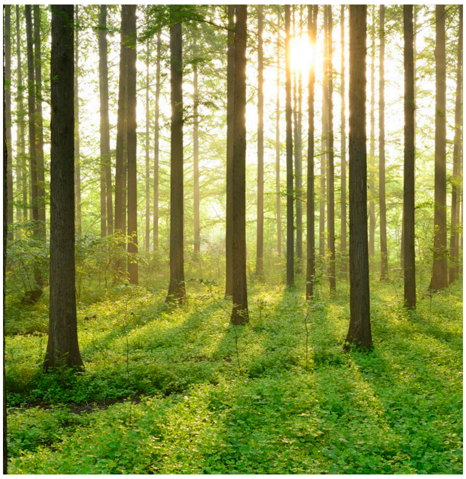
MONITOR X DIGITALIZATION IN HYDROPOWER

REPORT 2019:618



MONITOR X

Energiforsk

Monitor X Digitalization in Hydropower

Final Report

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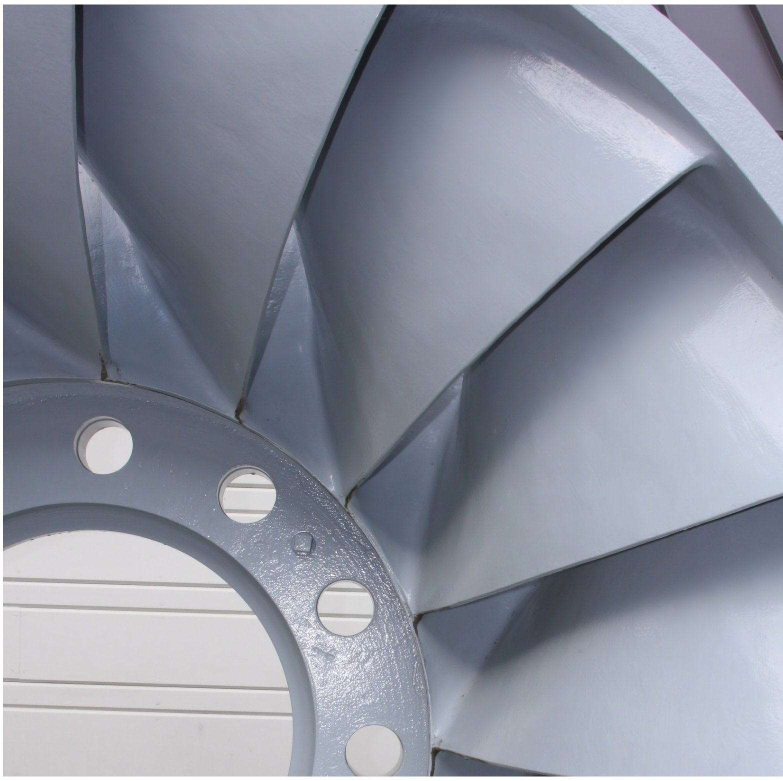
MonitorX - Final report

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Report

MonitorX

Summary of results, recommendations for use of results, and suggestions for further work

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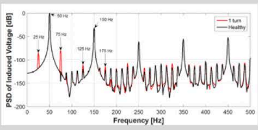
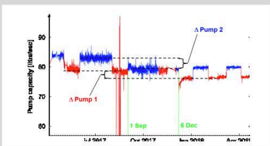
C1 - Rotor fault detection

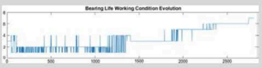


C2 - Pump condition monitoring

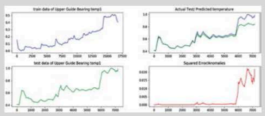


C3 - Audio surveillance

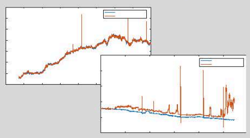
C4 - Condition monitoring of rotating equipment using vibration data



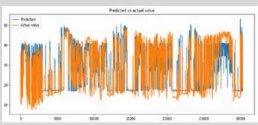
C5 - Condition monitoring of generator bearings



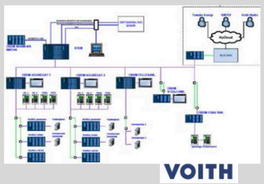
C6 - Condition monitoring of Kaplan turbine hydraulic system



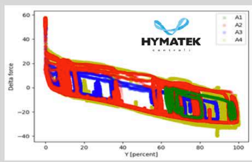
C7 - Fault detection for power transformers



C8 – SCADA data collection system



C9 – Continuous Servomotor monitoring



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ABSTRACT

This report provides a summary of the results from the joint industry project "MonitorX – Optimal utilization of hydropower asset lifetime by monitoring technical condition and risk". In MonitorX, data analysis models and algorithms for condition monitoring and predictive maintenance of components in hydropower plants have been developed and tested. The most important benefits of using such models is fewer manual inspections and shorter maintenance downtime by using more condition-based and less time-based maintenance, and reduced costs for corrective maintenance due to early warnings of failures. The project was an important forum for knowledge-building and exchange of experience between hydropower plant operators, equipment manufacturers/service providers and research institutions.

The work in MonitorX was case-driven, meaning that identification of practical cases and development of these cases with the industry partners was the main approach. This report provides an overview of all cases in the project. The results from each case are briefly summarized in the report and explained in more detail in the appendices. Based on the obtained results and experience from testing, recommendations for use of the project results and suggestions for further work are given.

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APPENDICES

1 Introduction

This report has been written in the joint industry project "MonitorX – Optimal utilization of hydropower asset lifetime by monitoring technical condition and risk". The report provides a summary of results from the project, recommendations for use of results at the industry partners, and suggestions for further work.

MonitorX was led by Energi Norge (Energy Norway – the Norwegian electricity industry association) in cooperation with Energiforsk (the Swedish Energy Research Centre). More than 20 Norwegian and Swedish power companies participate in the project, as well as a number of equipment manufacturers and service providers. Furthermore, the research institutions SINTEF Energy Research (Trondheim, Norway), Comillas Pontifical University (Madrid, Spain), and the Norwegian University of Science and Technology, NTNU (Trondheim) participated. MonitorX started in July 2015 and lasted until June 2019. The project was financially supported by the Research Council of Norway, grant no. 245317, and the industry partners.

All MonitorX project partners are listed below:

Project leader
Energy Norway (EN)

R&D partners
SINTEF Energy Research
Norwegian University of Science and Technology (NTNU)
Comillas Pontifical University

Norwegian hydropower companies
BKK Produksjon AS
E-CO Energi AS
Hafslund Produksjon AS (until merger with E-CO)
Gitre Energi Produksjon AS (before: EB Kraftproduksjon)
Eidsiva Vannkraft AS
Hydro Energi AS
Lyse Produksjon AS
NTE Energi AS
Sira-Kvina Kraftselskap AS
Skagerak Energi AS
Statkraft Energi AS
TrønderEnergi Kraft AS
Østfold Energi AS

Swedish power companies represented by Energiforsk
Vattenfall Vattenkraft AB
Umeå Energi AB
Vattenfall Indalsälven AB
Fortum Generation AB
Uniper - Sydkraft Hydropower AB (before: E.ON Vattenkraft Sverige AB)
Sollefteåforsens AB
Statkraft Sverige AB
Skellefteå Kraft AB
Holmen Energi AB
Jönköping Energi AB
AB Edsbyns Elverk
Varberg Energi AB
Karlstads Energi AB
Jämtkraft AB

OEMs and service providers
Voith Hydro AS
Karsten Moholt AS
Andritz Hydro AS
Hymatek Controls AS

Financing
The Research Council of Norway
(+ industry partners)

The goal of MonitorX was to develop models and algorithms for data analysis, condition monitoring and predictive maintenance of components in hydropower plants. The work in MonitorX was case-driven, meaning that identification of practical use cases and development of these cases with the industry partners was the main approach that has been used to reach the goal. See chapter 2 for a more detailed overview of the MonitorX project.

The expected benefit of using models and algorithms as developed in the MonitorX project and implementing advance condition monitoring and intelligent data analysis in hydropower plants are:

- Better knowledge about the real technical condition of the components, and the relation between operation conditions, loads, degradation and lifetime.
- Fewer manual inspections and shorter maintenance downtime by using more condition-based and less time-based maintenance.
- Reduced cost for corrective maintenance due to early warnings of failures, and thus reduced probability of failure.

Furthermore, the project contributed to knowledge building and exchange of experience within the field of data collection and data analysis, as well as implementation and use of condition monitoring and predictive maintenance in hydropower plants. In Chapter 6, these benefits are discussed in more detail and illustrated by several examples.

1.1 Structure of report and corresponding result documentation

This report is the final and main report of the MonitorX project. The report provides a project summary and overview and is organised as follows: Chapter 2 gives a brief description of the project. The results from a survey on status of condition monitoring, data collection and data analysis in Norwegian and Swedish hydropower plants is presented in Chapter 3. Chapter 4 introduces and briefly describes the cases that have been developed in the project. Chapter 5 provides an overview of the project results and deliverables. Potential benefits of using the project results are briefly discussed in Chapter 6. In Chapter 7, recommendations for use of the results at the industry partners are given. Conclusions and recommendations for further work can be found in Chapter 8. Appendix A provides an overview of the documentation, codes and data sets for the MonitorX cases. More detailed case descriptions and results for the cases can be found in appendices B – H.

In addition to providing an overview of the project and its results, the main report is intended to guide the reader to the documentation of the MonitorX cases, including example code that has been developed for many cases. The basic structure of the MonitorX documentation is illustrated in Figure 1-1. After getting the general overview of the project and the cases in the main report, the reader is recommended to proceed to the case summaries in the appendices of the report, where more technical details for each case can be found. For further reading, the reader is then referred to the additional documentation that is available for most of the cases. Appendix A provides an overview of the additional case documentation.

The main report and the case summaries can be downloaded from the web page www.energinorge.no/monitorx. On this page, there will also be a link to the *MonitorX Results* Sharepoint, where all additional documentation and codes can be found. The Sharepoint area has restricted access. Representatives from all the companies that participated in the project have access.

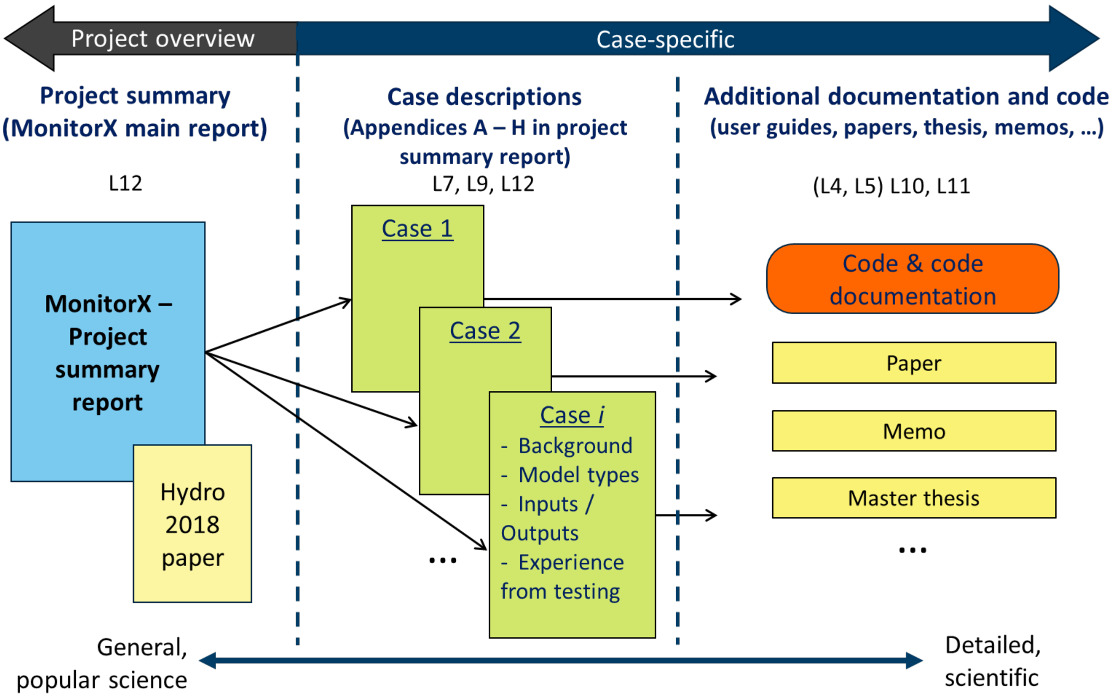

Figure 1-1: Relation between main report and case documentation. L4-L12 are deliverables as specified in the project proposal to the Research Council of Norway submitted in autumn 2014.

The additional documentation is structured as follows: For each case where such documentation is available, a folder exists in the Sharepoint area containing reports, papers, memos, student thesis and example code. The folder name is <<*Case no. – Case name*>>.

Each case folder contains the case descriptions, as attached to this report, and three additional folders named "Code", "Data" and "Docs", see Figure 1-2. The content of these folders is:

- *Code*
  - This folder contains the example code for the models and algorithms developed and tested in the project; if code is available for the case.
  - For some cases, different models and algorithms have been developed, either with the same data, or with different data sets. The different code variants are numbered K*x*.1, K*x*.2, K*x*.3, etc., where *x* is the case number. Note that some codes are general and can be applied to different cases, which means that there are cross references from one case to the code and code documentation from a different case.
- *Data*
  - This folder contains example data files; if data is available for the case. Note that some data files contain only a small extract of the data that have been used for code development and testing. The reason for this is anonymisation and that the data should not uncover production strategies or other sensitive information. Ten data samples are usually provided for the cases where not the full data set is given.
- *Docs*
  - This folder contains all additional documentation.
  - The additional documentation is numbered D*x*.1, D*x*.2, D*x*.3, etc., where *x* is the case number. Note that some documentation is valid and useful for several cases, which means that there are references from one case to documentation from a different case.

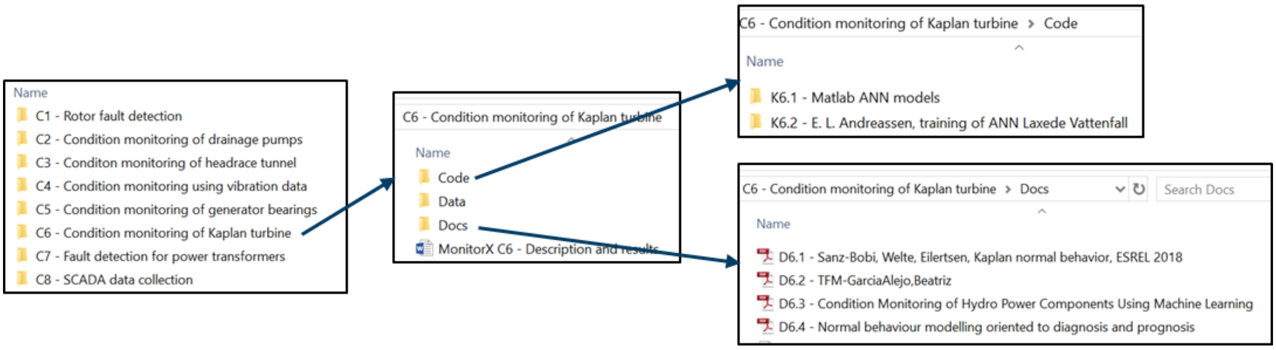

Figure 1-2: Additional documentation and code: folder and file structure.

1.2 Requirements for implementation and use of MonitorX results

Implementation and use of the MonitorX results require programming knowledge, preferably in the programming languages Python and/or MATLAB. Knowledge about machine learning, and especially artificial neural networks (ANN), is an advantage. Implementation and use of the MonitorX results are further discussed in Chapter 6.

Other requirements are access to historical data (long enough time series with historical data) and availability of data that has sufficient quality (e.g. high enough resolution)[1]. Systems/platforms for data collection and extraction play an important role to make the data easily accessible.

[1] See chapter 7 and MonitorX case descriptions for discussion about requirements regarding data history and resolution.

2 MonitorX project description

The aim of the MonitorX project was to develop models, algorithms and corresponding software prototypes for optimal lifetime utilization of hydropower components based on monitoring of technical condition and risk. Here, optimal lifetime utilization means to perform maintenance and component replacements when required, i.e. not too late, but not too early either. To reach the aim of optimal lifetime utilization, methods, models and algorithms for condition monitoring and early warning of faults are necessary.

The project focus on data analysis models and algorithms was chosen because one of the starting points of the project was the assumption that sensor and measurement data are not much used for planning and optimization of maintenance and refurbishment. Thus, a project with focus on model and algorithm development will be useful to motivate plant operators to accelerate and implement solutions for (online) data collection and analysis.

MonitorX mainly focuses on models based on machine learning and artificial intelligence. The models have been developed in a number of cases, where each case focuses on a specific type of hydropower component. Data from selected hydropower plants were used to develop the models. The models were tested with data from one or several power plants.

The MonitorX project started with an initial phase where the status for collection of monitoring data and use of monitoring data in the power companies were analysed and where a list with relevant use cases were developed together with the industry partners. Furthermore, an introduction to methods and models for data analysis was performed. Results from the status analysis (MonitorX deliverable L1) and the introduction to methods (deliverable L2) can be found in separate reports [1, 2]. A sketch of the timeline for MonitorX including deliverables (L) and the developed cases is shown in Figure 2-1. A case overview is given in the next chapter.

Note that MonitorX did not focus on development of systems and platforms for data handling and analysis, such as solutions for data collection and storage. A number of different systems and platforms are available on the market, and it is assumed that these solutions serve most of the current needs, even though further developments may be required, e.g. within system security and interoperability (both towards data sources and towards systems and software for data analysis). One of the aspects that the MonitorX project discussed and illustrated through the cases, however, is requirements regarding data resolution (sampling frequency) and data quality.

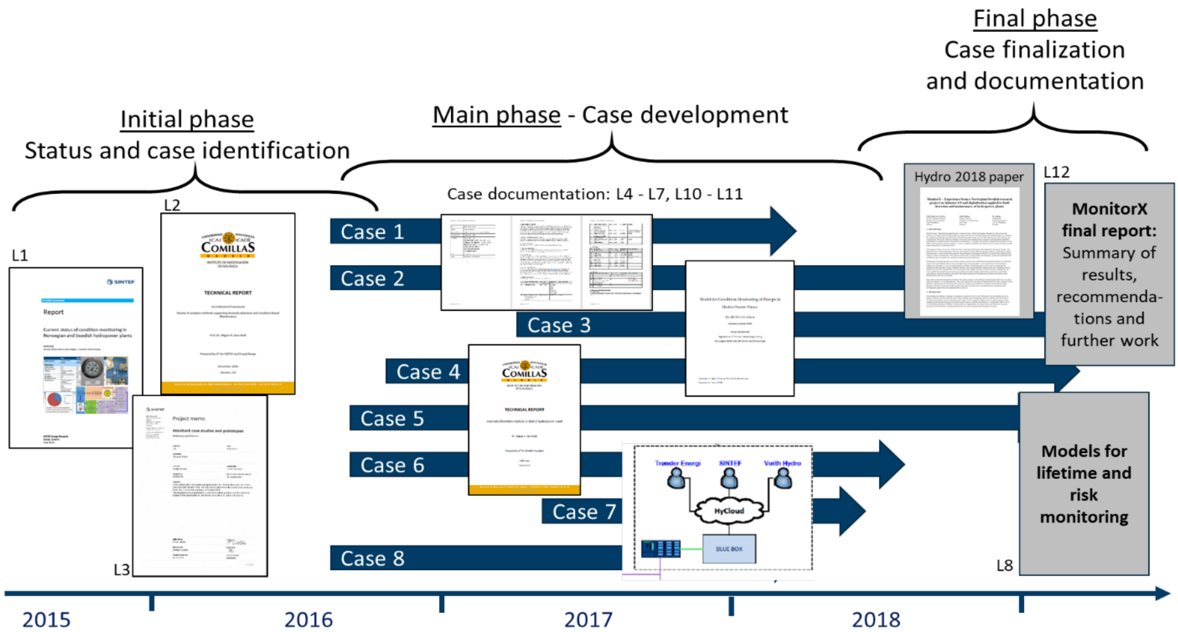

Figure 2-1: Sketch of MonitorX project timeline including deliverables (L1-12) as specified in 2014 in the Research Council project proposal. L12 is the present report.

2.1 Relation between cases and work packages

The work package (WP) structure of the MonitorX project is shown in Table 2-1, as presented in the project proposal to the Research Council of Norway submitted in autumn 2014.

Table 2-1: MonitorX work package (WP) structure.

WP no.	WP title and aim
1	**Condition monitoring data and models for data analysis** Aim: To identify and develop models for condition monitoring data analysis
2	**Models for monitoring of lifetime and risk** Aim: To develop models for estimation and monitoring of remaining lifetime and risk (economy, safety, environment)
3	**Prototype development** Aim: To develop a MonitorX software prototype (based on the models developed in WP1 and WP2)
4	**Prototype testing** Aim: Test of prototype in hydropower stations of participating companies
5	**Postdoc-project** Aim: Educate Postdoc (3 years) on advanced condition monitoring methods, diagnosis and prognosis of condition and lifetime
6	**Project administration** Aim: Administration of project, coordination between partners and steering committee
7	**Dissemination** Aim: Publishing of results to the public via internet, conferences and journals, and to the users via project web/hotel, workshops and courses.

Since much of the project work was part of the cases developed in the MonitorX project, the original WP structure must be related to the case-based research approach. This relation is illustrated in Figure 2-2. Each case should be related to the WPs 1, 3 and 4, where the aims were to develop models for data analyses, develop prototypes (code) and conduct tests with data from selected power stations. Some of the cases were assisted by the postdoc work. Furthermore, some of the cases investigated aspects that were addressed in WP2, where remaining lifetime and risk monitoring was the topic.

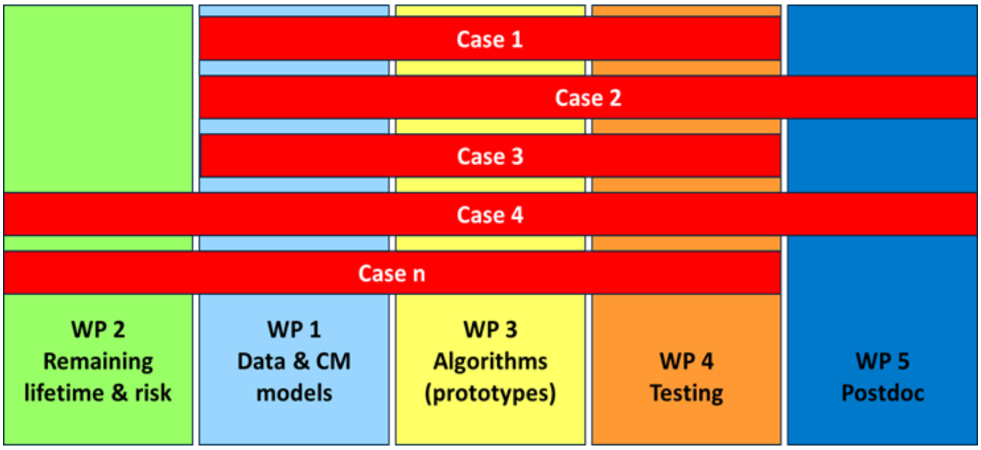

Figure 2-2: Work packages vs. cases (case numbering is arbitrary).

The research topics of WP1 and WP2 were also addressed in three separate MonitorX reports (the numbers L1, L2 and L8 refer to the deliverable numbering in the project proposal to the Research Council of Norway):

- WP1 - Condition monitoring data and models for data analysis:
  - L1: Current status of condition monitoring in Norwegian and Swedish hydropower plants [1]
- WP2 - Models for monitoring of lifetime and risk
  - L2: Review of analytics methods supporting anomaly detection and condition based maintenance [2]
  - L8: Lifetime and maintenance modelling utilizing monitoring data [3]

3 Survey of status regarding condition monitoring

One of the first activities in the beginning of the MonitorX project (i.e. autumn 2015) was an analysis of the general status for collection of monitoring data and use of monitoring data in the power companies that participate in the project. In addition to interviews with selected project participants, a survey was conducted. Six power companies replied to the survey and some of the results are presented in this section. The survey was repeated at the end of the project (June 2019) to identify areas of progress and changes, as well as topics for further research.

The surveys covered questions related to the following main topics:

1. Measurements and sensors
2. Data storage
3. Systems for data collection and IT infrastructure
4. Data access
5. Data analysis
6. Use of data in decision making process (maintenance and reinvestment)
7. Benefits and cost-benefit evaluation of condition monitoring
8. Competence and requirements

3.1 Survey results 2015

The survey was conducted as a set of statements to which the companies could express their agreement or disagreement on a scale from 0 (disagree) to 10 (fully agree). The questionnaire included also some yes/no-questions. The results for these questions are shown together with the 2019 results in section 3.3. Figure 3-1 shows results for the agree/disagree-questions from the 2015 analysis. The blue bar is the average of the answers and the green error bars (± 1 standard deviation) illustrate the variation of the answers.

The companies neither agreed nor disagreed completely with most of the statements. This can be because there are already some solutions for data collection, analysis and condition monitoring in use, but there is need for improvement. For example, most of the companies had access to some monitoring data, mostly via SCADA or via special measurement systems and sensors. The access via the SCADA system led usually to some restrictions regarding ease of data access, available history and data resolution. For example, manual data download and transfer to a data analysis system/programme is often required. Furthermore, many SCADA systems overwrite high resolution data after some time due to restricted storage capacity. Before overwriting, the data is compressed, for example by calculating a 1 hr average value, resulting in low data resolution for historical data. The survey clearly confirmed the initial hypothesis for the MonitorX project that the available data is hardly used for making decisions on reinvestment (i.e. refurbishment and replacement) and maintenance, even though some of the larger companies already started to visualize and analyse data and to use different types of models for data analysis.

An interesting observation from the 2015 survey was that the companies partly agreed with the statement that the benefit of condition monitoring systems is well-known to them, whereas they do not have an estimate of this benefit. This indicates a challenge and need for further work within cost-benefit estimation of condition monitoring. The numerical examples presented in Chapter 6 are an attempt to address this problem. It is important to mention that the willingness to invest in monitoring solutions depends on the ability to prove the benefit and return of investment for such solutions. It can also be pointed out that several companies indicated in 2014/2015 that the authorities have high requirements, e.g. regarding data security.

