Data analysis to facilitate offshore seawater ultrafiltration membrane replacement decision and scheduling of chemical wash

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Unmanned and minimum manned offshore platforms are recently getting much attention due to their cost-saving potentials. They are expected to maintain continuous production for 24/7 while being operated from onshore control rooms. Such status is closely linked to the achievement of near zero- downtime performance which would require cost-effective maintenance strategies and data-dependent decision support system. Traditional corrective and scheduled maintenance practices may not be adequate in that regard and predictive maintenance for decision support may add new values. In the era of digitalization, like many other industries, huge amount of data are being collected in o&g sector that are also offering opportunities to move towards predictive maintenance. In this paper, we consider ultrafiltration membranes used to pretreat seawater in water injection process that are subject to degradation and required replacement in 3-5 years. It is believed that, due to associated lead time and lack of redundancy, predictive support for replacement may bring additional values. Data from an offshore platform in North Sea is collected and analyzed to identify prognostics and maintenance optimization options. A possible condition indicator for prognostics model development for replacement decision and a possible optimization scope for optimal chemical wash sequence is discussed constrained under existing limitations and challenges.

Keywords: Predictive maintenance, degradation, offshore o&g,

1. Introduction

It is unlikely to experience a significant reduction in demand for O&G over the next decade or even more (Telford et al. (2011)). Due to their non-renewable nature and continuing exploration, conventional O&G reserves in proximity are getting scarce day by day (Telford et al. (2011)). Intuitively, future O&G production will be mostly from fields that are not in production today. According to (World-Economic-Forum (2017)) such non-traditional source will account for 12% of global supply and out of which 18% will be accounted by offshore energy. In order to compete with other renewable and cleaner energy, reducing operational costs is going to be a significant factor. In such context, fully automated unmanned platforms with minimum visit concept are seeming to gain popularity due to their cost saving nature as site personnel is one of the major contributor of OPEX in the offshore operation (Pinosofa et al., 2010).

Remote operations, especially for unmanned operations, human involvements are expected to be mostly diminished and in order to check equipment condition, human sensing and visual inspections are being replaced by condition monitoring where sensors and advanced measurement techniques are being utilized. Achieving near zero downtime performance with fully functional 24/7 online real-time operation requires cost-effective maintenance strategies and data-dependent decision support system. Traditional maintenance practices such as corrective and calender-based maintenance, in this regards, are being challenged as they are often associated with high planned and unplanned downtime(Liyanage, 2008). However, according to a Baker Hughes study, 76% of O&G operators are still relying on either reactive or calender-based maintenance strategies.[a]. Predictive maintenance strategies allow to take maintenance actions only when justified by the evident abnormal behaviors of a physical asset derived from condition monitoring information (Jardine et al., 2006) and there has been a significant rise in the research areas of prognostics and RUL estimation approaches over the last decade (Lei et al.,

[a]The Impact of Digital on Unplanned Downtime- An Offshore Oil and Gas Perspective, Baker Hughes, Published October 2016

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2018).

In this paper, a seawater ultrafiltration (UF) system is considered to identify scopes of prognostics for supporting timely replacement decision and optimization opportunity for chemical wash sequence. UF systems require frequent cleaning to maintain its functionality and currently such cleanings are conducted according to pre-fixed schedule and sometimes re-actively. There are reasons to believe that, such practice is not optimum and can be improved by condition-based maintenance. In addition, the membranes used in UF system has limited lifetime of 3-5 years before they need replacement. In the context of unmanned offshore remote operations with fewer maintenance opportunities, prediction ability of a required membrane replacement should bring additional value. Therefore in this study available offshore process and operational data and external literary sources have been studied and analyzed to investigate how predictive maintenance can be implemented in this specific case study. To the best of author's knowledge, such systems were not studied before from the perspective of implementing predictive maintenance and this study attempts to discuss the associated scopes and challenges of practical implications of predictive maintenance by available data stream. In the following section, the basic process is described with essential details.

2. Process Description

During carbohydrate extraction, water is often re-injected in some reservoirs to compensate the depleted pressure during hydrocarbon recovery. Injected seawater must be treated first in order to minimize scale formation during mixing with produced water and bacterial activity in the reservoirs. Usually filtration with reverse osmosis (RO) is eventually used to remove sulphate from the seawater but it has become a common practice to use UF prior to RO as a pre-treatment to avoid biological fouling in the membranes of sulphate removal unit. In this paper, we focus on only ultrafiltration membranes and it will be based on a real process in an offshore platform in Norwegian Continental Shelf (NCS).

