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A road map for applied data sciences supporting sustainability in advanced manufacturing: the information quality dimensions

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Abstract

Data science is a multidisciplinary blend of data inference, algorithm development, and technology in order to solve analytically complex problems. Sustainability is a critical asset of a manufacturing enterprise. It enables a business to differentiate itself from competitors and to compete efficiently and effectively to the best of its ability. This paper is a review of data analytics, and how it supports advanced manufacturing with an emphasis on sustainability. The objective is to present a context for a roadmap for applied data science addressing such analytic challenges. We start with a general introduction to advanced manufacturing and trends in modern analytics tools and technology. We then list challenges of analytics supporting advanced manufacturing and sustainability aspects. The information quality (InfoQ) framework is proposed as a backbone to evaluate the analytics needed in advanced manufacturing. The eight InfoQ dimensions are: 1) Data Resolution, 2) Data Structure, 3) Data Integration, 4) Temporal Relevance, 5) Chronology of Data and Goal, 6) Generalizability, 7) Operationalization and 8) Communication. These dimensions provide a classification of advanced manufacturing analytics domains. The paper provides a roadmap for the development of applied analytic techniques supporting advanced manufacturing and sustainability. The objective is to motivate researchers, practitioners and industrialists to support such a roadmap.

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Keywords: Advanced manufacturing, Industry 4.0, Information Quality (InfoQ), Data Science, Analytics.

1. Introduction

In this paper, we present a roadmap for data science and applied statistics with an emphasis on industrial applications and challenges posed by Industry 4.0. Data is increasingly cheap and ubiquitous. The rise of "big data"

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has the potential to deepen our understanding of phenomena ranging from physical and biological systems to human social and economic behavior. Working with this data requires distinctive new skills and tools. The data is also more heterogeneous than the highly curated data of the past. Digitized text, audio, and visual content, like sensor and blog data, is typically messy, incomplete, and unstructured; it is often of uncertain provenance and quality; and frequently must be combined with other data to be useful. Working with user-generated data sets also raises challenging issues of privacy, security, and ethics. A system approach to the design for sustainability is presented in [27]. The paper provides an overview of the challenges of systems engineering in designing for sustainability by involving all interested stakeholders, dealing with the entire life cycle value chain of products, practicing corporate social responsibility and managing the relevant risks and opportunities. In parallel with these developments, the last several years have seen a significant growth in the number of courses and new programs titles “Data Science”, “Business Analytics”, “Predictive Analytics”, “Big Data Analytics”, and related titles. Different programs have a different emphasis depending on whether they are housed in a business school, a computer science department, or a cross-departmental program. What is however common to all of them, is their focus on data (structured and unstructured), and specifically, on data analysis. Many Statistics and Operations Research programs and departments have been restructuring, revising, and rebranding their courses and programs to match the high demand for people skilled in data analysis (see [3]).

Applied statistics is about meeting the challenge of solving real world problems with mathematical tools and statistical thinking. In a paper discussing the expanded role of statistics in research, business, industry, and service organizations. The paper in [9] proposes a life cycle view that combines an inductive-deductive learning process. The main point in this proposal is that effective statistical work is much more than properly applying statistical methods. One needs to emphasize that statistical analysis is a collaborative venture whose success depends essentially on the effectiveness of the communication between the statistician and the client. The statistician needs to exercise social and communicative skills for his work to have an impact. In addition, a systematic assessment of the impact and the quality of information generated by the statistical analysis requires additional activities not usually performed by statisticians. A particularly important area of application to data science and applied statistics is industry and manufacturing operations. The first industrial revolution was triggered by the introduction of the steam engine and the mechanization of manual work in the 18th century. Electricity drove mass production in the second industrial revolution in the early 20th century. The third revolution in manufacturing was due to the use of electronics and computer technology for manufacturing and production automation. We are now entering the fourth phase, labeled advanced manufacturing or Industry 4.0. For a perspective on the evolution of production and quality conceptual frameworks, from inspection to process improvement to quality by design, see chapter 1 in [13].

