

A Strategy Evaluation Framework Based on Dynamic Vulnerability Assessments

Thomas Münzberg

Institute for Nuclear and Energy Technologies
Karlsruhe Institute of Technology
thomas.muenzberg@kit.edu

Marcus Wiens

Institute for Industrial Production
Karlsruhe Institute of Technology
marcus.wiens@kit.edu

Frank Schultmann

Institute for Industrial Production
Karlsruhe Institute of Technology
frank.schultmann@kit.edu

ABSTRACT

Assessing a system's vulnerability is a widely used method to estimate the effects of risks. In the past years, increasingly dynamic vulnerability assessments were developed to display changes in vulnerability over time (e.g. in climate change, coastal vulnerability, and flood management). This implies that the dynamic influences of management strategies on vulnerability need to be considered in the selection and implementation of strategies. For this purpose, we present a strategy evaluation framework which is based on dynamic vulnerability assessments. The key contribution reported in this paper is an evaluation framework that considers how well strategies achieve a predefined target level of protection over time. Protection Target Levels are predefined objectives. The framework proposed is inspired by Goal Programming methods and allows distinguishing the relevance of time-dependent achievements by weights. This enables decision-makers to evaluate the overall performance of strategies, to test strategies, and to compare the outcome of strategies.

Keywords

Dynamic vulnerability assessment, strategy evaluation, goal programming, decision support

INTRODUCTION

To prepare organizations and societies for managing emerging threats and risks, the identification, evaluation, and selection of strategies are core activities in disaster management. Strategies are understood to be combinations of measures to predict, mitigate, or transfer negative impacts on a system that needs to be protected. The results are frequently used to formulate contingency and business continuity plans.

While selecting strategies, decision-makers in the area of disaster management are often faced with common challenges (Bertsch, 2008, Comes 2011): a multitude of alternative strategies and multiple goals need to be considered and multiple actors are involved. This is also one of the reasons why decision selection has to be examined transparently with regard to the strategy's necessity, benefit, and appropriateness. This also ensures commensurability and acceptance of the selected decision.

Thus, the need for decision support arises. Before strategies can be discussed, the associated risks need to be understood and assessed in a first step. Depending on the type of risk, context, and discipline, multiple tools and methods are available for risk assessments. Indicator-based vulnerability assessments are frequently used methods in assessing natural and environmental risks (Birkmann and Wisner, 2006). In recent years, it became obvious that for some risks like climate change, coastal vulnerability, or flood management it is no longer adequate to assess static vulnerability. These developments give space to a growing number of dynamic, temporal or spatial-temporal vulnerability assessments. Considering the dynamic aspects of vulnerability also implies new needs in the evaluation of strategies. Strategies may predict, delay or minimize a system's

Proceedings of the 11th International ISCRAM Conference – University Park, Pennsylvania, USA, May 2014
S.R. Hiltz, M.S. Pfaff, L. Plotnick, and P.C. Shih, eds.

vulnerability over time. Strategy evaluations need to consider how well strategies perform regarding their time-dependent influence on vulnerability. This issue is addressed by our paper.

To the best of our knowledge, there is no evaluation approach or model in literature that considers the dynamic influence of strategies on the vulnerability of a system. To fill this gap, we introduce a new strategy evaluation framework based on a given dynamic vulnerability assessment model and on the achievement of so called Protection Target Levels (PTLs).

The framework proposed may be based on any dynamic vulnerability assessment that allows simulating the performances of strategies. To consider how well the strategies influence the vulnerability of a system over time, we introduce PTLs. PTLs are time-dependent objectives for the performances of strategies and express e.g. the socially acceptance of consequences over time. The dynamic vulnerability assessment model as well as the determination of PTLs are context dependent and may be implemented in different ways referring to the field of application and purpose.

To evaluate strategies, the deviations between PTLs and indicator values or overall vulnerability values are calculated and weighted in a way similar to Goal Programming. This provides the advantage to take relevancies of indicators, of time-periods as well as desired and undesired achievements into account. The evaluation results reflect how well the strategies achieve PTLs for the given decision-makers preferences.

This paper is organized as follows: in the first section, we introduce the idea of dynamic vulnerability assessments and briefly discuss the problem background of how to evaluate strategies by their time-dependent influences on vulnerability. In the second section, we present the development of a strategy evaluation framework based on a dynamic vulnerability assessment. Finally, the proposed framework is applied to a practical example in the field of sea level rise in the third section. The application and the interpretation of the example's results are discussed and a conclusion is drawn.

COMBINING STRATEGY SELECTION WITH DYNAMIC VULNERABILITY ASSESSMENT

Dynamic Vulnerability Assessments

Today, assessing vulnerability is a key activity in disaster preparedness. It enables the decision-maker to analyze potential disaster impacts (Birkmann and Wisner, 2006) and to identify weaknesses in disaster management (Borgadi, 2004). Hence, vulnerability assessments are valuable methods in risk assessments. Basically, a risk represents a function of the probability of a hazard and the potential damage caused by the said hazard (see Bogardi, 2004 and Cannon, 2006). In recent publications, the term vulnerability is included in risk definition. There are multiple definitions of the term vulnerability depending on context and discipline. Reviews of the terminology of vulnerability and its use in risk definitions are given by e.g. Thywissen (2006), Manyena (2006), and Hufschmidt (2011).

