Qualitative Operational Value at Risk for an Electric Utility based on the Guidelines of the Basel Committee

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Abstract

***Purpose*:** This paper presents a model for determining value at operational risk "OpVaR" in electric utilities, with the aim to confirm the versatility of the *Bank for International Settlements* (BIS) proposals. The model intends to open a new methodological approach in risk management, paying special attention to underlying operational sources of risk.

***Methodology/Approach*:** The aim of this article is to systematically analyze the primary sources of operational risk in the electric industry. The analysis is based on questionnaires handed over to both management and operational workers.

The paper presented herein is primarily supported by qualitative methods based on expert decision arrays for identification and risk assessment applying the suggestions of the Basel Committee.

Another aim is to establish a measure of risk assessment expressed in electrical terms (MWh) which are not affected by macroeconomic values over time.

The proposed model comprises the following steps:

i. Interviews with managerial and technical staff.
ii. Techniques for collecting and analyzing information to identify critical process areas.
iii. Transform qualitative data to quantitative data using a Likert scale.
iv. Design of Cross Flowchart for critical processes.
v. Identification of activities and operational risk assessment.
vi. Top-Down and Bottom-Up Risk Analysis.
vii. Compound Operational Loss Models and Derivation of Operational Value at Risk.

***Findings*:** In the electric utilities under study, the Lognormal distribution is the best option for describing the operational loss magnitudes and the Poisson distribution is the best option for describing the operational frequency magnitudes.

The “Loss Distribution Approach” is modeled with the convolution of frequency distribution (Poisson) and severity distribution (Log-normal) implementing Monte Carlo’s simulation for a sample of observations of the Loss Distribution. The convolution allows us to obtain the VaR for 99.9% percentile of the Loss Distribution Approach.

The metrics of the banking industry are then transformed into energy parameters that make it possible to determine the maximum amount of loss that is expected to occur over a pre-specified time horizon at a pre-specified confidence level.

In the electricity utility under study, it is found that the nature of operational risk is crucially linked to internal processes (people and systems seem to have little impact) and external events.

Furthermore, the quality processes already developed by the company are fully integrated together with the complementary assessment of operational risk arising from the Basel Accord financial framework in order to yield a unified model for the whole operational risk of the company.

***Research limitations/implications*:** The operational risks were typically studied by the financial sector and an important part of this study’s contribution is to present how methodologies to detect operational risks can be implemented in companies of non-financial sectors. In this paper this has been applied to electric power companies.

***Originality/Value of paper*:** The model manages to merge methods commonly used in engineering or technical firms with a model originally designed for the financial system (Total Quality Management, Crisis Management Plan and Operational Risk Management).

Another contribution of this paper is that it can express the operational value at risk in electrical units such as Megawatt-hours (MWh). These units are unaffected by fluctuations of macroeconomic variables such as currency exchange rates controls and inflation among other. Thus, when international financial agents try to analyze the time series of operational risks abroad, they only need to transform data in MWh to monetary units and they can establish a more realistic value about of the phenomenon or problem under study.

At the time this analysis was performed the usual approach was to use time series of risk variables. However, when quantitative data of operational risks do not exist or when are scarce then it is necessary to obtain qualitative data based on experts’ decision to understand the behavior of the OpR. The qualitative methods just started to be implemented seriously in the financial system after the global financial crash of 2008. Therefore this article introduces a financial innovation because it presents a study based on qualitative data from surveys that were made by experts.

The versatility of the Monte Carlo method in the calculation of value at risk, when data comes from qualitative variables has been proven.

***Keywords*:** Operational risks, Basel Committee, Electric utilities, Value at risk.

Introduction

“The story of this storm in the global markets is the story of how the government intervened to solve the previous crisis and laying the foundation for a new one” (Norberg, 2009). Following the same author, the government’s mismanagement of the crisis did not help and we are now dangerously repeating many similar mistakes that were made such as an errant monetary policy, lack of good subprime policy, and not yet properly regulated financial innovations.

At the beginning of the twenty-first century, the dot-com bubble (Mandel, 2000; Lowenstein, 2004) was further complicated by the collapse of the giant Enron (Steffy, 2013; Sterling, 2002) and world trade center attacks in NYC (Jorion, 2007), thus resulting in an acute financial crisis; a new bubble was then generated, the subprime bubble (Shiller, 2008) that broke out as expected in early 2007 as governments, private companies, families and individuals acquired huge debts they could not repay. The US increased its debt in just 5 years by an amount equivalent to what was borrowed in 200 years; similar cases occurred in Spain, China, Greece, Qatar, UAE, etc.

This crisis still persists; however, the solution offered by most governments has been to increase or drastically reduce public spending, nationalize or inject multimillion amounts to banks, which generally involve foreign borrowers in countries around the world; USA, for instance, has doubled its foreign debt in just 4 years, increasing jobless ratios at the same time. Similar situations occurred in countries with higher country risk: Venezuela, Greece, Ireland, Portugal, Italy, Spain, etc., pushing an array of bankruptcy of companies, banks, and other business. This has entailed a higher risk of bankruptcy of entire countries like Greece, Portugal and Spain, among others. This debt crisis may last for many years although strong measures are being undertaken to lessen their potentially catastrophic effects (Norberg, 2009).

It should seem that the world's governments do not properly address suggestions from experts like the Basel Committee among others that intend to make continuous improvements in processes, seeking the root of the problems and tackling long term solutions.

This paper presents a model for determining Operational Value at Risk “OpVaR” (Jorion, 2008; Chernobai et al, 2008) in electric utilities, with the aim to confirm the versatility of the *Bank for International Settlements* (BIS) proposals (BIS, 2011a; BIS, 2010). The model intends to open a new methodological approach in risk management, paying special attention to underlying operational sources of risk.

Preliminary Results

Exponential, Log-normal, Weibull, Gamma, Generalized Pareto, and Burr distributions were used in order to fit the loss distribution or severity. Poisson, Geometric, Binomial and Negative Binomial were used in order to fit the frequency distribution, (Chernobai et al, 2008; Gregoriou, 2009 and Jorion, 2007). In the electric utilities under study, the Lognormal distribution is the best option for describing the operational loss magnitudes and the Poisson distribution is the best option for describing the operational frequency magnitudes.

