DNV·GL

DNV GL GROUP TECHNOLOGY AND RESEARCH
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UNDERSTANDING SENSOR SYSTEMS RELIABILITY

SAFER, SMARTER, GREENER

Preface:
Sensors intersect society in myriad ways. Their role in our world will accelerate tremendously due to increasing miniaturization of sensors, use of materials with novel functionalities, and ubiquitous wireless connectivity. The automated communication of data between systems containing sensors will also expand. Autonomous vehicles and other equipment will employ a large number of interconnected sensors able to communicate data and make decisions from them. Exemplifying all this is the ambitious plan proposed by Hewlett Packard to distribute billions of sensor motes for creating the "Central Nervous System for the Earth". However, regardless the scale of application, an immediate challenge that all industry sectors will face is to ensure the reliability of sensors systems, especially for long term usage or for mission critical applications. This position paper presents a high level view of the issues surrounding sensor system reliability and how we can address this in a holistic fashion.

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1: smartphoneworld.me/hello-world-2. (Figure 2)
2: http://memoria.ebc.com.br/agenciabrasil/galeria/2009-06-14/14-de-junho-de-2009 (Figure 5)

CONTENT

SENSORS AND SENSOR SYSTEMS

DEFINITION

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:

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;

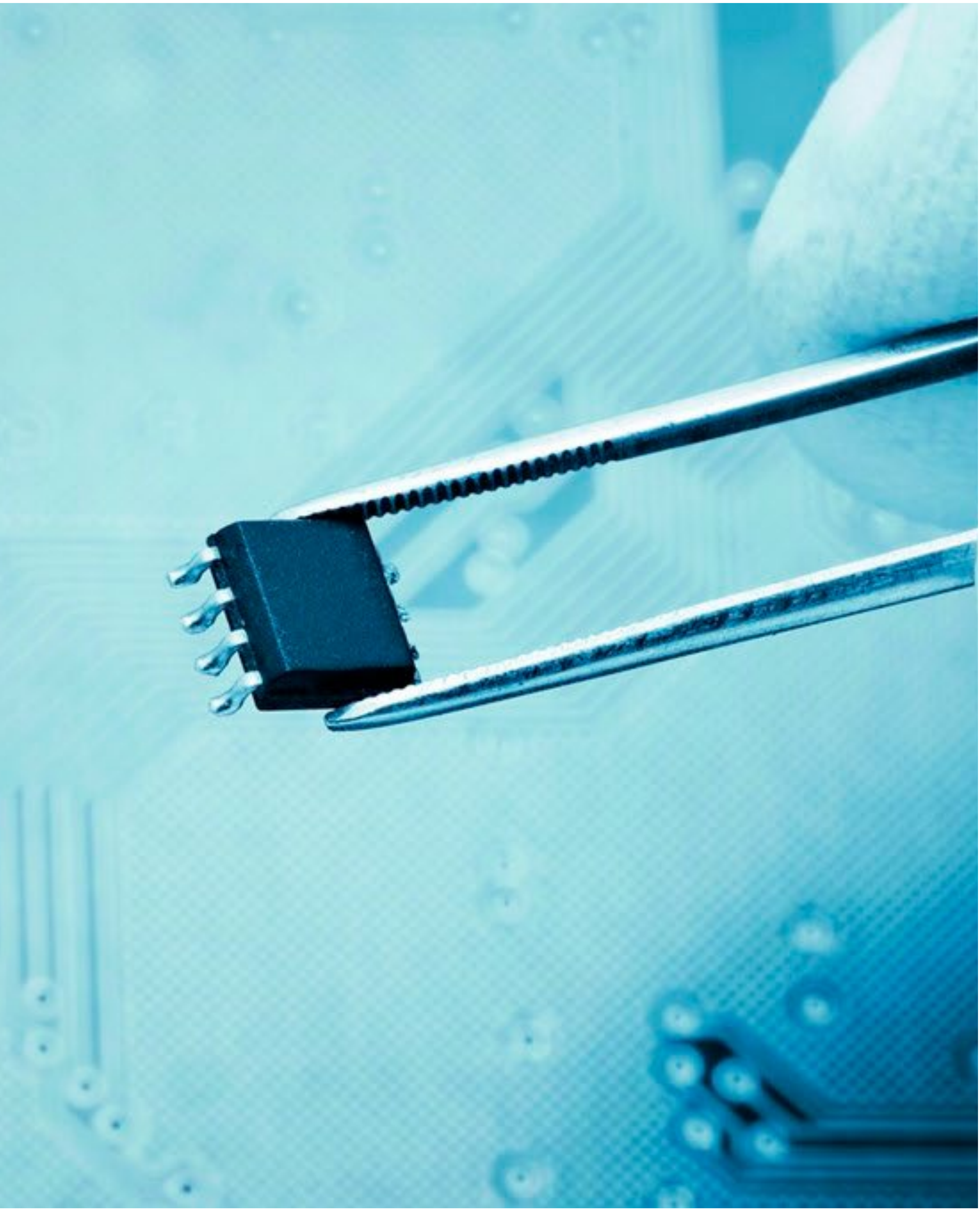
4. A power system to provide external power resources or to harvest energy

MARKET

Sensors are everywhere, and can interact with all aspects of our everyday life. The last decade witnessed an unprecedented growth in the number of products and services applicable in a broad domain, including environment, medicine, commerce and industry, that utilizes information from sensors. BCC Research estimated that the global market revenue for sensors was $101.9 billion in 2015, expected to increase to $113.2 billion by 2016 and $190.6 billion by 2021, at a compound annual growth rate of 11.0%. [1]

One trend in sensor development is to produce smaller and smarter sensors (miniaturization). Take a smart phone, for example. Around fourteen types of sensors are integrated into the handheld device to fulfil the communications and entertainments functions desired by the consumer (Figure 2).

Another noteworthy trend is the increasing application of sensors for healthcare including strip sensors, wearable sensors, implantable sensors, invasive/non-invasive sensors, and ingestible sensors. It is expected that by 2020, the global market revenue of sensors for consumer healthcare will reach $18 billion. [2] The reliability requirement for sensors used in healthcare is typically high, which is especially true for implantable sensors that may encounter issues arising from corrosion of components, bio-incompatibility and internet or communication based problems that could significantly degrade the health of the patient.
To meet the strict regulation requirements from the



