Failure detection in a water treatment system of a biomass CHP

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Abstract

To keep energy systems in an optimal state it is necessary to ensure proper maintenance and optimized operation. Both of these goals can be achieved with implementation of predictive maintenance. Based on sensor data, it is a perfect option to fulfil diagnostics and prognostic tasks, and optimize long time operation of the power plant. Prediction of failures and outlier detection methods are the basis of predictive maintenance. Several outlier and failure detection algorithms have been presented so far, but still have limitations concerning implementation. We propose a predictive maintenance approach for a water treatment system of a power plant of BERTSCHEnergy. We investigate methods for failure detection and find that only a combination of data-driven and knowledge-based leads to the desired result.

Keywords: Predictive maintenance, expert system, power plant, water treatment, failure prediction, intelligent thermal energy systems.

Introduction

Biomass power plants are complex systems in which components do not work independently from each other. It is therefore difficult to achieve proper maintenance by solely focusing on conventional maintenance in intervals or based on thresholds. Instead, it is necessary to predict failures of all components reliably to provide stability of the working cycle, achieve high availability and reliability, and improve the efficiency of power plant units. Often, it is a problem for the operator to detect certain issues like deterioration of water quality or blocking of fuel supply chain and to locate promptly the equipment which was involved in this process. One step to cost-efficient operation is to perform corrective and predictive maintenance of power plants [1]. Its integration can ensure enhanced reliability, enhanced safety, and reduced maintenance costs. Moreover, predictive maintenance might eliminate breakdowns by 70-75%, reduce breakdown time by 35-45%, and increase production by 20-25% [2].

Prediction of failures and outlier detection methods are the basis of predictive maintenance. Several outlier and failure detection algorithms have been presented so far. Qi et al. [3] implemented the original Grubbs' method and modified Grubbs' method based on median and median absolute deviation [4]. Hubballi et al. [5] pr oposed the nearest neighbor-based outlier detection algorithm (NDoT), evaluated this method experimentally, and compared results with a classical outlier detection method LOF (Local Outlier Factor). In turn, LOF was described by Breunig et al. [6]. Wang and Mao [7] applied the Gaussian process for process monitoring and process control, and moreover developed several detection algorithms and implemented all of them on both synthetic and real-life datasets. Chow et al. [8] implemented a k-means clustering algorithm for the real-time industrial process at a wastewater treatment plant. A lot of algorithms such as principal component analysis (PCA), partial least squares (PLS), smallest

half volume (SHV), resampling by half-mean (RHM) have been applied for outlier detection and compared between each other [9].
Despite the numerous studies on anomaly detection just a few of all predictive maintenance approaches have been implemented so far. One study describes data screening for use in anomaly detection and predictive maintenance applications [10]. Also, authors classified a working regimes of the mill fan system in a coal fired power plant with use of a rule based model in [11]. Agarwal et al. [12] show a very simple data-driven approach based on only one sensor of amount of neutron flow with a very specific problem of data variation of this sensor. Wang and Liu [13] described the knowledge- and data driven approach which are related to only one small piece of equipment. Moleda et. al [14] implemented the algorithm for predicting failures in feed water pump and compared them with other usable algorithms. As the schemes of the power plants are individual, parts of these papers are highly specialized. In turn, our goal is the prediction of failures in a biomass fired power plant and the development of an intellectual reporting system.

Background

The object of our research is a makeup water treatment system of a biomass fired power plant with a nominal electric power output of 8.1 MW or 40.5 MW firing capacity. The water treatment system sustains continuous flow of fresh clean water to power plant. If the process fails, the quality of make up water will deteriorate and may decrease the power output of the power plant. If the failure mode lasts longer than the water storage tanks can compensate, the power plant has to be shut down or expensive equipment might be damaged. This motivates to choose the right water treatment at the stage of planning and to sustain the continuous operation of the process.

The water treatment system in Fig.1 consists of a water softening stage with two Na-cation exchangers and two reverse osmosis (RO) units that form the first desalination stage, electrodeionization (EDI) as a second desalination stage, and lastly a water polishing stage with two mixed-bed filters (MBF).

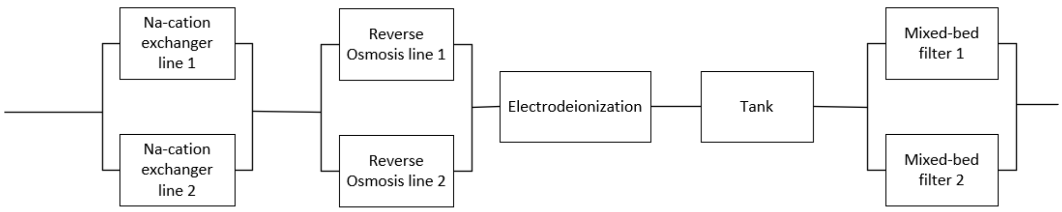

Figure 1. Flow chart of the water treatment system

After the mixed-bed filter, the polished water enters the deaerator and is then directed as feed water to the boiler (Fig.2(left)). The main part of it goes to the drum, the other one goes to the steam superheater (Fig.2(right)). Hence, impurities from water treatment system go directly to superheater surfaces and turbine blades; expensive repairs and equipment downtime would arise from that.