The “Loss Distribution Approach” is modeled with the convolution of frequency distribution (Poisson) and severity distribution (log-normal) implementing Monte Carlo’s simulation (Sobol, 1975) for a sample of observations of the Loss Distribution. Figure 1, shows how this convolution allows to obtain the OpVaR to the 99.9% percentile of the Loss Distribution Approach.

The metrics of the banking industry are then transformed into energy parameters that make it possible to determine the maximum amount of loss that is expected to occur over a pre-specified time horizon at a pre-specified confidence level.

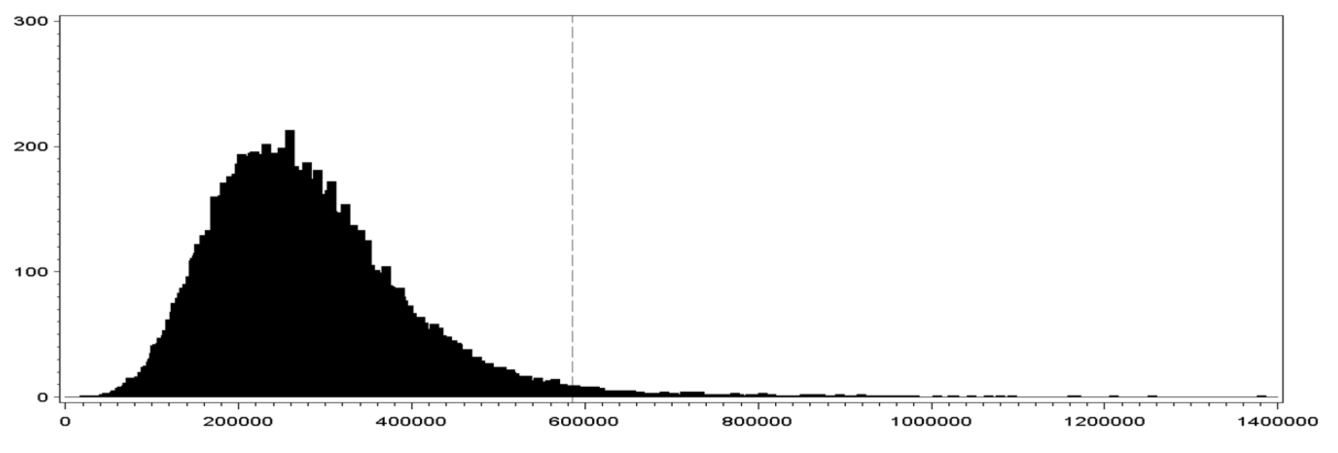

Fig. 1. Loss Distribution Approach
Source: Peña et al. (2013)

In the electricity utility under study, it is found that the nature of operational risk is crucially linked to internal processes (people and systems seem to have little impact) and external events (Fig. 2).

Furthermore, the quality processes already developed by the company are fully integrated together with the complementary assessment of operational risk arising from the Basel Accord financial framework in order to yield a unified model for the whole operational risk of the company.

Practical and Social implications

The operational risks were typically studied by the financial sector and an important part of this study's contribution is to present how methodologies to detect operational risks can be implemented in companies of non-financial sectors. In this paper this has been applied to electric power companies.

Operational Risk

The formal definition of operational risk that is currently accepted was proposed by the *BIS* (*BIS*, 2011a) as follows: *Operational risk is the risk of loss resulting from inadequate or failed internal processes, people or systems, or from external events*.

The topology of Operational Risks, adapted from BIS definitions for an electricity utility, is summarized in Figure 2.

Under the advanced measurement approach of the Basel II & III Accord, banks are required to measure their total annual operational risk exposures (Gregoriou, 2009; BIS, 2011b).

Operational Value at Risk (OpVaR)

The concept of value at risk (VaR) has been generally used as a measure of market risk (Jorion, 2008), however, it has also been commonly implemented as a measure of operational risk in the present century (BIS, 2001a).

