Condition Monitoring of Subsea Sensors. A Systems of Systems Engineering Approach

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Abstract: - Deeper waters, remote locations and the current market reality has led to higher complexity of subsea production and processing systems oriented to increase oil recovery, reduce capital expenditures (CAPEX) and operational expenditures (OPEX), provide operational flexibility and health, safety and environment (HSE) benefits. This fact demands development of digital applications to support condition monitoring, supervision, integrated diagnosis and efficient control and operation of subsea facilities. Digital applications are highly dependent on reliable instrumentation and associated data, which might be impaired by measurements uncertainties related to sensor failures, degradation in time or unavailability. This paper explores the use of a "systems of systems engineering" approach and model based fault detection methods to develop a framework to support condition monitoring of subsea sensors to be used on digital applications.

Key-Words: - Condition Monitoring, Fault Detection, Subsea Sensors, Systems of Systems, Underwater Technology, Digital Applications.

1 Introduction

A fundamental aspect in the design of a complex system is the use of systems concepts, principles and laws in terms of a holistic view of the problem under study [1]. The growing interest of systems of systems (SoS) as new generation of complex systems has opened many challenges for systems engineers. Performance, optimization, robustness, and reliability together with an emerging group of heterogeneous systems, to realize a common goal, have become the focus of various applications; including military, security, aerospace, manufacturing, service industry, environmental systems among others. [2]. There is an increasing interest for achieving synergy in independent systems to obtain higher capabilities and performance. The use of SoS concepts to develop a framework to support intelligent control, supervision and integrated diagnosis applicable for subsea production and processing systems was considered in [1], complementing an initial framework in [3].

Digital applications are highly dependent on reliable instrumentation and associated data, which might be impaired by measurements uncertainties related to sensor failures, noise, drift, offset, degradation in time or unavailability. Therefore, it is important to address the evaluation, processing and validation of the measurements in a systematic manner to guarantee the quality of information fed to digital applications. There is a set of valuable contributions in literature e addressing sensor modelling [4], fault handling in networked sensors [5, 6], sensor fault detection [7, 8], data validation [9] and statistical data quality improvements [10]. This paper explores the condition monitoring of subsea process sensors to support digital applications within a "systems of systems engineering" (SoSE) approach, considering the state of art, as well as the challenges associated to limited instrumentation, limited data and limited infrastructure of mature brown fields.

This paper is structured as follows: section 2 and 3 present an overview of subsea sensors and digital applications in subsea production and processing systems. Section 4 and 5 present sensor fault classification and model based fault detection methods. Section 6 describes a SoSE approach using hybrid systems and intelligent event detection methods that is suitable to address condition monitoring of subsea sensors.

2 Subsea Sensors in Production and Processing Systems

Subsea sensors are key to enable monitoring and control of subsea assets in oil and gas production facilities. Subsea sensors are installed at multiple locations on the trees, manifolds and flowlines. Subsea sensors on a subsea tree are normally tree-mounted pressure sensors and temperature sensors that provide measurements upstream and downstream of the chokes. They can also be part of separate flow control modules. Software and electronics in the subsea control modules acquire sensor data and system status information with unique addresses and time-stamp validations to transmit to the topside system. Process sensors used in conventional production systems typically comprise pressure and temperature sensors, sand / erosion detectors, pig detectors and flowmeters. Additional instrumentation can also be installed to support condition and performance monitoring in production facilities such hydrocarbon leak detectors, salinity sensors, vibration monitors and more complex acoustic and electrical condition monitoring systems [11]. Complex sensors are normally equipped with a more extensive set of housekeeping signals compared to traditional process sensors that allow determining status and health of sensors during the service life. Some sensors / sensor systems are even equipped with self-diagnostic capabilities.

This paper focus on conventional process sensors such as pressure, temperature and flowmeters where advanced self-diagnostic capabilities are not normally present. Usually, critical pressure and temperature sensors are redundant, especially if they are part of shut down sequences. These sensors are commonly used to evaluate production and process performance as well as decision-making aid for process optimization and increased recovery.

