# PREDICTION OF SENSOR SYSTEM RELIABILITY

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## Abstract

This paper summarized influencing factors to the sensor system reliability used in Oil and Gas industry. A management plan based on criticalities of influencing factors to the overall system is proposed. Prediction of sensor system reliability will be especially useful in the situation where sensor systems can degrade over time in service. A modeling approach has been carried out in this paper to combine the Bayesian network modeling and "Analytical Redundancy relations" methodology for assessing sensor reliability in a digital downhole application.

**Key words**: Sensor; Reliability; FMECA; Bayesian network; Digital downhole.

## Introduction:

A sensor is a device that measures a physical quantity by generating a functionally related output which can be read by an observer or by an electronic instrument. Sensors can be categorized in many different ways based on the mechanism by which they transform a particular input into an output, for example as physical, chemical, biochemical, and electrochemical sensors. Most sensors produce an electrical output for ease of transmission, storage, and read out. "Sensor" is often used interchangeably with the term "sensing element". However, most state-of-the-art sensors consist of multiple components. For example, "smart sensors" or "sensor systems" use built-in compute resources to perform predefined functions upon the detection of specific input and then process data before passing it on. A working sensor system is a composite of four distinct parts shown as a block diagram in Figure 1 including 1) A sensing element, which produces an electrical response when the device is stimulated by external factors; 2) A signal conditioning element that modifies and processes the electrical signal to be understood properly by the receiver; 3) A sensor interface that allows the device to acquire, store, and communicate with an external interface, and; 4) A power system to provide external power resources or to harvest energy.

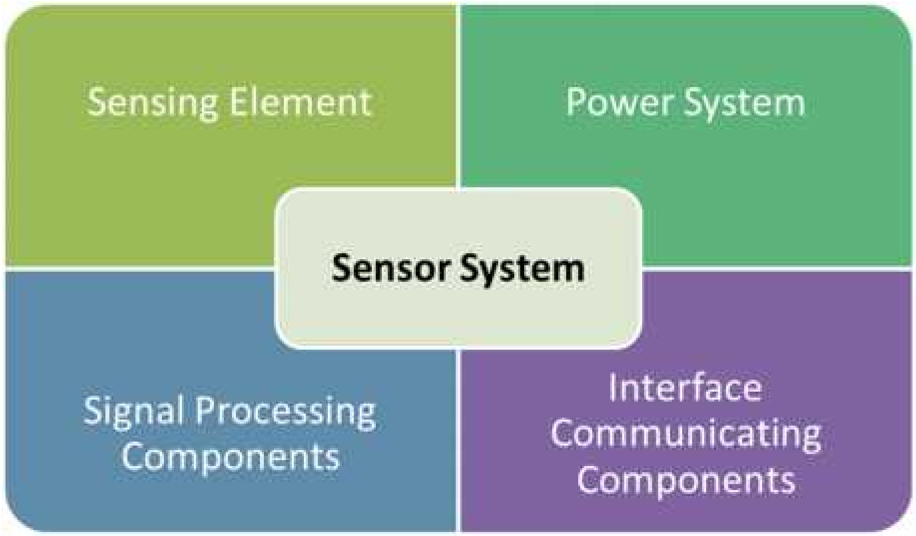


Figure 1. A schematic of a sensor system

Sensor system reliability can be defined as the ability of a sensor system to perform its required functions under stated conditions for a specified period. For this reason, the reliability of a sensor system will be strongly dependent upon its age, context and application. Assessing sensor system reliability is a major challenge in developing new sensors and sensor selection. It is not uncommon that a sensor system possesses a high reliability in one application but becomes unreliable in another situation. Additionally, reliability requirements depend upon how and where the sensors are applied. To ensure long-term performance, embedded or permanent sensors that are difficult to calibrate will need to have a higher reliability than temporary or manually operated sensors. A high reliability is especially critical for the following application scenarios as illustrated in Figure 2 including 1) Complex and smart sensor systems (e.g. Sensor Fusion); 2) Highly integrated miniature sensor systems (e.g. MEMS/NEMS sensors); 3) Long term monitoring requirements (e.g. Condition Monitoring); 4) High Consequence /Mission Critical applications (e.g. Leak Detection or Aviation); 5) Application requires dynamic response (e.g. Dynamic Positioning System); and 6) Harsh and extreme working environments (e.g. High Temperature High Pressure in Oil &Gas fields). Any equipment including sensors will eventually fail regardless of how superior the design is and how well it is maintained. During the lifecycle of a sensor system, its failure rates tend to follow the ‘bathtub’ curve. To reduce cost, a typical strategy that sensor users adopt is to extend the time of “wear-out” period as long as possible. This could be realized through a well-defined and well-executed maintenance plan. In some situations, with detailed knowledge of the sensor system and enough statistical data, it is possible to estimate the remaining useful life. However, for each application scenario, the lifecycle curve may not be identical even for the same sensors manufactured in the same batch. Therefore, when predicting the remaining life of a sensor system, many factors including sensor design, materials selection, manufacturing and packaging process, maintenance and calibration, and the sensor working environment should be systematically considered.

