Journal of Manufacturing Systems 72 (2024) 38–58

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Review

Reliability assessment of manufacturing systems: A comprehensive overview, challenges and opportunities

Jonas Friederich [a,*], Sanja Lazarova-Molnar [b,a]

[a] Mærsk Mc-Kinney Møller Institute, University of Southern Denmark, Campusvej 55, Odense, 5230, Denmark
[b] Institute AIFB, Karlsruhe Institute of Technology, Kaiserstr. 89, Karlsruhe, 76133, Germany

ARTICLE INFO

Keywords:
Reliability assessment
Manufacturing systems
Literature review
Challenges and opportunities

ABSTRACT

Reliability assessment refers to the process of evaluating reliability of components or systems during their lifespan or prior to their implementation. In the manufacturing industry, the reliability of systems is directly linked to production efficiency, product quality, energy consumption, and other crucial performance indicators. Therefore, reliability plays a critical role in every aspect of manufacturing. In this review, we provide a comprehensive overview of the most significant advancements and trends in the assessment of manufacturing system reliability. For this, we also consider the three main facets of reliability analysis of cyber–physical systems, i.e., hardware, software, and human-related reliability. Beyond the overview of literature, we derive challenges and opportunities for reliability assessment of manufacturing systems based on the reviewed literature. Identified challenges encompass aspects like failure data availability and quality, fast-paced technological advancements, and the increasing complexity of manufacturing systems. In turn, the opportunities include the potential for integrating various assessment methods, and leveraging data to automate the assessment process and to increase accuracy of derived reliability models.

1. Introduction

The manufacturing industry is currently undergoing numerous transformations including shorter development and innovation times, individualized products, increased flexibility in production and product development, reduction of hierarchies, and resource efficiency [1]. To cope with these transformations, industry moves toward a new level of value chain organization and control, often referred to as Industry 4.0. This development is being propelled by advancements in a multitude of technologies, such as the Internet of Things, Cloud Computing, Big Data, and Artificial Intelligence. These technologies have not only redefined the way manufacturers operate but also how they respond to the evolving challenges of the marketplace [2].

The adoption of new technologies and paradigms increases the complexity of manufacturing systems, making it more difficult to maintain the systems and to identify possible vulnerabilities that affect their reliability. To this end, reliability assessment includes a number of techniques for planning and monitoring manufacturing systems and for detecting such vulnerabilities [3]. The goal of reliability assessment of any system operated in industry is to ensure a continuous operation without failures and to restore the system as quickly as possible in the event of a failure. Thus, overall production costs and downtime can be kept to a minimum if reliability is maintained at a high level [4].

Reliability assessment refers to the systematic process of evaluating the performance of a product, system, or service under specified conditions to determine its ability to perform its intended function without failure over a defined period of time [5]. Failures not only affect the performance of a manufacturing system, but can also cause accidents [4]. Traditional reliability assessment encompasses various statistical and probabilistic methods used to understand and quantify the reliability, availability, and maintainability of a system. To maximize profit, reliability assessment of such a system must be performed during the design phase and applied until the system is finally replaced. Ideally, a new assessment should be performed whenever changes are made to the system.

In addition to the general, overarching approach to reliability assessment, evaluating mission reliability is critical for many manufacturing systems [6]. Mission reliability assessment focuses on whether the manufacturing system can successfully accomplish a specific mission or task without failure. This involves evaluating the system's performance under predefined conditions and within a certain time frame, aligning its reliability with the achievement of particular goals or objectives. While both assessments aim to enhance the reliability of manufacturing systems, they differ in their application — one evaluates the overall reliability in a broad sense, while the other is more task-oriented,

* Corresponding author.
E-mail address: jofr@mmmi.sdu.dk (J. Friederich).

https://doi.org/10.1016/j.jmsy.2023.11.001
Received 10 July 2023; Received in revised form 2 November 2023; Accepted 13 November 2023
Available online 27 November 2023

Nomenclature

AGVs	Autonomous Guided Vehicles
AHP	Analytic Hierarchy Process
ASEP	Accident Sequence Evaluation Program
ATHEANA	A Technique for Human Analysis
BBN	Bayesian Belief Network
BDDs	Binary Decision Diagrams
BNs	Bayesian Networks
CBM	Condition-based Maintenance
CPT	Conditional Probability Table
CREAM	Cognitive Reliability and Error Analysis Method
DBN	Dynamic Bayesian Network
DDRA	Data-driven Reliability Assessment
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode and Effects and Criticality Analysis
FMS	Flexible Manufacturing System
FTA	Fault Tree Analysis
HCR	Human Cognition Reliability
HEART	Human Error Assessment and Reduction Technique
HEP	Human Error Probability
HFEs	Human Factors Experiments
HURA	Human Reliability Assessment
HWRA	Hardware Reliability Assessment
IIoT	Industrial Internet of Things
MDDs	Multi-valued Decision Diagrams
MM	Markov Modeling
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
PHM	Prognostics and Health Management
PNs	Petri Nets
PSF	Performance Shaping Factor
RBDs	Reliability Block Diagrams
RMS	Reconfigurable Manufacturing System
SLIM	Success Likelihood Index Methodology
SPAR-H	Standardized Plant Analysis Risk - Human Reliability Analysis
SWRA	Software Reliability Assessment
THERP	Technique for Human Error Rate Prediction
UGF	Universal Generating Function

concentrating on the accomplishment of specific missions within the manufacturing process.

In this article, we review the most significant existing approaches for reliability assessment of manufacturing systems and identify challenges and opportunities for future research. While the general approach to reliability assessment is our main focus, we also include significant studies addressing mission reliability assessment of manufacturing systems. We consider manufacturing systems, i.e., systems in which manufacturing operations take place. The term *manufacturing* is used to denote a general activity to transform raw material into consumable products such as cars or smartphones. *System* refers to a set of resources involved in this transformation process and their dependencies which allows all resources to work together [7]. These resources can be grouped into categories, such as hardware (e.g., machines and tools), software (e.g., Supervisory Control and Data Acquisition, Manufacturing Execution System, Enterprise Resource Planning) and humans (e.g., operators, maintenance engineers, supervisors).

Other theories, such as 5M1E, consider men (humans), machine (hardware), method, and measurement (software), as well as environment and material as main contributors to manufacturing system reliability [8]. In this article, however, we specifically focus on the influence of hardware, software, and humans on manufacturing system reliability.

We illustrate the types of manufacturing systems and their production resources considered in this article in Fig. 1. Within this system, a production management system, such as a Manufacturing Execution System (MES), controls the production process. Raw materials and finished products are stored in a warehouse, and material handling systems, such as mobile robots, move parts between the warehouse and an assembly line, which could be a belt conveyor. Various production cells carry out assembly operations, encompassing scenarios involving human-only interaction, human–machine interaction, or machine–machine interaction.

The remainder of the paper is structured as follows: In Section 2, we provide general background on reliability assessment of manufacturing systems. We discuss related reviews in Section 3. In Section 4, we present the results of our review of the most significant contributions to the field of reliability assessment of manufacturing systems. We extract challenges and opportunities for the field from the reviewed literature in Section 5. In Section 6, we summarize the findings and provide an outlook for future research.

2. Reliability assessment of manufacturing systems

As noted in the introduction, manufacturing systems may integrate hardware, software and human components. All three component types pose unique challenges to their reliability assessment, which has led to a variety of methods to address these challenges. Although many systems integrate two or all three component types, in this paper we focus mainly on their individual reliability assessment [9].

Furthermore, quality is, while not the main focus of this article, intrinsically linked to reliability when assessing the performance of manufacturing systems. Quality denotes the degree to which a system or component meets specified requirements and delivers the intended functionality. Reliability mitigates the incidence of defects and deviations, thereby directly influencing the quality of the manufactured products. Conversely, an enhancement in quality parameters such as precision and accuracy can improve the reliability of the system by reducing variability and unforeseen failures [10]. Therefore, optimization of quality and reliability in tandem is important for achieving advanced performance in manufacturing systems.

