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Reliability Assessment in the Context of Industry 4.0: Data as a Game Changer

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Abstract

Reliability is the measure of the likelihood that a product, system or service will perform its intended function adequately for a specified period of time. Low reliability of a manufacturing system, besides the costly repairs and replacements, also implies reduced production, and consequently, significantly reduced profits. Therefore, it is very important to have a way to assess reliability, as a key performance metric for manufacturing systems, and cyber-physical systems in general. The newly developed information and communication technologies that are increasingly becoming part of the current and future manufacturing systems, both allow and invite for more sophisticated approaches to assessing reliability of manufacturing systems as opposed to the traditional expert knowledge-based approaches. In this paper, we describe the significance of evaluating reliability for the progress and acceptance of the Industry 4.0 technologies, as well as the new directions and possibilities for enhanced reliability analysis that these new technologies can provide. Finally, we provide an overview of the implications of these novel ways of analyzing reliability in the context of Industry 4.0.

Keywords: manufacturing systems; reliability; data collection; challenges; opportunities

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1. Introduction

Reliability evaluates the likelihood that a product, system or service will perform its intended function adequately for a specified period of time. Low reliability of a manufacturing system, besides the costly repairs and replacements, also implies reduced production, and consequently, reduced profits. Reliability of manufacturing systems has been of great importance for many decades [1, 2]. This fact has not changed throughout the years; on the contrary, reliability has maintained increased its significance as a vital measure of the operability of manufacturing facilities with their increasing complexities [3, 4]. What has changed, though, is that data that can enable more efficient and accurate reliability analysis of systems have now become even more easily obtainable. Therefore, a great portion of the expert knowledge that was typically leading and supporting reliability analysis has gotten an opportunity to be both enhanced and validated.

Reliability of a manufacturing system affects a number of other efficiency performance metrics, such as production costs, maintenance costs and spare parts management costs, ultimately affecting productivity and revenue, as low reliability implies that machines have frequent breakdowns, and thus, frequent interruptions in manufacturing processes. Related metrics, such as availability, also take into account systems' and components' downtimes due to repairs, so some of these performance metrics provide a more comprehensive way to assess. With the emergence of Industry 4.0, there are new opportunities of automating processes that are relevant for performing reliability analysis of manufacturing systems, allowing for new types of data to be collected on all relevant phenomena, including humans, and human-machine interactions. The development of new technologies and data infrastructures also enables the development of validation approaches for all historically used reliability models, and their enhancements or calibrations.

Moreover, recently predictive and prescriptive maintenance of machines has been identified as the most important application of industrial data analytics, as stated by Columbus in [5]. Since reliability is one of the more relevant measures to evaluate maintenance schedules, strategies or sequences of actions, consequently accurate reliability analysis and assessment are just as important. Throughout history we have been witnesses of a large number of oversimplified and wrong reliability models that have been used for making costly decisions [6, 7]. Decisions made based on inaccurate models can often be damaging to the performance of a system, affecting also both its safety and its security.

The goal of this paper is to discuss the significance of reliability analysis in the context of Industry 4.0 and provide directions for enhancing the processes related to reliability analysis of manufacturing facilities, given the new Information and Communication Technologies (ICT) developments.

We begin by providing background and preliminaries in Section 2, followed by a study of the meaning of reliability in the Industry 4.0 context in Section 3. In Section 4, we discuss the implications of the new opportunities for performing reliability analysis in the context of Industry 4.0, taking into consideration the latest technological developments.

2. Background

In this section we elaborate the context of Industry 4.0 and its principles, as well as summarize the advancements in reliability analysis for manufacturing systems.

