Cluster tren

for control loop assessment

A new mechanism for control loop performance monitoring and equipment fault detection, based on cluster trending analysis, is very sensitive to small signal variations and capable of detecting the abnormal signals embedded in the normal signals.

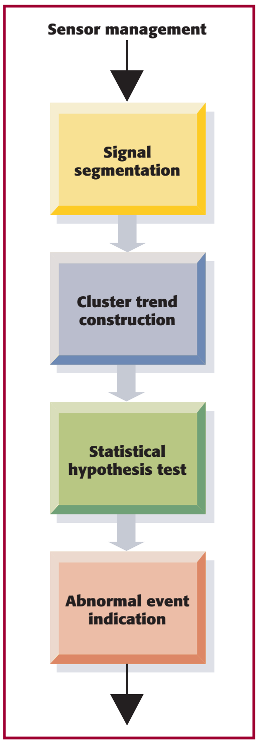


Fig 1: Major components in our system.

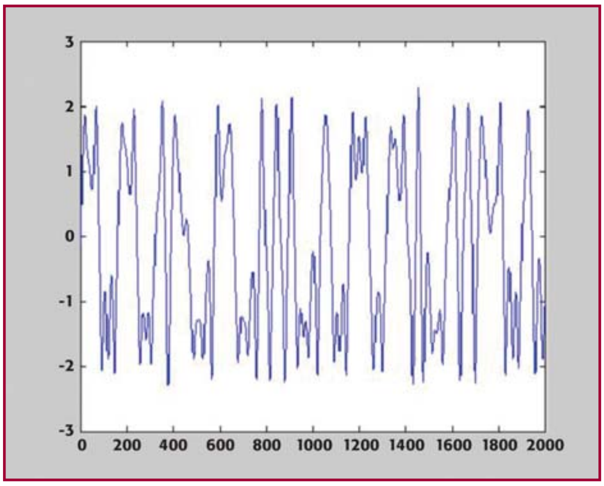


Fig 2: A time series of sensor measurement.

A new mechanism for control loop performance monitoring and equipment fault detection, based on cluster trending analysis, is very sensitive to small signal variations and capable of detecting the abnormal signals embedded in the normal signals.

Highly reliable automated systems require health monitoring capable of detecting any equipment faults as they occur and identifying the faulty components. Control loop performance depends on the operating environment and equipment health status. Loop re-tuning can improve the performance when the operating environment has changed. However, if some equipment in the loop is malfunctioning, the simple control loop re-tuning will be less effective in improving the loop performance. Therefore, it is important to design a loop performance monitoring system with the capability of monitoring both the loop performance and the faults of equipment in-loop.

Component fault detection has been the subject of numerous studies in the past few decades. Initial work in this area employed a variety of paradigms to both detect and characterise faults. Traditional time-based machinery maintenance is being replaced by maintenance based on the condition of the machinery. A common problem in the fault detection is how to avoid false alarms that might be provoked due to the presence of equipment noisy signals. In our view, the statistical hypothesis tests, together with feature-based trend analysis over the historical data, can effectively assist the maintenance decision-making.

We take a different approach towards the loop performance monitoring problem. Instead of treating performance monitoring and equipment fault detection as two separate problems, we take a unified approach in the sense that we solve these two seemingly different problems in terms of abnormal event detection. Specifically, an abnormal event is defined as a statistically significant deviation of sensor measurements from so-called normal behaviours determined *a priori*. The main advantage of our approach is to easily identify the root of

ding analysis and diagnosis

by B. Ling, S. Dong, and U. Venkataraman

performance degradation in a control loop. For example, if an equipment in-loop is malfunctioning, controller re-tuning will not improve the overall loop performance.

We present a new mechanism for the control loop performance monitoring and equipment in-loop faults detection. Our method is based on the cluster trending analysis which is very sensitive to small signal variations and capable of detecting the abnormal signals embedded in the normal signals. We will also present two test cases based on the real measurement data. We will use the real control loop data to monitor the loop performance. Based on the sensor data, we detect the faulty conditions of an industrial pump in near-real time.