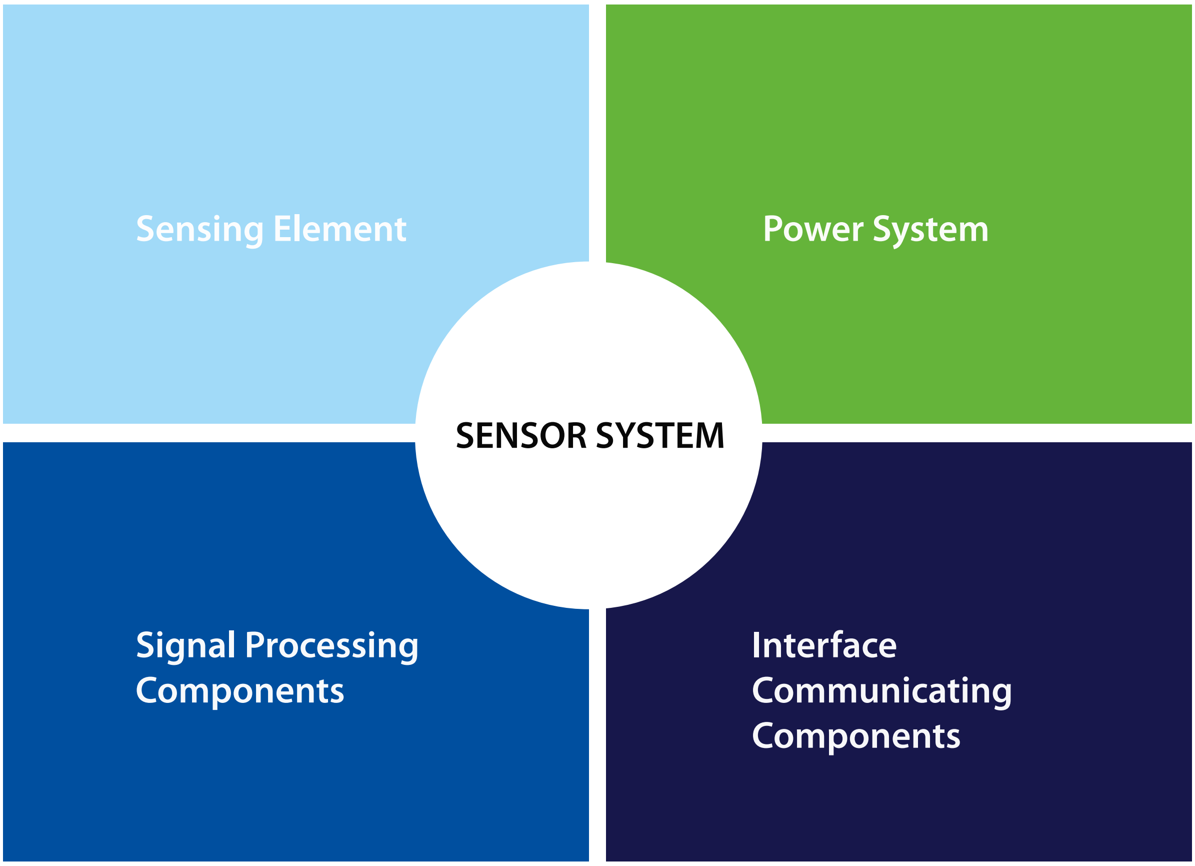
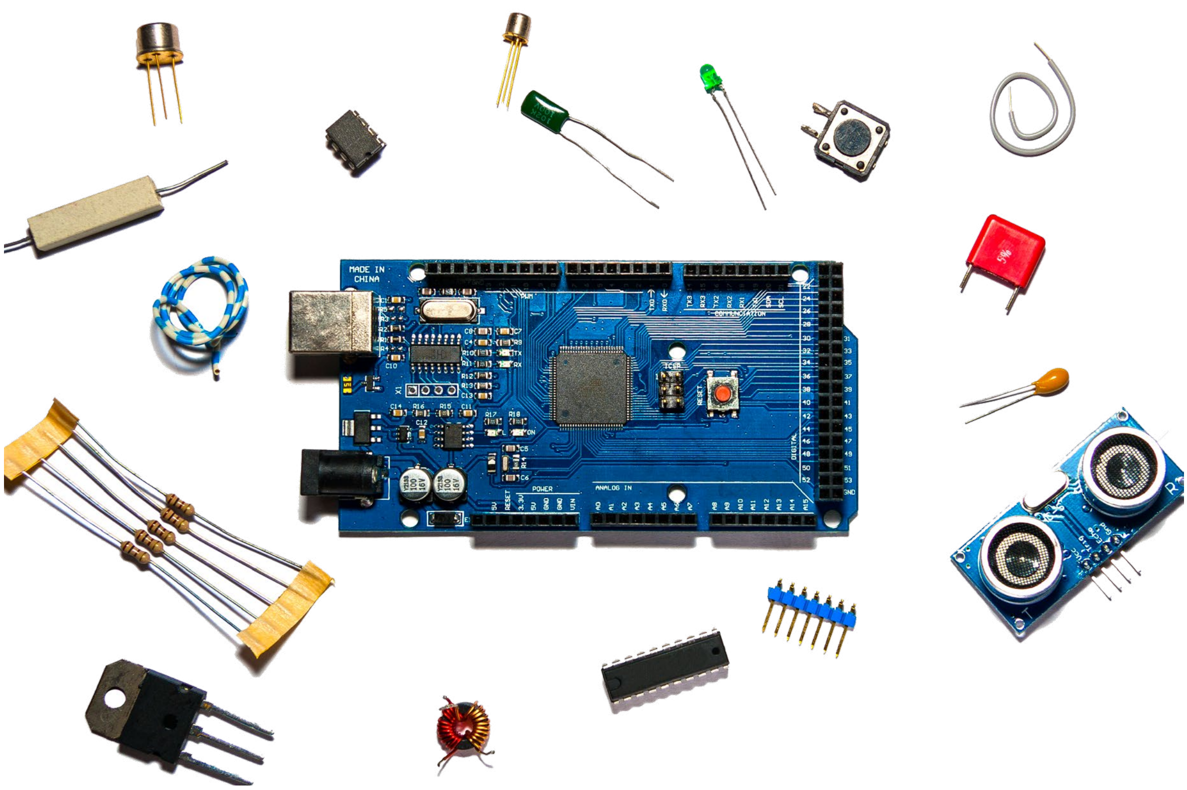


Figure 1. A schematic of a sensor system.

US FDA (US Food and Drug Administration), sensor manufacturers continuously improve, validate and predict the reliability of sensor systems. [3]

The last trend is accelerated by further advance of automation in production processes to deliver precise, reliable and intelligent data to improve product quality, reduce operational costs and save energy. In some traditional industrial sectors, advanced sensing technologies have revolutionized their business model. For example, in the shipping industry, classification societies are actively moving towards digital approval to keep up with the global pace of digitization. In the foreseeable future, instead of relying on surveyors to examine the dangerous and difficult-to-access portions of a vessel, unmanned vehicle (UV) equipped with multiple smart sensors can reach these locations easily and finish the inspection within minutes. Information obtained by sensors can be remotely evaluated, and if compliant with class rules, the vessel can be digitally approved. At DNV GL, drone (unmanned aerial vehicle) based ship hull inspections have been successfully tested revealing a strong potential for accelerating the survey and reducing staging. This example and other similar automations rely on reliable sensor data for assessment and decision-making. Therefore, it is becoming critical to ensure that sensors systems are able to deliver reliable and accurate information (sensor data), especially for long term usage or for mission critical application.

Figure 2. A "Smart Phone" integrated with fourteen types of sensors. [Image Credit 1]



SENSOR SYSTEM RELIABILITY

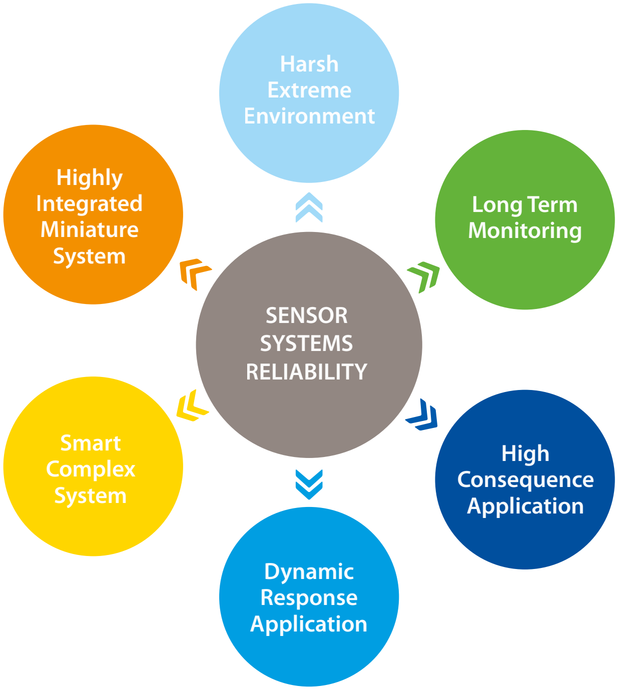


Figure 3. Application scenarios where sensor system reliability is extremely important.

INTRODUCTION

"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 of time. 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. In order 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 3:

- Complex and smart sensor systems (e.g. Sensor Fusion)
- Highly integrated miniature sensor systems (e.g. MEMS/NEMS sensors)
- Long term monitoring requirements (e.g. Condition Monitoring)
- High Consequence /Mission Critical applications (e.g. Leak Detection or Aviation)
- Application requires dynamic response (e.g. Dynamic Positioning System)
- 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, depicted in Figure 4. 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.