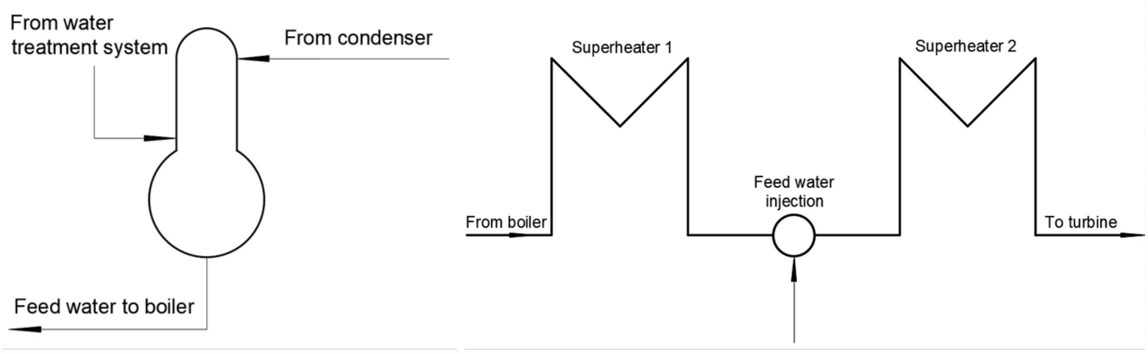

Figure 2. Path of the additional water: deaerator (left), steam line (right)

To avoid such impurities, the mixed-bed-filters are set to a maximum conductivity of 0.1 µS/cm. This threshold value is ensured by cation and anion layers of exchanging resin. Positively and negatively charged impurities go from the water to the resin. The lifetime of the mixed-bed filters varies with the water quality it is supplied with. So, if all stages upstream the mixed-bed filters work properly the expected lifetime of the unit is six months.
However the conductivity sensor downstream MBF in Fig.3 represents several time periods of up to three weeks when the threshold value is exceeded by up to a factor 50, leading to a maximum conductivity of 5 µS/cm. Hence, the lifetime of the mixed-bed filer is reduced to less than one month.

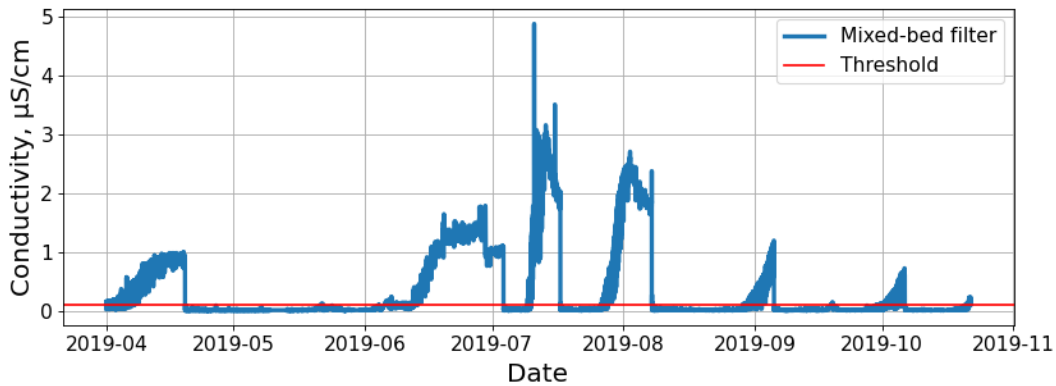

Figure 3. Mixed-bed filter lifecycle

To prevent this behaviour in our system and give valuable insights for predictive maintenance in thermal power plants, we want to answer the following research question:

How is it possible to reduce malfunction of the water treatment system by using a multimodal approach for failure prediction?

To answer this question, we analyze historical data of the system components upstream of the MBF, identify dependencies and develop an intelligent reporting system.

Methods

According to Montero Jimenez et.al [2] the first two steps of predictive maintenance are historical data collection and data pre-processing (see Fig.4). As the power plant investigated doesn't

have an automated cloud-based data acquisition and analyzing system, operational data has to be exported manually.
Our raw data set contains 156 sensors with data collection started in August 2017. In a first step, we preprocessed the data to a common format. We used Jupyter Notebook/Lab as a Python [15] environment as framework and pickles as common file format. Pickles are used for serializing and de-serializing Python object structures, also called marshalling or flattening.

