**8TH CONFERENCE ON APPLIED INFRASTRUCTURE RESEARCH**

**9-10 OCTOBER 2009, BERLIN**

# Implicit discrimination in Quality Regulation: Risk Premium Variation due to Size and Age Distribution of Electricity Networks

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*Abstract*

Evidence has repeatedly shown that at the introduction stage of incentive regulation investment may be hampered by strong incentives to save costs. Consequently, investment or quality regulation is necessary to guarantee socially efficient investment. Quality regulation can bear implicit discrimination potential towards network operators when certain heterogeneous characteristics do occur. Two such relevant characteristics are the size (e.g. km cable length, n° of circuit breakers, n° of transformers, etc.) and the age distribution of an electricity network. Whereas the size of a network is observable with few effort, the latter can lead to hidden characteristic problems, because accounting often solely considers aggregated values, fails to distinguish between capital and operating-based expenditure for replacement or simply did not record actions in the past properly. Resulting structural disadvantages may, firstly, exist due to worse expected quality indices (elder networks suffer from a higher number of component failures and thus outages). Secondly, greater variation coefficients of these expected quality indices may lead to a disadvantageous (higher) risk exposure, because smaller and elder networks suffer higher stochastic influences in their overall failure behavior. Both effects will require higher capital costs for a risk-averse investor/manager which in turn leads to discrimination. Short-term adjustment of the two characteristics is quite difficult: The adjustment of network size leads to the search for an efficient scale of production, which can only be influenced over years. The modification of the age distribution of assets depends on several bottlenecks such as financial liquidity, infrastructural restrictions (e.g. planning and building permissions), or workforce capacity restrictions leading to similar complications. It is up to the regulator to decide whether to consider initial disadvantages (that namely companies are not responsible for) as stranded costs or to punish companies with structural disadvantages. The risk of not considering stranded costs incurs increased transaction costs due to potential bankruptcies. The aim of this article is to analytically demonstrate and further quantify potential discrimination by quality penalization resulting from increased incurred risk due to differences in size, different ratios of reinvestment to quality related cost, and different aging characteristics of the network as different average age and different, heterogeneous age structures.

*Keywords*
*Incentive and quality regulation, discrimination, optimal replacement, risk, age and size effects, electricity networks*
*JEL-Classification: G, L*

*The authors are solely responsible for the contents which do not necessarily represent the opinion of the Chair for Management Science and Energy Economics.*

## 1. Introduction

Evidence has repeatedly shown that at the introduction stage of incentive regulation investment may be hampered by strong incentives to save costs.[1] Consequently, input-based investment or output-based quality regulation is necessary to guarantee socially efficient investment. Quality regulation can bear discrimination potential towards network operators when certain heterogeneous network characteristics occur. Two such relevant characteristics are the size and the age distribution of an electricity network. Whereas the size of a network is observable with few effort, the latter can lead to hidden characteristic problems, because accounting often solely considers aggregated values, fails to distinguish between capital and operating-based expenditure for replacement or simply did not record actions in the past properly. Resulting structural disadvantages may, firstly, exist due to worse expected quality indices (elder networks suffer from a higher number of component failures and thus outages). Secondly, greater variation coefficients of these expected quality indices may lead to a disadvantageous (higher) risk exposure, because smaller and elder networks suffer higher stochastic influences in their overall failure behavior. Both effects will require higher capital costs which in turn leads to discrimination. Short-term adjustment of the two characteristics is quite difficult: The adjustment of network size leads to the search for an efficient scale of production, which can only be influenced over years. The modification of the age distribution of assets depends on several bottlenecks such as financial liquidity, infrastructural restrictions (e.g. planning and building permissions), or workforce capacity restrictions leading to similar complications. It is up to the regulator to decide whether he wants to consider initial disadvantages (that namely companies are not responsible for) as stranded costs or to punish companies with structural disadvantages. The risk of not considering stranded costs incurs increased transaction costs due to potential bankruptcies.

Instruments that regulatory authorities use in order to increase or reduce investment incentives are mostly input-based fixed equity return rates in cost-based regulation or output-based quality penalties/bonuses with regard to incentive regulation. In the end, both regulatory regimes will have to determine some cost of capital to target an envisaged level of remuneration and investment incentive.

One major driver of the companies' capital cost and thereby investment incentives is the return risk due to the stochasticity in the production function of a distribution network. The valuation of investment in physical assets follows rules developed in financial economics: The investment decision of a firm should, according to standard textbooks such as Brealey and Myers (2003, pp. 93-121), depend on the net present value (NPV) of a project and is thus related to two major components: the value of the future cash-flows and the discount factor, which is governed by the cost of capital.

An investment following Dixit and Pyndick (1994, pp. 3) can be considered as "the act of incurring an immediate cost in the expectation of future rewards" which makes it somehow more independent of the investment notion from an accounting point of view. Investments will be discounted with equity return rates as this is the opportunity cost of capital (if the project is cancelled, the company will return the funds to its shareholder). Leveraging is

[1] Bühler et al. (2004) investigate the effects of regulation on investment and infrastructure quality. Using a static model it is shown that giving up the vertical integration of former monopolists reduces investment incentives and may lead to an underinvestment problem. This problem of underinvestment is tightly linked with a decrease in infrastructure quality. Bühler et al. (2006) present an analytical model which reveals the existence of the price-quality-trade off. They present evidence that regulatory authorities cannot simultaneously attain a lower retail price and higher infrastructure quality proving the existence of a trade-off between quality and price. Sappington (2005) reviews different concepts of service quality in the context of telecom regulation and extracts some factors that will be influenced if socially desired service quality is delivered. He offers several options for the regulator to obtain a target service quality. Possible instruments are minimum quality standards, service quality bonuses and penalties, low-powered reward schemes and market structures and interaction. Joskow (2006) examines several countries' approaches to incentive regulation and reveals typical elements of quality regulation as mechanisms targeted at the frequency and duration of outages, service quality and customer satisfaction. In the UK for instance, overall 4% of the revenue on the downside and an unlimited fraction on the upside are subject to quality and service incentive mechanisms.

considered by substituting the equity return by the weighted average cost of capital (WACC), which considers equity/debt-ratios and thereby gives a notion of the gearing and finally the level of capital costs.[2] The cost of equity itself can be estimated e.g. by the capital asset pricing model (CAPM) whereas the cost of debt is regarded mostly as being given by observable market conditions. The CAPM was developed among others by Sharpe (1965) and indicates that a rational investor can attain any point on the capital market line, representing the set of efficient portfolios or, in other words, the return-standard deviation combinations with the lowest standard deviation for a given expected return. Depending on the willingness to take risks, his expected returns will be lower or higher. The risk of a portfolio is measured by its beta, which accounts solely for the systematic risk, the correlation between the investor's portfolio and market return. Beta serves as multiplier for the market (risk) premium in order to obtain the required equity rate of return. Due to perfect hedging, all specific risks are excluded and a portfolio's required rate of return depends solely on the portfolio risk (beta), the overall market return and the riskless interest rate.

In the context of network operation, one central and important necessary assumption of the CAPM is not met: The investor/manager as an agent is not perfectly diversified, because he naturally owns one network and cannot hedge by selling/acquiring specific parts of networks. He can only sell shares in his network and buy shares in other networks which in most countries is very difficult, as often such transactions have to be acknowledged by regulatory, competition and municipal authorities. Partial indivisibility and illiquidity result from these facts. Hausman and Myers (2002) use a real options approach to demonstrate the utility, or respectively the disutility, of waiting. They find that a rate on return regulation that does not consider irreversibility and the ability to wait will lead to return rates that are falling short by about 30% to 85%. This will force investment below economically efficient levels und will create an underinvestment problem.

Another reason for the risk aversion of the firm and the necessity to account for specific risk is given by agency theory. Lacking possibilities of diversification of the management's wealth will lead to in-company diversification (Stulz (1984), Smith and Stulz (1985)). Furthermore, risk mitigation prevents volatile results being misinterpreted as lacking effort or incompetence due to information asymmetries between agent and principal. Ultimately, these principle-agent conflicts are also a result of market insufficiencies since they either presume significant hurdles for the management to diversify, or information asymmetries between management and firm owners.

Consequently, unsystematic risk has to be taken into account by a network investor. In literature, mostly size, macroenvironment, industry and the company itself are considered as specific risk factors. Unfortunately, theoretical or empirical research on specific risks is scarce. Ben-Horim and Levy (1980) decompose a security's total risk $\sigma_i^2$ into a diversifiable risk $\sigma_{u_i}^2$ and a non-diversifiable risk $\beta_i^2\sigma_m^2$. Using data from 1952 to 1960, they find that the diversifiable risk amounts from 23,6 to 44,6%. Thus, the assumption that individual risk might play a significant role in an investor's decision appears to be plausible. To our knowledge, there exists no specific research focusing network operators' specific risk.

Some of these specific risk related costs are easily observable, as e.g. the originate industry's production function as given by the service obligation to connect consumers to the distribution grid. Utilities can profit enormously of economies of scale (that partially account for implicit discrimination), which have been investigated since the beginning of the 1970s. Unfortunately, only very few authors distinguish generation, transmission/distribution and sales.[3] Huettner and Landon (1978) present empirical evidence that economies of scale do exist regarding electricity distribution. Based on a sample of 74 US electricity firms with data from 1971, they show that firm size (measured by output) is significant and an appropriate sign for a U-shaped long-run average cost curve. Opposed to the authors' expectations, a higher network density (measured by the number of transformers per customer) leads to higher distribution costs.[4] Roberts (1998) analyzes production and distribution unit costs of 65

[2] In regulated industries the leverage level is often determined by the regulator, as e.g. in Germany.

[3] Cf. for instance Christensen and Greene (1978) and Nemoto et al. (1998).

[4] One major reason therefore might be that network density is higher in urban areas. Consequently, higher costs may offset density effects.

privately owned vertically integrated US utilities companies using data such as prices, quantities, number of customers, invested capital, labor cost, delivered energy, size of service area etc. He defines three measures of economies of scale and density (elasticity of total cost to output, elasticity of total cost to customer density, elasticity of total cost to the size of the service area) and finds that only the first is really significant. Filippini (1998) analyzes a sample of 39 Swiss municipal electricity distribution companies using data from 1988-1991. The cost function accounts for output in kWh, capital, input in kWh, labor cost, a load factor, the size of the service territory and the number of customers. He finds that economies of size (linked to service territory) and economies of density (linked to the number of customers) are significant. He concludes that most Swiss network utilities operate with a too small service territory and should increase customer density. This whole body of research indicates economies of scale linked to network size, but is not adequate in order to separate the major effects (fixed cost degradation vs. lower earning risk).

The above mentioned factors, indivisibility and illiquidity, did not merit much attention in the network and regulatory economic research literature yet. Because assets are indivisible and illiquid, higher stochasticity caused by smaller operating size or by an elder network structure (or just by a more unfortunate age distribution) may become an important specific risk in connection with quality-based penalties. The expected returns on investment will have to cover expected costs to trigger investment activity, but the stochasticity of networks modifies the standard deviation of these expected returns leading to a higher downside risk, which will in turn lead to a smaller utility if the investor is assumed to be risk-averse. A distinction has to be made between size- and age-related risk markups. Whereas size is quite easy to observe, age should be understood more as virtual age and is much dependent upon the condition an asset has. Much operating cost-based reinvestment (as maintenance) can upgrade an asset's condition, but the accounting age will grow independent of this. This as well as weaknesses in accounting (as mentioned above) will systematically discriminate smaller and elder networks. In the long run, the network operator with the higher risk position will invest suboptimally and may go bankrupt.

The aim of this paper thus is to provide evidence on the degree of explicit and implicit discrimination due to network structure characterized by size and age of networks under output-based socially optimal quality regulation. Age characteristics are further separated in average and structural differences between networks.

We suggest simulation techniques to be an adequate approach to identify the riskiness and effects of explicit and hidden discrimination linked to network structure. Solver (2005) uses a simulation approach based on a test system and analyzes the incentives caused by different regulation schemes. He finds that price caps and revenue caps linked to quality regulation create a strong term incentive towards higher reliability, which may, depending on the situation, not be suitable. Bertling et al. (2005) link the concepts of optimal replacement strategies to approaches of distribution system reliability. The authors develop a reliability-centered asset maintenance method (RCAM), which provides a quantitative relationship between preventive maintenance and total maintenance costs. The main stages in the development process of their RCAM systems are (1) System reliability analysis, (2) Component reliability modeling and (3) System reliability cost/benefit analysis. Using disturbance data for the Stockholm city power system from 1982 to 1999 (high and medium voltage cables), the authors analyze the impact of different maintenance strategies (no preventive maintenance, rehabilitation method and replacement method) on the systems overall costs and reliability indices. Both papers use similar simulation approaches, but do not address the influence of network structure.

The theoretical background about the relationship between network structure and investment incentives will be discussed. An analytical production model of network operation is developed and will be shown that the variation coefficient as a risk measure is negatively correlated with size and depends ambiguously on reinvestment cost, the quality penalty, and failure behavior of assets. Empirical research was conducted to obtain typical network sizes and age structures considering the electricity distribution in Germany. The data gathered was used in a simulation model that computes distribution of quality indices based on network size and age. Using estimates from other studies on the magnitude of external welfare losses to consumers caused by outages, we find that quality-related risk is tightly linked to network size and age. The structure of the paper is as follows. In the second section, the analytical model and its implications will be discussed. The first part of section three describes the simulation model and its major assumptions. The second part of section three presents the survey conducted and the structure of German electricity distribution. Simulation results are summarized and discussed in chapter four. The last section concludes and indicates areas for potential future research work.

## 2. Theoretical model

### 2.1 Theoretical Model for Private Investment: Incentive Structure of the Agent

In the following section, the replacement model will be presented briefly. Consider a network operator under quality regulation that optimizes its replacement strategies. The costs considered correspond to the capital expenditure for replacement of equipment $C$ and penalties $S$ for not delivering the quality expected by the grid customers.[5] The decision variables are the replacement ages $t_j$ at which asset $j$ is subject to planned replacement. In order to keep the problem analytically tractable, we chose a stationary setting and focus on the equilibrium state. Thus, time in our model is represented by the index $t$ (which can be considered equivalent to the asset's age) and the replacement age $t_j$.[6] The failure probability of depends on its conditional failure rate $r(t)$, its unconditional failure rate $f(t)$ and its cumulative survival distribution $1-F(t)$ with $f(t)=dF(t)/dt$. The link between unconditional and conditional failure is as follows:

( 1 ) $$r(t)=\frac{f(t)}{1-F(t)}$$

Another expression necessary to identify the optimal replacement age in a stationary state is given by the expected utilization period $G(t_j)$. It corresponds to:

( 2 ) $$G(t_j)=\int_o^{t_j}(1-F(t))dt$$

$G(t_j)$ and the cumulative survival distribution $1-F(t)$ are required to identify the lifetime distribution $H(t,t_j)$ that will occur in stationary state, where $D_{ref}$ is the standard reference time interval for the optimization decision:

( 3 ) $$H(t,t_j)=\frac{1-F(t)}{G(t_j)/D_{ref}}$$

Equipment that fails has to be replaced, which leads to the differentiation of planned replacement $R_{norm}$ (due to the fact that the asset's age attains the decision variable replacement age, thus $t=t_j$) and premature replacement $R_{prem}$ (due to failure while $t<t_j$). Premature replacement is given by:

( 4 ) $$R_{prem}(t_j)=\int_0^{t_j}(H_j(t;t_j)\cdot r(t))dt=\int_0^{t_j}\left(\frac{1}{G_j(t_j)/D_{ref}}\cdot f(t)\right)dt=\frac{F(t_j)}{G(t_j)/D_{ref}}$$

Planned replacement can be calculated as follows:

( 5 ) $$R_{norm}(t_j)=H(t,t_j)=\frac{1-F(t_j)}{G(t_j)/D_{ref}}$$

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[5] The penalty is based on customer failures. Nevertheless, for an identical customer and network structure, this is equivalent to a revenue based penalty.

