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Strategic rehabilitation planning of piped water networks using multi-criteria decision analysis

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Abstract

To overcome the difficulties of strategic asset management of water distribution networks, a pipe failure and a rehabilitation model are combined to predict the long-term performance of rehabilitation strategies. Bayesian parameter estimation is performed to calibrate the failure and replacement model based on a prior distribution inferred from three large water utilities in Switzerland. Multi-criteria decision analysis (MCDA) and scenario planning build the framework for evaluating 18 strategic rehabilitation alternatives under future uncertainty. Outcomes for three fundamental objectives (low costs, high reliability, and high intergenerational equity) are assessed. Exploitation of stochastic dominance concepts helps to identify twelve non-dominated alternatives and local sensitivity analysis of stakeholder preferences is used to rank them under four scenarios. Strategies with annual replacement of 1.5-2 % of the network perform reasonably well under all scenarios. In contrast, the commonly used reactive replacement is not recommendable unless cost is the only relevant objective. Exemplified for a small Swiss water utility, this approach can readily be adapted to support strategic asset management for any utility size and based on objectives and preferences that matter to the respective decision makers.

Keywords

Strategic water asset management, failure and rehabilitation modeling, water supply, multi-criteria decision analysis, decision support, scenario planning

1. Introduction

1.1 Strategic Asset Management (SAM)

Awareness about the need for long-term rehabilitation planning of our aging water infrastructure has risen globally during the past two decades (AWWA, 2001; Burns et al., 1999; Herz, 1998; Kleiner and Rajani, 1999; Sægrov, 2005; Selvakumar and Tafuri, 2012; Vanier, 2001). Infrastructure asset management (IAM) is increasingly applied to rehabilitation planning on the strategic, tactical, and operational levels (Cardoso et al., 2012; Christodoulou et al., 2008; Fuchs-Hanusch et al., 2008; Haffejee and Brent, 2008; Heather and Bridgeman, 2007; Marlow et al., 2010; Ugarelli et al., 2010).

Recently, the CARE-W (Sægrov, 2005) and AWARE-P (Cardoso et al., 2012) research projects have greatly contributed to the development and implementation of structured IAM approaches, including strategic asset management (SAM). Both rely on (i) knowledge about the expected useable lifetime and condition of assets over time (failure models), (ii) knowledge about the consequences of rehabilitation alternatives (rehabilitation models), but are weak in (iii) systematic and transparent decision support, and (iv) thorough accounting for planning uncertainty.

Application of the available SAM approaches in the water sector is still limited, given the high need for human, informational, and data resources (Alegre, 2010). In Switzerland, SAM is a specific challenge due to the sector's high fragmentation (Lienert et al., 2013a) and prevalence of mostly small water providers, the majority with < 10'000 beneficiaries (SVGW, 2006).

1.2 Failure models

To compare water network rehabilitation options, knowledge about the expected useable lifetime and condition of pipe assets is crucial (Selvakumar and Tafuri, 2012). Probabilistic water pipe failure models to predict age-dependent pipe deterioration abound (reviewed in Kleiner et al., 2009; Kleiner and Rajani, 2001; Liu et al., 2012). Whereas their practical value has been shown especially in connection to larger water networks (e.g. Alvisi and Franchini, 2010; Eisenbeis et al., 1999; Poulton et al., 2007; Renaud et al., 2012), their calibration to the local conditions is usually infeasible in small to medium-sized water networks because of their high data demand. Hence, there is a lack of failure models that support rehabilitation planning in the very common small to medium-sized networks in Switzerland, but also in other European countries such as Austria, Germany, and France. Additionally, common data particularities, namely left-truncation, right-censoring, and selective survival bias, are usually not explicitly considered in model parameter inference, which may lead to biased predictions of failures (Le Gat, 2009; Mailhot et al., 2000; Renaud et al., 2012; Scheidegger et al., 2011). A general approach as well as a specific model to avoid biases in pipe failure models due to these particularities were recently proposed by Scheidegger et al. (2013). The problem of short networks (small sample size) and limited failure records in pipe failure model calibration can be overcome by Bayesian parameter inference (Dridi et al., 2009; Watson et al., 2004).

1.3 Comparing rehabilitation alternatives

The available rehabilitation models are mostly used to support operational and tactical (i.e. short to mid-term) pipe repair and replacement planning (for a review see Engelhardt et al., 2000). Nonetheless, software to support strategic (long-term) rehabilitation decisions exists, usually combining pipe deterioration and evaluation models with decision support features (e.g. KANEW (Kropp and Baur, 2005), PiReM (Fuchs-Hanusch et al., 2008), D-WARP (Kleiner and Rajani, 2004), Aware-P (Cardoso et al., 2012), Casses (Renaud et al., 2012), WilCO (Engelhardt et al., 2003), PARMS Planning (Burn et al., 2003)). From the information available, and examining four software products in detail, we judged none suitable to simultaneously meet core requirements of our approach: a) combinability with our failure model, b) flexible implementation of rehabilitation strategies and performance measures, and c) propagation of parameter uncertainty. We therefore selected the sector-independent asset management software FAST (Fichtner Asset Services & Technologies, 2013) which is based on a set of interacting differential equations as used in system dynamic modeling.E.g. Rehan et al. (2011) follow a system dynamic approach for the long-term planning of water and wastewater systems and studying the financial sustainability of different rehabilitation strategies.

1.4 Decision support

As noted by others, e.g. (Alegre, 2010; Giustolisi et al., 2006; Selvakumar and Tafuri, 2012), the evaluation and prioritization of water system rehabilitation alternatives should be supported by robust and feasible decision support tools. In water engineering, single- or multi-objective optimization and cost-benefit analysis are commonly used to support decisions (Engelhardt et al., 2000; Giustolisi et al., 2006) although they often ignore subjective stakeholder preferences. In a long-term and multi-stakeholder context like strategic rehabilitation planning, the integration of stakeholder preferences by multi-criteria decision analysis (MCDA) seems more appropriate (Keeney, 1982).

MCDA has been applied to water infrastructure asset management at least twice (Baur et al., 2003; Carriço et al., 2012); both using ELECTRE of the outranking family of MCDA methods (Roy, 1991). Many other MCDA approaches are available, see e.g. Belton and Stewart (2002) and Figueira et al. (2005) for an overview. Another well-established MCDA approach is multi-attribute value and utility theory (MAVT/MAUT). Four important reasons for choosing MAVT/MAUT to support asset management decisions (further explained in Schuwirth et al., 2012) are: 1) foundation on axioms of rational choice, 2) explicit handling of prediction uncertainty and stakeholder risk attitudes, 3) ability to process many alternatives without increased elicitation effort, and 4) possibility to include new alternatives at any stage of the decision procedure.

1.5 Uncertainty assessment

A major concern for long-term planning is the consideration of uncertainty about future developments, the probabilistic description of which is difficult due to high ambiguity (Rinderknecht et al., 2012). Scenario planning has been proposed to handle these uncertainties (Schnaars, 1987) and mitigate under- and over- prediction of change (Schoemaker, 1995). It is increasingly incorporated into both IAM and MCDA to evaluate the robustness of decision alternatives to future change (Cardoso et al., 2012; Goodwin and Wright, 2001; Karvetski et al., 2009; Montibeller et al., 2006; Stewart et al., 2013). While scenario thinking can be interpreted as a way to cover in-between uncertainties of a range of possible futures, uncertainty quantification and propagation of model outputs combined with sensitivity analysis allows the consideration of uncertainty within future scenarios (Stewart et al., 2013).

1.6 Goal and structure

Recent reports confirm that the need for water infrastructure rehabilitation in Switzerland is higher than actual rehabilitation (Martin, 2009), but strategic planning is missing. Higher rehabilitation needs have also been recognized in other places, e.g. Australia (Burns et al., 1999), and the USA (Selvakumar and Tafuri, 2012). Our main objective is to show ways out of this planning backlog. We demonstrate a novel approach on how long-term rehabilitation strategies can be evaluated by integrating failure and rehabilitation modeling into a multi-criteria decision analysis (MCDA) and scenario planning framework. We aim at answering two key questions:

1. Which outcomes are expected for different pipe rehabilitation strategies?
2. Which are the best rehabilitation strategies under given preferences and how robust are they under different future scenarios?

A small Swiss water utility ("D") serves as practical example to illustrate that SAM is possible even in small utilities. The deterioration model and its calibration are geared to small networks and can be replaced by other approaches depending on the amount of data available and the desired sophistication of failure modeling. The overall MCDA approach, however, should scale well for any utility size.

The remainder of this manuscript is organized as follows: In section 2.1, a new length homogenization procedure is presented to allow the comparison of four water networks, A-D. Secondly, parameters for the failure model are estimated for networks A-C and aggregated into one prior parameter distribution (2.2). The posterior failure parameters for D are obtained by Bayesian inference; failures before the start of failure recording in D are also predicted. Thirdly, the posterior parameters from (2.2) are inputs to model the outcomes of 18 rehabilitation alternatives under four future scenarios by means of a rehabilitation model (2.3) for utility D. Fourthly, the rehabilitation alternatives' outcomes are evaluated with MCDA, assuming different stakeholder preferences (2.4-2.9). To remove irrelevant alternatives, dominance concepts are exploited. A local sensitivity analysis determines the robustness of the alternatives' ranking to preference changes under future scenarios. Additional information and figures, including a list of symbols and abbreviations, is given in the supporting information (SI)

2. Material and methods

2.1 Data preparation

Four Swiss water suppliers of different size provided their data to this study. The three larger ones (A-C) are used to infer the Bayesian prior and the smallest is the target utility (D). To facilitate comparison, the pipe and failure data of A-D are prepared in the same manner.

Failures occurring in the installation year are discarded as they are likely caused by installation deficiencies and not structural aging. After plausibility checks, pipes are grouped by shared properties, known to affect pipe deterioration, especially material, date of laying, and diameter (Carrión et al., 2010; Giustolisi et al., 2006; Kleiner and Rajani, 1999). Relevant groups for D are, differentiated by material and laying period: 1st and 2nd generation ductile cast iron (DI1 before, DI2 after 1980; both centrifugal casting, but DI1 only with lacking outer corrosion protection), 2nd and 3rd generation grey cast iron (GI2 before, GI3 after 1930; vertical and centrifugal casting, respectively), asbestos cement incl. Eternit (FC), steel (ST), and polyethylene (PE). In utility D, pipe laying dates of ca. 98% of pipes were known precisely. For the remaining 2%, the midpoint of the stated time interval was used. The results from Bayesian inference did not significantly differ when taking the minimum or maximum point of the intervals (not shown), such that uncertainty arising from this was neglected. Further specification of sub-groups into diameter classes or external influences (e.g. road traffic, soil conditions) is avoided in order not to excessively stratify the already few failure data available.

The influence of pipe length on failure prediction is important in failure modeling (Carrión et al., 2010; Fuchs-Hanusch et al., 2012; Gangl, 2008; Poulton et al., 2007), because failures are often triggered by previous failures in the vicinity (Rajani and Kleiner, 2001). One solution would be its explicit consideration as additional model covariate, requiring more parameters to be estimated. Instead, we homogenize the data by merging and splitting, based on the observation of a large Austrian water network (Graz), where roughly 95 % of subsequent failures were within 150 m distance of the first, and practically none after 200 m (Gangl, 2008). If the geographic location of pipes is available, (Fuchs-Hanusch et al., 2012) and (Poulton et al., 2007) indicate ways to homogenize pipe lengths. In our case, GIS data were not provided, leading us to leave, merge, or split pipes dependent on their length, material and date of laying (Appendix A).

2.2 Pipe failure and replacement model

The used probabilistic Weibull-exponential pipe failure model is described in Scheidegger et al. (2013). It models the time between the first failure and the laying date t_0 (in years) with a Weibull distribution with shape parameter θ_1 and scale parameter θ_2 so that

$$p_1(t|t_0,\Theta) = \frac{\theta_1}{\theta_2}\left(\frac{t-t_0}{\theta_2}\right)^{\theta_1-1} e^{-\left(\frac{t-t_0}{\theta_2}\right)^{\theta_1}} \qquad (1)$$

and the times between subsequent failures as exponential distributions with scale parameter θ_3:

$$p_i(t|t_0,\dots t_{i-1},\Theta) = \frac{1}{\theta_3} e^{-\left(\frac{t-t_{i-1}}{\theta_3}\right)} \quad ,i>1 \qquad (2)$$

where t_i denotes the point in time of the ith failure. To consider m different pipe characteristics m-1 regression coefficients $\beta_1 \dots \beta_{m-1}$ are estimated together with Θ. The parameter vector for pipe k is then computed as

$$\Theta_k = (\theta_1, \alpha_k\theta_2, \alpha_k\theta_3)^T \qquad (3)$$

where

$$\alpha_k = \beta_1^{z_{k,1}} * \cdots * \beta_{m-1}^{z_{k,m-1}}$$

The indicator variables $z_{k,j}$ equal to one if the jth characteristic is met by pipe k and otherwise zero.

To estimate the failure model parameters, the influence of past replacement on the recorded data needs to be considered. To enable an unbiased estimation of these parameters, the failure model is coupled with a replacement model in which the probability π of a pipe not to be replaced after occurrence of each failure is assumed to be constant (Scheidegger et al., 2013). Replacement due to other reasons than pipe condition, i.e. managerial replacement due to collaboration with other infrastructure providers, is not covered as it has no influence on the parameter estimation and cancels out algebraically.

2.2.1 Model calibration

Because the data of D do not suffice to calibrate the model using purely data-driven methods such as Maximum Likelihood Estimation (MLE) (Harrell, 2001), the failure and replacement model parameters are determined by Bayesian inference. This is widely used in statistical and engineering science and has already been applied to pipe failure models (Dridi et al., 2009; Economou et al., 2009; Watson et al., 2004). Using Bayes' theorem, a prior probability distribution of the failure model parameters is updated with observed data of target water supplier D (for the concept see e.g. Gelman et al. (2004)).

2.2.2 Estimation of prior parameter distribution

A prior distribution provides a mathematical description of the current knowledge about the parameters in question. An informative prior can be obtained by e.g. expert elicitation (the assessment of unknown quantities from experts), literature study, or analysis of additional data. Based on experience with expert elicitation for a much simpler model (Scholten et al., 2013), we judged elicitation to be considerably more complex than maximum likelihood estimation (MLE) from available data. The prior parameter distribution for utility D (61 km) was then estimated from data of three large to mid-size Swiss water utilities A-C (> 220 km distribution network each):

First, the model parameters for each network are separately determined using MLE. For each water utility *u*, the parameters ${\Theta_u}^* = \ln(\Theta_u)$ are approximately multivariate normal distributed: $p_u(\Theta^*|\mu_u, \Sigma_u)$. The parameters of the failure model Θ_u for each utility are thus lognormal distributed with $p_u(\Theta|\mu_u, \Sigma_u)$. Second, the three parameter distributions are aggregated into one prior distribution by an equally weighted mixture of distributions and smoothing to ensure unimodality (Scholten et al., 2013).

Owed to strong correlation with the other model parameters, and identifiability issues during pre-tests, π is not directly estimated for B and C. Instead, it is fixed to a defined level and the other parameters are inferred freely. To propagate the uncertainty linked to the choice of π, we assume a beta distribution with parameters α=15 and β=2.5, π~Beta(α,β), and perform MLE at the 0.01, 0.1, 0.2, …, 0.9, 0.99 quantiles. α and β are chosen based on expert information from water supplier B and C who estimated the probability not to be replaced after a failure (π) as approx. 0.88-0.82 (B) and 0.88-0.97 (C) for the last 1-3 years. The resulting parameter distributions are aggregated using the probability density at the quantiles as weights to obtain one separate distribution for each B and C. Since no FC pipes are present in B and C, the same correlation to the other parameters as in network A is assumed.

2.2.3 Estimation of posterior parameters

The Bayesian posterior is obtained by Markov Chain Monte Carlo (MCMC) sampling using the aggregated prior of A-C, the conditional likelihood, and the network and failure data of D. Of 50'000 samples, the first 25'000 are discarded as burn-in and the posterior parameter distribution is obtained from the remaining.

2.2.4 Prediction of unrecorded failures

Taking the failure order as indicator of pipe condition, knowledge about the previous number of failures is needed to correctly apply condition-dependent rehabilitation strategies. Since only the times and orders of failures within the observation period are known, the number of previous failures of each pipe before the start of observations can be predicted, see supporting infomation B.

2.2.5 Prediction of future failures

Failures are predicted by embedding the failure model into the asset management software FAST (Fichtner Asset Services & Technologies, 2013). As compromise between computational time and stability, 1'000 parameter combinations randomly sampled from the posterior are imported to propagate the uncertainty of the failure model parameters. For PE pipes, further assumptions of failure model parameters are necessary given the absence of failure data for inference. The mean parameters of the Weibull distribution are set at $\theta_{1,PE}$=4.11, $\theta_{2,PE}$= 74.4 with standard deviations as $\sigma_{1,PE}$= 1.21, $\sigma_{2,PE}$= 26.73 (Scholten et al., 2013, Table 4), and $\theta_{3,PE}$= 39.7 and $\sigma_{3,PE}$= 12.8 for the exponential distribution (mean expected value; mean standard deviation of posterior θ_3 for remaining materials). After prediction and assignment of unrecorded failures to single pipes, π is no longer needed for prediction of future failures because the probability of future replacement is determined by the rehabilitation strategy.

2.3 Network rehabilitation model

Rehabilitation modeling in FAST is based on a system of coupled (non-linear) differential equations which describe the condition of the assets over time. Within each *aging chain* (Sterman, 2000), pipe condition is defined by the number of occurred failures governed by an age-dependent deterioration process (pipe failure model). We defined six condition classes from "zero" to "five or more" failures (Figure 1). Each pipe group is associated to its own, unique aging chain. Fifteen aging chains were implemented to model network expansion and deterioration of five pipe groups (DI1, DI2, GI3, FC, and PE), subdivided into three diameter classes (low, medium, and high criticality, section 2.5.2). Other processes that influence pipe condition over time are also modeled: network expansion, deterioration, repair, and replacement (Figure 1).