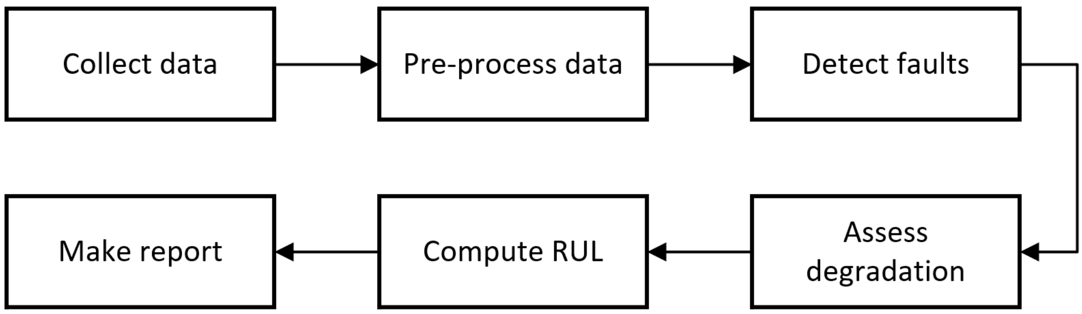

Figure 4. Predictive maintenance diagram (adapted from Jimenez et al.[2])

The third step is the combination of the next three points: fault detection, assessment of degradation and computation of remaining useful lifetime (RUL).
Fault detection methods in predictive maintenance are divided into three categories: Knowledge-based (KB), Data Driven (DD) and Physics-based (PB). Knowledge-based models hinge on experiences expressed by rules, cases, etc. Data-driven models use data accumulated over the years of operation. Physics-based models use the laws of physics to estimate ageing of components. All of these methods can be used separately or in combination. In Fig.5 the simple scheme of predictive maintenance methods is represented. Thus, it is possible to combine all of these methods according the needs of the problem given.

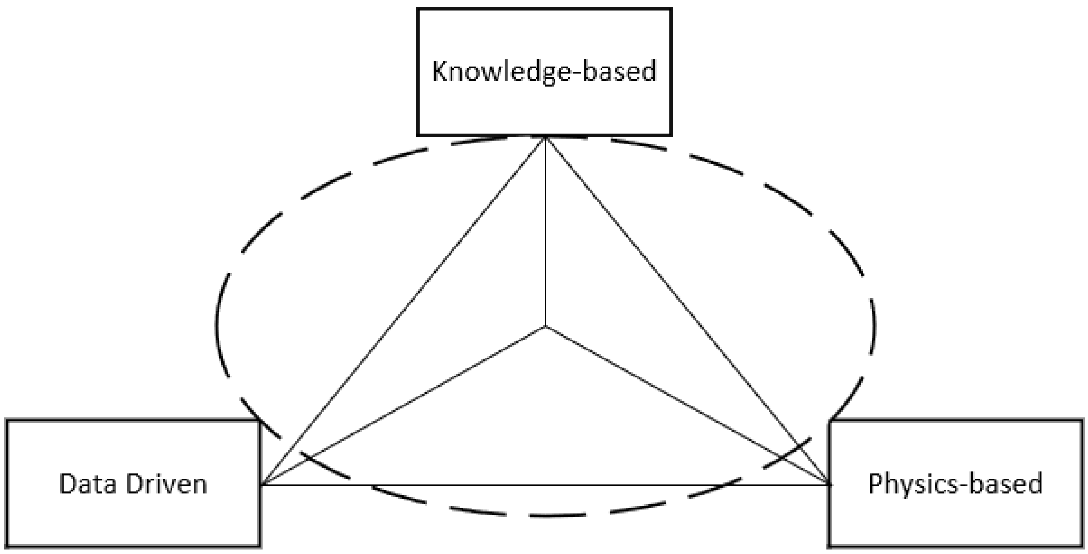

Figure 5. Predictive maintenance methods (adapted from Jimenez et al.[2])

Results and Discussion

Based on a broad historical data set, we first focused on a data-driven solution. However, typical failure detection algorithms as LOF [6], Grubbs, and modified Grubbs methods [3], etc. require steady sensor signal. In Fig.6 we can see 6-month data of conductivity after each water purifying stage. Blue color represents the measured conductivity, red color demonstrates the required conductivity threshold. It is obvious that mostly the data is not steady, instead, it has strong fluctuation due to various peaks.

