An influence diagram for urban flood risk assessment through pluvial flood hazards under non-stationary conditions

Un diagramme d'influence pour l'évaluation des risques d'inondations urbaines au travers des dangers de rejet pluvial dans des conditions non-stationnaires

Åström H.[1], Friis Hansen P[2]., Garré L.[3], Arnbjerg-Nielsen K.[4]

[1] Department of Environmental Engineering, Technical University of Denmark, DK-2800 Lyngby, Denmark, hlaa@env.dtu.dk; [2] Det Norske Veritas, 1322 Høvik, Norway, peter,friis,hansen@dnv,com; [3] Det Norske Veritas, 1322 Høvik, Norway, luca.garre@dnv,com; [4] Department of Environmental Engineering, Technical University of Denmark, DK-2800 Lyngby, Denmark, karn@env.dtu.dk

RÉSUMÉ

Une inondation en zone urbaine présente un risque considérable pour la société. Les décideurs doivent s'accorder sur la façon d'adapter les zones urbaines à l'inondation. La non-stationnarité engendre une incertitude accrue qu'il est difficile d'intégrer à la prise de décision concrète. Des méthodes transparentes sont nécessaires pour faciliter le processus de prise de décision. L'objectif principal de cette étude était de développer un cadre pour l'évaluation des risques et l'aide à la décision concernant les risques d'inondation pluviale en zone urbaine dans des conditions non-stationnaires en utilisant un Diagramme d'Influence (DI), un Réseau Bayésien (RB) étendu avec des nœuds de décision et d'utilité. La non-stationnarité est considérée comme découlant de l'influence du changement climatique où la configuration des précipitations extrêmes change au cours du temps. Le risque global est quantifié en termes monétaires exprimés en dommages annuels attendus (DAA). Le réseau est dynamique dans la mesure où il estime le risque à différents points dans le temps pour évaluer la non-stationnarité dans le système urbain. Ce cadre fournit aux décideurs des moyens pour évaluer la façon dont différentes décisions concernant l'adaptation aux inondations affectent le risque aujourd'hui et à l'avenir. Pour le développement du RB, nous avons utilisé le logiciel HUGIN. Les résultats du DI ont été élargis avec une analyse coûts-bénéfices définissant les bénéfices nets pour les plans d'investissement. Nous avons testé notre cadre dans une étude de cas où le risque d'inondation avait été évalué sur une voie ferrée à Risskov (Aarhus). Des améliorations du système d'assainissement sont planifiées pour la zone et notre étude de cas présente la façon dont le DI développé illustre l'augmentation du risque au cours du temps et la baisse du risque grâce à l'amélioration planifiée.

ABSTRACT

Urban flooding introduces significant risk to society. Decision-makers need to agree on how to adapt urban areas to flooding. Non-stationarity leads to increased uncertainty and this is shown to be difficult to include into actual decision-making. Transparent methods are needed to facilitate the decision-making process. The primary objective of this study was to develop a risk assessment and decision support framework for pluvial urban flood risk under non-stationary conditions using an Influence diagram (ID) which is a Bayesian network (BN) extended with decision and utility nodes. Non-stationarity is considered to be the influence of climate change where extreme precipitation patterns change over time. The overall risk is quantified in monetary terms expressed as expected annual damage (EAD). The network is dynamic inasmuch as it assesses risk at different points in time to evaluate the non-stationarity in the urban system. The framework provides means for decision-makers to assess how different decisions on flood adaptation affect the risk now and in the future. For the development of the BN we used the HUGIN software. The result from the ID was extended with a cost-benefit analysis defining the net benefits for the investment plans. We tested our framework in a case study where the risk for flooding was assessed on a railway track in Risskov (Aarhus). Drainage system improvements are planned for the area and our case study presents how the developed ID illustrates the increase in risk over time and the decrease in risk due to the planned improvement.

KEYWORDS

Bayesian network, Flood risk assessment, Influence diagram, Non-stationarity

1 INTRODUCTION

Climate change contributes to non-stationarity through increasing occurrence of extreme weather conditions, such as heavy rainstorms (Grum, et al., 2006; van Luijtelaar, et al., 2005). Urban systems hold many valuable assets and are particularly vulnerable to flood hazards. Consequently, adaptation strategies are needed to maintain risk at an acceptable level (Arnbjerg-Nielsen & Fleischer, 2009). In urban areas extreme flood events can grow into national threats if timely adaptation and protection measures are not implemented. More information is needed to understand climate change impacts at the regional scale for development of suitable adaptation strategies (Arnbjerg-Nielsen & Fleischer, 2009).

Infrastructures are important assets in urban environments and their continuous operation is crucial to society. Urban infrastructures have a long technical lifetime. For example the technical lifetime for drainage systems is often assumed to be 100 years. On these time scales the effects of climate change will be statistically evident; because of this, adaptation of long-lived infrastructures should be investigated well ahead of their construction. Decision-makers need to agree on appropriate strategies for the society to fully gain from flood adaptation (Arnbjerg-Nielsen & Fleischer, 2009). While decision-makers can gain an understanding of future climatic changes through scenarios and projections there is still a considerable knowledge gap between different projections and actual decision-making based on these projections. The large uncertainties introduced by future projections can lead to aversion in making a decision and investing in flood adaptation and mitigation.