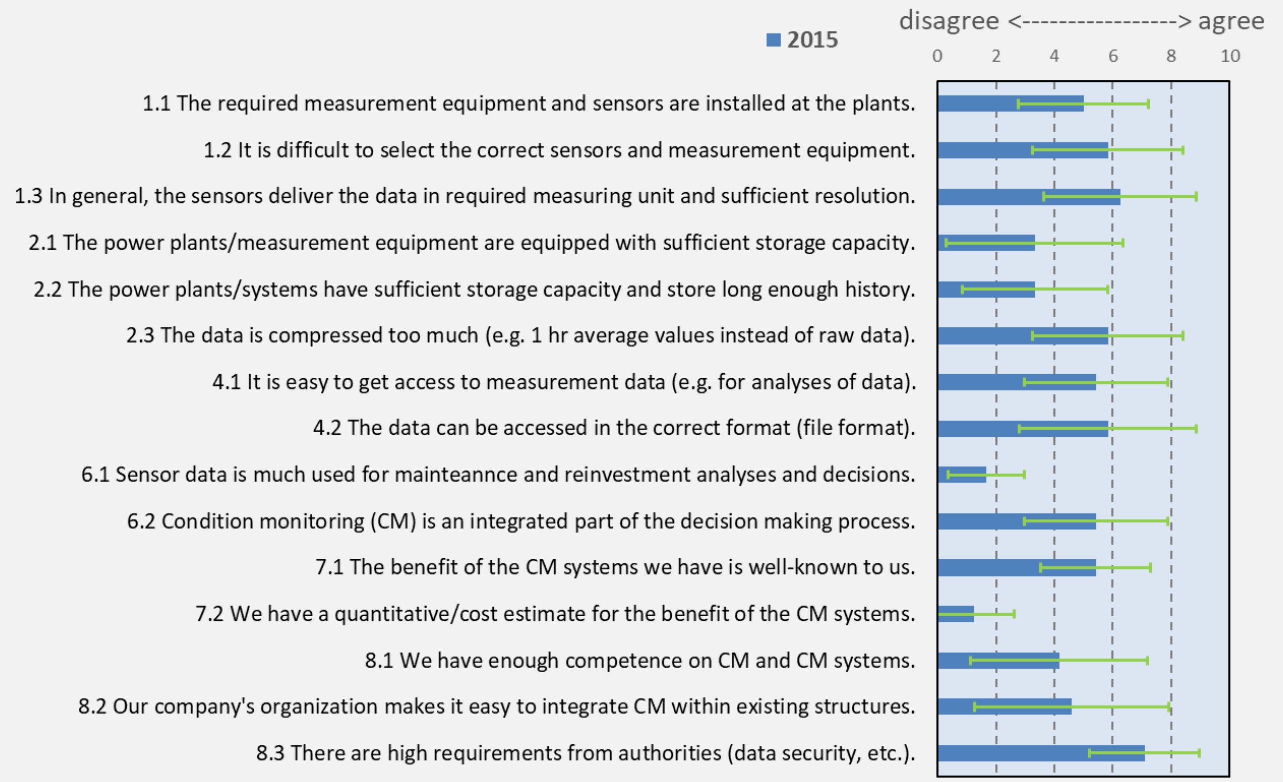

Figure 3-1: Results from survey in the beginning of the MonitorX project (autumn 2015). 'A' in the question numbers 'A.B' refers to the main topic, as shown in the list in the introduction to this section.

In 2014/2015, most hydropower companies did not have better access to monitoring and SCADA data than the access that the monitoring equipment and the SCADA system itself offers. This means that specific IT infrastructure or systems for data collection, permanent data storage and data access were not much in use. This also means that monitoring data for analysis had to be directly extracted from the SCADA system or from the monitoring equipment, which sometimes required some manual work, such as travelling to the plant to copy the data to an external storage device.

3.2 Developments 2015-2019

In recent years, several of the plant operators that participate in the MonitorX project started to systematically collect monitoring data from their hydropower plants by using a central data collection and storage solution (i.e. a software system or digital platform, called big data platform in the following). The overall aim is to establish better access to the data that is already available in various other systems (SCADA, measurement equipment, sensors, etc.) to make the data available for analyses.

To be able to develop, test and implement data analysis models, an integration of data analysis, presentation and visualization of analysis results, and data collection/storage is desired. The automatization of the data stream from sources via storage and analysis to result presentation requires also integration. Thus, the big data platform and the solutions for data analysis and visualization must be integrated. Several plant operators have started to use big data platforms that include solutions for data analysis and result presentation and visualization. Where the analysis is not directly conducted in the big data platform, models or software code developed in data analysis software, such as MATLAB, Python and R, can be called or run from the big data platform. Result presentation and visualization includes hand-hold devices, such as tablets and smart phones, and fault alarms automatically sent by email or SMS.

3.3 Survey results 2019

The results from the 2019 survey are shown in the three diagrams below. 'A' in the question numbers 'A.B' refers to the main topic, as shown in the list in the introduction to this chapter. The results in Figure 3-2 are for the questions (statements) where the answers are given as a degree of agreement/disagreement. Figure 3-3 shows the results for questions that should be answered with 'yes' or 'no'. In both figures, the 2019 results are presented together with the 2015 results. In Figure 3-4, a direct comparison with the 2015 results is not possible, because the figure shows a list of challenges mentioned in the 2015 survey, and where the task in 2019 was to express the degree of agreement/disagreement with these challenges, i.e. to assess to what degree these challenges are still valid and exist.

The survey was anonymous, and it is not possible to identify answers from specific companies. Even though MonitorX consists in 2019 of the same partners as in 2015 (apart from four partners that joint later in the project period), different companies and persons may have responded the survey in 2015 and 2019. This makes the interpretation of the survey results and challenges observed quite difficult. The observed changes can be caused by different respondents that answered the questions in the survey, but the differences may be also explained by contributions from the MonitorX projects, or general trends and changes. Some of the trends and changes that can be observed are discussed in section 3.4. Note that the observed changes are statistically not significant. Nevertheless, they can be an indicator of developments and trends.

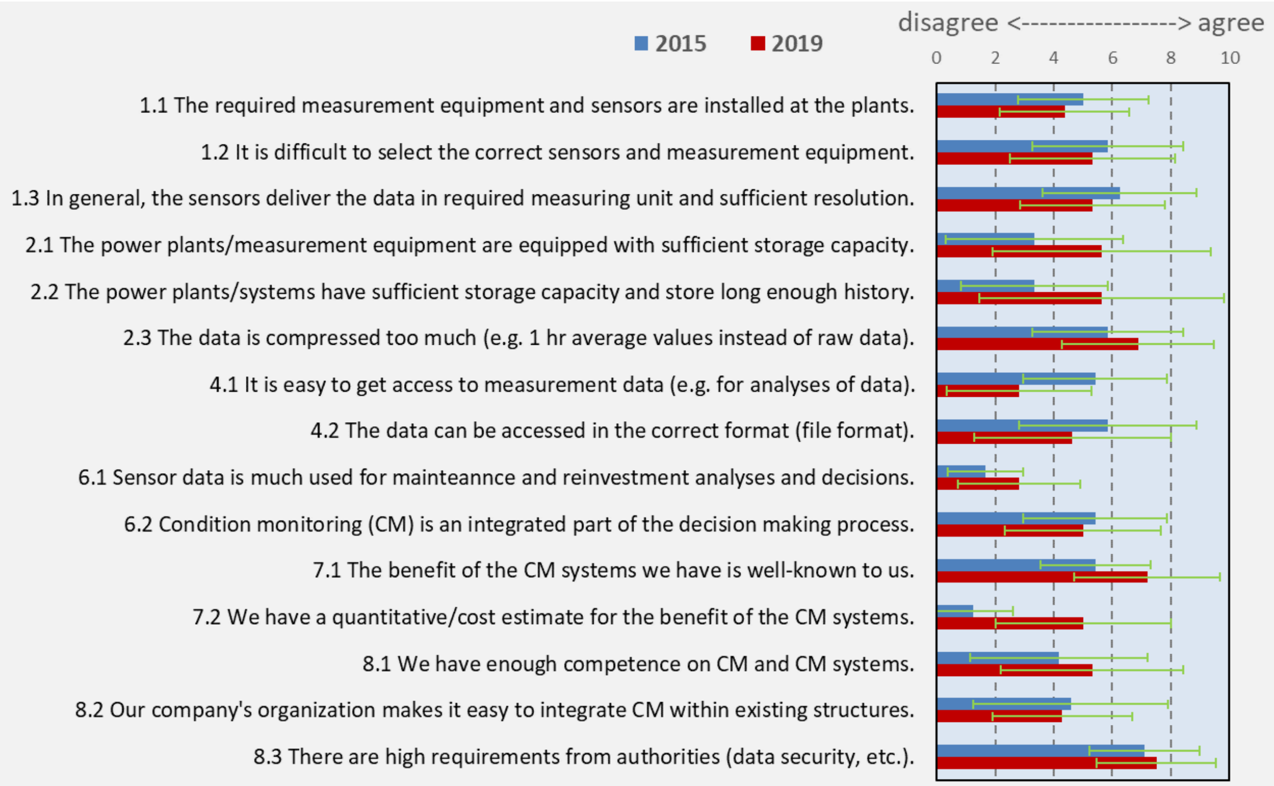

Figure 3-2: Results from survey at the end of the MonitorX project (June 2019), compared with the 2015 results.

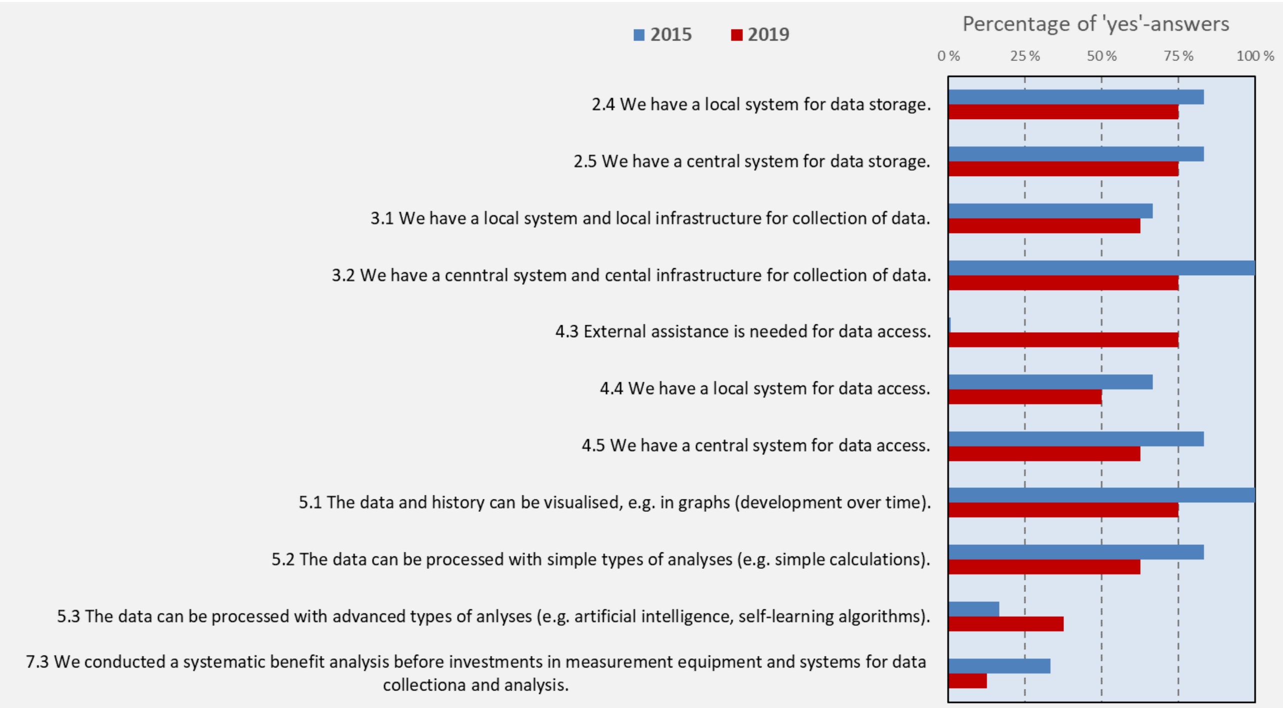

Figure 3-3: Results for the yes-no-questions, given as percentage of 'yes'-answers.

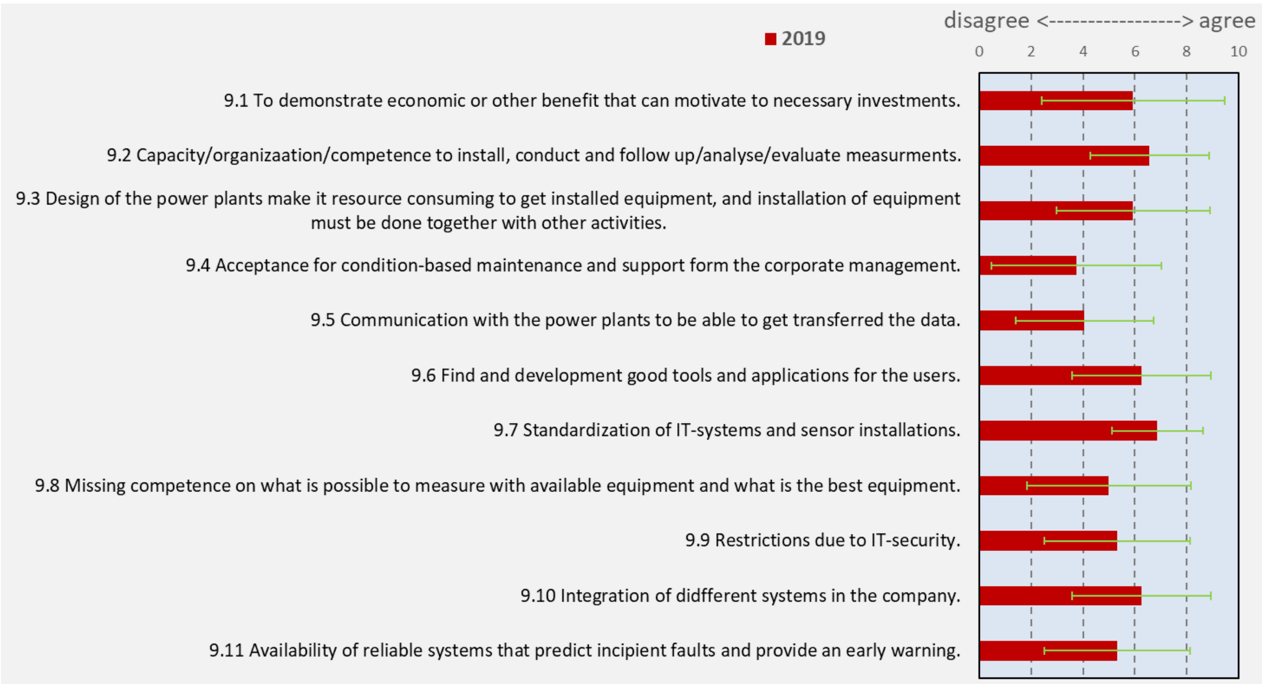

Figure 3-4: Results for the evaluation in 2019 of challenges identified in 2015.

3.4 Changes since 2019

For some of the answers, one rather expected a positive development than a negative development, because the impression during the project period was that most of the project participants, and the industry in general, focuses in recent years much on the topic of digitalization, data collection and preventive maintenance. Furthermore, some of the companies started to use systems for data collection and data analysis. Nevertheless, the results look like a negative development, for example (see Figure 3-2), for statements 1.1 and 1.3 (measurements and sensors), 4.1 and 4.2 (data access) and 6.2 (use of data in decision making process). This may be an effect of that different partners answered the 2015 and 2019 survey. However, this may also be an effect of more competence and awareness about what a good status is within the mentioned topics. For example, an instrumentation with sensors and measurement equipment that 2015 was considered as good, may not be considered as good today, because new technologies and possibilities appeared since 2015. When no big changes of instrumentation were made, i.e. the status regarding sensors and instrumentation is in 2019 the same as in 2015, the relative status has worsened compared to a changing and developing "reference" (i.e. the state-of-the-art within the field, which is continuously developing).

The field "data storage" shows some positive developments regarding resolution and storage capacity (2.1 and 2.2), which means that the data quality has improved since 2015, even though 2.3 indicates a slightly negative trend. It looks like that the knowledge regarding benefit of condition monitoring is improved (7.1 and 7.2), even though the answer for 7.3 (see Figure 3-3) indicates that benefit analysis is not conducted systematically before investments.

There is some positive development regarding competence on condition monitoring and condition monitoring systems (8.1), but requirements from authorities (such as data security) are still considered to be high (8.3).

From Figure 3-3, where most of the results indicate a negative development, one gets the impression that the hydropower industry developed in direction of less digitalization. Especially 4.3 shows a surprising change. The explanation of these results is difficult.

5.3 shows – in contrast to 5.1 and 5.2 – a positive development that indicates more use of advanced types of data analysis. However, it seems strange that this at the same time means that visualization (5.1) and simple analysis methods (5.2) are less used than before.

Many of the challenges indicated in 2015 are to some degree, or for some companies, still challenges in 2019 (see Figure 3-4). However, acceptance for condition-based maintenance and support from the corporate management seems to be large. Challenges regarding communication with the power plant (absence of powerful networks/connections, such as fibre, for transfer of large amount of data), a problem that was mentioned in the beginning of the MonitorX project, is less critical in 2019.

Conclusions

The results show that digitalization, condition monitoring, use of condition monitoring data and predictive maintenance are fields that require more development and implementation work. Some companies have just started to use new technologies, systems and solutions, but they are mostly in an early development and testing phase, and full implementation and utilization is still several steps ahead.

4 Overview of MonitorX cases

An overview of the MonitorX cases is shown in Table 4-1. Since the project focus was on models and algorithm for data analysis, most cases include model and algorithm development and testing. However, since data access is a key requirement for all cases, one of the cases (C8) focused on collection of data from the hydropower plant's local control system. The hydropower equipment manufacturer Voith developed a new solution for data access to supply the project with a data set of high quality. All other cases aim to detect faults or degradation of hydropower components through monitoring of carefully selected parameters, and then analysis of these parameters with respect to the normal behaviour of the component (i.e. detecting deviations from normal behaviour, where deviations may indicate a problem or fault).

Table 4-1: Overview of MonitorX cases.

No	Title	Aim	R&D partners	Industry partners	Power stations
C1	Rotor fault detection	Develop new methods for online fault detection of generator rotor faults	NTNU	Vattenfall, Eidsiva, Statkraft	Kalvedalen (Eidsiva)
C2	Condition monitoring of drainage pumps	Detect faults and degraded condition for drainage pumps in hydropower plants using SCADA data	NTNU, SINTEF	Vattenfall, TrønderEnergi, Voith	Brattset (TrønderEnergi)
C3	Audio surveillance	Anomaly and fault detection in power station by monitoring sound/noise in the hydropower station	-	Andritz, Statkraft	Svorka (Statkraft)
C4	Condition monitoring of rotating equipment using vibration data	Anomaly and fault detection in power station by monitoring vibration from the hydropower unit	NTNU	Statkraft	-
C5	Condition monitoring of generator bearings	Develop algorithms for early detection of bearing faults using SCADA data	Comillas, SINTEF NTNU	BKK	Dale, Nygard
C6	Condition monitoring of Kaplan turbine hydraulic system	Develop algorithms for monitoring of condition for Kaplan turbine regulating mechanism and hydraulic system using SCADA data. Develop algorithms for detection of oil leakages using SCADA data	Comillas, SINTEF, NTNU	Glitre, Vattenfall, Skellefteå	Embretsfoss 4 (Glitre), Laxede (Vattenfall)
C7	Fault detection for power transformers	Detect transformer faults through monitoring of temperature behaviour	SINTEF	Skagerak	Uvdal (Skagerak)
C8	SCADA data collection system	Establish good and continuous access to SCADA data	-	TrønderEnergi, Voith	Brattset (TrønderEnergi)
C9	Continuous servomotor monitoring	Detecting changes in servomotor forces	-	Hymatek	-

A summary for all cases is presented in Section 4.2. Further details can be found in the Appendices and the additional documentation. The cases C1 and C3 are conducted in collaboration with the Norwegian Research Centre for Hydropower Technology (HydroCen) [4]. Case C7 included a collaboration with the SAMBA project [5]

The list of cases is based on the results from a workshop that was organized by the MonitorX project in April 2016 in Oslo. The list of selected cases was originally longer, but some of the cases were not further developed for different reasons. Cases that were identified, but were not chosen to be developed are (title and aim):

- Monitoring of turbine efficiency
    - Develop intelligent algorithm for turbine efficiency monitoring
- Rotor windings short circuit detection
    - Use measurements from excitation system (+ possibly vibration measurements) to determine the state of the rotor windings in hydropower plants
    - This case is closely related to case C1, but the focus should be on measurements available from the excitation system.

The results from the Oslo workshop include additional ideas for cases. The ideas can be found in the minutes of meeting from the workshop and might be a basis for further activities after the MonitorX project.

In addition to the cases shown in Table 4-1, a case (X1)) on integration of normal behaviour models (such as the models used in cases C6 and C7) in the commercial software tool OSIsoft PI [6] has been conducted. The reason for the integration in OSIsoft PI was that several MonitorX participants started to use OSIsoft PI for collection, storing, presentation and analysis of data.

4.1 Types of models

Different types of models and algorithms have been used in the MonitorX cases. This is illustrated in Figure 4-1, in which all cases have been categorized in terms of the basis and physical understanding (physics-based – data-driven) and complexity (simple – advanced). The cases in the upper half of the complexity scale (e.g. frequency analysis, machine learning) typically requires specialized competence. Note that for some cases, several models have been tested. See references [5] and [7] for further discussions about types of models, their properties, and their advantages and disadvantages.

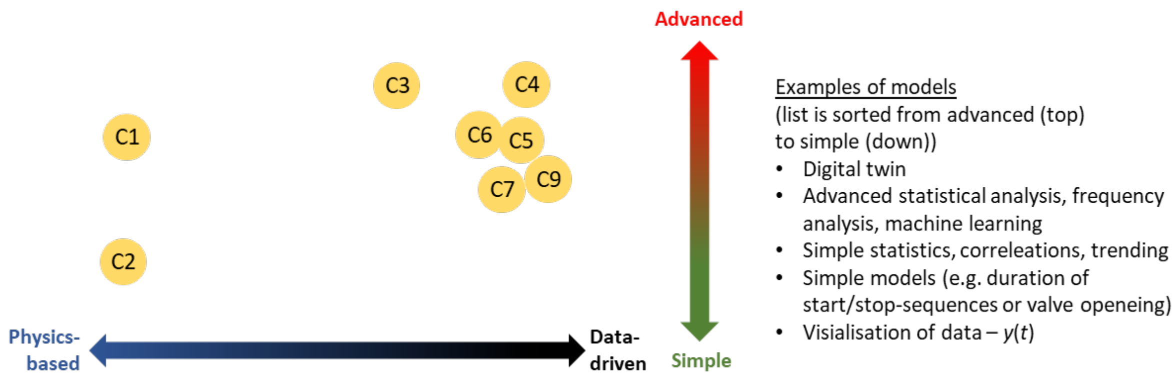

Figure 4-1: Illustration of the different models used in the MonitorX cases (C1, C2, etc. refer to the MonitorX cases as shown in Table 4-1).

The machine learning models applied in MonitorX are designed as *normal behaviour models*. Normal behaviour models are models that learn the relations and patterns that are typical for operation of the equipment that does not have a fault or other problems. Then, the normal behaviour model can be used for *anomaly detection*, i.e. the normal behaviour described by the model is compared with the real behaviour, and when the real behaviour deviates from the learned normal behaviour, a warning can be given, because this indicates that an abnormal situation is detected. The reason for using this approach is that hydropower components are often unique designs, there are few of them, and they have a high reliability and long lifetime. Therefore, there are few faults, Thus, learning from historical faults is usually not feasible. See MonitorX report L2 [2] for an introduction to and a review of analytics methods supporting anomaly detection and condition based maintenance.

The normal behaviour approach, as for example used for the neural network models in MonitorX cases C5 and C6, is illustrated in Figure 4-2. In many cases, we can identify or assume a correlation between some measured input variables $\boldsymbol{X}$ and one or several measured output variables $\boldsymbol{Y}$. The relation between $\boldsymbol{X}$ and $\boldsymbol{Y}$ is given by the real physical processes in a hydropower plant. A bearing temperature, for example, will depend on how the power plant is operated (actual output, head, etc.), ambient temperature, cooling (cooling water temperature, cooling system status (on/off), …), etc. For a bearing, one could then build a process model (e.g. with artificial neural networks) that represents the relation between bearing temperature ($\boldsymbol{Y}$) and head, ambient temperature, cooling, … ($\boldsymbol{X}$). The model could then be used to calculate an estimate of the bearing temperature, denoted $\widehat{\boldsymbol{Y}}$, and compare the estimate with the measured (real) bearing temperature ($\boldsymbol{Y}$). The difference between estimated and real temperature ($\widehat{\boldsymbol{Y}}$- $\boldsymbol{Y}$) can then be used an anomaly indicator.

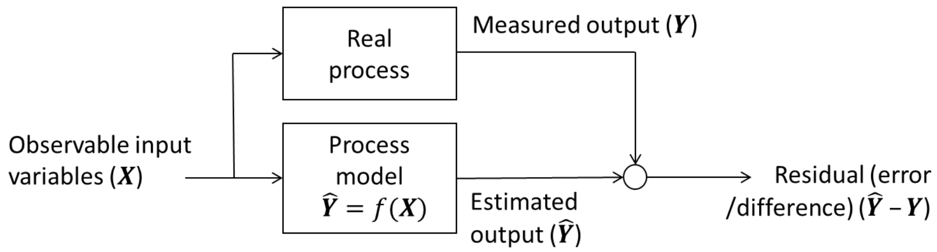

Figure 4-2: Anomaly detection with normal behaviour models (based on a figure by Prof. M.A. Sanz-Bobi, Comillas University [2])

4.2 Case descriptions

In the following, brief descriptions of the cases are provided, including one or two figures to illustrate the main idea, model and/or results. For the interested reader, more technical details and results are provided in appendices and the additional case documentation.

Case C1 – Rotor fault detection

The aim of this case was to propose methods for on-line detection of rotor short-circuit faults and other faults in hydro generators. This case was carried out in close collaboration with HydroCen, and the work was carried out by NTNU postdoc Mostafa Valavi and master student Kari Gjerde Jørstad [8], [9] in close collaboration with the hydropower plant operators and MonitorX industry partners Eidsiva, Vattenfall and Statkraft. In the first stage of their work, an idea was evaluated to use available SCADA data for fault detection. However, simulation of the generator in healthy and faulty state by FEM (finite element method, electromagnetic field simulation) showed that this idea is not feasible. Thus, a new fault detection method was proposed, and its feasibility was evaluated in the second stage of the work.

