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Anomaly indicators for Kaplan turbine components based on patterns of normal behavior

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ABSTRACT: This paper describes and proposes some indicators for continuous monitoring of anomalous conditions in the hydraulic system of a Kaplan turbine using SCADA data. The indicators are based on significant deviations between the estimated values for key variables describing the current working conditions of the components at the plant, and those actually observed. This monitoring strategy requires models describing the expected values for variables through the whole range of possible working conditions of the monitored components. These models are normal behavior models able to characterize the typical relationships between a set of variables used as inputs to the models and the corresponding output of a target variable whose expected value has to be predicted. The criteria to select the variables to use in the models are based on the physical working principles of the component. The paper is focused on models of normal behavior applied to a real case of condition monitoring of a Kaplan turbine regulating mechanism.

1 INTRODUCTION

Hydropower is the leading renewable global source for electricity generation supplying 71% of all renewable electricity and reaching 1,064 GW of installed capacity in 2016 (WEC, 2017). It generated 16.4% of the electricity produced in the world from all sources. Hydropower is the most flexible and consistent of all the renewable energy resources, capable of meeting base load electricity requirements, as well as with pumped storage technology, meeting peak and unexpected demand due to shortages or the use of intermittent power sources. Also, hydroelectricity is a source of electrical energy coming from water that is clean and safe.

A large number of data is logged in the SCADA system (Supervisory Control And Data Acquisition) in hydropower plants, but the current status in Norway and Sweden is that SCADA data—apart for their use to control the plant—is not much used for other purposes, such as condition monitoring and maintenance planning. Thus, there is a large potential for using SCADA data for these new purposes. This may contribute to increased availability and energy production due to prevention of failures and shut downs.

The identification of possible failure modes in a hydropower plant (Topliceanu, 2016) is one of the key points in order to identify how failures could be detected in an early state. The analysis of the causes and effects of these failure modes can suggest the variables that can be useful for the detection of abnormal behaviors or anomalies (Chandola, 2009). Several references can be found in scientific literature proposing different methods for anomaly detection, and, in general, fault detection in industrial processes (Garcia Matyos, 2013) based on values of some variables measured in real time. One area in hydropower plants with an important research activity is related with the vibrational analysis focused on some key components (Mohanta, 2017), also the health condition of the components observed through several types of measurements is the goal of other studies such as those referred to in (Jamil, 2013) and (Selak, 2014).

In this paper, the hydraulic system of a Kaplan turbine was identified as a target of analysis and in particular the detection of a possible oil leakage in the system. This analysis is part of the results obtained in the research project MonitorX – "Optimal utilization of hydropower asset lifetime by monitoring of technical condition and risk". MonitorX is a joint industry project initiated and 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, a number of equipment manufacturers and service providers, and the research institutions Comillas Pontifical University, SINTEF Energy Research and the Norwegian University of Science and Technology as R&D partners. The project is financially supported by the Research Council of Norway.

The aim of the MonitorX project is to develop models and algorithms for condition monitoring and the detection of faults in hydropower equipment. The main focus in the project is on models based on machine learning and artificial intelligence. The project is case-driven, and several relevant cases have been identified in the beginning of the project, whereof the case related to monitoring of the Kaplan turbine regulating mechanism and corresponding hydraulic system was considered as relevant for further work. Since several components and parts of the system are difficult to inspect, models that can be used to monitor the system condition and detect failures are valuable. Furthermore, oil leakage from the hydraulic system may cause environmental damage, especially when oil leaks into the river.

Usually, no separate condition monitoring systems are installed in power stations to surveil the condition of the regulating mechanism. The data that normally is available is from the SCADA system of the plant that usually presents one hour average values. Thus, one of the aims of the presented case is to study if such type of data is useful for modelling the normal behavior of hydropower components and detecting with these models anomalies that are related to faults.

The paper is organized in the following sections. Section 2 describes the method and objectives used for the creation of normal behavior models and detection of anomalies. Section 3 presents a description of the hydraulic system of the hydraulic power plant analyzed. Section 4 includes the description and development of normal behavior models used as references for detection of anomalies. Section 5 presents several cases about how the normal behavior models can be used as reference patterns for the detection of anomalies. Finally, section 6 summarizes some conclusions of the analysis developed throughout the paper.

