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Pumps condition assessment in water distribution networks ⋆

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Abstract: This paper presents a method for the detection of faults in electrical pumps. The method relies on the computation of two features, the pump efficiency and the hydraulic balance, that present reference values during healthy pump operation and change when the pump is affected by a fault. In this paper, the CUSUM Change Detection Test and the Mann-Whitney Change Point Method are proposed as change detection algorithms to process both features. The method has been applied to a real installation with several pumps and the results are reported in the paper.

Keywords: Fault detection, water pumps.

1. INTRODUCTION

Maintenance is an important process in the management of technical systems since it has a great impact in systems operational costs. Good maintenance policies help to exploit technical systems in the most profitable way. Three basic types of maintenance strategies can be distinguished (Manzini et al., 2009): *corrective maintenance*, when repair or replacement of a system component is performed after a fault or failure has occurred; *time-based maintenance*, when time intervals between maintenance operations are predefined and preventive maintenance according to *a priori* expected degradation and lifetime of components is planned; and *condition-based maintenance*, when components are repaired or replaced according to their current estimated condition state.

Condition-based maintenance is supported by the implementation of fault diagnosis systems. The goal of these systems is to determine the occurrence, location, type and magnitude of faults. In particular, the following tasks are distinguished (Isermann, 2006): *fault detection* - determination of the presence of a fault and the time of its appearance; *fault isolation* - determination of the location and/or the type of fault; *fault identification* determination of the magnitude (fault estimation) and time evolution of the fault. Fault magnitude estimation is directly related to condition assessment and it is required for condition-based maintenance.

Water Distribution Networks (WDN) are critical infrastructure systems that provide drinking water to final consumers. WDNs are subject to severe availability and efficiency requirements (water and energy) that can be faced in different ways (see for instance (Gama et al., 2015)), in particular by implementing proper fault diagnosis and condition-based maintenance policies. For instance, the management and diagnosis of leaks has received remarkable attention in recent years (Puust et al., 2010; Pudar and Ligget, 1992; Pérez et al., 2011; Blesa et al., 2016; Soldevila et al., 2016, 2017). On the other hand, other works recognize the importance and focus their attention on the management and diagnosis of pumping systems (Gama et al., 2015; Beebe, 2004).

This paper proposes a method to assess the condition of electrical pumps. The method relies on the computation of two features, the pump efficiency and the hydraulic balance, that achieve reference values during healthy pump operation and are degraded when the pump is affected by a fault. These two features can be processed by different standard change detection algorithms to detect the presence of a fault and estimate its magnitude. The method has been applied to a real installation with several pumps and the results are reported in the paper.

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The rest of the paper is organized as follows. Section 2 presents the problem to be solved. Section 3 details the proposed solution method. Section 4 describes the case of study and reports the obtained results. Finally, Section 5 draws some conclusions.

2. PROBLEM DESCRIPTION

Given a set of available sensors, the problem is to relate their measurements to the main faults which are relevant to pump anomalies and assess the condition of the pumps at hand by processing the signals obtained by the sensors.

2.1 Faults

The typical faults affecting performance of pumps that are considered in the literature are the following (Beebe, 2004):

- Damaged impeller
- Damaged external seals
- Eroded casing
- Worn sealing rings
- Eccentric impeller
- Bearing damage
- Bearing wear
- Mounting fault
- Unbalance
- Misalignment
- Overload
- Inlet total or partially closed

The table in Figure 1 presents how these faults could be detected by means of the sensors available nowadays (Beebe, 2004), described in the following section.

2.2 Sensors

Revising the literature about health monitoring of pumps, the following measurements are usually considered as key variables to detect the abovementioned faults (Beebe, 2004):

- Vibration: Measurements are carried out by means of so-called impact sound sensors. The sensor, performing as an acceleration sensor, measures the vibration in terms of the pump in g (Earth acceleration: 9.81 $[\mathrm{m}/s^2]$). The sensor is either screwed on tightly at the spiral casing of the pump, or fastened with a magnet foot, for the mobile measuring or monitoring.
- Temperature: Temperatures can either be measured by means of thermocouples or by means of PT 100 sensors. Test points are critical pump- or plant-components like mechanical seals, ball bearings, motors, pipes as well as the delivery medium on the pressure or suction end. A noticeable increase or change of the temperature indicates an error or a wear out initiating itself. A temperature monitoring is already integrated in many electric motors, to the protection from overload (PTC thermistor).
- Pressure: The monitoring of the upstream pressure guarantees that the flow of the fluid remains constant and does not stall. Pressure fluctuations, pulsations, pressure surges and also negative pressure can be controlled and recorded by corresponding systems.

