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Condition monitoring for early failure detection. Frognerparken pumping station as case study

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Abstract

A case study has been carried out to investigate how process data from *Frognerparken Pumping Station* can be used more efficiently to get an early detection of degradation or failures of the pump systems. The technical condition is described by use of a single number from 0 to 100, denoted as the Technical Condition Index (TCI), where maximum value describes the design condition as new and the minimum value describes the state of total degradation. As presented in this paper, the pump station is broken down to subsystems where each subsystem consists of several nodes with its own TCI value. The overall pump station's TCI number is then computed by aggregating a weighted sum of all the subsystems' TCIs.

A method for early failure detection is also developed and is based on combining energy balance law together with the nonlinear extended Kalman filter to estimate model parameters for both the heating and the cooling phase of the pump. The model parameters are directly related to the temperature change and will give an indication of degradation during the transient phase even if the pump is working properly. During a visual inspection one of the pump had significantly higher temperature and vibration compared to the other pumps, and based on received timeseries for that specific day, we were able to validate the proposed method with realistic data.

Keywords: Condition monitoring; Fault-diagnosis; Technical condition index; Extended Kalman filtering; Case study

1. Introduction

The overall importance of condition monitoring for Oslo Water and Sewerage Works (Oslo VAV) is to prevent unwanted equipment failure, emissions to the environment and especially the loss of reputation if serious unwanted events should happen. Condition monitoring techniques are used to monitor parameters or conditions in a machinery or process, such that a significant change is indicative of a developing failure, see Isermann (2011). The main idea is to derive an indication that should results in an action to avoid consequences of failure, before the failure occurs. The project "Secure and Monitored Service from Oslo VAV", see Ugarelli et al. (2012), aims to improve the efficiency and

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the security in monitoring and control of the urban water and wastewater system of Oslo and as a part of this project, a case study has been carried out to investigate how all process information and available data from the different sites of the infrastructure can be used more efficiently for early detection of degradation or failures.

Inspired by other disciplines like marine and process and gas transportation system, a methodology for condition monitoring has been applied to this case study, see Nystad (2008) for details. Today, too much data are often available for the operator or maintenance people, so there is a need for smart methods to aggregate or analyze the big amount of data (sensor fusion techniques) and then present some key performance values or key performance indexes to describe the overall condition. The key index is denoted as the Technical Condition Index (TCI) and is number from 0 to 100 used to quantify the condition. The maximum value describes the design condition and the minimum value describes the state of total degradation. The pump station is divided into several subsystems and the overall pump station's TCI number is a weighted sum of all the subsystems' condition indices. By using already available measurements there is a potential to derive valuable information for the condition without added extra instrumentation. The main idea is to use simple physical laws (first principle laws) combined with estimation techniques on-line to estimate important process parameters that could be applied to quantify the condition. Another approach is to post-process available measurement to give trends in the signals. A trend may indicate a degradation that has to be considered in the maintenance plan. If a failure occurs there is also a need for a simple "drilldown" system, such that important data are available immediately for doing the right action to reduce the consequence.

In this paper we present a method for failure detection of a wastewater pump using the available measurements together with parameter estimation techniques. The method combines *principal energy and heat transfer laws* together with the *discrete Extended Kalman Filter (EKF)* to estimate important parameters used for on-line failure detection. As seen, there are several other measurements that simultaneously indicate that one of the pump is working under "bad condition". By using the method of technical condition index to describe the condition of each component, a technical condition index (TCI) can be associated to the overall pumping station as a key indicator of its condition.

1.1. Frognerparken Pumping Station

The Frognerparken Pumping Station is located at Frogner in Oslo (the Capital of Norway) and is operated by Oslo VAV. The pump station is used to lift the sewer flow from Oslo downtown up 30 meters into a tunnel where the sewage is transported to a large treatment plant. 6 equal pumps are installed and 4 out of the 6 pumps must be available all time to handle maximum capacity.