Reliability assessment can be carried out using both **qualitative** and **quantitative** methods. Qualitative methods involves the use of models, diagrams, or other visual representations to analyze and understand the reliability of a manufacturing system and its components. Qualitative models are often used to identify potential failure modes and assess the impact of these failures on system performance. These models are typically based on the experience of experts in the field, and may involve the use of fault trees, event trees, or other similar techniques to evaluate the likelihood of different failure scenarios.

Quantitative methods, on the other hand, involves the use of mathematical and statistical tools to evaluate the reliability of a system and its components. This analysis typically involves the use of data on system performance, such as failure rates, mean time between failures, and other relevant metrics, to quantify the likelihood of failure over time. Quantitative analysis can help identify potential weaknesses in a system, and can be used to design more reliable systems that can better withstand the stresses of the manufacturing environment.

One key advantage of qualitative methods is their ability to identify potential failure modes and assess the impact of these failures on

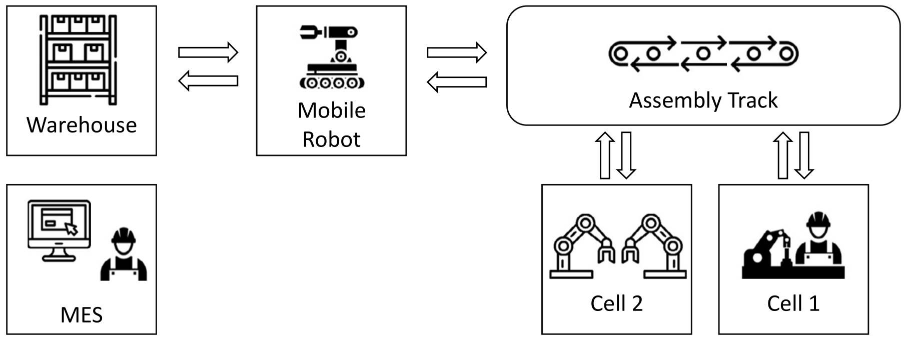

Fig. 1. Illustration of a manufacturing system integrating different production resources.

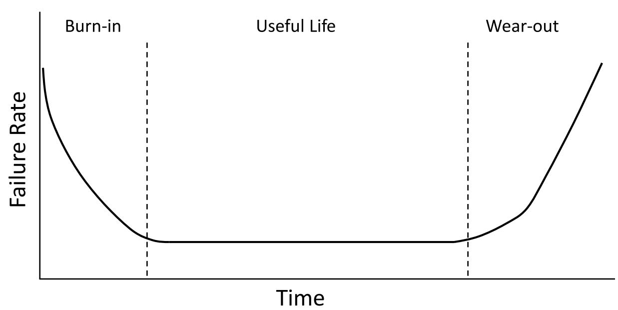

Fig. 2. Bathtub curve for hardware reliability [12].

system performance. Quantitative methods, on the other hand, provides a more rigorous and precise assessment of system reliability, based on empirical data and statistical analysis. In practice, both qualitative and quantitative methods are often used in combination to provide a comprehensive reliability assessment of manufacturing systems. In the following, we provide further background on hardware, software and human reliability assessment.

2.1. Hardware reliability assessment

Hardware reliability is an important criteria for the planning and operation of manufacturing systems. Manufacturing systems consist of various interconnected components, such as machinery, equipment, and tools that are used to produce goods. Each of these components in itself forms a system, consisting of interconnected parts. These systems and their components are highly dependent on hardware, and any failure or malfunction of the hardware can result in significant downtime, quality issues, and financial losses. Therefore, it is critical to assess the hardware reliability of both manufacturing systems and all of their components to minimize the risks associated with failures.

Most hardware systems and components follow the *Bathtub* curve which describes the failure rate of hardware over time due to degradation (Fig. 2). The bathtub curve is an important tool for hardware reliability assessment (HWRA), as it allows manufacturers to analyze the failure rate of hardware over time and take steps to minimize the likelihood of failures occurring. By understanding the factors that contribute to each stage of the bathtub curve, manufacturers can take appropriate measures to ensure that their hardware is reliable and long-lasting [11].

The first stage of the bathtub curve is the burn-in stage. This stage is characterized by a high failure rate, usually attributed to defects, design flaws, or improper installation. The burn-in stage is critical for HWRA because it can provide insight into the design of manufacturing systems and their components to reduce the number of failures.

The second stage of the bathtub curve is the useful life stage. This stage is characterized by a low and relatively constant failure rate. During this stage, hardware is performing its intended function correctly and is operating as expected. The useful life stage is ideal for hardware to operate because it represents the period of optimal performance.

The third and final stage of the bathtub curve is the wear-out stage. During this stage, the failure rate of hardware begins to increase again. This is usually due to the cumulative effects of wear and tear on the hardware, which eventually lead to system or component failure. The wear-out stage is the time when the hardware's useful life has been exhausted, and it can no longer perform its intended function reliably.

Hardware reliability is a critical aspect of any manufacturing system, as it directly impacts the availability, maintainability, and safety of the system and its components. These factors are closely interrelated and must be carefully considered for any HWRA activity. According to the *IEEE Standard Computer Dictionary* [13], these criteria are defined as follows:

- **Reliability** refers to the ability of a hardware system or component to function under stated conditions for a specified period of time. A reliable system or component should be able to operate as intended without failing, even under stressful conditions such as high heavy loads or high temperatures. In manufacturing systems, reliability is critical for minimizing downtime, preventing product defects, and ensuring consistent product quality.
- **Availability** is the degree to which a system or component is operational and accessible when required for use. A highly available system is one that is always ready to perform its intended function, with minimal downtime or delays. In manufacturing systems, availability is important for maintaining production schedules and meeting customer demand.
- **Maintainability** is the ease with which a system or component can be modified to correct faults, improve performance, or adapt to a changed environment. A maintainable system should be easy to repair or upgrade, without requiring extensive downtime or costly repairs. In manufacturing systems, maintainability is critical for minimizing production downtime and reducing repair costs.
- **Safety** refers to the ability of a system or component not to damage the environment or cause harm to personnel during its operation. A safe system should be designed and operated in a way that minimizes the risk of accidents or environmental damage. In manufacturing systems, safety is critical for protecting workers and minimizing the risk of accidents or product defects.

Formally, reliability can expressed as the probability of success

$$R(t) = Pr\{T > t\} = \int_t^\infty f(x)dx \tag{1}$$

where $f(x)$ is the failure probability density function and t represents the period of time. This probability can be estimated using various methods, such as detailed analysis, historic data, or reliability modeling. For repairable systems, availability is often used as a measure of system reliability, which takes into account both the time a system is available for use and the time it is unavailable due to repairs or maintenance [4]. Other relevant measures of reliability include the mean time to failure (MTTF) for non-repairable systems, and the mean time between failures (MTBF) and mean time to repair (MTTR) for repairable systems. It is important to note that these measures assume that both repair times and inter-failure times are exponentially distributed, with constant rates. However, if failures and repairs follow a non-exponential distribution, then the concepts of failure distributions and repair distributions are used to model the system's reliability [14].

In the manufacturing domain, various methods and techniques are used to assess the reliability of hardware systems and components . This article aims to discuss the most commonly used approaches for modeling system reliability. While structured analysis methods, such as Failure Mode and Effects Analysis (FMEA), its extension, Failure Mode and Effects and Criticality Analysis (FMECA), and Hazard and Operability Study, are commonly used as inputs for reliability modeling techniques, they are not the focus of this article.

2.2. Software reliability assessment

Software plays an increasingly important role in modern manufacturing systems, from controlling automated processes to managing supply chain logistics. Ensuring the reliability of software is crucial to maintaining the overall reliability of the system. Software reliability assessment (SWRA) is the process of evaluating the probability of software failure and its impact on system performance. Software reliability is the probability that software will function without causing system failures during a given operating time. In contrast to hardware reliability, SWRA focuses on design flaws and has a different approach. Improving software reliability involves error prevention, fault detection and removal, and measurements to maximize reliability [15].

