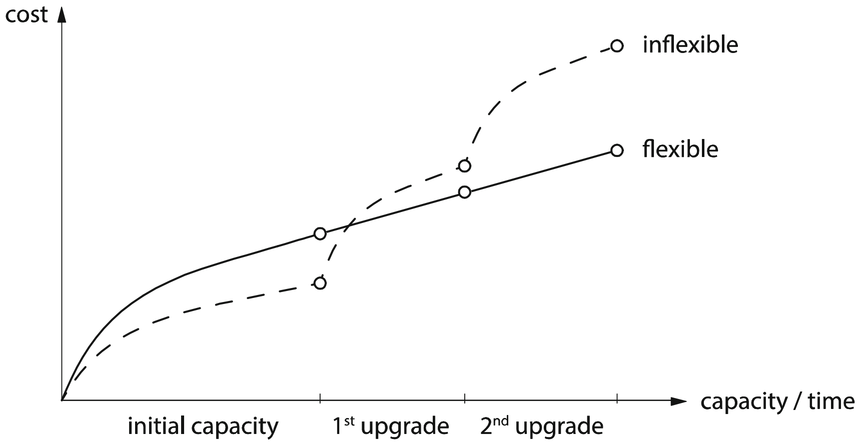


**Fig. 1** Illustration of the total development cost for a flexible versus an inflexible system. Shown are the costs associated with establishing the initial capacity and the costs associated with the 1st and 2nd upgrade conditional on existing levels of capacity. While the inflexible system is typically cheaper initially, it may lead to larger lifetime costs when updates become necessary

systems that enable flexible floor plans or flood defense systems where land for future extension is reserved. Because such flexibility comes at an additional cost, an optimization should be carried out to understand if it pays off. Furthermore, if a system is more flexible, the optimal design of the system might change (if transmission cables can be added later, fewer cables might be installed initially).

We propose to measure flexibility through the cost of establishing capacity. Conceptually, Fig. 1 shows two systems with higher and lower flexibility.

### *2.1 A Measure of Flexibility*

To formalize the analysis of flexibility, we proposed a quantitative measure $\varphi$ of flexibility in Špačková and Straub (2016) and Špačková et al. (2015). The measure is based on the costs of establishing and upgrading a system. Let $c(v)$ denote the cost of establishing a system capacity $v$ initially. In a flexible system, the cost $\Delta c$ of increasing the system capacity from a value $v'$ to a higher $v''$ should be comparable to the difference of the costs for establishing $v''$ and $v'$ initially. Therefore, one can write this upgrading cost $\Delta c$ as

$$\Delta c(v', v'') = c(v'') - \varphi \cdot c(v'). \tag{1}$$

It follows that the measure of flexibility is defined as

$$\varphi = \frac{c(v'') - \Delta c(v', v'')}{c(v')}. \tag{2}$$

All costs in Eqs. (1) and (2) are undiscounted values, since the system flexibility measure should not depend on time. The actual net present value of upgrading the system from $v'$ to $v''$ might therefore be lower than $\Delta c$ according to Eq. (1).

## 3 Sequential Decision Analysis

The optimization of infrastructure system capacity over time can be approached with sequential (Bayesian) decision analysis, which originated in mathematical economics (Raiffa and Schlaifer 1961) and was further developed in artificial intelligence and planning (e.g. Kaelbling et al. 1998; Kochenderfer et al. 2015). Decisions are optimized following the expected utility principle, which here corresponds to a minimization of expected present value life cycle costs. Uncertainties are modelled probabilistically, and the effect of future information on the uncertainties is accounted for by Bayesian analysis.

Following Špačková and Straub (2016), infrastructure capacity planning can be generically represented by a partially observable Markov decision process (POMDP). This only requires the demand process to be modelled as a Markov process.[1] The generic POMDP, and its special case, the MDP (Markov decision process), are represented by the influence diagrams (IDs) in Fig. 2. An ID is an extension of Bayesian networks that includes decision and utility (cost) nodes; the former are represented by squares, the latter by diamond-shaped nodes. IDs can mostly be understood intuitively, the detailed semantics are described e.g. in Jensen and Nielsen (2007). An important aspect of an ID are the links pointing towards a decision node. They reflect the flow of information, as they indicate that the parent node is known at the time of making the decision.

