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## Statistical Review of Nuclear Power Accidents

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# Statistical Review of Nuclear Power Accidents

Marius Hofert and Mario V. Wüthrich

## **Abstract**

A statistical analysis which provides a risk assessment of nuclear safety based on historical data is conducted. Classical probabilistic models from risk theory are used to analyze data on nuclear power accidents from 1952 to 2011. Findings are that the severities of nuclear power accidents should be modeled with an infinite mean model and, thus, cannot be insured by an unlimited cover.

**KEYWORDS:** nuclear power accidents, loss frequency, loss severity

**Author Notes:** The authors would like to thank Prof. Hans Bühlmann (ETH Zurich) for raising this issue and fruitful discussions, Prof. Benjamin K. Sovacool (National University of Singapore) for providing us with the updated loss database, and Prof. Paul Embrechts (ETH Zurich) for fruitful discussions.

# 1 Introduction

Safety is the central issue in nuclear energy production. Nuclear power accidents can be disastrous as the examples of Kyshtym (Soviet Union, 1957), Three Mile Island (United States, 1979), Chernobyl (Ukraine, 1986), or Fukushima (Japan, 2011) show. Therefore, nuclear safety is of highest priority and there needs to be a continuous improvement in safety design and culture; see, for instance, the work and purpose of the International Atomic Energy Agency (IAEA, [www.iaea.org](http://www.iaea.org)). Currently, nuclear power plants of so-called Generation III and Generation III+ are built, some of them are already in operation. Nevertheless, nuclear power plants are highly complex systems that are exposed to several risk factors such as mechanical breakdowns, material failure, human errors, earthquakes, tsunamis, floods, terrorism, etc., and there is always a (hopefully small) probability of a nuclear disaster. Owing to scarce data, it is difficult to assess this probability and the fact that we cannot test reactor designs in practice does not make the situation any easier.

The probability of a nuclear disaster is often calculated with the so-called Probabilistic Safety Assessment (PSA) technique. This approach can be understood as a bottom-up scenario analysis. The starting points are initiating events that occur with a given (small) probability. These initiating events generate sequences of accidents whose severities are quantified. As a result, one then obtains estimates for nuclear disasters. Such an analysis quantifies, for example, the probability of an annual core damage between  $3 \times 10^{-8}$  and  $1 \times 10^{-5}$  for different boiling water reactors (BWRs), see Hinds and Maslak (2006). A German PSA analysis quantifies the annual probability of a severe accident for the German plant Biblis to be of order  $3 \times 10^{-5}$  (see Wikipedia, 2011b). A study by Hirschberg et al. (1998) gives a whole frequency curve of loss exceedances for the Swiss plant Mühleberg: a loss exceeding 1 billion USD has an annual probability of approximately  $1 \times 10^{-6}$  and a loss exceeding 10 billion USD has an annual probability of approximately  $1 \times 10^{-7}$ . Of course, such an analysis about financial damages heavily depends on the probabilities assigned to the events, on safety standards and on plant location, for example, whether it is situated in a densely populated area. A comprehensive historical review of nuclear power plant safety is given by Sehgal (2006) which describes the report WASH-1400 (U.S. Nuclear Regulatory Commission, 1975). The latter gives the first assessment of public risks of nuclear power accidents. Tables 1 and 2 in Sehgal (2006) (taken from WASH-1400) give insight into short- and long-term consequences of nuclear power accidents. With a rather high annual probability of  $1 \times 10^{-6}$ , one should anticipate long-term health damages (such as cancer), whereas high financial damages exceeding 8 billion USD only occur with a rather low annual probability of  $1 \times 10^{-8}$ .

How reliable are these estimates? The aim of this study is to statistically back-

test them based on a database on nuclear power accidents provided by Sovacool (2008, 2011). Similar to Sornette et al. (2011), we analyze nuclear safety from a purely statistical point of view using these past observations. Although one may question the extent to which historical data allows us to assess current (and future) nuclear safety, it provides useful insight into the calibration of PSA safety analysis as well as insurability and costs of nuclear power accidents.

## 2 Statistical Modeling Approach

For the modeling of the overall loss process of nuclear power accidents we choose a compound Poisson process. The loss-count process is modeled with a non-homogeneous Poisson process  $(N_t)_{t \geq 0}$ , and the loss-severities  $Y_i$ ,  $i \in \mathbb{N}$ , are assumed to be independent and identically distributed (i.i.d.) and independent of the loss-count process. The total annual losses  $(S_t)_{t \in \mathbb{N}}$  are then independent and in year  $t \in \mathbb{N}$  given by a compound Poisson distributed random variable

$$S_t = \sum_{i=N_{t-1}+1}^{N_t} Y_i, \quad (2.1)$$

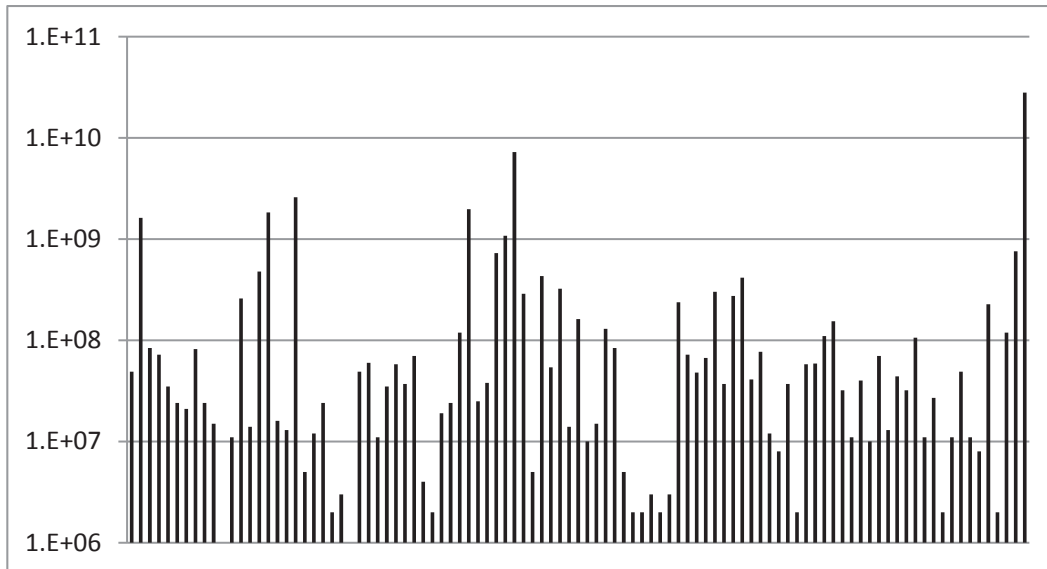
where

- (a) the total number of accidents  $M_t = N_t - N_{t-1}$  in year  $t \in \mathbb{N}$  is Poisson distributed with mean  $\lambda w_t$  [i.e.,  $M_t \sim \text{Poi}(\lambda w_t)$ , independently for different  $t$ ] where  $\lambda > 0$  denotes the intensity and  $w_t$  denotes the number of reactors in operation in year  $t$ ;
- (b) the loss-severities  $Y_i$ ,  $i \in \mathbb{N}$ , are i.i.d. copies of a non-negative random variable  $Y \sim F$  and independent of the loss-count process  $(N_t)_{t \geq 0}$ .