According to common understanding, vulnerability describes the inherent character of a system to suffer from adverse effects under the impact of hazards (e.g. see Thywissen, 2006, Cardona, 1999, and Birkmann and Wisner, 2006). Vulnerability is frequently characterized by a function of exposure, susceptibility, and coping capacities (see e.g. Kaspersen, Kaspersen, and Turner, 1995, Brooks, 2003, and Adger, 2006). Usually, indicator frameworks are used to assess vulnerabilities (ibid.). The indicators describe aspects of vulnerability generation. In combination with indicator weights that express the relevance of selected indicators, weighted sums are predominantly used to calculate vulnerability. Due to the selection of indicators and the development of a framework structure are tailored to the purpose of the assessment and the field of application, there are different kinds of vulnerability assessment models each with a different definition of vulnerability.

The vulnerability of a system can be assessed statically or dynamically. Dynamic (or temporal/spatial-temporal) vulnerability assessments enable decision-makers to analyze the changes of vulnerability over time. Dynamic vulnerability assessments are mostly associated with adaption management and the consideration of long-term environmental, social, and political processes (Bankoff, Frerks, and Hilhorst, 2004, Kienberger, Blaschke, and Zaidi, 2013). Typical dynamic vulnerability assessments are related

- to climate change (e.g. Metzger and Schröter, 2006; Aubrecht, Steinnocher, Köstl, Züger, and Loibl, 2013),
- to sea level rise (e.g. Sahin and Mohamed, 2010),
- to earthquake risks (e.g. Debnath, 2013),
- to flood risks (e.g. Rodríguez-Gaviria, and Botero-Fernández, 2013), or
- to industrial risks (e.g. Belliveau, Smit, and Bradshaw, 2006).

Selection of Strategies Considering Satisfaction

Regarding a tangible hazard, strategies mostly aim at managing risks to maintain a business (or process) continuity and to ensure the survival of a crisis or disaster. Strategies are understood to be combinations of measures which may address the exposure, susceptibility, or the coping capacities of a system to reduce potential damages. Strategies influence the vulnerability of a system. They may be implemented in disaster preparedness plans as discussed e.g. by Quarentelli (1997).

In the context of this paper, it is assumed that a set of strategies is given. To protect a system, one strategy needs to be selected and implemented before a risk occurs (non-sequential). Each strategy reduces, delays, or prevents the increase of vulnerabilities. The individual short-, medium-, and long-term impacts on vulnerability may differ. Additionally, we assume that the decision-makers preferences are also time-dependent and may change over time. As a result, for instance, the short-term impact on vulnerability might be more important as long-term impacts.

To evaluate the strategies, the individual performance of a strategy as well as the decision preferences need to be taken into account. To solve such kinds of multi-objective problems, Gen and Cheng (2000), and Chen and Xu (2012) distinguished between ‘generating schemes’ and ‘preference-based schemes’. Generating schemes focus on the determination of the whole set of optimal solutions or their approximations. Preference-based schemes aim at determining solutions in trading off the multiple objectives. In the context of this paper, the evaluation of strategies aims at investigating the strategy which perform “good enough” in the meaning of “satisfying” rather than “maximizing” or “minimizing” (conflicting) objectives (see also Parker, de Bruin, Fischhoff, 2007). Hence, optimizing means identifying a strategy out of a set of strategies, which gives the best possible value (see also Jones and Tamiz, 2010). This understanding aims at achieving a practical solution rather than finding an optimal result. That is why a preference-based approach seems to be more appropriate for our purpose.

Two of the most frequently used preference-based schemes are the weighting method and Goal Programming. The weighting method can be used to aggregate multiple objectives into a single objective. Goal Programming enables decision-makers to investigate solutions considering multiple objectives regarding predefined goals (Charnes and Cooper, 1961). Due to Goal Programming allows considering multiple priorities of objectives and facilitates evaluations (Chen and Xu, 2012; Durbach and Stewart, 2003), we decided to use the principles of Goal Programming to develop an evaluation framework that takes the performance of strategies over time and time-depend preferences of decision-makers into account.

To evaluate how well strategies perform over time, it is required to integrate predefined goals. Therefore, we use Protection Target Levels (PTLs) that express time-dependent maximum acceptable level of vulnerability as a reference. PTLs are context-dependent and may be generated from experience, from commonly accepted practice, from social acceptability, or determined by loss calculation, impact analyses or business continuity management. PTLs could be applied for the overall vulnerability or to the vulnerability indicators.

Usually, the predefined goals are determined as optimal values and Goal Programming aims at achieving minimal deviations from these optimal values. This addresses a minimization problem. In our approach, PTLs express time-dependent acceptable values. In some points in time, a strategy may reach a PTL, in other points in time a strategy may deviate from a PTL. Positive and negative deviations from PTLs indicate how well a strategy may reach the goal of PTLs. Deviations may be desired or undesired and can be weighted corresponding to the decision-makers preferences. When applying a PTL to the overall vulnerability value at a point in time, for instance, a positive deviation is defined as undesired and a negative deviation is defined as desired. When applying PTLs to vulnerability indicators, the above definition may change depending on the indicator. In any case, the calculation of deviations allows considering how well a strategy satisfy the PTLs.

