

Chapter 10: Enhancing quality control and safety through smart sensors and predictive maintenance models

10.1. Introduction

In the last decade, rapid developments in sensing technologies have generated an unparalleled quantity of data associated with industrial processes, enabling a shift from traditional quality control practices to quality aware production chains. The availability of smart sensors for condition and quality monitoring, together with advances in predictive maintenance models, can contribute to the reduction of production variability, increased end-product quality, and optimization of safety and cost effectiveness. Noting that quality control has been traditionally associated with the inspection of finished products and processes, the opportunity for the development of quality aware production processes is studied. It is emphasized that efforts should be directed towards ensuring that the necessary conditions are satisfied while the product is under construction. If actions are undertaken to control and optimize the key process variables associated with quality, then the finished products will not need to undergo expensive destructive inspection when their quality is assessed. It is recognized that the incentive for the development of real time quality control practices lies with the reduction of production costs, achieved through reduced inspection requirements and lower warranty costs. Furthermore, real-time information associated with product quality can utilize causal databases to allow companies to optimize their quality, by directing them to situations in which the establishment of product quality is compromised. Traditionally quality control would not look for insights into production improvement, while today by employing modern quality control practices, companies can fulfill today's expectations for product quality, reliability, and safety (Qin et al., 2016; Esposito et al., 2017; Sivarajah et al., 2017).

Additionally, the operators could miss some faults leading later to product damage, which might last more than a short period of time. Because of that, the quality control policy might not be efficient if the final check is performed by humans only. In fact, it

is essential that the whole process execution time is accounted for to guarantee that the final product remains fault free during its entire life cycle. To fulfill these objectives, various automatic visual systems have been developed to be used as a support to the human operators. As additional sensors and measurements become available, more sophisticated quality indices and methods are being developed for monitoring and control operations (Venkatesh & Bala, 2013; Tao et al., 2018).

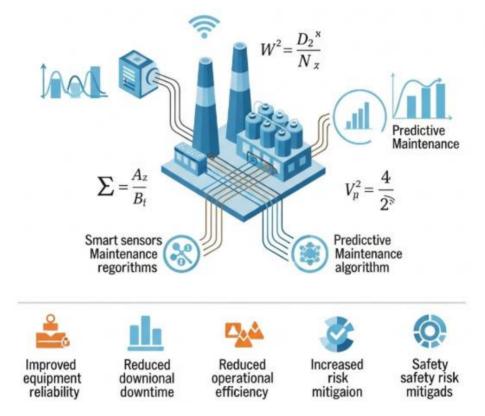


Fig 10.1: Enhancing Quality Control and Safety

10.2. Overview of Quality Control

Quality control (QC) is a policy used to evaluate the characteristics of the acquired product and ensure that it is able to match the pre-defined requirements. The main goals of this procedure are to evaluate, recognize, and eliminate any defects spotted inside the final product before it is delivered to the customers to guarantee that the product is able to match the market specifications. Furthermore, quality control is usually driven by the necessity to decrease the degree of competence of the final product in order to avoid returning and repairing costs. As a relatively old policy, quality control has been used for many years in different industries such as cinema, food, and pharmaceuticals.

Particularly, in the industrial systems, the quality control policy was commonly used to observe the characteristics of the final and semi-final products. Consequently, quality control systems have been performed by humans and have to rely on those operators' experience and mood. This is a hard task for humans due in part to the fast, repetitive cycles over which machines work, where frequent inconsistencies might indicate faults that require more than basic decision-making criteria. However, it is not viable for humans to be present in the production line during the entire time of their working schedules.

10.3. Importance of Safety in Manufacturing

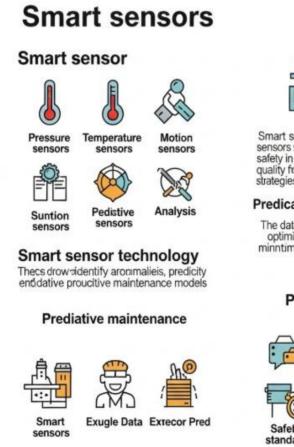
Since the Industrial Revolution, an increasing number of workers have reported accidents in factories. The reason for this is the automated elaboration of products that impacts on the workers' health and safety. In fact, during manufacturing products, workers can be hit by machines and tools, crushed, burned, injured, electrocuted or poisoned. In addition, overexertion is one major cause of injury: the arrangement of the machines is frequently incorrect, imposing workers to acclimatise themselves to it. In Europe, it is necessary to reduce the number of work-related accidents in order to support the sustainability of the economy.

