Improved Risk Analysis Through Failure Mode Classification According to Occurrence Time

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***Abstract*—Nowadays, risk-based asset management is commonly adopted throughout electricity utilities as a business model. Potential risks are registered, and after selection the influence of the risk is assessed. This paper discusses the possible shortcomings with regard to current risk assessment methods. Based on an improved risk assessment approach, it is shown that risk might be underestimated when the economic loss of failures are not incorporated in the assessment. Furthermore, with the advent of the intelligent networks of the future (intelligent grid), the more user-centric requirements should anticipate an improved risk assessment approach for asset management. Moreover, emerging dynamic pricing, demand-side-management, two-way information transfer, etc., might provide tools to measure the reliability indicator "Energy Not Supplied" even at distribution network levels. In this contribution, a case study of 50/10 kV transformer failures is analysed according to the failure occurrence time and loss of load. The results are applied as input for an improved risk assessment approach, which, ultimately, reveals that risks are likely to be underestimated. In conclusion, we show that without considering the occurrence time of failure, the risks of failures will be underestimated for 7% to 13%.**

Keywords- risk; failure occurrence time; asset management.

I. INTRODUCTION

Generally, the main objectives of power sector reform is to improve quality and efficiency levels [1]. Regulators are responsible for monitoring quality of supply and, additionally, promote high economic efficiency. To most customers, network reliability is important with regard to quality of supply. Therefore, network reliability is prioritised by regulators when starting regulating quality of supply. For Distribution Network Operators (DNOs), the most commonly used indicator for network reliability by European regulators are [1]:

- SAIDI (System Average Interruption Durations Index, which provides a measure of average time that customers are interrupted)
- SAIFI (System Average Interruption Frequency Index, which measures the number of outages experienced by customers)

Additional to legal obligations of the regulator, most DNOs employ detailed key performance indicators (KPI's) such as, causes of interruptions, worst served customer, etc. Regulators consider the DNO to be the responsible party for outages, as the DNO is the only party who could prevent the outage or limit their consequences [2]. However, the end-user of electricity can generally not be expected to be interested in the cause of an outage, as it is the end-result rather than the cause that would interest him. Literature shows [3] that the end-user is also interested in the timing of an outage i.e. the time at which the outage occurred. This has a direct impact on the costs.

Different customers (groups) value outages differently. Interruption costs are driven by a number of factors and has been extensively studied in literature [3]. Amongst others, one of the influencing factors is the timing, or rather occurrence time, of outages. Interruption costs varies in accordance to the time in the year, day in the week and time in the day. This is also dependent on the type of customer. For example, for residential customers, winter interruptions have higher impact than summer interruptions. Likewise, morning or afternoon interruptions are less costly than evening ones [3]. Yet, many European regulators have agreed to regulate DNOs on their average performance namely, SAIFI and SAIDI [4]. The disadvantage of averaging is that detailed information is lost e.g. when all failures are in the peak hours of the load, the amount of interrupted customer is the same when compared to the off-peak hours, however the economic value of the failures in peak hours is significantly higher. A potential method to avert this shortcoming might be to apply the "Energy Not Supplied (ENS)" rather than SAIDI/SAIFI as is done for example in Norway [5].

Usually, ENS is measured on transmission system level and, because of lack of measurements, it has not been extensively applied on distribution system level [2]. Meanwhile, the transition towards intelligent grids imposes significant challenges on network companies. While there is no single definition for intelligent grids, there is consensus that such a grid will be; user centric, and focused on outputs [3]. It is also accepted that the challenges will be different for transmission and distribution with the potential planning and operational changes being more significant for distribution networks. One of the main priorities for regulators is to focus more on the output of network operators [6].

With the advent of the intelligent grid and its capabilities, the asset manager will be expected to reconsider the way risks are assessed. This paper argues that the dynamic energy price (changing energy price according to demand, also known as demand-side management) in the scenario of an intelligent

This research has been performed in close collaboration with Stedin (a Dutch Distribution Network Operator, DNO) and reviewed by Dr. Viren Ajodhia (DNV KEMA).

978-1-4673-1018-5/12/$31.00 ©2012 IEEE

grid potentially creates hazards in the risk assessment process. In section II, we discuss that expected failure loss can be underestimated when the failure probability and consequences are positively correlated. This is typical when both demand and price for electricity increase simultaneously. In section III, an approach to address this problem is proposed. Here, failures are investigated, not only according to their technical cause, but also their occurrence time.

