Methods and Tools for Performance Assurance of Smart Manufacturing Systems

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The emerging concept of smart manufacturing systems is defined in part by the introduction of new technologies that are promoting rapid and widespread information flow within the manufacturing system and surrounding its control. These systems can deliver unprecedented awareness, agility, productivity, and resilience within the production process by exploiting the ever-increasing availability of real-time manufacturing data. Optimized collection and analysis of this voluminous data to guide decision-making is, however, a complex and dynamic process. To establish and maintain confidence that smart manufacturing systems function as intended, performance assurance measures will be vital. The activities for performance assurance span manufacturing system design, operation, performance assessment, evaluation, analysis, decision making, and control. Changes may be needed for traditional approaches in these activities to address smart manufacturing systems. This paper reviews the current methods and tools used for establishing and maintaining required system performance. It then identifies trends in data and information systems, integration, performance measurement, analysis, and performance improvement that will be vital for assured performance of smart manufacturing systems. Finally, we analyze how those trends apply to the methods studied and propose future research for assessing and improving manufacturing performance in the uncertain, multi-objective operating environment.[1]

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1. Introduction

Maintaining high performance required for today's manufacturing systems requires employing methods and tools to manage performance throughout the system life cycle. During system design, for example, methods and tools model, analyze, and test the system so that anticipated manufacturing needs and operating

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environments are investigated before the system is built. In the operation of the system, methods and tools are employed to ensure that the system maintains planned performance through monitoring, assessing performance, and responding appropriately to performance deviations. In this paper, we review three categories of methods and tools used in manufacturing systems for the following high-level objectives:

- Performance measurement
- Performance analysis
- Performance improvement

We discuss how these methods, tools, and systems can be used in, and are impacted by, emerging changes to the manufacturing environment. The new era of manufacturing systems, known as smart manufacturing systems (SMS), is marked by a wide availability of operational performance data that was previously not available for performance management. In the past, such data was either not collected at all or, when collected, was used primarily for production control on the factory floor. The availability of Information and Communications Technologies (ICT), such as ubiquitous sensors and wireless communications, is resulting in an onslaught of readily accessible data that could also be used for planning at higher organizational levels, so long as context and meaning can be deduced from the data. Poor interoperability of this data is still a barrier, in large measure because the data is digital, and therefore commonly available in proprietary, mutually incompatible, formats. Current efforts to solve the data interoperability challenge across manufacturing hierarchical levels will blur historical lines between organizational planning and operational control.

Another shift in the manufacturing environment relates to the type of performance being measured. Traditionally, productivity and quality were the primary gauges of performance. A more productive system is one with higher throughput for a given amount of input resources, which positively impacts a business's bottom line. However, two other motivating factors are now taking on a more critical role: sustainability and agility. Sustainable manufacturing refers to the creation of manufactured products employing processes that are non-polluting, energy- and natural-resource conserving, and economically sound to the manufacturing organization and consumers. Sustainable manufacturing focuses on three main impact areas: environmental, economic, and social. Agility refers to an organization's ability to anticipate, respond quickly to, and even take advantage of, changing market demands and changing flow of supplies as well as responding to internal disruptions and disturbances. Increased attention to these two new performance factors could negatively impact productivity but is crucial for an organization to succeed in today's markets. Techniques for assessing and balancing multiple factors using operational data in real time are still needed and are an area of ongoing research in SMS. In a 2010 report, the Smart Manufacturing Leadership Coalition (SMLC), an independent, public-private partnership, defined a vision for SMS [1]. That vision states that the future holds a "fundamental shift in manufacturing processes toward demand-dynamic economics, flexible factories, and demand-driven supply chain service enterprises." As discussed in Davis et al. [2], the SMLC believes that this vision is multi-dimensional – it must be implemented vertically across planning levels and horizontally across the product life cycle. In this paper, we focus on one part of that vision: the manufacturing plant.

Fundamental to assuring performance is measuring performance. All of the methods and techniques described in this paper rely on measurement. Performance measurement provides the state of performance. At higher levels in the factory, the measurements are rolled up into key performance indicators (KPIs). An organization can include, within its strategy, the improvement of a set of KPIs (e.g., environmental sustainability), which may influence the specification of hardware and software as well as data collection and measurement policy. For example, SMS are accompanied with greater investment in automation and ICT to pursue KPIs that are defined by today's performance objectives. Performance measurement is followed by performance analysis so that critical factors governing performance are identified and decisions are made for improvement.

Our motivation in this paper is to understand current trends in existing methods and tools in support of SMS, and to identify opportunities provided by emerging technologies for performance assurance within the manufacturing plant. The rest of the paper is arranged as follows. Section 2 is a background to SMS, performance measures, and aggregate performance indicators. Section 3 reviews a variety of methods and tools, and the previous research in their application to manufacturing operations management. Section 4 discusses performance assurance issues and the adaptation of current methods and tools for SMS. Section 5 concludes the paper with a summary and future research needs.

2. Background

This section overviews the performance challenges and approaches to performance measurement and improvement.

2.1 Understanding Performance Assurance for Smart Manufacturing Systems

Performance assurance establishes confidence that the system performs as intended. This requires the ability to assess a proposed design and monitor performance of a manufacturing system operation. In essence, performance assurance emphasizes the proactive approach, i.e., forecasting and monitoring, and preventing problems [3]. Figure 1 provides an illustration of the context of the manufacturing performance assurance challenge. This figure shows a system with a given input purposed to result in a level of desired performance but subjected to both internal and external disruptions and disturbances. By our definition, disruptions are those whose occurrence results in temporary shutdown of at least one unit of the manufacturing operations, while disturbances are events that do not lead to stoppage of production. Internal disruptions and disturbances can be both planned and unplanned events on the manufacturing floor. Traditionally, these events are anticipated and appropriately planned for to achieve and maintain required performance.

Figure 2 offers a schematic representation of a rigorous approach to manufacturing performance assurance during system design and development. The first activity is to specify appropriate KPIs. The second activity is to establish the target system performance envelope according to the KPIs. The goal is that the system built will achieve and maintain minimum performance requirements, within the set bounds, irrespective of disturbances and disruptions. The third activity is to determine needed system components to deliver the required performance. The integration of such components (physical and virtual) requires developing a system architecture. The system component models of hardware, software, information, and tools are integrated based on system engineering principles and tools [4]. Lastly, predictive tools such as simulations are applied to test the system performance in a virtual environment to determine if the desired system behavior will be obtained. The results of the test may show that the system needs modifying or redesigning with a different set of components and retesting until the system performance for the anticipated range of operational conditions and inputs is within the performance envelope.
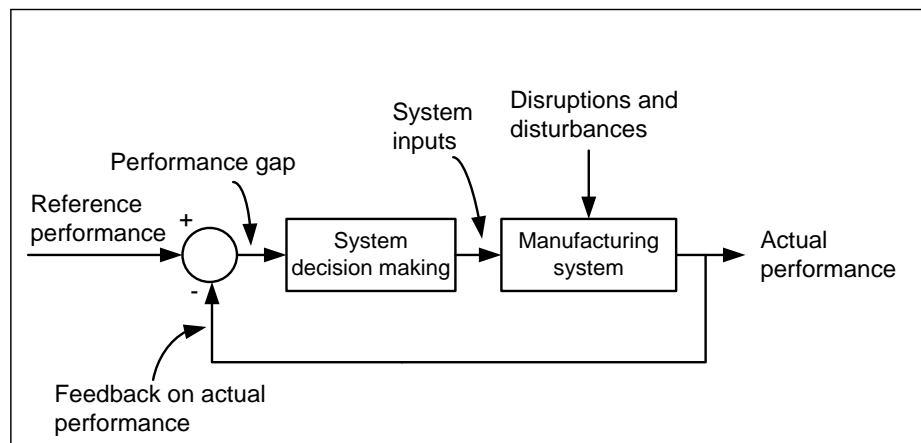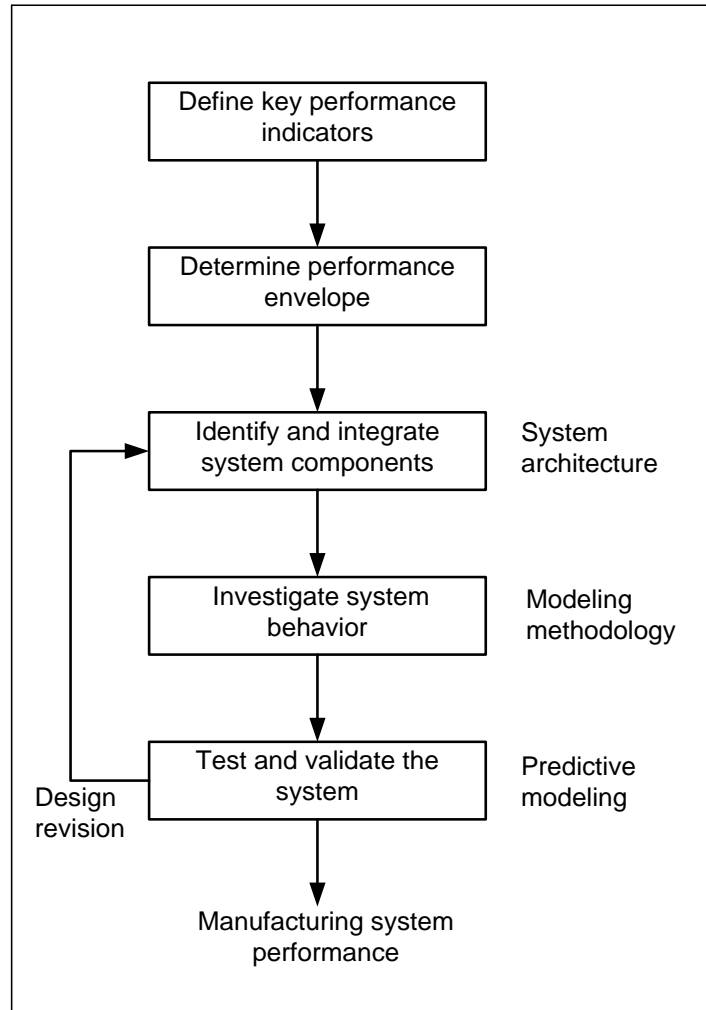

Fig. 1. Performance assurance context for a manufacturing system.

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Fig. 2. Performance assurance process during manufacturing system design.

Performance assurance requires methods and tools to track performance, recognize the effects and sources of disruptions and disturbances, and guide decision making. Tracking a system over time with a view to improving performance through corrective actions can be modeled using classical control theory. Applying control theory to a manufacturing system has been a research area for some time and is still ongoing. As early as 1979, Parnaby [5] argued that manufacturing systems are too complex to apply control theory for continuous real-time overall optimization. Instead, he proposed a theoretically-based heuristic procedure for discontinuous control. Considering that today's manufacturing systems are more automated, monitored, and controlled, research that includes continuous control is now sensible. There are different methods of control, including supervisory control, discrete-event control, hierarchical control, intelligent control, optimal control, and adaptive control. We describe one of these types of control: adaptive control, and how it can be applied to performance management.

Adaptive control is a set of techniques that provides a systematic approach for automatic adjustment of control settings in real-time to achieve or maintain required performance as system operating parameters change [6]. Knowledge of system characteristics is obtained while the system is operating and a controller adapts to the changes. In addition, the control laws change themselves as the system changes. In SMS, the adaptive control approach could conceivably be used to monitor performance as the internal situation (e.g., increase in energy usage of a machine) of the manufacturing system changes and determine required inputs to achieve or maintain required performance.

Performance assurance for SMS is analogous in purpose and scope to that of software systems and architecture and therefore, similar approaches and methods are applicable [7]. Performance assurance systems for software ensure that the software features and functionality meet requirements and that the code is bug free. By analogy, the "features" of manufacturing systems are hardware, software, and management systems while "functions" are behaviors defined by the purpose for which each system is built. "Bug free" is the elimination or minimization of performance failures triggered by disruptions and disturbances and the system being properly aligned with the intended performance objectives.

Dan Shoemaker [8] reviewed the state of the practice for software assurance. Two notable activities in this area include the Standard Assurance Environment standards emerging from Object Management Group (OMG) [9] and the Common Weakness Enumeration (CWE) repository at MITRE [10]. The OMG environment developed a rigorous framework and method for the user to specify test cases for systems assurance. The CWE is a database of known weaknesses in systems engineering, including discussion of the problems and solutions. The CWE also includes a risk assessment framework for analyzing and prioritizing the potential weaknesses relative to a given project to better understand where to focus testing efforts.

2.2 Performance Assurance as Quality Assurance

The purpose of performance assurance is for a system to perform as intended. A closely related activity for a product is quality assurance [11]. Quality assurance covers all activities (from product design to delivery) performed so that a product or service fulfills its performance requirements. If a manufacturing system is considered as a product, then the principles of product quality assurance can apply to a manufacturing system.

Table 1 compares the objectives, methods, and scope of product quality assurance with those for manufacturing system performance assurance. Performance is defined relative to how well specific objectives and goals are achieved. Examples of these are overall equipment effectiveness [12], agility [13], and energy consumption [14]. Regardless of the goals that an organization may have, the first activity is always focused on taking measurements. As such, making measurements is discussed next.

Table 1. Comparing performance assurance with quality assurance.

	Product quality assurance	System performance assurance
Objectives	Achieving high-quality product and preventing design/production mistakes/defects	Achieving high performance and preventing performance deterioration
Tools and Methods	Statistical methods Right first time	Systems engineering methods and tools Diagnostics and prognostics methods
Scope	Fit for purpose	System performs as desired
Simulation purpose (Exemplar method)	Failure testing	Simulated testing over the performance envelope

2.3 Importance of Measurement

Measurement provides necessary information to decision makers and plays a role in monitoring performance, enhancing communication, and diagnosing and solving management problems [15]. Taticchi et al. [16] noted that the process of measurement is crucial to improving business performance. Keegan et al. [17] and Ahmad et al. [18] proposed that performance measures should be derived from and be aligned with the business strategy. They synthesized a set of common performance objectives for manufacturing, namely: safety and environment, flexibility, quality, and dependability. They carried out an extensive review of performance measures used at that time, and synthesized those necessary for "world-class manufacturing," namely: top management commitment, customer service, price/cost, quality, facility control, speed, innovation, and technology.

Hon [19] extensively reviewed performance measures and identified that in addition to cost, manufacturing-oriented factors commonly assessed use are quality, productivity, time, and flexibility. Chen et al. [20] identified measures to be on-time delivery, cost of quality, and quality rate. We discuss how existing sets of indicators and measures can be adapted for SMS. But first, we clarify related terminology used in this paper.