The ID of Fig. 2b shows the POMDP model, in which the demand node $\theta_t$ cannot be observed directly before a decision is made at $t+1$. Instead, an indicator variable $Z_t$ is observed, which represents partial information on the demand variable. Unfortunately, this partial observability leads to computationally challenges in identifying optimal decision policies. An introduction to POMDP is found in Kochenderfer et al. (2015). POMDP has previously been applied to planning of inspections in deteriorating structure and infrastructure (e.g. Madanat 1993; Corotis et al. 2005; Papakonstantinou and Shinozuka 2014; Memarzadeh and Pozzi 2016).

[1]As discussed in Špačková and Straub (2016), this is not a strong limitation, since most non-Markovian processes can be transformed into a Markovian process by augmenting the state space.

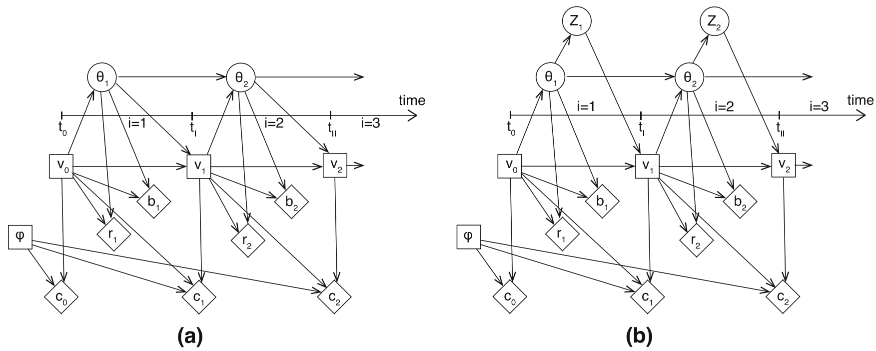


**Fig. 2** Influence diagram representing the general infrastructure capacity planning problem. **a** Markov decision process (MDP). **b** Partially observable Markov decision process (POMDP). The variables at each time step $t$ are: $\theta_t$: demand, $Z_t$: measurement, $v_t$: capacity, $\varphi$: flexibility, $b_t$: benefits, $r_t$: risk (associated with demands exceeding capacity), $c_t$: cost of system update. (Figure from Špačková and Straub 2016)

A special case of this model arises when the demand at any time $t$ can be observed with certainty. In this case, the POMDP reduces to the MDP (Fig. 2a), which is substantially easier to solve. For details on the computation of such POMDP or MDP models in the context of planning in adaptable infrastructure systems, the reader is referred to Špačková and Straub (2016).

In a POMDP/MDP, the decision to be taken at each time is described by a policy, which describes the action to be taken conditional on the available information. In an MDP, this information is the current state of demand $\varphi_t$, in the POMDP, this is the current state of belief, which summarizes all past observations. If these policies are not changing with time, they are called *stationary policies*. An approximate solution to a POMDP can be found by defining a stationary policy through a limited number of parameters **d** (a heuristic), computing the expected total utility by means of a Monte Carlo approach for a given heuristic, and then performing an optimization over **d**. Such approaches are common in risk-based inspection planning (e.g. Straub and Faber 2006).

# 4 Numerical Illustrations

## *4.1 Case 1: Infrastructure Capacity*

In this example, we consider a generic model for infrastructure capacity planning, where the demand at present is observable with high accuracy. Examples of such problems include transportation infrastructure, water resource systems or electrical power networks. The problem setting is summarized by the ID of Fig. 3. In Fig. 3a, the actual model is shown where the demand at each time step is defined conditional on the trend $\tau$, which reflects the mean change in the demand. An equivalent