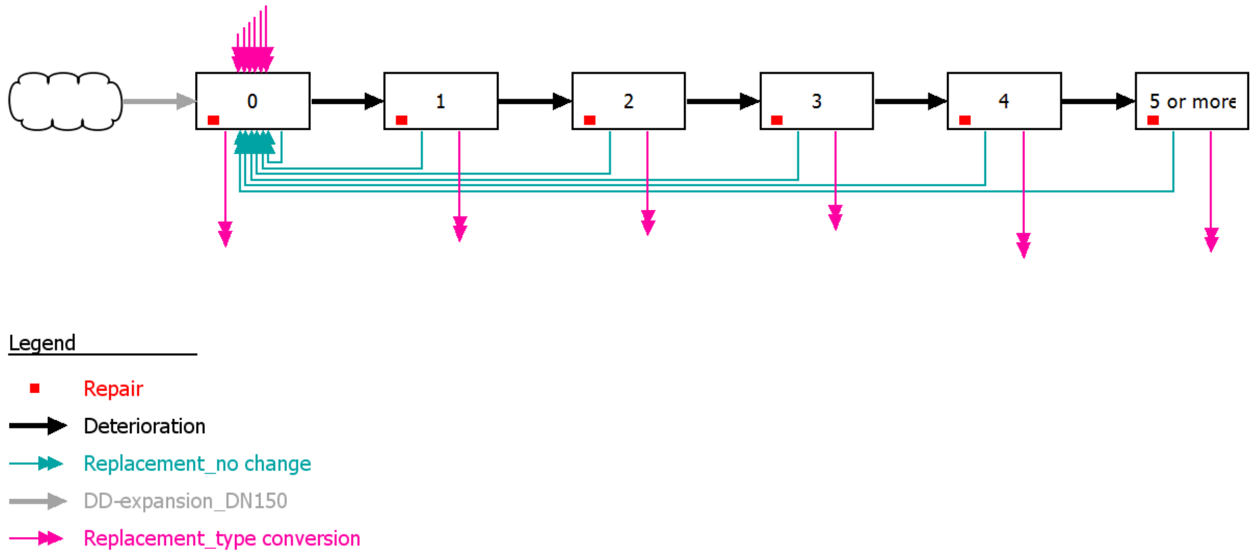

Figure 1: Exemplary aging chain with relevant processes as displayed in FAST. Boxes represent the condition state (number of failures) of its pipe members, arrows the transition between condition states and pipe groups. DD-expansion_DN150: distribution network expansion of 150 mm pipes; replacement_type conversion: replacement through pipes of another material.

2.3.1 Deterioration

In accord with the failure model of Scheidegger et al. (2013), the age-dependent transition from no failures to condition 1 (1st failure) is described by a Weibull distribution. The time to subsequent failures follows an exponential distribution with identical parameters.Scheidegger et al. (2013) made this choice based on the manageable complexity of this model layout and its successful application in the past by Mailhot et al. (2000).

2.3.2 Reactive rehabilitation (repair)

To warrant continuous water supply, we assume that all failed pipes are immediately repaired. Thereafter, a pipe is considered fully functional but one condition class higher (worse) on the aging chain due to the higher failure order.

2.3.3 Proactive rehabilitation (replacement)

A defined number of pipes with specified characteristics are replaced by new pipes (condition 0). The amount and characteristics depend on the rehabilitation strategy. Historical materials which are no longer available, i.e. DI1, GI2, GI3, and AC, are replaced by other materials used in Switzerland (PE pipes replace FC, DI2 replaces GI2, GI3, and DI1). Failed pipes are removed from the aging chain and an equal number of new pipes are created in the target aging chain of the same or new material. All other materials pipes are replaced by new pipes of the same material. It is also possible that pipes without failures are removed. One example is managerial replacement caused by collaborative ground works with other infrastructure providers or for other reasons requiring the removal of a specific material such as asbestos pipes. Managerial replacement is not considered in this study.

2.4 MCDA framework

MCDA allows exploring different *alternatives* (in engineering terms: options, measures, strategies, solutions, scenarios) regarding their performance on *fundamental objectives* (criteria, goals). The preferences of stakeholders are quantified based on *attributes* (quantitative performance indicators, metrics) associated to the objectives. The performance of an alternative is based on combining the prediction of its *outcome* (e.g. expected costs) with the preferences of the stakeholders for this outcome (Eisenführ et al., 2010; Keeney, 1993).

In the first structuring phase, the decision problem and boundary conditions are defined and main stakeholders identified (see Lienert et al. 2013a, b). Objectives, attributes, and alternatives are formulated. Secondly, the outcomes (attribute levels) of each alternative are predicted, e.g. from model outputs or expert estimates. Then subjective preferences of the decision makers (and other stakeholders) regarding the objectives are elicited. By help of a multi-attribute value model (MAVM), the overall value of each alternative is calculated by combining the outcomes with the individual preferences. The alternatives are ranked, based on overall values and discussed with the decision maker(s).

2.5 Objectives and attributes

Predominantly economic, hydraulic, water quality, and reliability criteria should be included in rehabilitation decision models (Engelhardt et al., 2000; Selvakumar and Tafuri, 2012). Most of these “criteria”, however, are poorly formulated in terms of decision analysis because the fundamental objectives remain unclear, or because they more likely represent attributes (e.g. life cycle cost) or means objectives (e.g. low failure rate, good system condition). Means objectives are pursued to achieve another, more fundamental objective and indicate a poorly designed system of objectives (Eisenführ et al., 2010). A reformulation of the criteria mentioned in (Engelhardt et al., 2000; Selvakumar and Tafuri, 2012) results in at least three fundamental objectives of good rehabilitation strategies which we use to compare alternatives (but with other attributes; see also discussion of objectives and attributes in Lienert et al. (2013b)):

1) low costs (mentioned: cost of replacement/ damage/ repair/ maintenance/ leakage and water loss/ life cycle cost),
2) high reliability (mentioned: probability/ percentage of the time the system is operational/ ability to supply required quantity and quality of water),
3) high intergenerational equity (mentioned: failure/ break rate/ net present value [for financial sustainability]).

2.5.1 Low costs (attribute: % of mean annual per capita income)

Costs are expressed as percentage of the mean annual per capita income in the region (viz. 65’093 CHF in 2010) and are affected by future development (Appendix B). Only direct costs for repair and replacement are considered. Unit costs are 6’500 CHF per failure (median in neighboring utility, 2005-2010) covering repair, disinfection, and temporary above-ground services during interruption. Replacement cost is 910 CHF m^{-1}, including valves and fittings (mean rate charged by local engineering companies for open trench replacement). We use real incomes and assumptions about real income changes under the four future scenarios (section 2.9) and relate annual costs to annual incomes to unlink costs and inflation. The resulting percentages are then independent of any assumptions regarding future inflation and discount rates. This choice is also beneficial in view of elicitation from decision makers. It avoids an anchoring to certain absolute monetary levels compared to which higher future costs can be perceived as loss (reference point effect, see Kahneman and Tversky, 1979) even though the relative percentage compared to the mean income is the same.

2.5.2 High reliability (attribute: system reliability)

The reliability of a system (*R*) is linked to the frequency and impact of interruptions (Farmani et al., 2005; Mays, 1996). In the absence of detailed hydraulic models, we use a criticality index *C* to represent the severity of a failed pipe's impact. Assuming that larger pipe diameters result in higher property damage and number of people affected (at least in ramification networks as typical for small networks), pipes are rated into three criticality classes depending on inner diameter. Small distribution pipes (usually ≤ 150 mm): $C_{low} = 1$, intermediate distribution pipes (150-250 mm): $C_{medium} = 5$, major distribution pipes and trunk mains (≥ 250 mm): $C_{high} = 10$.

$$R = 1 - \frac{\sum_{i=1}^{3} C_i \cdot n_{f,i}}{\sum_{i=1}^{3} C_i \cdot n_i} \tag{4}$$

with C_i… criticality index (or importance weight) of diameter group
$n_{f,i}$…number of pipe failures in diameter group
n_i… number of all pipes in diameter group

2.5.3 High intergenerational equity (attribute: degree of rehabilitation)

The mean failure rate (failures per km and year) of an alternative compared to a reference (no replacement) indicates the degree of implementation of the rehabilitation demand D_{reha}, or "degree of rehabilitation".

$$D_{reha} = 1 - \frac{r_s}{r_{ref}} \tag{5}$$

with r_s… failure rate of strategic alternative s (failures per km and year)
r_{ref}… failure rate of reference strategy A_{ref} (failures per km and year)

If the rehabilitation demand of a generation is not responded to, the average age of the network and its likelihood of failure, water losses, and water quality impairment increases. Consequentially, future generations have to invest potentially higher efforts than needed by the current generation to maintain a good condition.

2.5.4 Uncertainty of attribute predictions

The uncertainty of the attribute predictions results from the failure predictions. These predictions incorporate the random behavior of pipe failures and the uncertainty due to parameter uncertainty of the model described in section 2.2. Variation under the four different future scenarios arises from the parameters assumed for network expansion and socio-economic development (section 2.9). Further plots regarding the sensitivity of the attribute outcomes to different criticality indices and unit costs are shown in the supporting information (section F).

2.6 Strategic rehabilitation alternatives

We compare 18 strategic rehabilitation alternatives which follow three qualitative regimes: *minimal*, *average*, and *extensive* (Table 1). Failures are always repaired, regardless of the alternative. *Minimal* stands for mostly reactive alternatives, i.e. only pipes of very bad condition are replaced, a common strategy in many places (Selvakumar and Tafuri, 2012). The *average* regime describes simple replacement strategies of moderate effort, e.g. reaching a predefined lifespan or a certain number of failures (e.g. 3rd, 4th) . The *extensive* regime contains more elaborate strategies typical for large water utilities. Performance is assessed over 40 years, until 2050. To understand long-term outcomes over more than one pipe generation, calculations are done until 2110.

Table 1: Strategic rehabilitation alternatives. Failures are repaired in all alternatives. The strategies are not adapted over time, i.e. if all pipes in the worst condition states (e.g. 5 or more failures) are replaced, pipes from the next-worst condition class (e.g. 4, 3 and so on) are replaced. If there are more pipes in a certain condition class of an aging chain than should be replaced (e.g. 20 pipes in worst condition, but only 2 are replaced), the oldest pipes are selected.

Alternative		#	Description	Regime
Reference	A_{ref}	1	no. of failures if only repairs are done. i.e. function is maintained but condition deteriorating	none
Based on no. of failures (condition)	$A_{f2\ldots5+}$		replacement only if a certain condition, applies:	
		2	- A_{f2+}: replacement after 2nd failure	average
		3	- A_{f3+}: replacement after 3rd failure	
		4	- A_{f4+}: replacement after 4th failure	minimal
		5	- A_{f5}+: replacement after 5th failure	
	$A_{f0.5\%\ldots2\%}$	6	% of network replaced by condition: worst condition first*	
		7	- $A_{f0.5\%}$: 0.5 % of network	average
			- $A_{f1\%}$: 1 % of network	
		8	- $A_{f1.5\%}$: 1.5 % of network	extensive
		9	- $A_{f2\%}$: 2 % of network	
Based on pipe age	$A_{cyc80\ldots100}$	10	all pipes older than defined replacement cycle are replaced	
		11	- A_{cyc100}: replacement cycle = 100 years	average
			- A_{cyc80}: replacement cycle = 80 years	
	$A_{a0.5\%\ldots2\%}$		% replacement by age, eldest first	
		12	- $A_{a0.5\%}$: 0.5 % of network	average
		13	- $A_{f1\%}$: 1 % of network	
		14	- $A_{a1.5\%}$: 1.5 % of network	extensive
		15	- $A_{a2\%}$: 2 % of network	
Based on no. of failures and risk (pipe criticality)	$A_{fr1\%\ldots2\%}$		% replacement by condition, riskiest first*	
		16	- $A_{fr1\%}$: 1 % of network	extensive
		17	- $A_{fr1.5\%}$: 1.5 % of network	
		18	- $A_{fr2\%}$: 2 % of network	

2.7 Modeling preferences

In the MCDA, "objective" outcomes of each alternative (e.g. the total costs) are combined with the "subjective" preferences of the decision maker into an overall value (see e.g. Eisenführ et al., 2010). To be able to compare very different types of attributes (e.g. costs with system reliability) on equal footing, the attribute levels are converted to a neutral value between and including 0 and 1 with help of a value function v(x). For each alternative *A*, the different values (outcomes) of each attribute are aggregated to derive the overall value V(*A*). For the aggregation, weights are needed, which reflect the relative importance that the decision maker assigns to the different attributes (or objectives). Hence, following components of the multi-attribute value model describe specific aspects of the decision makers' preferences:

Weights w_j (scaling factors) represent the relative importance of an objective j to the other objectives conditional on the range of possible attribute levels x_j and take values within [0,1]. If an additive aggregation model is used, the weights sum up to 1.

Single-attribute (or marginal) value functions $v_j(x_j)$ describe how well objective j is fulfilled by achieving attribute levels x_j, thus converting attribute levels to dimensionless values between 0 (worst level, e.g. highest expected costs) to 1 (best level; lowest expected costs). Measurable value functions not only order, but also allow for strength of preference statements (Dyer and Sarin, 1979). Here, we use a common function, the exponential (measurable) value function.

$$v_j(x_j) = \begin{cases} \dfrac{1-e^{-c_j\tilde{x}_j}}{1-e^{-c_j}}, & c \neq 0 \\ \tilde{x}_j, & c = 0 \end{cases} \tag{6}$$

with $\tilde{x}_j = (x_j - \min(x))/(\max(x) - \min(x))$. Constant c_j determines whether the function is concave (> 0), convex (< 0) or linear (= 0). The value functions are defined over the range of the alternatives' outcomes, rounding up resp. down to the nearest 0.05 multiple for the degree of rehabilitation and 0.01 for reliability and costs.

A multi-attribute aggregation function aggregates the preference information of weights assigned to the different objectives and the values achieved for each attribute into one score returned from the MAVM, the overall value V(*A*) ∈ [0,1] of each alternative *A*. An overall value of 1 means that the outcomes of an alternative regarding all objectives are on their best level (i.e. here: costs are on their lowest-possible level, system reliability and degree of rehabilitation on their highest-possible level). Because of its simplicity, the additive model is often used (Eisenführ et al., 2010). The overall additive value of alternative *A* is

$$V(A) = \sum_{j=1}^{m} w_j \cdot v_j(x_j(A)) \quad ; \sum_{j=1}^{m} w_j = 1 \tag{7}$$

and the additive weights sum to unity. Value functions describe preferences under certainty. For risky (uncertain) outcomes, multi-attribute utility functions (Keeney, 1993) are required, with additional axioms to be satisfied. Value functions can be transformed into utility functions if the decision maker's intrinsic risk attitude is known (Dyer and Sarin, 1982; Keeney, 1993). For risk neutral decision makers, value and utility functions coincide.

For simplification, we assume that there is only one decision maker. In a real decision situation, the parameters of the MAVM are typically inferred from preference statements of each stakeholder separately (methods for elicitation of the weights, value/utility functions, and aggregation function are presented in e.g. Eisenführ et al., 2010; Keeney, 1993). We assess the influence of different preferences on the alternative ranking with a local sensitivity analysis over varying weights and value functions (Table 2).

Table 2: Preference parameters for local sensitivity analysis (reliab= reliability, reha= intergenerational equity). 1st set: sensitivity of different weights attributed to the three objectives, assuming linear value functions. 2nd set: sensitivity to different shapes of value functions, assuming equal weights.

	preference	w_1 (reliab)	w_2 (costs)	w_3 (reha)	c_1 (reliab)	c_2 (costs)	c_3 (reha)
weights	v.lin.eqw	1/3	1/3	1/3	0.00		
	v.lin.w1a	1.00	0.00	0.00	0.00		
	v.lin.w2a	0.00	1.00	0.00	0.00		
	v.lin.w3a	0.00	0.00	1.00	0.00		
	v.lin.w1h	0.50	0.25	0.25	0.00		
	v.lin.w2h	0.25	0.50	0.25	0.00		
	v.lin.w3h	0.25	0.25	0.50	0.00		
v(x)	v.1cv.eqw	1/3			-4.00	0.00	0.00
	v.2cv.eqw	1/3			0.00	-4.00	0.00
	v.3cv.eqw	1/3			0.00	0.00	-4.00
	v.acv.eqw	1/3			-4.00	-4.00	-4.00
	v.1cc.eqw	1/3			4.00	0.00	0.00
	v.2cc.eqw	1/3			0.00	4.00	0.00
	v.3cc.eqw	1/3			0.00	0.00	4.00
	v.acc.eqw	1/3			4.00	4.00	4.00

2.8 Dominance and ranking of alternatives under uncertainty

To reduce unnecessary complexity in MCDA, it is recommended to exploit dominance relationships as first step (e.g. Eisenführ et al., 2010). Hereby, the analysis is simplified by removing dominated (hence irrelevant) alternatives before calculating the overall values (or utilities). For risky outcomes, stochastic dominance concepts can be used (Hadar and Russell, 1969; Hanoch and Levy, 1969; Rothschild and Stiglitz, 1970).

First- degree stochastic dominance (FSD) is fulfilled if alternative *A*'s probability of achieving better attribute levels than alternative *B* is higher for at least one attribute and equally high for all others. FSD can be determined graphically using risk profiles 1-P(X) of the attributes' cumulative probability functions P(X) (Eisenführ et al., 2010). *A* dominates *B* regarding attribute x if the risk profile of *A* is always above that of *B*. If the risk profiles intersect, additional information about the decision makers' preference under risk is needed to determine dominance. Practically, for each year between 2010 to 2050, the outcome of the three attributes for each of the 1000 parameter samples are computed. From these results, the cumulative probabilities are calculated.

For risk averse decision makers, second-degree stochastic dominance (SSD) delivers further insights. SSD is satisfied if the area under the cumulative probability curve of *B* exceeds the cumulated area under that of *A* for all x (Graves and Ringuest, 2009). As the necessary pairwise comparisons of distributions get computationally very expensive for 18 alternatives under four scenarios, we use the mean and risk-adjusted mean-Gini summary statistic (Graves and Ringuest, (2009). In the mean-Gini model, mean μ and risk-adjusted mean μ' (Gini's Mean Difference, GMD) of the alternatives are compared directly (Shalit and Yitzhaki, 1994). *A* dominates alternative *B* if the mean attribute outcome of *A* is larger than or equal to that of *B*, $\mu_A \geq \mu_B$, and if

$$\mu'_A \geq \mu'_B \text{ or}$$
$$\mu_A - 2\,cov\big(X_A, P_A(X_A)\big) \geq \mu_B - 2\,cov\big(X_B, P_B(X_B)\big), \tag{8}$$

where X_A is the random variable describing the attribute outcome of alternative A, and $P_A(X_A)$ is its cumulative distribution, see (Yitzhaki, 2003). Conveniently, this approach is not only applicable to non-normal probability distributions, but also fulfills the necessary conditions of SSD without requiring pairwise comparisons. If the risk profiles cross once at most, the sufficient conditions for SSD are additionally fulfilled (Shalit and Yitzhaki, 1994). Practically, alternatives are ranked by μ and μ' of the outcomes between 2010 and 2050. Those with better ranks dominate those with worse ranks whenever the rank relationship order of μ and μ' is maintained (Graves and Ringuest, 2009). To establish an overall rank for comparison within and across scenarios during sensitivity analysis considering different preferences, the average of μ and μ' of the aggregated value (eq. 7) per alternative and set of preference parameters (Table 2) is used.