To prevent errors during software design, it is essential to use well-defined and standardized development processes, such as the Capability Maturity Model Integration , which aims to improve the software development process's quality and predictability [16]. Another approach to error prevention is the use of formal methods, which employ mathematical models to ensure software correctness.

Fault detection and removal refer to the identification and correction of software defects before they cause failures. This is achieved through testing and debugging activities. Testing ensures that software functions correctly under different conditions and scenarios, whereas debugging aims to identify and eliminate errors in the software code. Techniques such as model-based testing, fault injection, and code analysis are commonly used to detect and remove software faults [17].

Measurements to maximize software reliability are critical, particularly those that support error prevention and fault detection and removal. These measurements can be quantitative or qualitative and should be integrated into the software development process to improve the software's quality and predictability. Examples of such measures include code complexity metrics, defect density, and testing coverage [18].

The revised bathtub curve is a model that extends the traditional bathtub curve and provides a useful framework to explain software reliability and assess the probability of software failure throughout its lifecycle (Fig. 3). During the integration and test phase, software has the highest failure rate. As errors are eliminated during the test phase, the failure rate decreases and stabilizes until the next upgrade. Unlike hardware components, software does not have a "wear-out" phase in which the failure rate increases. Instead, the final phase for software is obsolescence, when components become outdated, and upgrades are no longer available. One significant difference between software and hardware reliability is that software reliability is not time-dependent, whereas hardware reliability is. However, software reliability is highly sensitive to changes in the environment, such as updates to hardware or software components, as well as other relevant events [14].

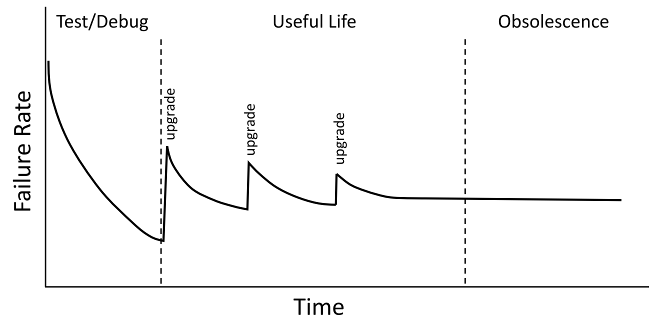

Fig. 3. Revised bathtub curve for software reliability [12].

The field of SWRA has seen the development of numerous models over time, which can be categorized into two main categories: predictive models and reliability growth models. Predictive models are designed to estimate future reliability indicators based on the software's design features. These models typically use parameters such as lines of code, loop nesting, external references, and inputs/outputs to predict the number of errors that may occur in the software.

In contrast, reliability growth models are statistical models that attempt to correlate error detection data with known functions, such as an exponential function. The idea behind these models is to use the correlation between past error detection data and a known function to predict the future behavior of the software in terms of its reliability. If the correlation between the data and the function is positive, the function can be used to predict the software's future reliability performance [19].

It is worth noting that both types of models have their strengths and weaknesses, and their effectiveness may vary depending on the context and application. For instance, while predictive models can be helpful in identifying potential weaknesses in software design, they may not always accurately reflect the software's actual behavior during its lifecycle. Reliability growth models, on the other hand, can provide more insight into the software's actual reliability performance over time, but they may require a significant amount of data to be effective.

2.3. Human reliability assessment

Human reliability assessment (HURA) is a critical aspect of manufacturing systems as humans are often responsible for operating, maintaining, and repairing equipment. The human element can significantly impact the reliability and safety of a system. HURA is the process of evaluating the likelihood of human error, its contextual factors and its consequences on system performance [20]. Methods for HURA evaluate the contribution of human operators to system reliability, predict human error rates, and assess the degradation of human-machine systems. HURA draws from a range of disciplines, including psychology, ergonomics, engineering, reliability assessment, and systems analysis, highlighting the interdisciplinary nature of this field [21].

Human reliability is a critical factor in manufacturing systems, and it is highly dependent on the task being performed. In environments where workers perform repetitive tasks in shifts, such as automotive production, the bathtub curve can also be used to explain human reliability, as it is used in HWRA (Fig. 4). The error rate function of a human operator during a shift represents the combination of learning, and fatiguing mechanisms as well as pure random mechanisms.

At the start of a shift, the human error rate decreases due to changing from rest mode to work mode and with the introduction of new duties, which is known as the process of "setting in motion". This decrease is caused by the learning mechanism, as operators become familiar with the equipment and learn new routines and procedures

Table 1
Overview of related work.

Contribution	Focus	Covered system resources
Chlebus & Werbińska-Wojciechowska [22,23]	Production process reliability assessment	Hardware
Hoffmann Souza et al. [24]	Decision making based on system reliability	Hardware
Li et al. [25]	Influence of production quality and equipment reliability on manufacturing systems	Hardware
Haase & Woll [26]	Product reliability assessment	Hardware & Humans
Jardine et al. [27], Vogl et al. [28]	Machine diagnostic and prognostic for improved reliability	Hardware
French et al. [29]	Limitations and opportunities for HURA	Humans, Software & Hardware
Havlikova et al. [30]	Reliability assessment for man-machine systems	Humans & Hardware
Di Pasquale et al. [20]	HURA in manufacturing	Humans
Di Pasquale et al. [31]	Reliability assessment for manual assembly systems	Humans
Franciosi et al.	PSFs for HURA	Humans
Petruni et al. [32]	Decision support for the selection of reliability assessment methods	Humans
Hou et al. [33]	Bibliometric review of methods for HURA	Humans

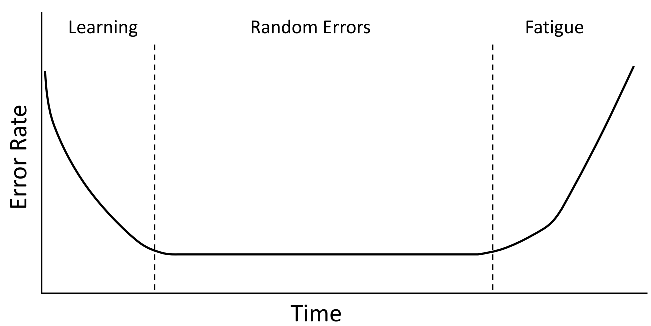

Fig. 4. Bathtub curve for human reliability [7].

to reduce errors. After the initial decrease, an optimum level of work is achieved, where the error rate is relatively low due to random error mechanisms. During this phase, operators have become familiar with the equipment and have developed routines and procedures to reduce errors. Finally, the human enters a process of fatiguing, which is characterized by an increasing error rate. The longer the shift, the more fatigued the operator becomes, resulting in a higher error rate [7].

The information drawn form the bathtub curve can be used to implement measures to reduce the likelihood and consequences of human errors. For example, during the *learning* period, additional training can be provided to operators, and procedures can be established to reduce the risk of errors. During the *fatigue* period, operators can be provided with rest breaks and other measures to reduce fatigue. Several factors can influence the shape of the bathtub curve for HURA, including the complexity of the equipment, the level of automation, and the experience and training of operators. For example, highly automated equipment may have a shorter *learning* period due to reduced operator interaction.

The ability of a human operator to perform a given task within specific conditions and time intervals is an essential factor in determining the overall reliability of a system. This ability is mathematically defined as Human Reliability, which is the complement of Human Error Probability (HEP). HEP is the probability that a given task within a specific time interval was accomplished with errors [34]. Thus, Human Reliability is mathematically defined as follows:

$$Human\ Reliability = 1 - HEP \tag{2}$$

Factors which influence the likelihood of a failure occurring are so called *Performance Shaping Factors* (PSFs) [35]. These PSFs can be environmental or personal factors that positively or negatively affect the performance of a human operator. The identification and analysis of these factors are a fundamental feature of all HURA methods [36]. To date, more than 50 different HURA methods have been proposed, which can be divided into two generations [30]. The first-generation quantitative methods involve probabilistic modeling of the human operator's behavior and the system in which they operate. These methods usually require significant amounts of data and are often used in industries with high safety–critical requirements, such as nuclear power plants and aviation. The quantitative methods use the HEP and other data to calculate the likelihood of a human error leading to a system failure. These methods rely on statistical analysis to calculate human error rates and the impact of these errors on system reliability.