[6] In the context of this analytical model, the initial (or starting) age of an asset is not of relevance. In dynamic models however, the initial age structure of equipment is highly relevant in the context of optimization.

With $K$ corresponding to the unit costs for replacement, the maintenance cost adds up to:

$$C(t_j) = K \cdot \left(R_{prem}(t_j) + R_{norm}(t_j)\right) = \frac{K}{G(t_j)/D_{ref}} \qquad (6)$$

The cost related to quality penalties depends on network reliability (which is primarily governed by the number of failures and the network structure). For the sake of simplicity, we assume a direct link between the number of failures and the corresponding quality penalties. For each failure, a penalty $s$ has to be paid to the regulator. Thus we can write:

$$S(t_j) = sR_{prem} = \frac{sF(t_j)}{G(t_j)/D_{ref}} \qquad (7)$$

Assuming an optimization for one single asset, the network operator's objective function is given by:

$$\begin{aligned} &\min_{t_j}\left(C(t_j) + S(t_j)\right) \\ &= \min_{t_j}\left(\frac{K + sF(t_j)}{G(t_j)/D_{ref}}\right) \end{aligned} \qquad (8)$$

By deriving the objective function, the optimality condition is obtained.

$$\begin{aligned} &\frac{\partial C(t_j)}{\partial t_j} + \frac{\partial S(t_j)}{\partial t_j} = 0 \\ &\Leftrightarrow -K_s - F(t_j) + r(t_j)G(t_j)/D_{ref} = 0 \end{aligned} \qquad (9)$$

In this stationary equivalent-age replacement model, the objective function of a network operator with *n* assets is given by:

$$\min_{t}\left(\sum_{i=1}^{n}\left(\frac{K_i + s_i F_i(t_j)}{G(t_j)/D_{ref}}\right)\right). \qquad (10)$$

Assuming identical assets, shares of expected premature replacement $nR_{prem}$ and normal replacement $nR_{norm}$ lead to expected total cost

$$\begin{aligned} &\mu\left[C(t_j) + S(t_j)\right] = n\left((K + s)R_{prem} + KR_{norm}\right) \\ &\Leftrightarrow \mu\left[C(t_j) + S(t_j)\right] = n\left(K\left(R_{prem} + R_{norm}\right) + sR_{prem}\right). \end{aligned} \qquad (11)$$

Expected total cost stems from regular replacement and quality penalties. Obviously, cost increases in *n*. Without having further knowledge or making further assumptions about how the shape of the failure rate affects optimal replacement $t_j$, it will not be possible to derive further results about the behavior of expected total cost $\mu$. The variance of planned premature replacement $R_{prem}$ can be calculated, assuming premature failure to follow the binomial distribution with failure probability $P_{prem}$, by $nP_{prem}(1 - P_{prem})$. Whereas in the expected total cost model $R_{prem}$ represents the share of assets expected to be replaced in the current year, care has to be taken interpreting $R_{prem}$ and $P_{prem}$ in the context of calculating the variance. As $R_{prem}$ and $P_{prem}$ are defined by $F(t_j)/(G(t_j)/D_{ref})$, this expression describes as well the cumulative unconditional failure density which has appeared until $t_j$ divided by the expected lifetime of anasset given a certain $t_j$. In other words, by using $P_{prem}$ the expression $F(t_j)/(G(t_j)/D_{ref})$ will instead be interpreted as an average yearly failure probability of the stationary calculus by division of $F(t_j)$ by $G(t_j)/D_{ref}$ .
Total cost in dependence of $R_{prem}$ varies according to

( 12 ) $$\mathrm{var}[C+S]=\mathrm{var}\left(\sum_{i=1}^{n}K\left(R_{prem}+R_{norm}\right)+s\left(R_{prem}\right)\right).$$ [7]

In this simplified model, premature failure does not impose extra (re-)investment cost.[8] Nevertheless, variance in total costs stems both from the quality penalty and usual reinvestment due to premature failure. Premature replacement is caused by assets that are younger than $t_j$. Normal or planned replacement on the other hand is caused by assets of age $t_j$ which are replaced in the usual replacement process. Assuming identical assets, total cost variance follows the binomial distribution law. With the probability $P_{prem}$ for the event of premature failure, variance is given by

( 13 ) $$\mathrm{var}[C+S]=(K+s)^2 nP_{prem}\left(1-P_{prem}\right).$$

Evidently, variance in absolute terms will increase with the number of assets. To obtain a scale-invariant evaluation of the risk position, the increase in variance has to be standardized by expected cost. Taking the square root of the variance, we obtain the standard deviation and normalize it by expected cost. This ratio known as the variation coefficient consists of two expressions of same dimension. This variation coefficient then is scale independent and makes an assertion of the relative size dependence of risk possible.

( 14 ) $$\frac{\sigma}{\mu}=\frac{(K+s)\sqrt{nP_{prem}\left(1-P_{prem}\right)}}{n\left((K+s)P_{prem}+KP_{norm}\right)}.$$

With regard to the definition of $P_{prem}$, ( 14 ) can be transformed into the following expression, with $K_s=K/s$:

( 15 ) $$\frac{\sigma}{\mu}=\frac{(K+s)\sqrt{\frac{F(t_j)}{G(t_j)/D_{ref}}\left(1-\frac{F(t_j)}{G(t_j)/D_{ref}}\right)}}{\sqrt{n}\left((K+s)\frac{F(t_j)}{G(t_j)/D_{ref}}+K\frac{1-F(t_j)}{G(t_j)/D_{ref}}\right)}$$
$$=1/\sqrt{n}\left[\frac{K_s+1}{K_s+F}\sqrt{\frac{G(t_j)}{D_{ref}}-F(t_j)}\sqrt{F(t_j)}\right].$$

Clearly, the variation coefficient decreases with $n$. Regarding the impact of $K$ and $s$, the situation is more complex as the optimal replacement age and thus $F(t_j)$ and $G(t_j)/D_{ref}$ also vary with $K$ and $s$. From (15), similar to expected total cost, we can see that there is no unambiguous relationship between the parameters $K$ and $s$ on the one hand and the variation coefficient on the other hand, due to the fact that the effect of a change in these parameters on the lifetime of assets is not clear. Two major effects in the variation coefficient and expected costs, a price and a quantity effect, will occur. Whereas the price effect is straightforward, the quantity effect is not clear a priori. At this place, we do not know yet whether e.g. a higher penalty will shorten or prolong the optimal replacement age. Depending on the shape of the failure rate, the variance may as well be increased or decreased by a change in the optimal replacement strategy. This concerns the variation coefficient as well as expected costs themselves.[9]

[7] Independence between asset failures is assumed. Cases for positive or negative correlation are both imaginable and would lead to an additional covariance term, which then could be positive or negative as well. As these effects are of second order, they are of minor interest for the analysis.

[8] Nevertheless, *s* could alslo be interpreted as an extra cost for maintenance.

[9] Examples causing such perverse behavior induced by e.g. rollercoaster failure rates are given for example in Gupta and Warren (2001) or Finkelstein (2008) including numerous references.

Given the complexity stated, the total effect on the variation coefficient is hard to trace. To get further insights, a uniform distribution of $f$, which permits deriving an optimal replacement age and calculating thereof dependent $F$ and $G$, is chosen to explicitly model the dependence (cf. Figure 1). The uniform distribution is convenient, because it is still analytically tractable and practically relevant because of its increasing conditional failure rate property.

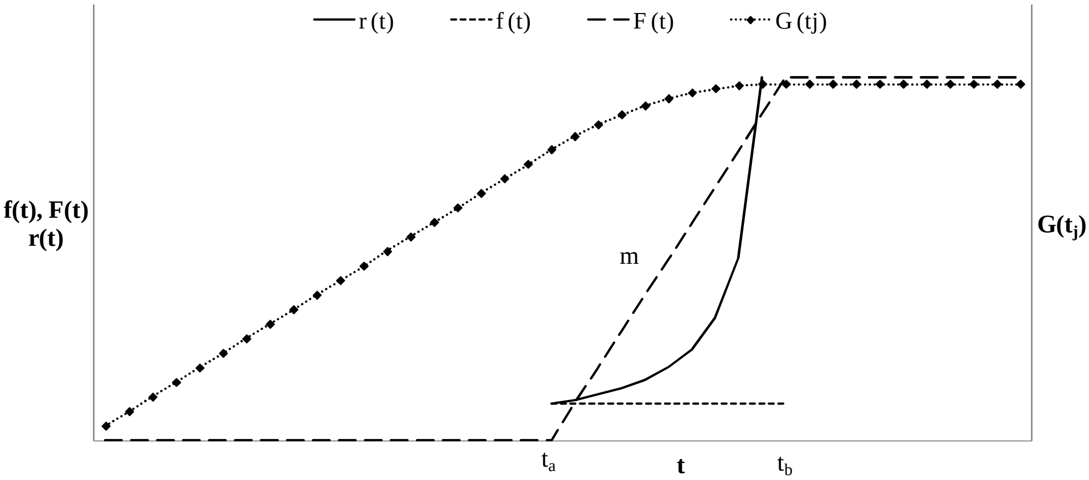


Figure 1: Uniform distribution

A uniform distribution of $f(t_j)=m$, for $t_a \le t_j \le t_b$ and zero otherwise, results in a linear increasing $F(t_j)$ and an exponentially increasing conditional failure rate $r(t_j)$. The corresponding CDF and lifetime distribution functions are:

$$F(t_j)=\begin{cases}0 & \text{, for } t_j < t_a \\ m(t_j-t_a) & \text{, for } t_a \le t_j < t_b \\ 1 & \text{, for } t_j \ge t_b\end{cases}$$

( 16 )
$$G(t_j)=\begin{cases}t_j & \text{, for } t_j < t_a \\ t_j-\frac{m}{2}\left(t_j-t_a\right)^2 & \text{, for } t_a \le t_j < t_b \\ t_b-\frac{m}{2}\left(t_b-t_a\right)^2 & \text{, for } t_j \ge t_b\end{cases},$$

$t_a$ and $t_b$ describe the starting and ending points of aging, $t_j$ the replacement age. $m$ is the slope of the unconditional failure rate $f$. From the optimization based on expected values and using the optimality condition (9) and the specification of the uniform distribution (16), we obtain an optimal replacement age.[10]

( 17 )
$$t_j^*=t_a+\frac{\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s}{m}$$

Clearly, an increase in $K$ leads to longer optimal utilization periods whereas it is the contrary for $s$.

[10] Cf. Weber et al. (2010).

With this knowledge we can now return to equation (11) and analyze the behavior of expected total cost with respect to a variation of $K$ and $s$. Partial derivation of expected total cost $\mu[C+S]$ with respect to $s$ reveals following tradeoff.

$$\mu[C(n,K,s)+S(n,K,s)] = n\left( (K+s)\frac{F(t_j(K,s))}{G(t_j(K,s))/D_{ref}} + K\frac{1-F(t_j(K,s))}{G(t_j(K,s))/D_{ref}} \right)$$

( 18 ) $$\text{or, inserting } F(t_j) \text{ and } G(t_j),$$

$$= ns\left( \frac{K_s + m(t_j - t_a)}{t_j - \frac{m}{2}(t_j - t_a)^2} \right) D_{ref}.$$

After inserting $t_j^*$ and some rearrangements, following expression can be derived for total cost.[11]

( 19 ) $$\mu[C(n,K,s)+S(n,K,s)] = ns\left( \frac{\sqrt{K_s^2 + 2K_s - 2mt_a}}{\left( t_a + \frac{1}{2m} - \frac{1}{2m}\left(\sqrt{K_s^2 + 2K_s - 2mt_a} - K_s - 1\right)^2 \right)} \right) D_{ref}.$$

The expectation for total cost (explicitly dependent on $K_s$) can now be derived with respect to $K_s$.[12]

( 20 ) $$\frac{\partial \mu}{\partial K} = 2D_{ref}mns\left[ (K_s+1)mt_a - \sqrt{K_s^2 + 2K_s - 2mt_a} \right]\left( \left( \sqrt{K_s^2 + 2K_s - 2mt_a} - K_s \right) - 1 \right)^2$$

As the last term in brackets is always greater than zero, the sign of the expression depends on the first term in brackets. Consequently, we have to make the additional (conservative) assumption $mt_a > 1$[13] to obtain economically meaningful results. Otherwise, an increase of the price of the investment good would lead to a decrease in the capital annuity. This is caused by a greater elasticity of $G(t_j(K,s))$ compared to expected total cost $K + sF(t_j(K,s))$ with regard to $K$. Of course, as this means that the period of aging has to be shorter than the period without aging before, which imposes quite a restriction. Nevertheless, simulations have shown that the estimation of the above restriction is quite conservative, and that instead aging periods can be substantially longer relative to no-aging periods. Also, the model is still reliable regarding the demonstration of inherent tradeoffs. The derivation of expected total cost with regard to $s$ leads to similar reasoning.

( 21 ) $$\frac{\partial \mu}{\partial s} = n\left( \frac{G(K,s) - K\frac{\partial G(K,s)}{\partial s}}{G(K,s)^2} + \frac{F(K,s)}{G(K,s)/D_{ref}} + s\frac{\partial\left( \frac{F(K,s)}{G(K,s)/D_{ref}} \right)}{\partial s} \right).$$

Knowing the nature of dependence of $t^*$ on $K$ and $s$, we can state that $\partial G/\partial s$ is negative, now. Thereby, the conclusion can be drawn that the first term in (20) is positive. $\partial R_{prem}/\partial s$ is ambiguous and depends on the variation in $F(K,s)$ and $G(K,s)$. For example, a high decrease of $F(K,s)$ in $s$ because of a high failure rate slope in the relevant region may be

[11] Cf. Appendix A.

[12] Cf. Appendix B.

[13] Cf. Appendix C

accompanied by a quite small variation in $G(K,s)$, because assets exhibit small failure rates over the years before and $G(K,s)$ is relatively large. This could overcompensate the increase in $s$ and lead to a decreasing influence of the third term in brackets on the increase in total costs induced by the other two terms. Of course, expected costs will always have to increase in $s$ in total, and, it will increase in $K$ as well, as long as the above restriction is met. Regarding the risk position and given the derived optimal replacement age, which depends on expenditure parameters $K$ and $s$ as well as parameters characterizing the failure behavior, equation (15) can be transformed to

$$(22)\qquad \frac{\sigma(n,K,s)}{\mu(n,K,s)}=\frac{1}{\sqrt{n}}\frac{(K_s+1)\sqrt{\left(G(t_j(K,s))\big/D_{ref}-F(t_j(K,s))\right)}\sqrt{F(t_j(K,s))}}{(K_s+F(t_j(K,s)))}.$$

The explicitly depicted dependence of the variation coefficient on failure rate shape parameters and expenditure parameters reveals multiple dependencies, where the decreasing influence of the number of assets $n$ is obvious. After some algebraic transformations, we obtain[14]

$$(23)\qquad \frac{\sigma}{\mu}=\frac{1}{\sqrt{n}}\frac{K_s+1}{K_s+F}\sqrt{-\frac{m}{2D_{ref}}\left(t_j^*-t_a-\frac{1}{m}+D_{ref}\right)^2+\frac{1}{D_{ref}}t_a+\frac{1}{mD_{ref}}(1-mD_{ref})^2}\sqrt{m(t_j^*-t_a)}.$$

Thereby, a simple condition for the influence of marginal variations in $K$ and $s$ shows that under the usual assumption of an IFR, the variation coefficient and risk will increase in $K$ and decrease in $s$. This is obvious, as the first, second and last terms of (21) increase in $K$ and the sole variable affected by a variation of $K$ for the third term is $t_j^*$. As long as

$$(24)\qquad \begin{aligned} & t_j^* < t_a+\frac{1}{m}-D_{ref} \\ \Leftrightarrow\ & t_j^* < t_b-D_{ref}, \end{aligned}$$

the third, square rooted, term in ( 21 ) will also increase in $K$. This is usually the case as $t_b$ is the assumed maximum age and $D_{ref}$ is the basic time period, a rather small fraction of $t_b$, e.g. a month or a year. The analysis concerning $s$ is analogous and leads to the opposite result.