DEVELOPING A FRAMEWORK TO EVALUATE STRATEGIES

Steps in Developing a Strategy Evaluation Framework

To evaluate strategies, we propose a strategy evaluation framework based on dynamic, indicator-based vulnerability assessments, as was discussed above. Irrespective of the context of the dynamic vulnerability assessment, our proposed generic strategy evaluation framework consists of the following steps:

1. Defining strategies and calculating their dynamic influence on vulnerability (vulnerability assessment).
2. Determining objectives defined by time-dependent PTLs.
3. Calculation and normalization of deviation values.

4. Defining evaluation weights.
5. Formulation of an achievement function.
6. Formulation of an evaluation function to consider additional objectives.
7. Visualizing and ranking of strategies.
8. Sensitivity analyses.

The evaluation framework resembles a Goal Programming approach, but is customized to our field of research.

For some steps the input of decision-makers is needed. The first input of decision-makers is required for the definition of strategies and the PTLs. Like discussed before, different ways to determine PTLs are possible depending on the application domain. Moreover, relevance information is needed after the deviations values were calculated. At this step the preferences of decision-makers can be considered by relevancies. The relevancies are expressed by weights for the used indicators, the kind of deviations, and the time-dependent achievement of PTLs. After the strategies are evaluated and a ranking result is provided, decision-makers may change weights to conduct a sensitivity analyses. This might increase the understanding of trade-offs and insights. In this way, a systematic and comprehensive decision support is offered. The core steps of the framework proposed are reflected and discussed below.

Determining Objectives Defined by Time-Dependent Protection Target Levels (PTLs)

Based on Jones and Tamiz (2010), the generic form of a Goal Programming approach consists of decision variables g_1, \dots, g_j and j goals q_1, \dots, q_j , where j is the number of decision variables and goals, $j \in \mathbb{N}$. q_k is the target level for decision variable g_k , $k = 1, \dots, j$. Target levels are predefined by decision-makers and are applied to a strategy. We assume there are m strategies, which we give the index $r = 1, \dots, m$. $f_r(g_k)$ describes the value of decision-variable g_k for the r th strategy at a point in time.

In the context of our approach, we use vulnerability indicators as decision variables. Hence, a PTL is defined for each indicator. For some vulnerability indicator frameworks, it may not be suitable to define PTLs based on the vulnerability indicator. In this case, a PTL referring to the overall vulnerability could be used instead.

The value of an objective may deviate from the target level. n_k denotes a negative deviation and p_k denotes a positive deviation in a point in time t_n . This leads to the basic Goal Programming formulation for each strategy

$$f_r(g_k) + n_k - p_k = q_k \quad n_k, p_k \geq 0, k = 1, \dots, j \quad (1)$$

$$\text{with } n_k = \begin{cases} q_k - f_r(g_k), & \text{if } q_k > f_r(g_k) \\ 0, & \text{else} \end{cases} \quad \text{and } p_k = \begin{cases} f_r(g_k) - q_k, & \text{if } f_r(g_k) > q_k \\ 0, & \text{else} \end{cases}, k = 1, \dots, j.$$

In the generic approach of goal programming, expression (1) is used to formulate an objective optimization function $f(n_k, p_k)$ to minimize the deviation variables or to find a solution that performs well in achieving the desired target levels. In this case, the solution with the minimum deviations from the target level is the best solution. In our context of evaluating strategies, however, the overall vulnerability or the vulnerability indicators are used as decision variables. For instance applied to the overall vulnerability, the best solution is the solution having a small positive deviation and a large negative deviation from the PTL. This turns negative deviations into desired objectives and positive deviations into undesired objectives.

In generic Goal Programming target levels are static. In the context of this paper, PTLs are time-dependent. Deviations are calculated for all points in time. These should allow for an evaluation of how well strategies influence the vulnerability of a system over time. Assuming that the indicator values may never reach the PTLs at all time step, the protection target levels should be understood as soft constraints.

Normalizing Deviation Variables

Normally vulnerability indicators have different scale units. Thus, the indicator values need to be normalized to ensure comparability. Although the deviations have desired and undesired aspects that need to be considered in the evaluation, different normalizations could be used in the final achievement function. Jones and Tamiz (2010) introduce three kinds of normalizations: (1) Percentage normalization using a percentage value away from its target level, (2) zero-one normalization for a single-objective maximization using the value one for the worst and zero for the lowest value of the deviation, and (3) Euclidean normalization using a Euclidean mean.

For illustration purposes, we take a linear normalization function form which corresponds to percentage normalization. The overall highest deviation value of an indicator is used as a reference taking all strategies into

account. For undesired achievements, an inverse normalization function is used. Hence, the higher the weight for undesired deviations, the more a decision-maker emphasizes how relevant a small or better no undesired deviation should be reached. The score illustrates the relative degree to which the objective is reached by a strategy compared to all other strategies. This is suitable, especially if the deviations have a wide value range. If the deviations are very similar, the highest deviation scales will be relatively overrated. Such effects need to be considered in the selection of the normalization.

As is shown in Table 1, we distinguish between desired and undesired achievements.

