Preprint

Quality 4.0: A Step Forward in the Zero Defects Vision

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Preface

If you have been drawn to this book, you are most likely aware of the extraordinary potential of using artificial intelligence in manufacturing, but you must also be well aware of the challenges and concerns posed by this technology. We are researchers from *Amazon*, *Tecnologico de Monterrey*, and *General Motors*, and we have developed, published, and implemented novel technologies to solve real problems and create value. In this book, we describe our experiences with the use of artificial intelligence in the manufacturing sector; we discuss the challenges we have faced and share our vision.

Today, the industrialization of artificial intelligence is a major megatrend, and its application for quality control is one of the most cited priorities. Therefore, manufacturing companies can competitively position themselves among the most advanced and influential companies by successfully implementing *Quality 4.0*; this will provide opportunities to quality professionals to become a leading force in the industry. However, this is not an easy task because quality management leaders often have difficulty developing a vision for *Quality 4.0*; they need to learn the new technologies and paradigms to keep innovating and achieving professional growth. In this book, we focus on applying machine learning techniques to process-derived data for monitoring, controlling, predicting, and improving the quality of discrete manufacturing systems. We have made a conscious effort to keep the math and coding aspects at levels that are easily understandable for most engineers. Thus, it is possible to focus more on the practical aspects of selecting and solving engineering intractable problems through machine learning. However, for an in-depth perspective of the mathematics and coding details of machine learning, we recommend the following books: (1) Machine Learning: A Probabilistic Perspective (2012) by Kevin P. Murphy, (2) An Introduction to Statistical Learning: with Applications in R (2021) by Gareth James , Daniela Witten , et al., and (3) Introduction to Machine Learning with Python: A Guide for Data Scientists (2016) by Andreas C. Müller and Sarah Guido.

This book presents a *Quality 4.0* initiative that was developed in the *Manufacturing Systems Research Lab of General Motors* supported by a novel *Problem-Solving Strategy*, which evolved from the traditional *Six Sigma* cycle of design, measure, analyze, improve, and control. We review the theoretical background of the *Quality 4.0* initiative and describe its concrete applications and new quality control paradigms. We also present several case studies and identify areas of concern. This book will enable engineers without any coding knowledge to develop intelligent predictive systems. Also, managers without any *Artificial Intelligence* background will develop the capacity to identify valuable business projects, and directors will be able to successfully deploy a business vision for *Quality 4.0*.

Name

Chapter 1

Introduction

Chapter Subtitle

ABSTRACT

The manufacturing industry plays a predominant role in boosting a country's economy. *Smart Manufacturing* has ushered in a new era of using technological innovations in the manufacturing process; the processes involved exhibit rapidly increasing complexities. Many of the founding techniques and paradigms of traditional quality control methods are not able to handle all these dynamics. Therefore, in the last decade, traditional quality management philosophies have plateaued, and quality control professionals started stagnating with little innovation to offer. Today, the industrialization of *Artificial Intelligence* (*AI*) is a megatrend that dominates the business landscape, and it requires the attention of industry managers. The application of *AI* to manufacturing systems for quality control and improvement drastically improves upon the *Zero-Defects* vision proposed by Crosby. Consequently, the industrialization of *AI* offers an excellent opportunity for quality professionals to return to their lead roles in the manufacturing sector.

KEYWORDS

Smart manufacturing, Quality control, Machine learning

1.1 MOTIVATION

The manufacturing industry plays a predominant role in boosting a country's economy. The added value and employment contribution to the global *Gross Domestic Product* (*GDP*) have not changed significantly since since 1970 in developing countries [63]. At present, manufacturing is the driving economic force of the most advanced countries [122]. The global market for manufacturing is forecasted to grow from US $ 649.8 billion in 2020 to US $ 732.2 billion in 2027 [56]. The nations with high manufacturing output [158] also have the highest *GDP*, [69]. Manufacturing increases the living standards by increasing the purchasing power of the people living in industrialized societies. Advanced manufacturing companies are leaders in innovation, productivity, exports, and research and development. Most technological advances have originated in these companies [162].

In the *US*, for every dollar of domestic manufacturing value-added, another $3.60 of economic activity is generated elsewhere across the economy and for every manufacturing job; there are 3.4 jobs created in non-manufacturing industries. No other sector comes close to these numbers, [59]. Today, China is the world's largest manufacturing economy and it is considered one of the most competitive nations in the world, this sector helped China to rise as a global economic superpower, [50, 83]. In today's global competitive market, delivering high quality products is a top priority for most manufacturing companies. High quality improves customer retention, builds brand trust, and boosts return-on-investments, enabling business growth, [19].

Quality has been defined variously by researchers and experts. The *American Society of Quality* (*ASQ*) defines a quality item as a product or service that is free of deficiencies [3]. Joseph Juran defines quality as "fitness for use [98]." According to Joseph Juran, quality begins by understanding who the customers are and how and why they would use a product. This information is then used to drive all improvement activities and develop a customer-focused business strategy. A more extensive definition of quality considers eight dimensions: (1) performance, (2) features, (3) reliability, (4) conformance, (5) durability, (6) serviceability, (7) aesthetics, and (8) perceived quality [53]. Philip Crosby states that good, bad, high, and low quality are relative concepts, and the meaning of quality is conformance to requirements. For the ideas conveyed in this book, Crosby's definition of quality was the most appropriate.

Crosby also introduced the concept of zero defects in manufacturing [25]; it was one of the four absolutes of quality management [26]. However, when Crosby proposed the idea of zero defects in 1980, the manufacturing process was labor intensive and depended largely on the skills of human operators. Because of the technological limitations of the time, the zero-defects concept remained mainly a managerial tool that acknowledged the importance of quality and motivated employees to do their best to reach this goal. The creation of unrealistic standards was criticized by E. Deming and J. Juran [11, 71][1]. In this context, Crosby stated, "It is merely setting performance standards that no one can misunderstand [25]."