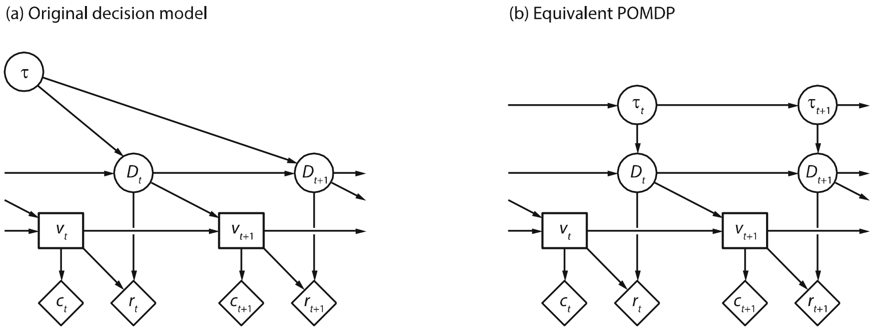


**Fig. 3** Influence diagram representing the investigated infrastructure capacity planning problem. $\tau$ is the trend in the demand, $D_t$ is the system demand, $v_t$ is the system capacity, $c_t$ is the cost associated with upgrading the system, and $r_t$ is the cost associated with the demand exceeding the capacity

POMDP is obtained by replacing the common variable $\tau$ with identical copies $\tau_t$ (corresponding to an augmentation of the state space).

The remaining uncertainty in observations of the demand $D_t$ can be neglected, therefore there is a link from $D_t$ to the decision node $v_{t+1}$, indicating direct observability of $D_t$. Note that the process is nevertheless only partially observable, because the trend variables $\tau_t$ can be inferred only indirectly.

The considered service life is 50 years, with a 2 % discounting rate. For the numerical investigation, the parameters of the model are according to Table 1. The trend is modelled by a discrete random variable with three possible scenarios. The demand is modelled as a lognormal random process.

It is assumed that decisions on upgrading system capacity are made every 5 years. A reduction of capacity is not considered, as there are no benefits associated with such a reduction.

The optimal life-cycle strategies are identified by means of the heuristic approach in combination with Monte Carlo sampling.

**Table 1** Parameters of the infrastructure capacity case study

| Parameter | Type | Description |
|---|---|---|
| Trend $\tau$ | Discrete random variable | $p_\tau(0) = 1/3, p_\tau(0.01) = 1/3, p_\tau(0.02) = 1/3$ |
| Demand $D_t$ | Lognormal random process | $D_0 = 1$<br>$\ln D_t \vert \ln D_{t-1} \sim N(\ln D_t + \tau, \sigma_{\Delta D})$<br>$\sigma_{\Delta D} = 0.05$ |
| Capacity $v_t$ | Decision process | Optimization parameter |
| Capacity cost | Function | $c(v) = \ln(1 + v)$ |
| Cost of demand | Function | $r_t = D_t - v_t$, if $D_t > v_t$, else 0 |
| Discount rate $\rho$ | Deterministic | 0.02 |

The stationary decision policy for $t > 0$ is parametrized as follows:

- Extend capacity when the demand times a tolerance parameter $\alpha$ exceeds capacity, i.e. if $\alpha \cdot D_t > v_t$.
- If the capacity is extended, then to a value $\gamma \cdot D_t$. Here, $\gamma$ represents the overdesign of a system modification.

The initial capacity is selected as $v_0 = SF \cdot D_0$, where $SF$ is a safety factor (initial overdesign). Therefore, the optimization parameters are $\mathbf{d} = [SF; \alpha, \gamma]$.

In Fig. 4, the expected net present value of the life-cycle costs in function of flexibility and the initial safety factor are shown. Costs decrease with increasing flexibility, as expected. The optimum safety factor, i.e. the initial overdesign, increases as the flexibility decreases, from a value of around 1.4 (for $\varphi = 1$) to 3 (for $\varphi = 0$).

In Fig. 5, the optimal expected net present life-cycle costs are plotted for varying system flexibilities (these are the values found along the white line of Fig. 4). The largest costs are incurred for the inflexible system. The reduction in costs for higher values of flexibility reflects the *value of flexibility*.

The temporal distribution of optimal expected costs varies in function of the system flexibility (Fig. 6). In case of the inflexible system, the optimal strategy is to invest initially, and then accept the possibility of costs because of insufficient capacity towards the end of service life. For the fully flexible system, the costs are most equally distributed over the service life. Whenever the capacity is insufficient, or if it is likely that the capacity will become insufficient in the next years, the system is upgraded.