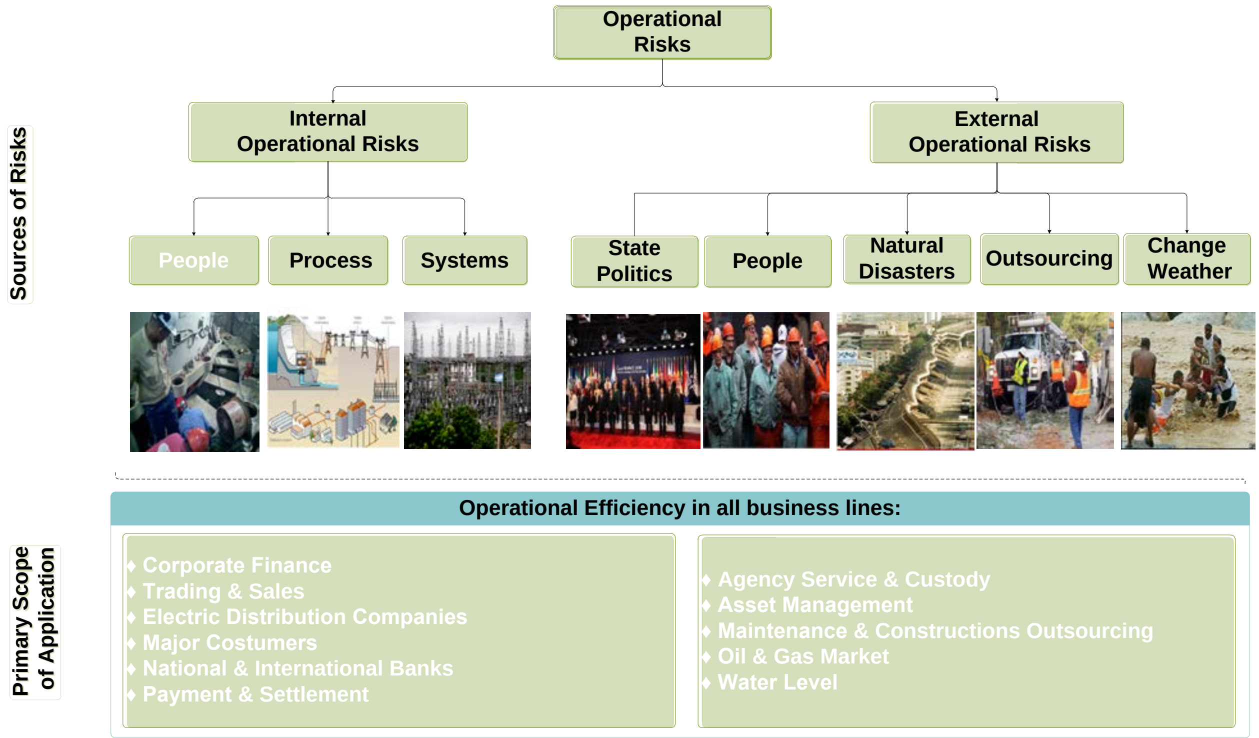

Fig. 2. Topology of Operational Risk in Electrical Corporation.
Adapted by: Authors (2011).

VaR, called OpVaR when it involves operational risks, is a statistical estimate that indicates the maximum predicted loss, in monetary units, of a market position within a time horizon and for a given confidence interval (BIS, 2001b).

The Basel Committee (BIS, 2006) indicates that, in the case of operational risk, estimations must be referred to a time horizon of one year.

(BIS, 2006) establishes a 99.9% confidence interval for financial companies; however, (Jorion, 2007) suggests to establish it at 95% for non-financial companies. The present work uses both confidence intervals for the sake of clarity.

BIS, (2001a) proposed the Lognormal distribution to approximate the severity and the Poisson distribution to fit the frequency. However, (Chernobai et al, 2008) proposes a series of distributions to find the best fit given the historical data of the company. For frequency distributions they suggest Binomial, Poisson, Negative Binomial and Geometric; impact distribution functions suggested are Weibull, Log-normal, Gamma, Beta and Exponential.

The World Financial Crash, BIS, (2009) has refocused the studies form mainly time series analysis to qualitative studies, the latter being based on expert's opinions as they believe this is the only way to grasp understanding of low frequency events of low frequency and high impact such as the aforementioned crisis.

Monetary units have been always considered as the underlying measure for performing a VaR analysis. An important turning point proposed by the authors of this paper is to change, precisely, the commonly accepted metrics: Instead of a monetary unit, a simple measure is proposed to quantify and independent of each country's macroeconomic variables (inflation or exchange rate, for instance). MWh is the proposed metrics, which can be used to analyze the results from any country or area irrespectively of its macroeconomics (Peña et al., 2013).

To estimate the OpVaR, Chernobai et al, (2008), BIS, (2001b) & Jorion, (2008) propose various techniques such as those summarized in Figure 3. BIS, (2011b) suggests Advanced Measurement Models Approach (AMA) and the Loss Distribution Approach (LDA) as the most accurate and sophisticated models to forecast the OpVaR. The authors have thus adopted this methodology.

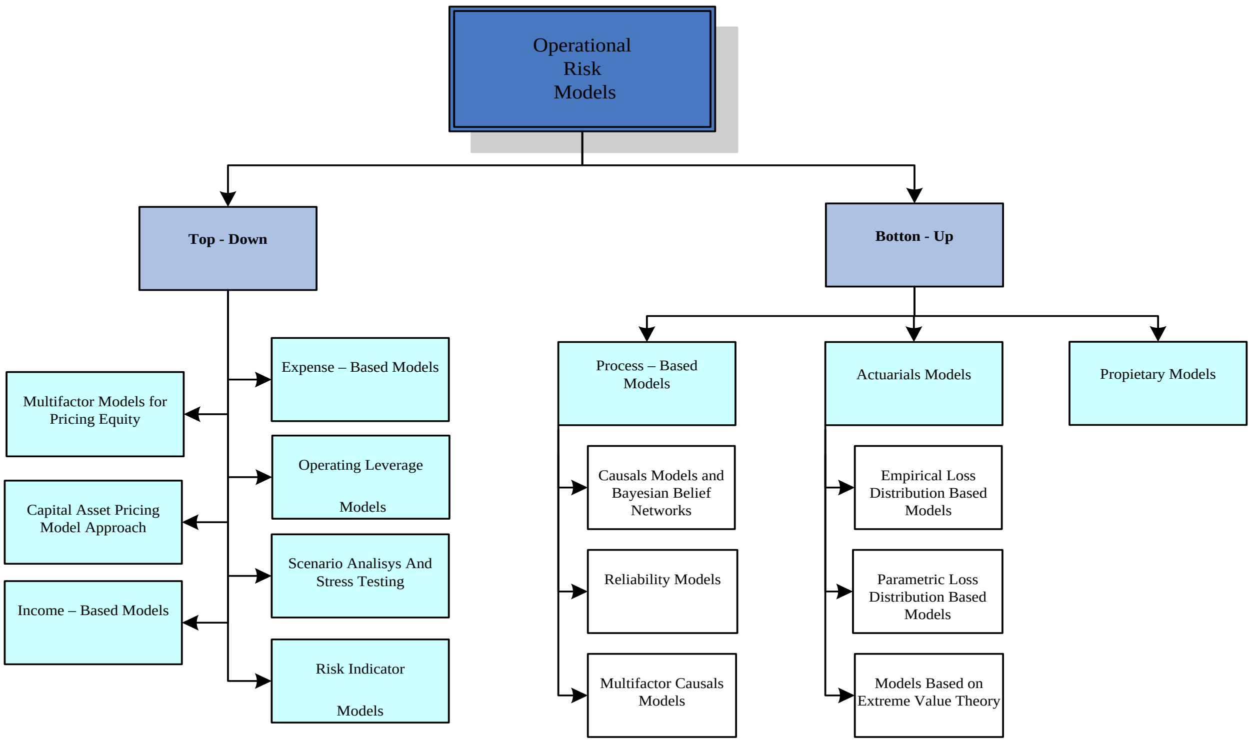

Figure 3. Topology of Operational Risk Models.
Source: Chernobai (2008)

Gregoriou, (2009), Jorion, 2007 & Delgado, (2002) suggest the Monte Carlo method (Sobol, 1975) as the most accurate one to calculate the LDA, to which convolution of the probability distributions should further be implemented (both for frequency and severity distributions).