Evaluation aspect	Description	Normalization function
Desired achievements	Negative deviations n_{q_j} from the PTLs describe desired achievements. The objective level is below the maximal accepted PTL.	$\frac{n_k}{n_k^{\max}}$
Undesired achievements	Positive deviations p_{q_j} from the PTLs describe undesired achievements. The objective level is above the maximal accepted PTL.	$\frac{p_k^{\max} - p_k}{p_k^{\max}}$

Table 1. Normalization functions considering positive and negative deviations from PTLs

Defining Evaluation Weights

There are two approaches in Goal Programming taking the relevance of objectives into account: Preemptive and non-preemptive approaches. Preemptive approaches use ordered or ranked objectives instead of weighted objectives in non-preemptive approaches (for more details, see Jones and Tamiz, 2010). However, it should be possible for decision-makers to conduct sensitivity analyses. Thus, we prefer a (non-preemptive) weighted objectives approach. Depending on the decision-makers’ preferences, we distinguish three kinds of evaluation weights for presenting the relevance of indicators ($w_k^{\text{indicator}}$), the relevance of time periods (w_b^{period} , where $b = 1, \dots, h$ is the number of time periods under consideration, $h \in \mathbb{N}$), and the relevance of positive and negative deviations from the PTL (w_k^{negdev} and w_k^{posdev}) (see Figure 2). It is important to ensure that $w_k^{\text{indicator}}$, w_b^{period} , w_k^{negdev} , and w_k^{posdev} satisfy the constraints

$$\sum_{b=1}^h w_b^{\text{period}} = 1 \quad \sum_{k=1}^j w_k^{\text{indicator}} = 1 \quad \sum_{k=1}^j w_k^{\text{negdev}} = 1 \quad \sum_{k=1}^j w_k^{\text{posdev}} = 1$$

$$w_b^{\text{period}} \geq 0 \quad w_k^{\text{indicator}} \geq 0 \quad w_k^{\text{negdev}} \geq 0 \quad w_k^{\text{posdev}} \geq 0$$

for all objectives.

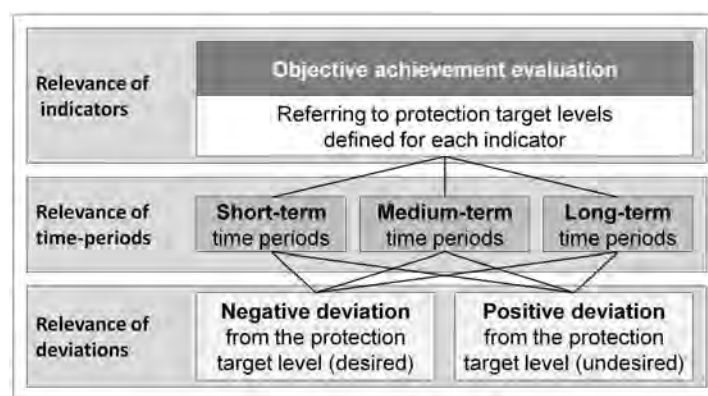


Figure 2. Objective evaluation weights defined in the framework. Weights for indicators, time periods, and deviations can be introduced to emphasize relevancies in the evaluation.

As shown in Figure 2, multiple preferences might be taken into consideration to emphasize achievements in the evaluation. For example, decision-makers may emphasize a desired underachievement of PTLs and therefore increase the weight of negative deviations.

Aubrecht, Freire, Neuhold, Curtis, and Steinnocher (2012) discussed the relevance of short-term and long-term

vulnerabilities. In our context, short-term developments of some indicators might be more important than long-term developments. This relevance could be represented by different weights referring to time periods. Since the importance of indicators may vary, weighting of indicators might be considered. In any case, it is important to verify the weighting definition in the context of the decision conditions, regardless of the nature of weights.

Formulating an Achievement Function to Satisfy Protection Target Levels (PTLs)

As our approach is aimed at identifying a strategy of a set of strategies that performs best, an achievement function is needed instead of an objective function. This non-preemptive approach needs an achievement function, including weighted positive and negative deviations from a predefined reference understood as an accepted PTL.

This then leads to the achievement function that reflects the overall achievement of a strategy for one point in time

$$a = w_b^{\text{period}} \times \sum_{k=1}^j \left(w_k^{\text{indicator}} \left(\frac{w_k^{\text{negdev}} n_k}{n_k^{\text{max}}} + \frac{w_k^{\text{posdev}} (p_k^{\text{max}} - p_k)}{p_k^{\text{max}}} \right) \right) \quad (2).$$

EXAMPLE

To illustrate the proposed strategy evaluation framework based on dynamic vulnerability assessment we use a fictive example from the field of coastal vulnerability to sea level rises. The example used in this paper corresponds to the dynamic vulnerability consideration of Sahin and Mohamed (2010). They considered a raising sea level leading to an increased baseline at coastal areas. The consequences of storm surges occurring in conditions of higher sea level may also impact further inland. The increasing flooding and erosion storm surges are likely to assume a greater damage at infrastructures and natural ecosystems (ibid.). All these effects enhance the vulnerability of a coastal area over a long-time period. To improve the adaption to these effects in a city, dynamic vulnerability information is required.

Therefore, Sahin and Mohamed (2010) developed a decision tool to assess coastal vulnerabilities taking spatio-temporal effects into account. Their tool links System Dynamics modeling and Geographical Information Systems through dynamic data exchange. This allows considering complexity and dynamic nature of coastal systems with dynamic feedbacks and dependencies. As a result, the vulnerability can be assessed in a temporal and spatial way.

