Data quality and reliability: a cornerstone for PHM processes

Jean-Baptiste Leger[1], Pierre-Jean Krauth[2], Guillaume Groussier[3], Maxime Monnin[1], Alain Mouchette[2], Fayçal Lawayeb[2],

[1]*PREDICT 19, Avenue de la Forêt de Haye, CS 10508, 54519 Vandœuvre-Lès-Nancy, FRANCE*
maxime.monnin@predict.fr
jean-baptiste.leger@predict.fr

[2]*ArcelorMittal Global Research and Development, Maizières-Lès-Metz, France*
pierre-jean.krauth@arcelormittal.com
faycal.lawayeb@arcelormittal.com
alain.mouchette@arcelormittal.com

[3]*ArcelorMittal, Florange, France*
guillaume.groussier@arcelormittal.com

ABSTRACT

In most of industrial processes, the measurement are central to the process control and quality management. This become even truer when measurement data are used to develop and support PHM strategies. In this context, many software are installed in order to collect data for providing quality assessment at each step of the manufacturing process. However, measurement error or drift are not considered leading to downgrading / rejected products / suboptimal running conditions that comes from measurement drift not detected on time. In concrete, these lead to bigger penalty than losses of production due to stopping time for repairing sensors. Indeed, generally speaking, process data is the "raw material" for many business processes, starting from process control strategy, PHM strategies to Business Intelligence. Thus being able to ensure data quality and reliability is of first importance. Towards this end, methods and tools are required to support online measurement monitoring, predictive diagnosis and reliability enhancement.

In this paper, a dedicated approach developed in collaboration with ArcelorMittal Research is presented. It consists in the development of intelligent software that would enable sensor measurement validation taking into account process parameters and operational conditions. An illustrative case study is extracted from an ongoing application developed for the finishing line in ArcelorMittal plant at Florange in France. Results regarding measurement reliability assessment as well as sensor failure anticipation will be described.

1. INTRODUCTION

Today, industrial measurement reliability is essential to answer the big challenges of European industries: improving product quality, creating high-added value products and improve process control. Indeed, industrial measurements are used to feed databases and then analyzed in order to improve process control. Therefore, the process control strongly depends on the reliability of measurements.

Usually, measurements devices are monitored thanks to quality assurance and preventive maintenance. However this is not satisfying since it relies on punctual verifications of measurements reliability that covers only a fraction of instruments (less than 10%), and because controls are isolated. Such an approach does not guarantee full-time measurement reliability.

Besides, many sensors management software and process monitoring software are available on the market, such as CompuCalTM/CompucalTM Plus, GESSICA, OPTI MU, HASTING, DECA, SPLI 4M, Wonderware Archestra IDE, which are mainly dedicated to:

- management of instruments' calibration and maintenance actions (planning, monitoring, cost evaluation, definition of procedure, assistance on calibration, etc),
- database of instruments' measurements (report on deviation, definition of uncertainty and capability, audit trail, etc),
- process performance monitoring solutions based on Data Reconciliation and Validation, which enables to rely on reliable and accurate information. Measurements errors are highlighted, corrected. Such system computes a series of unmeasured data that are

often key for performance improvement. These systems however do not run in real-time and in closed loop with control systems.

In many cases such an approach does not allow identifying immediately a sensor drift. For example, during rolling, an out of gauge information does not allow discriminating a sensor drift from other causes such as rolling actuator failure or a problem linked to the metallurgical feature of the rolled product. These systems do not allow distinguishing individual sensor drift from the process, actuators and control systems behaviors.

Lots of examples can be quoted to illustrate the damages caused by this lack of measurement reliability. In particular, changes in the condition of use of the sensors can influence the sensor measurement accuracy and have important consequences if they are not detected. For instance:

- distance between the sensors and the target;
- alignment of the temperature sensors in an oven can influence the measurement and consequently lead to over-heating;
- dirtying of the sensor optic can lead to an abnormal measurement.