The second-generation qualitative methods, on the other hand, focus on the analysis of the human operator's cognitive processes, decision-making, and problem-solving. These methods are often used in industries where the human operator's performance is critical to system reliability, such as manufacturing. The qualitative methods use a range of techniques, such as interviews, observations, and task analyses, to identify the PSFs and their influence on human performance. These methods allow for a deeper understanding of the factors that influence human reliability and can be used to develop training programs and interventions to improve human performance.

3. Related work

The field of reliability assessment has a long history in both academia and industry. Nevertheless, the interest in this topic has increased as technologies have evolved. In the following, we present and critically evaluate relevant publications aiming to review the field of reliability assessment with the specific focus on manufacturing systems. Table 1 summarizes the publications in terms of their research focus and the resources covered (i.e. hardware, software and human resources of a manufacturing system). Based on existing related work, we provide an updated and extended review of the field in this article. It should be noted that we could not retrieve any reviews that specifically address software reliability for manufacturing systems. Although there is a substantial body of research on software reliability assessment and many methodologies have been proposed (as elaborated in Section 2.2), there is a research gap regarding its application to manufacturing systems.

3.1. Hardware reliability assessment

We discovered a significant number of articles that aim to review and analyze tools and methods for **hardware reliability assessment**. Chlebus & Werbińska-Wojciechowska [22] focus specifically on production process reliability assessment. They extend their work in [23] by classifying previously identified reliability assessment methods and proposing a method which aims to structure the different phases of production process reliability assessment. Hoffmann Souza et al. [24] carry out a survey on decision-making based on system reliability in the context of Industry 4.0. Haase & Woll [26] conduct an empirical survey on the application of assessment methods for product reliability in manufacturing enterprises. A recent review by Li et al. [25] covers reliability modeling of manufacturing systems considering product quality and equipment reliability. Finally, Jardine et al. [27] and Vogl et al. [28] provide seminal reviews covering diagnostic and prognostic practices for improved maintenance and reliability. Below, we highlight the key findings of the mentioned articles.

Chlebus & Werbińska-Wojciechowska [22] state, that production process reliability is influenced by many factors such as time, quantity, quality and cost. Thus, many tools and methods have been developed for its assessment. The authors contribute a comprehensive overview of these methods and which reliability criteria (e.g., costs, repair time, lead time) the methods aim to address. Even though a plethora of reliability assessment methods have been proposed over the last few decades, the evaluation of their actual application in real world manufacturing facilities is only partly possible because of two major reasons. First, data and results of their application are often classified as private or secret and are, thus, impossible to be published. Second, such information is often not stored, which prevents further analysis. In an extension of their review, Chlebus & Werbińska-Wojciechowska [23] aim to structure the different phases of production process reliability assessment by distinguishing between the *pre-assessment phase*, *data collection phase*, *data analysis phase* and *aggregation phase*. The pre-assessment phase covers the identification and classification of hazards, the data collection phase covers the acquisition of statistical and qualitative data, the data analysis phase covers the actual analysis of the actual production process and the aggregation phase covers the aggregation of results of the previous phase.

The study by Hoffmann Souza et al. [24] emphasizes the importance of incorporating all aspects along a company's value chain into reliability models to realize the full potential of recent trends, such as the Internet of Things, cyber–physical systems and data mining. However, the authors note that many conventional reliability modeling methods focus on individual assets, which contradicts the previous statement. Identified methods and techniques are classified according to their technical focus: communication (e.g., sensors, micro-services and IoT), ingestion (e.g., data validation, transformation and noise reduction), analysis (e.g., Petri nets, Weibull analysis and simulation) and storage (data storage process). Hoffmann Souza et al. conclude that the distance between the three fields of reliability, Industry 4.0 and decision making is a major obstacle for development of new reliability modeling methodologies. Reliability is closely linked to the exact sciences, Industry 4.0 to information technology and decision making to administrative management. The study provides interesting insights and a taxonomy for reliability in Industry 4.0. However, the identified methods are not examined in-depth, and since studies that do not explicitly mention the term Industry 4.0 were excluded from the literature corpus, relevant studies may be missing.

In their survey, Haase & Woll [26] differentiate their results by industry, product lifecycle phase, and specific reliability assessment method. Methods such as FMEA, fault trees and RBDs are widely used by companies, while Petri nets, fuzzy logic or neural networks are not widely used, although they potentially yield large benefits to reliability analysis. The work by Haase & Woll provides useful quantitative insights on the use of reliability assessment methods in today's companies. However, since the authors focus specifically on product reliability, the impact of their study on reliability assessment of manufacturing systems is limited.

Li et al. [25] state that there is a complex relationship between equipment reliability and product quality. Therefore, reliability modeling methods that have been specifically developed for product quality and equipment reliability as well as methods that consider the interaction between both are examined. Furthermore, optimization methods for manufacturing system maintenance and production strategy are reviewed. The authors conclude, however, that the interaction between product inherent reliability and manufacturing system reliability have not been sufficiently defined yet. Furthermore, comprehensive reliability models for complex multi-stage and multi-state manufacturing systems need to be developed to improve production policies and preventive maintenance actions.

Prognostics and health management (PHM) technologies are used to improve maintenance through efficient and cost-effective diagnostic and prognostic measures [28]. In addition, while not the core focus of reliability assessment, improved equipment maintenance has a positive impact on the reliability of a system. In their review, Jardine et al. [27] focus on machinery diagnostics and prognostics by implementing condition-based maintenance (CBM). The authors review popular methods along the CBM pipeline which consists of three phases, namely data acquisition, data processing and maintenance decision making. Vogl et al. [28] provide an overview of recent advances in PHM research and highlight challenges, requirements, methods, and best practices for the successful application of PHM in manufacturing systems. The authors state that areas such as diagnostics, prognostics, dependability analysis, data management and business contribute to the successful development of a PHM system. While both reviews provide useful insights into the field of diagnostics and prognostics, reliability implications are rarely addressed. Furthermore, the reviewed methods focus often on specific entities or subsystems but rarely on compound systems like production lines. We still found it useful to include these two studies into our work, as they emphasize the importance and interdependencies between maintenance management and system reliability. Especially the evolution of maintenance paradigms from purely reactive (i.e., fix when it breaks) to preventive (i.e., maintain based on a schedule) to predictive (i.e., avoid failure based on condition) has led to significant incremental improvements in system reliability [28]. The impact of recent developments toward self-maintenance (i.e., systems monitor themselves) on reliability has yet to be evaluated, but will likely yield interesting results.

3.2. Human reliability assessment

There are several articles that review and analyze **human reliability assessment** methods and tools in the domain of manufacturing. French et al. [29] conduced a seminal review of HURA methods without domain-specific assumptions. Nevertheless, their findings are valuable and apply to the manufacturing domain as well. Havlikova et al. [30] discuss HURA methods and their applicability for man-machine systems. Di Pasquale et al. [20,37] provide a comprehensive overview of techniques for analyzing human reliability in manufacturing in general as well as in assembly systems. Franciosi et al. [31] propose a taxonomy of performance shaping factors for human reliability analysis in industrial maintenance. Petruni et al. [32] introduce a method to support the choice of a suitable HURA method for automotive manufacturing systems. A very recent bibliometric analysis and review of human reliability analysis methods was conducted by Hou et al. [33]. Below, we highlight the key findings of the mentioned articles.