2.9 Robustness under four future scenarios

Four future development scenarios were formulated: *Status quo* (no change/baseline), *Boom* (massive growth), *Quality of life* (qualitative growth), and *Doom* (decline). Their characteristics cover a range of technical, environmental, and socio-economic aspects, see Lienert et al. (2013b) for details and Appendix B for a summary of the information relevant to this work.

Diverging notions about robustness prevail in the decision sciences and operational research (Roy, 2010). We mean robustness in the context of stability and sensitivity, i.e. how stable the ranking of alternatives under different future scenarios is.

Following Goodwin and Wright (2001), all alternatives are separately evaluated and ranked under each future scenario. Their approach assumes that the preferences are independent of the scenario and that consequently, only the attribute outcomes depend on the scenarios. This is in contrast to the assumption of different preferences under each future scenario (Montibeller et al., 2006; Stewart et al., 2013) , where for example, the costs might be judged relatively more important in a dire economic future scenario than in a prospering future scenario. We propose to consider changing preferences due to learning and different boundary conditions as part of an adaptive management plan. Hereby validation – or if necessary – re-assessment of the decision makers' preferences after some time would be necessary. This seems less problematic than eliciting hypothetical scenario-adjusted preferences from decision makers others have resorted to (e.g. Karvetski et al., 2009; Ram and Montibeller, 2013). In our case, the overall robustness of each alternative is derived from changes in the rankings under the four scenarios.

2.10 Implementation

Except rehabilitation modeling in FAST , data handling, parameter inference, preference modeling, and evaluation are implemented in the freeware language and environment for statistical computing R (R Development Core Team, 2011) and supported by R packages: *optimx* (Nash and Varadhan, 2011), *DEoptim* (Mullen et al., 2011), *adaptMCMC* (Scheidegger, 2011), *utility* (Reichert et al., 2013), and *ggplot2* (Wickham, 2009).

3. Results

3.1 Network data

The length distributions of the four water suppliers' raw data are strongly diverging (Fig. 2). Modal pipe lengths decrease from water supplier A to D, as well as distances between the 5 to 95 % and 25 to

75 % quantiles. After homogenization, water networks A to C share similar distributional properties. The goal of creating homogeneous lengths of 100-200 m was achieved for at least 75 % of pipes in A-C, but less in D.

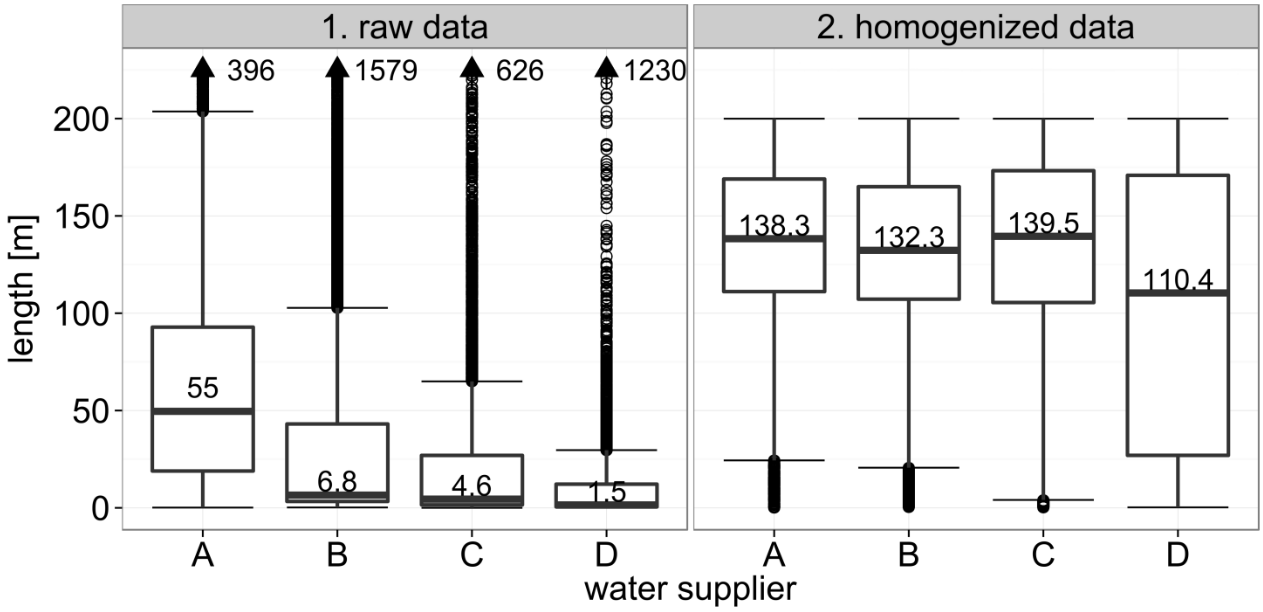

Figure 2: Pipe length distributions before and after length homogenization. The boxes and whiskers represent the 5, 25, 75, and 95 % quantiles; the thick horizontal line indicates the modal length of pipes in network A-D.

Figure 3, shows the material distributions of the four networks. The largest portions are ductile cast iron (DI1, DI2) and grey cast iron (GI2, GI3) pipes, followed by differing portions of fiber/asbestos cement (FC), steel (ST), and polyethylene pipes (PE) installed mostly after 1950.

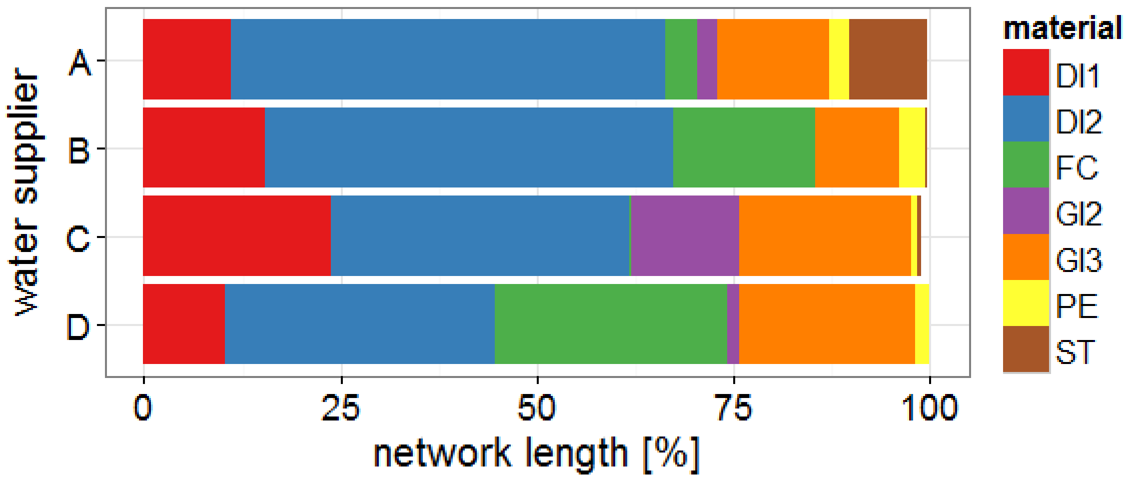

Figure 3: Material proportions in the four water supply networks. DI1 and DI2: ductile iron pipes (1st :1964-80; 2nd : > 1980), FC: fiber and asbestos cement, GI2 and GI3: grey cast iron (2nd: <1930, 3rd : >1930), PE: polyethylene, and ST: steel.

Although DI2 is the most prevalent material, only few recorded failures are available in utilities B-D (Table 3). Additionally, there are no or very few higher order failures on DI2 pipes in B-D. This can lead to parameter estimation difficulties, also for other materials with few recorded failures (FC, ST).

Most failures were recorded on DI1 and GI3 pipes with proportionally more failures in network A and C, also regarding higher order failures.

Table 3: Network characteristics and failures of the four water networks (A-D) after length homogenization.

	A	**B**	**C**	**D**
observation period	2000-2010	2001-2011	1996-2011	2001-2010
total length [km]	715	385	227	61
ø pipe length [m]	134.7	127.3	129.2	102.0
total failures/ *higher-order failures*	669/*233*	182/*32*	279/*97*	40/2
DI1	140/*47*	95/*19*	89/*28*	13/*0*
DI2	133/*38*	19/*0*	12/*2*	3/*0*
GI2	46/*18*	0/0	51/*20*	0/*0*
GI3	240/*88*	59/*12*	121/*46*	18/*2*
FC	14/*0*	8/*1*	0/*0*	6/*0*
ST	96/*42*	0/*0*	1/*0*	0/*0*
PE	0/*0*	1/*0*	3/*0*	0/*0*

3.2 Failure model

The estimated failure model parameters from MLE (networks A-C), the aggregated prior, and the posterior parameters are presented in Table 4. Parameters from MLE with fixed π of B and C are shown in the supporting information (Table S.1). Networks A-C show the same ordering of times to failure, FC ≥ DI2 >> GI3 ≥ DI1, despite considerable differences in the parameters. This order is also maintained in the resulting prior and posterior distributions.

Table 4: Summary statistics of the marginal parameter distributions of networks A–C individually and aggregated, as well as the posterior for network D. For B and C, only the aggregated parameter distributions of eleven MLE runs each with fixed π are shown.

		all	DI1		DI2		GI3		FC	
		$\hat{\theta}_1$	$\hat{\theta}_2$	$\hat{\theta}_3$	$\hat{\beta}_{DI2}\hat{\theta}_2$	$\hat{\beta}_{DI2}\,\hat{\theta}_3$	$\hat{\beta}_{GI3}\,\hat{\theta}_2$	$\hat{\beta}_{GI3}\hat{\theta}_3$	$\hat{\beta}_{FC}\,\hat{\theta}_2$	$\hat{\beta}_{FC}\hat{\theta}_3$
Posterior (A-C,D)	$\hat{\boldsymbol{\theta}}$	***1.47***	***72.1***	***20.5***	***217.0***	***62.1***	***89.7***	***25.8***	***274.7***	***81.3***
	$\mathrm{sd}(\hat{\theta})$	*0.18*	*14.3*	*5.1*	*61.11*	*22.0*	*12.7*	*6.8*	*78.3*	*37.6*
Prior (A-C)	$\hat{\boldsymbol{\theta}}$	***1.60***	***77.1***	***17.3***	***195.7***	***44.8***	***88.7***	***20.2***	***280.3***	***70.4***
	$\mathrm{sd}(\hat{\theta})$	*0.24*	*20.0*	*6.8*	*65.7*	*22.4*	*16.1*	*8.2*	*122.8*	*55.6*
A	$\hat{\boldsymbol{\theta}}$	***1.59***	***70.0***	***10.1***	***159.9***	***23.0***	***86.8***	***12.5***	***154.0***	***22.2***
	$\mathrm{sd}(\hat{\theta})$	*0.13*	*14.3*	*2.01*	*30.0*	*4.0*	*18.6*	*2.7*	*35.7*	*5.1*
B	$\hat{\boldsymbol{\theta}}$	***1.75***	***59.5***	***22.2***	***169.8***	***63.1***	***76.4***	***28.5***	***304.3***	***113.2***
	$\mathrm{sd}(\hat{\theta})$	*0.27*	*6.1*	*4.8*	*53.3*	*22.3*	*8.9*	*6.0*	*94.5*	*40.3*
C	$\hat{\boldsymbol{\theta}}$	***1.43***	***97.2***	***16.6***	***245.7***	***41.7***	***95.7***	***16.4***	**-**	**-**
	$\mathrm{sd}(\hat{\theta})$	*0.19*	*13.8*	*2.6*	*79.6*	*12.5*	*11.9*	*2.6*	-	-

Whereas the Weibull and exponential scale parameters ($\hat{\theta}_2, \hat{\theta}_3$) of FC and DI2 are of similar magnitude in network A, in network B the parameters for FC are significantly larger. DI1 and GI3 pipes are, according to the magnitude of the parameters, most durable in network C ($\hat{\theta}_{2,DI1} = 97.2$, $\hat{\theta}_{2,GI3} = 95.7$), followed by A ($\hat{\theta}_{2,DI1} = 70.0$, $\hat{\theta}_{2,GI3} = 86.8$) and then B ($\hat{\theta}_{2,DI1} = 59.5$, $\hat{\theta}_{2,GI3} = 76.4$). The uncertainty of the DI2 and FC parameters is considerable in A-C, also in the aggregated prior and posteriors. As the smaller variance of the posterior indicates, something could be learned even from the (few) data of network D, especially for DI1 and GI3.

Because some pipe rehabilitation strategies are condition-based, failures before the start of formal failure recording were predicted for D (i.e. failures before 2001). The predicted number of failures is 149 and results from a single run of the prediction model as described in section 2.2.4.

3.3 Outcomes of strategic alternatives

The outcomes of the 18 alternatives regarding costs, reliability, and intergenerational equity over time are visualized in Figure 4. Here, we show the relative performance of each alternative for each of the three attributes alone, without considering possible preferences of decision makers and without aggregating to an overall value for each alternative in the MCDA.

Note that the outcomes for reliability and intergenerational equity are identical in the Status quo and Doom scenario (because of identical framework conditions).

Compared by their median outcomes (lines), $A_{f1.5\%}$ and $A_{f2\%}$ (global replacement by condition; see Table 1; purple) and $A_{a1.5\%}$ and $A_{a2\%}$ (global replacement by age; red) often outperform the other alternatives - visible from them being below the others for costs, and above for reliability and intergenerational equity. Notably, the median outcomes of the condition-risk dependent strategies ($A_{fr1\ldots2\%}$; blue lines) perform rather badly compared to less sophisticated alternatives (e.g. $A_{cyc80\ldots100}$, orange; $A_{f2...5+}$; green lines). The median of the reference alternative A_{ref} (solid black line) performs worst for all attributes, except for costs in all scenarios.

Since the 0.05-0.95 inter-quantile ranges of the alternatives (shaded areas) regarding reliability and rehabiliation are large and considerably overlap, any ranking based on the attribute outcomes alone is speculative. The outcomes change substantially after the defined planning horizon 2050, such that the extension of the evaluation horizon to 2110 could potentially result in a different ranking.

Looking at costs separately, Figure 4 displays a continuous increase over time for all alternatives except $A_{cyc80...100}$ in the Doom scenario. In the other scenarios, the costs of all alternatives initially decrease and then stabilize or increase again slightly. Costs are highest in the Doom scenario, the maximum increase expected for alternatives $A_{fr2\%}$ and $A_{f2\%}$ (median costs about 0.4 % in 2050, 1.1 % in 2110). The median costs of other alternatives in the Doom scenario increase at lower rates, except for the cyclic alternatives (A_{cyc80}, A_{cyc100}; orange). Peak costs of the cyclic alternatives indicate peak investments (also in the other scenarios), reaching up to 7.11 % for A_{cyc100}. In the Status quo, costs for all alternatives decrease slightly and stabilize for all alternatives except $A_{cyc80...100}$.

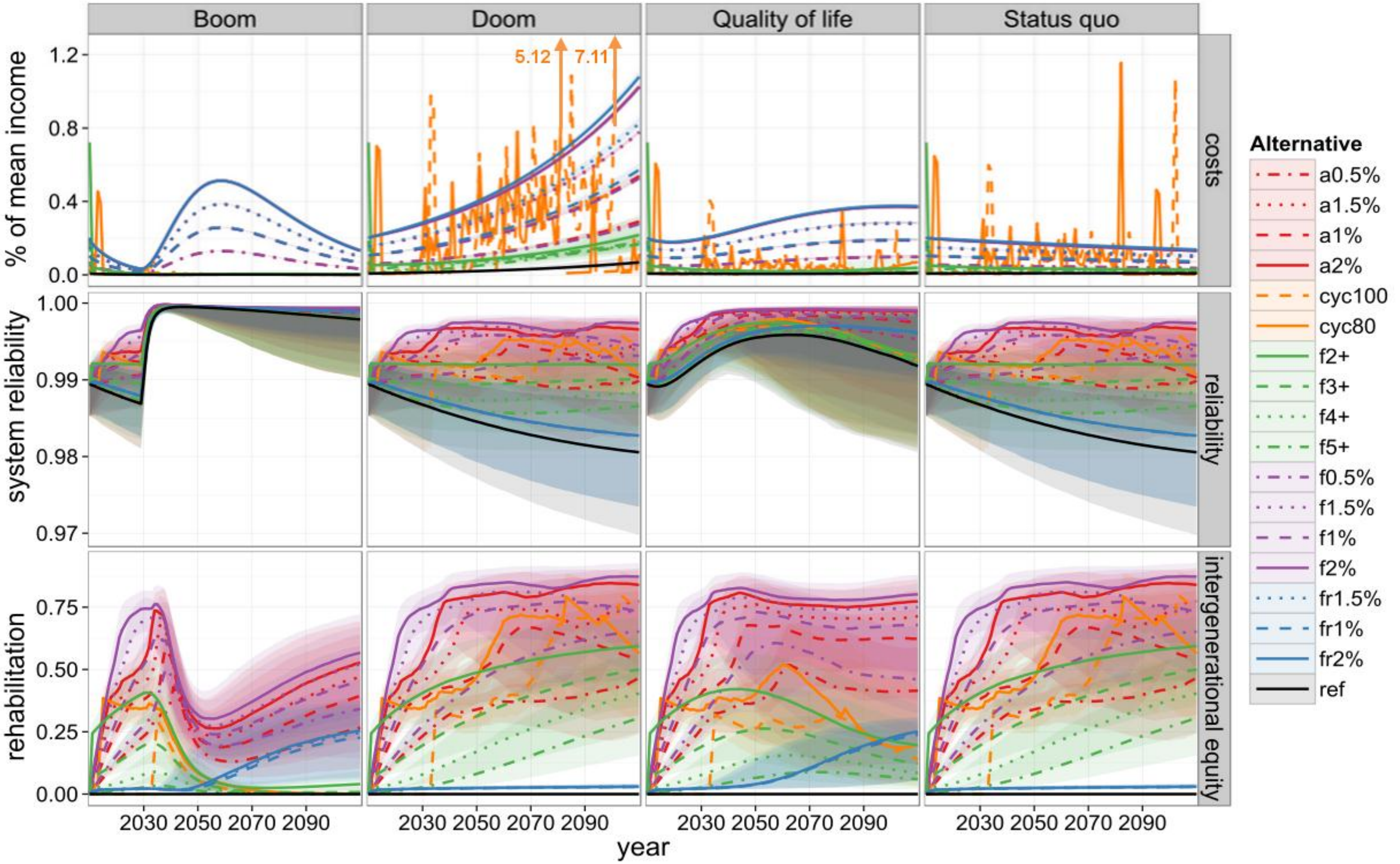

Figure 4: Outcomes of 18 strategic planning alternatives under four scenarios until 2110. We show the outcomes on the attribute levels: % of mean income, system reliability as R based on the criticality index, and rehabilitation as D_{reha} based on failure rates (see 2.5). These results do not contain assumptions about the preferences of decision makers, and thus there is no aggregation of the three attributes to an overall value for each alternative (as done later in the MCDA). More results can be found in the additional tables and figures of the supporting information. Lines represent the 0.5 (median), shaded areas the 0.05-0.95 quantiles. Costs improve with decreasing values, reliability and intergenerational equity with increasing values. Note that for better visibility the % mean income is zoomed in, and two peaks exceeding the visible range are indicated by arrows. Costs for $A_{a1\ \ 2\%}$ and $A_{f1\ \ 2\%}$ overlap with $A_{fr1\ \ 2\%}$ under most scenarios.