Note that compound Poisson processes have several desirable aggregation and decomposition properties; see Mikosch (2006) Proposition 3.3.4 and Theorem 3.3.6. Our aim is to calibrate the compound Poisson process (2.1) to the distribution of the observed nuclear power losses. Thus, we need to estimate the intensity  $\lambda > 0$  and calibrate the loss-severity distribution  $F$  of  $Y$ .

## 3 Data

The database of Sovacool (2008, 2011) contains 102 accidents from 1957 (Kyshtym, Soviet Union) to 2011 (Fukushima, Japan), it reports date and location of the accident, fatalities, and costs in USD (as of 2010). Figure 1 provides the costs per



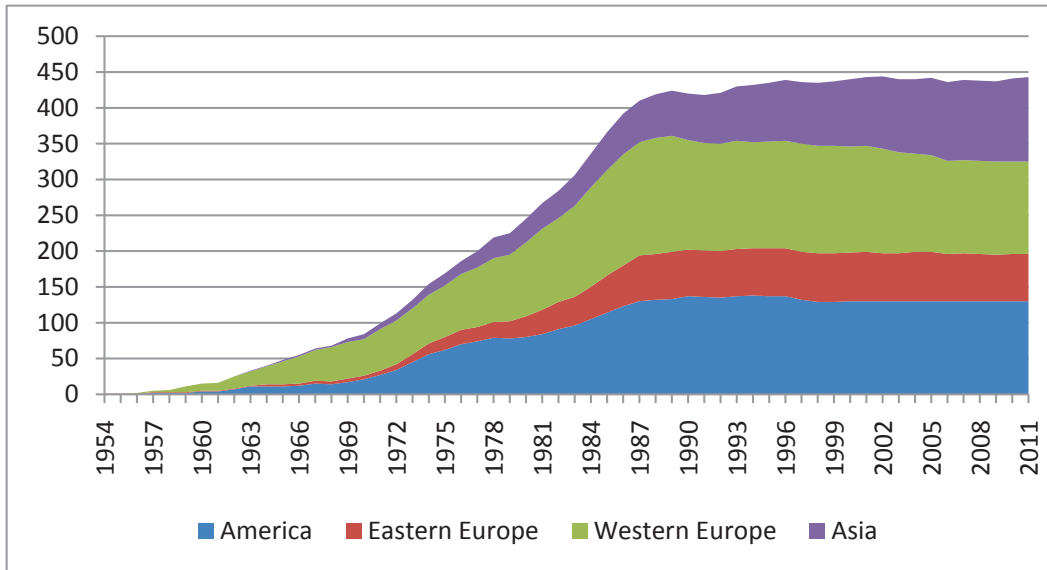
**Figure 1:** Nuclear power accidents from 1957 to 2011: costs (severities) in USD (as of 2010) per accident on logarithmic scale, data source Sovacool (2008, 2011). The 102 reported accidents are ordered chronologically.

accident in chronological order. The last reported loss in Figure 1 is Fukushima (Japan, 2011) which was set, as a first estimate, to 28 billion USD. We will discuss the (in-)completeness of this database later.

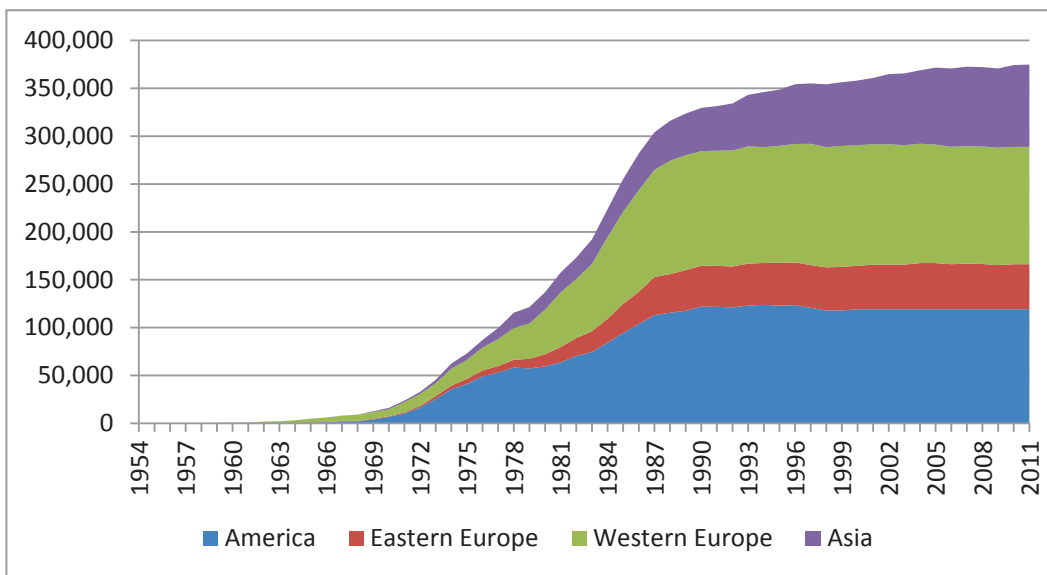
As a measure of exposure for our analysis we use the information provided by the International Atomic Energy Agency (IAEA) (2010, 2011). Figure 2 shows the number of reactors in operation from 1954 to 2011. They are divided into four regions: America (including Africa), Eastern Europe, Western Europe, and Asia. From 1988 onward the number of reactors in the regions America and Eastern Europe is stable, in Western Europe it is decreasing, and in Asia it is increasing. Figure 3 provides the total (net) capacity in megawatts (MW) for these four regions. We see rather stable graphs after 1988 except for Asia where we observe a growth in energy production as well as in the number of reactors. Comparing Figures 2 and 3, we also see that the average capacity per reactor is increasing in Western Europe.

## 4 Statistical Analysis

After a more detailed analysis of the description and information about the loss data, we decided to model the losses  $Y_i$  which exceed a threshold of 20 million USD (i.e., we fix the threshold  $u = 2 \times 10^7$ ). Below this threshold  $u$  the reporting



**Figure 2:** Number  $w_t$  of reactors in operation from  $t = 1954$  to 2011, data source: International Atomic Energy Agency (2010, 2011).