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The terms indicators, metrics, and measurements are sometimes used interchangeably. Technically, they are different. Feng et al. [21] distinguished indicators from metrics. An indicator is a parameter, which points to, provides information about, or describes the state of a phenomenon with significance and relevance to performance objectives. According to ISO 22400-1 [22], a KPI is one that is critical to the current and future success of the organization. Indicators should, among other things, be numerically and precisely quantifiable. On the other hand, a metric is a measurable quantity for tracking an indicator or indicators. A metric can be composite, i.e., made up of two or more measurements. Measurements are the magnitude or values of actual data gathered from the process based upon a standard or unit of measurement. To track the performance of a system with respect to an indicator, it is necessary to perform appropriate and accurate measurements. To develop a measurement system for performance of manufacturing processes, we can borrow questions proposed by Tsourveloudis et al. [23]. For instance, what do we measure? How and when do we measure? How do we interpret the results? In this paper, we discuss factors that determine *what* and *when* to measure. How to measure will be covered in future work.

2.4 Measuring to Achieve Strategic Goals

Digalwar et al. [24] established that a prerequisite to managing performance is measuring performance. The nature of performance is that it is constantly changing and is unique to the system and operational situation. Establishing a single set of performance metrics across manufacturing enterprises would not only be impractical, but would also fail to address the dynamic nature of performance. Competitive priorities identified for performance management typically vary from one firm to another and shift with business demands. Measurements and metrics for performance management originate from both internal and external sources and are also driven by performance priorities of each organization [25]. In most cases, a manufacturing strategy is formulated to exploit core competencies or to target market segments that help achieve competitive advantages, and appropriate measures are determined based on the above-mentioned performance priorities and their origins.

Developing measurements that are useful for decision making has been a challenge for some time and is commonly discussed in the context of a knowledge or DIKW (Data, Information, Knowledge, Wisdom) pyramid [26]. This first pyramid in Fig. 3 illustrates how intelligence, or wisdom, is built by drawing conclusions from data, turning it first into information when context is added, then into knowledge where meaning is drawn from the information, and finally into wisdom where it can be used to guide decision making. The image suggests that each level in the hierarchy can be derived from the others. We adopt this image to illustrate the importance of measurement to performance assurance.

The second pyramid in Fig. 3 applies this image in the context of performance management. At the top level of the pyramid are the strategic goals. At the base are the measured values. Measurements are abstracted by metrics into indicators. Indicators provide a context for the measures turning them into information. Indicators in turn can be structured to logical deductions leading to KPIs, which are the basis for decision making. The final pyramid provides an example of measures, indicators, a KPI and a strategic goal. The strategic goal example is sustainability, for which a major factor can be water consumption during production. The measurements for water are water consumed, waste water, and number of parts produced. The percentage of water reclaimed is one of the indicators calculated from the measures. Ultimately, interest is in water usage per part as a KPI that can be compared with previous periods, a benchmark, a set target, or a standard. Other KPIs can be likewise abstracted.
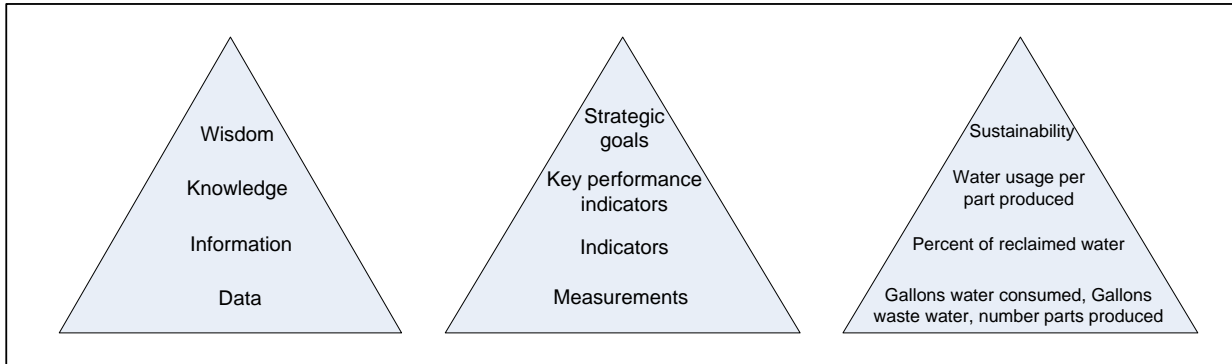
Fig. 3. The DIKW pyramid (left) applied to performance management (center) and manufacturing sustainability due to water consumption (right).

2.5 Existing Sources of Metrics and Indicators

Metrics abound. Every organization and, indeed, every opportunity for measured improvement has its own metrics. The performance measurement frameworks discussed in Sec. 3 produce a large number of metrics. Other sources for metrics include industry associations, public repositories, and research projects. Metrics developed from manufacturing research often take on the focus of a given performance objective, such as productivity, energy consumption, agility, and sustainability. We summarize some of these.

In 2014, Technical Committee 184/Subcommittee 5 (TC 184/SC 5) within the International Organization for Standardization (ISO), published the first two, i.e., ISO 22400-1 [22] and ISO 22400-2 [27], of four parts of the ISO 22400 standard on KPIs for manufacturing operations management. Manufacturing Enterprise Solutions Association (MESA) and the Supply Chain Council are two industry associations, particularly relevant to Smart Manufacturing, that publish material related to performance metrics. NIST has also established a public repository of metrics for sustainability assessment which consolidates the work of a number of organizations in the sustainable manufacturing area [28].

Further, MESA has established a metrics working group as a forum for manufacturers to share information and best practices about performance measurement and improvement [29]. The group hosts several activities, including the development and maintenance of a metrics guide book. MESA is also working with ISO on plant-level assessment standards by defining KPIs at the level of manufacturing operations management to help supply chain partners by providing commonly accepted performance measures [22, 27]. NIST, in a joint effort with the MESA metrics group, is developing a method and models for selecting KPIs appropriate for any manufacturing process. The standardized method should simplify the KPI selection process while maintaining the reliability and validity of measurements [28].

The Supply Chain Council published the Supply Chain Operation Reference (SCOR) [30]. The SCOR model was established for evaluating and comparing supply chain performance. SCOR consists of four major sections: performance, processes, practices, and people. The first, i.e., performance, specifies metrics to describe process performance and define performance goals. It also acts as a diagnostic tool for improving supply chain management and can also help in implementing targeted strategic objectives. SCOR was designed for supporting the supply chain of an organization but is useful within the organization as well.

A key requirement of SMS is that they should minimize impact on the natural environment. Research efforts are underway to develop indicators for sustainable manufacturing. In 2001, the Lowell Center for Sustainable Production, University of Massachusetts, proposed an indicator framework for raising companies' awareness and towards sustainable manufacturing [31]. The research proposed twenty-two indicators and a guide to their application in manufacturing production. Kibira et al. [32] specified high-level indicators for the environmental, economic, and social dimensions of sustainability. Joung et al. [33] categorized indicators for sustainable manufacturing, while Feng et al. [34] and Reich-Weiser et al. [35] overviewed metrics for sustainable manufacturing.

3. Methods for Assuring Performance of Manufacturing Systems

Thomann [36] defined methods as "rules or procedures that guide someone in accomplishing a purpose." Methods consist of guidelines or rules of thumb. The procedures of evaluation may be both qualitative and quantitative. Tools are based on methods and are often supplied as computer software. A software tool may be based on more than one method. In this section, we review performance measurement systems, research trends in performance measurement, performance analysis systems, emerging methods for performance analysis, performance improvement systems, and software tools.

3.1 Performance Measurement Frameworks

Performance measurement is the process of collecting, analyzing, and reporting performance information. The decision on what to measure stems from the objectives and policies of the organization. Measurements from the shop floor are analyzed and results are rolled to higher levels to determine system performance. These processes are illustrated in Fig. 4. This section reviews a sample of the measurement frameworks. Performance assurance involves (i) setting a performance target level and (ii) comparing prevailing performance against the target. The most commonly used performance measurement frameworks are:

- balanced score card [37],
- performance measurement matrix [38],
- strategic measurement and reporting technique – SMART [39],
- performance prism [40].

Efforts to enhance these frameworks to advance measurement systems to address changing industrial needs, and discussed in this paper, have been:

- integration of performance measurement [41],
- dynamic measurement [42],
- enhancement of performance measurement systems with various techniques and tools [43, 44],
- change management [45].

3.1.1 Balanced Score Card

Traditionally, manufacturers have used financial measures to evaluate performance [46]. Such measures typically assess current performance against previous periods. Current manufacturing systems are, however, characterized by change, and the effects of this change must be tracked both periodically and continuously [2, 47]. Therefore, cost and profit measures alone would not be timely in revealing areas within the organization that need to be improved. Manufacturing systems need measures for evaluating and guiding future investments, and long-term retention and acquisition of customers, suppliers, and employees.

The balanced score card (BSC) was developed to provide such features. In addition to financial measures, the BSC includes "operational measures on customer satisfaction, internal processes, and the organization's innovation and improvement activities–operational measures that are the drivers of future financial performance" [37]. Since the BSC was first developed, it has undergone two refinements to make it easier to define measures and to provide more relevance [48, 49]. Table 2 summarizes the perspectives and measurements for the balanced score card.
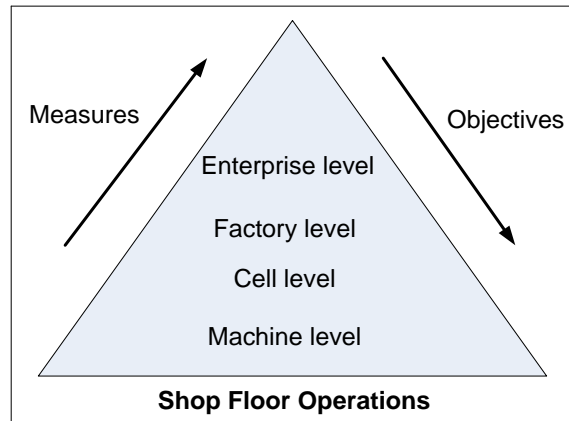
Fig. 4. Flow of performance information from shop floor to enterprise level.

Table 2. Balanced score card measurements.

Perspective	Generic measurements
Financial	Return on capital employed, value added, sales, capital flow
Customer	Customer satisfaction, retention, acquisition, profitability, market share
Internal business process	Innovation – how well the company identifies customer needs
	Operations – quality, cycle time, costs
	After-sales service – repair, service, returns
Learning and growth	People – employee retention, training, skills, morale
	Systems – measures of availability, real-time information

3.1.2 Performance Measurement Matrix

The performance measurement matrix was also developed to answer the need for balanced measurement. It was proposed by Keegan et al. [38] after realizing that many organizations have far too many irrelevant performance measures. It was felt that some of these measures were obsolete and inconsistent and that they could actually frustrate implementers of organizational strategy. The premise of the performance measurement matrix is that measures have to be classified into financial and non-financial impacts on business performance, each depending on both internal and external drivers. Neely et al. [50] modified the original performance measurement matrix. The modified measurement matrix assumes two basic types of performance measures, those that relate to results (competitiveness, financial performance), and those that focus on the determinants of the results (quality, flexibility, resource utilization, and innovation). The results are termed "lagging" while the determinants are "leading" indicators.

3.1.3 Strategic measurement and reporting technique – SMART

The SMART performance measurement framework was developed by Wang Laboratories, Inc. to improve performance measurement over the traditional measures [39]. SMART integrates organizational objectives with operational performance [51]. The SMART performance criteria and their definitions, which originated with Doran [52], used in the SMART framework have become iconic:

- **S**pecific – what are we going to do for whom?
- **M**easurable – is it quantifiable?
- **A**ttainable/Achievable – can we get it done within the time frame?
- **R**elevant – will this objective affect the desired goal?
- **T**ime bound – when will this objective be accomplished?

The SMART framework uses both external and internal performance measures. There are four levels in the pyramid of objectives and measures (Fig. 5): corporate vision and strategy, market and financial

performance measures for business units, objectives and measures (e.g., customer satisfaction and flexibility, and quality, delivery, process time), and cost for each department and work center. SMART's strength is in its direct intention of integrating corporate objectives with operational performance, as well as its focus on managing strategic objectives. However, as Striteska et al. [53] have pointed out, SMART's weakness in comparison with BSC and the measurement matrix is that it does not provide a mechanism for specifying KPIs.
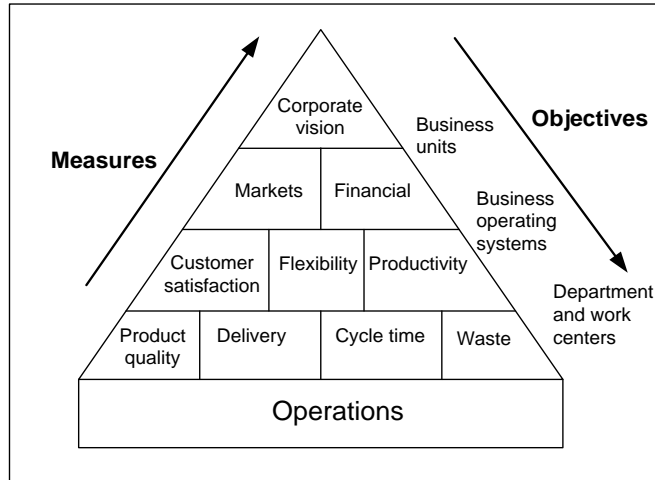

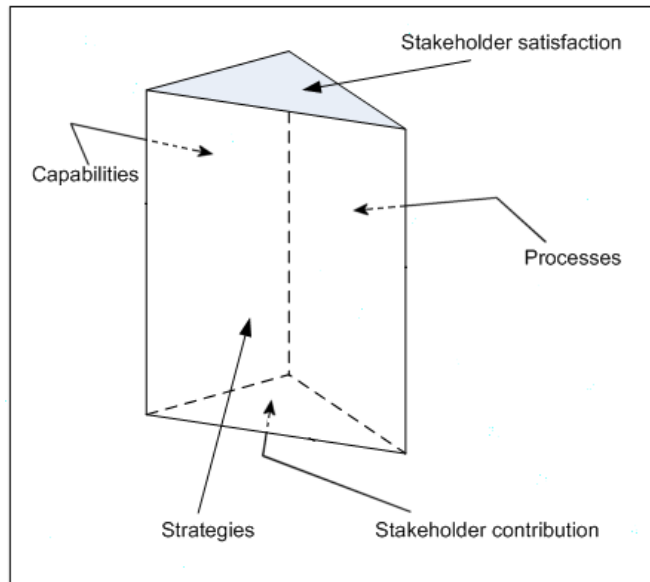**Fig. 5.** The SMART performance measurement framework.

Fig. 6. Performance prism.

3.1.4 Performance Prism

The focus of the performance prism is to identify all of the stakeholders and to deliver appropriate value to them [40]. As the name suggests, its concepts can be illustrated using a triangular prism, as Fig. 6 shows. The base represents stakeholder contribution while its opposing side represents stakeholder satisfaction.