The following section presents the technique which has been implemented to obtain the qualitative data of frequency and severity based on experts' opinions in a studied case of the electricity industry, although this does not limit the application to other industries.

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Qualitative Operational Risk Measurement

These are simple techniques designed by authors from BIS suggestions (Gregoriou, 2009). Basically the authors carried out a deep investigation about internal and external activities, processes, systems and others considerable issues inside the organization.

This article describes risks associated and the experts should expose their impressions and opinions with a Likert scale (Sampieri, 1995) predefined about frequency and losses of operational risk detected. See Table I to review the application on real case.

Table I. Adaptation of Frequency and Loss to Likert Scale

Lickert Scale	Loss [MWh]
1	1000
2	5000
3	10000
4	30000
5	60000
6	100000
7	300000

Lickert Scale	Frequency
1	1
2	2
3	4
4	8
5	12
6	16
7	20
8	24
9	28
10	32
11	36
12	40
13	44
14	48

Source: Peña et al. (2013)

This arrangement is generally dimensioned with M files and N columns, therefore it is a rectangular matrix M x N. It generally has one level where the information provided about the risks and its associated activities are described.

Likewise to the previously described matrices, the number of people surveyed is associated to the number of experts who have done the arrays. In the Table II, expert´s numbers were 58 and were reviewed more than 200 operational risks with this technique.

Table II. Applying Qualitative Operational Risk Measurement – Real Case

Comparison among management levels	
1	Much less important than
2	Less important than
3	Moderately Relevant than
4	More important than
5	Much more important than

# OpR	Activity Name or Process Name	Operational Risk (OpR) Name	Operational Risk (OpR) Description	OpR Atributes	OpR Categories	Average Frequency	Average Severity
R1	Forecasting Energy Monthly Sales	Forecasting Energy Monthly Sales Erroneously	This OpR is caused for external events or fortuitous events since its occurrence is associated with biggest costumers do not meet their plans and energy consumption programs as result of reducing their production, fluctuations in its market, internal process failures, variations in their maintenance plans, deviation in the planning of rotating equipment and production units, strikes, reduced shifts, climate change, new laws or decrees among others.	Practices of customers, products and business unsuitable	External Event	2	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
R35	Procurement Management and Storage Management	Not to Dispose Fixed Assets	Delays occurs in retirement of fixed assets (equipment or equipment's parts) or smoothly, mainly due to theProcurement Management and Storage Management processes has many bottlenecks.	Clients, products and business practices	Process	7	3
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
R45	Manage Applied Research	Manage Applied Research Erroneously	This OpR are produced when research projects are not aimed at improving or optimization to the organizational neuralgic processes.	Internal Fraud	Process	7	5
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Source: Peña et al. (2012)

The following section explain how was applied according to the methodology of this paper in electric utilities.

Applying Methodology to know OpVaR

There were carried out cross-functional diagram, in which it was stabled the most critical flow charts of the process based on the interview with the experts and the information of the quality management system, where it was explained the risk, the associated activities *and finally it is propose a chart with the expert qualitative estimate of the frequency* range and impact of operational risks according to the proposed by (Gregoriou, 2009).

Figure 4 is obtained after applying the previously described procedure for all the risks involved. It can be observed in this imamogram (Martínez, 2004) with the preliminary data how the sources of the operational risks are unequally distributed among external events, human resources, technologies and processes. "External Events" with 35% and "Processes" with 34% of the total operational risks are therefore the first data to be analyzed in order to design the strategies that will minimize the OpR in the enterprise under study according to BIS suggestions.