Broadly speaking, quality systems are divided into three categories: *Quality control* (*QC*), *Quality Assurance* (*QA*), and *Quality Improvement* (*QI*). *QC* is the process of applying statistical and analytical techniques to determine if a manufactured item conforms to the design specifications. According to *ASQ*, *QC* involves operational techniques and activities used to fulfill quality requirements. QA refers to all the planned and systematic activities implemented within the quality system that can be demonstrated to provide confidence that a product or service will fulfill the quality requirements [3]. *QI* is the process of constantly identifying projects aimed at creating breakthrough levels of performance by eliminating defects. *QI* requires a good managerial team that has the ability to identify relevant projects, create a successful team, and allocate the required resources. The three synergized systems (*QC*, *QA*, & *QI*) have helped create a high conformance production environment. Therefore, in today's manufacturing

1. "Eliminate slogans, exhortations, and targets for the work force asking for zero defects and new levels of productivity." This is clearly aimed at zero defects.

world, most mature companies operate their processes at very low *Defects Per Million Opportunities* (*DPMO*).

Modern manufacturing systems have ensured that defects are rarely generated; however, quality standards need to be further improved because customers expect perfect quality. Intense global competition has led to low profit margins [73, 37]; therefore, warranties can make the difference between profit and loss [13]. Moreover, customers now use the Internet and social media tools (e.g., *Google* product review, *YouTube*, *Facebook*, and *Instagram*) to share their product experiences, which can potentially go viral in a couple of days or even hours; this leaves organizations with little flexibility to recover from their mistakes [128]. Thus, a single negative customer experience can immediately affect a company's reputation and can influence loyal customers [68]. Today, the introduction of *Artificial Intelligence* (*AI*) into the manufacturing process vastly improves upon the zero-defects vision promoted by Crosby more than four decades ago. This book presents a *Quality 4.0* initiative[2] aimed at driving *AI*-based innovation. This initiative improves upon the zero-defects vision from a technological perspective.

1.2 SMART MANUFACTURING

Early adopters of *Smart Manufacturing* (*SM*) will inevitably dominate the business landscape. The clean energy *Smart Manufacturing Innovation Institute* (*CESMII*) [144] defines SM as "leveraging digital transformation, through the use of new *Industry 4.0* technologies, within Manufacturing to drive performance, increase quality, reduce cost and scrap, improve reliability and agility, and save energy." The term "smart" refers to the transformation of the US manufacturing sector, which results from the upending of traditional business, organizational, operational, and market structures by digitalization. The *National Institute of Standards and Technology* (*NIST*) defines SM as "a vision fully-integrated, collaborative manufacturing systems that respond in real-time to meet changing demands and conditions in the factory, in the supply network, and in customer needs" [103]. The term *SM* was initially introduced at the National Science Foundation workshop on cyberInfrastructure in 2006 [30]. Regardless of the particularities of the definition, *SM* helps manufacturers increase their efficiency, stay ahead of competition, and explore new business models and practices.

Today, *SM* has gained interest worldwide and is part of the comprehensive economic development strategy of several countries. In 2013, the German government started the *Industry 4.0* initiative [72, 160] with the objective of positioning Germany's manufacturing industry (with political support) as the world leader in digitized production technologies. McKinsey defines *Indus-*

2. Merriam-Webster defines initiative as the power or opportunity to do something before others do it. They also define it as a plan or program that is intended to solve a problem.

try 4.0 as “digitization of the manufacturing sector, with embedded sensors in virtually all product components and manufacturing equipment, ubiquitous cyberphysical systems, and analysis of all relevant data [157].” In 2015, *China* presented its *SM* national strategy called “Made in China 2025.” This initiative strives to secure *China*’s position as a global powerhouse among high-tech industries [8, 64]. In the United States, the *NIST* published a paper in 2016 titled “Standards Landscape for Smart Manufacturing” to describe the standards within and across three manufacturing lifecycle dimensions: product, production system, and business [86]. *CESMII* was also formed the same year to increase its manufacturing competitiveness and to create sustainable research and development infrastructures [145]. In 2017, the *Singapore Economic Development Board* in partnership with a network of leading technology companies and academic experts developed the *Smart Industry Readiness Index* (*SIRI*) tool and the prioritization matrix—a suite of frameworks and tools to help manufacturers start, scale, and sustain their manufacturing transformation journeys in the country. *SIRI* is founded on three building blocks of *Industry 4.0*: technology, process, and organization [127]. The prioritization matrix is a tool used to evaluate digital maturity and to identify potential gaps in the digital transformation. Finally, in 2019, the *Council on Competitiveness, University of California, Los Angeles*, and the *CESMII* published a program that focused on leveraging the democratization of *SM* innovation in the *United States* [145].

1.2.1 Technologies

The new disruptive technologies of the *Fourth Industrial Revolution* are moving forward the frontiers of manufacturing sciences. According to Mckinsey, in the previous industrial revolutions, most of the value was created by upgrading manufacturing assets. However, the value and innovations in the Fourth Industrial Revolution are not necessarily linked to major machinery upgrades [157]; instead, innovation comes from the cognitive computing capabilities that drive disruptive technologies [20, 137, 163, 143, 78] such as *AI*, *Industrial Internet of Things* (*IIoT*), and *Cloud Storage and Computing* (*CSC*)[3](see Fig. 1.1). Their combination enables a smart and connected manufacturing environment

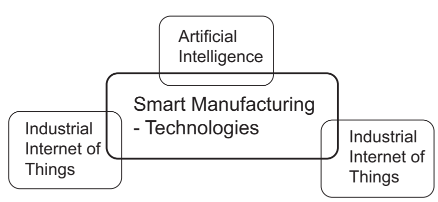

FIGURE 1.1 Smart Manufacturing enabling technologies.

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3. This list is not a comprehensive review of the technologies in SM, instead, it is shortened list of the most relevant technologies discussed in this book and the most cited technologies.