The new method uses spectral analysis of stator voltage and current for fault detection. The results of the spectral analysis are illustrated for two examples in Figure 4-3, where the frequency spectrum of both a generator with healthy rotor winding and a rotor winding with faults are shown. In a case of an inter-turn short-circuit, in addition to the amplitudes at 50 Hz and its odd multiples, sideband harmonics appear at each side of the main harmonics. These sideband harmonics could be used as indicator for fault detection. The method requires a much higher data resolution (voltage or current) than usually available through the SCADA-system, and a sampling frequency of at least 500 Hz is recommended. However, the data collection must not necessarily be continuous, but samples of at least 2 seconds could be collected regularly, e.g. once in a day or week.

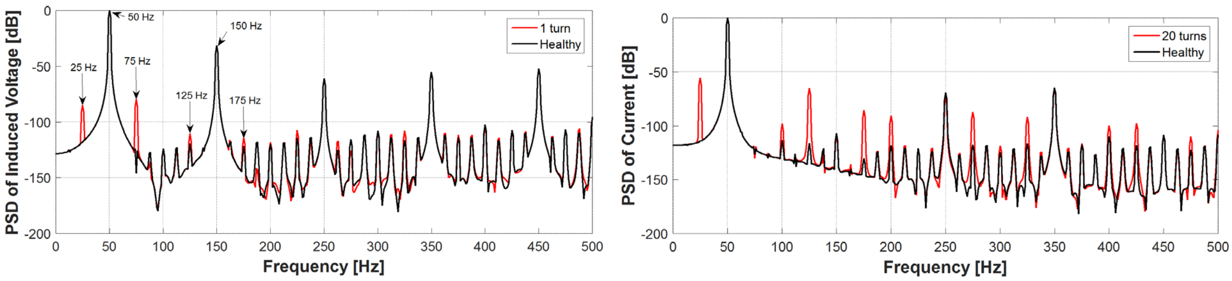

Figure 4-3: Frequency spectrum of induced voltage at no-load, healthy vs. 1 turn short-circuited (left), and frequency spectrum of stator current at full-load, healthy vs. 20 turns short-circuited (right). Courtesy of K. G. Jørstad [8]. PSD: power spectral density.

The detection of rotor inter-turn short-circuits was primarily investigated, but also detection of other types of faults, including eccentricity and bearing faults, were studied. A detailed description of the work and the results can be found in Appendix B and in references [8] and [9].

Case C2 – Condition monitoring of drainage pumps

The aim of this case was to develop and test models for monitoring the performance and condition of drainage pumps in hydropower plants. Even though drainage pumps usually are not considered as the most critical equipment of hydropower plants, they play an important role for protecting the power station from flooding. The drainage system is designed as a redundant system with two or several pumps in parallel, and an ejector as the last barrier if all pumps fail. If one of the pumps has failed, it must be quickly replaced to maintain the high reliability of the redundant system, since the reliability of a redundant (i.e. parallel) system drops significantly if one of the components fail.

The drainage system is usually not specifically equipped with sensors and monitoring systems. The information that often is available is the on and off signal for the pumps and/or the water level of the drainage pit. Some other signals, such as the motor current, may be available in some cases. The on and off cycles of the pump result in a quite regular pattern (see the left part of Figure 4-4) given that the pump and the surrounding systems work faultless. The pump pattern will change when the inflow changes (e.g. due to changed operating conditions of the plant, seasonal effects, or increased leakage water inflow to the drainage pit from faulty surrounding equipment) or when the capacity of the pump changes (e.g. due to pump degradation) [10]. Thus, the analysis of the pump cycles and the inflow pattern can indicate problems with the surrounding equipment, and the analysis of the pump capacity can indicate problems with the drainage pumps and drainage system.

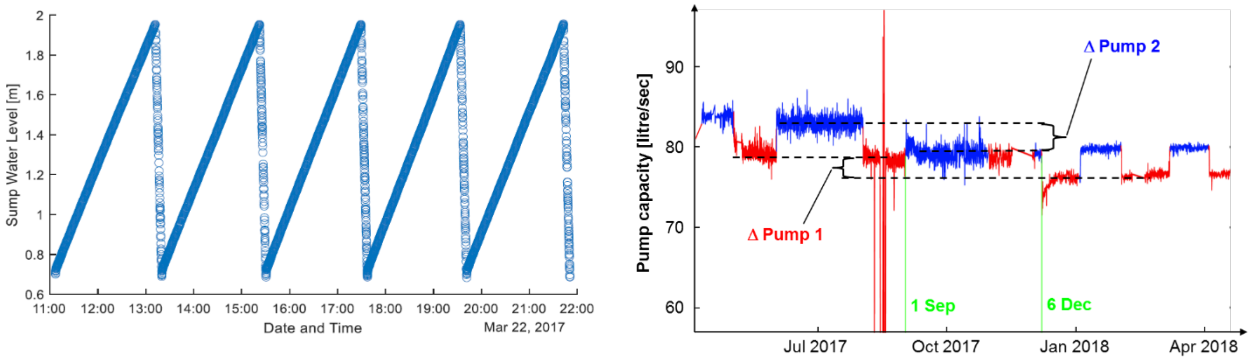

Figure 4-4: Raw data, i.e. drainage sump water level (left), and pump capacity (right). Courtesy of K. Prajapati [11].

In a master student project carried out by NTNU master student Kishan Prajapati [11], a model for estimating the pump capacity was developed. This model considers the inflow and outflow of the drainage pit as a function of different operating conditions. Thus, it can – in addition to detecting changes in the pump capacity – also be used for detecting abnormal changes of the inflow. The model was developed and tested with data from Brattset power plant (2 x 40 MW, Francis, head: 273 m) were two drainage pumps are installed. The two pumps are used alternately. The estimated pump capacity is shown in the right part of Figure 4-4, where both the estimates for pump 1 (red) and pump 2 (blue) are illustrated. See also Appendix C for further details.

Changes of the pump capacity can be seen at the points in time indicated in the diagram (1 September and 6 December). The pump capacity dropped significantly, by 5 to 7 %. The reason for this is not clarified, but maintenance carried out at the plant is a likely cause. Nevertheless, the example indicates that the approach may be used for detecting pump capacity changes, whether caused by maintenance, degradation of the pumps or other factors.

Case C3 – Audio surveillance

The aim of this case study is to use airborne sound monitoring to detect various failures. This idea partly can be considered to mimic operators' knowledge accumulation via auditive stimuli. In a hydro power plant, the standard instrumentation consists in dedicated sensors to monitor specific components such as accelerometers and proximity probes for shaft line vibration or pressure probes to monitor flow conditions. In contrast to these examples, sound monitoring offers the possibility to gather information from a large number of components with a single sensor (microphone) or a sensor array. This enables the recording of the sound patterns (signatures) emitted by the regarded components. The patterns may be associated with different conditions of the components. Then, the evolution of these patterns can be analyzed, thus providing characteristic features of various sound developments. This kind of monitoring is investigated as it offers various advantages in comparison to other methods: the simplicity of the installation and operation is a cost-effective solution, anomalies of several machines may be regarded accumulative and there is no need of cabling sensors directly on the machine. Additionally, an early on recognition of approaching issues shall be enabled.

In order to prove the concept, measurements were taken by Andritz at Statkraft's Svorka power plant during the first months of 2019. At the power plant, studio microphones with a sampling frequency of 44,1 kHz and ultrasonic microphones with a sampling frequency of 200 kHz were used. Recording covered short sound samples at regular intervals. The samples were collected by edge devices which can handle 1-4 sensors each and sent to a central server on the server's request. Processing and analysis were performed in Graz with dedicated HPC servers. The results of the analysis were then made accessible via the Andritz digitalization platform METRIS, which enables the management, control and investigation of data and processes.

The initial objective was to detect specific events according to their sound signatures:

- Stone impact
- Cavitation
- Early detection of bearing failure

To distinguish the sound signatures of various events, advanced machine learning technics are necessary. First, audio signals are converted from time domain signals to spectrogram representations. Spectrograms are a widely used approach to compress audio data and to identify and compare respective features. In a second step, the number of dimensions describing the features of each sound sample is reduced using a neuronal network. Eventually, in this reduced space, the distance between the different samples is evaluated to quantify the anomaly score of each sample. Furthermore, a clustering algorithm is applied to group samples with similar features allowing a fast labelling with a limited amount of user interaction.

Figure 4-5 shows that similar results are obtained using standard and studio microphones. Some additional events are detected using the ultrasonic microphones, which can be largely accounted to noises emerging in the ultrasonic range, which were not detectable by the studio microphones. Further investigation is needed to assess if those events are related with the presence of cavitation in the runner and if long-term trends can be derived from these findings. A limited number of clusters have been identified and are most probably related to various mode of operation of the units.

Not only specific targets like definite recognition of cavitation and other data assignments could be considered in the future, but also further hardware- and software-technical developments. Such improvements and research may address a better ruling to filter human-voice out of signals, implementation and exploitation of sensor arrays for finer signal separation or pre-calculations in edge devices.

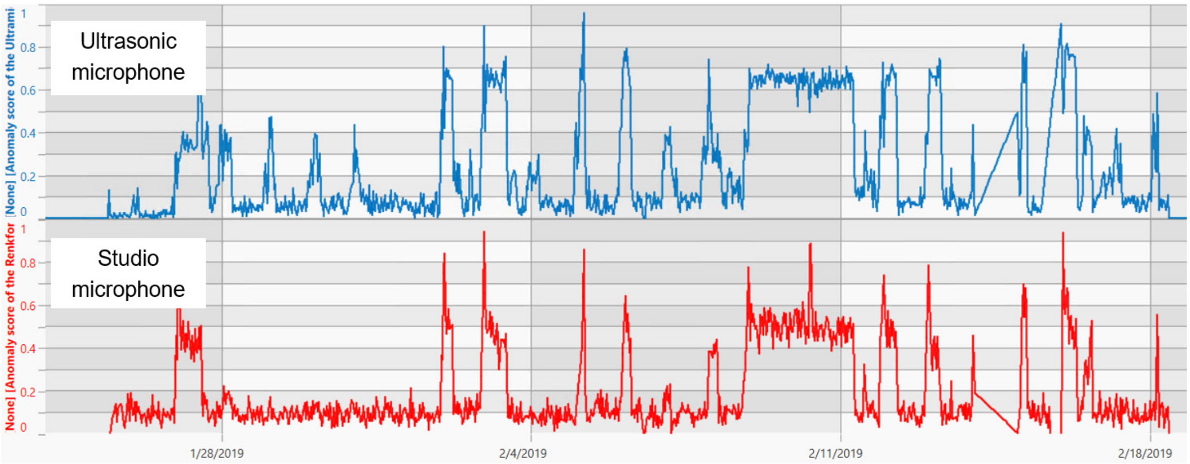

Figure 4-5: Time evolution of anomaly score using studio and ultrasonic microphone.

Case C4 – Condition monitoring of rotating equipment using vibration data

The aim of this case was to develop algorithms and models for fault detection and prediction of remaining useful life (RUL) of rotating equipment based on high frequency sensor data (kHz resolution and larger) from vibration sensors (accelerometers), acoustic emission sensors and microphones. Such high frequency data is normally not available in power plants. Thus, the model development was carried out with publicly available test data from roller bearings used in laboratory tests, see Appendix D for further details.

The case resulted in a set of models for analysis of the vibration data for the purpose of RUL estimation and anomaly detection and classification. The modelling of RUL and anomalies does not use the monitoring data (i.e. the vibration data) directly, but the data is pre-processed in the *feature extraction* modelling step in order to calculate a parameter (*feature*, *health indicator*) that can be tracked and trended over time. Health indicators can be calculated in time and frequency domain, or combination of both (such as continuous wavelet transform - CWT). Mean of the signal, kurtosis, maximum amplitude, root mean square (RMS) and square mean root (SMR) are examples of features.

RUL estimation is based on trending the health indicator, as illustrated in Figure 4-6. In the beginning, illustrated in the left diagram for the (current) time 426[2], the uncertainty regarding further development of the indicator is quite large. This is indicated with the blue lines representing different possible trajectories for the further health indicator development. The red line is the mean (expected) development, representing the mean lifetime of the bearing, given the observations until current time. The uncertainty decreases when more data become available, as illustrated in the middle and right diagram. The predicted lifetime will be updated step by step, as more data becomes available. Consequently, the RUL estimate, which is the difference between current time and predicted lifetime, can also be updated step by step.

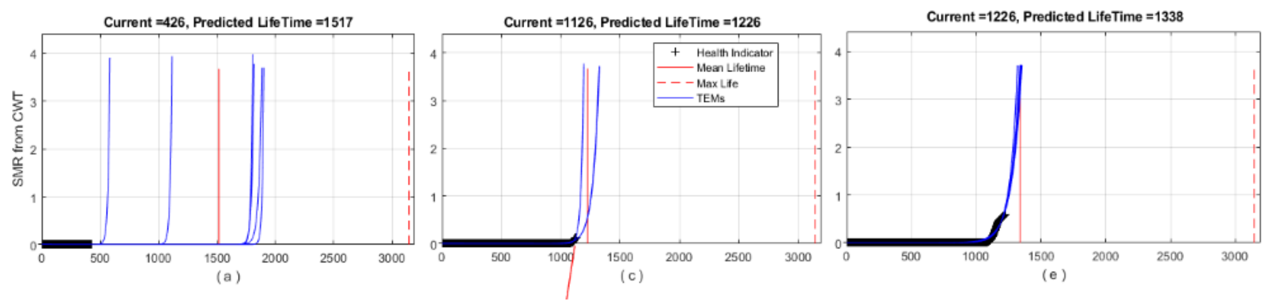

Figure 4-6: Lifetime prediction and RUL estimation, and updating step by step over time, illustrated for three examples representing different times in early life (left, current time = 426), middle of the life (middle, current time = 1126) and close to end of life (right, current time = 1226). Courtesy of J. Yuan [12].

The approach of anomaly classification (i.e. the classification of anomalies in different states from slight to large/significant) allows for monitoring the development of degradation from a condition *as good as new* (no degradation, no anomalies, normal behaviour) to a condition with major degradation (large anomalies). An example is illustrated in Figure 4-7 where the evolution of the condition over the bearing lifetime is illustrated on a condition scale from 1 (working condition) to 7.

[2] The time may be measured e.g. in hours, or operational hours, or as data/indicator count, meaning that 426 represents the 426th time that the health indicator that is calculated. If, e.g. the health indicator is calculated every 6th hours of operation, 426 corresponds to 2556 hours of operation time.

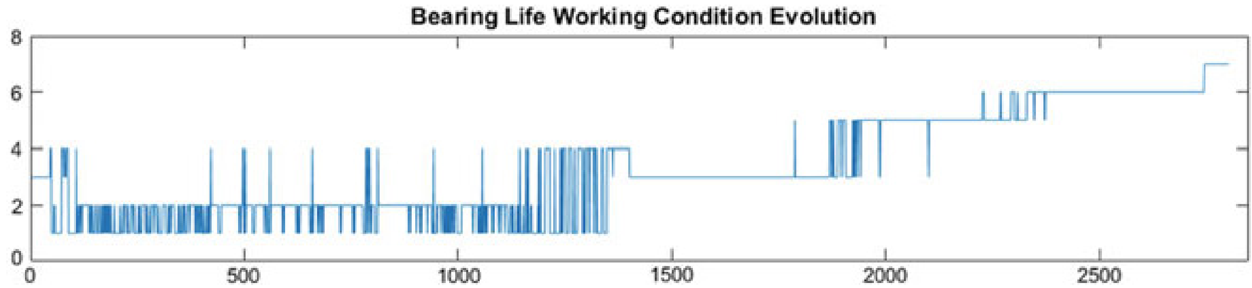

Figure 4-7: Anomaly classification (classification in condition states 1 to 7) and evolution of condition over bearing life [13].

Case C5 – Condition monitoring of generator bearings

Bearings are important generator and turbine components that have been known to cause problems when aging, such as vibrations, bearing wear, lubrication problems or misalignment. The aim of this case is to develop algorithms for early detection of bearing degradation or faults using available SCADA data.

To enable dynamical condition monitoring, models that predict the normal behaviour of bearing temperature have been built and tested using artificial neural networks (ANNs). Both multilayer perceptron, recurrent neural networks, self-organizing maps and long short term memory (LSTM) neural networks have been tested. The models predict the normal relation between multiple parameters, such as power, bearing temperature and bearing vibration. Comparing the model predictions with actual measurements, deviations from normal behaviour can be identified.

The challenge for the selected examples (Dale and Nygard power plants) is that the data sets for which the models have been trained and tested do not represent a period of stable normal behaviour, because a degradation process (bearing wear) is ongoing, resulting in a continuously changing situation with increasing damage and bearing temperature. This resulted in less than ideal results for models built with multilayer perceptrons and recurrent neural networks (see appendix E).

To overcome this problem, a long short term memory (LSTM) neural network model was tried [14]. LSTM is one of the most successful modern recurrent neural networks architectures for sequence learning tasks. An LSTM model was built for the Nygard power plant to predict the current bearing temperature from a sequence of foregoing measurements of the temperature. Selected results are shown in Figure 4-8. The upper left diagram illustrates the training of the model, the lower left diagram the testing of the model, the upper right diagram the testing of the model compared with actual measurements, and the lower right diagram the model error (the difference between the predicted and measured values). It is in the two right diagrams seen that the model at first predicts the increasing bearing temperature well, but that the prediction gradually deviates from the actual measured values. This is seen as a sign of anomalies, i.e. that the way in which the bearing temperature is increasing is changing.

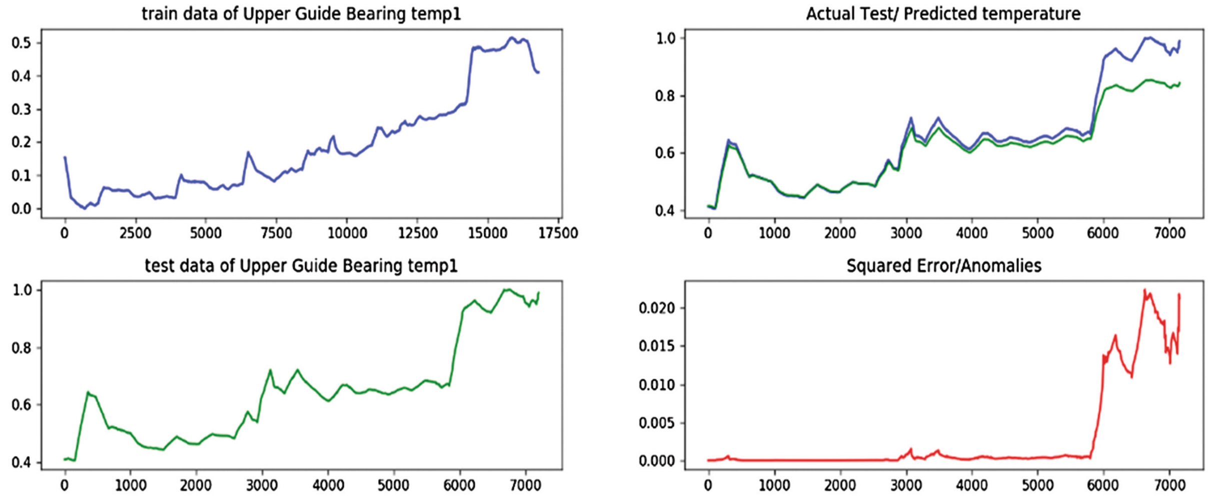

Figure 4-8: LSTM based prediction of upper guide bearing temperature. Courtesy of J. Yuan [14].

Finally, a clustering technique was tried for the Nygard power plant [15] using data for active power, guide vane opening and bearing temperature. It was illustrated how such a technique can identify and illustrate patterns of normal behaviour for the bearing in terms of these parameters. The technique yielded promising results for tracking the abnormal bearing temperature developing at Nygard.

Case C6 – Condition monitoring of Kaplan turbine hydraulic system

The aim of this case was to develop algorithms for monitoring the condition of the hydraulic regulation system for a Kaplan turbine using SCADA data. The work was carried out by professor Miguel Sanz-Bobi from Comillas Pontifical University in Madrid, Spain, in close collaboration with the hydropower plant operator and MonitorX industry partners Glitre and Vattenfall. Part of the motivation for this work is that the Kaplan propeller and hub is not accessible for inspection during production. A method for online condition monitoring without the need for unwanted production stops is therefore beneficial. The hydraulic system is of special interest as it is vital for the control of the turbine, and because e.g. oil leakage is a known issue.

A Kaplan turbine is regulated by adjusting the position of the wicket gates and the turbine runner blades. This is done by a high-pressure hydraulic system, typically consisting of an oil tank, oil pumps, valves, filters, coolers, and accumulator banks for the wicket gates and runner blades. To enable dynamical condition monitoring of this system, a normal behaviour model was developed for the level in the oil tank, using artificial neural networks (ANN). This model predicts the normal state of a variable, in this case the oil level, from other explanatory variables. Based on a physical understanding of the system, the explanatory variables were chosen to be the power, the oil tank temperature, and the oil level in the accumulators. Before the model can be used for anomaly detection, the model first learns the normal behaviour from carefully selected historical data. Once trained, the model can be used to detect anomalies, i.e. deviations from normal behaviour; see Appendix F and references [16] and [17] for further details.

Selected results are shown in Figure 4-9. The left diagram illustrates the training of the model, and the right diagram testing of the model for anomaly detection. It can be seen that the model accurately predicts the systems normal behaviour for the training set (left), and that an apparent anomaly is detected in the test set (right). The increasing deviation between the model (estimated value) and real data (real value) in the test set indicates a possible oil leakage. This was confirmed by the plant operator to be a leakage in one of the accumulators.

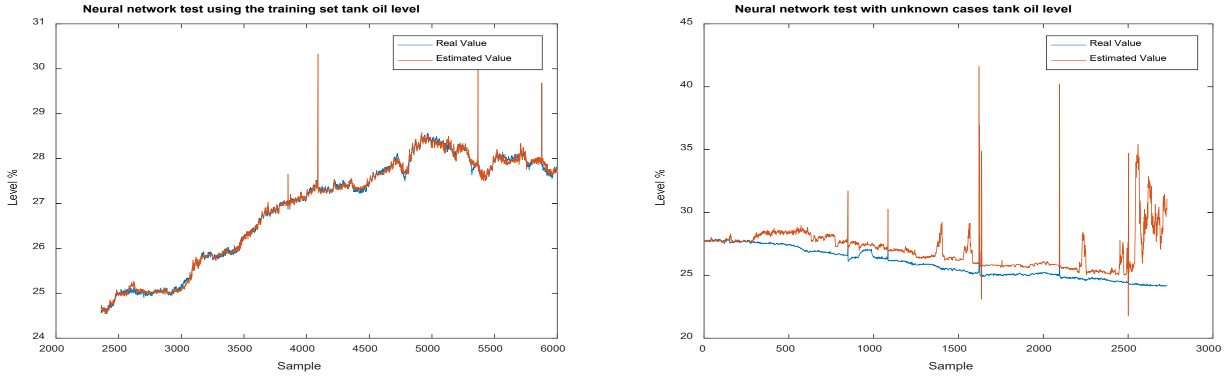

Figure 4-9: Estimated value from the ANN model and real measured value for the oil tank level for the training data set (left) and the test data set (right). Courtesy of Prof. M. A. Sanz Bobi.

The model was also tested on data from the hydropower plant operator and MonitorX industry partner Vattenfall. The test confirmed the ability of ANNs to accurately predict the normal behaviour of the hydraulic system. The ANN model must however be rebuilt and trained for the hydraulic system at hand, showing that significant work is required to deploy such models for multiple turbines.

Case C7 – Fault detection for power transformers

An efficient and working cooling system is important to limit the temperature of the oil in power transformers, since high temperatures cause aging of the winding insulation paper. The aim of this case was to develop and test models for monitoring the performance of the transformer cooling system. To this aid, a feed forward neural network model was developed to predict the top oil temperature from the transformer load and the cooling water temperature. Comparing this prediction with actual values can then identify possible cooling system fault. All data used in the case were from Skagerak's Uvdal 1 power plant. As seen in Figure 4-10, the trained model for the transformer top oil temperatures is not that accurate. However, it still follows most trends, and with a suitable threshold value, the accuracy may be good enough to be used to discover severe degradation in cooling performance. Further details can be found in Appendix G.

There are multiple possible causes for the inaccuracy. The top oil temperature is only predicted from two parameters, and there may be other factors affecting the temperature. The internal design and temperature sensor placements of transformers varies, and this affects the extent to which the top oil temperature is governed by the transformer load and cooling water temperature. Since the load on the transformer varies a lot, the transformer is in general not in steady state. Hence, a time-dependent model may be more suitable. To this aid, a model was also developed using a recurrent network. This model performed only slightly better than the simple feed forward network. The improvement may have been limited by a time resolution of only one hour that not necessarily captures all important dynamics.

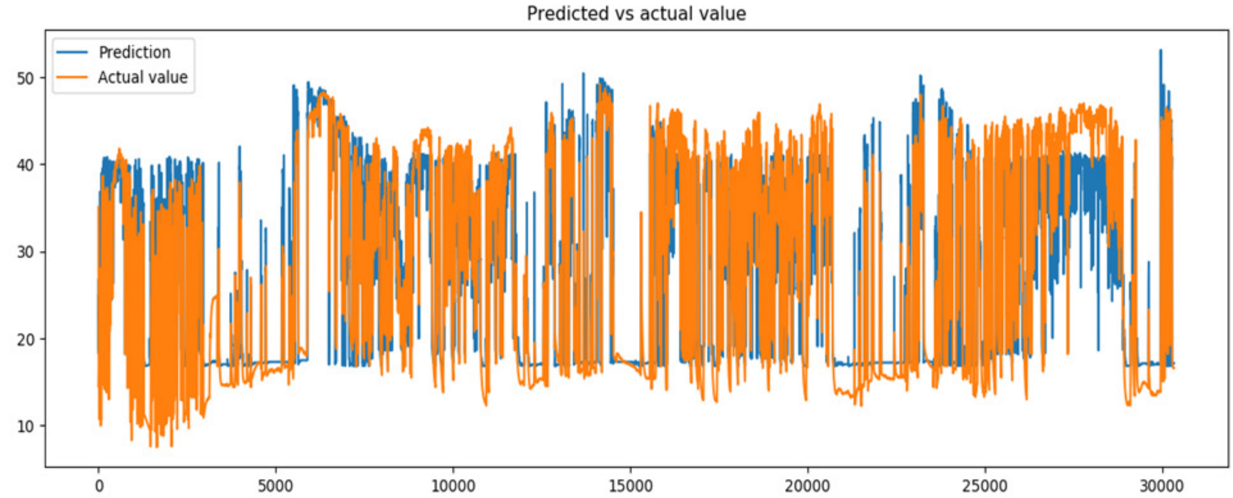

Figure 4-10: Prediction of the top oil temperature of the transformer in Uvdal 1 power plant using a feed forward network.