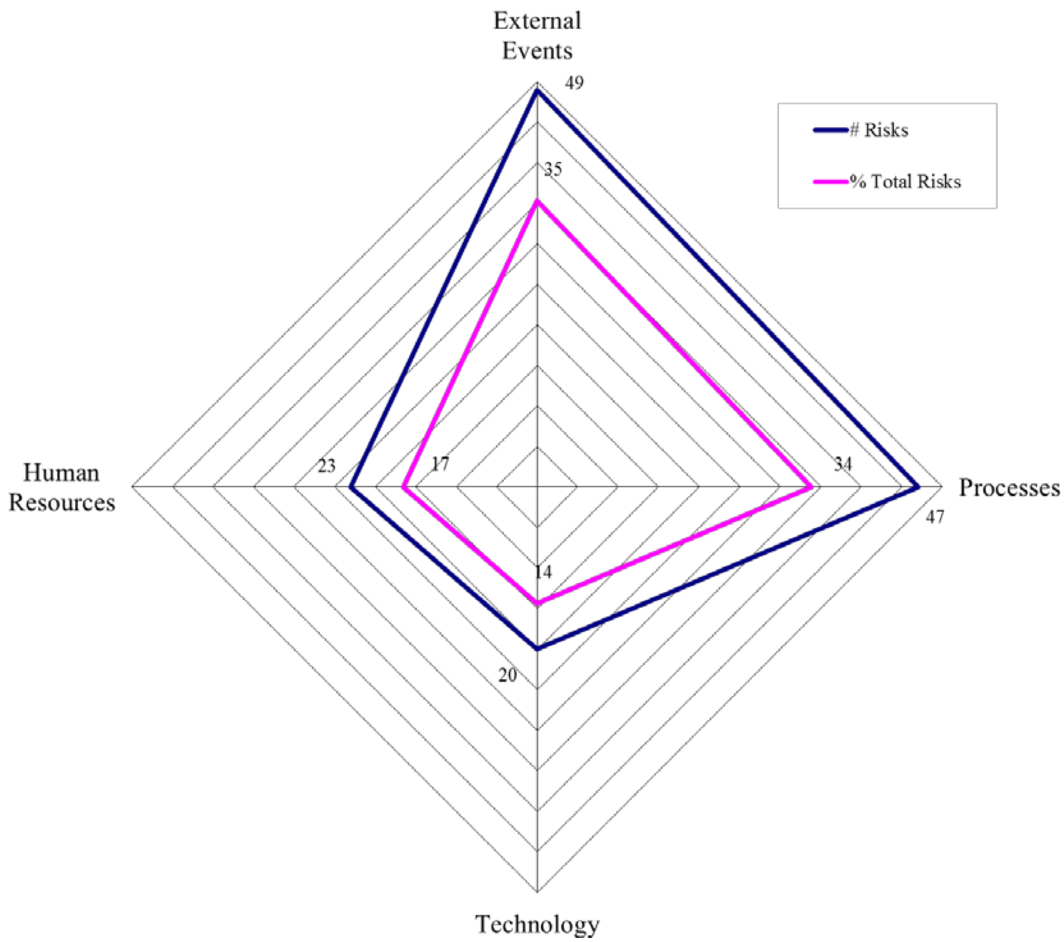

Figure 4. Risk Imamogram
Source: Authors

In general, two kinds of models are implemented to value the operational risk: Top down & Bottom up Approach presented in Chernobai et al (2007) and Delgado (2002) and Figure 3. Nevertheless Fernández (2010) and BIS (2010) establish that the actuarial models of advanced measurement (AMA: Advanced Measurement Approach) like Bottom Up are shown as the ones that allow more accurate values and less clumsy than Top Down, which is based on the unrealistic hypothesis that the operational risks increase proportionally with the overall income.

Alexander (2004) defines the events that should be mainly important, but regrettably the data is bound to be subjective due to the fact they come from either expert's opinions or else risk – self assessments which have a high level of uncertainty.

To apply this qualitative value the operational risks are classified in function of the frequency: The event's loss numbers which happen in a determine period of time are estimated in a year according to BIS (2011a).

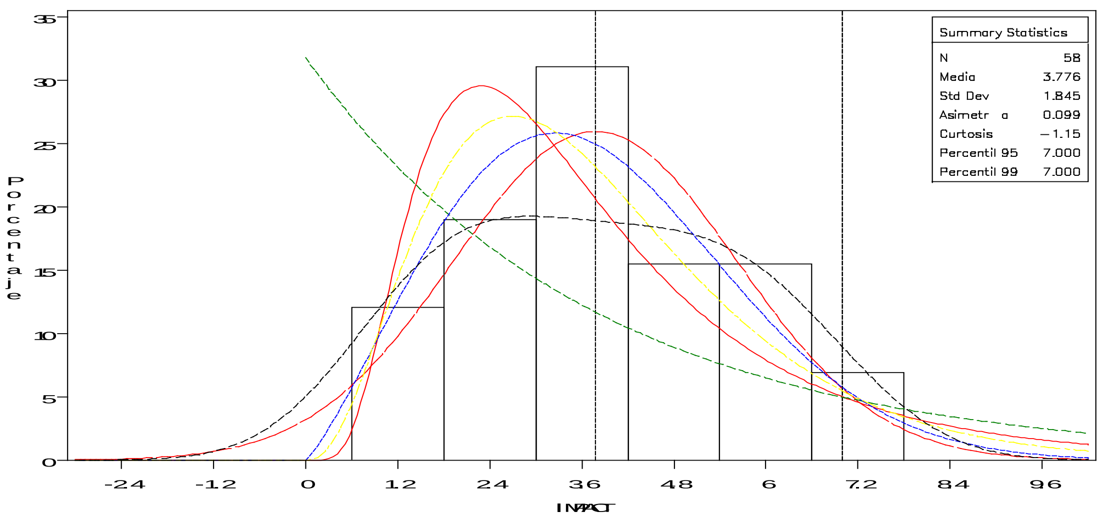

Figure 5. Severity Distributions Statistical Fit
Source: Authors

Chernobai et al (2007) and Jorion (2007) propose that normal probability distributions, binomial, geometric, Poisson, negative binomial and the mixture among them such as the normal distribution, exponential, log-normal, Weibull, gamma, beta, Pareto and Burr like the typical to describe the severity's behavior or impact.

In SAS (2004) and (2008), the applied methodology is presented as soon as the SAS 9.2 software is implemented to make an adjustment in these distributions. In the figure 5, an example of this proof has been done to show a risk's severity.

Similarly this test was done for the frequency and for each operational risk.

The aforementioned statistical fit allowed to confirming Gregoriou (2009), Alexander (2004) & BIS (2001c) proposal, because most of the frequency's probabilities distribution behave as a Poisson distribution and severity's probabilities distribution behave generally as a Weibull or Log-normal distribution [Fernández, (2010); Walpole et al, (2007) & Montgomery (2003)].

Gregoriou (2009), Chernobai et al (2007), Jorion (2008) and Morgan (1996) propose the method of calculation of value at risk (VaR) like the most practical an assertive way to establish the exposure levels to risk. Additionally, (Gregoriou, G., 2009) states that having a qualitative analysis, the OpVaR is possible to determinate through the convolution of probability distribution of frequency and loss.

To calculate the previously described convolution is necessary apply Montecarlo method presented by Hillier (2006), Rubinstein (1981) and Sobol (1976) that among many others such as Jorion (2008) is proposed as the most effective and exact to the value at risks calculation.

Alexander (2004) proposes an algorithm to determine the Loss Distribution Approach which is an AMA- Bottom-Up model (BIS, 2010) considered to be among the best in the financial sector and for this reason it has been chosen to determine the OpVaR in this study.