2 METHOD AND OBJECTIVES

This section describes the main steps of the process to build anomaly indicators for detection of abnormal behavior in some functional characteristics of components in a hydropower plant. These indicators are based on patterns previously obtained from observing the typical normal behavior of the monitored components. The following sequential steps are required in order to detect anomalies based on an estimation for these indicators:

a. Selection of a data training set for learning the typical normal behavior of the component. This includes data selection and filtering, removing of outliers and treatment of missing measurements.
b. Identification of failure modes that could be detected with the variables available in the SCADA system, and selection of variables. Information available in a Failure Modes and Effects Analysis (FMEA) may help to select relevant failure modes and variables. The variables will be used for the characterization of normal behavior patterns developed in the next step.
c. Building of normal behavior patterns of a component described through variables collected in real-time from the hydropower plant. The cases studied in this paper are based on data samples collected every hour. The patterns were built using multi-layer perceptrons (Bishop, 1995), (Bishop, 2006). This technique is supervised requiring previous knowledge of behavior considered as normal and covering all the typical working conditions of the plant. A good selection of this behavior, considered as normal, is crucial in this method because the normal behavior will be learnt by the models as a reference to watch when new information is coming from the power plant.
d. Estimation of anomaly indicators. Once the previous steps are completed, the indicators of anomalies can be estimated. Its objective is to warn about data collected from the hydropower plant that do not correspond to the expected behavior by the reference patterns. The evolution of the values of the anomaly indicators over time will suggest whether or not it is necessary to pay attention to the components monitored from the point of view of scheduled maintenance and operation.

Sections 4 and 5 will describe details about each of the previous steps with examples demonstrating their use.

3 SYSTEM ANALYSED

The cases analyzed in the paper are from Embretsfoss 4, which is a hydropower plant using a Kaplan turbine for the production of electric energy. The Kaplan turbine is a propeller type turbine controlled by the operation of the turbine runner blades (turbine blades) and the wicket gates (guide vanes). See illustration in Figure 1. A Kaplan turbine is a typical run-of-river turbine, which can be operated at different flows and at varying head. For each head and flow, there is a given ideal combination of the wicket gate and runner blade position to ensure the best efficiency of the turbine.

A turbine regulator controls and operates the turbine. Based on information about head and flow it uses predefined combination curves for the runner and wicket gate. The regulator controls the turbine by adjusting the blade and wicket gate positions with a correlated movement between the two. The acting mechanism for the wicket gates and runner blades are based on high-pressure hydraulics where an HPU (high-pressure unit) and an accumulator bank provide high-pressure oil for actuation of hydraulics servomotors.

3.1 *The high-pressure hydraulic system*

The turbine regulator controls the wicket gates and the runner blades by the use of a high-pressure hydraulic system which consist of the following main components:

- Turbine governor oil sump tank with oil pumps (HPU – High Pressure Unit)
- Pressure accumulator banks. One bank for runner blades and one bank for the wicket gates
- Hydraulic oil cooling/heating system
- Wicket gate control system
- Runner blade control system

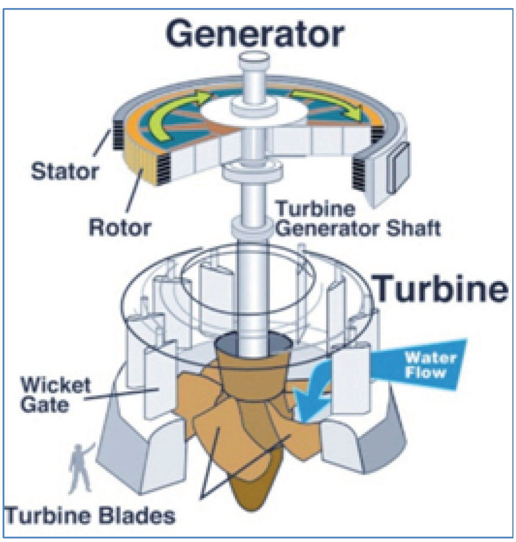

Figure 1. Illustration of the Kaplan turbine (Courtesy of Wikipedia).

- Quick stop/Emergency stop system
- Oil system for runner hub. The runner hub is the lowermost part of the runner. The cone part just below the runner blades. See Figure 1.

