Use case testing
SAMBA WP5 report
### Report

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SAMBA WP5 report

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1 of 4
Executive summary

This report describes testing of selected use cases for future improved asset management at Statnett and concludes the work in WP5 of the SAMBA project. The selection of use cases based on input from Statnett’s experts in workshops, available data at Statnett today, and available models/methods from industry and research partners. Testing of the selected use cases has been carried out by ABB, GE Grid Solution and SINTEF Energy Research in cooperation with Statnett. The tested use cases were developed in WP2 of the project, as documented in a separate report.

The testing consists of developing algorithms/codes to carry out the functions described in the use cases, and then applying this to real data from Statnett. For some of the use cases the models to be used for testing were readily available for testing, i.e. asset health indexes for transformers. The testing highlights possibilities and benefits of implementing the use cases in Statnett, as well as identified limitations and problems. For some use cases, poor quality of the available data has been identified and/or desired data is not available today.

Use cases are not static descriptions and must be updated and further developed after the SAMBA-project. The data input sources and accessibility will probably change as Statnett makes decisions on installing sensors, new ICT systems and architectures. For the use case testing, data was provided by Statnett in Excel spreadsheets. In the future, data exchange is expected to change as ICT architectures are built with exchange of data in mind. In addition, some companies are establishing test platforms for external actors to perform testing instead of transferring data. There are important decisions to be made when implementing the use cases from SAMBA in Statnetts operations:

- Which use cases to prioritize for implementation?
- How much resources should be utilized to find, and quality assure historical data?
- Which of the suggested new measurements should be performed and for how many components?
- Who in Statnett should be responsible for each use case? How will the results will be implemented?
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**Abbreviations**

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<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>AI</td>
<td>Artificial intelligence</td>
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<tr>
<td>BEN</td>
<td>Digital fault recorder</td>
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<td>BPMN</td>
<td>Business process model and notation</td>
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<td>DGA</td>
<td>Dissolved gas analysis</td>
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<td>DTS</td>
<td>Distributed temperature sensing</td>
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<td>FAT</td>
<td>Factory acceptance test</td>
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<td>MSA</td>
<td>Multivariate statistical analysis</td>
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<td>PQ</td>
<td>Power quality</td>
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<td>VBA</td>
<td>Visual basic for applications</td>
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1 Introduction

The main objective of this report is to provide results from testing of selected use cases for improved asset management at Statnett. A use case is a standardized way to describe an existing or desired function. The selection of use cases based on input from Statnett’s experts in workshops, available data at Statnett today, and available models/methods from industry and research partners. Testing of the selected use cases has been carried out by ABB, GE Grid Solution and SINTEF Energy Research in cooperation with Statnett. This report concludes the work in WP5 of the SAMBA project. The use cases have been selected from the WP2/3 report [1], which provides detailed descriptions of all use cases in the SAMBA project.

The testing consists of developing algorithms/codes to carry out the functions described in the use cases, and then applying this to data from Statnett. For some of the use cases the models to be used for testing were readily available for testing, i.e. asset health indexes for transformers. The testing has been done with real data, but outside Statnett’s systems, at industry or research partners.

Assessing the usefulness of the results delivered by the use cases and identifying possible problems that need to be overcome before the use cases can be implemented in Statnett’s operations are important parts of the testing. Problems may be e.g. poor data quality or missing data.

The report is organized as follows. Chapter two gives a short description of the use case methodology and an overview of the selected use cases, summarized from the WP2/3 report. Chapter three gives a summary of results from the testing, including recommendations and identified problems. The testing includes use cases for:

- Transformers
- Overhead lines
- Cables
- Circuit breakers
- Voltage transformers
- Asset management

Chapter four and five contain concluding remarks and references, respectively. Details from the testing of some of the use cases are given in the appendices.
2 Overview of use cases in SAMBA

2.1 Use case methodology and standards

Use case is an important scientific method in the SAMBA-project. A use case is a description of the interaction between one or more actors (an actor can be a person, systems, database, algorithms and so on), represented as a sequence of steps to be performed to fulfil some function. The use cases developed in the project illustrate the connections between e.g. input data, calculation models such as ageing models, and results such as health indices.

By developing use cases, requirements for information flow, interoperability and security is clarified. The use cases serve also as a basis for identifying which hardware and software architecture that best supports the needs and possibilities for asset management at Statnett.

The IEC standard 62559-2 [2] provides a template for describing use cases which is adopted in this project. The template is a standardized table for detailing the main parts that make up a use case:

- Scope and objectives
- Brief description
- Prerequisites for the use case to be carried out
- List of actors involved in the use case. An actor is typically a system, e.g. a system holding relevant data
- Step-by-step detailed description
- List of information (data) exchanged between actors

More details can be found in IEC 62559-2 and in the WP2/3 report [1] which details all the use cases developed in the Samba project. In addition to the IEC 62559-2 template, all SAMBA use cases have been illustrated by BPMN (Business Process Model and Notation) diagrams. A BPMN diagram is a standardized way to illustrate a function or a process that enables both interactions and data flow between actors (systems) to be illustrated. Some BPMN diagrams can be seen in appendix V1.

The IEC standard 62559-2 also provides a template for evaluating use case testing. The template is a standardized table for detailing which steps of the use case that have been tested, how the use case has been tested, and experiences/lessons learned for each step during the testing. In this project, the template has been used as a basis for evaluating testing, but the template has not been filled out for each use case.

2.2 Selected use cases

Several use cases were developed in WP2 of the project by industry and research partners in SAMBA in collaboration with Statnett. Focus was on use cases that provide potential for improved asset management at Statnett and that can be tested with a reasonable amount of effort. For an overview, the reader is referred to the WP2/3 report. All the use cases cannot be tested within the frames of the SAMBA-project. Hence, use cases were selected for further testing based on data availability, the expected amount of effort to extract this data from different systems and analyse it, and the interest of Statnett and industry and research partners in the project.

Most of the use-cases focuses on selected components, i.e. transformers, overhead lines, cables, voltage transformers and circuit breakers. Some use cases have a more general scope covering several asset management functions and applying to several different type of components.

The use cases selected for testing are as follows (the numbering in parentheses refers to the WP2/3 report):
**Transformer**

1. Online gas data analysis (T2.1)
2. Event detection (O2.5)
3. Thermal winding aging (T3.1)
4. Periodic oil and gas analysis (T3.5)
5. Health index (T3.6)

**Overhead lines**

6. Failure prediction and preparedness (L2.4)
7. Connector condition (L3.2)
8. Condition assessment through sample testing (A3.5)

**Cables**

9. Oil Filled Termination Measurements Results (C2.3)
10. Thermal conditions (C2.4)

**Circuit breakers**

11. Re-ignition monitoring of reactor breakers (CB3.6)
12. Estimation of residual lifetime, probability of failure, and risk (A3.1)
13. Temperature measurement on GIS circuit breaker (CB3.7)

**Asset management and operation**

14. Technical-economic analysis of maintenance and reinvestment (A3.2)
15. Registration and analysis of historical costs (A3.3)
16. Event detection (O2.5)

**Voltage transformers**

Use case on voltage transformers is in progress as an internal project in Statnett, and therefore not described in the use case format, but the status of this work is reported here.

Use case O2.5 Event detection is considered both as a general case and as a transformer specific case. The use cases listed above have been described and illustrated using BPMN diagrams, which can be found in appendix V1. In the diagrams, the system (actor) that carries out the new activities suggested by the use case, i.e. functionality that does not exist at Statnett today, is named asset management (abbreviated asset mng.). The numbering of the use cases is taken from the WP2/3 report, and more details on the use cases can be found here.

Use cases have also been tested by the industry partners, ABB and GE Grid Solutions:

- Health indices for transformers (both ABB and GE Grid Solutions)
- Asset investment planning (ABB)

The results from these tests are reported here. ABB and GE Grid Solutions has presented examples of analysis that can be performed, using their tools, on data from Statnett. This has provided Statnett with information about the functionality of their asset management tools.
3  Summary of results from testing

The results from the testing are summarized in this chapter. For each use case, the following results are given when relevant:

- Experiences gained or lessons learned during the testing, including identified problems
- Costs of implementing the use case and benefits from applying the use case
- Suggestions for improvements of the use case and recommendations for implementation of the use case at Statnett

Details on how the testing was carried out are given in appendices.

3.1  Use cases developed by Statnett and SINTEF Energy Research

3.1.1  Transformer

Five use cases have been tested for transformers. "Online gas data analysis" (T2.1) describes how to evaluate warning signals from online gas analyzers (Hydran) to decide appropriate actions upon received warning signals. "Event detection" (O2.5) describes how anomalous stress to the transformer due to irregular events in the transmission system can be detected through automatic feature extraction / pattern recognition. "Thermal winding aging" (T3.1) describes how aging of the windings can be estimated based on historical load and temperature data series. The aging is quantified in terms of the degree of polymerization of the insulation paper, which is a measure of the mechanical strength of the paper, and hence the paper's ability to withstand stresses. "Periodic oil and gas analysis" (T3.5) describe how to evaluate gas concentration measurements from periodic oil tests using multivariate statistical analysis (MSA), to identify transformers in anomalous states and/or poor condition. "Health index" (T3.6) describes how the current overall condition status of the transformer can be estimated both per transformer sub-component and overall for the transformer. The condition is quantified in terms of a health index, based on condition information that is regularly updated, including oil and gas data and winding aging from T3.5 and T3.1.

Three of the use cases (T3.1, T3.5 and T3.6) have been tested in full (i.e. all steps of the use cases have been tested), while for use case T2.1 only selected steps have been tested. In appendices V2 to V5 details from the testing of these use cases can be found. O2.5 was not tested due to limited data. In general, the testing was performed to illustrate the functionality of the use cases. Benchmarking of results against known data was neither possible nor within scope. Acquiring and quality assuring all necessary data required considerable manual effort. Efforts have been made to quality assure both input data and results, but there is still a need for the data owner (Statnett) to verify all data before implementing the use cases on their side. Due to the many data sources, consistency between data sources should be checked. The testing shows that T3.1 and T3.6 function well as intended and may be implemented at Statnett today, but that live testing in operation at Statnett is desirable.

The winding aging model T3.1 have been implemented in detail to take into account arbitrarily long load and temperature data series, regulation of the cooling system (on/off), and the effect of any drying of the insulation paper previously carried out. The model is general so that different kind of input data may be applied based on availability. The testing shows that the model accuracy accordingly depends on the kind and amount of input data, thus illustrating which input data that is desired. Detailed modelling may be possible for relatively new transformers with good data availability, whereas for older transformers simplifications may be necessary. The testing also illustrates that there is significant uncertainty in the model, especially for older transformers with limited data availability, so that the results should be used with some caution.
The testing of use case T3.5 Periodic Oil and Gas Analysis has explored the use of multivariate statistical analysis (MSA) methods on transformer gas data as a tool for condition assessment of transformer health. The evaluation has demonstrated that multivariate statistical analysis (MSA) is a useful tool for identifying and visualizing risk outliers in the transformer population, as well as uncovering hidden fault-gas correlations and clustering between different groups of transformers. Importantly, the use case testing has also led to the development of 90% normal operation gas concentration limits valid for the provided Statnett transformer database. Such 90% typical gas concentration values can be used as predictive tools for transformer maintenance needs that effectively targets Norwegian conditions.

The health index proposed in T3.6 is a general model that can be based on any available condition data that can be graded and that affects the failure probability of the transformer, including winding aging calculated in T3.1 and oil and gas data analysed in T3.5. The model ensures that the health index is a number between 0 and 100% (where 100% is a perfect condition) and that the health can never be better than that signified by the condition data with the assumed largest effect on the health. Since the effect of each condition data on the overall health is uncertain, the use case should be further tested over some time to gain experience with the calculation model, and possibly readjust the model, if desired. Due to data limitations, the model has only been applied to the active part of the transformer (core, windings and oil), and this works well. The model can easily be applied to other parts when appropriate data becomes available.

For use case T2.1 the first two steps have been tested, i.e. collection of data and analysis of data for correlations. As illustrated in appendix V1, the use case starts when a warning signal is received from the Hydran due to increasing/increased gas concentration. This is a sign of an anomalous transformer state that may imply that the condition of the transformer is degrading. In order to verify the anomalous state, and to investigate the nature and severity of the warning, service data are collected and correlation of these data with the Hydran data is analyzed. This has been tested for about 60 of Statnett's transformers that are equipped with Hydran. The results show that it is difficult to use correlation analysis to investigate the nature or severity of Hydran warnings in an automatic manner using service data that are readily available for the transformers. It is recommended that a Hydran alarm is verified by other means.

For testing use case O2.5, data for relevant irregular events in the transmission system are needed. Unfortunately, such data are in general not available today. After discussing with Statnett, the only promising data that has been found are data from Elspec meters, that Statnett has installed some places. Investigation of these data was however not carried out in SAMBA but can be a follow-up activity.

Further results from the testing of transformer use cases are summarized in Table 3-1.
<table>
<thead>
<tr>
<th>Use case</th>
<th>Gained experiences / lessons learned</th>
<th>Costs and benefits</th>
<th>Suggested improvements and recommendations</th>
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| Online gas data analysis (T2.1)       | • There is a significant amount of inexplicable data for the gas concentration (e.g. spikes, outliers) that probably do not signify a real issue with the transformer. This indicates the need for checking of the data quality  
• For several but not all transformers there seems to be a weak seasonal variation in the gas concentration and a weak general increase in the gas concentration over time, that shows some dependence on temperature  
• There does not seem to be any general correlation between Hydran gas concentration data and service data such as load or temperature data. It is hence difficult to use such correlations to investigate the nature or severity of Hydran warnings in an automatic manner | • Acquiring necessary data requires per today some manual effort  
• Online gas data (Hydran) can provide early warning of transformer issues, but Statnett has had some problems with their Hydrans, such as false warnings | • In general, it is recommended that a Hydran alarm is verified by other means than evaluating correlations between Hydran gas concentration data and service data such as load and temperature data. Correlating alarms to irregular events in the transmission system may be a more viable way (see O2.5)  
• For transformers where some correlation between Hydran data and oil temperature or moisture is identified, this correlation might be monitored as a means to check if the Hydran is working as expected |                                                                                                                                                                                                                                                                                                                                                                               |
| Event detection (O2.5)                | • Data for relevant irregular events in the transmission system are in general not available                                                                                                                                                                                                                                                                         | NA                                                                                                                                                                                                                                                                                                                                                                               | Statnett has installed Elspec meters some places, that can maybe provide some relevant data and this should be a follow-up activity                                                                                                                                                                                                                       |
| Thermal winding aging (T3.1)          | • Data quality must be checked, as for some transformers it may be too poor for the use case  
• The calculation is sensitive to several input parameters. The most important parameters are:  
  o Temperature (preferably hot-spot, alternatively top oil)  
  o Parameters for temperature modelling, including cooling system data and data from transformer heat run test  
  o Water content in oil  
• For the load and temperature data series, a time resolution of one hour is sufficient  
• Detailed modelling may be possible for relatively new transformers with good data availability, whereas for older transformers simplifications are typically necessary | • Acquiring necessary data requires per today considerable manual effort  
• Cleaning and quality assurance of data requires per today considerable manual effort. Poor data in some cases hinders meaningful results  
• The use case provides an estimate of the winding paper condition, but the uncertainty is significant | • Automate and standardize collection and storage of input data  
• If available, the calculation should be based on load and temperature series from the whole lifetime of the transformer  
• To maximize the reliability of the calculation, the calculation should ideally be based on:  
  o Directly measured hot-spot temperature (using fibre optic sensor)  
  o Relative humidity measurement in the oil (using e.g. Hydran)  
• To enable estimation of water content in the paper from oil test results, every oil test (T3.5) should include information about (at time of test) water content in oil, load, top oil temperature, hot-spot temperature (if available) |
| Use case                              | Gained experiences / lessons learned                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     | Costs and benefits                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Suggested improvements and recommendations                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
|---------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Periodic oil and gas analysis (T3.5) | • DGA data quality must be thoroughly checked and cleaned before applying statistical analysis because external gas sources may lead to statistical artefacts and misleading interpretation of the results  
  • Per today, single DGA measurement series data files of the .xml-type, or similar datasets stored in Excel worksheets are not structured in a way that facilitates statistical analysis. Automatic functions in Python have been implemented to transform the datasets into a useful structure  
  • In the context of statistical analysis, incomplete data (such as generic gas concentration values of 1 ul/l for measurements below the detection limit) is to some extent worse than no data, because misleading statistical correlations may arise from incomplete and bad data  
  • Information about transformer designs (such as air-breathing vs. closed casket and communicating on-load tap changers) are in general not included with the DGA data, but may have a large influence on the analysis results                                                                                                                                                                                                                                                                                                                                 | • Acquiring necessary data requires per today considerable manual effort. In addition, acquiring useful and generalizable statistical results require per today considerable manual effort in data cleaning  
  • Multivariate analysis of DGA values is a potentially powerful tool for identifying outlier and risk transformers in a large dataset. However, the method is only indicative, and follow-up investigations and surveillance of risk transformers are required  
  • Statistical treatments of DGA data can be used for finding new limits for actions – to complement and tune IEC standards to local (e.g. Norwegian) operating conditions  
  • For the statistical analysis to give trustworthy results, DGA samples should be taken on a regular basis (e.g. once every year) on a large population of transformers, also including all healthy transformers. It is recommended to review and improve how the data is stored  
  • Along with the DGA concentration values, information about the design (e.g. communicating tap changer, air-breathing, etc.) of the transformer should be easily accessible  
  • DGA from transformers that have incomplete or invalid data for known reasons should not be mixed with healthy / unknown transformers  
  • Measured DGA values that are below the detection limit of a particular gas should be stored as "below the detection limit" and not as generic values of 1 ul/l. Such entries obscure the real statistical correlations and introduce artefacts in the analysis  
  • For the statistical analysis to give trustworthy results, DGA samples should be taken on a regular basis (e.g. once every year) on a large population of transformers, also including all healthy transformers. It is recommended to review and improve how the data is stored  
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  • For the statistical analysis to give trustworthy results, DGA samples should be taken on a regular basis (e.g. once every year) on a large population of transformers, also including all healthy transformers. It is recommended to review and improve how the data is stored  | • Automate and standardize collection and storage of input data  
  • Establish grading criteria for oil test parameters based on national statistics (instead of international statistics taken from IEC 60599 / CIGRE 443). See T3.5  
  • Extend the model to other parts than the active part of the transformer  
  • Due to the inherent subjectivity of such models, test the use case for some time to gain experience with the calculation model, and possibly readjust the model, if desired                                                                                                                                                                                                                                                                                                                                                                                                                                                                 |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                 |
Based on the testing, an overall scheme for continuous condition assessment of transformers has been suggested in Figure 3-1. This scheme provides key parameters for decision makers, such as the risk of transformer failure and the transformer remaining life, using the tested use cases and some additional use cases. In Figure 3-1, the grey boxes represent input data, while the blue boxes represent use cases. The use cases are classified according to their purpose, i.e. whether they detect anomalies, analyze condition, conclude the overall condition status, or make prognosis for the life of the transformer. Note that anomalies do not necessarily affect the transformer condition, as illustrated by the dotted line from the anomaly detection use cases. The output of all the use cases for anomaly detection may in the future also be included in the health index calculation in the prototype. This is however not straightforward, as it must first be considered which anomalies that affect the transformer condition in a negative way.

The use cases that have been tested in this report are shown in bold blue boxes in the figure. The other use cases in Figure 3-1 have been included for added functionality. These are:

- **Risk**: This use case is based on work carried out in the project "Trafotiltak" [3]. It translates the health index of the transformer into the risk of transformer failure, by relating the health index to databases of scrapped and failed transformers [3]. There is ongoing work in another project to improve these databases, and hence improve this estimation of risk.

- **Remaining life**: This use case is taken from the project "Trafotiltak" [3]. It calculates the expected remaining life from the yearly risk of major transformer failure (i.e. full breakdown) [3].

- **Hot-spot temperature**: This use case is taken from a master's thesis at NTNU that was carried out within the SAMBA project [4]. Using machine learning algorithms, this use case enables the future hot-spot temperature to be estimated based on historic hot-spot temperatures and expected future load. Results from testing indicate that the use case can yield reasonably reliable estimates of the future hot-spot temperature.

The main part of the scheme in Figure 3-1 has been implemented in a software prototype for testing. This prototype is built on a prototype developed earlier in the project "Trafotiltak". In the prototype all use cases below the input data boxes in the figure are included, except for the "hot-spot temperature" prognosis use case. As illustrated by the dashed line, this latter use case also fits well into the prototype and is straightforward to include. Including this use case will enable better estimation of the future hot-spot temperature.

The prototype also includes models for estimating risk and assessing reinvestment alternatives. The latter model is not shown in Figure 3-1. Results from these models are shown in Figure 3-2 and Table 3-2. The underlying data for these results is those given in the appendices for use cases T3.1 and T3.6. In addition, scrapping/failure statistics and cost data was needed. The scrapping statistics used have been taken from the project "Trafotiltak" [3]. Detailed cost data for the transformers could not be obtained. Therefore, a simple model has been utilized to obtain the cost of breakdown. This model simply estimates the cost of breakdown as only the cost of energy not supplied due to the breakdown and the cost of buying a new transformer. Both are estimated based on the transformer rated power and voltage, as well as some historic cost data from Statnett for energy not supplied. In a realistic case, the cost data should be set by Statnett and include all relevant economic consequences of failure.

In the reinvestment analysis in Table 3-2 the remaining life without replacing the transformer (T19) is shown, as well as the net value of the cost incurred during the chosen analysis period (here 20 years) for selected measures/actions (i.e. for replacing the transformer some years in the future). The technical-economic analysis used to establish these results is described in Ref. [3] and bare similarities with the one described in section 3.1.6. For this transformer, the model predicts that the most profitable course of action is to delay
replacement, although the transformer is in relatively poor condition\(^1\). Note that this is mainly due to the fact that the only cost of failure included is cost of energy not supplied, and therefore is relatively low. It must also be remembered that replacing the transformer has other positive effects not accounted for by the present model, such as the fact that replacement means that also all other parts than the active part become new.

\[\text{Figure 3-1: Suggested scheme for continuous condition assessment of power transformers}\]

\[\text{Figure 3-2: Risk plot for selected transformers}\]

\(^1\) This transformer was in fact scrapped a few years ago
Table 3-2: Selected results for one of the transformers (T19): Remaining life and net value of the cost incurred during the analysis period (here 20 years) with and without replacing the transformer. Remaining life is the expected time to failure.

<table>
<thead>
<tr>
<th>Measure/action</th>
<th>Remaining life (years)</th>
<th>Cost incurred (kkr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No measure/action</td>
<td>30</td>
<td>1917</td>
</tr>
<tr>
<td>Replacement, year 0</td>
<td>-</td>
<td>11397</td>
</tr>
<tr>
<td>Replacement, year 5</td>
<td>-</td>
<td>7700</td>
</tr>
<tr>
<td>Replacement, year 10</td>
<td>-</td>
<td>5043</td>
</tr>
</tbody>
</table>

3.1.2 Overhead lines

Three use cases have been described for overhead lines. Failure prediction and preparedness (L2.4) has not been tested and will not be discussed in this report. Connector condition (L3.2) and Condition assessment through sample testing (A3.5) are closely related, as the connector condition is input to the testing of A3.5.

The connector condition (L3.2) has been tested using a method, the pulse current method that accurately determines the condition of the electrical contact interface of the connectors. The condition of the connector is classified to be Very Good, Good, Poor, and Very Poor, based on the condition of the electrical contact interface. A connector in a Very Good or Good condition does not experience any accelerated thermal ageing of the electrical contact interface at nominal load currents, while a connector in Poor condition does experience accelerated thermal ageing of the electrical contact interface at nominal load currents. A Very Poor connector has deteriorated to a level where the continued operation of connector might cause failure.

In the SAMBA-project, the condition of 78 joints and two dead ends from the Statnett’s 300 kV overhead line between Sauda and Karmøy has been determined using the pulse current method. All the tested joints and dead ends were in a very good condition, see appendix V6 for more details.

Condition assessment through sample testing (A3.5) describes a strategy where sample testing is used to describe the technical condition of the whole population of a given asset. In this case line connectors are used as an example. The use case is based on an assumption that the population can be divided into archetypes based on factors related to the design and stresses assumed to affect the technical condition. Detailed condition assessment on a selection of components of each archetype, or only components of the archetype which is assumed to have the worst technical condition, can provide important information for decisions about maintenance and reinvestments. Appendix V7 illustrates how condition assessment through sample testing fits into a replacement process. Use case (A3.5) was tested on a population of line connectors that had been replaced from the line Sauda – Håvik. First the population was divided into different archetypes, then detailed condition assessment was performed on all line connectors to see if there was any significant difference in the technical condition of the components in each archetype. All line connectors were in good condition, so it was not possible to verify the assumption.
### Table 3-3 Summary of results from testing of the overhead line use cases

<table>
<thead>
<tr>
<th>Use case</th>
<th>Gained experiences / lessons learned</th>
<th>Costs and benefits</th>
<th>Suggested improvements and recommendations</th>
</tr>
</thead>
</table>
| Connector condition (L3.2)                    | • Due to the short length of conductor left at the ends of each connector, the condition of all the connectors could not be determined  
  • For the tested connectors there were no ambiguity in the condition | • Very accurate condition determination  
  • Requires physical access to the connectors                                          | • The marking of components removed from service should be better (and more consistent) to clearly identify the component |
| Condition assessment through sample testing (A3.5) | • All line connectors were in very good condition. Replacements was not based on the technical condition.                     | • Better knowledge of the technical condition of the assets will be useful input when determining replacement strategies | • Test the use case on another set of line connectors or other components i.e.    |
3.1.3 Cables

Two use cases have been described for cables. Oil Filled Termination Measurements Results (C2.3) has not been tested and will not be discussed in this report. Thermal conditions (C2.4) deals with temperature measurements from cables and aims to answer two questions:

- Can cable temperature be presented in an intuitive way as a function of position and time?
- Does the data provide a basis for dynamic ampacity calculation and forecasting based on data science tools?