French et al. [29] critically evaluate established methods and describe their limitations for current and future challenges in human reliability analysis. Established HURA methods focus on easily describable, sequential, generally low-level tasks, that are not the primary source of systemic errors. They also focus on errors rather than the effects of all forms of human behavior. The authors conclude that there is a significant need for further research and development of HURA methods to provide managers with the guidance they need to safely manage complex systems – "The key question is not how likely an individual's behavior is to impact a system, but how well the organizational structures around and within that system enable the system to run safely and reliability, and how well they will recover if an unexpected event threatens or happens".

Di Pasquale et al. [20] review contributions to both generations of HURA methods that have been used in manufacturing scenarios, highlighting strengths and weaknesses. In addition, the positive effects of rest breaks on human reliability and the potential negative effects on workflow and task completion are discussed. The authors conclude that while there is a plethora of HURA methods, most of them lack an empirical basis and are static, i.e., cannot capture the dynamics of an ongoing accident or general human behavior. Di Pasquale et al. [37] extend their previous work by systematically reviewing approaches for human reliability analysis in manual assembly systems. They show that HURA methods can be successfully used to predict human error probability and identify key error influencing factors for such systems. Furthermore, identified literature emphasizes the role of human error in causing quality defects. The taxonomy proposed by Franciosi et al. [31] is based on the two previously described reviews [20,37] and structures the literature corpus with respect to the PSFs addressed. Factors such as available time to complete a task, ergonomics and task complexity are considered. The analysis highlights the relevance of considering human error in maintenance, as different types of errors occur during the maintenance process with non-negligible effects on the system under study.

Petruni et al. [32] use Analytic Hierarchy Process (AHP) to support the evaluation and choice of a suitable HURA method for the automotive industry. AHP is a technique to structure a problem in a hierarchical way and to determine the benefit and cost of a project. As criteria for the AHP-based HURA method selection the authors consider the suitability for the automotive sector, economic factors, usability and utility. Approaches such as that presented by Petruni et al. are becoming important as the number of available HURA methods increases.

Recently, Hou et al. [33] extracted a cooperation network to identify the most productive scientists and groups in the field, a co-citation network to the most important journals, and a keyword co-occurrence network to identify important research hotspots and trends. Based on trends and blind spots in the literature, possible future research directions are suggested. Although there is no domain-specific focus for this work, a significant number of the papers reviewed relate to human reliability analysis for manufacturing systems.

Based on the presented related work, we provide an updated and extended review of the field in this article. None of the mentioned articles covers both hardware and human reliability assessment of manufacturing systems extensively. Furthermore, we provide a systematization of the reviewed literature and extract challenges and opportunities for future research. Finally, we highlight the rising importance of data for reliability assessment of manufacturing systems.

4. Contributions addressing reliability assessment of manufacturing systems

Building upon the related work discussed in the previous section, we provide an updated and extended review of the field of reliability assessment of manufacturing systems in this section. We first outline our review methodology in Section 4.1 before we present relevant literature for HWRA 4.2 and HURA 4.3. As mentioned in the previous section, research on software reliability of manufacturing systems is scarce, which is why it is not considered as a separate section.

4.1. Review methodology

The goal of this literature review is to provide an overview of the current state of research on reliability assessment of manufacturing systems, with a focus on both hardware and human system components. The review aims to identify the latest trends and developments in the field (Section 4) and highlight challenges and opportunities for reliability assessment based on the reviewed literature (Section 5).

To achieve this goal, we have formulated the following guiding research questions:

1. What are the current methods and techniques for reliability assessment of manufacturing systems, particularly those that consider both hardware and human system components?
2. What are the main challenges and opportunities in assessing the reliability of manufacturing systems?

To identify relevant literature, we conducted a systematic search of common computer science and engineering literature databases, including IEEE Xplore, ScienceDirect, and ACM. Our search strategy comprised two phases: a broad search and a targeted search.

In Phase 1, we identified key contributions to the field of reliability assessment of manufacturing systems by using a broad search string – a combination of *reliability assessment* and related terms (i.e., reliability modeling, reliability analysis and reliability evaluation) with *manufacturing systems* and related terms (i.e., production, industry). In Phase 2, we narrowed our search to specific methods commonly used for reliability modeling of manufacturing systems by using a more targeted search string – a combination of reliability and related terms, manufacturing and related terms, and a specific method such as *fault tree analysis*, *petri net* or *technique for human error rate prediction*. In both phases, the AND operator was used to combine the search terms.

The selection of contributions was based on the title, keywords and abstract. We focused on the most relevant articles addressing reliability assessment of manufacturing systems. The identified literature corpus consists of 33 articles that have been published between 1999 and 2021.

4.2. Hardware reliability assessment of manufacturing systems

This subsection provides a review of relevant literature on hardware reliability assessment of manufacturing systems, categorized by modeling formalisms. Quantitative evaluation methods such as discrete-event simulation, Monte Carlo simulation, or proxel-based simulation are not the primary focus of this review. Specifically, we first review contributions that use specific modeling formalisms such as Reliability Block Diagrams, Fault Trees, or Petri Nets, before examining those that use a combination of different modeling formalisms for reliability assessment of manufacturing systems.

In the appendix, Table 9 provides a comprehensive overview and systematization of the reviewed literature, including:

- The respective article,
- the applied reliability modeling method,
- the research goal of the study,
- the data sources or expert knowledge used to model the studied system,
- the used metric to assess reliability,
- and the type of manufacturing system studied.

It is important to acknowledge that many of the reviewed articles provide only a limited system description of manufacturing system employed in their research. Although a more detailed categorization of these systems, such as Flexible Manufacturing System (FMS) or Reconfigurable Manufacturing System (RMS), could be valuable, we refrained from including it in the table due to the lack of available information in the reviewed literature.

4.2.1. Contributions utilizing Reliability Block Diagrams

Reliability Block Diagrams (RBDs) are an effective method for analyzing and assessing the reliability of complex systems. They provide a graphical representation of the system and its individual components, which enables engineers to identify the weakest links in the system [38]. RBDs are acyclic graphs that have an entry and exit point, and the blocks are connected by arcs that reflect the relationships between different components. The system is considered to be working if there is a path of success, i.e., a sequence of functioning components between the entry and exit point. RBDs allow for modeling sequential

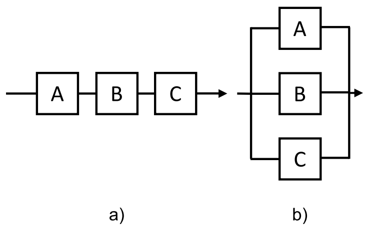

Fig. 5. RBD with system in sequential (a) and parallel (b) configuration.

and parallel systems (Fig. 5). In sequential systems, any component failure results in system failure, whereas parallel systems continue to function even if one or more components fail [4].

After modeling the RBD of a system, its reliability can be calculated. This depends on whether the components of the system are connected in series or in parallel. For a series of N connected components, the overall reliability of the system is defined as:

$$R(t) = \prod_{i=1}^{N} R_i(t) \tag{3}$$

For N parallel-connected components, the system reliability is defined as:

$$R(t) = 1 - \prod_{i=1}^{N} (1 - R_i(t)) \tag{4}$$

RBDs are often used in combination with the Universal Generating Function (UGF) [39]. The UGF is a mathematical approach used to analyze the performance and reliability of complex systems. It models the system's state by associating each state with a polynomial coefficient. Combining RBDs with UGF offers a synergistic approach. While RBDs provide a visual representation and a basic understanding of system reliability structure, UGF provides the mathematical backbone for more detailed reliability and performance analysis.

Table 2 lists the most significant contributions that utilize RBDs for hardware reliability assessment of manufacturing systems. Mubarok et al. [40] propose a framework to evaluate reliability in cloud manufacturing systems. Liu et al. [41] present a method to jointly assess the reliability of a manufacturing system and its associated processes. Erozan [42] proposes a method to aid restructuring decisions of manufacturing systems. Tont et al. [43] use RBDs to analyze critical and sensitive components of a turbogenerator.