For a simplified view of the high-pressure hydraulics system, see Figure 2. The HPU is located at the turbine floor and it supplies the wicket gate and runner blade control system with high-pressure oil. The main components of the HPU are the oil reservoir, the oil pumps, valves, filters and coolers. In addition to supply oil to the control system, the HPU is "charging" in total five accumulator banks. The accumulator system is a safety system designed to handle a predefined number of safe shutdown cycles, in case of malfunction of the HPU system or a blackout of the station. The HPU have systems for monitoring the oil level, temperature and water-in-oil content. To prevent the pollution of the oil, each of the HPU pumps are equipped with a filter system.

For maintenance reasons, the oil reservoir is designed to be big enough for storage of all the oil in the system. However, during operation, the oil is in the different components of the hydraulic system hence only a limited amount of oil is contained in the reservoir. A minimum level is however required in the reservoir for avoiding dry running of the HPU pumps.

The hydraulics system has an oil cooling (and heating) system. The cooling system cools the oil during operation and the heating system heats the oil during standstill.

The wicket control system controls the wicket gates by the use of two hydraulic servos (cylinders). The servos actuate the control ring, which again provides the open/close movement on the wicket gates. When the control ring, seen from the top, turns clockwise, the wicket gates close.

The runner blade control system controls the position of the runner blades by the use of a servo actuator located in the runner hub. The actuator high-pressure oil supply/return is routed through the center of the turbine shaft via the oil supply head located at the top of the shaft.

The system is equipped with a system for safe emergency stopping of the turbine. This can be activated by a manual activation of the emergency stop or if the turbine is speeding and the overspeed trip valve is activated.

The turbine hub is filled with oil and has an oil pressure that is slightly higher than the surrounding water pressure. In the case of runner blade sealing degradation, this pressure prevents water from entering the hub. The oil pressure in the hub is a static pressure created by the elevated location of the hub oil tank (see Figure 2). The oil in the hub oil tank is pumped up from the HPU oil reservoir. The hub oil

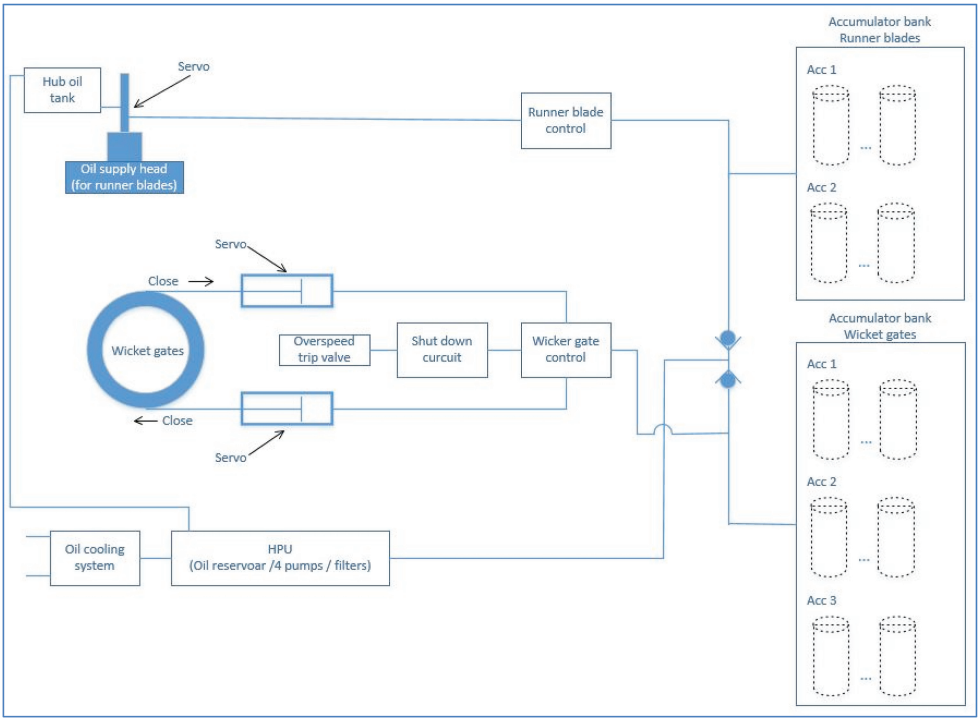

Figure 2. Simplified view of the hydraulic system.

tank and the hub oil are not a part of the high-pressure circuit, but a leakage in the runner blade servo will influence the oil level in the hub oil tank and will eventually sound an alarm or stop signal.