In the following, the dynamic vulnerability assessment by Sahin and Mohamed (2010) will be used as an example to demonstrate the basic ideas of the strategy evaluation framework proposed. In doing so, only the timing calculations of coastal flooding and its impacts are from particular interest. To assess vulnerabilities, Sahin and Mohamed (2010) assumed that the vulnerability of coastal areas works through flooding caused by coastal storms and sea level rises. The extent, timing, and impacts of coastal flooding are assessed by using the two indicators g_1 population and g_2 number of residential properties affected within a defined flood level ($j = 2$). Correspondingly, a higher number of population and residential properties will be affected through a rising sea level in a region.

To manage the impacts of rising sea levels, there might be several adaption strategies s^T under consideration. Each strategy consists of a combination of measures like building barrages, resettlement of population, enhancing infrastructural capacities to resist storm impacts, implementation of early warning systems etc. The strategies reduce, delay, or prevent the overall vulnerability over time. This also influences the vulnerability indicator values. In a long-term perspective, the way how each strategy influences the affected population and residential properties differs over time and its effectiveness.

Additionally, Protection Target Levels that describe what degree of sea level raise impacts are socially accepted in the future may be known due to experiences, conducted surveys or other analyses.

Both the dynamic vulnerability assessment model as well as the predefined PTLs required fundamentals to demonstrate the framework proposed. We assume, there might be three adaption strategies s^1 , s^2 , and s^3 identified as a result of a strategy identification process. Decision support tools like this of Sahin and Mohamed may simulate the impact of each strategy. Here we assume the tool provides strategy specific indicator values $m_k^E(t)$ at eleven successive time steps t_0, \dots, t_{10} like shown in Table 2.

Strategies	Indicators	Time steps										
		t ₀	t ₁	t ₂	t ₃	t ₄	t ₅	t ₆	t ₇	t ₈	t ₉	t ₁₀
s ¹	g ₁	0	50	60	70	80	90	100	120	130	160	220
	g ₂	0	10	10	10	25	50	75	75	75	75	100
s ²	g ₁	0	25	25	25	50	60	70	75	90	190	200
	g ₂	0	10	20	30	40	50	55	60	65	80	80
s ³	g ₁	0	25	50	70	80	90	120	150	170	170	170
	g ₂	0	10	20	20	30	35	40	45	50	65	70

Table 2. Values of the indicator population (g₁) and number of residential properties (g₂) representing the influences of three strategies on vulnerability over time

Usually, to calculate the overall vulnerability the indicator values need to be normalized. Here, the following indicator value function is used

$$u_k^r = \frac{m_k^r(t)}{m_k^r(t)^{\max}} \quad (3).$$

Additionally, we assume indicator weights of $w_1^{\text{indicator}} = 0.60$ for the indicator population and $w_2^{\text{indicator}} = 0.40$ for each time step and all strategies. To calculate the overall vulnerability for each strategy and for each time step, we use a weighted sum of the normalized indicator value. The vulnerability aggregation function is represented by

$$V^r(t) = \sum u_k^r w_k^{\text{indicator}} \quad (4).$$

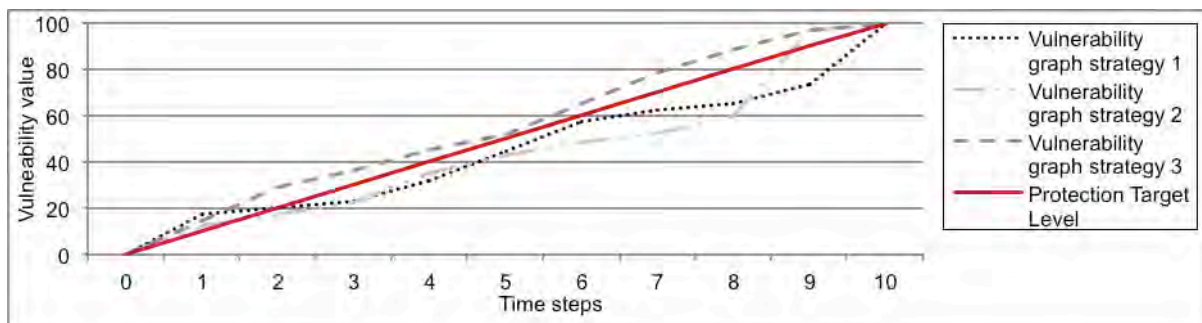


Figure 3.1 Visualization of the vulnerability values over time V^r(t) for the performances of the three strategies.

Figures 3.1 and 3.2 display the results of the overall vulnerability of each strategy for each time step and. For all three strategies it is visualized how well each indicator value process at each time step. At different time steps some of the strategies may over-satisfy and some may under-satisfy the protection level. Figure 4 shows how well the single indicators satisfy the indicator-based PTLs.