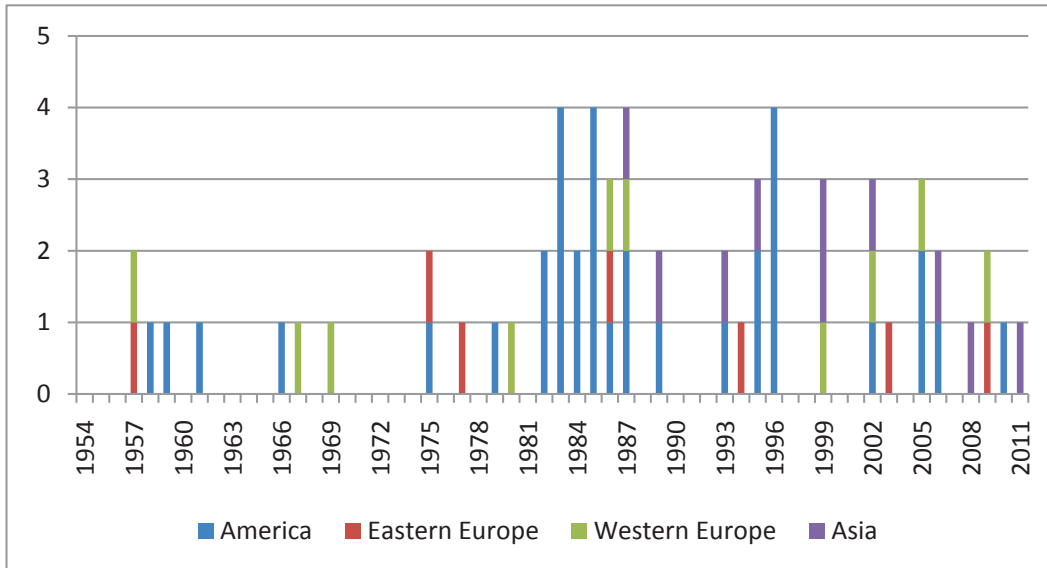


**Figure 3:** Total (net) capacity in MW from  $t = 1954$  to 2011, data source: International Atomic Energy Agency (2010, 2011).

of a loss seems rather arbitrary. More than half of the reported losses below  $u$  are from the United States (US) (which indicates that there might have been a different reporting philosophy in the US). Typical cases of such small losses are that a maintenance worker fell through an unmarked manhole, shutdowns due to concerns of earthquake, safety problems, or extensive recirculation system damage, etc. In these situations, the safety systems have worked and the reported costs are mainly paid for the repair of the system. We observe 61 losses exceeding the threshold of 20 million USD.

### 4.1 Annual Loss-count Distribution

We first model the distribution of the total number of annual nuclear power accidents  $M_t$ . Figure 4 provides the number of nuclear power accidents exceeding the



**Figure 4:** Number of nuclear power accidents exceeding a threshold of 20 million USD.

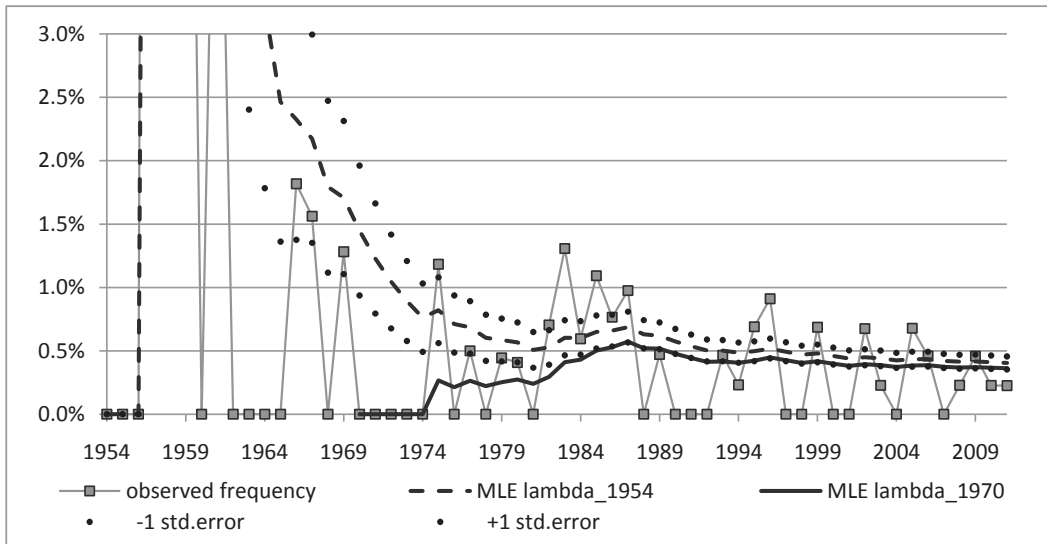
threshold  $u = 2 \times 10^7$ . If we compare Figures 2 and 4, we see that the years before 1970 correspond to an early development phase of nuclear power plants in America and Europe. The total net capacity in this early period is negligible compared to today, see Figure 3, but 8 out of the 61 events fall into this early period.

### 4.1.1 Constant Intensity $\lambda$

In a first step, we assume a constant intensity  $\lambda$  and model  $M_t$  via

$$M_t \stackrel{\text{indep.}}{\sim} \text{Poi}(\lambda w_t), \quad t \in \{1954, \dots, 2011\},$$

i.e., we choose independent Poisson distributions with mean  $\lambda w_t$ . We estimate  $\lambda$  using the maximum likelihood estimator, which is simply the sample mean of  $M_t/w_t$  for the corresponding time points  $t$ . For  $t \in \{1954, \dots, 2011\}$ , we denote the maximum likelihood estimator (MLE) based on the set of observations  $\{M_{1954}, \dots, M_t\}$  by  $\hat{\lambda}_{1954}^{(t)}$ . The same estimator is applied for the set of observations  $\{M_{1970}, \dots, M_t\}$ ,  $t \in \{1970, \dots, 2011\}$ , which provides the time series  $\hat{\lambda}_{1970}^{(t)}$ . The result is presented in Figure 5. In the first period, we see a clear decrease in  $(\hat{\lambda}_{1954}^{(t)})_{t \in \{1954, \dots, 2011\}}$



**Figure 5:** Observed annual loss-frequency (per reactor in operation) together with the MLEs  $\hat{\lambda}_{1954}^{(t)}$  and  $\hat{\lambda}_{1970}^{(t)}$ . For the time series  $\hat{\lambda}_{1954}^{(t)}$ ,  $t \in \{1954, \dots, 2011\}$ , we also plot the  $\pm 1$  std. error bounds.