4 MODELS OF NORMAL BEHAVIOUR

An industrial component or system can be stressed due to normal operation, extraordinary operation and extreme environmental conditions or to a combination of all. Over time, these facts along with ageing factors can produce different ranges of typical values observed in measured variables even when the functional objectives of the component or system as expected have been reached (Sanz-Bobi, 2011). However, when a component has been stressed or overloaded over time, an increasing risk of occurrence of a failure is probable. For this reason, it is important to characterize the normal behavior expected for an industrial component or system when it is performing its function under several typical working conditions, because any deviation with respect to this behavior could alert about the presence of an incipient failure. The sooner this is detected, the sooner it is possible to mitigate the effect of a failure.

This section describes real examples of normal behavior models. These models are able to characterize the typical dynamical evolution of variables when the component is working under different operating conditions without symptoms of failure or stress.

In particular, the models developed and presented as an example in this paper, are based on information collected in real-time from a hydraulic power plant located in Norway. The models developed use neural networks based on multi-layer perceptrons (Bishop, 1995; Kruse, 2013) because this is a method able to approximate non-linear relationships among variables.

An basic model to characterize the normal behavior of the hydraulic power plant can be expressed by function *f* in Equation 1

$$P = f(GVP, WF, HW - TW) \tag{1}$$

where:

P: Power generated by the power plant in MW
GVP: Guide Vane Position in percentage
WF: Water flow through the turbine in m^3/s
HW-TW: Difference between headwater and tailwater levels in m.

Equation 1 tries to predict the power generated as function of the values of the main variables contributing to the power generation.

In order to build a normal behavior model characterizing the function *f* in Equation 1, a training set was selected covering different seasonal conditions from January 1 to August 20, 2015. The data set is based on hourly values for the variables considered. The model was developed with a multi-layer perceptron based on one hidden layer containing 20 neurons and using the Levenberg–Marquardt algorithm for learning. The model obtained is very good, as it can be observed in Figure 3, where the estimated values for the power generated and the real values observed are almost identical. The mean value of their difference (error of the trained model) is 0.0012 MW and the standard deviation is 0.067 MW. This error is distributed according to a normal distribution with narrow shape.

An interesting family of models will be presented in the following for the characterization of the normal relationships that exist between the tank oil level of the turbine regulator and variables observed in different components of the turbine regulator that uses this oil. It is important to monitor that the oil in the tank is at the expected level, because if this is not the case, a possible leakage could be present.

The first normal behavior model of the family that was tested is described in Equation 2 using the function *f*1.

$$OTL = f1(P, OTT, A1TR) \quad (2)$$

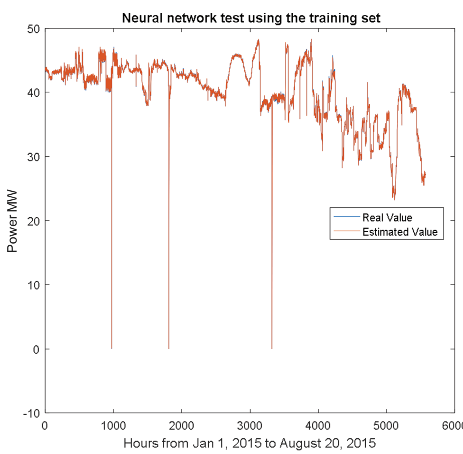

Figure 3. Estimated value for power generated predicted by the normal behavior model and the real value observed for the training set using the guide vane position, the flow through the turbine and the difference between headwater and tailwater level.

where:

OTL: Oil tank level in the HPU in percentage

P: Power generated by the power plant in MW

OTT: Oil tank temperature in ºC

A1TR: Oil level in accumulator 1 of the turbine runner.

Equation 2 tries to predict the oil tank level in the HPU of the turbine regulator knowing the working conditions of the plant, the level of one oil accumulator of the turbine runner and the temperature of the tank oil.

The model for *f*1 was obtained with a similar architecture as for *f* in Equation 1. Also, the same dates as in the previous case were used to obtain the samples of the training set. The model obtained is good, which can be observed in Figure 4 where the estimated values for the oil tank level and the real observed are very close. The oil tank level is measured in percentage (%). The mean value of their difference (error of the trained model) is 0.0007% and the standard deviation 0.0644%. This error is distributed according to a normal distribution shape.