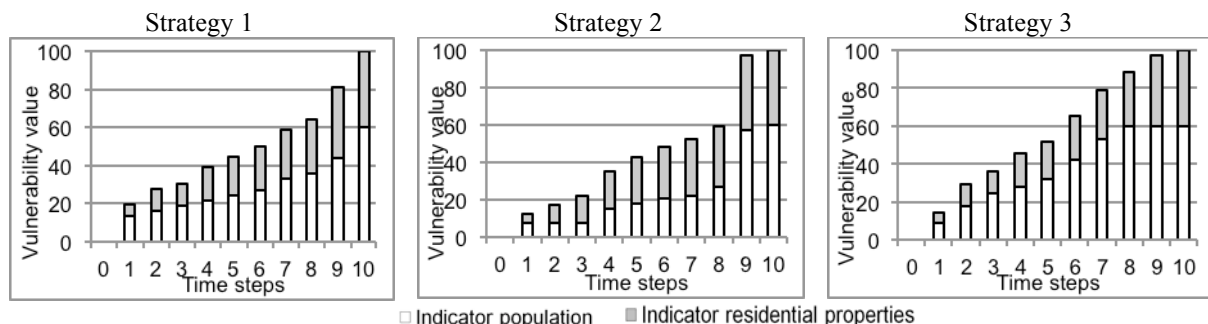


Figure 3.2 The individual performances of the strategies displayed as stacked bar presenting the values of both vulnerability indicator population and number of residential properties for each time step

Based on the visualizations of Figures 3.1 and 3.2 it is not intuitive or evident to determine the strategy with the best relative performance. Thus, the need for a comprehensive strategy evaluation decision support arises. Therefore, the undesired and desired deviations from the PTL are used. Figure 4 displays the positive and

negative deviations between PTLs and indicator values. To evaluate the strategies, the deviations are calculated and normalized according to equation 3 for each time step and each indicator.

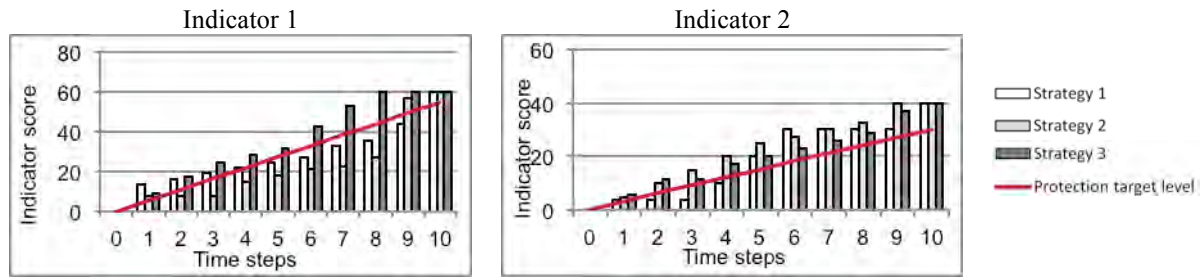


Figure 4. Visualization of the increasing indicator values over time and PTLs for the individual indicators
 Subsequently, undesired and desired deviations at each time step are weighted regarding their relevance and acceptance by the decision-maker. As desired negative deviations are assumed to be more important than positive deviations of the PTLs, we choose the weight as $w_k^{negdev} = 0.75$ and $w_k^{posdev} = 0.25$. Additionally, we consider the different relevance of achievements in the short, medium, and long term. For example, the prompt and successful adaption to short-term sea level raises has a high relevance. In this case the achievement of short-term PTLs is more important as the achievement of long-term protection targets. Therefore, we define three time periods ($b = 3$) $w_1^{period} = 0.50$ for t_0 to t_3 (short-term), $w_2^{period} = 0.30$ for t_4 to t_7 (medium-term), and $w_3^{period} = 0.20$ for t_8 to t_{10} (long-term). Finally, also the importance of each indicator may be considered to be different. Therefore, we use the same indicator weight values as in the vulnerability assessment. The achievement function (equation 2) is processed using parameters for every time step. The sum of all achievement values for each strategy leads to the final evaluation result shown in Figure 5.

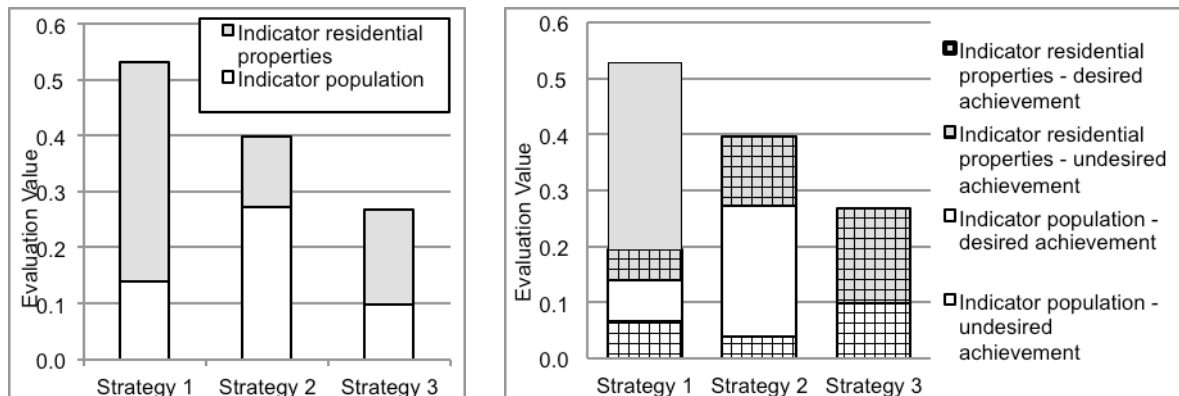


Figure 5. Representation of the final evaluation results

The results of the strategy evaluation are displayed as stacked bars. The stack bars in Figure 4 present the strategy’s achievement of satisfying the PTLs for both vulnerability indicators taking the relevance of time-period, indicator and deviation type into account. Based on these findings, it is now possible to interpret how well the strategies reach the target level for each indicator compared to the other strategies. Compared to strategy 2 and 3, the overall achievement of strategy 1 is the best. The key aspect is the achievement of PTL for the indicator residential properties. No other strategy achieves the target better than strategy 1. Although, the performances of strategy 2 and 3 are different. According to the achievement of the target for the indicator population, strategy 2 performs best. All three strategies perform relatively similar in achieving the objective for undesired deviation of the indicator population.