## 2.2 Results of Analytical Observations

As a result of these analytical observations of expected total costs and the risk position, we are able to state that an increase in $K$ and $s$ will shift expected total costs upwards, whereas an increase in $K$ will also increase the variation coefficient but an increase in $s$ will decrease the variation coefficient. Consequently, regarding $K$, the effect of an increase in risk relative to the importance of increases in expected total costs depends very much on the actual parameterization and the levels of the respective variables with regard to each other. An increase in $s$ will always increase expected total costs, but risk exposure gets less important. Regarding the impact of suboptimal replacement ages $t_j$ on expected total costs, of course, a deviation from optimal replacement ages $t_j^*$ will lead to an increase in total costs. Contrarily, the variation coefficient will always increase in $t_j^*$, analogous to the dependence on $K$.[15] A clear effect of the impact of network size on risk can be stated. As the size increases, relative risk becomes less important. Of course, total expected cost will increase, but average cost is unaffected.

At this stage, we can make the following distinction. E.g., independent of the degree of risk aversion, the agent will always be worse off when network size is reduced. The effect of a

[14] Transformation of term $G(t_j(K,s))/D_{ref}-F(t_j(K,s))$, cf. Appendix D.

[15] Here we refer to the *single* asset case, not the whole asset park under observation. From a simple economic-life age-replacement model these structural effects are difficult to obtain.

variation of $K$ is also clear cut: relative risk increases as well as expected total cost. Thereby, an agent is always worse off from an increase in $K$. For e.g. the quality penalty, the increase in $s$ will, of course, also induce a loss of utility in absolute terms. Though, it is smaller than the loss from an increase in $K$, because the variation coefficient decreases. Also, it depends very much on the degree of risk aversion, whether an agent profits from an increase in $s$ relative to other firms. Given that all firms loose from an increase in $s$ in absolute terms, a more risk-averse firm will always be better off relative to the other companies in the new state as relative risk reduces. Similar to the quality penalty, the effect on the agent's utility from temporarily suboptimal asset ages, as this is often the case at the introduction stage of incentive regulation, is negative in absolute terms. Nevertheless, a further distinction is necessary: For elder assets than the optimal replacement age cost as well as risk increase and the agent's utility progressively decreases. Relatively young assets also induce an increase in expected cost, but relative risk decreases. This leads to a declining decrease in absolute utility. To quantify these effects and to assess the possible burden imposed on companies by ignoring risk effects of size and age, investment cost and quality penalty variation, an empirical-simulative analysis will answer some questions on the practical relevance of the derived effects. Regarding the influence of the average age and the age distribution of asset parks, it is quite difficult to obtain results from a simple economic-life age-replacement model. The framework of a simulation-based empirical analysis will also be helpful to this regard.

## 3. Empirical Analysis: Simulation Assumptions and Data Description of German Electricity Distribution

In the following section, the groundwork for the empirical analysis and its results will be summarized. In the first part, an overview of the simulation model and the relevant assumptions will be given. In the second part, the gathered data describing the structure of German network distribution companies will be presented.

### 3.1 Simulation Model and Assumptions

#### 3.1.1 Procedure

Monte-Carlo-Simulation technique is used in order to evaluate risks linked to the size and the age structure of network operators.[16] Data of German network operators is used to simulate random events and to derive meaningful results. A one-year period is simulated. As we assume an age structure, where no single asset is older than its optimal replacement age, no planned replacements have to be simulated. The stochasticity of the model is generated via asset group and age dependent random failure events, which lead to probability distributions for quality indices. Based on the number and the age of assets, asset failures leading to a necessary replacement investment (i.e. fatal failures) are generated. Three sources of uncertainty are included in the model. First, asset failure may or may not occur for any single asset in the network. This individual failure is linked to the asset age; a binomial distribution with a conditional failure rate for each given age is used. Second, asset failures may lead to outages if assets are not redundant, meaning that another network component may take the function of the failed equipment. A binomial distribution based on redundancy assumptions generates random outages based on failures and links the outages to the number of customers that will be affected in the case of an outage. Third, the duration of outages varies significantly. Failure times for each outage are simulated via a Weibull distribution. A standard simulation consists of n=1.000 single simulations. With more than 200.000 assets simulated in every simulation run (which corresponds to the biggest network operator simulated), the total calculation time is inferior to 5 minutes. An overview of the simulation procedure is given in Figure 2.

[16] Matrices based programming language Matlab was used.

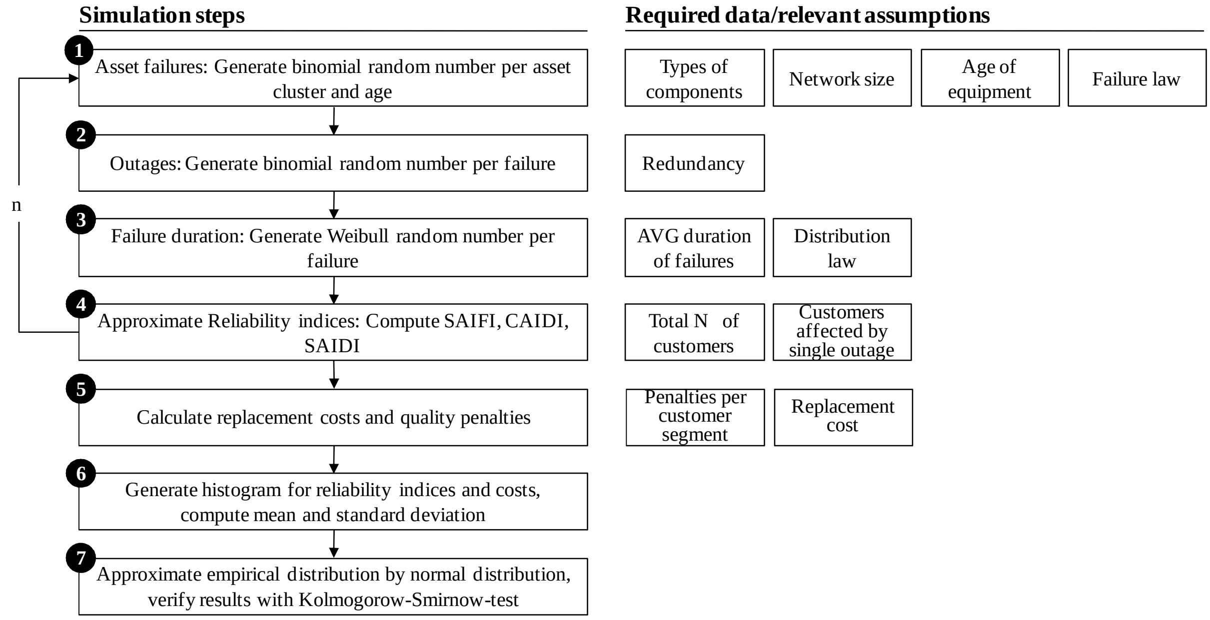

Figure 2: Monte-Carlo-Simulation procedures

Reliability is measured via two major quality indices. The system average interruption frequency index (SAIFI) indicates the average number of outages one customer will suffer from in the defined time period of one year. The customer average interruption duration index (CAIDI) indicates the duration an average customer will not be supplied with power. Other quality indices such as the energy not supplied were not modeled, as they would require further assumptions.[17] Absolute risk will be measured with the standard deviation $\sigma$ and the 95-% of quality index distribution $Q_{95}$. The relative risk measures traced are with the variation coefficient $\sigma / \mu$ and the standardized 95%-quantile $Q_{95} / \mu$. In the following sections, the relevant assumptions and the relevant data will be presented.

### 3.1.2 Relevant Assumptions

#### 3.1.2.1 Network Components

The Monte-Carlo-Simulation assumes a network consisting of single assets linked in a network structure. One first major assumption targets the network components considered in the approach and their relevant numbers in order to build a network. Obergünner (2005) presents a standard urban and a standard rural distribution network operator in German electricity distribution. The network components (or asset clusters) include transformers, circuit breakers, overhead lines and cables (both medium and low voltage) and relay stations. The network components and dimensions of this urban operator will be used in this paper as basic network operator. The rural operator will not be considered in this paper as its basic structure (apart from size) resembles very much the urban operator.

[17] Cf. BNetzA (2006) and Billington and Allen (1996) for further examples and calculation schemes of reliability indices.

| Equipment | Urban Operator |
|---|---|
| Transformer (as part of transformer station) | 12 # |
| Circuit breaker (as part of transformer station) | 90 # |
| Cables (mv) | 450 km |
| Overhead lines (mv) | 150 km |
| Relay stations | 600 # |
| Cables (lv) | 1.200 km |
| Overhead lines (lv) | 200 km |

Figure 3: Basic network configuration (based on Obergünner 2005)

Different network sizes will be accounted for via a size parameter, which will be handled as multiplier for the basic structure with 12 transformers, 90 circuit breakers, 600 relay stations and 2.000 km of cables and overhead lines.

#### 3.1.2.2 Network Structure, Failure Model and Redundancy

Besides the types and number of components, one major assumption had to be made about how components are linked one with another to form a network. The overall structure is as follows: Transformer stations (with the components transformers and circuit breakers), that are connected to the transmission grid, transform electricity to medium voltage and feed into medium voltage rings. A medium voltage ring consists of cables and overhead lines, which connect several relay stations per ring. At each relay station, electricity is transformed to low voltage and fed into low voltage cables and overhead lines which provide households via a string structure. This corresponds to a typical distribution network operator's structure. An illustration of basic network structure is presented in Figure 4.

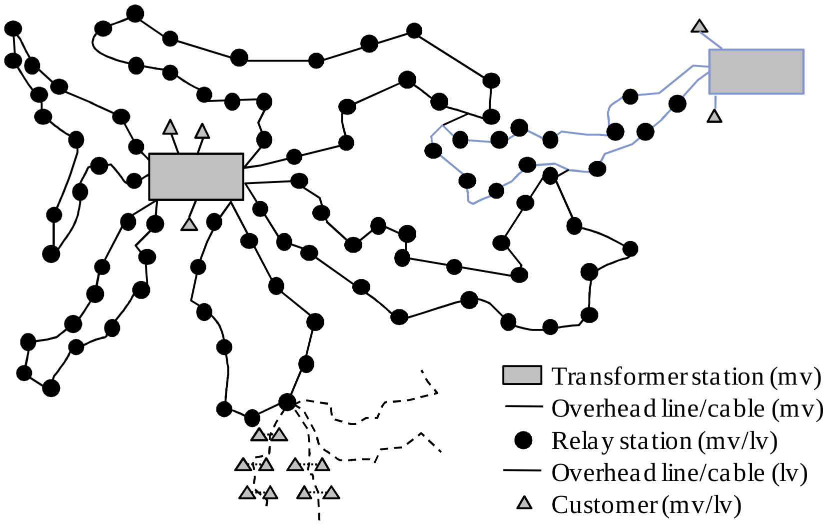


Figure 4: Basic network structure

Assumptions about the customers connected to the network and the underlying methodology of calculus can be seen in Figure 5. Households will all be connected only via low voltage cables and overhead lines. The same will be assumed for the third customer segment which comprises commercial and all other customers (i.e. traffic, agriculture, public institutions). Industry customers will be connected directly to a transformer station.

| Customer segment | Germany (Total) | | | Basic Network |
|---|---|---|---|---|
| | Consumption (MWh)[18] | Consumption (MWh)/Customer[19] | # of Model Customers | # of Model Customers |
| Household | 139.500.000 | 3,5 | ≈40.000.000 | 57.400 |
| Industry | 256.000.000 | 24.000 | ≈10.670 | 15 |
| Commercial/Rest | 146.700.000 | 50 | ≈2.934.000 | 4.200 |

Figure 5: Customer segments connected to the Standard network

Some further assumptions were required to distribute all components in this standard network. We derive from an analytical network modeling approach in Consentec et al. (2008), that 5 medium voltage rings, each 20 km in length, are connected to each transformer station. Each ring includes 20 relay stations, from which 4 low voltage lines per relay station (each 600 m in length) connect households. All failures are independent, i.e. a failure for one component has no technical impact on the state of any other component. If one component fails, redundancy may prevent failures because another component compensates the failed component. As no representative data about network redundancy is available, some assumptions are made in this context. A fatal failure of transformer or circuit breaker leads to outage, because power reserve will not be sufficient in 25% of cases. If an outage occurs, all rings that are not connected with another transformer station will be without power. 25% of rings are connected with other transformer stations. Failures of relay station or line/cable (medium voltage) in one ring lead to outages in the whole ring with a length of 20 km. Failure of relay station lead to outages in the four connected low voltage lines/cables. Failure of low voltage line/cable lead to outages for all customers connected to this line/cable because, usually, network structures are not redundant on a low voltage level.

#### 3.1.2.3 Failure Duration/downtimes

Failure durations or downtimes indicate the time span during which customers are not supplied with power; they consequently have a significant impact on quality indices. Average failure durations are available in outage statistics as for instance VDN (2005, pp.28). As this publication focuses only average durations, distribution laws are estimated based on confidential project data available to the authors and adapted in order to match the average failure durations from the published source.

| Equipment | Average Duration | Weibull-α | Weibull-β |
|---|---|---|---|
| Transformer | 99 min | 1,2 | 104,80 |
| Circuit breaker | 99 min | 1,2 | 104,80 |
| Cables (mv) | 97 min | 1,2 | 102,27 |
| Overhead lines (mv) | 138 min | 1,2 | 146,97 |
| Relay stations | 96 min | 1,2 | 102,48 |
| Cables (lv) | 183 min | 1,2 | 195,42 |
| Overhead lines (lv) | 220 min | 1,2 | 238,18 |

Figure 6: Average failure durations (VDN, 2005, pp.28) and estimated Weibull parameters

The use of a Weibull distribution is an appropriate approach of modeling failure durations due to its skewness.[20] In practice, the majority of outages are relatively short, while some few outages may last very long. The distributions laws used in this model can be seen in Figure 7.

[18] Cf. BDEW (2008/II).

[19] For customer segmentation and assumptions about average (households) and minimum consumptions (all other customer groups) cf. BNetzA (2008, pp.45).

[20] Data from VDN (2005, pp. 66) shows that failure duration distribution are skew, caused by a small number of very long outages.