The hydraulic power plant studied has another similar accumulator given the number 2 in the turbine runner. A normal behavior model was fitted and the results obtained were very similar to those obtained for accumulator 1 of the turbine runner.

Other important components in the turbine regulator of the hydraulic power are three oil accumulators for the guide vanes. These are very important for the correct regulation of the hydraulic turbine. Three models, one considering each of the oil accumulators, were developed such as in Equation 2. For simplicity, only one of them will be presented. Equation 3 describes it using function *f*2.

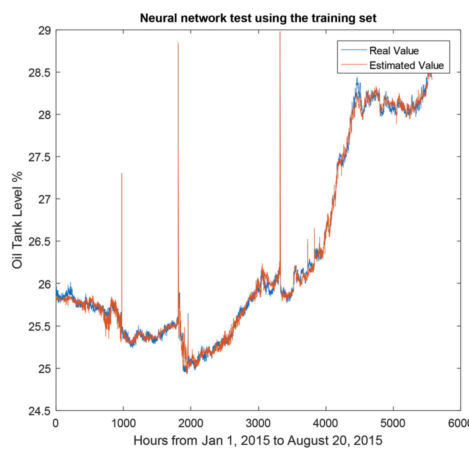

Figure 4. Estimated value for oil tank level in percentage predicted by the normal behavior model and the real value observed for the training set using as inputs the power generated, the oil tank temperature and the oil level in accumulator 1 of the turbine runner.

$$OTL = f2(P, OTT, A3GV) \quad (3)$$

where:

OTL: Oil tank level in percentage

P: Power generated by the power plant in MW

OTT: Oil tank temperature in ºC

A3GV: Oil level in the accumulator 3 for the guide vanes.

Equation 3 tries to predict the oil tank level in the turbine regulator knowing the working conditions of the plant, the level of the oil accumulator 3 for the guide vanes and the temperature of the tank oil.

The model for $f2$ was obtained following the same method as in the previous cases described. However, the main difference was that the data used in the training set covered the period from April 9, 2016 to October 13, 2016, because before that period some measurements of the oil accumulators of the guide vanes were not collected correctly. In any case, more than half of this period overlaps with the one used for obtaining f and $f1$. The model resulting for $f3$ obtained is good, as it can be observed in Figure 5 where the estimated values for the oil tank level (in percentage %) and the real observed values (in percentage too) are very close. The mean value of their difference (error of the trained model) is 0.0022% and the standard deviation 0.09%. This error is distributed according to a normal distribution shape.

Good results were also obtained for the two models that are similar to the one in Equation 3, where the variable oil level in accumulator 3 has been changed to the oil levels in the corresponding accumulators with numbers 1 and 2, respectively.

5 ANOMALY DETECTION BASED ON PATTERNS OF NORMAL BEHAVIOUR

Once a normal behavior model has been elaborated, it can be used in real time with real-time values from the required inputs. The output from the model can then be compared with the corresponding real measured output variable. The prediction will correspond to the expected value for normal behavior under the current working condition. Any incipient failure will produce a deviation between the expected value and the real value measured of the monitored variable. This section presents how the normal behavior models obtained in the previous section respond to new inputs of data collected after the training set dates. This will allow for the discovery of abnormal behavior different to the one expected.

Model f was used with data not contained in the training set, covering the period from November 25, 2015 to May 31, 2017. Figure 6 shows the results obtained by the model. The real behavior observed is very near to the predicted one and this confirms that the behavior observed in this new period of time is similar to the previous one in the training set. No abnormal behavior was detected in the power generation according to model f. The mean value of their difference (error) is –0.017 MW and the standard deviation is 0.7 MW. Both are higher than what was obtained for the training data set, but the prediction is still reasonable. Also, this error is distributed according to a normal distribution shape.