Case C8 – SCADA data collection system

Making data available from the power plant is a basic starting point for any analytics or algorithms for predictive maintenance. At the start of the MonitorX project in 2015, it was a particular challenge to get access to data from power plants. One of the reasons for this was that it was not accepted to access the SCADA and dispatch center to extract the data.

Voith Hydro AS agreed to look at this challenge, in a cooperation with TrønderEnergi, and to develop and test new solutions for better data access. Voith had supplied a new control system to TrønderEnergi's power plant Brattset in 2014. The new solution for data access, that was added to the control system, transfers the data to a server in Heidenheim (Voith head office), Germany, from where TrønderEnergi, SINTEF and other MonitorX partners could download the data via a simple interface. The data was used for different tests and verification, including the above described case C2.

The PLC configuration of the solution is shown in Figure 4-11. The additional hardware that was added to transport the data out of the plant is shown in the upper right corner. Further details can be found in Appendix H. The data has been collected directly from the PLCs with a time resolution of approximately 1 second. In total approximately 1200 signals are transferred, out of this approximately 10 % are analogue values (measurement values like temperature, current, pressure, etc.) and 90 % are digital signals (status changes, alarms or commands like on/off, open/closed, alarm level crossed, etc.). In total 32 GB of raw data is stored from March 2017 until May 2019.

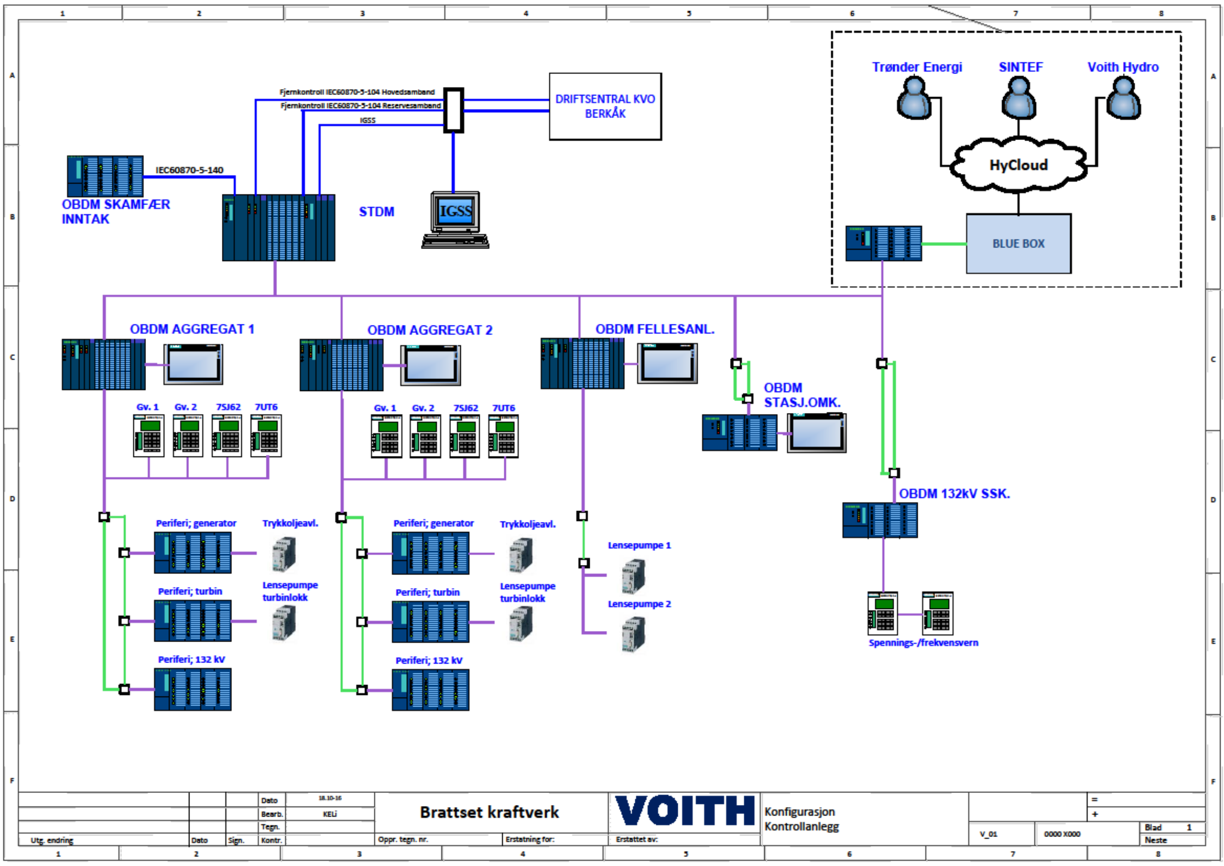

Figure 4-11: Brattset PLC structure.

Case C9 – Continuous servomotor monitoring

By monitoring the development in friction forces on the guide vanes in a Francis turbine over time, changes in the condition of the turbine and servo system can be determined. In this case study, changes in servomotor forces are determined using a machine learning method. Four identical large Francis turbines (> 300 MW) from the same plant are studied, called unit A1-A4. The work was carried out by Anders Willersrud from Hymatek Controls, and Master student Asgeir Aasnes [18], [19].

Today the friction forces are typically inspected manually by logging and investigating the differential pressure in the servomotors while performing a "servo indication". During this operation the guide vanes are slowly operated from 0-100-0 % opening. The goal in this case study is to investigate how the manual inspection can be automated by constantly monitoring friction forces during operation, through differential pressure measurements in the hydraulic system.

Friction forces are calculated from pressure measurements during production. As can be seen to the left in Figure 4-11, the different servos requires different differential pressure ("Delta force") to change direction, indicating different levels of wear and/or friction in the turbine and mechanical system.

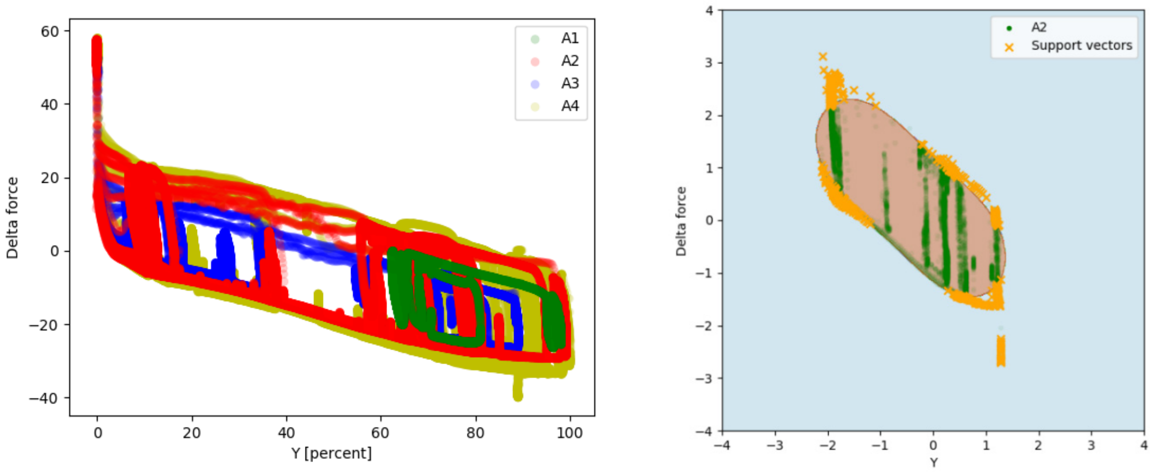

Figure 4-12: Differential servo forces (Delta force) for all four units during production (left). Support Vector Machines defining the boundary of the data for unit A2 (right).

One Class Support Vector Machine (OC SVM) is used for the analysis, and was found to create a model that accurately defines the boundary for the servo forces, being able to detect changes in the servo forces. The results for unit A2 is seen to the right in Figure 4-11. Similar results were found for the three other units, and are therefore left out. The boundary found using OC SVM is plotted as a red line, the support vectors used to create the model are also plotted. All data located inside the boundary is classified as normal, data located on the outside as abnormal.

Any new data will be checked against the boundary found by the machine learning model, where increase in wear will change the friction band for a given opening/load of the turbine. The trained method can then be used to classify new data as normal or degraded, giving a method for continuously detecting wear of the Francis turbine.

Case X1 – OSIsoft PI model integration

For the Laxede plant, it was shown how normal behaviour models, such as the models used in case C6 and C7, can be integrated with the commercial software tool OSIsoft PI for live continuous anomaly detection [20]. Several MonitorX project partners started to use OSIsoft PI for collection, storing, presentation and analysis of data and analysis results. To be able to run models and algorithms and models developed in Python or MATLAB, an integration between OSIsoft PI and Python/MATALB is required. OSIsoft PI offers several possibilities for integration, and in a student project carried out at SINTEF in summer 2018, Eivind L. Andreassen has tested and evaluated three options for integration of models into OSIsoft PI:

1. OSIsoft PI Asset Analytics' native integration solution with MATLAB Production Server
2. Accessing an API written in a language other than MATLAB
3. Using the PI Server Web API

Further details for these three options can be found in [20]. An example for the option no. 2 (Accessing an API written in a language other than MATLAB) can be found as open source code at GitHub [21].

5 Overview of deliverables and other MonitorX results

Deliverables from MonitorX project and various other results are summarized in this chapter. This consists of:

- Reports and memos (see Section 5.1)
- Articles in scientific journals and conference proceedings (see Section 5.2)
- Presentations at workshops, seminars and conferences (see Section 5.2)
- Master student theses and summer student reports (see Section 5.3)
- Meetings and seminars organized by the project (see Section 5.4)
- Spin-off projects (see Section 5.5)
- Models, algorithms and corresponding codes (see summary in Section 4.2 and corresponding appendices)

5.1 Reports and memos

Table 5-1 provides an overview of the MonitorX reports that are not related to a specific case, but that discuss general topics or provide a project or case overview.

Table 5-1: MonitorX reports and memos that are not related to a specific case.

No. [3]	YY-MM	Title	Responsible institution and main contributors/authors
L1	16-08	Current status of condition monitoring in Norwegian and Swedish hydropower plants [1]	SINTEF: T. Welte, M. Istad, M.L. Kolstad, E. Solvang
L2	16-12	Review of analytics methods supporting anomaly detection and condition based maintenance [2]	Comillas University: M. A. Sanz-Bobi
L8	19-06	Lifetime and maintenance modelling utilizing monitoring data [3]	SINTEF: T. Welte, J. Vatn, M.A. Sanz-Bobi, H. Srivastav
L12	19-06	MonitorX - Summary of results, recommendations for use of results, and suggestions for further work (present report)	SINTEF: T. Welte, J. Foros

In addition to the reports in Table 5-1, two reports were prepared in the project that present results related to specific cases; see Table 5-2. For other case-specific results, see Sections 5.2 (Dissemination) and 5.3 (Student projects), and the appendices to this report. These results present different models and algorithms for condition monitoring in different versions, as well as descriptions and specifications regarding input data requirements, model application and modelling results. Thus, these results represent the project deliverables L4 - L7 and L9 - L11[3]. There is also a memo (L3 "MonitorX case studies and prototypes – Preliminary specifications" [22]) that were written in an early phase of the project and that presents preliminary ideas and specifications for selected MonitorX cases.

[3] The numbers L1 - L12 refer to deliverables specified in the MonitorX project proposal submitted to the Research Council in 2014. The original planned deliverables are: L4, L5 and L10: Prototypes of models/algorithms in different versions. L6: PostDoc report. L7: Models for condition monitoring. L9: final specification of prototypes. L11: User guides. Since the approach in MonitorX was case-based, it was decided to rather have documentation per case. This documentation covers the content of the originally planned deliverables L4 - L7 and L9 - L11.

Table 5-2: MonitorX reports and memos that are related to a specific case.

Year	Type: Title	Responsible institution and main contributors/authors	Case no.
17-03	Report: Anomaly Detection Analysis in Dale 2 hydropower plant [23]	Comillas University: M.A. Sanz-Bobi	C5
19-02	Report: Normal behaviour modelling oriented to diagnosis and prognosis [17]	Comillas University: M.A. Sanz-Bobi	C6

5.2 Dissemination – Presentations and articles

Table 5-3 shows a list of dissemination results. Dissemination results are presentations, papers and articles that have been published in open publication channels, such as national and international seminars and conferences, web sites, and papers and articles in journals and magazines. MonitorX has published (number of publications in parenthesis, + indicates planned publications):

- Scientific articles in journals and conference proceedings (4 + 1 submitted)
- Presentations at international conferences and seminars (4)
- Presentations at Scandinavian (NO/SE) conferences and seminars (10)
- Articles and interviews published in trade magazines (5 + 1)
- Articles published on web sites not owned by a project participant (2)

Table 5-3: MonitorX dissemination results that are publicly available or that have been presented at open conferences and seminars.

	Date	Title	Author(s)	Type of publication	Publication channel	Type of publication channel	Issue, pages	Place	Case
1	Oct. 2015	Mer vedlikehold for pengene	Atle Abelsen (journalist)	Article (interview)	Energiteknikk	Trade magazine (NO)	nr. 7, Oct. 2015, pp. 18-19		
2	March2017	Nytteverdier av digital transformasjon	Thomas Welte, Børge Stafne (SINTEF)	Article	Energiteknikk	Trade magazine (NO)	nr. 2, March 2017, pp. 32-33		
3	2017-03-06	Nytteverdien av digital transformasjon i vannkraftbransjen	Thomas Welte, Børge Stafne (SINTEF), Øyvind Holm (Voith)	Presentation	Production-technical conference (PTK)	Conference (NO)		Stavanger	
4	2017-03-23	Digital transformasjon - Nåsituasjon og muligheter for vedlikehold av vannkraftverk	Thomas Welte (SINTEF)	Presentation	Watervalley annual conference	Conference (NO)		Oslo	
5	2017 June (?)	Digitalisering ska forbättra møjligheterna at hitta fel	Daniel Løfsted (journalist ERA)	Article (interview)	ERA	Trade magazine (SE)	nr. 6, 2017, p- 33		
6	2017-10-26	Digital transformasjon nåsituasjon og muligheter for vedlikehold av generatorer for fremtiden	Thomas Welte (SINTEF), Mostafa Valavi (NTNU)	Presentation	Forum for generatorer	Conference (NO)		Gardermoen	C1
7a	2017-12-22	Graver i fjellets hemmelige gullgruve	Claude Olsen (journalist)	Article (interview)	Gemini	Web page (NO)			
7b	2018-01-03	Graver i fjellets hemmelige gullgruve	Claude Olsen (journalist)	Article (interview)	enerWE - Energibransjens digitale kanal	Web page (NO)			
8a	2017-09-11	Deep Learning Approach to Multiple Features Sequence Analysis in Predictive Maintenance	Jin Yuan (NTNU, Shandong Agricultural University), Kesheng Wang (NTNU), Yi Wang (Plymouth University)	Presentation	IWAMA 2017 - International Workshop of Advanced Manufacturing and Automation	Conference (international)		Changzhou	C4

	Date	Title	Author(s)	Type of publication	Publication channel	Type of publication channel	Issue, pages	Place	Case
8b	2018-02	Deep Learning Approach to Multiple Features Sequence Analysis in Predictive Maintenance	Jin Yuan (NTNU, Shandong Agricultural University), Kesheng Wang (NTNU), Yi Wang (Plymouth University)	Article (article collection/conference proceeding)	In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VII. IWAMA 2017. Lecture Notes in Electrical Engineering	Conference proceeding	Lecture Notes in Electrical Engineering, no. 451, pp. 581-590		C4
9	2018-03-20	Prediktivt underhåll - Erfarenheter från MonitorX	Thomas Welte (SINTEF)	Presentation	Workshop (Energiforsk): Digitaliseringen inom energisektorn	Workshop/ seminar (SE)		Stockholm	
10	2018-04-12	MonitorX - Experience from a Norwegian-Swedish project on digitalization of hydropower inspection and maintenance	Thomas Welte (SINTEF)	Presentation	Workshop/seminar (VGB): Digitalization in Hydropower	Workshop/ seminar (SE)		Wien	
11	2018-06	Allerede resultater fra MonitorX	Atle Abelsen (journalist)	Article (interview)	Energiteknikk	Trade magazine NO)	nr. 5, June 2018, p. 38		
12a	2018-06-19	Anomaly indicators for Kaplan turbine components based on patterns of normal behavior	Miguel A. Sanz-Bobi (Comillas), Thomas Welte (SINTF), Lasse Eilertsen (Glitre)	Presentation	European Safety and Reliability Conference (ESREL) 2018	Conference (international)		Trondheim	C6
12b	2018-06-19	Anomaly indicators for Kaplan turbine components based on patterns of normal behavior	Miguel A. Sanz-Bobi (Comillas), Thomas Welte (SINTF), Lasse Eilertsen (Glitre)	Article	S. Haugen, C. van Gulijk, T. Kongsvik, J.E. Vinnem: Safety and Reliability – Safe Societies in a Changing World, CRC Press, June 2018	Conference proceedings	pp. 1003-1010		C6

	Date	Title	Author(s)	Type of publication	Publication channel	Type of publication channel	Issue, pages	Place	Case
13a	2018-10-17	MonitorX – Experience from a Norwegian-Swedish research project on industry 4.0 and digitalization applied to fault detection and maintenance of hydropower plants	Thomas Welte, Jørn Foros (SINTEF), Martin H. Nielssen (Energy Norway), Monika Adsten (Energiforsk)	Presentation	Hydro 2018	Conference (international)		Gdansk	
13b	2018-10-17	MonitorX – Experience from a Norwegian-Swedish research project on industry 4.0 and digitalization applied to fault detection and maintenance of hydropower plants	Thomas Welte, Jørn Foros (SINTEF), Martin H. Nielssen (Energy Norway), Monika Adsten (Energiforsk)	Article	Proceedings Hydro 2018	Conference proceeding			
14	2018-10-25	MonitorX - Foreløpige resultater	Thomas Welte (SINTEF)	Presentation	Digitalisering i vannkraften	Workshop/ seminar (NO)		Gardermoen	
15	2019-03	Bør finne digitale allierte	Atle Abelsen (journalist)	Article (interview)	Energiteknikk	Trade magazine NO)	nr. 2, March 2019, pp. 16-17		
16		LSTM Based Prediction and Time-Temperature Varying Rate Fusion for Hydropower Plant Anomaly Detection: A Case Study	J. Yuan (NTNU)	Presentation	IWAMA 2018 - International Workshop of Advanced Manufacturing and Automation	Conference (interational)		Changzhou	C5
16a	2018-12-15	LSTM Based Prediction and Time-Temperature Varying Rate Fusion for Hydropower Plant Anomaly Detection: A Case Study	J. Yuan (NTNU), Y. Wang (Plymouth University), K. Wang (NTNU)	Article (article collection/ conference proceeding)	In: Wang K., Wang Y., Strandhagen J., Yu T. (eds) Advanced Manufacturing and Automation VIII. IWAMA 2018.	Conference proceeding	vol. 484, pp. 86 - 94		C5

	Date	Title	Author(s)	Type of publication	Publication channel	Type of publication channel	Issue, pages	Place	Case
					Lecture Notes in Electrical Engineering				
17	2019-03-05	MonitorX – Resultater fra FoU-prosjektet og erfaringer fra overvåkning av Kaplan-hydraulikksystem	Thomas Welte (SINTEF), Mattias Nässelqvist (Vattenfall)	Presentation	Production-technical conference (PTK)	Conference (NO)		Oslo	
18	2019-04-25	Digital reise mot prediktivt vedlikehold innenfor kraftproduksjon. MonitorX – et norsk-svensk samarbeidsprosjekt.	Thomas Welte (SINTEF)	Presentation	The Norwegian Smart Grid Centre, Technical seminar	Workshop/ seminar (NO)		Trondheim	
19	2019-05-09	MonitorX - Et norsk-svensk samarbeidsprosjekt om tilstandsovervåking og prediktivt vedlikehold	Thomas Welte (SINTEF)	Presentation	Digitalisering i vattenkraften - Nya möjligheter till prediktivt underhåll	Workshop/ seminar (SE)		Arlanda	
20	2019-05-09	Tillståndsövervakning med OSI PI och oljevolyms-övervakning i Laxede	Mattias Nässelqvist (Vattenfall)	Presentation	Digitalisering i vattenkraften - Nya möjligheter till prediktivt underhåll	Workshop/ seminar (SE)		Arlanda	C6
21	2019-05-09	Tidsbesparende tilstandskontroll av lensepumpe i Brattset kraftverk: Kan en enkel nivåmåler si noe om tilstanden?	Viggo G. B. Pedersen (NTNU)	Presentation	Digitalisering i vattenkraften - Nya möjligheter till prediktivt underhåll	Workshop/ seminar (SE)		Arlanda	C2

	Date	Title	Author(s)	Type of publication	Publication channel	Type of publication channel	Issue, pages	Place	Case
22	June 2019	Anomalideteksjon for å avdekke feil i vannkraftanlegg	Thomas Welte, Jørn Foros (SINTEF)	Article	Energiteknikk	Trade magazine (NO)	nr. 4, June 2019, pp. 36-37		
23	Sub-mitted (June 2019)	Anomaly detection method based on the evolution of patterns in industrial components. Application to a hydropower plant	Pablo Calvo Báscones, Miguel Ángel Sanz Bobi (Comillas), Thomas M. Welte (SINTEF)	Article	Engineering Applications of Artificial Intelligence	Journal			C5
24	planned public-cation	Twin Exponential Degradation Model for Online Remaining Useful Life Prediction	Jin Yuan, Kesheng Wang (NTNU)	Article					C4

5.3 Student projects and student reports/master theses

Cases C1, C2, C5, C6, C7 and X1 involved master students, either as part of regular studies where the students work with semester and master projects (Table 5-4), or as summer student projects at SINTEF (Table 5-5).

Table 5-4: Master student projects.

Student	Title	Type	University	Department	Date	Case no.
Frøydis Kvinen	Model for Condition Monitoring of Pumps in Hydro Power Plants [10]	Semester project report	NTNU	Electric Power Engineering	January 2016	C2
Kari Gjerde Jørstad	Modelling, simulation, and on-line detection of rotor fault in hydrogenerators [8]	Master thesis	NTNU	Electric Power Engineering	June 2016	C1
Kishan Prajapati	Condition monitoring of pump in hydropower plants [11]	Semester project report	NTNU	Mechanical and Industrial Engineering	May 2018	C2
Beatriz García Alejo	Definition of anomaly indicators and condition prognosis on components of a hydropower plant [24]	Master thesis	Comillas University	Institute for Research in Technology	July 2018	C5 / C6
Kishan Prajapati	Topic: Condition-based maintenance of pumps in hydropower plants	Master thesis	NTNU	Mechanical and Industrial Engineering	To be decided	C2

Table 5-5: Summer student projects.

Student	Title	Date	Case no.
Torfinn Tyvold	Analysis of increasing guide bearing temperatures at Nygard power plant [25]	January 2016	C5
Eivind Lie Andreassen	Condition monitoring of hydro power components using machine learning [20]	June 2016	C6, C7, X1

5.4 Meetings and seminars

5.4.1 Project meetings

During the MonitorX project, eight meetings with the project's steering committee were organized. These meetings were often extended with a technical programme or a side event, see Table 5-6.

Table 5-6: MonitorX meetings and side events/programme to these meetings.

Date	Place, country (host)	Technical side programme or other side event
2015-10-21…22	Uppsala, SE	-
2016-04-14…15	Oslo, NO (Energi Norge)	Workshop on case identification on day 2 of meeting.
2016-10-19…20	Bergen, NO (Karsten Moholt)	Visit of Karsten Moholt's workshop.
2017-04-25…26	Stockholm, SE (Energiforsk)	Seminar at Svenska Kraftnät.
2017-11-28…29	Trondheim, NO (Voith)	-
2018-04-24…26	Älvkarleby, SE (Vattenfall)	Visit of Vattenfall RnD laboratories. Visit of Forsmark nuclear power plant. Seminar together with nuclear power plant operators, see Table 5-7.
2018-10-24	Jevnaker, NO (Andritz)	Visit of Andritz' workshop. Seminar at Gardermoen the day after the meeting, Table 5-7.
2019-05-08	Arlanda, SE	MonitorX final seminar arranged the day after the meeting, see Table 5-7.

5.4.2 Seminars and sessions co-organized by MonitorX

The MonitorX project contributed to the organization of two seminars on digitalization and predictive maintenance of hydropower. Furthermore, a workshop with the nuclear power industry and two conference sessions were co-organized by Energy Norway, Energiforsk and the project, see Table 5-7. The aim of these events was to disseminate MonitorX results and to exchange knowledge and experience with other industries and companies that did not participate in the MonitorX project.

Table 5-7: Workshop, seminars and conference sessions co-organized by Energy Norway, Energiforsk and the MonitorX project.

Date	Place (host)	Title	Type	Comment
2018-04-26	Forsmark	Predictive maintenance in nuclear power and hydropower	Workshop	Workshop organized by Energiforsk
2018-10-25	Gardermoen	Digitalisering i vannkraft - tilstandsovervåking og prediktivt vedlikehold (Digitalization in hydropower - condition monitoring and predictive maintenance)	Seminar	Seminar organized by Energi Norge together with MonitorX
2018-03-05	Oslo	Produksjonsteknisk konferanse (PTK) – Production-technical conference	Conference session	To sessions organized by MonitorX: • Session 2C2: Bransjens felles innsats for økt digitalisering • Session 2C5: Oppspill og paneldebatt: Monitorering og tilstandsovervåkning: Hvor er vi om ti år? Og hva vil kreves av selskapene for å komme dit?
2019-05-09		Digitalisering i vattenkraften	Seminar	Seminar organized by Energiforsk together with MonitorX

5.5 Spin-off projects and activities

5.5.1 RDS Hydro

In hydropower, there are a number of reference designation systems (RDS) that are used for different purposes and that are applied in the companies to various degree. These include, e.g.:

- RDS-PP [26], and its international implementation ISO/TS 81346-10:2015, which is the further development of the proven identification system for power plants KKS
  - RDS-PP is a proprietary standard developed by VGB [27]
  - ISO/TS 81346-10:2015 is currently under review by ISO and a new version is under development. The new version will probably not be based on RDS-PP.
- EBL code (EBL-kodeplan), the RDS currently used by most Norwegian hydropower plant operators, developed by EBL/Energi Norge
  - This system has number of drawbacks, and is a special national system
- NEK 321 – 322
  - Has been withdrawn by the Norwegian electrotechnical committee (NEK)
- A number of (proprietary) designation systems used by manufacturers and service providers

The drawbacks of the EBL code required a further development of the EBL code, or a completely new development of a hydropower specific RDS. A working group, consisting of twelve of the largest Norwegian power companies, and supported by the Swedish hydropower industry (represented by Energiforsk), were established in 2018 by Energi Norway and the MonitorX project to discuss the mentioned challenges and develop solutions. The working group decided to develop a new RDS based on the principles in IEC/ISO 81346 [28], [29], and a spin-off project (RDS NES – Norwegian Energy System) were started for this purpose. The final result of the spin-off project is a new and consistent RDS for hydropower plants (RDS-HYP, available since 2019) that follows the principles of IEC/ISO 81346.