Reliability increases strongly in the Boom and Quality of Life scenario until about 2030-2050, and especially abruptly for A_{ref} and risk-condition dependent rehabilitation alternatives (A_{ref}, $A_{fr1\%...2\%}$; blue). It stabilizes after 2050 between 1 and 0.99 or decreases slightly (A_{cyc80}, A_{cyc100}, $A_{f2...5+}$). Reasons for this abrupt change are discussed in section 4.3. It comes along with a strong improvement of the degree of rehabilitation until 2050 (up to 90 %) but also a strong setback, especially in the Boom scenario, with only slow recovery thereafter. In the Doom and Status quo scenarios, reliability decreases for A_{ref}, $A_{fr1...2\%}$, A_{f5+}, as well as A_{f4+} and increases for the other alternatives (until stabilization).

3.4 Outcomes of strategic alternatives and dominance

There is a visible ordering of risk profiles within strategy groups, indicating first-degree stochastic dominance (FSD) of some alternatives and attributes (Figure A.1-3, Appendix); e.g. $A_{f2\%}$ is always better than $A_{f1.5\%}$, $A_{f1\%}$, and $A_{f0.5\%}$. This ranking is reversed regarding the cost attribute. In addition, some of the risk profiles cross (e.g. $A_{cyc80...100}$, $A_{f2...5+}$), and no clear ordering is apparent. Thus, no FSD dominance which is stable across all scenarios and attributes can be determined.

Assuming risk-aversion, the results from mean-Gini analysis are more insightful (see Table 5 for ranks, Table S.2 – S.4 in supporting information for outcomes). There is a stable dominance order for reliability and intergenerational equity regarding both mean and risk adjusted mean in the $A_{f0.5...2\%}$, $A_{a0.5...2\%}$, $A_{cyc80...100}$, and $A_{f2...5+}$ groups under all scenarios. Additionally, $A_{f2\%}$ has rank 1 (best) and A_{ref} rank 18 (worst) for both attributes under all scenarios.

For costs, the rank order within groups is inversed; A_{ref} has the first rank, and $A_{f2\%}$ rank 16 under all scenarios. Nonetheless, same dominance reletionships which are stable across scenarios are apparent: the mean and risk-adjusted mean of, A_{f2+} and A_{f3+} are better than those of $A_{fr1...2\%}$ under all scenarios, indicating dominance. $A_{fr1...2\%}$ are hence removed, because they will always be less preferred by a rational decision maker. Furthermore, $A_{f0.5\%}$ dominates $A_{a0.5\%}$, $A_{f1\%}$ dominates $A_{a1\%}$, and $A_{f2\%}$ dominates $A_{a2\%}$, leading to the exclusion of $A_{a0.5\%}$, $A_{a1\%}$, and $A_{A2\%}$. Finally, twelve non-dominated alternatives remain: $A_{f2\%...0.5\%}$, $A_{a1.5\%}$, $A_{cyc80...100}$, $A_{f2+...5+}$ and A_{ref}. In continuation, only these are considered.

<< INSERT TABLE 5 ABOUT HERE >>

Table 5: Mean attribute ranks and risk-adjusted mean attribute ranks of 18 strategic alternatives over the time horizon 2010-2050. Shaded: dominated alternatives. Future scenarios: BO - Boom, DO - Doom, QG - Quality of Life, SQ - Status quo.

	Alternative	$A_{f2\%}$	$A_{f1.5\%}$	$A_{a2\%}$	$A_{a1.5\%}$	A_{cyc80}	A_{f2+}	$A_{f1\%}$	$A_{a1\%}$	$A_{f0.5\%}$	$A_{a0.5\%}$	A_{f3+}	$A_{fr2\%}$	$A_{fr1.5\%}$	$A_{fr1\%}$	A_{f4+}	A_{f5+}	A_{cyc100}	A_{ref}
Costs (mean annual per capita income)																			
BO	rank(μ_{cost})	16	15	17	14	7	6	10	11	8	9	5	18	13	12	4	2	3	1
	rank(μ'_{cost})	16	15	17	14	6	7	10	11	8	9	5	18	13	12	4	3	2	1
DO	rank(μ_{cost})	16	13	17	14	10	8	9	11	6	7	4	18	15	12	3	2	5	1
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1
QG	rank(μ_{cost})	16	13	17	14	9	6	10	11	7	8	4	18	15	12	3	2	5	1
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1
SQ	rank(μ_{cost})	16	13	17	14	9	8	10	11	6	7	4	18	15	12	3	2	5	1
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1
Reliability (system reliability)																			
BO	rank($\mu_{reliab.}$)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	rank($\mu'_{reliab.}$)	1	2	3	4	6	8	5	7	9	10	11	12	13	14	15	17	16	18
DO	rank($\mu_{reliab.}$)	1	2	3	4	7	6	5	8	9	10	11	14	15	16	13	17	12	18
	rank($\mu'_{reliab.}$)	1	2	3	5	6	8	4	7	9	10	11	14	15	16	13	17	12	18
QG	rank($\mu_{reliab.}$)	1	2	3	4	8	7	5	6	9	10	11	12	13	15	16	17	14	18
	rank($\mu'_{reliab.}$)	1	2	3	4	7	8	5	6	9	10	11	13	14	15	16	17	12	18
SQ	rank($\mu_{reliab.}$)	1	2	3	4	7	6	5	8	9	10	11	14	15	16	13	17	12	18
	rank($\mu'_{reliab.}$)	1	2	3	5	6	8	4	7	9	10	11	14	15	16	13	17	12	18
Intergenerational equity (degree of rehabilitation)																			
BO	rank($\mu_{rehab.}$)	1	2	3	4	8	7	5	6	9	10	11	14	15	17	13	16	12	18
	rank($\mu'_{rehab.}$)	1	2	3	5	9	7	4	6	8	10	11	14	15	17	13	16	12	18
DO	rank($\mu_{rehab.}$)	1	2	3	5	7	6	4	8	9	10	11	15	16	17	13	14	12	18
	rank($\mu'_{rehab.}$)	1	2	3	5	8	6	4	7	9	10	11	15	16	17	13	14	12	18
QG	rank($\mu_{rehab.}$)	1	2	3	5	8	7	4	6	9	10	11	15	16	17	13	14	12	18
	rank($\mu'_{rehab.}$)	1	2	3	5	9	7	4	6	8	10	11	15	16	17	13	14	12	18
SQ	rank($\mu_{rehab.}$)	1	2	3	5	7	6	4	8	9	10	11	15	16	17	13	14	12	18
	rank($\mu'_{rehab.}$)	1	2	3	5	8	6	4	7	9	10	11	15	16	17	13	14	12	18

3.5 Ranking and sensitivity under different preference assumptions

The ranking of the non-dominated alternatives is sensitive to alterations of the preference model, especially the weights (Figure 5), but also the value function form (Figure 6), see also Eq. 6 and 7, and Table 2. The observed rank order under the assumption of linear value functions and equal weights (V.lin.eqw, black diamond) is: $A_{f2\%} > A_{f1.5\%} > A_{f2+} \sim A_{f1\%} > A_{a1.5\%} > A_{cyc80} > A_{f0.5\%} > A_{f3+} > A_{f4+} \sim A_{cyc100} > A_{f5+} > A_{ref}$ ("Rank" in Fig. 2 meaning the mean rank of μ and μ', alternatives from best to worst). The rank order of the best and worst-ranked three alternatives is inverted under all scenarios, if only costs are important (V.lin.w2a, purple squares, receiving all the weight), and also very sensitive to zero weights for intergenerational equity (V.lin.w3n, green triangles). If costs receive half the weight (w_2 = 0.5, V.linw2h, purple circle), only the order of the top-ranked alternatives is affected, either A_{f2+}or $A_{f1.5\%}$ becoming best- ranked and $A_{f2\%}$ third

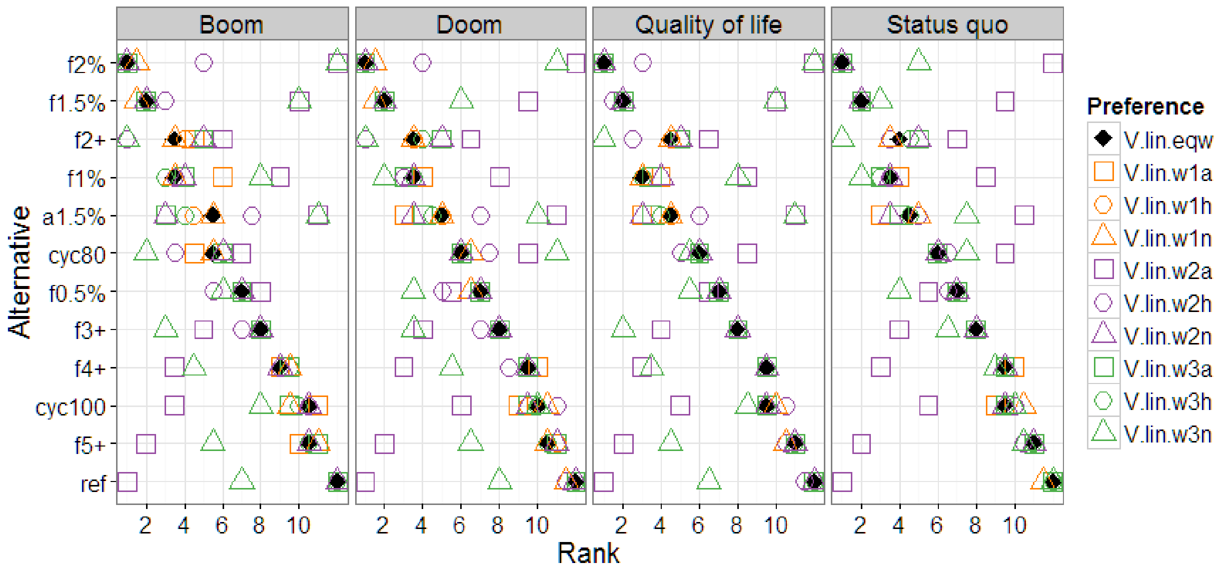

Figure 5: Sensitivity of the ranking of alternatives to weight changes under four scenarios over the time horizon 2010-2050. w_1= reliability, w_2= costs, w_3= intergenerational equity, see Table 2.

The ranking is less sensitive to the value function form, see Figure 6. Most distinct are the ranking changes due to all- convex value functions (V.acv.eqw, black dots), resulting in considerably worse ranks for $A_{a1.5\%}$ in all scenarios, and for $A_{f1...2\%}$ in the Boom scenario. In addition, the ranks of A_{ref}, $A_{f3...5+}$, and A_{cyc100} improve greatly. Furthermore, if only the costs value function is concave (V.2cv.eqw, blue dots), A_{f2+} becomes the best-ranked alternative while $A_{f2\%}$ and $A_{f1.5\%}$ are second to fourth-ranked. Apart from these cases, the ranking is fairly robust across scenarios and preferences.

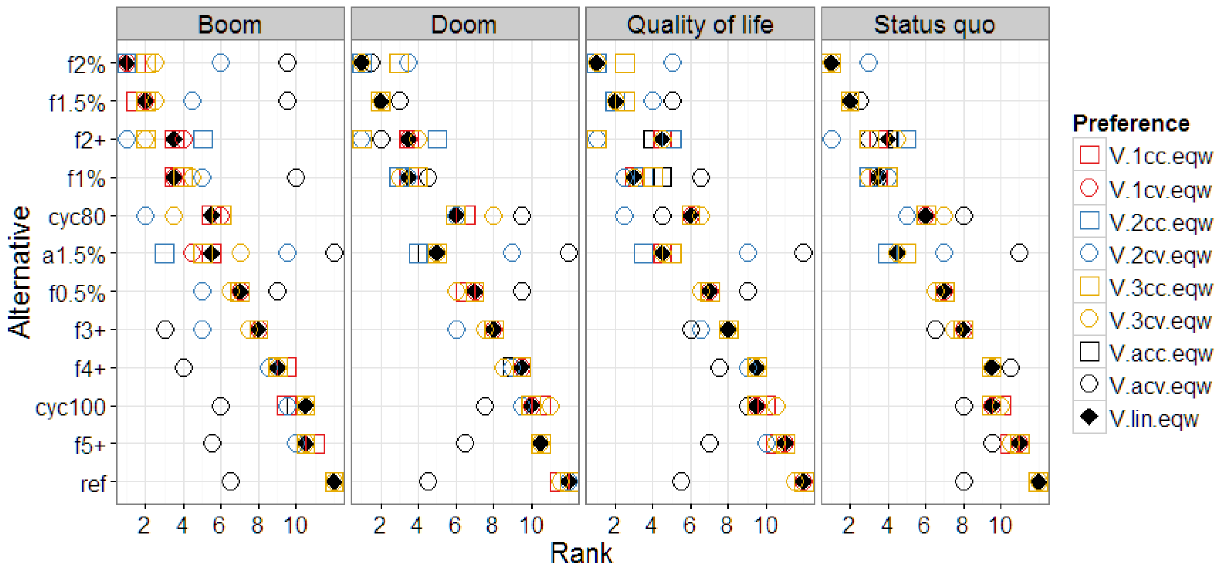

Figure 6: Sensitivity of the alternative ranking to value function changes under four scenarios over the time horizon 2010-2050. c_1= reliability, c_2= cost, c_3= intergenerational equity, see Table 2.

The complete ranking and corresponding values of all alternatives without assuming risk-aversion for second-degree stochastic dominance (SSD) is shown in the supporting information (Figure S.1, S.2).

4. Discussion

4.1 Data preparation

The homogenization approach led to satisfactory homogenization of the pipe length distributions of water networks A-D, being slightly less satisfactory in the smaller pipe network D. Although more homogeneous than the raw data, many short pipes remained unmerged; likely impeded by their unique material-diameter-laying date combinations. A drawback of the approach is that merged pipes do not necessarily have a distinctive location because pipes are merged by grouping without consideration of their detailed location, see section 2.1. This could be improved by a GIS-based merging procedure which considers the location and other pipe characteristics (Fuchs-Hanusch et al., 2012). If electronic GIS data are unavailable, the presented novel data preparation approach delivers satisfying results for strategic asset management and the individual length of pipe sections can be overcome to reduce the influence of pipe lengths on pipe failure behavior. For tactical and operational asset management, however, the knowledge of pipe location and its consideration during pipe grouping is central both to homogenize the data accordingly and to prioritize pipe rehabilitation projects.

4.2 Failure and rehabilitation model

The selected failure model of Scheidegger et al. (2013) is a choice of suitability, not of conviction. Despite being reasonably simple, its big advantage is its capability of handling left-truncated and right-censored data subject to potential survival bias from deleted historical records. Together with the Bayesian approach, this makes the model suitable also for small networks.

Sensible failure model parameters for water utility D could be determined. The order of times to failure of the pipe groups (FC> DI2> GI3> DI1) is in line with results from a former analysis of pipe lifetimes in Switzerland (Scholten et al., 2013). Differences between prior and posterior parameters are visible, but small. Consequentially, the uncertainty of the failure model parameters is large which is reflected in the considerable uncertainty of the resulting attribute predictions. This is not surprising, considering the small number of observed failures (40). Consequentially, the priors (based on 1130 failures of utility A-C) are very influential. The mean parameters of material groups with few first and subsequent failures (DI2 and FC in network B, C) are remarkably large and highly uncertain. This might be indicative of lacking identifiability under purely data-driven MLE, as also observed concerning the already remediated parameter estimation with fixed π for B and C. These difficulties did not arise, however, in network A with more network and failure data. To achieve a better adaptation to local pipe failure behavior and reduce parameter uncertainty, the model parameters should be updated once additional failure data of D become available. Model validation as commonly performed with help of hold-out samples (e.g. Renaud et al., 2012) is difficult in situations where purely data-driven approaches do not suffice to parameterize the model, as mainly the consistency of the prior distributions would be tested. The use of simulated data to testify general model suitability is thus recommended (Scheidegger et al., 2011; Scheidegger and Maurer, 2012; Scheidegger et al., 2013). Formulation of the prior should be done with great care, e.g. by eliciting and discussing these with local experts (Scholten et al., 2013).

Considering that water suppliers A–C are amongst the larger and rather well-documented water networks in Switzerland, the applicability of more complex failure models applying purely frequentist inference procedures to small networks is questionable. Model simplicity, however, was traded against strong assumptions:

a. Weibull model for time to first failure: the hazard rate begins at zero, not accounting for initial failures on the "bathtub curve" (Kleiner and Rajani, 2001). Practically, this was handled by removing failures in the pipe laying year.
b. Subsequent failures are described by identical exponential distributions and therefore do not account for decreasing times between failures with increasing failure orders.
c. One covariate β_k per material used to scale both θ_2 and θ_3 does not allow for separate adjustment of time to first failure and subsequent failures relative to the baseline.