1.2.2 Building Blocks

Cyberphysical Systems (*CPS*), data-driven approaches, real-time iterations , self-learning adaptations and executions are the most important building blocks of SM (see Fig. 1.2).

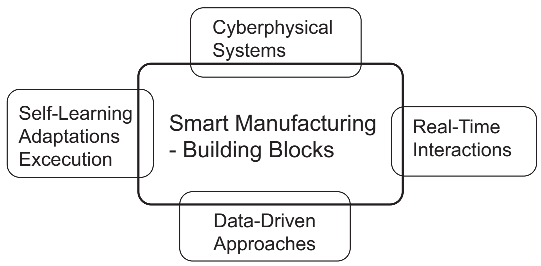

FIGURE 1.2 Smart manufacturing building blocks.

A *CPS* integrates the aforementioned technologies to fuse the virtual world with the physical world to develop smart solutions that enable *SM*. According to [134], "*CPS* are integrations of computation, networking, and physical processes. Embedded computers and networks monitor and control the physical processes, with feedback loops where physical processes affect computations and vice versa." The concept of CPS is broad and not limited by a particular implementation or application. Instead, they focus on the fundamental intellectual problem of conjoining traditional engineering models and methods with computer science fundamentals and *Machine Learning Algorithms* (*MLA*) [81]. In the context of *QC*, cyberphysical integration and real-time interactions were developed to optimize, automate, monitor, and control processes [84]. Although the origin of CPS is traced back to 2006 [55], *CPS* application in the manufacturing sector is still in its developmental stage [137], and it poses a significant intellectual challenge for the manufacturing industry. It is a top research priority in the *United States* [109].

Data-driven approaches are also part of the building blocks of the *SM* model. The new generation of manufacturing is changing from engineering-based to a combination of data-driven and engineering-based approaches [137, 165, 75]. For example, at the process level, high data volumes enable data-driven knowledge discovery. Preconceived engineering notions are used to observe the process using connected devices, such as smart sensors, and they generate high volumes of relevant observational data[4], which is further analyzed from an engineering perspective. This analysis helps to generate a hypothesis about the underlying physics of the system and guide randomized experiments to generate experimental data [94] and augment engineering knowledge (see Fig. 1.3).

4. Collected data based on what is observed. Not generated to find true cause-and-effect relationships [92].

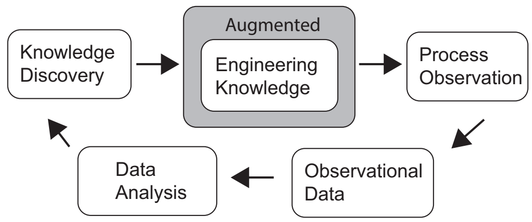

FIGURE 1.3 Observational-data-driven- and engineering-based augmented knowledge.

Data-driven modeling is another approach that is growing exponentially. Enabled by the high data volumes, new modeling techniques, and increased computer power, data-driven modeling augments often even replace engineering- and physics-based models. It is an efficient approach to derive models from patterns and signals in the data itself, as opposed to being limited to making assumptions about the form of the real-world model.

Data-driven modeling allows engineers to automate a whole range of processes faster. Although success stories are emerging in which data-driven modeling has contributed to significant efficiency gains [54, 102, 2, 146], most industrial data sciences fall short of expectations. The application of data science to solve hard industry problems is currently a complicated exercise . Therefore, it is always important to use engineering knowledge to avoid making the wrong decisions driven by wrong models. Figure 1.4 shows the most relevant applications based on data-driven modeling.

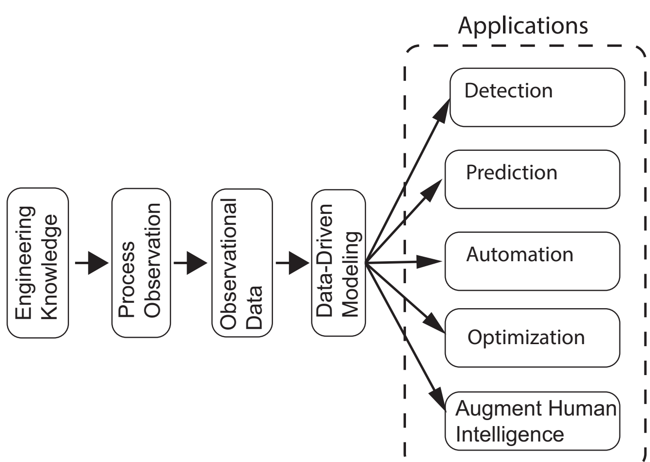

FIGURE 1.4 Observational-data-driven- and engineering-based modeling applications.

- *Detection*. For this application, a model is developed to detect defective items. Quality patterns of the process data are learned by *MLA* to identify the defective items while they are manufactured. For example, the *ultrasonic metal welding* of the battery tabs process generates several signals such as acoustic and *linear variable differential transformer signals*. *MLA* learns the good quality signals and the defective signals and applies a trained classifier to detect the signals in real-time defective welds [1, 39].

