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Health index calculation using failure modes, effects, and criticality analysis for high-voltage circuit breakers

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The electric power system lies at the heart of modern society. To optimize the total cost of the system a trade-off between investment and reliability must be made. Power system reliability analysis (PSRA) typically quantifies the reliability of the system using fixed component failure rates. However, the probability of failure for a component increases with usage. Therefore, a health index model based on failure modes, effects, and criticality analysis (FMECA) is presented to facilitate in the calculation process. FMECA is used to identify the failure mechanisms and assign a risk priority number (RPN) based on the severity, occurrence, and detectability of each failure mechanism. The health index is then evaluated based on failure mechanisms rather than directly from condition data and each failure mechanism's contribution to the overall health index is weighted relative to the RPN. A case study is presented where the health indices for a fleet of high-voltage circuit breakers (HVCBs) are evaluated based on data obtained from the Icelandic transmission system. The trip coil current (TCC) is a readily available measurement that can detect electrical and mechanical issues within HVCBs and was used as a key assessment criterion in determining the health indices for the HVCB fleet.

Keywords: Asset management, System reliability, Risk assessment, Risk management, FMECA, Condition monitoring, Health index, High-voltage circuit breaker.

1. Introduction

1.1. *Background*

Power system reliability analysis (PSRA) is a field of study that deals with the reliability assessment of the electric power system. PSRA typically models the reliability of a system consisting of generators, transmission lines and occasionally transformers. However, high-voltage circuit breakers (HVCBs) are also essential components within the substation.

When adding an individual component into PSRA we are interested in estimating its probability of failure which increases with component wear. Condition monitoring techniques have advanced through the years and can indicate the amount of wear a component has encountered. However, this information is rarely compiled into a single index that determines the health of a component and its probability of failure.

HVCBs are mechanical switching devices which protect equipment against damage due to sustained over currents (Garzon, 2002). The overall operation of an HVCB control circuit is shown in Fig. 1. When there is a fault on a line the current transformer (CT) detects the increased current and increases the current in the auxiliary circuit. This causes actuator A1 which is normally open to close, completing the trip circuit. The trip coil in the trip circuit energises eventually causing actuator A2 to hit the HVCB latch. This releases the stored energy within the HVCB operating mechanism and opens the HVCB contacts. The fault is now isolated.

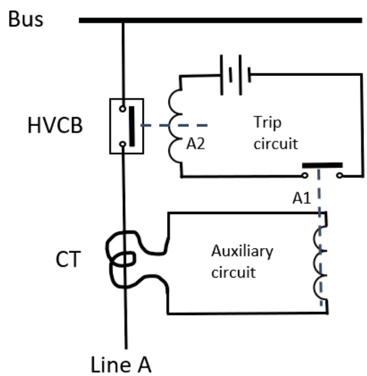

Fig. 1. HVCB control circuit

When an HVCB is carrying a current in the closed position its reliability is dependent on the HVCB opening on command and the HVCB not opening without a command (Forootani et al., 2012). These two failure modes result in the non-fulfilment of the HVCBs function of system protection.

Condition-based maintenance strategies have been shown to lead to improvements in reliability (Janssen et al., 1992). Consequently, asset managers are transitioning from predetermined (time-based) preventive maintenance to condition-based maintenance strategies. Therefore, methodologies are needed to assess the relative health of HVCBs.

The doubt concerning HVCBs lies in the first trip. The first trip is the first operation of an HVCB after a long period of idleness (Sweetser et al., 2002). HVCBs can fail in the closed position but continue to carry the current. Therefore, uncertainty is associated with whether an HVCB can be relied upon without actually taking the HVCB out of operation to conduct functional tests. Methodologies that can use already acquired condition data to determine the relative health of a fleet of HVCBs will guide asset managers in making more informed decisions.

Transmission System Operators (TSOs) collect a wide range of data related to the health of a component. Issues such as data being hidden, determining which data are relevant or figuring out how to interpret the data, are of concern. Displaying a single-valued health index can help to alleviate these issues. Having a single-valued health index is useful when performing condition-based maintenance. However, when performing PSRA using Monte-Carlo simulation methods, failure rates are needed as input. Therefore, for this purpose, the health index based on condition data needs to be converted into a condition-dependent failure rate.