Network size and data allowing, the model of (Le Gat, 2009; Renaud et al., 2011) could be an alternative as it is based on different assumptions and also able to deal with selective survival and left-truncated-right-censored data.

Additional to future uncertainty (captured by four scenarios) failure model parameter uncertainty is propagated to the rehabilitation model outcomes. The propagation of the uncertainty adherent to the prediction of previous failures (before recording) is limited for practical reasons. Because the FAST rehabilitation model runs on one specific network of pipes with corresponding condition at a time, propagation of prediction uncertainty regarding unrecorded previous failures was impracticable. This effect is reduced by the prediction of the number of unrecorded failures prior to failure recording for each individual pipe, see section 2.2.4. If there are many pipes in the network, the overall number and distribution of previous failures over the network approximates the distribution obtained if this uncertainty was explicitly accounted for. To improve predictions for small networks, the adaptation of the software to allow for the consideration of uncertainty regarding the number of unrecorded failures is necessary.

4.3 Outcomes of strategic planning alternatives

We found that infrastructure costs (relative to the mean taxable income) increase strongly in the Doom scenario, but are rather stable, if not decreasing, in the other scenarios (Figure 4). The higher costs in the Doom scenario are due to decreasing population size and decreasing real incomes. On the contrary, the initial cost decrease in the growth scenarios (Boom, Quality of Life) can be attributed to population growth, which reduces per capita costs. Unless choosing A_{cyc80} and A_{cyc100} , peak costs arising from a group of pipes suddenly needing replacement are not likely to occur. The comparatively small uncertainty of costs (Fig.4) is due to the little influence of the uncertainty of the number of failures in light of about fifteen times higher replacement costs.

Reliability and intergenerational equity increased for most alternatives and scenarios (Figure 4). Two outcomes are surprising: 1) the strong increase in reliability and intergenerational equity under the Boom scenario until 2030 followed by a strong decrease until 2050 (less pronounced in Quality of Life), and 2) the comparatively bad performance of the condition-risk based alternatives $A_{fr1\%...2\%}$. Both can be explained by network expansion and the link to the failure rate (see also Figure S.3, supporting information). Besides improvement of pipe condition caused by the rehabilitation strategy, expansion with new pipes leads to an additional enhancement of the overall network condition. This is especially remarkable in the Boom scenario, since here, the proportion of large pipes in the network increases faster and the number of pipes per inhabitant decreases. The influence of network expansion leads even the reference alternative A_{ref} to experience a strong increase in reliability in the Boom scenario. The low performance of strategies $A_{fr1\%...2\%}$ (1 % to 2 % annual condition-based replacement by criticality), can be explained by the low number (34) of high criticality pipes in the small utility D. These strategies are more effective when there are substantial numbers of high criticality pipes in higher condition classes, as indicated by the increase in rehabilitation performance after 2050 in the growth scenarios. Additionally, their performance might improve considerably if damage costs were comprised (expecting higher damage from high-criticality pipes).

4.4 Ranking of alternatives and sensitivity

First-degree stochastic dominance analysis of the risk profiles did not lead to finding any dominated alternative. Without further knowledge about the decision maker's risk attitude, the 18 alternatives would need to be evaluated combinedly. Furthermore, if risk aversion (hence: second-degree stochastic dominance) can be assumed, the non-dominated set is reduced to twelve alternatives (all except $A_{fr1..2\%,}$ $A_{a0.5\%}$, $A_{a1\%}$, $A_{2\%}$). Risk aversion implies that a decision maker can prefer a less risky to a more risky alternative, even if the expected multi-criteria value is higher for the more risky prospect (Eisenführ et al., 2010). It is a commonly encountered risk behavior (Ananda and Herath, 2005; Pennings and Garcia, 2009), but needs to be validated during preference elicitation.

The top-ranking four alternatives ($A_{f2\%}$> $A_{f1.5\%}$> A_{f2+}~ $A_{f1\%}$) are characterized by medium to high replacement by condition which is favorable regarding the objectives, and especially reliability and intergenerational equity. Costs decrease while reliability increases due to lower failure rates, hence requiring less repairs. The higher replacement rates improve intergenerational equity. The reasoning is similar for A_{cyc80}, but its performance might drop if the average time to failure was much shorter (implying higher failure rates), e.g. due to different material composition or less favorable environmental conditions.

Local sensitivity analysis showed that changes of the weights lead to rank reversals in the non-dominated alternatives and that these are most significant for costs. The value function form had little impact under all scenarios unless all value functions are strongly concave (Figures 5, 6). If extreme preferences (such as costs being assigned all the weight or intergenerational equity having zero weight) are excluded, the relative ranking of alternatives is rather stable.

The differences in attribute predictions and MCDA rankings under different future scenarios reveal the importance of scenario analysis for strategic rehabilitation planning to inform decision makers about the long-term robustness of different strategies.

For short- and mid-term (i.e. tactical and operational) asset management, these strategies can be extended to account for savings potentially achieved from (1) collaborative asset management with other network infrastructures (e.g. wastewater, gas, telecommunications, road works), and (2) flexible adaptation of annual replacement rates to short-term rehabilitation demands.

4.5 Outcome of the case study

For our case study the main results are: If the decision maker is risk-averse (to satisfy the assumption of second-degree stochastic dominance) and unless low costs are most important (very high w_2), $A_{f2\%}$ or $A_{f1.5\%}$ (1.5-2 % annual replacement of oldest pipes in worst condition) is the preferred strategy. If the weights are substantially uncertain, a lower annual replacement rate of 1 % or replacement after the second failure (A_{f2+}) could also be considered, since $A_{f1\%}$ and A_{f2+} are third or fourth-ranked under most assumptions and more robust to weight changes than $A_{f2\%}$ and $A_{f1.5\%}$. Annual replacement of about 1.5 % is typical for larger utilities in Switzerland. Contrarily, the most frequent strategy of small Swiss water utilities and according to (Selvakumar and Tafuri, 2012) also in the USA, namely reactive rehabilitation (A_{ref}), performs well if the only objective pursued is cost minimization. Otherwise, the performance of purely reactive rehabilitation strategies is rather poor and should thus be discouraged. This conclusion is drawn without eliciting weights and risk attitudes, which should be done before deriving final recommendations.

Finally, the decision maker should be cautioned against uncertainty arising from the long-term nature of the predictions (> 40 years) and the limited data basis. The aim should be to embed the strategic rehabilitation plan into an adaptive framework which allows for adjustment of framework conditions, model parameters, and a revision of preferences.

5. Conclusions

We suggest a novel approach of combining methods from strategic asset management, failure modeling, decision analysis, and scenario analysis to identify robust long-term rehabilitation strategies for water utilities. The specific problem of pipe failure prediction in small networks with few failure data was successfully overcome by Bayesian estimation of failure model parameters from local data (here: 61 km and 40 recorded failures) and a prior distribution inferred from three larger utilities. The failure modeling procedure extends existing approaches to situations with very limited data, but comes along with important simplifications in data preparation routines and failure modeling which might not be desirable in cases where the available data supports more advanced analyses (sections 4.1-4.2).

MCDA served as a robust, feasible, and transparent approach to support rational decision making. This is missing in most of the existing approaches, but at the same time demanded by the strategic asset management community (see section 1.4). In this paper, we hope to have demonstrated the usefulness of integrating systematic approaches borrowed from decision analysis into engineering modeling approaches. Moreover, we found the combination of MCDA with scenario planning to be highly beneficial. Scenario planning is a new trend in the decision sciences (Montibeller et al., 2006; Stewart et al., 2013). It allows to consider the often neglected future uncertainty regarding the alternative outcomes, as well as assessing the robustness of the alternative rankings under different preferences. Local sensitivity analysis over diverging preference assumptions showed that, in this case, the alternative ranking is most sensitive to the stakeholder's weighting of the objectives, especially under the Boom scenario. Our approach can be easily adapted to other objectives and/or attributes so that alternatives are compared based on aspects that matter to the respective decision maker(s).

Although purely reactive repair (A_{ref}) is the cheapest alternative in terms of rehabiliation costs, it can be expected to perform less well in cases where damage costs to tertiary parties are included. Because its performance regarding intergenerational equity and system reliability is additionally poor, following a proactive rehabilitation alternative is preferable to the still (too) common reactive rehabilitation practice of water utilities.

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APPENDIX A) Length homogenization procedure

Since GIS data was not provided, pipes were left as is, merged or split as follows:

Leave: Pipes and their recorded failures are left unchanged if the pipe length is between 100 and 200 m.

Split: Pipes longer than 200 m are split into separate pipes of equal length and their failures randomly assigned to a position on the pipe. The position of the first failure is sampled from a uniform distribution over the length of the pipe before splitting, while subsequent failures are sampled from a normal distribution N(μ= 0, σ= 75) around the position of the first failure, implying that roughly 95 % of the failures fall within 150 m of the previous. Sample points leading to positions outside the extensions of the pipe before splitting are rejected.

Merge: Pipes shorter than 100 m are merged by subsequently adding pipes of equal laying date, material and diameter subsequently until a further addition would lead to exceed a total of 200 m. Merged pipes are thus not necessarily neighboring pipes. Pipe failures are added from the merged pipes and failure orders recalculated according to their order of occurrence after reassignment. Failures on the same date on one pipe are deleted.

APPENDIX B) Future scenarios

Future network expansion is linked to population increase. Based on the scenario numbers defined in a stakeholder workshop for the case study region, including water supplier D[1], population increase was assumed as:

$$Population\,[inh.]\colon P = P_0 \,\cdot\, e^{(T-T_0)\cdot cr} \qquad \text{(A.1)}$$

P_0 is the population in the reference year T_0 (here: P_0= 9'540 inhabitants in T_0= 2010), T the evaluation year (e.g. 2050), and cr the scenario-dependent population change rate. Future network expansion after 2010 is derived thereof, assuming a current ($l_{P,0}$) and future per person expansion length l_P, and two adjustment factors g_1 and g_2 to account for changing diameter proportions in the overall pipe network:

$$Expansion\,[m]\colon E \;=\; g_2\left(l_P \cdot P_0 \,\cdot\, e^{(T-T_0)cr\cdot g_1} - l_{P,0} \cdot P_0\right) \qquad \text{(A.2)}$$

Network expansion is assumed as PE and DI2 only, being the most strongly increasing materials during recent years in Switzerland[2]. Diameters ≤ 150 mm are assumed to expand as PE pipes, larger diameters as DI2 pipes. The detailed parameters of the four future scenarios are stated in Table A.1.

Table 6: Main characteristics of the four future scenarios*

		Population and network expansion			
Name	**Socio-economic situation**	**c**	**l_P [m/inh.], $l_{P,0}$[m/inh.]**	**g_1**	**g_2**

[1] Lienert, J., Scholten, L., Egger, C., Maurer, M., 2013. Structured decision making for sustainable water infrastructure planning under four future scenarios. Submitted.

[2] SVGW, 2006. Statistische Erhebungen der Wasserversorgungen in der Schweiz, Zürich, Schweizer Verein des Gas- und Wasserfaches.

Status Quo	As today: rural region near Zurich with extensive agriculture, leisure areas and nature protection zones. Real income change: +0.4 %/year	No change	No change	No change	No change
Boom	High prosperity, dense urban development, strong nature protection, new transportation. Real income change: +4.0 %/year	$5.284 \cdot 10^{-2}$	l_P: 3.641, $l_{P,0}$: 9.513 Higher building densities lead to less pipes per capita	**<DN150:** 0.5447 **DN150-250:** 0.8643 **> DN250:** 0.6698	1
Quality of life	Prosperous region with moderate population growth, limited expansion of building areas, high environmental awareness. Real income change: +2.0 %/year	$4.558 \cdot 10^{-4}$	$l_P = {}_{P,0}=9.513$ Similar building densities as today.	1	**< DN150:** 0.64 **DN150-250:** 0.32 **> DN250:** 0.04
Doom	Economic recession causes strong financial pressure on municipal budgets, slight population decline but no system expansion/deconstruction. Real income change: -1.5 %/year	$-1.282 \cdot 10^{-3}$	No change	No change	No change

* The mean income in 2008 was 64'575 CHF. With 0.4 % observed increase, the income in 2010 is 65'093 CHF

APPENDIX C) First-degree stochastic dominance- risk profiles

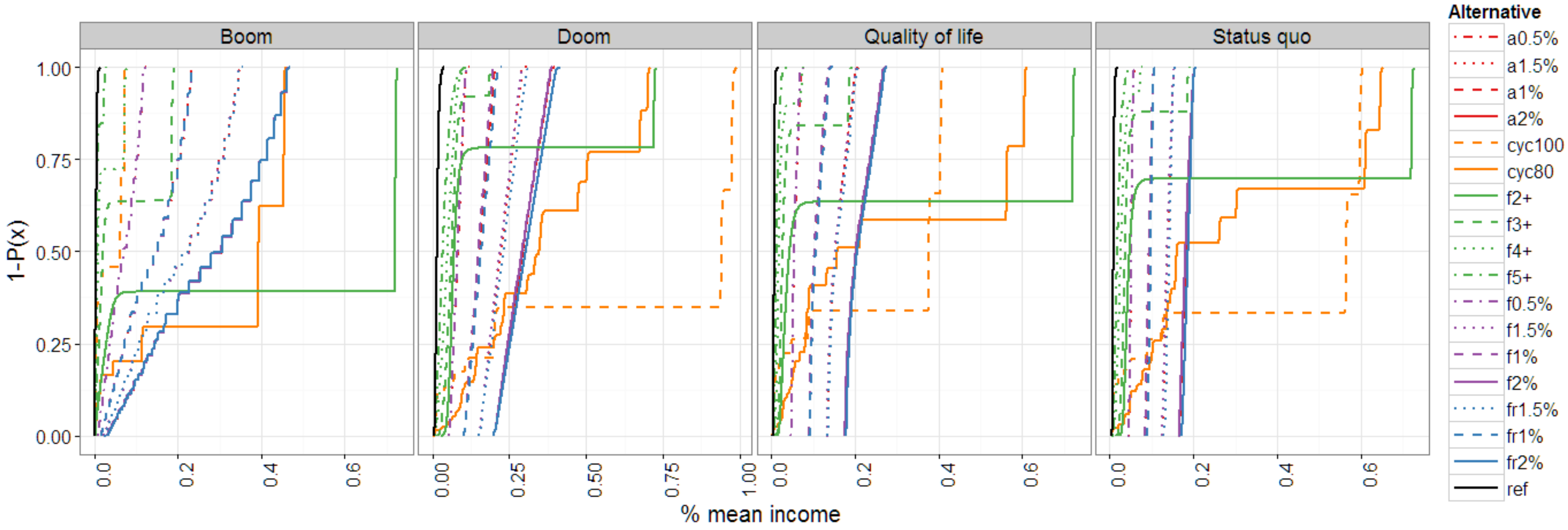

Figure A.1: Risk profiles of the alternatives for costs (attribute: % of the mean annual income) over the time horizon 2010-2050.

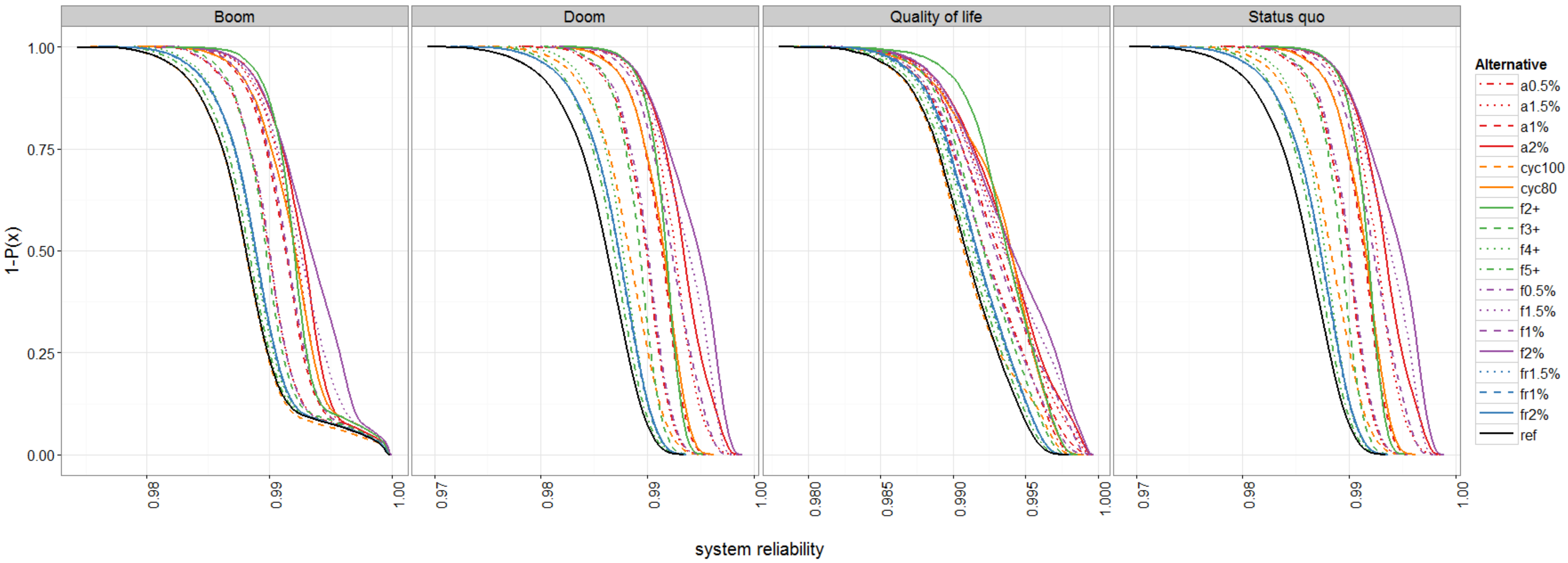

Figure A.2: Risk profiles of the alternatives for reliability (attribute: system reliability) over the time horizon 2010-2050.