The targeted UF package is a series of 6 twin vessels consisting of hollow fibre hydrophilic Polyvinylidene Difluoride (PVDF) membranes that conducts pressure driven separation of materials such as particulate and microbial contaminants from a feed solution. Depending on the feed water temperature, UF unit may have one or two redundancy and therefore able to deliver required output when at least four twin vessels are available in some cases.

During the normal operational periods, UF membranes are subject to fouling which is basically capturing of materials on and/or inside the porous membrane matrix. It leads to reduced flow of feed water through membranes and increase pressure drop across the filters. Fouling is not reversible during a normal operation and require frequent cleaning in order to function optimally.

2.1. *Operational Features*

With the increase of fouling, Trans membrane Pressure (TMP) increases and the process shuts down if TMP reaches a pre-defined threshold level. In order to lower down TMP, membranes are subject to regular and different cleaning sequences. Among them, backwash (BW) is the most basic wash which is mainly a mechanical wash where the membranes are shaken to get rid of the solids and dirt off the membranes. In order to prevent more severe fouling chemical washes are required and two types of chemical washes are performed here- maintenance wash (MW) and clean-in-place (CIP). Both of these wash use sodium hypochlorite (NaOCl) as oxidizing agent. The recovery from fouling of MW is better than BW but not as much as CIP which is supposed to remove all the fouling accumulated in between CIP intervals. The cleaning sequences are summarized in the table 1.

Table 1. Summary of associated membrane cleaning (general guideline, actual operation may vary)

Cleaning method	Frequency	Duration
BW	Every 1 hour	5-7 minutes
MW	Every 2nd day	30-60 minutes
CIP	Every 2-12 days	6-8 hours

Here BW and MW are automatically triggered by the control system regardless of the membranes' condition. CIP is typically triggered by a fixed schedule but it will be prioritized if level of TMP crossed a preset level or maximum preset interval is passed without CIP cleaning.

3. Potential Benefits of Prognostics and Maintenance Optimization Opportunities

The membrane elements used in UF packages are not expensive but may associate with downtime if requires immediate replacement or too many frequent washes. When the pressure drop across the membranes is higher than expected, visual inspection may reveal the damaged membranes and can be easily replaced. However for remote operations with minimum visit opportunity, such approach is intuitively not optimal. These membrane elements require special procedure for storage when they are not in operation and therefore keeping extra spare inventory is not possible and expensive lead time and production downtime is associated if corrective replacement is required. In the context of remote and unmanned operation, focusing on to decision making regarding physical maintenance requirements such as replacement of membrane elements, prognostics information of membrane may bring more value by allowing planning for spare parts, maintenance crews, grouping other activities, etc. In addition, the corresponding platform in this paper, is heavily equipped with condition monitoring sensors that are transferring real-time condition information to onshore that are ready to be utilized. Utilizing such existing information to support predictive decision making is valuable even when the equipment is not as critical as, for example, rotary machines. Furthermore it has been experienced from the operational experience that, demand for CIP washes increase as the membranes grow older. Therefore it is of interest to investigate if chemical washes negatively impact on the degradation rate of the subsequent operations. Increasing demand of CIP washes have several negative consequences. First of all, CIP washes are longest in terms of duration which uses the available redundancy and increase the probability of process shutdown. Secondly, concerning the environmental regulations, chemical uses are required to be limited and high requirement for CIP washes may trigger premature membrane replacement. Finally, if high usage of chemical use has detrimental impact on the degradation rate during the subsequent operation then by optimizing the CIP wash sequence one can expect to increase the useful operational life of membrane elements.

4. Associated Degradation Mechanism

Despite BW and MW with their limited ability of removing all irreversible fouling, the TMP will gradually increase during normal operation. Over time membrane resistance to flow increases slowly caused by a fouling mechanism. It can occur when materials are captured on and/or inside the porous membrane matrix which leads to reduced flow or increased pressure drop of the filter (Jagschies et al., 2018). Generally fouling process is not reversible during a process and CIP washes are required to keep the TMP stable by removing foulants to avoid irreversible fouling. For UF membranes biofouling is possibly the most obvious fouling threat where organic materials like algae forms a layer of gel on the membrane surface by secreting extracellular polymer substances (EPS) and contributes to increased TMP, decreased permeate flux and chemical degradation of the membrane material to practically reducing the membrane lifetime (Lau et al., 2014).