  The pressure measuring is carried out on both sides, downstream and upstream, to get meaningful values regarding the pressure change. A differential pressure transmitter registers the difference in pressure between inlet and outlet.
- Power (Current/Voltage): It can be measured with a wattmeter or through the measure of current/voltage. Electrical power can be compared against the hydraulic power to assess the pump efficiency.
- Flow sensors: They measure the flow through the pump that allows to establish a balance with the pressure difference.

		Measurements										
		Vibration	Temperature	Pressure (head or vacuum)	Speed	Current (Power)	Flow	Length/ dimensions	Fluid Leakage	Time to coast down	Wear debris in oil	Oil leakage
Fault	Damaged impeller	X	X	X	X	X	X	X		X		
	Damaged external seals	X		X	X		X	X	X			
	Eroded casing							X				
	Worn sealing rings			X		X	X					
	Eccentric impeller	X	X	X	X	X	X			X		
	Bearing damage	X	X		X	X		X		X	X	X
	Bearing wear	X	X					X		X	X	
	Mounting fault	X	X									
	Unbalance	X										
	Misalignment	X						X				
	Overload		X		X							
	Inlet total or partially closed			X	X							

Fig. 1. Relation between faults and sensors.

3. PROPOSED METHOD

According to the framework and nomenclature proposed in the literature (Isermann, 2006), fault detection can be achieved after *feature extraction* and *change detection*. The goal of the feature extraction (or feature generation) stage is to obtain relevant signals for fault detection purposes, from available measurements; the change detection stage detects changes in the features that can be associated to systems faults.

3.1 Feature extraction

Basic signals that are typically measured by pump supervision systems allow to compute two features that are suitable for the detection of faults in pumps: the pump efficiency and the hydraulic balance.

Pump efficiency. A key indicator to predict the pump degradation is the pump efficiency, which can be computed according to (Beebe, 2004) as

$$\eta_t = \frac{\rho q_t (H_t^i - H_t^a)}{E_t} \tag{1}$$

where ρ is the water density, $q_t = \frac{Vol_t}{3600}$ is the hourly mean flow in $[\mathrm{m}^3/\mathrm{s}]$ obtained from the hourly pumped volume Vol_t in $[\mathrm{m}^3]$, H_t^i is the downstream head in meters water column [mwc] that can be obtained from the pressure as $p_t = \rho q_t H_t^i$, H_t^a is the upstream head that can be computed analogously, and E_t is the hourly consumed energy in [kWh].

Hydraulic balance. Another key indicator that can be used for the health monitoring of pumps is obtained from a hydraulic balance (Beebe, 2004) as

$$K_t = \frac{q_t}{\sqrt{H_t^i - H_t^a}} \tag{2}$$

being K_t a parameter whose reference value can be obtained from the characteristic curves of the pump.

3.2 Change detection

Given a sequence of time-ordered observations of a feature S, denoted as $s_1, ..., s_t$, on-line change detection algorithms aim at detecting and estimating possible changes in these variables. In this paper, two different algorithms will be used to detect changes in the pump efficiency η and the hydraulic balance K features defined in Section 3.1.