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Three sides represent the strategies, capabilities, and business processes that deliver products and services. There are five perspectives that the prism seeks to integrate through five fundamental questions:

- **Stakeholder Satisfaction:** Who are the stakeholders and what do they want and need?
- **Stakeholder Contribution**: What is wanted and needed from the stakeholders?
- **Strategies:** What strategies need to be put in place to satisfy these sets of wants and needs?
- **Capabilities:** What capabilities – people, practices, technology and infrastructure – need to be put in place to allow us to operate processes more effectively and efficiently?
- **Processes:** What processes need to be put in place to satisfy the wants and needs?

3.1.5 Comment on Performance Measurement Systems

Performance measurement systems and frameworks need improvements to be more relevant for smart manufacturing assurance. The features lacking in existing frameworks are:

- Integration with other management and manufacturing systems and data,
- Multi-level dynamic performance assessment,
- Real-time dynamic performance assessment across multiple criteria,
- Integration into operational control systems, which would require not only evaluation of multiple performance indicators but mechanisms for specifying constraints for optimizing among multiple criteria,
- Methods and framework for collecting and communicating measurements from the shop floor.

Research efforts to address the first two bullets are reviewed in Secs. 3.2.1 and 3.2.2 while the remaining three bullets are discussed in Secs. 5.1 and 5.2.

3.2 Enhancements to Performance Measurement Frameworks

This section discusses integrated performance, multi-level performance measurements, and the use of tools to enhance measurement frameworks. We also address needs for performance measurement frameworks to address change in operating environment.

3.2.1 Integrated Performance Measurement

Integrated performance measurement systems introduce a proactive closed-loop control system in performance management where corporate strategies are employed in all business processes, activities, and tasks. Feedback is obtained through actual measurement from the lowest level activities progressively to higher levels, e.g., from business activities, to business processes and business units all the way up to corporate level. Integrated performance measurement seeks to establish structural relationships between performance measures, and develop a reference model for comparing different integration approaches [54, 55].

3.2.2 Multi-level, Dynamic Performance Measurement

Research into this area is geared to developing measurement systems in continuous pursuit of company objectives. An example is the integrated dynamic performance measurement system (IDPMS), which provides an approach to support alignment of objectives across managerial and operational levels [41]. The system comprises and integrates three main areas that facilitate performance measurement and improvement, i.e., management, process improvement team, and shop floor. The system has feedback loop between the shop floor and the process improvement team. The three areas are linked through specification and reporting on the defined areas of success, performance measures, and performance standards. The feedback on performance as the operating environment changes provides the dynamic updates [42]. These concepts are illustrated in Fig. 7.

Although research in this area has been ongoing for almost two decades, fully developed systems in use are not common in literature. The results from this research, if published, could be used to complement performance improvement frameworks such as the Plan-Do-Check-Act cycle (discussed in Sec. 3.6).
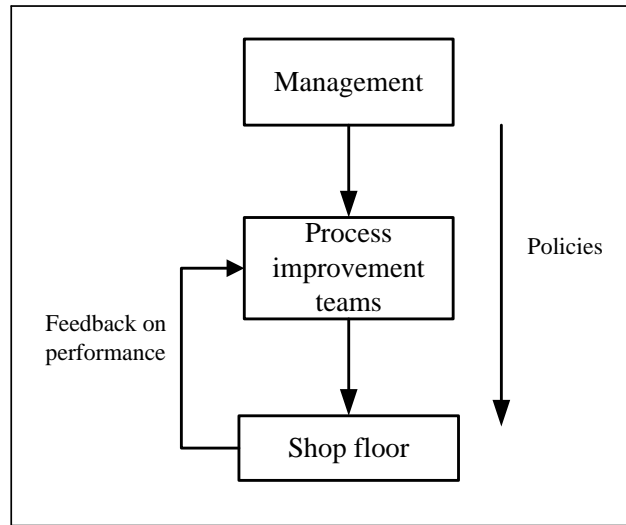
Fig. 7. The integrated dynamic performance measurement system framework.

3.2.3 Integration with New Tools and Techniques

Specific tools and techniques to enhance performance measurement include Data Envelopment Analysis (DEA) [43] and Analytical Network Process (ANP) [44]. Examples of applications of these are Ucal and Öztaysi [56], who used ANP to quantify performance of a manufacturing system based on selected performance criteria and sub-criteria of a manufacturing firm, and Benbarka [57], who explained how DEA can be used as a tool to measure organizational performance over time.

Other forms of enhancing measurement systems are expected through application of emerging technologies. The prospects for adapting current approaches to performance assurance are to be discussed in Sec. 4. In the following bullets, we summarize recent technology trends that will impact measurement frameworks:

- increased availability of real-time system information,
- improved acquisition and communication of information such as customer orders to the design and production system, enhancing the ability for mass customization,
- improved integrated performance management systems for addressing multiple objectives of manufacturing,
- increased proliferation of continuous improvement programs and standards,
- integrated performance measurement becoming part of overall planning and operational systems.

Some of the main challenges to leveraging the above trends in technology are inconsistent information quality and lingering interoperability limitations [58, 59]. SMS applications are composed of different components and heterogeneous technologies. New standards need to be developed or existing standards enhanced for interfacing between different platforms to enable data processing, analytics, and use. Automated tools still require human expertise to reliably extract and identify relevant data for existing analytical tools.

3.2.4 Research to Develop New Frameworks

Wibisono [60] argued that performance measurement systems are becoming obsolete and that new dynamic frameworks are needed. In particular, the observation is that current systems cannot balance short-term vs long-term measures, internal vs external measures, and financial vs operational measures. He identified nine steps in formulating an improved performance measurement system for manufacturing. These are (i) determine a PMS framework, (ii) identify company environment, (iii) formulate a company's mission

statement, (iv) analyze current PMS, (v) determine performance variables, (vi) determine cause-effect amongst variables, (vii) determine performance standards, (viii) determine improvement priority, and (ix) formulate recommendations to address gaps in performance. Wibisono's ideas were tested by conducting interviews and a field survey in ten large manufacturing industries. Each company provided experts to validate the framework in terms of their KPIs, suitability of the indicators, benchmarking of the indicators, and linkage amongst the indicators. The response from this exercise indicated that the framework would offer advantages over the existing balanced score card and performance prism, which require "further adjustments" before implementation.

3.2.5 Performance Measurement and Change in Operating Environment

Manufacturing systems are characterized by constant change. Major changes that routinely affect manufacturing systems include type of products made and environmental regulations, yet most assessment and measurement systems used today tend to be static. Change also affects the ability of measurement frameworks to address user assessment needs. To address change needs, Salloum [61] developed a framework for manufacturing organizations to develop dynamic performance measurement systems. To be effective, performance measurement systems have to be integrated into existing management information systems (MIS). In this context, Nudurupati et al. [62] proposed roles for MIS in implementing a performance measurement system from its design through implementation, use, and review.

The above publications indicate that future performance measurement frameworks for SMS might enable users to continuously update measurement systems as technology and strategic goals change.

3.2.6 Change Management

Change management is the systematic approach to dealing with transitioning from one state of an organization to a different future state. Recognition that purely financially based performance measures are no longer adequate has led to changes in performance measurement frameworks. Concerted efforts are needed while transitioning from using one framework to another especially since it has been observed that many attempted implementations of new systems fail [63]. This is because the process of implementing new performance measurement systems requires careful change management. Engineering change management is a process for which the Automotive Industry Action Group (AIAG) has done extensive work in collaboration with global OEM-supplier VDA-Germany, GALIA-France, Odette-Sweden, and JAMA-Japan [45]. AIAG has published recommendations for change management that could be applied globally.

3.3 Performance Analysis Methods

Smart manufacturing systems are characterized by machines being outfitted with sensors and monitors and then networked together using wireless technologies. These devices and technologies are collecting larger amounts of data than was previously available [64]. The data being collected across the manufacturing operation—and external data from customer orders, product field data, and suppliers—is flooding into manufacturing enterprises. This abundance of data calls for enhanced or new analysis methods.

The methods discussed in this section are widely used in analysis and decision making among manufacturing systems. Methods commonly employed for analyzing data produced by manufacturing systems employ a variety of techniques, each with its own strengths, limitations, and success record depending on the situation to which it is applied. Established methods include statistical methods and machine learning, decision theory, computer simulation, and operations research.

3.3.1 Statistical Methods and Machine Learning

Manufacturing engineers on the shop floor cannot observe or record a system's entire body of data and have traditionally relied on a collected sample to draw conclusions about the system. The data mining and analytical methods being developed, however, are poised to provide conclusions from not only large volumes of static data but also in real time from large streaming data. These methods are discussed in subsequent sections. Still, conventional statistical techniques (as reviewed in the next two paragraphs) will continue to be

important since they are also part of advanced analytics methods being developed by research organizations and industry.

Statistical analysis methods include statistical process control, correlation analysis, regression analysis, hypothesis testing, categorical modeling, analysis of variance (ANOVA), general linear model, computational statistics, and computational Bayesian modeling. Statistical methods are particularly useful during operation to measure, predict, and control performance of systems. One area of application is quality control where statistical methods analyze regular measurements of a quality characteristic of a product [65]. The analysis results indicate whether the system is operating as intended. Correlation analysis determines whether there is a relationship between sets of data; and where a relationship exists, it is determined through regression analysis. Hypothesis testing tests a claim about a parameter in a population, using measured data. Analysis of variance is used to compare three or more data sets.

Statistical methods applications in manufacturing are for process improvement and productivity gains, in addition to product quality improvement. Because of the increasing complexity of the systems and the larger number of parameters involved, statistical methods, through modeling, optimization of manufacturing parameters, and monitoring and control, have greatly increased [66]. One of the critical areas for statistical methods for performance assurance is in establishing and maintaining reliability of manufacturing equipment. Raheja et al. [67] define assurance as processes for ensuring that a product performs well during its expected life. In the case of machines on the shop floor, accelerated experiments and other assurance methods are used to reduce equipment failures during actual use. Barabady [68] used the term "production assurance" to describe the methods for ensuring that equipment and machines are available to meet the requirements for demand deliveries. Lastly, statistical methods are now poised to analyze the vast data available to obtain more insight and to better predict future system status [69].

Machine learning is a discipline of constructing algorithms that can recognize and learn from patterns in data [70]. The algorithms can be from a variety of fields including statistics and information theory. Machine learning uses data as a learning set for future decisions. Statistical methods and machine learning are poised to become leading methods for performance assurance because of the large increase in data obtained from manufacturing systems in real time. Section 3.6 discusses the role of these methods in continuous performance improvements based on data analysis.

3.3.2 Operations Research Methods

The field of Operations Research (OR) comprises analytical methods that are employed to obtain optimal or near-optimal solutions to complex decision problems. Examples of the methods are linear programming, nonlinear programming, stochastic programming, network flow programming, integer programming, queuing theory, inventory theory, and data envelopment analysis. OR methods help model the structure of complex situations, and utilize this understanding to predict system behavior and improve system performance. OR applications in manufacturing include part routing, workflow improvements, elimination of bottlenecks, inventory control, business process re-engineering, site selection, facility layout, and general operational planning [71].

A major area of OR for manufacturing applications is production scheduling [72]. Solutions to scheduling problems can lead to improved performance through optimal use of resources. Engau [73] proposed OR methods for solving environmental sustainability problems. There are a number of OR techniques and methods from which to select for particular applications in specific SMS environments. To optimize multiple performance objectives, OR methods can be combined with data analytics and simulation models. For example, they could be used in conjunction with multi-criteria decision making methods to optimize manufacturing performance through several simulated scenarios. In summary, potential areas for OR are:

- Optimizing layout and configuration of the manufacturing system,
- Deriving a production plan that optimizes a given objective such as minimum cost,
- Assessing, comparing, and tracking performance of different units.

This potential notwithstanding, currently OR has had little impact in real life manufacturing environments. This is mainly because solutions from these models are often obtained after unrealistic assumptions and are time-consuming [74]. Moreover, the situation on the shop floor changes continuously. Summary of general weaknesses of OR are:

- They mainly apply where factors can be quantified. In many cases such as human behavior, this many not be possible,
- They involve assumptions that require assigning quantitative values to factors, with a result that can be subjective and inaccurate,
- They are less efficient for systems with continuously changing data,
- The techniques and models described in literature are often different from those actually used in practice [75],
- Optimal solutions are often computationally complex [75].

3.3.3 Decision Theory

Decision theory is the study of preferences, uncertainties, and other issues related to making choices for obtaining the best outcome of a situation. Dieter and Schmidt [76] described several steps for making decisions. The steps start with determining and prioritizing objectives, and end with making and evaluating the future impact of the decisions. The authors also describe three situations that make decision making difficult. These are (i) decision under uncertainty—each state of nature has an assigned probability of occurrence, (ii) decision under risk—each action can result in two or more outcomes, but the probabilities of occurrences unknown, and (iii) decision under conflict—where decisions to improve any performance objective results in a deterioration of another.

A first step in making a decision is to precisely describe the objective(s). The potential presence of more than one objective has led to the development of multi-criteria decision-making methods. Multiple criteria decision making (MCDM) refers to making decisions in the presence of multiple, often conflicting, criteria. Triantaphyllou [77] determined that there are many ways to classify MCDM problems and that one of them is by the type of data they use. Data can be deterministic, stochastic, or fuzzy. However, the methods for solving MCDM problems are largely of two types, and they depend on the problem setting: one type utilizes a finite number of alternative solutions, while the other utilizes an infinite number of solutions.

During manufacturing system design or operation, the characteristics, parameters, or attributes upon which a decision has to be made can take any value within a given range. Therefore, the potential alternative solutions can be infinite. The problem is then referred to as a multiple objective optimization problem. Selection of a solution can depend on the preferences of the stakeholders. Triantaphyllou [77] reviewed a number of MCDM methods used. They include the weighted sum method (WSM), weighted product method (WPM), and analytic hierarchy process (AHP), elimination and choice translating reality (ELECTRE), and technique for order preference by similarity (TOPSIS). Another common approach is to rank the alternatives from the best to the worst, based on the stakeholder's preference precedence. The Analytical Hierarchy Process (AHP), developed by Saaty [78, 79] is one of the most commonly used ranking methods in industries. It can handle both qualitative and quantitative attributes.

SMS with multiple objectives related to several indicators would benefit from multi-criteria decision making methods. An example of MCDM in manufacturing is the selection of a process plan and machine settings for manufacturing a machined product. Performance indicators are often conflicting such that improving one (e.g., energy consumption) diminishes the performance of another (e.g., cutting tool life). Given that, in a typical job shop, there are alternative resources that can generate the same feature on a part, specifying the best set of resources (i.e., the optimal selection of process plan) is the main objective problem. The resources and corresponding processes can be specified in an operation method matrix. Before determining the process plan that has the optimal impact on environmental sustainability and productivity, a range of process plan parameters (process settings) has to be assigned. MCDM through multi-objective optimization can address this problem.