These issues are encountered not only in steel industry but also in many other industries (glass production, polymer production, etc). That makes the challenges of ensuring the reliability of industrial measurements even more important since it will enable the rationalization of both energy and raw material use as well as maintenance costs. In particular, it will have the following impacts:

- increase productivity (by decreasing unintended production line stoppage),
- rationalize maintenance costs leading to a decrease of 15% of maintenance time,
- decrease non-conformity of final products and increase process control,
- decrease energy consumption of production lines (by avoiding over-heating due to non-reliable temperature measurements),
- decrease the early wear of tools (for instance an excessive roll force due to a faulty measurement can induce damage of the work rolls , mechanical transmission , ...)
- optimizing the maintenance actions through the availability of a dedicated tool for anticipating and rationalizing the service operations of sensors.

In parallel, sensor and measurement fault detection and diagnostic have rather constant interest in literature in various industrial domains. One can refer to (Samy et al. 2011), (Reppa et al. 2012), (Lee et al. 2011), (Zhang et al, 2012) for relevant and recent work focused on sensors and measurement fault detection and diagnostic. However, most of the results rely on complex modelling, or have been developed on top of simulation model (not reflecting fully industrial constraints) and for which the need on computer infrastructure to apply the approach (Miletic et al. 2008) is not fully addressed.

All in all, since industrial measurements are used not only to feed database but also for supporting condition monitoring and analysis in order to improve process control, the reliability of measurements is still a key issue.

Today, maintenance team does not dispose of tools allowing anticipating sensors failures. This means that those failures are discovered during the analysis of incident on production lines or during the analysis of out-of-specification products. For example in the hot strip mill of Seremange, 28% of production line stoppages are due to sensors failures (this represents more than 200000 Euros for only one production line in Seremange).

However, as described in the European Factories of the Future 2020 Roadmap [1], three of the six Research and Innovation Priorities are the creation of high-added value products, Adaptative and smart manufacturing systems – including control and monitoring – and Digital virtual & Resource efficient factory – including Prognostic and Health Management (PHM).

Thus the enhancement of industrial measurement reliability is a sine qua none condition for industries to be able to improve product quality, create high-added value products, improve process control and enhance performance through PHM deployment.

To tackle such issue and further develop and deploy PHM system, intelligent information technologies are required in order to enable sensor measurement validation taking into consideration steel process parameters correlation and operational conditions. To this aim, an integrated software platform is currently developed under the umbrella of the PRIME project (ERA-Net / Manu-Net program) in order to enhance the reliability of on-line and real-time industrial measurements. This innovative solution based on the CASIP/KASEM® platform integrates both an individual monitoring of sensors measurements and inter-measurements consistency monitoring.

Section 2 presents the scope and framework of the project. In section 3, the case study is introduced and the proposed method is presented along with its application. Finally section 4 concludes the work.

2. PROJECT CONTEXT AND FRAMEWORK

2.1. Outlook of the developed approach

The PRIME (ERA-Net / Manu-Net program) project, aims at developing an integrated software platform in order to

[1] http://www.effra.eu/attachments/article/129/Factories%20of%20the%20Future%202020%20Roadmap.pdf

enhance the reliability of on-line and real-time industrial measurements.
The project objectives follow a PHM approach in that sense that it aims at:

- detect in a short delay and anticipate sensor failure
- detect and localize abnormal measurements,
- set a diagnosis and propose a solution to correct or compensate failures in a short delay;
- propose, whenever it is possible, an alternative measurement solution to ensure service continuity;
- Enhance the accuracy of production database

Towards this end, a specific approach is developed in order not only to focus on measurement individually but also to enable a global and consistent consideration of measurement behavior.
In concrete terms, the integrated platform will gather:

- A toolbox for individual monitoring of sensors measurements: enabling the real-time, in situ monitoring of individual sensors measurements.
- A toolbox for inter-measurements consistency: it will use physical relations between measured parameters as well as models in order to improve the inter-measurement consistency, to identify confidence interval and to propose replacing measurements.