4.1. *Health Condition Indicator*

Monitoring upstream process variables are critical in identifying upstream process related problems and troubleshooting but may not be equally reasonable as a health condition indicator for membranes. For example, rise in TMP and/or reduction in filter water quality can be an indication of membrane damage. In such case, Slit Density Index (SDI) test is conducted for UF unit with highest Pressure Decay Test (PDT) k value in order to identify the need for membrane replacement. This empirical SDI test is not based on fouling mechanism and this static measurement of resistance assumes a linear permeate flux decline and therefore it is not a good candidate to predict fouling rates (Ruiz-García et al., 2017). On the other hand, TMP depends on membrane fouling, temperature and flow through the membranes and may not provide an intuitive measure for the membrane condition. Fouling can be measured in relation to Darcy's law (Jagschies et al., 2018) in terms of overall membrane resistance to flow (R) and mathematically it can be expressed as,

$$R = \frac{1}{\mu}\frac{\Delta P}{J} \tag{1}$$

Here J is the filtration flux (flow rate over/ membrane surface area), ΔP is the pressure drop over the membrane, μ is the viscosity of the feed. According to relevant industry guideline, this equation is valid in the temperature range $T = [5, 30]^0C$, and seawater with salinity of $35g/l$. Assuming overall membrane resistance (R) as a condition indicator of the membrane's health, vendor's specification is adopted as failure threshold stating that value of R should typically be in between 2.5 to maximum 10 for new and damaged membranes respectively.

5. Data Collection, Processing and Analysis

Estimated membrane resistance to flow using the main principle stated in Eq.(1) is readily available through the industrial data platform. An average R value for each twin vessels are available and in this study data from one of them out of six is used. Besides R, available process variables are also collected such as inlet feed water temperature T (^0C), UF inlet flow F (m^3/h), UF vessel pressure P (barg), vessel level L (%) and TMP (bar). Considering the wash frequency and duration sampling rate of 1 minute is believed to be reasonable for data collection.

The complete dataset consists of data from February 2017 to December 2019. However, until this point actual and complete operational data and event information is not available and therefore wash boundaries and events had to be identified directly from the data. Upon visual inspection, the data before May 2018 and after May 2019 seemed to show irregular patterns. Therefore in order to minimize the risk of identifying anomalous operations as normal operations, only 1 year of data from May 2018 to May 2019 are analyzed. The data has consecutive NA series which have been utilized to differentiate between operational and non-operational periods. Non-operational periods are further labelled as different washes based on the general practice of wash duration and frequency mentioned in table 1 where it is assumed that any non-operational period from 5-30 minutes are BW, from 30-60 minutes are MW and above that are CIP wash. However, non-operational period more than 6 hours are considered as shutdown events.

5.1. *Degradation Behavior*

Due to the frequent cleaning procedures, degradation paths are always perturbed as shown as figure 1 where an example of two possible cases of MW and CIP starting points are shown with vertical lines. In between, there are number of BWs that are distinguishable with a minimal recovery and smaller duration. Because of these frequent interventions, degradation paths are individually considered between two consecutive washes. To the best of authors' knowledge, degradation behavior due to fouling is not well studied before to select a degradation model from reference candidates. Visual inspection of data between two wash periods show some hints that the membrane resistance, linearly increases over time. For any normal operation i between any two consecutive washes, R is linearly dependent on time as Eq.(2)-

$$R(t) = \beta_{I_i} + \beta_{S_i}(t - t_{0_i}) + \varepsilon(t) \qquad (2)$$

Here $\beta_{0,i}$ is the intercept and t_{0_i} start time of operation i). Slope β_{s_i} is considered as degradation rate of R.

Adjusted coefficient of determination (R^2) value is calculated to check how much of the total variance in R is captured by linearity assumption. In addition, p-value is calculated to check the model significance. We will assume our assumption of linearity is correct if R^2 is significantly large (> 0.60) and p-value is reasonably low (< 0.05). In addition, negative slopes are not acceptable as it only means during a normal operation membrane condition is rather improving. Finally, upon visualizing the slope distribution, few occasions of extremely high slopes (> 0.01) are identified as shown in figure 2.

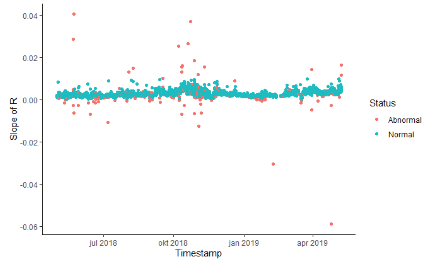

Fig. 2. Distribution of degradation slopes before cleaning

For each of the identified 3892 operations, only 6.5% operations deviated from the linearity assumptions based on the above conditions which can be caused by improper identification of normal operation or anomalous behavior for some process related issues, etc. Instead of simply removing these values, associated values for these instances are replaced with immediately previous value assuming that slope has not been changed in those particular operations. After cleaning of the data, the average R^2 value is 0.85 with a standard deviation of 0.16. Therefore the linearity assumption of R value depending on time during any normal operation seems to be a reasonable assumption. Figure 3 portraits the progression of degradation rates after the adjustment of obvious outliers.