3.3.4 Computer Simulation

Simulation provides the ability to model, analyze, and iteratively test manufacturing systems in a virtual environment to optimize plans before implementation, after which, failures become costlier. The main methods for simulation are system dynamics, discrete event simulation, virtual reality modeling, agent-based simulation, and Monte Carlo simulation. A simulation model can incorporate production schedules,

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priorities, equipment capabilities, layout, costs, and other factors. Different simulation models can be built to analyze a system depending on the stage in the system life cycle. Simulation models built for manufacturing system concept development and design traditionally differ from models for operational decision-making. Here we examine these models in turn; however, in SMS these distinctions may begin to blur as more real-time data becomes available.

An early application area for computer simulation in manufacturing decision-making was the general domain of production system design. The results of running simulation models are useful to plan for long-term demand and demand variations to determine plant capacity requirements, and inventory levels. The main goal identified by Košturiak et al. [80] is that in a production system design, the planned and actual requirements and resources are correlated as much as possible. To facilitate this undertaking, Chomiakow [81] used system dynamics to develop a generic pattern for modeling manufacturing plants that includes factors such as production capacity and inventory, demand and sales, costs, and sales price. The generic pattern can be adapted to different systems and operating environments.

The design and development of a manufacturing system is preceded by the discovery of general production requirements through the use of system dynamics models. The output of these models can form the input to discrete-event simulation models for decision making regarding process design, resources selection, and layout. Negahban and Smith [82] carried out a survey which showed that the major concerns investigated by discrete-event simulation during systems design are production rates, general system layout, material handling, cell systems, and automation equipment. At the process level, virtual reality modeling facilitates workstation design and human task performance analysis.

Simulation is often criticized for not directly providing optimal solutions. Nonetheless, it is one of the most widely applied methods for assuring manufacturing performance [83, 84]. Simulation enables data input at fine levels of detail and limitless configurations, sometimes referred to as "what if" scenarios, to be considered. Simulation can be used to generate and fill gaps in missing data so that a manufacturing system can be analyzed by other methods. It can provide system operation visualization capabilities to allow better understanding of component interactions and performance. Simulation applications are projected to have wider applications in SMS. For example, Shao et al. [85] demonstrated how simulation can be used to generate data to evaluate manufacturing data analytics applications. For this approach to be effective in real application, however, data-generating models require improved verification and validation methods. Other potential applications include use of simulation in the loop for continuous SMS performance improvement and for filling gaps in system-collected data.

Despite great potential for SMS, in their report on role of simulation for future manufacturing, McLean and Leong [86] observed major challenges for wide-spread application of this technology. These are (i) cost, which is mainly driven by requirement for modeling expertise and cost of software acquisition, and (ii) data interface problems, which are due to limited interoperability between manufacturing applications and simulation tools. Other problems are the burden of having to produce each new simulation from scratch, the need for a diverse set of skills, verification and validation of models, data availability, and interpretations of simulation outputs. In addition, simulation models may need high levels of fidelity to be of use in SMS.

Since that publication [86], there have been efforts to address some of the above challenges, although the solutions are still limited in scope. For example, simulation tools are providing more visualization capabilities, which allow the user to manipulate objects and optimize a design in a virtual environment. Such tools enable the creation of a virtual enterprise that can be operated side-by-side with the real system to optimize operation in real time. Secondly, simulation tools are becoming more readily available and easier to learn. Regarding integration of tools, many simulation applications are still not easy or possible to integrate if obtained from different vendors. However, efforts have been initiated for integration through developing standards for neutral data representations. Examples are the Core Manufacturing Simulation Data (CMSD) and the OAGIS standards.

The CMSD standard was developed so that data can be shared between simulations and manufacturing applications [87]. CMSD can facilitate exchanging data across different simulation models in a supply chain or between departments. A limitation is that it does not support integrating simulations along a vertical scale, i.e., across hierarchical levels. Another standard for data interoperability is the OAGIS [88] from the Open Applications Group. OAGIS approaches the integration problem by establishing integration scenarios for a set of applications including enterprise resource planning, production scheduling, manufacturing execution system, and capacity analysis. The main emphasis of the OAGIS standard is at the enterprise level. There is

also the ISA-95 standard, which defines interfaces between enterprise activities and shop floor activities [89]. This standard is oriented primarily towards the operations level. There remain gaps in these standards for modeling the exchange of data between and amongst different manufacturing applications, models, and simulation tools.

3.4 Emerging Methods for SMS Performance Analysis

Systems engineering is a discipline expected to play a significant role in SMS. Systems engineering uses requirements analysis to develop functional and physical definitions as a basis for systems and product designs [4]. OMG standardized SysML as a language for representing system designs for more widespread deployment of system engineering by creating a market for vendor support of SysML-based tools [90]. SysML is a diagramming method based on the Unified Modeling Language (UML) and is specifically tailored to the needs of system representation. SysML supports the coupling of system requirements with the system design. A large advantage in this approach is that requirements for a system can be managed along with the system. Changes to either can be automatically processed to identify the implications for the other. SysML also facilitates system deployment in automating the development of tests of an implemented system based on the planned requirements. Fundamentally, SysML supports a style of design known as Model-based System Engineering where the model of a system becomes the master of the system as opposed to a more traditional document-centric approach [91].

As already observed, manufacturing system operations need decision making to achieve and maintain desired performance. Such decisions must be made using different types of models and large amounts of dynamically collected data. These models, including operations research, data analytics, and machine learning, need unification so that the user does not have to generate inputs multiple times using different data abstractions. Decision Guidance Management System (DGMS) is an example of a platform that provides such unification. DGMS is a productivity platform for fast development of applications that require closed-loop data acquisition, learning, prediction, and decision optimization [92]. Brodsky and other researchers at George Mason University conceived DGMS to support closed-loop data acquisition learning, prediction, and decision optimization by using a decision-guidance database and a productivity tools' platform for fast development of decision-guidance databases. Decision guidance management systems (DGMS) support what-if analysis, monitoring and control, statistical learning, and decision optimization using the Decision Guidance Query Language. Application of DGMS to SMS is still in the research stage but its potential has been demonstrated for decision making to minimize energy consumption in machining operations [93].

3.5 Performance Improvement Methods

Performance improvement involves analyzing the operations of an organization and setting up approaches to improve performance. A widely used performance improvement method is Plan-Do-Check-Act (PDCA) [94]. PDCA is a four-step cycle for affecting positive change and has been applied in various areas of performance improvement [95]. Performance improvement methods such as Lean manufacturing, Six Sigma, and Total Quality Management that are discussed later in this section were conceived and are implemented on the basis of the PDCA cycle. The PDCA cycle emphasizes that even after improvements have been identified and implemented, further improvements are sought. PDCA is now the foundation of all ISO management standards [96]. The PDCA approach is to plan, implement, check for improvements, and act by revising plans to achieve better results, in a continuous cycle. PDCA can be used at any stage of the SMS life cycle and can be integrated with other methods. In the following section, we review derivatives of the PDCA cycle in manufacturing and provide an introduction to real-time performance improvement approaches.

3.5.1 Derivatives of the PDCA Cycle

Deming [97] introduced the Plan-Do-Study-Act (PDSA) cycle, which is a modification of the PDCA. In PDSA "study" replaces "check." PDSA also involves asking questions such as "what did we learn?" and "what went wrong?" It is considered to be more effective than PDCA. Langley, Nolan, and Nolan [98] modified the PDSA cycle by appending three activities and produced a "model for improvement." The

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activities added are: defining an acceptable level of performance, feeding back information to learn whether the change is an improvement, and specifying the changes necessary to result in improved performance. Another derivative is the Define-Measure-Analyze-Design-Verify (DMADV), which is sometimes called Design for Six Sigma (DFSS). DFSS is useful for designing and testing [99]. There is also the Design-Measure-Analyze-Improve-Control (DMAIC) [100], which stresses means for identifying root cause of problems and developing solutions. The solutions to the problems can be generic or specific to the given problem. Although many of these methods were developed for quality improvement, they equally apply to other performance objectives. They are also often used hand-in-hand with lean techniques for eliminating waste in manufacturing.

3.5.2 Lean Manufacturing, Six Sigma, and Total Quality Management

Lean manufacturing, Six Sigma, and Total Quality Management are among the common performance improvement methods used in manufacturing. The following paragraphs overview these methods.

Lean manufacturing is a systematic process for eliminating waste within manufacturing processes [101]. Waste is any activity that does not add value to the final product. Lean manufacturing emerged from the Toyota Production System (TPS), which aims to minimize work-in-progress inventories in the manufacturing process. TPS uses Just-in-Time tools. The goal of lean manufacturing is broader than TPS in that it focuses on the systematic elimination of all forms of waste from the operations [102]. One major method to implement lean manufacturing is to use the PDCA cycle where waste reduction is performed on a continuous, iterative basis. Tools have been developed to identify, measure, and eliminate waste in manufacturing systems.

Six-Sigma is a paradigm that emphasizes the idea of getting to the root cause of quality problems to improve the process [103]. It achieves this by a process of continuous improvements such as the PDCA cycle [104]. Six-Sigma was originally developed by Motorola during the 1980s. Six Sigma techniques and tools aim to have only 3.4 defective parts per million cases. Improving a process inevitably incurs a cost to implement and the decision for improvement of each process in the manufacturing system depends on the strategic importance of the process as well as the benefits expected.

Total Quality Management (TQM) focuses on achieving objectives of providing products and services with a level of quality that the customer wants [105]. The approach to achieving these objectives is employee involvement and developing an integrated systematic approach for continuous improvement. TQM evolved out of the work done by Deming to improve quality of Japanese-manufactured products. When American manufacturers started losing market share to Japanese products, they decided to employ TQM techniques in the 1980s. Ford Motor Company, under Chief Executive Officer Donald Petersen, was one of the first major manufacturers to implement TQM in the U.S. Almost instantly upon TQM implementation, Ford's market share rebounded and for two consecutive years; 1986 and 1987 was more profitable than General Motors [106, 107]. There are twelve points to implement TQM: committed leadership, adoption and communication of TQM, closer customer relationships, closer supplier relationships, benchmarking, increased training, open organization, employee empowerment, zero-defects mentality, flexible manufacturing, process improvement, and measurement.

3.5.3 Using Real-time Data Analytics for Continuous Performance Improvement

Continuous improvement refers to ongoing efforts to improve products or processes. Improvement can occur in a "breakthrough" event all at one time or may manifest itself in the form of "incremental innovation" over time [108]. Incremental innovation is the action of performing a series of small improvements in the product or production process. Incremental innovation implies real changes in the product design as required by consumers or changes in the manufacturing process due to, for example, advances in technology [109]. The concept of continuous improvement has existed in manufacturing since the beginning of the industrial revolution. The techniques that have been discussed in this section (Sec. 3) are part of the activities that generally drive an organization towards "continuous improvement." An example framework for continuous performance improvement of manufacturing systems was proposed by Hernandez-Matias et al. [110]. This framework increases the capability of modeling tools to model systems by creating a structured database with different levels of detail to obtain KPIs. The following paragraphs discuss how data

from a manufacturing process can be harnessed for real-time continuous improvement of manufacturing systems.

Many engineered systems are designed with clear objectives and are usually operated under controlled conditions; therefore, performance improvement activities based on mechanistic models and first principles can be reliably applied [111]. During operation, however, circumstances emerge that were not factored into the design. In such cases, data becomes an indispensable asset for improvement. The large amount of constantly streaming data seen today has created a need to increase pace in the advancement of data analytics methods. Many new approaches are under development to use state-of-the-art real-time data-processing technologies recently available from the information technology community [112]. Among these are the real-time analytical systems being looked at to augment performance improvement activities of enterprises. Driven by the motivation to increase adaptability and responsiveness of SMS, new capabilities are being developed for analytics' solutions to process large amounts of data to develop actionable intelligence and may even be introduced into automated controls.

A McKinsey report defined four types of data analytics important to manufacturing: data visualization, correlation analysis, significance testing, and neural networks [113]. The report describes the application of these techniques to identify patterns to prioritize data collection and analysis, identify core determinants of performance deviations, test the significance of variables in root cause analysis of problems, and model complex processes for optimization. These types of analysis can be applied in a manufacturing environment to improve performance at all levels of the business from machine performance issues through higher-level enterprise optimizations. For example, at the machine level, Park et al. [114] described a data-driven method for energy prediction for a milling machine that would help make design decisions based on energy demands. At the enterprise level, Song et al. [115] used data analytics to identify system bottlenecks and improve the design of system flow.

To realize the potential of big data for performance improvement of an organization, understanding the relationship between proper analytical techniques and disparate data sources to extract usable insight is currently under investigation, but has yet to see widespread application. Creating fully deployable analytics solutions is a complex process requiring skills from many disparate areas. To successfully build a real-time analytical solution for a manufacturing organization requires rethinking and reengineering operational processes and data collection, storage, and analysis [116]. Advanced tools, software, and systems are required to capture, store, manage and analyze data sets, all in a timeframe that preserves the intrinsic value of data [117]. Kumaraguru et al. [118] identified the need for integrating such data analytical tools into a continuous performance management cycle for SMS. In view of this, Zhao et al. [119] noted that focused research efforts are needed to link the foundational elements of SMS with operational and enabling elements of such systems.

Continuous performance improvement methods frequently employ data-driven prediction models. Bridging the gap between predicted performance and actual performance will need diagnostic and problem-resolution capabilities. Continuous monitoring of indicators and metrics at different strategic, tactical, and operational levels in real-time will enable drilling-down to root causes of performance problems. Further, in order to determine the best course of action based on metrics, models that describe relationships between indicators, metrics and data at different levels of the decision hierarchy is required. This is an area of research as integrated system modeling approaches such as virtual factory or the digital twin that are being advanced. The next section provides a sample of software tools that are currently available for various purposes in manufacturing analysis and decision making.

As we close discussion on data analytics, it is pertinent to mention a new technique: process mining. Process mining is similar to data analytics and has potential to enhance performance improvement efforts. Process mining focuses on analyzing information from event logs produced by manufacturing and business processes to plan, analyze, and optimize operations in a dynamic environment [120, 121]. Process mining has already proved feasible and effective in identifying areas in processes that need improvement. Yahya [122] provides existing industrial works on process analysis in manufacturing using process mining.

3.6 Software Tools

Many commercial platforms, tools, and performance management systems have been developed for specific evaluation, analysis, and improvement of manufacturing systems. Table 3 provides a sample of

methods and software categories. Many vendors also provide solutions with abilities to integrate data from different organizational departments and subsystems. While Table 3 categorizes software according to methods of application discussed in this paper, they are often marketed for specific functions such as bill-of-materials processing, planning and scheduling, order promising, demand forecasting, and inventory management. MESA has compiled a list of software vendors from among its members [123]. To analyze tools available from vendors, various dimensions for classifications may be employed. One approach is to identify tools needed in each phase of a manufacturing system life cycle that includes conceptual design, detailed design, testing, improvement, and operation. Another dimension could be tools required for various hierarchies of business processes from enterprise decision-making to shop floor activities.