This study acknowledges that a gap between future scenarios and actual decision-making practices weakens flood adaptation and aims at developing a decision support tool to incorporate uncertainty into the decision-making process. The aim is to help decision-makers understand the boldness of action/in-action and in this way increase confidence in the decision-making process in urban flood risk adaptation. For a tool to improve the decision-making process within urban flood risk management some essential criteria that the tool shall possess were identified. The tool should be: 1) transparent and robust, 2) easy to communicate between different research fields, and 3) based on best available knowledge, techniques and data. Moreover, the tool should be grounded on well-established theoretical frameworks for decision making under uncertainty. In this respect, it is argued that risk should be quantified as the expected monetary loss. This choice is consistent with the foundations of risk-based decision making (Ditlevsen and Madsen, 2007) and ensures that risk is understood similarly by every decision-maker and expert involved in the process.

In this study the tool is represented by an Influence diagram (ID) which is an extension to a Bayesian Network (BN). The ID is used for flood risk assessment and decision support for critical urban infrastructures, in which various sources of uncertainties can be modelled and accounted for. The method introduces a transparent way to evaluate how a decision on flood adaptation affects the risk at different points in time and this will help decision-makers to improve urban flood adaptation and mitigation.

In the methodology chapter, we start with a short explanation of Influence diagrams (ID). Then, we describe how a risk assessment is conducted in an ID, using a general risk assessment framework developed by Fenton and Niel (2011). The structure of the developed BN for flood risk assessment is thereafter illustrated in detail. Finally, a case study is used with the objective to apply and exemplify the methodology described in this paper.

2 METHODOLOGY

2.1 Bayesian networks

Bayesian networks (BNs) are based on Thomas Bayes' theorem developed in the 18th Century (Bromley, et al., 2005). The theorem expresses the relationship between probabilities P(A) and P(B) and the conditional probabilities P(B|A) and P(A|B) of two variables A and B(Charniak, 1991). According to a Bayesian interpretation of the theorem, the posterior distribution P(A|B) is computed as the product of the prior distribution P(A) and a term accounting for evidence, the so-called likelihood function P(B|A). Construction of a BN starts with developing a graphical depiction of essential variables in a system and defining their causal relationships (Borsuk, et al., 2004). Variables are presented as nodes, called *chance nodes*. Each node contains the domain of possible states taken by the node therein represented (Castelletti & Soncini-Sessa, 2007). Causal relationships among variables are indicated as arrows.

Figure 1A presents an Influence Diagram (ID, Carriger & Newman, 2011). An ID is obtained adding decision (rectangular) and utility (diamond) nodes to a Bayesian Network (BN), The latter is composed of chance (elliptical) nodes. In the ID shown in the figure, variable C is connected to variables A and B, called *parent nodes* (Bromley, et al., 2005; Charniak, 1991). Node C is conditionally dependent to its parent nodes. B and A have no parent nodes and are therefore called *root nodes*. Node D has no outgoing links and is called a *leaf node*. Data input to BNs is presented by so called *Conditional Probability Tables* (CPTs). These tables describe the probabilities of any state of the node, conditional to every combination of values of the parent nodes (Borsuk, et al., 2004). In order to specify the probability distributions of the different variables, first, the CPTs of all nodes have to be entered.

A root node is not conditional to any other nodes and, hence, a single column table containing the prior probability density function (pdf) of the variable described in the given node is defined. The multivariate pdf of all variables is then obtained via compilation of the network, which corresponds to factoring all CPTs in the network according to the so-called chain-rule. Once the network is compiled, Bayesian inference can be performed, i.e., the posterior probabilities of the nodes in the network are computed when values of other nodes are observed and entered as evidence. When new evidence is entered the posterior probabilities are updated (Charniak, 1991).

A conventional BN or ID is static, i.e., it doesn't have a temporal dimension. In many cases the system under study evolves over time and a temporal dimension is needed to describe temporal dependence of the multivariate pdf of the system variables. A Dynamic Bayesian Network (DBN) includes such a temporal dimension. The easiest way to extend BNs to DBNs is by including time slices and linking these slices together (HUGIN, 2012). This is illustrated in Figure 1A. Here, nodes A and B in the current state of the system are linked to the nodes A1 and B1 which describes the same variables in the future (HUGIN, 2012). Several time slices can be included to a DBN to describe future changes in the system in more detail. In the present tool the BN models variables related to the system process.

In contrast to BN, IDs model also how decisions affect the process (Varis, 1997). In an ID, decisions that provide the highest expected utilities are recognized as being the optimal choices. IDs are very useful in showing the structure of the decision problem: besides the types of nodes previously mentioned, they contain two types of arcs: influence and informational. In an ID, when a link enters a decision node, it indicates that the state of the predecessor node is known at the time the decision is made (Carriger & Newman, 2011).