The framework of the project comes from industrial statement and consideration. Sensors are not followed form a continuous point of view in spite of the impact of false measurement or drift measurement can affect the whole product quality. Furthermore, depending on the part of the process, inter-measurement relationships becomes mandatory to distinguish between sensor and process degradation. As results, the innovation of the project is based on the consideration of operational conditions and on the combination of these two complementary toolboxes that will enable to enhance measurement reliability through failure anticipation and dynamic corrective strategies application. Indeed, considering operation condition brings the necessary segmentation of data that enable process behavior to be compared over time since the condition of comparisons are known and well defined. This approach falls within the whole methodology developed at PREDICT.

The toolbox for individual monitoring of sensors measurements enables a local approach of data validation. It integrates operational conditions in the validation process in order to provide on-line confidence value to raw data and allows early drift or abnormal value detection. The toolbox for inter-measurements consistency will thus benefit from the individually validated data and will concentrate on interrelationship between measurements.

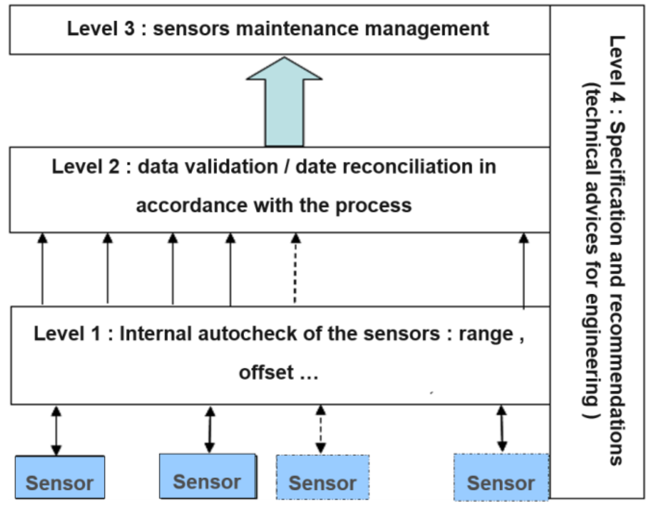

Figure 1. Framework of the proposed approach.

Moreover inter-measurement validation will improve to distinguish between individual sensor drift from the process, actuators and control systems faulty behaviors since it relies on interrelation linking different measurements.

As shown in Figure 1, on top of that, it is also expected to investigate a fleet-wide dimension for sensor measurement. The objectives of investigating the fleet dimension is to enlarge knowledge about sensors behavior in order to share this knowledge by means of the software platform. As a consequence solutions to fix problem can be more easily and quickly deployed over all the process measurement. The fleet dimension rely on the capacity to deal with similar/heterogeneous equipment (from sensor to large and complex equipment (e.g; engine…)), taking benefit form already developed approaches (Monnin et al. 2011a, Voisin et al. 2013).

2.2. Software platform foundations and features

In addition to the structuration of the underlying approach, a key success factor relies on the ability to provide within an integrated platform, the data processing means that will run on-line in an industrial environment with a smooth integration in the existing architecture and infrastructure. Towards this end, the project platform is based on the CASIP/KASEM® software platform designed and developed by PREDICT (Leger 2004, Monnin et al. 2011b). The platform has been designed to support Asset Health Management (AHM) including Condition Based Monitoring (CBM), Predictive Diagnostic, Prognostic & Health Management (PHM), Fault-Tolerant Control (FTC) and Proactive Therapy. Towards this end, the platform is built on top of a knowledge-based system. The database formalizes information and knowledge and makes it more synthetic and shareable between users (experts, technicians, and operators).
For supporting the toolboxes, the platform is not limited or constrained by particular modelling techniques and

integrates a programing environment. That allows to develop and execute algorithms and gather data-driven/statistics based algorithms as well as models (physical models, setting-up models…). Specific algorithm can be directly coded within the programming environment of KASEM®, while existing one can be integrated in the toolbox as DLL to be further used. Thus, starting from process raw data acquisition, algorithms are structured by means of sequence of treatments in order to provide real-time and on-line monitoring (e.g. drift indices monitoring and detection).