Quality management systems and occupational health and safety management systems are the best-known management tools to be applied to improve the working conditions in manufacturing companies. These systems are focused on ensuring the quality of products and services, while ensuring that the companies have an adequate approach to managing occupational health and safety issues. Moreover, the introduction of these systems is now mandatory for certain categories of companies in some countries. In fact, various nations have introduced legislation obliging companies to report on their health and safety performance through indicators. The interest of society in obtaining information on such indicators originates from the need for assurance that companies manage health and safety in an appropriate manner.

10.4. Smart Sensors: Definition and Functionality

Smart sensors are devices that can accompany an inertial sensor to enhance overall accuracy and reliability, enabling high level and real time application. Smart sensors can perform various simple computational tasks, such as internal calibration, digital filtering and data compression through digital signal processing. They usually feature a microcontroller for computational capability, embedded firmware to run the calibration and processing algorithms, and an embedded memory and/or other appropriate input or output ports to store or transmit the calibration parameters. A smart sensor can improve

the system performance by functioning as a multi-function data preprocessing analog front-end. It can provide error detection and correction capability and intelligence for the precision and/or the reliability of the inertial sensor output by means of real-time data validation algorithms. Smart sensor technology overcomes the selection of measurement design approach by allowing the use of optimum design of each subcomponent and subfunction and subsequently achieving superior overall performance. Smarter sensors can send data, gain access to other data, and run onboard diagnostics. Next generation sensors must be networkable, central processing unit autonomous, self-repairing, and most importantly, intelligent. Intelligent sensors with onboard diagnostic capability will allow smart sensors to assess their own reliability and accurately respond to a sensor array's threat environment and adjust the array sensor upgrades accordingly.





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Fig 10.2: Smart Sensors: Definition and Functionality

10.5. Predictive Maintenance: Concepts and Benefits

Predictive maintenance (PdM) is a service within the predictive operations management model that requires a basic physical-cyber system (PCS) operational model to be previously created. It cooperates mainly with three generic services; condition monitoring (CM) that allows knowing the status of the monitored asset, diagnostics or remaining useful life (RUL) when an incipient failure occurs, and prognosis that forecasts when a supported decision can be made. Preventing a machine or industrial facility from an unexpected failure, stopping the productive activity, and producing heavy economic losses, is truly the main advantage of implementing any system within the predictive operations management model. Those premature failures are typically avoided with a prepaid cost incurred before the failure occurs, an activity called maintenance. Traditionally is based on a calendar policy, incurring costs either too late or too early. The last situation is solved by implementing predictive maintenance models that take advantage of the current condition of the equipment. Thus, PdM models start reducing the general maintenance costs by relying on the state of health of each machine instead of on a fixed calendar-based policy.

Within the vision area, recent advances in deep learning and computer vision for the analysis of images or videos allow the monitoring with cameras for various product or process parameters. That capability is exploited through the embodiment of condition monitoring within industrial facilities. Predicting the moment when a monitored asset will malfunction becomes a solution when not investing the optimum interval time that the assets produce before breaking down, considering the impact of the associated downtime and the cost control.

10.6. Integration of Smart Sensors in Predictive Maintenance

The development of predictive maintenance (PdM) has evolved since the early eras of vibration monitoring with transducers, through data acquisition to Computerised Maintenance Management Systems, until the current era of digitization with technologies such as the Industrial Internet of Things, sensory applications of Artificial Intelligence modelling. With IoT-based systems, sensors continuously monitor and transmit equipment status information to cloud servers, which produce short-term predictions of future status based on predictions of Health Index, Time-to-Failure, Remaining Useful Lifetime, thus allowing timely decisions about maintenance and enabling the smooth flow of information from the sensors to the organisation and back to the asset. Thus, the technological evolution of PdM, and the leveraging of modern information and communication technology, particularly AC and the IIoT, have led to important PdM developments.