1.2. Instrumentation

Each pump-system is very well instrumented and the following measurements are available:

- Electrical motor current (all three phases together)
- Motor winding temperatures (one for each phase)
- Motor bearing temperature (NDE and DE)
- Pump bearing temperature (NDE and DE)
- Flow measurement (top of pipe)
- Pump vibration measurement

In addition, there are level measurements in the sump (4 radar sensors for redundancy) that are used in the PLC for starting and stopping the pumps. Instrumentation for the electrical power system and other sensors are also available for security. All process data are available as time series with a sample time of 1 minute. It is assumed that the reported data are averaged or filtered every 60 seconds.

Fig. 1. Manual inspection

1.3. Manual observation of degradation

SINTEF ICT and SINTEF Building and Infrastructure visited Frognerparken Pumping Station 20th September 2012 and observed that one of the six pumps had much higher temperature and vibration level than the other pumps, see Fig. 1. Based on the human hand sensor, the temperature was significant higher on Pump #4 than Pump #1. This observation was later documented by received timeseries from Oslo VAV. The timeseries were therefore used to make the initial algorithms for failure or degradation detection.

2. Technical Condition Index (TCI)

Based on available information from the process control systems and condition monitoring system, the technical condition of the different items is quantified by a technical condition index (TCI). In this chapter, we will derive an example for generating TCI number for each component of the pump-system and then aggregate the values to a higher level for an overall TCI number related to the complete pump system, including all six pumps.

2.1. Definition of Technical Condition Index

The software package TeCoMan developed by MARINTEK, see TeCoMan (2006) white paper, shows how a total system can be broken down to sub-components or tree-structures. In Eriksen (2010), a model for calculating the TCI for a ship engine auxiliary system is also presented. The complete system is broken down to different levels, where each level consists of a set of nodes with its own TCI numbers. All information is then computed from bottom up to top.

When aggregating TCI values from a lower (child node) to higher level (parent node) in the tree-structure, the following formula is used:

$$TCI_{parent} = \frac{\sum\limits_{i=1}^{n} (TCI_i \cdot w_i)}{\sum\limits_{i=1}^{n} w_i} \tag{1}$$

where TCI_{parent} is the aggregated technical condition number for the parent node, TCI_i is technical condition number for the child node i, w_i is weight of the child node i, and n is number of child nodes. Typical intervals of the TCI are:

Table 1. Technical Condition Index

Value	Action	Colour
90-100	No further action needed	GREEN
80-90	Observe the trend and assess the needs for improvements	YELLOW
0-80	Need for action and improvements	RED

2.2. Pump Station's TCI number

The following main tree-structure has been suggested for the pump station:

- Pump system (7 children)
    - Pump system #1
    - ..
    - Pump system #6
    - Sump with level measurements
- PLS
- Power system instrumentation

For example each pump system can be broken down to the following TCI nodes:

- Real versus nominal effect on motor
- Flow meter measurement (range checking)
- Real vibration compared to nominal vibration level
- Real start current compared to normal start current on motor
- Real pump temperature compared to nominal level
- Real change in temperature on pump compared to nominal value
- Electrical motor temperature compared to nominal values
- Difference in winding temperatures

For simplicity, we only consider Pump #1 and Pump #4 in this case study.

3. Estimation of pump temperatures

The pump and motor temperatures are one of the main indicators of the component's condition. In case of damaged bearings, increased friction or other obstruction in the pump system, both the temperature and also vibration level will normally increase. In our case study, we measured the temperature at different locations for pump and motor and also the vibration at the pump. All these measurements are available and can be combined in different ways to indicate the condition of the system. Since the pump can work in degraded condition without loss of pumping capacity, it is difficult to detect degradation when only using a flow meter. By using principal laws of energy together with estimation techniques it is possible to estimate model parameters that is not possible to measure directly. A discrete implementation of the nonlinear *extended Kalman filter* is used for estimating the unknown model parameters, see Fossen (2011) for details.