RDS HYP was presented to the ISO/IEC working committee ISO/TC 10/SC 10 responsible for RDS and the IEC/ISO 81346 series. Since RDS HYP is quite general, the idea is to upgrade RDS HYP to a new RDS for the whole power system (RDS PS) that includes all types of power production, power distribution and power transmission assets.

5.5.2 PhD on generator fault detection at NTNU (HydroCen)

The activities in case C1 in MonitorX were restricted to theoretical analyses and data received from FEM. In order to follow up the results that have been obtained, a new PhD-position was established in HydroCen, the Norwegian Research Centre for Hydropower Technology. A new PhD candidate (Hossein Ehya) started in autumn 2018. The title for the PhD work is "Electromagnetic analysis and on-line fault detection in hydropower generators". The work includes testing of methods developed in MonitorX case C1 with data from laboratory test and from the field. For this purpose, NTNU has purchased and installed a lab-scale generator that has a very similar design as many hydro generators. With the lab generator, one has the possibility to introduce typical generator faults, such as winding short circuits and eccentricity (eccentric alignment of rotor shaft) and test methods for condition monitoring and models for fault detection.

First results are expected before summer 2019 from two master student projects (students: Ingrid Linnea Growth and Johan Henrik Holm Ebbing). The master theses will be finished June 2019 and can usually be found later (autumn 2019) in the academic libraries' data base "Oria" [30] or in the open access data base NTNU Open [31].

6 Project benefits

The MonitorX results consist of a set of models and algorithms for condition monitoring, detection of faults and prediction of remaining lifetime. The use of such types of models by power plant operators results in better maintenance and reinvestment decisions and allows for a transition to a more predictive maintenance strategy.

In section 6.1 follow examples that illustrate the potential benefits of using project results, and condition monitoring and predictive maintenance in general. In section 6.2, the potential benefit of using condition monitoring for hydropower plant tunnels (headrace/tailrace tunnels) is illustrated with a benefit estimate for a specific power plant. Such estimates could be in principle also calculated for other power plants and monitoring use cases.

Note that the benefits described in sections 6.1 and 6.2 require that results as developed by the MonitorX project in form of models and algorithms actually are used for condition monitoring by the power plant operators to realize a predictive maintenance strategy. A direct benefit of the MonitorX project is knowledge building and exchange of experience, as discussed in Section 6.3.

6.1 General benefits and benefit estimates for Norwegian hydropower plant operators

In a study conducted for the Research Council of Norway [32] [33], the potential benefit of condition monitoring and predictive maintenance for Norwegian hydropower plant operators was described and estimated as follows:

- 650 MNOK (ca. 68 MEUR) as an effect of postponed investment costs as a result of better knowledge about the component's actual condition and remaining lifetime.[4]
- 4 000 MNOK (ca. 420 MEUR) as a consequence of reduced production losses due to less downtime for corrective and preventive maintenance.[5]
- Reduced inspection costs due to fewer manual inspections
- Shorter maintenance downtime by using more condition-based and less time-based maintenance.
- Reduced cost for corrective maintenance due to reduced probability of failure.
- Better knowledge about the real technical condition of the components and the relation between operation conditions, loads, degradation and lifetime.

The quantitative benefit estimates above are calculated with a general approach and with cost figures representing all Norwegian hydropower plant operators. The benefit of a monitoring solution for a specific power plant component is exemplified in the following section.

[4] This estimate is based on a survey conducted by SINTEF when the MonitorX project proposal was developed in 2014. Ten Norwegian hydropower plant operators were asked about their reinvestment needs for the next ten years. It was assumed that some of these reinvestments can be postponed by some years due to better knowledge about the technical condition as a result of condition monitoring. In the presented study in references [32] and [33], the estimate was improved by e.g. assuming that not all of the investment costs can be postponed, but a large part of the costs, whereas a minor part of the investments will come earlier than originally expected (due to detection of faults).

[5] Estimated present value of reduced production losses for Norwegian hydropower operators over a period of 40 years. It was estimated that the average production losses in Norwegian hydropower plants is around 1.25 % and that condition monitoring and predictive maintenance can contribute to a reduction from 1.25 % to 0.5 % within 10 years.

6.2 Benefit of head and tailrace tunnel fault detection

The example was developed in a cooperation between Impello Management, SINTEF and two Norwegian power plant operators and is described in reference [33].

Rock falls in tunnels can result in head losses and reduced plant efficiency. With currently applied methods, it can take very long time (up to several months or a year) to detect rock falls that result in partly blockage of the tunnel. By using a model that estimates the head losses, a plant operator can monitor the losses and thus can detect larger rock falls that result in head losses much earlier than without a monitoring solution. Such a monitoring solution can be of relevance for many power plants in Norway; it was estimated that approximately half of the Norwegian power production from reservoir power plants would have a benefit of using such a monitoring solution.

The potential benefit was estimated for a real power plant where a rock fall event and partly blockage of a tunnel happened. The power plant has a head of 450 m, and the rock fall in the tunnel caused a head loss of approx. 6 m. The head loss results in approx. 1.3 % of production loss. Table 6-1 shows how much of the power production is lost[6] when this kind of rock fall event occurs, depending on how long time it will take to detect the rock fall. The monitoring solution provides the possibility of earlier detection of the rock fall, presumably up to several months earlier than without a monitoring solution. This means that much of the losses can be avoided with tunnel condition monitoring.

Table 6-1: Lost production as a function of time until the tunnel rock fall is detected.

Time until rock fall that causes the losses is detected	Lost power production	Lost revenues
1 week	0.3 GWh	0.1 MNOK
1 month	1.4 GWh	0.4 MNOK
1 year	16 GWh	4.8 MNOK

6.3 Knowledge building and exchange of experience

An important benefit of the MonitorX project was the exchange of experience and knowledge between hydropower operators, equipment manufacturers and research. The project participants acknowledged the opportunity to discuss different topics related to data collection and analysis in the MonitorX consortium. The experience and knowledge exchange were useful for the participating companies to identify good solutions and best practice. This may have accelerated the implementation of data collection and condition monitoring solutions. Furthermore, this exchange stimulated to new activities and spin-off projects, see as described in Section 5.5.

[6] Assumed market price for electricity: 0,3 NOK/kWh.

7 Recommendations

This section summarizes some recommendations for use of the results from the project, based on the lessons learned throughout the project execution. Some of the learnings and recommendations below have already been discussed and presented in the MonitorX overview paper presented at the Hydro 2018 conference [34].

7.1 System and platform for data collection and handling

Even though MonitorX did not focus on solutions for data collection and storage, exchange of experience with different systems and platforms was part of the project activities. A central system or platform (big data platform) is one of the requirements for providing effective and easy access to monitoring and sensor data. Thus, the big data platform is an important link between the data sources and the data users. Automatization and continuous monitoring require that solutions (i.e. algorithms, models and software) for data analysis can be integrated in the systems/platforms or can be interconnected.

One of the Monitor cases (case C8) focused on collection of data from the hydropower plant's local control system. The hydropower equipment manufacturer Voith developed a new solution for data access to supply the project with high quality data. The developed solution has been tested in the Brattset power plant, and data for case C2 was accessed with this solution. In case X1, it was shown how normal behaviour models can be integrated with a commercial big data platform (in this case OSIsoft PI) for live continuous anomaly detection.

7.2 Type of data and data resolution

The different cases illustrate recommendations and requirements for data availability and resolution. While cases C5 and C6 use historical data available in already aggregated form as average values from the SCADA system with 1 hr resolution, and case C2 uses raw data from the plant's control system with approx. 30 sec. resolution, requires case C1 high resolution data with 1 kHz sampling frequency or higher. These examples illustrate that the required data resolution depends on the type of model that is used for data analysis. Furthermore, the physical effects and phenomena that are analysed influence the requirements regarding data resolution. Slow effects, such as temperature changes and developments in large technical components that require several hours for heating up and cooling down (e.g. case C5), can be modelled with data of low resolution, whereas high frequency phenomena, such as sideband harmonics around and beyond the grid frequency of 50 Hz, require high resolution data.

7.3 Scalability

So far, the MonitorX models have only been developed for selected components. If such models are to be implemented on a large scale throughout an organization, the time and resources needed to do this should be considered. Typically, the scalability (or transferability) is a larger issue for the advanced models than the simple models. For example, the ANN model for Kaplan turbines (case C6) must be rebuilt and trained for each turbine, whereas the pump model (case C2) may be used as-is for drainage systems with the same design and sensor measurements available. Furthermore, maintenance-related changes in the plants may influence the model's predictability and accuracy and may require a re-training. Hence, approaches for automatic model training and updating would be helpful.

7.4 Competence requirements

The extended use of digital systems requires an extension of available, or new, resources and competences. More ICT competences and resources are required to carry out the implementation of a big data platform. Furthermore, new resources such as data analysts or scientist might be valuable. One important aspect in this discussion is outsourcing of competence, i.e. to which degree the power plant operator wishes and needs to have new competences inhouse, or if these are bought from external service providers, hydropower equipment manufacturers and consultancies.

When a plant operator wants to use the MonitorX results and wants to implement and run the models and algorithms in the own systems, knowledge on programming (MATLAB, Python) and machine learning is required.

7.5 Selection of models and "where to start"

In the cases in the MonitorX project, different models that are both of the simple and advanced type (see section 4.1) were developed and tested for several different components (rotor, pumps, bearings, turbine, transformer, etc.). The testing showed promising results, indicating that the models are good candidates for implementation at the companies. Selection of models for implementation should be done on basis of the needs of the company, as well as system/platform availability, data availability, model scalability and competence availability, as discussed above. In any case, it is recommended to start with models of the simple type. A very first start should be to implement and test simple monitoring of variables, or combination of variables, and monitor these variables with respect to some limit or alarm levels.

7.6 Acceptance criteria and alarm levels

The models should be combined with reasonable limits for acceptable deviations from normal behaviour ("acceptance criteria"), such that anomalies can be identified, and alarms can be activated upon a detected anomaly. In this way, the operators will have control over the plant condition and can plan for the next inspection or overhaul. In some of the MonitorX cases, for example the cases where normal behaviour models where used and where the error between an estimated and observed signal was used as indicator for anomalies, it was demonstrated that the alarm levels can be chosen based on historical observations and model errors that have been observed for the training and test data sets (error must be larger than the observed errors for an alarm). Furthermore, random, intermittent and momentary anomalies are rejected, because they are usually caused by noise.

8 Further work

On the one hand, MonitorX supported the project partners with knowledge and information about new concepts related to predictive maintenance and digitalization. On the other hand, the project provided a set of methods and models for different monitoring purposes. The project demonstrated through practical cases how these concepts can be applied to optimization of maintenance by using these methods and models for condition monitoring and fault detection. Furthermore, the cases demonstrated the practical application of different models and their advantages and disadvantages. Based on these results, recommendations regarding model development, application and implementation were given in the previous section.

The project can be followed-up in different areas, such as:

- Further model development and testing (incl. upscaling)
  - Applying models to all plants and components in a company
  - More advanced models, such as digital twins
- Testing of models with field data
  - E.g. model developed in case C1, because until now only tested with FEM)
- Developing of methods for simulation of faults in power plants (i.e. introducing "artificial" and "virtual" faults)
  - The purpose is testing and proof of concept of models and algorithms
- Development of methods and models for evaluation of cost-benefit of new monitoring and fault detection solutions
- Development of standards that simplify the exchange and use of data for different purposes
- Development of methods and models for identification of causes for identified anomalies, estimate the criticality of anomalies, and propose suitable actions.

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Appendix A

Monitor cases: Case documentation, codes and data set

Table A.1: Documentation, codes and data sets for the MonitorX cases.

Case	Appen-dix	Codes	Data sets	Documentation		Refe-rence [2]	Comments
				No. [1]	Type: "Title"		
C1 - Rotor fault detection	B			D1.1	Master thesis: "Modelling, Simulation, and On-line Detection of Rotor Fault in Hydrogenerators"	[8]	In this case, a data set with simulated data was used. The simulations were made with a finite element model of the Kalvedalen generator.
				D1.2	Paper: "Electromagnetic analysis and electrical signature-based detection of rotor inter-turn faults in salient-pole synchronous machine"	[9]	
C2 - Condition monitoring of drainage pumps	C			D2.1	Semester project report: "Model for condition monitoring of pumps in hydropower plants"	[10]	Some data from Laxede power plant was used
				D2.2	Semester project report: "Condition monitoring of pump in hydropower plants"	[11]	Data from Brattset power plant was used
C3 - Audio surveillance	-						No documentation exists other than the description given in the main text
C4 - Condition monitoring of rotating equipment using vibration data	D	K4.1 K4.2	PHM IMS	D4.1	Paper Draft: "Twin Exponential Degradation Model for Online Remaining Useful Life Prediction"	[12]	The datasets (PHM and IMS datasets, see [35] and [36]) used in this case are not from hydro power plants, but from roller bearing test benches.
				D4.2	Paper: "Deep Learning Approach to Multiple Features Sequence Analysis in Predictive Maintenance"	[13]	

[1] () means that the case documentation can be found in the documentation for another case.
[2] Number refers to the reference list of the main report.

Monitor cases: Case documentation, codes and data set

Case	Appen-dix	Codes	Data sets	Documentation No. [1]	Type: "Title"	Refe-rence [2]	Comments
C5 - Condition monitoring of generator bearings	E	K5.1 K5.2	Dale Nygard	D5.1	Memo: "Anomaly Detection Analysis in Dale 2 hydropower plant"	[23]	
				D5.2	Memo: "Analysis of increasing guide bearing temperatures at Nygard power plant"	[25]	
				D5.3	Poster: "Intelligent condition monitoring of hydroelectric power plants"	[37]	
				D5.4	Paper: "LSTM Based Prediction and Time-Temperature Varying Rate Fusion for Hydropower Plant Anomaly Detection"	[14]	
				D5.5	Paper draft: "Anomaly detection method based on the evolution of patterns in industrial components. Application to a hydropower plant"	[15]	
C6 - Condition monitoring of Kaplan turbine hydraulic system	F	K6.1 K6.2	Embrets-foss Laxede	D6.1	Paper: "Anomaly indicators for Kaplan turbine components based on patterns of normal behavior"	[16]	
				D6.2	Master thesis: "Definition of anomaly indicators and condition prognosis in components of a hydropower plant"	[24]	
				D6.3	Memo: "Condition monitoring of hydro power components using machine learning"	[20]	
				D6.4	Report: "Normal behavior modelling oriented to diagnosis and prognosis"	[17]	
C7 - Fault detection for power transformers	G	(K6.2)	Uvdal	(D6.3)		[20]	This case uses the same type of model and code as used in case C6. Documentation can be found in section 2 in D6.3.
C8 - SCADA data collection system	H						
C9 - Continuous servomotor monitoring	-			D9.1	Master thesis: "Condition Monitoring of Hydroelectric Power Plants"	[18]	Additional information can be found in reference [19]
X1 - OSIsoft PI model integration	-	KX1.1 [21]		(D6.3)		[20]	OSIsoft PI model integration is described in section 4 in D6.3.

Appendix B

Case no.:	**C1**
Title:	**Rotor fault detection**
R&D partners:	Mostafa Valavi, Arne Nysveen (NTNU) Kari Gjerde Jørstad (student, NTNU, 08/16 – 07/17)
Industry partners:	Joakim Gundersen, Tormod Kleppa (Eidsiva) Magnus Holmbom (Vattenfall)
Date:	2019-06-04
Editor:	Thomas Welte (SINTEF), Mostafa Valavi (NTNU)

MonitorX Case C1 – Rotor fault detection

1. Short description (abstract)

The aim of the case was to propose and assess methods for on-line detection of rotor short-circuit fault and other faults in the hydrogenerators. The idea is to use spectral analysis of stator voltage and current for fault detection. The project started with investigation of rotor inter-turn short-circuits and has been further developed to include other types of faults, including eccentricity and bearing faults. The work was carried out as theoretical study. Data from power plants were not available for this case, because available SCADA data with current resolution cannot be used for this purpose. Thus, as an initial attempt to assess the proposed monitoring method, finite element methods (FEM) were used to simulate faults and their influence on the electro-magnetic field in a generator and finally on the current and voltage in the stator. The simulated voltage and current signals have then be used for evaluation of the fault detection method. The results were promising, and the plan is to follow up the work with lab experiments and analysis of data from the field.

2. Benefit, motivation and potential users

The aim is to be able to detect rotor faults (short circuits in winding insulation) and other faults under operation (online). Traditional methods are based on measurements and inspections when the generator is not in operation. An online method will provide the possibility to detect faults continuously (i.e. when they appear, and not only at planned inspections) and before they lead to a catastrophic failure. The method can also be basis for predictive maintenance when the method is extended with a model that predicts damage development.

3. Selected power plants for testing

The fault detection method developed in this case has been tested with simulated data received from simulations of the generator installed in Kalvedalen hydropower plant (Eidsiva) using FEM. High frequency stator voltage and current measurements from Kalvedalen have been collected. However, the measurements have not been analysed, yet.

4. Methods and models

Finite element methods (FEM) were used to simulate faults and their influence on the electro-magnetic field in a generator and finally on the current and voltage in the stator. Both rotors in a healthy and faulty state were simulated. The simulations result in (simulated) voltage and current signals. These signals were then used in and spectral analyses, i.e. the frequencies in the voltage/current signal are assessed with fast Fourier transform (FFT) methods; see D1.1 [1] and D1.2 [2] for further details. The MATALB fft function [3],[4] has been used for the FFT-analysis. The frequency spectrum of a generator in healthy and faulty state are compared and difference in the frequency spectra can be used as indicator for faults.

5. Input data

Input data for the method are either current or voltage measurements from the stator. Available SCADA data with current resolution cannot be used for fault detection. A sampling frequency of at least 500 Hz (or better: 2 – 4 kHz) and a signal length of at least 2 seconds are required.

6. Other information

This case was a collaboration between FME HydroCen (www.ntnu.no/hydrocen) and MonitorX. The work was initiated by MonitorX based on an idea by Joakim Gundersen (Eidsiva) and Magnus Holmbom (Vattenfall). NTNU (Prof. Arne Nysveen, Mostafa Valavi) have been contacted by MonitorX and the topic was then be carried out as a master student work by Kari Gjerde Jørstad. The work by Mostafa Valavi was financed by HydroCen.

There are a number of other related activities to this case. Some of them are ongoing, see section 9 on *Plans for further work* for further details. A master thesis related to this case was the thesis by Andreas Blix Møller on "Modelling, Simulation, and On-line Detection of Rotor Eccentricity in Hydropower Generators" [5].

7. Deliverables

The following deliverables have been prepared:

No.	Deliverable (description/title)	Author (person)	Type of deliverable	Reference
D1.1	Modelling, Simulation, and On-line Detection of Rotor Fault in Hydrogenerators [1]	Kari G. Jørstad	Master thesis	./Docs/D1.1 Kari Gjerde Jørstad, master thesis
D1.2	Electromagnetic analysis and electrical signature-based detection of rotor inter-turn faults in salient-pole synchronous machine [2]	M. Valavi, K.G. Jørstad, A. Nysveen	Paper	./Docs/D1.2 Valavi, Jorstad, Nysveen, IEEE TRANSACTIONS ON MAGNETICS

8. Summary of results

The new method uses spectral analysis of stator voltage and current for fault detection. The results of the spectral analysis are illustrated for two examples in Figure 1., where the frequency spectrum of both a generator with healthy rotor winding and a rotor winding with faults are shown. In a case of an inter-turn short-circuit, in addition to the amplitudes at 50 Hz and its odd multiples, sideband harmonics appear at each side of the main harmonics. These sideband harmonics could be used as indicator for fault detection. The method requires a much higher data resolution (voltage or current) than usually available through the SCADA-system, and a sampling frequency of at least 500 Hz is recommended. However, the data collection must not necessarily be continuous, but samples of at least 2 seconds could be collected regularly, e.g. once in a day or week.

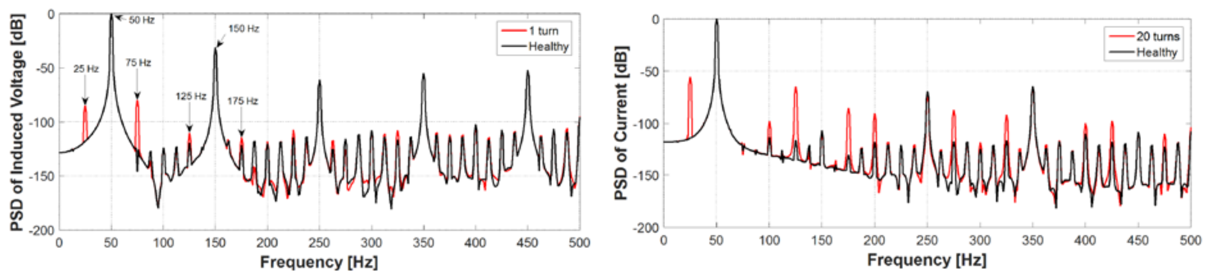

Figure 1: Frequency spectrum of induced voltage at no-load, healthy vs. 1 turn short-circuited (left), and frequency spectrum of stator current at full-load, healthy vs. 20 turns short-circuited (right). Courtesy of K. G. Jørstad; D1.1 [1]. PSD: power spectral density.

The detection of rotor inter-turn short-circuits was primarily investigated, but also detection of other types of faults, including eccentricity and bearing faults, were studied. A detailed description of the work and the results can be found in D1.1 [1] and D1.2 [2].

9. Plans for further work

Since the method has been evaluated with simulated data (from FEM), the proof of concept with data from a real power plant is part of further work. High frequency stator voltage and current measurements from Kalvedalen have been collected. However, the measurements have not been analysed, yet. The challenge is that the proof of concept with data from a real power plant requires measurements from a generator in faulty and healthy states, to be able to analyse differences between both states.

This case will be followed up by NTNU and in HydroCen research centre with master projects and a recently started PhD work (November 2018 – November 2021, PhD candidate: Hossein Ehya) with working title "Electromagnetic analysis and on-line fault detection in hydropower generators". The plan is to test the described fault detection method, together with other methods, in a laboratory set up consisting of a generator where faults can be introduced. Furthermore, it is planned to extend the work to include measurements from generators installed in power plants.

In spring 2019. There are also two master student projects ongoing; students: Ingrid Linnea Growth and Johan Henrik Holm Ebbing. Their master theses will be finished June 2019 and can usually be found later (autumn 2019) in the academic libraries' data base "Oria" [6] or in the open access data base NTNU Open [7].

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Appendix C

Case No.:	**C2**
Title:	**Condition monitoring of pumps in hydro power plants**
R&D partners:	Thomas Welte, Jørn Foros, Eivind Solvang (SINTEF) Jørn Vatn, Frøydis Kvinen, Kishan Prajapati (NTNU)
Industry partners:	Magnus Holbom (Vattenfall) Gorm Aukrust (TrønderEnergi) Øyvind Holm (Voith)
Date:	04.06.2019
Editor:	Jørn Foros, Thomas Welte (SINTEF)

1. Short description (abstract)

Case C2 studies operation of pumps in drainage systems in hydropower plants. Drainage pump data from Vattenfall's Akkats plant and TrønderEnergi's Brattset plant have been analysed. In both cases, methods to monitor the pump condition (represented by the pump capacity) from the available data have been investigated and tested. By calculating and continuously monitoring e.g. the experienced pump capacity, anomalies can be identified. For the Brattset plant, promising results are achieved, but for the Akkats plant, additional parameters appear to be needed for the model.

2. Benefit, motivation and potential users

The problem this case addresses is the uncertainty of not knowing the condition of pumps in hydropower stations. Today, a limited number of parameters are available for continuous online condition monitoring of drainage pumps in hydropower plants, and pumps are typically inspected, maintained and tested on a time-basis. Furthermore, the drainage system in hydropower plants is a redundant system with usually two or more pumps that are used in alternation, and often an additional drainage method (such as an ejector). Thus, the failure of one of the pumps is not critical, and one can operate the system with a run-to-failure strategy. Nevertheless, a failed pump should be replaced quickly, to ensure the redundancy and reliability of the drainage system. Furthermore, manual inspection and testing of the pumps requires two persons and some hours of work (which may include travelling to the power plant). Therefore, a condition-based pump maintenance strategy is desirable. This can enable a condition-based and predictive maintenance strategy, including degraded pumps to be replaced during planned maintenance visits, thereby avoiding extra visits for corrective maintenance. The aim is to achieve a better picture of the pump conditions that can provide predictability for the plant operator.

The potential users are hydropower companies that have a system with automatic measurements of required parameters that are available for remote monitoring and analysis, or will acquire such a system, and thus can implement the model in their systems.

3. Selected power plants for testing

TrønderEnergis Brattset power plant is a reservoir power plant with Francis turbines located in Rennebu, Trøndelag, Norway. Built in 1982, it has output 2 x 40 MW and average annual production 390 GWh. Vattenfalls Akkats power plant is a hydro power plant in the river Luleälven in the north of Sweden. The power plant is equipped with Kaplan turbines, and it has output 150 MW and average annual production 590 GWh. It was built between 1969 and 1973 and upgraded in 2008.

4. Methods and models

The model calculates parameters for monitoring pump condition, e.g. pump run time per cycle (time used to empty the reservoir) and experienced pump capacity (actual pumping rate). Anomalies are detected by comparing the results with a reference level, defined e.g. by historical data from which the pump was operating properly or the rated pump capacity from the pump data sheet.

The model consists of simple equations and algorithms. The exact algorithm depends on the available data, which differs for the Brattset and Akkats plants (see section 4). The model consists of the following general steps:

1. Identification of time points for start and stop of pumps. If on/off signals are not directly measured, this is inferred from reservoir level measurements.