3. APPLICATION CASE AND RESULTS

In this section, the proposed approach and technique for the individual monitoring toolbox is described along with their implementation within the KASEM® platform. In order to progress in the development of the toolboxes, the production site of ArcelorMittal in Florange has provided a data set reflecting the current situation in order to develop early demonstrator to show the potentiality of the supporting tools and techniques and highlight the added value of the approach with regard to the current situation. Focused on the application and capability of existing tools and methods, this paper does not deal with a strict comparative study. The presented results are evaluated with regard to the existing alarm system implemented on site.

3.1. Hot strip mill case study

The study takes place with the hot strip mill (Figure 2) of the production site which produces high-performance steel mainly for the automotive industry.

Figure 2. Hot Strip Mill at Florange

The proposed case study was concentrated on the finishing part of the process and more precisely on the finishing scale breaker (FSB) (Figure 3). Indeed the efficiency of the descaling directly impact the end product quality. Thus the descaling process is monitored thanks to the pressure measurement of the water supply circuit. Actually, a sensor failure can be detected by means of thresholds within the PLC.

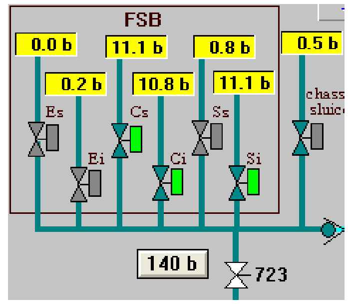

Figure 3. FSB supervision system screenshot

The descaling process is controlled by means of the water supply circuit configuration according to the opened/closed valves and the outlet pressure is acquired and stored every 3ms seconds. In normal condition when the valve is open the pressure in the corresponding line is around 10 bar and null when the valve is closed. Currently, a quality alarm is triggered by the PLC when the mean pressure on 1 second is less than 7 bar.

In Figure 4, the red signal corresponds to the opening command of the valve and in black the corresponding pressure measured from line E_i (see Figure 3). Here, the last period before the sensor replacement is shown. It corresponds to one day of data and around 2 million of values for the pressure.

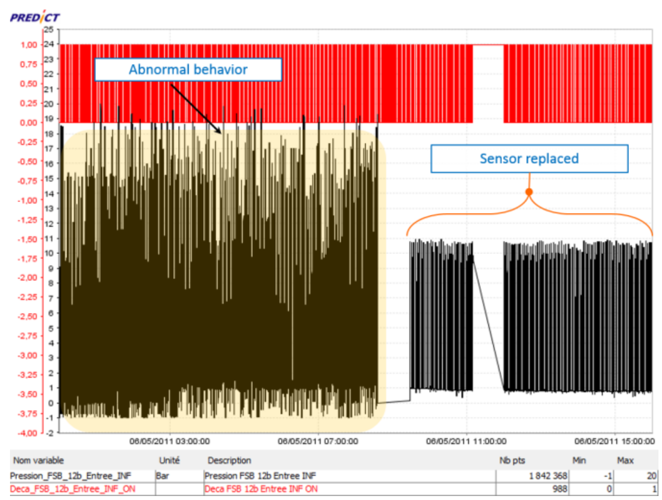

Figure 4. Pressure signal from the KASEM visualization tool

In this context, the work was focused in the scope of individual measurement monitoring in order to develop the first tool within the toolbox for individual measurement monitoring. In the next section the method applied and the corresponding results of monitoring and early detection are presented.

3.2. Individual measurement monitoring and detection

In order to develop monitoring and detection tool for the individual measurement, the proposed approach relies on 3 majors steps. First the operating conditions are determined. Then abnormal behavior are investigated and condition monitoring indices are defined and finally detection process is developed.

According to the circuit presented in Figure 3, 7 binary signals are available (one for each valve and draining). Based on that, 34 combinations have been identified in the dataset and ranked according to (i) their duration time and (ii) their occurrence number. The 2 combinations with the highest duration where E_i is opened and E_i is closed are kept for further analysis. In spite of the applicability of the proposed approach in each of the combination, the highest duration combinations represent the most "current" process behavior and then the combinations in which the probability of encounter problem increase. Moreover, the corresponding amount of data provides more accuracy in the statistical approach to assess thresholds for detection.