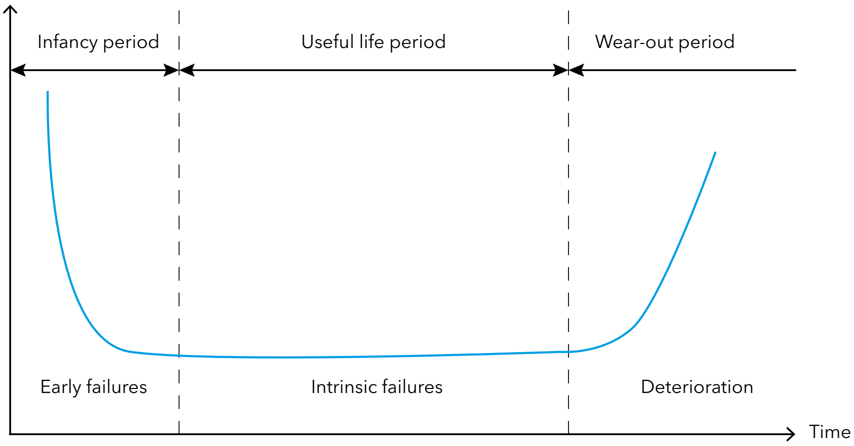


Figure 4. Lifecycle failure rates, the 'bathtub' curve

CONSEQUENCES OF UNRELIABLE SENSOR SYSTEMS

In many cases, a sudden sensor failure or malfunction may cause considerable financial losses or even result in a catastrophic accident. An example for this situation is the crash of Air France Flight 447 in 2009 that killed all 228 passengers and crew on board. Investigation of the accident revealed that a speed sensor was malfunctioning when the co-pilot tried to lift the plane, and this was believed to be the major cause of the crash. [4] There are also many other plane crashes that have occurred, in part, due to failed sensors including ice sensors, fuel gauge, altimeter, etc. In other industries where sensors are heavily applied for automation, faulty sensor systems can also result in serious consequences. The French Ministry of Ecology, Sustainable Development and Energy studied the safety issues related to sensors used in automation in four industrial sectors: Chemicals and Pharmaceuticals, Petroleum Refineries, Metallurgical industry, and Food Processing. It was found that the presence of sensors reduced the frequency of occurrence of accidents involving fire and explosion. However, results also showed that sensor failures resulted in serious accidents. For example, 42% of automated control and safety malfunctions at the facilities of 10 international petroleum groups were due to sensor failures (Figure 6). Another major cause of accidents due to unreliable sensors is false detection, mainly arising from either measurement drift or faulty calibration. This failure mode accounts for over 20% of all accidents involving sensor failure. [5]

FACTORS AFFECTING SENSOR RELIABILITY

In order 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. [6]

Figure 5. Wreckage of Air France flight 447 plane. [Image Credit 2]

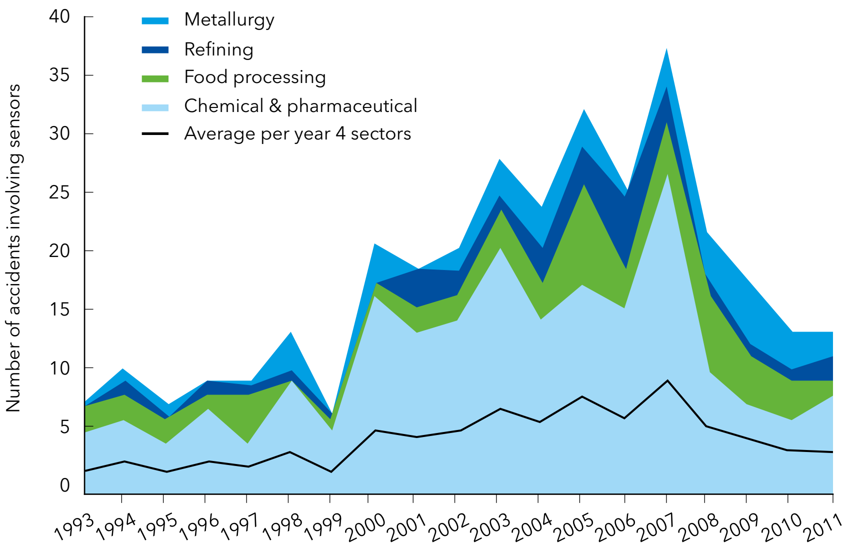


Figure 6. Annual number of accidents involving sensors by industrial sectors (1992-2011). Redrawn from source5. [5]

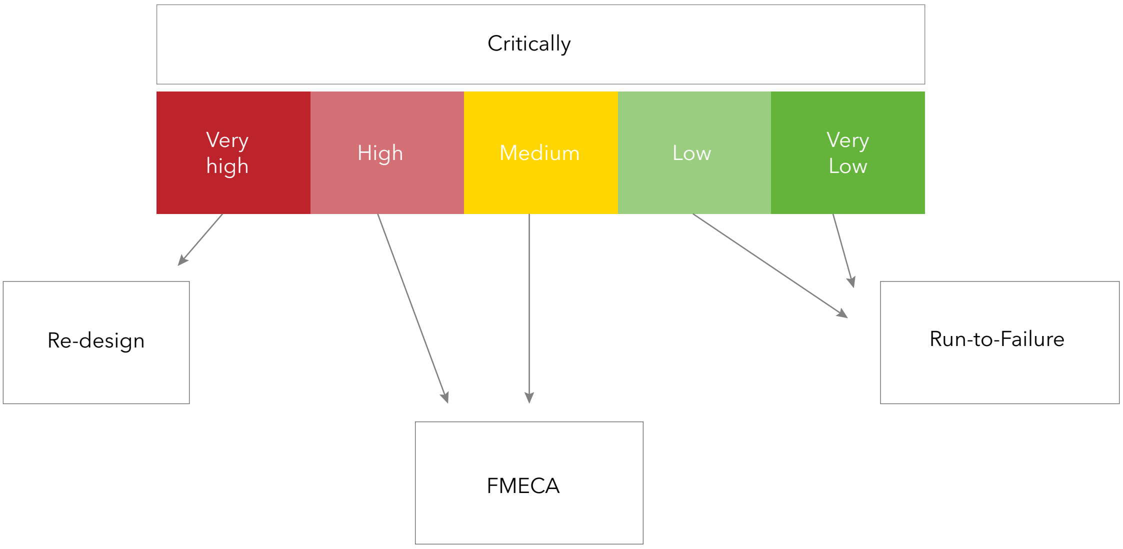


Figure 7. The criticality definition and the corresponding actions for the reliability of a sensor system.

Sensor System Components	Failure Modes	Criticality				
		Very low	Low	Medium	High	Very High
Sensor elements	Degradation of Sensing Material					
	Thermal Induced					
Signal Processing Components	Degradation of contacts or connections					
	Thermal Induced					
	Degradation of Signal Processors					
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					

Table 1. Affecting Factors and Their Criticality Ranking for the Reliability of a Pressure Sensor System

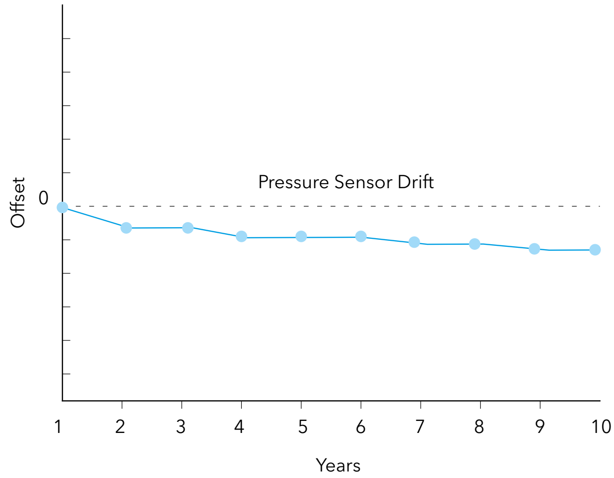


Figure 8: (left) WEPS-100 Series Subsea Pressure Sensors, [7] and (right), A schematic of pressure sensor drift.