2. If two or more pumps are used alternately, identification of when each pump is used. If on/off signals are not directly measured, this is inferred from pump motor current measurements.
3. Identification of maximum and minimum reservoir levels during each pump cycle (i.e. the levels at which the pump is started and stopped).
4. Determination of average reservoir filling rate and emptying rate during each pump cycle. If pump on/off signals are measured, filling/emptying rate may be calculated from these. If not, filling/emptying rates are calculated from linear regression of reservoir level measurements (assuming that the filling/emptying rates are constant during each cycle).
5. Determination of the experienced pump capacity per cycle, given as filling rate plus emptying rate.

In addition, data cleaning is generally required before utilising the model. The model is physics-based, and relatively simple, i.e. it does not require specialized competence to utilise. The model developed for the Brattset power plant is described in more detail in Chapter 5 in D2.2 [2].

5. Input data

Data has been received live from Akkats (Vattenfall) via an OSIsoft PI server from autumn 2017. Data from Brattset (TrønderEnergi) has been available via the Voith Bluebox server since end of August 2017.

The following data has been utilised, if available:

- Pump operation data: on/off signals (only available for Akkats)
- Water level in drainage reservoir and other connected reservoirs
- Reservoir volumes
- Pump data sheet (rated capacity, efficiency, etc.)
- Turbine power
- Pump motor current (only available for Brattset, for indification of pump start and stop times)

Note the different data availability for Akkats and Brattset.

6. Other information

Not relevant.

7. Deliverables

The following deliverables have been prepared:

No.	Deliverable (title)	Author	Document type	Reference
D2.1	Model for condition monitoring of pumps in hydropower plants	F. Kvinen (NTNU)	Specialization project, autumn 2016.	Docs – D2.1 [1]
D2.2	Condition monitoring of pump in hydropower plants	K. Prajapati (NTNU)	Specialization project, spring 2018.	Docs – D2.2 [2]

8. Summary of results

The drainage system at Akkats was described in a specialization project at NTNU in the fall of 2016, and a first attempt of a pump condition monitoring model was made; D2.1 [1]. After a data connection to Akkats was set up via a PI server in the fall of 2017, and data could be received live, analysis of the drainage pumps was continued[1]. There are two pumps that are run alternately, and the pump that is in operation is switched on and off according to reservoir level setpoints.

Selected results of the analysis are shown in Figure 1. Here the pump run time per cycle (i.e. the time used to empty the reservoir down to the lower setpoint) is shown together with the reservoir inflow rate[2], which was approximated by the average inflow rate during the last 15 minutes before each pump start[3]. The results show that the pump run time is increased at certain times, and that this cannot be explained by the estimated inflow rate. It seems likely that this is due to some extra inflow to the reservoir occurring only at certain times, that is not captured by the calculation. After discussing with Vattenfall, it was concluded that there is indeed some extra inflow that is not measured today, and that is pumped into the reservoir in intervals. This issue makes it difficult to make a condition monitoring model in terms of pump run time or pump capacity (calculated by inflow rate plus emptying rate). A possible simple solution to circumvent the problem is to monitor the running median pump time, which effectively will remove the instances of increased run time.

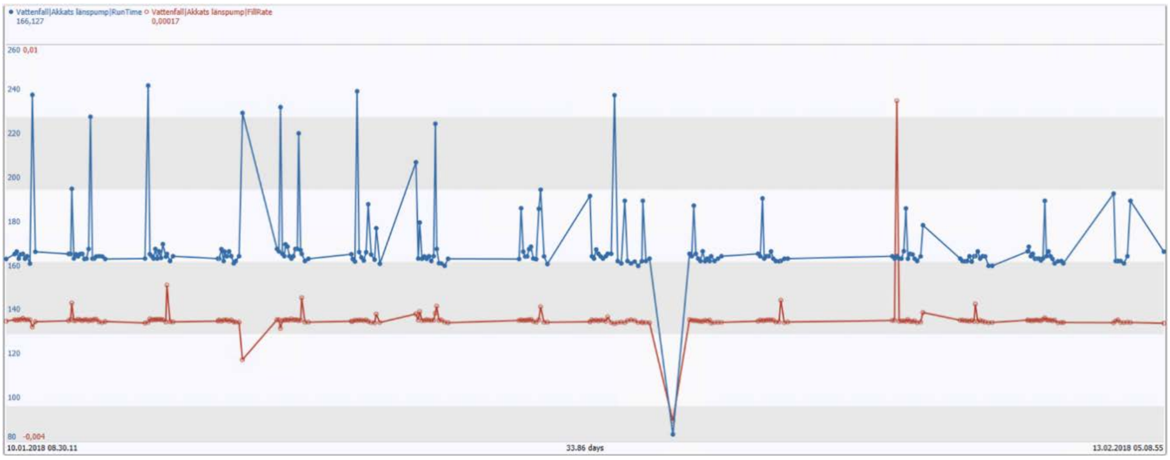


Figure 1: Run time for one of the drainage pumps (blue line) and estimated reservoir filling rate (red line) at Akkats. In the periods without any data, the other drainage pump was run. The calculation has been done in PI and the plot has been taken directly from PI, without any filtering of the data.

A similar analysis was carried out for the Brattset plant, from which data could be received through the preliminary called "Voith Bluebox system", which is a system developed by Voith for extraction and transfer of data from the power plants control system. As for Akkats, there are two pumps that are run alternately, i.e. one pump is in operating mode, whereas the other pump is in standby mode. Switching between the pumps (operating/standby) is performed manually, but the pump that is in operating mode is switched on and off according to reservoir level setpoints. Selected results of the analysis are shown in Figure 2 for both pumps. Here, the calculated pump capacity per cycle (inflow rate plus emptying rate) is shown as a function of time. It is also illustrated how these results may be utilised for continuous condition monitoring by comparing the results with a reference level (green lines), thereby identifying deviations. For both pumps, the results reveal points in time during which

[1] The analysis was performed for the pumps in the leakage pit at Akkats

[2] Measured in m/s, i.e. change of reservoir level per time

[3] This approximation was necessary since the inflow is not measured, and since it is not possible to estimate it during which the pump is running

the pump capacity was significantly reduced. The cause of this has not been identified, and was for the Battset case probably caused by maintenance, but in general it may be a sign of deteriorating condition or some alteration made to the drainage system/pumps.

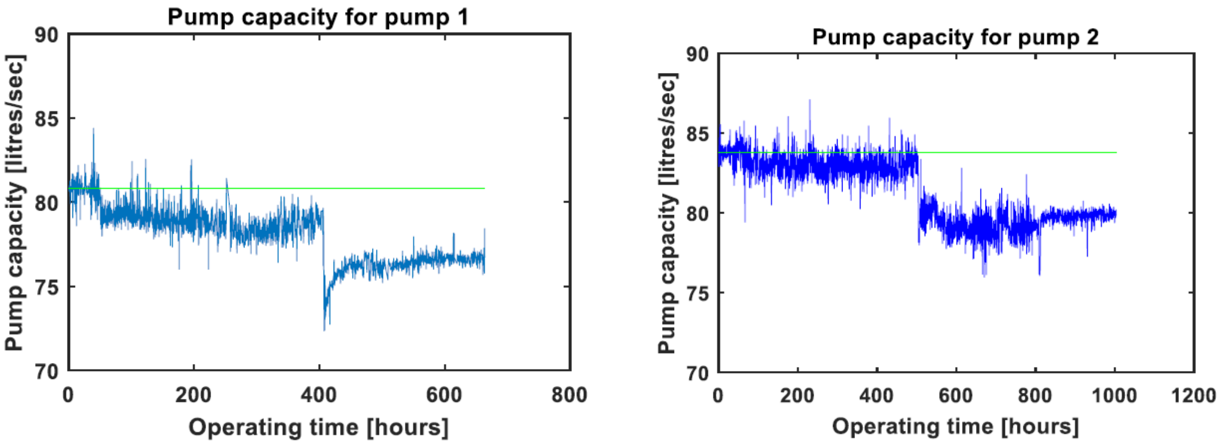


Figure 2: Calculated capacity for drainage pumps at Brattset as a function of time; D2.2 [2]. The green lines illustrate reference capacity levels to which the capacity may be compared. An alarm level could be defined as pump capacity deviation larger than an accepted percentage or amount of the reference capacity level.

In conclusion, the above results illustrate the potential use of pump condition models, but also some limitations. To build such models it is necessary to understand which parameters that govern the parameter that is modelled, and that all such explanatory variables are available. If the monitored parameter (e.g. the pump capacity) is expected to be constant, constant alarm limits for what is considered normal may be applied. When deviations from normal behaviour are identified, it is necessary to investigate the cause of this. The cause may be deteriorating pump condition, but could also be related to e.g. changes in how the pump is operated or maintenance activities. This illustrates that there should be additional information available for improving the models and explain observed changes, such as operational data and maintenance data.

9. Plans for further work

There is one master thesis project related to case C2 still ongoing at NTNU (June 2019); student: Kishan Prajapati. When the master thesis is finished, one can usually found it later in the academic libraries' data base "Oria" [6] or in the open access data base NTNU Open [7].

The models should be combined with reasonable limits for normal pump condition, such that anomalies can be identified, and alarms can be activated upon a detected anomaly. In this way, the operators will have control over the pump condition and can plan for the next inspection or overhaul. A possible extension of the models is to identify causes for identified anomalies, estimate the criticality of anomalies, and propose suitable actions.

10. References

[1] F. Kvinen, "Model for condition monitoring of pumps in hydropower plants", specialization project, December 2016.
[2] K. Prajapati, "Condition monitoring of pump in hydropower plants", specialization project, May 2018.
[3] “Oria - Norwegian academic libraries’ data base.” [Online]. Available: www.oria.no.
[4] “NTNU Open.” [Online]. Available: https://ntnuopen.ntnu.no.

Appendix D

Case No.:	**C4**
Title:	**Condition monitoring of rotating equipment using vibration data**
R&D partners:	Jin Yuan, Kesheng Wang (NTNU) Thomas Welte, Jørn Foros (SINTEF)
Industry partners:	Erik Wiborg (Statkraft)
Date:	04.06.2019
Editor(s):	Espen Hafstad Solvang, Thomas Welte (SINTEF)

MonitorX Case C4 - Condition monitoring of rotating equipment using vibration data

1. Short description (abstract)

The aim of this case was to develop algorithms and models for fault detection and prediction of remaining useful life (RUL) of rotating equipment based on high frequency sensor data (kHz resolution and larger) from vibration sensors (accelerometers), acoustic emission sensors and microphones. Such high frequency data is normally not available in power plants. However, initiatives exist to collect such type of data and make it available for analysis purposes. Due to the absent of data from hydropower plans, the model development was carried out with publicly available test data from roller bearings used in laboratory tests, see section 4 for further details.

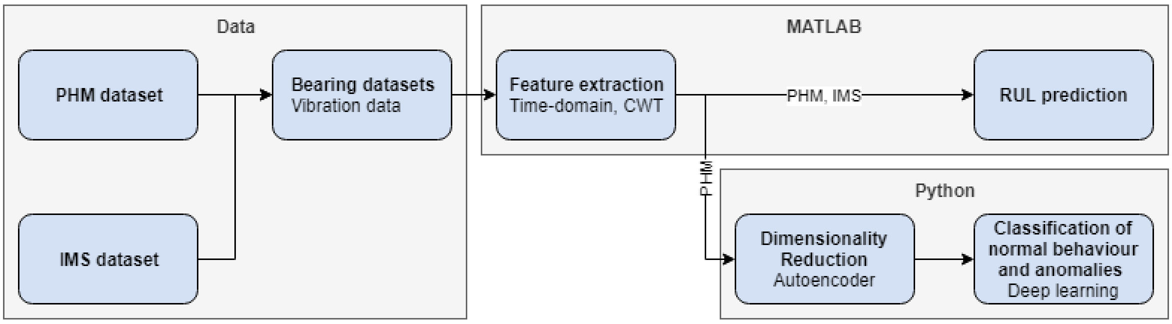
The case resulted in a set of models for analysis of the vibration data for the purpose of RUL estimation and anomaly detection and classification. The hydropower components of main interest for application of such models are the generator-turbine set including the bearings. The methods and algorithms developed may also be used for other rotating equipment in the power plants.

2. Benefit, motivation and potential users

The motivation of the case is to gain insights in potential use of bearing vibration data to classify normal behaviour of rotating equipment in hydropower plants and detect when it is likely that there is an anomaly in the hydropower plant. The bearing vibration data may also be used to predict the remaining useful life (RUL). If anomalous operating states in hydropower plants can be detected and classified, the plant operators may receive early alerts that the plant is not operating normally. It may then be possible to utilize available resources such as technical expertise or human personnel to initiate maintenance or to investigate what might cause the anomaly prior to contingencies resulting in costly hydropower plant disconnections. Similarly, if accurate remaining useful life predictions are achieved then the power plant operators may initiate maintenance procedures prior to equipment failure, while at the same time not replacing costly components long before failure would occur.

3. Methods and models

The different models (modules) used in this case, and dataflow and connection between the models/modules, is illustrated in the figure below.



CWT: Continuous wavelet transform (time and frequency domain). RUL: Remaining useful life.

Figure 1: Overview of datasets, methods applied and code in case 4.

The vibration data sets (PHM dataset and IMS dataset, see section 4 on "Input data") are passed to the feature extraction module. The RUL prediction in MATLAB utilizes both the PHM and the IMS dataset. The Python code uses only the PHM dataset.

Feature extraction and RUL prediction

Raw vibration data is used for feature extraction. For each dataset, the raw data is transformed into wavelets using the continuous wavelet transform (CWT). Wavelets are useful as they combine comprehensive details from both the time-domain and the frequency-domain. Statistical features based on wavelets (such as *crest factor*, *waveform factor*, *skewness*, *kurtosis*, etc.) depict the condition of the system. These features are then used in RUL prediction, modelled by a novel Twin Exponential Degradation (TED)-model for online prediction. The TED model aims to unify modelling of the whole evolving process from steady stage to incipient fault stage and even to rapid degradation stage (D4.1, [1]).

Dimensionality reduction and anomaly detection

The data is passed to an autoencoder [2] to reduce dimensionality of the features. The autoencoder attempts to reduce dimensionality by extracting the dataset's representative features (D4.2, [3]) and is shown in Figure 2.

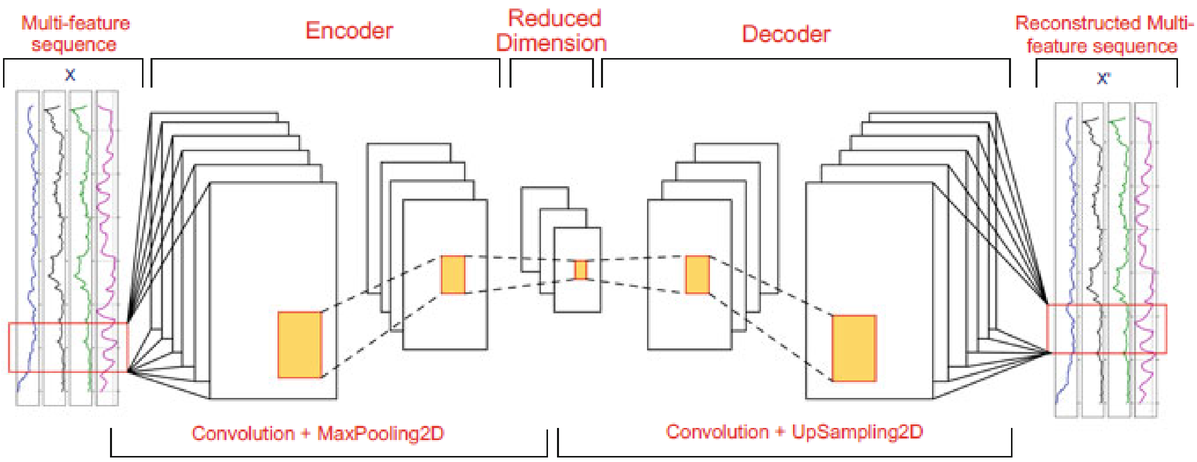


Figure 2: The structure of Convolutional Autoencoder with encoder subnetwork and decoder [3].

The data with reduced dimensionality is then passed to the normal behaviour and anomaly detection module. A deep learning model is implemented in Python using the neural network library "Keras" to classify normal behaviour and anomalies. For further details, see section 7 *Summary of results*.

4. Input data

The input data consists of two datasets, the Prognostics and Health Management (PHM) dataset [4] and the Intelligent Maintenance Systems (IMS) dataset [5]. The PHM dataset consists of bearing health monitoring data such as rotation speed, temperature, vibration and load force. The data is captured under a setup for accelerated degradation of bearings. The IMS dataset consists of vibration signal snapshots with sampling at 20 kHz occurring at frequent intervals. Please, see the given references for more details.

5. Other information

The original intention for this case was to use data acquired by ultrasonic (US) microphones at Svorka hydropower plant. The original case title was "audio surveillance". The original plan was to cooperate with an audio monitoring system supplier, and to install and use the system in cooperation with Andritz in a Statkraft power plan. However, the plan could not be finalized. Therefore, the dialogue with Statkraft led to an agreement that high frequency vibration and audio surveillance data was to be collected at the Svorka hydropower plant. After a format for the measurement data was specified (which was similar to the format for the IMS dataset, i.e. vibration snapshots) and a trial run to collect test data had been successfully completed, data collection for a longer time period was initiated. After the system had been collecting data for approximately half a year, the storage unit containing measurement data was retrieved, but the data was not present in the disk, either due to HDD failure or some other issue. An alternative data set for bearing vibrations was thus necessary.

The IMS and PHM datasets were selected for this purpose. In the meanwhile, the initial idea of audio surveillance was further developed as a concept and product by the MonitorX industry partners Voith (OnCare.Acoustic) and Andritz (see MonitorX case C3), and commercial solutions are or will soon come on the market.

6. Deliverables

The following deliverables have been prepared:

No.	Deliverable (description)	Author (person)	Type of deliverable	Reference
D4.1	Paper draft for Remaining Useful Life-prediction [1]	Jin Yuan, Kesheng Wang, Thomas Welte	Paper draft	Docs – D4.1
K4.1	Code for Remaining Useful Life-prediction	Jin Yuan	MATLAB Code	Code – K4.1
D4.2	Paper on deep learning approach to multiple features sequence analysis [3]	Jin Yuan, Kesheng Wang, Yi Wang	Paper	Docs – D4.2
K4.2	Code for AutoEncoder, classification of normal behaviour and anomalies	Jin Yuan	Python code	Code – K4.2

7. Summary of results

D4.1 - Remaining Useful Life Prediction

The TED model can reasonably accurately estimate the remaining useful life (RUL). To do so, it requires suitable prior knowledge in the form of a failure threshold. The failure threshold must be selected based on previous experience or must be judged by experts. Two run-to-failure benchmark datasets of bearings are used to validate the effectiveness of the TED model online RUL prediction. The results indicate that the TED model approach performs well at predicting RUL in the steady stage of the degradation process. In most cases, the estimated RULs fall into or close to the confidence bounds.

Example results are given in Figure 3. RUL estimation is based on trending the health indicator. In the beginning, illustrated in the left diagram for the (current) time 426[1], the uncertainty regarding further development of the indicator is quite large. This is indicated with the blue lines representing different possible trajectories for the further health indicator development. The red line is the mean (expected) development, representing the mean lifetime of the bearing, given the observations until current time. As more data become available, the uncertainty decreases and the prediction for lifetime is updated. The middle and right diagram illustrate how the uncertainty decreases as more data becomes available. The RUL estimate, which is the difference between current time and predicted lifetime, is also updated as more data becomes available.

[1] The time may be measured e.g. in hours, or operational hours, or as data/indicator count, meaning that 426 represents the 426th time that the health indicator that is calculated. If, e.g. the health indicator is calculated every 6th hours of operation, 426 corresponds to 2556 hours of operation time.

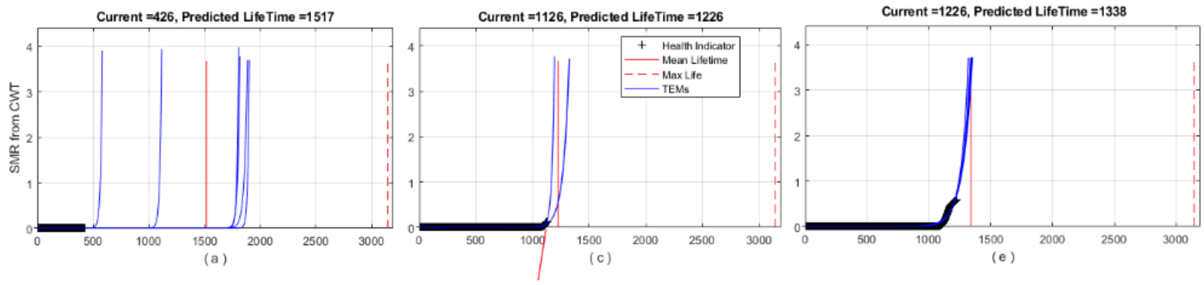


Figure 3: Lifetime prediction and RUL estimation, and updating step by step over time, illustrated for three examples representing different times in early life (left, current time = 426), middle of the life (middle, current time = 1126) and close to end of life (right, current time = 1226); D4.1 [1].

D4.2 - Deep learning approach to multiple features sequence analysis

The features calculated based on the vibration raw data were in the Python module for anomaly detection and condition (health state) classification analyses by means of the autoencoder approach. Different types of autoencoder have been tested, and some of the results are shown in Figure 4 for a fully connected and a convolutional autoencoder. The convolutional AutoEncoder (b) is, in contrast to the fully connected AutoEncoder (a), able to reduce the high-dimensional data to a lower dimensional feature space that shows clear clusters developing over time (the colours in the figure represent the time), representing the development of the condition of the bearings over time.

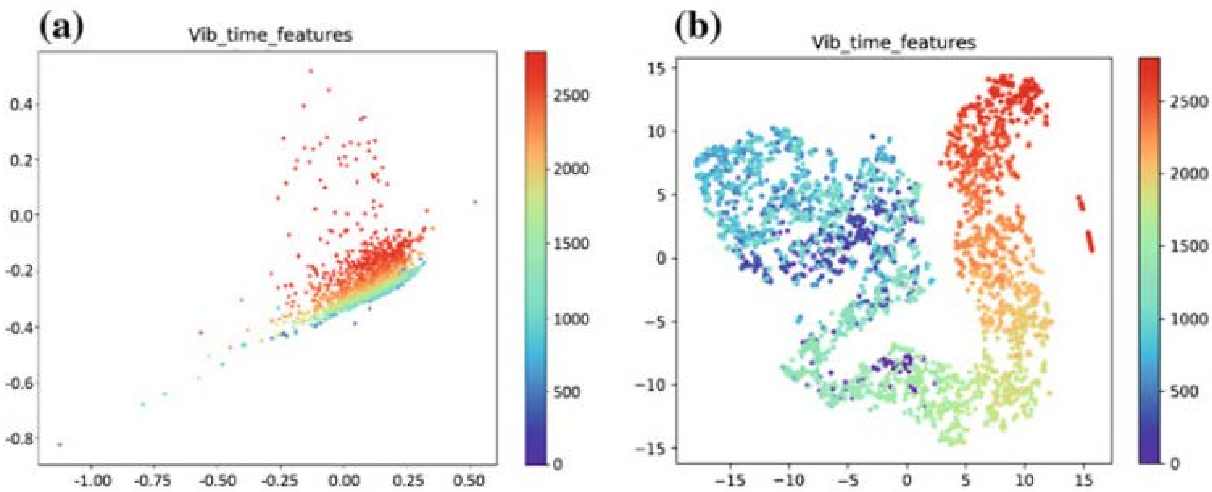


Figure 4: Visualization of deterioration process of bearing life cycle dataset in 2-dimensional space and using (a) a fully connected AutoEncoder, and (b) a convolutional AutoEncoder; D4.2 [3].

Using the results from the convolutional autoencoder, a clustering scheme with 7 clusters has been used, and the changes of the condition of a bearing over its lifetime can be plotted, as illustrated in Figure 5. Figure 5 shows that the condition of the bearing gradually moves from cluster 1 (where the condition may be *as good as new*) to cluster 7 (where the condition may be considered as *major degradation/large anomalies*). Albeit the signal is noisy or jittery, we see that there is some change occurring over time.

Such a clustering technique and evolution of condition over bearing life may help decision making in predictive maintenance as multiple features sequences may be classified into clusters representing the condition of the bearing. The clustering approach is an example of an anomaly classification (i.e. the classification of anomalies in different states from slight to large/significant) and allows for monitoring the development of degradation from a condition *as good as new* (no degradation, no anomalies, normal behaviour) to a condition with major degradation (large anomalies).

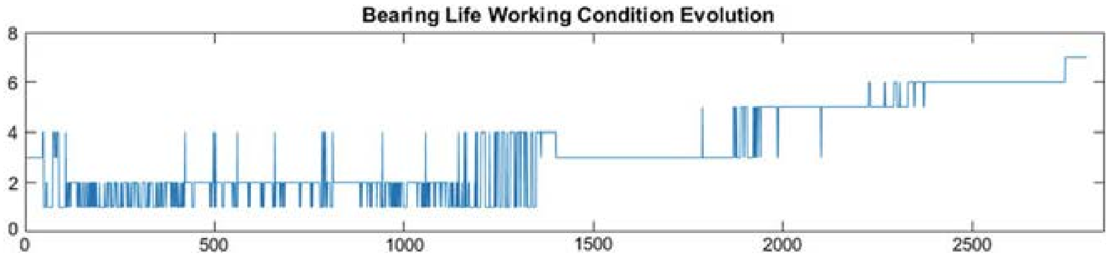


Figure 5: Anomaly classification (classification in condition states 1 to 7) and evolution of condition over bearing life; D4.2 [3].

8. Implementation of results

The code has not been implemented at any industry partners' locations, since the models were developed with data from bearing lifetime test set-ups. Test set-ups were used due to lack of data from industry partners' hydropower plants. See section 5 for details.

9. References

[1] J. Yuan, K. Wang, and T. M. Welte, “Twin Exponential Degradation Model for Online Remaining Useful Life Prediction,” Paper draft, May-2019.
[2] Wikipedia, “Autoencoder.” [Online]. Available: https://en.wikipedia.org/wiki/Autoencoder.
[3] J. Yuan, K. Wang, and T. M. Welte, “Deep Learning Approach to Multiple Features Sequence Analysis in Predictive Maintenance,” in *Advanced Manufacturing and Automation VII*, Changshu, China, 2017.
[4] P. Nectoux *et al.*, “PRONOSTIA: An Experimental Platform for Bearings Accelerated Life Test,” presented at the IEEE International Conference on Prognostics and Health Management, Denver, CO, USA, 2012.
[5] J. Lee, H. Qiu, G. Yu, J. Lin, and and Rexnord Technical Services (2007). IMS, University of Cincinnati, “Bearing Data Set,” NASA Ames Research Center, Moffett Field, CA.