2. Data Science and Applied Statistics in Advanced Manufacturing

Advanced manufacturing requires analytics and operational capabilities to interface to devices in real time, at an individual level. Software development has become agile and commonly applied DevOps operations provide continuous delivery (see [14]). Moreover, processing and analytic models evolve to provide a high level of agility as organizations realize data agility, the ability to understand data in context and take the right business action, is the source of competitive advantage (see [19]). The emergence of agile processing models enables the same instance of data to support batch analytics, interactive analytics, global messaging, database and file-based models. More agile analytic models are also enabled when a single instance of data can support a broader set of tools. The result is an agile development and application platform that supports the broadest range of processing and analytic models. Tools and methods implemented to verify if process behavior is consistent with normal operating conditions include functionalities such as: i) Detection - rapidly detect abnormalities in process operation ,ii) Diagnosis - look for the root cause of abnormal behavior ,iii) Fault criticality assessment - assess potential severity of the fault and iv) Decision - stop the process and fix the problem or accommodate the fault and proceed.

In this paper, we focus on applications of statistics and data science to “Sustainable Manufacturing”. In the US, a president team on sustainable manufacturing, emphasized the need to maximize every atom of matter and joule of energy using technologies and systems that enable optimal raw material, energy, and resource utilization. The objective is to achieve manufacturing processes with lower energy - consumptions, savings in energy and higher efficiencies. Advanced manufacturing builds on emerging technologies to critically enhance economic competitiveness of individual manufacturers and enhance sustainability of the whole industrial sector profitability. Data science and analytic tools supporting advanced manufacturing can be classified in 9 domains: 1) Engineering Design, 2) Manufacturing Systems, 3) Decision Support Systems, 4) Shop Floor Control and Layout, 5) Fault Detection and Quality Improvement, 6) Condition Based Maintenance, 7) Customer and Supplier Relationship Management, 8) Energy and Infrastructure Management and 9) Cybersecurity and security related issues

In each of these domains, there are opportunities for advancing sustainability of the products, the processes and even of the organization. Each of these domains is described below with examples of the analytic support required to perform the related tasks. The examples are designed to demonstrate the role of analytics in advanced manufacturing and sustainability. For each domain, we discuss how to enhance sustainability through data analytics. A follow up section lists challenges that need to be addressed in developing and implementing such methods.

2.1. Engineering Design

Modelling and simulation is an integral part of modern design and engineering. Fast prototypes today are based on 3D printing for testing design alternatives and enable multidimensional optimization during the design and engineering process. Advanced manufacturing opens new options for personalized production and low volume high mix processing. As an example, [26] discuss simulations used to compare mathematical models for tissue mimicking with 3D printers processing. Recent advances in computer-aided design (CAD) have provided a rapid and low-cost method to generate patient-specific tissue-mimicking phantoms from computational models that are constructed from CT or MRI results of individuals. They designed and fabricated metamaterials with three microstructures and applied finite element analysis (FEA) to predict their mechanical behaviors under tensile loadings. For more on such computer experiments see [11]. Modern computer experiments and simulations provide the means to achieve robust designs with effectiveness and efficiency that are way beyond the pioneering work in [24].

The engineering phase is the right stage to introduce sustainability into the designed products and/or systems. Most of the CAD models include information on material and energy consumptions. The designer should incorporate the Design for Sustainability features while using the CAD models. The designing of products for 3D printing is conserving materials and resources. Data analytics can support sustainability during the Engineering Design by introducing quantitative measures for the sustainability of the designed product. In addition, there are number of initiatives on indicators and frameworks for sustainable development. see [23].

2.2. Manufacturing Systems

There is an increasing tendency in industry towards data-rich environments characterized by “intelligent” and autonomous machine tools, where several sources of information (i.e. sensors installed in production systems) are available for many purposes (e.g., monitoring, diagnostics, predictive maintenance, etc.). In this framework, many technological advances pave the way for a systematic and extended use of sensor data for industrial quality control. Furthermore, in many industrial applications, the process naturally switches from one operating mode to the following one, producing streams of data from different distributions that follow one another over time. This kind of process is referred to as “multimode process”. The monitored variables usually represent quantities that originate from one or multiple sensors, and each one of them requires dedicated pre-processing and raw signal elaboration steps [4] . A crucial issue in sustainable manufacturing is resource consumption. An advanced manufacturing policy promotes the use of sensors as internet of things (IoT) systems for real time monitoring of the resources consumptions, including sophisticated data analytics. For example, the system introduced by Lightapp (www.lightapp.com) monitors air pressure in companies all over the world. It is also used for benchmarking energy consumption in production plants.