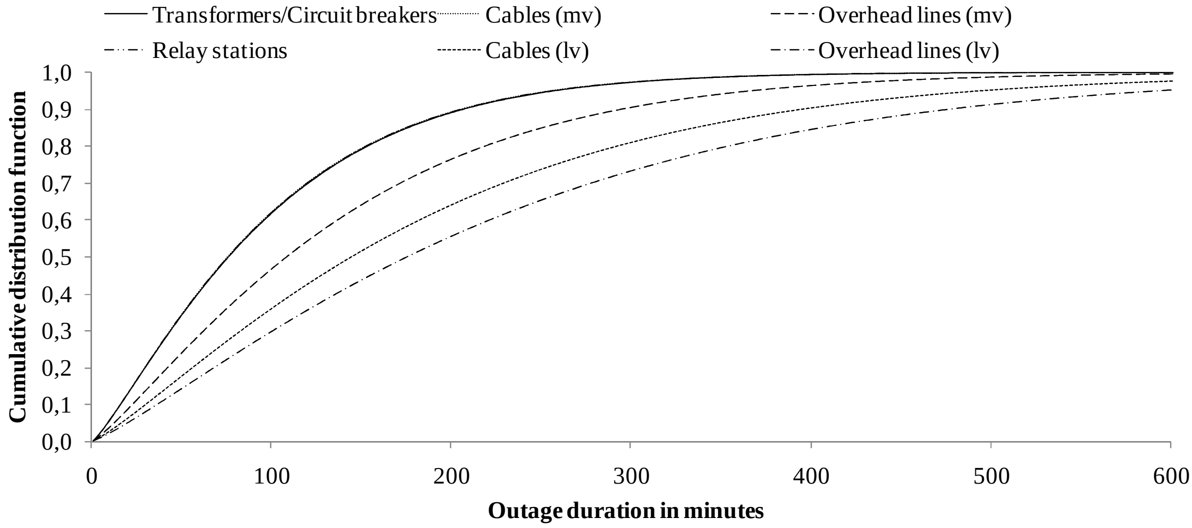

Figure 7: Weibull failure duration distribution laws

#### 3.1.2.4 Failure Rates

Components' failure rates technically depend on a lot of different internal and external factors such as age, electrical stress (for instance overload) and mechanical stress (wear and tear by e.g. tension, pressure, and vibrations)[21]. With a focus on network simulations, many approaches are limited to the influence of age as complete data sets for all other influencing factors are rarely available and the age of a network is tightly linked to investment strategies. In this simulation model age dependent failure rate curves are based on two major expectations and approximated via Weibull distributions. The 80% survival age indicates the age that 80% of assets will attain without replacement or major repair (the value of the cumulative distribution function CDF attaining 0,2), the 20% survival age indicates the age at which 80% of assets in one cluster will have failed (CDF=0,8). The survival ages in Figure 8 reflect practitioners' current expectations about assets' lifetimes.[22]

| Equipment | 80% Surv. Age | 20% Surv. Age | Depreciation[23] |
|---|---|---|---|
| Transformer | 25 years | 35 years | 25-35 years |
| Circuit breaker | 25 years | 35 years | 25-35 years |
| Cables (mv) | 40 years | 60 years | 40-45 years |
| Overhead lines (mv) | 35 years | 50 years | 30-40 years |
| Relay stations | 25 years | 35 years | 30-40 years |
| Cables (lv) | 40 years | 60 years | 40-45 years |
| Overhead lines (lv) | 35 years | 50 years | 30-40 years |

Figure 8: Expected survival rates

[21] Cf. Densley (2001) for an overview of major factors regarding cables.

[22] A vast body of empirical research about the lifetime of network components has been published until today. One research paper regarding cables is Densley (2001). Lindquist et al. (2008) analyze reliability of circuit breakers. FGH (2008) present aging models for all sorts of different component types. Unfortunately, there is no single paper that summarizes research in this field and is able to provide consistent lifetime distributions for all asset types required in the simulation. A first obstacle is the vast amount of possible different definition of survival age and the approach of modeling it. Secondly, research focuses mostly transformers, circuit breakers and cables. To our knowledge, there is no extensive research available on relay stations. Consequently, the cumulative failure distributions are derived as assumptions from practical insights.

[23] Depreciation recommendation for assets to be considered in the regulatory cost base, cf. StromNEV (2005, Anlage 1).

Based on these assumptions, Weibull failure distribution laws for the conditional failure rate have been estimated (cf. Figure 9 for cumulated distribution functions).

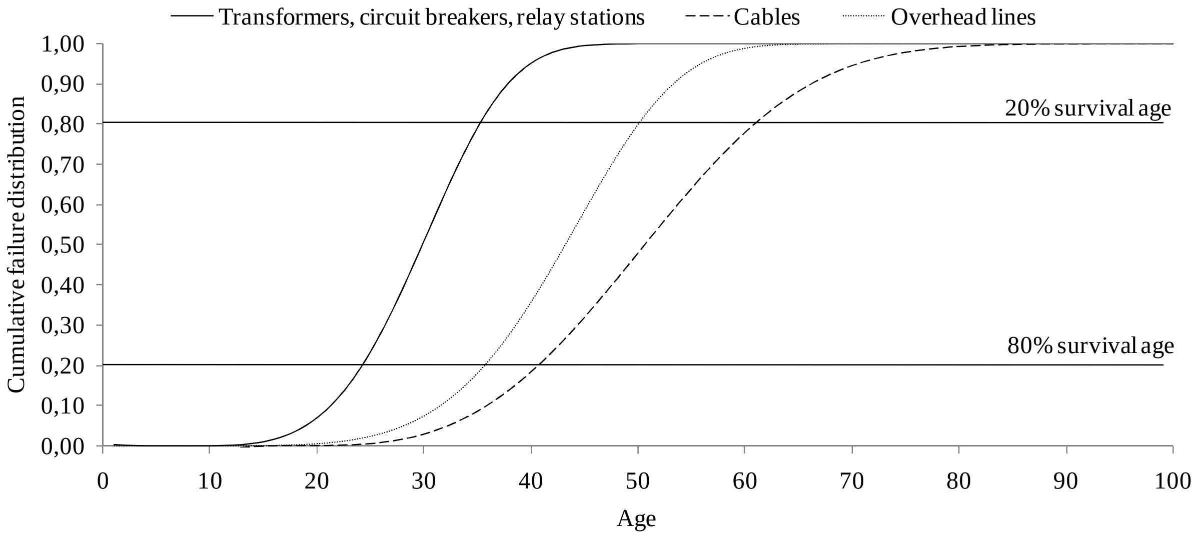


Figure 9: Cumulative failure distribution based on Weibull law

The major part of asset deterioration happens between the ages of the 80% and the 20%-quantiles of the cumulated survival density. In the asset age structures that will be used in simulation, we assume replacement with an optimal age replacement policy as described in the analytical section. This prevents biased results from assumptions about the overall maximum lifetime of an asset class which is very difficult to estimate, because a prori an asset could survive an infinite time span with an infinitesimal probability. Consequently, no cable will be older than 61 years and no overhead line will be older than 46 years in the underlying age structures.

| Equipment | Opt. Policy |
|---|---|
| Transformer | 33 years |
| Circuit breaker | 32 years |
| Cables (mv) | 61 years |
| Overhead lines (mv) | 46 years |
| Relay stations | 28 years |
| Cables (lv) | 61 years |
| Overhead lines (lv) | 46 years |

Figure 10: Optimal age replacement policies

### 3.1.2.5 Identification of Representative Age Structure: 4 age structure scenarios

As failure rates depend on age, the age structure of the simulated network has a major impact on network quality. The influence of network age will be analyzed using four different settings. The first setting corresponds to a uniform age distribution (referred to as ‘uniform’). In this case all assets within one class will be uniformly distributed until the optimal replacement age. The second setting (‘new west’) considers an age distribution, which has been derived from historical investment data from BDEW (2008), cf. Figure 11. A West German network operator, that has consequently replaced network equipment starting in 1975, will be considered. In this setting, assets will be uniformly distributed up to their optimal replacement age following the investments made between 1975 and today.

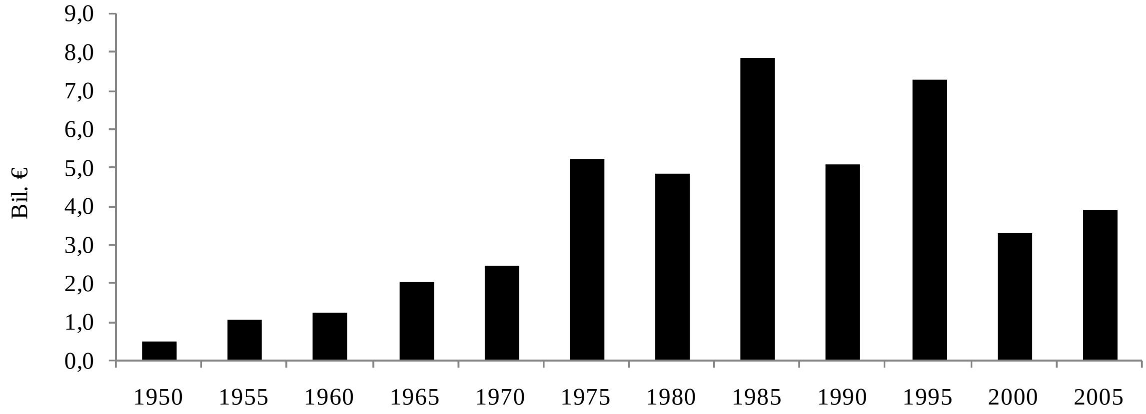


Figure 11: Investment in German Electricity Infrastructure (BDEW, 2008/I)

The third setting ('new east') represents the case of a complete and recent network renewal, as it has happened e.g. in East Germany after the reunification in 1990. In this case, all assets will be relatively new. Considering 20 years of investments, the assets are distributed following the total equipment investments in East Germany starting in 1991 until today (cf. Figure 12).

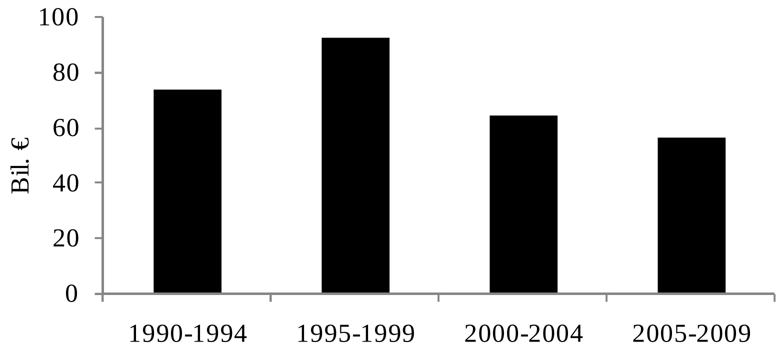


Figure 12: Investment in East German Equipments (BMWI, 2008)

A further scenario ('distort') permits the comparison of a distortion, which is caused by quality regulation that is solely based on targets for expected outages. This setting uses the uniform setting as a benchmark. The age distribution opposed to this benchmark is heterogeneous and disposes of two uniform distributions with half of the assets belonging to the youngest quarter of the asset lifetimes and the other half belonging to the oldest quarter of asset lifetimes. Using these data sets on the asset clusters, age structures for all four settings are derived. Serving as example, Figure 13 presents the age structures obtained for cables within all four settings. Age structures regarding all other asset classes are similar in shape, but vary due to their optimal replacement age. Overall, the distort structure will have the highest number of old network components while the East German structure will represent the newest network.

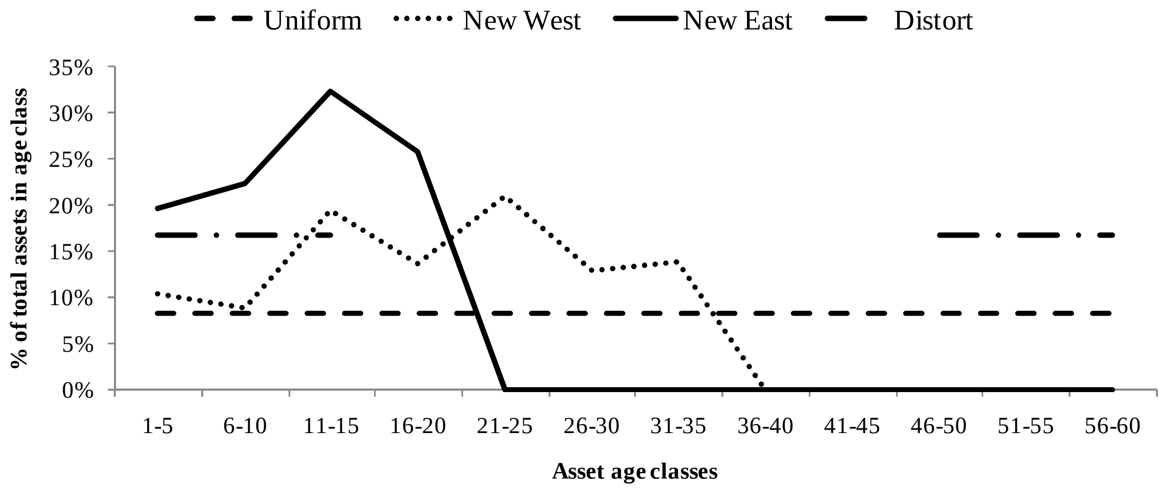


Figure 13: Cable age structure in all four age structure settings

Figure 13 clarifies, why aging structure may solely described by the age distribution function for each asset cluster: 'Distort' and 'uniform' will have the same average age of network components while one can expect 'distort' to be more risky as failure rates to not increase linearly but exponentially.

#### 3.1.2.6 Penalties, replacement costs and network tariffs

In order to quantify the impact of network structure on risk, some cashflow components are included in the model. A quotient of uncertain cash-out (consisting of replacement costs and penalties) to cash-in (network tariffs) is calculated. The simulation will enable us to provide evidence about standard deviations and quantiles of this cashflow-measure. The customers disconnected in case of failure were derived from the network structure. Penalties per customer and outage (cf. Figure 14) were based on the average duration of a failure (cf. Figure 6), average consumption (cf. Figure 5) and a penalty of 10€ per kWh of energy not supplied[24].

| **Equipment** | **Asset replace-ment cost[25]** | **Penalty/customer (Industry) €** | **Penalty/customer (Commer./Rest) €** | **Penalty/customer (Household) €** |
|---|---|---|---|---|
| Transformer | 615 T€ per unit | 49.452 | 95 | 7 |
| Circuit breaker | 40 T€ per unit | 49.452 | 95 | 7 |
| Cables (mv) | 140 T€ per km | - | 93 | 6 |
| Overhead lines (mv) | 30 T€ per km | - | 133 | 9 |
| Relay stations | 60 T€ per unit | - | 93 | 7 |
| Cables (lv) | 65 T€ per km | - | 176 | 12 |
| Overhead lines (lv) | 25 T€ per km | - | 212 | 15 |

Figure 14: Failure costs (replacement and penalties)

Standard revenues for the basic operator were calculated based on average transmitted energy per km network length. Average network tariffs were used to derive network revenues for the standard network operator (cf. Figure 15). Information presented in the first two columns of the figure were gathered in the survey that will be explained in the following section. Based on the figures, the BASIC network operator with 2.000 km of cables and overhead lines

[24] This assumption is made based on Billington (2000) and Roberts (2001).

[25] Replacement cost represent averages from Consentec et al (2008, pp.113). Unplanned replacements are assumed to be more costly that planned replacements, for instance due to required security stocks and provisional solutions. Thus a surcharge of 20% on planned replacement costs is included in the model.

receives network tariffs of 43 Mio. €. This cashflow will be used to standardize financial risk positions in later sections.

| Voltage level | Energy transmitted (GWh) | MWh/km total network length | Tariff[26] (€ per MW) | Total network tariff (Million €) |
|---|---|---|---|---|
| HV | 269.394 | 231 | 15 | 6,9 |
| HV/MV | 217.834 | 187 | 15 | 5,6 |
| MV | 220.272 | 189 | 15 | 5,7 |
| MV/LV | 118.977 | 102 | 55 | 11,2 |
| LV | 139.603 | 120 | 55 | 13,2 |
| Total | 966.079 | 829 | - | 43,0 |

Figure 15: Network revenues of BASIC operator

## 3.2 Structure of German Electricity Distribution

In the last section, the procedure and relevant assumptions for a network Monte-Carlo-Simulation were presented. This section focuses the empirical data gathered to quantify network sizes. In order to collect size information about German distribution network operators, extensive empirical research has been conducted.

### 3.2.1 Methodology and Data Collection

Research work, regulation authority publication or similar documents describing the size and the structure of German network operators have not been subject of published research work until today. Consequently, we have been conducting a survey gathering relevant data from all German network operators. This data describing network structures in 2008 has been gathered on the network operators' websites. This is possible due to the fact, that German distribution network operators are obliged to publish a significant amount of structural data due to legal obligation.[27] The data sets surveyed are presented in Figure 16. Especially line lengths are published relatively detailed with a distinction between cables and overhead lines as well as between voltage levels.

| Gathered data | Unit | Differentiation |
|---|---|---|
| Line length | Km | Cable/overhead lines, Voltage level |
| Energy | MWh | Voltage level |
| Points of consumption | # | Voltage level |
| Supply area | km2 | - |
| Area based on §23 StromNEV | km2 | Voltage level |
| Inhabitants | # | - |

Figure 16: Coverage of data

The survey started in July 2009 and is still at a work in progress status, we expect the survey to be completed until October 2009. The results discussed in this paper are based on the actual data pool of 440 network operators, which represents roughly 50% of the total numbers of German distribution network operators and 69% of network km. With the completion of the survey, we expect to cover roughly 100% in all three categories.