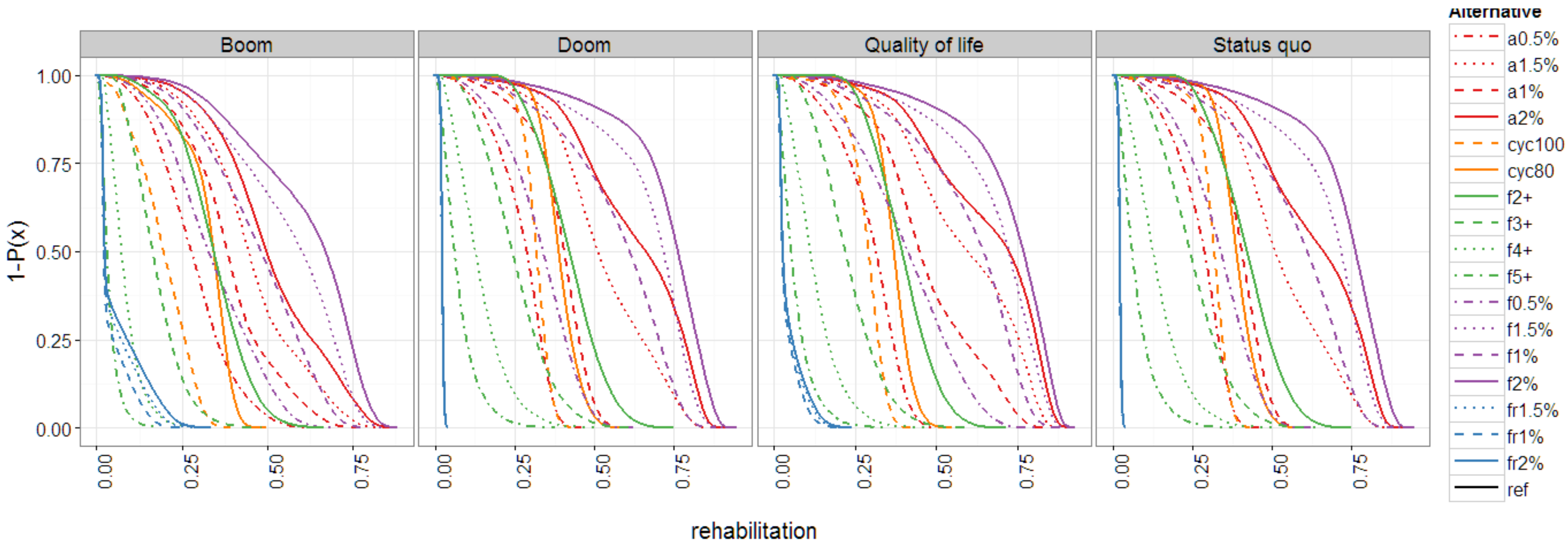

Figure A.3: Risk profiles of the alternatives for intergenerational equity (attribute: degree of rehabilitation in %) over the time horizon 2010-2050. The outcome for Aref equals zero (not shown).

A) Symbols and abbreviations

SYMBOL OR ABBREVIATION	**INTERPRETATION**
Main text	
A,B	Hypothetical alternatives A, B
$A_{a0.5\%...2\%}$	See explanation in Tab.1 of the main text.
$A_{cyc80\quad 100}$	See explanation in Tab.1 of the main text.
A-D	Four water utilities: A, B, C, and D
$A_{f0.5\%...2\%}$	See explanation in Tab.1 of the main text.
$A_{f2\quad 5+}$	See explanation in Tab.1 of the main text.
$A_{fr1\%...2\%}$	See explanation in Tab.1 of the main text.
A_{ref}	See explanation in Tab.1 of the main text.
β_m	Regression coefficient / covariate
C_i	Criticality index (importance weight) of pipe diameter group i
c_j	Constant that determines the curvature of marginal value function over the attribute linked to objective j.
DI1	First generation ductile iron; centrifugal casting, before 1980
DI2	Second generation ductile iron; centrifugal casting, after 1980
D_{reha}	Degree of rehabilitation
ELECTRE	ELimination Et Choix Traduisant la REalité (Elimination and Choice Expressing Reality)
$P_A(X_A)$	Cumulative distribution of X_A
FAST	Fichtner asset services and technologies (asset management software)
FC	Fiber cement/asbestos cement incl. Eternit
GI2	Second generation grey cast iron; vertical casting, before 1930
GI3	Third generation grey cast iron; centrifugal casting, after 1930
IAM	Infrastructure asset management
k	Pipe index
m	Pipe characteristic, e.g. material
μ'_A, μ'_B	Mean of alternative A, B
μ'_A, μ'_B	Risk-adjusted mean of alternative A, B
$\boldsymbol{\mu_u}$	Parameter vector of means of the multivariate normal distribution
MAUT	Multi-attribute utility theory
MAVM	Multi-attribute value model
MAVT	Multi-attribute value theory
MCDA	Multi-criteria decision analysis
$n_{f,i}$	Number of pipe failures in pipe diameter group i
n_i	Number of pipes in pipe diameter group i
PE	Polyethylene
R	system reliability
r_{ref}	Failure rate of the reference strategy A_{ref} [#/(km*a)]
r_s	Failure rate of strategic alternatives s [#/(km*a)]
$\boldsymbol{\Sigma_u}$	Parameter vector of standard deviations of the multivariate normal distribution

SYMBOL OR ABBREVIATION	INTERPRETATION
SAM	Strategic asset management
ST	Steel
t	Evaluation year
t_0	Laying year
V(*A*)	Aggregate value of alternative *A*
v.1cc.eqw, v.2cc.eqw, v.3cc.eqw	See Tab.2 in main text
v.1cv.eqw, v.2cv.eqw, v.3cv.eqw	See Tab.2 in main text
v.acv.eqw, v.acc.eqw	See Tab.2 in main text
v.lin.eqw	See Tab.2 in main text
v.lin.w1a, v.lin.w2a, v.lin.w3a	See Tab.2 in main text
v.lin.w1h, v.lin.w2h, v.lin.w3h	See Tab.2 in main text
$v_j(x_j)$	(Marginal) value function over the attribute linked to objective j
$v_j(x_j(A))$	(Marginal) value function over attribute linked to objective j of alternative *A*
w_1, w_2, w_3	See Tab.2 in main text
w_j	Weight of objective j
X_A	Random variable describing the attribute outcome of alternative A
x_j	Attribute level regarding objective j
$z_{k,j}$	Indicator variable, equals 1 if *j*th characteristic is met, else 0.
$\boldsymbol{\theta}$	Failure model parameter vector
θ_1	Weibull shape parameter
θ_2	Weibull scale parameter
θ_3	Exponential scale parameter
π	Probability not to be replaced after a failure
Appendices	
cr	Scenario-dependent change rate
g_1,g_2	Adjustment factors to account for changing diamter proportions in the overall pipe network
l_p	Future per person expansion length
$l_{p,0}$	Current per person expansion length
P	Population
P_0	Original population in reference year T_0
T	Evaluation year; here= 2010
T_0	Reference year; here = 2010

B) Prediction of unrecorded failures

The number of failures of a pipe between its date of laying t_o and the beginning of the failure recording period *a* is distributed according to

$$Prob\left(n^{(1)}|n^{(2)}, t_1^{(2)} \dots t_{n^{(2)}}^{(2)}, in\ [t_o, a]\right)$$
$$= \int_{t_0}^{t_1^{(1)}} \dots \int_{t_{n^{(1)}-1}^{(1)}}^{a} \frac{p\left(n^{(1)} + n^{(2)}, t_1^{(1)} \dots t_{n^{(1)}}^{(1)}, t_1^{(2)} \dots t_{n^{(2)}}^{(2)}|in\ [t_o, b]\right)}{p\left(n^{(2)}, t_1^{(2)} \dots t_{n^{(2)}}^{(2)}|in\ [a, b]\right)} dt_{n^{(1)}}^{(1)} \dots dt_1^{(1)} \quad \text{(S.1)}$$

The distribution is conditioned on the known $n^{(2)}$ observed failures at $t_1^{(2)} \dots t_{n^{(2)}}^{(2)}$ within the observation period $[a, b]$. The enumerator is given in equations (14) and (15) in Scheidegger et al (2013). To sample from (S.1) an expression that is proportional to it is sufficient so the evaluation of the denominator is not required.

C) Estimated failure model parameters for runs with fixed π in water utilities B and C

Table S.1: Summary statistics of parameters after inference with fixed π in water network B and C

	π [quantile]	B $\hat{\theta}_1$	B $\hat{\theta}_{2,DI1}$	B $\hat{\theta}_{3,DI1}$	B $\hat{\beta}_{DI2}$	B $\hat{\beta}_{GI3}$	B $\hat{\beta}_{2,FC}$	C $\hat{\theta}_1$	C $\hat{\theta}_{2,DI1}$	C $\hat{\theta}_{3,DI1}$	C $\hat{\beta}_{DI2}$	C $\hat{\beta}_{GI3}$	C $\hat{\beta}_{2,FC}$
$\hat{\boldsymbol{\theta}}$	**0.619** [0.01]	**1.69**	**45.65**	**15.50**	**2.95**	**1.28**	**5.25**	**1.28**	**64.73**	**11.26**	**3.26**	**0.91**	-
$sd(\hat{\theta})$		*0.27*	*3.35*	*3.20*	*0.93*	*0.14*	*1.63*	*0.17*	*6.53*	*1.58*	*1.06*	*0.13*	-
$\hat{\boldsymbol{\theta}}$	**0.745** [0.1]	**1.71**	**52.55**	**18.50**	**2.83**	**1.28**	**5.05**	**1.36**	**81.44**	**13.60**	**2.73**	**0.96**	-
$sd(\hat{\theta})$		*0.27*	*4.09*	*3.78*	*0.84*	*0.13*	*1.51*	*0.18*	*8.90*	*1.88*	*0.79*	*0.11*	-
$\hat{\boldsymbol{\theta}}$	**0.793** [0.2]	**1.72**	**55.00**	**19.65**	**2.79**	**1.28**	**5.00**	**1.38**	**87.07**	**14.57**	**2.60**	**0.97**	-
$sd(\hat{\theta})$		*0.27*	*4.48*	*4.00*	*0.82*	*0.13*	*1.48*	*0.18*	*9.99*	*2.01*	*0.72*	*0.11*	-
$\hat{\boldsymbol{\theta}}$	**0.825** [0.3]	**1.72**	**56.59**	**20.41**	**2.77**	**1.28**	**4.96**	**1.40**	**90.59**	**15.23**	**2.52**	**0.98**	-
$sd(\hat{\theta})$		*0.27*	*4.76*	*4.14*	*0.81*	*0.13*	*1.46*	*0.18*	*10.74*	*2.09*	*0.69*	*0.11*	-
$\hat{\boldsymbol{\theta}}$	**0.850** [0.4]	**1.73**	**57.82**	**21.01**	**2.75**	**1.28**	**4.93**	**1.41**	**93.26**	**15.76**	**2.47**	**0.98**	-
$sd(\hat{\theta})$		*0.27*	*4.98*	*4.26*	*0.80*	*0.13*	*1.44*	*0.18*	*11.33*	*2.16*	*0.66*	*0.11*	-
$\hat{\boldsymbol{\theta}}$	**0.871** [0.5]	**1.73**	**58.86**	**21.52**	**2.74**	**1.28**	**4.91**	**1.42**	**95.48**	**16.22**	**2.43**	**0.99**	-
$sd(\hat{\theta})$		*0.27*	*5.18*	*4.35*	*0.79*	*0.13*	*1.43*	*0.19*	*11.84*	*2.22*	*0.64*	*0.11*	-
$\hat{\boldsymbol{\theta}}$	**0.890** [0.6]	**1.73**	**59.80**	**21.99**	**2.73**	**1.28**	**4.89**	**1.43**	**97.46**	**16.64**	**2.40**	**0.99**	-
$sd(\hat{\theta})$		*0.27*	*5.37*	*4.44*	*0.78*	*0.13*	*1.42*	*0.19*	*12.31*	*2.27*	*0.63*	*0.10*	-
$\hat{\boldsymbol{\theta}}$	**0.909** [0.7]	**1.73**	**60.69**	**22.45**	**2.72**	**1.28**	**4.88**	**1.44**	**99.31**	**17.05**	**2.37**	**0.99**	-
$sd(\hat{\theta})$		*0.27*	*5.56*	*4.53*	*0.78*	*0.13*	*1.41*	*0.19*	*12.75*	*2.33*	*0.61*	*0.10*	-
$\hat{\boldsymbol{\theta}}$	**0.928** [0.8]	**1.74**	**61.60**	**22.92**	**2.70**	**1.28**	**4.86**	**1.44**	**101.16**	**17.48**	**2.34**	**1.00**	-
$sd(\hat{\theta})$		*0.27*	*5.75*	*4.62*	*0.77*	*0.13*	*1.40*	*0.19*	*13.21*	*2.38*	*0.60*	*0.10*	-
$\hat{\boldsymbol{\theta}}$	**0.950** [0.9]	**1.74**	**62.62**	**23.45**	**2.69**	**1.28**	**4.84**	**1.45**	**103.21**	**17.97**	**2.30**	**1.00**	-
$sd(\hat{\theta})$		*0.27*	*5.97*	*4.72*	*0.76*	*0.13*	*1.39*	*0.19*	*13.73*	*2.44*	*0.58*	*0.10*	-
$\hat{\boldsymbol{\theta}}$	**0.983** [0.99]	**1.74**	**64.12**	**24.24**	**2.68**	**1.28**	**4.81**	**1.47**	**106.16**	**18.70**	**2.26**	**1.00**	-
$sd(\hat{\theta})$		*0.27*	*6.30*	*4.86*	*0.75*	*0.13*	*1.38*	*0.19*	*14.50*	*2.54*	*0.56*	*0.10*	-

D) Second-degree stochastic dominance analysis

Table S.2: Mean reliability $\mu_{reliab.}$, risk adjusted mean $\mu'_{reliab.}$, and corresponding ranks (2010-2050).

	Alternative	$\mathbf{A_{f2\%}}$	$\mathbf{A_{f1.5\%}}$	$\mathbf{A_{a2\%}}$	$\mathbf{A_{a1.5\%}}$	$\mathbf{A_{cyc80}}$	$\mathbf{A_{f2+}}$	$\mathbf{A_{f1\%}}$	$\mathbf{A_{a1\%}}$	$\mathbf{A_{f0.5\%}}$	$\mathbf{A_{a0.5\%}}$	$\mathbf{A_{f3+}}$	$\mathbf{A_{fr2\%}}$	$\mathbf{A_{fr1.5\%}}$	$\mathbf{A_{fr1\%}}$	$\mathbf{A_{f4+}}$	$\mathbf{A_{f5+}}$	$\mathbf{A_{cyc100}}$	$\mathbf{A_{ref}}$
Boom	$\mu_{reliab.}$	0.9967	0.9961	0.996	0.9956	0.9954	0.9954	0.9953	0.9951	0.9944	0.9943	0.9941	0.9936	0.9936	0.9936	0.9935	0.9933	0.9932	0.9931
	rank($\mu_{reliab.}$)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
	$\mu'_{reliab.}$	0.9985	0.9982	0.998	0.9978	0.9976	0.9975	0.9976	0.9975	0.9971	0.997	0.9968	0.9966	0.9966	0.9966	0.9965	0.9964	0.9964	0.9963
	rank($\mu'_{reliab.}$)	1	2	3	4	6	8	5	7	9	10	11	12	13	14	15	17	16	18
Doom	$\mu_{reliab.}$	0.9954	0.9945	0.9942	0.9931	0.9917	0.9918	0.993	0.9915	0.9902	0.99	0.9894	0.9875	0.9875	0.9875	0.9879	0.9871	0.9887	0.9864
	rank($\mu_{reliab.}$)	1	2	3	4	7	6	5	8	9	10	11	14	15	16	13	17	12	18
	$\mu'_{reliab.}$	0.9967	0.9958	0.9956	0.9943	0.9928	0.9926	0.9944	0.9926	0.9913	0.9912	0.9904	0.9891	0.9891	0.989	0.9892	0.9886	0.9902	0.9882
	rank($\mu'_{reliab.}$)	1	2	3	5	6	8	4	7	9	10	11	14	15	16	13	17	12	18
Qual. of life	$\mu_{reliab.}$	0.9965	0.996	0.9959	0.9954	0.9946	0.9947	0.9952	0.9947	0.9939	0.9937	0.9933	0.9927	0.9927	0.9926	0.9925	0.9922	0.9926	0.9919
	rank($\mu_{reliab.}$)	1	2	3	4	8	7	5	6	9	10	11	12	13	15	16	17	14	18
	$\mu'_{reliab.}$	0.9981	0.9977	0.9976	0.9971	0.996	0.9959	0.997	0.9964	0.9957	0.9954	0.9948	0.9942	0.9942	0.9942	0.9942	0.9938	0.9946	0.9936
	rank($\mu'_{reliab.}$)	1	2	3	4	7	8	5	6	9	10	11	13	14	15	16	17	12	18
Status quo	$\mu_{reliab.}$	0.9954	0.9945	0.9942	0.9931	0.9917	0.9918	0.993	0.9915	0.9902	0.99	0.9894	0.9875	0.9875	0.9875	0.9879	0.9871	0.9887	0.9864
	rank($\mu_{reliab.}$)	1	2	3	4	7	6	5	8	9	10	11	14	15	16	13	17	12	18
	$\mu'_{reliab.}$	0.9967	0.9958	0.9956	0.9943	0.9928	0.9926	0.9944	0.9926	0.9913	0.9912	0.9904	0.9891	0.9891	0.989	0.9892	0.9886	0.9902	0.9882
	rank($\mu'_{reliab.}$)	1	2	3	5	6	8	4	7	9	10	11	14	15	16	13	17	12	18

Table S.3: Mean intergenerational equity (rehabilitation) $\mu_{rehab.}$, risk adjusted mean $\mu'_{rehab.}$, and corresponding ranks (2010-2050).