2.3. Decision Support Systems

Groger et al. [6] present indication-based and pattern-based manufacturing process optimization as data mining approaches provided by in advanced manufacturing. They discuss dashboards that are typically part of manufacturing execution systems (MES) and custom business intelligence (BI) applications based on online analytical processing (OLAP). Their proposal relies on a data integration layer that integrates process and operational manufacturing data in a holistic process centric data warehouse. The analytic tools they discuss include Bayesian classification, neural networks, support vector machines and decision trees. For more on such tools see [10]. Usually, Business Intelligence (BI) includes the measurements of sustainability indicators. As the sustainability approach promotes a triple bottom line model, [22], the BI should include measures that support these bottom lines.

2.4. Shop Floor Control and Layout

Shop floor control is inherently a multivariate problem. With modern computing power and advanced integration and visualization platforms, multivariate statistical process control (MSPC) is becoming operational and critical to advanced manufacturing. For a background on MSPC see [16]. The authors in [26] evaluate the effect of control parameters on 3D printed meta-materials designed to mimic the strain-stiffening behavior of soft tissues. They evaluate, with simulation and physical experiments, the effects of design parameters such as wavelength, amplitude, and radius of fiber on the sinusoidal wave design, pitch, radius of helix, and radius of fiber on the double helix design. Modern experimental design methods permit to effectively account for nonlinearities in such responses (see [11]). In terms of factory layout, an early model of a process with a testing and repair stations has been proposed in [1]. In that paper, the authors investigate the impact of the defect distribution on system performance measures such as yield, production lead time, and work-in-process inventory and provide management guidelines for short term control decisions such as identifying potential bottlenecks under increased workloads and allocating additional resources to release bottlenecks. They also discuss budget allocation method for process improvement projects initiated in order to meet the long-term goal of continuously decreasing defect levels. Optimal shop floor control and layout serves sustainability objectives. An improved shop floor layout saves time, energy and increases employee satisfaction. A real time shop floor control activated by data analytics ensures that the shop floor is well managed, also from sustainability aspects.

2.5. Fault Detection and Quality Improvement

Hybrid systems consist of continuous behavior and discrete states represented by modes. In each mode, the system is governed by continuous dynamics, and different modes correspond to different continuous models. System health monitoring is a key feature for early detection of faults, failure prevention, reliability, and condition-based maintenance. A health monitoring system integrates four main skills, namely: 1) fault detection; 2) fault isolation; and 3) fault parameter estimation and 4) prediction of time to maintenance or replacement. In hybrid system diagnosis, two different types of faults are defined. The first is a parametric fault, where one or more model parameters are deviating from their nominal value to an unknown value. The second type is fault mode; in this case, the faulty state is known a prior and can be modeled by known parameters only. A health monitoring framework for hybrid system is presented in [2] and [15]. The work in [4] and [13] describe various process monitoring methods such as Shiraryev-Roberts (SR) detection procedure, multivariate statistical process control (MSPC), SPS, signal decomposition and Empirical Mode Decomposition (EMD). [21] present an automation framework for the effective usage of diagnosis tools in the performance testing of clustered systems. One of the possible relationships among Quality Improvements and Sustainability is the Cost of Quality (CoQ) which most of it is the cost of producing and delivering non quality products. The measure of CoQ through data analytics helps companies to lower the CoQ through quality improvements initiatives. Lower CoQ improves sustainability. In addition, quality improvements may prevent companies from events like products recalls. Some of these recalls turn to be disasters for companies like auto manufacturing companies. These recalls can be prevented if the early failures data was correctly analyzed and interpreted. Such recalls are real risks for the sustainability of companies and preventing theses recalls is crucial for the sustainability.