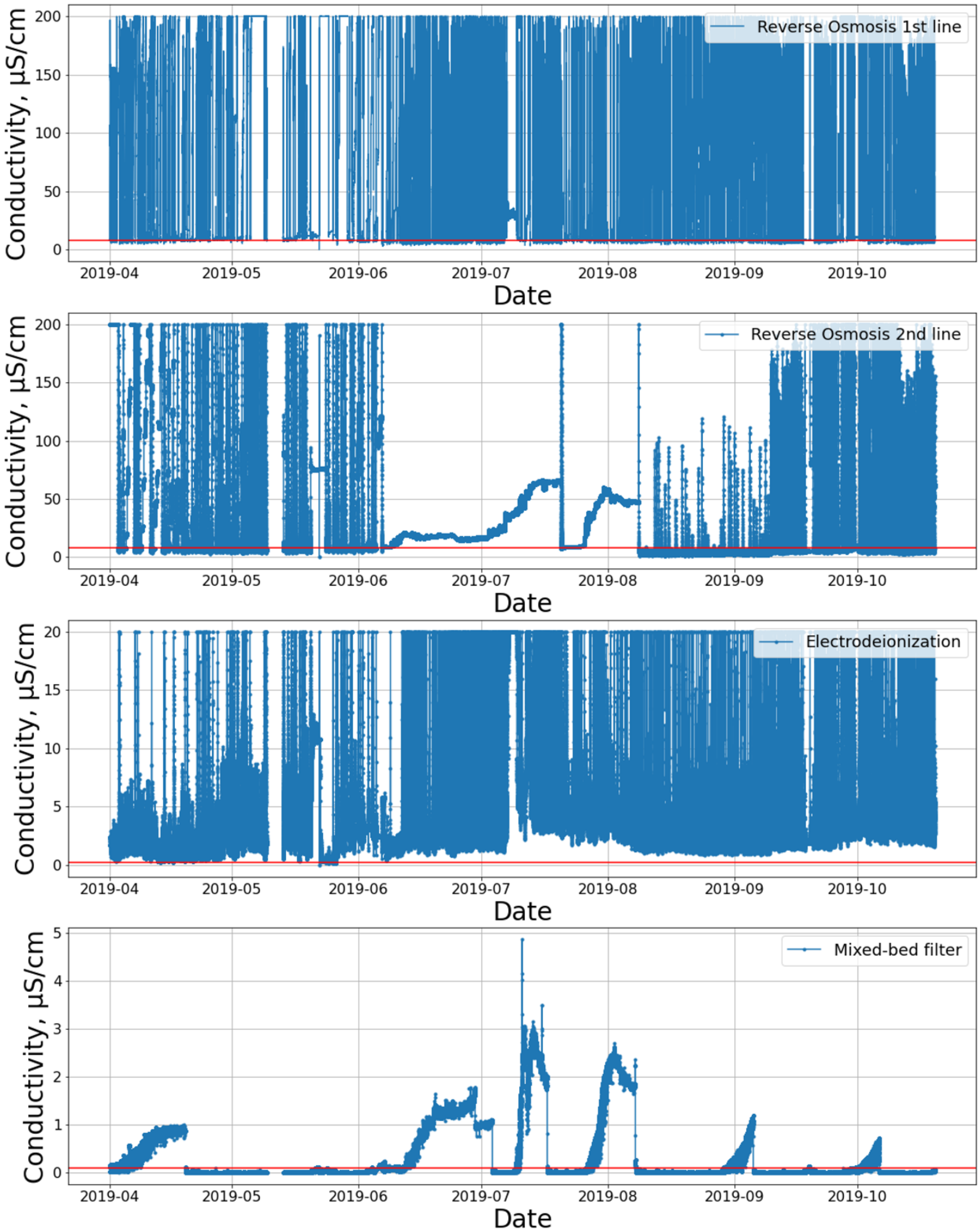

Figure 6. Conductivity after each stage of the water treatment system

Furthermore, the long-term trend in Fig.6 of the data shows:

- RO1 shows a strong fluctuation with values distributed between 0 µS/cm and 200 µS/cm where 200 µS/cm is the upper limit of the sensor.
- RO2 shows the same fluctuation but in a period of two month the conductivity is steady, but constantly above the threshold.
- EDI also shows fluctuation of conductivity. These peaks correlate with the peaks of conductivity in RO1 and RO2. Whereas the conductivity during the whole period exceeds the threshold.
- MBF data are steady values due to the tank upstream that provides continuous flow. This leads to a clear trend when the conductivity is above and when it is below the threshold.

Although a pure data-driven approach seems not to be the right choice for the long-term trend, analyzing the data within a short period of several hours, a first correlation can be identified. In Fig.7 blue and red color represent conductivity after RO1 and RO2 respectively and black color the water flow of the WTS. This figure clarifies that the peaks in conductivity are associated with the water flow through the water treatment system. Moreover, the data show that peaks alternate. This can indicate an interchangeable working pattern of the RO system.