3.1. Estimation of temperatures and model parameters

Physically, the measurement process represents an energy/heat transfer problem. When running the pump, the supplied power will be used to transport water from one level to another and represent the reversible power. In

addition there will be some friction and other power losses that will increase the temperature for both pump and motor. Since we can derive both the supplied power and the used power from the available measurements, we can compute the power loss directly. The temperature change for the pump or motor is then assumed to be proportional to the power loss using the principal law for energy balance. Define the pump or motor temperature around the sensor as T, then the dynamic temperature change $\dot{T} = \frac{dT}{dt}$ can be obtained from:

$$c_p V \dot{T} = -h (T - T_a) + P_a \tag{2}$$

where

- c_p is the heat capacity factor for the volume around the temperature sensor
- V is the heated volume around the temperature sensor
- h is the heat capacity transfer coefficient between the volume and ambient temperature
- T_a is the ambient measured temperature
- P_a is the added power to heat the volume around the temperature sensor

The added power P_a to heat up the volume around the sensor is an unknown fraction α of the supplied power P_s minus power used to transport the flow P_r (reversible power). The difference represents the power loss in the electrical motor and the mechanical pump. The model can then be formulated as:

$$\dot{T} = -\frac{h}{c_p V} (T - T_a) + \frac{\alpha}{c_p V} (P_s - P_r)$$
$$\dot{T} = -a (T - T_a) + b (P_s - P_r) \tag{3}$$

where parameter $a = \frac{h}{c_p V}$ and parameter $b = \frac{\alpha}{c_p V}$. During the cooling phase, the model will be a pure time constant given by:

$$\dot{T} = -a (T - T_a) \tag{4}$$

and for the heating phase when pump is running, the model is:

$$\dot{T} = -a (T - T_a) + b (P_s - P_r) \tag{5}$$

To estimate the two parameters a and b, we have suggested a method for estimating parameter a only during cooling phase and then use the estimated value for parameter a when estimating parameter b during the heating phase.

The supplied power from the motor is given by:

$$P_s(k) = \sqrt{3} U I(k) \cos \phi \tag{6}$$

where index k represents discrete time, the voltage $U = 400V$, $\cos \phi = 0.86$ and $I(k)$ is the measured current for all three phases. The reversible power used by pump to transport the fluid can be written as:

$$P_r(k) = \Delta p(k) q(k) / n = \rho g \left[29.0m - h(k) \right] q(k) / 0.78 \tag{7}$$

where $h(k)$ is the measured height of the sump and $q(k)$ is the measured flow in l/s. The pump efficiency factor n was found to be $n = 0.78$ from the pump characteristics. The value 29.0 m represents the height of the tunnel relative to the pump inlet, $\rho = 1.024 \ kg/l$ is the water density and $g = 9.81 \ m/s^2$ is the gravitational constant. Define the input $u(k)$ as

$$u(k) = P_s(k) - P_r(k) = \sqrt{3} U I(k) \cos \phi - \rho g \left[29.0m - h(k) \right] q(k) / 0.78 \tag{8}$$

The input $u(k)$ is the power loss and will normally force the temperature to a stationary value given by:

$$T_f = T_a + \frac{b}{a} (P_s - P_r) \tag{9}$$

where T_f is the final stationary temperature. Seen from Eq.(9) , the temperature difference between final and ambient temperature will be proportional to the power loss when assuming the model in Eq.(5). Since parameter a is the same

for all equal pumps, the parameter b can be used to detect failures or degradation. The computed power loss for the normal Pump #1 and the degraded Pump #4 is shown in Fig. 2.

To estimate the parameters a and b, we define two different dynamic models; one for the heating and one for the cooling phase. During cooling the parameter a is estimated whereas during heating the parameter b is estimated using the estimate of parameter a, i.e. only one parameter is estimated at a time. The cooling model can be written in state-space form as:

$$\begin{aligned}
\dot{x}_1 &= -x_3(x_1 - x_2) + e_{11}w_1 \\
\dot{x}_2 &= e_{22}w_2 \\
\dot{x}_3 &= e_{33}w_3
\end{aligned} \qquad (10)$$

where the states x_1, x_2 and x_3 are given by:

$$\mathbf{x} = [x_1, x_2, x_3]^T = [T, T_a, a]^T \qquad (11)$$

and w_1, w_2 and w_3 are white process noise with zero mean value and $E = diag\{e_{11}, e_{22}, e_{33}\}$, see Appendix A. The available measurements y_1 and y_2 are the temperature sensor measurement T and the ambient temperature T_a. Notice, that parameter a is not measured, only estimated, so we can write the measurement vector as:

$$\mathbf{y} = [y_1, y_2]^T = \mathbf{Hx} + \mathbf{v} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{x} + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \qquad (12)$$

where v_1 and v_2 are white measurement noise with zero mean value and the output matrix $\mathbf{H}$ is defined in Appendix A. In the same manner as the cooling phase, the model for the heating phase when pump is running can be written as:

$$\begin{aligned}
\dot{x}_1 &= -\hat{a}(x_1 - x_2) + x_3u + e_{11}w_1 \\
\dot{x}_2 &= e_{22}w_2 \\
\dot{x}_3 &= e_{33}w_3
\end{aligned} \qquad (13)$$

where the states x_1, x_2 and x_3 are given by:

$$\mathbf{x} = [x_1, x_2, x_3]^T = [T, T_a, b]^T \qquad (14)$$

and w_1, w_2 and w_3 are white process noise with zero mean value and $E = diag\{e_{11}, e_{22}, e_{33}\}$. The available measurements y_1 and y_2 are still the temperature sensor measurement T and the ambient temperature T_a. Notice, that parameter b is not measured, only estimated, so we can write the measurement vector still as:

$$\mathbf{y} = [y_1, y_2]^T = \mathbf{Hx} + \mathbf{v} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{x} + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \qquad (15)$$

Notice, that $\hat{a}$ in Eq.(13) is the estimate of parameter a found from the cooling phase. The implementation of the discrete nonlinear Kalman filter is given in Appendix A. The estimated temperatures for Pump #1 and Pump #4 are shown in Fig. 3 and the corresponding estimates of a and b are presented in Fig. 4. The estimated value of parameter a is $\hat{a} = 0.0025$, which corresponds to a time constant of $T = 1/a = 400$ minutes. Also observe that the estimate of a converges to the same values for both Pump #1 and Pump #4, which is reasonable because the parameter actually expresses the heat transfer coefficient to the surroundings. The other parameter b is found to be $\hat{b} = 0.004$ for Pump #1 and $\hat{b} = 0.05$ for Pump #4, i.e. more than ten times higher for Pump #4. In other words, the change in temperature when starting the pump is much higher for Pump #4 compared to Pump #1, which is expected and can therefore be used for detection of degradation.

This study demonstrates that it is possible to derive parameters by using the extended Kalman filter for parameter estimation. However, there will be a challenge to find good tuning matrices $\mathbf{Q}$ and $\mathbf{R}$ and initial states for the filter. The advantage of using the extended Kalman filter is that it can estimate parameters online and give an indication of failure/degradation during the transient phase even if pump is working properly (enough capacity).
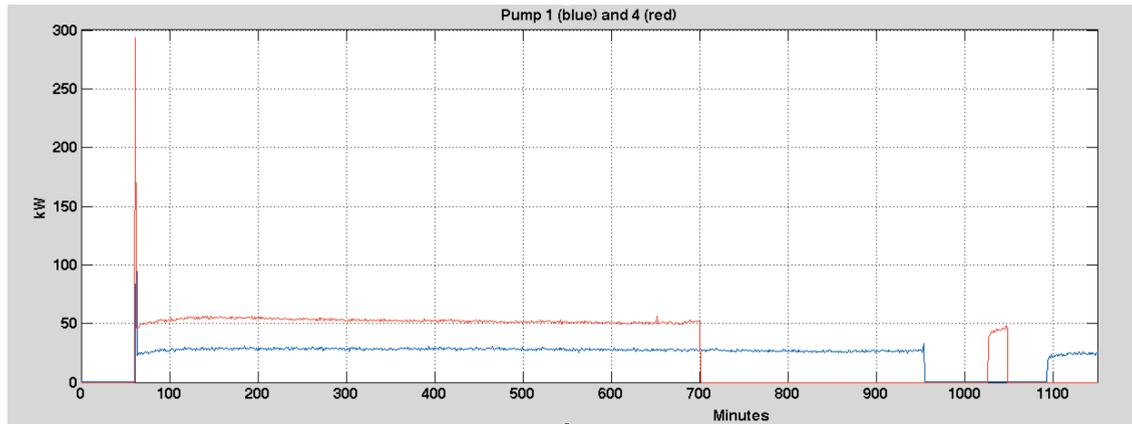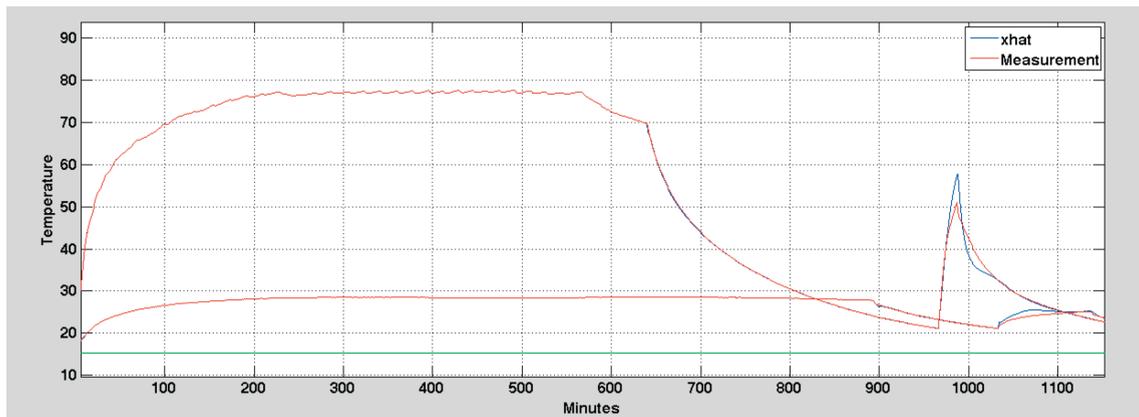
Fig. 2. Power loss for Pump #1 and Pump #4 [*kW*].