CUSUM-CDT. The CUmulative SUM Change Detection Test (CUSUM-CDT) (Page, 1954) is a good indicator to detect variations on monitored signals (Basseville et al., 1993), but it has a better performance for steady (constant indicators, or indicators with a fixed drift) streams of data. As proposed in (Misiunas et al., 2006), to apply this method, feature s_t can be first filtered using an adaptive Recursive Least Squares (RLS) filter

$$\theta_t = \lambda\theta_{t-1} + (1-\lambda)s_t \tag{3}$$

where θ_t is the estimated value of the indicator without noise, s_t is the current measurement (or processed indicator) and $\lambda \in [0, 1)$ is the forgetting factor. Then, the increment respect to the previous value is computed as

$$e_t = \theta_t - \theta_{t-1} \tag{4}$$

The increment e_t is used to feed the CUSUM-CDT and detect positive changes as follows

$$\begin{aligned} &G_0 = 0 \\ &G_t = \max(G_{(t-1)} + e_t - \nu, 0) \\ &\text{if} \quad G_t > h^+ \Rightarrow t_d^+ = t \end{aligned} \tag{5}$$

where G_t is the output of the CUSUM-CDT, ν is a drift compensator parameter and h^+ is the threshold to decide if a positive change has happened. Negative changes can be detected changing max by min in (5) and defining the negative threshold h^-.

Mann-Whitney CPM. The Mann-Whitney Change Point Method (MW-CPM) (Hawkins and Deng, 2010) is a non-parametric test that detects changes in the median between two data sets by ranking their values. This procedure makes this test robust against outliers that can lead to false positives or increase the Detection Delay (DD) in other tests. This can be exploited in the field of detection by partitioning the data stream where is suspected that might be a change for every point and perform the test between these two subsets to assess whether a change is produced at any of these points. This test also provides the position where the change is produced. So, the general formulation of the Mann-Whitney CPM for the change detection in feature monitoring is the following: splitting a time-ordered observations of feature S: $s_1, ..., s_t$ in two data sets $s_1, ..., s_{k-1}$ and $s_k, ..., s_t$ and then, computing the variable $U_{k,t}$ as

$$U_{k,t} = \min\{U_{k,t}^-, U_{k,t}^+\} \tag{6}$$

being

$$U_{k,t}^- = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \tag{7}$$

$$U_{k,t}^+ = n_1 n_2 + \frac{n_2(n_2+1)}{2} - R_2 \tag{8}$$

where n_1 and n_2 are the number of elements of first an second splitted data sets and R_1 and R_2 are the sum of all ranking positions of the two data sets. If the value $U_{k,t}$ is bigger than a dynamic threshold h_t indicates that there is a change in the data stream at instant $k \leq t$. According to (Ross et al., 2011), the dynamic threshold h_t in order to guarantee a given False Alarm Probability (FAP) α

$$P(U_{\max,t}) = \alpha \tag{9}$$

being

$$U_{\max,t} = \max_k U_{k,t} \tag{10}$$

and

$$\widehat{T}^* = \operatorname*{argmax}_k U_{k,t} \tag{11}$$

is the estimated change instant that guarantee an average time between false alarms, also known as Average Run Length (ARL_0), with value

$$\text{ARL}_0 = \frac{1}{\alpha} \tag{12}$$

In (Ross et al., 2011), the following polynomial approximation of computing h_t given a particular ARL_0 is proposed

$$\begin{aligned} h_t = {}& c_0(\text{ARL}_0) + c_1(\text{ARL}_0)t^{-1} + c_2(\text{ARL}_0)t^{-3} \\ & + c_3(\text{ARL}_0)t^{-5} + c_4(\text{ARL}_0)t^{-7} + c_5(\text{ARL}_0)t^{-9} \end{aligned} \tag{13}$$

4. CASE STUDY

4.1 Description

The case study is based in a real pumping station of a water distribution network. This pumping station is composed by two impulsion systems of equal characteristics. In turn, each impulsion systems is composed by several pumps grouped in two groups. A long period of data from one of the impulsion systems is available and it can be used to asses the degradation of pumps performance. These data include the response to a real fault, consisting in a flow inversion in the first group of pumps due to

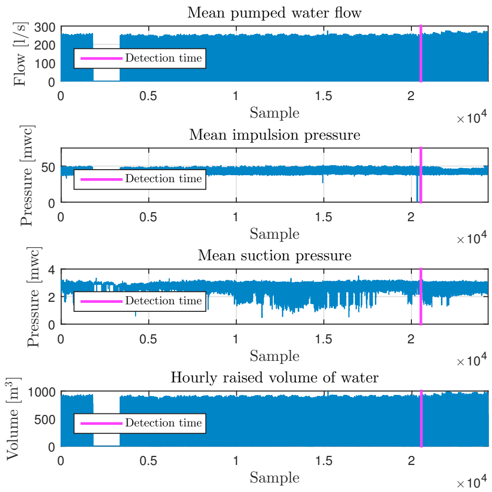

Fig. 2. Measurements at the impulsion level.