- *Prediction*. For this application, a model is developed to predict future events based on the data generated early in the process. For example, the *Body-In-White* (*BIW*) dimensional variability control is one of the most relevant challenges for multistage manufacturing *QC*. Undetected significant devia-tions from the nominal are propagate and amplified downstream generating quality-related and difficult-to-fix problems in the final assembly. Recent ad-vances in vision and information systems have enabled real-time monitoring systems. Hundreds or even thousands of under-body dimensional deviations are collected, and the quality patterns are learned by *MLA* [44, 110]. Then, a regression or classification model is developed for early prediction in the process and for potential downstream problems, such as significant misalign-ment. It will be expensive and time-consuming to fix them later because the number of work-in-process or finished items may be too large.
- *Automation*. For this application, a model is developed to replace the monotonous and trivial tasks, such as object detection. Usually, human inspectors perform visual quality checks on the production line. These inspections are often subject to the operators' inherent biases and tiredness that result from the repetitive nature of the task; therefore, their accuracy in manufacturing is approximately 80 % [123]. A model that is trained based on *Deep Learning* (*DL*) replaces human vision inspections. For example, an operator visually checks each transmission to ensure that a critical component is present. Although a missing event rarely occurs, the business implications of a missing event are critical. *DL*-based technologies have shown better accuracy than human performance [104, 10].
- *Optimization*. For this application, a model is developed to optimize the parameters of a machine. Then, the optimized parameters increase the process performance and quality. For example, a tungsten inert gas welding machine has 15 parameters, such as initial current, duty cycle, and pulse frequency, which the user needs to set to optimize the welding strength. The parameter combinations are infinite. An *MLA* is applied to learn the linear and non-linear relationships between the input parameters and the process outcome. The regression model is used to predict the welding strength of the different combinations, which enables virtual process optimization. Superior predicted combinations are then physically studied to optimize the process. Although traditional statistical methods, such as *Response Surface Methodology* (*RSM*) [97], have been widely applied to perform this task, *Artificial Neural Networks* (*ANN*) have consistently shown superior performances [35, 76].
- *Augmentation of human intelligence*. For this application, a model is developed to perform sensitivity analyses. Complex linear and nonlinear rela-

tionships between the independent variables and the variables of interest are learned by *MLA*. Then, the trained model is interrogated to expedite troubleshooting. For example, in the *BIW* application, if a multioutput regression model [12] has accurately learned the relationships between many underbody dimensional deviations and many final assembly deviations, then it can be used to calibrate the process [44]. During the troubleshooting analysis, dimensional engineers can predict or virtually evaluate the effect on the final assembly of potential process adjustments by inputting the observed underbody deviations derived from the adjustments into the model. This is a valuable tool to keep the process in good operating conditions because it is very difficult for engineers—and even for those using traditional statistical methods—to learn nonlinear relationships between many inputs and many outputs. The model helps to manage the complexities of real-time interactions using innovative *IIoT* solutions [95, 139] and promotes the deployment of sensors to generate real-time streamed data from each product (100 % observation inspection , tracking, and monitoring) and across its life cycle [137, 105, 74]. The systematic computational analysis of data enables the creation of intelligence in all the aspects of manufacturing [136, 77] . Intelligence comes in the form of strategic actions, predictions, optimizations, simulations, and smart monitoring and control. For example, the manufacturing processes are monitored in real-time, which enables adjustments and actions in a timely manner to control the product quality. Moreover, streamed data support in the rapid diagnosis of the root causes of faulty operating conditions [136, 163].

Advanced data-driven systems are capable of self-learning and adapting to new sources of variations, they can self-execute [136]. Self-learning allows the system to keep improving without intensive human intervention as more data become available. Usually, systems are deployed after the patterns of interest are learned at some level of accuracy. This feature allows the deployed system to keep learning the same patterns to improve accuracy. However, manufacturing systems are constantly exposed to new sources of variations that generate new patterns. The developed system needs to have the capacity to automatically learn new patterns, and it should automatically execute.

1.2.3 Characteristics

Beyond disruptive technologies, *CBS*, data-driven approaches, and real-time interactions [24, 147], there are eight relevant *SM* characteristics with respect to business and tactics, namely, flat, sustainable, agile, people oriented, profitable, innovative, current, and competitive.

- *Flat*. In this characteristic, the layers of management between the top and the bottom of the organizational pyramid are removed. In *SM*, data are democratized and analyzed using smart technologies to extract information and make decisions; this helps reduce or eliminate the need for reports and

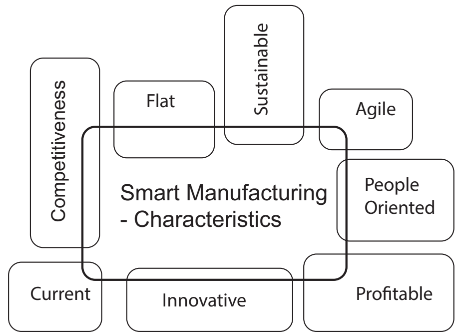

FIGURE 1.5 Smart manufacturing characteristics.

meetings. Employees are empowered by data and algorithms.

- *Sustainable*. This characteristic includes topics, such as fair trade, safety, social and environmental responsibilities, and work practices. Companies have set up traceability in their supply chains to provide the information required to prove that suppliers are operating in a sustainable and fair manner. To develop a strong business strategy, company leaders recognize the need for including people from diverse cultural backgrounds, genders, and races [115]. Sustainability is also changing the way plants are designed, as is seen in the case of *Factory ZERO* in *Detroit, United States* [57]. This modern manufacturing plant supports the *GM* goal to completely phase out vehicles using internal combustion engines and to go carbon neutral at all facilities worldwide by 2035 [36].
- *Agile*. This characteristic involves real-time data generation, collection, analysis, and interpretation, which enables faster decision-making by predicting potential problems or by detecting them early in the process. This capability helps decision makers to respond early to changes and unforeseeable challenges, which decreases wastage and increases efficiency.
- *People oriented*. This characteristic helps smart technologies help workers perform better at their jobs. Although 40 % of the current jobs may be replaced by automation and *AI* technologies by 2034 [118], the first jobs to disappear are the monotonic, mortifying, and dehumanizing ones. AI is good at learning these types of tasks; the handling of such limited tasks by machines is known as narrow *AI* [48, 29]. Narrow *AI* will help to free human minds and to take advantage of human intelligence to solve complex cognitive problems. Therefore, in the coming decades, *AI* is expected to keep augmenting human intelligence (not replace it) [31] and to create more jobs [28]. From the First*' *Industrial Revolution* onward, technology has been used to create jobs that require high levels of training and education [159, 90].
- *Profitable*. This characteristic implements *SM* techniques to increase productivity and generate profits and growth. According to the *MPI* Group,

most manufacturing leaders who implemented *IIoT* technologies attributed their increase in profitability to these technologies [121]; their profitability increased by 88%. Other factors supporting business growth also increased; productivity, product quality, and customer satisfaction increased by 88%, 48%, and 43%, respectively [61, 67].

