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A transformer outage duration model with application to asset management decision support

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Transformers are key components in the power system and transformer failures can cause long power outages with high costs to society. Transformer failures are rare, and each case is unique with respect to its consequences. This shapes the data and statistics we have available to predict future failures and related consequences. Models to support risk assessments and asset management decisions for these critical assets should rely on practical approaches to include both available data as well as expert judgements. This paper looks at outage duration, an important parameter in risk evaluation and asset management decisions. It presents a transformer outage duration model which can be conditioned on relevant asset management input variables. A use case is constructed to exemplify the usage of the model in an asset management decision context.

Keywords: Reliability, resilience, vulnerability, transformers, decision support, outage duration, asset management.

1. Introduction

Modern society is dependent on a reliable supply of electricity, and extraordinary events in the power system, such as major blackouts, can have severe consequences. Long power outages are particularly critical and can have societal costs which go well beyond the direct financial damages the outage may cause (Dugan et al., 2023). Transformers are key components in the power system and transformer failures can cause long average outage durations, with very long outlier observations. Combined with their large investment costs, informed asset management of transformers is an important part of power system risk management (Khuntia et al., 2016; Ekisheva et al., 2016).

This paper presents a model for estimating transformer outage durations, extending previous work on overhead transmission lines (Kiel and Kjølle, 2020). A Bayesian Network (BN) approach is used to build the model, and parameters are populated by eliciting expert judgments to compensate for scarce data when neccessary. The model constructs outage duration distributions conditional on relevant asset management input variables, specifically component condition or the provision of spare parts. Making use of the full distribution of estimated outage durations, rather than only the expected value can contribute to communicate potentially extreme events to decision-makers. A case study is constructed to show the applicability of the outage duration model as an asset management decision support tool, where it is used to evaluate the impact of different spare part strategies on key reliability of supply indices.

2. Theory

Asset management involves balancing of costs, risks, opportunities and performance related to assets (ISO, 2014). The choice of maintenance and spare strategies, investment- and operational costs, and criticality of components are all highly relevant questions, affecting a risk-based approach to asset management decision making. Knowledge of the failure rate and outage duration of assets also inform system development by identifying weak parts of the grid, or short-term operation as an aid for credible risk analyses (Mirhosseini and Keynia, 2021; Abu-Elanien and Salama, 2010; GARPUR Consortium, 2015). The concept of resilience is closely related to that of risk and is particularly focused on the ability to prepare and recover from an unwanted event. Managing for resilience thus involves the ability to plan and prepare for an unwanted event, and if necessary, rapidly recover (Zio, 2018).

Transformer outages can have large consequences. Temporary failures may only require switching actions, but a permanent fault *remain unless it is removed by some intervention* (ENTSO-E, 2021), such as repair. The latter can cause outages with very long outage durations.

The outage duration of transformers are tied to which component of the transformer fails and can range from a few hours to a year or more, and the failure of some components often leads to the transformer being scrapped and replaced (Ekisheva et al., 2016; Mbuli et al., 2020; Tenbohlen et al., 2011). A distinction between active parts (windings, core and oil) and non-active parts (tap changer, bushing, cooling system, etc) is made in Toftaker et al. (2023), where the former components are understood as non-repairable due to the associated repair costs, while the latter are treated as repairable. The failure of an active part is associated with a breakdown and a need for a full replacement of the transformer, consequently leading to long outage durations.

Transformers can be considered strategic spare parts (Cavalieri et al., 2008): Transformers have a critical role in the power system, and are often highly specific in their production with availability limited to certain suppliers. They are also expensive, with unforeseeable wear-out times and long lead times. Thus, it is necessary to strike the right balance between cost and benefit when deciding on spare transformer inventory to cover for unforeseen failures (Mijailovic, 2013; Hamoud, 2012; Wang et al., 2002).

There have been developed numerous methods to estimate the current and future failure rate of individual transformers, based on e.g. aging models and health indices which is used to give insight into the transformer condition and failure probability (Foros and Istad, 2020; Jürgensen et al., 2016; Azmi et al., 2017). These variables are affected by different maintenance strategies (Mirhosseini and Keynia, 2021; Abu-Elanien and Salama, 2010). Importantly, the condition of the transformer affects which component is more likely to fail, and some component failures are more likely than others to lead to a transformer breakdown. This, in turn, affect the demand for a spare transformer.