[26] Based on BNetzA (2008, pp. 45). LV-tariffs calculated as average of lb and ld tariffs, mv-tariff calculated as average of lg values, only data from 2008 was considered.

[27] Cf. § 27 Stromnetzentgeltverordnung (StromNEV).

| Category | Data pool | Total (estimated)[28] | Percentage |
|---|---|---|---|
| Number of network operators | 440 | 855 | 51% |
| Network km (medium/low voltage) | 1.125.000 | 1.622.178 | 69% |
| Inhabitants | 59,1 | 82,0 | 72% |

Figure 17: Status of survey (completion degree)

In the next step, a closer look at the structure of German distribution network operators will be taken.

### 3.2.2 Overview of Network Size and Structure

In order to structure the data sets, network operators were sorted via total network km. The overall range is from 106.000 km (EnBW Regional) to 30 km (several very small local operators). 5%-quantiles regarding network km were built, each containing 22 network operators. Consequently, the 0-5%-quantile includes the 22 largest network operators. Figure 18 shows the repartition of structural indices by cumulated classes. The figure reports cumulative densities.

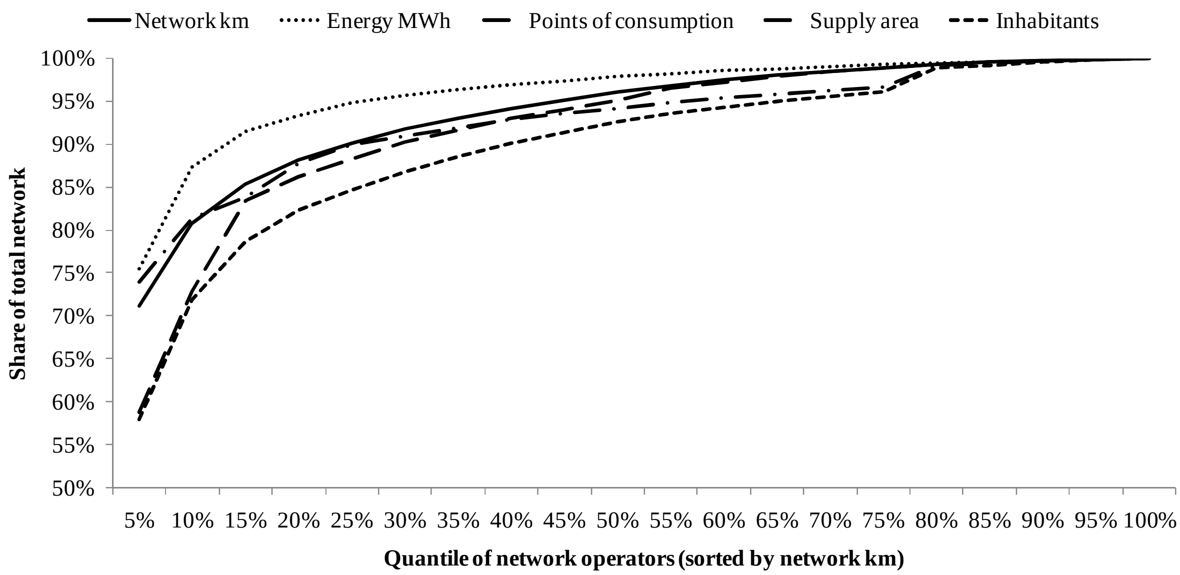


Figure 18: Structure of network operators

A very high concentration of network activity within the big operators is a first, very obvious result. The 22 largest operators operate about 70% of total network km, provide 75% of energy through their network and cover 60% of inhabitants. With the completion of the survey, this concentration may even rise as Figure 17 indicates that the missing 440 operators will be of a smaller average size than the operators in the actual data pool. Gini-coefficients were computed to describe the degree of concentration of German distribution network business (cf. Figure 19).

[28] Total network km numbers as well as network operators are based on BNetzA (2008, pp.27), total inhabitants data are based on Statistisches Bundesamt (2008).

| Measurement | Gini-coefficient |
|---|---|
| Line length | 0,82 |
| Energy | 0,87 |
| Points of consumption | 0,79 |
| Supply area | 0,81 |
| Inhabitants | 0,75 |

Figure 19: Gini-coefficients

In the next step, we will present more data describing the quantiles that were used in simulation. Therefore, a fictive average operator in each quantile was calculated.

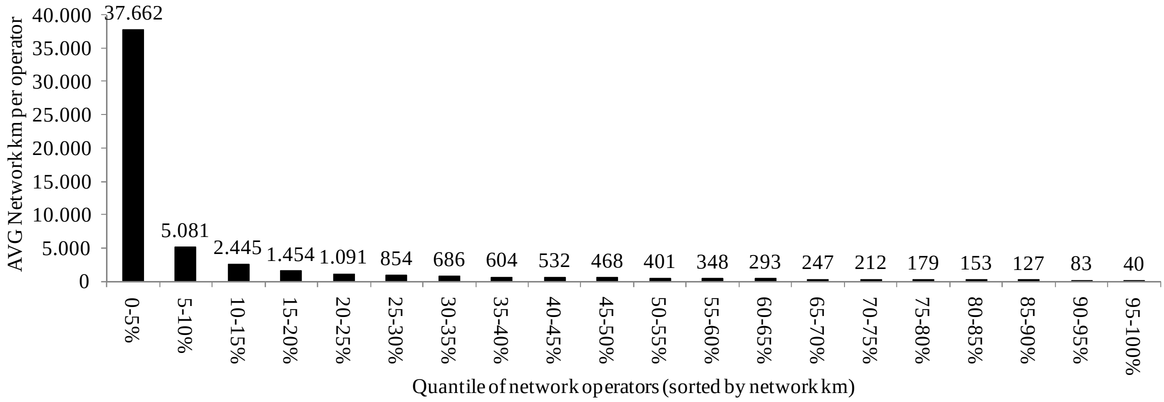


Figure 20: Average network km per operator in each class

The biggest network operators (EnBW Regional, RWE Rhein-Ruhr and E.ON Bayern) operate networks with up to 80.000-106.000 km. This accounts for the fact, that an average operator in the 0-5%-quantile has about 37.600 km. The average in the second quantile is significantly smaller (about 5.100 km). Within the given sample, 80% of network operators operate networks with less than 1.000 network km.

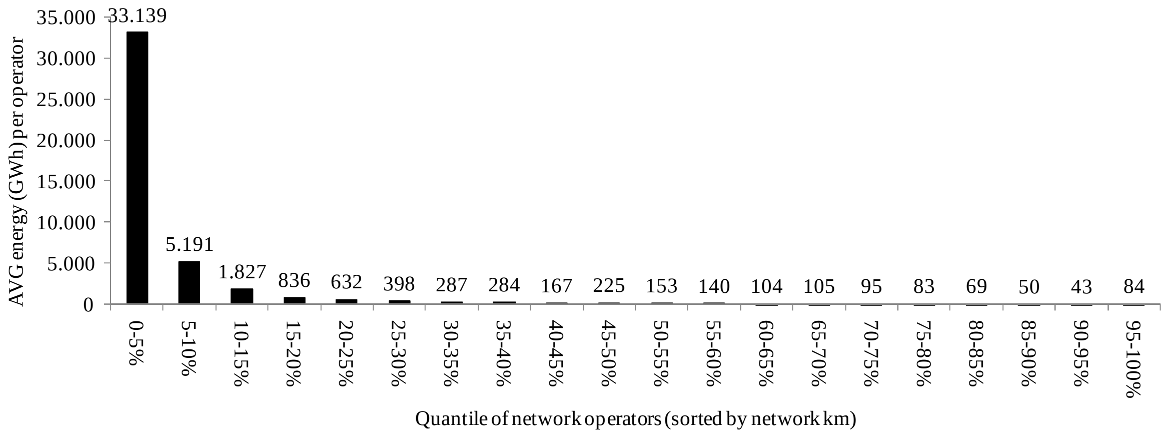


Figure 21: Average transmitted energy (MWh) per operator in each class

Data about transmitted energy (cf. Figure 21) or the number of consumption points (Figure 21) does reinforce the overall image, as the shapes resemble very much Figure 20. The other data sets are excluded from discussion, as they are of no relevance in the context of the simulation.

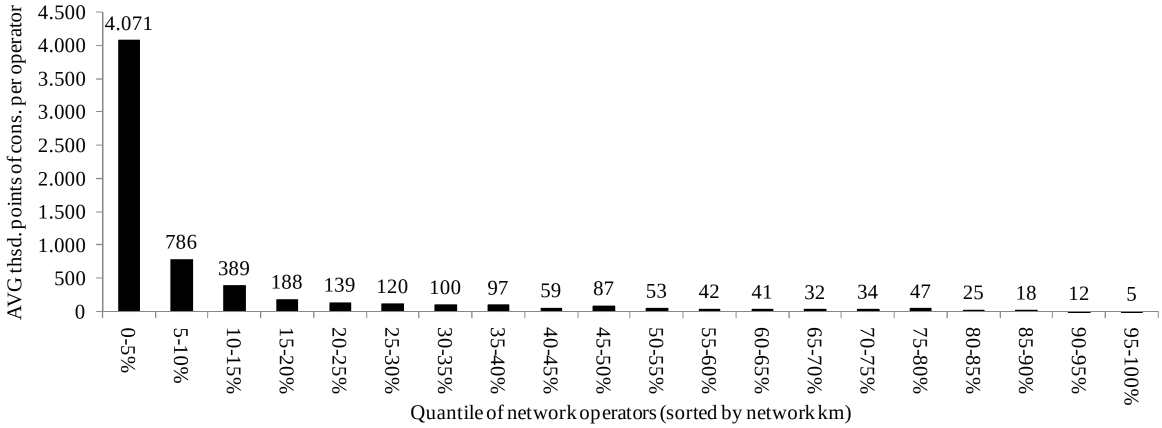

Figure 22: Average number of consumption points per operator in each class

From all data and figures presented, one can conclude a very high degree of concentration. Some top-5% network operators with very large networks capture roughly 60-80% of network business, while about 80% of companies operate less than 1.000 network km. This will be of significant impact in the simulation, as we expect big network operators to be less affected by single network events and consequently less risky. Furthermore, we expect missing data to reinforce concentration tendencies.

### 3.2.3 Clustering of Network Operators for Further Analysis

In the simulation, network operators' data is used to focus the analysis of the impact of network size and age on risk. Therefore the average network km value for each quantile is used to approximate an average network operator for every 5%-class. This is achieved by scaling up or down the number of all network components with a size factor that is handled as a multiplier on the basic network configuration (with a size of 1). Because of the fact that assets are not divisible, some bias occurs considering small network sizes (i.e. there is always at least one transformer, even if the size parameter indicates only 0,24 transformers). In addition to the basic operator (named BASIC in figures and tables) and the average of each 5%-class, results will always indicate a MAX-operator with a size of 53. This operator is the largest German distribution network operator EnBW Regional with about 106.000 network km.

| Quantile | Network km | Transformers | Circuit breakers | Relay stations | Size parameter |
|---|---|---|---|---|---|
| BASIC | 2.000 | 12 | 90 | 600 | 1,00 |
| 0-5% | 37.996 | 228 | 1.710 | 11.400 | 19,00 |
| 5-10% | 5.000 | 30 | 225 | 1.500 | 2,50 |
| 10-15% | 2.510 | 15 | 113 | 750 | 1,25 |
| 15-20% | 1.490 | 9 | 68 | 450 | 0,75 |
| 20-25% | 1.110 | 7 | 50 | 330 | 0,55 |
| 25-30% | 862 | 5 | 39 | 258 | 0,43 |
| 30-35% | 676 | 4 | 31 | 204 | 0,34 |
| 35-40% | 600 | 4 | 27 | 180 | 0,30 |
| 40-45% | 538 | 3 | 24 | 162 | 0,27 |
| 45-50% | 462 | 3 | 21 | 138 | 0,23 |
| 50-55% | 400 | 2 | 18 | 120 | 0,20 |
| 55-60% | 338 | 2 | 15 | 102 | 0,17 |
| 60-65% | 290 | 2 | 14 | 90 | 0,15 |
| 65-70% | 248 | 1 | 11 | 72 | 0,12 |
| 70-75% | 234 | 1 | 10 | 66 | 0,11 |
| 75-80% | 186 | 1 | 8 | 54 | 0,09 |
| 80-85% | 172 | 1 | 7 | 48 | 0,08 |

| | | | | | |
|---|---|---|---|---|---|
| 85-90% | 124 | 1 | 5 | 36 | 0,06 |
| 90-95% | 76 | 1 | 4 | 24 | 0,04 |
| 95-100% | 48 | 1 | 4 | 12 | 0,02 |
| MAX | 106.000 | 636 | 4.770 | 31.800 | 53 |

Figure 23: Network operator size definitions

As all assets have to be attributed to a specific age, the uniform setting will be used for the analysis of size effects. This requires to equally distribute very few assets (especially transformers) for network operators with a size inferior to about 0,3. We consequently expect results to be biased starting with the quantile at about $Q_{40-45}$.

## 4. Empirical Results

The aim of this simulation approach is to provide empirical results about how the distribution of quality indices and expenses for quality penalties and premature replacements may vary due to size and age structure of network operators. A second question targeted will be, which impact quality penalties will have on network risk. Therefore, a Monte-Carlo-Simulation based on representative assumptions is run in order to obtain average quality indices and cumulative distribution functions for these quality indices. Absolute network risk is measured with two risk measures, the standard deviation $\sigma$ and the 95%-quantile $Q_{95}$. Relative network risk considers the mean values $\mu$ and is consequently be measured with the coefficient of dispersion $\sigma / \mu$ and with $Q_{95} / \mu$. The following results will show that absolute risk decreases with size and increases with age, while relative risk will decrease with size and with age. The influences of both size and age on network risk are significant.

### 4.1 Effect of Network Size

In the first step, the absolute failures are simulated in n=1.000 runs following the binomial law with respect to redundancy assumptions. For all sizes inferior to 1, simulation was repeated with n=10.000 runs to verify overall results. Figure 24 summarizes data about the minimum, maximum and average outage numbers for each of the 10.000 simulations. One can see that with a size of about 0,1-0,2 the minimum number of failure becomes very small and may even be zero. This will lead to some skewness in the distribution of quality indices.

| Quantile | Network km | Size | Minimum | Maximum | Average |
|---|---|---|---|---|---|
| 0-5% | 37.996 | 19,00 | 1206 | 1458 | 1296 |
| 5-10% | 5.000 | 2,50 | 135 | 216 | 170 |
| 10-15% | 2.510 | 1,25 | 53 | 124 | 85 |
| 15-20% | 1.490 | 0,75 | 24 | 78 | 51 |
| 20-25% | 1.110 | 0,55 | 13 | 59 | 37 |
| 25-30% | 862 | 0,43 | 12 | 55 | 29 |
| 30-35% | 676 | 0,34 | 8 | 44 | 23 |
| 35-40% | 600 | 0,30 | 6 | 38 | 20 |
| 40-45% | 538 | 0,27 | 5 | 36 | 18 |
| 45-50% | 462 | 0,23 | 4 | 31 | 16 |
| 50-55% | 400 | 0,20 | 2 | 28 | 14 |
| 55-60% | 338 | 0,17 | 2 | 27 | 11 |
| 60-65% | 290 | 0,15 | 1 | 23 | 10 |
| 65-70% | 248 | 0,12 | 0 | 20 | 8 |
| 70-75% | 234 | 0,11 | 0 | 18 | 7 |
| 75-80% | 186 | 0,09 | 0 | 17 | 6 |
| 80-85% | 172 | 0,08 | 0 | 15 | 5 |
| 85-90% | 124 | 0,06 | 0 | 12 | 4 |
| 90-95% | 76 | 0,04 | 0 | 10 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| 95-100% | 48 | 0,02 | 0 | 8 | 1 |
| BASIC | 2.000 | 1,00 | 45 | 100 | 68 |
| MAX | 106.000 | 53,00 | 3402 | 3780 | 3611 |

Figure 24: Total outage numbers

Total failure numbers are transformed into reliability indices SAIFI and CAIDI using assumptions about failure durations (modeled via a Weibull law) and connected customers. The results are presented in the three following figures.