Fig. 3. Estimated and measured NDE temperature, Pump #4 (upper curves) has highest temperature [$^\circ C$].

4. Case Study - Online calculation of TCI value

In this case study we have implemented the calculation of TCI values using the Microsoft Excel application. The timeseries were read directly into Excel and a simple macro for calculating the TCI was developed. For simplicity we have defined the following TCI function for all nodes:

$$TCI(x) = \begin{cases} 100 & \text{if } x \in [\min, \max] \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

where min and max are minimum and maximum values describing the normal operating range of the signal. Of course, other continuously and more experience-based functions could be defined, but for simplicity we define the TCI as 100.0 when value is within normal operating range and 0.0 when not. We use the same weight $w_i = 1.0$ for all child nodes. For both pump systems #1 and #4, 11 TCI child nodes values are defined in Table 2 to describe the overall condition of the pump. As seen from Fig. 5, the TCI value for Pump #1 is 100 most of the the time. The drop from 100 down to 91 is when pump is starting and it takes some time to estimate correct value of parameter b. This drop could probably be removed if the filter is better tuned. For Pump #4, the TCI decreases from 100 to 64 when the pump is running. Notice, since parameter b is not updated when the pump is stopped, the TCI will remain around 91 also in the cooling phase. When running Pump #4, we can see from the timeseries that the motor current (Node 1), the pump NDE temperature (Node 8), the pump vibration (Node 10) and parameter b (Node 11) all will exceed their nominal ranges. In our case, 4 of 11 nodes indicate degradation or failure and action should be taken to investigate where the failure is located and if the pump should be taken out for service.
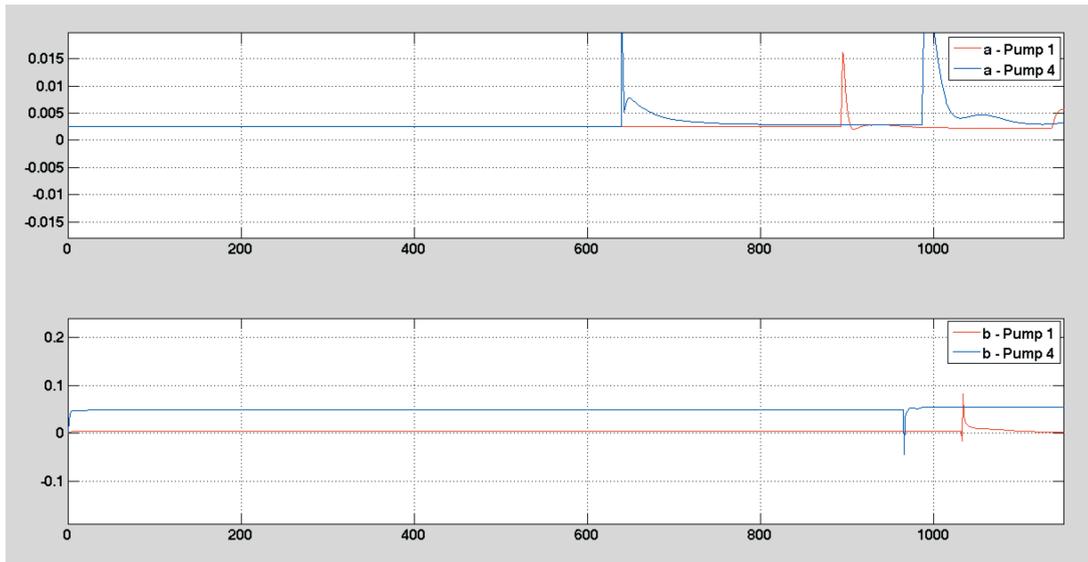
Fig. 4. Estimated parameters $\hat{a}$ and $\hat{b}$ for both pumps.