Alternatively, software tools can be analyzed after classifying their applications with respect to performance objectives of SMS. An example of a performance objective is sustainability. Sustainability relies heavily on life cycle assessment, which is a technique to assess the environmental and potential impacts of a product, process, or service. Tools have been developed over the years for analyzing operations to achieve some aspect related to the other high-level objectives of smart manufacturing.

Table 3. Example software tools from each category.

Category	Method	Purpose
Performance measurement	Learning, statistical, various analyses	Implementing a nine-step metric assessment, action planning, and performance collaboration
Performance analysis	Statistical method	Addressing operational readiness, equipment monitoring, maintenance, and system effectiveness and improvement
	Machine learning	Inductive inference
	Operations research	Optimization
	Simulation	Manufacturing process Simulation
	Data analytics	Predictive analytics
	Process mining	Extracting knowledge from event logs
Performance improvement	Lean Six Sigma	Lean process improvement
	Total quality management	Automating processes, integrating business systems, and fostering collaboration and continuous improvement

4. Applying Performance Management Methods to SMS

This section discusses development of an SMS performance-assurance system based on the methods discussed. It first reviews current manufacturing performance objectives at a higher level as discussed in the introductory chapter. These are: agility, which is driven by the need for rapid adaptability of manufacturing processes in response to customer needs and internal impediments; sustainability, which is driven by an increased global awareness of the impact of human activity on the natural environment; and, productivity, which is a business driver for maximizing returns on investments. We then discuss sources of and challenges to overcoming performance exceptions and data collection. This section ends with proposed general steps for performance assurance methodology.

4.1 Targeted Performance Objective for Smart Manufacturing – Agility

A central theme for performance of SMS is agility because of the need to respond to unpredictable events that are a feature of today's manufacturing environment. The high-level focus to achieve agility is on customer satisfaction, learning, and willingness to change. Agility provides an organization with strategic ability to adjust operations as requirements change and able to reorganize after major stress or shock. Jung et al. [124] illustrates an understanding of agility by tracking the percentage of orders that are perfectly fulfilled where there is a disturbance in operations that lead to inferior system performance. A resilient organization minimizes performance deterioration in any measure during such conditions. Agility is the key for achieving resiliency. To make manufacturing systems more agile, solutions such as modular organizations, flexible-manufacturing systems, lean manufacturing, holonic manufacturing systems, and virtual corporations have been proposed and deployed.

Literature review shows that many researchers have investigated agile performance of manufacturing systems over the years [125, 126, 127, 128, 129]. Each research analyzed particular attributes of agility,

mainly at two organizational levels: enterprise and manufacturing operations. In a major review of performance measurements, Hon [19] perceived agility from only the perspective of flexibility and responsiveness but did not define agility measures. Sherehiy et al. [128] carried it further and added responsiveness, culture of change, speed, integration and low complexity, high quality and customized products, and mobilization of core competencies.

The SCOR model describes business activities associated with satisfying a customer's demand and identifies performance attributes for reliability, responsiveness, agility, costs, and asset management efficiency [30]. SCOR defines agility as the "ability to respond to market place changes to gain or maintain competitive advantage." Although this perspective has traditionally viewed agility as a capability to effectively respond to events that are external to the organization, a recent trend has been to include internal events as well. SCOR defines non-computable agility metrics for flexibility and adaptability. While the model specifies computable metrics for the other performance attributes, i.e., reliability, responsiveness, costs, and asset management, it does not do the same for flexibility and adaptability, even though these attributes would enable defining the necessary specific measurements for agility. However, the SCOR model identifies business processes for which agility measures can be specified.

To design an agile manufacturing system, it is necessary to focus on essential characteristics that affect agility, e.g., changeover time, product variety, and versatility. Modeling methods and tools (e.g., simulation) can be used to select and investigate   agility performance of a particular configuration of the manufacturing system when subjected to disturbances and disruptions. A trade-off can then be made between the cost of the required system components and the desired system performance. Ramasesh et al. [126] applied this simulation approach and developed a modeling methodology for appraising a system's performance and justifying decisions by exploring the financial value of investing in technologies that facilitate defined agility characteristics.

4.2 Targeted Performance Objective for Smart Manufacturing – Sustainability

There are various ways and levels of assessing the sustainability of manufacturing systems, processes, and products. One of the most commonly used methods is Life Cycle Assessment (LCA); however, the approach is mainly product-centric in that the assessment treats the manufacturing stage of a product as a single transformation event. As such, the majority of research efforts for manufacturing sustainability have not particularly focused on process assessment. The sustainability of operations of a manufacturer can be improved directly through operational process change, if the state of sustainability performance could be assessed. Process level assessment requires methods and tools for modeling the operation of the production process to analyze the inputs, transformation process, outputs, and its environmental impacts such as energy consumption [130, 131]. Such methods use manufacturing data associated with material and manufacturing process to quantify the inputs, outputs, and by-products. This approach enables aggregation of impacts and comparison of alternative processes. In this section, we overview tools, standards, and life cycle data. We also discuss how sustainable manufacturing practices can be integrated into continuous improvement efforts.

4.2.1 Standards for Sustainable Manufacturing

Over the last few decades, many standards have been developed so that manufacturing companies can steer their operations towards sustainable practices. Candidate standards for process assessment include ISO 20140-1:2013, Automation Systems and Integration, which provides a framework for assessment of environmental influence of manufacturing processes from a work unit to the entire factory [132]. ISO 20140-1:2013 is for automation systems and integration and defines the requirements for the environmental-influence data to be captured from individual manufacturing equipment.

Other standards include BS 8905, which provides a framework for the concepts, techniques, tools, and methodologies that can be used to support decisions regarding the sustainable use of materials including use in the manufacturing process, i.e., conversion of materials into products [133]. There are also standards for assessing particular products such as electronics [134, 135], plastics [136], or office equipment [137]. These product standards are used to analyze the environmental impact of a product during its entire life cycle based on given impact categories.

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Although best-known for sustainability assessment, LCA standards in the ISO 14000 series are not specifically suitable for manufacturing processes as they were developed for the entire product life cycle. To focus on sustainability in manufacturing, standards are needed that assess material consumption, energy usage, and waste in associated manufacturing processes and operations. ASTM International recently formed a subcommittee on Sustainable Manufacturing to oversee development of standards to complement already-existing standards such as ISO 20140 [132], ISO 50001 [138], and ULE 880 [139]. Already, the first two standards were recently accepted: ASTM E2986-15 [140] and ASTM E3012-16 [141]. ASTM E2986-15 is a guide for gate-to-gate evaluation of environmental aspects of sustainability of manufacturing processes. The second standard, ASTM E3012-16, is a guide for sustainability characterization of manufacturing processes. These two standards will support the calculation of sustainability performance of a specific process and thereby provide a basis for assessing and improving sustainability of manufacturing systems.

4.2.2 Reference Data

Reference data is needed to consistently quantify resource consumption and environmental impacts of manufacturing processes, products, and services. This data is needed both during design and operation of a manufacturing system. An example of this data is life cycle inventory (LCI) data. LCI is the amount of resources and ways they are used during manufacture of a product, as well as residual materials generated during processing, and scrap at the end of a product's life. In an effort to avail this data, a consortium, the Unit Process Life Cycle Inventory (UPLCI), at Wichita State University is, among others, developing and compiling life cycle data from researchers and manufacturers [142, 143]. There is also the Cooperative Effort on Process Emission in Manufacturing Project (CO2PE!), a collaborative effort that has developed a methodology for availing high-quality LCI data for assessment and in-depth analysis of individual manufacturing unit processes [144]. The LCI Data Commons is a US government effort to consolidate and provide reference data as well [145].

4.2.3 Sustainable Practices and Continuous Improvement

Sustainable practices may affect traditional performance since optimum operating parameters of a system for both performance objectives may not be the same. Walker [146] proposed the enhancement of performance analysis systems to include environmental sustainability. We also note that some of the objectives of sustainable manufacturing are the same as those of performance improvement methods. Although performance improvement methods such as lean manufacturing, Six Sigma, and TQM do not directly address sustainability, these strategies can improve sustainability performance by reducing waste and lowering resource consumption [147]. These strategies can purposely be aligned to become part of the organization's sustainable manufacturing strategy [148]. Smart manufacturing planning can include these strategies to simultaneously achieve objectives of process efficiency and sustainability without modifications to their underlying principles.

4.3 Targeted Performance Objective for Smart Manufacturing – Productivity

Traditionally, productivity is defined as the measure of output compared with a given input [149]. Examples of inputs are labor hours, machine hours, and material. Productivity can be measured at different levels of the organizational hierarchy from a single machine to the entire organization. Productivity is distinguished from commonly used performance objectives such as return-on-investment (ROI), which is a cost-based measure often used at the highest level in the organization. Analytical tools such as simulation and statistical analysis play a role in analyzing productivity through examination of their output reports. Advanced statistics can also analyze historical process data, identify patterns and relationships among discrete process steps and inputs, and optimize factors with the greatest effect on yield and productivity [113]. With SMS, the shift is to use real-time shop-floor data and to develop advanced analytics to track productivity performance and improve operations in real time.

With the need for proactive or forward-looking measurements, some researchers believe that new metrics are needed for productivity since traditional metrics such as utilization rate are not helpful for isolating problem causes and identifying opportunities for improvement [117]. Cesarotti et al. [12] proposed overall

equipment effectiveness (OEE) as a quantitative measure of productivity of production equipment in industry. OEE has been used to monitor and control production and can be used to enhance availability, performance, and quality by using smart technologies. Muchiri et al. [150] reviewed the application of OEE as a measure of manufacturing performance.

In addition to a new outlook towards productivity measurement for smart manufacturing, different strategic objectives and operating situations may require different measures. Herron et al. [151] developed a methodology for quantifiable productivity improvement that starts with a productivity needs analysis, to give an overview of the current manufacturing situation and identify key productivity measures. Since productivity is highly linked with equipment availability, a manufacturing system can be designed for high productivity by selecting manufacturing equipment that is easily maintained so as to minimize any possible downtime during operations. This would be complemented by making asset status an essential part of the company information system. Many productivity factors can be measured only during operation of the system through tracking, monitoring, predictive analytics, and control. In this regard, SMS will need a framework to define productivity measures relevant to the industry and operating conditions.

While discussion of productivity metrics is on-going, a new perspective on assessment of SMS recently emerged. Davis et al. [2] point out that performance objectives focusing on productivity (input/output) should be replaced by those that target improving customization, flexibility, responsiveness, energy efficiency, and overall environmental effectiveness. White [152] presented case studies of actual implementations of new measurements, modeling, analysis and control for SMS while Cesarotti et al. [12] proposed additional measures including capacity utilization, saturation, quality, and availability.

4.4 Challenges to Overcoming Operational Exceptions

An important decision concerning performance measurement is when to measure. Traditionally, performance measurements are conducted periodically to detect performance deviations, as well as spontaneously when an event takes place that may potentially lead to performance deterioration. Long- and short-term performance goals determine the planned period between consecutive performance measurements, whereas measurements triggered by operational exceptions are rarely predictably scheduled [153]. A sample of operational exceptions, described as disruptions and disturbances, is shown in Table 4. The consequence of disruptions and disturbances is deterioration in performance. Two such events that occur with high frequency in manufacturing operations are hereby selected for further discussion: (i) system failures, including failure of equipment, tools, sensors, and control systems; and (ii) customer order reprioritizations, including rush orders, changes in priorities, changes in part mix, and order cancellations. Approaches to reduce the impact of these types of events are discussed in the next two paragraphs.

Two strategies to minimize the impact of system failures on performance are periodic performance monitoring and preventive maintenance scheduling. Preventive maintenance is typically scheduled based on statistical distributions of past data. This preordained scheduling strategy may not be optimal. This traditional approach is termed preventive-maintenance forecasting. On the other hand, periodic performance monitoring is a maintenance practice based on predictive analytics that relies on monitoring of performance metrics and continuous evaluation of operations. In predictive analytics, machine learning techniques are employed and system failures are predicted based on patterns of data in routinely monitored performance metrics. By identifying performance deterioration patterns in real-time, preventive maintenance can be scheduled only when the failure is imminent, consequently cutting down unnecessary preordained scheduled maintenance as in the case of forecasting. This strategy may offer a more optimal solution. Determining what to measure so as to predict maintenance needs is an active research area and significant progress is being made as a result of ubiquitous sensors [154].

Customer order reprioritization is a production planning and control problem. Typically, a master production schedule is developed from firm customer orders, demand forecasts, and resources availability. The arrival of a new, higher-priority, order or change in an existing order creates a "disturbance" that invalidates the existing schedule by requiring production reprioritization. Changes in a schedule often impact cycle times and thus invalidate already-promised due dates. In addition, customer orders often arrive with unpredictable frequency. Reprioritizing orders and other activities has to rely on information to dynamically integrate manufacturing needs through the production system. Appropriate response to changing production

requirements and priorities requires multi-level integrated production planning, modeling, and monitoring. Research work is needed in this area.

Table 4. Operating characteristics requiring agile manufacturing systems.

	Internal	External
Disturbances	Labor shortage	Rush order
	Deterioration in quality output	Order cancellation
	Changing labor performance levels	Order change
	New equipment installation	Product returns
	New software installation	Customer order reprioritization
	Product quality deterioration	Raw material unavailability
	Changed product routing	Changing regulations
	New product introduction	
Disruptions	System failure	Natural disasters, e.g., bad weather
	Scheduled maintenance	Power or water outages
	New production line configuration	Delayed material supply
	Changed product line	Poor or wrong material supply

4.5 Challenges with Collection and Use of Data for Performance Improvement

Kennerley and Neely [155] classified factors affecting the evolution of performance measurement systems under process, people, systems, and culture. Further reflecting upon the systems perspective, they suggested that the evolution of performance management systems will vitally depend on flexible IT systems to effectively and efficiently acquire, collate, sort, analyze, interpret, and disseminate data. Since then, there has been an explosion in availability of data for manufacturing enterprises. The major source of data is the manufacturing system shop floor using smart devices.

There are inherent challenges in making sense of all this data at each level of the DIKW pyramid (Fig. 3). At the data level, there are challenges of collecting and using data, sometimes called the 7 Vs of big data— large volume, high velocity, large variety, uncertain veracity, uncertain validity, volatility (timeliness), and value [156]. Structured Query Language [157] is one of the means of storing and retrieving the data. In addition to devices, automated data collection needs communication interfaces for obtaining data directly from machine controllers or a collection device developed for the machine. The data are communicated using a neutral format such as XML.

At the information level, challenges exist with regards to associating data with the relevant performance question. In addition to collected operational data, there is other data from disparate functional units involved in product design, manufacturing planning, enterprise planning, and human-machine interfaces. This includes resources data, inventory data, manufacturing process data, life cycle inventory data, and product data. External sources such as customer orders and partners in the production network also generate data. This type of large-scale data collection and transformation poses data compatibility and interoperability issues. Most systems today are not designed to integrate at such a scale.