Even in normal conditions, the transient behaviors of the pressure can affect the detection. It becomes necessary to consider the pressure value in reliable open or close mode in order to avoid for instance peaks or delay when the valve opening or closing and concentrate on real expected value. Towards this end the opening and closing modes are re-evaluated. In Figure 5 an example is provided where the new stopping condition (in blue) is evaluated to avoid, in this case, oscillations.

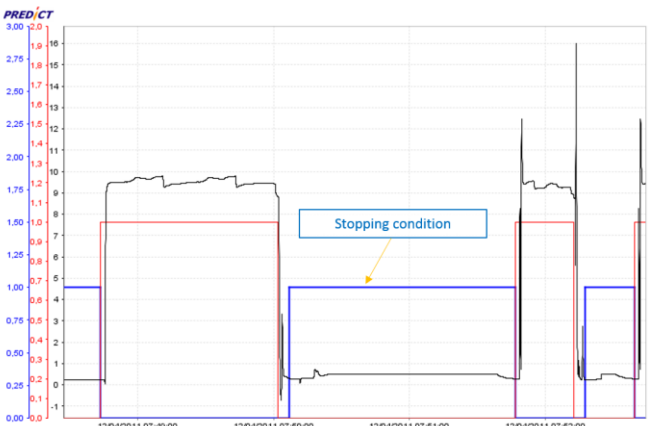

Figure 5. Example of stopping condition recalculation

In order to propose an accurate and robust monitoring and detection tool, statistical approaches have been used both for monitoring and detection.

The statistical approach combines the evalutation of median and confidence interval. Given the high sample rate and pressure behavior, it is important to provide accurate and consistent indicators. Indeed, due to its easy computation and robustness property the median is a efficient way to summarize such time series data. In addition the confidence interval calculation allows to assess accurate threshold to built detections. Working with the median for each opening and closing sequence reduces effect of signal noise since it acts as a sliding median filter and allow to reduce fasle alarm and missed alarm. Thus for each conditions (i.e. valve opening and closing) theses statistical indices are computed. An example for 2 valve opening sequences is provided in Figure 6.

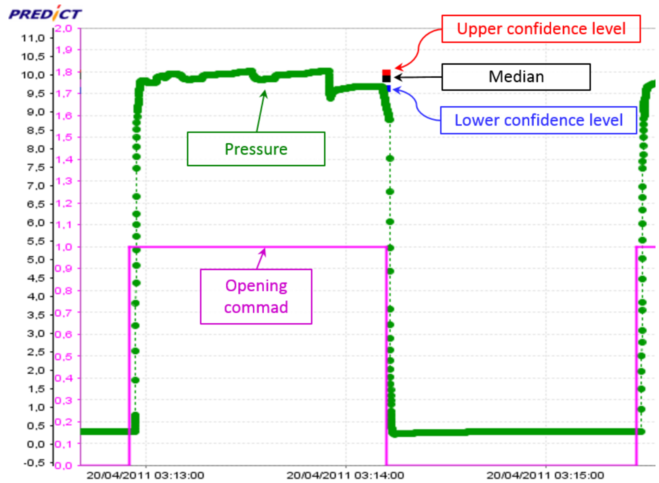

Figure 6. Example of statistics calculation

In this example, the upper level is set at 90% and the lower level is set at 10%. In order to provide generic toolbox, each of these parameters for the statsical indicators can be tuned.

From these indicators, it is possible to defined the detection thresholds and algorithms. Indeed, by statistically summarising the behavior it allows to provide more robust and efficient detection.

Towards this end, the upper and lower thresholds for detection have been defined according to the upper and lower confidence level obtained from the data set (Figure 7).