2.1. On Industry 4.0

Industry 4.0 is the term that has been adopted to denote the latest digital industrial revolution [8]. The major drive for this industrial revolution is the data, i.e. the convenience and ease with which it is being collected and analyzed. This is, of course, facilitated by the large storage and computing power and the development of advanced and efficient methods for analyzing data and transforming it into decisions. All industries have been affected by these technologies and advancements, thus, utilizing them to enhance production by a large number of performance criteria [9], such as profit, costs, customer experience, energy efficiency, customer lifetime values and customer loyalty, to name a few [10-14]. The emergence and development of Industry 4.0 is currently creating significant pressure on manufacturers to have to collect and analyze data, in order to stay competitive on the market, which is expected to be pretty hard on small and medium enterprises (SMEs) due to their typically limited resources.

Nine main components of Industry 4.0 have been recognized as main drivers of its development and convergence [15], i.e.: System Integration, Big Data and Analytics, Simulation and Virtualization, Internet of Things (IoT), The Cloud, Cybersecurity, Autonomous Robots, Augmented Reality, and Additive Manufacturing. The core of these nine components is the data and its processing to permit automation and improvement of manufacturing and other related processes. Most of the components (6 out of 9) provide useful supports for collecting, storing and processing manufacturing data, as illustrated in Fig. 1, where we recognize the nine main components of Industry 4.0 into operations-related and data-related components. This further shows how important and central data is with respect to the Industry 4.0.

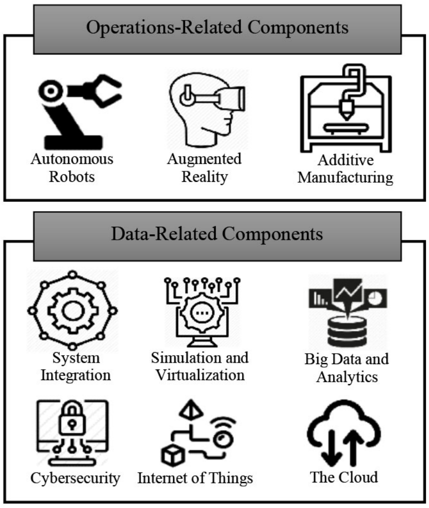

Figure 1. The important components of Industry 4.0.

The main aims of the Industry 4.0 are to improve manufacturing efficiency and diminish the associated cost. Measuring and enhancing reliability has a substantial impact on realizing these aims. The advantages of the new industrial revolution, however, also bring along new challenges. The development of Industry 4.0 is expected to effect important changes in the society. In Germany, for instance, as a leading manufacturing nation, they have recognized four main areas that are going to be impacted by the Industry 4.0 [9], as follows:

- Productivity, by ca. 10-30% increase,
- Income growth, by ca. 1 percent of Germany's GDP,
- Employment, by alteration in the requirement of skills, e.g. employees skilled in mechatronics and software developments are predicted to have an improved demand, at the expense of low-skilled laborers, and
- Investment, by expecting investment of ca. EUR 250 billion during the next ten years in Germany in adapting Industry 4.0.

Alike impacts are anticipated on a global scale [16], although at slightly different paces.

2.2. Reliability in Manufacturing Systems

Manufacturing systems, being cyber-physical systems, have three factors that affect their reliability: software reliability, hardware reliability, and reliability due to human interaction. All three factors have distinctive natures, and as such, need to be analyzed first individually, and then combined to provide a unifying measure of the overall reliability.

As elaborated in [17], in Figure 2 we illustrate failure rates of software and hardware components [18]. Hardware components have three phases: in the beginning while they are burning in, when the effect of manufacturing errors occurs, then the failure rate stabilizes until the "wear out" period, when, again, there is an increased failure rate due to the components' aging. Software components have the highest failure rate at the beginning, during integration and test. During this testing phase faults are being removed and the failure rate decreases and stabilizes, until the next upgrade. In Figure 1b we can see that software components do not exhibit the last "wear out" phase when the failure rate increases. Instead, the last phase with software is the Obsolescence, where the component becomes obsolete and no upgrades are being provided. One of the biggest differences between software and hardware reliability is that software reliability does not depend on time, whereas the hardware reliability does. On the other hand, software reliability is highly dependent and sensitive to changes in the environment, such as updates of hardware of software components, as well as other relevant events.