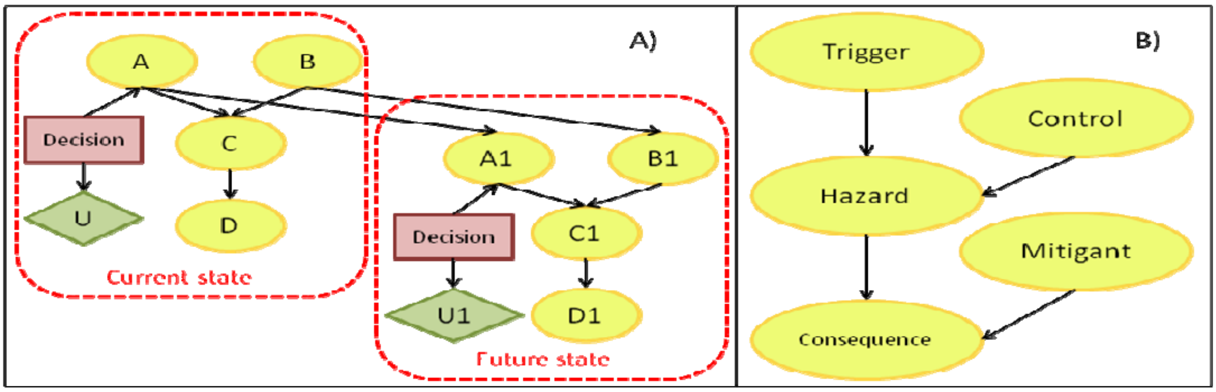

Figure 1 – A) An ID describing different relationships between nodes and providing an example of a Dynamic network. The yellow nodes are the so called chance nodes, which together form a Bayesian Network and functions as the basis of the ID b) Risk map (BN) developed by Fenton and Niel (2011) which forms the basis for our risk assessment tool.

2.1.1 Describing risk in a Bayesian network

Risk is traditionally defined as the expected loss. In operative terms, it corresponds to the product of the probability of one hazard times the consequence of that hazard. The total risk of the system is observed by summing together all possible risks coming from all possible hazards. The present tool embodies some of the aspects of risk assessment illustrated by Fenton and Niel (2011): risk assessment requires a holistic view of risk, where the system functions as one unit and a complete understanding of the risk in the system cannot be understood solely by viewing the components separately. In addition, risk should be assessed by considering the causal context in which risk happens. Fenton & Neil (2011) introduces a general risk map to describe the risk by means of interconnected events. This map is presented in Figure 1B, with adjustments in the terminology to be in accordance with hydrologic tradition as used by e.g. Zhou et al (2012a).

The risk map is divided into 5 events: trigger, control, hazard, mitigant, and consequence events. The trigger event is defined as the initiating event, i.e. the component that introduces hazard to the system. A control event mitigates the effects from the trigger event and may stop the trigger event from initiating the risk. The hazard event defines the hazard variables in the system, i.e. a factor that may have a negative impact. A consequence event characterizes the potential impacts of the hazard event. A mitigant event helps to avoid consequences by means of protecting valuables from the hazard event. A risk map can include several events of the same kind. For example, there may be several trigger events that together initiate the risk in the system. The outcome of the risk map is multivariate pdfs for risk and consequence events conditional to their parent nodes.

2.2 An Influence diagram for flood risk assessment

BNs have been used within many fields to describe the system and communicate risk transparently. The visual description of the system in a BN facilitates an equal understanding of the system for all stakeholders. The importance in having a transparent risk assessment lies in the fact that the system is often complicated and transparency in the chosen method encourages discussing and questioning the described system; hence, it decreases the chance that the system is wrongly modelled. Further, BNs can integrate data from different fields of research and this makes them suitable for multi-disciplinary research.

According to our knowledge, BNs have not yet been used for pluvial flood risk assessment in urban areas under non-stationary conditions. The aim of this study is therefore to introduce this method to a new field of research and application. We present a static network to describe risk at one specific point in future time which we develop further into a dynamic network to describe the non-stationarity caused by climate change. The network is defined in general terms and can therefore be used for any urban system to conduct a variety of flood risk assessments. We use the risk map (Fenton & Neil, 2011) as the basis for our method and we develop the risk map further to include decision and utility nodes, transforming it to an Influence diagram. The final outcome of our ID is risk defined as Expected Annual Damage (EAD). HUGIN software is used for the development of the ID.

2.2.1 Static Influence diagram to assess risk a one point in time

A static ID to assess risk at one specific point in the future is presented in Figure 2. The developed network can be used to: 1) understand how climate change (trigger event) may impact flood variables (hazard events), 2) assess impacts (consequence events) due to flooding and their probability of occurrence, 3) quantify risk in monetary terms (in EAD), and 4) evaluate the reduction of risk due to different flood adaptation initiatives (control and mitigant events).

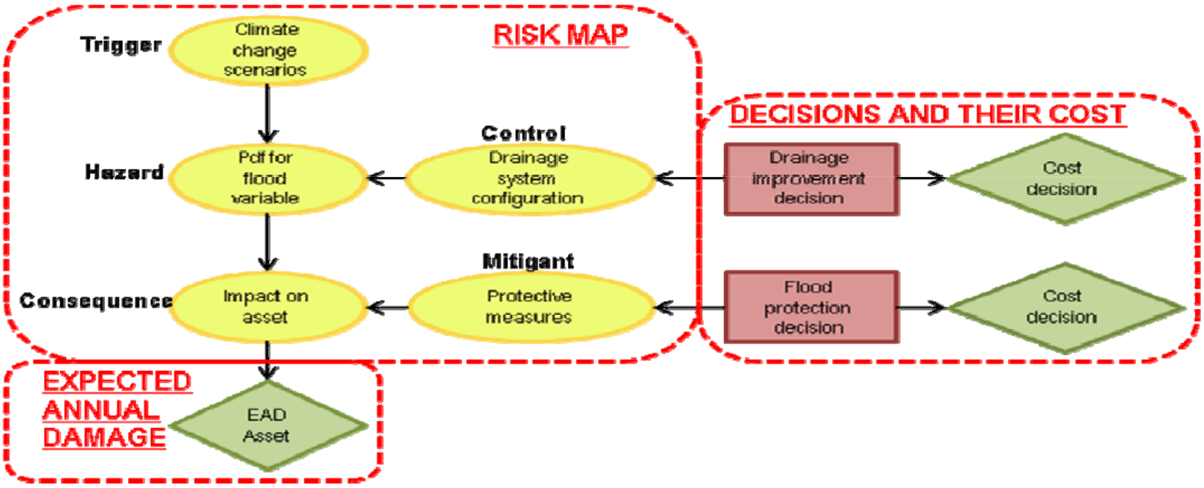

Figure 2 – An ID for urban flood risk assessment. This network defines risk at one specific point of time in the future and describes how a decision at that point will influence the risk.