II. Asset Management

A. *Current Risk Assessment Approach*

Asset management (AM) is a discipline with growing importance in European utility companies [7]. In a utility company, the asset manager connects the asset owner, who operates and invests on the network, with the service provider, who maintains and monitors the components [7]. The goal of AM is to optimize the cost, performance and risks of the assets through proper decision making processes [7]. In today's AM, the process of "risk register" is commonly applied to understand the effect of failures on the company and the society. Typically, a category of failures is registered as a risk with information about the probability and consequences. Risks are compared to each other according to their expected loss, namely the product of multiplying probability (e.g. in figure 1) with consequence. The risk, is assessed through equation (1):

$$E(R) = E(F).E(C) \qquad (1)$$

where *E()* is the expected value, *R* is the economic output of the risk, *F* is the failure probability and *C* is the failure consequence. Risk assessment can be accomplished through applying risk matrix [9].

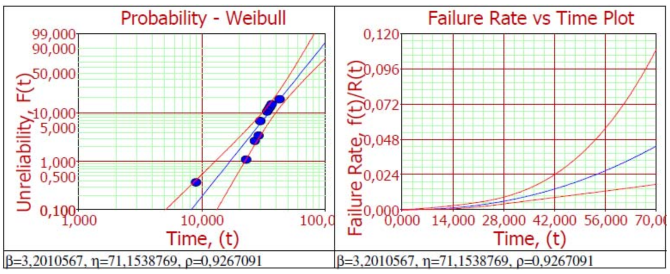

Figure 1: Example of fitting time-to-failure data into a Weibull distribution (in left figure) and estimating failure rate vs. service age (right figure) of distribution transformer [8]. The predicted failure rate can be further used in the "Probability" column of Table 1.

B. *Problem Statement*

The implementation of equation (1) is straightforward because of a practical reason: the occurrences of failures can be predicted scientifically by asset workers and service providers with technical backgrounds while the failure costs are predicted economically by stakeholder relationship departments of asset owners. Equation (1) is correct only when *C* is deterministic, or when *C* is a random variable independent from *F*. In other words, the risk will be overestimated when *F* and *C* are positively correlated and underestimated when they are negatively correlated. In the current situation, the uncertainty of *C* is mainly caused by mixing failure modes, i.e. failures of different causes and/or in different components are analyses as follows; their time-to-failure are fitted into a single probability distribution such as figure 1. Consequently, *F* and *C* are negatively correlated, because failures with larger impacts and/or components with higher ratings tend to occur less frequently. This leads to an overestimation of the risk, which is preferred by the asset manager rather than the opposite. However, in a future intelligent grid scenario with e.g. dynamic energy pricing, it is expected that a positive correlation between failure probability and consequence will occur. For example, in a high demand period, the price of energy will increase. As a result of the high demand (load), the temperature of assets is expected to increase, which ultimately accelerates aging and increases failure probability of power system components, such as cables, transformers, overhead lines, etc. Thus, one could argue that time intervals of higher prices tend to be linked with increased possibility of failures. Hence, a potential underestimation of risks according to current risk assessment methods. Therefore, the asset manager might need to apply modifications in the risk assessment.

C. *Research Approach*

In this contribution, a possible solution to deal with the preceding problem about risk assessment in the future is discussed. A case study with transformers at distribution level regarding their failure data and load profile data is analysed. In figure 2, the steps followed in this study are shown. The improved risk analysis is incorporated, shown in the orange boxes. The failure data for 50/10 kV transformers are divided into multiple groups according to the occurrence time of the failures. Similar to the grouping of the failures, the historic load data for the transformers is classified for the same occurrence time intervals.

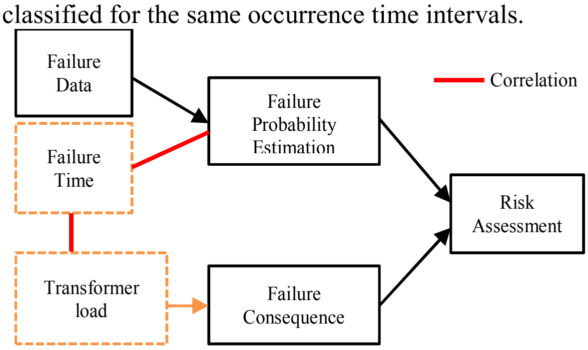

Figure 2: Research approach applied in this paper. The black boxes and arrows indicate the current Risk Assessment procedure. The orange boxes and arrows indicate the improved Risk Assessment.

III. Improved Risk Assessment

A. *Failure Data Analysis*

As mentioned previously, failure data of 50/10 kV transformers are analysed. Failure data for the period 2004-2010 was consistently available from a Dutch DNO. Instead of calculating the failure rates based on the physical cause of the failure, a correlation between the failure data according to the occurrence time (time of interruption) was considered. The authors prefer to estimate a failure rate invariant with the service age, because of two facts: Firstly, the failure data is available for only 7 years. This period is insufficient to reflect the aging phase of transformer lifecycle which is typically several decades. Secondly, the concern of this paper is to indicate the correlation between failures and their occurrence time. Therefore, the application of life data analysis, such as fitting time-to-failure data into a Weibull distribution is not necessary, since its output mainly reveals the aging of asset population at a yearly time frame.