2.6. Condition Based Maintenance

Man-made systems are prone to deterioration over time and therefore require ongoing maintenance to avoid malfunctioning. Accordingly, it is essential to undertake an effective preventive maintenance (PM) policy that minimizes the life cycle cost (LCC) of the system and maximizes its operational profit. [8] presents a condition-based maintenance method to define a PM policy per the state of the system at various time periods by combining both a simulation model of the system and a predictive metamodel. [16], [17] and [25] review challenges of big data to modern reliability engineering. As mentioned above, preventive maintenance and predictive maintenance based on sensors and data analytics, is a perfect tool for optimizing Life Cycle Costs. An example of this technology is provided by Augury (www.augury.com) which develops products measuring and monitoring magnetic signals of rotors and predict motor repair or subsystem replacement.

2.7. Customer and Supplier Relationship Management

Supply chain management (SCM) is a systematic progression in which an organization manages the flows of products, services, money, etc. The aim is to obtain maximum profit with minimum costing as well as fulfilling the customer's demand. SCM includes the movement and storage of raw materials, work-in-process inventory, and finished goods i.e., from raw material to point of consumption. Among others, [20] looked at this interconnected network. They developed a three-layer supply chain model with production-inventory model for re-workable items including an inventory model for deteriorating items price and stock dependent demand. They propose an economical order quantity model with imperfect quality and shortage backordering under inspection errors and deterioration. The ISO20400 new international standard guides how to manage sustainability in the procurement process and along all supply chain and system. The standard provides principles, policies, processes and enablers for introducing and assuring sustainability in the procurement process and along the supply chain. The standard is based on the ISO26000 standard which is dealing with Corporate Social Responsibility. Data collected about suppliers provides valuable information for evaluating the supply chain sustainability. Today, there are various systems over the web which provide data about customers and their market status and position. This information can support the evaluation a company sustainability.

2.8 Energy and Infrastructure Management

The authors in [18] consider data gathered from operation and service of off-shore wind turbines. They use and analyze field data or so-called Product Use Information (PUI) to improve maintenance activities and to reduce the costs. Their data is from sensors on the turbines, alarms information, signals from the condition monitoring and supervisory control and data acquisition (SCADA) systems used in maintenance activities. To make the right decision, it is important to understand which PUI data source and which data analysis methods are suitable for what kind of decision making task. The aim of their study is to discover how big data analytics of PUI can help in the maintenance processes of off-shore wind power, thus ensuring their sustainable operations.

2.9 Cybersecurity and security related issues

The definition used in the EU Cybersecurity Strategy is: "Cyber-security commonly refers to the safeguards and actions that can be used to protect the cyber domain, both in the civilian and military fields, from those threats that are associated with or that may harm its interdependent networks and information infrastructure. Cyber-security strives to preserve the availability and integrity of the networks and infrastructure and the confidentiality of the information contained therein." [5]. Cybersecurity is a critical concern in advanced manufacturing sustainability. [7] proposes an application that characterizes the behavioral patterns of suspect users versus non-suspect users based on usage metadata. These are examples of a growing area of research. In today's world, cybersecurity is a big challenge for companies' sustainability. Data analytics, like pattern recognition and anomaly detection is applied in efforts securing companies sustainability against cyber-attacks.

3. A Roadmap of Data Science and Analytic Tools in Advanced Manufacturing

Big data has been around for some time, e.g. satellite imaging, genomics, particle physics. And the collection, provision and analysis of data is now a huge industry. The term data science is commonly used to describe these activities. Big data is considered to offer a high potential for learning, even though it is largely observational. The main challenges are due to i) a need for transitioning from monitoring the mean, to dispersion, to correlation, ii) from stationary, to dynamic, to non-stationary, iii) from sensor data to higher-order profiles and iv) from detection, to diagnosis, to prognosis thus assuring the sustainability of the production process

Continuous processes are characterized by a stable operation window. Classical approaches are based on the assumption of independent and identically distributed variables, which is rarely valid for industrial processes due the existence of inertial elements (big process units) coupled with fast acquisition rates. For dealing with autocorrelation, three types of approaches can be followed:

1. Adjusting the control limits (this is feasible only for very simple systems).
2. Estimating a multivariate time series model and monitor the residuals with over a dozen variables.
3. Using a transformation in the time domain that decorrelates the autocorrelation of the series (namely the wavelet transform)

Batch processes monitoring is a much more challenging task than monitoring continuous processes. In this context, all variables can change in each cycle or batch. The batch process is therefore intrinsically multivariate and non-stationary. Moreover, in this case, non-linearities are more noticeable that in continuous processes with more or less consistent cycles. To characterize these challenges, we refer to a comprehensive framework designed to plan and assess the level of information quality provided by analytic tools and methods. .