SINTEF Energy Research have developed a script that displays the cable-temperature as a function of position and time. This is already delivered to the cable-department in Statnett and have received a positive feedback. Furthermore, when working to answer question two, extensive data exploration is done that presents valuable insights for the cable operators.

The second research question in this use case aims at taking the first steps towards a dynamic ampacity calculation for cables. The key component is then accurate predictions for the temperature in the cable. This is solved by exploiting correlations between cable temperature, air-temperature and load on the cable. These are correlations that only recently are plausible to exploit, due to investments in distributed temperature sensing (DTS) systems and release of open data from the Norwegian Metrological institute. Furthermore, developments in processing power and open source programming languages make this a much more achievable task than just some years ago.

Data for this use case was gathered from three different data sources and came in five different formats. Extensive work has been done in ensuring that the timeseries data align correctly, exploring the data for correlations and synthesizing variables that to a high degree explains the correlation. The importance of data management cannot be understated. For cost-efficient data-driven projects in the future, proper framework for data management is highly recommended.

After the exploratory data analysis, multiple machine learning models are trained and tested on actual data. In Figure 3-3 the performance of five models are displayed for two arbitrary dates in the test dataset. From the figure one can observe that the performance of the different machine learning models is quite similar. In accordance with general consensus, it is found that the data quality is of much higher importance than what algorithm to use. Furthermore, it is crucial to include domain experts when deriving knowledge from data.

The use case has used data from 2015-2018 when deriving models and insights. The user should keep in mind that such models can fall short if any situations occur, that are not present in the current dataset. Statistical data is used for the air-temperature, so using forecasted temperature for the coming days will introduce some uncertainty to the models.

Further description on the work done is found in the use case documentation. Additionally, the code that is developed in the use case is included in the form of jupyter notebooks. These scripts are built so that any employee at Statnett can verify what is done, gain better insights and efficiently transfer competence. The intention is to lower the threshold for implementing operational models and create an environment where the user them self can expand the model framework and add new features.

The use case concludes that using big data and machine learning techniques can indeed be utilized for smarter asset management.
Figure 3-3: Performance of predictions for March 12th and April 11th
Table 3-4 Summary of results from testing of the cable use cases

<table>
<thead>
<tr>
<th>Use case</th>
<th>Gained experiences / lessons learned</th>
<th>Costs and benefits</th>
<th>Suggested improvements and recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>C2.4 Distributed Temperature Sensing (DTS)</td>
<td>• Intuitively plotted data adds value to the grid-operator</td>
<td>• Can be automated</td>
<td>• Data mining and preparation is tedious. Platforms for data management should be considered.</td>
</tr>
<tr>
<td></td>
<td>• The future temperature in the cable can be predicted, using load and air temperature.</td>
<td>• High performance on the dataset available for the use-case.</td>
<td>• Not all states present in the dataset. Hybrid modelling should be investigated for robustness.</td>
</tr>
</tbody>
</table>
3.1.4 Circuit breakers

Three use cases have been described for circuit breakers. Re-ignition monitoring of reactor breakers (CB3.6) describes how re-ignitions in reactor circuit breakers can be identified by analysing current measurements. The use case has been tested on historical data from BEN fault recorders installed at the reactor breakers in Holen. The algorithm was written in python based on the specifications in appendix V8. The algorithm was not implemented in AutoDIG but tested directly on data from the database. The tests confirmed that the algorithm was able to identify re-ignitions. Out of 360 breaker operations the algorithm successfully revealed 30 re-ignitions. The algorithm is considered ready to be implemented in Statnetts Big Data and analysis platform for continuous monitoring of all reactor breaker equipped with fault recorders.

Estimation of residual lifetime, probability of failure, and risk (A3.1) is tested and reported as part of use case Technical-economic analysis of maintenance and reinvestment (A3.2), see chapter 3.1.6.

Temperature measurement on GIS circuit breaker (CB3.7) was tested in a pilot with temperature sensors installed on GIS breakers in Tegneby. The data gathered from the installation indicated temperature rise in one of the phases. After thermography of the breaker temperature rise and hot spots was detected. The breaker was opened and burn marks were found. This type of simple sensor technology could be used for condition-based monitoring to detect hot spots and temperature rise in GIS circuit breaker and also disconnectors. No further testing of this use case will be performed in SAMBA because no current sensors are installed on GIS breakers. Further investigation of better adapted sensor and system should be performed, since this type of simple sensor technology could be used for condition-based monitoring to detect hot spots and temperature rise in GIS circuit breaker and also disconnectors by comparing temperature measurements of different phases.
### Table 3-5 Summary of results from testing of the circuit breaker use cases

<table>
<thead>
<tr>
<th>Use case</th>
<th>Gained experiences / lessons learned</th>
<th>Costs and benefits</th>
<th>Suggested improvements and recommendations</th>
</tr>
</thead>
</table>
| Re-ignition monitoring of reactor breakers    | • Possible to detect re-ignitions using the proposed algorithm | • Avoid failures on reactor breakers  
• Monitoring of re-ignitions in reactor breakers  
• The method uses data from existing fault recorders. | • Implement the algorithm in the new big data and analysis platform for automatic and continuous monitoring of reactor breakers. |
| (CB3.6)                                       |                                      |                                                                                     |                                                                                                              |
| Temperature measurement on GIS circuit breaker| • Possible to detect temperature rise and hotspots in GIS circuit breakers         | • Installing of sensors can give an online indication of temperature rise that can be checked by thermography  
• Avoid circuit breaker failure  
• Simple sensors | • Investigate better adapted sensors and systems for temperature monitoring on circuit breakers  
• Evaluate cost/benefit for temperature sensor related to failure rate for relevant failure mechanisms and cost of installation versus current monitoring using time-based thermography  
• Include temperature sensors in the Statnett sensor strategy |
| (CB3.7)                                       |                                      |                                                                                     |                                                                                                              |
3.1.5 Voltage transformers

The work on voltage transformers has been performed as an internal project in Statnett and is therefore not described in the use case format. The project aim is to develop condition monitoring of capacitive voltage transformers, with detection of deviations in voltage differences. Deviations provide an early warning about possible equipment degradation. This information can be used to plan the replacement of the equipment prior to failure. The calculation of voltage differences is based on automatically collected phase voltages data. This data is stored in a Datawarehouse. Today, the voltage differences are measured manually, typically every quarter, and the results are evaluated subjectively by the operator conducting the measurement. Automatic analysis based on data from the Datawarehouse could make this work more efficient and the calculations can be done i.e. daily. This will make it possible to monitor deviations in measurements and perform replacements before failure.

The pilot testing of this has been initiated in Statnett including 24 stations with 449 voltage transformers. Statnett has over 2000 voltage transformers in total. Data is captured every 10 seconds, but it is decided to provide measurements once a day to the operators. Hence data is available every day and not just every third month. The vendors deliver equipment with a tolerance limit for deviations at 0.2V. But this value can in some instances be too low and provide alarms when there is no problem. In order to avoid such false alarms an option to override the vendor value is added and the tolerance limit can be adjusted to fit with the experience with the measurements and which values are the correct alarm values.

The pilot was conducted in October and November 2018. During the pilot several of the measurements had large deviations and generated alarms. Some of the largest deviations at 132kV busbars were investigated manually and faults in voltage transformers were disclosed. The surveillance center at Sunndsåsra are going through the deviations in cooperation with maintenance planners and technical staff in order to build more competence on the solution. More measurements will be installed in the near future.

3.1.6 Asset management and operation

Three use cases have been described for asset management and operation. Event detection (O2.5) has not been tested and is not therefore not a part of this report.

Introduction to A3.1 and A3.2

It has been a combined (common) testing of the following to use cases:

- A3.1 - Estimation of residual lifetime, probability of failure and risk (circuit-breaker)
- A3.2 - Technical-economic analysis of maintenance and reinvestments projects (cost-benefit)

The purpose of the testing has been to show how technical conditions for components can be used in cost-benefit analysis of maintenance and reinvestment alternatives. The testing is carried out according to a method that includes the following models:

- Deterioration models specifying expected residual life of components based on technical condition and external and operational related stresses
- Failure models for estimating the probability of failure and consequences of failure
- Models that describe predefined maintenance and reinvestment alternatives (options)
- Models for present value analysis of predefined maintenance and reinvestment alternatives (total cost calculation)

The method and the models have been tested on 20 fictitious identical SF$_6$ circuit-breakers in a 300kV substation.
An important challenge today in prioritizing and determining the right time for maintenance and reinvestment projects is the gap between the available information about the technical condition of components (asset health) and the decision making. In order for decision-making to become more condition-based and data-driven, the information about the technical condition must be available and arranged in such a way that it is directly applicable to the decision-maker. This means that the information must be analyzed and result in a ranking of the options in terms of risk and total cost.

The method and models included in the testing of A3.1 and A3.2 help to reduce the gap between the available information about asset health and the decision making as illustrated in Figure 3-4. In use case A3.1, the probability of failure and associated risk is estimated based on technical condition. This is input to the cost-benefit analysis in use case A3.2 and is included in the calculation of total costs for each predefined maintenance and reinvestment alternative.

The condition assessment is based on information from performed condition monitoring and on-site inspections. Decision making can include optimal timing of projects as well as preparation of plans and strategies for maintenance and reinvestment in the short, medium and long term.

The total cost of the predefined replacement alternatives is automatically calculated when the information from the performed condition assessment of the components is uploaded to the tool used for the testing of the use cases. The tool (prototype) and associated method (REPLAN) has been developed by SINTEF Energy for Energy Norway and 8 Norwegian grid operators [5].

**Deterioration models (A3.1)**

All technical items are subject to deterioration, and deterioration leads to a poorer technical condition of the components. This may have the following consequences:

- Increased failure probability
- Reduced remaining life
- Reduced ability of the components to perform their required function

Usually, the technical condition worsens gradually, which at the same time means that deterioration increases. The condition development can be illustrated by a curve as shown in Figure 3-5.

---

**Figure 3-4 The use cases A3.1 and A3.2 reduce the gap between the information about asset health and the decision making**

**Figure 3-5 Technical condition states and life curve [6]**
The curve is denoted deterioration curve or life curve and shows the relation between time (or another measure of usage) and the technical condition. The curve is related to one failure mechanism of an item. Thus, several life curves may be required for modelling the remaining lifetime and failure probability of the component, because several failure mechanisms usually occur at the same time and with different deterioration speed.

The deterioration model used for the testing of use case A3.1 is according to a classification system with five states [6] as shown in Figure 3-5. The general description of the deterioration states is provided in Table 3-6.

Table 3-6 General description of deterioration states [6]

<table>
<thead>
<tr>
<th>State</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No indication (&quot;as good as new&quot;)</td>
</tr>
<tr>
<td>2</td>
<td>Minor deterioration. The condition is noticeable worse than &quot;as good as new&quot;.</td>
</tr>
<tr>
<td>3</td>
<td>Major deterioration. The condition is considerable worse than &quot;as good as new&quot;.</td>
</tr>
<tr>
<td>4</td>
<td>The condition is critical. Serious considerations should be made to repair immediately.</td>
</tr>
<tr>
<td>5</td>
<td>The component is unable to fulfil the function (fault).</td>
</tr>
</tbody>
</table>

Provided that no maintenance is carried out, the classification system implies that the item’s technical condition will run through all four states until a failure occurs which brings the item’s condition to the fifth state. Using the concept of technical condition states and life curves means that the item’s technical condition will stay some time in state 1, some time in state 2, and so one. These times/durations are called sojourn times (residence times) and are denoted $T_1$, $T_2$, $T_3$ and $T_4$ in Figure 3-5.

The condition assessment of the components covered by the testing of use case A3.1 is to determine a deterioration grade (DG) in line with the classification in Table 3-7. The deterioration grade is set equal to 1 if the condition is considered to be in accordance with the criterion for state 1, deterioration grade 2 represents state 2, etc. In use case A3.1, the deterioration grades are related to the recommended time for replacement as shown in Table 3-7. The replacement times are in line with the general criteria in Table 3-6.

Table 3-7 Replacement times according to the REPLAN method [5]

<table>
<thead>
<tr>
<th>DG</th>
<th>Replacement times</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Replacement is not expected to be necessary within the period of analysis (20 years)</td>
</tr>
<tr>
<td>2</td>
<td>Same as DG=1</td>
</tr>
<tr>
<td>3</td>
<td>Replacement is relevant in year 6 and is expected to be necessary at the latest in year 11</td>
</tr>
<tr>
<td>4</td>
<td>Replacement is relevant in year 1 and is expected to be necessary at the latest in year 6</td>
</tr>
<tr>
<td>5</td>
<td>Replacement must be done in year 1</td>
</tr>
</tbody>
</table>

The latest time for replacement is the expected year at which replacement at the latest can be done while keeping the probability for failure at a tolerable level. A tolerable level is user specific and may be e.g. a 10% probability of failure before replacement (see the failure probability model below).
The plan was to perform a condition assessment of some selected circuit breakers as part of the testing, but this could not be done because of limited personnel resources at Statnett for this task. The following describes a fictitious testing that will show how the method, models and tools can contribute to an effective cost-benefit analysis of reinvestment alternatives for circuit breakers.

The circuit-breakers subject for fictitious testing are divided in these six components:

- Breaker chamber
- Breaker contacts
- Field control capacitor
- Vertical column insulator
- Operating device
- Pressure tank

The fictitious condition assessment is to determine a deterioration grade for each of the six components. In this case, it is assumed that the components only have one failure mechanism. If there had been more than one failure mechanism, then a deterioration grade had to be determined for each failure mechanism. The deterioration grades are then aggregated to a common deterioration grade for each component, e.g. by using the worst deterioration grade. Table 3-8 shows the results from a fictitious on-site condition assessment of the 20 circuit-breakers which are assumed to be subject to the testing of the two use cases A3.1 and A3.2.

<table>
<thead>
<tr>
<th>Deterioration grade</th>
<th>Breaker chamber</th>
<th>Breaker contacts</th>
<th>Field control capacitor</th>
<th>Vertical column insulator</th>
<th>Operating device</th>
<th>Pressure tank</th>
</tr>
</thead>
<tbody>
<tr>
<td>DG=5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>DG=4</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>DG=3</td>
<td>4</td>
<td>10</td>
<td>2</td>
<td>2</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>DG=2</td>
<td>14</td>
<td>9</td>
<td>16</td>
<td>17</td>
<td>8</td>
<td>17</td>
</tr>
<tr>
<td>DG=1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sum</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

Failure models (A3.1)

A failure model is defined per component enabling calculation of annual failure probability as a function of the components’ technical condition given by the deterioration grades. Annual failure probabilities and the corresponding failure consequences are input to the cost-benefit analysis of maintenance and reinvestment alternatives. Failure models include:

- Failure mechanisms (causes)
- Failure events
- Probability distributions for calculating annual probability of failure. The parameters of the probability distributions are governed by the component deterioration grade, as well as external stresses to the component.
• Failure consequences; repair/replacement and outage times and costs due to failure. Outage cost is cost of energy not supplied (CENS). The outage times are specified per component and are dependent on the component’s location in the network.

One circuit-breaker may have several failure mechanisms. In this study, these are merged into a common failure mechanism for each circuit-breaker component. This means that the failure models include failures due to:

• Breaker chamber
• Breaker contacts
• Field control capacitor
• Vertical column insulator
• Operating device
• Pressure tank

The selection of failure mechanisms for the relevant circuit breaker type is based on Statnett’s Reliability Centered Maintenance plan (RCM). The same is the selection of these four failure events that the failure models include:

• The circuit-breaker does not start
• The circuit-breaker does not break
• The circuit-breaker does not insulate over the breaker gap
• The circuit-breaker does not insulate against earth potential

A failure model is established for each failure mechanism including the corresponding failure events. Table 3-9 shows which failure events that are caused by each of the failure mechanisms. For each failure event, the failure models also include a specification of consequences as shown in Figure 3-6.

Table 3-9 Failure events caused by the various failure mechanisms

<table>
<thead>
<tr>
<th>Failure mechanisms for the circuit-breaker (C-B)</th>
<th>C-B does not start</th>
<th>C-B does not break</th>
<th>C-B does not insulate over the breaker gap</th>
<th>C-B does not insulate against earth potential</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breaker chamber</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Breaker contacts</td>
<td></td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Field control capacitor</td>
<td></td>
<td></td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Vertical column insulator</td>
<td></td>
<td></td>
<td></td>
<td>x</td>
</tr>
<tr>
<td>Operating device</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Pressure tank</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>
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Figure 3-6 Failure events and corresponding consequences for breaker chamber

Figure 3-7 shows an example of a probability distribution, in this case for a circuit-breaker that has been evaluated to have DG=3. The distribution is generated from two parameters: The mean residual life (MRL) and the 10-percentile (P_{10}). The mean residual life for this distribution is 20 years. The 10-percentile, i.e. the period in which the failure probability sums up to 10%, is 10 years. The figure also shows the corresponding cumulative probability distribution. The distribution represents the annual probability of failure from the time the condition assessment was made.

After repairing or replacing a circuit-breaker component after failure, the deterioration grade is set to DG=1, and the probability distribution is updated. This enables proper calculation of the failure probability and failure cost both before and after failures.

Predefined replacement alternatives (A3.2)

Relevant replacement alternatives are identified based on the condition assessment criteria in Table 3-7. For circuit-breaker components with DG=1 or DG=2, replacement is not relevant. For components with DG=3, DG=4 or DG=5, the points in time at which replacement is relevant are shown in Figure 3-8. This is replacement in the present year (denoted R1), replacement in year 6 from now (R6), replacement in year 11 (R11) or replacement in year 16 (R16). The period of analysis is 20 years, meaning that replacement later than this is not considered.
For the alternatives R16 for DG=3 and R11 for DG=4, the probability for failure before replacement is expected to become higher than acceptable. These alternatives are included in order to assess the cost of such high-risk alternatives.

The cost-benefit analysis has included the following ten predefined replacement alternatives based on the replacement times shown in Figure 3-8:

Alt. 1  DG=5 (R1), DG=4 (R1), DG=3 (R1)
Alt. 2  DG=5 (R1), DG=4 (R1), DG=3 (R6)
Alt. 3  DG=5 (R1), DG=4 (R1), DG=3 (R11)
Alt. 4  DG=5 (R1), DG=4 (R6), DG=3 (R6)
Alt. 5  DG=5 (R1), DG=4 (R6), DG=3 (R11)
Alt. 6  DG=5 (R1), DG=4 (R11), DG=3 (R16)
Alt. 7  DG=5 (R1), DG=4 (R1), DG=3 (no replacement)
Alt. 8  DG=5 (R1), DG=4 (R6), DG=3 (no replacement)
Alt. 9  DG=5 (R1), complete replacement (R6)
Alt. 10 Complete replacement (R1)

The alternatives should be understood as follows. For example, alternative 1 means that all components with DG=5, DG=4 and DG=3 are replaced in year 1. Alternative 9 and 10 means complete replacement of the whole installation. The alternatives represent both early replacement, replacement according to the condition criteria and late replacement. Based on this, the decision maker can assess profitability against current risk.

Cost-benefit analysis of predefined replacement alternatives (A3.2)

Figure 3-9 shows the summary of the results from the cost-benefit analysis of the ten predefined replacement alternatives. The figure is an excerpt from the main screen picture of the Excel-based tool that was used for the cost calculation [5]. All amounts (NOK) are current values.

The results from the fictitious on-site condition assessment (number of occurrences) are as shown in Table 3-8.

The column labeled "PM" includes on-site condition assessment during the period of analysis. The cost of scheduled replacement is divided into "R1", "R6", "R11" and "R16". "CENSn" is the cost of notified interruptions related to scheduled replacement. In this analysis it is assumed that the replacement will be carried out without interruption (CENSn = 0 NOK). "Repair" is the cost of repair after failure. "CENS" is the cost of energy not supplied due to failure. The rightmost column shows the percentage value of the total cost where the total cost for the alternative with the lowest total cost is set to 100%.
Alt. 5, alt. 4 and alt. 3 have the lowest total cost. It is not profitable with even earlier replacement due to relatively low CENS due to failure compared to alt. 1 and alt. 2. This is also the reason why the total cost for alt. 7 and alt. 8 is only 18% and 15% higher than for alt. 5, although no components with DG=3 are replaced during the period of analysis. Complete replacement of the circuit-breakers in alt. 9 and alt. 10 results in low costs due to failures, but this is not enough for these alternatives to be profitable.

The testing shows that systematic technical-economic analysis of renewal alternatives can be automated when the condition assessment is based on criteria for technical condition related to predefined residual lives and associated replacement times. Automation here means the minimum use of time to carry out the actual analysis. The analysis shows that condition-based replacement of individual components can provide a significant lifetime extension to the circuit-breakers.

The method used in the analysis of optimum replacement of circuit-breakers is equally suitable for other switchgear as well as for overhead lines components (towers, feeders, joints).

Use case A3.3

The testing of the use case "Registration and analysis of historical costs (A3.3)" was performed by Elin Viborg, trainee working at Statnett in the department maintenance and renewal (DAA). This use case provides insights into how Statnett currently is reporting and recording cost data related to maintenance and replacement projects. The results are very important for Statnett to identify what improvements in cost registration are needed in order to be able implement the methodology described in use case A3.2. The testing included analyses of costs on organization levels, types of work done, trending analysis for component groups including strategy analysis. The strategy analysis shows how cost is distributed on preventive respectively corrective maintenance correlated to number of failures for different components. The use case provides examples of how cost data can be presented in dashboards and charts, examples are shown in Figure 3-10 and Figure 3-11.

Both the trending and strategy analysis are good methods to visualize costs to increase awareness of how much different maintenance actions costs, providing a background for improving maintenance strategies to reduce costs and illustrate the cost of failures. The benefits are many, while the cost and work to implement such analyses are relatively small. However, in order to take these results into practice Statnett needs to reconsider its analysis and decision-making processes and increase awareness of the importance of cost registration and the use of cost information in decision making.
Figure 3-10: The figure to the left displays the distribution of the total maintenance cost between different operation groups. The figure to the right displays total number of work orders for work type maintenance.
Figure 3-11 16 selected transformers from the strategy analysis of transformers. The upper left figure displays the age, the upper right figure displays the number of failures reports for the transformers and their priority (how quickly the problems must be fixed), the lower left figure displays the failure classes and the lower figure to the right displays the performed maintenance of the 16 selected transformers.
### Use case testing - SAMBA WP5 report

#### Table 3-10 Summary of results from testing of the asset management and operation use cases

<table>
<thead>
<tr>
<th>Use case</th>
<th>Gained experiences / lessons learned</th>
<th>Costs and benefits</th>
<th>Suggested improvements and recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation of residual lifetime, probability of failure and risk (A3.1)</td>
<td>• The testing shows that systematic technical-economic analysis of renewal alternatives can be automated when the condition assessment is based on criteria for technical condition related to predefined residual lives and associated replacement times. Automation here means the minimum use of time to carry out the actual analysis.</td>
<td>• The analysis shows that condition-based replacement of individual components can provide a significant lifetime extension to the circuit-breakers. Using the method for systematic technical-economic analysis of predefined replacement alternatives shows that there may be large cost differences between different alternatives. Choosing the right alternative can therefore result in great savings.</td>
<td>Carry out a case study that includes:</td>
</tr>
<tr>
<td>Technical-economic analysis of maintenance and reinvestment (A3.2)</td>
<td>• The method used in the analysis of optimum replacement of circuit-breakers is equally suitable for other switchgear as well as for overhead lines components (towers, feeders, joints)</td>
<td></td>
<td>• Consider how the method demonstrated in A3.1 and A3.2 can improve maintenance and reinvestment decisions (project types, limitations, adaption to other methods in use (RCM), etc.)</td>
</tr>
<tr>
<td>Registration and analysis of historical costs (A3.3)</td>
<td>• One problem with the cost history data is that costs related to breakdowns are difficult to find. When a severe failure is registered as a work order and the maintenance is large or the components need replacement, a project is created to restore the function without correct registration of what has been done and corresponding cost on component level. The cost is therefore difficult to trace back to the faulted component. The registration of cost data on overhead lines is on high level meaning that Statnett does not have an overview of how much maintenance of each component costs.</td>
<td>The following benefits can be seen with visualization of costs in a dashboard:</td>
<td>• Establish deterioration criteria for components related to e.g. bays (switchgear)</td>
</tr>
</tbody>
</table>
|                                                     | • The registration of cost data on overhead lines is on high level meaning that Statnett does not have an overview of how much maintenance of each component costs. | • Create an awareness of costs  
• Benchmark Statnett’s maintenance on different organization levels  
• Trending and follow up of maintenance strategies and programs to support RCM  
• Trending and follow up of correct registration of work types  
• Provide supplementary information to be used in benchmark programs such as iTOMS and VVO | • Perform on-site condition assessment  
• Perform cost-benefit calculations of predefined renewal alternatives  
• Evaluate the potential using this method |
|                                                     |  | • Make breakdown costs available for analysis e.g. build up a logic to distribute the costs registered on round work orders  
• Develop dashboard functionality to display the trending and strategic analysis  
• Reconsider the analysis and decision-making processes and increase awareness on the importance of cost registration and the use of cost information in decision making  
• Further recommendations can be found in a report made for internal Statnett use |
3.2 Use cases developed by industry partners

3.2.1 GE Grid Solutions

This chapter describes the main results obtained when mapping STATNETT data from a few Power Transformers on the Asset Health Models hosted by the GE GRID APM software (Asset Performance Management). GE APM is the software from GE’s GRID SOLUTIONS to support customer decisions on maintenance and replacement of their electrical assets. Asset Health Models (aka “Digital Twins”) have been created in GE APM by GRID SOLUTIONS SERVICES to model the equipment present in electrical grids, including assets for HV, MV, AIS, GIS, AC and DC. These models are stored in a Library reusable by all GE Customers.