2.1. *Risk and uncertainty*

There are societal aspects that must be considered in risk management of power systems, and acceptable risk in the power system is a political question that goes beyond pure economics: Certain consequences are not acceptable due to their severity, impacted customers or frequency, regardless of the socieconomic optimum (Doorman et al., 2006; Smit et al., 2006).

There are many different definitions of risk (Aven and Renn, 2009), but it is here understood in the classical sense as a set of triplets describing a scenario and its associated probability and consequence (Kaplan and Garrick, 1981). In this traditional interpretation of risk, uncertainty is described as an addition to potential damage, or a variation around a central tendency akin to a statistical error-term. Other interpretations take a broader approach, where uncertainty is understood as a range- or cause of variation, which may or may not be quantifiable (Samson et al., 2009).

Uncertainty is often divided into aleatory and epistemic uncertainty encompassing inherent or irreducible randomness, and lack of knowledge or data, respectively. This distinction is often a matter of subjective interpretation, but can guide modeling choices and measures to reduce or communicate uncertainties (Kiureghian and Ditlevsen, 2009; Winkler, 1996). Another categorization is that of parameter-, model- and completeness uncertainty (Vesely and Rasmuson, 1984; Parry, 1996). Parameter uncertainty can be understood as being a property of the input data, model uncertainty is related to the appropriateness of the model and methods employed, while completeness uncertainty is related to what is or is not incorporated into the model. These uncertainties should be communicated to a decision-maker. Subjective probabilities or interval ranges of outcomes are some available approaches to quantify uncertainty, however model and completeness uncertainty which are more difficult to quantify could be communicated through other means, such as transparency of modeling choices and what is included in the final model (Flage et al., 2014; Parry, 1996).

2.2. *Bayesian networks and expert judgments*

One method to reason under uncertainty is by using a BN, which is a directed acyclic graph where edges represent conditional dependencies between a set of variables represented as nodes. The joint probability distribution of the model is given by the chain rule for BNs in Eq. (1): The probability of a random variable X_i is given by its parents, $Pa(X_i)$, making it conditionally independent from other variables in the BN. A BN is thus a transparent and efficient way of modeling causal relationships between variables (Pourret et al., 2008; Langseth and Portinale, 2007).

$$P(X_1, ..., X_n) = \prod_i P(X_i|Pa(X_i)) \quad (1)$$

Jakeman et al. (2006) and Chen and Pollino (2012) provides guidelines for the development and evaluation of BN models. They suggest that a conceptual model describing existing knowledge – i.e. as an influence diagram – is constructed in cooperation with domain experts and relevant stakeholder groups to serve as a starting point for structuring the final BN. Model parsimony should be sought after in the BN. Model complexity, depth, and variables should be subject to stringent evaluation before inclusion into the model. The model can be parameterized using e.g. statistical data, known models, or expert judgments.

The Norwegian disturbance database collects component reliability data from the Norwegian power system, but repair and outage duration data is not mandatory to report (Kjølle et al., 2016), and there is scarce statistics on transformer outage durations in Norway. Lack of available data and a variety of preconditions for each failure makes it hard to characterize and generalize failure behavior to predict future failures (Rocchetta et al., 2018). One possible solution to this challenge is to use expert knowledge. Expert judgments are quantifications of experts' beliefs, which can compensate for limited data. Different methods of expert elicitation incorporating uncertainty are discussed in Hanea et al. (2021). Although there are limited empirical comparisons between available methods, the recent IDEA protocol (Hemming et al., 2018) offers a well structured method of eliciting continuous value distributions.

3. Model development

The understanding of outage duration in this paper follows that found in ENTSO-E (2021), as *the period from the initiation of an outage occurrence until the component or unit is returned to the in-service state*, with some limitations: The proposed model assumes no voluntary waiting time and that the component is re-energized once it is able to perform as required/reach the up state as defined by the IEC (2015). The model is only applicable to estimate outage durations assuming that a permanent fault has already occurred and makes no attempt to model individual transformer failure frequencies.