The service-age-constant failure rate can be calculated as follows. Firstly, since failures before 2004 were not recorded, the operation time of the whole transformer population is neglected. 86 transformers have been operated between 2004 and 2010, and 2 new transformers were installed in 2009. Accordingly, the total transformer year number, label as n in the below equations, is 86*7+2=806. Naturally, the failure rate can be estimated as $k/806$, where k is the total number of recorded failures with specified occurrence time, in our case. Secondly, since the failure rate is constant, the total number of failures follows a binominal distribution. Since n is large, the binominal distribution is approximately a Poisson distribution. Therefore, the 90% confidence interval of the failure rate estimation can be calculated through the χ^2 percentiles in the two equations below.

$$LCB = \frac{\chi^2_{2k,5\%}}{2n}$$

$$UCB = \frac{\chi^2_{2(k+1),95\%}}{2n} \qquad (2)$$

From the above steps, the failure rates can be estimated with confidence intervals as below:

Failure Occurrence Time Interval	*# of failures*	*Upper Conf. Bound*	*Failure Rate*	*Lower Conf. Bound*
0:00 - 06:00	1	0,0079	0,0017	0,0001
06:00 - 12:00	8	0,0239	0,0133	0,0066
12:00 - 18:00	7	0,0218	0,0116	0,0055
18:00 - 24:00	7	0,0218	0,0116	0,0055
Total	*23*	*0,054*	*0,0381*	*0,0261*

Table 2: 50/10 kV transformer failure data categorized according to failure occurrence time intervals.

B. Transformer Load Data

As mentioned previously, interruption costs, hence sales loss and interruption costs, varies according to the time of the interruption. To take this into account transformer load data for a period of 1 week for a summer and winter season are analysed. A summer load for a period of 1 week is shown in figure 3. Similar to the time intervals as defined for the failure rates, the transformer load data is categorized. Notably, no correlation between recovery duration and failure occurrence time has been found. Over the period of 1 week, the average load for the particular time interval has been estimated. Two types of transformer loading have been considered, namely: *industrial + residential (region 1)* and *residential + commercial (region 2)*. The load classification according to specific time intervals for summer and winter loads for region 1 and 2 are given in table 3 and 4, respectively.

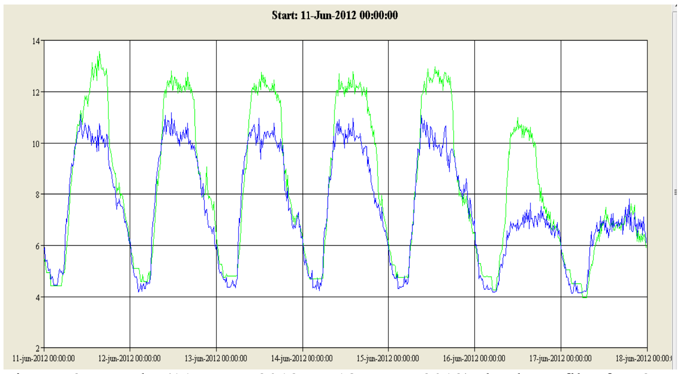

Figure 3: Week (11 June 2012 – 18 June 2012) load profile for 2 transformers in a substation of region 1.

		Summer Load		***Winter Load***	
Region 1 *Industrial + Residential*	*Failure Occurrence Time Interval*	*TR1 Load (MW)*	*TR2 Load (MW)*	*TR1 Load (MW)*	*TR2 Load (MW)*
	0:00 - 06:00	4.87	4.72	5.12	5.68
	06:00 - 12:00	9.39	9.37	10.70	10.75
	12:00 - 18:00	10.21	12.65	13.69	11.78
	18:00 - 24:00	7.73	8.27	9.52	9.77
	Total	*32.20*	*35.01*	*39.03*	*37.98*

Table 3: Summary of analysed average transformer load data categorized according to time intervals for region 1 with *industrial and residential* loads. In this substation 2 transformers are used and arbitrarily named TR1 and TR2.

		Summer Load		***Winter Load***	
Region 2 *Commercial + Residential*	*Failure Occurrence Time Interval*	*TR1 Load (MW)*	*TR2 Load (MW)*	*TR1 Load (MW)*	*TR2 Load (MW)*
	0:00 - 06:00	4.04	4.37	3.80	4.48
	06:00 - 12:00	5.80	6.09	6.28	8.22
	12:00 - 18:00	6.84	7.07	7.26	9.92
	18:00 - 24:00	5.40	5.74	6.19	8.53
	Total	*22.08*	*23.27*	*23.53*	*31.15*

Table 4: Summary of analysed average transformer load data categorized according to time intervals for region 2 with *commercial and residential* loads. In this substation 2 transformers are used and arbitrarily named TR1 and TR2.