The purpose of the test was to evaluate the results obtained from the existing data and produce guidelines for the future data management to be built in STATNETT after the SAMBA research project is completed.

OVERVIEW OF THE TEST CONFIGURATION

Available Data have been entered for 4 Transformers as shown below:

![Figure 3-12 Age, asset health index and completeness index for four selected transformers](image)

These data are hosted in a configuration managed by GE in SaaS mode (Software as a Service). Resulting Analytics have been discussed with STATNETT SAMBA engineers in a meeting in OSLO in September 2017. The focus was put on the Ageing calculations, linked to the Asset Health Index (AHI), as per GE Methodology. From 2 to 20 yearly samples were available for each asset.

SELECTED ASSET MODEL FOR AGEING CALCULATIONS (AHI)

The AHI model used for this test has been created from GE standard Library. Small updates have been done to take into account STATNETT data context.

The starting point is GE standard Power Transformer Model. This model is a full view, using current condition data only.

The model retained for STATNETT has been compared with GE standard model, and to other customers having customized the model to meet their operational context. Details have been made available in the Internal STATNETT report.

COMPLETENESS

Completeness Index (CPLI) is the % of data present vs the data required by the model. Weight of each piece of data in the AHI equation is considered in the CPLI calculation.
When using the data available at the time of the test, about 40% of the condition parameters required by the model could be fed as shown in the screen capture in section 1.2. This is relatively low and although the results are good, it should be improved to increase the confidence.

Available data were: DGA, Age, and a few Oil Quality condition parameters.

Main missing data fall under the following categories:

- Electrical tests
- Furans (from Oil Analysis)
- Results of Visual Inspections (corrosion condition, serviceability condition, sealing condition).

ASSET CONDITION. LESSONS LEARNT

Although 40% of data only were present, the Analytics produced by GE APM were considered by STATNETT experts as quite consistent. Residual life, Probability of Failure and Risk levels were considered as quite meaningful, and in line with the condition of the equipment as known by STATNETT experts.

Details are provided in STATNETT internal report only:

- Dashboard for an individual asset
- Condition Parameters for an individual asset:
- Fleet oriented dashboard:
- Sortable, filterable Fleet Tabular View

From these results, it appeared that:

1. Asset Health Models (aka “Digital Twins”) have demonstrated their capability to support effectively Asset Management decisions
2. STATNETT existing data are a good start. They have been loaded easily thanks to flexible GE software tools. An improved completeness index is achievable with acceptable efforts.
3. Data Collection, Data Management scheme, Methodology and Model Management are critical tasks. Expertise in these areas is the key success factor.
4. Although the software is of course essential to produce the actual results, use of SaaS mode has proven to be a good way here to eliminate the IT work and Administration tasks, and accelerate the availability of the results.

RECOMMENDATIONS

Main Recommendations are listed below:

1. Transformer Condition Data: Complement Oil Analysis with FURANS; this measurement alone will increase significantly the completeness index, for a very low extra cost (just a small cost increase in the Oil Lab, no new data flow to create)
2. Transformer Condition Data: Complement Oil Quality measurements; same, this will add some more information for a very low extra cost.
3. Transformers Condition Data: Define a policy for Transformer electrical tests. A good option is to do systematic assessments at mid-life of the equipment: this is an excellent point to orient the long-term strategy for each asset. To do this as accurately as possible, a full set of condition data is needed, including the results of electrical tests.
4. All Assets: Engage a digitalization program for the visual inspections performed on site (see below)

The Digitalization program for the site inspections is a priority action to be engaged. The main objectives are:
• Integrate the field inspection data into the decisions in a systematic manner for all assets. In the considered Transformer Model, Visual inspections represent about 30% of the condition parameters. A part of these required parameters is already collected by STATNETT, the remaining challenge is to complete them, store them consistently and use them effectively in the calculations.
• Standardize the field inspection data, with precise definitions, in order to get a good consistency between inspection teams
• Normalize the data definition: define accurately the various condition levels for each Condition Parameter, either via direct numerical measurements or well defined severity levels in case condition is to be evaluated by the operator in a number of discrete states. The goal is to get rid of cryptic descriptions, ambiguous or subjective entries, and ensure reproducibility between inspections.
• Streamline and automate the flow of data from the inspection tasks up to the Enterprise level; For this, Tablet applications must be made available to the field crew, with integrated data flows up to Enterprise servers.

From GE experience on the deployment of such projects, a solid pool of Data Analysts experts in Electrical Grid domain is critical to the success. This group will bring expertise & experience on:
• Grid equipment, both for ageing models and failure modes analysis
• inspection techniques,
• management of asset models,
• digitalization and data validation
• complex data management schemes, automation of data flows & interfaces
• criticality and risk modelling
• etc...

COST BENEFITS ANALYSIS

The expected levers for ROI include the following:
• Reduction of failure costs
• Optimization of maintenance resources (OPEX)
• Extension of Asset Life duration (CAPEX)

Detailed figures for Return On Investment have been communicated to STATNETT in other documents.

3.2.2 ABB

TRANSFORMER ASSET HEALTH

In this Use Case, ABB, Statnett and Sintef set out to confirm how an analytics solution could work for Statnett. The original Use Case description was, “ABB proposes to set up a secure, cloud-based tenant in the Asset Health Center specific for the validation of this Statnett use case. A project team of ABB, Statnett and (if desired) Sintef employees will format and load historical data and review results with ABB Transformer Service specialists.” During the time of the SAMBA project, ABB changed the name of the Asset Health Center solution to ABB Asset Performance Management, but the rest of the description of the Use Case remained the same. Statnett provided data for 11 transformers. For each of the transformer’s nameplate information as well as 4 oil samples (one per year from 2013-2017) were provided. This represented the data that Statnett has available for their assets and highlights one of the main issues that will be discussed in the Recommendations section below: limited amounts of available data.

The critical points that came out of this use case are:
- Even with relatively little data, the system was able to identify and highlight a high risk of failure transformer.
- Additional data points could have provided more analytical results and trending.
- It is easy to load Statnett’s data into the system.
- The system did not require any configuration or programming. Directly loading Statnett’s available data into off-the-shelf software can provide benefits of visibility, analytics and recommendations.
- The basis for usage across a wider set of asset types could be created via such a solution.

A further point about the Transformer model which was used in this use case: While ABB’s transformer model is quite mature, customers are always working with us to expand it further based on additional data points they have. Significant work on Bushings has been completed with other customers and is now available for all customers. Partial Discharge work done with other customers is now available for all customers.

**Recommendations**

**Change Process and Systems to gather additional data**

This use case demonstrated that with a minimum of data it is still possible to identify critical issues occurring with transformers. It also, however, highlighted how much additional data could be gathered. There are different approaches to getting additional data which Statnett should consider:

1. Find additional sources of already existing data: Historical DGA readings:
   - While data was provided for the past 4 years, some of the transformers were much older. Surely DGA test have been done prior to that, but this data often only in paper form. For the most critical transforms, gathering such information can also provide better trending information.
   - Historical service records: Information about when oil processing was done, when bushings were replaced and when LTC service/replacements took place can provide good inputs to transformer analytics. Often analytics can highlight simple things like bushings which should be replaced which otherwise would be overlooked.
   - Other inspection results: Many customers are performing additional periodic tests on their transformers. This can include partial discharge monitoring, bushing test, visual inspections of foundations. This information is often recorded in inspection reports but not captured in ways that make them easy to use for analysis and comparisons.
   - Heat Run Tests, SCADA loading data and ambient temperatures: With such information (when combined with ambient temperatures) it is possible to use analytics to calculate thermal aging of the insulation paper. While this is problematic for today’s old transformers (because the history is not there), putting this in place now for newer transformers will give future transformer analysts invaluable data.

2. Implement a Workforce Management (WFM) solution: Modern workforce management solutions significantly simplify the capture of large volumes of data in digital form during inspections. Standardized inspection scrips with drop-down choice lists ensure that inspection results are not just in raw text format. Some companies are now working with hands-free devices to allow workers to capture data via voice while performing their work in the substation. (ABB is partnering with RealWear in this space.) The other benefit of such solutions is that they also are capable of capturing information about time spent on tasks. This also generates additional data for use in analytics.

3. Install sensors on critical transformers

   Nine gas DGA sensors: The implementation of DGA sensors does not provide additional information, but it does provide a greatly increased frequency of information. As was seen with the Alta transformer in
the use case, somewhere during 2014 something changed. This would be a good transformer to retrofit with a modern ABB Coresense M10 sensor to allow ongoing usage of the transformer, and yet be able to identify quickly if the gassing again starts increasing.

The newest generation of transformer sensors eliminate many of the past issues (e.g. filters, additional piping) which lead to sensor problems and increased sensor maintenance. What AEP has done is define a clear sensor/monitoring package which is included in the specification for all new XHV transformers. ABB will gladly work with Statnett to assist defining characteristics for various levels of additional sensors.

Additional monitors: Statnett should investigate the benefits associated with putting in place additional transformer monitors. Alternatives to consider are bushing monitors (Capacitance), partial discharge monitors, additional temperature measurements and potentially external thermal imaging monitors. These monitors should be seen as providing more than just the red flag when there is already a problem. Their biggest value is when their measurements are analysed, and trends are identified before problems occur.

**Plan Organizational Structure and Business Process Change**

As was discussed with American Electric Power and First Energy, there are organizational and business process changes which are needed to enable Statnett to achieve the benefits of advanced transformer analytics.

1. Define the Asset Performance team: Statnett should define the team to “own” the data standardization, collection, analysis and use of insights gathered. This team needs to include enabled people from the transformer maintenance, asset management and IT organizations. Ideally such a team would not be dedicated to any one asset type but would work across all asset types to define data available, analytics available, additional data needed, results visualizations required, and processes to change standard maintenance and asset replacement procedures.

2. Require capture of data as defined by the Asset Performance team: This could require a change to the internal procedures for capturing data, ideally capturing data electronically via field-level Workforce Management tools. This could also require a change to the contracts in place with external service providers to require them to record the data in a specific format using a specific tool. Another aspect of this could be the implementation of standard policies to ensure appropriate sensors are included in new equipment specifications and for when to retrofit assets with what kind of additional sensors (related to suggestions in section 2.4.1 above).

3. Change procedures for Asset Management to leverage Analytics: Ensure that senior management requires that data analytics are driving all maintenance and replacement decisions.

4. Change Management KPIs: By changing the KPIs that management sees, reviews and presents externally Statnett clarifies to everyone in the organization the importance of the quality of data and quality of results. Often the biggest challenge to collecting good data is the belief that it will not be used. Making this a clear management measure encourages people to get the data right and helps the organization achieve the goals of ISO 55000 Asset Management.

5. Change procedures for field workers to capture data and leverage Analytics: Providing mobile Workforce Management tools as described above (2.4.1-section 2) are also only effective when appropriate changes are made to require workers to use them to capture the data.

6. Change safety procedures: Ensure maintenance people check transformer conditions prior to entering substations or beginning work. This should be included in a pre-work checklist.
Use case testing - SAMBA WP5 report

**Use standard, off-the-shelf software**

This use case demonstrated that there are now solutions available which can immediately be used by Statnett without any customization or further development. Statnett has two very clear advantages in using standard, off-the-shelf software rather than building a custom solution.

1. **Get Rapid time to value:** Development of a custom solution requires months to years of work, during which time little to no analytics are actually occurring. If the initial design is wrong this could lead to additional lost years of analytics. By implementing a system that is available on the market today Statnett can begin immediately getting value. Many of the systems on the market today are already second- or third-generation products which have been improved upon over the past five years. AEP talks about several transformers which were saved in the first year.

2. **Expand and Integrate with Statnett-specific requirement:** Statnett has a wealth of knowledge and experience and some very unique requirements. Critical for any implementation will be the ability for Statnett to add functionality, experiment with new techniques and technologies, integrate to other unique Statnett applications. The recommendation is to find solutions which were developed to enable open expansion using standard tools.

3. **Benefit from Ongoing Developments:** The Asset Performance Management area is seeing very rapid advancements. By using off-the-shelf software Statnett benefits as the systems advance. The reason that off-the-shelf software is so valuable is that the development work is basically shared across multiple companies. Enhancements needed by one organization are made available to all organizations. Quality issues solved by one organization also benefit all organizations.

**Leverage learning & models already in use at other Transmission operators**

As with the recommendation above for the platform, Statnett should also ensure that they leverage models available and in use by other companies. Transformers have too many possible failure modes and fail too rarely for any one company to build complete models based only on their own experiences. This is also an area where there are major benefits to sharing models across organizations. Certainly, there will be some differences in the Statnett fleet compared to others in other countries, but these differences can more easily be compensated for in existing models than building out completely new models.

Also, as in the point above, the data analytics area continues to rapidly advance. Where Machine Learning models in the past were not contributing to transformer analytics, today ABB is working to leverage these advances. See the “Best Paper” from CIGRE 2018, (A2-206) “Machine Learning Tools in Support of Transformer Diagnostics.”

**Implement solutions that make it easy to build Statnett-specific dashboards**

This Use Case could not include the design and setup of any Statnett-specific dashboards. All the dashboards shown above were standard dashboards provided out-of-the-box.

ABB’s experience, however, has shown that the ability to define custom dashboards is often critical for adoption. The recommendation is that Statnett ensure that whatever solution they chose leaves the option to create custom dashboards open.

**Use a single solution for many different asset types**

Finally, while this Use Case looked at only a single asset type, transformers, the recommendation is that Statnett define a single solution for all critical asset types. The benefits that have been discussed here for transformers also apply for many other asset types.
ASSET INVESTMENT PLANNING

In this Use Case, ABB, Statnett and Sintef set out to confirm how a software solution could work for Statnett. The original Use Case description was, “Technical-economic Analysis of Maintenance and Reinvestment Cost-Benefit and it is used to describe the activity to be investigated.

The base for the analysis was to ascertain which of a series of maintenance and replacement profiles for a circuit breaker, set over 30 years, was the most cost effective.

Sintef have already carried out some work using analysis tools and were the originators of the data used in this investigation. ABB were provided with the following same data as used in chapter 3.1.6.

ABB proposed to use the Asset Investment Planning – AIP- software to process the same data as Sintef and show how commercially developed software can be applied in this case and show how the current process could be augmented.

Results

One example of the results is shown below and further results can be found in appendix V9.

The cost data from Statnett had already be processed in NPV terms and the probability of failure calculations had been applied across the scenarios. This data was loaded into the ABB AIP software on this basis. This dictates the way the cost is presented as one ‘project’ over 30 years.

No custom development was done. This is a critical point which will be mentioned in the recommendations section below: Use standard, off-the-shelf software where possible.

The AIP software can manage many complex scenarios. As an example, it allows multiple projects and multiple options associated with one or many of the projects. It allows the user to link projects to each other or exclude one project based on the inclusion of another. Resources, KPI goals, groups as well as cost can all figure in the analysis. It has always been the aim of this exercise to work through from a simple scenario adding options one at a time to expose the impact on the outcome.

The projects base data summary is

A1 Replace year 26 Cost= 546KKr
A2 Replace year 21 Cost= 519KKr
A3 Replace year 11 Cost= 630KKr
A4 Replace year 6 Cost= 782KKr
A5 Replace year 1 Cost= 853KKr

The following results step through the output of the systems analysis of the base data.

Using one project with 5 options A1 to A5:
Figure 3-13 Analysis results in AIP

The output from the system shows that option A2 to replace at year 21 with a NPV costing of 519KKr has been chosen. There are no unselected projects as there was only one. This view illustrates how the system can deliver the correct result using options but the next method used will give a more open view of the system by showing A1 to A5 as separate projects.

Conclusions

The following can be concluded from the processing of the Statnett data in the Asset Investment Planning – AIP – system from ABB.

The analysis of the data delivered the output as expected and compares to that which had been processed in the examples provided to ABB.

The AIP system is capable of processing data to set a maintenance/replacement strategy for assets, however the system is built to manage the analysis of more complex mixes of projects and scenarios in which the benefit of doing one project over another is based on the availability of labour, prioritising of one project over others and achievement of KPI value. The KPI value can be many KPIs included together with weightings and benchmark values that can include the risks and opportunities that an organisation uses to evaluate performance. Examples used in the use case were improved safety and downtime reduction. Others can be

- Public safety
- Customer satisfaction
- Profits
- Reliability
- Good public image
- Satisfying the regulator

The AIP system was not tested in a way that allowed variations in available budget to be made and show how the use of funds can be optimised to give a selection of projects and their options to deliver the most value or utility. This would be beneficial to Statnett when managing expenditure on their portfolio of assets. Decisions could be made on what projects, such as refurbishment of substations, improvements to the grid or maintenance should be carried out if there is a limited budget. The budget would be spent effectively to deliver the most benefit. Above all different scenarios can be tried, documented and thus are an auditable record of prudence.
4 Concluding remarks

In WP5 selected use cases have been tested with available data from Statnett. Some data is not available today and other data is limited to certain time resolutions or time periods, or selected components. The use cases require high quality data, and when testing them, the consequences of any lacking or poor data become apparent. Recommendations has been made for what Statnett can do to increase the value of the use cases.

For some use cases, data availability is higher for newer components. For example, fiber-optic temperature measurements are available for new power transformers while only top oil temperature is available for some of the older transformers. This impacts the accuracy of the modelling of ageing of the transformer windings, and is important to have in mind when using the results as basis for decision-making.

Some of the use cases developed by SINTEF Energy Research and the industry partners are very similar. For example, SINTEF, ABB and GE have tested use cases for estimating health/risk indices of power transformers. However, comparing the results from these models is not straightforward, as the units and possible ranges for the health indices are not the same. Some differences between the model results should therefore be expected. For Statnett, an important consideration is which data they believe a health index model should be based on. For example, in the GE model, the age of the transformer has a large effect on the estimated health. In the current version of the SINTEF model on the other hand, the age does not contribute to the health, so that the health index is fully a result of the evaluation of condition data.

There are important decisions to be made when implementing the use cases from SAMBA in Statnetts operations:

- Which use cases to prioritize?
- How much resources should be utilized to find and quality assure historical data?
- Which of the suggested new measurements should be performed and for how many components?
- Who in Statnett should be responsible for each use case? How will the results will be implemented?
5 References


V1 BPMN diagrams

BPMN diagrams for all use cases selected and tested by SINTEF Energy Research are shown below. These are reproduced from the WP2/3 report [1].
Use case testing - SAMBA WP5 report – V1

Figure V1.1: BPMN diagram for use case T2.1, “online gas data analysis”.
Figure V1.2: BPMN diagram for use case O2.5, "event detection".
Thermal Winding Aging

4.1 Collecting hot spot temperature data from fibre optic sensors

4.2 Collecting load data in stored database

4.3 Collecting DGA dissolved gas analysis

4.4 Moisture in paper estimation

4.5 Estimate A and E for hydrolysis and oxidation

4.6 Calculate thermal winding hot spot aging from winding hot spot temperature

4.7 Get top oil temperature

4.8 Calculate thermal winding hot spot aging from top oil temperature

4.9 Get external cooling medium temperature data

4.10 Calculate thermal winding hot spot aging from cooling medium temperature

Asset Management

Sufficient data
Not available

Oxygen
Humidity

IFS

GOT, Periodic Oil measurements with temperature in oil, DGA

HISweb

Load
Temperature

Thermal winding aging calculation finished

Material data, H-factor etc.

Figure V1.3: BPMN diagram for use case T3.1, “thermal winding aging”.
Figure V1.4: BPMN diagram for use case T3.5, "periodic oil and gas analysis".
Figure V1.5: BPMN diagram for use case T3.6, “health index”.

Use case testing - SAMBA WP5 report – V1
Figure V1.6: BPMN diagram for use case L2.4 "Failure prediction and preparedness".
Figure V1.7: BPMN diagram for use case A3.5 "Condition assessment through sample testing."
Figure V1.8: BPMN diagram for use case C2.3, "oil-filled termination measurements results".
Use case testing - SAMBA WP5 report – V1

Figure V1.9: BPMN diagram for use case C2.4, "distributed temperature sensing (DTS)".

- **C2.4:** Distributed Temperature Sensing (DTS)
  - **Asset mng.:** Collect measurements
  - **DTS computer:** Evaluate periodic DTS report
  - **Hyweb:** Store T and I log
  - **IFS:** Store T and I log in database
  - **met.no/imr.no:** No change of state or action required
  - **Database:** Condition T and I log
  - **Analytics/Compare to specification:** Take action:
    - Monitoring
    - Cond. assessment
    - Load limit
  - **Change of state:**
    - Yes
    - No

- **Periodic collection of data:**
  - **C1.6:** Load data
  - **C1.1:** Technical data
  - **C1.7:** Temperature data
  - **Environmental data:** Evaluate periodic DTS report
  - **Change of state:** Yes
  - **Store T and I log in database:** No change of state or action required

**Take action:**
- Monitoring
- Condition assessment
- Load limit
Figure V1.10: The BPMN diagram of use case CB3.6 "Re-ignition monitoring of reactor breakers".
Figure V1.11: The BPMN diagram of use case O2.5 "Event detection".
V2  Testing of use case T2.1 - Online gas data analysis
Online gas data analysis
Testing of SAMBA use case T2.1
Report

Dokumentet sendes til: Arne Smisethjell / UPX
Saksbehandler/Adm. enhet: Jørn Foros/SINTEF Energy Research

Til orientering: Fornavn Etternavn / UPX
Ansvarlig/Adm. enhet: Fornavn Etternavn / UPX

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Dato:

Forsidebilde: Skjomen i Narvik, Statnetts bildedatabase
Executive summary

This report describes testing of use case T2.1 "Online gas data analysis" in WPS of the SAMBA project. The testing consists of developing algorithms to carry out the function described in the use case, and then applying this to real data from Statnett. Only the first two steps of the use case have been tested, i.e. collection of data and analysis of data for correlations. The results show no strong correlations between gas concentration measurements and other service data. Hence, it seems difficult to use correlation analysis to investigate the nature or severity of Hydran warnings in an automatic manner using service data that are readily available for the transformers. It is recommended that a Hydran alarm is verified by other means. Correlating alarms to irregular events in the transmission system may be a more viable way (see O2.5), if event data becomes available. Significant differences between transformers and some seemingly inexplicable Hydran data (such as temporary gas concentration increases where the concentration quickly returns to its previous value) also make it difficult to draw general conclusions applicable to many transformers. This may be in part due to design differences between the transformers, but also indicates a need for checking of the data quality for the Hydran gas concentration measurements.
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Online gas data analysis – testing of SAMBA use case T2.1

Abbreviations

BPMN  Business process model and notation
DGA  Dissolved gas analysis
1 Introduction

This report provides a brief documentation of the testing of use case T2.1 "online gas data analysis" in SAMBA. The testing consists of developing algorithms to carry out the function described in the use case, and then applying this to data from Statnett. The testing has been done with real data, but outside Statnett's systems (i.e. at SINTEFs location).

The use case is described in detail in the WP2/3 report [1]. For reference, the BPMN diagram illustrating the use case is reproduced in Figure 1-1 below. As illustrated, the use case starts when a warning signal is received from the Hydran due to increasing/increased gas concentration. This is a sign of an anomalous transformer state that may imply that the condition of the transformer is degrading. In order to verify the anomalous state, and to investigate the nature and severity of the warning, service and event data are collected and correlation of these data with the Hydran data is analyzed. If a correlation is identified, a warning signal is sent to the dispatch center for consideration and appropriate action.

![BPMN diagram for use case T2.1, "online gas data analysis"](image-url)

*Figure 1-1: BPMN diagram for use case T2.1, "online gas data analysis"*
2 Input data

Historic time series data was downloaded for about 150 transformers from Innsikt by Statnett. The availability of data varies for the transformers, both in terms of type of data and length of the data series. The following data was included where available:

- Gas concentration (as measured by the Hydran)
- Relative humidity (as measured by the Hydran)
- Winding temperature (hot-spot and/or average winding temperature)
- Oil temperature (top oil)
- Three phase power, active power and/or reactive power
- Line-to-line voltage and/or phase voltage (for each phase)
- Line current (for each phase)
- Tap changer position

The length of the data series is up to a maximum of 10 – 15 years. The sensors are in general not operating all the time. A time resolution of one hour is used. It is possible to get data with one minute resolution if required.

The Hydran is mainly sensitive to hydrogen, but to some extent also to carbon monoxide, acetylene and ethene [2]. The measured gas concentration is therefore foremost a measure of the concentration of dissolved hydrogen. Hence, the Hydran measurements should be closely related to the Hydrogen measurements done in regular periodic dissolved gas analysis (DGA), as discussed in use case T3.5 "Periodic oil and gas analysis". In use case T3.5 hardly any transformers were identified to be gassing hydrogen. However, in that analysis only recorded DGA data after 01.01.2016 was included, as compared to here where several years are included.

Event data (earth faults, lightning strikes etc.) was requested but this is in general not registered and documented today.
3 Results from testing

For T2.1, limited testing of the first two steps of the use case has been carried out. These steps are collection of data and analysis of data for correlations. The testing was carried out using Python's Pandas package, which is well suited for analysis of time series data. Live collection of data suitable for live operation of the use case was not tested.

The availability of data is in general good, except for event data (earth faults, lightning strikes etc.). All the data listed in chapter 2 is available for many of the transformers. About 60 of the 150 transformers for which data was downloaded had data for gas concentration (i.e. from Hydran). Testing of the use case could therefore only be done for these.

3.1 Transformer Hasle T1

For a first analysis, the transformer Hasle T1 was chosen. In Figure 3-1, the scatter matrix for data from about 2011 to 2018 is shown. The data includes Hydran gas concentration, Hydran relative humidity, tap changer position, primary winding current phase L1, primary winding average temperature and top oil temperature. In the figure, each parameter is plotted against each of the other parameters, in order to look for correlations. The figure indicates that the Hydran gas concentration is not strongly correlated to any of the other data. The only strong correlation apparent in the figure is winding temperature and oil temperature. This is expected as the winding temperature is not measured but inferred from the oil temperature. In addition, some correlation is visible between oil/winding temperature and current, and oil/winding temperature and humidity, as could also be expected.