Information quality (InfoQ) is defined in [12] as the potential of a dataset to achieve a specific (scientific or practical) goal using a given empirical analysis method. InfoQ is different from data quality and analysis quality, but is dependent on these components and on the relationship between them. Technically, the definition of InfoQ is the derived utility (U) from an application of a statistical or data analytic model (f), to a data set (X), given the research goal (g). This can be written algebraically as: $InfoQ(f, X, g, U) = U(f (X|g))$. [12] proposes eight dimensions of InfoQ:

1) **Data Resolution**: The measurement scale and level of aggregation of the data relative to the task at hand must be adequate for the study

2) **Data Structure**: The data can combine structured quantitative data with unstructured, semantic based data

3) **Data Integration**: Data is often spread out across multiple data sources. Hence, properly identifying the different relevant sources, collecting the relevant data, and integrating the data, directly affect information quality

4) **Temporal Relevance**: A data set contains information collected during a certain time window. The degree of relevance of the data in that time window to the current goal at hand must be assessed and is crucial to attain sustainable control of the process or the product

5) **Chronology of Data and Goal**: Depending on the nature of the goal, the chronology of the data can support the goal to different degrees. For example, in process control applications of discrete parts, we might collect data from previous processes that is relevant to a specific part. If the goal is to quantify the effect of previous manufacturing steps on the specific part' quality, then the chronology is fine. However, if the goal is to predict the final quality of a part, then the required information builds on data collected in future manufacturing steps, and hence the chronology of data and goal is not met

6) **Generalizability**: Two types of generalizability are statistical and scientific generalizability. Statistical generalizability refers to inferring from a sample to a target population. Scientific generalizability refers to applying a model based on a particular target population to other populations

7) Operationalization: Action operationalization is about deriving concrete actions from the information provided by a study

8) **Communication**: If the information does not reach the right person at the right time in a clear and understandable way, then the quality of information becomes poor.

The InfoQ dimensions provide a roadmap for assessing data analytics methods in the 9 advanced manufacturing domains listed in section 2.

4. Discussion

Eventually, analytics and statistics analysis is performed to generate information and to support decisions. In this paper, we review the general role of data science and specifically the role of analytics in the context of advanced manufacturing and sustainability. We list examples of analytic methods and open challenges. The framework of information quality (InfoQ) is presented as an infrastructure for evaluating analytic methods and tools. The elements of a roadmap for applied data science require linking industry and academia and provide test bed environments where new analytic algorithms can be tested and information hubs where knowledge can be documented and shared. Education programs are needed at different levels (schools, colleges, universities, workers, managers, scientists) in order to prepare human resource infrastructures for data analytics developments. As more companies draw on analytics for their competitive edge and sustainable growth, several complementary organizational trends are emerging around the emphasis on data. Businesses that take data seriously are organized around data as an asset. These businesses are democratizing the access to data and "bring the right information to the right person at the right time". These businesses promote and support data sharing. Data sharing requires many parts of the organization to work together. The objectives of this paper are to provide a context for the development of applied data science in advanced manufacturing and sustainability

References

[1] Agnihothri, S. and Kenett, R.S. (1985) The impact of defects on a process with rework, European Journal of Operational Research, 80, 308-327

[2] Arogeti, S., Wang, D. and Low, C. (2010). Mode Identification of Hybrid Systems in the Presence of Fault, IEEE Transaction on Industrial Electronics, 57(4), 1452-1467.

[3] Coleman, S. and Kenett, R.S. (2017) The Information Quality Framework for Evaluating Data Science Programs, Encyclopedia with Semantic Computing, World Scientific Press.

[4] Colosimo, BM, Mammarella, F and Petro, S (2010) Quality control of manufactured surfaces, Frontiers in Statistical Quality Control 9, 55-70

[5] EU, Scientific Advice Mechanism (2016). Cybersecurity, https://ec.europa.eu/research/sam/pdf/meetings/hlg_sam_012016_scoping_paper_cybersecurity.pdf

[6] Groger, C., Niedermann, F. and Mitschang, B. (2012) Data Mining-driven Manufacturing Process Optimization, Proceedings of the World Congress on Engineering 2012 Vol III WCE 2012, July 4 - 6, 2012, London, U.K.