Failure modes, effects, and criticality analysis (FMECA) is a well-known risk analysis method to assist in the failure analysis of complex systems. A failure mode is how a failure has occurred, but does not state why the failure occurred. This is left to failure mechanisms, which are the physical processes that lead up to the failure modes (Rausand and Hoyland, 2003). The information collected by experts within an FMECA could be useful when creating a component health index model.

1.2. *Related work*

Health index models for transformers derived from condition data using a multi-criteria analysis approach have been developed in Jahromi et al. (2009). Condition data gives an idea of the amount of wear a component may have experienced and can be used to predict the probability of failure. Jahromi et al. (2009) assess the condition data directly when creating the overall health index and do not create the health index model by assessing the probability of specific failure modes. Foros and Istad (2020) combine the transformer health index model with failure statistics to determine an apparent age of a transformer; the authors indicated the need for future work in creating a health index model based on failure modes to give a more physical basis for the health index.

Lorin et al. (2016) illustrate the use of FMEA to create a transformer fault tree from operational parameters leading to transformer failure. Much work has been conducted with respect to the health of power transformers but not with HVCBs.

Runde (2012) presented an analysis of HVCB failure frequency as a function of age. It was found that most but not all of the HVCBs analysed had a higher failure frequency with increasing age. However, no work was conducted on how the failure rate depends on the deterioration of the component's technical condition.

1.3. *Outline and contributions*

In this paper, an FMECA will be conducted for HVCBs. A risk priority number (RPN) will be calculated for all failure mechanisms and used to provide a justification for the weighting factors used within the health index model. The weighting of the failure mechanisms based on the RPNs are multiplied by a score based on expert judgement, which is named the expert judgement score (EJS). The summation is taken for all failure mechanisms and normalised to provide a single health index. Thus, the paper makes the first steps towards estimating condition-dependent failure rates of HVBCs. More specifically, the contributions will be to:

(i) Present a health index model based on failure mechanisms
(ii) Propose the use of RPN values from an FMECA to justify the weighting factors for the failure mechanisms within the health index model
(iii) Propose the use of an expert judgement score (EJS) based on the evidence of a failure mechanism occurring
(iv) Evaluate the methodology using HVCB condition data
(v) Investigate the correlation between age and health index for a fleet of HVCBs.

The rest of the paper is organised as follows: Section 2 will introduce the overall framework. Section 3 will present an FMECA for HVCBs. Section 4 will discuss the condition data available which is used as the evidence to detect the presence of failure mechanisms. Section 5 will present the final health index model based on failure mechanisms. A case study will be presented in Section 6 followed by conclusions in Section 7.

2. General framework

The methodology that we propose in this paper to convert condition data into a health index is shown in Figure 2. This methodology makes use of an FMECA which is conducted by an evaluation team consisting of subject experts. The output of the FMECA is the RPN and information linking failure mechanisms to condition data. The evaluation team assesses the evidence for each failure mechanism occurring based on the condition data using their expert judgement to derive an expert judgement score (EJS). To automate the process the evaluation team can also set appropriate limits for deriving the EJS from condition data and revise these limits when necessary. The RPN and EJS are then used as inputs into the health index model. The RPN is used as a relative weighting factor and is multiplied by the calculated EJS for each failure mechanism. The results are then summed and normalised to provide a single health index. This health index based on condition data can be used by TSOs to more accurately identify the components in need of maintenance.

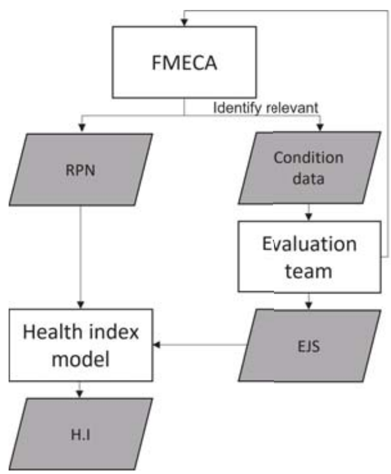

Fig. 2. Health index calculation using FMECA.

3. Failure modes, effects, and criticality analysis (FMECA)

FMECA is conducted as per standard IEC 60812 (IEC, 2018). It is a systematic tool for compiling the knowledge of various subject experts about how a component can fail. The standard FMECA template from Rausand and Hoyland (2003) was modified to also include RPN values, which will be used as a structured way of assigning weighting factors in a component health index model. The RPN can be calculated as per Equation 1. A high RPN indicates that the failure mechanism has a high risk of affecting the reliability of the device.

$$RPN = S \times O \times D \tag{1}$$

where:
S = Severity of the consequences
O = Occurrence rate
D = Detectability of the failure mechanism.