To further investigate possible correlations, the data for Hasle T1 was investigated in more detail. Figure 3-2 shows the Hydran gas concentration and top oil temperature as a function of time. This plot reveals that there seems to be a weak correlation between these parameters, i.e. the gas concentration seems to weakly follow the seasonal variation of the oil temperature. To arrive at this plot, outliers and physically unreasonable data points were first removed from the data series. Next, the exponential moving average was calculated, to smooth out short-term fluctuations (noise). It is also seen from Figure 3-2 that the gas concentration in general increases slightly each year.

However, Figure 3-2 also shows examples of some challenges with Hydran measurements. There is an unexplained dip in 2016, and the measurements take a long time to stabilize both in the beginning and after this dip.

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1 Line-to-line voltage and phase voltage was not included. However, in special circumstances it has been seen that gas concentration is correlated to the voltage [3]. Partial discharges can cause gassing, and depend on the voltage.
Online gas data analysis – testing of SAMBA use case T2.1

Figure 3-1: Scatter matrix for data for transformer Hasle T1. The figure includes (from top to bottom and left to right: Hydran gas concentration, Hydran relative humidity, tap changer position, primary winding current phase L1, primary winding average temperature and top oil temperature. The diagonal from top left to bottom right shows the distribution of each of the parameters. Note that no cleaning of the data (i.e. removal of outliers and physically unreasonable data points) has been performed before making this plot.

Figure 3-2: Gas concentration and top oil temperature as a function of time for transformer Hasle T1. To smooth out short-term fluctuations (noise) the plot shows the exponential moving average of the variables.
For a more detailed correlation analysis for Hasle T1, the change in gas concentration per month was calculated, and it was investigated if this is correlated to the change in top oil temperature. The results are seen in the scatter plot in Figure 3-3, which shows the monthly change in gas concentration as a function of the monthly change in top oil temperature. The correlation is weak. The Spearman correlation coefficient for this case was calculated to 0.3.

![Figure 3-3: Monthly change in gas concentration as a function of the monthly change in top oil temperature for transformer Hasle T1](image)

### 3.2 Several transformers

To check if the results for Hasle T1 applies to the other transformers, the same analysis was carried out for all transformers where gas concentration data was available. The results show that there does not seem to be any general correlation between Hydran gas concentration data and top oil temperature. This is seen from Figure 3-4 and Figure 3-5, which shows histograms of correlation coefficients for all transformers for two different time scales – per hour and per month. The results show no apparent trend for the correlation coefficient – it varies a lot. A similar analysis has also been performed where hot-spot temperatures was used instead of top oil temperatures, with similar results.
Furthermore, it was also checked if there is some general correlation between the yearly gas concentration increase and the average yearly oil temperature, i.e. if the gas concentration can be expected to increase faster for transformers at high temperatures. The results are shown in Figure 3-6. A very weak trend that the gas concentration increases faster at higher temperatures can be seen.
Figure 3-6: Yearly change in gas concentration as a function of the average top oil temperature for all transformers with gas concentration data

Tap changer operations are known to produce gases. For transformers where these gases can migrate from the tap changer to the main oil volume, an increase in gas concentration with the number of tap changer operations can hence be expected. Figure 3-7 shows the yearly change in gas concentration as a function of the number of tap changer operations per year for all transformers with gas concentration data. No apparent trend can be seen in the figure. Note that this figure includes both transformers where gas contamination from the tap changer is possible and impossible, since information on this was not available. This may mask trends in the data. Also, it should be remembered that the Hydran's sensitivity towards acetylene, which is the gas typically generated by tap changer operations, is low.

Figure 3-7: Yearly change in gas concentration as a function of the number of tap changer operations per year for all transformers with gas concentration data
### 3.3 Several transformers: Gassing

It is interesting as well to isolate and analyze the instances where the Hydran gas concentration increases, i.e. when a transformer is reported to be gassing. To check this, the gas concentration increase was calculated per hour for all transformers, and correlations with other data at the timepoints where these increments were significant (above 25 ppm) were analyzed. The results are shown in Figure 3-8 in terms of a correlation matrix for all parameters that includes all transformers. Looking at the correlations of the gas concentration with other parameters, no significant correlations are identified except with moisture and three phase power. The latter is based on very few data points (i.e. very few transformers had three phase power measurements) and so should not be trusted.

Note that the calculated correlation coefficients are just an indication of linear correlation between variables, and not other types of correlation. Also, since Figure 3-8 includes all transformers, of differing types and design, some correlations appear weaker than they in fact are. This applies e.g. to the correlation between current and power.

![Figure 3-8: Correlation matrix for all parameters including all transformers. The correlation coefficients have been calculated for the hourly change for the parameters for the instances when the hourly change in gas concentration is above 25 ppm, in order to look for possible correlations when the Hydran is reporting gassing.](image)

To check the quality of the measurements of gassing, it was analyzed whether gas concentration increases are typically temporary or not. Temporary increases where the concentration quickly returns to its previous value may not indicate a real issue with the transformer. To check this, the gas concentration increase was calculated both per hour (Figure 3-8) and per day (Figure 3-9). The results show a total of 140 instances with an increase above 25 ppm per hour but only 70 per day, indicating that a considerable amount of the registered gas concentration increases is temporary.
Online gas data analysis – testing of SAMBA use case T2.1

Figure 3-9: Histogram of gas concentration increase per hour for all transformers with gas concentration data. Only increments above 25 ppm are included.

Figure 3-10: Histogram of gas concentration increase per day for all transformers with gas concentration data. Only increments above 25 ppm are included.
3.4 Conclusions

From the above results, and from closer inspection of data for selected transformers, the following preliminary conclusions can be drawn:

- There is a lot of variation between the transformers
- There is a significant amount of inexplicable data for the gas concentration (e.g. spikes, outliers) that probably do not signify a real issue with the transformer. This indicates the need for checking of the data quality for gas concentration measurements and is a source of error when analyzing the data for correlations.
- For several but not all transformers there seems to be a weak seasonal variation in the gas concentration
- For several but not all transformers there seems to be weak general increase in the gas concentration over time, that shows some dependence on temperature

Significant differences between transformers and seemingly strange data make it difficult to draw general conclusions applicable to many transformers. This may be in part due to design differences between the transformers.

Hence, it seems difficult to use correlation analysis to investigate the nature or severity of Hydran warnings in an automatic manner using the data that are readily available for the transformers. It is recommended that a Hydran alarm is verified by other means. Correlating alarms to irregular events in the transmission system may be a more viable way (see O2.5), if event data becomes available.

For transformers where some correlation between Hydran data and oil temperature as well as correlation between Hydran gas concentration and moisture is identified, these correlations might be monitored to check if the Hydran is working as expected. If the correlations are sufficiently strong, they can also be monitored for anomaly detection, i.e. to identify when there are unnormal relationships between variables.

The following recommendations are hence made:

- There is a significant amount of temporary gas concentration increases in the data, that probably do not indicate a real transformer issue and should be disregarded
- Instead of employing correlations with transformer data series to verify Hydran alarms, it is suggested that in some cases correlations may be used to monitor if the Hydran is working as expected. Normal Hydran operation can for some transformers perhaps be monitored by correlation between gas concentration and moisture, and a weakly seasonal variation and a weakly yearly increase of the gas concentration in part due to the oil temperature
- Automatic correlation analysis does not seem viable, without first increasing the quality of the data. Also, implementing automatic correlation analysis of the entire transformer fleet is challenging due to inherent differences between transformers
- Instead of automatic analysis, manual analysis to verify alarms may be done. Moisture and temperature readings (and possibly tap changer operations) may confirm that the Hydran previously has been working as expected
4 References


V3 Testing of use case T3.1 - Thermal winding aging
Thermal winding aging
Testing of SAMBA use case T3.1
Report

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Til orientering: Fornavn Etternavn / UPX
Ansvarlig/Adm. enhet: Fornavn Etternavn / UPX

Sign:

Dokument ID: [000000]
Dato:

Forsidebilde: Skjomen i Narvik, Statnetts bildedatabase
Executive summary

This report describes testing of use case T3.1 "thermal winding aging" in WP5 of the SAMBA project. The testing consists of developing algorithms and code to carry out the function described in the use case, and then applying this to real data from Statnett. The testing shows that the use case functions successfully and may be implemented at Statnett today. However, there are considerable differences in the quantity and quality of input data for the transformers, which affects the credibility of the results. Detailed modelling may be possible for relatively new transformers with good data availability, whereas for older transformers simplifications may be necessary. Live testing at Statnett for selected transformers is desirable to benchmark the model.
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### Abbreviations

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<th>Description</th>
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<td>BPMN</td>
<td>Business process model and notation</td>
</tr>
<tr>
<td>DP</td>
<td>Degree of polymerization</td>
</tr>
<tr>
<td>FAT</td>
<td>Factory acceptance test</td>
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<tr>
<td>IEC</td>
<td>International electrotechnical commission</td>
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<tr>
<td>OD</td>
<td>Oil directed</td>
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<tr>
<td>OF</td>
<td>Oil forced</td>
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<tr>
<td>ONAF</td>
<td>Oil natural air forced</td>
</tr>
<tr>
<td>ONAN</td>
<td>Oil natural air natural</td>
</tr>
<tr>
<td>VBA</td>
<td>Visual basic for applications</td>
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</table>
1 Introduction

This report provides a brief documentation of the testing of use case T3.1 "thermal winding aging" in SAMBA. The testing consists of developing algorithms and code to carry out the function described in the use case, and then applying this to data from Statnett. The testing has been done with real data, but outside Statnett's systems (i.e. at SINTEFs location).

The use case is described in detail in the WP2/3 report [1]. For reference, the BPMN diagram illustrating the use case is reproduced in Figure 1-1 below.

The use case describes degradation of the windings. The insulation paper in transformer windings degrades over time due to the cellulose molecules decomposing to shorter molecules. The length of the molecules can be expressed as a degree of polymerization (DP), which is the average number of monosaccharide units in the molecules. Insulation with short molecules have less mechanical strength, and hence is more prone to failure if the transformer is exposed to mechanical stress such as due to a short-circuit. A DP-value of 200 is commonly taken as the end-of-life criterion for the paper and thus the transformer. The DP-value can be measured in a laboratory, but this requires a paper sample to be taken from the windings, which is usually not feasible. Therefore, estimating the DP-value based on the historic loading of the transformer is desirable.

![BPMN diagram for use case T3.1, "thermal winding aging" [1]](image-url)
2 Calculation routine

To test this use case, a detailed calculation model for thermal winding aging has been implemented in Excel VBA. The model uses historic load and temperature data to estimate the degree of polymerization. The model builds on a model previously established in the Trafotiltak project [2], but has been extended and improved based on data that typically is available for Statnett’s transformers. The new model considers e.g.

- arbitrarily long load and temperature data series (ideally data series for the whole transformer lifetime should be used),
- regulation of the cooling system (on/off, i.e. maximum two cooling modes can be taken into account),
- the effect of any drying of the insulation paper previously carried out on the transformer (“midlife rehabilitation”).

The model is documented in the following, in terms of descriptions of how of each of the steps in the BPMN diagram is implemented. Note that the model does not differentiate between windings (primary/secondary), i.e. any differences in rated power or differences in insulation paper (standard/thermally upgraded) between the windings are not taken into account.

1. Collecting hot spot temperature data from fibre optic sensors

The collected data should be a data series with hot spot temperature $T_{hs}$ as a function of time. The series should ideally cover the entire lifetime of the transformer, i.e. from commission to today. The resolution should be high enough to include daily temperature variations, i.e. a resolution of one hour or similarly is desirable. The time interval between data points should be constant, or close to constant. For transformers with only two windings (primary/secondary), data should ideally be collected for the winding that is aging fastest. Otherwise, data should be collected for the primary winding.

2. Collecting load data in stored database

This data is only required if hot spot temperature data is not available. The collected data should be a data series with load as a function of time. The series should ideally cover the entire lifetime of the transformer, i.e. from commission to today. The resolution should be high enough to include daily load variations, i.e. a resolution of one hour or similarly is desirable. The time interval between data points should be constant, or close to constant. Either of the following type of load data may be collected:

- Load relative to rated load (p.u.)
- Absolute load (MVA)
- Current (A)

For transformers with only two windings (primary/secondary), data should ideally be collected for the winding that is aging fastest. Otherwise, data should be collected for the primary winding.

3. Collecting dissolved gas analysis

The collected data should be a data series of oxygen content in the oil as a function of time, collected from all dissolved gas analyses carried out over the lifetime of the transformer.

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1 The typical example is an ONAN/ONAF transformer that can be run both without (ONAN) and with (ONAF) air fans running. It is assumed that the rated load is reduced with the same percentage for both the primary and secondary windings in the reduced cooling mode.
4. Moisture in paper estimation

The water concentration in the insulation paper is estimated from the measured water content in the oil, using current best knowledge [2, 3, 4]. Measured water content in the oil should be collected from all oil tests carried out over the life time of the transformer, together with load and top oil temperature (alternatively, bottom oil temperature) at the time of the test. The goal here is to estimate the concentration of water where the paper degrades fastest, i.e. at the hot spot, for use in calculation of thermal winding aging.

An oil sample is often taken from the bottom of the transformer while the transformer is in normal operation. Measured water content therefore represents the water content of the oil during the operational conditions that the oil sample was taken. There are uncertainties related to such a measurement due to possible contamination during sampling and transport, as well as due to the actual measurement process (Karl Fischer titration).

Estimating the concentration of water in the insulation paper from water content in the oil is difficult and uncertain. This is due to the fact that the load and temperature of the transformer can vary considerably over time, there are high temperature gradients inside the transformer, and that the ability of the oil and paper to hold water depends on the temperature. Water content in oil and paper, and diffusion of water between oil and paper, therefore vary with time and place. To obtain an estimate of the water concentration in the paper from data that typically are available for Statnett's transformers, the problem can be simplified with the following assumptions:

- The water content in the oil is approximately the same everywhere (as the rate of circulation of oil in the system is high relative to the rate of diffusion of water between oil and paper).
- The ability of the oil to hold water is constant, i.e. it does not change with the oils acidity and aging. This simplification is used in the absence of a better model [6].
- The transformer runs at steady state during the sampling of oil, i.e. the load does not vary. The transformer needs to be loaded (e.g. cold substitute emergency transformers needs to be loaded before they can be diagnosed).
- There is moisture equilibrium between the oil and paper at any point in the transformer at the time of sampling, i.e. the water vapor pressure is the same in the oil and in the paper.

Because of variation in load and temperature over time, the last assumption is likely not correct [7]. The goodness of the assumption depends on the load variations, which may be high, especially for network transformers. Nevertheless, this assumption is often used, in the absence of a better model.

The measured water content in the oil, and hence the estimate of water concentration in the paper, depends on the time and operating conditions when the oil sample was taken, which may be more or less random. Utilising all oil tests carried out over the life time of the transformer will reduce the effect of the time of sampling on the estimation of water concentration in the paper. The concentration of water in the paper at hot spot is therefore estimated through the following steps:

1. The absolute water content of the oil at the hot spot is assumed equal to the water content of the oil sample.
2. The hot spot temperature at the time of oil sampling is calculated from the top or bottom oil temperature measured at sampling using the temperature model in the IEC loading guide 60076-7 [8] for steady state (see below for explanation).
3. Water concentration in the paper at hot spot is calculated at each time of oil sampling from the moisture equilibrium chart for paper / oil (see below for explanation).
4. Using data from all historic oil samples, the concentration of water in the paper at hot spot as a function of time is estimated for the entire lifetime of the transformer by linear regression.
Thermal winding aging – testing of SAMBA use case T3.1

For simplicity, this calculation is suggested carried out only for the primary winding. Given the uncertainty in the calculation of water concentration in paper, this is sufficient.

With the assumption of steady state, the hot spot temperature $T_{hs}$ at the time of oil sampling is calculated from the top oil temperature $T_{to}$ by [8]

$$T_{hs} = T_{to} + H g_r K^y,$$  \hspace{1cm} (1)

where $H$ is the hot spot factor, $g_r$ is the average winding to average oil (in tank) temperature gradient at rated load, $K$ is the load factor (load current/rated current) at the time of oil sampling, and $y$ is the winding exponent [8]. If top oil temperature is not available, the hot spot temperature is calculated from the bottom oil temperature $T_{bo}$ by

$$T_{hs} = T_{bo} + \Delta T_{to-bo} \left( \frac{1 + RK^2}{1 + R} \right)^x + H g_r K^y,$$  \hspace{1cm} (2)

where $\Delta T_{to-bo}$ is the top oil temperature rise above bottom oil temperature at rated load, $R$ is the ratio of load losses at rated current to no-load losses, and $x$ is the oil exponent. The required constants in these two equations should be found from the transformer temperature rise test in the factory acceptance test (FAT) report. The oil and winding exponents must however be found from IEC 60076-7, as these constants are normally not provided in the temperature rise test. If a temperature rise test is not available, sample values for the other constants can also be found in IEC 60076-7. Values from IEC 60076-7 including the oil and winding exponents are reproduced in Table 2-1. These values are likely conservative for most transformers, and therefore some non-conservative sample values are given in addition for ONAN and ONAF transformers. These have been established from examination of temperature rise tests for a selection of transformers in Norway in the SINTEF project Trafotiltak [2].

Table 2-1: Typical sample values for the constants in the temperature model per cooling type, taken from IEC 60076-7 [8] (denoted IEC in the table). Some typical sample values are also provided from examination of temperature rise tests for a selection of ONAN and ONAF transformers in Norway in the SINTEF project Trafotiltak [2] (denoted NOR)

<table>
<thead>
<tr>
<th></th>
<th>ONAN</th>
<th>ONAF</th>
<th>OF</th>
<th>OD</th>
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<td>15</td>
<td>26</td>
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<td>Top oil temperature rise (K)</td>
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<td>51</td>
<td>52</td>
<td>48</td>
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<tr>
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<td>-</td>
</tr>
<tr>
<td>Winding exponent, $y$</td>
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<td>-</td>
<td>1.3</td>
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</tr>
</tbody>
</table>

This formula is an adjustment of the temperature model in IEC 60076-7 [8] to enable calculation based on the bottom oil temperature, which is often the temperature stated in oil test results.

IEC naming convention, as used in IEC 60076-7
In equation (1) and (2), both the cooling mode and the tap changer position of the transformer should ideally be taken into account. For example, for an ONAN/ONAF transformer, the ONAN characteristics should be used when air fans are off, and ONAF characteristics when air fans are on. Fans are typically set to start and stop based on the top oil temperature. However, taking this into account may be difficult in practice, as this information is not normally documented when oil samples are taken. The characteristics of the high cooling mode is then suggested to be used, as these are more often available than the low cooling mode characteristics. This gives some added uncertainty to the calculation of water concentration in the paper.

Note that using generic values (i.e. from the IEC 60076-7) as compared to transformer specific values significantly increases the uncertainty in the calculation of the hot spot temperature.

With the assumption of moisture equilibrium between the oil and the paper, the water concentration in paper is related to the water content in oil at e.g. 20°C by [6]

\[ w_{p,T=20\degree C} = w_{o,T=20\degree C}^{0.63}, \]

where \( w_{p,T=20\degree C} \) and \( w_{o,T=20\degree C} \) is the water concentration in paper (in %) and water content in oil (in ppm, mg/kg or µg/g), respectively. By utilizing a temperature correction factor for the water content in oil from IEC 60422 [9], this is rewritten to

\[ w_{p,hs} = \left( w_{o,T=T_{hs}} \cdot 2.24e^{-0.04\cdot T_{hs}} \right)^{0.63} \]

for the water concentration in paper at the hot spot at the time of oil sampling. Here \( w_{o,T=T_{hs}} \) is the water content in oil at the hot spot temperature (in °C) at the time of oil sampling, which as discussed above can be assumed equal to the water content of the oil sample.

Using data from all historic oil samples, \( w_{p,hs} \) can be estimated as a function of time for the entire lifetime of the transformer by linear regression. The water concentration when the paper/transformer was new is assumed to be 0.5% [3]. If the insulation paper at any time has been dried ("midlife rehabilitation"), this should be taken into account in the regression. In this case, the regression should be split in two so that \( w_{p,hs} \) is estimated as a function of time separately before and after the midlife rehabilitation. In practice, this may however be difficult, as the number of data points may not be sufficient for this separation.

5. **Estimate \( A \) and \( E_a \)**

These parameters determine the thermal winding aging and depend on the type of isolation paper in the transformer (standard / thermally upgraded). \( A \) is an environment factor that depends on the moisture and oxygen content in the oil and \( E_a \) is the activation energy. The parameters \( A \) and \( E_a \) are not independent and have been estimated in laboratory experiments both for standard Kraft paper and thermally upgraded Insuldur paper [6]. If the paper type is not known, one of the following assumptions is made:

- If the transformer was manufactured by National Industri between 1965 and 1982: The paper type is thermally upgraded paper (Insuldur type) [3].
- In all other cases: The paper type is standard (Kraft type)

The activation energy \( E_a \) is determined by the paper type, and reads [6]:

- 111 kJ for standard paper (Kraft type)
- 86 kJ for thermally upgraded paper (Insuldur type)

Here and in the following, all types of thermally upgraded papers are assumed identical to the Insuldur kind, although in practice, this is not the case.
Thermal winding aging – testing of SAMBA use case T3.1

The parameter $A$ is determined by the water concentration in the paper in % and oxygen content in the oil, in addition to the paper type, and is for the hot spot estimated by [6]

$$A(t) = \begin{cases} 
4 \cdot 10^8 w_{p,hs}(t) \cdot O & \text{for standard paper (h}^{-1}) \\
(1.3 \cdot 10^4 w_{p,hs}(t) + 14000) \cdot O & \text{for thermally upgraded paper (h}^{-1}) 
\end{cases}$$  \hspace{1cm} (5)

where $w_{p,hs}(t)$ is the concentration of water in paper (in %) at the hot spot and $O$ is a multiplication factor for the presence of oxygen. $w_{p,hs}(t)$ is taken from paragraph 4, and the factor $O$ is estimated by [6]

$$O = \begin{cases} 
2 & \text{for open conservators} \\
< 2 & \text{for other conservators} 
\end{cases}$$  \hspace{1cm} (6)

for standard paper. The oxygen content from paragraph 3 may aid in determining $O$ appropriately for other conservators than the open ones, but this is challenging. Hence, a factor of 2 is here conservatively used for all transformers, both for standard and upgraded paper.

6. Calculate thermal winding hot spot aging from winding hot spot temperature

There are typically strong temperature gradients in transformers, and this causes the winding aging and hence the DP-value to vary within the transformer. For condition monitoring purposes it is desirable to estimate the DP-value at the location in the transformer where the paper degrades fastest, i.e. at the winding temperature hot-spot. If hot spot temperature data from fibre optic sensors are available from paragraph 1 and parameters $A$ and $E_a$ are available from paragraph 5, the DP value today, $DP_{now}$, is calculated by

$$DP_{now} = \frac{DP_0}{1 + DP_0 \int A(t) e^{-E_a/RT_{hs}(t)} dt} \approx \frac{DP_0}{1 + DP_0 \frac{\sum_{n=1}^{N} A(t_n) e^{-E_a/RT_{hs,n}}}{N}} ,$$  \hspace{1cm} (7)

where $DP_0$ is the initial DP value at $t = 0$, $t_n$ is the time at which the element $T_{hs,n}$ in the hot spot temperature series was measured, $N$ is the total number of data points in the hot spot temperature series, and $\tau$ is the total duration from $t = 0$ to today, $t_N$ (in hours). Typically, $t = 0$ will be taken to be the installation date of the transformer, i.e. when the transformer was new. In this case, a typical initial DP-value is 1000, and $\tau$ is the age of the transformer. In equation (7), it is assumed that the time interval between hot spot temperature data points is constant.

In many cases, a hot spot temperature series may only be available for parts of the life time of the transformer. This can be handled by the above equation, by assuming that the known temperature series is applicable for the entire lifetime.

If the insulation paper at any time has been dried ("midlife rehabilitation"), this must be taken into account in the calculation. In this case, $A$ will differ before and after the midlife rehabilitation (see paragraph 4). Also, the drying itself causes a reduction in the DP-value. It is hard to assess the magnitude of this reduction without measuring it, but a rough estimate may be to assume that is similar to the reduction experienced when drying a new transformer before installation. For a new transformer, the DP-value is typically reduced from about 1200 to 1000, i.e. about 17 %, during pre-installation drying [3]. A 17 % reduction is therefore used as rough estimate for the midlife rehabilitation.

7. Get top oil temperature

This data is only required if hot spot temperature data is not available. The collected data should be a data series with top oil temperature as a function of time. The series should ideally cover the entire life time of the transformer, i.e. from installation date to today. The resolution should be high enough to include daily

\hspace{1cm} 4 But recall that $A$ will change throughout the lifetime according to paragraph 5
temperature variations, i.e. a resolution of one hour or similarly is desirable. The time interval between data points should be constant, or close to constant.

8. **Calculate thermal winding hot spot aging from top oil temperature**

If hot spot temperature data from fibre optic sensors aren’t available from paragraph 1, the hot spot temperature series is calculated from the top oil temperature series from paragraph 7 with equation (1). Next, DP is calculated as described in paragraph 6. In the calculation of hot-spot temperature, any time-varying cooling mode of the transformer should be taken into account. For example, for an ONAN/ONAF transformer, the ONAN characteristics should be used when air fans are off, and ONAF characteristics when air fans are on. In some cases, only the characteristics of the high cooling mode, ONAF in this case, are known from the temperature rise test. The characteristics of the low cooling mode is then taken from Table 2-1. The added uncertainty due to this is limited if the low cooling mode is only used at low temperatures, as the contribution to the aging (ref. equation (7)) at low temperatures is low.