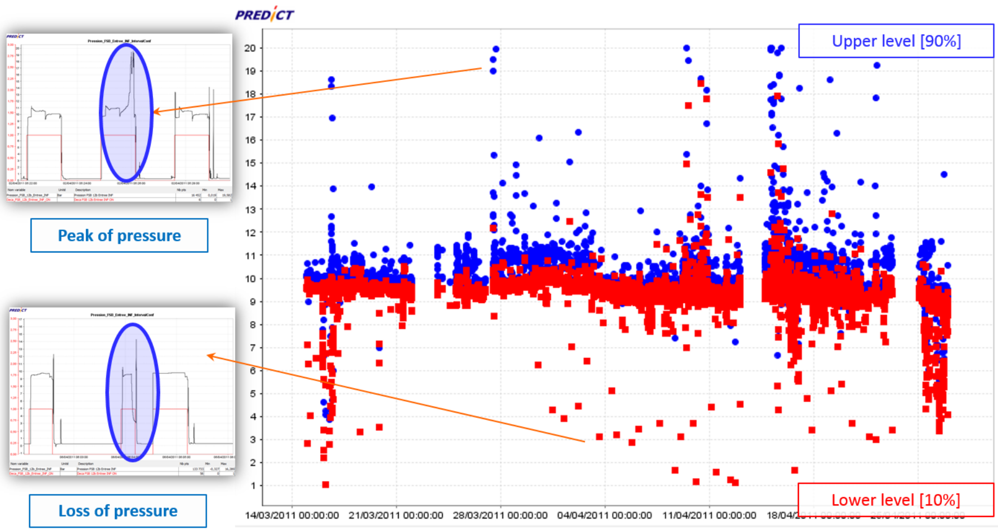

Figure 7. Example of the evolution of the upper and lower levels in functioning mode (i.e. valve open)

Thus, the threshold obtained, as median of the upper and lower levels considered, are 8 bar for the lower threshold and 12 bar for the upper threshold. Since the thresholds are determined, the abnormal behavior detection can be set up. Given this process, only two steady states are achieved for the pressure (namely opening and closing) leading to fix upper and lower thresholds for each mode. In case of more complex process with different steady states, adaptatvies thresholds would have been defined and applied.

For the detection, a first approach relies on considering the median of the pressure value as shown in Figure 6 and to trigger alert when the upper or lower thresholds are overpassed. The results of the simple approach are shown in Figure 8. For the period considered (~1,5 month) before the sensor replacement, the pressure signal leads to 17063 values of median (i.e. 17063 valve opening sequences) and in that case, 370 detections have been triggered for both the upper and lower thresholds.

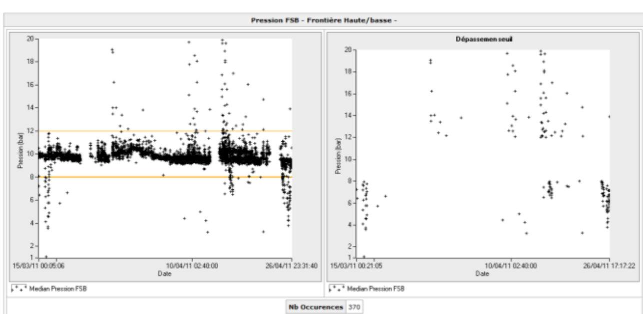

Figure 8. Example of statistics detection

Even if the median calculation for the detection can be set-up on-line for real-time detection, another approach have been investigated to get closer to the process and sensor behavior.

A moving window detection approach has been defined. Given that one valve opening sequence corresponds to around 2500 pressure values, a moving window of 300 points have been defined. If 200 points in the window exceed the threshold then a alert is triggerd. Finally, given the process dynamic, there are around 50 valve opening sequences per hour. Then in order to avoid untimely alarms, we consider a consolidated detection that delivers the number of triggered alert (based on the moving window detection) every 50 opening valve sequences.

3.3. Comparative results

As stated in the introductory part of section 3, the purpose of this work within the project context was to show the potentiality of the supporting tools and technique and highlight the added value of the approach with regard to the current situation.

Towards this end, the existing alarm rule (i.e. “alarm is triggered if mean pressure on 1 second is less than 7 bar”) was also integrated in the KASEM® platform in order to compare the detection. Additionally we also setup the consolidated detection every 50 opening valve sequences for the detection rule. The results are highlighted in Figure 9.