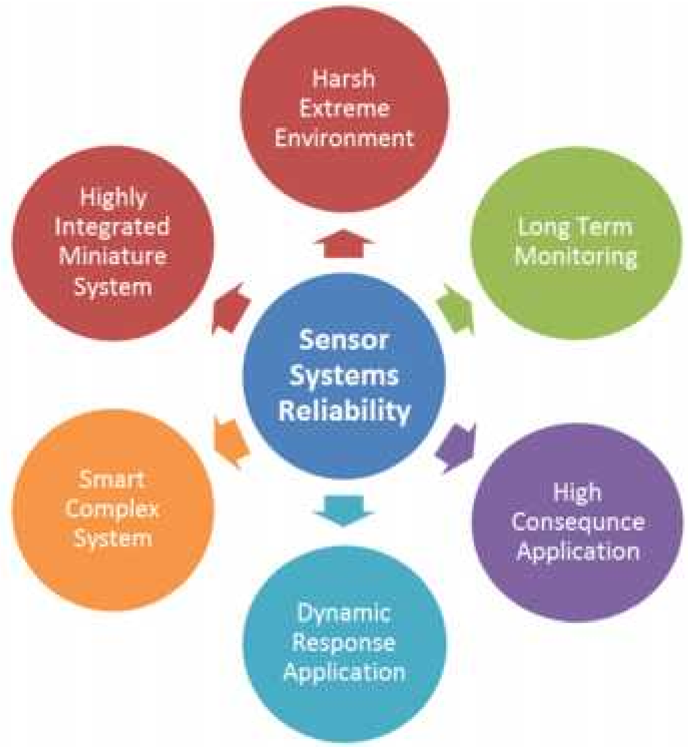


Figure 2. Application scenarios where sensor system reliability is extremely important

**Factors Affecting Sensor Reliability**

To evaluate, predict or improve the reliability of a sensor system, it is necessary to know the reliability of each component of the sensor system i.e. sensor element, signal processing components, power system, and interface communicating components. Additionally, design, manufacturing, packaging, installation, maintenance, and calibration will also play a role on sensor system reliability. The software used by a sensor system also affects its reliability. One method for assessing sensor system reliability is to apply Failure Mode, Effects and Criticality Analysis (FMECA), which is an extension of Failure Mode and Effects Analysis (FMEA, or just referred to as "failure mode"). In this methodology, a risk assessment is made of each failure mode to determine its criticality. Criticality is derived from an assessment of the probability that a particular failure will occur combined with the severity of the failure if it does occur (i.e. the consequence).

To carry out FMECA for a sensor system, a systematic analysis need to be performed based on the sensing mechanism, the working environments and the overall redundancy. Table 1 shows the criticality of a pressure sensor (generic) used in subsea processing, where the criticalities were divided into five categories of Very Low, Low, Medium, High, and Very High. Factors with a criticality of Very Low or Low can be subject to corrective maintenance. Factors with a criticality of Very High must be considered for re-design or adding redundancy to decrease criticality. The factor ranked with a criticality of Medium to High is to be evaluated further, for example, to consider its effects on other components as well as on the overall system. [1]