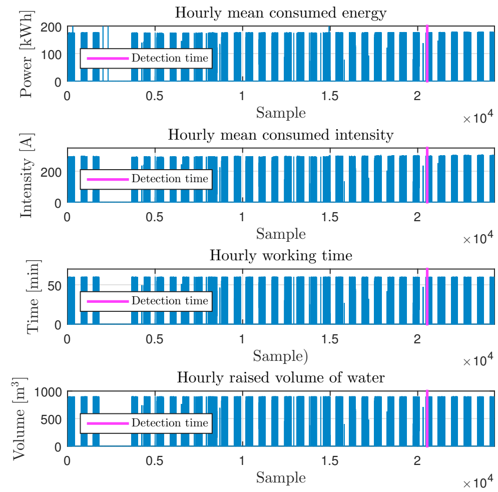

Fig. 3. Measurements at the first pump group.

an anomaly in the upstream valve (corresponding to a damaged external seals fault in the table of Figure 1).

Measurements are available with a sampling time of one hour at the two different levels, i.e. impulsion and station. At the impulsion level, the following processed measurements are on-line available:

- The mean flow pumped at every hour in [l/s].
- The mean pressure at the inlet of the impulsion at every hour in [mwc].
- The mean pressure at the outlet of the impulsion at every hour in [mwc].
- The accumulated volume of water pumped each hour in [m^3].

On the other hand, at the pump level, the following measurements are collected:

- The accumulated electrical energy consumed each hour in [kWh].
- The mean intensity consumed each hour in [A].
- Minutes of operation in each hour in [min].
- Number of operations (i.e., the number of times that the pump station has started) in each hour.

The period of data that covers the presented real case starts the 1^{st} of January of 2014 and lasts until the 13^{th} of October of 2016 (two years and nine months). The time series of all the measurements available at the impulsion level are shown in the Figure 2. At the pump level, the measurements for the two groups of pumps are presented in Figures 3 and 4.

As it can be observed in Figures 3 and 4, the use of the pump groups is toggled approximately every two weeks. The pumps are usually used at a regular hours (at night when the electricity is cheaper) and this pattern only changes when the water tanks fall from a certain level and it is necessary to fill them in order to maintain the required flow and pressure.

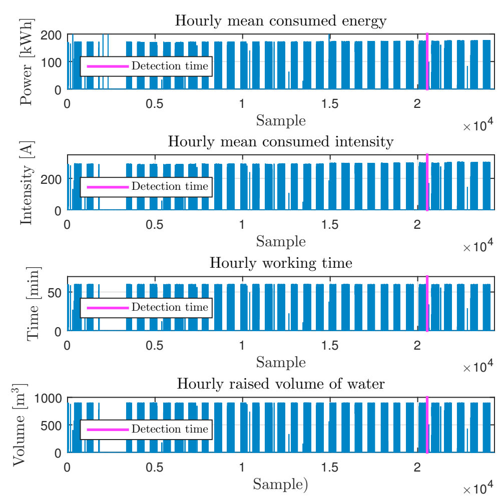

Fig. 4. Measurements at the second pump group.