5.2. *Progression of Degradation Rate*

At this point we are interested in how degradation rate (slope β_{s_i} changes over it's lifetime and what they are dependent upon. Therefore collected process parameters are investigated to understand

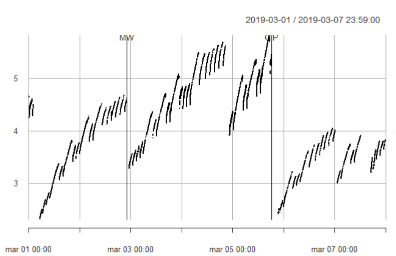

Fig. 1. Effect of different washes

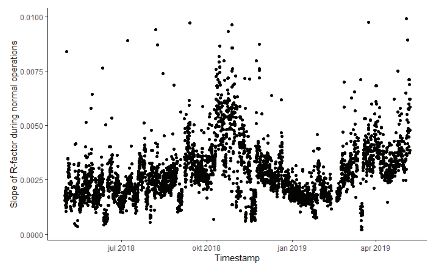

Fig. 3. Evolution of degradation rates with time

how they contribute to explain the degradation rates. For each normal operation i, average is taken of each process variables (x_i) for that particular operation. A multiple linear regression model is used as in Eq. (3).

$$\beta_s = \beta_0 + \sum_{j=1}^{n} \beta_j.x_j + \varepsilon \qquad (3)$$

Where $n = 5$ to represent explanatory variables and coefficients of T, F, P, L and TMP and ε is normally distributed error term of the regression model. Adjusted R^2 value of 0.5 indicates that about 50% of the variance in β_s can be explained using these explanatory variables. P-values of the coefficients indicate that vessel level is statistically insignificant in the model. With further analysis multi-collinearity is observed in the model with inlet flow and vessel pressure indicated by high variance inflation factor. Reduced model with variables T and TMP still explain about 49.2% of the total variance. Therefore the average inlet temperature and average TMP during a normal operation can explain 50% in the variance of the degradation rate.

5.3. *Seasonal Effect*

Although we are analyzing data for only one year, seasonality can still be observed supported by our physical understanding of the process. As the summer approaches it is expected to experience more fouling due to increased biological growth in the seawater. Intuitively intlet seawater temperature (T) should explain this effect but additional attempt is taken to capture monthly seasonal effect to investigate if additional variance can be explained that were not captured by T only. Some dummy variables are introduced in the Eq. (3) by extending $n = 14$ where $i = 1, 2$ represents T and TMP while $i = 3, ..., 14$ are the dummy variables to represent each months. The updated result shows a significant improvement of R^2 to 0.6004. A reasonable explanation is related with the algae blooming in the seawater in connection with fouling. The algae blooming season in that particular area of NCS is tentatively observed starting from February increasing until mid April and again starting around August until October. This pattern is visible in figure 3.

5.4. *Negative Impact of Chemical Washes in the Degradation Rate*

From the operational experience, it is observed that membranes demand more frequent CIP washes in the later stages of their lives to keep the TMP down to avoid shutdown. An intuitive expectation was that, CIP washes gradually lose their effectiveness to remove all the irreversible fouling and therefore reversible fouling accumulates as time progresses. However from the figure 4 it is rather clearly seen that while recovery due to washes by BW and MW are quite dependant on the initial R before washes; recovery due to CIP wash is independent of initial R value. Considering the baseline R is on average 2.5, CIP washes bring down the level to baseline meaning that they are able to clean all the fouling. Therefore CIP is rather perfect wash against fouling. Given the observation, it can be speculated that, it is the degradation rate that increases gradually resulting in faster accumulation of fouling and therefore demanding more frequent CIP washes. Previous scientific literature have been preliminary studied that provide some evidences of the possible increase in degradation rate of subsequent operations as a function of exposure to chemicals like NaOCl used in chemical washes (both MW and CIP in different amount). Summary of literature review is provided below.