Table 1. Failure Modes and Their Criticality Ranking for the Reliability of a Pressure Sensor System

| Sensor System Components | Failure Modes | Criticality | | | | |
|---|---|---|---|---|---|---|
| | | Very Low | Low | Medium | High | Very High |
| Sensor Elements | Degradation of Sensing Materials | | | | | |
| | Thermal Induced | | | | | |
| Signal Processing Components | Degradation of contacts or connections | | | | | |
| | Thermal Induced | | | | | |
| | Degradation of Signal Processor | | | | | |
| Power System | Degradation of contacts or connections | | | | | |
| | Faulty Electronics | | | | | |
| | Loss of Power | | | | | |
| Interface Communicating Components | Degradation of contacts or connections | | | | | |
| | Faulty Electronics | | | | | |
| | Poor/Insecure Signal | | | | | |

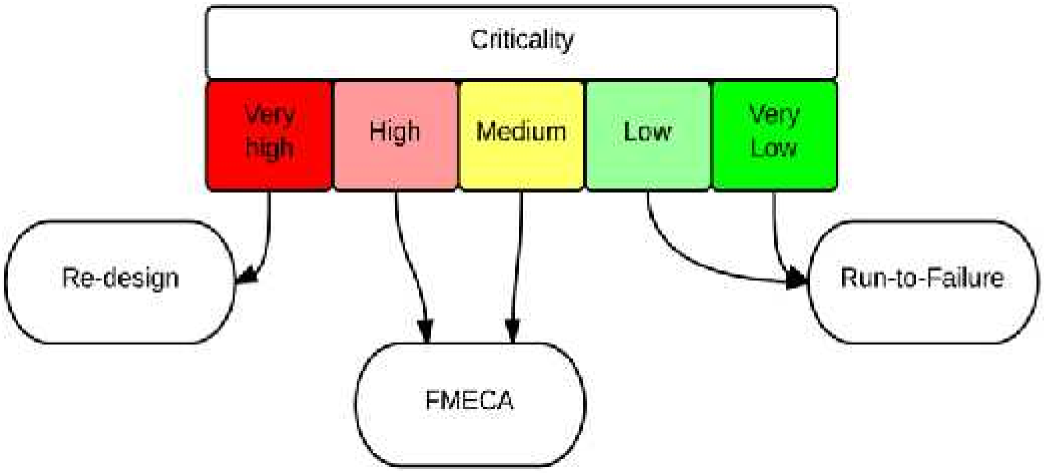


Figure 3. The criticality definition and the corresponding actions for the reliability of a sensor system

One of the most important factors affecting the reliability of a sensor system is degradation, primarily because of materials aging, corrosion, and wear. In general, three classes of sensor system degradation should be considered including 1) Degradation of the sensing element itself, e.g., in harsh environment, accelerometers' sensitivity and accuracy gradually getting worse; 2) Degradation of connectors, usually a problem that results in false positives. For example, a false positive from water-in-oil sensors can cause dry-dock of the ship unnecessarily, thus resulting in huge financial loss; and 3) Degradation of power systems – this is especially important for sensing systems operated via batteries. For example, for acoustic sensors used to sense buried pipeline leaks, it is difficult to replace the battery without excavation.

Since ageing and degradation of a sensor system are time dependent, the reliability will inevitably decrease over time and thus the potential for faults and failures will increase. Unfortunately, this issue is not always considered during the planning phase of sensor deployment. Taking the condition monitoring of ship machinery as an example, sensor degradation may not disable the monitoring system, but will likely create false positive or negative readings. False positive may lead to unnecessary actions to rectify a potential problem or, if sufficient false positives are seen, may lead to de-sensitization of staff to an event. False negatives may lead to ignoring a potential threat. Degradation can also result in imprecise sensor data in the form of drift or bias. In such cases, errors will be produced in the system condition diagnosis resulting in ineffective control. A typical example can be found in the drift of pressure sensors. While the exact mechanism of pressure sensor drift is not understood completely, typically it is believed to result from the change in response of the physical properties of the sensor materials to external environments, including the frequency of the pressure changes and the exposure to temperature extremes. An example of this phenomenon is the SIEMENS WEPS-100 Series Subsea Pressure Sensor. According to the data sheet provided by the sensor manufacturer, brand new ("out of the box") sensor yield a reading accuracy of +/- 0.35

bar, which increase to +/- 9.1 bar after 25 years of usage [2]. That is, one can experience averages of 100% drift each year! In theory, the drift can be corrected through calibration, while in special situations, such as applications in subsea oil and gas processing, it is impractical to calibrate the sensors without interference with production.