> “The main advantage of our approach is to easily identify the root of performance degradation in a control loop”

SYSTEM OVERVIEW

Our system is primarily developed to detect so-called abnormal event (for example, an abnormal event can be control loop performance degradation or equipment in-loop malfunctioning). There are four major components in our detection system, which are shown in Figure 1.

The raw sensor measurements are segmented based on a moving window with its size determined from the normal data *a priori*. In each window, the number of clusters is automatically estimated based on our machine learning scheme. As this window moves forward in time, a cluster trend is constructed. This cluster trend is statistically compared with the normal cluster trend. If they are statistically significantly different, an abnormal event is declared. In the following sections, we will describe the details of individual components.

CLUSTER TRENDING PROFILE

Suppose we have a time sequence of a discrete sensor measurement, where k represents the time instant at kth sampling time. One example of such a signal is shown in Figure 2. For simplicity, the sampling time T is omitted.

In the traditional time series analysis, k is required to be consecutive, meaning that $k + 1$, $k + 2$, …, $k + n$ represent n time instants sampled consecutively. This condition is partially relaxed in our system. For →

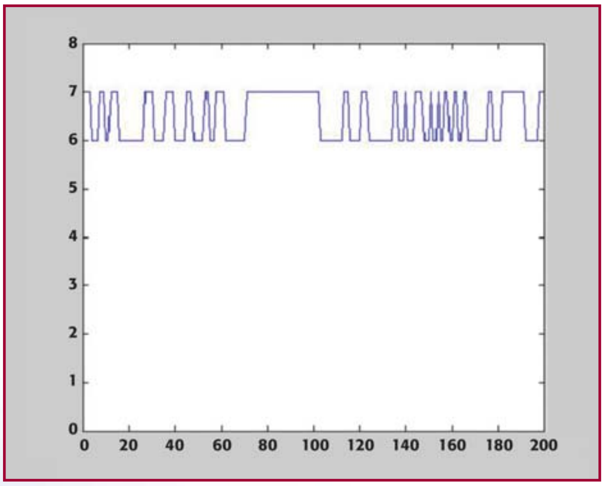


Fig 3: An example of cluster trend.

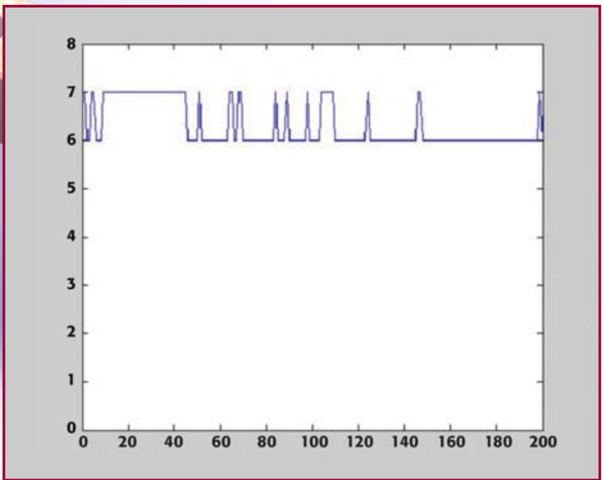


Fig 4: A cluster trend based on real-time operation data.

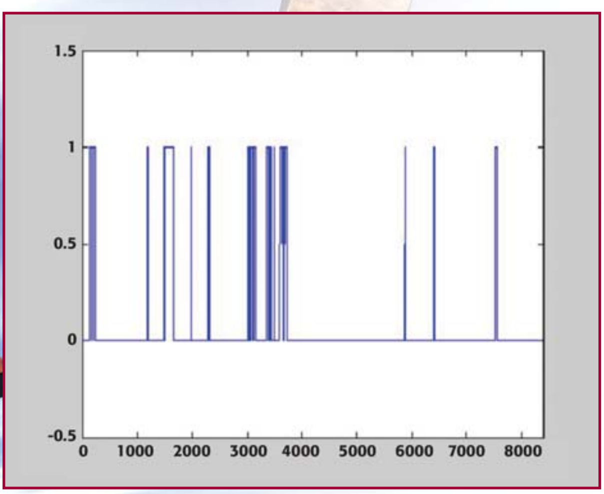


Fig 5: Indicators of abnormal events.

example, our system works with not only the usual sequence of data $k = 1$ to N but also as k = N+p, to M, where p ≥ 1. Being able to process this type of data sequence is important because a small portion of measurement data required for monitoring can be missing or unusable for various reasons (for example, a control loop was in manual mode for certain period of time).