9. **Get external cooling medium temperature data**

This data is only required if neither hot spot temperature data nor top oil temperature data are available. The collected data should be a data series with external cooling medium temperature as a function of time. The series should ideally cover the entire life time of the transformer, i.e. from installation date to today. The resolution should be high enough to include daily temperature variations, i.e. a resolution of one hour or similarly is desirable. The time interval between data points should be constant, or close to constant.

10. **Calculate thermal winding hot spot aging from cooling medium temperature**

If hot spot temperature data from fibre optic sensors aren’t available from section 1, and top oil temperature data aren’t available from paragraph 7, the hot spot temperature series is calculated from the external cooling medium temperature series from paragraph 9, before DP is calculated as described in paragraph 6. The hot spot temperature is calculated from the cooling medium temperature $T_a$ by [8]

$$T_{hs} = T_a + \Delta T_{to-a} \left( \frac{1 + RK^2}{1 + R} \right)^x + Hg_1K^y,$$

(8)

where $\Delta T_{to-a}$ is the top oil temperature rise above cooling medium temperature at rated load. Any time-varying cooling mode of the transformer should be taken into account as in paragraph 8.

---

5 There may be cases where it is not possible to find characteristics for the low cooling mode, neither from the temperature rise test nor Table 1. In such cases, the characteristics of the high cooling mode is used for all data points.

6 In case of an ONAN transformer, this is the ambient temperature.
# 3 Input data

The model requires several input parameters. At Statnett today this data is scattered and not necessarily available in the desired format. In general, the data is collected as follows:

- Installation/technical data can be found in IFS
- Oil test data can be found in the oil test database
- Load and temperature data series are downloaded from Innsikt (or HISweb)
- Temperature rise test data must be manually read from the factory acceptance test (FAT) report

Acquiring all necessary data hence requires considerable manual effort. Due to the many data sources, consistency between data sources should be checked.

The desired input data to run the use case is summarized in Table 3-1. The list is long but not all the data is needed. Minimum needed data is rated load/current, cooling type, water content from oil tests, one temperature data series, and one load data series. The water content from oil tests must be accompanied by the load and temperature at sampling to enable the water concentration in the paper to be calculated. Load data series can in general be given in terms of relative load, absolute power or absolute current, but only one is needed. Likewise, temperature data series can in general be given in terms of hot-spot temperature, top oil temperature or cooling medium temperature, but only one is needed. Also, if the hot-spot temperature is given, load data series is not needed at all.

Additional data beyond the minimum data will improve the results. Temperature rise test data improves the temperature modelling. Without it, generic data from Table 2-1 must be used, adding uncertainty. Specifying the reduced cooling mode, if relevant, also improves the temperature modelling. Without it, the normal/high capacity cooling mode data must be used throughout. The added uncertainty due to this is limited if the low cooling mode is only used at low temperatures, as the contribution to the aging (ref. equation (7)) at low temperatures is low. Specifying the date for midlife rehabilitation adds accuracy to the calculation of water concentration in the paper as a function of time, as well as to the calculation of the DP-value.

Note that winding temperature has not been included in Table 3-1, although it is measured for most of the transformers. This is because this is an indirect measurement, inferred from the top oil measurement. Using the top oil measurement directly is therefore better.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Type</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Installation data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rated primary load (MVA)</td>
<td>According to name plate. Only needed if the load series used (see further down) is given in terms of power</td>
<td>Numerical value</td>
<td>MVA</td>
</tr>
<tr>
<td>Rated secondary load (MVA)</td>
<td>According to name plate. Only needed if the load series used (see further down) is given in terms of power</td>
<td>Numerical value</td>
<td>MVA</td>
</tr>
<tr>
<td>Rated primary current (A)</td>
<td>According to name plate. Only needed if the load series used (see further down) is given in terms of current</td>
<td>Numerical value</td>
<td>A</td>
</tr>
<tr>
<td>Rated secondary current (A)</td>
<td>According to name plate. Only needed if the load series (see further down) is given in terms of current</td>
<td>Numerical value</td>
<td>A</td>
</tr>
<tr>
<td>Rated load at reduced cooling</td>
<td>According to name plate. To be given relative to the rated load, i.e. must be between 0 and 1. Assumed to apply both for the primary and secondary windings. Only relevant for transformers with two cooling modes</td>
<td>Numerical value</td>
<td>-</td>
</tr>
<tr>
<td>Has thermally upgraded paper?</td>
<td>Alternatives: Yes / No</td>
<td>Text</td>
<td></td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-------------------------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>Cooling type</td>
<td>According to IEC name convention. If the transformer has two cooling modes, the highest capacity (normal) mode is given here. Alternatives: ONAN / ONAF / OFAN / OFAF / OFWF / ODAN / ODAF / ODWN / ODWF.</td>
<td>Text</td>
<td></td>
</tr>
<tr>
<td>Cooling type, reduced cooling mode</td>
<td>Cooling mode for reduced cooling, if relevant. Alternatives: ONAN / ONAF / OFAN / OFAF / OFWF / ODAN / ODAF / ODWN / ODWF.</td>
<td>Text</td>
<td></td>
</tr>
<tr>
<td>Start setpoint, cooling (C)</td>
<td>Setpoint for start of cooling, i.e. moving from reduced cooling mode to normal cooling mode, specified in terms of top oil temperature. Only relevant for transformers with two cooling modes</td>
<td>Numerical value</td>
<td></td>
</tr>
<tr>
<td>Stop setpoint, cooling (C)</td>
<td>Setpoint for stop of cooling, i.e. moving from normal cooling mode to reduced cooling mode, specified in terms of top oil temperature. Only relevant for transformers with two cooling modes</td>
<td>Numerical value</td>
<td></td>
</tr>
<tr>
<td>Midlife rehabilitation (date)</td>
<td>Date for midlife rehabilitation, i.e. rehabilitation that includes drying of the insulation paper, if relevant. To be specified with the date when the rehabilitation was finalized</td>
<td>Date (dd.mm.yyyy)</td>
<td></td>
</tr>
</tbody>
</table>

**Oil test data (for all available historic oil tests)**

<table>
<thead>
<tr>
<th>Date</th>
<th>Date when the oil sample was taken</th>
<th>Date (dd.mm.yyyy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reduced cooling at sampling?</td>
<td>State if the transformer was running in the reduced cooling mode when the oil sample was taken. Alternatives: Yes / No</td>
<td>Text</td>
</tr>
<tr>
<td>Primary winding relative load at sampling (-)</td>
<td>Primary winding load when the oil sample was taken, stated relative to the rated primary load, i.e. normally between 0 and 1 (not to be given in %). Not necessary if the absolute load is given</td>
<td>Numerical value</td>
</tr>
<tr>
<td>Primary winding load at sampling (MVA)</td>
<td>Primary winding absolute load when the oil sample was taken. Absolute value (not relative). Not necessary if the relative load is given</td>
<td>Numerical value</td>
</tr>
<tr>
<td>Top oil temperature at sampling (C)</td>
<td>Top oil temperature when the oil sample was taken. Preferred over bottom oil temperature</td>
<td>Numerical value</td>
</tr>
<tr>
<td>Bottom oil temperature at sampling (C)</td>
<td>Bottom oil temperature when the oil sample was taken. Not necessary if top oil temperature is given</td>
<td>Numerical value</td>
</tr>
<tr>
<td>Water content (mg/kg)</td>
<td>Water content at the operating temperature when the oil sample was taken, given in amount of water per amount of oil (according to IEC 60422/60814)</td>
<td>Numerical value</td>
</tr>
</tbody>
</table>

**Load and temperature data series (ideally covering the entire lifetime of the transformer, with hourly resolution)**

<table>
<thead>
<tr>
<th>Date</th>
<th>Date for measurement of load and temperature</th>
<th>Date (dd.mm.yyyy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Time for measurement of load and temperature</td>
<td>Time (tt:mm:ss)</td>
</tr>
<tr>
<td>Reduced cooling at time of measurement?</td>
<td>State if the transformer was running in the reduced cooling mode when load and temperature was measured. Alternatives: Yes / No</td>
<td>Text</td>
</tr>
</tbody>
</table>
### Primary winding

- **Relative load**
  - Description: Primary winding relative load at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: pu

- **Load (MVA)**
  - Description: Primary winding absolute load at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: MVA

- **Current (A)**
  - Description: Primary winding current at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: A

### Secondary winding

- **Relative load**
  - Description: Secondary winding relative load at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: pu

- **Load (MVA)**
  - Description: Secondary winding absolute load at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: MVA

- **Current (A)**
  - Description: Secondary winding current at time of measurement. Not necessary if other load series or hot-spot temperature is given.
  - Numerical value: A

### Hot-spot temperature

- **Primary winding (C)**
  - Description: Fibre optically measured hot-spot temperature for the primary winding. Preferred over top oil temperature or external cooling temperature.
  - Numerical value: C

- **Secondary winding (C)**
  - Description: Fibre optically measured hot-spot temperature for the secondary winding. Preferred over top oil temperature or external cooling temperature.
  - Numerical value: C

### Top oil temperature (C)

- Description: Top oil temperature at time of measurement. Not necessary if hot-spot temperature is given.
- Numerical value: C

### External cooling medium temperature (C)

- Description: External cooling temperature. Not necessary if hot-spot temperature or top oil temperature is given.
- Numerical value: C

### Temperature rise test data

- **Load losses at rated current (kW)**
  - Description: Load losses at rated current (and 75°C), as defined in IEC 60076-7.
  - Numerical value: kW

- **No-load losses (kW)**
  - Description: No-load losses, as defined in IEC 60076-7.
  - Numerical value: kW

- **Top oil temperature rise (K)**
  - Description: Difference between top oil temperature and external cooling medium temperature at rated current, as defined in IEC 60067-7.
  - Numerical value: K

- **Bottom oil temperature rise (K)**
  - Description: Difference between bottom oil temperature and external cooling medium temperature at rated current, as defined in IEC 60067-7.
  - Numerical value: K

- **Average winding to average oil temperature gradient, primary winding (K)**
  - Description: Difference between average winding temperature and average oil temperature, as defined in IEC 60067-7, for primary winding.
  - Numerical value: K

- **Average winding to average oil temperature gradient, secondary winding (K)**
  - Description: Difference between average winding temperature and average oil temperature, as defined in IEC 60067-7, for secondary winding.
  - Numerical value: K

- **Hot-spot-factor, primary winding (-)**
  - Description: Hot-spot-factor for primary winding.
  - Numerical value: -

- **Hot-spot-factor, secondary winding (-)**
  - Description: Hot-spot-factor for secondary winding.
  - Numerical value: -
4 Results from testing

The model has been tested on 12 transformers. During data collection, the following was noted:

- The type and amount of available data can differ considerably for the transformers, especially for old versus new transformers. Data availability is best for new transformers
- Paper type is not always known
- The calculation of water concentration in the insulation paper is in several cases hindered by lacking data. Load and top oil temperature at sampling are often lacking, and only a few historic oil tests are available. In some cases, the oil temperature is given without stating if it is the top or bottom oil temperature
- Load and temperature data series are available with hourly resolution for the last 10 – 15 years. Hence, data series are not available for the full lifetime of older transformers
- Load and temperature data series are stored for the transformer location. If a transformer has been moved between locations, it may be difficult to identify the correct data series
- Temperature rise test data are found from the FAT report, but in some cases it is difficult to identify the desired parameters from these reports
- Temperature rise test data are in general not available for old transformers
- Many of Statnett's new ONAN/ONAF transformers are rated to 70% capacity in ONAN mode. As many transformers are moderately loaded, these transformers may hence be run mostly in the ONAN mode. It may then be important to accurately model the hot-spot temperature in this cooling mode
- The cooling mode is not directly registered – instead it must be inferred from the cooling start and stop temperature setpoints
- Midlife rehabilitation causes a challenge for the model. Previous rehabilitations are normally documented with the rehabilitation date but the long term effect is not documented. To properly estimate the water concentration in the paper both before and after the rehabilitation, necessary oil test data should be readily available from both before and after the rehabilitation. This is however often not the case

Due to the above, the input and output data from this use case should be checked by Statnett and updated as needed if the use case is to be put in live operation.

The varying data availability is handled by the model, but it does affect the accuracy of the results, as discussed in chapter 3. The following recommendations can be made regarding data storage and collection:

- The paper type (standard/thermally upgraded) should be documented for all transformers
- The load, top oil temperature (and hot-spot temperature if available) and cooling mode at oil sampling should be documented for all oil tests
- The necessary data from temperature rise tests should be documented in an easily accessible format for new transformers. All cooling modes should be included
- All data should in general be made easily accessible in a practical format for use in analysis

During testing it was seen that data quality is poor for some transformers. For example, by looking at correlations between different load and temperature series, it was seen that the fibre-optically measured hot-spot temperature for the transformer Tegneby T3 didn't make sense. It was later concluded that this likely was due to the temperature sensor not being correctly installed or not properly calibrated. Also for some other transformers some seemingly odd data for the fibre-optically measured hot-spot temperature was identified (Frogner T51, Høyanger T1, Høyanger T2). Therefore, in testing this use case, no fibre-optically measured hot-spot temperature data series have been used.
Thermal winding aging – testing of SAMBA use case T3.1

An example of seemingly correct data is shown in Figure 4-1. Here it can be seen that the top oil temperature (red line) varies with the ambient temperature (blue line) and the load (yellow line), as expected. This data has a time resolution of one hour, which ensures that daily variations are included, and is sufficient for long term thermal aging calculations. The figure shows the load and temperature for a (random) full year, so that seasonal variations are included. If the loading during other years is similar, assuming that all years are equal to this one may be sufficient for an approximate aging calculation. Ideally, the calculation should however be based on load and temperature series from the whole lifetime of the transformer.

![Figure 4-1: Example of load and temperature data for one full year. The data shows that the measured top oil temperature and calculated hot-spot temperature depend on both the load and the ambient temperature](image)

In Figure 4-1, the calculated hot-spot temperature for one of the windings is also shown (grey line). The hot-spot temperature has been calculated from the load and the top oil temperature with the IEC temperature model. It has been shown that there is significant uncertainty in this calculation [10], since it is a simplified steady state calculation that uses transformer specific design parameters that have only been measured at the rated load (typically found in the heat run test in the FAT report). Hence, fibre-optically measured hot-spot temperature data series are desirable if available and the sensors have been properly installed and are functional.

In Figure 4-5, the calculated water concentration in the insulation paper, which is used in the aging calculation, is shown as a function of time for transformer Kvandal T2. The water content is calculated from the periodically measured water content in the oil (i.e. the yearly oil tests). It is known that there is considerable uncertainty in this calculation [7], since the distribution of water between the oil and the paper varies with the transformer temperature, and hence with the location within the transformer and the transformer operation. Also, the loading and hence the temperature of the transformer when an oil sample is taken is relatively random. This results in the large variation in water concentration seen in Figure 4-5. To reduce the uncertainty in the calculated water content somewhat, linear regression is used to estimate the present water content, taking into account all previous oil measurements and assuming that the water content in the paper when the transformer was commissioned was about 0.5% [3].
The uncertainty in the calculation of water concentration in paper may be reduced if the calculation is based on online relative humidity measurements [11] (e.g. Hydran) instead of periodic oil sample measurements. Using relative humidity measurements instead of absolute water content measurements from oil samples reduces the uncertainty in several ways:

- Continuous measurements provide data for all operational conditions
- There is no need to take oil samples and transport the samples to a laboratory. This reduces the risk of sample contamination
- Since it is the humidity relative to saturation that is measured, the age dependent water solubility of the oil is implicitly included
- The measurement is less temperature dependent

Relative humidity measurements are available for some newer transformers. For these transformers it is recommended to base the calculation of water concentration in paper on these measurements. Use of relative humidity measurements has however not been implemented in the aging model at this time.

Results are presented for 12 transformers in Figure 4-3 in terms of reduction in DP-value from the start value DP=1000. The results are compared with the calculations with two other models, the Trafotiltak model and a simplified model that does not take into account cooling turning on and off. The Samba and Trafotiltak models agree fairly well, but there are some important changes in the improved Samba model. The comparison with the simplified Samba model indicates that taking into account cooling turning on and off is not very important, but note that this has only been tested for three transformers. Figure 4-3 also includes comparison with actual measured values for two transformers. These transformers were already scrapped a few years ago, and has been included here only for this comparison. The agreement with the measured value is fairly good, especially taking into account that heat run test data from FAT reports were not available for these transformers (instead IEC example values have been used7). The underestimation by the model is likely due to both underestimation of the water concentration in the paper and the hot-spot-temperature.

---

7 A simple test of the importance of applying actual FAT data instead of IEC example values has been carried out for three other transformers, indicating in these cases limited importance. This however is of course entirely determined by the values of the heat run test data as compared to the IEC values for the transformer in question.
Thermal winding aging – testing of SAMBA use case T3.1

Figure 4-3: Reduction in DP-value from the start value DP=1000 for selected transformers. Results are shown for three different models, as well as compared to actual measured values for two transformers.

The calculated DP-values are shown for the same 12 transformers in Figure 4-4 as a function of transformer age. The DP-values appear to generally decrease with the transformer ages, as expected, although there are individual variations. The individual variations may be due to differences in design (e.g. paper type), loading, maintenance etc.

Figure 4-4: Calculated DP-values for selected transformers as a function of age.
Testing of the use case including also midlife rehabilitation in the aging calculation was not possible at this time. This requires oil test data readily available from both before and after the rehabilitation, in order to estimate the water content both before and after. This is often not available. However, for transformers with relative humidity measurements, these measurements may be used instead. It is therefore suggested that this functionality in the future is designed and tested for transformers with humidity measurements.

In conclusion, this use case provides an estimate of the winding paper condition but depending on the available input data the uncertainty may be significant, and hence the results should be used with some caution. There are considerable differences in the quantity and quality of input data for the transformers, which affects the credibility of the results. The accuracy may be increased by basing the calculation on the most accurate measurements, such as hot-spot temperature and relative humidity measurements, that may be available for relatively new transformers. It is recommended that the model is tested further at Statnett to gain more experience with its accuracy. The best way to do this is to take paper samples when transformers are scrapped, measure the DP-value at the hot-spot, and then compare this with the DP-value from the thermal winding aging calculation.

The following topics may be considered for further improvement of the above calculation routine:

- Assess the primary and secondary windings separately to estimate DP for each of them
- Calculation of the water concentration in paper using data from online relative humidity measurements (Hydran, Vaisala or other relative humidity sensors installed in the oil flow), and data from fiber optic hot spot temperature measurement
- Adjustment of the A-parameter for transformers with low oxygen content. The new Norwegian condition database can possibly give a foundation for revising the model to do this
- Applying a dynamic temperature model instead of a steady state model. This will however require data that is not commonly known, and hence is not feasible today
Thermal winding aging – testing of SAMBA use case T3.1

5 References


V4  Testing of use case T3.5 Periodic Oil and Gas Analysis
Use Case Transformer:
T3.5 Periodic Oil and Gas Analysis – Multivariate Analysis of DGA dataset using Python
# Report

**Sak:** Report from SAMBA-Project

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<thead>
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<th>Dokumentet sendes til:</th>
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<td>Erlend Grytli Tveten / SINTEF Energy Research</td>
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Use Case Asset Management

T3.5 Periodic Oil and Gas Analysis – Multivariate Analysis of Gas Components with Python

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1 Description of the use case

1.1 Name, scope and objective of the use case

The scope of the use case T3.5 Periodic Oil and Gas Analysis is to include a database of test results from dissolved gas analysis (DGA) systems of transformers and subsequently perform multivariate statistical analysis (MSA) on the dataset. The main objectives are the following:

- Use MSA for condition assessment of transformers.
- Use MSA to identify risk outliers in the transformer population.

The results from the use case testing should facilitate a better basis for deciding maintenance activities and renewal of Statnett's transformer population.

1.2 Actors

The following table can be found in the description of the use case T3.5 Periodic Oil and Gas Analysis in the Use Case Status Report from WP2 / WP3 in SAMBA:

<table>
<thead>
<tr>
<th>Actors</th>
<th>Grouping</th>
<th>Group description</th>
<th>Further information specific to this use case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asset mng.</td>
<td>System</td>
<td>System executing MSA (future system – does not exist today)</td>
<td></td>
</tr>
<tr>
<td>IFS</td>
<td>System</td>
<td>System that stores DGA results</td>
<td>Some information indicate that this information is stored in “anlegsguiden”</td>
</tr>
<tr>
<td>Hisweb</td>
<td>System</td>
<td>System that holds service and event data.</td>
<td></td>
</tr>
</tbody>
</table>

As a descriptive tool for the asset management described in this use case, a BPMN diagram has been developed, see Figure 1.
1.3 Persons involved in the testing

SINTEF Energy Research:
- Erlend Grytli Tveten, main developer of code and MSA.
- Espen Eberg, support for interpretation of MSA data.
- Lars Lundgaard, support for interpretation of MSA data.

Statnett:
- Ståle Fjogstad, provider of transformer DGA data.

1.4 Information about the testing / evaluation

SINTEF ER has developed a Python script, written as a notebook in the Jupyter\(^1\) environment, for importing and reading DGA data, applying quality and consistency control, and performing multivariate analysis of dissolved gas concentrations (DGA) from a database of transformers provided by Statnett. The aim of the script is to serve as an example of the possibilities and challenges related to applying MSA to DGA data. The script has been developed to be useful for future as well as existing DGA data. The Jupyter notebook exists as the file DGA_analysis.ipynb. For best benefit, the reader is encouraged to open and follow the script in the Jupyter notebook in parallel while reading this report. The following chapters present the script and discuss challenges and possibilities of multivariate analysis.

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\(^1\) Project Jupyter
2 Introduction and description of database

2.1 Dissolved gas analysis

The insulation of power transformers typically consists of a combination of liquid transformer oil and solid impregnated cellulose. To avoid costly failures of such major power systems equipment, it is important for transformer operators to be able to assess the health of the transformer insulation. The major fault causes of transformer insulation oil is ageing and deterioration of insulation caused by thermal stresses, electrical stresses, mechanical stresses, and moisture [1]. The standard way of testing for cellulose degradation is by determining the degree of polymerization (DP). However, the need for a paper sample from inside the transformer, which requires removal of the transformer from service, makes this method costly and time consuming. Instead, samples of the insulating oil can be extracted while the transformer is energized. By subsequently applying a dissolved gas analysis (DGA), a fault diagnosis for the transformer can be conducted based on the amounts of characteristic fault gases dissolved in the insulation oil.

Transformer (mineral) insulating oils are typically made of a blend of different hydrocarbon molecules, which contain CH₃, CH₂, and CH chemical groups linked together by C-C molecular bonds. Thermal and electrical stresses may lead to bond breaking and the subsequent formation of gas molecules such as H₂, CH₄, C₂H₂, C₂H₄, C₂H₆, or higher order hydrocarbon gases. The gases formed dissolve in the oil or accumulate as free gases if produced rapidly in large quantities.

Standards [2] have been developed for interpreting the dissolved gas concentrations (and ratios between key fault gases) and link the DGA data to characteristic fault patterns for transformers. However, traditional DGA relies on cost-ineffective and time-consuming tabular lookup of dissolved gas concentrations and ratios of concentrations for a single transformer. Additionally, any increased fault gas concentrations are only indications of (incipient) faults, and the limits of safe operation are typically set from experience of previous incidents of insulation breakdown. These safety limits of DGA fault gas concentration values may vary for different transformer operation conditions. Therefore, such limits should be determined locally for distinct transformer populations.

In this use case, it is described how multivariate statistical analysis (MSA) of a DGA database can be used for condition assessment of a population of transformers. This method can potentially identify correlations that are not possible to observe using traditional methods and identify outliers in a transformer population that should be further investigated. In addition, typical operation limits of DGA concentrations are defined for the transformer database provided by Statnett, as well as methods and visualization techniques for gas ratios and gassing rates.

2.2 Introduction to multivariate analysis

MSA is a tool for describing and analyzing systems that depend on several independent or dependent variables. In practice, all real physical systems that are not placed in a controlled atmosphere are multivariate systems. MSA includes statistical tools to determine the importance of each of the independent or dependent variables, and can be used to detect hidden correlations in large datasets that cannot readily be studied using unitary analysis only.

For transformers, one can use MSA methods on DGA measurements to find the most important gas indicators for transformer failures. Different gases are indicators of different failure mechanisms.

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2 IEC 60599:2015
Therefore, information about the dissolved gas content can give valuable information about single transformer failures as well as statistical data of general failure trends in a large population of transformers. The gassing rates, which represent the time evolution of the dissolved gas concentrations in the transformer oil, are also important factors that should be included in the analysis of this use case.

The following statistical analysis implemented in the Python coding language is based partly on the Python tutorial website A Little Book of Python for Multivariate Analysis [3].

2.3 Description of DGA dataset format and quality

For the testing of SAMBA use case T3.5, Statnett has provided a test database of DGA data from a population of 142 transformers. The following statistical analysis is based on the data provided in this Excel worksheet (file called 20170927_IF_OP.xlsx). The format and quality of the source dataset is crucial for the quality of the multivariate model, and therefore the appearance of the source DGA database will be presented and discussed here.

The source database consists of an Excel spreadsheet with headings such as MCH_CODE (transformer code in IFS database), PARAMETER_CODE (what is measured), MEASURED_VALUE (numerical value), and REG_DATE (date of registration), NOTE (comments from the analysis team) + a few other headings, see Figure 2 for an example screenshot. In this worksheet, a single measurement (of e.g. a single gas value for a single transformer) occupies one row. To be able to perform statistical analysis on the dataset, the data must be imported in a way that is orderly and readable for Python routines. In the Jupyter notebook, a data loading routine (read_DGA) is developed that stores all relevant data in a Python dictionary with keys corresponding to single transformers, which have been anonymized with simple codes such as 'T#', where # corresponds to a number between 1 and 142 (the total number of transformers in the dataset.
The parameters that are measured for each transformer are presented in Table 1. The green-tagged parameters comprise gases that are normally associated with DGA. The yellow-tagged parameters are also used as reference parameters in the following discussion / analysis and imported into the Python framework. The remaining parameters are excluded from the following statistical analysis because of insufficient data or bad data quality.