Furthermore, model $f1$ was used with data not contained in the training set, covering the period from November 25, 2015 to May 31, 2017. Figure 7 shows the results obtained from the model. The real behavior observed is near to the predicted

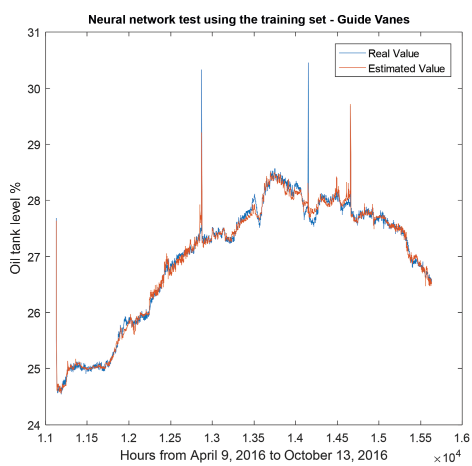

Figure 5. Estimated value for oil tank level in percentage predicted by the normal behavior model and the real value observed for the training set using the power generated, the oil tank temperature and the oil level in accumulator 3 for the guide vanes.

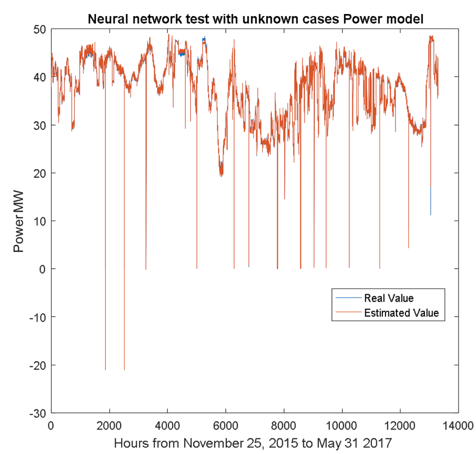

Figure 6. Estimated value for power generated predicted by the normal behavior model and the real value observed for the testing data set using the guide vane position, the flow through the turbine and the difference between the headwater and tailwater levels.

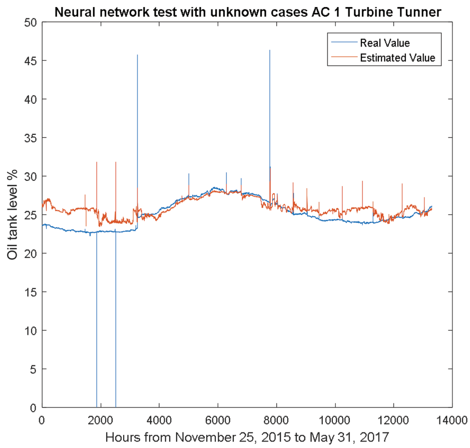

Figure 7. Estimated value for oil tank level in percentage predicted by the normal behavior model and the real value observed for the testing data set using as inputs the power generated, the oil tank temperature and the oil level in accumulator 1 of the turbine runner.

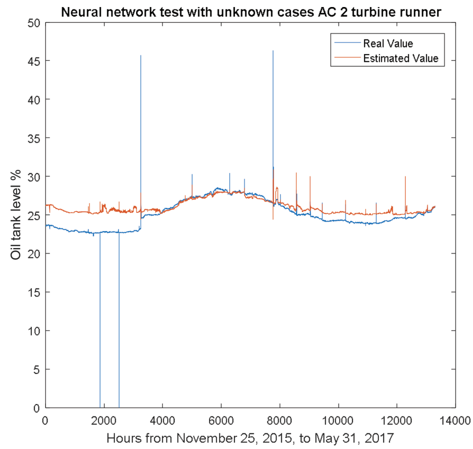

Figure 8. Estimated value for oil tank level in percentage predicted by the normal behavior model and the real value observed for the testing data set using as inputs the power generated, the oil tank temperature and the oil level in accumulator 2 of the turbine runner.

one in some cases in the central part of the figure and different in the rest of the period studied. This means that the behavior observed in the training data set is different from the one observed in the new test data set at some periods. An abnormal behavior was detected in the relationships between the output and input variables of this model for the test period. Once this was detected, it became necessary to investigate the cause.

The cause of abnormal behavior detected that is breaking the relationship modelled by $f1$ can be any of the variables used in this model. The variable power generated cannot be the cause due to the test carried out in model f and presented in Figure 6 which confirms that no abnormal generation of power exists. The rest of the variables could be candidates to be anomalous and they are related with the oil tank (level and temperature) and the accumulator 1 level of the turbine runner.

A model similar to the one presented in Equation 2 was developed replacing the variable A1TR (Oil level in accumulator 1 of the turbine runner) by another equivalent model, but measuring the oil level in accumulator 2 of the turbine runner. The model obtained was very good and similar to that presented in Figure 4. This model was checked with data not contained in the training set, covering the period from November 25, 2015 to May 31, 2017 as for accumulator 1 of the turbine runner.