(and the corresponding error bounds), which questions the assumption that  $\lambda$  is constant over the entire observation period. By contrast, the time series  $(\hat{\lambda}_{1970}^{(t)})_{t \in \{1970, \dots, 2011\}}$  is more stable. We could now try to model the decay in the annual frequency parameter which stabilizes for later years, but we go for the easier option and model  $\lambda$  non-time dependent for later years neglecting the first years of observations for the estimation of this frequency parameter. The MLEs (with standard errors in



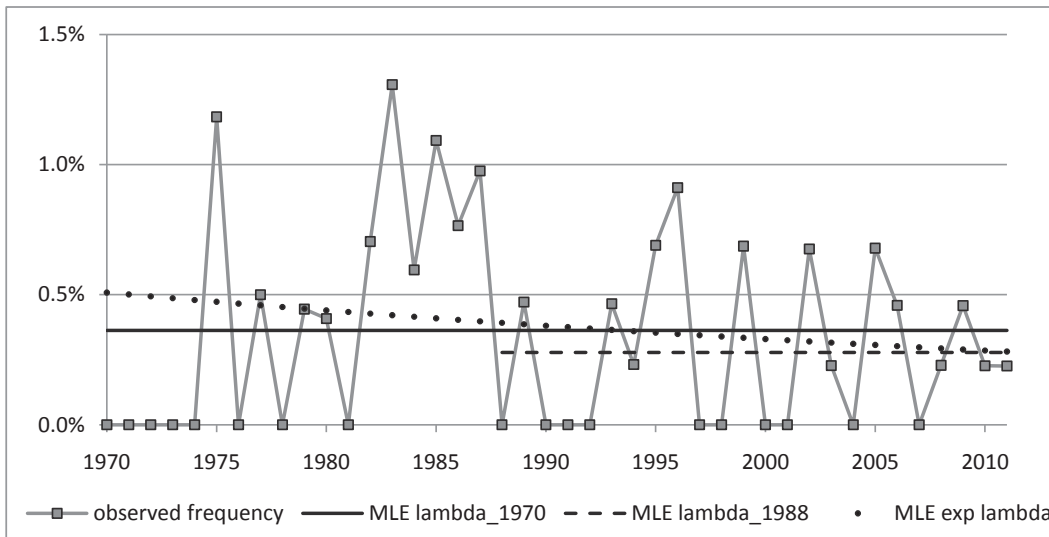
parentheses, i.e., the sample standard deviation divided by the square root of the sample size) for the initial years 1970 and 1988 are given by

$$\begin{aligned}\widehat{\lambda}_{1970}^{(2011)} &= 0.363\% \quad (0.050\%), \\ \widehat{\lambda}_{1988}^{(2011)} &= 0.278\% \quad (0.052\%).\end{aligned}$$

The corresponding estimates for the expected number of nuclear accidents for 2011 are thus

$$\begin{aligned}\widehat{\lambda}_{1970}^{(2011)} w_{2011} &= 1.6081 \quad (0.2215), \\ \widehat{\lambda}_{1988}^{(2011)} w_{2011} &= 1.2315 \quad (0.2304).\end{aligned}$$

Figure 6 displays the observed intensity of losses  $(M_t/w_t)_{t \in \{1970, \dots, 2011\}}$  including the MLEs  $\widehat{\lambda}_{1970}^{(2011)}$  and  $\widehat{\lambda}_{1988}^{(2011)}$ . We obtain frequency parameter estimates of 0.363%



**Figure 6:** Observed annual loss-frequency (per reactor in operation) together with the MLEs  $\widehat{\lambda}_{1970}^{(2011)}$  and  $\widehat{\lambda}_{1988}^{(2011)}$ . Moreover, we plot the estimated exponential decay  $\lambda_t^{\text{exp}}$ , see Eq. (4.1), of the annual loss-frequency.

and 0.278%, respectively. If we consider the exposure in Figure 2 we observe a strong growth in the period from 1970 to 1988, which can also be considered as a development phase. Moreover, in 1979 there was the accident at Three Mile Island (US). After this event we see a rather high annual reporting frequency of events in the US which may be some sort of overreaction (reporting bias) to this severe nuclear power accident in 1979; see Figure 6. Pearson's  $\chi^2$ -test provides  $p$ -values of 17.3% (for the initial year 1970) and of 30.2% (for the initial year 1988) which both do not reject the fitted Poisson model on a 5% level.

### 4.1.2 Fitting an Exponential Decay

So far we have assumed that  $\lambda$  is a positive constant. This contradicts the outline in Section 1: nuclear power plant operators and regulators claim that there is a continuous improvement in safety design and culture. This should reflect in a decreasing loss-frequency parameter function  $\lambda_t$  over the time period  $t \in \{1970, \dots, 2011\}$ . We therefore set in a next modeling approach

$$\lambda_t^{\text{exp}} = \gamma \exp\{-(t - 1969)\beta\}, \quad (4.1)$$

and estimate  $\gamma$  and  $\beta$  with their MLEs

$$\begin{aligned} \hat{\gamma} &= 0.515\% \quad (0.144\%), \\ \hat{\beta} &= 1.443\% \quad (1.096\%). \end{aligned}$$

Thus, we obtain a slight decrease of the annual loss-frequency; see Figure 6. For 2011, we obtain the estimator  $\hat{\lambda}_{2011}^{\text{exp}} = 0.281\%$ . However, the uncertainty in the estimate of the decrease parameter  $\beta$  is high and if we perform the estimation only on the data after 1988 we do not observe any decrease of the annual loss-frequency. Therefore, we will focus on a constant annual loss-frequency parameter  $\lambda$  for the years after 1988; see Eq. (4.2) below.

### 4.1.3 Modeling Regions Separately

Next we differentiate between the different regions. For each region we choose the observations  $t \in \{1988, \dots, 2011\}$ , which provide MLEs for the (local) intensities of the annual number of nuclear accidents

$$\begin{aligned} \hat{\lambda}_{1988}^{\text{America}} &= 0.410\% \quad (0.114\%), \\ \hat{\lambda}_{1988}^{\text{EurEast}} &= 0.188\% \quad (0.108\%), \\ \hat{\lambda}_{1988}^{\text{EurWest}} &= 0.116\% \quad (0.056\%), \\ \hat{\lambda}_{1988}^{\text{Asia}} &= 0.409\% \quad (0.136\%). \end{aligned}$$

Whereas one may question these estimates on the basis of data scarcity we do notice substantially lower annual loss-frequency estimates in Europe (EurEast and EurWest) compared to America and Asia. This may reflect different safety standards but also a different reporting culture. Particularly in Asia, we observe that all reported accidents have occurred either in India or Japan and it seems surprising that there are no (reported) events in other Asian countries.