**Table 1: Parameter codes for measurables collected via DGA oil sampling routines.**

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BV</td>
<td>(breakdown voltage)</td>
</tr>
<tr>
<td>COM</td>
<td>(comments)</td>
</tr>
<tr>
<td>COMSO</td>
<td>(comments)</td>
</tr>
<tr>
<td>DBPC</td>
<td>(oxidation inhibitor)</td>
</tr>
<tr>
<td>DDF</td>
<td>(dielectric diss. fact.)</td>
</tr>
<tr>
<td>FARGE</td>
<td>(colour)</td>
</tr>
<tr>
<td>GFS</td>
<td>(unknown)</td>
</tr>
<tr>
<td>NLO</td>
<td>(number of LTC op.)</td>
</tr>
<tr>
<td>PAS</td>
<td>(power at sampling)</td>
</tr>
<tr>
<td>SYRE</td>
<td>(acid number)</td>
</tr>
<tr>
<td>O-TE</td>
<td>(oil temperature)</td>
</tr>
<tr>
<td>COM</td>
<td>(comments)</td>
</tr>
<tr>
<td>CO</td>
<td>(oil temperature)</td>
</tr>
<tr>
<td>C2H2</td>
<td>(acetylene)</td>
</tr>
<tr>
<td>C2H4</td>
<td>(ethylene)</td>
</tr>
<tr>
<td>C2H6</td>
<td>(ethane)</td>
</tr>
<tr>
<td>C3H6</td>
<td>(propylene)</td>
</tr>
<tr>
<td>C3H8</td>
<td>(propane)</td>
</tr>
<tr>
<td>O2</td>
<td>(oxygen)</td>
</tr>
<tr>
<td>N2</td>
<td>(nitrogen)</td>
</tr>
<tr>
<td>CO2</td>
<td>(carbon dioxide)</td>
</tr>
<tr>
<td>H2</td>
<td>(hydrogen)</td>
</tr>
<tr>
<td>C3H8</td>
<td>(propane)</td>
</tr>
<tr>
<td>N2</td>
<td>(nitrogen)</td>
</tr>
<tr>
<td>CO</td>
<td>(carbon monoxide)</td>
</tr>
<tr>
<td>O2</td>
<td>(oxygen)</td>
</tr>
<tr>
<td>N2</td>
<td>(nitrogen)</td>
</tr>
<tr>
<td>CO2</td>
<td>(carbon dioxide)</td>
</tr>
</tbody>
</table>

After importing the data for the relevant parameter codes, a single dictionary entry (representing a single transformer) consists of a pandas (Python Data Analysis Library) DataFrame object such as the
one depicted in Figure 3 for the anonymized transformer 'T59'. This particular DataFrame contains three DGA measurement series, from 2014, 2016, and 2017. The DGA value entries for C2H2, C2H6, and C3H8 (and H2) reveal a recurrent problem with the data quality in this DGA dataset; the use of the generic value of 1 (or 5 for H2) means that this particular gas concentration value has not reached the detection limit. Although a gas level of 1 (ppm) is insignificant and indicates good transformer health, these values are problematic for statistical analysis because they conceal and obscure correlations between different gas levels. For the statistical analysis to reveal trustworthy correlations and trends between different gas concentration levels, such entries should ideally be removed from the dataset before applying some of the statistical methods. However, removing data points from a statistical analysis should for the most part be avoided. This challenge will be further outlined in the following section 3.

![Figure 3: Example of a dataset dictionary entry for transformer T59.](image)

### 2.4 Visualization of the dataset

To get an overview of the DGA dataset, all measurement series for all relevant transformers (some transformers must be discarded due to insufficient data, see Jupyter notebook for procedure) can be plotted in a diagram for visualization, as exemplified in Figure 4. It is evident that DGA measurements for this transformer population has in general been conducted in 2013, 2014, 2016, and 2017, with no measurements in 2015. However, the dataset is far from complete, because only a few (13) transformers have DGA data from all of these four years, and a large percentage of the transformer population only has a single DGA measurement series.
In the following statistical analysis, only a single measurement series from each transformer will be included in the MSA to avoid that DGA values from transformers with several measurement series are weighted more strongly than those with only a single measurement series. For the most up-to-date analysis, it makes sense to retain only the most recent (and relevant) measurement series, e.g. from 2016 and later.
3 Refining dataset

3.1 Data cleaning

A prerequisite for carrying out meaningful statistical analysis of a dataset is good quality data. This means that any bad or questionable data values with known cause should be considered removed before applying statistical methods because such data points may cause false correlations and conclusions. However, for a large dataset such as this, it is cumbersome to manually search all the data points for suspicious elements. Instead, some automatic routines can be implemented in Python, which will be described in the following sections.

3.2 Gassing rates

The gassing rate is defined as the "increase in gas concentration" per year, and transformers with significant gassing rates should routinely be checked for developing faults. IEC 60599 defines 90% typical rates of gas concentration values as well as typical rates for the increase for different gases observed in power transformers. These values are given in Table 2.

Table 2: IEC 60599 90% typical gas concentrations and typical rates of gas increase.

<table>
<thead>
<tr>
<th>Gases</th>
<th>C₂H₂</th>
<th>H₂</th>
<th>CH₄</th>
<th>C₃H₄</th>
<th>C₂H₆</th>
<th>CO</th>
<th>CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>90% typical concentrations</td>
<td>2 – 20 (60 – 280)a</td>
<td>80 – 150</td>
<td>30 – 130</td>
<td>60 – 280</td>
<td>20 – 90</td>
<td>400 – 600</td>
<td>3 800 – 14 000</td>
</tr>
<tr>
<td>90% rates of increase</td>
<td>0 – 4 (21 – 37)a</td>
<td>35 – 132</td>
<td>10 – 120</td>
<td>32 – 146</td>
<td>5 – 90</td>
<td>260 – 1 060</td>
<td>1 700 – 10 000</td>
</tr>
</tbody>
</table>

a With communicating on-load tap changer (OLTC)

For C₂H₂ gas levels, there is a possible discrepancy arising from the transformer design, which is based on whether they have an on-load tap changer (OLTC) with an oil reservoir that communicates with the main oil tank in the transformer. If this is the case, some fault gases from the OLTC may contaminate the main oil tank, and especially C₂H₂ gassing is typically higher from the OLTC than in the main transformer tank. However, these higher gas concentrations should not be interpreted as signs of incipient faults.

Unfortunately, it is not known in advance which of the transformers in the database that have OLTC communication. For some transformers, OLTC information is given in the comments that accompany the DGA measurement series (e.g. "denne type lastkobler gir smitte via felles konservator"), and in the Jupyter notebook, an automatic function is defined to find all transformers that contain such information. However, due to incomplete or insufficient information in the comments, the resulting OLTC transformer list is probably not complete. As a consequence, the gassing rate analysis will use the highest (for communicating OLTC) C₂H₂ gassing rate limits for all transformers in the dataset.
In the notebook, two functions (`make_gassing_dict` and `plot_gassing`) are defined to automatically find all transformers that show abnormal (above IEC limits presented in Table 2) gassing rates in between two measurement series, and to plot the gassing development from these risk transformers. Such a gassing development plot is presented in Figure 5.

Supplementary inspection of the DGA data must be done manually, e.g. via using the defined function `print_trafo_note` (see Figure 6 for an example for transformer T66), from which it can be concluded that transformer T6 can be cleared from the list of abnormal behavior because the high gassing rate is an expected reaction after a recent regeneration. The other transformers should be considered removed from the statistical source database for various reasons: For example, the high H₂ levels in T141 is believed to be caused by contamination from paint, and hence not indicative of an imminent fault. Such abnormal data points will introduce artifacts in the statistical data basis.
3.3 Gas ratio analysis

The comments section of each transformer in the dataset can reveal if the transformer has been associated with specific faults such as those defined by IEC 60599, see Table 3.

Table 3: DGA interpretation table from IEC 60599 [2].

<table>
<thead>
<tr>
<th>Case</th>
<th>Characteristic fault</th>
<th>( \frac{C_2H_2}{C_2H_4} )</th>
<th>( \frac{CH_6}{H_2} )</th>
<th>( \frac{C_2H_4}{C_2H_6} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>PD</td>
<td>Partial discharges</td>
<td>NS(^a)</td>
<td>&lt; 0.1</td>
<td>&lt; 0.2</td>
</tr>
<tr>
<td>D1</td>
<td>Discharges of low energy</td>
<td>&gt; 1</td>
<td>0.1 – 0.5</td>
<td>&gt; 1</td>
</tr>
<tr>
<td>D2</td>
<td>Discharges of high energy</td>
<td>0.6 – 2.5</td>
<td>0.1 – 1</td>
<td>&gt; 2</td>
</tr>
<tr>
<td>T1</td>
<td>Thermal fault (T &lt; 300°C)</td>
<td>NS(^a)</td>
<td>&gt; 1 or NS(^a)</td>
<td>&lt; 1</td>
</tr>
<tr>
<td>T2</td>
<td>Thermal fault (300°C &lt; T &lt; 700°C)</td>
<td>&lt; 0.1</td>
<td>&gt; 1</td>
<td>1 – 4</td>
</tr>
<tr>
<td>T3</td>
<td>Thermal fault (T &gt; 700°C)</td>
<td>&lt; 0.2(^b)</td>
<td>&gt; 1</td>
<td>&gt; 4</td>
</tr>
</tbody>
</table>

\(^a\) NS: Non-significant whatever the value

\(^b\) An increasing value of \(C_2H_2\) may indicate that the hot spot temperature is higher than 1000°C

In addition to the gas ratios in Table 3, three other gas concentration ratios are considered to be important indicators of transformer health: \(CO_2/CO\), \(O_2/N_2\), and \(C_2H_2/H_2\).

\(CO_2/CO\) ratios less than 3 are generally considered as an indication of possible carbonization of paper insulation. On the other hand, high values of \(CO_2\) and \(CO_2/CO\) ratios (>10) – can indicate mild overheating of paper or oil oxidation. However, the \(CO_2/CO\) ratio is also affected by the transformer design (e.g. air-breathing vs. closed), so abnormal values cannot directly be associated with developing faults.
O₂ and N₂ are not fault gases, but are typically found in oil as a result of contact with atmospheric air. The ratio O₂/N₂ is typically ∼ 0.5. However, in service this ratio may decrease as a result of oil oxidation. Ratios less than 0.3 are generally considered to indicate excessive consumption of oxygen.

For the C₂H₂/H₂ ratio, (OLTC) operations produce gases corresponding to discharges of low energy (D1), and may lead to wrong fault diagnosis if one is not aware of possible oil communication between the OLTC and the main oil tank. C₂H₂/H₂ ratios higher than 2-3 is usually considered to be an indication of OLTC contamination.

IEC 60599 recommends calculating gas ratios for transformers if one or more DGA results show abnormal concentration values and gassing rates above typical values. However, care must be taken if some (or all) of the gas concentration levels are not high enough to be reasonably accurate, i.e. the values are close to the detection limit S. In the Jupyter notebook, a function (perform_fault_analysis) has been defined to perform fault analysis based on calculated gas ratios. If any of the gas concentrations show values below twice the detection limit (2xS), the gas ratio calculations should not be trusted, and the gas values should be investigated manually. The result from such an automatic fault analysis routine is presented in Table 4.

Another possibility for visualizing the fault transformers identified from the calculation of IEC 60599 gas ratios is to use a Duval triangle [4]. However, for such ternary plots, the gas ratios of C₃H₆, C₃H₈, and CH₄ must be transformed into triangular coordinates by defining the parameters %C₃H₆, %C₃H₈, and %CH₄, which represent the percentage share of gas levels spanned by these three fault gases. An example of such a Duval triangle is given in Figure 7 for the transformers identified in Table 4. However, such a triangle plot must be used with care because there is no region for normal operation. Consequently, the use of such triangles are not guaranteed to find all fault transformers and can sometimes identify normal operation as an incipient fault. Duval triangles will not be further used in the following.
3.4 Automatic screening procedures

In the Jupyter notebook, several functions have been developed to automatically pick out abnormal transformers as part of the dataset inspection procedure. For detailed descriptions of these methods, the reader is referred to the notebook. However, short summaries of these functions are given here:

- **find_faulty_trafos**: Iterates the dataset and searches the comments associated with each DGA measurement series for fault codes such as those indexed in Table 3. In addition to IEC 60599 fault codes, the script also searches for any comments that contain the words "regenerering" or "oljeskift", which means that the transformer shows signs of oil ageing and is recommended for maintenance and oil regeneration.

- **make_gassing_dict**: Identifies all transformers that show gassing rates that are above IEC 60599 limits presented in Table 2, and sorts these transformers according to the gases that show abnormal gassing rates. Returns also a set of all gassing transformers.

- **find_O LTC_trafos**: Finds all identified risk transformers associated with OLTC contamination. The script searches for comments such as "felles konservator" in the comments sections. The returned set of transformer codes is probably incomplete, because the information in the comments section is not extensive.

- **old_data_trafos**: Finds all transformers with no recorded DGA data after 01.01.2016.

- **perform_fault_analysis**: Automatically sorts all transformers that have abnormal fault gas ratios according to IEC 60599 standards.

*Figure 7: Example of Duval triangle for identifying fault transformers, including risk transformers from Table 4.*
In addition, data from one transformer (T31) has been labeled as not trustworthy because the
comments revealed that the DGA concentration values measured were contaminated by large air
bubbles in the test syringe, which led to high (and misleading) concentrations of \( \text{N}_2 \), \( \text{O}_2 \), and \( \text{CO}_2 \).

After running all these automatic functions, the original dataset consisting of DGA data from 142
transformers have been reduced to 78 normal operation transformers that do not show signs of
abnormal data. Note, however, that this does not imply that all the 64 removed transformers are faulty
transformers, only that their DGA data series indicate abnormal operation conditions for various
reasons. Good quality data is paramount for the usefulness of statistical analysis. For this particular
database, almost half of the entries have been sorted out for different reasons. In the following
analysis, both the original (complete) and the "cleaned" dataset will be used when appropriate. As a
general rule, the original dataset should be used unless there is a good reason not to include all data
points.

### 3.5 90% normal operation limits for Norwegian conditions

IEC 60599 recommends developing 90% typical operation gas levels also for local populations of
transformers, because there might be discrepancies between different transformer populations due
to different weather / temperature and operating conditions. Such an overview of 90% typical
operation gas levels in Norway is valuable information for Statnett’s population of transformers. For
larger populations of transformers in Norway, it is easy to develop local 90% typical values that
subsequently can be used as predictive tools for transformer maintenance needs.

However, note that the 90% typical values are not equivalent to safe operation limiting values, but
given here for information only, as a maintenance and predictive tool. The 90% typical gas levels
indicate that 90% of the DGA values in service are below the 90% typical values, whereas 10% are
above. In the Jupyter notebook, two functions are defined that calculate the 90% typical concentration
values for selected fault gases and plots cumulative distribution histograms for the transformer
population. Examples are given in Figure 8. Other such plots are given in the Jupyter notebook.

Table 5 presents 90% typical gas concentration values for the provided Statnett transformer
population. Values are given both for the original (complete) transformer population as well as the
"cleaned" dataset where risk and fault transformers (including OLTC communication) have been
removed. Compared with the IEC 60599 values in Table 2, it is evident that the 90% typical gas
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Concentration values for this particular population of transformers is lower (H$_2$, CH$_4$, C$_2$H$_6$) or similar (C$_2$H$_2$, C$_2$H$_4$, CO, CO$_2$) to the IEC values. This implies that this transformer population as a whole is in general good health. However, there might be significant differences in operating conditions (e.g. weather, temperature, load patterns) between Norwegian populations of transformers and transformers in other parts of the world. Therefore it is recommended that Statnett develops local statistics of typical DGA fault-gas levels in transformers using similar statistical techniques as the ones presented here in SAMBA use case T3.5.

Table 5: 90% typical gas levels for Statnett’s transformer population with recent (2016-2017) DGA measurement series.

| Gases | C$_2$H$_2$ | H$_2$ | CH$_4$ | C$_2$H$_4$ | C$_2$H$_6$ | CO | CO$_2$
|-------|-----------|-------|--------|------------|-----------|----|------|
| 90% typical gas levels | 19.7$^a$ (2.2) | 22 (12) | 11.5 (6.4) | 67 (39) | 8.3 (4.6) | 520 (410) | 4600 (3300)

**NOTE:** Values in parentheses are for a population of transformers with identified fault and risk transformers removed.

*$^a$Population includes transformers with communicating OLTC.
4 Multivariate statistical analysis

NOTE: In the example of multivariate statistical analysis presented in this chapter, the DGA data from the "cleaned" (78) transformers database is used, where transformers with known abnormal, faulty, and/or incomplete data have been excluded. This does not necessarily mean that all the remaining transformers are in healthy condition. The cleaned dataset is used here to emphasize the natural correlations between different dissolved gas concentrations in expected normal transformer operation. However, in the Jupyter notebook, a similar analysis can also be made with the "complete" dataset as the statistical input. The functionality of the MSA methods remain the same in this case.

4.1 Scatter plots

An important part of multivariate statistical analysis (MSA) is to visualize the dataset. For quick visualization of DGA data points, scatter plots are useful tools for rapidly identifying outliers in the dataset. Figure 9 presents two examples of such scatter plots, for the non-fault gases O₂ vs. N₂ and CO₂ vs. CO gas concentration values.

![Scatter plots of O₂ vs N₂ (left) and CO₂ vs. CO (right) gas concentrations from the cleaned transformer population where known abnormal DGA readings and fault/risk transformers have been excluded. The red ellipses represent the 2-sigma (95%) covariance values, which means that 95% of readings from this transformer population is expected to fall inside this ellipse. More scatter plots, including possibilities for interactive zoom/pan, can be found in the Jupyter notebook.](image)

The O₂ vs. N₂ plot reveals that the transformers group into two sections for the non-fault gases O₂ and N₂. This grouping is probably related to the different transformer designs, open-air vs. closed-casket transformers. Transformer oil that is in contact with atmospheric air in the conservator typically have N₂ / O₂ gas concentration levels of 60 000 / 30 000 ul/l. For this specific transformer population, there seems to be both air-breathing and closed transformers in the dataset.

Another interesting scatter plot is presented in Figure 10, showing H₂ vs. C₂H₂ gas concentrations for all transformers in the cleaned dataset (without fault / risk and OLTC communicating transformers). As evident from the plot, the majority of the DGA measurement series have only recorded the generic values of 1 (for C₂H₂) or 5 (for H₂). These values represent the detection limit for these fault gases, meaning that the majority of the transformers in this dataset have DGA values below the detection limit. Although DGA measurements below the detection limit are signs of good transformer health, such values do not give any information about hidden correlations in the DGA dataset. A quick analysis
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shows that 74 out of the 78 transformers in the dataset have one or more DGA values that are at the detection limit, which will unfortunately obscure the correlations in the following statistical analysis.

(In the Jupyter notebook a function (replace_ones) is defined that replaces all DGA value entries that are at the detection limit with random values below this limit, to replicate real randomized statistical data. However, this function is not used in the following, because tampering with statistical data should be done with extreme caution to avoid introducing additional artifacts to the dataset.)

Some outliers can be found in the scatter plots in Figure 9 and Figure 10, such as T70 (high CO concentration), T33 (high CO₂ concentration), T75 and T2 (high C₂H₂ concentration), and T44 (high H₂ concentration). Although none of these gas values are alarming (according to IEC 60599), these plots exemplify the power and simplicity of this visualization technique. More scatter plots can be found and generated via the Jupyter notebook.

4.2 Parameter correlations

Before applying statistical analysis to the transformer dataset, the DGA concentration data should be scaled in such a way that all parameters (DGA gases) are equally weighted with a variance of 1 and mean of 0. By doing this, one avoids that gases which appear with naturally high concentrations (e.g., O₂ and N₂) are treated as more significant parameters than gases which naturally appear with low concentrations (e.g., hydrocarbons). Information about the scaling process is given in the notebook.

Correlations between the different gases are useful numbers that can be visualized via a correlation matrix as depicted in Figure 11. Correlation values are defined such that a one-to-one / linear relationship between two parameters gives a correlation of unity (1). A negative linear relationship gives -1, and completely uncorrelated variables have a correlation of zero (0). By definition, the "self-correlation" values along the diagonal are 1. The most highly correlated DGA variables are O₂ and N₂ (0.93), which is not surprising, since these gases are the main constituents in air. In addition, it can be seen that CH₄ levels are closely correlated with C₂H₆ (0.87) and H₂ (0.77).
For the non-DGA parameters a similar routine can be implemented, showing that there is a medium strong negative correlation (-0.48) between water-in-oil (WIO) and breakdown voltage (BV), which is also expected, since humidity in the oil impairs the withstand strength of the insulation. More details about how to extract the correlations can be found in the notebook.

![Correlation Matrix](image)

*Figure 11: Correlation matrix for relevant DGA gases. Along the diagonal, the self-correlation is (by definition) 1. The most highly correlated gases are N2 and O2, which is not surprising, as they are the main constituents of air.*

### 4.3 Principal component analysis

In a multivariate dataset, not all variables are equally important for the statistical variance. For DGA values in transformer oil, some gas concentrations do not vary much between transformers, whereas other gases have a large natural variance. For analysing such datasets, it is helpful to reduce the complexity of the dataset by introducing principal components.

Principal component analysis (PCA) is a statistical tool that can be used to visualize the most important variables in a dataset. PCA transforms the original dataset of (usually) correlated variables into new linearly orthogonal (uncorrelated) variables that are linear combinations of the original variables. In this way, the most important parameters can be identified and described via the principal components, the complexity of the dataset is effectively reduced, and the statistical trends are easier to follow.
The PCA performed in this use case on the DGA dataset mostly follows built-in functions from the *Scikit-learn* machine learning library for the Python programming language. These functions are presented and further discussed in the notebook, and tutorials for these methods can be found on the website *A Little Book of Python for Multivariate Analysis*.

To perform a PCA, the data is first standardized such that all gas concentration measurement series have a mean of 0 and a variance of 1. If PCA is performed on an unstandardized dataset, the variables with the largest numerical value of the variance will dominate the first principal components. By standardizing, it is assured that all variables are treated equally.

In short, PCA takes data from an $n$-dimensional dataset (with $n$ variables) and "rotates the coordinate system" such that the principal axes represent the properties for which the dataset displays the most statistical variance. In this use case, we have chosen the nine DGA "fault" gases CO, CO$_2$, H$_2$, O$_2$, N$_2$, CH$_4$, C$_2$H$_2$, C$_3$H$_4$, and C$_4$H$_6$. The result of the PCA is a set of nine new variables, called "principal components", which are all linear combinations of the original variables.

Table 6 presents the results of a principal component analysis of the 78 transformers in the cleaned DGA dataset. After rotating the coordinate system into new principal components, the idea is to isolate only a few variables that can explain most of the statistical variance in the dataset. All principal components that have a variance larger than 1 represents more of the statistical variance in the dataset than any single original variable does. In the above table, PC1, PC2, and PC3 all have variances larger than 1. Together these three principal components represent approximately 79% of the total variance in the dataset.

The PCA results are elegantly visualized via a scree-plot such as in Figure 12, which plots the variance for each principal component. A "rule-of-thumb" in PCA is either to retain all variables that have a variance larger than 1 or to retain all variables to the left of any "kinks" in the scree-plot. For this particular dataset, PC1 and PC2 represent the two most important principal components, but PC3 is...
also retained in the following for further analysis and visualization. In this way, the complexity of the multivariate dataset have been reduced from, in this case, nine to three variables.

Figure 12: Scree-plot showing the importance of each principal component. The importance is defined by the amount of the total dataset variance held by each component.
4.4 Loading of principal components

The *loadings* (the weight by which each original variable should be multiplied to get the principal component scores) of the three most important principal components can be visualized via a bar chart as depicted in Figure 13.

The loading plot reveals that the first principal component (PC1) consists mainly of data from the CO, CO\textsubscript{2}, and hydrocarbon gases measurements. Importantly, PC1 contains only small loads of the "non-fault" gases N\textsubscript{2} and O\textsubscript{2}, as well as insignificant loads of C\textsubscript{2}H\textsubscript{2}. PC1 does not resolve or distinguish the most prominent fault-gases, which might be related to that the transformer population studied here is for the most part healthy, and any hidden correlations between hydrocarbon gases is typically obscured by low-valued DGA entries at the detection limit, see Section 4.1. However, PC1 serves as a general parameter for fault-gas trends, where effects from non-fault gases and OLTC contamination (C\textsubscript{2}H\textsubscript{2}) is filtered out.

PC2 is dominated by large loads of N\textsubscript{2} and O\textsubscript{2}. As mentioned above, these gases are not fault-gases, but indicative of dissolved air. Therefore, high values of PC2 should not be interpreted as alarming.

PC3 is dominated by a significant loading of C\textsubscript{2}H\textsubscript{2}, a gas which is typically related to high-temperature (>700°C) thermal faults, arcing, and/or OLTC contamination. Plotting PC1 vs. PC3 will therefore serve to accentuate differences between normal operation, low-temperature thermal faults and low-energy discharges on one hand, and high-temperature thermal faults and arcing on the other hand.

![Figure 13: Bar chart of the loadings of the three most important principal components. Note that negative loadings appear because the data have been standardized to a mean of 0 and a variance of 1 before performing the principal component analysis.](image)
Another interesting observation from Figure 13 is that PC1, PC2, and PC3 all have similar loadings of H₂, which is considered to be a key gas signature for partial discharges (PD). Since all the obvious fault transformers have been filtered out (see Section 3.4) prior to this example of principal component analysis, it is a reasonable assumption that no transformers in the source database show significant PD activity. Hence, the PCA confirms that H₂ is an insignificant gas in this case.