The severity, occurrence and detectability of each failure mechanism can be graded on a scale from 1 to 10 with the help of expert judgement. The scales used for scoring the occurrence, severity and detectability can be found in Tables 1.1 to 1.3 respectively in Liu (2016). The detectability refers to how detectable the failure mechanism is using current procedures. A failure mechanism that is easily detectable will receive a low score reducing the RPN. Kapur and Pecht (2014) provide an RPN classification scheme according to risk level, whereas Liu (2016) provides a numerical quantification scheme. This numerical quantification of the RPN is more useful for our purposes when creating a health index.

The Switchgear Committee of the IEEE Power and Energy Society (Mitchell et al., 2019) conducted a failure modes and effects analysis (FMEA) for HVCBs. This information collected by experts in the field was used to identify the failure modes and mechanisms experienced with HVCBs. Based on the information in (Mitchell et al., 2019), RPN values were then calculated for all of the failure mechanisms. Table 1 shows the calculated RPN values for the 14 identified HVCB failure mechanisms.

The results of the FMECA indicate that when an HVCB is in the closed position the failure mechanisms with the highest RPNs are failure mechanisms 1 and 10 which are open or shorted trip coil and trip latch not secure respectively.

4. Condition data

Condition data can be used to give an indication of a component's health. It is used as evidence for the scoring of the likelihood that a failure mechanism will occur. Component condition data can come in the form of condition monitoring data, maintenance records, operation records and other sources (Cole and Macarthur, 2019).

Table 1. Calculated RPN values for each HVCB failure mechanism.

Failure mechanism	RPN
1. Open or shorted trip coil	90
2. Improper lubrication of the trip latch	80
3. Loss of spring energy	81
4. Control circuit failure	81
5. HVCB operation blocked	64
6. Mechanism failure	56
7. Trip latch surface wear	64
8. Mechanism below rated temperature	9
9. External circuit failure	81
10. Trip latch not secure	96
11. Stray current in trip circuit	48
12. Ground on trip circuit	48
13. Self-protective feature of CB	80
14. Loss of voltage on undervoltage trip	24

4.1. *Condition monitoring data*

There are many condition monitoring techniques available for HVCBs such as coil current, travel curve, dynamic resistance, vibration and thermal measurements (Razi-Kazemi and Niayesh, 2020). However, the trip coil current (TCC) measurement is a widely available measurement which contains information related to both the electrical and the mechanical functionalities of an HVCB (Chen et al., 2021).

A typical trip coil current measurement is illustrated in Fig. 3. The TCC measurement is a reading of the current through the coil in the trip circuit of Fig. 1 versus time. The coil current has a specific characteristic signature and changes in the signature can signify issues with the HVCB. Parameter A with current I_1 and time t_1 is associated with the charging of the trip coil. The location of parameter A can be used to assess the onset of failure mechanism 1. Parameter B with current I_2 and time t_2 is associated with the movement of the armature which activates the trip latch. It can be used to assess failure mechanisms 2, 7 and 10.

The overall noisiness of the TCC measurement can be used to evaluate the occurrence of failure mechanisms 11 and 12.

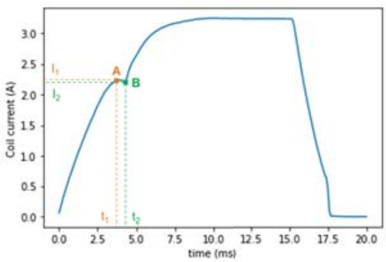

Fig. 3. Typical trip coil current measurement.

4.2. *Maintenance records*

Maintenance records contain useful information related to physical checks of a component which can be used to update the health index model. TSOs keep detailed maintenance records but usually do not incorporate this information into the health index model. Maintenance records can be used to assess failure mechanisms 3, 5 and 13.

4.3. *Operation records*

The overall operation of the system can be used to assess the health of a single component. For example, when HVCBs are triggered by the TSO, the response time, ability to switch and the associated voltages and currents are monitored. This information about the HVCB operation can be used to assess its health. Operation records can be used to assess failure mechanisms 4, 6, 9 and 14.

4.4. *Other data*

Any other sources of information that can be used to assess the occurrence of failure mechanisms should be put to use. Other sources can include indirect indicators of component wear such as age (Cole and Macarthur, 2019). The failure mechanism related to other data in our health index model is the temperature data of the operating mechanism in failure mechanism 8.