A conceptual model of outage duration was developed in cooperation with experts from the Norwegian Transmission System Operator (TSO), using the understanding of repair time as defined by the Norwegian FASIT system and ENTSO-E (Kjølle et al., 2016; ENTSO-E, 2021) as a starting point. The conceptual model was reduced in cooperation with the domain experts, considering which variables and relationships had a substantial impact on transformer outage durations, and what was possible to model. The model also included relevant risk-influencing factors as input variables, such as the unit's technical condition, the timing of the failure, the provision of spare transformers, and the accessibility of the failure site. The resulting model after reducing the conceptual model can be seen in Fig 1. The IDEA protocol

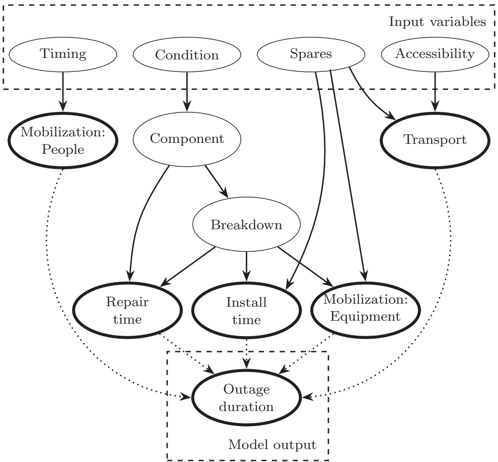

Fig. 1. Final model structure. Continuous variables illustrated by ellipses with a bold outline.

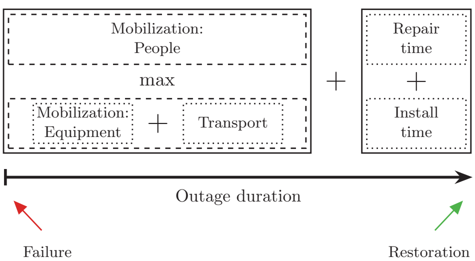

Fig. 2. Modelled outage duration process.

(Hemming et al., 2018) was used for expert elicitation of realistic minimum and maximum values, and best estimates for all continuous variables – except the outage duration – which was used to parameterize the variables as modified PERT distributions (Moskowitz and Bullers, 1979). The proposed model is a set of connected BNs which generates samples from these five key variables, which is combined into an outage duration.

The logic behind combining these samples into an outage duration is shown in Fig. 2: A failure in the active part of the transformer is considered as leading to a transformer breakdown, and consequently, an outage duration timeline consisting of mobilization, transport, and installation of a new transformer. Alternatively, if there is no transformer breakdown, the timeline consists of mobilization and repair time. The mobilization of people, and the mobilization and transport

Table 1. Variable descriptions.

Type	Variable	Categories
Categorical	Timing	*1 - Worst*
		2 - Expected
		3 - Best
	Condition	*1 - Best*
		2
		3
		4
		5 - Worst
	Spares	*1 - None*
		2 - Warm storage
		3 - Cold storage
		4 - Central storage (fit)
		5 - Central storage (unfit)
	Accessibility	*1 - Worst*
		2 - Expected
		3 - Best
	Component	*1 - Winding*
		2 - Core
		3 - Oil
		4 - Bushings
		5 - Tap-changer
		6 - Other
	Breakdown	*1 - Yes*
		2 - No
Continuous	Mobilization: People	
	Transport	
	Repair time	
	Install time	
	Mobilization: Equipment	
	Outage duration	

of equipment are considered parallel processes, while the physical work at the substation site is either performed as a repair of a component or the installation of a new transformer. This represents a simplification compared to existing definitions but has been found fit for purpose in cooperation with domain experts during the model development.

A more detailed description of the variables in the model is presented in Table 1. The relationship between the technical condition of a transformer and the probability of a failure of the active part was implemented using the methods developed in Foros and Istad (2020). The number of categories in the variables – and thus the number of expert elicitations needed to parameterize the model –

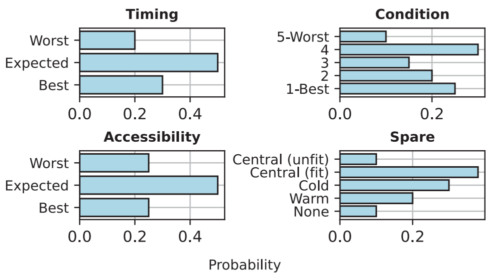

Fig. 3. Model input values, portfolio of transformers.