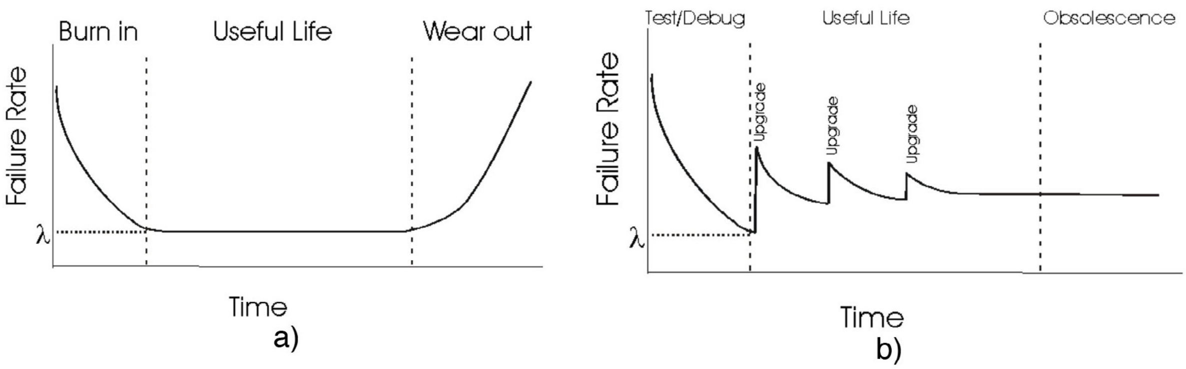

Figure 2. a) Bathtub curve for hardware reliability; b) Revised bathtub curve for software reliability [18]

Besides software and hardware-related reliability, we also need to consider the effect that human interaction has on a system's reliability as manufacturing systems are often operated by humans at certain levels. Human interaction increases the likelihood that the manufacturing system is used or operated in an unintended or wrong way, which would result in reduced reliability and greater vulnerability to faults. A large portion of manufacturing systems are designed for intensive interaction with humans and, thus, humans have, to a large extent, influence on the operation of these systems. There have been numerous research efforts directed at estimating the impact of unexpected and unintended human interaction with a wide range of Cyber-Physical Systems (CPS). One example of CPS with high level of human interaction are smart buildings, for which a lot of research has been done on the topic of occupants' behavior [19, 20]. Humans are highly uncertain and difficult to predict in their behavior. Therefore, modeling reliability-related human behavior needs different approaches from the ones applicable to software and hardware aspects.

Therefore, to obtain comprehensive measure of the reliability of a manufacturing system, all three types of reliabilities need to be considered, as well as their interplays and interdependencies. This is far from trivial to do, however, the availability of the IoT infrastructure may make it easier to extract and model relevant events and interdependencies accurately, such as to obtain accurate reliability measures.

3. Reliability Analysis in Industry 4.0 Context

With the development of the industrial Internet of Things (IoT), new opportunities for analyzing reliability of systems are being developed, as well as opportunities to validate the existing approaches. Typically, a lot of expert knowledge is utilized for reliability analysis, and to a large extent, expert knowledge will remain irreplaceable for safety-critical systems, where there is no option for collecting data on faults, as they should not happen at all due to their catastrophic consequences. One example, where a great level of expert knowledge is needed is the design of Fault Trees for reliability of aviation systems [21]. However, large portions of systems utilized in manufacturing are not safety-critical, i.e. their faults and failures do not cause damage to the people or the environment. Mainly, consequences of faults and failures in manufacturing systems are in terms of financial cost.

Therefore, the recent ICT developments and their use in manufacturing facilities create a significant opportunity to effectively gather data on faults and failures of these systems and utilize it to supplement expert knowledge and build more accurate reliability models. The development of Industry 4.0 has yielded a number of new moments and associated opportunities that can change the way in which reliability in manufacturing systems is analyzed and assessed. In particular, we focus on the following aspects:

1. Availability and ease of collection of data,
2. Large portion of systems being non-safety-critical,
3. Same flexible machines being utilized by different manufacturers for different purposes, and
4. New technologies lead to more complex and failure-prone systems.