5. Health index model

A conventional health index model is depicted in Fig. 4. Conventional health index models typically compare corresponding condition data between time intervals. The change in the condition data is associated with the amount of component wear and a score is assigned. This scoring process is conducted for all N condition data where they are then multiplied by a weight. The weight given to each condition data is relative to how much the condition data reflects the overall health of the component. However, with limited statistics on power system component failures due to their long lives and the practice of preventive retirement (Toftaker et al., 2022) it may be difficult to decide on the level of importance of each condition data.

Fig. 4. Conventional health index model.

The proposed health index model in this paper based on failure mechanisms is illustrated in Fig. 5. In this model the evaluation team analyses each failure mechanism FM_N against all the relevant condition data and uses their expert judgement (EJ) to determine an expert judgement score (EJS).

Fig. 5. Health index model based on failure mechanisms.

The EJS is a score derived by the evaluation team based on the signs of the failure mechanism occurring. The EJS grading scale proposed in this paper is shown in Table 2. The EJS is then multiplied by the RPN for each failure mechanism. The RPN is used to justify the relative weighting of each failure mechanism. The results are summed for each failure mechanism and then normalized to provide a single health index.

Table 2. Proposed scoring system for the evaluation of failure mechanisms based on evidence.

EJS	Description
1	Almost certain indication
2	Moderate indication
3	Small indication
4	No indication

The RPN is conceptually equivalent to the weight and the EJS is conceptually equivalent to the score of a conventional health index model.

Since the RPN number for each failure mechanism in Table 1 is used as a weighting factor, the fraction of the health index that each failure mechanism accounts for is its RPN divided by the sum of all RPNs. Table 6 groups the failure mechanisms into the categories of condition data that they can be detected by.

Condition data	N	RPN	H.I %
Condition monitoring data	1	90	47 %
	2	80	
	7	64	
	10	96	
	11	48	
	12	48	
Maintenance records	3	81	25 %
	5	64	
	13	80	
Operation records	4	81	27 %
	6	56	
	9	81	
	14	24	
Other	8	9	1 %
	Sum	902	

Fig. 6. Condition data and their proportion of the health index.

Six failure mechanisms, which comprise 47% of the total weight of the health index, can be assessed with the use of condition monitoring data. These failure mechanisms are 1, 2, 7, 10, 11 and 12. Three failure mechanisms, which comprise 25% of the total weight of the health index, can be assessed with the use of maintenance records. These failure mechanisms are 3, 5 and 13. Four failure mechanisms, which comprise 27% of the total weight of the health index, can be assessed with the use of operation records. These failure mechanisms are 4, 6, 9 and 14. One failure mechanism, which comprises 1% of the total weight of the health index, can be assessed with the use of other records. This is failure mechanism 8.

6. Case study

A case study was conducted on a fleet of HVCBs (Grant, 2023). The available condition data for the HVCB fleet were trip coil current (TCC) measurements. The TCC measurements allow for the assessment of failure mechanisms 1, 2, 7, 10, 11 and 12. The rest of the failure mechanisms were assumed to have a perfect score for all HVCBs rather than taken out of the indices. This means that the HI scale in our case in practice starts at 53% and the condition data determines the remaining 47% as per Fig. 6. The TCC measurements for the 14 HVCBs are shown in Fig. 7. Even though these 14 HVCBs are of the same model type, the measurements have different heights and lengths. This highlights the need for methodologies that can evaluate a health index based on expert judgement rather than only from the amount of deviation from the characteristic curve, which is used in conventional health index models such as Jahromi et al. (2009). The evaluation team would be responsible for completing the FMECA and also assigning the EJS for each failure mechanism from the condition data. However, in this case study the authors acted as the evaluation team.

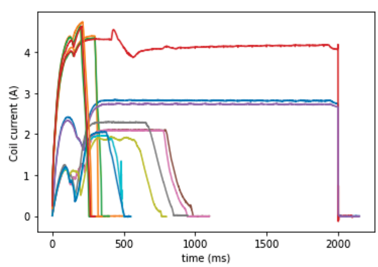

Fig. 7. Case study TCC data set.

Fig. 8 shows a plot of the health indices for the HVCB fleet vs calendar age. We can see that there is no evidence in the data of a link between increasing chronological age and deteriorating component health. This confirms the need for models which can calculate the health index based on condition data. The correlation coefficient for this small data set was 0.396.