We call our trigger event "Climate change scenarios". This node describes how the RCPs (Representative Concentration Pathways) influence the climate and hence, the precipitation patterns. RCPs are a set of projections of the components of radiative forcing that are to be used as input for climate modelling (van Vuuren, et al., 2011). The precipitation patterns from different climate change scenarios are used as input to flood simulations. The flood simulation results are developed into probability distributions of flood variables (hazard events). Several flood variables (water depth, velocity, flood duration etc.) can impact the risk.

Our control event is the urban drainage system which mitigates the negative effects introduced by climate change. Consequence events are here described as node "impact on asset", where asset refers to the valuables at risk. Flooding in urban areas has multiple consequences and these can be described with separate nodes to add transparency to the assessment. The chosen mitigant events (i.e. protective measure) in the system depend on the assets.

The difference between mitigant and control nodes is that control nodes reduce the overland runoff, whereas mitigant nodes protect the assets when the control events fail. Many control and mitigant events require a decision made by the municipality. Decision nodes are included to these events together with utility nodes to describe the costs of the measures. The decision-maker has full control over the decision nodes. Different adaptation measures can be tested in order to assess how they impact the total risk. The best control and mitigant measures are the ones with the highest expected utilities, i.e. largest change in EAD.

2.2.2 Dynamic Influence diagram to account for non-stationarity

The ID presented in Figure 3 has three time slices describing the system today, in 50 years and in 100 years. With this ID one can assess how risk changes over time. Understanding this gives the following advantages: 1) Means to define at what time in the future acceptable risk is exceeded with the existing flood protection, 2) Possibility to develop investment strategies for the future by assessing the benefits of investments at different points in time, and 3) Way to present risk in a transparent manner to all stakeholders with a clear description of timely changes of the risk, which helps to justify a decision.

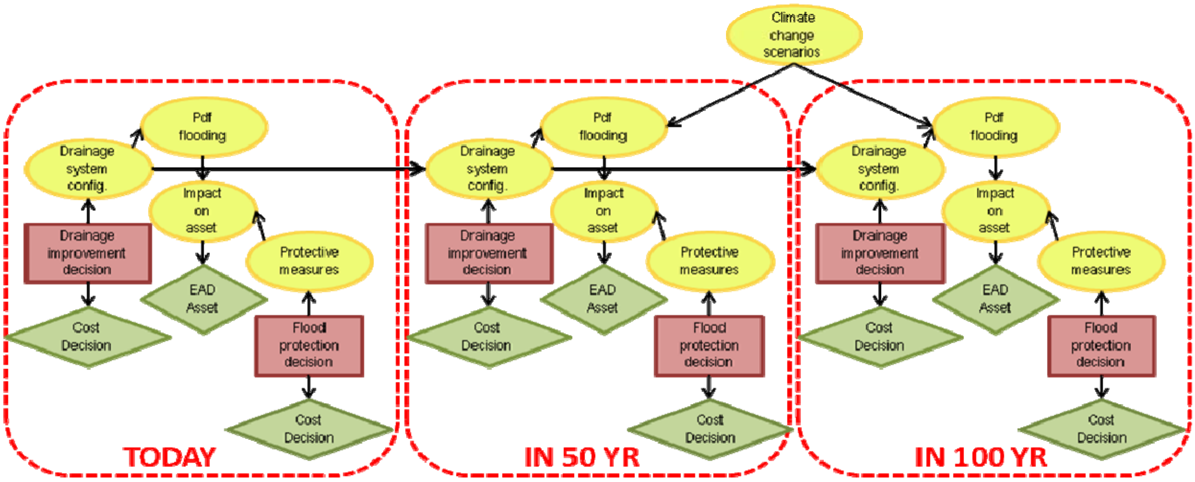

Figure 3 – Dynamic ID for flood risk assessment which describes how risk changes over time

The dynamic behaviour is defined in the ID, presented in Figure 3, by linking the drainage system configuration in every time slice with the following one. By doing so, it is recognized that an investment in flood adaptation today influences risk in the future. The trigger events are linked only to future time slices, assuming that the calculations for the time slice today are based on an assessment of current climate.

2.3 Cost-benefit analysis

A cost-benefit analysis is used as a supplement to the ID to assess the effectiveness of the adaptation options. The analysis compares costs and benefits of the adaptation measures. Total benefits for a time period are assessed as difference in flood damage before and after implementing an adaptation option for that time period. EAD is estimated by integrating flood damage over occurrence probabilities of the important flood variable (Zhou et al, 2012a). In the developed ID, EAD is estimated directly from the network. The hazard event defines the pdf of the flood variable and the consequence event models the pdf of monetary losses due to flooding. The expected monetary loss is obtained in the utility node "EAD Asset". Since the value of benefits and costs change over time, discounting is applied to express costs and benefits in present values for comparison. In Denmark the discounting rate 3% if often used in studies related to climate change adaptation (Damgaard et al, 2006). In a cost-benefit analysis a number of decision rules are used. For example, Net Present Value (NPV) indicates the net benefits of a project and is calculated by subtracting the gross costs from the gross benefits in their present value. When NPV is positive the project is economically attractive to implement (Zhou et al., 2012a). For a complete review of the described method we refer to Zhou et al. (2012a).