To detect abnormal event in the sensor measurement, instead of using the traditional features such as statistical or spectrum features, we extract cluster trending features from the data. In particular, we estimate the number of clusters in a small data window. As this window moves forward, a cluster trend is constructed.

Our estimation of cluster number in the data window is based on our unsupervised machine learning scheme called ASOM (Adaptive Self-Organising Maps) which is a variation of Kohonen's Self-Organising Maps (SOM). SOM emulates the unsupervised learning in an elegant, extremely simple manner. During self-organising procedure, the topologically close relationship of the organised information is maintained.

The learning rule of SOM is $\Delta w_i = h_{i,b}(x - w_i)$ where w_i denotes the winner node, and $h_{i,b}$ is a neighbourhood usually defined as a Gaussian or a Hubble function of the node indices i and b. It is well known that this learning rule is linked to an optimisation process which achieves both a minimum matching error on the input neurons and a reduced topological space. Unlike SOM, our ASOM has the following unique features:

- A similarity measurement based prototype matching;
- Automatic learning of number of nodes (clusters) without any prior knowledge; and
- Boundary points alignment for robust clustering.

ASOM starts with a null network and gradually learns the new prototypes when new data samples cannot be assigned to any existing prototypes. Figure 3 illustrates an example of such a cluster trend.

The normal cluster trend profile is constructed based on the normal operation data. For the control loop performance monitoring, the normal data can be obtained right after the loop is well turned. For the equipment fault detection, it can be collected when the equipment is considered to operate normally.

ABNORMAL EVENT DETECTION

Similar to the normal cluster trend profile construction, for a real-time sensor measurement, we can construct a cluster trend, as in Figure 4. To detect the abnormal event, we compare this cluster trend with the normal cluster trend profile.

There are many methods used to statistically compare the deviation between actual and normal cluster trends. In our system, we use the likelihood ratio test (LRT). Specifically, we estimate two predictive statistical distributions of observed x_n, namely, p_{normal} and p_{fault}, and detect the abnormal event by rejecting the null hypothesis via LRT:

$$LRT = \log (p_{fault}/p_{normal})$$

Figure 5 illustrates an example of abnormal events detected based on LRT. The value 1 indicates the existence of an abnormal event (loop performance degradation or equipment fault).

In other words, the abnormal event indicator is set to TRUE (1) if two cluster trends are statistically significantly different over a period of time. Since certain momentary disturbance can cause the deviation of actual and normal cluster trends, LRT alone is not sufficient to eliminate the false alarms.

In our system, we declare the occurrence of an abnormal event by calculating the entropy in the abnormal event indicators generated from LRT. Let X be a random variable taking a finite number of possible values $x_1, x_2, \ldots, x_n$ with the probabilities $p_1, p_2, \ldots, p_n$, an entropy is defined as:

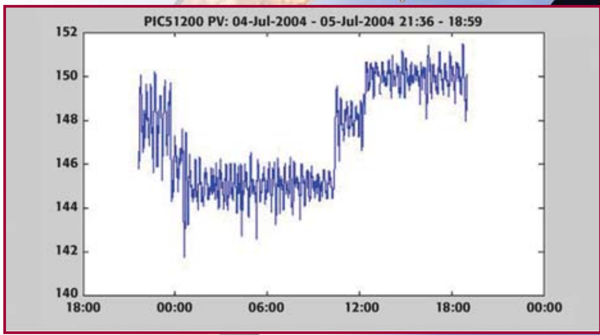
$$H = -\sum_{i=1}^{n} p_i \log p_i$$

If the entropy is greater than certain threshold level determined *a priori*, we set the indicator of an abnormal event to be value of 1, which implies the existence of the degradation of loop performance or malfunctioning of a piece of equipment in-loop.