Table 2. Children nodes TCI values

Node 1	Pump flow (min = 0, max = 600, nominal=420) $[l/s]$
Node 2	Motor current (min = 0,max = 400, nominal=300) $[A]$
Node 3-5	Motor winding temperature 1,2,3 (min = 0,max = 80, nom=75) $[^\circ C]$
Node 6-7	Motor NDE, DE temperature (min = 0,max = 70, nom=40 − 50) $[^\circ C]$
Node 8-9	Pump NDE, DE temperature (min = 0,max = 70, nom=40 − 50) $[^\circ C]$
Node 10	Pump vibration (min = 0, max = 6.5, nom=5.2 − 5.5) $[mm/s]$
Node 11	Parameter b in dynamic model (min = 0, max = 0.005, nom=0.0025) $[^\circ C/(s \cdot kW)]$

5. Conclusions

In this case study we have developed a methodology for detecting degradation or failure based on available process measurements from the *Frognerparken Pumping Station*. A method using the *Technical Condition Index* is proposed for aggregating process information from bottom to top to give a number from 0 to 100 to quantify the condition of the pumping station itself. For an operator or maintenance personnel, this number can be used to get an immediate indication of the pump station's condition (green, yellow or red traffic light).

In addition, a method for estimating model parameters in a dynamic energy/heat balance model is developed using the discrete *Extended Kalman Filter*. The model parameters can be used to detect the rate of temperature changes during the heating and cooling phase and will indicate if the pump is degraded. One of the benefit of using online estimation techniques is that any degradation or failure can be detected during the transient (heating) phase of the pump system even if pump is delivering the required capacity and there is no warnings or alarms.
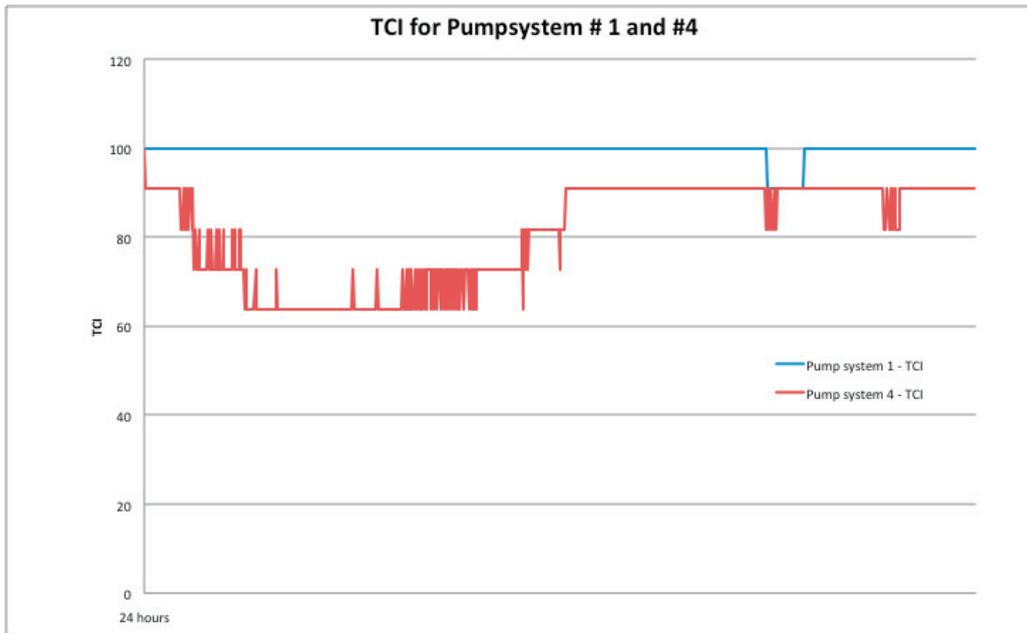
Acknowledgements