Each of the four listed aspects provides different benefits and challenges, detailed as follows.

The availability and ease of collection of data has yielded collections of new types of data, but also requested development of new and sophisticated approaches to enable full benefit of the data. E.g. typically, the data collected is in form of time series, without explicitly capturing faults occurrences. This implies that there is high necessity of approaches that focus on event detection, such that faults and other events occurrences can be extracted from the time series data. Furthermore, accurate root cause analysis methodology will be the next requirement; such as to extracts events dependencies and model them. Once such approaches are sufficiently advanced, reliability analysis of systems can be automated, such as to be automatically performed, based on data from manufacturing machines. The fact that most of the manufacturing machines are not necessarily safety-critical, and faults/failures are relatively common occurrences, makes the data-based approaches very adequate. Collection of data for reliability analysis in safety-critical systems would be impossible, as in those systems the failures can cost human lives. Examples are automotive systems or aircraft. This brings us to the second point that supports the first.

The third fact on our list is the anticipation for flexible machines that can perform different tasks, which implies that highly repetitive use same types of machines will be occurring. Thus, a lot more data can be collected for those machines, yielding more accurate models. However, as we state by the fourth aspect, the availability of data and the new technologies comes at a cost, which is the increased complexity of the systems. This increased complexity implies vulnerability to faults and failures. E.g., CPS' processes often depend on input from sensor data, so a fault in the sensors can lead to significant damaging and costly consequences. This vulnerability only emphasizes the need for accurate and efficient reliability and overall health assessment of the manufacturing systems.

To summarize, in Figure 3, we illustrate the feedback loop that can enabled by the data-based reliability assessment for smart factories. We begin from the bottom left corner of the figure, where we have the smart factory that collects a data from its manufacturing processes. This data then needs to be processed in a way that key reliability-related events are detected (such as fault occurrences, repair starting times and completion times, etc.) and extracted [22, 23]. Next, this data is used for learning fault models, including causality among faults and failures, which is followed by advanced simulation and data analytics. The results of simulation and data analytics are utilized for decision support on improved system configuration and generation of preventive maintenance schedules for increased reliability of the system (i.e. smart factory in this case).

It is evident that machine learning and simulation will play important role in making the data-based reliability analysis processes possible. Advanced event detection methods will be crucial for gathering data for building reliability-relevant models, and accurate and efficient simulation methods will be needed for evaluating the reliability of the built models. The automatically generated models can then be used for analyzing alternative configurations for given systems, with the purpose of optimizing their reliabilities.

The four described aspects that characterize the latest developments, captured in the Industry 4.0 initiative, are in favor of using data-based approaches for reliability assessment of manufacturing cyber-physical systems. In the following section, we discuss the implications of the data-based reliability assessment of manufacturing systems.