Gregoriou (2009) presents the distribution's equations:

The total loss in the time interval [t; t + τ] for element i, j is thus given by the random variable:

$$L_{i,j} = \sum_{n=0}^{N_{i,j}} \xi_{i,j;n}$$

$G_{i,j}$ is defined as the cumulative distribution of $L_{i,j}$. Then it is known:

$$G_{i,j}(x) = \begin{cases} \sum_{n=1}^{\infty} P_{i,j}(n) F_{i,j}(x)^{[n\otimes]}, x>0 \\ x=0 \end{cases}$$

Under this framework, the expected loss is:

$$EL_{i,j} = E[L_{i,j}] = \int_0^{\infty} x dG_{i,j}$$

and the unexpected loss at a confidence level a is:

$$UL_{i,j;\alpha} = G_{i,j}^{-1}(\alpha) - E[L_{i,j}]$$

Despite the Basel Committee's recommendation to calculate the capital charge, K, using Ki, j ;α = ULi, j ;α institutions tend to use:

$$K_{i,j;\alpha} = UL_{i,j;\alpha} + EL_{i,j} = G_{i,j}^{-1}(\alpha)$$

This has the advantage that K is a value at risk (VaR) measure (i.e., a quantile).

This has the advantage that K is a value at risk (VaR) measure (i.e. a quantile). The determination of the expected and unexpected loss and the quantile capital change that derives from the loss distribution is well represented in Figure 6.

This relation allows reassuring VaR will depend on a distribution's losses quartile and at the same time this quartile will be given according to BIS (2011b) a high confidence level of 99,9% or the most commonly used quartile of 99%. Companies in sectors different from the financial sector generally use 95%. This paper shows OpVaR for 99%.

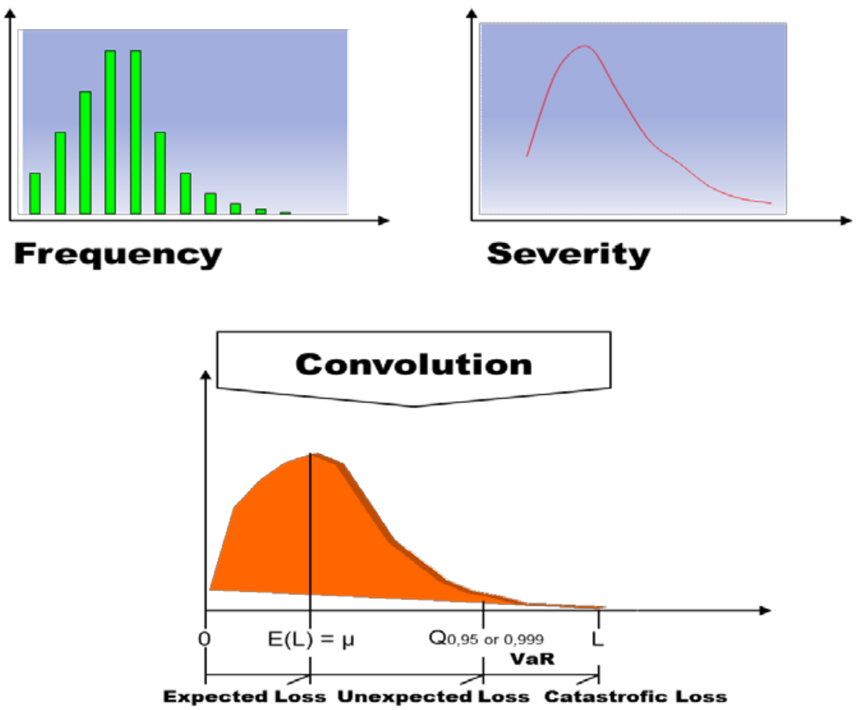

Figure 6. Loss Distribution Approach
Source: Chernobai et al (2008) & Gregoriou (2009)

In the figure 7, the methodology AMA-LDA has increased for a particular risk (R35). R35 is adjusted to a Poisson´s distribution to the parameterized frequency $\lambda = 19.13$. The loss was designed for a lognormal distribution parameterized $\mu = 9.07$ and $\sigma = 0.999$. Montecarlo´s simulation is used to find a sample of 1.000.000 observations from the Loss Distribution Approach (LDA) that it is a convolution of the frequency and loss or impact.

The Figure 7, shows the LDA resultant for R35, the dotted line points out the percentile 99%, coincident with the value P_{99} = 585.113MWH which is the OpVaR. The percentile 99.9 of the LDA is according to Jiménez (2011) matches Operational Value at Risk (OpVaR). Similarly it has been calculated for the remaining risks and Figure 7 has been obtained.

Gregoriou (2009) use of subjective information is based on expert knowledge. More precisely, the risk of each production process is valued by the respective process owner. To achieve this, standardized forms of information need to be used. The Complementary Loss Evaluation (CLE) procedure is based on a collection of subjective information through questionnaires, where all entries in the questionnaire are properly defined.

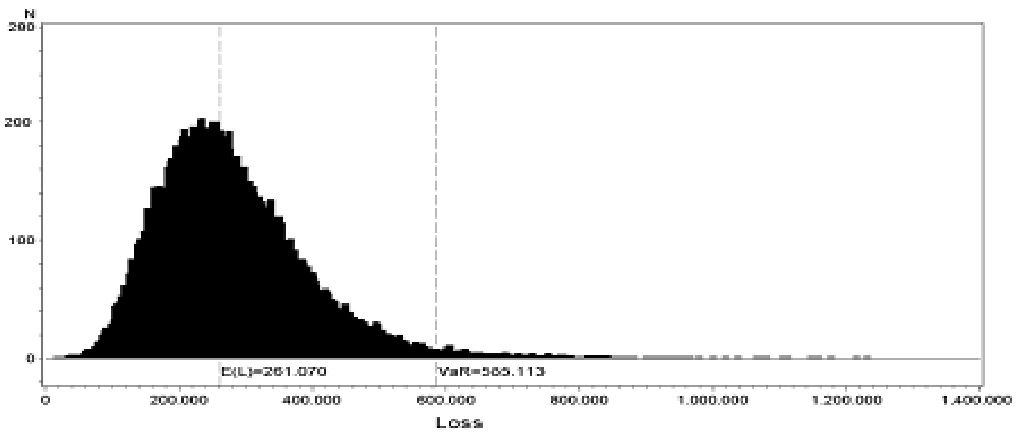

Figure 7. Loss Distribution Approach to R35
Source: Authors

Using expert data usually shall be considered that the data fully specify the risk information. The disadvantage of such data concerns their reliability. As Rabin (1998) demonstrates, people typically fail to apply the mathematical laws of probability correctly but instead create their own "laws," such as the so-called law of small numbers. Therefore, an expert-based database needs to be designed to circumvent the most important and prominent biases.