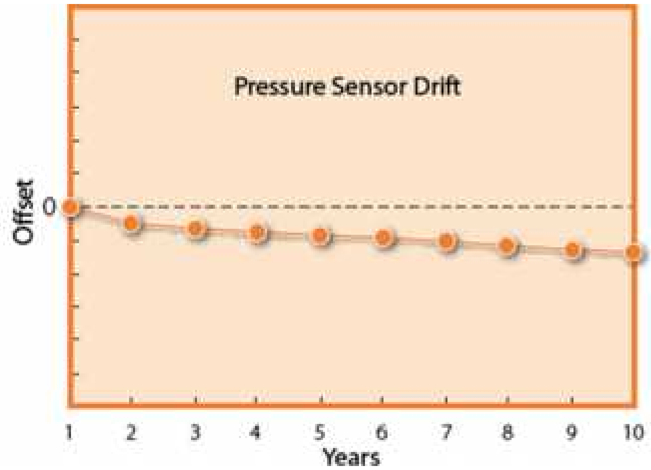


Figure 3. (left) WEPS-100 Series Subsea Pressure Sensors, [2] and (right), A schematic of pressure sensor drift.

**Prediction of Sensor System Reliability**

A number of algorithms have been developed to detect faulty sensor data as a screening tool prior to passing information on to decision-aid tools. These computational methods include 1) Principal Component Analysis (PCA); 2) Artificial Neural Networks (ANNs); 3) Recurrent Neural Networks (RNNs); 4) Auto-Associative Kernel Regression (AAKR); 5) Independent Principal Component Analysis; 6) Support Vector Machines (SVMs); and 7) Fuzzy Similarity, etc. As summarized by Sharma et al., four categories of detection methods can be discerned [3] including 1)Rule-based methods define heuristic rules/constraints that the sensor readings must satisfy; 2) Estimation methods define "normal" sensor behavior by leveraging spatial correlation in measurements at different sensors; 3) Time series analysis based methods compare a sensor measurement against its predicted value based on time series forecasting to determine if it is faulty; and 4) Learning-based methods infer statistically established models to identify faulty sensor readings using training data. These methods have been found to be useful in many application scenarios. However, there also exists the need to estimate the uncertainty attached to the sensor data being received. This information will be especially useful in the situation where sensor systems can degrade over time in service, and thus the data may need to be corrected or compensated before decisions can be made. From the condition based monitoring standpoint, it will be useful to predict when the reliability of a sensor system has become unacceptable, and thus action must be taken to calibrate or replace the sensors.

Assessing the probability of an unreliable sensor system failure using modeling tools is challenging for three reasons: 1) no model is accurate in all situations, 2) the input data used to run the models is never exact, and 3) the knowledge of the system is often incomplete or unclear. [4, 5] For this purpose, we introduce the concept of using Bayesian network modeling to assess the failure probability of a deployed sensor system. A Bayesian network is a probabilistic graphical model based on Bayes' theorem for combining prior knowledge and data. It can combine diverse models (i.e. mechanistic and empirical, with different sources and different programing languages) into one unified method. Therefore, the methodology makes it easy to update the overall framework when new knowledge is produced. If we learn enough information about a sensor system, including the working mechanism of sensors, its technical specifications, failure modes and working environments, it is feasible to construct a Bayesian network model for filtering and assessing unreliable sensor data. Figure 4 demonstrates the generic structure of a simplified Bayesian network that might be used to predict the reliability of sensor data under the influence of degradation and aging of the sensor components. It can be seen that the working environments, the maintenance, and calibration of the sensors will play a direct role on the reliability. A suitable algorithm, established through a consideration of the failure modes revealed through accelerated life testing and/or updateable field experience, will be able to compute the probability of unreliable sensor data. These degradation models can then be used to make decisions regarding sensor placement and timing for maintenance and/or replacement. The degradation models can also be used to help in the statistical determination of whether a constraint breaking event has occurred (i.e. distinguishing an actual fault from the noise). It is critical to be able to update the model through the technique of Bayesian inference, as sensor systems are often extended to new environments or longer service lives due to life extension programs, in which case new failure modes associated with materials ageing and other physical or chemical processes will emerge.