In summary, RBDs enable the evaluation of reliability at different levels, such as component, machine, and system, and provide comprehensive insights into mission reliability and system availability. The studies highlight the effectiveness of RBDs in analyzing the reliability of components and systems, identifying critical subsystems, and informing decision-making for system design, operation, and restructuring.

4.2.2. Contributions utilizing Fault Tree Analysis

Fault Tree Analysis (FTA) is a technique used in risk assessment and reliability engineering to analyze and predict the failure of a system or process. FTA was first introduced in the 1960s as a means to evaluate the safety of complex systems such as nuclear power plants and chemical processing facilities. Since then, FTA has been applied in a variety of fields including aerospace, transportation, manufacturing, and healthcare [44].

FTA is based on the logic of Boolean algebra and uses a graphical representation known as a fault tree to illustrate the potential causes of a system failure. A fault tree is a diagram that depicts the various combinations of events or conditions that can lead to the occurrence of an undesired event or top event. The top event is the ultimate undesirable outcome, and the events that contribute to it are represented as branches on the fault tree.

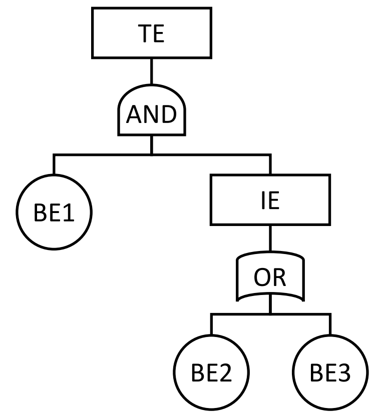

Fig. 6. Fault tree with top (TE), intermediate (IE) and basic events (BE).

FTA consists of four main steps: system definition, fault tree construction, qualitative evaluation, and quantitative evaluation [44]. During the system definition phase, the undesired event or failed state of the system is identified, and the system components are determined. The fault tree (see Fig. 6 for an example) is then constructed using the following main symbols [45]:

- **Top Event (Rectangle)**: Undesired state of the system caused by events occurring within the system
- **Intermediate Event (Rectangle)**: Fault event which occurs from a combination of other events
- **Basic Event (Circle)**: Basic fault event that requires no further development
- **Logic Gates**: Operators such as OR (Output fault occurs when at least one of the input faults occurs) and AND (Output fault occurs when all input faults occur)

In the qualitative evaluation phase, the fault tree is analyzed to extract minimal cut sets, minimal path sets, and common cause failures. This is done using deterministic methods or Monte Carlo simulation. Minimal cut sets are the minimum combinations of component failures that can lead to system failure. Minimal path sets are sets of components whose functioning ensures the functioning of the system, and common cause failures are multiple failures that can be caused by a single component.

Finally, in the quantitative evaluation phase, the actual probability of the top event is calculated along with reliability-related metrics such as mean time to failure (MTTF), mean time to repair (MTTR), and operational availability. This phase provides a quantitative assessment of the system's safety and reliability.

Various extensions to conventional FTA have been developed, such as dynamic fault trees, repairable fault trees, multi-state fault trees, and fuzzy fault trees. Dynamic fault trees consider the behavior and interactions of complex system components. Repairable fault trees provide the ability to describe repairs of system components. Multi-state fault trees consider components with multiple states and random probabilities. Fuzzy fault trees take into account unreliable factors that are difficult to predict using fuzzy set theory. These extensions enhance the applicability and effectiveness of FTA in different domains.

Fault trees are often converted into Binary Decision Diagrams (BDDs) or Multi-valued Decision Diagrams (MDDs) to streamline their analysis [46]. BDDs provide a compact representation of Boolean functions, while MDDs generalize BDDs for functions with multi-valued input variables, instead of just binary input variables. This simplifies the analysis of fault trees, especially for large-scale systems, and provides a more efficient means of evaluating system reliability.

Table 3 summarizes the most significant contributions that employ FTA for hardware reliability assessment in manufacturing systems.

Table 2
Contributions utilizing RBDs for reliability assessment.

Article	Summary and findings
Mubarok et al. (2018) [40]	• Propose hierarchical reliability assessment model for cloud manufacturing that evaluates reliability at component, machine, and system levels. • Use RBDs to analyze reliability of components and systems. • Highlight the importance of considering both manufacturing system and cloud system reliability in assessing overall reliability of cloud manufacturing. • Demonstrate the effectiveness of the model through a real-world case study. • Identify the need for future research to develop more accurate formulas for dynamic reliability at each level.
Liu et al. (2013) [41]	• Propose method for modeling mission reliability of discrete manufacturing systems using RBDs. • Break down the system into individual processes and models each process considering production disruptions, inspection errors, and substandard products. • Determine mission reliability of the entire system based on individual process reliability and their relationships. • Provide a comprehensive approach for evaluating mission reliability, particularly for low-automation systems. • Proposed method helps identify potential issues and inform decision-making for system design and operation.
Erozan (2011) [42]	• Proposes methodology for restructuring a manufacturing system using fuzzy logic and reliability assessment with RBDs. • Applies the methodology to a case study of a car component manufacturer and achieve improved system performance. • Emphasizes the importance of operational continuity and the need for new strategies and structural reforms in dynamic manufacturing environments. • Suggests the development of a fuzzy expert system program to make the methodology more accessible to manufacturing system managers.
Tont et al. (2008) [43]	• Propose methodology for availability assessment of complex manufacturing systems. • Utilize comparative analysis of different reliability analysis methods, highlighting the accuracy of RBDs compared to traditional methods like the binomial method. • Suggest the use of Monte Carlo simulations in conjunction with RBDs to evaluate the non-reliability impact of components on system availability. • Provide case study to demonstrate the methodology's application in identifying critical and sensitive subsystems/components and designing strategies for increased system availability.

Specifically, Cheng et al. [47] assess inventory risk, Mhalla et al. [48] utilize fuzzy FTA to estimate failure probability, Shu et al. [49] propose an innovative approach to FTA using intuitionistic fuzzy sets for fault interval calculation, Kumar & Lata [50] evaluate the reliability of piston manufacturing systems using FTA, and Relkar [51] propose a methodology for risk analysis of equipment failure using FTA.

In summary, the papers highlight the effectiveness of FTA as a valuable tool for reliability assessment in manufacturing systems. FTA enables the identification of root causes, prioritization of improvement options, and supports decision-making processes. The studies demonstrate the versatility of FTA in various domains, including inventory management, failure probability estimation, critical component identification, and maintenance planning, all contributing to enhanced system reliability and performance.

4.2.3. Contributions utilizing Petri nets

Petri nets (PNs) are a powerful modeling formalism used to describe the behavior of discrete-event systems and analyze their performance, safety and reliability. They were first introduced by Carl Adam Petri in the 1960s [52] and have since found numerous applications in fields such as computer science, control engineering, and manufacturing.

PNs consist of a set of places, transitions, and arcs connecting them. Places represent the states of the system, transitions represent events that can change the system state, and arcs specify the flow of tokens (or markings) between places and transitions. Tokens carry the information in PNs and represent entities (e.g., production orders) or state markers.

In addition to the original place-transition PNs, there are several extensions that allow for more complex modeling. For example, additional types of arcs, such as reset arcs (which empty a place when a connected transition fires) and inhibitor arcs (which disable a transition when tokens are in a connected place), can be used. Stochastic PNs allow for non-deterministic firing times of transitions, usually modeled as exponentially distributed. Colored PNs allow tokens to carry values, which can represent distinguishable entities in the model.

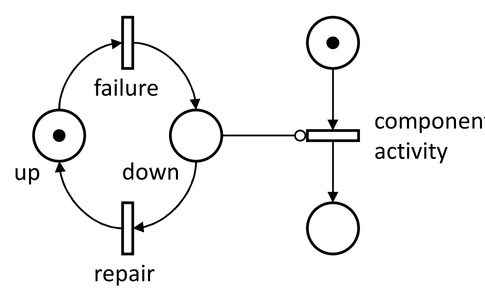

Fig. 7. Failure model of a system component.