Fig. 5. TCI values for Pump #1 and Pump #4.

Appendix A. The Extended Kalman filter

The extended nonlinear Kalman filter can be applied to nonlinear systems in the form:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}) + \mathbf{E}\mathbf{w}$$
$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v}$$

(A.1)

where $\mathbf{f}(\mathbf{x}, \mathbf{u})$ is a nonlinear function in $\mathbf{x}$ and $\mathbf{u}$. The discrete-time extended Kalman filter (EKF) implementation is given in Table A.1. The design matrices $\mathbf{Q} = \mathbf{Q}^T$ is the covariance of the process noise $\mathbf{w}$, $\mathbf{R} = \mathbf{R}^T$ is the covariance

Table A.1. Discrete-time extended Kalman filter

Design matrices	$\mathbf{Q}(k) = \mathbf{Q}^T(k) > 0, \mathbf{R}(k) = \mathbf{R}^T(k) > 0$ (usually constant)
Initial conditions	$\bar{\mathbf{x}}(0) = \mathbf{x}_0, \bar{\mathbf{P}}(0) = E\left[(\mathbf{x}(0) - \hat{\mathbf{x}}(0))(\mathbf{x}(0) - \hat{\mathbf{x}}(0))^T\right] = \mathbf{P}_0$
Kalman gain matrix	$\mathbf{K}(k) = \bar{\mathbf{P}}(k)\mathbf{H}^T(k)\left[\mathbf{H}(k)\bar{\mathbf{P}}(k)\mathbf{H}^T(k) + \mathbf{R}(k)\right]^{-1}$
State estimate update	$\hat{\mathbf{x}}(k) = \bar{\mathbf{x}}(k) + \mathbf{K}(k)\left[\mathbf{y}(k) - \mathbf{H}(k)\bar{\mathbf{x}}(k)\right]$
Error covariance update	$\hat{\mathbf{P}}(k) = [I - \mathbf{K}(k)\mathbf{H}(k)]\bar{\mathbf{P}}(k)[I - \mathbf{K}(k)\mathbf{H}(k)]^T + \mathbf{K}(k)\mathbf{R}(k)\mathbf{K}^T(k)$
State estimate propagation	$\bar{\mathbf{x}}(k + 1) \approx \hat{\mathbf{x}}(k) + \Delta T\mathbf{f}(\hat{\mathbf{x}}(k), \mathbf{u}(k))$
Error covariance propagation	$\bar{\mathbf{P}}(k + 1) = \mathbf{A}(k)\hat{\mathbf{P}}(k)\mathbf{A}^T(k) + \mathbf{B}(k)\mathbf{Q}(k)\mathbf{B}^T(k)$

of the measurement noise $\mathbf{v}$ and ΔT is the sampling time. The discrete-time quantities $\mathbf{A}(k)$ and $\mathbf{B}(k)$ can be found using *forward Euler* integration. Morover,

$$\mathbf{A}(k) \approx I + \Delta T \frac{\partial \mathbf{f}(\mathbf{x}(k), \mathbf{u}(k))}{\partial \mathbf{x}(k)}\bigg|_{\mathbf{x}(k) = \hat{\mathbf{x}}(k)}$$
$$\mathbf{B}(k) \approx \Delta T \mathbf{E}$$

(A.2)

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