	Alternative	$A_{f2\%}$	$A_{f1.5\%}$	$A_{a2\%}$	$A_{a1.5\%}$	A_{cyc80}	A_{f2+}	$A_{f1\%}$	$A_{a1\%}$	$A_{f0.5\%}$	$A_{a0.5\%}$	A_{f3+}	$A_{fr2\%}$	$A_{fr1.5\%}$	$A_{fr1\%}$	A_{f4+}	A_{f5+}	A_{cyc100}	A_{ref}
Boom	$\mu_{rehab.}$	0.5217	0.4663	0.4334	0.3813	0.2585	0.2901	0.3791	0.3152	0.2533	0.2109	0.1367	0.0263	0.0246	0.0221	0.0588	0.0226	0.0659	0.0000
	rank($\mu_{rehab.}$)	1	2	3	4	8	7	5	6	9	10	11	14	15	17	13	16	12	18
	$\mu'_{rehab.}$	0.6453	0.5860	0.5373	0.4767	0.3291	0.3587	0.4848	0.4013	0.3365	0.2802	0.1755	0.0363	0.0336	0.0299	0.0783	0.0316	0.1118	0.0000
	rank($\mu'_{rehab.}$)	1	2	3	5	9	7	4	6	8	10	11	14	15	17	13	16	12	18
Doom	$\mu_{rehab.}$	0.6388	0.5722	0.5310	0.4415	0.3460	0.3862	0.4626	0.3293	0.2553	0.2122	0.1962	0.0208	0.0204	0.0196	0.0905	0.0375	0.1295	0.0000
	rank($\mu_{rehab.}$)	1	2	3	5	7	6	4	8	9	10	11	15	16	17	13	14	12	18
	$\mu'_{rehab.}$	0.7610	0.6997	0.6585	0.5503	0.4051	0.4502	0.5911	0.4058	0.3333	0.2756	0.2532	0.0238	0.0234	0.0228	0.1256	0.0555	0.2091	0.0000
	rank($\mu'_{rehab.}$)	1	2	3	5	8	6	4	7	9	10	11	15	16	17	13	14	12	18
Qual. of life	$\mu_{rehab.}$	0.6356	0.5756	0.5508	0.4776	0.3251	0.3637	0.4803	0.3731	0.2984	0.2289	0.1825	0.0286	0.0277	0.0259	0.0834	0.0343	0.1157	0.0000
	rank($\mu_{rehab.}$)	1	2	3	5	8	7	4	6	9	10	11	15	16	17	13	14	12	18
	$\mu'_{rehab.}$	0.7604	0.7066	0.6856	0.6057	0.3812	0.4224	0.6131	0.4796	0.4009	0.2999	0.2333	0.0376	0.0363	0.0340	0.1146	0.0503	0.1880	0.0000
	rank($\mu'_{rehab.}$)	1	2	3	5	9	7	4	6	8	10	11	15	16	17	13	14	12	18
Status quo	$\mu_{rehab.}$	0.6388	0.5722	0.5310	0.4415	0.3460	0.3862	0.4626	0.3293	0.2553	0.2122	0.1962	0.0208	0.0204	0.0196	0.0905	0.0375	0.1295	0.0000
	rank($\mu_{rehab.}$)	1	2	3	5	7	6	4	8	9	10	11	15	16	17	13	14	12	18
	$\mu'_{rehab.}$	0.7610	0.6997	0.6585	0.5503	0.4051	0.4502	0.5911	0.4058	0.3333	0.2756	0.2532	0.0238	0.0234	0.0228	0.1256	0.0555	0.2091	0.0000
	rank($\mu'_{rehab.}$)	1	2	3	5	8	6	4	7	9	10	11	15	16	17	13	14	12	18

Table S.4: Mean costs (% of average income) $\mu_{cost.}$, risk adjusted mean $\mu'_{cost.}$, and corresponding ranks (2010-2050).

	Alternative	$A_{f2\%}$	$A_{f1.5\%}$	$A_{a2\%}$	$A_{a1.5\%}$	A_{cyc80}	A_{f2+}	$A_{f1\%}$	$A_{a1\%}$	$A_{f0.5\%}$	$A_{a0.5\%}$	A_{f3+}	$A_{fr2\%}$	$A_{fr1.5\%}$	$A_{fr1\%}$	A_{f4+}	A_{f5+}	A_{cyc100}	A_{ref}
Boom	μ_{cost}	0.1697	0.1285	0.1699	0.1279	0.0294	0.0289	0.0859	0.0860	0.0440	0.0441	0.0125	0.1706	0.1277	0.0864	0.0064	0.0038	0.0061	0.0023
	rank(μ_{cost})	16	15	17	14	7	6	10	11	8	9	5	18	13	12	4	2	3	1
	μ'_{cost}	0.0973	0.0744	0.0976	0.0737	0.0051	0.0065	0.0497	0.0498	0.0260	0.0261	0.0048	0.0984	0.0735	0.0504	0.0032	0.0023	0.0019	0.0014
	rank(μ'_{cost})	16	15	17	14	6	7	10	11	8	9	5	18	13	12	4	3	2	1
Doom	μ_{cost}	0.2824	0.0021	0.0028	0.0022	0.0015	0.0008	0.0015	0.0015	0.0008	0.0008	0.0006	0.0029	0.0022	0.0015	0.0004	0.0003	0.0007	0.0001
	rank(μ_{cost})	16	13	17	14	10	8	9	11	6	7	4	18	15	12	3	2	5	1
	μ'_{cost}	0.2519	0.1908	0.2532	0.1923	0.0573	0.0576	0.1303	0.1315	0.0705	0.0709	0.0449	0.2582	0.1963	0.1345	0.0280	0.0184	0.0147	0.0107
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1
Qual. of life	μ_{cost}	0.2064	0.1558	0.2069	0.1564	0.0689	0.0482	0.1054	0.1061	0.0555	0.0559	0.0286	0.2101	0.1591	0.1081	0.0177	0.0116	0.0289	0.0064
	rank(μ_{cost})	16	13	17	14	9	6	10	11	7	8	4	18	15	12	3	2	5	1
	μ'_{cost}	0.1909	0.1444	0.1916	0.1451	0.0225	0.0263	0.0981	0.0986	0.0521	0.0524	0.0213	0.1944	0.1474	0.1004	0.0137	0.0094	0.0068	0.0055
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1
Status quo	μ_{cost}	0.1812	0.1371	0.1821	0.1383	0.0933	0.0581	0.0935	0.0947	0.0507	0.0511	0.0377	0.1865	0.1419	0.0974	0.0243	0.0162	0.0426	0.0084
	rank(μ_{cost})	16	13	17	14	9	8	10	11	6	7	4	18	15	12	3	2	5	1
	μ'_{cost}	0.1755	0.1326	0.1763	0.1339	0.0336	0.0374	0.0902	0.0918	0.0490	0.0495	0.0300	0.1818	0.1384	0.0950	0.0186	0.0125	0.0093	0.0074
	rank(μ'_{cost})	16	13	17	14	6	7	10	11	8	9	5	18	15	12	4	3	2	1

E) MCDA results for all alternatives

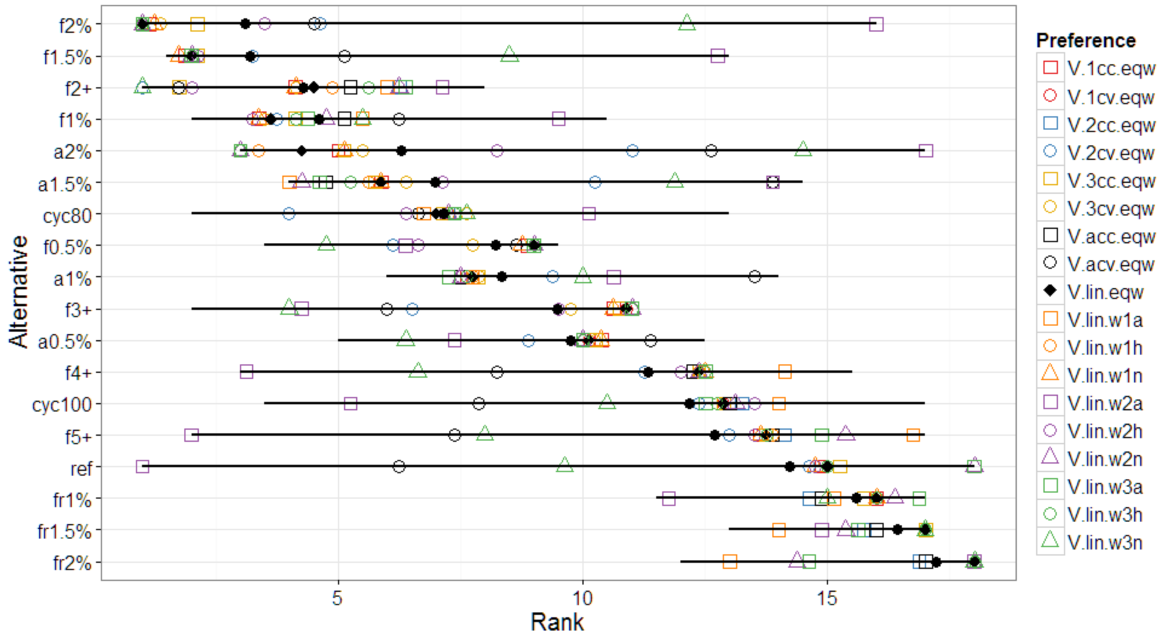

Figure S.1: Sensitivity of the ranking to different weights and value function forms without assumption of any specific risk attitude. The black point and line represent mean rank and rank ranges (minimum and maximum rank) of the outcomes of alternatives. Ranks are aggregated over the four scenarios

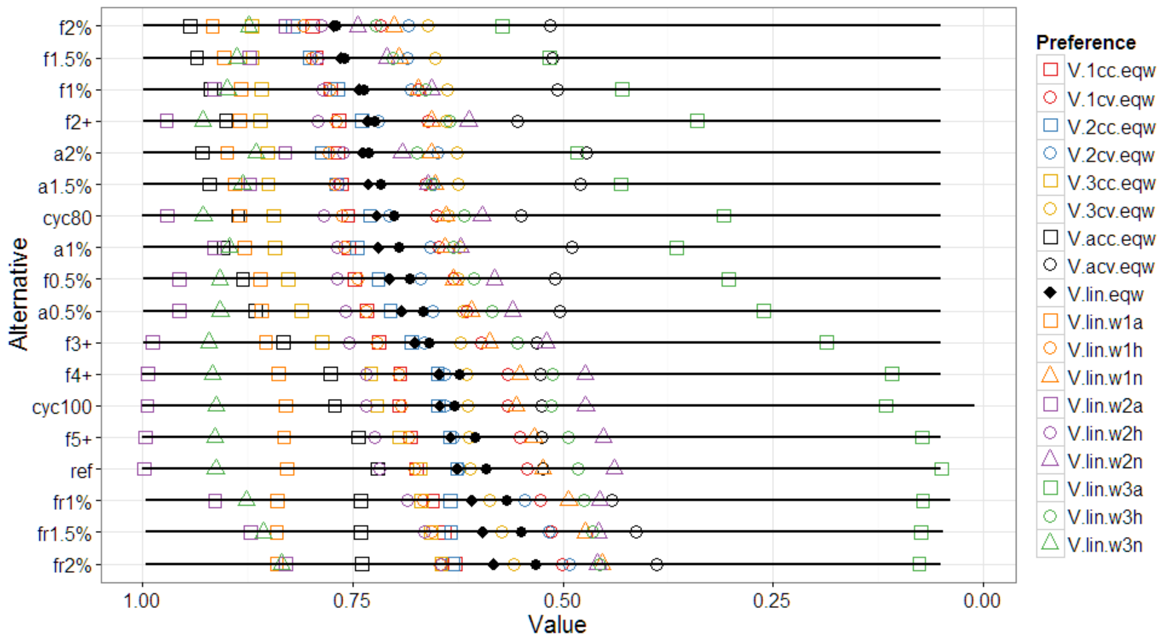

Figure S.2: Sensitivity of the overall value of the alternatives to weight and value function changes without assumption of any specific risk attitude. The black point and line represent mean values and value ranges (absolute minimum and maximum value) of the outcomes of alternatives. Values are aggregated over the four scenarios

F) Additional figures

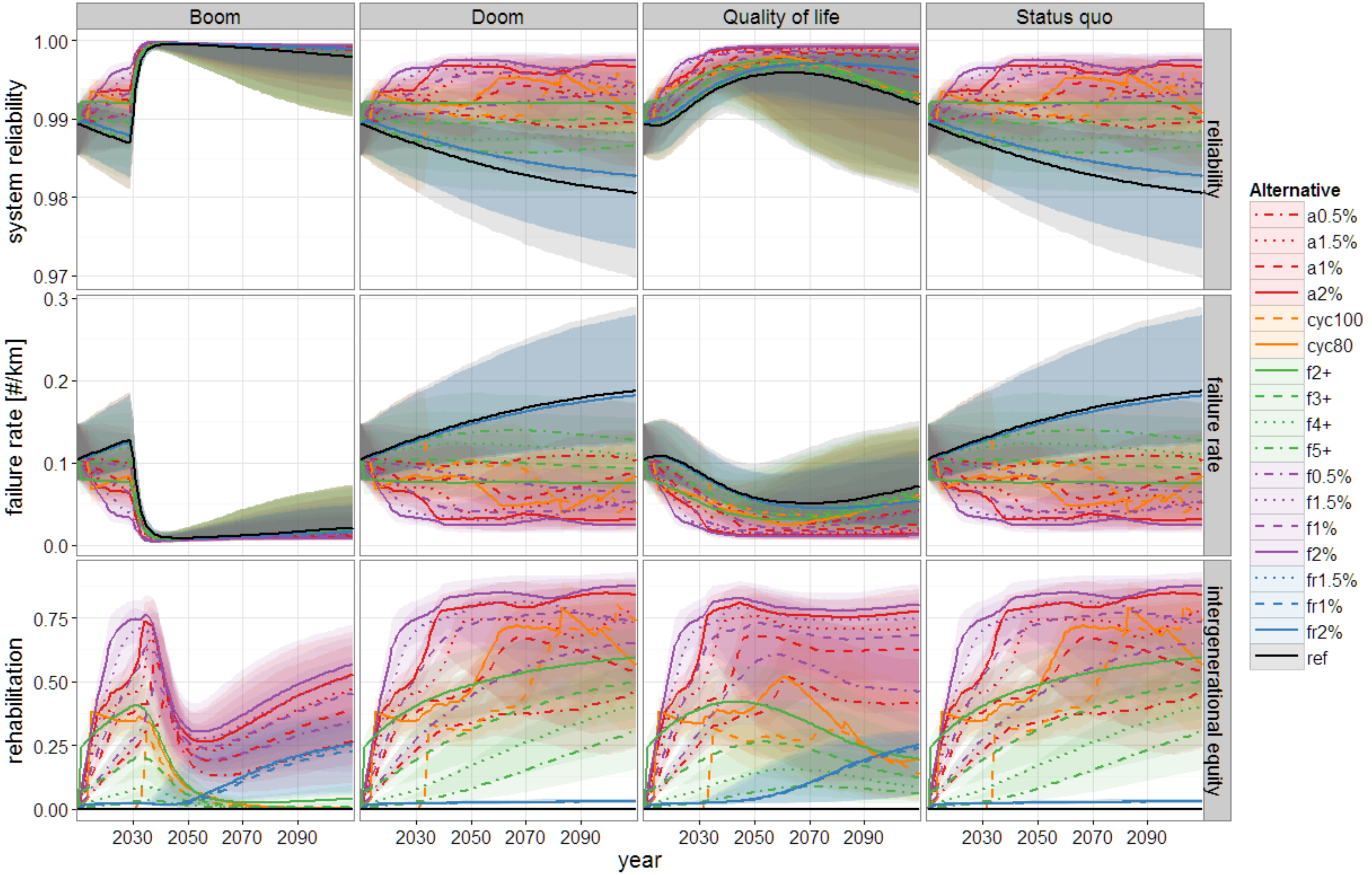

Figure S.3: Outcomes of the alternatives for reliability and intergenerational equity plotted against the development of the failure rate. The strong relationship especially between reliability and failure rate is apparent.

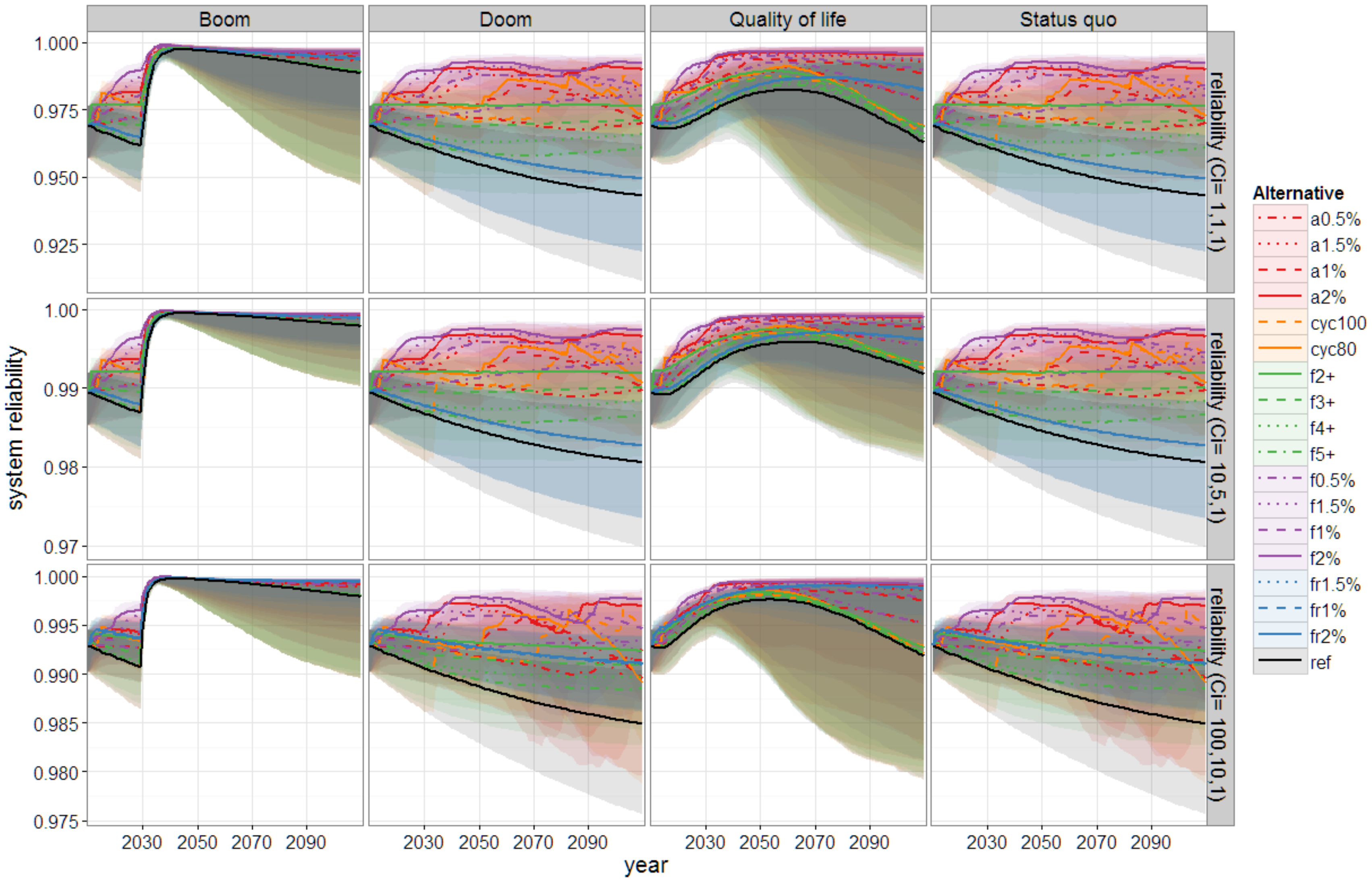

Figure S.4: Reliability under different assumptions for the criticality indices (in following order: ($C_{\geq 250\,mm}$, $C_{150\text{-}250mm}$, $C_{\leq 150mm}$). Note the considerable improvement of $A_{fr2\ldots1\%}$ (blue lines) with increasing criticality of larger pipes.