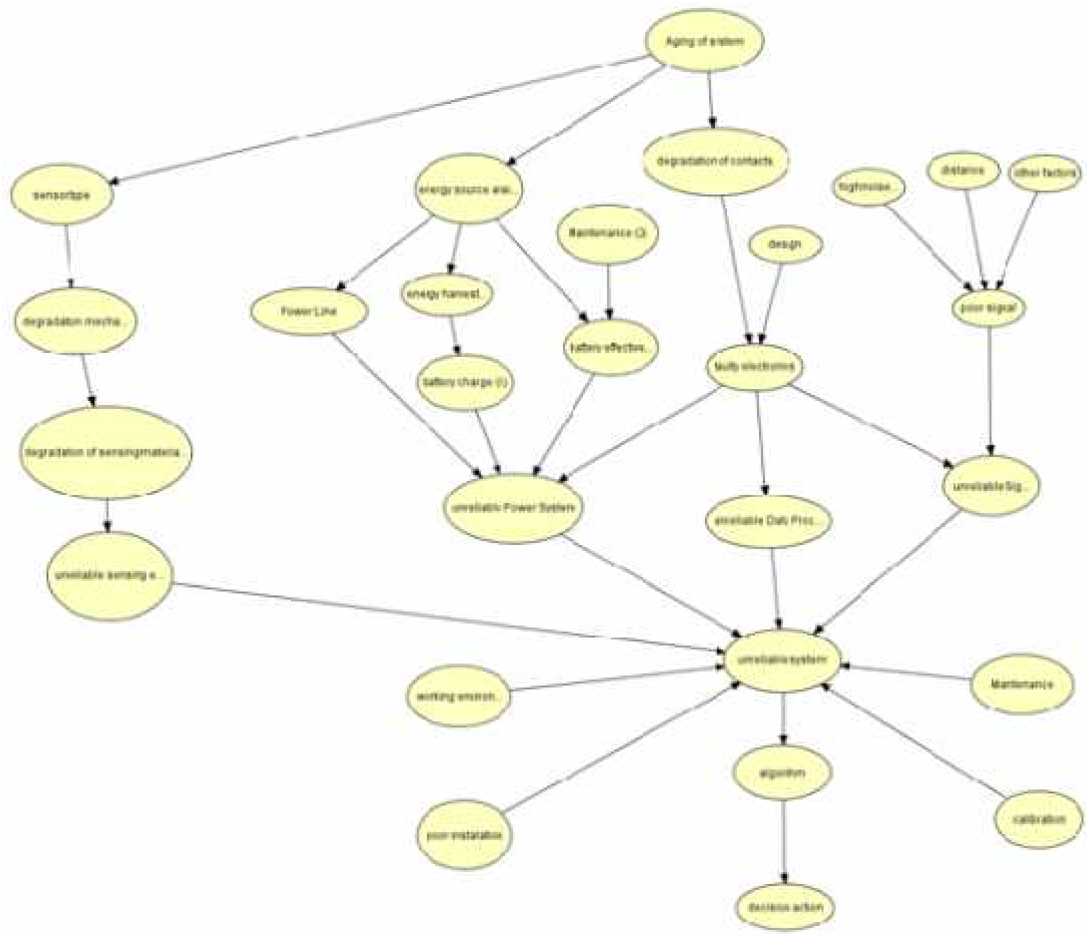


Figure 4. Using Bayesian network models to predict the effects of degradation on the reliability of sensor systems.

**Case Study: Predicting Sensor Reliability in the Digital Downhole**

The digital downhole refers to the entire instrumented drill string system, the sensor communication system, and the digital twin model [6]. As drilling operations in oil and gas have to deal with deeper wells, more aggressive environments, or more complex in geometries (think horizontal drilling and fracking), the drill string systems will need to become more "intelligent" so that operations can be conducted safely, economically and efficiently. Sensor systems provide the means for assessing the conditions downhole and reporting them to the operations managers. Sensors of significance include pressure and flow sensors, as well as sensors that can monitor temperature and chemistry of the fluid systems being encountered. The sensor data flowing back to the operations center provides the inputs needed to construct the real-time digital representation (i.e. the digital twin) of the downhole system, so that operators see an exact picture of the state of health, and can make adjustments to correct any deviations or initiate emergency procedures. Due to the aggressive nature of drilling operations, including abrasive wear from solids in the drilling fluids, high temperatures and pressures and the chemical environments themselves, the sensors will also be subject to degradation. But, how do we distinguish between faulty sensor data and a true alarm? One technique is to use Analytical Redundancy Relations that generate digital “fingerprints” for normal operations versus failure modes. [7] Analytical redundancy relations are derived from the physics that connects sensor readings from one part of the operation (say the pressure at the drilling fluid pump) to the readings at another part of the operation (say the downhole pressure- the differences should be related to the hydrostatic pressure plus losses proportional to the friction coefficient and the square of the fluid flow). The digital twin model is ideally poised to utilize such information in providing a first “health assessment” of the sensor data since it contains a complete multiphysics representation of the asset.  To give an example, consider the type of setup shown in Figure 5, adapted from the representation in Willersrud et al. [7] Sensors that measure flow rates and fluid pressure are placed along the assembly, including before and after the pump, at the drill bit, within the annulus and around the choke point. These sensors report back to the operating station at which point the signals are processed to update the digital twin model for the system.