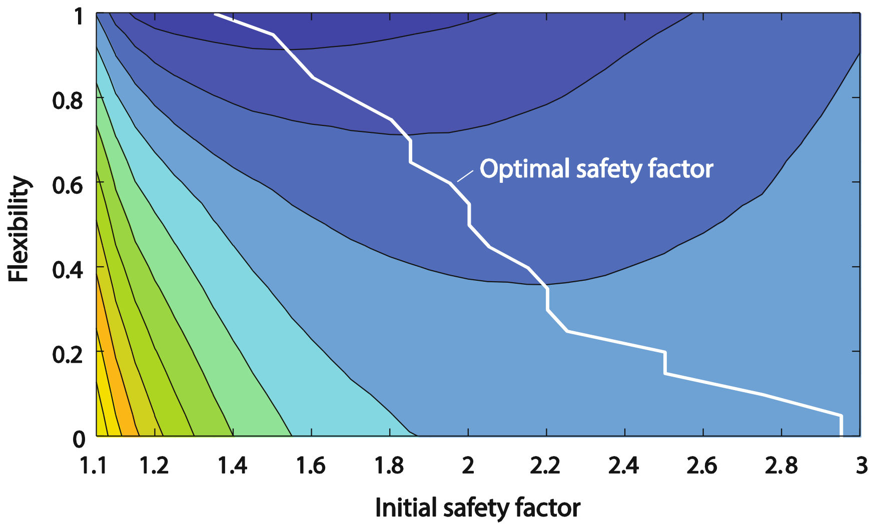


**Fig. 4** Expected net present value of life-cycle costs in function of the initial safety factor and the flexibility of the system, together with the optimal safety factor

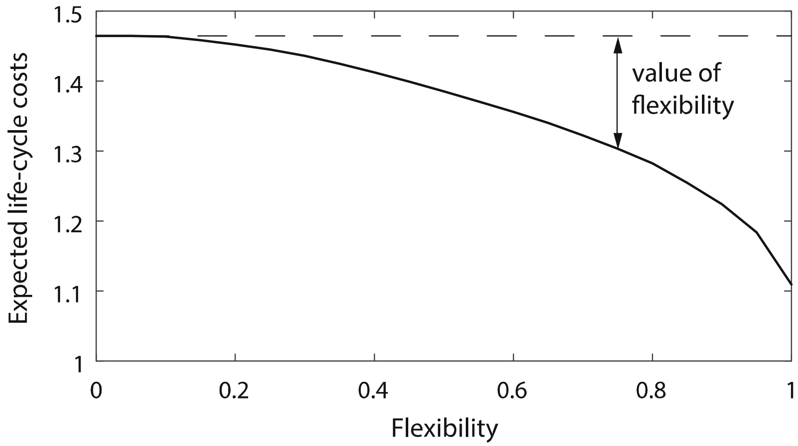


**Fig. 5** Optimal expected net present value of the life-cycle cost in function of flexibility. The difference relative to the value achieved with flexibility zero is the value of flexibility

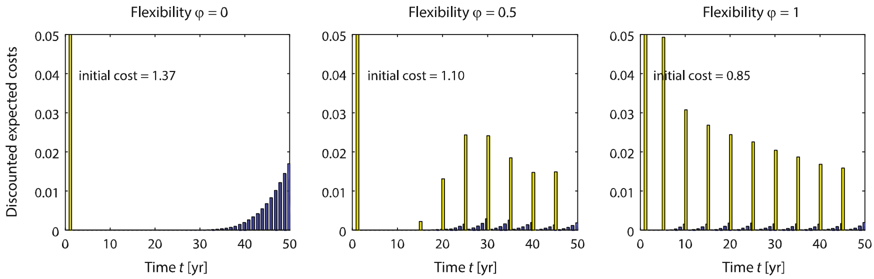


**Fig. 6** Distribution of expected discounted costs over the lifetime for the different flexibilities, when the optimal management strategy is implemented. The *yellow* (lighter) *bars* correspond to cost associated with building or upgrading the system $c_t$, and the *blue* (darker) *bars* are the expect costs associated with the demand $D_t$ exceeding the capacity $v_t$

## 4.2 Case 2: Disaster Risk Management

Disaster risk mitigation infrastructures, such as flood defences, are designed to protect society from extreme events. The frequency of extreme events is not directly observable—many years of observations are in fact needed to derive the frequency accurately (Dittes et al. 2016). This problem is intensified when the frequency and characteristic of extreme events changes in time (is non-stationary), e.g. due to climate change.