3 CASE STUDY – RISK ASSESSMENT FOR A RAILWAY TRACK

A case study is used to apply and exemplify the presented tool to flood risk assessment. The objective is to study how the ID can be used in a decision-making process.

3.1 Problem description

Risskov is a residential area located in Aarhus. The area has recently experienced considerable flood damage due to pluvial flooding. With climate change, flood risk is expected to increase. The municipality has put priority on developing Risskov by improving flood protection. Hence, a plan was set up to improve the drainage system with a cost of 24 MDKK. We assume that the drainage improvement is planned to be implemented presently. A cost-benefit analysis was conducted where total net benefits of the adaptations were estimated to be 147 MDKK over a 100 year planning zone (Zhou, et al.,2012c). The hazard map for a return period of two years for Risskov is presented in Figure 4 without adaptation (blue and purple area) and with adaptation (solely purple area).

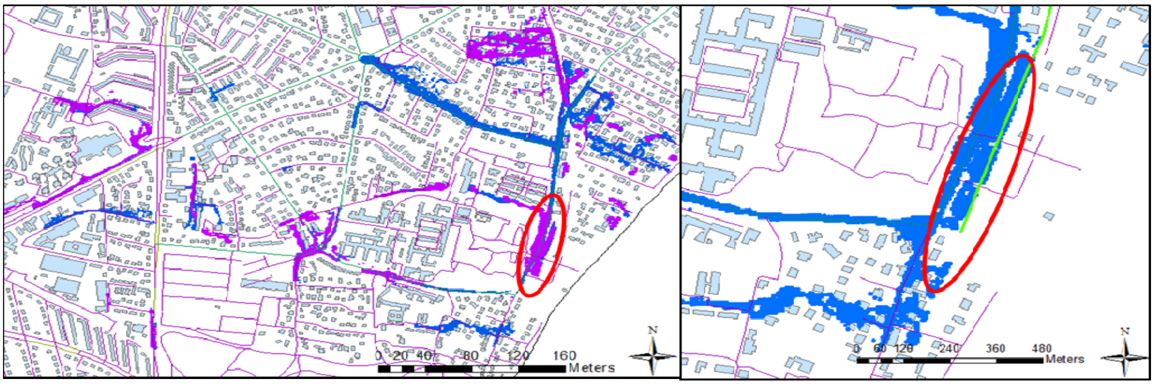

Figure 4 – Flood hazard map of Risskov area, return period 2 years, railway track shown with red circle

When municipalities implement new adaptation measures several stakeholders benefit from these. The municipality could argue that a large decrease in risk for main stakeholders could be sufficient reasoning for requiring the stakeholder to participate in the cost of the improvements. In Risskov, a railway track runs through the area. At a specific location of the track (shown in Figure 4 with red circle) flood consequences have already occurred. The question is: How significantly does the railway company benefit from the drainage system improvements planned by the municipality? How well can the developed ID describe the change in risk for the railway company? Can the result from the BN be used as means to evaluate whether the railway company should be included to the flood adaptation negotiations in the area?

We used the ID developed in paragraph 2.2.2 and developed it to fit our case study (see Figure 5). According to the ID, three time slices were used to assess risk change over time due to non-stationarity of the climate. The hazard event node “pdf flood depth”, describes flood water depths at the different time slices. Two consequence event nodes were added to the ID to model both losses due to delays and to track breakdown. The utility node “EAD Asset” calculates total EAD for each time slice. In this network only one decision node was included, i.e. investment in improving the drainage system in current time. The objective is to evaluate how the risk changes over time for the railway company if the municipality implements its drainage improvement plans in the early phase.

A number of assumptions are used in this case study. First, the investment is assumed to occur at year 0, i.e. no discounting is used for the cost. Second, the risk for the railway is assessed for only one location which was identified as vulnerable on the basis of previous floods. In reality floods might potentially impact several parts of the railway track and this increases the risk for the railway company. Further, only one flood variable is used, (water depth), while in reality other variables also contribute to the total consequences. For the consequence assessment, we identified minimum thresholds that the water level should reach to cause damage. Furthermore, damage is the same irrespective of the time it occurs. Also, we focus the risk assessment solely on extreme events simulating the flooding for return periods 2, 5, 10, 20, 50, 100, 250, 500 and 1000 years. Therefore, we assess the probabilities of an event to occur once in each time slice. Last, we consider a 1000 yr storm to be adequate for defining maximum water levels in this study since it was noted that a very large storm (for example 10 000 year storm) has a marginally higher water level in our system than the 1000 year storm. Consequently, higher return periods do not affect the EAD considerably.