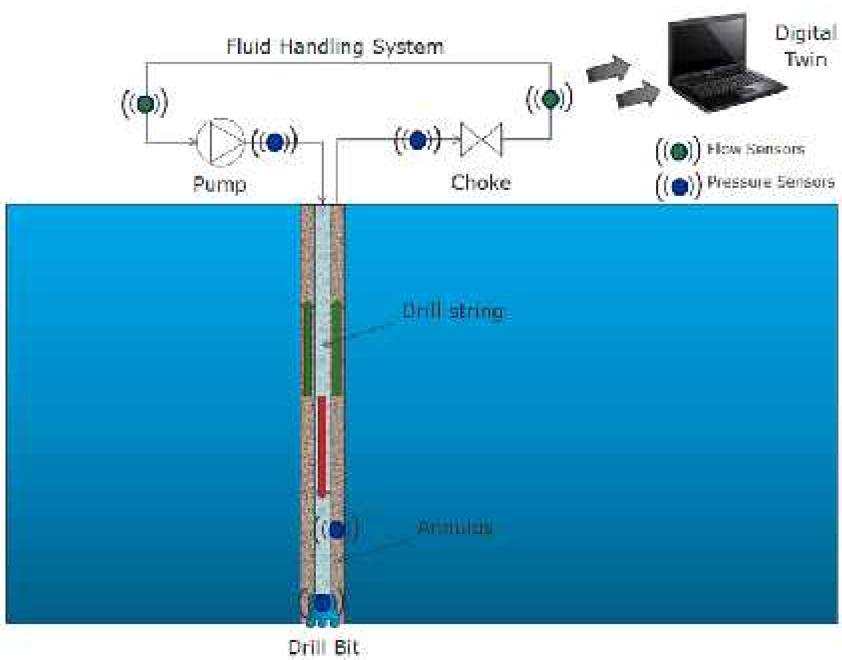


Figure 5. The Digital Downhole instrumented by pressure and flow sensors, in this example, reporting data back to update the Digital Twin at the operational station. [7]

At each of the sensor points, multiple sensors could be placed to provide redundancy. Even without this measure, however, there are "redundancy relations" that can be analytically derived. To take the example above, the pressure downhole, at the drill bit, should relate to the pressure at the pump according to the hydrostatic pressure (i.e. density x gravity x height difference) minus the losses according to the friction resisting fluid flow down the drill string (proportional to the square of the fluid flow rate). Thus, the sensors for pump pressure, downhole pressure, and fluid flow should be related according to a physical equation. This relationship is used to build a constraint in such a way that it will mathematically resolve to the value of zero under normal, fault-free conditions (within a noise threshold). Similar constraints can be derived for the other sensor signals in the system. When a fault occurs, however, one or more of these constraints will return a non-zero reading. It turns out that different failure modes will produce different responses in the non-zero constraint vectors (see Figure 6). A sensor failure at the pressure pump, for example, will break certain constraints but not others. Likewise, plugging of the bit nozzle by debris will have its own unique pattern of broken constraints. Accordingly, the constraint matrix will provide a way to fingerprint different kinds of system failures, thanks to the analytical redundancy relations that were encoded into the digital twin that handles the sensor data.