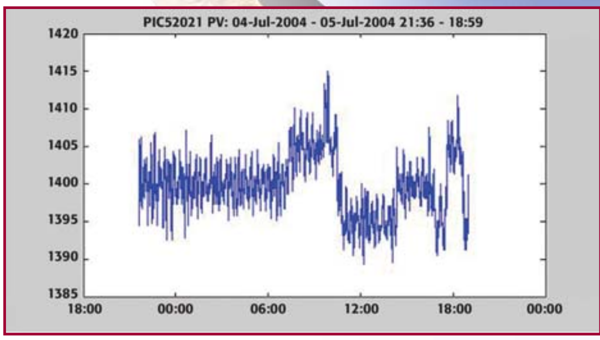
TEST CASE 1 – LOOP PERFORMANCE MONITORING

To test the algorithm, we obtained process control loop data from ExperTune (www.expertune.com). The datasets span 24-hour process operations, ranging from 7:00 p.m. in July 4th to 7:00 p.m. in July 5th, 2003. There are total 10 control loops with sampling time being one second. Data of four parameters are collected in each loop: SP, PV, OP and MODE. We have decided to only use PV, representing the measurement of controlled variable.

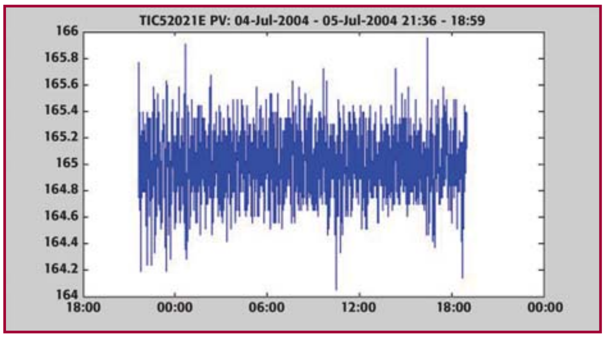
Among 10 loops, we only selected 4 loops which were operating entirely in AUTO mode during the 24-hour data collection period. Data associated with the loop in MANUAL mode should not be used. The four loops we have selected for testing are: PIC51200, PIC52021, TIC52021E and TIC52028E. Figure 6 shows the plots of the entire PV data of these four loops.



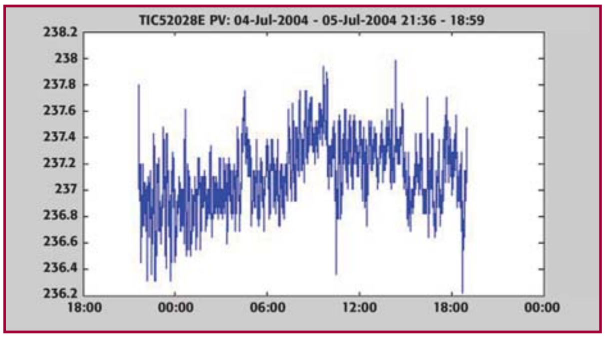
(a) PV of control loop, PIC51200.



(b) PV of control loop, PIC52021.