- *Innovative*. This characteristic accelerates innovation at all levels by the democratization of data, and the application of smart technologies boosts innovation at all levels of the company. Data-empowered employees engage in continuously improving work practices and driving innovation. They improve the product design, manufacturing process, and machine interfaces to develop high-value products that are manufactured better, faster, and cheaper [144].
- *Current*. This characteristic helps develops an *SM* strategy. Companies do not need to wait for new technology to be developed or perfected to launch an SM initiative. They can be developed in-house or outsourced based on the funding or readiness level of the company, but *SM* initiatives should be at the core of the business strategy. However, relatively few companies have turned the potential of *SM* into sustained action [147].
- *Competitive*. This characteristic helps manufacturing leaders to expect *SM* to increase their competitiveness. According to Gartner, 84% of the surveyed leaders see a range of actual or expected benefits from *SM*. The common denominator is operational excellence founded on agility, flexibility, automation, and optimization [147].

1.2.4 Research Areas

SM has emerged as a compelling topic for research scientists worldwide. Figure 1.6 shows the most relevant topics that move forward the frontiers of manufacturing science. All these areas are founded on the three disruptive technologies previously discussed, namely, *AI*, *IIoT*, and *CSC*.

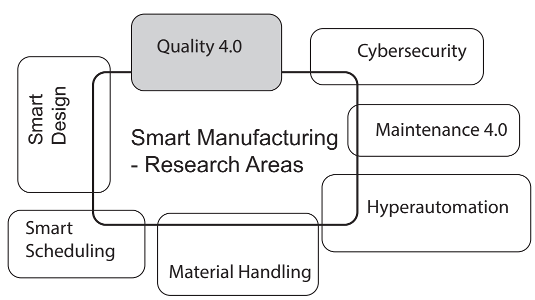

FIGURE 1.6 *SM* research areas.

Cybersecurity. The connection between the digital and physical environments poses a new challenge: cyberattacks. Information and machines can be accessed or controlled remotely; therefore, attacks from adversaries aiming at industrial espionage and sabotage is a matter of concern [143].

Maintenance 4.0. Real-time data enable the new generation of maintenance: predicted and optimized maintenance. Intelligent predictive systems are developed for early detection and diagnosis of machine failures [18, 150, 34]. Streamed data are used to estimate the component's remaining lifetime [125]. This prediction capability enables just-in-time maintenance [82].

Hyperautomation. This technology focuses on automating every process and task that can be automated. Besides automating repetitive tasks, the robotic process automation technology, which is a new robotics paradigm, focuses on mimicking human behaviors to automate process-led and repetitive tasks; these tasks include the more complex and long-running tasks that require human intervention. According to Gartner, hyperautomation was the top strategic technology trend in 2021 [107], and it could replace 40% of jobs in 15 years [118], which would improve the life quality and morale of the workers. Material handling in work-in-process units are tracked to deliver the right material to the right machine at the right time in the most efficient way. In-plant logistics is optimized using *Radio Frequency Identification* (*RFID*) and *Automated Guided Vehicle* (*AGV*) technologies [85]. *RFID* systems automatically identify and track manufacturing items, and *AGV* enables efficient transportation. Moreover, product traceability allows us to move forward in the value adding process to track defective items that were generated during production [164].

Smart scheduling. The connectivity and communication between the manufacturing entities enable the development of optimal machine schedule programs. Machine availability and real-time product statuses are used to optimize the machinery usage and energy consumption [135]. To develop production plans and optimal configurations, manufacturers use readily and rapidly available data from supply chains, sales figures , and inventory are used [129, 138].

Smart design. Product design involves shifting from engineering-based to data-driven design. Internet data are used to improve designs and foster new ideas [136]. New platforms, such as *Google* reviews, allow customer to share their experiences first-hand. This increasing trend is leveraged by manufacturers by selecting helpful online reviews [112].

Mass customization. Easy access to smartphones, social media, and design applications allows modern customers to quickly and precisely fulfill their requirements. Digital manufacturing enables companies to quickly and cost-effectively meet customization demands [154]. Thus, manufacturers and customers enjoy the new created value [141].

Today, companies are rapidly adopting *SM* technologies and paradigms to preserve their competitiveness in highly globalized and competitive markets. However, although technologies and practices have matured, their adoption has not "crossed the chasm" and moved beyond the early adopters into the early majority for wide adoption in the ecosystem.

1.3 EVOLUTION OF MODERN QUALITY CONTROL IN MANUFACTURING

In the *United States*, modern *QC* started a century ago with the statistician W.A. Shewhart, who worked in *Western Electric*. Shewhart began focusing on controlling processes using *Statistical Quality Control* (*SQC*) methods, which made quality relevant not only for finished products but also for the processes that manufactured them. After several years, Japanese manufacturers who were influenced by W.E. Deming and J.M. Juran increased their market shares significantly in the *United States* because of their superior quality. In response, many *CEO*s of major firms took initiative to provide leadership to the quality movement. Their responses not only emphasized employing *SQC* methods, but also employed a quality management approach that encompassed an entire organization; this approach was known as *Total Quality Management* (*TQM*). A few years later, B. Smith developed *Six Sigma*, a reactive approach to eliminate defects from all processes by identifying and removing the main sources of variations. This approach was extended to the designs of products and processes using the *Design for Six Sigma* process [71, 87, 88].

Traditional quality philosophies went through several evolutionary steps. Each of them employed a scientific method in the form of problem solving [91]. Figure 1.7 describes the evolution of the traditional quality philosophies in the modern quality movement along with their associated paradigms and *Problem-Solving Strategies*.