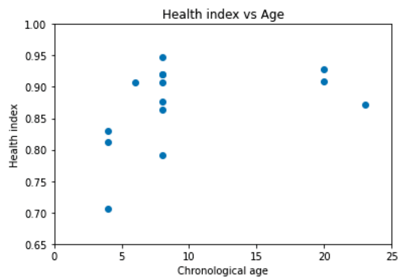

Fig. 8. Health index vs calendar age.

A demonstration of how the health indices were calculated can be found in (Grant, 2023). HVCB 7 had the highest ranking with a calculated health index of 95 %. The TCC measurement for HVCB 7 is shown in Fig. 9.

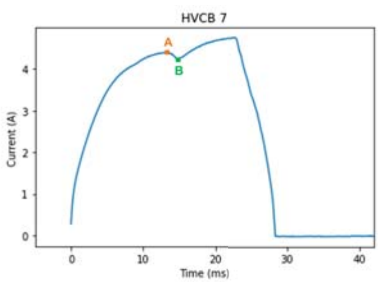

Fig. 9. Highest ranking HVCB.

HVCB 10 had the lowest ranking with a calculated health index of 71 %. The TCC measurement for HVCB 10 is shown in Fig. 10.

To assess the onset of failure mechanism 1, the elapsed time since the last TCC measurement was evaluated. A longer interval between tests was taken as a greater possibility that failure mechanism 1 had occurred. HVCB 7 had a relatively shorter time and HVCB 10 had a relatively longer time since the last TCC measurement was taken, and as such they received an EJS of 4 and 1 respectively. System operators may decide to con-

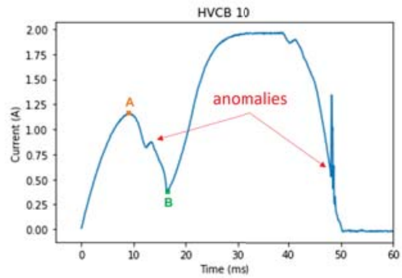

Fig. 10. Lowest ranking HVCB.

duct regular TCC measurements to remove the uncertainty associated with failure mechanism 1.

When considering failure mechanisms 2 and 7 the latch time and TCC signature were considered. The latch time was taken from parameter B and any anomalies that occurred between parameters A and B were noted. HVCB 7 received an EJS of 4 since the signature was smooth between parameters A and B and the latch time was within specifications. However, HVCB 10 received an EJS of 1.5 since the signature contained anomalies between parameters A and B and the latch time took slightly longer.

Failure mechanism 10 is associated with an unsecured latch. An unsecured trip latch can cause the failure mode of the HVCB to trip when not called for. When considering failure mechanism 10 the time to open the circuit was considered. The specified opening time for the HVCBs is 35 ms so opening times a lot quicker than 35 ms could indicate an unsecured trip latch. The limits were chosen to demonstrate the methodology; more data would be needed to revise the limits in future studies.

Failure mechanism 11 was assessed based on the presence of current spikes in the data. If a spike was present an EJS of 1 was assigned and 4 otherwise. HVCB 7 received an EJS of 4 since no spikes were present and HVCB 10 received an EJS of 1 due to the spike at the end of the TCC measurement possibly indicating a stray current. Failure mechanism 12 was scored based on the noisiness of the TCC measurement. HVCB 7 received an EJS of 4 and HVCB 10 received an EJS of 2. Future work would focus on quantifying the noisiness in terms of signal-to-noise ratio.

7. Conclusion and further work

A health index model based on failure modes, effects and criticality analysis (FMECA) was presented and analysed for HVCBs. The FMECA was used to calculate an RPN which is used as a weighting factor for each failure mechanism within the health index. The FMECA also highlighted what condition data can be used to detect each failure mechanism. The relevant condition data was then assessed and an expert judgement score (EJS) was derived based on the data. The EJS and RPN were then used to calculate a component health index.

We found in this paper that when assessing the health index of an HVCB based on failure mechanisms 47% of the health can be assessed with condition monitoring data, 25% from maintenance data, 27% from operation records and 1% from other sources. We also found during our investigations that the coil current data, even for the same HVCB type can have a wide range of shapes, meaning that there is an overlap between healthy and faulty responses. Finally, the results demonstrated the need for approaches which can quantify the health of a component from condition data rather than inferring the health from chronological age.

Further work will focus on how the health index can be converted into a condition-dependent failure rate.

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