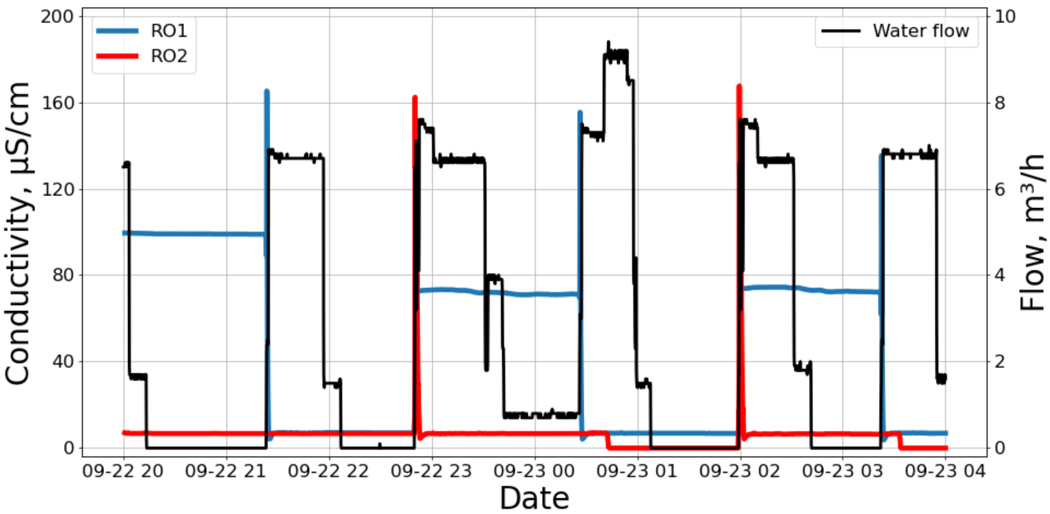

Figure 7. Reverse Osmosis short-term data

Still, the correlation can not be expressed as algorithm and it is necessary to develop a combination of knowledge-based and data-driven predictive maintenance models. First of all, in Fig.8 blue and red lines represent a flow of concentrate of RO1 and RO2 respectively and black color is the water level of the tank. The use of expert knowledge helps to understand that if the water level drops lower than 3000 mm in the water tank, an operational cycle in the WTS is started. Moreover, a flow of concentrate above the threshold value of 1 t/h signals that the unit was turned on. Several important notes can be drawn:

- the RO lines work in cycles.
- an algorithm controls the RO lines and it decides to switch the RO lines on or off.
- an algorithm shuts down the line if the conductivity which is provided by the equipment is higher than it should be.
- conductivity about 200 µS/cm at the beginning of the cycles is not a problem, because during first three minutes the conductivity stabilization process happens.

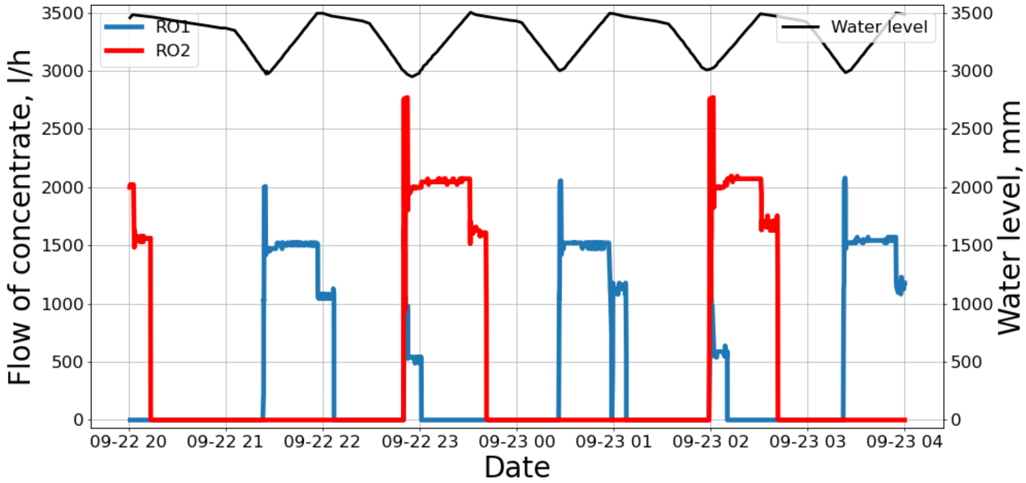

Figure 8. Flow of concentrate short-term data

Having analysed the data, the ultimate goal is to distinguish between normal behaviour shown and anomalies that might lead to serious damage of equipment. In other words: we want to identify short-problems that might cause long-term problems.