The CLE procedure is based on a collection of subjective information, conceived to:

- Reduce the freedom of evaluation left by ambiguous measuring scales, In order to do this, the questionnaire gathers quantitative information only.
- Contain the bias associated with subjective valuations. For this reason the questions focus on objective and easy-to-identify sizes.

Every unit manager completes the questionnaire, called Self Risk Assessment Questionnaire. The very first question examines whether a precise risk is present or not. In case of an affirmative answer, the manager is asked to provide personal valuations referring to a certain time-horizon and dealing with:

- Average frequency of the loss event
- Average severity of each individual loss
- Order of magnitude of the maximum severity of a loss event

To simplify answering, for each question the interviewee has to indicate the most suitable range of values. The experts were not choosing a number for a probability; rather they make a choice between different real life situations that are more unambiguously defined. For the severity self-assessment, the experts have to indicate both the mean and the maximum severity values in their respective processes.

The questionnaire approach aims at:

Obtaining a rating system for each operative unit indicating the risk level (unexpected losses) in a homogeneous way within the units in order to identify intervention priorities.

Getting an output that can be integrated with the results drawn from qualitative loss data. To do so, it is necessary an estimate of the expected loss (EL) and unexpected loss (UL) for each kind of loss, each risk factor and each organizational unit.

In order to obtain useful ratings, shall be considered a normalized measure of unexpected loss so that results from different operative units can be analyzed. Such normalization is achieved through dividing the unexpected loss by an exposure indicator (EI), which is, in line with the Basel Regulation, the gross income. The domain of the normalized unexpected loss (UL/EI) is then cut into several ranges, each of them representing a rating class. See Table III.

Table III. Rating class of Operational Risk

Class	Ranges	Situation comments/taking action
A	0%<UL/EI<10%	OK: Optimal situation, minimum operational loss risk
B	10%≤UL/EI<20%	ALERT: this state means a first alert signal
C	20%≤UL/EI<40%	RM CHECK: the situation is getting dangerous and it would be better to check the processes than to consider a mitigation action
D	UL/EI≥40%	MITIGATION: the situation is critical enough to adopt a mitigation action

Source: Gregoriou (2009)

The CLE methodology uses four rating classes presented in Figure 8 based on Table III:

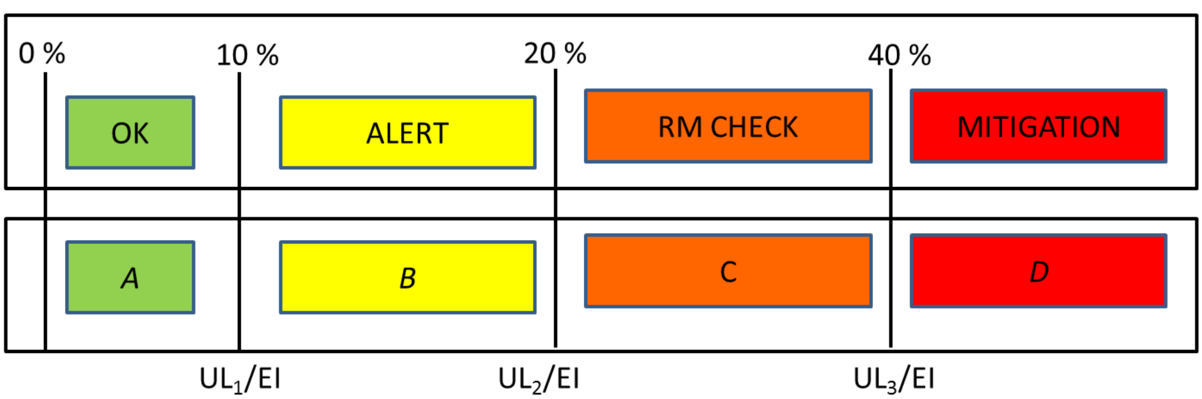

Figure 8. Rating class to making risk map
Source: Gregoriou (2009) and Chernobai et al (2008)

In such a framework, a benchmark value for the ratio UL/EI is 20% (value obtained by the Risk Management Group of the Basel Committee), which then represents the average systematic level. The UL values defining each single range are referred to the specific operative unit being investigated, and they aggregate all the risks the unit is exposed to.

Let us assume the cut offs are the same as reported in Figure 9 (0%, 10%, 20%, and 40%) and that the operative unit (OU) has a total gross income (GI). Dividing these thresholds by the number of risk typologies allows obtaining an approximation of the UL threshold values for each risk typology.