Appendix E

Case No.:	**C5**
Title:	**Condition monitoring of generator bearings**
R&D partners:	Miguel A. Sanz-Bobi, Pablo Calvo Bascones (Comillas) Jin Yuan (NTNU) Thomas Welte, Torfinn Tyvold (SINTEF)
Industry partners:	Tarald Espeland (BKK)
Date:	06.06.2019
Editor(s):	Jørn Foros, Espen Hafstad Solvang, Thomas Welte (SINTEF)

MonitorX Case C5 – Condition monitoring of generator bearings

1. Short description (abstract)

In this case, the condition of generator bearings is studied using SCADA data. Bearing data from BKKs Dale and Nygard hydropower plants have been received and analysed. Both Dale and Nygard are reservoir power plants with Francis turbines.

To enable dynamical condition monitoring, models for the normal behaviour of bearing temperature have been built and trained using artificial neural networks (ANNs). Applying the resulting model to other data than the training data set, the model can be used to identify deviations from expected behaviour. The viability of the approaches is demonstrated, and promising results have been achieved.

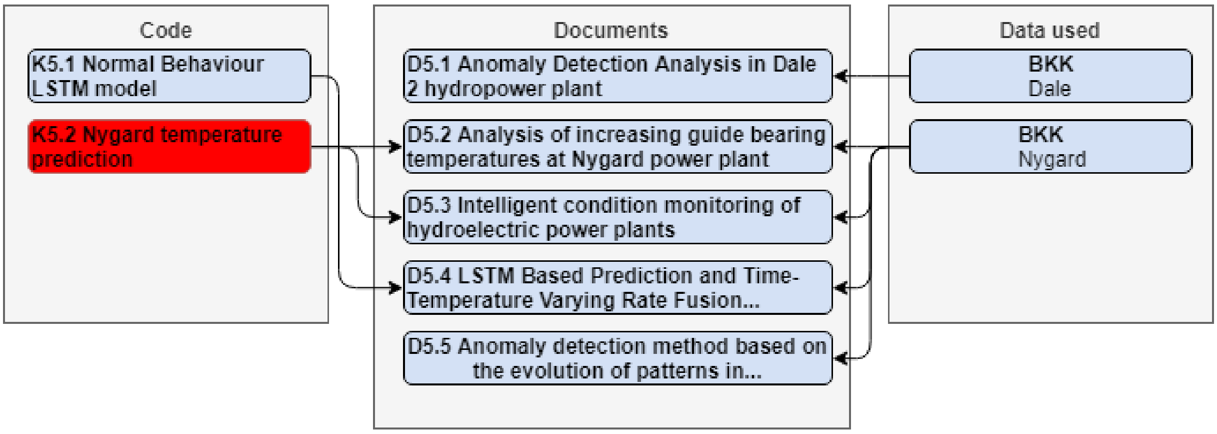


Figure 1: Overview of MonitorX case C5.

2. Benefit, motivation and potential users

Bearings are important components that have been known to cause problems when aging, such as vibrations, bearing damages, lubrication problems or misalignment problems. Thus, monitoring bearings is useful for detecting problems at an early stage. The aim of this case is to develop algorithms for early detection of bearing degradation or faults using available SCADA data.

The potential users are hydropower companies that have a system with automatic measurements of required parameters available for remote monitoring and analysis, or will acquire such a system, and thus can implement the models in their systems. Other potential users are maintenance system vendors that deliver condition monitoring solutions and predictive maintenance services.

3. Selected power plants for testing

BKKs Dale and Nygard are both reservoir power plants with Francis turbines located in Hordaland, Norway. Dale [1] is located in the Bergsdalen river system in Vaksdal and has output 146 MW and average annual production 677 GWh. Production started in 1927 and the latest reconstruction was in 2007 with a new generator. Nygard [2] is a pumped storage power plant located in Modalen with output 56 MW and average annual production 91 GWh. Production started in 2005.

4. Methods and models

Normal behaviour models have been built using artificial neural networks. Both multilayer perceptron [3], recurrent neural networks [4], self-organizing maps [3], [5] and long short-term memory (LSTM) neural networks [6] have been used. The models analyse the normal relation between multiple parameters, such as power, bearing temperature and bearing vibration. The modelling consists of the following general steps:

1. Data collection.
2. Data pre-processing. This includes as necessary e.g. filtering, removing of outliers, treatment of missing data, and converting to a suitable format.
3. Data selection. This includes extracting variables for the analysis, i.e. variables that characterize or correlate to the quantity of interest, which in this case is the bearing temperature. This selection is based on a physical understanding of the system and/or statistical analysis.
4. Building of normal behaviour pattern. This includes building the model artificial neural networks (ANN) and training it to know the normal behaviour of selected parameters. It is vital that a training data set that covers all typical operating conditions is used.
5. Anomaly detection. This means to apply the model to a data set differing from the training data set to analyse it for deviations from normal behaviour, which may be an indication of degradation or a developing fault.

The models are data driven and relatively advanced, i.e. specialized competence is required to utilise them. The models depend on the system design and available data. Data selection and building of normal behaviour patterns hence differ for the plants. The models developed for the Dale power plant are described in more detail in reference [3]. The models developed for the Nygard power plant are described in more detail in references [4], [5] and [6].

5. Input data

Data from Dale (BKK) from 2008 – 2017 and Nygard (BKK) from 2007 – 2017 was received as Excel files. The data are 1-hour average values. This resolution was sufficient to model effects that does not vary much and that have long time constants, such as temperature developments in bearings.

The following data has been utilised for the models:

- Active power (for Nygard)
- Guide vane opening (for Nygard)
- Guide bearing temperature (for Dale and Nygard)
- Thrust bearing temperature (for Nygard)
- Guide bearing vibration (for Dale and Nygard)
- Guide bearing oil level (for Dale)

Note that somewhat different data has been utilised to build the models, as commented in parentheses. Some other parameters were also received but not used in the models.

6. Other information

None.

7. Deliverables

The following deliverables have been prepared:

No.	Deliverable (description)	Author (person)	Description	Reference
D5.1	Anomaly Detection Analysis in Dale 2 hydropower plant	M. A. Sanz-Bobi (Comillas University)	Project memo	Docs – D5.1 [3]
D5.2	Analysis of increasing guide bearing temperatures at Nygard power plant	T. Tyvold (SINTEF)	Project memo	Docs – D5.2 [4]
D5.3	Intelligent condition monitoring of hydroelectric power plants	T. Tyvold (SINTEF)	Presentation poster	Docs – D5.3 [7]
D5.4	LSTM Based Prediction and Time-Temperature Varying Rate Fusion for Hydropower Plant Anomaly Detection	J. Yuan (NTNU)	Scientific paper	Docs – D5.4 [6]
D5.5	Anomaly detection method based on the evolution of patterns in industrial components. Application to a hydropower plant	P.C. Báscones, M. A. Sanz Bobi (Comillas University)	Paper draft	Docs – D5.5 [5]
K5.1	Normal Behaviour LSTM model	J. Yuan (NTNU)	Python code	Code – K5.1
K5.2	Nygard temperature prediction	T. Tyvold (SINTEF)	Python code	Code – K5.2

8. Summary of results

For Dale, normal behaviour models were built using both self-organized maps and multilayer perceptrons (D5.1, [1]). Self-organized maps were built using data for guide bearing vibration, temperature and oil level. It was illustrated how such maps can identify and illustrate patterns of normal behaviour for the guide bearing from these parameters, and how this can be used for anomaly detection. Similarly, a multilayer perceptron model was built for predicting the normal behaviour for the guide bearing vibration in the y-direction from the following parameters: Vibration in the x-direction, bearing temperature and oil level.

Selected results for the latter model are shown in Figure 1. The left figure illustrates the training of the model, and the right figure the testing of the model for anomaly detection. It is seen that the model fits the test set poorly. This is because it was difficult to define a suitable period of normal behaviour based on the available data (from year 2011 – 2012), since the data changed significantly from 2011 to 2012.

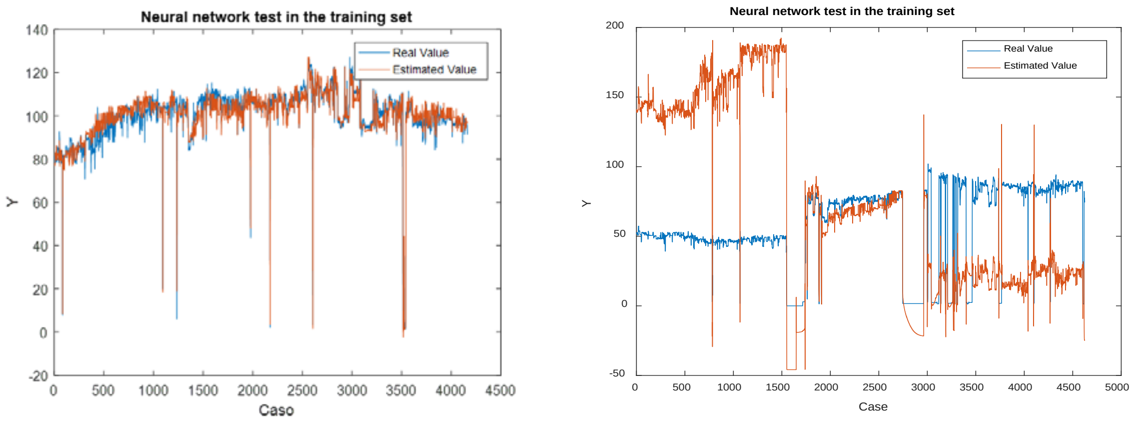


Figure 2: Estimated value from the multilayer perceptron model and real measured value for the guide bearing vibration for the training data set (left) and the test data set (right) for Dale; D5.1 [1].

For Nygard, a normal behaviour model was built using a recurrent neural network, see D5.2 [4]. The model predicts the guide bearing temperature from the current power, as well as from previous measurements of power and temperature (i.e. from one and two hours earlier). This is hence a model that possess memory. Selected results for the model are shown in Figure 2. The upper figure illustrates the training of the model, and the lower figure the testing of the model for anomaly detection. It is seen that the model fits the test set poorly. This is because the training data set was not from a period of normal behaviour, but rather from a period showing continuously increasing guide bearing temperatures. This is confirmed by BKK who discovered the increasing guide bearing temperature in 2017. An inspection done by GE Renewable Norway AS indicated that the cause of the steady temperature increase was most likely wear and tear or guide bearing skewness.

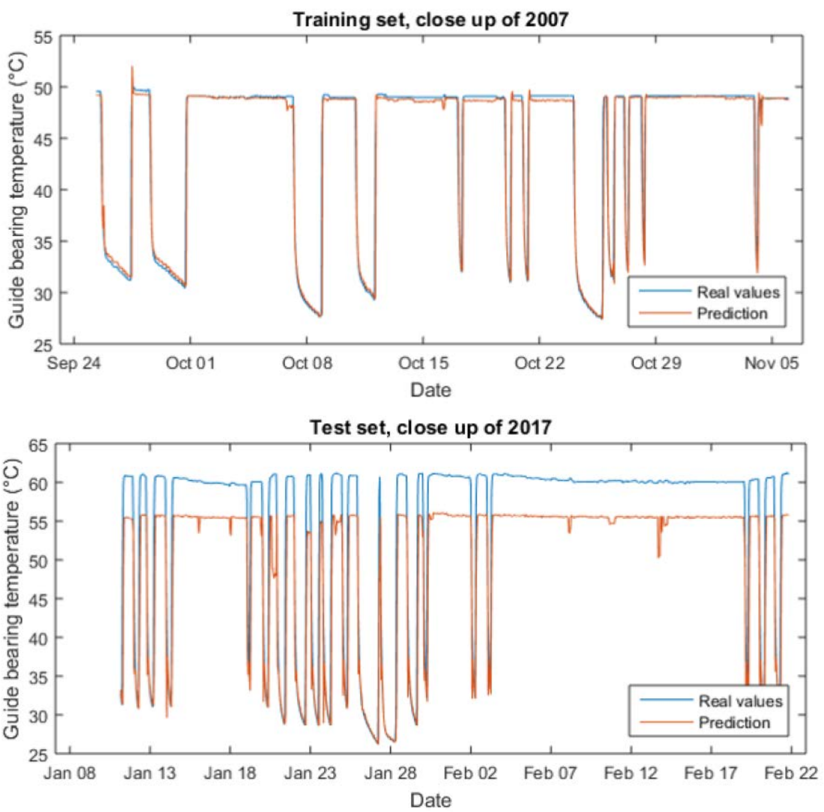


Figure 3: Estimated value from the neural network model and real measured value for the guide bearing temperature for the training data set (upper) and the test data set (lower) for Nygard, D5.2 [4].

The challenge for the above analyses is that the data sets for which the models have been trained do not represent a period of stable normal behaviour, because a degradation process (bearing wear) is ongoing, resulting in a continuously changing situation with increasing damage and bearing temperature. To overcome this problem, a long short term memory (LSTM) neural network model was tried instead [6]. LSTM is one of the most successful modern recurrent neural networks architectures for sequence learning tasks. An LSTM model was built for the Nygard power plant to predict the current bearing temperature from a sequence of foregoing measurements of the temperature. Selected results for the LSTM model are shown in Figure 3. The upper left diagram illustrates the training of the model, the lower left diagram the testing of the model, the upper right diagram the testing of the model compared with actual measurements, and the lower right diagram the model error (the difference between the predicted and measured values). It is in the two right diagrams seen that the model at first predicts the increasing bearing temperature well, but that the prediction gradually deviates from the actual measured values. This is seen as a sign of anomalies, i.e. that the way in which the bearing temperature is increasing is changing.

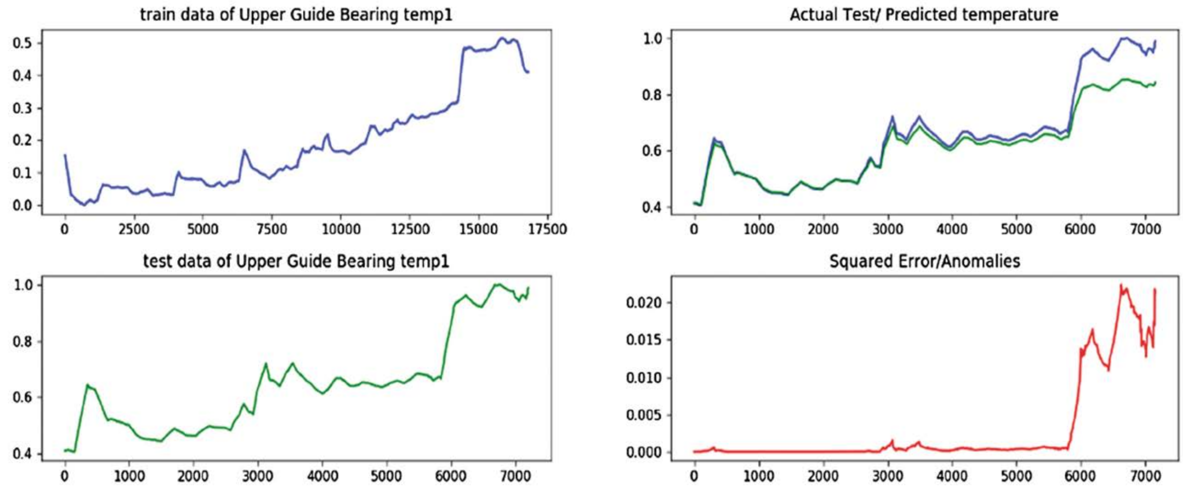


Figure 4: LSTM based prediction of upper guide bearing temperature; D5.4 [6].

Finally, a clustering technique was tried for the Nygard power plant (D5.5, [5]) using data for active power, guide vane opening and bearing temperature. It was illustrated how such a technique can identify and illustrate patterns of normal behaviour for the bearing in terms of these parameters. The year 2011 was used as the reference year with which patterns of subsequent years were compared. Pattern comparison is done in terms of the pattern's similarity value and the difference in the value of the underlying observations. Through this comparison deviations from the reference behaviour can be identified. Selected results are shown in Figure 5. The pattern comparison confirmed again that an abnormal bearing temperature is developing at Nygard. This is evident from the similarity value in Figure 5, which quickly becomes small after the reference year 2011.

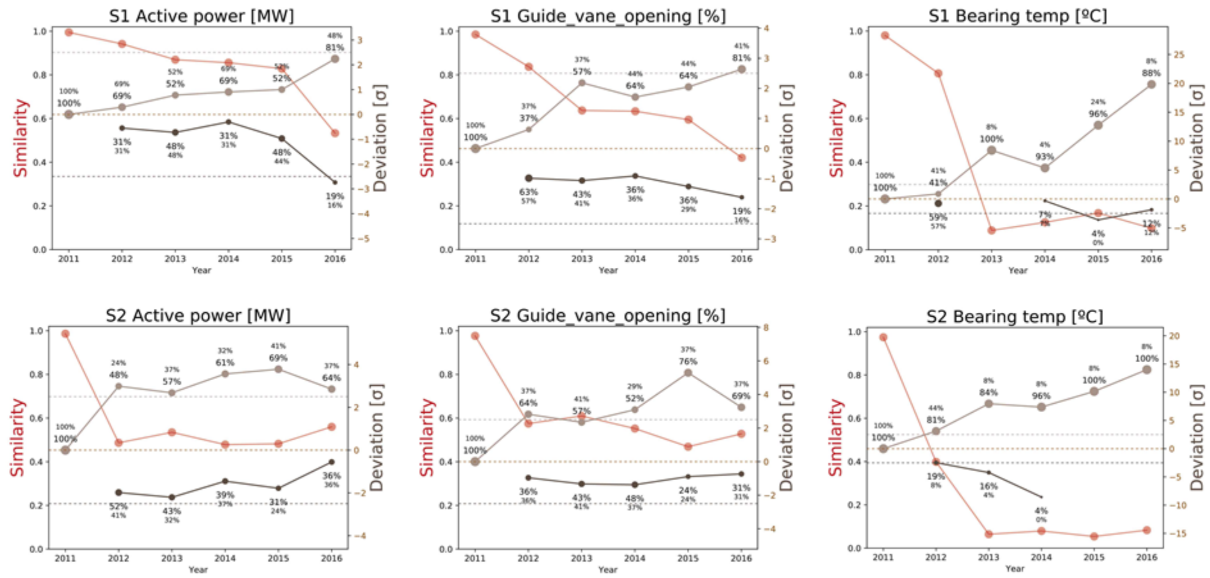


Figure 5: Results from pattern comparison of clusters built with the parameters active power, guide vane opening and bearing temperature. The three top figures apply when the power plant is pumping (S1), while the three bottom ones apply when it is producing power (S2). The results show the similarity value and the deviation of the patterns per year as compared to the pattern of the reference year 2011. Deviation are based on comparing new observations in the years 2012-2016 with a reference pattern from year 2011 (centroid of 2011 observations). Deviations can be positive (+) and negative (-), with zero deviation in year 2011, and increasing deviation over the years, indicating increasing deviations. See D5.5 [5] for further details.

9. References

[1] BKK, "Dale kraftverk." [Online]. Available: https://www.bkk.no/vannkraft/dale.

[2] BKK, "Nygard kraftverk." [Online]. Available: https://www.bkk.no/vannkraft/nygard.

[3] M. A. Sanz-Bobi, "Anomaly detection analysis in Dale 2 hydropower plant," IIT Comillas University, Mar. 2017.

[4] T. Tyvold, "Analysis of increasing guide bearing temperatures at Nygard power plant," SINTEF Energy Research, Trondheim, Aug. 2017.

[5] P. C. Báscones and M. Á. Sanz Bobi, "Anomaly detection method based on the evolution of patterns in industrial components. Application to a hydropower plant," paper draft, 2019.

[6] J. Yuan, Y. Wang, and K. Wang, "LSTM Based Prediction and Time-Temperature Varying Rate Fusion for Hydropower Plant Anomaly Detection: A Case Study," in *Advanced Manufacturing and Automation VIII*, 2019, pp. 86–94.

[7] T. Tyvold, "Intelligent condition monitoring of hydroelectric power plants," presented at the SINTEF Sommerforskerkonferanse, Trondheim, 17-Aug-2019.

Appendix F

Case No.:	**C6**
Title:	**Condition monitoring of Kaplan turbine hydraulic system**
R&D partners:	Miguel A. Sanz-Bobi, Beatriz Garcia Alejo (Comillas) Thomas Welte, Eivind Lie Andreassen (SINTEF)
Industry partners:	Lasse Eilertsen (Glitre) Magnus Holmbom (Vattenfall)
Date:	04.06.2019
Editor:	Jørn Foros, Espen Hafstad Solvang, Thomas Welte (SINTEF)

MonitorX Case C6 – Condition monitoring of Kaplan turbine hydraulic system

1. Short description (abstract)

In this case the condition of the hydraulic regulating system of Kaplan turbines is studied. A Kaplan turbine is regulated by adjusting the position of the wicket gates and the turbine runner blades. This is done by a high-pressure hydraulic system, typically consisting of an oil tank, oil pumps, valves, filters, coolers, and accumulator banks for the wicket gates and runner blades. To enable dynamical condition monitoring of this system, models that predict the turbine normal behaviour have been built.

Turbine data from Glitres Embretsfoss IV and Vattenfalls Laxede hydropower plants have been analysed. Using machine learning algorithms, normal behaviour models were developed for e.g. the level in the oil tank. Comparing the model predictions with actual measurements, deviations from normal behaviour can be identified. For both Embretsfoss and Laxede, good results were achieved. An overview of codes, documents and data used for case C6 is given in Figure 1.

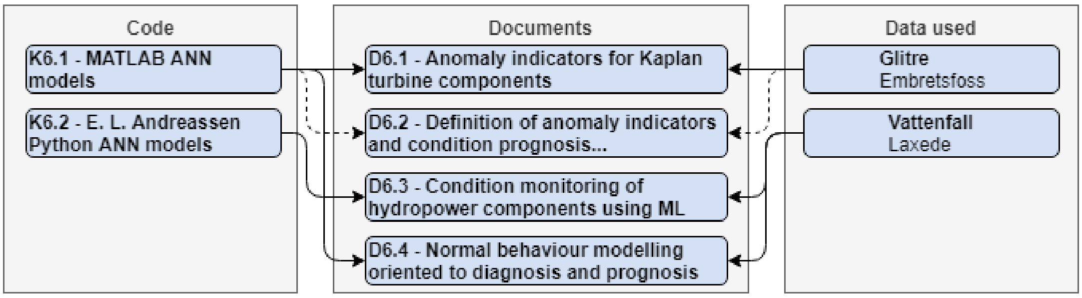


Figure 1: Overview of MonitorX case C6.

2. Benefit, motivation and potential users

The motivation for this work is that the Kaplan propeller and hub is not accessible for inspection during production. A method for online condition monitoring without the need for unwanted production stops is therefore desirable. The hydraulic system is of special interest as it is vital for the control of the turbine, and because oil leakages is a known issue.

The potential users are hydropower companies that have a system with automatic measurements of required parameters available for remote monitoring and analysis, or will acquire such a system, and thus can implement the model in their systems. Other potential users are maintenance system vendors that deliver condition monitoring approaches for predictive maintenance.

3. Selected power plants for testing

<u>Embretsfoss</u>

Embretsfoss IV is a run-of-river hydropower plant in the river Drammenselva in the Buskerud county, Norway. The power plant has a single 7m in diameter Kaplan turbine, making it one of Norway's largest Kaplan turbines. It has a head of 16.3m and a water discharge of 340 m^3/s. It has a capacity of 52.5 MW and a yearly production of 270 GWh/year. The power plant was commissioned in 2013 and is operated by Glitre Energi Produksjon.

<u>Laxede</u>

Laxede is a hydro power plant in the river Luleälven in the Norrbottens county in the north of Sweden. The power plant is equipped with Kaplan turbines, and it has a head of 25m and a water discharge of 570m^3/s. It is owned and operated by Vattenfall.

4. Methods and models

The models are built with artificial neural networks (ANNs) or support vector machines. The models predict the normal state of a variable, e.g. the oil level, from other explanatory variables. The modelling consists of the following general steps:

1. Data collection.
2. Data pre-processing. This includes filtering, removing of outliers, treatment of missing data, and converting to a suitable format if necessary.
3. Data selection. This includes extracting relevant variables, i.e. the explanatory variables for the variable to be predicted. This selection is based on a physical understanding of the system and/or statistical analysis.
4. Building of normal behaviour model. This includes building e.g. an ANN model and training it to represent the normal behaviour for a signal (measured quantity) of interest as a function of several other signals. It is vital that a training data set covers all typical operating conditions.
5. Anomaly detection. This means to apply the model to detect when the predicted variable deviates from the expected value (i.e. the measured value), which may be an indication of degradation or a developing fault.

The models are data driven, i.e. the physical relationship between variables is not investigated or utilised. This is an advantage in cases where this relationship is not known, or where no other good models are available to explain and predict the operational behaviour of the plant/components. The models are relatively advanced, i.e. specialized competence about machine learning models in general, and ANNs in particular, is required to utilise them.

The models depend on the system design and available data, which differs for the Embretsfoss and Laxede plants. Data selection and building of normal behaviour patterns hence differ somewhat for the Embretsfoss and Laxede models. The models developed for the Embretsfoss power plant are described in more detail in deliverable D6.1 [1]. The models developed for the Laxede power plant are described in more detail in deliverables D6.3 [2] and D6.4 [3].

5. Input data

Data from Embretsfoss (Glitre) from 2015 – 2017 was received as Excel files. Data from Laxede (Vattenfall) has been received live via an OSIsoft PI server that was in operation and connected to Vattenfall's OSIsoft PI server from autumn 2017. In addition, earlier data starting from May 2016 was received from Laxede in Excel files.