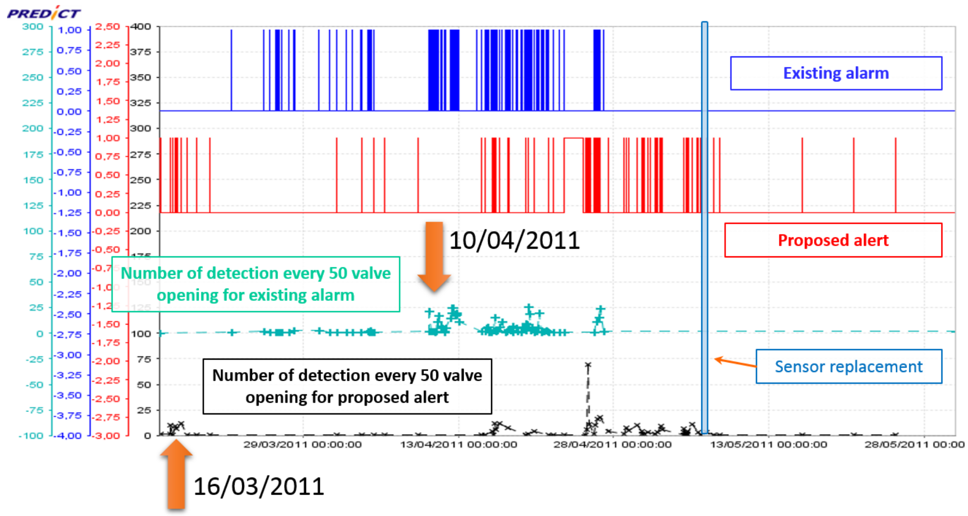

Figure 9. Detection results comparison over a 2.5 month period

.

The proposed approach has highlighted several benefits and improvements. The statistical evaluation of thresholds has permits to increase the lower threshold from 7 to 8 bar when valve is open. As a consequence, the early detection is greatly improved. Furthermore, by coupling the moving window detection with the consolidation per every 50 functioning sequence that allows to reduce untimely alarms without loss of accuracy and consistency. All in all, by considering only the detection of the same abnormal behavior as the existing one, i.e. the loss of pressure when the valve is open; the proposed approach with the consolidated detection provide an efficient mean to continuously follow-up the sensor behavior. Given the process dynamic, by considering that 10 detections per 50 opening valve sequences becomes critical, the implemented detection approach is able to early detect the sensor fault with around one month of anticipation compared to the existing alarm (cf orange arrows in Figure 9). From Figure 9, the data set start in middle of March, since we haven't get much data from early period, we were not able to assess if the proposed approach was able to provide much more early results.

3.4. Generic and modular toolbox

The approach has been developed in a generic way allowing to deploy the same detection method for the different operating modes and abnormal behaviors presented by the sensors. Indeed, for the closing valve sequence the same approach was applied. Upper and lower thresholds was identified by means of confidence level method. And the same detection method was deployed. Additionally, the peaks of pressure at opening were also studied as well as opening delays. Thus various monitoring indicators are now available for monitoring the sensor behaviors and included in the toolbox for individual monitoring of sensors. These indicators will also contribute to enhance the diagnosis capabilities of the platform. Figure 10 provides an example for the valve closing sequence. In this operating mode the upper threshold has been determined to 1 bar (by means of the confidence level approach as previously). The detection method presented here is the moving window on 300 points. The pressure signal is in black, the valve command in red and the detection in blue

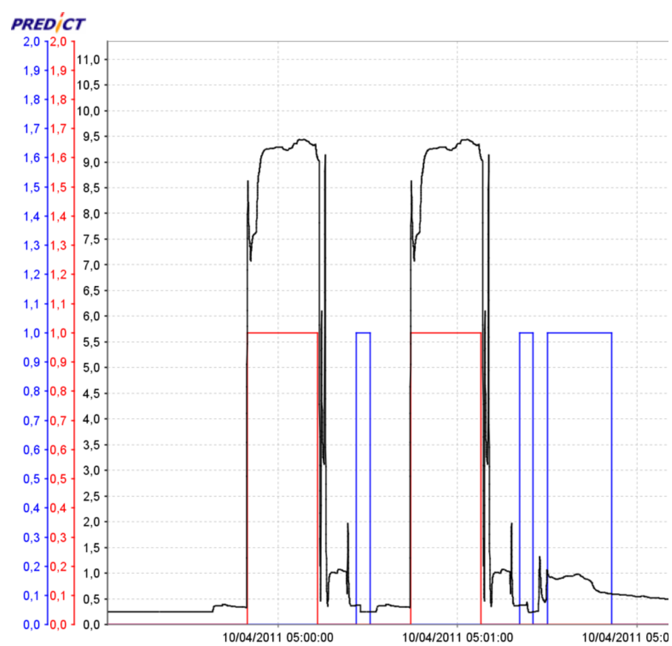

Figure 10. Example of moving window based-detection for the closing mode.