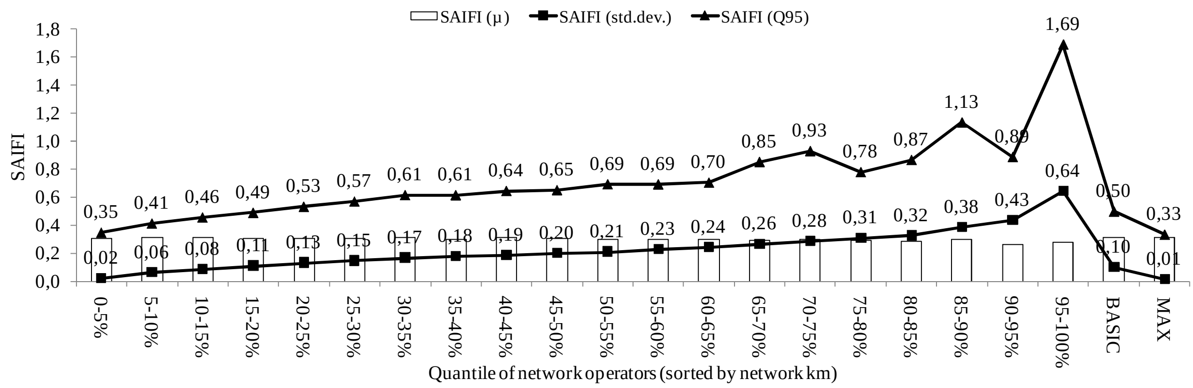


Figure 25: SAIFI - mean values, standard deviation and 95%-quantiles

The average SAIFI is about 0,31, overall simulation results following expectations. One may notice that results mean values get biased with shrinking network size (starting with $Q_{35-40}$) which is mostly due to two reasons. As failure numbers cannot be negative, the SAIFI-distribution is skew and means get a tendency to vary significantly from expectations. Second, assumptions about the distribution of single assets get an increasing influence with decreasing network size (cf. section 3.2.3). The absolute risk measures $\sigma$ and $Q_{95}$ significantly decrease with increasing network size, the standard deviation for instance increases from 0,02 ($Q_{0-5}$) to 0,64 ($Q_{95-100}$), an increase of factor 32. With regard to small network sizes, the standard deviation appears to be more stable as risk measure than $Q_{95}$.

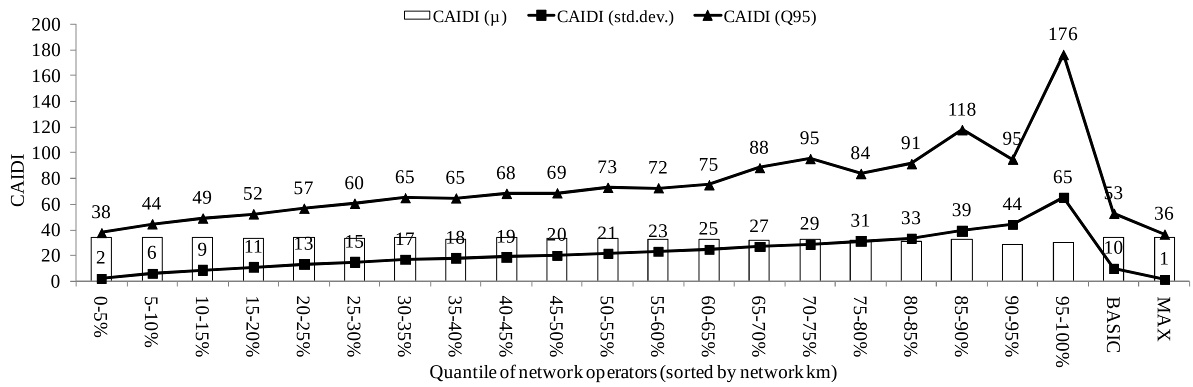


Figure 26: CAIDI - mean values, standard deviation and 95%-quantiles

Considering the average failure duration per customer CAIDI, the results appear to be similar to the SAIFI. The CAIDI is about 32 minutes per year, simulation means following expectations. This value appears very low, as European countries such as Italy or Greece report CAIDIs of more than 100 minutes. Three major assumptions are relevant to explain this low CAIDI-level: First, the uniform distribution of the age structure has an impact on CAIDI. Networks with a higher number of older components will see higher CAIDI-values. Second, an optimal replacement strategy that considers additional costs due to penalties and premature replacement is assumed. Third, average interruption durations are based on German data and may vary in other countries. If these assumptions were modified, CAIDI would increases significantly. Again, absolute risk appears to be decreasing with network size. However, the risk measures is more stable (until $Q_{50-55}$) which is due to stochasticity of failure duration.

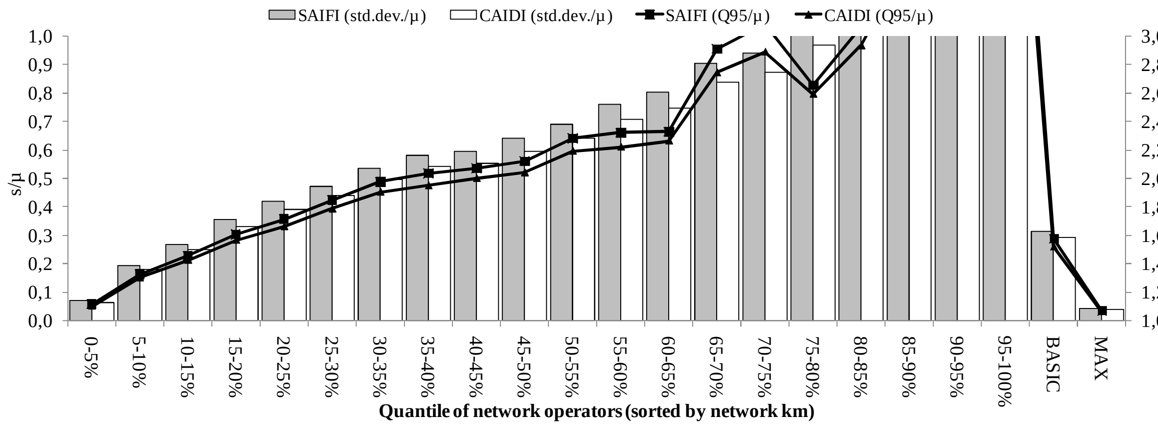


Figure 27: Relative risk measures

Relative risk measures in Figure 27 show significantly increasing risk with decreasing network size, the quality of relative measures becoming more volatile with decreasing size. Kolmogoroff-Smirnoff-tests at a 5%-level were conducted and suggest that the quality indices may be approximated via a normal distribution given a certain size. Considering SAIFI the minimal size corresponds to the average network in $Q_{15-20}$, considering CAIDI it corresponds to the average network in $Q_{10-15}$. To get more insights about the relationship between size and risk especially in the case of bigger networks, some more simulations were run with network size parameters between 1 and 60, the maximum size in the sample being 53.

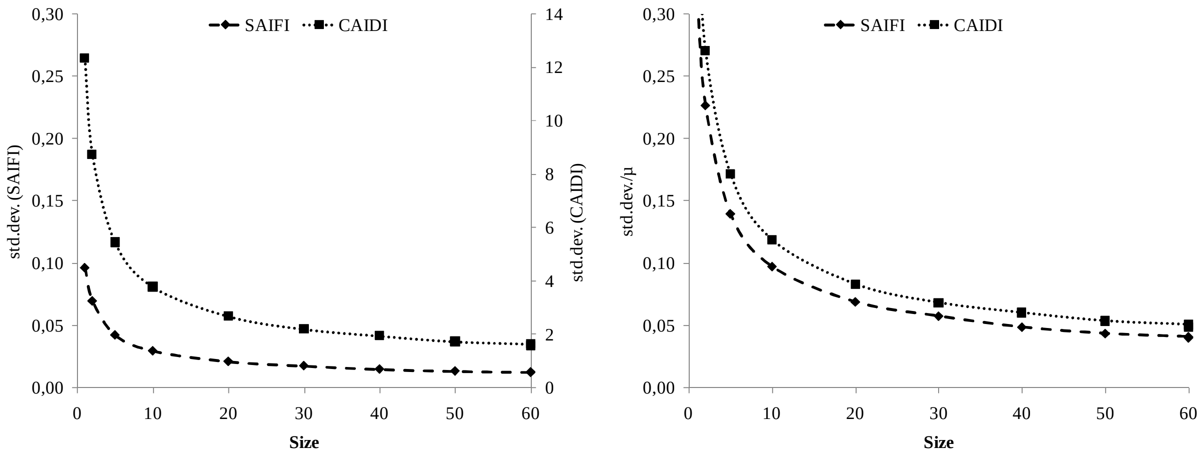


Figure 28: Absolute and relative risk measures based on standard deviation σ

Figure 28 and Figure 29 indicate a very important decline in absolute and relative risk until a size of 10 (corresponding to 20.000 network km) and some further decline until a size of 30. As means do not change with size, this effects are due to the increases of $\sigma$ and $Q_{95}$. Beyond this size, risk decreases further with size but much slower. Considering all results, the CAIDI standard deviation increases from 1,6 (with a given size of 60) to 89 (with a given size of 0,02), an increase by factor 55.

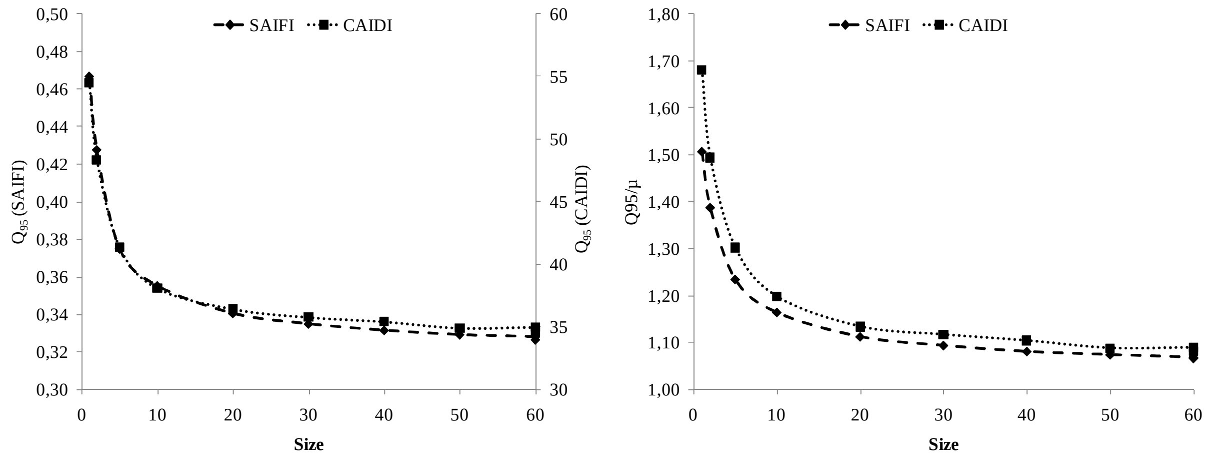


Figure 29: Absolute and relative risk measures based on the 95%-quantile ($Q_{95}$)

From all the results discussed to this point one conclusion is unambiguous: Network quality risk decreases significantly with network size. At this point, it does not matter if $\sigma$ or $Q_{95}$ is used to measure quality risk and both absolute and relative risk measures support this hypothesis. Considering our analytical model the conclusion is feasible, that $\sigma(C+S)/\mu$ will increase with decreasing network size as $\sigma(C+S)$ decreases with decreasing network size, but slow than the expectation with decreases by $1/Size$ . To reinforce our results, sensitivity of results was tested adjusting major simulation assumptions about redundancy, failure rates and failure duration. In the case of redundancy, assumptions of 90% and 0% for all asset clusters were tested. The expected 80% and 20% survival ages were modified by 5 years in both directions, thus equipment ages 5 years earlier or later. Expected average outage durations were reduced by 50% and increased to 200%. The resulting means can be seen in Figure 30, the results being not surprising at all.

| **Index** | **Stand. assum.** | **Red. =90%** | **Red. =0%** | **Earlier aging** | **Later aging** | **Longer outages** | **Shorter outages** |
|---|---|---|---|---|---|---|---|
| SAIFI | 0,31 | 0,04 | 0,39 | 0,65 | 0,11 | 0,31 | 0,31 |
| CAIDI | 32 | 4 | 40 | 67 | 13 | 16 | 64 |

Figure 30: Mean values from sensitivity analysis

One question of central interest is, if absolute and risk measures still increase in size even under different assumptions. Therefore all risk measures were computed and indexed to the value they take at a size of 1. Figure 31 shows that the relative increase of standard deviation in size holds for the different assumptions made in the sensitivity analysis. The $Q_{95}$ risk measure supports the claim of decreasing risk with size, the slope depending on the magnitude of assumptions. In the case of relatively few events (i.e. higher redundancy or later failures), the slope will be steeper.

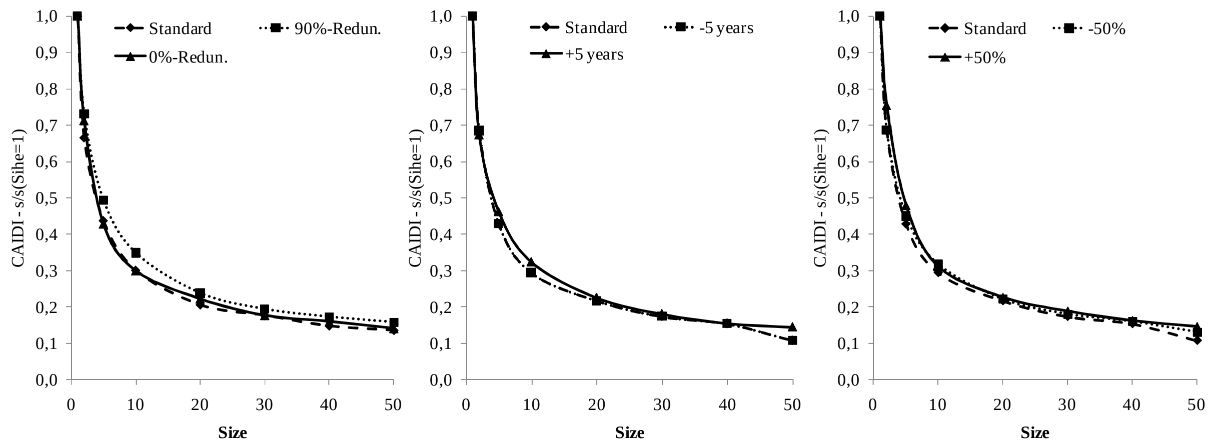


Figure 31: Indexed $\sigma$ within sensitivity analysis

The main result of this section being, that network risk decreases with network size, can be assessed as robust towards simulation assumptions.