If we consider the loss-count data of the entire world, we see a slight over dispersion (i.e., a larger variance compared to the mean) which argues against a Poisson

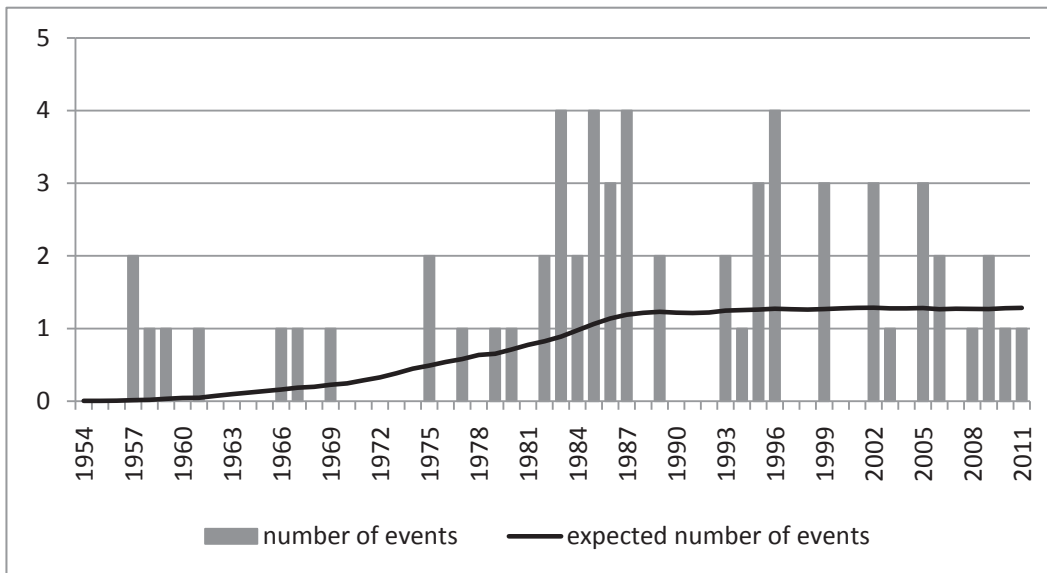
distribution (and is more in favor of a negative binomial distribution, for example). However, if we consider the local loss-count processes we see that this over dispersion can be explained by the data from America. For this reason, we stay with the choice of the Poisson loss-count process.

#### 4.1.4 Final Model for the Loss-count Distribution

The above considerations lead to the following choice of the estimated intensity of the annual number of nuclear accidents:

$$\hat{\lambda} = 0.290\%. \tag{4.2}$$

Finally, Figure 7 shows the observed number of annual events  $M_t$  and the estimated expected number of annual events  $\mathbb{E}[\widehat{M}_t] = \hat{\lambda} w_t$  for  $t \in \{1954, \dots, 2011\}$  using Eq. (4.2).

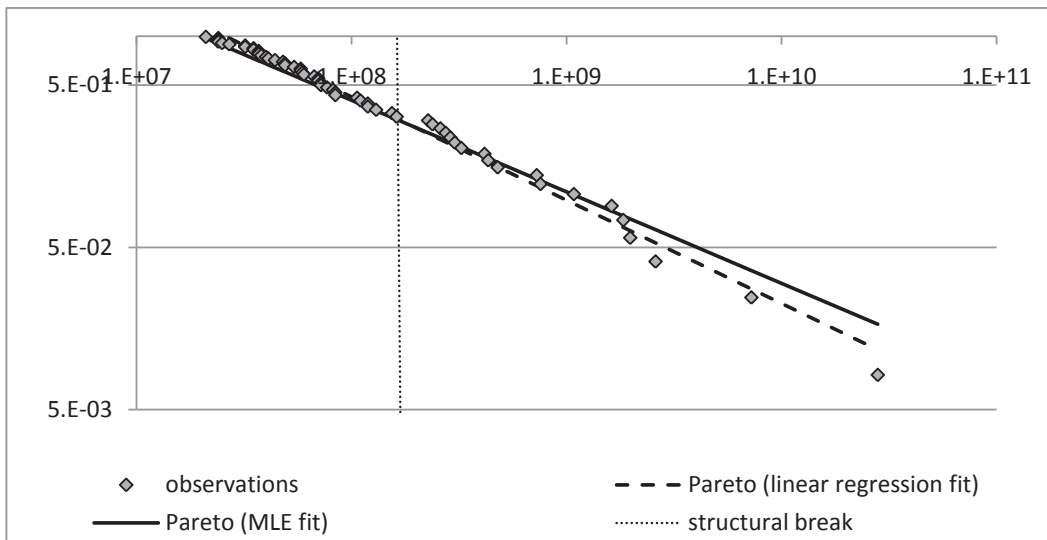


**Figure 7:** Observed number of annual events  $M_t$  and estimated expected number of annual events  $\mathbb{E}[\widehat{M}_t] = \hat{\lambda} w_t$  for  $t \in \{1954, \dots, 2011\}$  using the choice as given in Eq. (4.2).

## 4.2 Loss-severity Distribution

### 4.2.1 Maximum Likelihood and Linear Regression Estimators

We model the loss-severity distribution using all losses  $(y_i)_{i \in \{1, \dots, 61\}}$  (viewed as realizations of the  $Y_i$ ) that exceed the threshold of 20 million USD (as before all considered amounts are in USD as of 2010). Figure 8 shows the empirical survival function  $1 - \widehat{F}_{61}(\cdot)$  on a log-log scale, i.e.,  $(\log y_i, \log(1 - \widehat{F}_{61}(y_i)))_{i \in \{1, \dots, 61\}}$ ; for a more detailed description of these plots we refer to McNeil et al. (2005), Section 7.2.2. We observe that these observations form a fairly straight line with negative



**Figure 8:** Survival functions on a log-log scale, i.e., empirical survival function  $(\log y_i, \log(1 - \widehat{F}_{61}(y_i)))_{i \in \{1, \dots, 61\}}$  versus fitted Pareto survival function  $(\log y, \log(1 - F(y)))_{y \geq u}$ , fitted with linear regression and ML estimation. The vertical line displays the structural break mentioned in the text below.

slope which suggests the Pareto distribution as a natural candidate for modeling the loss-severity distribution: for  $\alpha > 0$  we set

$$Y \sim F(y) = \mathbb{P}[Y \leq y] = 1 - (y/u)^{-\alpha}, \quad \text{for } y \geq u = 2 \times 10^7.$$

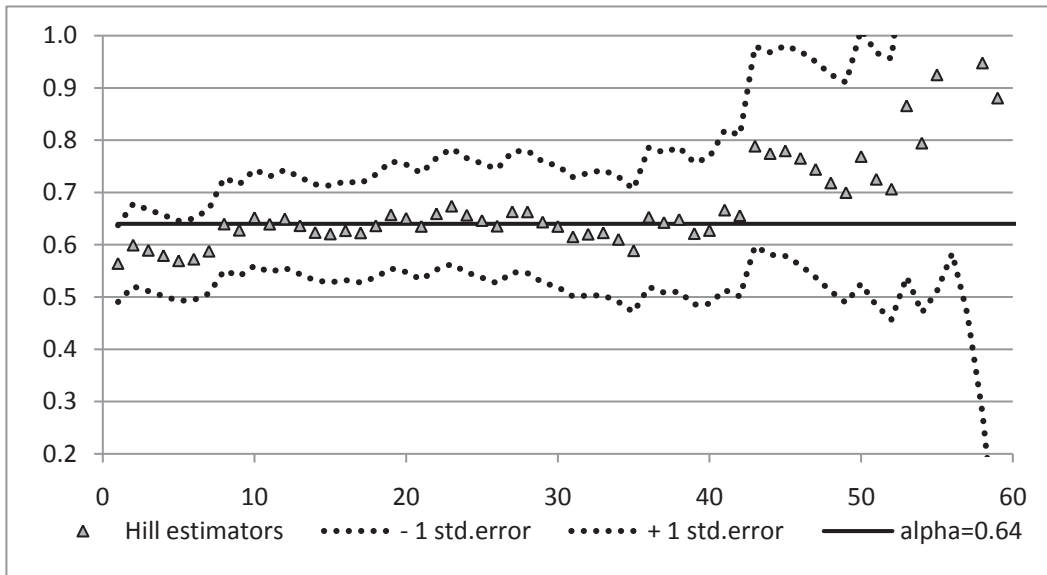
We fit the slope parameter  $-\alpha$  with maximum likelihood (ML) estimation and with linear regression; see Figure 8. The corresponding estimates of  $\alpha$  are (std. errors in parentheses)

$$\begin{aligned} \widehat{\alpha}^{\text{MLE}} &= 0.5641 \quad (7.34\%), \\ \widehat{\alpha}^{\text{regr}} &= 0.6365 \quad (0.83\%). \end{aligned}$$