Fig. 7 provides an example of a stochastic Petri net used for failure modeling of a system component. Once the *failure* transition fires, a token is created in the *down* place, blocking the transition representing the component activity with an inhibitor arc. Once the component is repaired, the *component activity* transition becomes unblocked and the component can continue its operation.

The reliability assessment of manufacturing systems using PN modeling formalism is summarized in Table 4, where the most significant contributions are discussed. Arena & Kiritsis [53] introduce an ontology-driven reliability modeling framework for manufacturing processes. Adamyan & He [54] analyze sequential failures in manufacturing systems. The authors further improve their work in [55] by incorporating counters in Petri nets. Wang et al. [56] present a fuzzy logic and Petri net-based approach for reliability assessment, and Nabi & Aized [57] employ colored PNs to model flexible manufacturing systems and evaluate their performance.

In summary, the papers highlight the application of PNs as a powerful tool for reliability assessment of manufacturing systems. PNs offer modeling capabilities for representing system behavior, analyzing failure sequences, and evaluating system reliability, safety, and performance. The studies demonstrate the effectiveness of PNs in various

Table 3
Contributions utilizing FTA for reliability assessment.

Article	Summary and findings
Cheng et al. (2013) [47]	• Explore the use of FTA in reducing inventory and improving turnover rate for an aerospace manufacturer. • Identify root causes of inventory issues and prioritize improvement options based on a risk reduction indicator. • Demonstrate that FTA is an effective tool for inventory management, resulting in a 30% improvement in inventory turnover rate. • Emphasize the importance of communication and contract management with suppliers and customers, while avoiding unplanned design changes. • Recommend focusing on risk reduction rather than just probabilities to enhance the inventory management system.
Mhalla et al. (2014) [48]	• Propose a novel fuzzy probabilistic method for analyzing the failure probability of a milk bottling unit. • Overcome limitations of traditional FTA by incorporating fuzzy set theory and the Buckley approach. • Utilize triangular fuzzy numbers to represent fuzzy characteristics of failure probabilities, providing more precision. • Demonstrate that the proposed method is more efficient than conventional FTA, enabling identification of critical components and computation of modified maintenance cost. • Conclude that further research is needed to incorporate maintenance and repair strategies into the proposed method.
Shu et al. (2006) [49]	• Propose of a new approach to FTA using intuitionistic fuzzy sets. • Intuitionistic fuzzy sets are utilized for fault interval calculation and identification of the most critical system component. • Apply the proposed method to a printed circuit board assembly (PCBA) failure analysis problem. • Results demonstrate that the proposed method provides more flexible estimation of failure intervals and effectively identifies the most critical system component in the PCBA manufacturing process. • Reveal areas for improvement to increase reliability and inform managerial decision-making.
Kumar & Lata (2011) [50]	• Examine the reliability of piston manufacturing systems using FTA and the risk reduction worth measure. • Identify insufficient lubrication as the most critical fault event impacting the system's reliability. • Findings are consistent with the actual performance of the manufacturing system. • Emphasize the importance of proper lubrication to improve the reliability of piston manufacturing systems. • Highlight the significance of reliable piston manufacturing for the proper functioning of internal combustion engines in automobiles and mechanical machinery.
Relkar (2021) [51]	• Propose a methodology for determining critical equipment in manufacturing facilities and reducing failure probability through maintenance actions. • Utilize FTA to determine the criticality index of available equipment. • Rank equipment based on their impact on production, safety, availability of standby, and equipment value. • Found that the proposed methodology was valuable for maintenance personnel in planning maintenance activities, mitigating the risk of failure, and identifying critical equipment within the production shop.

aspects of manufacturing systems, including ontology-driven instantiation, risk assessment, dynamic reasoning, and performance evaluation. The findings contribute to improving the reliability, safety, and efficiency of manufacturing systems.

4.2.4. Contributions utilizing Markov modeling

Markov modeling (MM) is a mathematical technique used to model systems that change over time, where the probability of a future state of the system depends only on its current state and not on its past states. It is based on the Markov property, which states that the probability of transitioning to a future state is determined only by the current state and the transition probabilities between states. Markov models can be used in a variety of applications, such as reliability assessment, finance, and natural language processing.

Markov models are a popular methodology for reliability assessment of complex systems, particularly for those with multiple failure modes, where the probability of failure depends on the current state of the system. By using this approach, the system is represented as a set of states, and the transition probabilities between these states are determined based on the system's failure and repair characteristics. This modeling technique can be particularly useful for reliability assessment of manufacturing systems, as it enables the prediction of system behavior over time and the identification of critical components, determination of optimal maintenance strategies, and evaluation of system performance under different scenarios.

Table 5 provides an overview of the most significant contributions that have utilized MM for assessing hardware reliability in manufacturing systems. Kharoufeh et al. [58] introduce two stochastic fault models for assessing the reliability of manufacturing equipment operating in complex environments. Che et al. [59] propose a reliability model for man-machine systems with mutual dependencies using Markov processes. He et al. [60] present a fuzzy multistate manufacturing system reliability assessment method based on an extended stochastic flow network. Guo et al. [61] utilize Markov processes to model the reliability and availability of multistage production systems.

In summary, MM provides a framework for capturing the stochastic degradation, failure, and repair processes in manufacturing systems, allowing for the evaluation of system reliability and availability. The studies present various models and approaches, including temporally nonhomogeneous continuous-time Markov chains, semi-Markov processes, Piecewise-deterministic Markov processes, and extended stochastic flow network models. The findings contribute to understanding the impact of degradation, human errors, and interdependencies on system reliability, and provide insights for decision-making and improvement in manufacturing systems.

4.2.5. Contributions utilizing Bayesian networks

Bayesian networks (BNs) are a powerful tool for modeling and reasoning under uncertainty in complex systems. In recent years, they have become increasingly popular in reliability engineering as a means to assess the performance and safety of manufacturing systems.

One of the main advantages of BNs is their ability to model the relationships between different components of a system and the potential sources of failure. This enables them to estimate the probability of failure of individual components or the system as a whole, given various environmental and operational conditions.

The core concept of BNs is Bayes' rule, which enables the probability of an event to be updated based on new evidence or information. In a BN, nodes represent variables, and edges represent the conditional dependencies between them. Each node has a conditional probability table (CPT) that specifies the probability of the node given its parents

Table 4
Contributions utilizing PNs for reliability assessment.

Article	Summary and findings
Arena & Kiritsis (2017) [53]	• Introduce a methodological framework for ontology-driven instantiation of manufacturing process models using PNs. • Exploit common ontology models to transform knowledge base elements into PN primitives, enabling the PN-based representation of automated assembly station knowledge for reliability assessment. • Highlight the effectiveness of inference rules in automatically instantiating PN-based manufacturing system models, resulting in a semantically enriched PN model with qualitative and quantitative assessment capabilities. • Present the development of the Automatic Assembly System Ontology (AASO) and the Petri Net Ontology for Reliability modeling (PNO4R) as two different models within the framework. • Demonstrate the potential of the proposed approach in ontology-based model transformation, PN-based simulation, and reliability analysis of a manufacturing system.
Adamyan & He (2008) [54]	• Present a novel method for assessing the reliability and safety of manufacturing systems with sequential failures. • Utilize PN modeling to identify and quantify the probabilities of occurrence of failure sequences. • Provide a comprehensive risk assessment tool for improving safety and efficiency in manufacturing systems. • Demonstrate the method's effectiveness through an example of an automated machining and assembly system. • Overcome limitations of current approaches by not assuming given sequences of failures, resulting in a more accurate assessment of reliability and safety in manufacturing systems.
Adamyan & He (2004) [55]	• Extend their method presented in [54] using PNs and counters for modeling complex systems with inhibitor arcs and loops. • Advantages of the extended method include the use of fewer variables compared to existing marking-based methods, accelerated computations, and the ability to handle any distribution of failure times. • Apply the method to the failure analysis of a specific system, the nitric acid cooler with temperature feedback and pump-shutdown feedforward loops. • The method can be used as a comprehensive risk assessment tool to enhance the safety and efficiency of manufacturing systems.
Wang et al. (2020) [56]	• Propose a dynamic adaptive fuzzy reasoning PN model for evaluating the reliability of a manufacturing system with multiple production lines. • Consider the stochastic capacity of each machine and the ambiguity of loading size and buffer level. • Formulate weighted fuzzy PNs to represent imprecise knowledge of reliability levels. • Demonstrate the effectiveness and flexibility of the method through a numerical experiment using a flow shop manufacturing system. • Highlight the potential extension of the method to other manufacturing systems with parallel, assembly, or disassembly structures. • Suggest future work to focus on simultaneously optimizing buffer capabilities, input materials, and machines' capabilities.
Nabi & Aized (2020) [57]	• Study the performance evaluation of a flexible manufacturing system (FMS) using PN methodology. • Develop a compact and editable FMS model using colored PNs, providing insights into dynamic behavior and system performance measures. • Identify key factors influencing system performance, including inter-cellular and intra-cellular routing flexibility, and variation in input factors such as machining and assembly time, material loading and unloading time, and number of operations between failure. • Recommend virtual commissioning of the proposed FMS system and further research on breakdown modes of material handling robots and unplanned breakdowns of machines. • Results demonstrate the successful applicability of colored PNs for modeling, simulation, and evaluation of FMS.