## 4.2 Effect of Network Age

In this section, evidence about the relationship between network age structure and risk measures is discussed. Therefore, simulations were run for the three different age structures introduced in section 3.1.2. In order to investigate the impact of size on results, all simulations were run for networks of size 1 and size 10.

| Age | Network km | Size | Minimum | Maximum | Average |
|---|---|---|---|---|---|
| Distort | 2.000 | 1 | 66 | 134 | 103 |
| Uniform | 2.000 | 1 | 45 | 93 | 67 |
| New West | 2.000 | 1 | 3 | 30 | 13 |
| New East | 2.000 | 1 | 0 | 8 | 2 |
| Distort | 20.000 | 10 | 928 | 1.129 | 1.025 |
| Uniform | 20.000 | 10 | 603 | 756 | 678 |
| New West | 20.000 | 10 | 96 | 164 | 131 |
| New East | 20.000 | 10 | 8 | 38 | 21 |

Figure 32: Total outage numbers

Figure 32 indicates that total failure number is highest for the distort age structure, which has the highest number of old network components. The East German network has by far the lowest failure numbers due to the fact that its components are at maximum 20 years old. This holds for all network sizes. These results support the hypothesis that failure numbers increase with the age of network components. Figure 33 states that absolute SAIFI and CAIDI-risk increase with network age due to a higher number of failures.

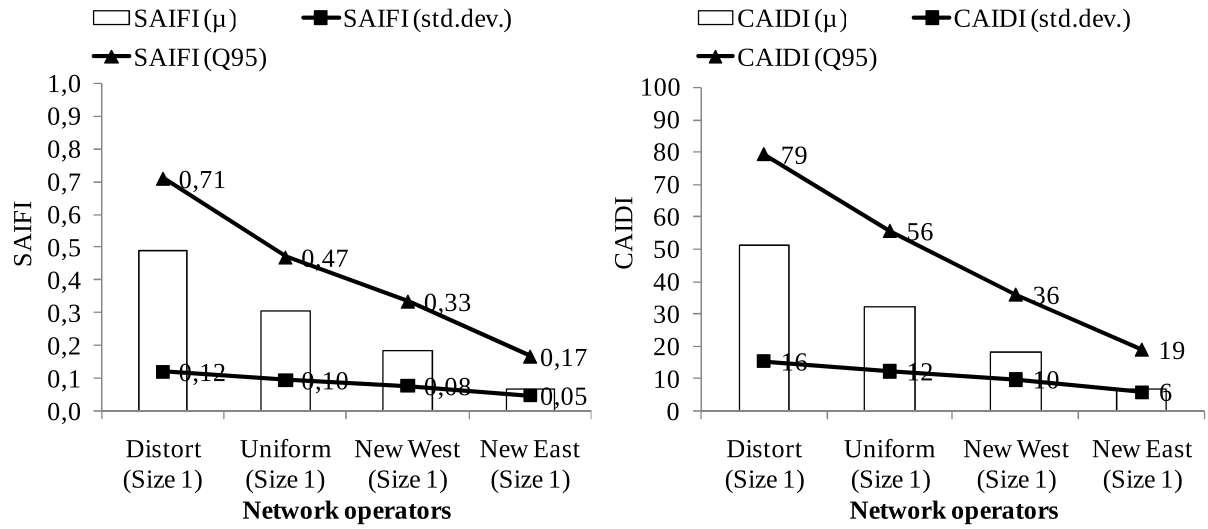


Figure 33: Absolute risk measures (size=1)

One can see, that the increase of mean values with network age appears to be more important than the increase of standard deviation, which will result in a variation coefficient that decreases with network age. An increase in size reduces the magnitude of the relationship, but the general result that SAIFI- and CAIDI-risk increase with age still hold (cf. Figure 34).

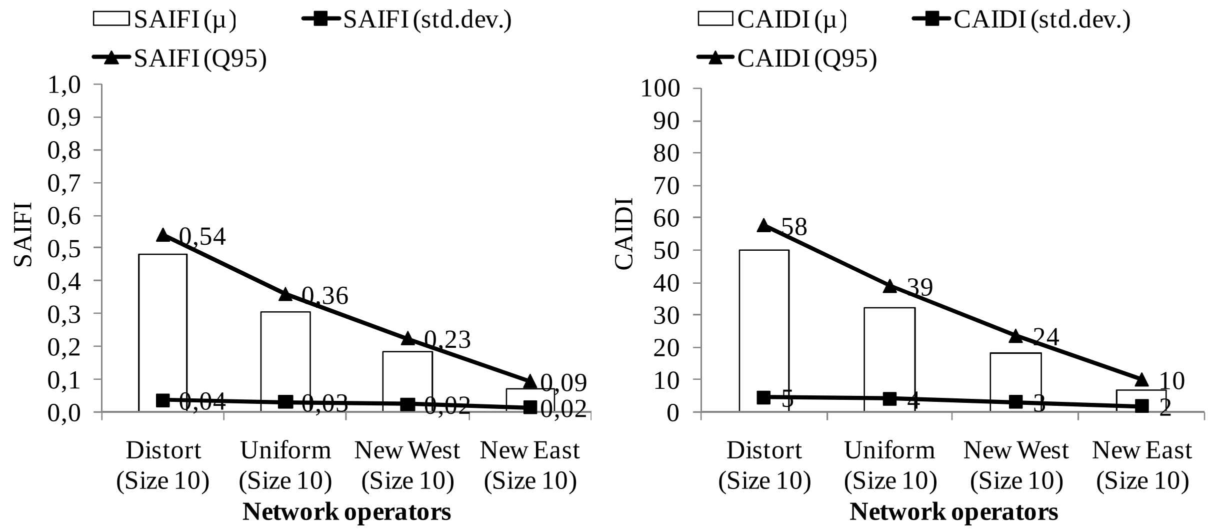


Figure 34: Absolute risk measures (size=10)

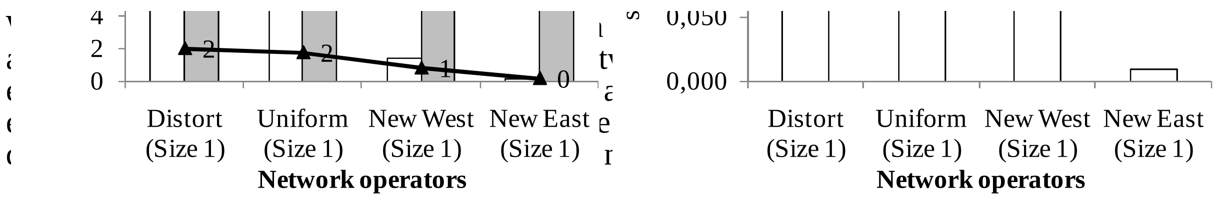


Figure 35).

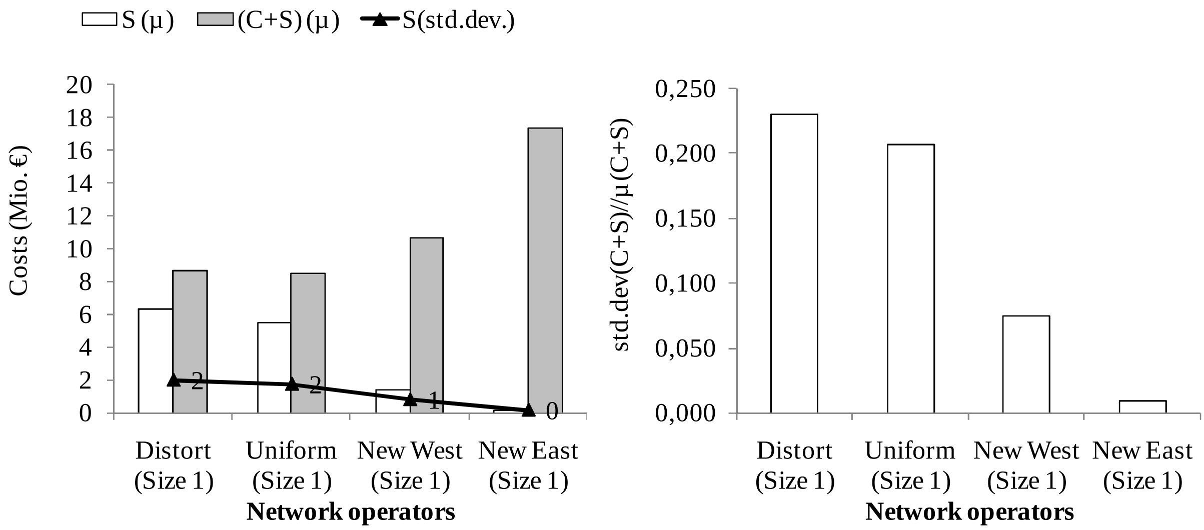


Figure 35: Relative risk measures

We thus conclude that network risk, if measured in absolute numbers increases with network age. If risk is measured in relative numbers, risk decreases with network age. An increase in network size reduces the impact of network age but does not change the fundamental relationship. With regard to total network operator cost $C+S$, expected cost will increase with network age. As optimal replacement strategies are assumed to be independent of the concrete age structure, $\mu(C+S)$ will be lower in a younger network. This is due to lower expected quality penalties and premature replacements on the one hand; their dependence on the age structure can be mapped to the development of the quality indices presented. On the other hand, normal replacement will be lower as well. Apparently, $\sigma(C+S)$ also decreases in younger networks the main question being, if the expectation or the standard deviation decreases faster. From what we can see with regard to our quality indices, we would expect $\sigma(C+S)/\mu$ to decrease in younger networks.

### 4.3 The Effect of Quality Penalties

Quality penalties influence the total risk position of a network operator. Higher penalties will on the one hand lead to earlier replacement; on the other hand financial risk will increase due to higher penalty expenses. The basic assumption of 10€/kWh was extended by three other settings: 1€/kWh, 50€/kWh and 100€/kWh. This leads to new optimal replacement strategies.

| **Cluster** | **1€/kWh - opt. replacement** | **10€/kWh - opt. replacement** | **50€/kWh - opt. replacement** | **100€/kWh - opt. replacement** |
|---|---|---|---|---|
| Transformer | 34 | 33 | 29 | 26 |
| Circuit breaker | 34 | 32 | 26 | 24 |
| Cables (mv) | 62 | 61 | 54 | 57 |
| Overhead lines (mv) | 47 | 46 | 41 | 38 |
| Relay stations | 33 | 28 | 22 | 20 |
| Cables (lv) | 62 | 61 | 57 | 54 |
| Overhead lines (lv) | 47 | 46 | 42 | 39 |

Figure 36: Modified replacement strategies under different penalty assumptions

We suspect quality indices to improve with increasing quality penalties. Consequently, absolute risk measures will decrease with penalties (cf. Figure 36). Quality penalties, if made significantly punishing, appear to be an effective instrument to incentivize a social optimal quality standard. With a penalty of 1€/kWh, a CAIDI-level of 60 minutes results. A penalty of 100€/kWh will lead to a CAIDI-level of 8 minutes.

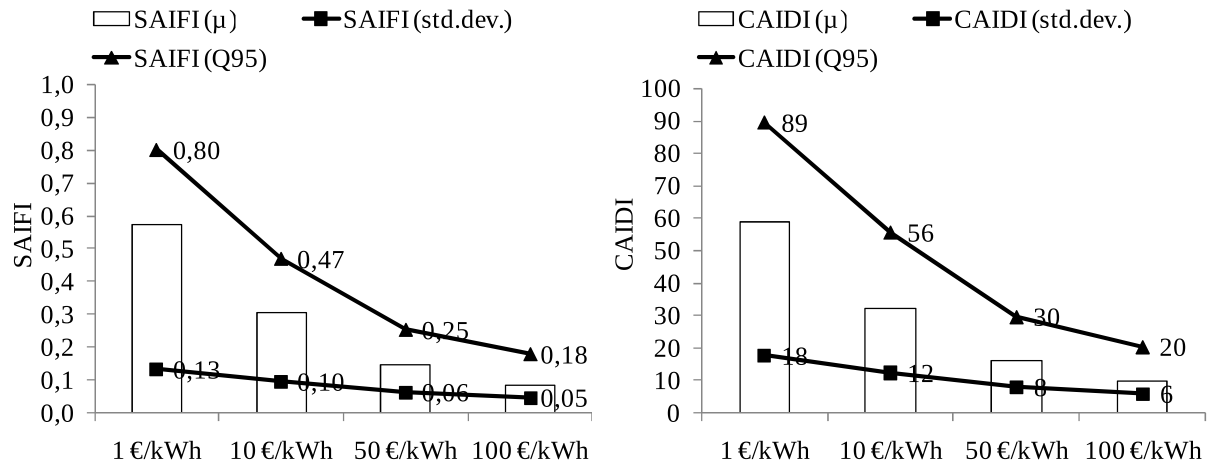


Figure 37: Absolute risk measures regarding quality penalties

Risk measured with the variation coefficient $\sigma / \mu$ and the ratio $Q_{95} / \mu$ increases, as mean values decrease faster with rising quality penalties than the standard deviation and $Q_{95}$. The reduction in mean value is due to the agent's attitude towards a higher penalty: As a consequence of a new penalty, he adapts his replacement strategy and modifies the age structure of his network. These results consequently illustrate stationary state. Assuming that the agent has no option to adapt the age structure on the short run and leaves the age structure unchanged, a higher penalty would result in no change of quality indices. Nevertheless, expectation and variance of $C + S$ would increase.

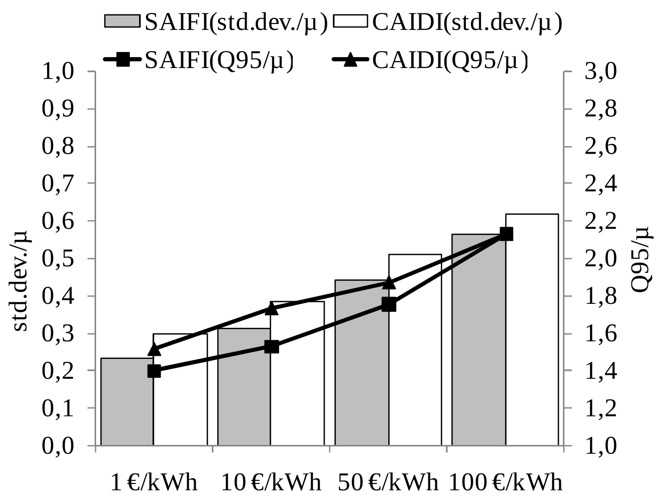


Figure 38: Relative risk measures with regard to quality penalties

Consequently, quality indices' variation coefficients are decreasing with the level of quality penalties.

## 4.4 Quantification of total Cash-flow-risk

After presenting empirical evidence, that size and age matter in evaluating network risk, the question remains whether network risk has as significant impact on financial risk. Financial risk can be measured on a cashflow-basis to avoid effects due to different amortization approaches. Thus, expenses (which consist of premature replacement and quality penalties) and corresponding standard deviation and $Q_{95}$ are used to quantify risk. All expenses have to be financed with cash-in, which consists basically of network tariffs. Network tariffs (as discussed in section 3.1.2, cf. Figure 15) increase proportionally in size and can thus be used to standardize absolute risk measures. A second measure ('expense/tariff ratio') describes the share of network tariffs, which is used to finance the risky cash flow.

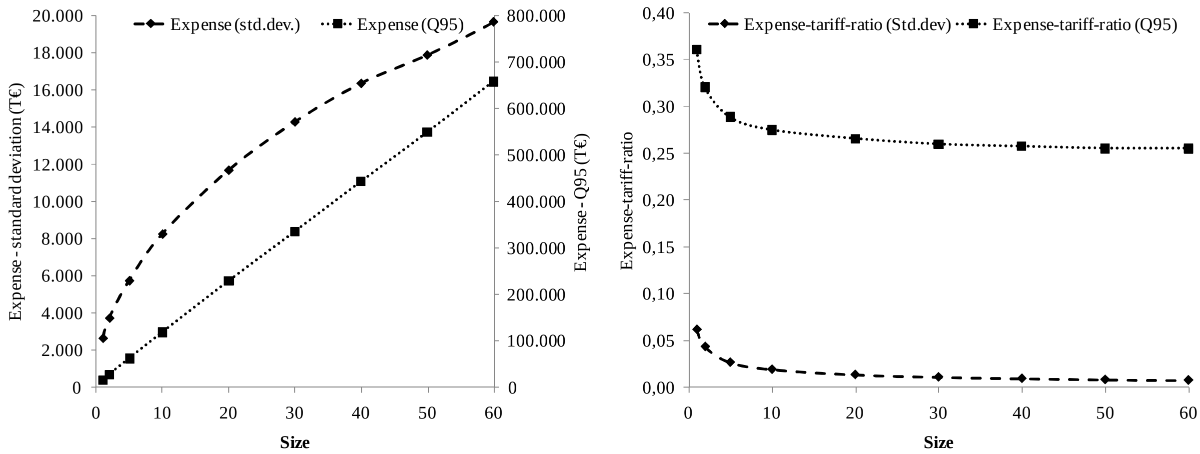


Figure 39: Network operator size and financial risk

For a network operator of size 1 a value of about 6% of the cash-in the network operators receive is required to finance the standard deviation (2,7 Mio. €) of expenses for replacement and quality penalties. The total expense for premature replacement and quality penalties adds up to 10,3 Mio. €, which is significant considering total network tariffs of 43 Mio. €. Interestingly, quality penalties only account for 3% of total expenses under given assumption of 10€/kWh. For much larger operators, only 1% of network tariffs are required to finance the standard deviation. The same analysis was conducted for the different age structure settings (cf. Figure 40).