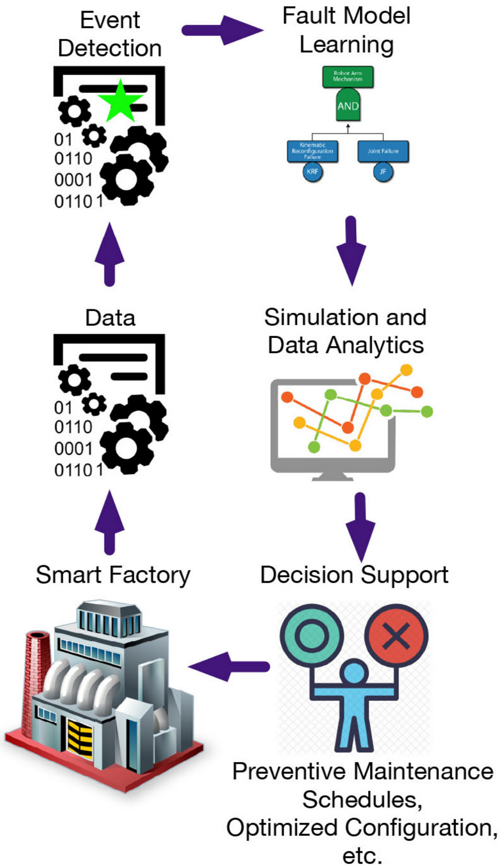

Figure 3. Data for supporting reliability modeling in smart factories

4. Implications

Managers and engineers in different manufacturing industries continuously plan with intention to improve productivity, quality, and reliability of their manufacturing processes and the quality of their products. At the same time, they constantly attempt to cut down manufacturing expenses, improve resource utilizations, and increase manufacturing safety. These objectives can be achieved well with leveraging the capabilities of Industry 4.0 for manufacturing. As both IoT and CPS are used to enable connectivity among different manufacturing components and smart cyber controls, more accurate data about different manufacturing processes can be collected, stored, and analyzed. In addition to this data from manufacturing processes, other business data from different enterprise systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Supply Chain Management (SCM), and Product Life Cycle Management (PLM) can provide detailed information about all production and related processes.

With this collected data, manufacturers can be armed with better data-driven decision making to significantly improve their operations and profitability. Different advanced cyber techniques such as simulation, data mining, process optimizations, and machine learning algorithms can be applied to this data to improve the reliability of different manufacturing systems, processes, and their products. For example, the collected data can be utilized by a number of data-driven decision-making processes to enhance reliability of different manufacturing processes with an aim to reduce materials, resources, and energy used to produce different products.

In addition, the collected information from different systems and processes can be utilized to optimize maintenance schedules and perform preventive diagnostics. Cost and time are two important aspects in manufacturing systems [24]. Consequently, manufacturing systems' maintenance is a tremendously important process that allows to keep manufacturing machines in outstanding operating settings and avoid unexpected accidents that may outcome in process interruptions and down-times as well as costly repairs. In addition, maintenance and support costs are estimated to be around 60 to 75% of the total lifecycle costs [25]. To optimize maintenance and decrease interruptions and repair costs, the collected information can be applied to form a knowledgebase to store, organize and analyze information using smart algorithms to propose optimizations for the maintenance schedules and assist in noticing potential problem areas before an actual problem happens.

Another significant opportunity is the potential for Collaborative Data Analytics among manufacturing facilities [11], which presents an opportunity to faster build more accurate fault models of machines that partake in the different flexible manufacturing systems. By joining data on matching machines, and thus sharing the conditions under which their machines operate, manufacturers can easily detect optimal configurations for their machines, as well as obtain accurate fault models for designing maintenance schedules that reduce the costs and downtime. This service could be either provided by a third party, or by joint companies' initiative, in the form of an interest group, which will guarantee anonymity and protection of companies' data. We are aware that many companies will be initially skeptical about sharing data, but we believe the necessity for survival will have an impact in changing these views and subscribing to the pragmatic initiatives.

5. Summary and Outlook

In this paper we examined the concept of reliability within the context of Industry 4.0, especially the impact of the obtainability and availability of data has on reliability analysis and assessment. The relevance of providing accurate and efficiently calculated reliability assessment of a manufacturing system has been high priority for a long time. What has changed now is the availability of new Information and Communication Technologies that have the potential to transform the traditional approaches, and enhance the quality of the provided assessments. The biggest game changer is the ease of obtaining and processing data on various phenomena related to the reliability. In line with the new advancements, we outlined fours aspects that can impact the ways of assessing reliability for manufacturing systems within the Industry 4.0 developments. One challenge that we foresee for obtaining useful reliability-related data is obtaining data on events, such as faults, failures, repairs, etc. This event data is typically facilitated through the challenging and intrusive process of event logging, or through advanced data analytics approaches in event detection, which again need to train on some data as well, so event logging to some extent cannot be avoided. Therefore, we see the success of the new and automated approaches on reliability assessment of manufacturing systems to a large extent dependent on the development of approaches for accurate event detection and process mining.

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