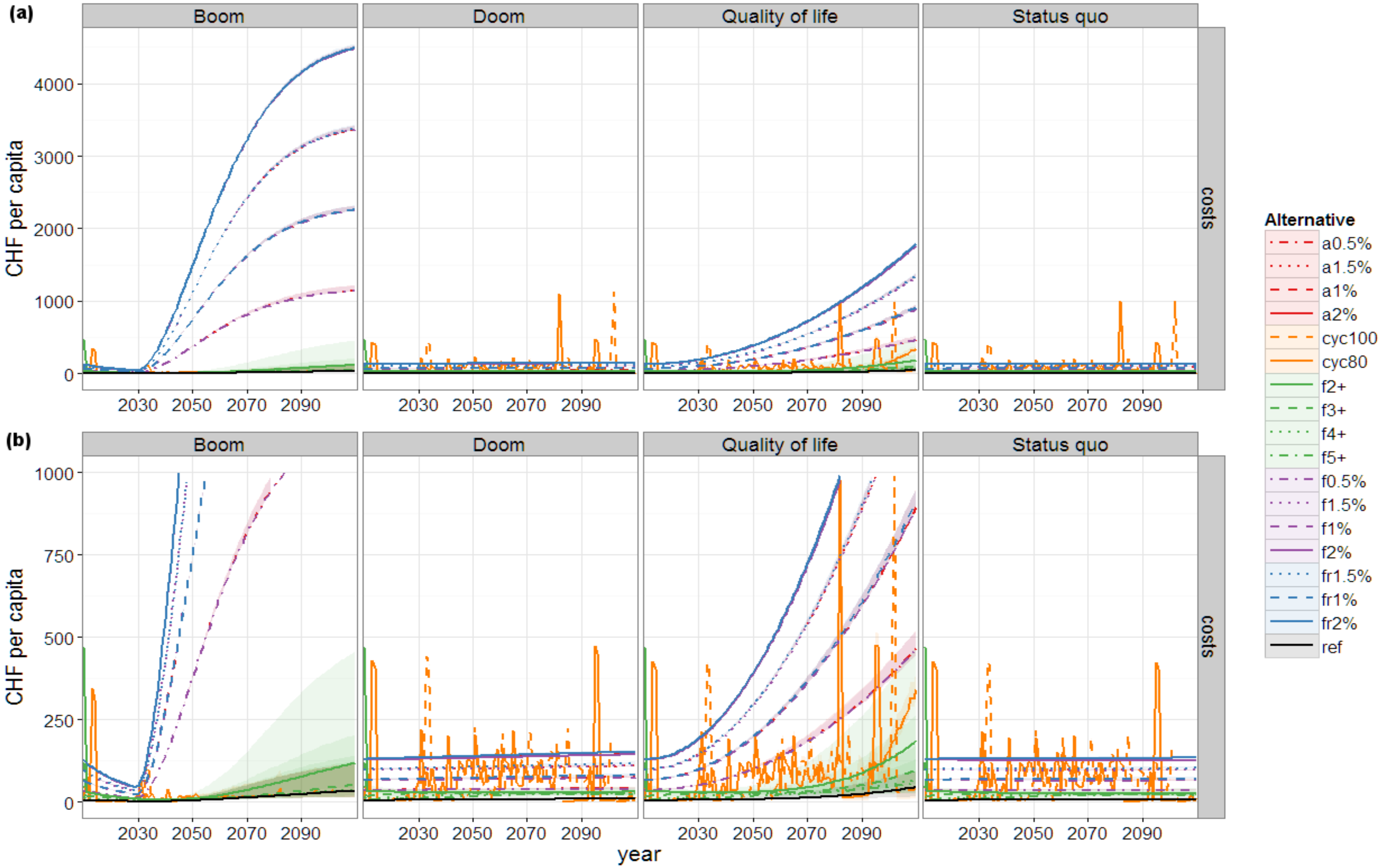

Figure S.5: Development of absolute per capita costs. (a) shows the results on original scale, (b) on a rescaled scale to better demonstrate results <250 CHF per capita. The results are displayed without considering neither discount rates for repair and replacement costs, nor inflation of incomes. Note the strong increase of costs in scenarios with high infrastructure expansion. Note the strong cost increase of alternatives with network-length dependent replacement strategies in scenarios with high infrastructure expansion.

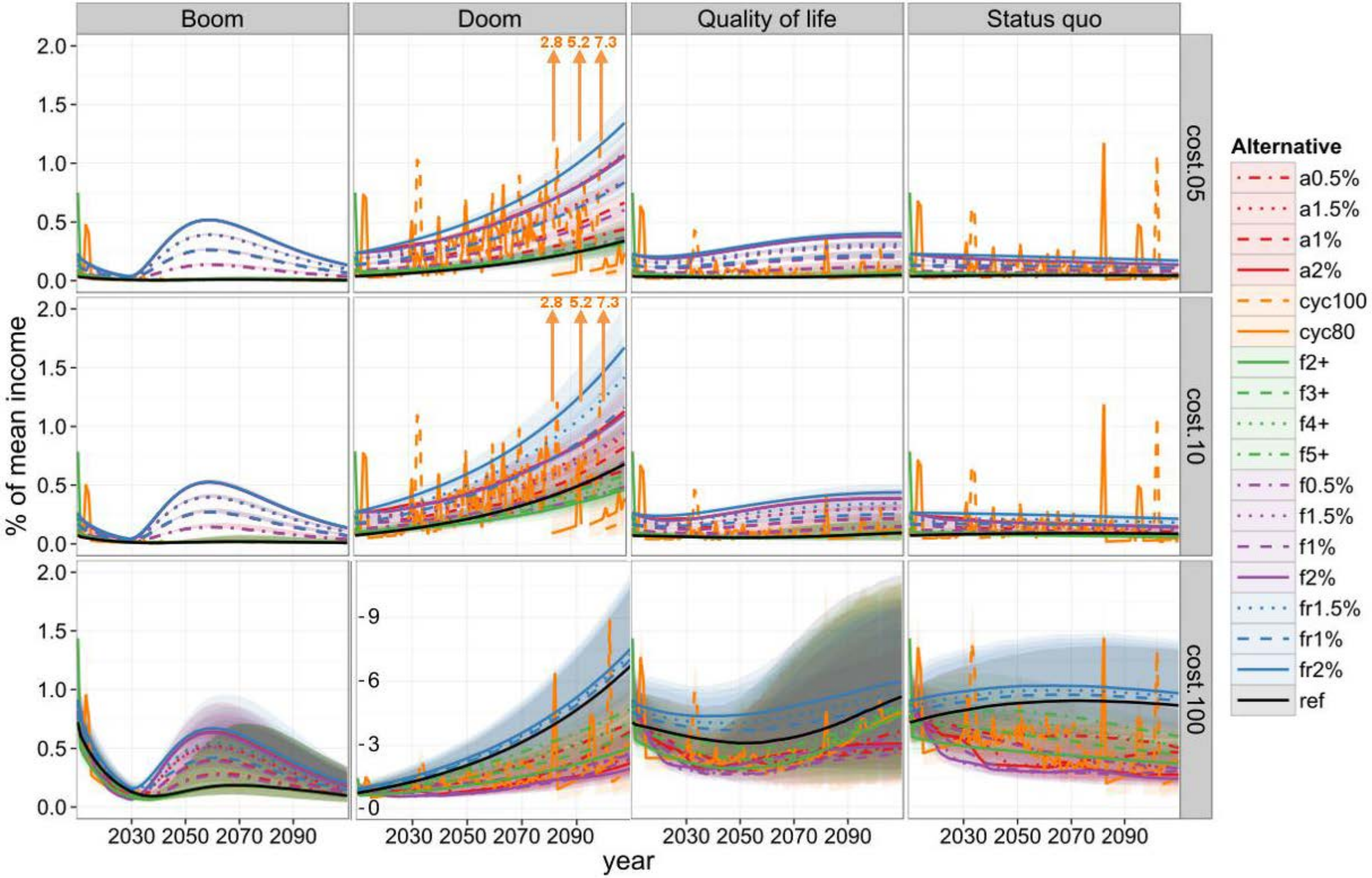

Figure S.6: Sensitivity of the attribute outcomes for costs to different unit cost assumptions. Note the adapted zoom for "cost.100" under the Doom scenario. "Cost.05" stands for five times higher repair costs, "cost.10", and "cost.100" for ten and a hundred times higher repair costs (i.e. 32'500, 65'000, 650'000 CHF prer repair respectively). This is equivalent to repair to replacement cost ratios of approx. 1:3, 1:1.5, 1:0.15 while the ratio underlying the assumptions and results presented in the main text is 1:15. Note the increase of uncertainty with increasing repair costs (as only parametric uncertainty of the failure model is propagated).

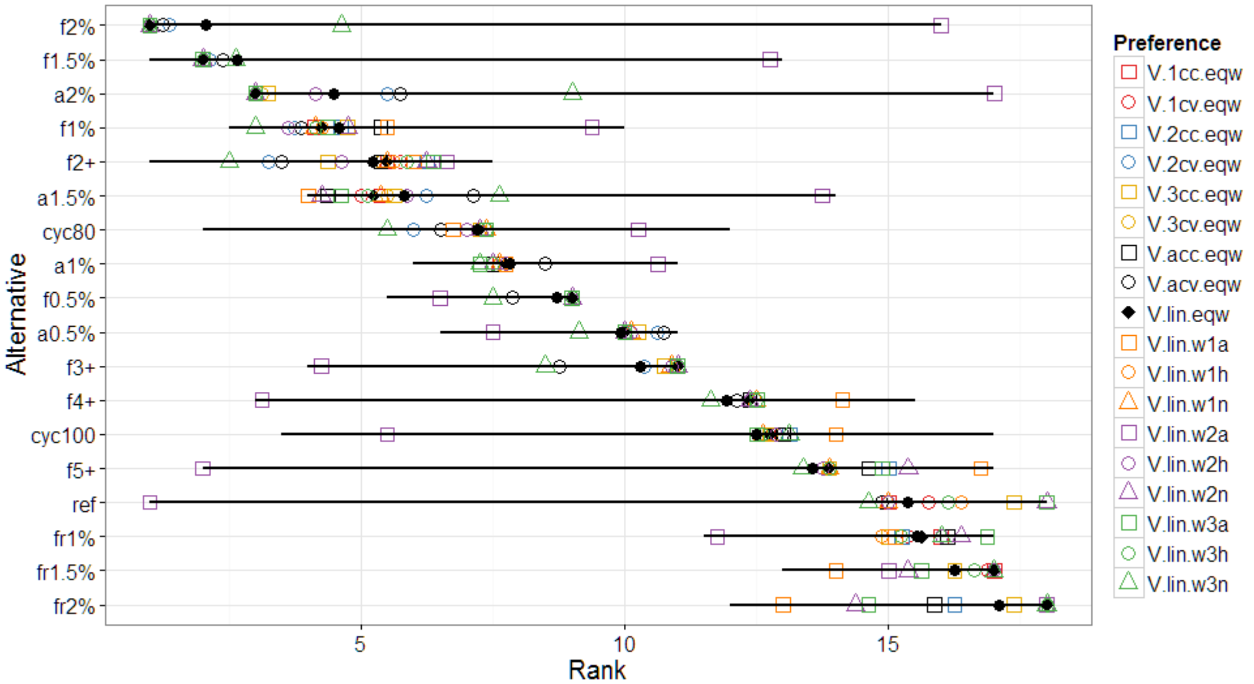

Figure S.7: Sensitivity of the ranking assuming five times higher repair costs to different weights and value function forms without assumption of any specific risk attitude. The black point and line represent mean rank and rank ranges (minimum and maximum rank) of the outcomes of alternatives. Ranks are aggregated over the four scenarios

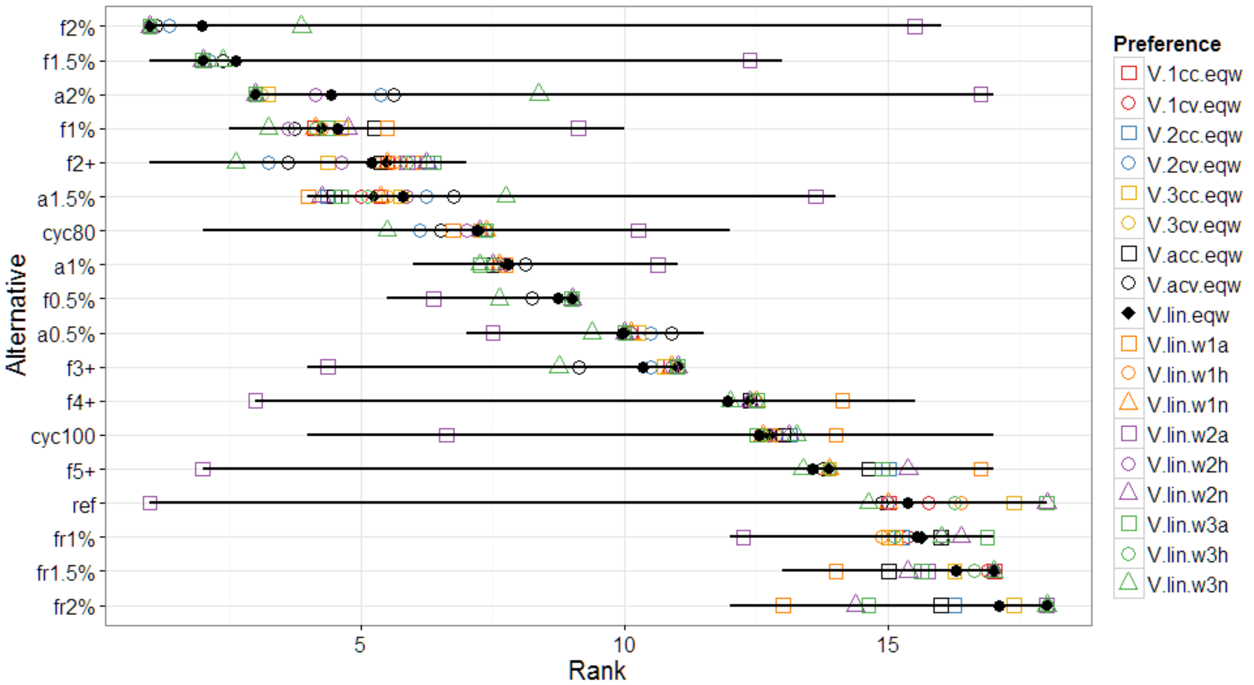

Figure S.8: Sensitivity of the ranking assuming ten times higher repair costs to different weights and value function forms without assumption of any specific risk attitude. The black point and line represent mean rank and rank ranges (minimum and maximum rank) of the outcomes of alternatives. Ranks are aggregated over the four scenarios

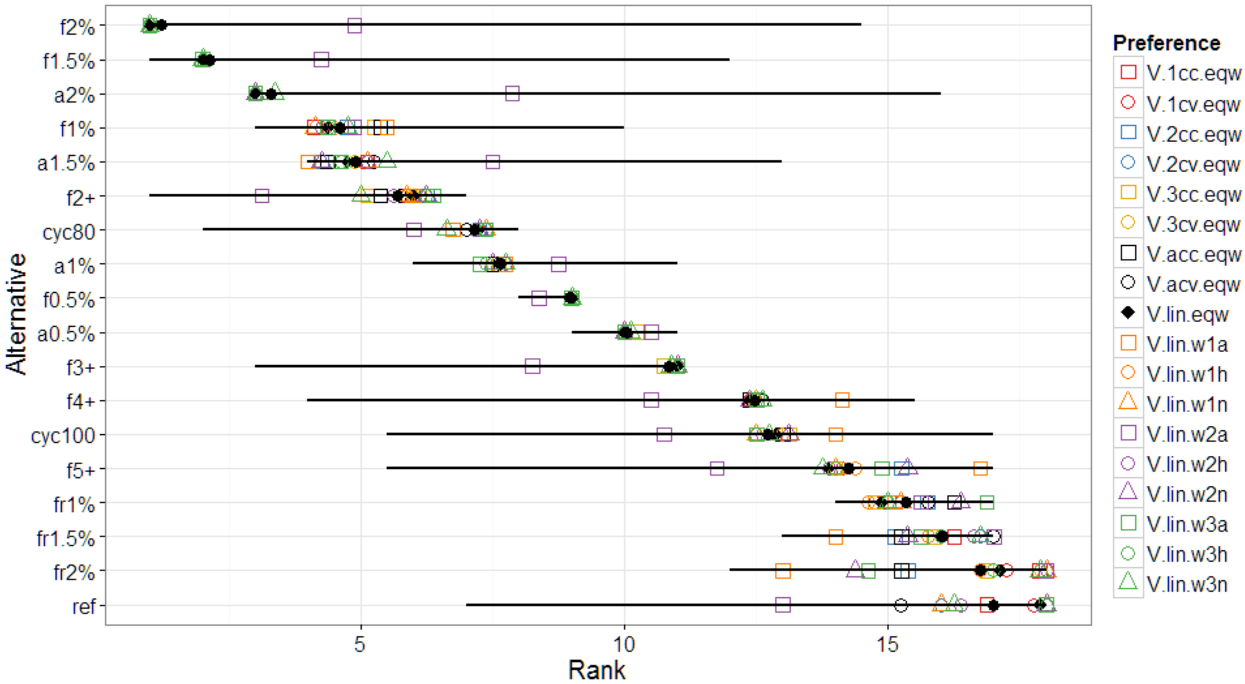

Figure S.9: Sensitivity of the ranking assuming a hundred times higher repair costs to different weights and value function forms without assumption of any specific risk attitude. The black point and line represent mean rank and rank ranges (minimum and maximum rank) of the outcomes of alternatives. Ranks are aggregated over the four scenarios