At this point it is also possible to analyze the sensitivity of the evaluation results by changing the evaluation weights. This may also enhance the understanding of the impact of uncertainties and tradeoffs. It also provides insights of how well the strategies perform. Such kinds of interpretations are only possible by using the framework proposed. The example illustrated the evaluation of strategies taking the influences of strategies on vulnerability into consideration. It may be also possible to include additional objectives like ‘cost’ or ‘acceptance’ of strategies that have no influence on vulnerability.

DISCUSSION

The evaluation framework proposed enables decision-makers to evaluate strategies and to compare their performances over time based on how well strategies achieve predefined Protection Target Levels. To take the

preferences of decision-makers into account, the framework allows considering different relevancies of the used indicators, the kind of deviations of predefined PTLs, and the time-dependent achievement of PTLs. As mentioned in the example, it is imaginable to include additional criteria like ‘costs’ or ‘acceptance’ in the evaluation.

The framework requires a given dynamic vulnerability assessment model that allows to simulate the performances of strategies. Additionally, a determination of PTLs is needed that describes e.g. the socially acceptance of consequences over time. Both are context dependent and may be implemented in different ways referring to the field of application and its purpose. The selection of the dynamic vulnerability assessment model and the determination of PTLs influence the evaluation results fundamentally and should be considered carefully.

The used example in this paper addresses long-term changing vulnerabilities and refers to the selection of adaptation strategies. The framework proposed may also be applied for vulnerabilities that evolve over hours or days after the occurrence of a hazard. For instance, the vulnerability against a food supply disruption depends on the duration of the disruption. This time factor leads also to dynamic vulnerabilities that increase over time according to the duration of the disruption. Resilience strategies to ‘bounce back’ may also be evaluated using the framework proposed.

A weak aspect of the framework proposed can be seen in the assumption that all impacts of strategies can be measured by the selected vulnerability assessment model. If the impacts cannot be expressed by the outcome of the vulnerability assessment, it is not effectively possible to evaluate strategies because of the missing aspects. The framework is suitable in domains where the causal interactions as well as the uncertainties are well known. For complex and high uncertainty environments other decision support methods like scenario planning (Wright and Goodwin, 2009) are perhaps more appropriate.

The proposed framework is a first attempt to assess dynamic vulnerability and leaves room to a wide range of extensions. For instance, it is not possible to validate the results of the framework proposed. Another aspect refers to the regional distribution of vulnerabilities. Many vulnerability models assess vulnerability in a spatial way. The spatial distribution of vulnerabilities may also be considered in strategy evaluations. Additionally, in some cases it is required to rethink response directions and then may change the strategy at later time step. These aspects of sequential decision making that, beside others, also consider the update of information may also be a field for upcoming researches.

CONCLUSION

Due to the increasing number of dynamic vulnerability assessments, the consideration of strategies’ influences to the vulnerability of a system over time becomes an issue in strategy evaluation. To provide a decision support, we introduced an evaluation framework using the results of a given indicator-based dynamic vulnerability assessment model and predefined time-dependent Protection Target Levels (PTLs). To evaluate strategies, the deviations between PTLs and indicator values or overall vulnerability values are calculated and weighted similar to Goal Programming. This enables decision-makers to take preferences for indicators and relevancies of time-periods as well as desired and undesired achievements into consideration. The advantages of the framework regarding the test and the comparison of strategies were demonstrated by an example in the field of sea level raise. The systematic evaluation provides decision-makers with insights that enable to consider the influence of strategies over time. The example illustrated that the evaluation framework is strongly related to the used dynamic vulnerability assessment model and the determination of PTLs. Additionally, some questions need to be analyzed more detailed in our continuing researches, e.g. how the framework can be extended for sequential decision making and for spatial vulnerability assessments.

REFERENCES

1. Adger, N. (2006) Vulnerability, *Global Environ Change*, 16, 268-281.
2. Aubrecht, C., Freire, S., Neuhold, C., Curtis, A., and Steinnocher, K (2012) Introducing a temporal component in spatial vulnerability analysis, *Disaster Advances*, 5, 2.
3. Aubrecht, C., Steinnocher, K., Köstl, M., Züger, J., and Loibl, W. (2013) Long-term spatio-temporal social vulnerability variation considering health-related climate change parameters particularly affecting elderly, *Natural Hazards*, 68, 3, 1371-1384.
4. Bankoff, G., Frerks, G., and Hilhorst, D. (2004): Mapping Vulnerability, Disasters, Development, and People, *Earthscan Publications*, London.
5. Belliveau, S., Smit, B., and Bradshaw, B. (2006) Multiple exposures and dynamic vulnerability: Evidence
Proceedings of the 11th International ISCRAM Conference – University Park, Pennsylvania, USA, May 2014
S.R. Hiltz, M.S. Pfaff, L. Plotnick, and P.C. Shih, eds.