The challenge of providing relevant and compelling views of information for different users exists at the knowledge level. The ability to deliver such views pervasively across the organization will provide decision guidance. At this level, the challenges lie in the ability to correlate the KPIs to operating parameters and to create a plan for making appropriate adjustments to meet performance targets.

5. Conclusion

This paper has discussed how existing methods and tools can be enhanced by emerging technologies to measure, analyze, and improve the performance of SMS. Performance measurement frameworks were developed for enterprise level assessment. The availability of workstation, machine, and process data, and the need to assess performance at these levels, will require that these methods are also adapted to lower operational levels. Interoperability and communication will become more crucial if this shop floor data and performance analyses are to be used for enterprise level planning. Also related to communication is cyber security in smart manufacturing due to increasing interconnections between products and manufacturing

systems. If the information infrastructure is not adequately secured, performance objectives may not be achieved. Major concerns include theft of technical information, alteration of data, and deliberate disruption of controls. Research efforts are underway to address this problem [158, 159]. Performance analysis methods such as computer simulation project system performance according to a defined set of inputs. The availability of large streaming data puts additional requirements on the modeling and analysis of systems. Regarding performance improvement, it has been discussed that methods such as DMAIC provide a framework for selecting improved system components and configurations during systems design as defined by performance objectives. Below we describe activities for applying the principles we have discussed and conclude with directions for further research.

5.1 Activities for Performance Assurance for SMS

The activities supporting performance assurance SMS can be broken down as follows:
- Set strategic goals,
- Establish key performance indicators (KPIs),
- Define SMART (specific, measurable, actionable, realistic, time-based) metrics that relate to the goals,
- Establish and set performance benchmarks,
- Test the system over a performance envelope,
- Measure performance against benchmarks,
- Trace the source(s) or causes(s) of problems,
- Take actions that will result in desired performance.

Setting strategic goals: These are the long-term achievement targets of an organization, and clearly articulating them is a crucial responsibility of management. These goals, in turn, drive definition of the indicators and measures that track performance of the manufacturing system. The complex challenges of SMS require an organization to set high-level goals and targets that balance system responsiveness and adaptability with productivity and sustainability needs.

Establishing KPIs: This is the process of specifying KPIs that should be emphasized. KPIs that define SMS performance are mainly related to responsiveness to changes of demand, environmental sustainability, and high return on investments. Other KPIs can be defined depending on such factors as type of industry, geography, production costs, and regulations.

Choosing SMART metrics and perform measurements: This activity specifies computable metrics that track performance according to the KPIs. During system development, data used in analysis is based on original equipment manufacturer specifications, as well as projections of system operation and external environments. During system operation, sensors, radio-frequency identification (RFID) of component parts, meters, and other instruments collect data in real time. Choosing appropriate measurements will be instrumental to appropriate ICT hardware and software investments.

Establishing performance benchmarks: Performance benchmarks are the desired performance levels of indicators and are often influenced by external drivers. There are different ways of setting performance benchmarks such as considering the best organizations or best-in-class performance. Other means of setting benchmarks include surveys, interviews, focus group meetings, and site visits. They may also be based on a standard or may be obtained from publications.

Testing the system: Testing includes forecasting the operation of a system to determine if required performance can be achieved. The process is often carried out in a virtual environment. A performance envelope is defined by setting a minimum and maximum range of desired performance according to the KPIs and metrics. Because of multiple KPIs, conflicts may occur, for instance between cost and quality. Typically, each KPI has bounds of acceptability. A measure of the trade-off between cost and quality can be productivity. Smart manufacturing also requires a performance envelope related to sustainability. Thus, if productivity and sustainability set the boundaries for performance, agility, as defined by ability to respond to disruptions and disturbances, has to be maintained within that performance envelope.

Measuring performance: Performance measurement is a report on the state of the KPIs. Measurement frameworks have been discussed in previous sections. Performance evaluation compares obtained measures with benchmarks so as to look for deviations. Performance measurements require data: some is collected

other data is stored in databases. Through improvements in computing technology, data stored across many applications and databases, each with a specific functional role, can now be better accessed from multiple network-linked locations. For example, material data can be accessed by more than one functional unit of the enterprise including procurement, product development, testing, manufacturing, and marketing.

Tracing the source of performance problems: This activity is carried out after noticing measurements that are inferior to benchmarks (or set targets) in one or more KPIs. The manufacturing processes and measurements relevant to the KPIs are investigated to determine the source of poor performance. Data analytics methods and techniques such as Pareto Analysis, Cause & Effect Analysis, and Failure Mode Effect Analysis can be applied to distinguish multiple factors contributing to performance problems in a complex system.

Taking action to produce required performance: The actions needed to produce the desired performance are obtained from decision models based on performance analysis and improvement methods reviewed. Multi-objective optimization models are examples of such models. The models can be constructed and employed for decision making based on current state of the system, data analysis, and required future performance. The type of models and the input data depends on the type of system, performance indicator, and operating environment, among other factors.

5.2 Future Research: Addressing Requirements for Performance Assurance for SMS

While automated equipment such as sensors, embedded systems, and networks collect and communicate performance data, they also introduce new forms of possible failure and increase the requirements for modeling and analyses. We summarize, at a high level, the challenges and needed research directions for measurement, analysis, and improvement of SMS.

Performance measurement: Performance-measurement frameworks were originally developed for use at the enterprise level of the organization, using data collected only periodically. Measurement and assessment are now needed, however, continuously and in real time, requirements that are further complicated by the challenges of operation in a big-data environment. Realization of performance measurement for SMS requires research in the following areas:

- **Identifying correct data elements:** Accurate performance assessment of SMS cannot be accomplished without proper data sourcing, collection, and supply. Data analytics is a viable method to associate data type to required performance, but research is needed to improve this method to continuously update an analyzed data set, adding new elements while removing no-longer-needed ones,
- **Assessing in real time:** The capability to consistently provide current-status models throughout an SMS does not yet exist. Research is needed, for example, to partition streaming data into data blocks that are continuously updated. Other needs include improved performance measurements that use efficient computational algorithms to perform assessments, and highly interoperable interfaces to assure distribution of those assessments.

Performance analysis: Performance analysis requires developing a mathematical, logical, abstract, or other type of model of a system. The models for SMS need high levels of abstraction, especially at the process level of the hierarchy. The larger number of indicators and metrics for SMS increase requirements for analysis that is likely to be more complex, costly, and time-consuming. To enable performance analysis for SMS, research work is needed in the following areas:

- **Integrated analysis:** Methods such as simulation, data analytics, and optimization can be combined to obtain better analysis results. To this end, research work is needed to develop better integration interfaces between and among analysis models and data sources such as the shop floor and databases,
- **Dynamic optimization**: This is the process of determining the maximum or minimum of an objective function over time. Research work will be needed to effectively combine real-time assessment methods with optimization.

Performance improvement: The activities for performance measurement and analysis are geared to achieving performance improvement. Performance improvement requires feedback from performance assessment so as to decide on an appropriate course of action. Major challenges are timely and accurate

communication of performance information and the decision action that needs to be made. Therefore, research in the following areas is needed:

- **Enhancement of performance improvement frameworks**: Performance improvement frameworks such as DMADV or DMAIC rely on planning, assessment, and analysis. Research work should be directed to enhancing these frameworks to provide the timely information retrieval and sharing required by SMS,

- **Adaption of approaches for performance improvement in other domains**: Common weakness enumeration has been developed for assurance of computer software. This method identifies common known weaknesses in software including a discussion of solutions. If high-fidelity models can be developed for SMS, research can investigate, classify, and create a database of common failures in performance of SMS. While new situations emerge that were not factored into system design, those that are encountered as the system is operated can be regularly included in the database. This can help direct system testing efforts during development and determine proper response after performance failure.

Finally, standards are fundamental to enabling the flow of information and control the manufacturing enterprise. Lu et al. [160, 161] first, analyzed standards requirements and then reviewed organizations working to develop and align standards to enable smart manufacturing systems. Kibira et al. [162] analyzed standards for simulation-based production planning and identified standards needs into two major application categories: data collection and interoperability. Lastly, Choi et al. [163] analyzed current technologies and associated standards for assuring performance of smart manufacturing systems. These on-going works will result in the creation of standards-based manufacturing ecosystems that are able to leverage emerging technologies to foster incremental, pervasive, reliable, and resilient improvements in manufacturing performance.

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6. References

[1]   SMLC (Smart Manufacturing Leadership Collation) (2010) *U.S. Public-Private Partnership Program in Smart Manufacturing: Questions and Answers about a Partnership.* https://smart-process-manufacturing.ucla.edu/presentations-and-reports/spm-publications/SMLCpublicprivatepartnership.pdf/at_download/file (Accessed 12/7/2013)

[2]   Davis J, Edgar T, Porter J, Bernaden J, Sarli M (2012) Smart manufacturing, manufacturing intelligence and demand-dynamics performance. *Comput Chem Eng* 47:145-156. http://dx.doi.org/10.1016/j.compchemeng.2012.06.037

[3]   King B (2005) *Performance Assurance for I.T. Systems* (Auerbach Publications).

[4]   Kossiakoff A, Sweet WN, Seymour SC, Biemer SM (2011) *Systems Engineering: Principles and Practice* (John Wiley Sons, Wiley InterScience), 2nd Ed.

[5]   Parnaby J (1979) Concept of a manufacturing system, *International Journal of Production Research* 17(2):123-135. http://dx.doi.org/10.1080/00207547908919600

[6]   Landau I D, Lozano R, M'Saad M, Karimi A (2011) *Adaptive Control, Algorithms, Analysis and Applications* (Springer-Verlag, London Limited). http://dx.doi.org/10.1007/978-0-85729-664-1_1

[7]   Rotithor H (2013) A taxonomy of performance assurance methodologies and its applications in high performance computer architecture. *International Journal of Software Engineering Applications* 4(2):1-17. http://dx.doi.org/10.5121/ijsea.2013.4201

[8]   Shoemaker D Mead N R (2016) Software assurance measurement – State of the practice. *Technical Note* (Software Engineering Institute, Carnegie Mellon University). http://www.sei.cmu.edu

[9]   OMG (2013) *How to Deliver Resilient, Secure, Efficient, and Easily Changed IT Systems in Line with CISQ Recommendations.* http://www.omg.org/CISQ_compliant_IT_Systemsv.4-3.pdf (Accessed 7/3/2015)

[10]   Common Weakness Enumeration (CWE) (2014) *A Community-Developed Dictionary of Software Weakness Types.* http://cwe.mitre.org (Accessed 1/21/2015)

[11]   Dale B G, van der Wiele T, van Iwaarden J (2007) *Managing Quality* (Blackwell Publishing), 5th Ed.

[12]   Cesarotti V, Giuiusa A, Introna V (2013) Using overall equipment effectiveness for measuring manufacturing system design. *Operations Management*, ed Schiraldi MM (InTech), pp 51-80. http://dx.doi.org/10.5772/56089

[13]   Putnik G D, Sluga A (2007) Reconfigurability of manufacturing systems for agility implementation. *Digital Enterprise Technology* 91-98. http://dx.doi.org/10.1007/978-0-387-49864-5_10

[14]   Yang L, Deuse J, Jiang P (2013) Multiple-attribute decision-making approach for an energy-efficient facility layout design. *Int J Adv Manuf Tech* 66 (5-8):795-807. http://dx.doi.org/10.1007/s00170-012-4367-x

[15]   Chen, K-Y (2006) Performance measurement of implementing manufacturing execution system. *Mater Sci Forum* 505-507:1117-1122.

[16]   Taticchi P, Tonelli F, Cagnazzo L (2010) Performance measurement and management: a literature review and a research agenda. *Measuring Business Excellence* 14(1):4-18. http://dx.doi.org/10.1108/13683041011027418

[17]   Keegan DP, Eiler RG, Jones CR (1989) Are your performance measures obsolete? *Management Accounting* 71:45-50.

[18]   Ahmad MM, Dhafr N (2002) Establishing and improving manufacturing performance measures. *Robot Cim-Int Manuf* 18(3-4):171-176. http://dx.doi.org/10.1016/S0736-5845(02)00007-8

[19]   Hon KKB (2005) Performance and evaluation of manufacturing systems. *Cirp Ann-Manuf Techn* 54(2):675-690.

[20]   Chen CC, Cheng WY (2007) Customer-focused and product-line-based performance measurement. *Int J Adv Manuf Tech* 34(11-12):1236-1245. http://dx.doi.org/10.1007/s00170-006-0686-0

[21]   Feng S C, Joung C B (2010) Development overview of sustainable manufacturing metrics. In *Proceedings of the 17th CIRP International Conference on Life Cycle Engineering* (Heifei, China).

[22]   ISO (2014) ISO 22400-1: 2014(en) Automation Systems and Integration – Key Performance Indicators (KPIs) for Manufacturing Operations Management – Part 1: Overview, Concepts and Terminology. https://www.iso.org/obp/ui/#iso:std:iso:22400:-1:ed-1:v1:en (Accessed 2/14/2015)

[23]   Tsourveloudis N, Valavanis K P (2002) On the measurement of enterprise agility. *J Intell Robot Syst* 33(3):329-342. http://dx.doi.org/10.1023/A:1015096909316

[24]   Digalwar A K, Metri B A (2005) Performance measurement framework for world class manufacturing, *International Journal of Applied Management and Technology* 3:83-101.

[25]   Hallgren M Olhager J (2009) Lean and agile manufacturing: external and internal drivers and performance outcomes. *International Journal of Operations and Production Management* 29(10):976-999. http://dx.doi.org/10.1108/01443570910993456

[26]   Rowley J (2007) The wisdom hierarchy: representations of the DIKW hierarchy. *J J Inf Sci* 33(2):163-180. http://dx.doi.org/10.1177/0165551506070706

[27]   ISO (2011) ISO 22400-2: Automation Systems and Integration – Key Performance Indicators (KPIs) for Manufacturing Operations Management – Part 2: Definitions and Descriptions of KPIs. ftp://ftp.nist.gov/pub/mel/michalos/Software/MTConnectCmdSimAgent/doc/ISO-TC184-SC5_N1143_ISO_DIS_22400-2.pdf (Accessed 7/3/2015)

[28]   NIST Manufacturing Engineering Laboratory Programs (2009) Sustainable Manufacturing Indicator Depository. http://www.mel.nist.gov/msid/SMIR/index.html (Accessed 12/1/2014)

[29]   MESA International (2016) Metrics Working Groups. http://mesa.org/en/committeeactivities/metricsworkinggroups.asp (Accessed 10/8/2014)

[30]   Supply Chain Council (SCC) (2012) *Supply Chain Operations Reference Model* (Supply Chain Council, USA), Revision 11.0.