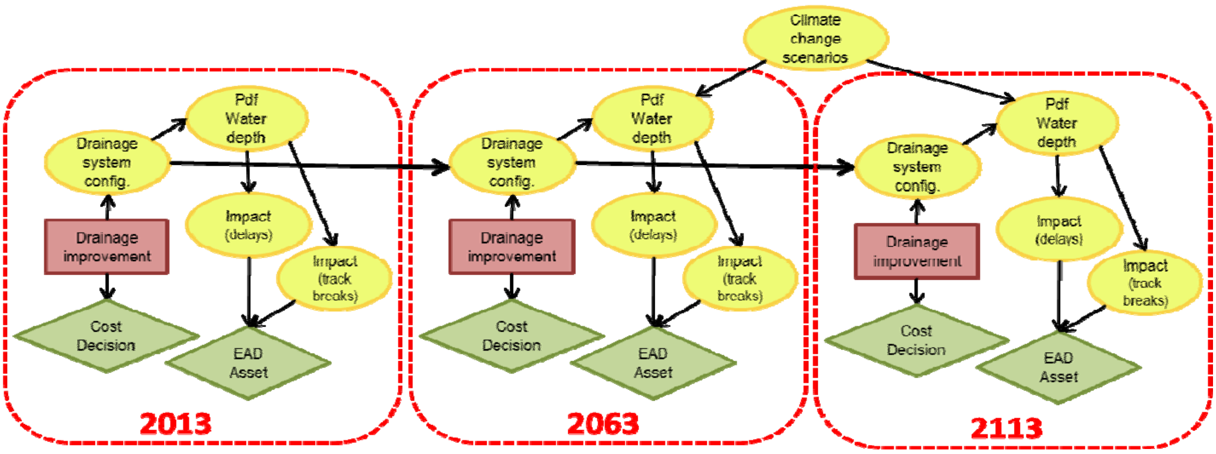

Figure 5 – Dynamic ID for risk assessment of railway track in Risskov. Red boxes represent the 3 time slices used in the assessment.

3.2 Data presentation

Data input to an ID is made by defining a Conditional Probability Table (CPT) to all nodes except for our root nodes “Pdf Water depth” in time slice 2013 and “Climate change scenarios” in slices 2063 and 2113 for which unconditional probabilities are defined. The risk assessment was conducted at a specific location along the railway which was identified as the location with the highest risk. 1D-2D simulations were run for return periods 2, 5, 10, 20, 50, 100, 250, 500 and 1000 using design rains in MIKE URBAN periods to evaluate the increase in water depths on the railway track with and without the drainage system improvement. Hence, two separate drainage descriptions were used in MIKE URBAN. Simulations were also run, for the same return periods, for the future time slices (2063, 2113) where return periods were adjusted by means of climate factors to correspond with future precipitation patterns. Climate factors 1.15 and 1.4 were used for time slices 2063 and 2113, respectively (Zhou et al 2012b). Climate factors account for the expected increase in the magnitude of the extreme rainfall events during the technical lifetime of the drainage system and is defined as the ratio between the best estimate of the design intensity in the future and the design intensity at present (Gregersen et al. 2011; Arnbjerg-Nielsen 2012).

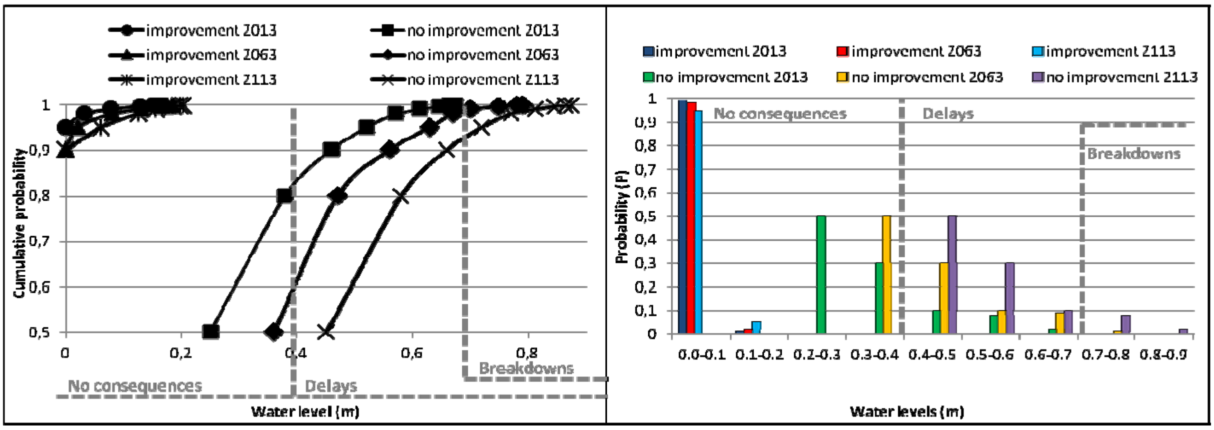

Figure 6 – cumulative probability distribution for flood water depths on railway track, result from simulations in MIKE URBAN. The results are converted into histograms in order to get an input suitable for a BN. Clustering into 10 cm intervals was found to be appropriate.

Figure 6 provides the result for the simulations (left graph) by means of cumulative probability distributions of the water level onto the railway, including the consequences thresholds. This was adjusted into histograms where the water levels were clustered into 10 centimeter intervals (right graph) and used as input to the hazard event node (PDF for flood variable) in the ID. The conversion is made since an ID requires data input as histograms and cumulative probability distributions cannot therefore be directly included into the CPTs.Consequences for flooding on the railway track were defined as breakdown of the track and delays in train traffic due to instability of the track foundation. We used water depth thresholds and unit costs for the calculation of damage (Zhou et al. 2012b). At a water depth of 0.4 meters, the traffic along the track is assumed to stop causing delays. When the water depth 0.7 meter is exceeded we assumed a breakdown of the track leading to major repair work and long lasting traffic disruptions. Unit costs are used to describe the consequences. Delays are assessed to 0.05 MDKK/event. The unit cost for track breakdown is assumed to be 100 MDKK/event.