One of the most important factors affecting the reliability of a sensor system is degradation, primarily as a result of materials ageing, corrosion, and wear. In general, three classes of sensor system degradation should be considered:

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.

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") sensors yield a reading accuracy of +/- 0.35 bar, which increase to +/- 9.1 bar after 25 years of usage [7]. 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.

There is no simple solution that can completely prevent sensor systems from degradation. Shorter inspection intervals and frequent calibrations may provide effective methods in some cases but with the sacrifice of additional operating costs.

Smart sensors with self-calibration functions can be utilized but even they will degrade over time (but perhaps with longer life expectancies) because of other influencing factors. A more holistic approach is to employ a combination of accelerated testing, in-service inspection and modeling and prediction, which requires a deep understanding of the overall sensor system as well as a comprehensive knowledge of the mechanisms by which degradation occurs.

IMPROVING SENSOR SYSTEM RELIABILITY

Design/Manufacturing

The most effective strategy to improve sensor system reliability is through careful system design and well-controlled manufacturing quality. Additionally, a current tendency is to rely on a single vendor who can perform the entire process of sensor design, manufacturing, and testing. For example, consider one particular case of a variable capacitance silicon MEMS accelerometer commonly used in implantable devices such as rate responsive heart pacemakers and defibrillators. To be used in implantable medical devices, sensors must possess extremely high reliability and a tiny footprint, and therefore the silicon based MEMS sensor is a preferred choice. The resultant design provides excellent stability, low hysteresis, and ruggedness. According to the technical data sheet for one particular model, the MEMS accelerometer holds a +/-2g full scale for measurement of fractional-g accelerations, a repeatability of less than 0.035 pF, a frequency response of 40 Hz, a linearity of less than 1%, and a transverse sensitivity of less than 1%. Microstructurally, air damping is employed to create an inertial system that is over damped, and this accelerometer enables an over-range stop mechanism with provisions to eliminate electrostatic sticking (Figure 9). The MEMS device was surface micromachined utilizing the method for IC processing including oxidation, lithography, deposition and etching, the batch process of which ensures the accuracy of fine features and repeatability of devices performance. According to the manufacturer, this MEMS sensor shows such high reliability that no field failures have been reported among the four million parts delivered to leading medical device manufacturers. [8]

CHOOSING THE SUITABLE SENSOR SYSTEMS

The reliability of a sensor system will be strongly influenced by the working environment into which it is applied. In general, the environmental conditions affecting the reliability of sensors may include, but are not limited to, factors such as vibration, shock, humidity, temperature, pressure, viscous flow, noise (mechanical and magnetic), radioactivity, corrosion, contamination, conduction, turbulence, electrostatic signals, magnetism, and volatile compounds.

For mission critical purposes or long term usage such as condition monitoring of infrastructures, certain levels of testing (normally including destructive testing) are necessary before deploying sensors into the field. There have been attempts to develop computer based models such as "Multi Criteria Decision Making" models for aiding sensor selection. [9] However, in practice, the majority of sensor selections are based on manufacturer provided technical data sheets, sensor users' past experience, or expert knowledge and recommendations.

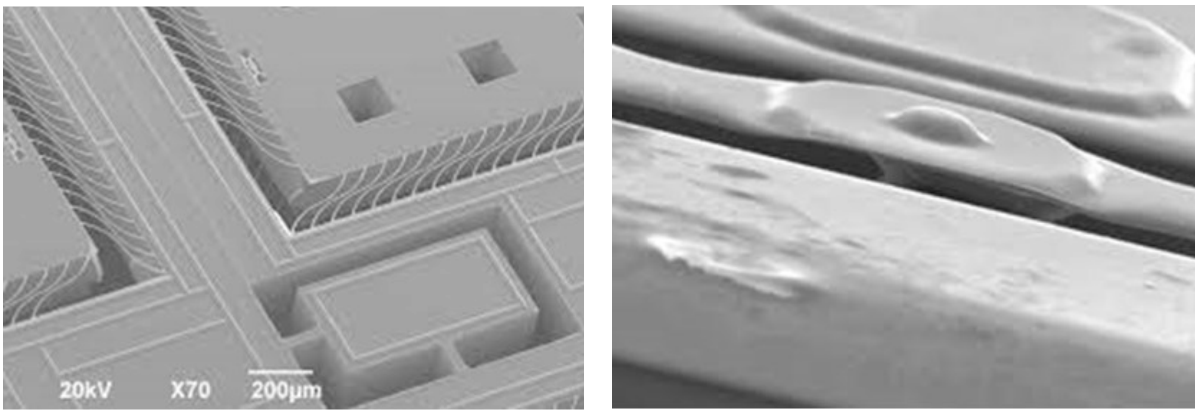


Figure 9. Features of Endevco Model 40366 Micro-structures for creating air damping inertial system (left) and anti- electrostatic sticking features (right). [8]

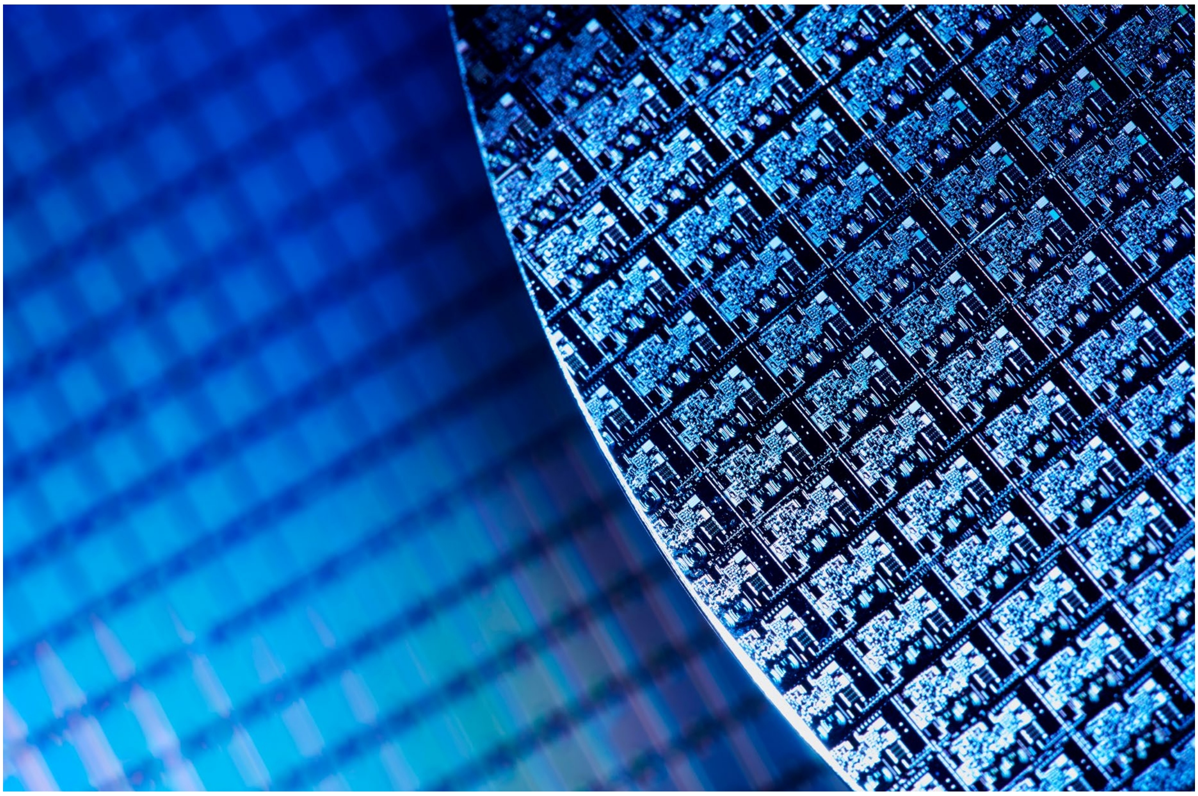


Figure 10. Batch microfabrication using IC processing ensures high accuracy in device sizes, and thus high reliability.