[7] Gruber, A. and Ben Gal, I. (2017). Using targeted Bayesian network learning for suspect identification in communication networks, International Journal of Information Security, DOI 10.1007/s10207-017-0362-4

[8] Gruber, A., Yanovski, S. and Ben-Gal, I. (2013) Condition-Based Maintenance via Simulation and a Targeted Bayesian Network Metamodel, Quality Engineering, 25:4, 370-384.

[9] Kenett, R.S. (2015) Statistics: A Life Cycle View" Quality Engineering (with discussion), 27(1),111-129.

[10] Kenett, R.S. (2017) Bayesian networks: Theory, applications and sensitivity issues, Encyclopedia with Semantic Computing and Robotic Intelligence, World Scientific Press, 1(1), 1-13. http://www.worldscientific.com/doi/abs/10.1142/S2425038416300147

[11] Kenett, R.S. and Nguyen N-K (2017) New Frontiers in Evaluating Experimental Conditions for Enhanced Information Quality, Quality Progress, in press.

[12] Kenett, R.S. and Shmueli. G. (2016). Information Quality: The Potential of Data and Analytics to Generate Knowledge, John Wiley and Sons, Chichester, UK.

[13] Kenett, R.S. and Zacks, S. (2014). Modern Industrial Statistics: with applications in R, MINITAB and JMP, John Wiley and Sons, Chichester, UK.

[14] Kenett, R.S., Ruggeri. G. and Faltin, F. (2017). Analytic Methods in Systems and Software Testing, John Wiley and Sons

[15] Low, C, Wang, D. and Arogeti, S. (2010). Quantitative Hybrid Bond Graph-Based Fault Detection and Isolation, IEEE Transaction on Automation Science and engineering, 7(3), 558-569.
[16] Lu L. and Anderson-Cook, CM (2015) Improving Reliability Understanding Through Estimation and Prediction with Usage Information, Quality Engineering, 27:3, 304-316
[17] Meeker, W. and Hong, Y (2014) Reliability Meets Big Data: Opportunities and Challenges, Quality Engineering, 26:1, 102-116.
[18] Nabati, E. and Thoben, K. (2017) Data Driven Decision Making in Planning the Maintenance Activities of Off-shore Wind Energy, Procedia CIRP 59. 160 – 165
[19] Olavsrud, T. (2017). 15 data and analytics trends that will dominate 2017, http://www.cio.com/article/3166060/analytics/15-data-and-analytics-trends-that-will-dominate-2017.html
[20] Pal, S. and Mahapatra, G.S.(2017) A manufacturing-oriented supply chain model for imperfect quality with inspection errors, stochastic demand under rework and shortages, Computers & Industrial Engineering (2017), doi: http://dx.doi.org/10.1016/j.cie.2017.02.003
[21] Portillo-Dominguez, A.O., Perry, P., Magoni, D., and Murphy, J. (2017) PHOEBE: An Automation Framework for the Effective Usage of Diagnosis Tools in the Performance Testing of Clustered Systems. Software Practice and Experience, doi: 10.1002/spe.2500
[22] Savitz A.W (2003) The Triple Bottom Line, John Wiley and Sons, New York, USA.
[23] Singh R.K, Murty H.R,Gupta S.K, Dikshit (2012), An overview of sustainability assessment methodologies,Ecological Indicators 15(2012) 281-299
[24] Taguchi, G. (1978). System of Experimental Design. Unipub/Kraus International and American Supplier Institute.
[25] Vining, G. (2016) Recent Advances and Future Directions for Quality Engineering, Quality and Reliability Engineering International, 32 863–875.
[26] Wang, K., Wu, C., Qian, Z., Zhang, C., Wang, B. and Vannan, M. (2016) Dual-material 3D printed metamaterials with tunable mechanical properties for patient-specific tissue-mimicking phantoms, Additive Manufacturing, 12, 31–37
[27] Zonnenshain, A, Sheps, I (2008) Design for Sustainability- The Challenge for Systems Engineering, 18th International Symposium of INCOSE.