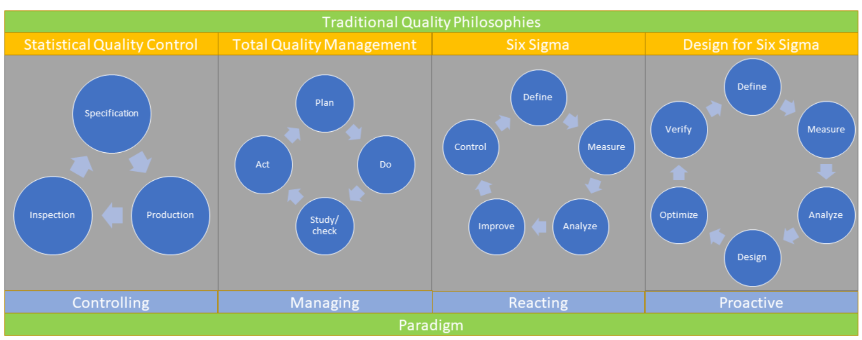

FIGURE 1.7 Evolution of the *problem solving strategy* in modern quality movement.

A *Problem-Solving Strategy* is an iterative management method used in business for controlling and improving the quality of products and processes, resolving problems, discovering new engineering knowledge, and driving innovation. It is the adaptation of the scientific method to the modern *QC* and was promoted by Shewhart and Deming [91].

In today's manufacturing world, most mature organizations have merged the traditional *QC* philosophies and statistical techniques to create highly efficient

QC, *QA*, and *QI* approaches. Process monitoring charts and acceptance sampling methods have been widely implemented in manufacturing to set a process capability index benchmark of Four Sigma [130, 124]. This sigma level generates 6210 *DPMO* [33, 51]. The necessity to generate and integrate data from the whole value adding process and after-sales service into the QC approaches to achieve the next sigma level (5σ, 233 *DPMOs*) was recognized early in [142]. Figure 1.8 illustrates the Four Sigma conformance rate using a normal distribution.

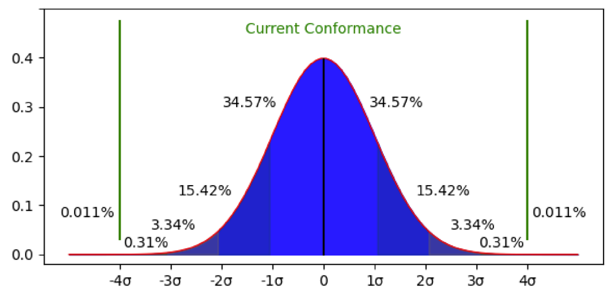

FIGURE 1.8 Four sigma conformance rate.

Although traditional quality philosophies based on statistics have raised manufacturing standards to very high conformance levels, they have plateaued and are limited in addressing the challenges posed in *Manufacturing Big Data* (*MBD*).

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1.4 BREAKDOWN OF TRADITIONAL QUALITY CONTROL METHODS

SM is founded on processes that exhibit rapidly increasing complexities, hyperdimensional feature spaces, high data volumes, transient variation sources, reduced lifetime, ultrahigh conformance, and non-Gaussian pseudo-chaotic behaviors. Most of the founding techniques and paradigms of traditional *QC* tools cannot handle these dynamics [161]. Seven of the most relevant limitations and differences of traditional quality philosophy techniques with respect to the founding techniques and paradigms of the Fourth *Industrial Revolution.*[5] are discussed below [43].

- *ANN*. These networks have shown better predictive modeling and optimization performance than *RSM* [76, 35]. According to the universal approximation theorem, the feedforward *ANN* with one hidden layer containing sufficient neurons can approximate any continuous function to a reasonable accuracy

5. The authors recognize that modern significant advances in *ML* techniques were developed by the statistical community; therefore, this analysis is limited only to comparing the current state of *AI* techniques, such as *DL* and *ML*, with the founding techniques of the traditional quality philosophies [47, 133, 9].

level [7, 32]. This provides an advantage over the limitations of the quadratic models or cubic models used by *RSM*. Therefore, *MLA* are better at learning complicated nonlinear relationships.

- *Modeling*. *Machine Learning* (*ML*) models are designed to make the most accurate predictions possible. Statistical models are designed to infer the relationships among variables [14]. However, many *Six Sigma* tools assume homoscedasticity and normality [62], and most *MLA* make minimal assumptions about the statistical distribution of the data-generating systems [52]. Moreover, in statistics, model significance is determined based on the p-values [60], whereas *ML* models are validated based on their ability to accurately predict new data, that is, to generalize [5].
- *Curse of dimensionality*[6]. Traditional statistical modeling was designed for data having a few dozen input variables and sample sizes that would be considered small or moderate by the current standards [14]. These methods can be highly effective for high-dimensional data [70], and MLAs can efficiently learn from high-dimensional data [22, 113, 27, 101].
- *Computation time*. There are two computational barriers for big data analysis: the data can be too big for a computer's memory, and the computing task can take too long to generate results [152]. Most traditional statistical methods were not developed keeping in mind these challenges. However, modern statistical methods have been developed in view of these challenges [152]. *MLA* have embedded computational efficiency concepts to enable computational feasibility when learning from big data (e.g., stochastic gradient descent [32] and *XGBoost* [22]).
- *Vision systems*. Shortly after *DL* networks achieved superhuman performance on image and object recognition [106, 65], a survey conducted in 2016 showed that almost half of the respondents claimed that their inspections were mostly manual [10]. This was expected because *DL* was not part of the quality tools and had not achieved proper recognition performance when the traditional quality philosophies were developed. Manual inspections are often subject to the inherent operator biases (80% accuracy) [123]. Today, the development and application of vision systems for *QC* is one of the most relevant research topics in hyperautomation [151, 66, 126].
- *Acceptance sampling*. This technique has been widely implemented to ensure good end-product quality [120]. In *SM*, the objective is to observe the quality characteristics of interest of all the end products; no statistical inference is required. Vision systems observe the quality of the *BIW* of all vehicles during the assembly process and after the final assembly [44].
- *Control charts*. These charts support fault detection and diagnosis of industrial processes and production results. However, univariate control charts [99] can-

6. The curse of dimensionality is the problem caused by the exponential increase in volume associated with adding extra dimensions to a Euclidean space. The error increases with the increase in the number of features. Patterns are harder to learn in high dimensions and often have a running time exponential in the dimensions [149].

not detect patterns in hyperdimensional spaces. Multivariate control charts, such as *Hotelling*'s T-squared statistic and the *Q*-statistic are calculated based on a model using the *Principal Component Analysis* (*PCA*), which makes it difficult for this method to identify the process variables that lead to the quality problems [114]. *MLA* can effectively learn patterns in hyperdimensional spaces and identify the driving variables of the process [21].