In some industry sectors, regulators, professional societies, classification societies etc. are able to develop regulations, standards, recommended practices, and class rules to guide or enforce the selection of suitable sensors. One such example is the development of ISO standard 8000: Data quality. This ISO standard is expected to cover a wide range of data sources and formats, as well as addressing the standardization of the format and quality of data obtained through sensors. Gauging the sensor system reliability will be a critical part of data quality assessment.

In the maritime industry, condition monitoring of ship machinery is a common practice with the goal to ensure safe and efficient vessel performance, and to realize condition-based maintenance. Currently, condition monitoring of ship machinery is voluntary in most of the ship class rules. One technical challenge associated with ship machinery condition monitoring is to select the best suitable sensor technology. The goal for ship owners is to have an economically viable, maintenance-free, technically reliable monitoring system. As of today, class rules defining the reliability requirements of sensors for ship machinery condition monitoring have not been established. As a result, classification societies are facing challenges processing data with different or unknown levels of reliability, incurring time and economic penalties when bad quality must be screened out. To meet the goal of digital approval, measures must be taken to assure that sensor data is compliant with the reliability requirement. It is therefore necessary for classification societies to develop recommended practices, class notations and standards for the purpose of ensuring high quality of sensor systems for condition monitoring.

As part of DNV GL's ongoing effort to ensure data quality towards digital approval, suitable requirements and recommendations for monitoring of components and systems on board marine vessels by means of reliable sensor systems are being drafted. The objective is to promote good practices when developing and installing sensor systems on marine vessels, without considering the intended applicationof the data collected by the sensor system. Following these recommendations are expected to lead to more reliable sensor systems and subsequently improved quality of the data collected and to be used for analysis and decision support in applications such as condition

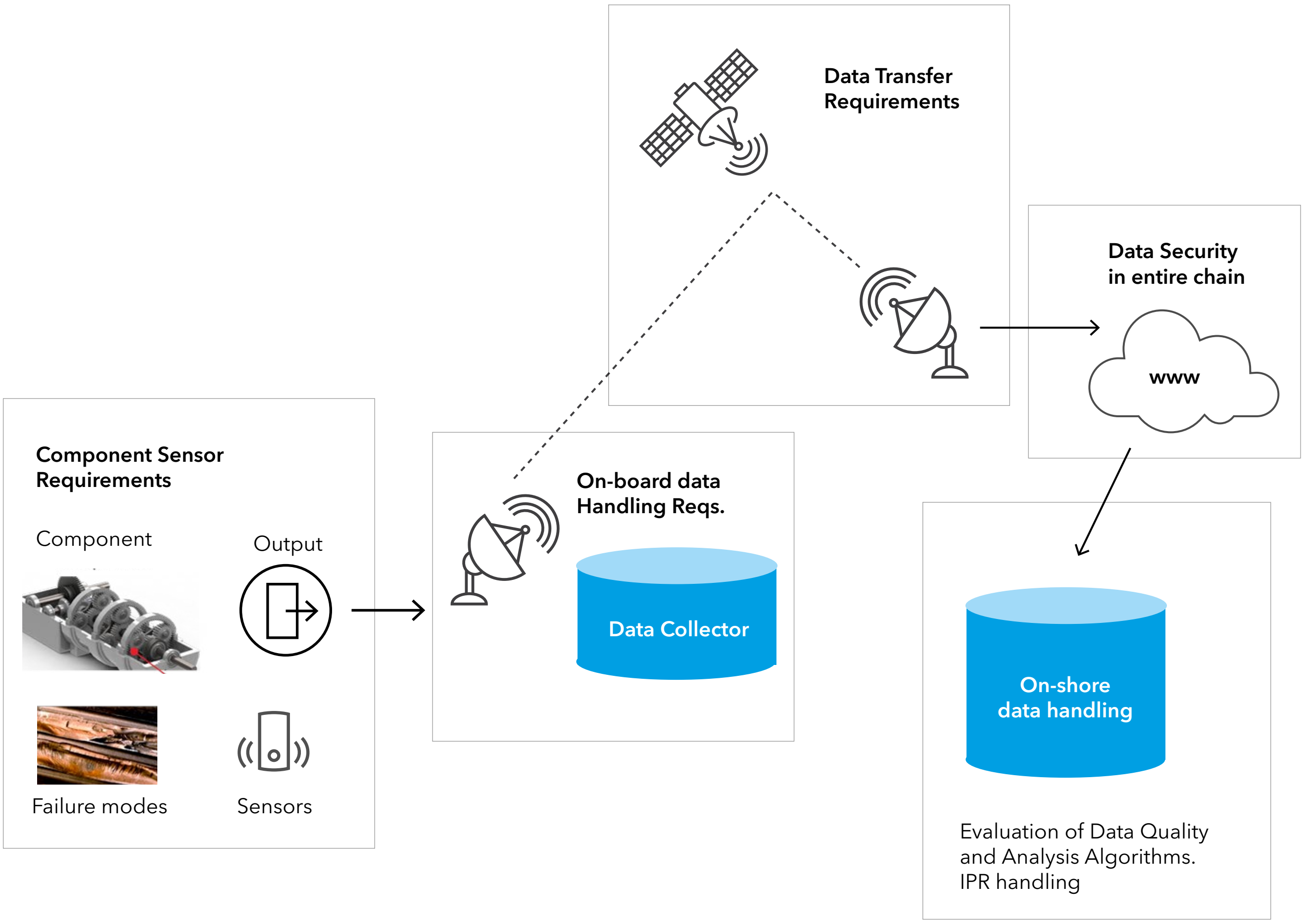


Figure 11. An overview of data flow of ship machinery condition monitoring. [10]

and performance monitoring of equipment installed on-board as well as environmental monitoring and sensing systems for increased automation and autonomous operation of ship and equipment.

DNV GL had collaborated with Rolls-Royce Marine and Farstad Shipping to develop a methodology for assessing a vessel's condition and performance, based on data collected from a broad spectrum of on-board systems, with an ultimate goal of creating a classification program for a new ship class which denotes conformance to safety through reliable condition monitoring practice. [10] Immediate technical challenges associated with these goals include selecting the suitable technology for sensor data flow, sharing and hardware of monitoring systems. To provide solutions to these challenges, a case study was carried out utilizing tunnel thrusters to demonstrate the general procedure of establishing a reliable condition monitoring process. Thirty-seven types of potential failure modes were identified from the components of a tunnel thruster and their criticalities to the system reliability were ranked. Based on which, the corresponding monitoring technologies and corresponding priorities are determined. It was recommended that four types of condition monitoring technologies are critical in order to establish a reliable condition monitoring including Vibration Monitoring, Acoustic Emission Monitoring, Wear Debris and Water in Oil Monitoring, and Thermal Monitoring. At the current stage, technical requirements of involving sensors are specified through a combination of on-board monitoring reports, DNV GL existing class rules and sensors manufacturer's data sheet. [6] It is expected that further efforts will be taken to create class notation for ensuring system level reliability through defining the minimum requirements of the lowermost level, i.e. sensor components in a future maritime condition monitoring system. (referring to the far-left side in Figure 11, a sketch of components of a class notation on sensor requirements for condition monitoring.)

A STRICTLY ENFORCED MAINTENANCE AND CALIBRATION PLAN

To ensure that sensor systems can be used with high reliability, efforts must be taken to eliminate human errors. A practical maintenance plan must be determined based on previous experience and intensive testing in both lab and field. After deployment, sensors require occasional testing and replacement of wear-out components. Most sensor manufacturers will provide guidance for the maintenance requirements, but users have to adopt these requirements into their own procedures. Calibration is essential for establishing the accuracy of a sensor in relation to standards. Some modern "smart" sensing systems have the capability of self-calibration due to integration with an ASIC (Application-Specific Integrated Circuit).