4. CONCLUSION

In this paper, a robust and efficient detection approach for sensor monitoring has been presented. The statistical approach makes the detection more robust and consequently more meaningful by reducing false alarm. In addition the consolidation and frequency approach avoid untimely alarm without making the system too less sensitive. The implementation within the KASEM® platform has allowed a generic and modular toolbox to be developed. Each step of the method has been easily deployed to the other signals considered in the application (i.e. 6 pressure signals of the FSB system) and for the 2 operating modes.

The efficiency and accuracy of the method has been assessed in real condition by comparison of the results with the existing alarm system running at the plant.

Based on that, future work will investigate on the one hand, how this approach could contribute to the toolbox for inter-measurements consistency. Especially when several indicators can be defined for the same sensor. In addition, inter-measurement methods could also allow to assess behavior within the confidence interval. For instance if a sensor start to tangent the higher or lower confidence level it could have impact on other measurement (in case of control loop for instance). On the other hand, other methods will be investigated thanks to different measurement sensor type with a focus on torque and force sensors.

Thus, the combination of consistent continuous follow-up indicators, early detection and diagnostic features, the toolboxes within the platform will directly contributes the reliability enhancement of sensor measurement.

REFERENCES

Lee, B. H., Jeon, N. J., & Lee, H. C. (2011, October). Current sensor fault detection and isolation of the driving motor for an in-wheel motor drive vehicle international conference on control, automation and systems (ICCAS 2011). In *Control, Automation and Systems (ICCAS), 2011 11th International Conference on* (pp. 486-491). IEEE.

Léger J-B. (2004). A case study of remote diagnosis and e-maintenance information system, *Keynote speech of IMS'2004, International Conference on Intelligent Maintenance Systems*, Arles, France.

Miletic, I., Boudreau, F., Dudzic, M., Kotuza, G., Ronholm, L., Vaculik, V., & Zhang, Y. (2008). Experiences in applying data-driven modelling technology to steelmaking processes. *The Canadian Journal of Chemical Engineering*, *86*(5), 937-946.

Monnin, M., Voisin, A., Leger, J. B., & Iung, B. (2011a). Fleet-wide health management architecture. In *Annual Conference of the Prognostics and Health Management Society.* September, Montreal, Quebec, Canada.

Monnin, M, Leger, J-B., Morel, D. (2011b). KASEM®: e-Maintenance SOA Platform, *in Proceedings of 24th International Congress on Condition Monitoring and Diagnostics Engineering Management*, 29th May – 1st June, Stavanger, Norway.

Reppa, V., Polycarpou, M. M., & Panayiotou, C. (2012, August). Distributed sensor fault detection and isolation for nonlinear uncertain systems. In *Fault Detection, Supervision and Safety of Technical Processes* (Vol. 8, No. 1, pp. 1077-1082).

Samy, I., Postlethwaite, I., & Gu, D. W. (2011). Survey and application of sensor fault detection and isolation schemes. *Control Engineering Practice*, *19*(7), 658-674.

Voisin, A., Medina-Oliva, G., Monnin, M., Leger, J. B., & Iung, B. (2013, October). Fleet-wide Diagnostic and Prognostic Assessment. In *Annual Conference of the Prognostics and Health Management Society 2013*.

Zhang, Y., Bingham, C., Gallimore, M., Yang, Z., & Chen, J. (2013, July). Sensor fault detection and diagnosis based on SOMNNs for steady-state and transient operation. In *Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 2013 IEEE International Conference on* (pp. 116-121). IEEE