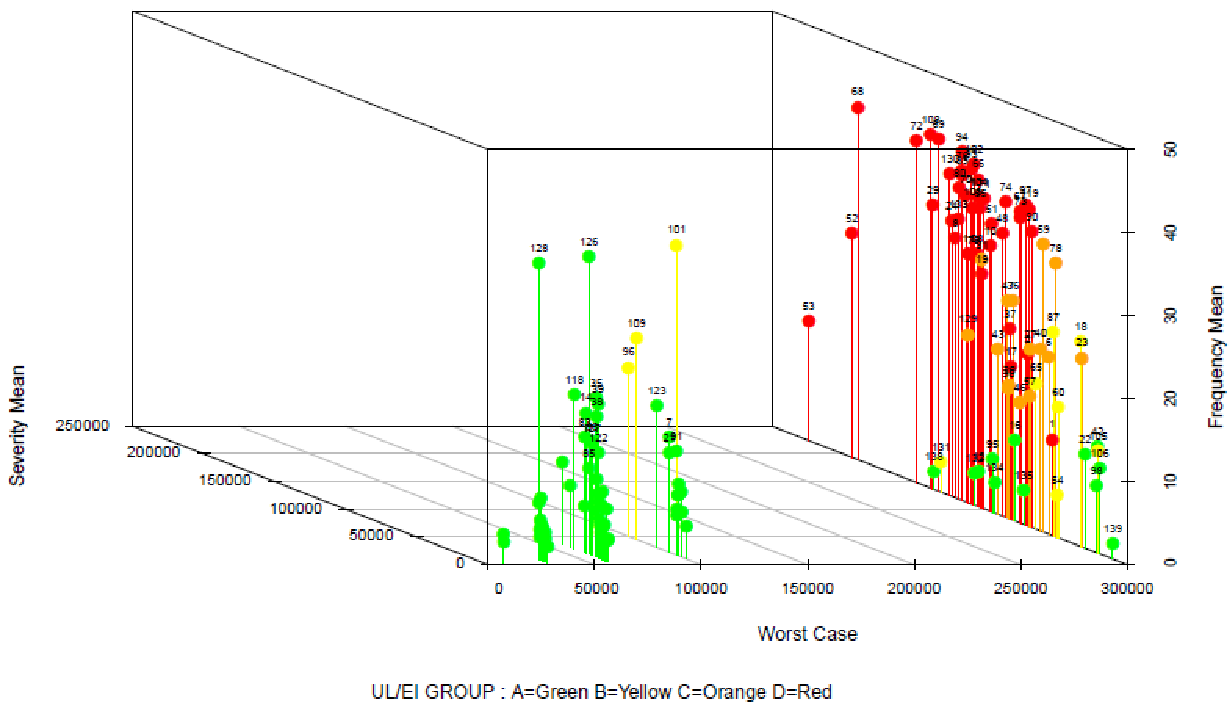

Figure 9. Preliminary Operational Risks' Comparison among frequency and severity and the worst case.
Source: Authors

The underlying hypothesis is that each risk has the same weight within the same operative unit. These weights basically describe the impact that each risk factor has on the riskiness of operative units. The assumption of uniform weights can be relaxed, whereby a specific weight reflecting the historical loss data can be applied to each risk factor. In this way can be dynamically adjust the weight and thus are able to capture a trend, if any, in the impact of each risk factor.

Figure 9 based on Table III shows how the risks have been classified in different groups. It is evident for this sample of risks that those included in the upper corner (R53, 52, 68, 72 and 108) are potentially the most critical ones because they represent the highest frequency and severity and also the worst cases according to the experts' opinion. Similarly, those risks in the lower corner are considered less critical and therefore left as a second choice at the moment of diminishing risk exposure.

Figure 10 shows the ranking of electric utility risks under study according to Figure 8: Green = Normal: UL/EI<10%, Yellow = Alert: 10%≤UL/EI<20%, Orange = Check:

20%≤UL/EI<40% and Red = Critical: UL/EI≥40% based on the criteria given on Table III.

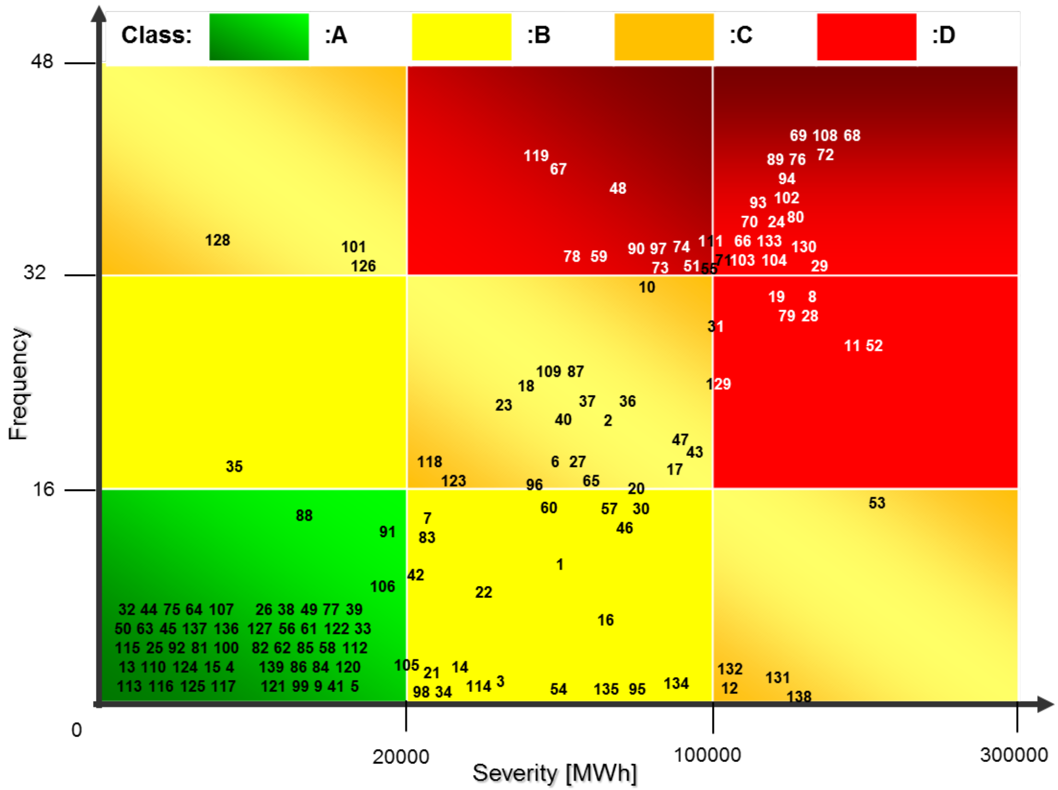

Figure 10. Risk Map
Source: Authors

Some results obtained in Figure 9 can be confirmed in Figure 10. For example, in this latter figure it is shown that operational risks identified as risks 68, 72 and 108 are the highest. These risks are therefore the first option to consider when implementing strategies to mitigate operational risks in the electric utility under study.

It is evident that risks 52 and 53 appear to be the worst cases according to Figure 9 but their UL/EI ratios are lower than those of other risks. Therefore, these risks would be a second priority when designing strategies.

Finally, it has been verified that crossing results shown in Figures 4, 9 and 10 the riskier areas and the highest operational risks in the organization under study can be detected

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