[31]   VelevaV, Ellenbecker M (2001) Indicators of sustainable production: framework and methodology. *Journal of Cleaner Production* 9(6):529-549. http://dx.doi.org/10.1016/S0959-6526(01)00010-5

[32]   Kibira D, Jain S, McLean C (2009) A system dynamics modeling framework for sustainable manufacturing. In *Proceedings of the System Dynamics Society* (Albuquerque, NM). http://www.systemdynamics.org/cgi-bin/sdsweb?P1285+0 (Accessed 12/7/2013)

[33]   Joung C B, Carrell J, Sarkar P, Feng SC (2013) Categorization of indicators for sustainable manufacturing. *Ecol Indicators* 24:148-157. http://dx.doi.org/10.1016/j.ecolind.2012.05.030

[34]   Feng S C, Joung C B (2010) Development overview of sustainable manufacturing metrics. In *Proceedings of the 17th CIRP International Conference on Life Cycle Engineering* (Heifei, China).

[35]   Reich-Weiser C, Vijayaraghavan A, Dornfeld D (2008) Metrics for Sustainable Manufacturing. In *Proceedings of the 2008 International Manufacturing Science and Engineering Conference* (Evanston, Illinois).

[36]   Thomann J (1973) Meta-Methodology: An Overview of what it is and how it was developed. *58th American Educational Research Association Annual Meeting* (New Orleans, Louisiana).

[37]   Kaplan R S, Norton D P (1992) The balanced scorecard--measures that drive performance. *Harvard Business Review* 70(1):71-79.

[38]   Keegan DP, Eiler RG, Jones CR (1989) Are your performance measures obsolete? *Management Accounting* 71:45-50.

[39]   Cross KF, Lynch RL (1988) The "SMART" way to define and sustain success. *National Productivity Review* 8(1):23-33. http://dx.doi.org/10.1002/npr.4040080105

[40]   Neely AD, Adams C, Kennerley M (2002) *The Performance Prism: The Scorecard for Managing Business Success* (Financial Times/Prentice Hall).

[41]   Bititci US, Carrie AS, McDevitt, L (1997) Integrated performance measurement systems: a development guide. *International Journal of Operations & Production Management 1*7(5-6):522-534. http://dx.doi.org/10.1108/01443579710167230

[42]   Ghalayini AM, Noble JS, Crowe, TJ (1997) An integrated dynamic performance measurement system for improving manufacturing competitiveness. *Int J Prod Econ* 48(3):207-225. http://dx.doi.org/10.1016/S0925-5273(96)00093-X

[43]   Charnes A, Cooper WW, Lewin, AY, Seiford LM (1995) *Data Envelopment Analysis: Theory, Methodology and Applications* (Kluwer Publishers).

[44]   Saaty TL (2009) *Theory and Applications of the Analytic Network Process: Decision Making with Benefits, Opportunities, Costs, and Risks* (RWS Publications).

[45]   Automotive Industry Action Group (AIAG). *Press Release.* https://oldsite.aiag.org/staticcontent/press/releases/GENERAL/PR_ECM_Final.pdf (Accessed on 12/14/2015)

[46]   Gomes CF, Yasin MM, Lisboa JV (2004) A literature review of manufacturing performance measures and measurement in an organizational context: a framework and direction for future research. *Journal of Manufacturing Technology Management* 15(6):511-530. http://dx.doi.org/10.1108/17410380410547906

[47]   Anosike AI, Zhang DZ (2009) An agent-based approach for integrating manufacturing operations. *Int J Prod Econ* 121(2):333-352. http://dx.doi.org/10.1016/j.ijpe.2006.10.013

[48]   Kaplan RS, Norton DP (2001) *The strategy-focused organization*. (Harvard Business School Press, Boston, MA).

[49]   Lawrie G, Cobbold I (2004) Third-generation balanced scorecard: evolution of an effective strategic control tool. *International Journal of Productivity and Performance Management* 53(7):611-623. http://dx.doi.org/10.1108/17410400410561231

[50]   Neely AD, Bourne M, Kennerley M (2000) Performance measurement design: Developing and testing a process-based approach. *International Journal of Operations & Production Management* 20(9-10):1119-1145. http://dx.doi.org/10.1108/01443570010343708

[51]   Cross KF, Lynch RL (1988) The "SMART" way to define and sustain success. *National Productivity Review* 8(1):23-33. http://dx.doi.org/10.1002/npr.4040080105

[52]   Doran G T (1981) There's a S.M.A.R.T. way to write management's goals and objectives. *Management Review* 70(11):35-36.

[53]   Striteska M, Spickova M (2012) Review and comparison of performance measurement systems. *Journal of Organizational Management Studies* 2012:1-13. http://dx.doi.org/10.5171/2012.114900

[54]   Bititci US, Carrie AS, McDevitt L (1997) Integrated performance measurement systems: a development guide. *International Journal of Operations & Production Management* 17(5):522-534. http://dx.doi.org/10.1108/01443579710167230

[55]   Kim G, Park CS, Yoon KP (1997) Identifying investment opportunities for advanced manufacturing systems with comparative-integrated performance measurement. *Int J Prod Econ* 50(1):23-33. http://dx.doi.org/10.1016/S0925-5273(97)00014-5

[56]   Ucal I, Öztayşi B (2009) ANP in performance measurement and its application in a manufacturing system. In *Proceedings of the International Symposium on the Analytic Hierarchy Process* (ABD Press, Pittsburgh, PA).

[57]   Benbarka A (2007) Assessment of Manufacturing Performance Using Data Envelopment Analysis. (University of Texas at Arlington).

[58]   Khan A, Turowski K (2016) A Survey of Current Challenges in Manufacturing Industry and Preparation for Industry 4.0. *Proceedings of the First International Scientific Conference "Intelligent Information Technologies for Industry" (IITI'16): Volume 1*, eds Abraham A, Kovalev S, Tarassov V, Snášel V (Springer International Publishing, Cham), pp 15-26. http://dx.doi.org/10.1007/978-3-319-33609-1_2

[59]   Zhang Y, Zhang G, Wang J, Sun S, Si S, Yang T (2015) Real-time information capturing and integration framework of the internet of manufacturing things. *Int J Comput Integ M* 28(8):811-822. http://dx.doi.org/10.1080/0951192X.2014.900874

[60]   Wibisono D A (2011) Framework of performance measurement system for manufacturing companies. *The South East Asian Journal of Management* 5(2):107-116.

[61]   Salloum M (2011) *Towards dynamic performance measurement systems: A framework for manufacturing organizations.* (Mälardalen University, Västerås).

[62]   Nudurupati SS, Bititchi US, Kumar V, Chan FTS (2011) State of the art literature review on Performance Measurement. *Comput Ind Eng* 60(2):279-290. http://dx.doi.org/10.1016/j.cie.2010.11.010

[63]   Bourne M, Neely A, Mills J, Platts K (2003) Why some performance measurement initiatives fail: Lessons from the change management literature. *International Journal of Business Performance Management* 5(2-3):245-269. http://dx.doi.org/10.1504/IJBPM.2003.003250

[64]   NIST Engineering Laboratory (2016). Digital Thread for Smart Manufacturing. http://www.nist.gov/el/msid/syseng/dtsm.cfm (Accessed 5/15/2016)

[65]   Montgomery D C (2009) *Introduction to Statistical Quality Control* (John Wiley & Sons, Inc.), 6th Ed.

[66]   Delorme A (2006) Statistical Methods. *Encyclopedia of Medical Devices and Instrumentation* (John Wiley & Sons, Inc.), pp 240-264. http://dx.doi.org/10.1002/0471732877.emd318

[67]   Raheja D G, Allocco M (2006) *Assurance Technologies Principles and Practices: A Product, Process, and System Safety Perspective* (Wiley-InterScience), 2nd Ed.

[68]   Barabady J (2007) Production Assurance: Concepts, Implementation and Improvement, *PhD Thesis*, Lulea University of technology, Division of Operations and Maintenance Engineering.

[69]   Halvorsen L A (2006) Comprehensive model for manufacturing analytics. *WBF North American Conference* (Atlanta, GA). http://www.controlglobal.com/assets/Media/MediaManager/wp_06_041_wbf_halvorsen.pdf (Accessed 10/20/2014)

[70]   Smola S, Vishwanathan, SVN (2008) *Introduction to Machine Learning* (Cambridge University Press).

[71]   Heger DA (2006) An introduction to operations research – benefits, methods and application. *Fortuitous Online Database*. http://www.fortuitous.com/docs/primers/OR-intro.pdf (Accessed 7/3/2015)

[72]   Mönch L, Fowler JW (2011) A Survey of problems, solution techniques, and future challenges in scheduling semiconductor manufacturing operations. *Journal of Scheduling* 14(6):583-599. http://dx.doi.org/10.1007/s10951-010-0222-9

[73]   Engau A (2012) Overview and Opportunities of Operations Research (OR/MS) in Sustainability and the Environment. *CSIS Seminar* (University of Colorado Denver). http://www.math.ucdenver.edu/~aengau/presentations/120207_csis_sustainability.pdf (Accessed 5/14/2014)

[74]   Semini M (2011) Applicability of operations research in manufacturing logistics, Doctoral Thesis. (Department of Production and Quality Engineering, Norwegian University of Science and Technology).

[75]   Brucker P (1979) NP-Complete operations research problems and approximation algorithms. *Zeitschrift für Operations Research* 23(3):73-94. http://dx.doi.org/10.1007/bf01951543

[76]   Dieter GE, Schmidt LC (2013) *Engineering Design* (McGraw-Hill), 5th Ed.

[77]   Triantaphyllou E (2000) *Multi-Criteria Decision Making Methods: A Comparative Study* (Kluwer Academic Publishers).

[78]   Saaty TL (1980) *The Analytic Hierarchy Process*, McGraw-Hill, New York, NY, 1980.

[79]   Saaty TL (1994) *Fundamentals of Decision Making and Priority Ttheory with the AHP* (RWS Publications, Pittsburgh, PA).

[80]   Košturiak J, McGregor M (1999) Simulation in production system life cycle. *Comput Ind* 38(2):159-172.
       http://dx.doi.org/10.1016/S0166-3615(98)00116-X
[81]   Chomiakow DA (2007) Generic Pattern for Modelling Manufacturing Companies.
       http://www.systemdynamics.org/conferences/2007/proceed/papers/CHOMI428.pdf (Accessed 8/16/2014).
[82]   Negahban A, Smith JS (2014) Simulation for manufacturing system design and operation: Literature review and analysis. *J Manuf Syst* 33(2):241-261. http://dx.doi.org/10.1016/j.jmsy.2013.12.007
[83]   Shipp SS, Gupta N, Lal B, Scott JA, Weber CL, Finnin MS, Blake M, Newsome S, Thomas S (2012) Emerging Trends in Advanced Manufacturing. (Institute for Defense Analyses), IDA Paper P-4603.
       http://www.wilsoncenter.org/sites/default/files/Emerging_Global_Trends_in_Advanced_Manufacturing.pdf (Accessed 8/7/2013)
[84]   Bryner M (2012) Smart Manufacturing: The Next Revolution. *A CEP Preprint*. (American Institute of Chemical Engineers, New York). http://www.aiche.org/sites/default/files/docs/embedded-pdf/1012_SmartManufacturing_Preprint.pdf (Accessed 8/28/2013)
[85]   Shao G, Jain S, Shin S (2014) Data analytics using simulation for smart manufacturing. In *Proceedings of the 2014 Winter Simulation Conference* (Savannah, Georgia).
[86]   McLean C, Leong S (2001) The role of simulation in strategic manufacturing. In *Proceedings of the 2001 International Working Conference on Strategic Manufacturing* (Aalborg, Denmark).
[87]   Simulation Interoperability Standards Organization (SISO). Core Manufacturing Simulation Data (CMSD) Standard.
       http://www.sisostds.org/StandardsActivities/DevelopmentGroups/CMSDPDGCoreManufacturingSimulationData.aspx (Accessed 12/6/2014)
[88]   Open Applications Group (OAGi) Open Application Group's Integration Specification (OAGIS).
       http://www.oagi.org/dnn2/DownloadsandResources/OAGIS100PublicDownload.aspx (Accessed 11/23/2014)
[89]   American National Standards Institute/International Society of Automation (ANSI/ISA)-95. (2005) *ANSI/ISA–95.00.03–2005 - Enterprise-Control System Integration: Part 3: Activity Models of Manufacturing Operations Management.*
[90]   OMG Systems Modeling Language. http://www.omgsysml.org (Accessed 2/14/2015)
[91]   Model-based System Engineering (MBSE) Works. What is MBSE Works? – What you need to know. http://mbse.works (Accessed 6/12/2015).
[92]   Brodsky A, Wang XS (2008) Decision-guidance management system (DGMS): Seamless integration of data acquisition, leaning, prediction, and optimization. In *Proceedings of the 41st Annual Hawaii International Conference on System Sciences* (Waikoloa, Big Island, Hawaii), pp 71–81.
[93]   Shao G, Kibira D, Brodsky A, Egge N (2011) Decision support for sustainable manufacturing using Decision Guidance Query Language. *International Journal of Sustainable Engineering* 4(3):251-265. http://dx.doi.org/10.1080/19397038.2011.574741
[94]   Imai M (1986) *Kaizen: The Key to Japan's Competitive Success*. (Random House, New York), pp 60.
[95]   Moen R, Norman C (2011) Evolution of the PDCA Cycle. http://pkpinc.com/files/NA01MoenNormanFullpaper.pdf (Accessed 8/14/2014)
[96]   ISO (2012) ISO Standards. http://www.iso.org/iso/home.html (Accessed 10/15/2014)
[97]   Deming WE (1986) *Out of the Crisis*. (MIT Press, Cambridge, MA), pp 88.
[98]   Langley G, Nolan K, Nolan T (1994) The foundation of improvement. *Qual Prog* 27(6):81-86.
[99]   Cronemyr P (2007) DMAIC and DMADV – Differences, Similarities and Synergies. *International Journal of Six Sigma and Competitive Advantage* 3(3):193-209. http://dx.doi.org/10.1504/IJSSCA.2007.015065
[100] De Mast J, Lokkerbol J (2012) An Analysis of the Six Sigma DMAIC Method from the Perspective of Problem Solving. *Int J Prod Econ* 139(2):604-614. http://dx.doi.org/10.1016/j.ijpe.2012.05.035
[101] Holweg M (2007) The Genealogy of lean production. *Journal of Operations Management* 25(2):420-437.
       http://dx.doi.org/10.1016/j.jom.2006.04.001
[102] Yang M G, Hong P, Modi, S (2011) Impact of lean manufacturing and environmental management on business performance: An empirical study of manufacturing firms. *Int J Prod Econ* 129(2):251-261. http://dx.doi.org/10.1016/j.ijpe.2010.10.017
[103] Schroeder RG, Linderman K, Liedtke C, Choo AS (2008) Six Sigma: definition and underlying theory. *Journal of Operations Management* 26(4):536-554. http://dx.doi.org/10.1016/j.jom.2007.06.007
[104] Andersson R, Eriksson H, Torstensson H (2006) Similarities and differences between TQM, six sigma and lean. *The TQM Magazine* 18:282-296.
[105] Oakland JS (2014). Total Quality Management and Operational Excellence. (Routledge, Taylor Francis), 4th Ed.
[106] Reference for Business. *Quality and Total Quality Management*. http://www.referenceforbusiness.com/management/Pr-Sa/Quality-and-Total-Quality-Management.html (Accessed 1/14/2016)
[107] Krebs M (2016) How CEO Donald Petersen turned third-ranked Ford into a sales powerhouse. *SellingPower* http://www.sellingpower.com/content/article/?a=3659/how-ceo-donald-petersen-turned-third-ranked-ford-into-a-sales-powerhouse (Accessed 5/14/2016)
[108] Sadikoglu E, Zehir C (2010) Investigating the effects of innovation and employee performance on the relationship between total quality management practices and firm performance: An empirical study of Turkish firms. *Int J Prod Econ* 127(1):13-26.
       http://dx.doi.org/10.1016/j.ijpe.2010.02.013
[109] Abernathy WJ, Utterback JM (1978) Patterns of industrial innovation. *Technology Review* 80:40-47.
[110] Hernandez-Matias JC, Vizan A, Perez-Garcia J, Rios J (2008) An integrated modeling framework to support diagnosis for continuous improvement. *Robot Comput-Integr Manuf* 24(2):187-199. http://dx.doi.org/10.1016/j.rcim.2006.10.003
[111] Sharma AB, Ivančić F, Niculescu-Mizil A, Chen H, Jiang G (2014) Modeling and analytics for cyber-physical systems in the age of big data. *SIGMETRICS Perform Eval Rev* 41(4):74-77. http://dx.doi.org/10.1145/2627534.2627558
[112] LaValle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N (2011) Big Data, analytics and the path from insights to value, *MITSloan Management Review* 52(2):21-31. http://sloanreview.mit.edu/article/big-data-analytics-and-the-path-from-insights-to-value/ (Accessed 8/28/2015)