The result is presented in Figure 8. The profile between predicted and real oil tank levels are almost the same in Figures 7 and 8. The same broken relationship is shown between the oil tank level and the oil level in accumulators 1 and 2 of the turbine runner. This induces the thought that it is not probable that the problem of the abnormal behavior observed is due to some anomaly in both turbine runner accumulators at the same time and it is therefore convenient to closely monitor the oil tank level.

In this way, model $f2$ was also tested with data covering the period from October 14, 2016 to May 31, 2017. This period includes data from sample 8000 till the end of the graphics in both Figures 7 and 8. Figure 9 presents the results of the application of model $f2$ to the data set mentioned. The discrepancy between predicted and real values for the oil tank level is clear. This is lower than expected for the working conditions of accumulator 3 of the guide vanes. In fact, it seems that the difference between the real and expected values for the oil tank level is increasing over time, except in the last part of the graphic in Figure 9 where the real and expected values are approaching.

Two similar models to $f2$ were built and tested during the same periods of time replacing the variable A3GV (Oil level in accumulator 3 for the guide vanes) by other equivalent elated respectively to accumulators 1 and 2 for the guide vanes. The results were similar.

According to the results obtained, all five models applied for anomaly detection in the oil tank level (three of them presented in Figures 7, 8 and 9) coincide in that they indicate a lower level of oil over time. This is an indicator of a possible leakage of oil in the oil tank level or surrounding locations. The accumulators are working as expected, but the total oil level in the tank of the HPU is decreasing. This was verified and a leakage was discovered from the oil side to the nitrogen side of the accumulators.

These examples demonstrate that the deviation values obtained from the comparison of the real value and predicted one by the patterns of normal

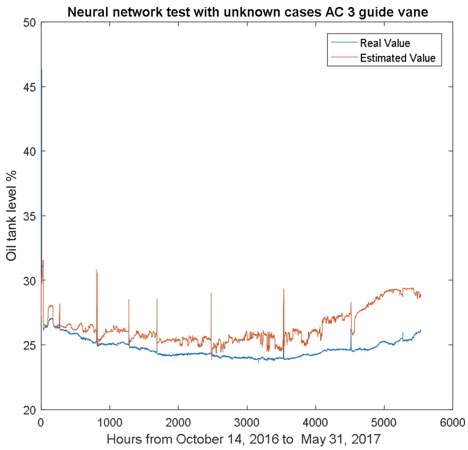

Figure 9. Estimated value for oil tank level in percentage predicted by the normal behavior model and the real value observed for the training set using the power generated, the oil tank temperature and the oil level in accumulator 3 for the guide vanes.

behavior can be good indicators for alerting when a typical relationship among variables could be broken.

In this case, the unexpected decreasing level in the oil tank must be monitored.

6 CONCLUSIONS

This paper describes a methodology for the early detection of anomalous behavior conditions of selected Kaplan turbine components. The method is based on discovering behavior patterns, also called normal behavior models, from the observation of the typical relationships existing between a set of variables used as inputs to the models and the corresponding output of a target variable whose expected value has to be predicted. The criteria to select the variables to use in the models are based on the physical working principles of the component in order to detect symptoms of abnormal behavior that can cause a possible failure mode.

The data set used for pattern discovering of normal behavior comes from the SCADA system of the plant. Abnormal behavior is any significant deviation or difference between the predicted output of the models and its corresponding real observation.

The paper presented some examples of normal behavior models for the cases of characterization of power generated by the hydropower plant and the oil tank level considered from different perspectives such as the oil level in the bank of accumulators of the turbine runner and the bank of accumulators of the guide vanes. Once the models were created, they were applied to new examples of operation. The predicted amount of generated power was always as expected, but the oil tank level was not. The analysis of deviations of normal behavior described in the paper shows that the oil levels in the accumulator banks were according to their working conditions, but the oil tank level was continuously decreasing during the time analyzed. This suggests a need for close monitoring of this level in order to search for the cause of this potential detected leakage.

In future works, an approach based on different algorithms working in parallel for anomaly discovering will be tested. This will improve even more the robustness of the anomaly detection method proposed.

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