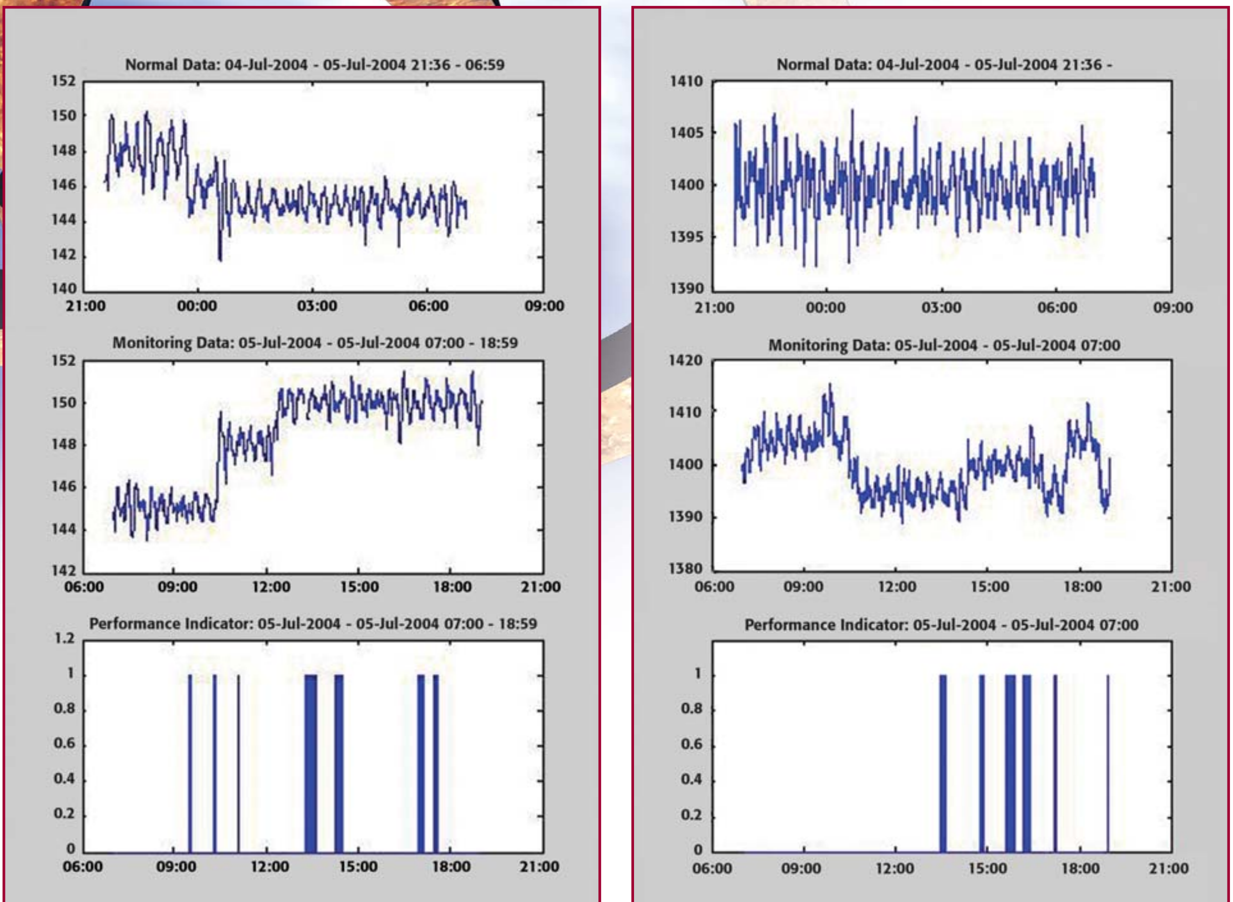


(c) PV of control loop, TIC52021E.



(d) PV of control loop, TIC52028E.

Fig 6: PV of four loops over 24-hour period.



(a) Loop PIC51200

(b) Loop PIC52021

Figure 7: Loop performance indicator of four loops.

We divided the data into two segments: *Data A* and *Data B*. Specifically, the data from 7:00 p.m. of July 4th to 7:00 a.m. of July 5th is grouped in Data A, which is treated as normal data and used to construct the normal cluster trend profile. *Data B* contains the data from 7:00 a.m. to 7:00 p.m. of July 5th are used to monitor the loop performance.

Figure 7 shows the test results for all four loops. The top portion of the figure shows the normal data considered in this paper, the middle portion is the data used for monitoring. The actual and normal cluster trends are statistically compared. The performance indicator is given at the bottom portion of the figure. Value 1 indicates the performance deviation from the normal behaviour of the loop.

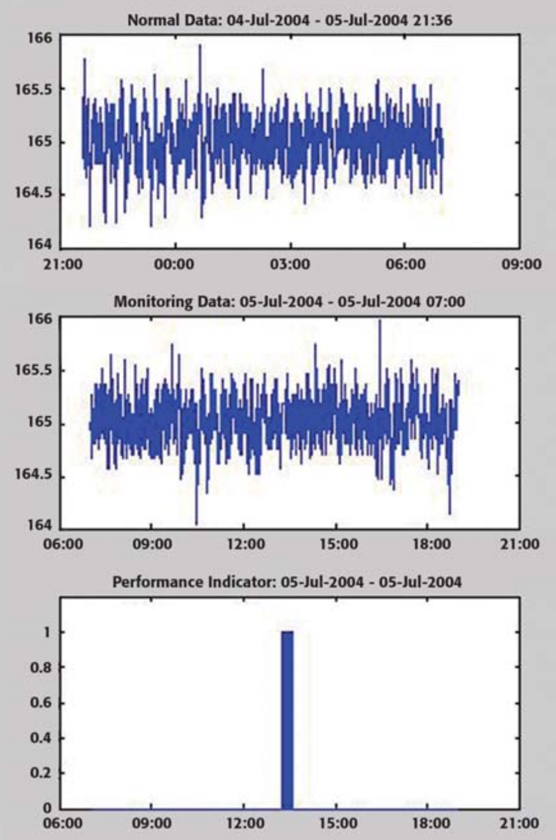
Our observations:

- It seems that there is a disruption around 1:30 p.m. The performance indicators of four loops all show significant deviation between the actual and normal signals around 1:30 p.m..
- The loop, TIC52028E, has shown certain performance degradation. Its performance indicators after 1:30 p.m. are more dense and persistent. Based on this, we would recommend the loop re-tuning.
- All other three loops perform at acceptable levels although the loop, TIC52021E, has the best performance (close to the normal behaviour).

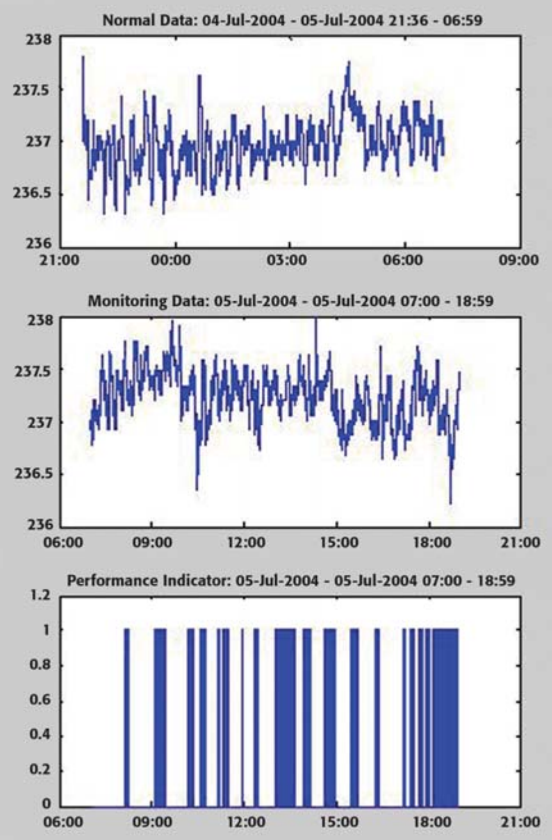
TEST CASE 2 – PUMP FAULT DETECTION

The data for this test case was acquired in the Delft “Machine diagnostics by neural networks” project with help from Landustrie B.V, The Netherlands. All datasets and help files can be downloaded freely at www.ph.tn.tudelft.nl/~ypma/mechanical.html. All references can be found at this web site as well.

The rotating machine for this test is a one-channel impeller submersible centrifugal pump. It rotates at 1,500 RPM, has a maximum flow of 1.7 cubic metres per minute, and a power consumption of 3 KW. The



(c) Loop TIC52021E



(d) Loop TIC52028E

submersible pump is a centrifugal pump and it consists of an impeller with a fixed blade, housed in a suitable shaped casing, mounted on a rotating shaft. The two ball-bearings in the pump casing keep the shaft in place. The shaft together with these bearings, the seal and the impeller, are responsible for most of the measured frequency components. The bearing-failures were induced to the machine in the data set we used for this test.

There are two sets of data representing both healthy and faulty conditions. Measurements are repeated for two identical pumps with similar power consumption, age and amount of running hours, where the first pump shows a progressed pitting (*i.e.* surface cracking due to unequal load and wear) in both gears, and the second pump is virtually fault free.