3 Digital Applications in Subsea Production Systems

Current challenges in the Oil & Gas market together with greater demands of climate change accountability, motivates the embracement of digital technologies within Upstream Industry to increase efficiency, reduce cost, minimize downtime and optimize performance to remain sustainable. Digital technologies are already available and deployed in other industries as well as midstream transportation, storage and downstream process facilities.

Increasing volume and complexity in hostile, remote locations (for example, arctic, offshore, and deep waters) require reliable remote monitoring and control of the assets. Automation becomes imperative ranging from process automation, data management, signal processing, modelling, simulation and analytics to support process performance, production optimization and decision making not only for green fields but also for mature and marginal fields. Digital processes and automation programs for green fields can be implemented as part of the project development. Brown fields, especially those approaching end of service life, have the challenge of limited and obsolete infrastructure, limited instrumentation and available data. New control system technology and instrumentation can be implemented as part of an upgrade for subsea retrievable equipment, especially for fields going for life extension. Permanently installed equipment can have complex retrofit solutions to suit demands of additional instrumentation.

Digital applications for subsea equipment typically range from virtual measurements to add analytical redundancy or complement needed instrumentation, such as virtual or analytical flow meters, automated logics to determine valve status subsea or downhole, general diagnostic applications to determine health of equipment, condition and performance monitoring applications [11] and supervisory systems to support production optimization, etc. For subsea power and processing facilities or electrical actuated systems, higher complexity digital applications may be encountered. For smart instruments with self-diagnostic capabilities the challenge is reduced but for applications using standard pressure sensors, temperature sensors and non-smart flow meters, data might be impaired by measurements uncertainties related to sensor failures, degradation in time or unavailability. Hence the importance of evaluation, processing and validation of the measurements in a systematic manner to guarantee the reliability and performance of the digital application.

4 Sensor Fault Classification

Measurement failures and uncertainties can arise due to external or internal factors respect to the sensor under scrutiny. The following categorization for sensor failures is presented in [6]:

External Faults: Caused by factors that influence environmental conditions in a way that process measurement is disturbed.

Transducer Faults: Electronic or mechanical failures within the sensor. For example, defective power supply or faulty voltage reference of the analog to digital converter.

Processing Faults: Software or hardware failures of a processing component.

Communication Faults: A mixture of internal and external failures. Internal failures, often depend upon sensor communication hardware. Some external failures may be interference, cross talk, limited bandwidth, I/O card problems associated to the controller or I/O device connected to the sensor in the network.

For the above sensor failures, a focus on transducer faults and communication faults are explicitly considered in [5, 6], although the focus in these publications is related to smart sensors, the fault classification is also applicable to any sensor connected to a network. Some of the applicable failures and the proposed mathematical models in [5, 6] are summarized below. Internal Transducer faults can be broken down according the tree diagram depicted in Fig. 1 [6]. Time constant faults represent a constant (relative) offset from the correct value. These may be in connection with calibration problems, zero / span errors or offset of an analogue-digital converter. A model for these faults is as follows

$$F(t) = K \tag{1}$$

Where K is a constant value. Time variant faults divides in continuous and non-continuous with linear and nonlinear deviations. They may be modelled as multiplicative failures respect to time or respect to a physical value that varies in time [6]

$$\begin{gathered} F(t) = C_t t \\ F(t) = C_y y(t) \\ F(t) = C_y y(t)^n \end{gathered} \tag{2}$$

Multiplicative faults relate to drift or transducer aging. Continuous faults may also occur due to communication problems, such as synchronization messages lost in the remote case sensors. Non-continuous failures categorizes as stochastic and non- stochastic disturbances. Non-stochastic disturbances can be permanent or temporary, occurring during a time-period T_d due to a specific environmental condition or intermittent condition producing the disturbance. Temporary faults can lead sensor to be stuck in a constant value X_c if the condition holds. If sensor completely crashes or the communication goes down completely for a longer period, fault classifies as permanent after a time instant T_c, and measurement can take an undefined