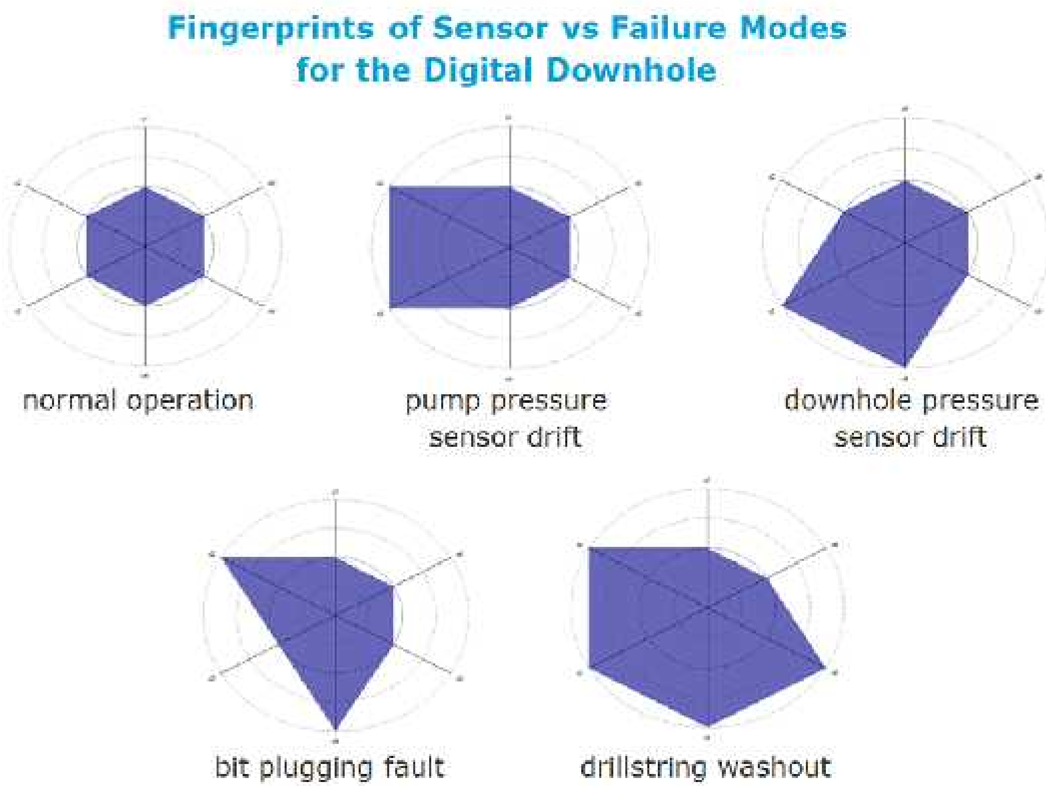

Figure 6. Each failure mode for the downhole system corresponding to a unique pattern of deviation in analytical redundancy relations can be used as fingerprints that allow fault detection and isolation within the Digital downhole system.

Like all physical components of the downhole system, the sensors are composed of materials that must meet structural, functional, and electronic/communication requirements for successful operation. In qualifying sensors for use in the Digital Downhole, the reliability of those materials must be assessed. The evolving probability of sensor part failure over time can be estimated in advance to some extent through accelerated testing. The "structured reliability assurance process" developed by Veneruso and co-workers [8] describes a system that integrates laboratory testing with continuous documentation of field data as a means for continuously improving the quantitative reliability assessment. The necessity to include field data comes about because laboratory testing can never fully replicate the range of conditions (nor the desired asset lifetimes) experienced by the materials when they are placed downhole. In interpreting data for materials health assessment through either experiment of collated field data, probability distributions provide a key way of quantifying the reliability. Most commonly, the "survival data" for materials exposed to the field are fitted to extreme value statistics, such as the Weibull distribution function. As an example, see the hypothetical case in Figure 7 based on a study of monitoring and control systems performed by Veneruso et al. [8]. An initial model, based on laboratory testing initially fits the survival probabilities well. However, due to testing constraints (such as only a short time available to perform testing), the model performs more poorly beyond a certain lifetime. At this point, the historical data can be used to update the probability of sensor survival and build a new model.

This example shows one way in which the sensor reliability assessment resulting from fingerprinting and the Digital Twin can be combined with survival probability models such as Bayesian network models. As the Digital Downhole system collects data and reports on sensor performance through the use of analytical redundancy relations, the Bayesian network models for the sensor reliability can be updated. Conversely, the updatable Bayesian network models, shown in Figure 7, can be used to internally assess the likelihood of a sensor failure. What does this mean? In performing the fingerprint analysis, as shown in Figure 6, the digital twin needs to be aware of "thresholds" that distinguish a true constraint-breaking event from the background noise. As the sensor systems age or adverse conditions are experienced, the likelihood for accepting a constraint-breaking event should increase. Hence, there will need to be a feedback between the construction of the internal models, and the decision to accept a broken constraint.