**Remark 4.1** Both estimation methods suggest an infinite mean model, i.e.,  $\mathbb{E}[Y] = \infty$ . Basically, this means that an unlimited cover against nuclear power accidents cannot be financed by a finite insurance premium and nuclear energy should be very expensive if it also accounts for an insurance cover against nuclear disasters. In the literature, such infinite mean models are also called “extremely heavy-tailed” models. These models do not have favorable properties for risk sharing in society; see Ibragimov et al. (2011) for more on this topic. Our results are in line with the findings of Sornette et al. (2011). These authors found an infinite mean model with slope parameter estimate of 0.7 (they use ML estimation for all accidents exceeding a loss of 30 million USD).

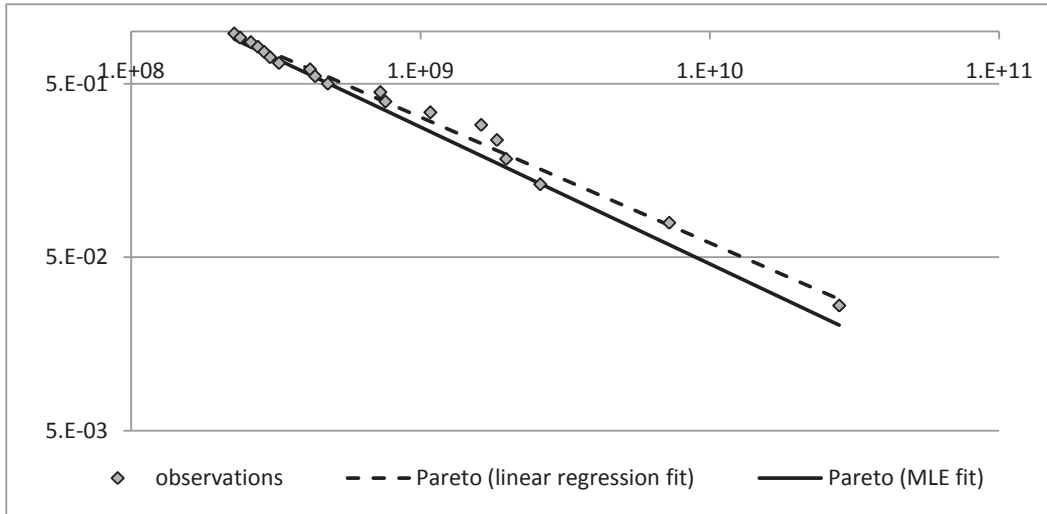
#### 4.2.2 Hill and POT Estimators

Other estimators for  $\alpha$  can be obtained from the Hill plot and the peaks-over-threshold (POT) method. We start with the Hill plot, see Formula (7.23) in McNeil et al. (2005). The Hill plot for  $\alpha$  based on the observations  $(y_i)_{i \in \{1, \dots, 61\}}$  is provided in Figure 9. It also suggests an infinite mean model with  $\alpha \in (0.6, 0.7)$ . Beyond



**Figure 9:** Hill plot for  $\alpha$  based on the observations  $(y_i)_{i \in \{1, \dots, 61\}}$  together with  $\pm 1$  std. error bounds.

that, we observe that there is a structural break in the data at position 42, and indeed this can also be observed in Figure 8 (vertical line). Therefore, we separate the ordered data into two parts  $(y_{(i)})_{i \in \{1, \dots, 42\}}$  and  $(y_{(i)})_{i \in \{43, \dots, 61\}}$ . We model the first part with a smoothed empirical distribution function; see Eq. (4.3) below. The



**Figure 10:** Survival functions on a log-log scale, i.e.,  $(\log y, \log(1 - F(y)))_y$  for the observations  $(y_{(i)})_{i \in \{43, \dots, 61\}}$  and for the estimated Pareto distributions fitted with linear regression and ML estimation.

slope parameter  $-\alpha$  in the second part  $(y_{(i)})_{i \in \{43, \dots, 61\}}$  is again estimated with ML estimation, linear regression, and with the Hill estimator; see Figures 10 and 11. This suggests the estimates

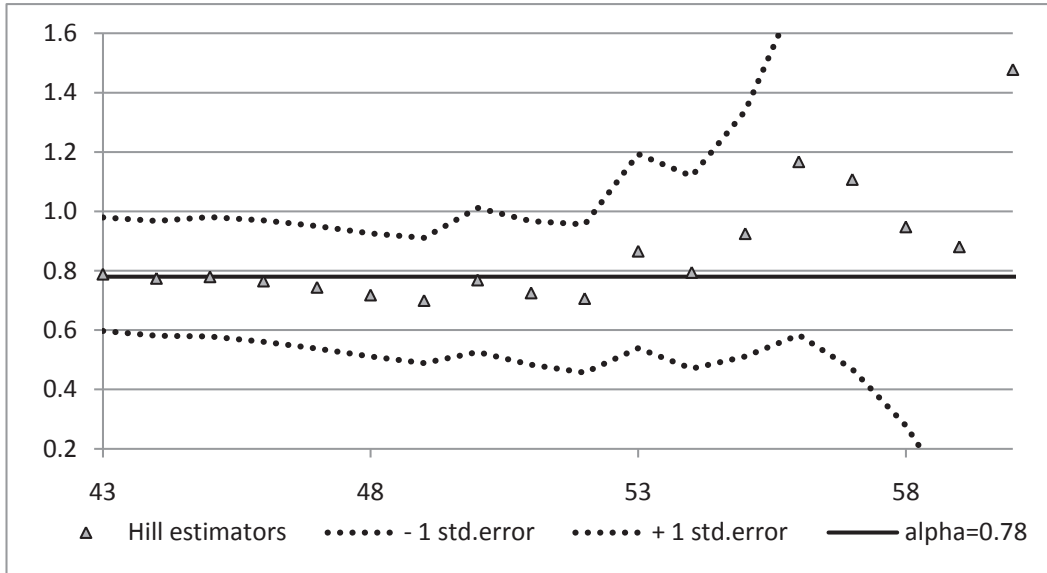
$$\begin{aligned} \hat{\alpha}^{\text{MLE}} &= 0.7885 \quad (19.12\%), \\ \hat{\alpha}^{\text{regr}} &= 0.7248 \quad (1.91\%), \\ \hat{\alpha}^{\text{Hill}} &= 0.7800. \end{aligned}$$

Thus, if we only consider the 19 largest losses we obtain a slightly less heavy-tailed distribution, but it still has an infinite mean.