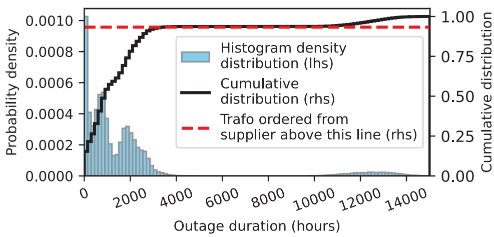

Fig. 4. Illustrative example of outage duration model output. 10 000 samples.

was kept to a minimum. A new transformer must be ordered from the supplier in the event of a breakdown if there is no spare in storage. Warm storage indicates that a spare transformer is located on-site and can be put into operation through limited effort and switching actions, whereas cold storage may require moving and installation of an on-site spare. Spares located at a central storage must be mobilized and transported to the failure site, and may either fit to be installed directly upon arrival, or need adaptations to accommodate the spare at the fault location.

The proposed model can be utilized in different ways. Single samples of transformer outage durations can be generated for use in a Monte Carlo Simulation (MCS) based reliability analysis, which is especially relevant when the distribution of input parameters change during the course of the simulation. Taking repeated samples would generate an outage duration distribution for the transformer, where input parameters are uncertain. Repeated samples could also be used to describe the estimated outage duration of a portfolio of transformers, giving some insights into the effect of a changed asset management strategy. An illustrative example of an analysis covering a portfolio of transformers can be seen in Fig. 3 and Fig. 4. These figures show how a possible distribution of input variables yields an associated output from the outage duration model. The dashed red line in the latter figure show the proportion of permanent faults which is expected to require ordering a new transformer from the supplier due to lack of a spare, which consequently lead to very long outage durations.

4. Case study

4.1. *Use case description*

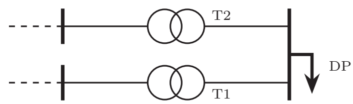

Fig. 5. Use case system. Two transformers feed a single delivery point.

The use case describes a stylized TSO decision problem. A delivery point (DP) is connected to the rest of the grid through two transformers, T1 and T2, which act as redundancies for each other. A single line diagram of the system can be seen in Fig. 5. The load at the delivery point consist of households and small businesses in a local community. A large industrial customer considers establishing a plant at the DP. The industrial customer cannot withstand prolonged and frequent power interruptions without its production lines being damaged or destroyed, and as such is highly concerned with the reliability of supply at the DP.

Transformer T1 is halfway in its lifetime and have an available spare in a central storage. Transformer T2 is approaching end of life and have no available spare. The question is what strategy the TSO should adopt with respect to planning for the eventuality of a failure of T2, to accommodate the reliability requirements of the potential new industrial customer at the DP. The TSO has three different alternatives for a spare T2 transformer:

Case 1: Warm-storage at the T2 site.
Case 2: Central storage, ready to install.
Case 3: Order from the supplier when needed.

The aim of the analysis is to evaluate the risk associated with the three scenarios. Interrupted power at the DP will only happen when there is a concurrent outage of both transformers, and the consequence of the interruption can be described by the corresponding interruption duration. Hence, the risk of each scenario is described by the interruption frequencies and durations at the DP. The risk evaluation could help the system operator decide which spare strategy to choose.

A base outage duration model for each transformer is conditioned on a set of input variables. Probabilistic best-guess estimates are entered into the model for the timing, technical condition, and accessibility variables. Only the spare-status of the T2 transformer is altered when considering the different cases. Outage duration samples are generated from the proposed model, and a MCS based reliability analysis is implemented for the case study to capture and communicate the variation in these samples.

4.2. *Monte Carlo Simulation*

The MCS method implemented for the use case employed is inspired by Solheim et al. (2018): A failure rate for each transformer is picked from a scaled beta distribution in each iteration, $\lambda \leftarrow \mathcal{SB} \sim (\alpha, \beta, a, c)$, where a is the minimum, and c is the maximum of the distribution. This step reflects parameter uncertainty through a distribution of the expected annual failure rate with a minimum and maximum $\pm 20\%$ of 0.0044, symmetrically distributed with $\alpha = \beta = 3$.