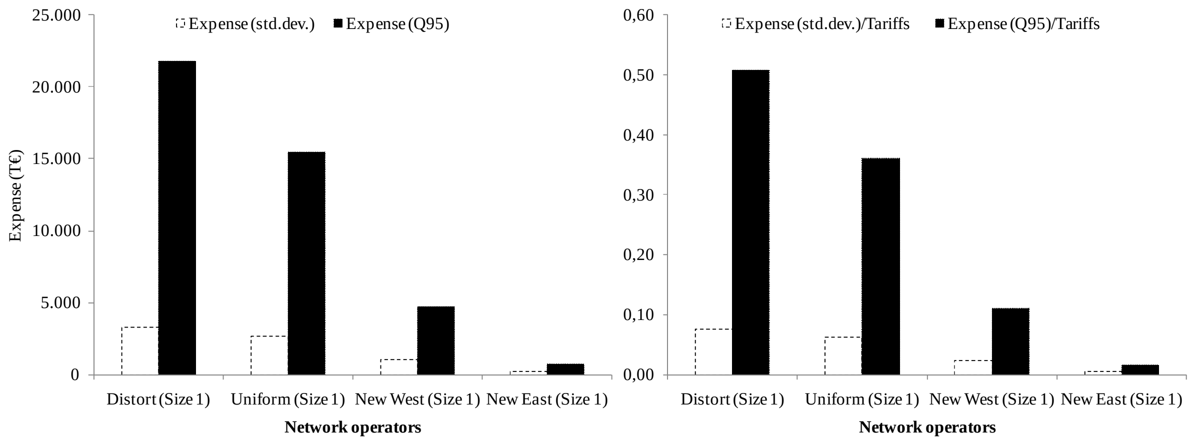


Figure 40: Network operator age structure and financial risk

A network operator with a distort structure expects total expenses 16 Mio. € and a standard deviation of 3,3 Mio. €. The expectations for the 'new west' structure (1,9 Mio. €) and the corresponding standard deviation (1,0 Mio. €) and for the 'new east' structure (0,3 Mio. € and standard deviation of 0,2 Mio. €) are considerably lower. Consequently, the financial risk depends significantly on network age and structure.

## 5. Conclusion

Within this paper, we have discussed the risk a network operator bears due to structural differences which are usually not considered by regulation authorities. A network operator will often be risk-averse which signifies that he has to consider specific, unsystematic risk which is linked to his network structure. Two such structural sources of specific risk analyzed analytically and empirically in this paper are the size and the age structure of a network operator in a setting of incentive regulation with quality penalties. Smaller or elder networks are subject to a higher stochasticity as failure events occur rarely and single, but very important failures may have a significant impact on the variance of expenses for quality penalties and on variance of expenses for premature replacements. As standardized mean values do not change with network size, a higher variance of cashflows will have to be compensated by higher expected returns on equity. Temporarily elder networks will also suffer higher average failure rates.

While the network operator's size may be easily observable by regulation authorities, data about the condition of a network, that is often described by the age of its components, is not that easily observable. Gathering data about single assets may be tricky, as companies' books often do not give valid information about single assets' ages. The cost for implementing an information system gathering information on single assets can be considered high, especially for smaller firms. Also, age is only a proxy for the condition of the asset, which in turn is decisive for the asset's failure propensity. Nevertheless, the network risk depends highly on its condition. Consequently, an agent investing in older networks will claim a higher equity return than an agent investing in a more recent network.

In order to discuss the effect of size and age as well as replacement cost and quality penalty variations on network risk, we presented an analytical age replacement model which considers expenses for planned replacement, premature replacement, replacement cost and quality penalties in a stationary framework. As central results of the analytical model, influences of the size, the current age, replacement cost, and the quality penalty on both the expected total cost as well as risk exposure could have been shown. Replacement cost $K$ and quality penalty $s$, the monetary parameters, both have an increasing influence on expected total cost. Contrarily, $K$ will as well increase relative risk exposure whereas $s$ will lower relative risk measured by the variation coefficient. This is due to an adaption of the replacement strategy: If $K$ increases, it is optimal for the agent to postpone replacement to obtain the lowest expected costs. This in turn will increase the agent's risk exposure. A variation in $s$ induces the opposite reaction of the variation coefficient. As a result, an increase in $K$ and $s$ will always leave the agent worse off in absolute terms of utility, whereas the effect is declining for $s$, because of the risk reducing effect of an increase in $s$, and progressive for $K$.

Independent of the degree of risk aversion, the agent will always be worse off when network size is reduced: Expected average cost stays the same, but risk increases. Similar to the quality penalty, the effect on the agent's utility from temporarily suboptimal asset ages, as this is often the case at the introduction stage of incentive regulation, is negative in absolute terms. Nevertheless, a further distinction is necessary: For elder assets than the optimal replacement age cost as well as risk increase and the agent's utility progressively decreases. Relatively young assets also induce an increase in expected cost, but relative risk decreases. This leads to a declining decrease in absolute utility.

To make these effects more transparent and show the practical relevance of the subject-matter, a simulation model has been used to generate empirical insights. Model assumptions have been based on a survey of German electricity distribution firms and published data with the aim of achieving a realistic simulation setting. Sensitivity tests were conducted to guarantee that the obtained results hold in a general context. Three major sources of stochasticity were included in the model: the failure event itself, the fact if a redundant network structure avoids outages if a failure occurs and the failure duration.

Supporting analytical findings, size reveals to have a significant impact on network risk, measured by quality indices as well as cashflow measures. Interestingly, not only the risk position itself decreases with size but the distribution of quality indices changes its nature. Considering bigger network operators, quality indices may be approximated with a normal distribution. Regarding smaller network operators, distributions are characterized by fat tails which may lead to the underestimation of extreme events. Four different age structure settings were used to show that network risk depends significantly on the underlying age structure.

Even two heterogeneous age structures with the same average asset age per asset cluster may lead to very different risk positions. Not surprisingly, the youngest network with no asset older than 20 years bears by far the lowest risk. By standardizing the expected expense for premature replacement and quality penalties and their respective standard deviation and 95%-quantile by revenue generated approximated with network tariffs, the importance of network risk is quantified. We find that large operators (with networks of 60.000 km of cables and overhead lines) suffer eventual losses at the standard deviation quantile of only 1% of network tariffs while smaller network operators (with 2.000 km) incur a risk of 8% of their network tariffs at the two third quantile.
The simulation results are in line with the insights obtained by the analytical model. One can summarize, that network size and age modify the network operator's risk position. Also, an increase of quality penalties will decrease differences in relative risk exposure. Though, smaller or older operators will have disadvantages from the start which might only be reduced. Risk aversion together with higher risk exposure due to smaller or older networks therefore might also lead to higher expected total cost as a result of substituting risk against expected cost.
As this risk will influence the investor's behavior, a regulation authority will have to answer the question whether the network operator shall solely have to bear the consequences, namely risk and increased expected cost. Incentive and quality regulation mechanisms that do not consider the specific risk may lead to stranded costs and result in network operator's discrimination and, in extreme cases, bankruptcy.

## List of symbols

| | |
|---|---|
| $C$ | Replacement cost of equipment |
| $f$ | Probability density function of unconditional failure |
| $F$ | Probability distribution function of unconditional failure |
| $G$ | Mean lifetime of asset class |
| $H$ | Probability distribution function of age (age structure of assets) |
| $j$ | Assets in asset class l |
| $K$ | Replacement cost for single asset |
| $K_s$ | Ratio of replacement costs to penalty costs |
| $m$ | Slope of probability distribution function |
| $\mu$ | Expectation |
| $R_{prem}$ | Probability of premature replacement |
| $R_{norm}$ | Probability of normal replacement |
| $r$ | Conditional failure probability (failure rate) |
| $S$ | Total penalty cost |
| $s$ | Penalty for not delivering quality to the customer |
| $\sigma$ | Standard deviation |
| $t_a$ | Starting point of the aging period |
| $t_b$ | End of the aging period |
| $t_j$ | Planned utilization period |

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# Appendix A

$$= ns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{t_a + \frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s}{m} - \frac{1}{2m}\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2}\right)D_{ref}$$

$$= ns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\frac{1}{2m}\left(2mt_a + 2\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right) - \left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2\right)}\right)D_{ref}$$

$$= ns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\frac{1}{2m}\left(2mt_a - \left(\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2 - 2\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)\right)}\right)D_{ref}$$

$$= 2mns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\left(2mt_a - \left(\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2 - 2\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)\right)\right)}\right)D_{ref}$$

$$= 2mns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\left(2mt_a - \left(\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2 - 2\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right) + 1 - 1\right)\right)}\right)D_{ref}$$

$$= 2mns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\left(2mt_a - \left(\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right)^2 - 2\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right) + 1 - 1\right)\right)}\right)D_{ref}$$

$$= 2mns\left(\frac{\sqrt{K_s{}^2 + 2K_s - 2mt_a}}{\left(2mt_a + 1 - \left(\left(\sqrt{K_s{}^2 + 2K_s - 2mt_a} - K_s\right) - 1\right)^2\right)}\right)D_{ref}$$

$$= ns\left(\frac{\sqrt{K_s^{\,2}+2K_s-2mt_a}}{\left(t_a+\frac{1}{2m}-\frac{1}{2m}\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s-1\right)^2\right)}\right)D_{ref}$$
.

## Appendix B

Derivation of expected total cost $\mu$

$$\mu = 2mns\left(\frac{\sqrt{K_s^{\,2}+2K_s-2mt_a}}{\left(2mt_a+1-\left(\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s\right)-1\right)^2\right)}\right)D_{ref}$$

with regard to $K_s$ will make the use oft he quotient rule necessary.

$$u' = \frac{\partial u}{\partial K} = \frac{K_s+1}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}$$

$$v' = \frac{\partial v}{\partial K} = \frac{\partial\left(2mt_a+1-\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s-1\right)^2\right)}{\partial K}$$

$$= -2\left[\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s-1\right)\left(\frac{K_s+1}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}-1\right)\right]$$

Since the denominator is always positive it can be skipped from the formula without any loss for the analysis.

$$u'v-uv'=$$

$$=\frac{K_s+1}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}\left(2mt_a+1-\left(\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s\right)-1\right)^2\right)$$

$$+2\sqrt{K_s^{\,2}+2K_s-2mt_a}\left[\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s-1\right)\left(\frac{K_s+1}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}-1\right)\right]$$

Algebraic transformations lead to the following result (last line).

$$=\frac{(K_s+1)\left(2mt_a+1-\left(\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s\right)-1\right)^2\right)}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}$$

$$+2\sqrt{K_s^{\,2}+2K_s-2mt_a}\left[\left(\sqrt{K_s^{\,2}+2K_s-2mt_a}-K_s-1\right)\left(\frac{K_s+1-\sqrt{K_s^{\,2}+2K_s-2mt_a}}{\sqrt{K_s^{\,2}+2K_s-2mt_a}}\right)\right]$$

$$= \left(K_s + 1\right)\left(2mt_a + 1 - \left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2\right)$$
$$+ 2\sqrt{K_s^{\,2} + 2K_s - 2mt_a}\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s - 1\right)\left(K_s + 1 - \sqrt{K_s^{\,2} + 2K_s - 2mt_a}\right)$$

$$= \left(K_s + 1\right)\left(2mt_a + 1 - \left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2\right)$$
$$- 2\sqrt{K_s^{\,2} + 2K_s - 2mt_a}\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s - 1\right)^2$$

$$= \left(K_s + 1\right)\left(2mt_a + 1\right) - \left(K_s + 1\right)\left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2$$
$$- 2\sqrt{K_s^{\,2} + 2K_s - 2mt_a}\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s - 1\right)^2$$

$$= \left[\left(K_s + 1\right)\left(2mt_a + 1\right) - \left(K_s + 1\right) - 2\sqrt{K_s^{\,2} + 2K_s - 2mt_a}\right]\left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2$$

$$= \left[K_s mt_a + mt_a - \sqrt{K_s^{\,2} + 2K_s - 2mt_a}\right]\left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2$$

$$= 2mnsD\left[\left(K_s + 1\right)mt_a - \sqrt{K_s^{\,2} + 2K_s - 2mt_a}\right]\left(\left(\sqrt{K_s^{\,2} + 2K_s - 2mt_a} - K_s\right) - 1\right)^2 .$$

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## Appendix C

The first term of (20) will be positive if $\left[\left(K_s + 1\right)mt_a - \sqrt{K_s^{\,2} + 2K_s - 2mt_a}\right]$ greater than zero.

$$\left[(K_s+1)mt_a-\sqrt{K_s{}^2+2K_s-2mt_a}\right]>0$$

$$\begin{aligned}
&\Leftrightarrow (K_s+1)mt_a>\sqrt{K_s{}^2+2K_s-2mt_a}\\
&\Leftrightarrow (K_s+1)mt_a>\sqrt{K_s{}^2+2K_s-2mt_a+2mt_a}>\sqrt{K_s{}^2+2K_s-2mt_a}\\
&\Leftrightarrow (K_s+1)mt_a>\sqrt{K_s{}^2+2K_s}\\
&\Leftrightarrow (K_s+1)mt_a>\sqrt{K_s{}^2+2K_s+1}>\sqrt{K_s{}^2+2K_s}\\
&\Leftrightarrow (K_s+1)mt_a>(K_s+1)\\
&\Leftrightarrow mt_a>1.
\end{aligned}$$

# Appendix D

$$\begin{aligned}
&G(t_j(K,s))\big/D_{ref}-F(t_j(K,s))\\
&=-\frac{m}{2D_{ref}}\left((t_j(K,s)-t_a)^2+2D_{ref}(t_j(K,s)-t_a)+D_{ref}^2\right)+\frac{t_j(K,s)}{D_{ref}}+\frac{m}{2D_{ref}}\\
&=\left(\frac{1}{D_{ref}}-m\right)t_j(K,s)-\frac{m}{2D_{ref}}(t_j(K,s)-t_a)^2+mt_a\\
&=\left(\frac{1}{D_{ref}}-m\right)(t_j(K,s)-t_a)+\frac{t_a}{D_{ref}}-\frac{m}{2D_{ref}}(t_j(K,s)-t_a)^2\\
&=-\frac{m}{2D_{ref}}\left((t_j(K,s)-t_a)^2-2(t_j(K,s)-t_a)\left(\frac{1}{m}-D_{ref}\right)+\left(\frac{1}{m}-D_{ref}\right)^2\right)+\frac{t_a}{D_{ref}}+\frac{m}{D_{ref}}\left(\frac{1}{m}-D_{ref}\right)^2\\
&=-\frac{m}{2D_{ref}}\left(t_j(K,s)-t_a-\frac{1}{m}+D_{ref}\right)^2+\frac{t_a}{D_{ref}}+\frac{(1-D_{ref})^2}{mD_{ref}}\ .
\end{aligned}$$