- from the grape industry in the Okanagan Valley, Canada, *Global Environmental Change*, 16, 364–378.
6. Bertsch, V. (2008) Uncertainty Handling in Multi Attribute Decision Support for Industrial Risk Management, PhD thesis, *Universität Karlsruhe (TH)*, Karlsruhe, 2008.
 7. Birkmann, J. and Wisner, B. (2006) Measuring the un-measurable. The challenge of vulnerability, *UNU Institute for Environment and Human Security (UNU-EHS)*, Source 5.
 8. Bogardi, J. J. (2004) Hazards, risks and vulnerabilities in a changing environment: the unexpected onslaught on human security?, *Global Environmental Change*, 14, 361-365.
 9. Brooks, N. (2003) Vulnerability, risk and adaptation: a conceptual framework, *Tyndall centre for climate change, working paper*, 38, 16.
 10. Cannon, T. (2006) Vulnerability analysis, livelihoods and disasters, RISK21- Coping with Risks due to Natural Hazards in the 21st Century - Ammann, Dannemann, and Vulliet (eds), *Taylor and Francis Group*.
 11. Cardona, O. D. (1999): Environmental Management and Disaster Prevention: Two Related Topics - A Holistic Risk Assessment and Management Approach, *Natural Disaster Management*, Ingleton, J. (ed.) Tudor Rose, London.
 12. Charnes, A. and Cooper, W. W. (1975) Management Models and Industrial Applications of Linear Programming, *Management Science*, 4, 1.
 13. Chen, A. and Xu, X. (2012) Goal programming approach to solving network design problem with multiple objectives and demand uncertainty, *Expert Systems with Applications*, 39, 4160-4170.
 14. Comes, M. (2011) Decision Maps for Distributed Scenario-Based Multi-Criteria Decision Support, PhD thesis, *Karlsruhe Institute of Technology*, Karlsruhe, 2011.
 15. Debnath, R. (2013) An assessment of spatio-temporal pattern of urban earthquake vulnerability using GIS: a study on Dhaka City, *Annals of GIS*, 19:2, 63-78.
 16. Durbach, I. and Stewart, T. (2003) Integrating scenario planning and goal programming, *Journal of Multi-Criteria Decision Analysis*, 12, 261-271.
 17. Gen, M. and Cheng, R. (2000) Genetic Algorithms and Engineering Optimization, *John Wiley & Sons, Inc.*
 18. Hufschmidt, G. (2011) A comparative analysis of several vulnerability concepts, *Natural Hazards*, 58, 2, 621-643.
 19. Jones, D. and Tamiz, M. (2010) Practical Goal Programming, *International Series in Operations, Research & Management Science*, Springer, Portsmouth, Kuwait.
 20. Kasperson, J.X., Kasperson, R.E., and Turner, B.L. (1995) Regions at risk: comparisons of threatened environments, *United Nations University Press*, New York.
 21. Kienberger, S., Blaschke, T., Zaidi, R.Z. (2013) A framework for spatio-temporal scales and concepts from different disciplines: the ‘vulnerability cube’, *Natural Hazards*, 68, 1343-1369.
 22. Manyena, S.B. (2006) The concept of resilience revisited, *Disasters*, 30, 4, 433-450.
 23. Metzger, M. J. and Schröter, D. (2006) Towards a spatially explicit and quantitative vulnerability assessment of environmental change in Europe, *Regional Environmental Change*, 6, 4, 201-216.
 24. Parker, A. M., de Bruin, W. B., and Fischhoff, B. (2007) Maximizers versus satisficers: Decision-making styles, competence, and outcomes, *Judgment and Decision Making*, 2, 6, 342-350.
 25. Quarantelli, E.L. (1997) Ten Criteria for Evaluating the Management of Community Disasters, *Disasters*, 21, 39-51.
 26. Rodríguez-Gaviria, E. M., and Botero-Fernández, V. (2013) Flood Vulnerability Assessment: A Multiscale, Multitemporal and Multidisciplinary Approach, *Journal of Earth Science and Engineering*, 2, 102-108.
 27. Thywissen, K. (2006) Components of Risk: A Comparative Glossary, *Publication Series of UNU-EHS*, Source 2.
 28. Sahin, O. and Mohamed, S. (2010) Coastal vulnerability to sea level rise: a spatio-temporal decision making tool, *Proceedings of the 2010 IEEE International Conference on Industrial Engineering and Engineering Management*, 29 Oct - 31 Oct 2010, Xiamen, China.
 29. Wisner, B., Blaikie, P., Cannon, T., and Davis, I. (2004) At Risk: Natural Hazards, People’s Vulnerability and Disasters, *Taylor & Francis Books Ltd*.
 30. Wright, G. and Goodwin, P. (2009) Decision making and planning under low levels of predictability: Enhancing the scenario method, *International Journal of Forecasting*, 25, 813-825.

Proceedings of the 11th International ISCRAM Conference – University Park, Pennsylvania, USA, May 2014
S.R. Hiltz, M.S. Pfaff, L. Plotnick, and P.C. Shih, eds.