4 RESULTS

Figure 7 presents time slice 2013 and time slice 2063 with monitor windows. Monitor windows show compiled results (i.e. posterior marginal distribution and expected utility) of each node. The state in the node with the highest utility is the most desirable state of that node. With no drainage improvement the decision node is defined as no investment, whereas an investment cost of 24 MDKK is included when the improvement is executed. From the monitor windows the probabilities for delays and track breakdowns can be read. Today the probability for delays is 0.2 and for breakdowns negligible (i.e. 0 with a maximum 1000 years storm) with no drainage improvement (see monitor windows for consequence events). With the drainage improvement the probability for consequences is negligible for both consequence classes. The EAD today is 0.01 MDKK with no improvement in the drainage. In 50 years the probability for delays increases to 0.5 and the probability for track breakdowns changes to 0.02. Hence, the EAD is 2.02 MDKK.

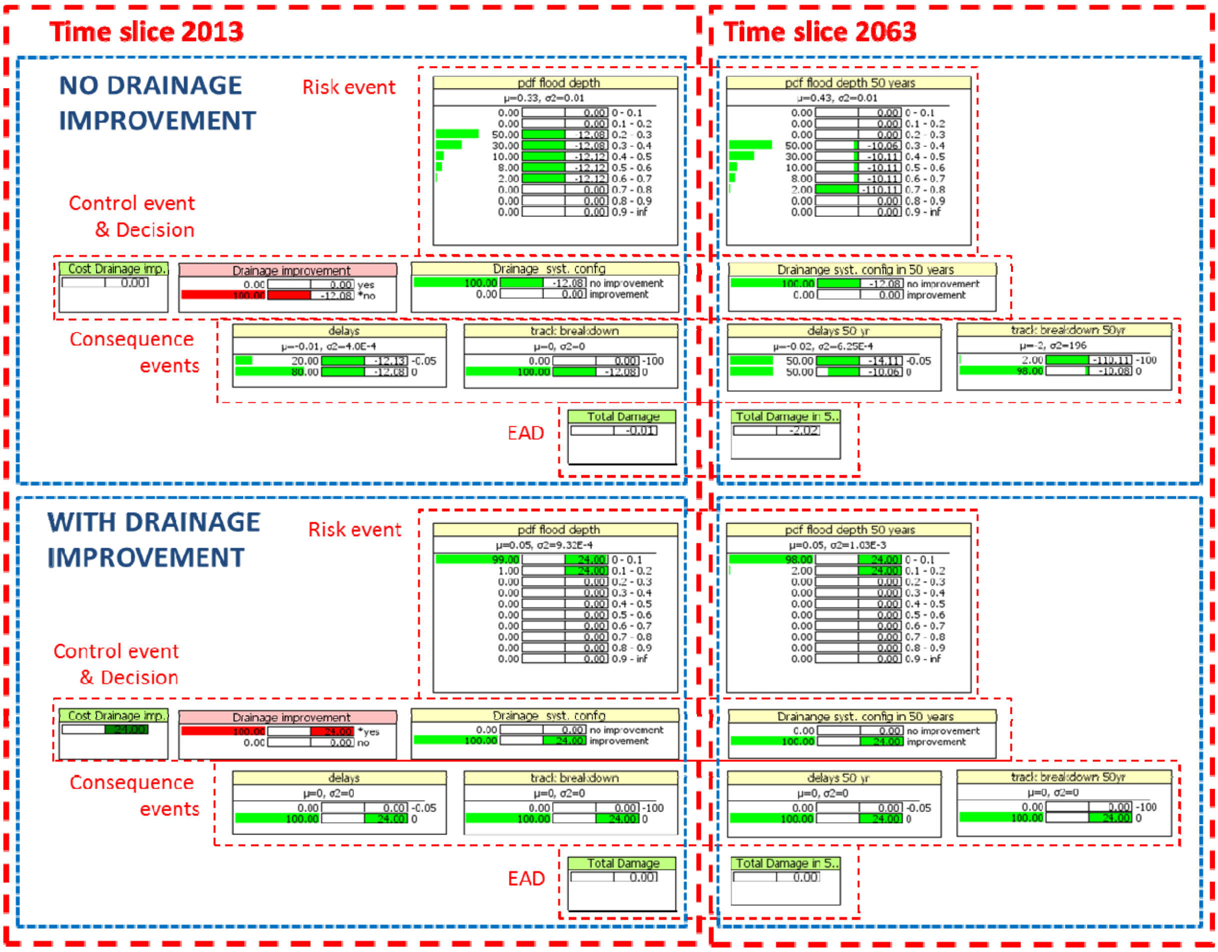

Figure 7 – Monitor windows for time slices 2013 and 2063 for both no drainage improvement and with drainage improvement. Monitor windows describe the posterior probabilities and expected utilities

In Figure 8 (left graph) the occurrence probabilities are described for delays and track breakdowns over the next 100 years. The markers present the numbers gathered from the ID and between the markers a linear behavior is assumed (dotted line). In 100 years the probability of delays to occur is 1. With the drainage system improvement the probability for both delays and track breakdowns to occur over the next 100 years will negligible. It should be noted that the probability of occurrence increase faster between 2063-2113 than between 2013-2063. This is in accordance with the chosen climate factors for future precipitation which suggest a non-linear trend in precipitation increase. The output of the ID is cost for the improvement and EAD for each time slice, presented in Figure 8 (right graph) as markers. When assuming linear behavior between the calculated EADs the total benefits can be estimated as the area between the two EAD lines with and without drainage improvement over the 100 years.