Finally, we apply the POT method to the estimation of the slope parameter  $\alpha$ ; see Section 7.4.2 in McNeil et al. (2005). Although this method considers a slightly different loss-severity distribution (generalized Pareto distribution), it gives additional insight into the estimation of  $\alpha$  because it also considers a slope parameter. Using the POT method from all data we obtain

$$\hat{\alpha}^{\text{POT}} = 0.7271,$$

which supports the estimates obtained from the other methods.



**Figure 11:** Hill plot for  $\alpha$  based on the observations  $(y_{(i)})_{i \in \{43, \dots, 61\}}$  together with  $\pm 1$  std. error bounds.

### 4.2.3 Final Model for the Loss-severity Distribution

We separate the loss-severity distribution into two parts. For a loss  $y$  in the interval  $[u_1, u_2] = [2 \times 10^7, 1.5 \times 10^8]$  we choose

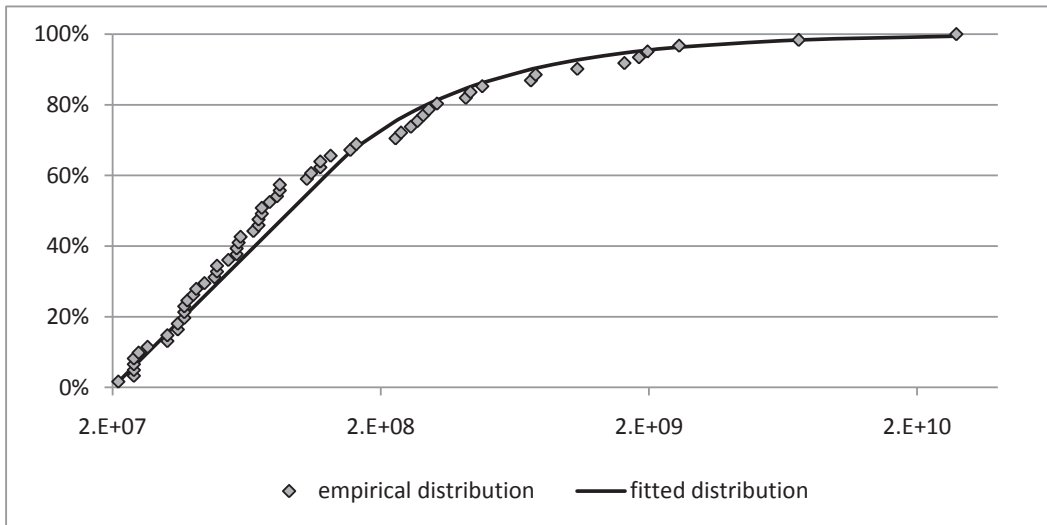
$$F(y) = \mathbb{P}[Y \leq y] = \pi \frac{\log(y/u_1)}{\log(u_2/u_1)}, \quad (4.3)$$

with  $\pi = 66\%$  (which equals the empirical probability of losses below  $u_2$ ). This choice provides a straight line on the log-log scale and a continuous continuation to the following distribution for the tail. For  $y \geq u_2$  we choose

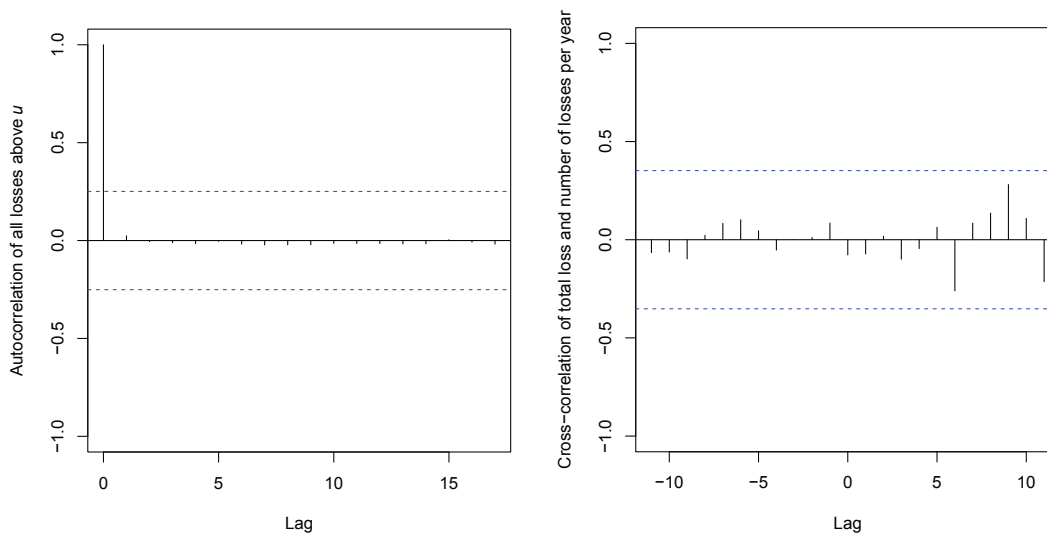
$$F(y) = \mathbb{P}[Y \leq y] = \pi + (1 - \pi)(1 - (y/u_2)^{-\hat{\alpha}}), \quad (4.4)$$

with Pareto parameter  $\hat{\alpha} = 0.7800$ . Figure 12 shows the resulting estimated loss-severity distribution together with the empirical loss-severity distribution.

**Remark 4.2** Before we continue, let us briefly address the model assumptions. To investigate the serial correlation between the losses above the threshold, we plot the autocorrelation function; see Figure 13 (left). For investigating the correlation between the total loss per year and the number of losses per year (two time series of length 31), we utilize the cross-correlation function; see Figure 13 (right). Both plots indicate no contradiction to the model assumptions. Also note that the correlation between the latter two time series is  $-0.0770$ .



**Figure 12:** Empirical and fitted loss-severity distribution  $F(y) = \mathbb{P}[Y \leq y]$ .



**Figure 13:** Autocorrelation function of all losses above the threshold  $u = 2 \times 10^7$  (left) and cross-correlation function of the total loss per year versus the number of losses per year (right).