The following data has been utilised for the models:

- Generated power
- Wicket gate position
- Runner blade position (only for Laxede)
- Head water level
- Tail water level (only for Embretsfoss)
- Turbine water flow (only for Embretsfoss)
- Turbine spiral pressure (only for Laxede)
- Hydraulic oil tank level
- Hydraulic oil tank temperature
- Hydraulic oil pressure (only for Laxede)
- Wicket gate accumulator bank level, all accumulators

- Runner blade accumulator bank level, all accumulators
- Oil cooler temperature, oil in, all coolers (only for Laxede)
- Oil cooler temperature, oil out, all coolers (only for Laxede)
- Oil cooler temperature, water in, all coolers (only for Laxede)
- Oil cooler temperature, water out, all coolers (only for Laxede)

Note that somewhat different data has been utilised to build the models for Embretsfoss and Laxede, as commented in parentheses. Some other parameters were also received but not used in the models.

Data pre-processing

Data pre-processing is concerned with preparing the raw data for input to the methods and models. Several methods may be applied to pre-process the data. The following describes some methods that have been attempted in some cases. Failure messages such as "Comm Fail" or "Bad" may be mapped to *NaN* (Not a number) values. Boolean fields with values such as "on" or "off" may be mapped to programming standard values "True" or "False" respectively. Further, columns that lack many data points may be dropped, as was done in D6.3 [2] where columns that were less than 75% full were dropped. Further, the data may be noisy and contain erroneous measurements that are outliers among correct measurement readings. Extreme outliers may be removed by e.g. dropping data that is more than 5 standard deviations away from the mean of their respective columns.

6. Other information

None.

7. Deliverables

The following deliverables have been prepared:

No.	Deliverable (title)	Author (person)	Description	Reference
D6.1	Anomaly indicators for Kaplan turbine components based on patterns of normal behavior	M. A. Sanz-Bobi (Comillas) et al.	Conference proceeding (ESREL)	Docs – D6.1 [1]
D6.2	Definition of anomaly indicators and condition prognosis in components of a hydropower plant	B. Garcia Alejo (Comillas)	Master thesis, spring 2018	Docs – D6.2 [4]
D6.3	Condition monitoring of hydropower components using machine learning	E. L. Andreassen (SINTEF)	Memo, summer internship 2018	Docs -D6.3 [2]
K6.1	Matlab ANN models	M. A. Sanz-Bobi (Comillas)	Matlab code for training of ANN and fault detection (prediction)	Code – K6.1
K6.2	Python ANN models	E. L. Andreassen (SINTEF)	Python code (tensor flow) for training of ANN and fault detection (prediction)	Code – K6.2
D6.4	Normal behaviour modelling oriented to diagnosis and prognosis	M.A. Sanz-Bobi (Comillas)	Technical report	Docs – D6.4 [3]

8. Summary of results

<u>Embretsfoss</u>

For Embretsfoss, two multilayer perceptron neural networks were built to model the normal behaviour of the generated power and the hydraulic oil tank level; see D6.1 [1]. The first model predicts the generated power from the wicket gate position, water flow, and the difference between headwater and tailwater levels. The second model predicts the oil tank level from the generated power, oil tank temperature, and the oil level in one of the accumulators.

The results obtained from the models were very good. Selected results for the model for oil tank level are shown in Figure 2. The left figure illustrates the training of the model, and the right figure testing of the model for anomaly detection. It is seen that the model accurately predicts the systems normal behaviour for the training set (left), and that an apparent anomaly is detected in the test set (right). The increasing deviation between the model and real data in the test set indicates a possible fault or an oil leakage. The leakage in an accumulator (from oil to gas side) was confirmed by Glitre.

To verify the robustness of this modelling approach, the Embretsfoss turbine was also analysed in a master thesis; see D6.2 [4]. It was confirmed that multilayer perceptron neural networks can predict normal behaviour of the hydraulic oil system very well. Models were also built using support vector machines and radial basis functions, showing results that were somewhat less good.

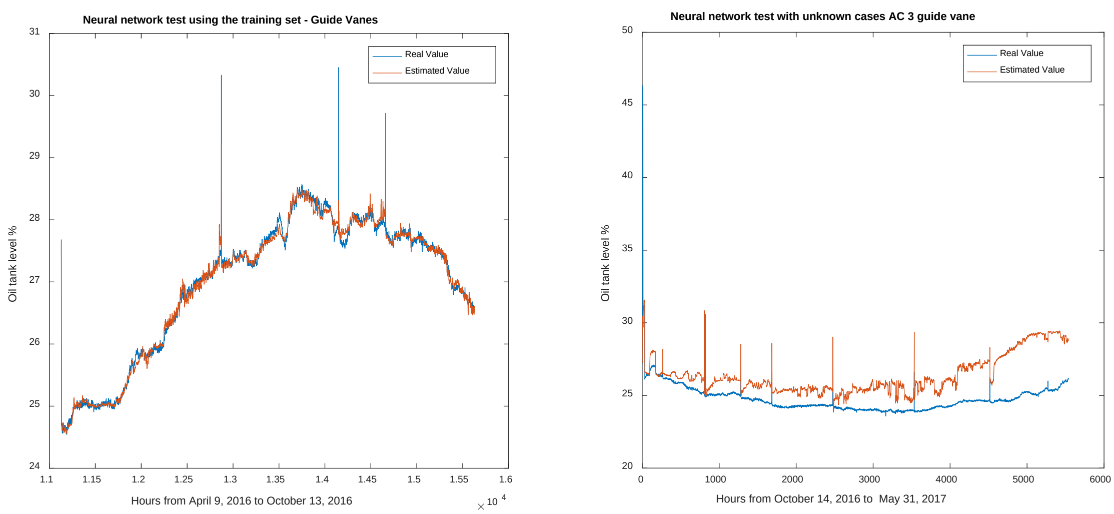


Figure 2: Estimated value from the ANN model and real measured value for the oil tank level for the training data set (left) and the test data set (right) for Embretsfoss; D6.1 [1].

Laxede

Similar models were also tested by SINTEF and Comillas on data from Vattenfalls hydropower plant Laxede (D6.3 [2] and D6.4 [3]). The test confirmed the ability of ANNs to predict the behaviour of Kaplan turbines. An example of prediction of oil cooler exit temperature is shown in Figure 3. A simpler linear regression model was also tested for modelling the power for the Laxede turbine, giving results with accuracy similar to an ANN model.

The Laxede Kaplan hydraulic system has two sensors for oil level in the oil tank. Thus, two ANN models were built, one for the oil level measured by sensor no. 1 and one for the oil level measured by sensor no. 2. In Figure 3, left part, the predicted oil tank level for Laxede is shown versus the real[1] (measured) oil tank level for an ANN model for sensor 2. Only the test data set is shown. Discrepancies can indicate a problem in the hydraulic system but does not reveal the cause of the problem. Figure 4, right part, then presents the time instants in which the model error (difference between the measured and the predicted oil tank level) in the testing period is greater than what was observed during the training of the ANN model. These anomalies are intermittent and therefore do not indicate a serious oil leakage problem. Investigations indicate that some of the anomalies may instead be due to maintenance work.

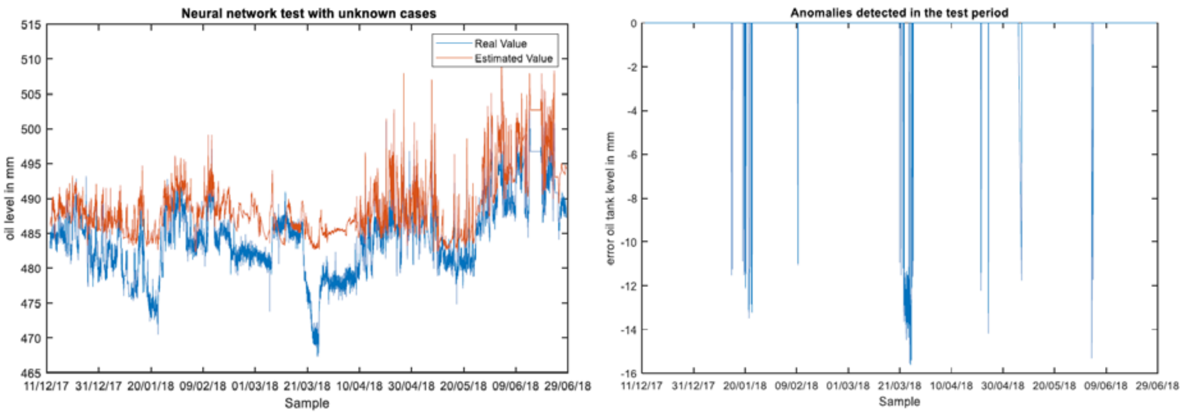


Figure 3: Sensor 2: Real oil tank level and predicted oil tank level for the testing period (left), and anomaly detection (right); D6.4 [3].

Similar to sensor 2 and Figure 3, the results for an ANN model for sensor 1 are shown in Figure 4. The anomalies for sensor 1 are large and the error is increasing over a longer period until the anomalies disappear. The cause for these anomalies is a sensor error. The measurements from sensor 1 are drifting, and the sensor measured increasingly too low oil levels, until it has been calibrated end of November 2017. When two or more sensors are installed, such sensor errors can easily be detected by comparing the measurements from the sensors. However, when only one sensor is installed, the ANN model provides a method of detecting sensor errors in an early stage. However, the model will not help to detect the cause of anomalies. Thus, when anomalies are detected, one should first check if the sensor is miscalibrated or there are other errors with the oil level measurements. Note that the erroneous oil level measurements may also be caused due to problems and errors of the system for data transfer and collection. When the oil level measurements are correct, the cause for the anomalies may be oil leakages and other faults in the power plant.

[1] Note that the term "real value" may be confusing, since the real value in this case represents the measured value (i.e. the value received from the sensor and stored in the data base). However, if there is a sensor or other measurement and data collection errors, the measured value does not correspond to the real oil level in the tank.

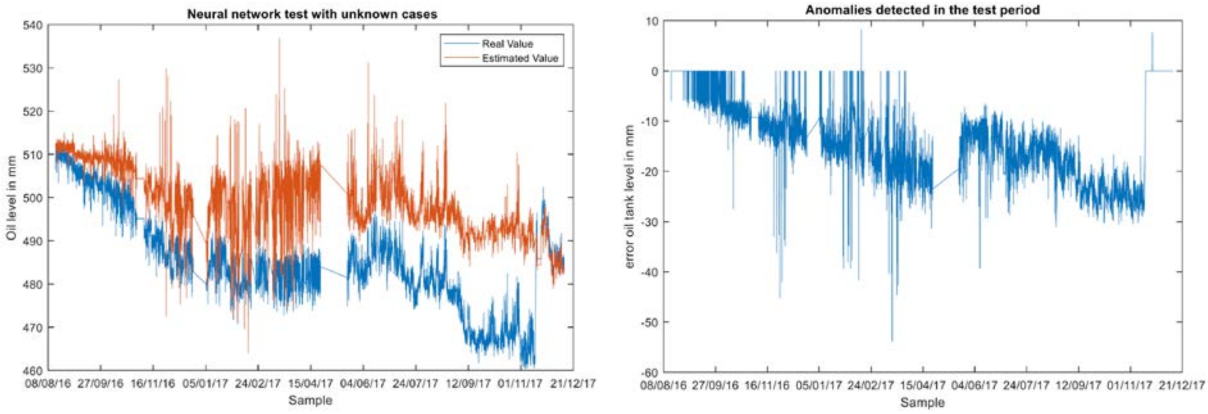


Figure 4: Sensor 1: Real oil tank level and predicted oil tank level for the testing period (left), and anomaly detection (right); D6.4 [3].

9. Plans for further work

Skellefteå Kraft has started a cooperation with a master student (Tina Stark) where the ANN models described above are tested with data from their power plants. The work is still ongoing, and results are therefore not described here.

10. References

[1] M. A. Sanz-Bobi, T. M. Welte, and L. Eilertsen, “Anomaly indicators for Kaplan turbine components based on patterns of normal behavior,” in *Proceedings of ESREL*, Trondheim, 2018.

[2] E. L. Andreassen, “Condition monitoring of hydro power components using machine learning,” SINTEF Energy Research, Trondheim, memo, Aug. 2018.

[3] M. A. Sanz-Bobi, “Normal behavior modelling oriented to diagnosis and prognosis,” Comillas Pontifical University, Santa Cruz de Marcenado, Madrid, Technical Report 4.0, Feb. 2019.

[4] B. G. Alejo, “Definition of anomaly indicators and condition prognosis in components of a hydropower plant,” Master thesis, Comillas Pontifical University, Madrid, 2018.

[5] E. L. Andreassen, “Python Production Server,” *GitHub*. [Online]. Available: https://github.com/Lagostra/python-production-server. [Accessed: 09-Apr-2019].

Appendix G

Case No.:	**C7**
Title:	**Condition monitoring for power transformers**
R&D partners:	Eivind Lie Andreassen, Thomas Welte, Jørn Foros (SINTEF)
Industry partners:	Aslak Hauggrav (Skagerak Energi Kraft)
Date:	04.06.2019
Editor(s):	Jørn Foros, Thomas Welte

MonitorX Case C7 - Condition monitoring for power transformers

1. Short description (abstract)

The aim of this case was to develop a model to describe the temperature behaviour of power transformers based on operational data. The normal operational behaviour of the transformer is modelled for an initial reference period, so that the model can be used to identify deviations from the normal behaviour for later periods. This can e.g. identify a cooling system fault.

An artificial neural network (ANN), similar to the one used in MonitorX case C6 (Kaplan turbine), have been applied in this case. The top oil temperature is modelled with the ANN, and deviations of the observed temperature from the modelled temperature is an indicator of fault.

2. Benefit, motivation and potential users

The condition of the winding insulation paper is regarded as one the main life-limiting factors for power transformers. The condition of the paper is determined by the temperature it is exposed to. To avoid high temperatures, an efficient and working cooling system is therefore important. Monitoring the cooling system can identify if the system is performing poorly, giving the transformer owner a chance to fix the system and thereby prolong the transformer life. The potential users are hydropower companies as well as grid operators. Other potential users are maintenance system vendors that deliver condition monitoring approaches for predictive maintenance.

3. Selected power plants for testing

Uvdal 1 (Skagerak Energi Kraft) is a reservoir power plant located in Uvdal in Buskerud. It has output 92 MW and average annual production 320 GWh. Production started in 1966.

4. Methods and models

A feed forward neural network with a single hidden layer consisting of 10 nodes was used to model the top oil temperature. The top oil temperature was modelled as a function of the load on the transformer and cooling water temperature. In addition, a recurrent neural network was tried. This network had two hidden layers: an LSTM layer with 10 nodes, and a dense layer with 10 nodes. It was trained with input sequences of 24 hours, and an output of the top oil temperature at the last hour.

5. Input data

The data used for modelling was extracted from multiple larger data sets and compiled into a single data set containing only relevant features. Data points with missing readings were dropped. The data was then resampled at an hourly interval. The input data consists of the following signals:

- Transformer top oil temperature
- The production of the corresponding generator (which is the same as the load on the transformer)
- Transformer cooling water temperature

In addition, the setpoint for when the cooling system is turned on was estimated based on the available data using the top oil temperature crossing a given threshold as an indicator for the status change (on/off) of the cooling system.

6. Other information

None.

7. Deliverables

The same type of model as for case C6 has been used in this case. Thus, for code and documentation, it is referred to document D6.3 and code K6.2.

No.	Deliverable (description)	Author (person)	Type of deliverable	Reference
D6.3	Condition monitoring of hydropower components using machine learning	E. L. Andreassen (SINTEF)	Memo, summer internship 2018	Docs -D6.3 [1]
K6.2	Python ANN models	E. L. Andreassen (SINTEF)	Python code (tensor flow) for training of ANN and fault detection (prediction)	Code – K6.2

8. Summary of results

The main results are shown in Figure 1. As seen, the trained model for the transformer top oil temperatures is not that accurate. There are multiple possible causes for the inaccuracy. The top oil temperature is only predicted from two parameters, and there may be other factors affecting the temperature. The internal design and temperature sensor placements of transformers varies, and this affects the extent to which the top oil temperature is governed by the transformer load and cooling water temperature. Since the load on the transformer varies a lot, the transformer is in general not in steady state. Hence, a time-dependent model may be more suitable. To this aid, a model was also developed using a recurrent network. This model performed only slightly better than the simple feed forward network. The improvement may have been limited by a time resolution of only one hour that not necessarily captures all important dynamics.

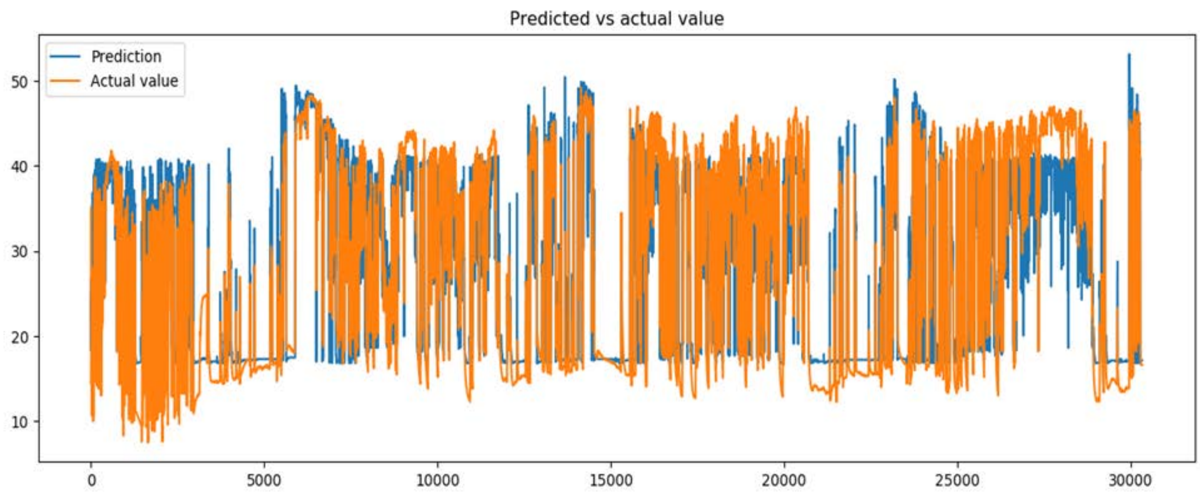


Figure 1: Prediction of the top oil temperature of the transformer in Uvdal 1 power plant using a feed forward network

9. References

[1] E. L. Andreassen, “Condition monitoring of hydro power components using machine learning,” SINTEF Energy Research, Trondheim, Memo, Aug. 2018

Extraction of data from Brattset Power plant – Experiences

Background

At the start of the Monitor X project in 2015, it was seen as a particular challenge to get access to data from power plants for testing of algorithms and hypothesis of different kinds. TrønderEnergi agreed to share their data from Brattset hydro power plant with the Monitor X project. However they did not have any way to transfer the data from the plant to a location where it could be made available to the research teams. For IT security reasons it was not accepted to access the SCADA and dispatch center to extract the data. Voith Hydro AS had supplied a new control system to Brattset in 2014 and agreed to make the transfer of the data to a server in Heidenheim, Germany from where TrønderEnergi, SINTEF and other Monitor X partners could download the data.

Figure 1 shows a sketch the PLC configuration of Brattset. The additional hardware that was added to transport the data out of the plant is shown in the upper right corner.

The data that is transferred are all the signals (messages, warnings/alarms and measurements, but not commands) from the PLCs connected to the station bus. The information in the subsystems lower down in the system architecture is not transferred in this project.

The chosen configuration has some characteristics and advantages seen from different perspectives: IT security requirements towards the control system itself are met by realizing a one way data traffic out of the control system combining a software and hardware setup to create a "data diode" without any possibility to transfer information or data in the other direction.

As the original use of the data in a control system is intended for smooth operation of the plant and avoid alarms due to normal transient events like start/stop, all control systems are able to suppress, filter or delay signals to a certain extent. The used configuration fetches all data as raw signals without any of the above signal distortions.

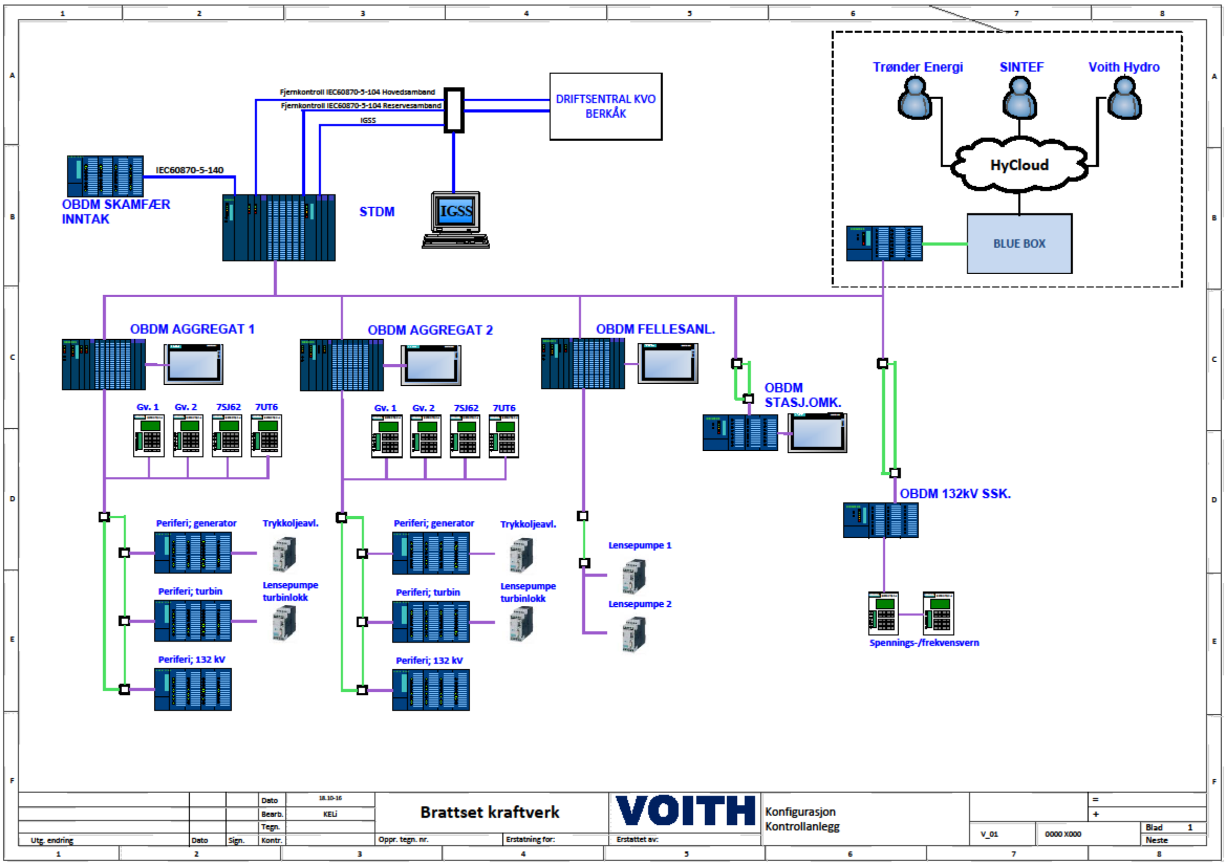


Figure 1. Brattset PLC structure.

Creating a parallel channel for information transfer out of the power plant also creates a lot of flexibility for a stepwise implementation of a wider monitoring scheme. The standard industrial computer, here as labeled Bluebox, can easily be equipped with a variety of SW and I/O options to allow connection to a virtually unlimited selection of additional sensors in parallel to the control system.

The data transfer

The data is transferred from the power plant to the Firewall of TrønderEnergi on an unencrypted protocol to enable the IT security systems of TrønderEnergi to monitor the activities.

From the Firewall towards the Voith Cloud the data is transferred in a VPN tunnel on the protocol AMQP.

The control system works with spontaneous transfer of changes/events and real-time processing of data with a cycle time <10 ms. Time stamping of the digital signals are with a cycle time 10 or 100 ms, depending on priority. Analogue signals are updated with a cycle time close to 1 s limited only by the processing time of the A/D converter of the O/I cards.

The data is transferred to the Voith Cloud cyclically approximately every 1 second. All signals are time stamped in the “Bluebox” for each transfer of data, and it is this timestamp that is transferred with the data to the Voith Cloud. This leads to a minor time delay up to 1 second compared to the timestamp given by the signal processing in the PLCs. In theory also a loss of digital data can happen in case on fast changing of signal status, like circuit breaker close/open sequence. The above limitations have not been seen as critical as the use of data was intended analyze time series of length very much longer than 1 second.

Accuracy on analogue values

The measurement accuracy of the Cloud data is defined by the original control system and sensors. The transfer to the Cloud itself do not affect the signal accuracy, expect for the above mentioned time delay.

Typical values of the physical measuring accuracy from the different steps of the signal processing:

Primary sensor accuracy	0,2-10% of full-scale reading
A/D converters	0,5 %
Digized values	0,05 % (12 bits) of full scale

In addition the calibration of the different signals is not known and therefore also some additional deviations for sensors that are typically drifting over time like flow meters and similar.

The above tolerances gives limitation in accuracy to any algorithms applied on the signals.

Amount of data

The amount of raw data collected with this system is 32 GB for two years since March 2017. This is much less than expected and is related to the fact that the machines run quite stable with less start/stop sequences and shifting load set-points than was foreseen by Voith. Indirectly it also indicates that there is little noise in the analogue signals that in turn indicates a well working plant.

Suggestions for further work

It appears that one of the overall challenges discovered during the Monitor X project is to provide sensor data from the plants to a centralized platform in a cost-effective way in parallel to the communication to the dispatch center.

One of the technical features that can support increased cost effectiveness is standardized formats and structures for generalized signal transfer based on the state of the art IoT-solutions. A long step in this direction will be an industry wide common agreement on what standards should form the basis.

It is recognized that the new ISO/IEC 81346-Part 10 (draft 2019) must be implemented over a long time. This means that the physical tagging of an existing plant will have to be different from the digital tagging until the control system and related primary equipment is renewed. To further support cost effectiveness in this topic, a standardized cross referencing systematic will be very useful.

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MONITOR X DIGITALIZATION IN HYDROPOWER

This report provides a summary of the results from the joint industry project ”MonitorX where data analysis models and algorithms for condition monitoring and predictive maintenance of components in hydropower plants have been developed and tested.

The most important benefits of using such models is fewer manual inspections and shorter maintenance downtime by using more condition-based and less time-based maintenance, and reduced costs for corrective maintenance due to early warnings of failures. The project was an important forum for knowledge-building and exchange of experience between hydropower plant operators, equipment manufacturers/service providers and research institutions.

The work in MonitorX was case-driven, meaning that identification of practical cases and development of these cases with the industry partners was the main approach. This report provides an overview of all cases in the project. The results from each case are briefly summarized in the report and explained in more detail in the appendices. Based on the obtained results and experience from testing, recommendations for use of the project results and suggestions for further work are given.

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