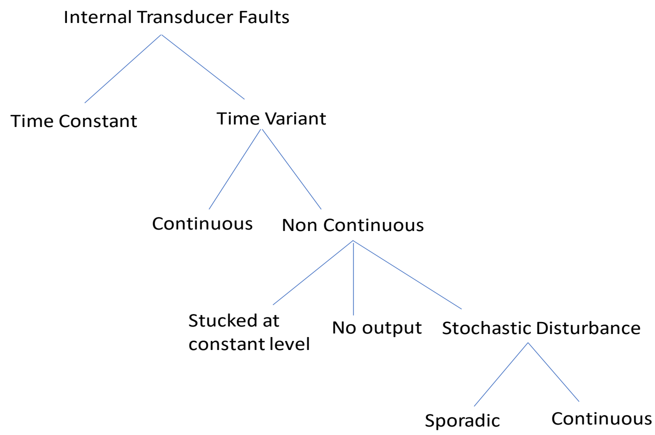

Fig.1 Categorization of internal transducer faults [6]

value depending on the nature of the failure. The above-described non-continuous failure may be modelled as follows

$$F(t) = \begin{cases} Xc, & t \in T_d \\ y(t), & t \notin T_d \\ undefined & t > T_c \end{cases} \tag{3}$$

Stochastic disturbances or outliers could be sporadic or continuous in time, including noise. They can be constant, time or value correlated and are representable as follows [6]

$$F(t) \sim N(\mu, \sigma) \tag{4}$$

Measurement delays are also present in process sensor measurements and their occurrence depend on communication network delays, limited sampling rates and time-consuming calculations. They may be inherent to the system structure and design. Unknown delays can result in a fault [6]. Delays are aclassified as constant, variable in time or value dependent if a process condition or specific operational set point produce the delay. They may be modelled as follows

$$F(t) = \begin{cases} y(t-a), & a \text{ is a constant} \\ y(t-a(t)), & a \text{ is time dependent} \\ y(t-a(y(t))), & a\ is\ value\ dependent \end{cases} \tag{5}$$

5 Model Based Fault Detection Methods

Different approaches for fault detection by using mathematical models have been developed over the last 30 years [12]. The task consists of detecting faults in the process, including all its subsystems, sensors and actuators by measuring inputs and output variables in each sub-process. The process is assumed to operate in open loop. A distinction is made between static, linear and nonlinear process models [3, 12]. There are three important model based fault detection methods [12-14]. They generate residuals in the following ways:

5.1 Parameter Estimation: Primarily recommended for corresponding faults in processes and faults that change actuators and sensors dynamics. Changes of parameters estimates $\Delta\theta$ are considered $P = F(\theta)$ or changes of process coefficients Δ_P.

5.2 State Estimation: Considers changes of states estimates $\Delta\hat{x}(t)$, output errors $e(t) = y(t) - C\hat{x}(t)$ or filtered output errors $r(t) = We(t)$. It is feasible for corresponding faults in sensors and actuators and some cases in processes. State observers represent a way to estimate state variables. Alternatively, output observers are an option if the reconstruction of the individual state variables is not of interest [13].

5.3 Parity Equations: Considers changes on output errors in Laplace domain. In this case, $e(s) = y(t) - G_M(s)u(s)$ or represented as polynomial error $e'(s) = A_M(s)y(s) - B_M(s)u(s)$, where $A_M(s)$ and $B_M(s)$ correspond to the numerator and denominator polynomials of the transfer function $G_M(s)$. It is also feasible for corresponding faults in sensors and actuators and some cases in processes.

If all faults are detectable in a process, different detection methods could be integrated to use their advantage in an appropriate manner. The integration will depend on the process nature, the faults to detect and the available computational capabilities. For multivariable processes, the analytical redundancy between measured input and output increases, and the associated cross coupling shall be considered to obtain reliable models.