To do so, we combine Fig.7 and Fig.8 and analyze the flow of concentrate in correlation to the conductivity for RO1 and RO2 (Fig.9). In a period of 24 hours the flow of concentrate indicates that RO1 is switched on five times (1-5), RO2 is switched on four times (A-D). However, analysing the conductivity, it is obvious that for RO2, all four attempts (A-D) to reduce the conductivity fail as the conductivity remains at around 32 µS/cm.

For RO1 a problem after switching on occurs in two cases (1,4) which is indicated by an increase in conductivity. However, all other periods of operation (2,3,5) work properly and keep the conductivity low. Integrating the expert knowledge from the industrial partner, such behaviour is classified as normal as it can occur once in a while that switching of the RO line fails. Therefore, within an automated monitoring system an algorithm to detect anomalies in RO operation has to be based on two rules (rule 1 and 2):

- if switching an RO line fails once or twice in a row, the behaviour is classified as normal.
- if switching an RO line fails more that twice in a row, an alert to the plant operator has to be given so that long-term problems are avoided.

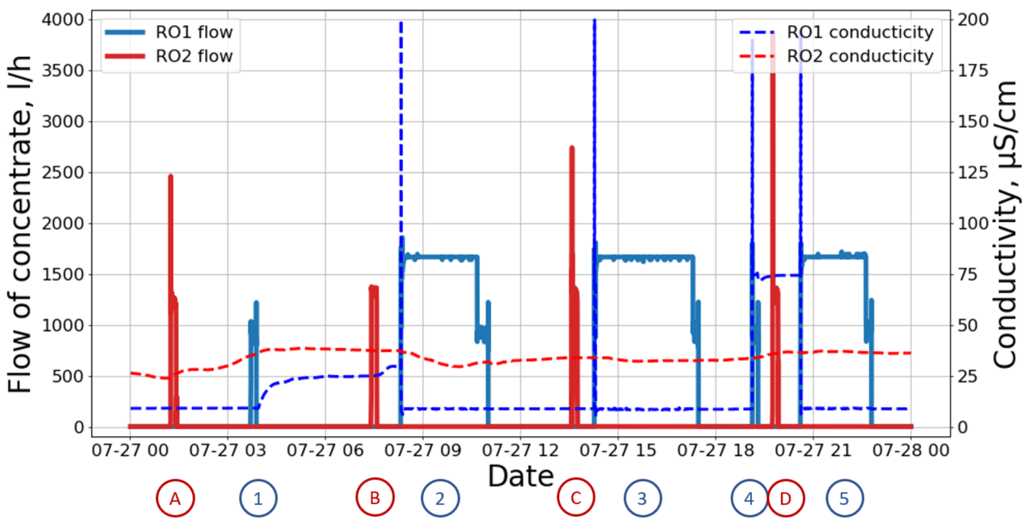

Figure 9. Short-term problem

Having developed the expert rules to identify short term problems it is necessary to analyze the influence of the short-term behaviour on long-term operation. Therefore, as it was stated above we apply a pre-processing rule (rule 3) for skipping the first three minutes of each operational cycle to pass the stabilization behavior, and then analyze the integrated mean conductivity of each cycle. The operational cycles are classified into three groups and displayed in Fig.10:

- operational cycles with normal behaviour (green)
- operational cycles with one or two anomalies in a row (orange)
- operational cycles with more than two anomalies in a row (red)

Based on this classification, many anomalies of class 2 (orange) are identified although the mixed-bed filter fulfills the threshold value. Additional data analysis leads to a solution on this aspect: if we exclude all operational cycles with a duration of less than 650 s (grey colored) which do not influence the long-term behaviour (rule 4), Fig.11 gives a clear correlation between short term problem and long-term behaviour.
In the first part of Fig.11, short-term problems (orange and red crosses) are frequently occurring mostly in RO1 and also sometimes in RO2. Furthermore, EDI seems not to work properly until December 2019 leading to several serious peaks in conductivity after the mixed-bed filter. From January 2020 on, only few problems larger than 650s (orange) occur, all other problems have a duration of less than 650s (grey) and it is obvious that they do not influence the EDI and the mixed-bed filter.
Hence, the combination of a data driven and a knowledge driven approach is successful to identify short-term problems and extend them to long-term behaviour.