5.4.1. *Literature Review Regarding Influence of Chemical Wash in Degradation Rate*

Due to their chemical and mechanical stability, routine CIP cleaning is common in UF membranes which are performed with strong oxidizing agents like hypochlorite. Although it is necessary to restore membranes permeability, however, can also be responsible for altering membrane's physical properties to affect membrane's lifespan (Wang et al., 2010). (Arkhangelsky et al., 2007) in their study, shows that, hypochlorite cleaning contributes in deteriorating the mechanical strength of UF membranes which is related to gradual chain breaking in membrane skin layer. (Puspitasari et al., 2010) shows based on flatsheet aged PVDF membrane that, degradation mechanism is a two step process where cleaning agent tend to gradually remove membrane's surface modification additives causing increased membrane resistance and hydrophobicity. PVDF is originally highly hydrophobic which is more vulnerable against fouling compare to hydrophilic materials. Therefore, hydrophilic additives are added during membrane preparation (Gao et al., 2016)). Based on

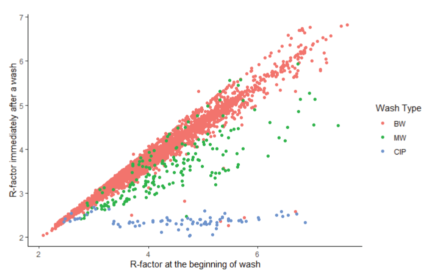

Fig. 4. R-factor immediately before and after a wash

experiment on microfiltration (MF) PVDF membrane, (Wang et al., 2010) claims that, although sodium hypochlorite cleaning showed good recovery against TMP but contributed in more severe fouling in the subsequent operation. They further remarked that, chemical cleaning has potential to modify the contact angle and tends to be more hydrophilic as cleaning time increases. (Gao et al., 2016) focused on the effect of sodium hypochlorite on the membrane's surface characteristics and investigated its impact on the chemical constitution of PVDF polymeric materials. They show that, membrane treated with NaOCl can cause more irreversible fouling due to the removal of PVS in PVDF.

Therefore based on the operational experience and literature study, number of chemical washes can be a contributing factor to the increase in the degradation rate. In order to test the hypothesis, all the slopes are labelled on the basis of how many chemical washes they were subject to. As there are two types of chemical washes, three different labelling are created to indicate for each slope separately to identify how many MW, CIP or either of them were used until that point. They were each added separately as an explanatory variable in the Eq.(3) with $n = 3$, representing T, TMP and number of the type of chemical wash exposure. Obtained results show that, this extra variable is not statistically significant indicated by p-value when considering a 5% significant level. Which means number of chemical wash is not contributing in explaining any variance in degradation rate during normal operations.

6. Conclusion

The main objective of this paper is to study the already available data to support membrane replacement decision and finding maintenance optimization opportunities to facilitate optimal usage of chemical washes. After analyzing currently available resources, it has been found that, it is rather difficult to develop any prognostics models at this stage due to several challenges. First of all there are not enough usable data to get a good sense of how a membrane element is approaching its end of life. There are not enough failure histories as well. In this study we were only able to use data for 1 year which shows non-monotonic degradation with strong significant seasonal components. However, the behavior of the degradation rate in consecutive years are not understood well due to lack of data. In addition, R-factor is more of an indicator of the cleaning efficiency rather than the actual physical condition of the membrane. Therefore the basis of replacement based on R-factor threshold is difficult to justify.

Although R-factor did not become evident to be useful in prognostics in this case, it shows promising implications in maintenance (cleaning) optimization. Current industrial practice dictates the use of calendar-based cleaning. In addition, if the TMP increases to warning or alarm level, emergency CIP can be executed. However, in this study it has been observed that, demand for CIP varies depending on the algae blooming in the seawater and increases as the membranes get older. Fixed CIP schedule is therefore may not be optimal and can possibly be further optimized. This issue is being addressed in our current work.

Possible negative impacts were discussed in section 5.4. The available data was not enough to validate the hypothesis that chemical washes have negative impact on the degradation rates. Currently more attempts are being taken to understand the relationship between the chemical washes and their negative impacts on the degradation rates. This relationship is quite important because if significant relationship is found then optimizing the washes will have potential effect on the life-extension of the membranes which will allow longer lifetime with fewer chemical washes.

There are several limitations of this study. First of all, due to unavailability of the operational data (e.g. actual time of different wash sequences, maintenance and replacement, shutdown events, etc), wash events are identified based on theoretical knowledge and therefore may lead to some erroneous detection. After receiving the actual data the claims should be cross validated. In addition, seasonal effects are visible from the available data but they are only consist of one year which may not be adequate to understand their dependence with degradation process. Furthermore, given the 3-5 years of expected lifetime of the membranes, only data analysis of one year long data stream may not be adequately representative of the complete story.

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