Manufacturing innovations and business strategies were driven by the principles of quality philosophies. Early adopters of *Six Sigma*, such as *Motorola*, *General Electric*, and *Honeywell*, have become the most valued and admired companies [132, 62]. Traditional quality philosophies have plateaued, and they have stagnated with little innovation to offer to the manufacturing industry [166].

Today, while traditional quality philosophies are still necessary, they are not driving SM innovations and interest[7] in these philosophies have decreased (see Fig. 1.9). Consequently, quality professionals have lost their leadership positions to data scientists.

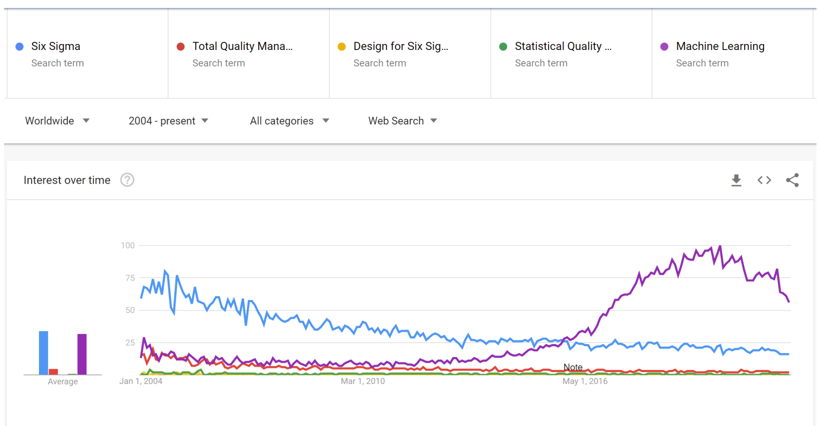

FIGURE 1.9 Google Interest of traditional quality philosophies with respect to *ML*.

1.5 THE RISE OF QUALITY 4.0

Quality 4.0 is the next natural step in the evolution of quality. The *Fourth Industrial Revolution* is the era of quality. Many of the limitations of traditional QC methods have been overcome, which has advanced the frontiers of manufacturing science and enabled the next sigma level. According to [79], *Quality 4.0* refers to "the application of *Industry 4.0*'s advanced digital technologies to enhance traditional best practices in quality management." For *ASQ*, *Quality*

7. Interest over time. The numbers represent the search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term.

4.0 is a term that references the future of quality and organizational excellence within the context of *Industry 4.0* [3].

Intense modeling is the foundation of *Quality 4.0*. Regression, classification, or clustering techniques [96] are applied to the observational data generated by the manufacturing processes to develop empirical models and identify the driving features [39, 15, 17, 42]. In [41], the authors define *Quality 4.0* as follows:

Quality 4.0 is the 5^{th} wave in the modern quality movement. This quality philosophy is based on the statistical and managerial fundamentals of the previous philosophies. It leverages *MBD*, *IIoT*, *CSC*, and *AI* to solve completely new sets of complex engineering problems. *Quality 4.0* is based on a new paradigm that enables smart decisions through empirical learning, empirical knowledge discovery, and real-time data generation, collection, and analysis.

Driven by the new technologies, building blocks, *SM* characteristics, and *MBD*, traditional *QC* and *QA* philosophies are in the middle of a paradigmatic transformation that requires the full attention of the management.

Industrialization of *AI* is today a megatrend that dominates the business landscape. According to [58, 100], 92% of the surveyed leaders are increasing their investments in big data and *AI*. According to an executive report from the *IBM Institute for Business Value* [49], QC is the most cited priority for the application of this technology; 66% of the surveyed executives expressed their interest in developing *AI* systems having the capacity to analyze data from the whole value adding process and after-sales service to identifying causal factors that led to quality problems. In this context, quality professionals need to learn new technologies to cope with the challenges posed to the Fourth Industrial Revolution. Even before the term *Quality 4.0* was coined, Montgomery made the following recommendation [93]: "Quality professionals are going to have to master some of the skills of computer science, such as understanding the structure of large databases, basic data-mining techniques, image processing, and data visualization techniques."

According to Forbes [89], the lack of powerful people is one of the biggest challenges facing these technologies in business. Quality professionals need to be well versed in statistical methods and problem-solving strategies. The *Fourth Industrial Revolution* is an excellent opportunity for the quality movement to become relevant again and for quality professionals to return to lead roles again [166, 4]. *ASQ* and [116] have proposed five distinctive attributes:

- Systems thinking
- Data-driven decision making
- Leadership for organizational learning
- Establishing processes for continuous improvement
- Understanding how decisions affect people—their lives, relationships, communities, well-being, health, and society. In general, *Quality 4.0* is founded on the following six areas of knowledge [45]:

- Quality
- Statistics
- Programming
- Optimization
- Learning
- Manufacturing

A *Problem-Solving Strategy* is required to combine them in a meaningful way to create value (see Fig. 1.10). The value propositions for *Quality 4.0* initiatives fall into the following seven categories [16, 116, 4]:

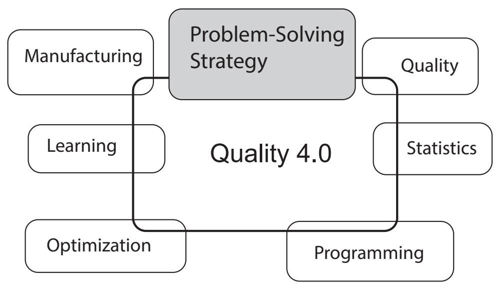

FIGURE 1.10 Areas of knowledge of *Quality 4.0*.