The main barrier for the PdM models implementation is related to how to predict the estimates reliably, given the high uncertainty in their estimation, and how long in advance should these predictions be made while still remaining useful, leading to additional related interdisciplinary challenges to traditional asset longevity maintenance research. The expected evolution of these remaining uncertainties of PdM estimates, and the prediction for present decision-making, are key PdM developments that require advances in Human Factors and Artificial Intelligence modelling, AC infrastructure improvement, and the emergence of a more asset-focused human-in-the-loop Company culture.

The availability of the right machinery capacity for the timely delivery of quality products or services while undertaking the gradual replacement of the aging workforce allows diagnosing possible delays and corrective work in the event of disruption due to labor unrest and picking the right combination of work efficiency and turnover to maximize income and profit while focusing on building and enhancing client loyalty.

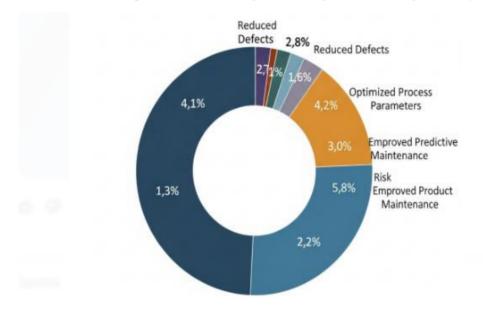


Fig 10.3: Quality Control and Safety through Smart Sensors and Predictive Maintenance Models

10.7. Conclusion

The aging workforce in the manufacturing and service sectors, especially in quality control, is contributing to and aggravating the scarcity of skills in advanced manufacturing systems, such as smart agribusiness and Industry 4.0. Smart sensors and predictive maintenance models play a crucial role in addressing these issues. Smart

sensors automate and facilitate the flow of information on product quality in both manufacturing and service processes, enhancing quality management and control while enabling workers to focus their knowledge-based contributions on more critical qualityrelated issues that require human intervention. In this way, the transfer of expertise and even tacit knowledge from retiring workers and experts to younger, less experienced personnel is facilitated not just through their daily work interactions but also through educational training. Moving from product quality control to product quality assurance, the actions taken by an automated smart sensor-enabled quality management system will ensure that the right thing is done at the right time without the need for manual intervention.

On the other hand, predictive maintenance models and systems facilitated by smart sensors allow companies, service industries in particular, to be less dependent on the availability of specialized experts by preventing the occurrence of unplanned breakdowns or stoppages of their key machinery, equipment, or even entire systems. In this way, the knowledge hoarding that accompanies the impending retirement of skilled experts with a wealth of theoretical and tacit knowledge on maintenance praxes is not considered a big risk, thereby contributing to effacing the skills shortage in advanced services and manufacturing.

10.7.1. Future Trends

The advancement of fifth generation (5G) technology enables a highly communication efficient system for industries like smart manufacturing and smart factories. The centralized system that consists of one radio tower does not have low latencies and large load capacity required for a new industrial revolution. The centralized radio tower cannot manage large load capacity during large events at the factories where many sensors input data for system analysis. The arrival of 5G provides communication technologies that have potential benefits for industrial transformations; 5G reduces impact of time delay and bottleneck while enabling a high number of connected devices. The drastic wireless connection improvements from enhanced Mobile Broadband communications and Ultra Reliable Low Latency Communications can cause a data explosion as everything becomes connected. Industry 4.0 will create massive new sources of data on devices, systems and transactions, generate ubiquity using Real-Time Monitoring, Machine Process, and Object Behavior, and establish mobility and automation utilizing Artificial Intelligence, in realizing an agile digital transformation. The design and deployment of smart, data-powered products and services enabled via Proper Data remains a challenge across industries.

While AI can leverage prevailing data to drive many industrial solutions, there is need for guidance on what data and algorithms together deliver high performance at low cost in which situations. Prior assessments and example projects can provide valuable pointers, but at speed and scale that is desired with Industry 4.0 needs a more systematic approach. Wider deployments of machine learning and AI will yield empirical results on what works best when. Such algorithms can not only help optimize the economic value of individual IIoT systems, but also leveraging AI for Federated Learning can create a wider ecosystem and, in turn, can support the Digital Twin of an Enterprise connecting 3D product designs with 3D factory operations.

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