4.2 Feature extraction

In practice, the computation of the two features presented in Section 3 (pump efficiency η and hydraulic balance K) cannot be applied directly to the raw measured signals and some preprocessing is needed. Using the "minutes of operation" measurement, the features are extrapolated from the impulsion level to the pump level by taking the hours where only one of the two groups of pumps (each group of pumps is treated separately) is working and removing the rest. The obtained signals are quite noisy due to the fact that the efficiency depends on the time instant where the conditions are evaluated and compared with the past ones and whether the pumps work in a steady state. Hence, the data with working minutes below a threshold are discarded in order to have a more smooth and reliable information. In this case, a threshold of 58 minutes of operation per hour is set. Finally, a median filter is used to remove the outliers and place a proper value instead of them. The final signals to monitor are depicted in Figure 5

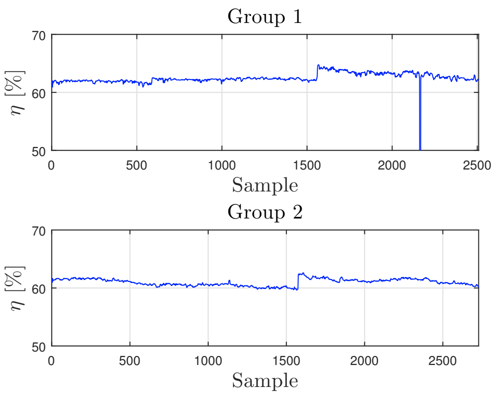

Fig. 5. Extracted, processed and filtered efficiency feature η at the pump level for the two pump groups.

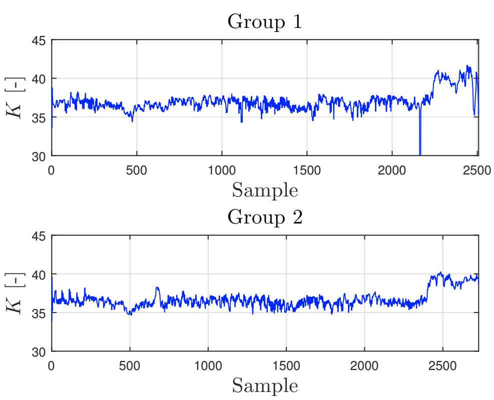

Fig. 6. Extracted, processed and filtered K parameter feature at the pump level for the two pump groups.

in the case of the efficiency η and in Figure 6 in the case of the K parameter. As it can be seen, finally only 2508 and 2729 effective data samples of each group of pumps have been used from the 24384 available raw data samples after removing the data samples of pumps which can lead to different amount of data for each group, and removing the non-steady data. This value can be increased or decreased using the minutes of operation per hour measurement threshold.

4.3 Change detection

The two proposed change detection techniques are applied to the signals depicted in Figures 5 and 6.

The CUSUM-CDT has been tuned with $\lambda = 0.25$ in the RLS filter (3). This value has been chosen to believe more the past values to avoid the remaining noise due to sensor resolution and the fact that not all the signals are processed exactly equal. The threshold h^- of the CUSUM-CDT algorithm has been chosen as -5 times the standard deviation of the first quarter of the feature signals which is fault-free. Note that the method is set to only detect negative drift in the feature, since the positive changes, such as the ones due to maintenance or reparations, do not generate alarms.

The MW-CPM is non-parametric, except for the ARL_0 parameter that is needed to set the dynamic thresholds.

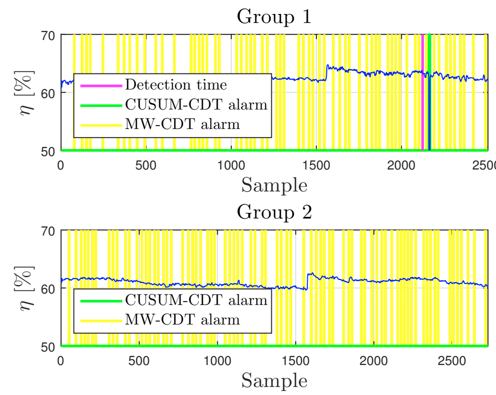

Fig. 7. Efficiency monitoring alarms by the CUSUM-CDT technique.

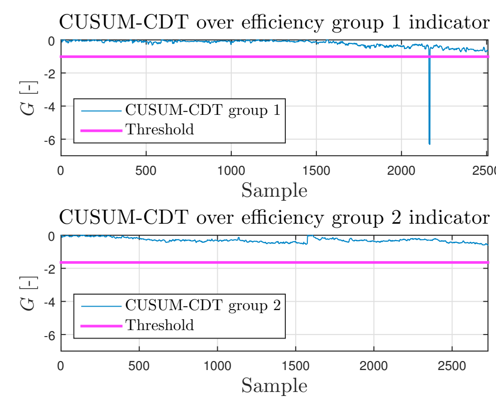

Fig. 8. CUSUM-CDT G indicator values for the efficiency monitoring.