EVALUATION AND PREDICTION OF SENSOR SYSTEM RELIABILITY

EVALUATION THROUGH TESTING

The most straightforward method to evaluate sensor system reliability is to perform testing. Testing can identify potential problems resulting from design and manufacturing and allows any defects discovered to be corrected at the earliest stage possible. Reliability testing may be performed at several levels, and there are different types of tests and levels of acceptance criteria. For example, patient monitoring systems consist of sensor components that are embedded in the body or are wearable. The US Food and Drug Administration (FDA) regulates devices by setting strict protocols for acceptance. Premarket approval (PMA), an FDA process, is required for scientific and regulatory review to demonstrate the safety and effectiveness of high risk and life sustaining (Class III) medical devices. It includes 'Non-clinical Studies' on microbiology, toxicology, immunology, biocompatibility, stress, wear, shelf life, and other laboratory or animal tests, along with 'Clinical Investigations' on patient safety, device failures and replacements. [11]

When sensor systems are to be used in a mission critical application, the manufacturer and/or users are normally expected to perform thorough testing that includes components (materials), circuit boards, unit modules, assembly, subsystem and system levels. Figure 12 shows the reliability test procedures required for cryogenic temperature sensors. [12] Since these sensors are utilized for mission critical applications, very high reliability is required.

Qualification tests were performed at the component and system levels. At the component level, die shear strength and wire bond strength were measured. Wire bond cross sections were examined and external bond pad bondability determined. At the system level, test performed including independent destructive physical analysis, outgassing, thermal shock (100 shocks), vibration testing, mechanical shock, and life tests up to 2,000 h. [12] Accelerated Life Testing (ALT) is typically employed to assess the long-term performance of a sensor in a short period of time. ALT stresses the sensor systems by exposure to purposely harsh environments to induce field failure at a much faster rate. Through ALT, failure modes can be discovered and more importantly, normal field life based on the high stress lab life can be predicted through suitable modelling that extrapolates back from the accelerated conditions. ALT procedures should include:

1. Define the scope
2. Collect required information about the sensor systems
3. Identify and determine the mechanisms of degradation and thus the appropriate types and levels of stresses
4. Conduct the accelerated tests
5. Predict the field life of the sensor system based on the accelerated tests

Even with ALT or alternative testing and qualification methods, it can be impossible to predict identically what will happen in the field, and therefore, additional methods to gauge sensor reliability such as statistical modelling and fault detection may be necessary.

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:

- Principal Component Analysis (PCA)
- Artificial Neural Networks (ANNs)
- Recurrent Neural Networks (RNNs)
- Auto-Associative Kernel Regression (AAKR)
- Independent Principal Component Analysis
- Support Vector Machines (SVMs)
- Fuzzy Similarity, etc.

As summarized by Sharma et al., four categories of detection methods can be discerned [13]:

1. Rule-based methods define heuristic rules/ constraints that the sensor readings must satisfy
2. Estimation methods define “normal” sensor behaviour 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
4. Learning-based methods infer statistically established models to identify faulty sensor readings using training data

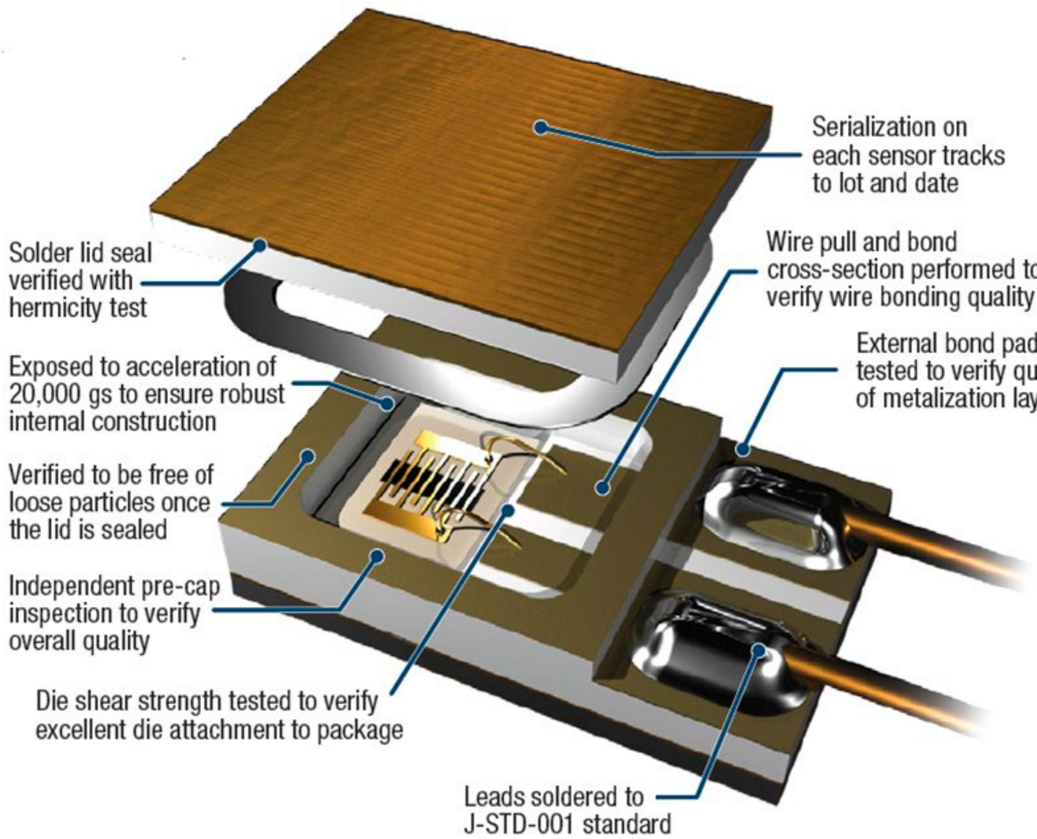


Figure 12. Reliability test of a cryogenic temperature sensor (Lake Shore Cryotronics) for mission critical applications. [12]

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. 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

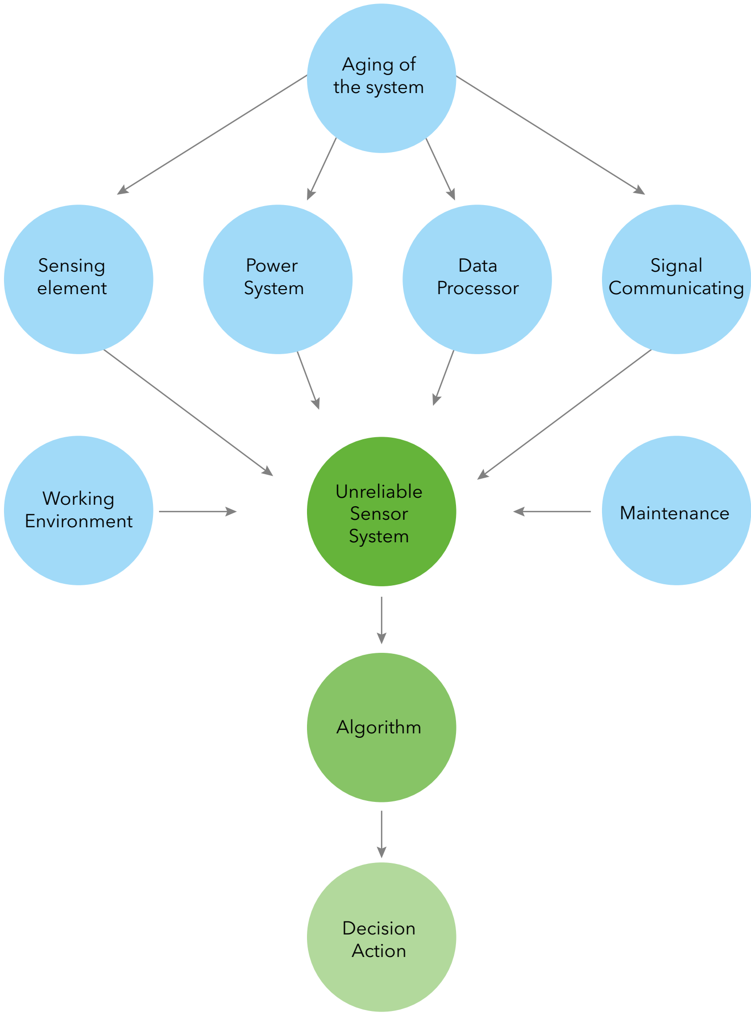


Figure 13. Using Bayesian network models to predict the effects of degradation on the reliability of sensor systems

unreliable sensor data. Figure 13 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 ageing 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 or not 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.