The following example on planning of flood mitigation measures under climate change uncertainty is taken from (Špačková and Straub 2016). The presentation here differs the one in the original paper. Three climate scenarios are considered: A—no change in extreme discharge frequency, B—moderate increase of frequency of extreme discharges and C—significant increase. These climate scenarios correspond to trend values $\tau = 0, 1, 2$, respectively. In the future, observed annual maximum discharges will be applied to update the probabilistic believes on the climate scenarios.

The model corresponds to the model shown in Fig. 3. Decisions on flood protection capacity are revised every 30 years, the total planning horizon is 90 years. Definitions of the utilized variables are provided in Table 2. The risk and cost functions are defined in the original paper.

In Table 3, the optimal initial designs of the flood protection system are summarized for stationary conditions (neglecting the effect of climate change, i.e., assuming that the probability of scenario A is 1) and under consideration of the uncertain effects of climate change. The latter results are shown for varying flexibility $\varphi$ (Fig. 7). The difference between flexible and inflexible systems is very low, indicating that the flexibility has limited value in this case.

**Table 2** Parameters of the flood protection case study

| Parameter | Type | Description |
|---|---|---|
| Climate trend $\tau$ | Discrete RV | $p_\tau(0) = 1/3,\ p_\tau(1) = 1/3,\ p_\tau(2) = 1/3$ |
| Ann.max discharge $D_t$ | Continuous RV | $D_t \vert \tau \sim Gumbel(1200 + 2 \cdot \tau \cdot t, 960 + 1.6\tau)$ |
| Capacity $v_t$ | Decision process | Optimization parameter |
| Discount rate $\rho$ | Deterministic | 0.02 |

**Table 3** Optimal initial design of the flood protection system excluding and including uncertain climate impact for different flexibilities

| | Neglecting climate change | Including climate change uncertainty | | |
|---|---|---|---|---|
| | | $\varphi = 0$ | $\varphi = 0.5$ | $\varphi = 1$ |
| Design discharge ($m^3/s$) | 4800 | 5240 | 5240 | 5220 |
| Design return period (year) | 220 | 400 | 400 | 380 |

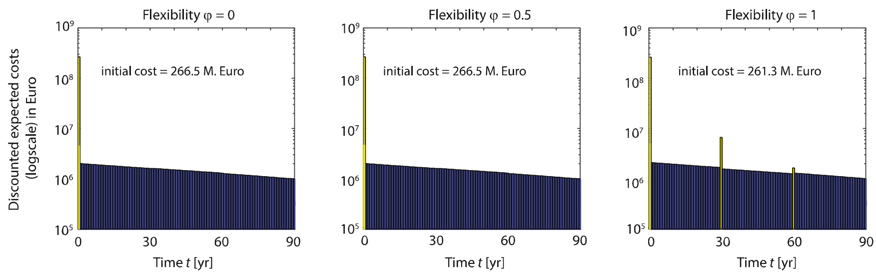


**Fig. 7** Distribution of expected discounted costs over the lifetime for the different flexibilities, when the optimal management strategy is implemented. The *yellow* (lighter) *bars* correspond to cost associated with building or upgrading the flood defense, and the *blue* (darker) *bars* are the discounted flood risks

## 5 Concluding Remarks

We present a framework that enables the investigation of the effect of adaptability (flexibility) in infrastructure systems in a systematic and quantitative manner. Adaptability is frequently mentioned as a potentially effective strategy to deal with uncertain climate change and other future changes and uncertainties. However, numerical investigations into its effect are lacking, which is the aim of this research. To enable a generalization of results from individual case studies, we propose a measure of flexibility. Taking basis in sequential decision analysis, it is then possible to quantify the *value of flexibility*.

The results of the two case studies, and others reported in Dittes et al. (2016) and Špačková and Straub (2016), indicate that the value of flexibility can be fundamentally different depending on a number of factors, which include the amount of uncertainty and the possibility for future learning (reducing uncertainty), the mean predicted changes of the system, the discounting rate as well as the cost and risk functions. Comparing the two presented examples, one can observe that the flexibility has a significant value in the infrastructure capacity example, where the learning process is strong. This is in contrast to the second example, where the uncertainty is on extremes, which are generally hard to predict. The presented example does underestimate the true capability for learning, because it is not accounted for improvements in climate models and other information that can be used to improve flood predictions. Nevertheless, the value of information will be limited also under modified assumptions, because increasing flood protection capacity is a no-regret strategy. That is, a conservative design has benefits under any future change, which is not the case in the first example.