In this application, the largest ARL_0 used in (Ross et al., 2011) has been chosen, which is 50,000, to avoid as many false positives as possible. Note that when the MW-CPM is performed and a detection is raised, the technique starts again searching for a change at the next sample after the detection.

The result of the application of both techniques over the efficiency features is depicted in Figure 7, where it is also plotted the time "Detection time" indicating when the fault was detected by the company, during an operational inspection.

As it can be seen in Figure 7 the CUSUM-CDT performs well avoiding false positives and detecting the fault while the MW-CPM fails in avoiding false positives. This technique is too sensitive to the natural fluctuations or noise of the monitored features. It should be noted that the fault is clearly detectable from the efficiency feature in the proposed filtering process. Also the technique is able to avoid false alarms due to maintenance positive changes in samples 550 and 1550 approximately. The CUSUM-CDT value G that is compared with the threshold is depicted in detail in Figure 8.

The results of the application of both techniques over the K parameter feature for both pump groups are depicted in Figure 9.

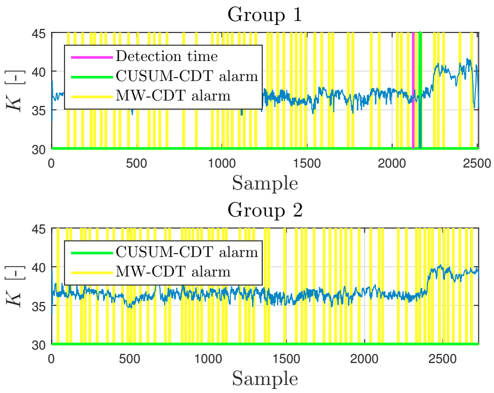

Fig. 9. K parameter monitoring alarms by the CUSUM-CDT technique.

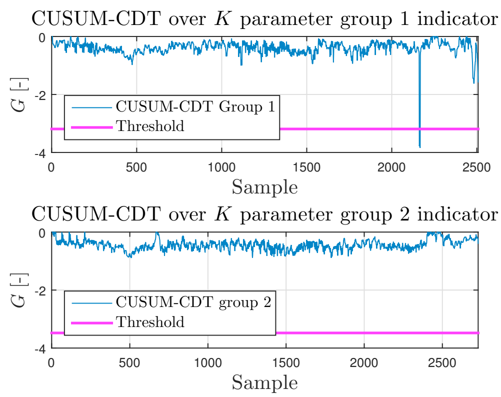

Fig. 10. CUSUM-CDT G indicator values for the K parameter monitoring.

The K parameter feature combined with the proposed filter also presents a good detectability since the fault can be detected without difficult. Both methods perform in the same way that in the case of the efficiency feature. The CUSUM-CDT performs very well detecting the fault and avoiding false positives while the MW-CPM is not able to manage the variability and the number of false positives is large. The CUSUM-CDT value G to be compared with the threshold for the case of the K parameter is depicted in Figure 10.

It should also be noted that in both Figures 8 and 10, the CUSUM-CDT technique is able to capture trends, in this particular case, of decreasing performance that can be exploited for the application of predictive maintenance through prognosis.

5. CONCLUSION

A method to assess the condition of pumps in water distribution networks has been proposed. Given the signals measured by the sensors of a typical pump supervision system, a feature extraction process is performed to compute two key indicators: the pump efficiency and the hydraulic balance. Changes in these two features from their reference (healthy) values are detected by means of the CUSUM-CDT and Mann-Whitney CPM techniques thus indicating the existence of a fault affecting the pump operation. The two extracted features from the measurements, efficiency and hydraulic balance, have shown a consistent trend in normal operation and a different one when the fault was present in the system. The method using the CUSUM-CDT has been successfully applied to a real pumping installation through a real case study while the MW-CPM failed to handle the false positives.

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