SENSOR SYSTEMS – THE EYES AND EARS OF THE DIGITAL TWIN

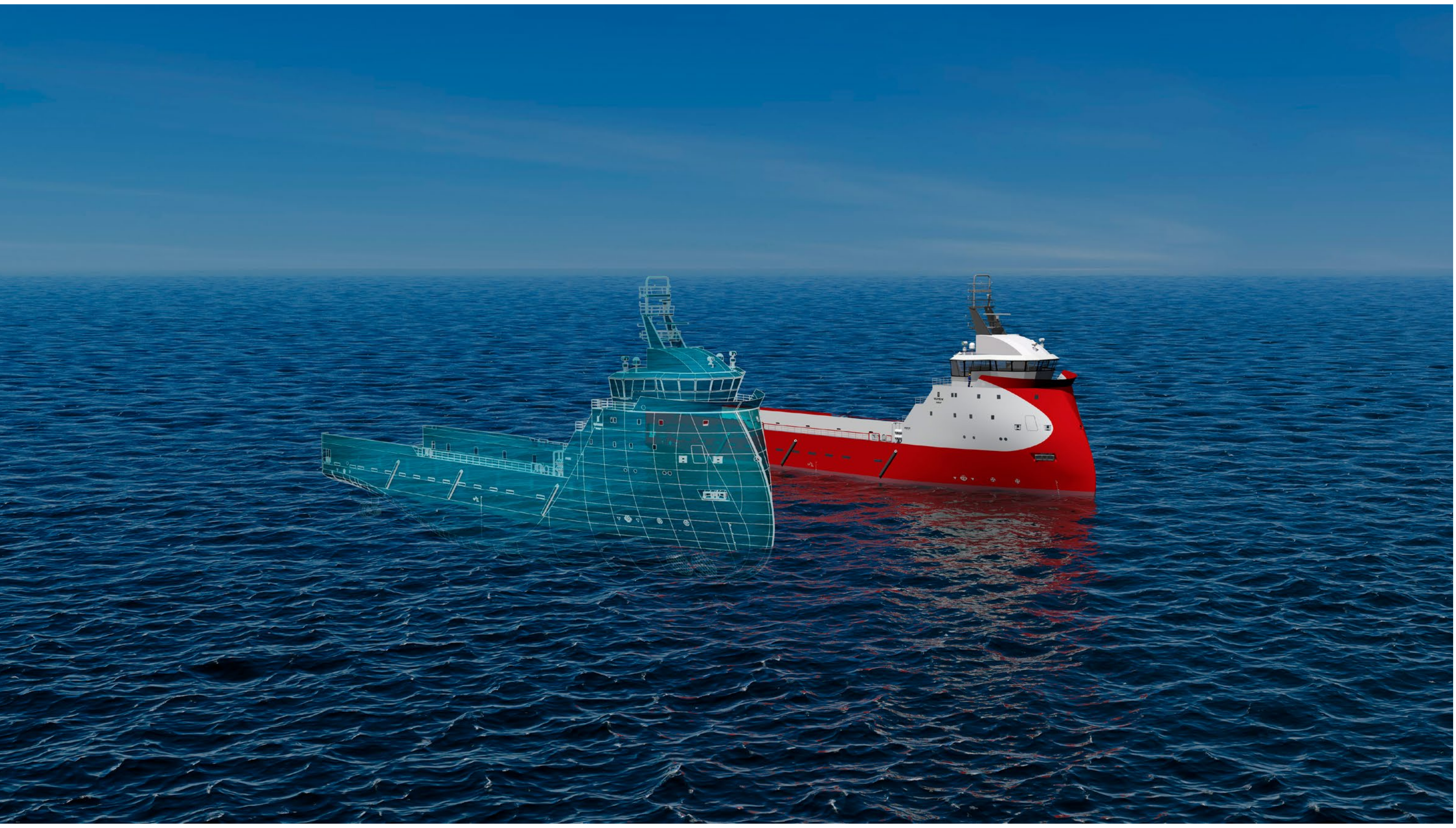
DIGITAL TWIN

Digital Twin representations of assets and processes provide real-time health monitoring and risk assessment through the use of virtual models that are based on statistical analysis and multiphysics simulation. The "eyes and ears" of the Digital Twin consist of sensor systems, as well as other data sources which may be maintenance reports or cloud data such as weather conditions and geospatial information. Just as good eyesight and hearing are essential assets for people in the industrial workplace, so too is it critical for Digital Twin to be able to assess the reliability of the sensor and cloud input they use to make their health and risk assessments. Next-generation solutions for assessing sensor reliability in asset management systems will couple statistical analysis of the sensor signals coming in alongside physics-based "reality checks" that can be used to provide systems-health fingerprints that will either register an OK response, report the existence of sensor faults, or sound an alarm for serious systems and/or process interruptions that must be addressed. In this section a case study based on an instrumented downhole drilling system will be presented showing how multiphysics simulation can play a role in assessing sensor health and creating "fingerprints" that can be used to distinguish between OK operation, sensor failures, and serious process interruptions that need to be addressed.

THE DIGITAL DOWNHOLE AND ANALYTICAL REDUNDANCY

What is the digital downhole? 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. The digital downhole refers to the entire instrumented drill string system, the sensor communication system, and the digital twin model.

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 (Willersrud et al. [14]) that generate digital "fingerprints" for normal operations versus failure modes. 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 14, adapted from the representation in Willersrud et al. [14] 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.

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-

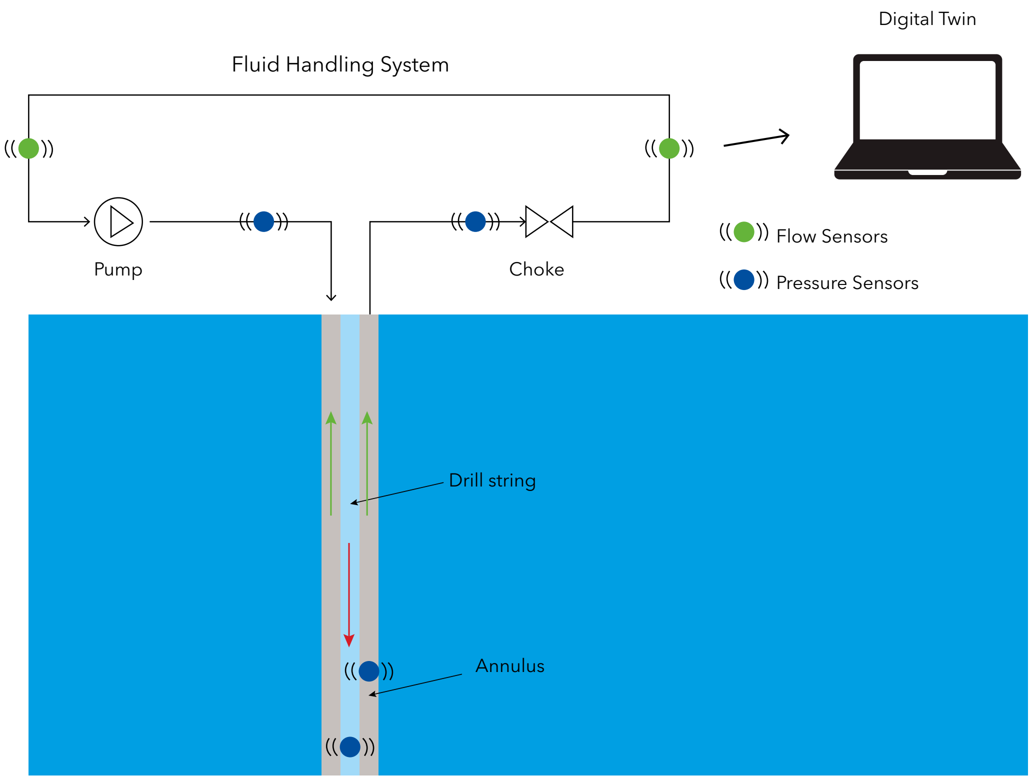


Figure 14. The Digital Downhole instrumented by pressure and flow sensors, in this example, reporting data back to update the Digital Twin at the operational station. [14]