### 4.5 Score plots and clustering

Scatter plots such as those used for single gas parameters in Section 4.1 can also be used to visualize the transformer DGA database in the coordinate system of the principal components. These useful plots are called score plots. A significant advantage of score plots from the most important principal components is that any outliers in such plots show general statistical trends of abnormality compared with the (assumed healthy) total transformer population, and not just abnormal single parameter values. A score plot of the most important principal components is therefore the best MSA representation of general transformer health indices that is achievable without including additional information about how each fault-gas concentration should be weighted in the statistical analysis. However, a score plot must be interpreted in light of the loadings of the principal components.

In the PC1 vs. PC3 score plot shown in Figure 14, the outlier transformers along the PC1 axis show a general trend of unhealthy fault-gas concentrations, and are thus candidates for further inspection for incipient fault development. Outliers along the PC3 axis show abnormal levels of C₂H₂, which are indicative of thermal faults of high temperature (>700°C). However, these high levels of C₂H₂ can also be a result of OLTC contamination of the main oil tank. Therefore further investigations into the transformer designs for these outliers should be performed before inspection of the transformers is recommended.

![Score plot of PC1 vs. PC3.](figure14.png)

*Figure 14: Score plot of PC1 vs. PC3. Outliers along the PC1 axis have a general trend of high fault-gas concentrations. Outliers along the PC3 axis have abnormal values of C₂H₂, which indicates high-temperature faults and/or OLTC contamination.*
In the PC1 vs. PC2 score plot presented in Figure 15, PC2 is dominated by the O$_2$ and N$_2$ concentration values, and the PC2 axis is thus not indicative of any incipient fault. However, this score plot serves as a good example of how different transformer designs may influence the statistical analysis of DGA data. Two clusters of transformers can clearly be discerned along the PC2 axis. In the Jupyter Notebook, a function (`plot_scatter_cluster`) is defined that uses methods from *Scikit-learn*, Python’s machine learning library, to automatically detect data clustering. In principal component score plots, the cause of such clustering must be interpreted in light of the principal component loadings.

For the particular case of Figure 15, the clusters along the PC2 axis represent two distinct groups of transformers with different levels of dissolved air in the oil samples. This clustering is probably related to the transformer design, e.g. air-breathing vs. closed-casket design, but this has not been confirmed. For larger datasets, the automatic detection of clusters of data points in statistical datasets is a powerful tool that can be used to reveal hidden / unknown correlations between the data points.

*Figure 15: Score plot of PC1 vs. PC2, including the results of an automatic cluster detection routine. Two obvious clusters can be discerned, as well as a few outliers. In this case, outliers along the PC2 axis show abnormal values of non-fault gases such as N$_2$ and O$_2$. The clusters can probably be attributed to different transformer designs, e.g. air-breathing vs. closed-casket.*
5 Conclusion

The testing of use case T3.5 Periodic Oil and Gas Analysis has explored the use of MSA methods on transformer DGA data as a tool for condition assessment of transformer health. The evaluation has demonstrated that MSA is a useful tool for identifying and visualizing risk outliers in the transformer population, as well as uncovering hidden fault-gas correlations and clustering between different groups of transformers.

After conversion of the source dataset into suitable formats for the Python programming language, MSA methods can be used directly as a means to visualize the complete dataset. However, to facilitate the interpretation of the analysis results, substantial data cleaning is typically required to ensure that all data points have sufficiently good quality data. A recurring problem for the DGA dataset is that measurements of low (good) fault-gas concentrations below the detection limit are registered with the generic value of 1 µ/l. Although low fault-gas values indicate healthy transformer operation, they can conceal or destroy the underlying statistical correlations between different fault-gas concentrations. It is recommended to record such data points with comments such as "below the detection limit" instead of generic values of 1 µ/l.

In addition to examples of MSA methods, the use case testing has developed and demonstrated methods for visualizing and detecting transformers with high gassing rates and abnormal fault-gas ratios according to IEC 60599 standards.

Importantly, in Section 3.5, the use case testing has also led to the development of 90% normal operation DGA gas concentration limits valid for the provided Statnett transformer database. Such 90% typical gas concentration values can be used as predictive tools for transformer maintenance needs that effectively targets Norwegian conditions.

References

V5 Testing of use case T3.6 – Health index
Health index
Testing of SAMBA use case T3.6
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<td>Arne Smisethjell / UPX</td>
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Executive summary

This report describes testing of use case T3.6 "Health index" in WP5 of the SAMBA project. The testing consists of developing algorithms and code to carry out the functions described in the use case, and then applying this to real data from Statnett. The testing shows that the use case can be implemented at Statnett today, but that acquiring and quality assuring input data is a challenge. Live testing in operation at Statnett is desirable to benchmark the model.
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Health index – testing of SAMBA use case T3.6

**Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPMN</td>
<td>Business process model and notation</td>
</tr>
<tr>
<td>DGA</td>
<td>Dissolved gas analysis</td>
</tr>
<tr>
<td>HI</td>
<td>Health index</td>
</tr>
<tr>
<td>VBA</td>
<td>Visual basic for applications</td>
</tr>
</tbody>
</table>
1 Introduction

This report provides a brief documentation of the testing of use case T3.6 "health index" in SAMBA. The testing consists of developing algorithms and code to carry out the function described in the use case, and then applying this to data from Statnett. The testing has been done with real data, but outside Statnett's systems (i.e. at SINTEFs location).

The use case describes how a quantitative measure of present condition, a so-called health index, can be calculated from available data for the present condition of the transformer. The use case is described in detail in the WP2/3 report [1]. For reference, the BPMN diagram illustrating the use case is reproduced in Figure 1-1 below.

![BPMN diagram for use case T3.6, “health index” [1]](image-url)


## 2 Calculation routine

To test this use case, a detailed calculation model has been implemented in Excel VBA. The model builds on a model previously established in the Trafotiltak project [2]. The new model has been improved such that any data that can be graded and that affects the overall transformer condition, and thereby reflects the transformer failure probability, can be included. The model ensures that the health index is bound in the range 0 – 100%, with 100% being a perfect condition. Furthermore, the health index can never be better than that signified by the condition data with the assumed largest effect on the health (i.e., the transformer is not better than its weakest "link"). The health index model is a simplified model in which all condition data are approximated as independent.

The model is documented in the following, in terms of descriptions of how each of the steps in the BPMN diagram is implemented. Note that the model has been extended as compared to how it was defined in the WP2/3 report [1] and in Figure 1-1: The health index model also includes the calculated DP-value from use case T3.1.

### 1. Retrieve and evaluate oil test results

For periodic oil tests, a result database has recently been established at Statnett, and all new oil test results are documented in this database. Oil test results can therefore be retrieved from this database. Results from all available oil tests should be retrieved, but minimally from the last two. To assess condition, each parameter must then be graded. Grading is based on the standards IEC 60599 [3] and IEC 60422 [4] and CIGRÉ brochure 443 [5]. The grading criteria are given in Table 3-1 - Table 3-3 for all oil test parameters. All grading is done individually per parameter.

**Table 2-1: Grading of measured gas concentrations according to IEC 60599 [3] / CIGRÉ 443 [5]**

<table>
<thead>
<tr>
<th>Grade</th>
<th>Gas concentration [µl/l]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H2</td>
</tr>
<tr>
<td>− ∞ (representing perfect condition)</td>
<td>&lt; 100</td>
</tr>
<tr>
<td>1</td>
<td>100 - 180</td>
</tr>
<tr>
<td>2</td>
<td>180 - 254</td>
</tr>
<tr>
<td>3</td>
<td>254 - 403</td>
</tr>
<tr>
<td>4</td>
<td>403 - 725</td>
</tr>
<tr>
<td>5 (pre-failure)</td>
<td>&gt; 725</td>
</tr>
</tbody>
</table>

---

1 For transformers where the oil is contaminated with gases (typically C2H2) generated from arcing during switching in the on-load tap changer. If it is not known whether the tap changer can contaminate the oil, the ratio C2H2/H2 is checked. C2H2/H2 ratios higher than 3 are a sign of contamination [3]
### Table 2-2: Grading of measured gas concentration increases according to IEC 60599 [3] / CIGRÉ 443 [5]

<table>
<thead>
<tr>
<th>Grade</th>
<th>H2</th>
<th>CH4</th>
<th>C2H6</th>
<th>C2H4</th>
<th>C2H2</th>
<th>CO</th>
<th>CO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>− ∞ (representing perfect condition)</td>
<td>&lt; 83</td>
<td>&lt; 65</td>
<td>&lt; 47</td>
<td>&lt; 89</td>
<td>&lt; 2 (&lt; 29³)</td>
<td>&lt; 660</td>
<td>&lt; 5850</td>
</tr>
<tr>
<td>1</td>
<td>83 - 179</td>
<td>65 - 175</td>
<td>47 - 176</td>
<td>89 - 218</td>
<td>2 – 7 (&gt; 29³)</td>
<td>660 - 1737</td>
<td>5850 - 15382</td>
</tr>
<tr>
<td>2</td>
<td>179 - 280</td>
<td>175 - 313</td>
<td>176 - 382</td>
<td>218 - 369</td>
<td>7 - 17</td>
<td>1737 - 3054</td>
<td>15382 - 27012</td>
</tr>
<tr>
<td>3</td>
<td>280 - 509</td>
<td>313 - 679</td>
<td>382 - 1074</td>
<td>369 - 745</td>
<td>17 - 47</td>
<td>3054 - 6491</td>
<td>27012 - 57351</td>
</tr>
<tr>
<td>4</td>
<td>509 - 1095</td>
<td>679 - 1825</td>
<td>1074 - 4015</td>
<td>745 - 1825</td>
<td>47 - 182</td>
<td>6491 - 17000</td>
<td>57351 - 150000</td>
</tr>
<tr>
<td>5 (pre-failure)</td>
<td>&gt; 1095</td>
<td>&gt; 1825</td>
<td>&gt; 4015</td>
<td>&gt; 1825</td>
<td>&gt; 182</td>
<td>&gt; 17000</td>
<td>&gt; 150000</td>
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### Table 2-3: Grading of measured oil parameters according to IEC 60422 [4]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Transformer category</th>
<th>Criteria for grades</th>
<th>1 (fair)</th>
<th>2 (poor)</th>
</tr>
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<tbody>
<tr>
<td>Breakdown voltage (kV)</td>
<td>&gt; 170 kV</td>
<td>&gt; 60</td>
<td>50 - 60</td>
<td>&lt; 50</td>
</tr>
<tr>
<td></td>
<td>72.5 – 170 kV</td>
<td>&gt; 50</td>
<td>40 - 50</td>
<td>&lt; 40</td>
</tr>
<tr>
<td></td>
<td>≤ 72.5 kV</td>
<td>&gt; 40</td>
<td>30 - 40</td>
<td>&lt; 30</td>
</tr>
<tr>
<td>Water content at operating temperature (mg/kg)</td>
<td>&gt; 170 kV</td>
<td>&lt; 15</td>
<td>15 - 20</td>
<td>&gt; 20</td>
</tr>
<tr>
<td></td>
<td>72.5 – 170 kV</td>
<td>&lt; 20</td>
<td>20 - 30</td>
<td>&gt; 30</td>
</tr>
<tr>
<td></td>
<td>≤ 72.5 kV</td>
<td>&lt; 30</td>
<td>30 - 40</td>
<td>&gt; 40</td>
</tr>
<tr>
<td>Acidity (mg KOH/g)</td>
<td>&gt; 170 kV</td>
<td>&lt; 0.10</td>
<td>0.10 - 0.15</td>
<td>&gt; 0.15</td>
</tr>
<tr>
<td></td>
<td>72.5 – 170 kV</td>
<td>&lt; 0.10</td>
<td>0.10 - 0.20</td>
<td>&gt; 0.20</td>
</tr>
<tr>
<td></td>
<td>≤ 72.5 kV</td>
<td>&lt; 0.15</td>
<td>0.15 - 0.30</td>
<td>&gt; 0.30</td>
</tr>
<tr>
<td>Dielectric dissipation factor at 40 – 60 Hz and 90 C (-)</td>
<td>&gt; 170 kV</td>
<td>&lt; 0.10</td>
<td>0.10 - 0.20</td>
<td>&gt; 0.20</td>
</tr>
<tr>
<td></td>
<td>72.5 – 170 kV</td>
<td>&lt; 0.10</td>
<td>0.10 - 0.50</td>
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<tr>
<td></td>
<td>≤ 72.5 kV</td>
<td>&lt; 0.10</td>
<td>0.10 - 0.50</td>
<td>&gt; 0.50</td>
</tr>
</tbody>
</table>
2. Retrieve and evaluate inspection results

Inspection results are not registered in a quantified form at Statnett today\(^6\), and hence cannot be included in the calculation of a health index. For future reference, some observations that could be registered during inspection, and then included in the health index are discussed in chapter 3.

3. Retrieve and evaluate audit results

As for inspections, observations after completed audit (preventive maintenance) are not registered in a quantified form at Statnett today, and hence cannot be included in the calculation of a health index.

4. Retrieve and evaluate thermography results

As for inspections, thermography results are not registered in a quantified form at Statnett today, and hence cannot be included in the calculation of a health index.

5. Calculate health index

Analogous to a fault tree model, the health index is given by

\[
HI = \prod_{j=1}^{n} \left(1 - R_j(\theta_j)\right),
\]

where \(R_j(\theta_j)\) is a function describing the effect on the health index of condition data \(j\) on a scale from 0 to 1, \(\theta_j\) is the grade of condition data \(j\), and \(n\) is the total number of condition data. The form of the health index function is derived as an analogy to a fault tree model with a single OR-gate between the top event (failure of the transformer – corresponding to \(1 - HI\)) and its independent basic events (failure causes – corresponding to condition data indicating a deteriorated condition). This ensures that the health can never be better than that signified by the condition data with the largest effect on the health. By requiring that \(R_j(\theta_j)\) is bound between 0 and 1, the health index is a number between 0 and 100%. Any condition data that can be graded and that effects the failure probability of the transformer can be included. All condition data are approximated as independent.

\(2\) Colour value has been added to the criteria from IEC 60422 based on NEK 240-1 [6]

\(3\) Only applicable to inhibited oils

\(4\) Percentage of original value, which in Norway typically is around 0.3% according to the maintenance handbook of "Brukergruppen for kraft- og industritransformatører" [7]

\(5\) The criteria for grading are an adjusted version of the criteria in IEC 60422

\(6\) Only observations that require some action to be taken, i.e. a work order to be issued, are registered.
In addition to being bounded between 0 and 1, it is natural to require that \( R_j(\theta_j) \) is monotonically increasing (or alternatively decreasing). Hence, \( R_j(\theta_j) \) may be suitably represented by a sigmoid function. Furthermore, defining the function piecewise makes it easier to tune it according to which condition data \( j \) it represents.

For condition data where an increasing grade \( \theta_j \) signifies a deteriorating condition, the function \( R_j(\theta_j) \) is therefore defined as

\[
R_j(\theta_j) = R_{j,r} \cdot \left(1 + r_{j,b}\right)^{-\theta_j - \theta_{j,r}} \quad \theta_j \leq \theta_{j,r}
\]

\[
R_j(\theta_j) = R_{j,m} - \left(R_{j,m} - R_{j,r}\right) \cdot \left(1 + r_{j,w}\right)^{-\theta_j - \theta_{j,r}} \quad \theta_j > \theta_{j,r}
\]

Here \( \theta_{j,r} \) is a reference condition that must be specified, \( R_{j,r} \) is the effect on the health index of the reference condition \((0 < R_{j,r} \leq 1)\), \( R_{j,m} \) is the maximum effect on the health index \((R_{j,r} \leq R_{j,m} \leq 1)\), and \( r_{j,b} \) is the rate of change of \( R_j(\theta_j) \) per unit of \( \theta_j \) when \( \theta_j \) is below \( \theta_{j,r} \). The constant \( r_{j,w} \) specifies the increase of \( R_j(\theta_j) \) when \( \theta_j \) is above \( \theta_{j,r} \) and is for \( r_{j,b} \ll 1, r_{j,w} \ll 1 \) and \( R_{j,m} \neq R_{j,r} \) approximated as

\[
r_{j,w} = r_{j,b} \frac{R_{j,r}}{R_{j,m} - R_{j,r}}
\]

by requiring that the derivative of \( R_j(\theta_j) \) is continuous for \( \theta_j = \theta_{j,r} \). The above definition of the function \( R_j(\theta_j) \) implies that the reference condition is the condition at which \( R_j(\theta_j) \) increases most rapidly. It also ensures that \( R_j(\theta_j) \) approaches 0 as \( \theta_j \) decreases towards minus infinity, and 1 as \( \theta_j \) increases towards infinity, as required. Hence, a perfect condition state \( \theta_j \) in this model is represented as minus infinity.

For some condition data, a decreasing grade rather than an increasing grade signifies a deteriorating condition. For such data, the function \( R_j(\theta_j) \) is defined as

\[
R_j(\theta_j) = R_{j,r} \cdot \left(1 + r_{j,b}\right)^{\theta_{j,r} - \theta_j} \quad \theta_j \geq \theta_{j,r}
\]

\[
R_j(\theta_j) = R_{j,m} - \left(R_{j,m} - R_{j,r}\right) \cdot \left(1 + r_{j,w}\right)^{\theta_{j,r} - \theta_j} \quad \theta_j < \theta_{j,r}
\]

The parameters for the function \( R_j(\theta_j) \) depend on the condition data \( j \) that it represents. All the condition data that are included in the health index are listed in Table 2-4, with a suggested specification of \( R_j(\theta_j) \). Included are data from periodic oil tests and the DP-value estimated from the winding degradation model; these are the data that are typically available for Statnett’s transformers. This means that the calculated health index only applies to the active part. For the parameters from the oil tests, the grading \( \theta_j \) is based on the standards IEC 60599 [3] and IEC 60422 [4] and Cigré report 443 [5]. These references provide criteria for the value of these parameters, e.g. typical normal values, alarm values, etc., that are used to set the grades. The tuning parameters \( R_{j,r} \) and \( R_{j,m} \) serve to weight the importance of the different condition data. Based on engineering judgment and knowledge of transformer failure modes, the DP-value and the gas parameters are set to be more important than the oil parameters in Table 2-4. The last tuning parameter \( r_{j,b} \) has been set to 1 for all parameters from the oil test, which means that \( R_j(\theta_j) \) doubles for each increment in \( \theta_j \). For the DP-value, a value of 0.01 for \( r_{j,b} \) ensures that \( R_j(\theta_j) \), and hence the effect on the health index, remains small until the DP-value is significantly reduced, which is in accordance with a generally accepted understanding of how the DP-value affects the transformer condition. The resulting \( R_j(\theta_j) \) is plotted in Figure 2-1 for both the DP-value and the gas parameters.

For the dissolved gases \((j = 1 \text{ to } 7)\), both the gas concentration and the gas concentration increase should be included in the model [3]. Hence, for each dissolved gas, the grade \( \theta_j \) is conservatively determined by
\[ \theta_j = \max(\theta_{j,c}, \theta_{j,ci}) , \]  

(5)

where \( \theta_{j,c} \) is the grade for the gas concentration and \( \theta_{j,ci} \) is the grade for the gas concentration increase. \( \theta_{j,c} \) should be evaluated from the last oil test, and \( \theta_{j,ci} \) from the difference between the last two oil tests.

*Not to be included for transformers where gas contamination from the tap changer is possible, as this is a common gas in tap changers.*

---

<table>
<thead>
<tr>
<th>( j )</th>
<th>Condition data</th>
<th>Specification of ( R_j(\theta_j) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>H2</td>
<td>( \theta_j = -\infty, 1, 2, 3, 4, 5 ) (perfect condition: ( -\infty ))&lt;br&gt;( \theta_{j,ref} = 5 )&lt;br&gt;( R_{j,ref} = 0.5 )&lt;br&gt;( R_{j,max} = 0.5 )&lt;br&gt;( r_{j,b} = 1 )</td>
</tr>
<tr>
<td>2</td>
<td>CH4</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>C2H6</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>C2H4</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>C2H2*</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>CO</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>CO2</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Breakdown voltage</td>
<td>( \theta_j = -\infty, 1, 2 ) (perfect condition: ( -\infty ))&lt;br&gt;( \theta_{j,ref} = 2 )&lt;br&gt;( R_{j,ref} = 0.25 )&lt;br&gt;( R_{j,max} = 0.25 )&lt;br&gt;( r_{j,b} = 1 )</td>
</tr>
<tr>
<td>9</td>
<td>Water content</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Acidity</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Dielectric dissipation factor</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Interfacial tension</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>Colour and appearance</td>
<td>( \theta_j = -\infty, 1, 2 ) (perfect condition: ( -\infty ))&lt;br&gt;( \theta_{j,ref} = 2 )&lt;br&gt;( R_{j,ref} = 0.125 )&lt;br&gt;( R_{j,max} = 0.125 )&lt;br&gt;( r_{j,b} = 1 )</td>
</tr>
<tr>
<td>14</td>
<td>Inhibitor content</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Corrosivity / passivator content</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>DP-value (( \theta_j = DP ))(^7)</td>
<td>( \theta_j = DP = 0 - \infty ) (perfect condition: ( \infty ))&lt;br&gt;( \theta_{j,ref} = 200 )&lt;br&gt;( R_{j,ref} = 0.75 )&lt;br&gt;( R_{j,max} = 1 )&lt;br&gt;( r_{j,b} = 0.01 )</td>
</tr>
</tbody>
</table>

\(^7\) The DP-value is taken from use case T3.1 "Thermal winding aging". The DP-value itself is used as the condition grade \( \theta_j \).
Figure 2-1: The resulting $R_j(\theta)$ for both the DP-value (left) and the gas parameters (right)
3 Input data

Since inspection, audit and thermography results are not registered in a quantified form at Statnett today, the health index can only be based on oil test data and winding aging results (from T3.1), and hence reflects only the condition of the active part of the transformer (core, windings and oil). This means that the estimated condition should be seen as a reflection of the probability for failure of the active part only, i.e. major internal failures that are often critical to the transformer.

All new oil test results are documented in the oil test database at Statnett. Currently, Statnett is completing this database with historic oil test data for all their transformers. Acquiring oil test data for the health index model can hence be automated (although this has not been done as part of the present work). For historic oil test data, it should be noted that some parameters may have been measured and documented in a different manner previously than they are today (this applies to e.g. water content and dielectric dissipation factor). This should be checked before using historic data. Some data may also be missing or incorrectly documented.

The desired input data to run the use case is summarized in Table 3-1. The DP-value from use case T3.1 comes in addition. Note that except for the rated voltage none of the data in Table 3-1 is mandatory for the model; the model can be run with any amount of available input data. Of course, with more input data, the results become more reliable.

Table 3-1: List of desired input data to run the use case. Oil test data should be retrieved from minimum the last two oil tests to get both the current values as well as the change from the second last test. The DP-value from use case T3.1 comes in addition

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Type</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Installation data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rated primary voltage (kV)</td>
<td>According to name plate</td>
<td>Numerical value</td>
<td>kV</td>
</tr>
<tr>
<td>Rated secondary voltage (kV)</td>
<td>According to name plate</td>
<td>Numerical value</td>
<td>kV</td>
</tr>
<tr>
<td>Has tap changer?</td>
<td>Alternatives: Yes / no</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td>Gas contamination from tap changer possible?</td>
<td>Alternatives: Yes / no</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td>Is inhibited?</td>
<td>Alternatives: Yes / no</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td>Is corrosive?</td>
<td>Alternatives: Yes / no</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td>Is passivated?</td>
<td>Alternatives: Yes / no</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td><strong>Oil test data (from minimum the last two oil tests)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date</td>
<td>Date when the oil sample was taken</td>
<td>Date (dd.mm.yyyy)</td>
<td>-</td>
</tr>
<tr>
<td>O2 (µl/l)</td>
<td>Concentration of dissolved oxygen in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td>N2 (µl/l)</td>
<td>Concentration of dissolved nitrogen in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td>H2 (µl/l)</td>
<td>Concentration of dissolved hydrogen in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td>CO (µl/l)</td>
<td>Concentration of dissolved carbon monoxide in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>CO2 (µl/l)</strong></td>
<td>Concentration of dissolved carbon dioxide in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td>----------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>-----------------</td>
<td>------</td>
</tr>
<tr>
<td><strong>CH4 (µl/l)</strong></td>
<td>Concentration of dissolved methane in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>C2H6 (µl/l)</strong></td>
<td>Concentration of dissolved ethane in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>C2H4 (µl/l)</strong></td>
<td>Concentration of dissolved ethylene in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>C2H2 (µl/l)</strong></td>
<td>Concentration of dissolved acetylene in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>C3H8 (µl/l)</strong></td>
<td>Concentration of dissolved propane in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>C3H6 (µl/l)</strong></td>
<td>Concentration of dissolved propene in oil (according to IEC 60599/60457/60567)</td>
<td>Numerical value</td>
<td>µl/l</td>
</tr>
<tr>
<td><strong>Breakdown voltage (kV)</strong></td>
<td>According to IEC 60422/60156</td>
<td>Numerical value</td>
<td>kV</td>
</tr>
<tr>
<td><strong>Water content (mg/kg)</strong></td>
<td>Water content at the operating temperature when the oil sample was taken, given in amount of water per amount of oil (according to IEC 60422/60814)</td>
<td>Numerical value</td>
<td>mg/kg</td>
</tr>
<tr>
<td><strong>Acidity (mg/g)</strong></td>
<td>Amount of KOH per amount of oil (according to IEC 60422/62021-1)</td>
<td>Numerical value</td>
<td>mg/g</td>
</tr>
<tr>
<td><strong>Dielectric dissipation factor (-)</strong></td>
<td>Dielectric dissipation factor at 40 - 60 Hz and 90 °C (according to IEC 60422/60247). Not to be given in %</td>
<td>Numerical value</td>
<td>-</td>
</tr>
<tr>
<td><strong>Interfacial tension (mN/m)</strong></td>
<td>According to IEC 60422/ASTM D971</td>
<td>Numerical value</td>
<td>mN/m</td>
</tr>
<tr>
<td><strong>Colour (-)</strong></td>
<td>According to ISO 2049. Alternatives: 0 – 8 in 0.5 intervals</td>
<td>Numerical value</td>
<td>-</td>
</tr>
<tr>
<td><strong>Appearance</strong></td>
<td>According to IEC 60296. Alternatives: Clear / Unclear</td>
<td>Text</td>
<td>-</td>
</tr>
<tr>
<td><strong>Inhibitor content (%)</strong></td>
<td>Inhibitor content given in % of oil (according to IEC 60422/60666)</td>
<td>Numerical value</td>
<td>%</td>
</tr>
<tr>
<td><strong>Passivator content (mg/kg)</strong></td>
<td>Passivator content given in amount of passivator per amount of oil (according to IEC 60422/60666)</td>
<td>Numerical value</td>
<td>mg/kg</td>
</tr>
</tbody>
</table>

For future reference, some observations that could be registered during inspection, and then included in the health index model are given in Table 3-2. This would enable health indices to be established also for the other parts than the active part, i.e. bushings, tap changer and cooling system. Suggested grading criteria for these observations are given in Table 3-3.
Table 3-2: Some suggested observations per transformer sub-component, that could be registered during inspection, audit or thermography. The list is just a suggestion and is not exhaustive

<table>
<thead>
<tr>
<th>Sub-component</th>
<th>Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tank</td>
<td>Inspection: Corrosion, surface treatment damage, gasket damage, leakage</td>
</tr>
<tr>
<td>Bushings</td>
<td>Inspection: Corrosion, surface treatment damage, gasket damage, cracking, leakage, oil colour, surface contamination</td>
</tr>
<tr>
<td></td>
<td>Thermography: Heating</td>
</tr>
<tr>
<td>Tap changer</td>
<td>Inspection: Corrosion, surface treatment damage, gasket damage, leakage</td>
</tr>
<tr>
<td></td>
<td>Audit: Locked position, carbonization, burned resistance, mechanical wear</td>
</tr>
<tr>
<td></td>
<td>Thermography: Heating</td>
</tr>
<tr>
<td>Cooling system</td>
<td>Inspection: Corrosion, surface treatment damage, gasket damage, leakage, mechanical wear, clogging</td>
</tr>
<tr>
<td></td>
<td>Thermography: Heating</td>
</tr>
</tbody>
</table>

Table 3-3: Suggested grading criteria for observations from inspection, audit and thermography

<table>
<thead>
<tr>
<th>Grade</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No sign of deterioration</td>
</tr>
<tr>
<td>2</td>
<td>Some sign of deterioration. Somewhat worse condition than new</td>
</tr>
<tr>
<td>3</td>
<td>Extensive sign of deterioration. Considerably worse condition than new</td>
</tr>
<tr>
<td>4</td>
<td>Critical condition</td>
</tr>
</tbody>
</table>
4 Results from testing

The model has been tested on 18 transformers, including four scrapped transformers, for which health indices have been calculated based on oil test data and winding aging results. The results are shown in Figure 4-1, in which the results are compared with the health indices calculated with the Trafotiltak model [2]. The models agree fairly well, but there are some important changes in the improved Samba model.