The value propositions for *Quality 4.0* initiatives fall into seven categories, [16, 116, 4]:

- Detect rare quality events
- Predict quality issues
- Eliminate visual and manual inspections
- Augment human intelligence
- Increase the speed and quality of decision making
- Improve transparency, traceability, and auditability
- Develop new business models

As *Quality 4.0* matures and different initiatives unfold across manufacturing companies, intractable engineering problems will be solved using new technologies. Advancing the frontiers of manufacturing science, enabling manufacturing processes to move to the next sigma level, and (in some cases) virtually achieving the zero defects vision have been widely discussed and redefined in quality movements [25, 26, 140, 117, 153, 108, 40, 23].

By successfully implementing *Quality 4.0*, manufacturing companies can competitively position themselves among the most advanced and influential companies in the world. However, at this point of time, there is no strong evidence of any successful implementation by any firm [166]. According to a recent survey, quality leaders are universally citing difficulties in developing a vision for *Quality 4.0* [79]. Although two-thirds of the respondents believe that

Quality 4.0 will significantly affect their operations within five years, only 16% have started to implement a *Quality 4.0* initiative, and 20% respondents have started to plan for implementation; 63% respondents have not even reached the planning stage yet, and zero respondents have done a full implementation [79]. In this context, the first successful end-to-end application of *Quality 4.0* is reported in, [46].

The successful deployment rate of ML models across industries lies between 13% and 20% [131, 119]; however, the current benchmarks of quality, conformance, innovation, and productivity in manufacturing set an even higher bar for the new technologies [111, 148, 124]. The manufacturing industry has been innovating, advancing, and evolving since the beginning of the *First Industrial Revolution*.

Successfully implementing *Quality 4.0* requires much more than just accessing the new technologies, generating data, and fitting a model. It is necessary to understand and address many managerial and practical challenges [6, 79, 41, 80]. The following steps are critical for successful implementation of *Quality 4.0*:

- Develop a vision and road-map
- Train the quality professionals in the new technologies
- Allocate budget for the new technologies
- Learn how to identify winning projects
- Define a strategy for data generation
- Understand the limitations of *AI*
- Consider if outsourcing would save money and complete projects quickly, while in-house expertise is developed.

According to [155], *Quality 4.0* developments will include *MLA* that will observe, collect, and distribute data and will creatively know what to do and how to improve the process. Smart solutions have the following characteristics

---

- *Systematize* thinking with *ML* and *AI*.
- *Industrialize* production using control systems and adaptive feedback loops.
- *Mechanize* operations by applying robotic technology and automated conveyance.
- *Automated information* collection with distributed sensor networks unified in cloud storage.
- *Integrated* communications using wireless networks and blockchain technology.
- *Humanized* leadership through innovative participation in designing and executing the system.

Despite the powerful new technologies available, it is important to keep applying the scientific method for problem investigation, diagnosis, and remediation [156].

In the following chapters, we will explain the *Learning Quality Control*

(*LQC*) system, which is a *Quality 4.0* initiative that focuses on the application of ML techniques to process-derived data for monitoring, controlling, predicting, and improving the quality of discrete manufacturing systems. *LQC* systems have the capacity to automatically learn quality patterns that exist in hyperdimensional spaces and to learn new and transient sources of variations. To guide its implementation, the scientific method was adapted to develop a new problem-solving strategy that is based on theory. The authors studied manufacturing systems and investigated the empirical evidence.

Appendix A

Appendix title

A.1 DEFINITIONS AND ACRONYMS

A few brief definitions are listed here for easy readability and understandability[1].

- Class, quality characteristic of the manufactured item, i.e., *good* or *defective*.
- Classification
- Binary classification
- Pattern
- Feature
- Label
- Training data
- Validation data
- Testing data
- Machine learning algorithm
- Hyperparameter
- Model
- Classifier
- Training
- Underfitting
- Overfitting
- Hyperdimensional space
- Separating hyperplane
- Classification performance
- Separable
- Generalization
- Confusion matrix
- Meta-learning algorithm
- Multiple classifier system

1. The readers are encouraged to consult more sources to reinforce understanding.

TABLE A.1 Acronym definitions

Acronym	Definition
AGV	*Automated Guided Vehicle*
AI	*Artificial Intelligence*
ANN	*Artificial Neural Networks*
ASQ	*American Society of Quality*
BIW	*Body-in-White*
CPS	*Cyber-Physical Systems*
CSC	*Cloud Storage and Computing*
DFSS	*Design for Six Sigma*
DL	*Deep Learning*
DPMO	*Defects Per Million Opportunities*
EDB	*Economic Development Board*
GDP	*Gross Domestic Product*
IBD	*Industrial Big Data*
IoT	*Internet of Things*
IIoT	*Industrial IoT*
IT	*Information Technology*
LVDT	*Linear Variable Differential Transformer*
ML	*Machine Learning*
MLA	*ML Algorithm*
NIST	*National Institute of Standards and Technology*
NSF	*National Science Foundation*
QA	*Quality Assurance*
QC	*Quality Control*
RFID	*Radio Frequency Identification*
RPA	*Robotic Process Automation*
RSM	*Response Surface Methodology*
SIRI	*Smart Industry Readiness Index*
SM	*Smart Manufacturing*
SQC	*Statistical Quality Control*
TQM	*Total Quality Management*
UMW	*Ultrasonic Metal Welding*

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