zero reading. It turns out that different failure modes will produce different responses in the non-zero constraint vectors (see Figure 15). That is to say, 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.

PREDICTING SENSOR RELIABILITY IN THE DIGITAL DOWNHOLE

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 [15] 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 16 based on a study of monitoring and control systems performed by Veneruso et al. [15]. An initial

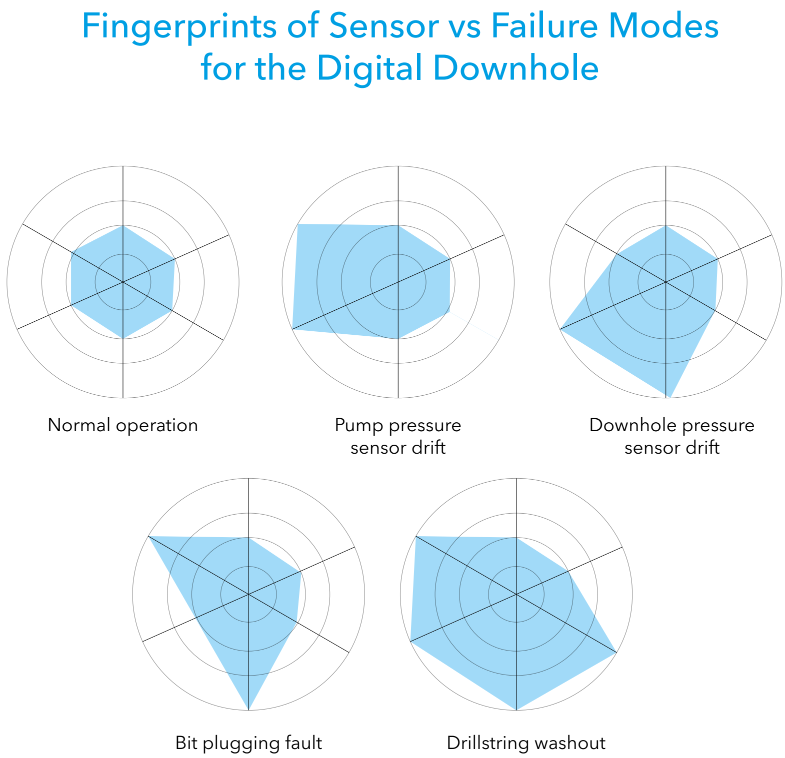


Figure 15. Each failure mode for the downhole system, whether an alarm condition (such as bit-plugging or drillstring washout) or a sensor failure (such as pump pressure sensor drift or downhole pressure sensor drift) will correspond to a unique pattern of devia-tion in analytical redundancy relations, expressed as a series of constraints c1-c6. These unique patterns can be used as fingerprints that allow fault detection and isolation within the Digital Downhole system.

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. As the Digital Downhole system collects data and reports on sensor performance through the use of analytical redundancy relations, the internal models for the sensor reliability can be updated. Conversely, the updatable Bayesian network models, shown in Figure 13, can be used to assess the likelihood of a sensor failure. What does this mean? In performing the fingerprint analysis, as shown in Figure 16, 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 Bayesian network models, and the decision to accept a broken constraint.

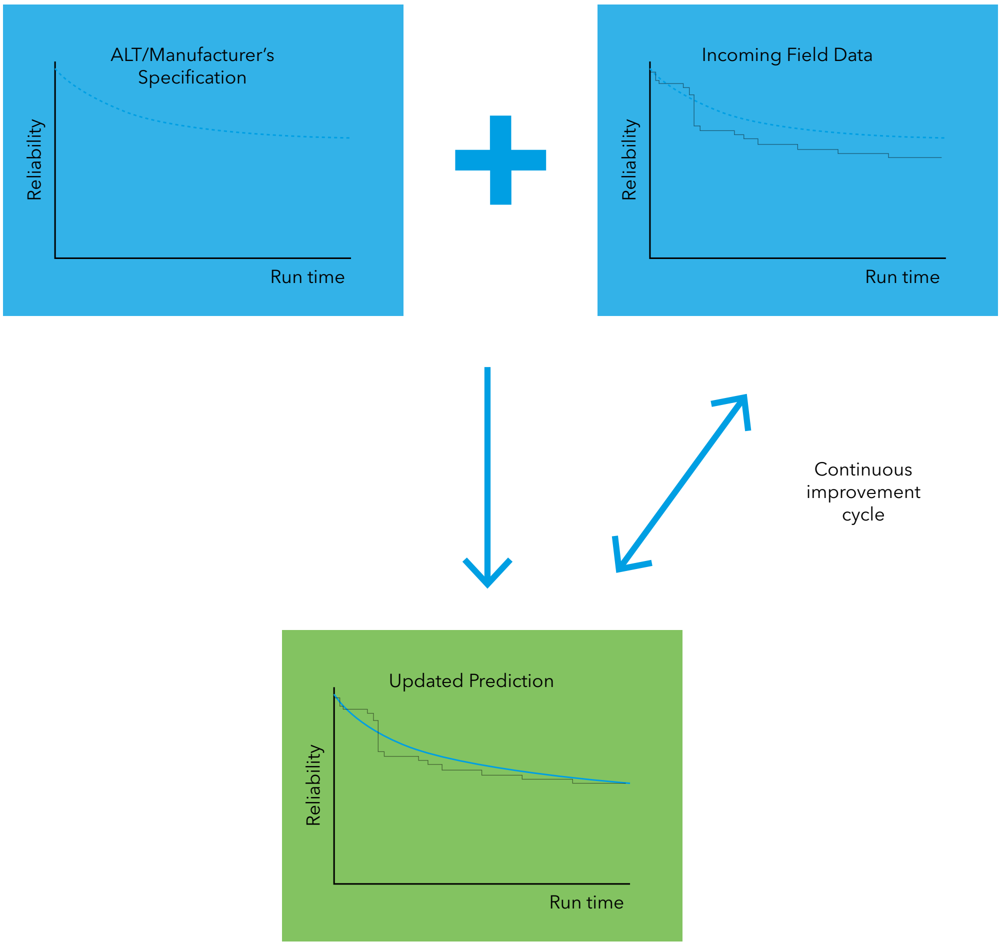


Figure 16. Updateable models for the survival probability of sensors components begin with an initial model constructed through lab-based testing, but are then updated in real-time by data coming in through "fingerprint" analysis performed by the Digital Twin.

LOOKING TO THE FUTURE

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. Despite that sensor manufacturers are striving to improve sensor system reliability through design and manufacturing, as well as performing extensive accelerated life tests to discover the root causes of failure. State-of-the-art sensors are complex systems, and the many components that form such systems will affect the overall reliability.

Additionally 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. Until one can ensure that sensor systems deployed in the field pass a reliability assessment, the data obtained from such system for analysis and decision making can be misleading.

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