The output from the ID can be extended with a cost-benefit analysis for a detailed description of benefits from the investment. Following the method described by Zhou et al (2012a) the NPV for the railway company was assessed as 49 MDKK over the next 100 years. In Figure 9 the change in net benefits and total NPV over the next 100 years for the railway company is presented. The table shows different cost contributions of the total cost (in percent) and describes how the total NPV changes over 100 years. Also the number of years it takes for the railway company to pay back the investment in means of savings in damage costs is calculated. The graph presents the net benefits over 100 years for no cost contribution and 100% cost contribution to the drainage system investment. This implies the range in which the railway companies' net benefits lie after an agreement on whether or not the company should contribute to the investment in upgrading of the drainage capacity of the area.

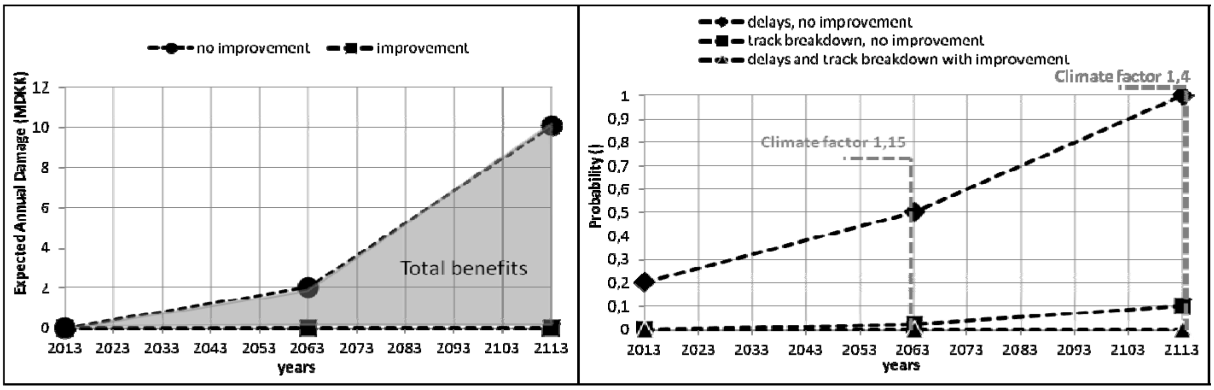

Figure 8 – probability for delays and breakdowns with and without drainage improvement (left). EAD over the next 100 years (right). Total benefits are assessed as the area between the two lines

Indicator	no cost	10%	30%	50%	80%	100%
Cost (MDKK)	0,00	2,41	7,22	12,04	19,256	24,07
Discounted benefits (MDKK)	49,71	49,71	49,71	49,71	49,71	49,71
NPV (MDKK)	49,71	47,30	42,49	37,68	30,45	25,64
Years for payback (MDKK)	0	13	24	34	49	58

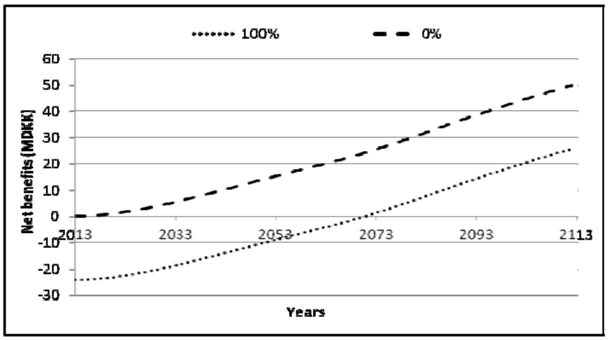

Figure 9 – Change in Net benefits and total NPV over the next 100 years with different cost contributions by the railway company

5 DISCUSSION

In our case study we assumed that the drainage improvement investment will be made presently. This is due to the fact that the municipality considers flood risk to be too high in the area of Risskov and improvements in flood protection are therefore needed now. The aim of the ID was to determine whether the railway company should be included to the investment costs. The results suggest that there is a basis for including the railway company in negotiations regarding investments since the railway company has a clear advantage from the plans.

Figure 8 shows that the current risk for the railway company (EAD=0.01) is negligible. The railway company could argue that the low current risk does not encourage the company to contribute to the investment cost. If the municipality makes the improvements over a longer period of time, the railway company could be more willing to participate in future costs. Step-wise investments can be included into the Influence diagram by adding decision nodes the other time slices.

6 CONCLUSIONS

The aim of our case study example was to present an Influence Diagram to model risk of flooding. Moreover, this tool can be used in contexts where adaptation measures benefit multiple stakeholders. In this respect, the ID offers insights as regards financing schemes of adaptation accounting for these aspects, such as the present railway case. The ID shows that the probability for consequences to occur increases over time and decreases significantly for the railway track with the planned drainage improvement.

The ID presents the results in a transparent way by using monitor windows where the probabilities and utilities for each node are shown. When changing the state of the decision node one can easily read the influence of the change in the networks monitor windows. Further, many different decisions and their interaction can be tested in the network to add transparency to the decision-making process. Hence, for a decision-making purpose the network provides a transparent tool for assessing the effect of decisions in a system under risk.

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