![Comparison of health indices calculated with the Samba and Trafotiltak models](image)

*Figure 4-1: Comparison of health indices calculated with the Samba and Trafotiltak models*

In Figure 4-1 the calculated health indices are shown as a function of transformer age, illustrating that the model is well suited for comparing transformers in a population. There are considerable individual variations, and only a weak general decreasing trend with age is indicated. The individual variations may be due to differences in design, loading, maintenance etc. This illustrates that evaluating transformers for maintenance or replacement simply based on age is not a wise approach.

The most common parameters causing low health indices are carbon monoxide and inhibitor content. Increased level of carbon monoxide can be a sign of paper degradation, while low inhibitor content renders the oil susceptible to oxidation.
In Table 4-1 the calculated health indices are listed including a so-called completeness index. The completeness index is a simple measure for how much of the desired input data (chapter 3) that was available and hence included in the calculation. In this table it is also commented which of the transformers that have already been scrapped, and it is seen that the scrapped transformers have the lowest health indices.

It is seen that the availability of input data is reasonably good. In some cases, all oil test parameters listed in chapter 3 were not available, which results in a lower completeness index. In some cases, data some data for calculating the DP-value was missing (see use case T3.1).

Table 4-1: Health index and completeness index per transformer

<table>
<thead>
<tr>
<th>Name</th>
<th>Age</th>
<th>Health index</th>
<th>Completeness index</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>BrokkeT12</td>
<td>10</td>
<td>94 %</td>
<td>96 %</td>
<td></td>
</tr>
<tr>
<td>BærumT2</td>
<td>32</td>
<td>100 %</td>
<td>86 %</td>
<td></td>
</tr>
<tr>
<td>FlesakerT4</td>
<td>57</td>
<td>78 %</td>
<td>80 %</td>
<td>Scrapped 2012</td>
</tr>
<tr>
<td>FrognerT51</td>
<td>7</td>
<td>100 %</td>
<td>62 %</td>
<td></td>
</tr>
<tr>
<td>HamangT1</td>
<td>53</td>
<td>96 %</td>
<td>74 %</td>
<td></td>
</tr>
<tr>
<td>HasleT1</td>
<td>57</td>
<td>82 %</td>
<td>67 %</td>
<td>Scrapped 2012</td>
</tr>
<tr>
<td>HasleT5</td>
<td>48</td>
<td>77 %</td>
<td>77 %</td>
<td>Scrapped 2013</td>
</tr>
<tr>
<td>HofT1</td>
<td>12</td>
<td>97 %</td>
<td>96 %</td>
<td></td>
</tr>
<tr>
<td>HøyangerT1</td>
<td>5</td>
<td>88 %</td>
<td>59 %</td>
<td></td>
</tr>
<tr>
<td>HøyangerT2</td>
<td>5</td>
<td>82 %</td>
<td>59 %</td>
<td></td>
</tr>
</tbody>
</table>
### Health index – testing of SAMBA use case T3.6

<table>
<thead>
<tr>
<th>Station</th>
<th>Value</th>
<th>Oil Test</th>
<th>Compliance</th>
</tr>
</thead>
<tbody>
<tr>
<td>KvandalT1</td>
<td>36</td>
<td>85 %</td>
<td>86 %</td>
</tr>
<tr>
<td>KvandalT2</td>
<td>37</td>
<td>100 %</td>
<td>86 %</td>
</tr>
<tr>
<td>LeirdølaT2</td>
<td>34</td>
<td>84 %</td>
<td>79 %</td>
</tr>
<tr>
<td>RødT2</td>
<td>56</td>
<td>85 %</td>
<td>48 %</td>
</tr>
<tr>
<td>RøykåsT3</td>
<td>49</td>
<td>100 %</td>
<td>66 %</td>
</tr>
<tr>
<td>TveitenT3</td>
<td>35</td>
<td>91 %</td>
<td>86 %</td>
</tr>
<tr>
<td>TveitenT4</td>
<td>44</td>
<td>96 %</td>
<td>86 %</td>
</tr>
<tr>
<td>VerdalT1</td>
<td>53</td>
<td>65 %</td>
<td>52 %</td>
</tr>
</tbody>
</table>

In the model, several different parameters are weighted to obtain the overall health index, as explained in chapter 2. The weighting is based on e.g. information from IEC standards, but is necessarily somewhat subjective. The model should therefore be further tested at Statnett to gain more experience with it, and the weighting adjusted based on this testing. Failure and scrapping statistics may also be useful for adjusting the model but is currently too limited for this purpose.

In the model, oil test data are graded according to international statistics taken from IEC and CIGRÉ. A straightforward improvement of the model is to establish grading criteria based on national statistics instead. This would be in accordance with recommendations in IEC standard 60599 [3]. There is not sufficient data available to do this today, but a national database with oil test data has newly been established, such that this may be possible in the future.

The new Norwegian condition database can also give a foundation for revising the model to take into account dependencies between oil parameters, when this database has been populated. Being analogous to a fault tree model, the health index model is not very suitable to take this into account, but this could be done by generalizing it to a Bayesian network.

Another way to improve the model is to include also other parts of the transformer than the active part. The most interesting components to include are bushings and tap changers, since these are known to have significant failure frequencies [6]. However, this requires that gradable condition data must be measured and registered also for these transformer parts. This may require some new sensors and an extension of the data grading system.

In conclusion, the health index model is a systematic approach to assess the overall condition of transformers in Statnett's fleet. This enables all transformers to be compared, and transformers requiring attention to be singled out. The calculated health index is assumed to reflect the probability of major failure of the active part. However, this probability (and hence the health index) can never be proven and is inherently uncertain. Therefore, the transformers should not be assessed based on the health index only, but also the underlying data, assumptions and uncertainties should be considered. The completeness index is useful as this highlights how much of the desired data that the health index is based on.
5 References


V6  Testing L3.2 Connector condition
Project memo

Overhead Joint Condition Assessment

Sauda-Karmøy 300 kV overhead line

VERSION 2.0  
DATE 2018-12-18

AUTHOR(S) Svein Magne Hellesø

CLIENT(S) Statnett

PROJECT NO. 502001227

ABSTRACT
The condition of 77 joints and two dead ends from the Statnetts 300 kV overhead line between Sauda and Karmøy has been determined using the pulse current method.

All of the tested joints and dead ends were in a very good condition.

PREPARED BY Svein Magne Hellesø

APPROVED BY Maren Istad

PROJECT MEMO NO. AN 18.14.10

SIGNATURE

CLASSIFICATION Open
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APPENDICES

A. Detailed Measurements Results
1 Introduction
As part of the SAMBA project at Statnett several compression type line joints and dead ends removed from Statnett's grid were made available to SINTEF. The joints and dead ends were removed and replaced as part of a program for replacing old joints and dead ends in Statnett's grid. The joints were installed on a 300 kV line between Sauda and Karmøy, and the line and joints etc were installed in the late 1960s.

SINTEF's task is to give an assessment of the electrical condition of the joints, as a means of determining the ageing of the joints.

2 Samples
The line joints were all the same type, hexagonal compression joints, shown in Figure 1. The joints were about one meter long. 82 joints and two dead-ends were received, giving a total of 84 components. The condition of 80 of these were determined, for 78 joints and the two dead ends. For the remaining 4 joints it was not possible to attach the measuring equipment, as the length of conductor protruding from the joint was too short.

Most of the joints and dead end were clearly marked with which span and phase they had been removed from, and the installation direction was also indicated.

14 of the joints were only marked with which span and phase they had been removed from, it was not possible to determine the installation direction.

12 joints were not marked at all.

The conductor was of the type ACSR (aluminium conductor steel reinforced) with a steel core with 19 strands (1+6+12, strand diameter approx. 2.7 mm) and 54 aluminium strands in three layers (12+18+24, strand diameter 4.2 mm).

The nominal load current for a conductor of this design is about 1400 A. (ref: http://www.nexans.no/eservice/Norway-no_NO/navigateproduct_432428/SAHF_481_Parrot.html#characteristics).

Figure 1. Hexagonal compression joint removed from service in Statnett's grid.

The conductor and joint had varying levels of pollution on the surface. An assessment of the pollution levels was made before doing any measurements, see Figure 2.
Eventually it turned out that the pollution level did have any obvious correlation with the condition of the joints.

### 3 Measurement setup

In order to assess the condition of the joints, measurements with the pulse current method were performed on the joints. With this method several current pulses, with increasing magnitude, is sent through the joint while the voltage drop is measured. For each current pulse the resistance of the joint is determined and based on how the resistance varies with the current magnitude an assessment of the joint condition is made.

The test set up is shown schematically in Figure 2.

![Figure 2. Pollution grading levels, from 1 (least) to 3 (worst).](image)

![Figure 3. Schematic overview of the measurement setup for the pulse current measurement.](image)
The measurements were carried out with the joints lying on the table in laboratory. One side of the joint was tested at the time. Current cables were connected on the short length of conductor protruding from the joint on each side. Due to the short length of conductor available for current connection, a custom current connection device was used. Voltage taps on the conductor with a copper string around the conductor, just outside the joint body. The voltage tap on the barrel was made using a conventional clip at the middle of the barrel. The surface of the conductor and of the joint had been lightly cleaned by using emery paper.

**Figure 4.** Current connection device, and voltage tap on conductor between the current connection and the joint body.

**Figure 5.** Laboratory setup with the joint to be tested on the table in the background.
4 Interpretation of measurements

As described in detail elsewhere (e.g. in IEEE Trans. Power Delivery, vol. 19, pp. 609-617, 2004), the condition of a contact can be assessed with basis in to what extent different current magnitudes $I$ will cause the contact spots to heat up and thereby change the contact resistance $R$. Three regions exist:

1. $R(I) =$ constant. The current is sufficiently low and/or the joint is sufficiently good so that no contact spot heating occurs.
2. $R(I)$ increases with increasing current in a reversible manner. The contact spots are substantially heated and the joint is deteriorated / carries more current than it can do in a safe way.
3. $R(I)$ changes significantly and in an irreversible manner between subsequent measurements. The contact spots are so heated that local melting occurs. The joint is severely deteriorated / overstressed.

From the above it follows that the current rating of the line must be taken into account when interpreting the measurements. For example, reversible contact spot heating starting at 1000 A does not indicate deterioration in the joint of a 70 mm$^2$ earth conductor, but does in a 1800 mm$^2$ phase conductor joint.

SINTEF has no information about the actual current ratings of the line from which the joints have been removed. A nominal current rating for this type of conductor has been found, indication a maximum load current of about 1400 A.

The electric condition of each side of the joints is here assessed according to the following criteria:

- **Very good condition:**
  $R(I)$ is constant for currents up to several times the estimated full load current.

- **Good condition:**
  $R(I)$ is constant for currents up to the estimated full load current.

- **Poor condition:**
  $R(I)$ increases in a reversible manner for currents below the estimated full load current.

- **Very poor condition:**
  $R(I)$ changes significantly and in an irreversible manner for currents below the estimated full load current.
5 Results from condition assessment of the joints

The condition of all 80 joints that have been tested was determined to be very good.

![Graph showing resistance values for joints](image)

**Figure 6.** Measured resistance values for joint on left phase between towers 167 and 168.
6 Dissection of selected joints

Three joints were selected for further inspection: the joint between towers 19-20 (inclined joint on right phase), towers 45A-46 (joint on middle phase in mountainous area 600 meters elevation) and towers 136-137 (joint on middle phase close to the coast/sea). The joint body of these were cut open to expose the interior of the joint, primarily to inspect the condition of the steel core inside the joint.

In joint 19-20 there was no visible signs of corrosion of the steel core. The compound injected into the joint to fill any voids has partially seeped out, leaving an air-filled void between the steel sleeve and the joint body. However, the air filled void has remained dry.

![Figure 7. Joint 19-20: Air filled void where the injected compound has seeped out.](image)

In joint 45-46 the compound injected into the joint to fill any voids has partially seeped out of the joint, leaving an air-filled void between the steel sleeve and joint body. There are signs of corrosion in the void, with precipitation of rusty dust. This indicates that water has entered the joint, contribution to corrosion. However, there are no visible signs that the steel core has corroded.

![Figure 8. Joint 45-46: Air filled void where the injected compound has seeped out.](image)

In joint 136-137 the compound injected into the joint seem to fill the void between the steel sleeve and the joint body. There are no signs of corrosion of the steel core or steel sleeve.
Figure 9. Joint 136-137: The injected compound fills the void between the steel sleeve and joint body.

7 Discussion and conclusions

All of the tested joints and dead ends were in a very good condition.

Not all of the joints were properly marked, which means it was not possible to determine the installation location of these joints.

The three joints that were cut open revealed that compound injected into the joints had seeped out in two of the joints, leaving behind an air-filled void.
## Appendix
### A. Overview of joints

#### Table 1

<table>
<thead>
<tr>
<th>Object identifier</th>
<th>Type</th>
<th>Condition</th>
<th>Marking</th>
</tr>
</thead>
<tbody>
<tr>
<td>M 4-5 LP</td>
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<tr>
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V7 Testing A3.5 Condition assessment through sample testing
This memo describes how the use case *Condition assessment through sample testing* can fit into a replacement process. Figure 1 shows an overview of a component replacement process. The analysis can be initiated by a triggering event, such as component condition, age, or number of years since the previous analysis. Then different archetypes and conditions (component properties, weather conditions and so on) for classification of the components into these archetypes are defined. The archetypes should be defined based on factors that are believed to have an effect on the degradation of the technical condition of the components, and the available data. Relevant data when defining archetypes include technical data, data on different stresses the components have been exposed to, and the maintenance history. When defining the condition for classification of the components it is important to include rules for how to handle overlapping archetypes, i.e. components that meet the conditions for several archetypes. The definition of archetypes and condition for classification should be done by component experts.

Detailed condition assessment is then performed on a number of components of each archetype. The condition assessment should result in a classification of the technical condition of the component, e.g. a grade from 1-4 or simply good / no good. Condition assessment for a number of component of each archetype will help assure that components with slightly different design and components exposed to different stresses, e.g. operation in different environment, are assessed. It is believed that this will be a more cost-effective way of assessing the technical condition of the whole group of components than simple random sample testing. In addition, weak groups of components within the population can be discovered. The results of the condition assessment will be used as input in a failure model where information about the technical condition of the component is used to estimate the probability of failure. This is combined with the consequence of failure to quantify the risk. The risk will provide useful input when preparing a replacement strategy. It is important to use the risk (combination of probability of
failure and consequences) to make a replacement strategy, as i.e. run-to-failure can be an option for less critical component. (See use case A3.1 Estimation of residual lifetime, probability of failure and risk - Circuit Breaker for more details on the failure model.)

When the components have been replaced, a number of components in each archetype should be tested in the lab to verify the condition assessment performed in the field and to gain more experience on the degradation process of the components. Post-mortem condition assessment might in some cases allow other, and often more accurate, assessment methods than is possible in the field. Finally, the definition of the archetypes and the replacement strategy should be evaluated in order to approve the process for future projects.

Figure 1 Overview of component replacement process. The dark grey rectangle represents the Condition assessment through sample testing use case.
V8 Testing CB3.6 Re-ignition monitoring of reactor breakers
Memo

Identify re-ignitions in reactor circuit breakers

PERSON RESPONSIBLE / AUTHOR
Magne Lorentzen Kolstad

DISTRIBUTION
Magne Lorentzen Kolstad

PROJECT NO / FILE CODE
Project No. or File code

DATE
2017-07-27

CLASSIFICATION
Restricted

This memo describes an algorithm to identify re-ignitions in reactor circuit breakers based on measurements of the reactor current. The algorithm is performed for all reactor breaker operations and the number of operations, and the number of re-ignitions is counted for each breaker. In addition to measurements of reactor current, information about breaker positions and operations are needed.
Figure 1 Current and arc quenching for a successful reactor disconnection with no re-ignitions.

**Step 1**
Identify the time of arc quenching in all three phases

<table>
<thead>
<tr>
<th>Input:</th>
<th>Output:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Current measurements</td>
<td>- $T_{L1}$, $T_{L2}$, $T_{L3}$</td>
</tr>
</tbody>
</table>

**Step 2**
Calculate the time between arc quenching

Rules:
- $T_{1-3} = T_{L3} - T_{L1}$
- $T_{3-2} = T_{L2} - T_{L3}$

<table>
<thead>
<tr>
<th>Input:</th>
<th>Output:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- $T_{L1}$, $T_{L2}$, $T_{L3}$</td>
<td>- $T_{1-3}$, $T_{3-2}$</td>
</tr>
</tbody>
</table>

**Step 3**
Determine if re-ignitions have occurred.

Rules:
- If ($T_{L1} < T_{L3} < T_{L2}$) and ($T_{1-3} = T_{3-2} = 3.33$ ms) -> Re-ignition = FALSE
- Else -> Re-ignition = TRUE

<table>
<thead>
<tr>
<th>Input:</th>
<th>Output:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- $T_{L1}$, $T_{L2}$, $T_{L3}$</td>
<td>- Re-ignition (TRUE/FALSE)</td>
</tr>
</tbody>
</table>
**Step 4**
If re-ignitions have occurred, determine in what phase re-ignitions have occurred.

Rules:

**Phase 1**
If \((T_{11} > T_{12}) \) or \((T_{11} > T_{13})\) -> Re-ignition phase L1 = TRUE
Else -> Re-ignition phase L1 = FALSE

**Phase 2**
If \((T_{32} > 3.33 \text{ ms})\) or \(((T_{13} > 3.33 \text{ ms}) \) and \((T_{13} < T_{12})\)) -> Re-ignition phase L2 = TRUE
Else -> Re-ignition phase L2 = FALSE

**Phase 3**
If \((T_{13} > T_{12})\) or \((T_{13} > 3.33 \text{ ms})\) -> Re-ignition phase L3 = TRUE
Else -> Re-ignition phase L3 = FALSE

Input:
- \(T_{11}, T_{12}, T_{13}\)
- \(T_{13}, T_{32}\)

Output:
- Re-ignition phase L1 (TRUE/FALSE)
- Re-ignition phase L2 (TRUE/FALSE)
- Re-ignition phase L3 (TRUE/FALSE)

**Step 5**
Identify the circuit breaker that disconnected the reactors and the time of operation

Rules:
Time of operations is the time were the circuit breaker operated interrupting the reactor current.

Input:
- SCADA data

Output:
- Breaker ID
- Time of operation

**Step 6**
Prepare results including all circuit breaker operations where the reactor current was interrupted.

Rules:

Input:
- Breaker ID
- Re-ignition phase L1 (TRUE/FALSE)
- Re-ignition phase L2 (TRUE/FALSE)
- Re-ignition phase L3 (TRUE/FALSE)

Output:
- Table 1, including all operations where the reactor current was interrupted.

**Table 1 Results template**

<table>
<thead>
<tr>
<th>Breaker ID</th>
<th>Time of operation</th>
<th>Re-ignition L1</th>
<th>Re-ignition L2</th>
<th>Re-ignition L3</th>
</tr>
</thead>
</table>

V9  Testing ABB Technical-economic analysis of maintenance and reinvestment
December 2018

ABB SAMBA Final Report

*Technical-economic Analysis of Maintenance and Reinvestment Cost-Benefit Use Case*
Results generated

The cost data from Statnett had already be processed in NPV terms and the probability of failure calculations had been applied across the scenarios. This data was loaded into the ABB AIP software on this basis. This dictates the way the cost is presented as one ‘project’ over 30 years.

No custom development was done. This is a critical point which will be mentioned in the recommendations section below: Use standard, off-the-shelf software where possible.

The AIP software can manage many complex scenarios. As an example, it allows multiple projects and multiple options associated with one or many of the projects. It allows the user to link projects to each other or exclude one project based on the inclusion of another. Resources, KPI goals, groups as well as cost can all figure in the analysis. It has always been the aim of this exercise to work through from a simple scenario adding options one at a time to expose the impact on the outcome.

The projects base data summary is

<table>
<thead>
<tr>
<th>Project</th>
<th>Year</th>
<th>Cost</th>
</tr>
</thead>
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<tr>
<td>A1</td>
<td>Replace</td>
<td>546KKr</td>
</tr>
<tr>
<td>A2</td>
<td>Replace</td>
<td>519KKr</td>
</tr>
<tr>
<td>A3</td>
<td>Replace</td>
<td>630KKr</td>
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</tr>
<tr>
<td>A5</td>
<td>Replace</td>
<td>853KKr</td>
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</tbody>
</table>

The following results step through the output of the systems analysis of the base data.

**Using one project with 5 options A1 to A5**

The output from the system shows that option A2 to replace at year 21 with a NPV costing of 519KKr has been chosen. There are no unselected projects as there was only one. This view illustrates how the system can deliver the correct result using options but the next method used will give a more open view of the system by showing A1 to A5 as separate projects.

**Using 5 Projects**
The system ran the data and the result show the selection A2 to replace at year 21 with a NPV costing of 519KKr.

The budget was set so that only one project would be chosen, this is purely to follow the desired analysis of the alternatives to maintenance and replacement. In normal operation, complex project mixes can be analysed to fit into a given budget, as demonstrated previously to Statnett.

From the graphic, the breakdown of cost and the position of expenditure at Q1 of 2019 is as given in the data.

These next views show the project duration across the 30 years.
A view of the project selected and those left unselected is now available.

A drill down into more detail shows the cost breakdown again but also includes a utility value. This was included on all projects at the same value and thus has no impact at this point. Further use was made of this in the next part of the investigation.
Using 5 Projects with a KPI on safety

This section of the investigation set out to explore how the system could include a way of optimising the results with the consideration of a minimum acceptable level of personal safety and ranking the options against that.

To do this the baseline level of acceptable safety performance was used and the differences in probabilities of A1 to A5 were tuned into KPIs for use in the AIP system. It is interesting to note that the original chosen option does not meet the required minimum.

Running the AIP system with the new KPI levels set appropriately yielded the following result.

The project chosen was A3 to replace at year 11 with a NPV costing of 630KKr
The reason for this result is that the system has selected the cheapest way to deliver the safety KPI. It happens that both A3 and A5 deliver the same safety performance but 'utility' or benefit to cost ratio is better. This detail is shown in the top of the graphic below.

Extending the use case to consider the way forward

The AIP system allows users to analyse a portfolio of projects

**Using 5 Projects with a KPI on safety and another on regulation**

The data provided had information on the probability of CENS cost being incurred and that was used to generate probable CENS cost. The probability values were turned into a value that AIP could use as a KPI and indicate the option that offered the lowest probability of incurring a CENS cost. This was labelled a regulatory KPI. The system
was run with both KPIs in operation, so the system was looking at the optimum result considering cost, safety and regulatory performance.

The project chosen was A5 to replace at year 1 with a NPV costing of 853KKr

This graphic now shows the interrelationship of the KPI utility and the Utility/Cost ratio that drives this decision.
The final outcome is the best value in terms of the safest and least interruption from the five scenarios.