5.4 Signal Models*:* In addition to the three basic methods described above, fault detection with signal models is also plausible [14]. Many measured signals show oscillations that are of either harmonic or stochastic nature or both. If changes in these signals relate to faults in the process, actuators or sensors, a signal analysis is then necessary as a further source of information [14]. Typical cases where signal models apply are processes containing turbo machinery equipment. Failure extraction can be restricted to amplitudes or amplitude densities within a certain bandwidth. Parametric signal models are also usable to estimate main frequencies and their amplitudes, which can be sensitive to small frequency changes [14]. Wavelet transforms are also among the techniques to detect and isolate process failures such as leaks in pipelines networks.

6. Hybrid systems based intelligent event detection. A SoSE approach

A SoS is a collection of task-oriented or dedicated systems that pool their resources and capabilities together to create a new, more complex system which offers more functionality and performance than simply the sum of the constituent systems [1,2]. The methodology for defining, abstracting, modelling, and analysing SoS problems together with processes, tools and methods to design, deploy and operate their solutions are typically referred as SoSE [1,2].

A SoSE based framework for intelligent control and supervision for subsea production and processing systems was presented in [1]. This philosophy based on hybrid systems can be utilized and adapted to enhance the capabilities of individual subsea production and processing systems to be promoted to SoS elements within the large subsea production system [1]. Digital applications supporting SoS capabilities will be fed with measurement signals from the subsea process. A system approach is needed to evaluate and validate sensor information within the system before the information is further processed in any digital application. The supervision scheme, for individual subsea systems proposed in [1] is illustrated in Fig. 2. The continuous process level represents individual subsea production or processing system interacting with the condition monitoring, fault detection and diagnostic system to monitor the equipment and support faults identification when they occur. The continuous level layout is illustrated in Fig. 3.

For the case under study in this paper, the maintenance tasks are related to process sensors of interest such as manual or automatic calibration via software, activation / deactivation of measurements to be considered in digital application using multiple / redundant input measurements, model based validation and correction of measurements. The fault detection and diagnostic module illustrated in Fig. 3,

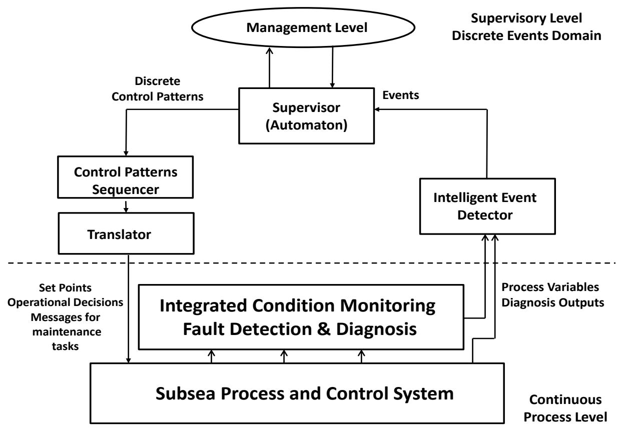

Fig.2 Intelligent supervisory scheme based on hybrid systems [1]

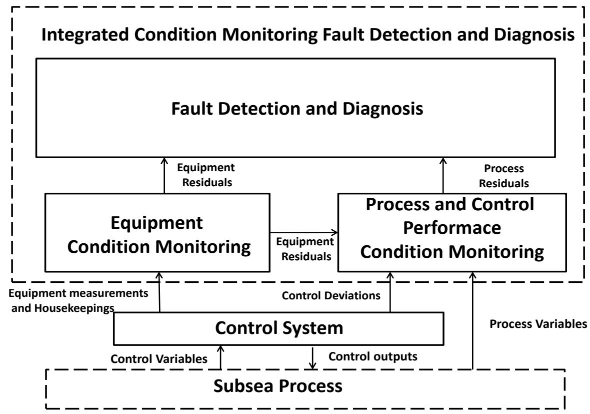

Fig. 3 Hybrid system continuous level layout [1]

shall pre-process equipment and process residuals and the intelligent event detector shall determine the type of failure event being produced. A differentiation between equipment and process failures will be already available within the event detector module for further actions.