C. Risk Assessment

As mentioned earlier, equation (1) is used in the current situation to assess the risks. For the proposed improved risk assessment, equation (1) is extended with more detailed information regarding the failure occurrence time, and is mathematically expressed as follows:

$$E(R) = (E(F_x).E(C_y)) + ((E(F_{x+1}).E(C_{y+1}) + \left(E(F_{x+\ldots}).E(C_{y+\ldots})\right) + (E(F_{x+n}).E(C_{y+n})) \qquad (3)$$

with, F_x being the failure probability for a particular time interval and C_y the loss of load for the same time interval.
Subsequently, equations (1) and (3) are used to assess the under- or over estimation of risk when the failure occurrence time is considered.

	Current Risk		*Improved Risk*		*Improved/Current*	
Region 1	*TR1*	*TR2*	*TR1*	*TR2*	***TR1***	***TR2***
Summer	0.31	0.33	0.34	0.37	**11%**	**13%**
Winter	0.37	0.36	0.42	0.40	**13%**	**11%**

Table 5: Improved risk assessment results. When load (loss of energy) is incorporated, according to failure occurrence time, then there is an estimated risk underestimation between 11% - 13% for region 1.

	Current Risk		*Improved Risk*		*Improved/Current*	
Region 2	*TR1*	*TR2*	*TR1*	*TR2*	***TR1***	***TR2***
Summer	0.21	0.22	0.23	0.24	**7%**	**7%**
Winter	0.22	0.29	0.25	0.33	**10%**	**11%**

Table 6: Improved risk assessment results. When load (loss of energy) is incorporated, according to failure occurrence time, then there is an estimated risk underestimation 7% - 11% for region 2.

From tables 5 and 6, it is found that with the current risk assessment approach an underestimation of risks is likely to occur. When the "current" risk analysis method is compared to the "improved" risk analysis, then there is a possible risk underestimation between 7% - 13%. Furthermore, we can conclude from this primary investigation that for the winter load period the risk uncertainty is slightly larger (about 3% to 4%) when compared to the summer load period. Additionally, we can tentatively conclude that region 1, which has a dominant industrial load, has a higher risk uncertainty exposure. These seasonal and regional difference are caused by the fact that the underestimation grows with the ratio between peak load and basic load.

D. Discussion

Here, the load is assumed proportional to the failure consequence, hence used to calculated risk directly. Based on this assumption, the results show a case that failure interruption costs can include any component of cost that are associated with asset failure, therefore, the calculated risk differences might even be more serious to the asset managers.
The authors realize that, in practise, failure costs can related to many other factors, such as additional emergency service costs, the cost of degraded operations, environmental costs, and loss of customer goodwill. These factors, in case that they are correlated with time, season and region, can further increase the underestimation of risk values.
These cost factors are not taken into account in the current study, because relevant data are not recorded. This reveals a shortcoming of failure analysis in the utility companies at this moment: The organization within utility companies separate the investigations on failure probability and those on failure consequences within technical and financial department respectively. Consequently, failure analysers can hardly trace the association between failure consequences and failure modes. Therefore, we strongly recommend utility companies to reconsider their information strategies, or at least investigate on possible factors which leads to correlation between failure rates and consequences.

IV. Conclusion

This study analyse risk of transformer failures with a differently defined failure consequences. The consequences are assumed to be proportional to the load of the transformer, which leads to a correlation between failure consequences and occurrence time. Meanwhile, the estimated failure rate also shows the same correlation with occurrence time. As a result, we have shown that: without considering the occurrence time of failure, the risks will be underestimated for 7% to 13%, depending on the above-stated correlations which is associated with other factors (e.g. season, type of feeding area).
To expand this simplified analysis, we recommend to (1) find out the reasons for the statistically estimated correlation between failure rate and time; (2) investigate on the repair duration, so that the lost energy instead of load can be used for the failure consequences; (3) in long term, investigate on the demand-side and understand the impact of failures on clients.
To sum up, it is still unclear, whether utilities are aware of these shortcoming in current risk assessment methods and how to incorporate these results into AM in practise. Besides, it also remains unclear what the consequences of these results are for utilities in terms of maintenance and operations. In future, with the roll-out of intelligent grids and increased user-centric involvement, improved risk assessments may become a serious topic of discussion.

Acknowledgement

The authors would like to thank Stedin B.V. and Dr. Viren Ajodhia (DNV KEMA) for their support, knowledge and access to data.

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