[113] Auschitzky E, Hammer MC, Rajagopaul A (2014) How big data can improve manufacturing.
       http://www.mckinsey.com/insights/operations/how_big_data_can_improve_manufacturing (Accessed 9/12/2014)
[114] Park J, Law KH, Bhinge R, Biswas N, Srinivasan A, Dornfeld DA, Helu M, Rachuri S (2015) A generalized data-driven energy
       prediction model with uncertainty for a milling machine tool using Gaussian Process. In *Proceedings of the ASME 2015
       International Manufacturing Science and Engineering Conference* (Charlotte, NC).
[115] Song Y, Routray R, Yangyang H (2014) Scalable data analytics platform for enterprise backup management.In *Network
       Operations and Management Symposium (NOMS)* (IEEE, Krakow), pp 1-7. http://dx.doi.org/10.1109/NOMS.2014.6838291
[116] Qin SJ (2014) Process data analytics in the era of big data. *AICHE J* 60(9):3092-3100. http://dx.doi.org/10.1002/aic.14523
[117] Huang S, Chen Y, Chen X, Li K, Xu X, Wang C, Halilovic I (2014) The next generation operational data historian for IoT based
       on informix. In *Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data* (ACM, Snowbird,
       Utah), pp 169-176.
[118] Kumaraguru S, Kulvatunyou B, Morris KC (2014) Integrating Real-Time Analytics and Continuous Performance Management
       in Smart Manufacturing Systems. *Advances in Production Management Systems: Innovative and Knowledge-Based Production
       Management in a Global-Local World*, eds Grabot B, Vallespir B, Samuel G, Bouras A, Kiritsis D (Springer Berlin Heidelberg),
       pp 175-182.
[119] Zhao JL, Fan S, Hu D (2014) Business challenges and research directions of management analytics in the big data era. *Journal
       of Management Analytics* 1(3):169-174. http://dx.doi.org/10.1080/23270012.2014.968643
[120] Pospišíl M, Mates V, Hruska T, Bartick V (2013) Process mining in a manufacturing company for predictions and planning.
       International Journal on Advances in Software 6(3-4):293-297.
[121] Son S, Yahya B, Song M, Choi S, Hyeon J, Lee B, Jang Y, Sung N (2014) Process mining for manufacturing process analysis:
       A Case study. In *Asia Pacific Business Process Management* (Brisbane, Australia).
[122] Yahya NY (2014) The Development of Manufacturing Process Analysis: Lesson Learned from Process Mining. *Jurnal Teknik
       Industri* 16(2):95-106. http://dx.doi.org/10.9744/jti.16.2.95-106
[123] MESA International. https://services.mesa.org/member (Accessed on 12/10/2015)
[124] Jung K, Morris KC, Lyons KW, Leong S, Cho H (2015) Using formal methods to scope performance challenges for smart
       manufacturing systems: Focus on agility. *Concurrent Engineering* 23(4):343-354. http://dx.doi.org/10.1177/1063293x15603217
[125] Gunasekaran A (1999) Agile Manufacturing: A Framework for Research and Development. *Int J Prod Econ* 62(1-2):87-105.
       http://dx.doi.org/10.1016/S0925-5273(98)00222-9
[126] Ramasesh R, Kulkarni S, Jayakumar M (2001) Agility in manufacturing systems: an exploratory modeling framework and
       simulation. *Integrated Manufacturing Systems* 12(7):534-548. http://dx.doi.org/10.1108/EUM0000000006236
[127] Amos J (2013) *Transformation to Agility: Manufacturing in the Marketplace of Anticipated Change* (Routledge), 3rd Ed.
[128] Sherehiy B, Karwowski W, Layer JK (2007) A review of enterprise agility: Concepts, frameworks, and attributes. *Int J Ind
       Ergonomics* 37(5):445-460. http://dx.doi.org/10.1016/j.ergon.2007.01.007
[129] Vinodh S, Sundararaj G, Devadasan SR, Maharaja R, Rajanayagam D, Goyal SK (2008) Dessac: A decision support system for
       quantifying and analyzing agility. *Int J Prod Res* 46(23):6759-6780. http://dx.doi.org/10.1080/00207540802230439
[130] Mani M, Johansson B, Lyons KW, Sriram RD, Ameta G (2012) Simulation and Analysis for Sustainable Product Development.
       Int J Life Cycle Ass 18(5):1129-1136. http://dx.doi.org/10.1007/s11367-012-0538-0
[131] Mani M, Madan J, Lee JH, Lyons KW, Gupta SK (2014) Sustainability characterization for manufacturing processes. *Int J Prod
       Res* 52(20):5895-5912. http://dx.doi.org/10.1080/00207543.2014.886788
[132] ISO (2013) 20140-1:2013 Automation Systems and Integration – Evaluating Energy Efficiency and Other Factors of
       Manufacturing Systems that Influence the Environment – Part 1: Overview and General Principles.
       http://www.iso.org/iso/home/store/catalogue_tc/catalogue_detail.htm?csnumber=54809 (Accessed 8/7/2014)
[133] British Standards Institution (BSI) (2011) BS 8905 - British standard 2011: Framework for the assessment of the sustainable use
       of materials. http://shop.bsigroup.com/en/ProductDetail/?pid=000000000030216209 (Accessed 7/28/2015)
[134] IEEE (2013) IEE 1680 Environmental assessment of electronic products. http://grouper.ieee.org/groups/1680/ (Accessed 9/6/2013)
[135] IEC (2011) TC111 TR 62725 Sustainability Assessment for Electrical and Electronic Products.
       http://www.iec.ch/dyn/www/f?p=103:38:0::::FSP_LANG_ID,FSP_APEX_PAGE,FSP_ORG_ID,FSP_PROJECT:25,20,1314,IE
       C/TR%2062725%20Ed.%201.0 (Accessed 2/6/2013)
[136] ANSI (2010) Sustainability assessment for Plastics.
       http://publicaa.ansi.org/sites/apdl/Documents/Standards%20Action/2010%20PDFs/SAV4106.pdf (Accessed 1/14/2013)
[137] ANSI (2007) BSR/GEI Electronic Office Equipment Sustainability Performance - 200x: A Standard for the Sustainability of
       Electronic Office Equipment Products and Applications.
       http://publicaa.ansi.org/sites/apdl/Documents/Standards%20Action/2007%20PDFs/SAV3834.pdf (Accessed 2/6/2013)
[138] ISO (2011) ISO: 50001 Assessment for Energy Use and Management (ISO Office, Geneva).
       http://www.iso.org/iso/home/standards/management-standards/iso50001.htm (Accessed 2/6/2013)
[139] Underwriters Laboratories Environment (ULE) (2010) ULE 880 Sustainability Assessment Standard Based on Governance,
       Environment Workplace, Customers and Suppliers, Social and Community (ULE, GreenBiz).
       http://www.greenbiz.com/blog/2010/08/02/introducing-ule-880-sustainability-manufacturing-organizations (Accessed
       11/20/2014)
[140] ASTM International (2015) Standard Guide for Evaluation of Environmental Aspects of Manufacturing Processes (ASTM
       International, West Conshohocken, PA), E2986 – 15. http://compass.astm.org/EDIT/html_annot.cgi?E2986+15 (Accessed 5/16/2016)
[141] ASTM International (2016) Standard Guide for Characterizing Environmental Aspects of Manufacturing Processes (ASTM
       International, West Conshohocken, PA), E3012 − 16. http://compass.astm.org/EDIT/html_annot.cgi?E3012+16 (Accessed 5/16/2016)
[142] Unit Process Life Cycle Inventory (UPLCI). http://cratel.wichita.edu/uplci/ (Accessed 5/16/2016)
[143] Overcash M, Twoney J (2012) Unit process life cycle inventory (UPLCI) – A structured framework to complete life cycle
       studies, Leveraging Technology for a Sustainable World. In *19th CIRP International Conference on Lice Cycle Engineering*
       (Berkeley, CA), pp 1-4.

[144]   Kellens K, Dewulf W, Overcash M, Hauschild MZ, Duflou JR (2012) Methodology for Systematic Analysis and Improvement of Manufacturing Unit Process Life Cycle Inventory (UPLCI) CO2PE! Initiative (cooperative effort on process emissions in manufacturing. Part 2: Case Studies). *Int J Life Cycle Ass* 17(2):242-251. http://dx.doi.org/10.1007/s11367-011-0352-0

[145]   USDA Life Cycle Assessment Commons. http://www.lcacommons.gov (Accessed 5/3/2016)

[146]   Waller A (2012) Witness simulation software. In *Proceedings of the 2012 Winter Simulation Conference*, eds Laroque C, Himmelspach J, Pasupathy R, Rose O, Uhrmacher AM (Winter Simulation Conference, Berlin, Germany), pp 1-12.

[147]   Herrmann C, Thiede S, Stehr J, Bergmann L (2008) An environmental perspective on Lean Production. *Manufacturing Systems and Technologies for the New Frontier: The 41st CIRP Conference on Manufacturing Systems May 26–28, 2008, Tokyo, Japan*, eds Mitsuishi M, Ueda K, & Kimura F (Springer London, London), pp 83-88. http://dx.doi.org/10.1007/978-1-84800-267-8_16

[148]   Wilson A (2014) White paper on sustainable manufacturing (Strategic Sustainability Consulting). www.sustainabilityconsulting.com (Accessed 9/29/2014)

[149]   Misterek DA, Dooley KJ, Anderson JC (1992) Productivity as a performance measure. *Journal of Operations & Production Management* 12(1):29-45. http://dx.doi.org/10.1108/EUM0000000001294

[150]   Muchiri P, Pintelon L (2008) Performance measurement using Overall Equipment Effectiveness (OEE): Literature review and practical application discussion. *Int J Prod Res* 46(13):3517-3535. http://dx.doi.org/10.1080/00207540601142645

[151]   Herron C, Braiden PM (2006) A methodology for developing sustainable quantifiable productivity improvement in manufacturing companies. *Int J Prod Econ* 104(1):143-153. http://dx.doi.org/10.1016/j.ijpe.2005.10.004

[152]   White DC (2003) The "smart" plant: Economics and technology. In *Proceedings Foundations of Computer-Aided Process Operations (FOCAPO2003)*, pp 519-526. http://www.nt.ntnu.no/users/skoge/prost/proceedings/focapo_2003/pdffiles/papers/090.pdf (Accessed 5/16/2016)

[153]   Bruccoleri M, Renna P, Perrone G (2005) Reconfiguration: a key to handle exceptions and performance deteriorations in manufacturing operations. *Int J Prod Res* 43(19):4125-4145. http://dx.doi.org/10.1080/00207540500140773

[154]   Cheng S, Azarian MH, Pecht MG (2010) Sensor systems for prognostics and health management. *Sensors-Basel* 10(6):5774-5797. http://dx.doi.org/10.3390/s100605774

[155]   Kennerley M, Neely A (2003) Measuring performance in a changing business environment. *International Journal of Operations & Production Management* 23(2):213-229. http://dx.doi.org/10.1108/01443570310458465

[156]   Khan MA, Uddin MF, Gupta N (2014) Seven V's of Big Data: Understanding big data to extract value. In *Proceedings of 2014 Zone 1 Conference of the American Society for Engineering Education (ASEE Zone 1)* (Bridgeport, CT), pp 1-5. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6820689 (Accessed 8/28/2015)

[157]   ISO/IEC 9075-1 (2008) Information Technology – Database Languages – SQL – Part 1: Framework (SQL/Framework). http://www.iso.org/iso/catalogue_detail.htm?csnumber=45498 (Accessed 12/7/2013)

[158]   NIST Engineering Laboratory (2013) Cybersecurity for Smart Manufacturing Systems. http://www.nist.gov/el/isd/cs/csms.cfm (Accessed 5/7/2016)

[159]   Smart Manufacturing Leadership Collation (SMLC) (2014) The Infusion of Intelligence that Transforms the Way Industries Conceptualize, Design, and Operate the Manufacturing Enterprise. http://www.arcweb.com/events/arc-industry-forum-orlando/arcindustryforumorlando2014presentations/Smart%20Manufacturing.pdf (Accessed 5/7/2016)

[160]   Lu Y, Morris K, Frechette S (2015) Standards landscape and directions for smart manufacturing systems. In *2015 IEEE International Conference on Automation Science and Engineering (CASE)* (IEEE, Gothenburg), pp 998-1005.

[161]   Lu Y, Morris K, Frechette S (2016) Current standards landscape for smart manufacturing systems (National Institute of Standards and Technology, Gaithersburg, MD), NISTIR 8107. http://nvlpubs.nist.gov/nistpubs/ir/2016/NIST.IR.8107.pdf (Accessed 5/14/2016)

[162]   Kibira D, Choi S, Jung K, Bardhan T (2015) Analysis of standards towards simulation-based integrated production planning. *Advances in Production Management Systems: Innovative Production Management Towards Sustainable Growth* (Springer International Publishing), pp 39-48.

[163]   Choi S, Jung K, Kulvatunyou B, Morris K (2016) An analysis of technologies and standards for designing smart manufacturing systems (Not yet published).

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