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# Freak Events, Black Swans, and Unknowable Unknowns: Impact on Risk-Based Design

**M.A. Maes and M.R. Dann**

**Abstract** To design means making informed decisions about suitable alternatives in the face of uncertainties. As a result, structural design criteria and inspection plans reflect the objective of satisfactory performance under well selected extreme conditions. The extent to which the extreme boundary is "pushed" depends on the design approach (ex: component vs system design), the nature and the consequences of the hazards, and risk acceptance, all of which fit neatly into the traditional framework of decision theory. This basic framework is also broad enough to include wider socio-economic and environmental objects, so that provisions with respect to robustness, resilience, sustainability, and risk mitigative measures in general, can be effectively accounted for. Various civil engineering fields suffer from a perception that we don't dig deep enough, that we fail to consider "beyond extreme" scenarios. Every major accident, or any exceptional natural disaster, or any surprising combination of circumstances, triggers a new call for re-examination of the design rationale: if a freak event can be explained, then surely it should be (have been) accounted for. This paper looks at what really lies beyond our "design frontier". We distinguish between three broad classes of events: far-out extremes for heavy-tailed hazards, scenarios marked by very unlikely combinations of events (perfect storms), and so-called unknowable unknowns. We identify, from a decision making point of view, which objectives, which tools, and which risk measures can be used, and which lessons can be learned.

**Keywords** Extreme design scenarios • Black swans • Perfect storms • Unknowable unknowns • Risk-based design

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## 1 Introduction

We live in a world of interconnected networks of almost everything. The interconnected world evidently offers a myriad of benefits to its “members”. This can easily be tracked in terms of ever increasing metrics ranging from efficiency, productivity, technological performances, to quality of life. However, any kind of disturbance—external or internal—has the potential of upsetting the system, paralysing the network, and causing damage far beyond its perceived boundaries (Jowitt 2010). In other words, interdependency has led to increased and more widespread vulnerability.

Very rare incidents having extraordinary consequences form the main subject of this paper. They are not new; they are in fact the same as all of the “mysterious” events ascribed by the ancient Greeks to the god Poseidon. A recent trend is to refer to them as beyond-extreme events or very exceptional disasters that carry metaphorical names such as black swans, freak events, perfect storms, nightmare scenarios, and, also, events perceived to have risen from the unknowable unknown.

## 2 Infrastructure: Evolving Expectations

It is important to reconsider the proper context of design decision making in order to evaluate the role and the impact of extraordinary events. Skilled builders, designers, architects and engineers serve as the custodians of past, current, and future infrastructure. Over the past 30 centuries, the needs of infrastructure have changed and expanded. This evolution occurred more or less at the same pace as the hierarchical expansion of human needs (Maes and Stewart 2004).

Historically, infrastructure has always been the sole and common stable platform upon which civilization rests. Its main role was to bring people and views together, to provide shelter and basic comfort, and to provide a true forum for interaction—in the literal sense of the meaning. Much later arose the need for infrastructure to be efficient, cost effective, and functional, as the human need for an acceptable quality of life became tied to basic infrastructure functions. The specific character of modern societies is largely defined by culture, heritage, and vision, all of which are heavily influenced by its infrastructure. In a sense, infrastructure came to “shape” our world (Jowitt 2010). It is only very recently in this historical sequence that the ultimate step in this hierarchy of needs appears: it focuses on a society’s vulnerability in times of unexpected distress and/or abnormal conditions. Hence the requirements for infrastructure to be resilient against disasters and sustainable in the long-term (Rodrigues-Nikl 2015). In summary, and in the order of historical evolution, we expect infrastructure to be:

- reliable and safe, since it is the critical stable platform upon which civilization depends
- efficient and functional, since our quality of life is linked to it

- equitable, since it "shapes" our world
- resilient and sustainable, since society has become painfully vulnerable when infrastructure systems fail.