Time series of failure probabilities covering ten years is constructed for each transformer, where the failure probability is considered constant. The number of failure occurrences in each iteration is picked from a binomial distribution, $\mathcal{BI} \sim (n, p)$, where $n = 8760 \cdot 10$, and $p \approx \lambda/8760$. Transformer failures are then allocated to a point in time from a uniform distribution $\mathcal{U} \sim (0, k)$, where k is the number of time steps considered in the analysis. An outage duration is then picked for each failure using the model proposed in this paper. Results are parsed to identify simultaneous outage occurrences of both transformers, before reliability indices are calculated.

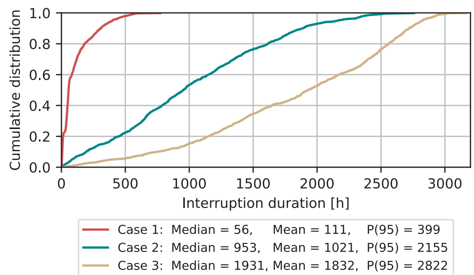

Fig. 6. Interruption duration at the DP due to the concurrent outage of both transformers.

4.3. *Results and discussion*

The different strategies result in vastly different distributions of interruption duration, as seen in Fig. 6. In case 1, the interruption duration in the DP is predominantly decided by the activation of the T2 spare which is kept in warm storage, leading to a median interruption duration of a little above two days. In case 3 the spare T2 must be ordered from the supplier, and the associated interruption duration is largely decided by the mobilization, transport and installation of the T1 spare. In case 2, the outage of either transformer is ended by acquiring a spare from a central storage.

Relying on expected values could conceal potentially very long outage durations, making a decision maker largely unaware of the risk of such events. If the TSO finds that a partial load curtailment in the DP for a period of up to six weeks is acceptable, e.g. due to local energy production at the low voltage level, both case 1 and 2 would be acceptable when considering the expected outage duration. However, by analysing the interruption duration curve, it is estimated that 23 percent of the interruptions in case 2 result in outages above nine weeks, which would represent an unacceptable consequence. A similar concealment of potential outcomes by the expected value could also happen if there is a multimodal outage duration distribution, as in Fig. 4: The expected value may communicate an outage duration which almost never occurs but is found somewhere between different peaks in the distribution.

Fig. 7 shows a risk diagram depicting the frequency and duration of interruptions at the DP for the different cases. A reduced outage duration of T2 has a notable impact on the interruption frequency at the DP, as seen when comparing case 1 and 3, through a decreased probability of overlapping outages of T1 and T2.

The TSO eventually chose case 1 as its preferred strategy, due to the prohibitively long outage durations represented by case 2 and 3.

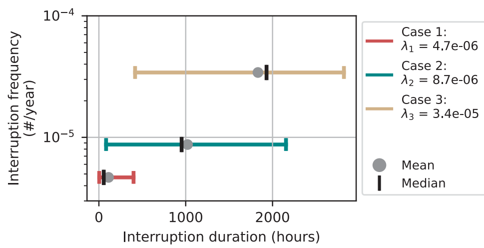

Fig. 7. Risk diagram. Interruptions at the DP. Colored lines show the 5^{th} and 95^{th} percentile of predicted interruption durations.

5. Conclusion

This paper has presented a transformer outage duration model, which has applications to reliability and risk assessments, supporting asset management decisions. The model takes into account important information about the assets, such as the technical condition and the availability of spares, as well as other relevant information. Domain experts informed the structure of the model, and expert elicitation was used to compensate for lack of empirical data when necessary. The BN structure and elicitation process helps incorporate uncertainty into the analysis in a clear and structured manner, making modelling-, completeness-, and parameter uncertainty explicit, and thus help convey this uncertainty to the decision maker. The relevance of the model as an asset management decision support tool was exemplified in a case study. The case study illustrated how the model could assist a TSO planning and preparing for an unwanted event in a risk-based manner and contribute to informed management of the system resilience.

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