Vibration was measured with 7 uni-directional accelerometers, placed near the driving shaft (in x-y-z directions), and upper and lower bearings supporting shafts of both gearboxes performing a two-step reduction of the running speed of the driving shaft to the →

“Cluster techniques can be used for control loops and machinery health monitoring”

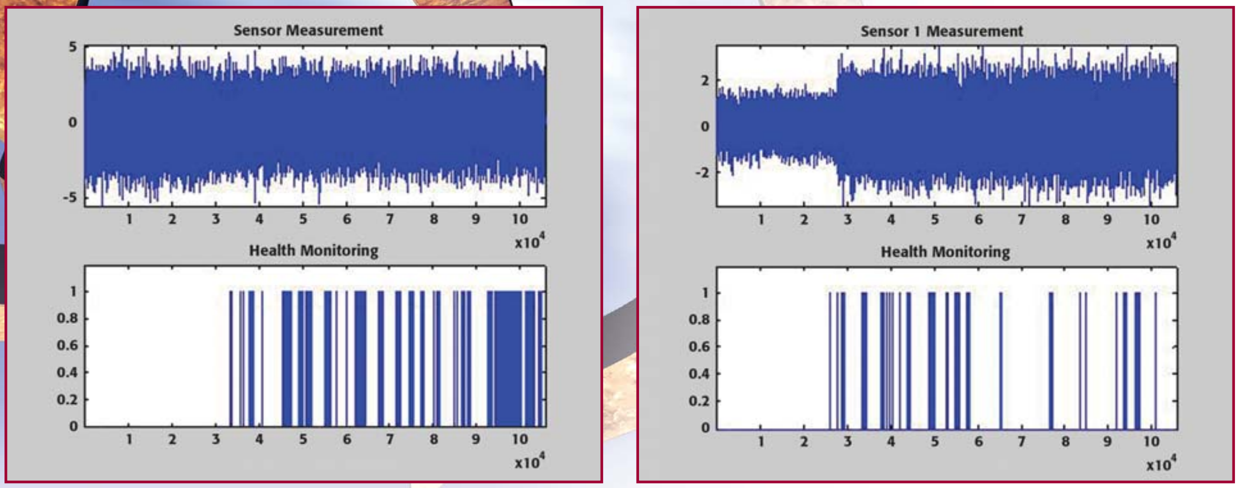


Figure 8: Test results of sensors 2 and 7. *(a) Measurement and faulty indicator at sensor 2.* *(b) Measurement and faulty indicator at sensor 7.*

outgoing shaft to which the impeller is attached.

The first three sensors (1, 2 and 3) correspond to three different measurement directions near the incoming axis. Sensors 4 to 7 are mounted on the gearbox casing. Sensors 4 and 5 are mounted near the first set of deceleration gears (sensor 4 is placed at the upper part of the casing; sensor 5 at the lower part of the casing). Sensors 6 and 7 are mounted near the second set of gears (sensor 6 is placed at the upper part of the casing; and sensor 7 at the lower part of the casing, near the outgoing shaft).

Data was measured for 24.3 seconds, lowpass-filtered (analogue) to 1 KHz and digitised at 3,200 Hz (*i.e.*, the sampling time is about 0.3 ms). There are total 77,824 data points for both healthy and faulty data sets.

We have found that the measurements of sensors 1 and 2 have given similar fault indications, which implies that we can use one of the sensors placed at the shaft. Furthermore, sensors 6 and 7 have the similar fault indications, implying that one of them should be used. All other sensors, 3, 4 and 5, are less effective. Overall, we would suggest that two sensors are enough to monitor the health condition of this submersible industrial pump.

> **"Cluster trending analysis has been effective in the two cases we have tried"**

Figure 8 shows the test results of sensors 2 and 7. The top portion of figure is the raw sensor measurements. We have added part of the healthy data to the beginning of the faulty data to show the starting point of the faulty condition. The measurement magnitude shows the data separation.

Our observations:

- Both sensors can effectively detect the faulty conditions of the second pump. To reduce the overall cost associated with sensors, one could use only one sensor (*e.g.*, sensor 2) to monitor the pump.
- Indicators of sensor 2 have shown more dense 1s (faulty indication) than sensor 7. This implies that the location of sensor 2 is more suitable for the failure detection of this pump application.
- There is a balance between cost and sensitivity of failure detection. If more sensors are used, the sensor fusion mechanism should be utilised to support the decision making.

In conclusion, we can say that our new unified approach for the control loop performance monitoring and equipment in-loop faults detection, based on the cluster trending analysis, has been shown to be effective in the two test cases we have tried. We are currently developing a commercial product for control loop performance monitoring and equipment failure detection. ■

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