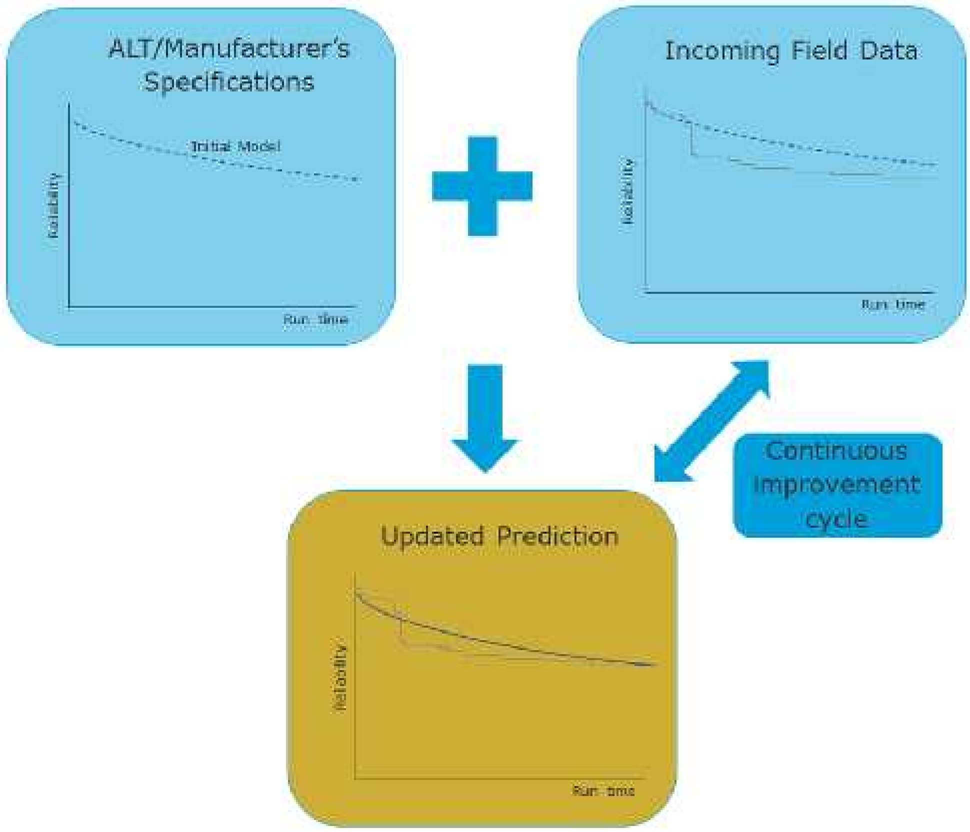


Figure 7. Updateable models for the survival probability of sensors components begin with an initial model constructed through lab-based testing, but are then updated in real-time by data coming in through "fingerprint" analysis performed by the Digital Twin.

## Conclusion

Sensor system reliability is a challenging yet critical issue that almost all industrial sectors are facing. As sensor utilization in the next ten years is expected to increase at a pace of more than 10% each year, all sectors of the modern industrial world, and society in general, will increasingly rely on information obtained from sensor systems. There is an increasing trend in sensors that are embedded or left in place in operating environments. These sensor systems then degrade due to exposure to the operating environments, affecting their reliability over time. Therefore, the risks associated with sensor system reliability need to be carefully evaluated. Algorithms for checking the reliability of sensor data need be developed using the best combination of physical, statistical and probabilistic modelling tools. In this paper, influencing factors to the sensor system reliability used in Oil and Gas industry are summarized, and a management plan based on criticalities of influencing factors to the overall system is proposed. This was demonstrated through identifying failure models and criticality ranking for the reliability of a generic pressure sensor system. Prediction of sensor system reliability will be especially useful in the situation where sensor systems can degrade over time in service. A modeling approach has been carried out in this paper to combine the Bayesian network modeling and "Analytical Redundancy relations" Methodology for assessing sensor reliability in a digital downhole application.

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