Digital applications in the supervisory level will sequence the control patterns and translate them into the appropriate messages and actions to be taken in the continuous level. For complex SoS, some diagnostic tasks can be performed in the continuous level and integrated in a higher level for event detection and supervision. For fault and event detection in sensors, the process in the continuous level may be simplified. Sensor failure models may be defined for each sensor according to equations (1-5). Process model representation, where sensors are part of the equipment process, may be modelled according to [3]. Residual generation and preliminary detection signals can be generated using one of the methods proposed in section 5. Selection of the process representation and residual generation methods will depend on the specific application where the sensors are installed. Inputs to the event detector will be process variables representing measurements of interest and/or pre-processed residuals from the simplified integrated condition monitoring fault detection and diagnosis module illustrated in Fig. 2.

There are many event detection techniques; however, within the SoS framework defined in this paper, based on hybrid systems, the method presented in [15] is considered a good option, considering it has been field proven in an industrial application, used in the supervisory level as proposed in Fig.2 and successfully implemented in a distributed control system without computational challenges [15]. Ideally, the available control and automation platforms should be used when possible to minimize implementation cost, especially for brown and mature fields where a control system infrastructure is already in place.

A linguistic model defined to map all inputs $U_1,...,U_m$ into the output variable V is showed in Fig. 4. There, B_{ij} and D_i, $(i=1....m),(j=1...r)$ are fuzzy and reference discrete subsets of the universe of discourse of inputs $X_1,....,X_m$ and events Y of U and V, respectively. τ_i is the firing level of $Rule_i$ and $F_i(y)$ is the fuzzy set output inferred by the i^{th} rule. The defuzzification method presented in [15] shall be applied to finally determine the event y_i with highest probability of occurrence, $P(y_i)$.

$$P(y_i) = \frac{1}{n} \tag{6}$$

If $y_i = \arg\{\max_{y\in V} F(y)\}$, where n is the number of elements of Y which attain the maximum membership grade in F. On the other hand, V is the output variable of the linguistic model defined for the event detection, and

$$P(y_j) = 0 \tag{7}$$

if $y_i \neq \arg\{\max_{y\in V} F(y)\}$. This corresponds to a uniform probability distribution, which has the lowest entropy [15]

7 Conclusions

This paper explores the use of a SoSE approach and model based fault detection methods to develop a framework to support condition monitoring of subsea sensors over digital applications.

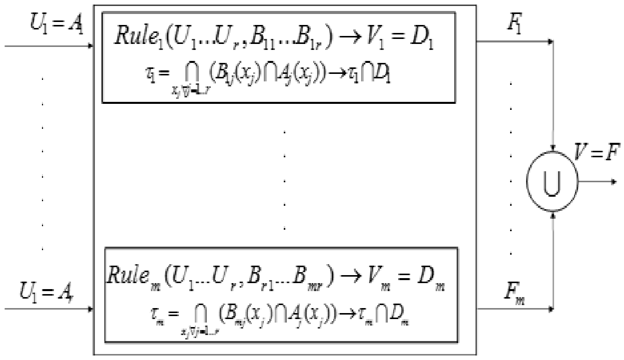

Fig. 4 Block diagram MISO linguistic model

The framework is applicable to conventional process sensors such as pressure, temperature and non-smart flowmeters where advanced self-diagnostic capabilities are not normally present. They are usually installed across the subsea production equipment and connected to a network of subsea control system, which is linked to the topside distributed control system, where all systems are integrated. A system approach is needed to evaluate and validate sensor information before the information is further processed in any digital application. The SoSE approach is based on hybrid systems and fuzzy event detection. This approach can be used in any system or system of systems; therefore, simplified models within this approach are also applicable for condition monitoring and event detection of subsea sensors as part of a whole SoS strategy.

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