## 3 What We Know, What We Should Know, What We Don't Know

In recent years the notion of the "unknowable unknown" (UU) has taken a life on its own. Because of its relation to extraordinary low-probability, high-consequence events, it is worthwhile examining its genesis, its use—and its misuse—from the point of view of decision making (DM). The notion and the use of UUs in offshore structures design and operations was popularized by Bea (1997). In an industry that is heavily self-centred and famous for its unwillingness to share experiences and its failure to learn and adapt in the wake of serious incidents, the UU transformed itself into the ultimate excuse: we did not know, we could not know, and we could never have known, no matter what.

In 1979 a British Columbia royal commission of inquiry into the benefits and the dangers of uranium mining first used the term UU in its final report (British Columbia Royal Commission of Inquiry 1979). The commission referred to UUs as "unforeseeable conditions which pose a potentially greater risk [than known unknowns] because they cannot be anticipated based on experience or investigations". In other words, should indicators of a threat to people be present or be suspected then these "known unknowns" (KU) can/should be the subject of scientific risk assessment. If neither indicators, nor an experience base, nor a knowledge base exist, then we deal with UUs. The question of whether or not a UU should "pose a potentially greater risk" is debatable, for if we know nothing about the UU, not even its existence, then there is a priori no compelling reason to fear "it", let alone associate it with potential greater risk.

A 1982 investigation of the metal fatigue failures of the 1950s Havilland aircrafts also cited the role of UUs. At the time of the incidents, fatigue was not an established concept of its own right. It was "unknown" as a cause of failure, but as failures accumulated, one can hardly continue to blame evidence of malfunction to an unknowable unknown: the effect was known but not the cause. This points to epistemic limitations rather than UUs: as the experience-base broadened and research intensified, a proper "name" was eventually given to the phenomenon. As in the case of a new virus or infectious disease, its sudden observation or realization ("discovery") is rather like a black swan: an epistemic breakthrough of something that was certainly not meant to remain "un-knowable".

It would be tempting to divide the knowledge base using the breakdown shown in Fig. 1a. Apart from the trivial class of knowns (K), the largest set of uncertainties consists of KUs, i.e. those of which decision makers are well aware and upon which their uncertainty modelling focuses (Maes and Milke 2015). Then there would be

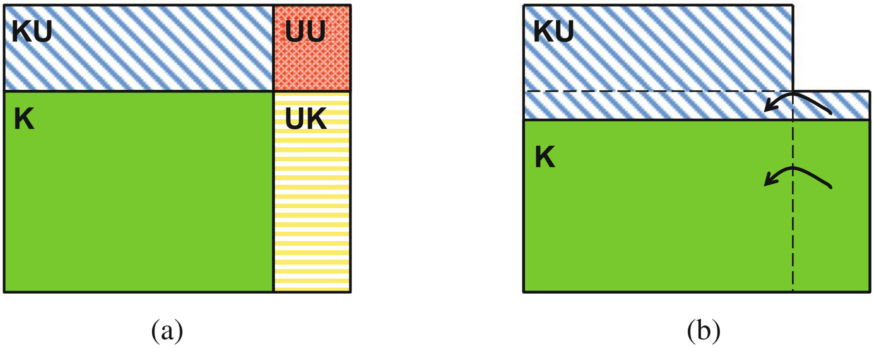


**Fig. 1** Knowledge base breakdown (K = known, KU = known unknown, UK = unknown known, UU = unknowable unknown)

the class of UK which would include information or data that is either not (easily) recalled or (intentionally) suppressed. Finally there would be a separate group of UUs (Haugen and Vinnem 2015).

However, this picture is definitely flawed by our obsession to break down (un) certainty along abstract lines. Informed decision making (DM) is intrinsically concerned with the framework for developing optimal decisions based on:

- what we know
- what we should know, or what we need to know

This basis for traditional DM therefore includes K and KU. We possess techniques to resolve, learn about, update, monitor, and model any of the uncertainties involved in this process. Now, to add a third component to the "knowledge basis" in the form of:

- what we do not know (and can never know)

would suggest that there are uncertainties we should be able to know but cannot know. But this leads to a paradox, as either such uncertainties are already part of system of beliefs/knowledge (but we may be unaware of them or give them different names), or else they lie truly outside our domain of knowledge. In the first case the supposed UU is in fact a KU; in the second case, Platonic logic tells us that we can never learn what we do not know since if we would "find" it, we would not be able to recognize it.