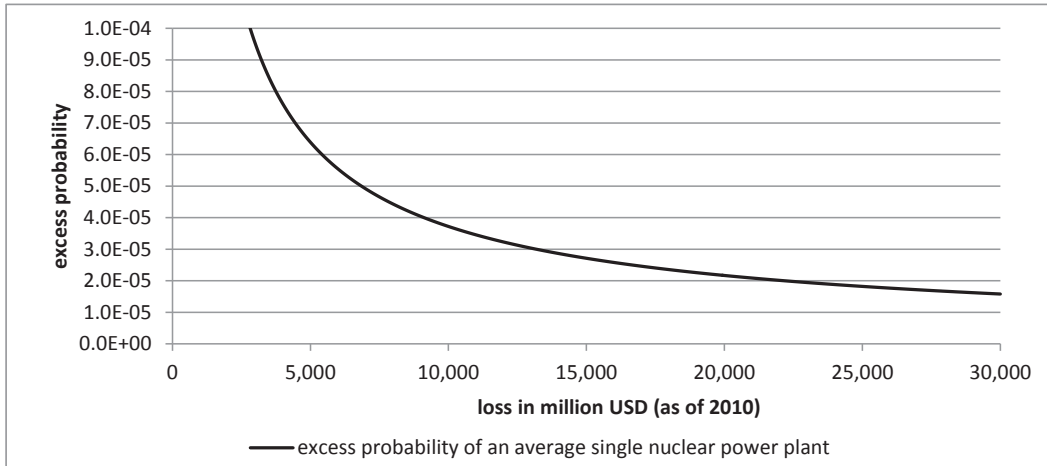


### 4.3 Annual Loss Distribution of Nuclear Power Accidents

Next we merge the annual loss-count distribution and the loss-severity distribution. We consider an average single nuclear power plant. We assume that this power plant has an annual loss  $S_t^{(m)}$  in year  $t = 2012$  which is independent of the other nuclear power plant losses and has a compound Bernoulli distribution with

$$S_t^{(m)} \stackrel{d}{=} Y \mathbb{1}_{\{B^{(m)}=1\}}, \tag{4.5}$$

where the loss  $Y$  is distributed according to Eqs. (4.3)–(4.4) and  $B^{(m)}$  is Bernoulli distributed with default probability  $p = 1 - \exp(-\lambda)$ , where  $\lambda > 0$  is estimated by Eq. (4.2). The resulting excess probabilities (i.e.,  $\mathbb{P}[S_t^{(m)} > x]$ ) for losses  $x$  greater than 20 million USD are presented in Figure 14. It turns out that based on histor-



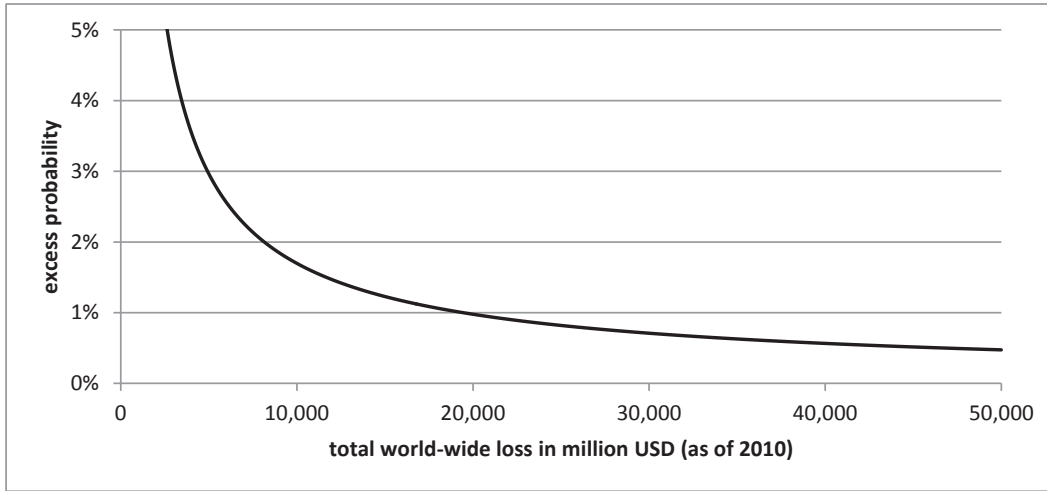
**Figure 14:** Annual nuclear power loss distribution for an average single nuclear power plant: estimated excess probability curve.

ical data, we judge nuclear losses much less optimistic. For example, the annual probability of a loss exceeding 10 billion USD for this average nuclear power plant is estimated by approximately  $3 \times 10^{-5}$ .

**Remark 4.3** We (can) only give annual nuclear loss distributions for an average nuclear power plant. Our analysis of historical nuclear power accidents did not respect local safety standards, plant location, or other factors that determine the loss distribution of a particular power plant. Therefore, our analysis only holds for an average nuclear power plant and the loss distribution of a particular power plant may very well differ according to relevant factors. However, if we aggregate over all nuclear

power plants that are in operation we obtain the correct overall annual nuclear loss distribution from this approach, if the composition of the portfolio remains stable; see Proposition 3.3.4 in Mikosch (2006). This stability may be questioned because types of power plants, etc., may change over time. Nevertheless, it gives reasonable ranges based on statistical analysis.

If we aggregate over all  $w_{2012} = 443$  nuclear power plants that are in operation in 2012, we can predict the aggregated annual nuclear loss in 2012 by



**Figure 15:** Total annual nuclear loss distribution aggregated over all nuclear power plants in operation in 2012: losses in million USD (as of 2010) and corresponding estimated excess probabilities.

$$S_{2012} \stackrel{d}{=} \sum_{i=N_{2011}+1}^{N_{2012}} Y_i = \sum_{i=1}^{M_{2012}} Y_{i+N_{2011}}, \quad (4.6)$$

i.e., by a compound Poisson distribution with annual loss-frequency parameter estimate  $\hat{\lambda} = 0.290\%$ , see Eq. (4.2), and loss-severity distribution of  $Y$  given by Eqs. (4.3)–(4.4). The resulting annual excess probabilities of the total nuclear losses aggregated over all nuclear power plants world-wide are presented in Figure 15. The graph suggests that for 2012 there is an estimated annual probability of 1% that we observe nuclear power accident losses exceeding 20 billion USD.

## 5 Conclusions

The data-based analysis carried out suggests an infinite mean model for the modeling of loss severities from nuclear power accidents. From a risk management and

insurance point of view, this implies that an unlimited insurance cover against nuclear power plant accidents cannot be financed. As stated in Wikipedia (2011a), nuclear safety should either reduce the frequency of nuclear power accidents or limit their consequences. Although this is obvious, and indeed highlighted in the conducted analysis, nuclear safety should focus on limiting the consequences of nuclear power accidents (due to the infinite mean model for loss-severities).

Note that the excess probabilities for nuclear disasters that were found in the present statistical analysis are (by far) less conservative than the figures mentioned in the introduction. Annual probabilities of nuclear disasters for an average single nuclear power plant are of order  $10^{-5}$ . This implies that, world-wide, the annual probability of a nuclear disaster is estimated to be between 1% and 2%. These are rather lower bounds due to missing data from several areas and due to expected growth of the number of nuclear power plants in developing countries.

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