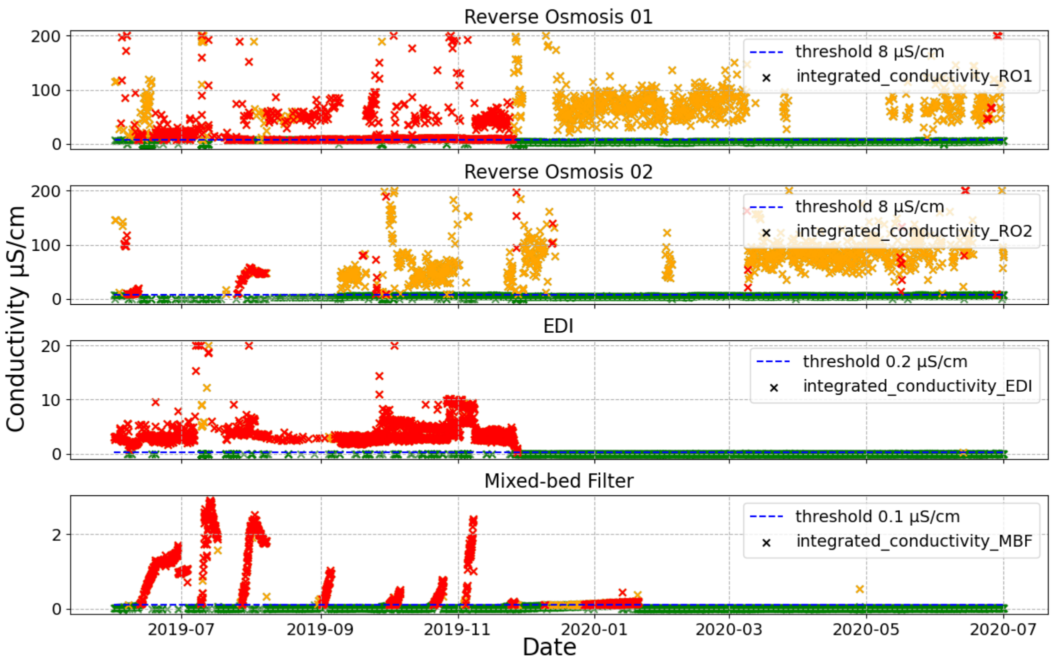

Figure 10. WTS with rules 1-3

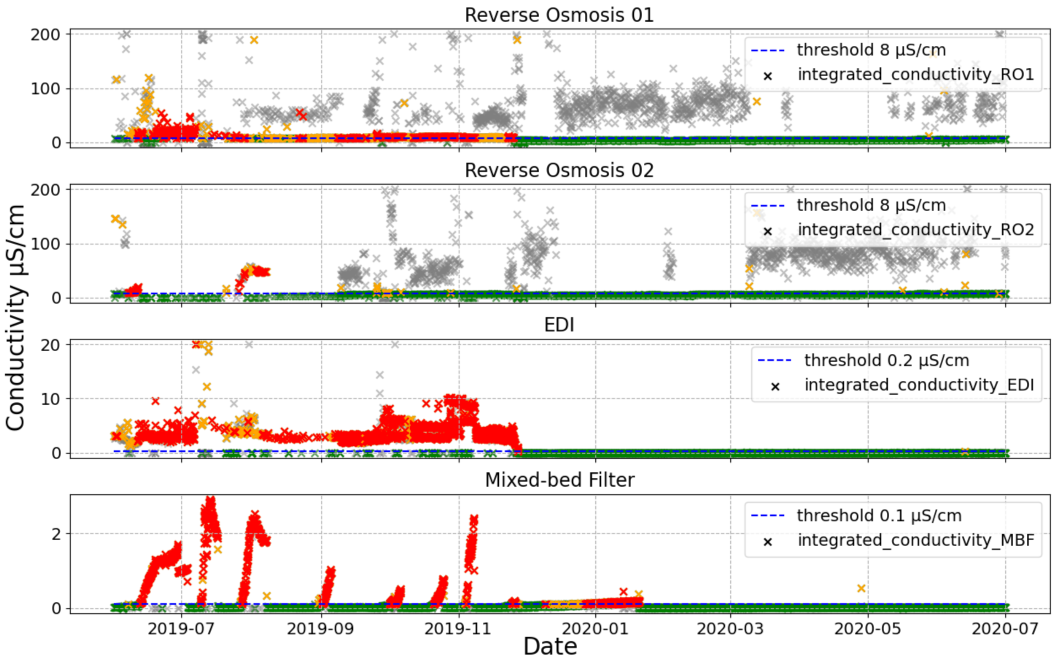

Figure 11. WTS with rules 1-4

Lastly, it is our goal to use this information to calculate the remaining useful lifetime(RUL) of the mixed bed filter (Fig.12). This is the first step to apply our method to predictive maintenance. To calculate the RUL it is necessary to know what is the current status of the equipment unit (what happened before) and to predict what will be in the future. Therefore, we implemented a simple knowledge-based rule (rule 5) to estimate the days until the next regeneration.