Either way the supposed UU can never be an issue in the context of rational and informed decision making. Therefore, a "true UU" can as well not exist since it can, by definition, never penetrate the state of knowledge and, accordingly it does not influence DM in any formal or informal way. If a specific uncertainty is marked as a UU, perhaps, but not necessarily, in an a posteriori sense, then it ceases to be a UU and becomes a KU since it is then part of the decision maker's basis of beliefs.

For informed DM, it is, on balance, better to replace Fig. 1a by Fig. 1b which does not show UUs and dilates UK into K (through investigation and research) or into KU (using uncertainty modelling).

## 4 Black Swans and Perfect Storms

Before 1697, expressions in the English language that used the term "black swans" (BS) were in fact very common. They pointed to something that was non-existent or physically or conceptually impossible. In that year the first reports of actual BS sightings in Western Australia reached Europe. Subsequently, the BS terminology became synonym of any perceived impossibility that is, or may, later be disproven.

In 2000 unexpected financial market fluctuations were baptized BSs and since that time BSs came to denote almost any unexpected high-impact event. In that same year the use of the term "perfect storm" (PS) was popularized by the movie based on Junger's (1997) novel. Both BS and PS concepts have many aspects in common:

- they are both "freakish" in nature, causing surprise and generating sudden newsworthiness
- they both may result in significant damage and widespread impact
- they can both be rationalized by hindsight (Taleb 2007):
  - a BS may never have been observed before but may have precursors or (at least) vague indicators: they can be imagined a priori and explained a posteriori
  - for a PS, root-cause scenarios can be proposed and verified; usually, the (regular) individual underlying events/processes are well understood, but, a priori, their very rare conjunction or sequencing is subject to considerable uncertainty

- before their occurrence or observation, they are considered "truly unthinkable"; this is normally a correct and rational point of view with respect to the specific knowledge base and the state of belief at the point in time that such an evaluation is made.

One possible distinction that could set apart a BS from a PS, is suggested by Paté-Cornell (2012): a BS engenders the ultimate epistemic uncertainty due to a profound lack of fundamental knowledge, while a PS embodies the ultimate rare conspiracy of aleatory uncertainties, an extremely bad roll of dice so to speak. It is important, however, to realize that even this possible distinction between BS and PS depends entirely on one's perspective and state of belief. It is hardly relevant before the fact, as well as after the fact.

In modern use, a BS or a PS refers to a very unexpected event (with respect to the a priori knowledge base), that is felt to be nightmarish in terms of the high profile consequences that it carries. This points to two explosive ingredients: *fear* and *surprise*.

*Fear* is known to possess considerable potential to interfere with informed DM and effective risk management (Maes and Milke 2015). As soon as fear looms over the decision making process, it has the potential to start weighing too heavily (Schneier 2013).

As pointed out in the case of UU, the knowledge base as well as the system of beliefs expand as a function of time. Any *surprise* event, i.e. yesterday's BS, is short lived once the event is experienced. The surprise punctures at least some bubble of (yesterday's) epistemic limitations.

There can of course be many epistemological reasons why the BS remained unexposed in the timeline before its first "sighting":

- inappropriate assumptions and models suggesting that such a BS cannot occur
- improper uncertainty models/analysis leading to incorrect likelihood evaluation
- overall chance of occurrence of a possible BS deemed too small to be considered; this assessment can either be valid, i.e. justified using risk-based acceptance, or may stem from incorrect analysis
- erroneous induction/deduction due to serious fallacies in logic
- incomplete information
- failure of the knowledge management systems (e.g. incompetence, illusory superiority)
- inappropriate belief structures, e.g. the use of priors that express faith in likelihoods (Haugen and Vinnem 2015)
- ignorance of lower-level signals/warnings/precursors
- local "thinking", i.e. focusing on one link in the chain rather than on the entire chain, and lack of creative thinking and network modelling

Following a similar line of thought, Aven (2015) identified three types of BSs:

(A) (true) UUs
(B) UUs only for the decision maker(s) prior to the occurrence of the BS, but not to (some) others
(C) UKs (originally) estimated to have a negligible probability of occurrence

The notion (A) of true UUs was questioned in the previous section; the second type (B) goes back to the above list of epistemological shortcomings. Group (C) is discussed next.