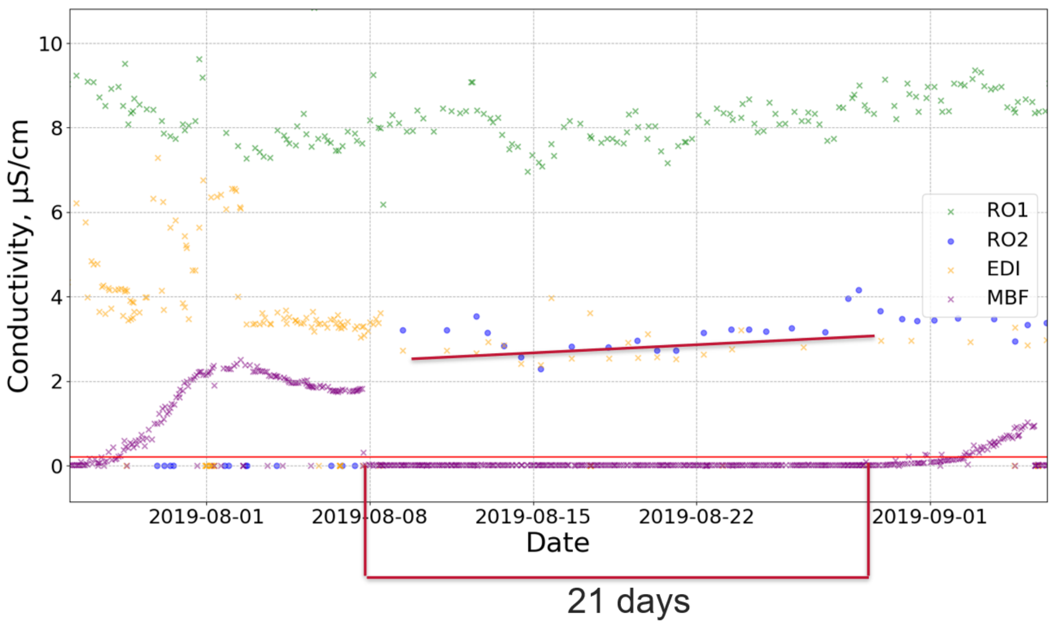

Figure 12. RUL expression (rule 5)

As it was stated in the background chapter, the mixed-bed filter has a certain capacity. After the capacity is exhausted water goes through MBF without purification. This can cause problems with power plant equipment due to deposits in boiler heating surfaces and turbine blades.

Especially if something will happen with the equipment upstream MBF the quality of make-up water will deteriorate very fast. With Eq.1 we can calculate the capacity of the MBF.

$$C = \int_0^{N_{days}} \lambda(t)\, dt \tag{1}$$

To calculate the number of days until the next breakout, we have to take an average conductivity of EDI during the considering period. Then we need to equate two capacities and then determine the number of days N_2 with Eq.2. In our project, we estimate the required water quality on the level of 0.2 µS/cm (required conductivity in the inlet of MBF) and the required duration of the operation 180 days (technical specs of MBF).

$$\begin{aligned} C_1 = C_2 \Rightarrow \lambda_1 \cdot (N_1 - 0) &= \lambda_2 \cdot (N_2 - 0) \\ 0.2 \cdot 180 &= \lambda_2 \cdot N_2 \\ N_2 &= 36/\lambda_2 \end{aligned} \tag{2}$$

For the example shown in Fig.12 this simple formula gives 15 days as a result. So that means that our monitoring system shows problems with the Mixed-bed filter, the plant operator has 15 days to fix the problem before the capacity is exhausted. This is a very simple approach but it allows to get a rough estimation of the number of days before the next break down.
The last step is the creation of the report. It will include the key results of fault detection and RUL estimation: how many and what type of anomalies have been found; estimation of the breakdown point; etc. These aspects will help the plant operator to detect faults way earlier than so far and to act as soon as possible.

Summary and Conclusions

Predictive maintenance is one of the most crucial directions in industrial research, whereas the interest will grow further in future. The predictive maintenance technique which was considered and showed on the example of the water treatment system is the first approach in a series of researches based on a broad collection of data from a biomass power plant. Here, we tried the methods which can help to reduce malfunction of the water treatment system, how the data fits for this task, and which methods we can use in the future. Our method is simple and straightforward but it meets our goals. It clearly describes the process from the beginning (data acquisition) untill the end (the report tool) with a simple example.
Moreover, our research give us a valuable result: to be successful in predictive maintenance approaches, based on real power plant data one has to use multimodal methods. Otherwise, the methods which are based only on one type of knowledge fail due to misunderstanding, lack of knowledge and a lot of assumptions.

Acknowledgment

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