in the graph. These CPTs are derived from prior knowledge or data and can be updated based on new observations using Bayes' rule.

Fig. 8 illustrates a Bayesian network for a machine failure, which shows how nodes can represent variables such as machine age, vibration, and operator competence, and how edges can represent the conditional dependencies between these variables.

By incorporating prior knowledge and expert opinion into the model, BNs can also help to quantify and manage uncertainty in the assessment process. This makes them particularly useful in situations where data is limited or unreliable, or where the consequences of failure are severe.

Table 6 provides an overview of the most significant contributions utilizing BNs to assess hardware reliability in manufacturing systems. The reviewed papers include Karaulova et al. [62] who present a framework for reliability estimation of manufacturing processes, Görkemli & Ulusoy [63] who propose a novel approach for modeling reliability and availability, Jones et al. who use BNs to improve maintenance planning [64], and Weber & Jouffe [65] who introduce a methodology for formalizing complex manufacturing processes with dynamic BNs.

In summary, BNs provide a probabilistic graphical modeling approach for capturing dependencies and uncertainties in complex systems. The studies demonstrate the effectiveness of BNs in fault analysis,

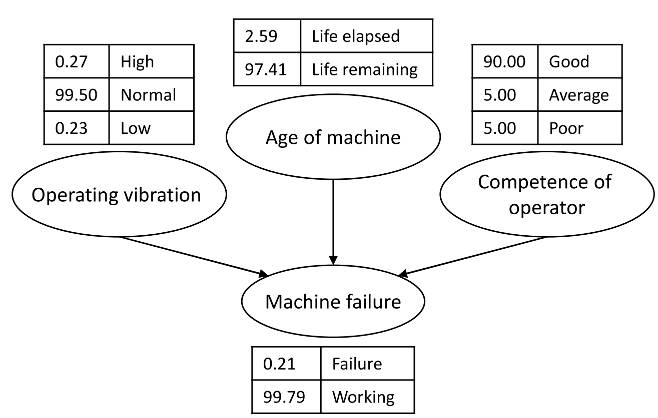

Fig. 8. Bayesian network for a machine failure.

process reliability improvement, reliability and availability assessment, maintenance planning, and optimal diagnosis and maintenance. The

Table 5
Contributions utilizing MM for reliability assessment.

Article	Summary and findings
Kharoufeh et al. (2013) [58]	• Propose two stochastic models for the reliability assessment of manufacturing equipment in complex environments with stochastic degradation leading to failure. • The first model utilizes a temporally nonhomogeneous continuous-time Markov chain environment and the second model assumes a temporally homogeneous semi-Markov process on a finite space. • Derive transform expressions for lifetime distributions and illustrate the models using examples. • Presented mathematical frameworks provide flexibility for scenarios where operating times in different states are non-stationary or non-exponential. • Suggest that the models can be beneficial in scenarios where effective modeling of the mapping between environmental conditions and degradation is possible, and can provide a macroscopic view of degradation that can be refined with guidance from subject matter experts.
Che et al. (2019) [59]	• Present a general reliability model for man-machine systems considering mutually dependent machine degradation and human errors. • Utilize a Piecewise-deterministic Markov process framework to capture the mutual dependence. • Include a mathematical model for human error rates considering fatigue-recovery and a multi-state machine degradation model. • Illustrate the model using the example of a lathe operated by a worker. • Findings indicate that mutual dependence results in lower reliability performance. • Suggest future work to incorporate maintenance considerations and expand the human error model to include mental fatigue and learn-forgetting effects.
He et al. (2020) [60]	• Propose an improved method for evaluating the mission reliability of fuzzy multistate manufacturing systems using an extended stochastic flow network (ESFN) model. • Consider the operating mechanism of the manufacturing system and analysis of task execution state, machine degradation state, and product quality state. • The proposed method is suitable to systems with uncertain parameters represented as fuzzy values. • Verify the proposed approach through a case study and sensitivity analysis of the model parameters. • Suggest future research on developing efficient algorithms to reduce the computational complexity of fuzzy mission reliability, as well as decision-making in production scheduling and preventive maintenance for fuzzy multistate manufacturing systems based on ESFN.
Guo et al. (2017) [61]	• Focus on defining and measuring reliability and availability in multistage production systems. • Investigate the interdependence between buffer resources/equipment and their reliability performance in each station and its impact on the overall system. • Propose to utilize Markov processes as models for system reliability and availability and demonstrate the relationship between these measures and traditional performance metrics such as cycle times and throughputs. • Verify the effectiveness of the proposed methods through simulation models in complex and varying multistage production settings.

utilization of BNs enhances decision-making, improves accuracy in failure rate estimation, and increases overall system reliability.

4.2.6. Contributions utilizing a combination of modeling formalisms

Table 7 lists the most significant papers that utilize a combination of different modeling formalisms to assess the reliability of manufacturing systems. Fazlollahtabar & Niaki [66] propose a combination of FTA and RBD to assess the reliability of complex robot systems. Yan et al. [67] compare the effectiveness of FTA and PPN modeling for mission reliability assessment. Coban et al. [68] utilize RBDs and MMs to determine the probability of failure of system components. Chang [69] use Monte Carlo simulation in combination with stochastic production networks to estimate reliability of manufacturing processes.

In summary, the studies demonstrate the effectiveness of combining different modeling approaches in assessing system reliability, fault detection, maintenance programs, mission reliability evaluation, and the analysis of human–robot interaction in assembly processes. The utilization of multiple modeling formalisms enhances the accuracy and comprehensiveness of reliability assessments, enabling informed decision-making and identification of potential failure conditions.

4.3. Human reliability assessment

This subsection presents a comprehensive review of the relevant literature concerning the assessment of human reliability in manufacturing systems. In Section 2.3, we discussed the classification of HURA methods into two generations: first-generation and second-generation methods. In the following, we describe both generations in more detail and then review relevant literature. In the appendix, Table 10 provides a comprehensive overview and systematization of the reviewed literature, including:

- The respective article,
- the applied reliability modeling method,
- the research goal of the study,
- the PSFs used,
- the data sources or expert knowledge used to model the studied system,
- the used metric to assess reliability,
- and the type of manufacturing system studied.

As with the reviewed articles for HWRA, the reviewed articles for HURA lack a detailed system description of the manufacturing system employed in their research (e.g., FMS, RMS, etc.). Consequently, we did not include this aspect as an additional column in the table.

First-generation HURA methods consider humans as just another mechanical component of systems. Many of these methods, such as Technique for Human Error Rate Prediction (THERP), Accident Sequence Evaluation Program (ASEP), Human Cognition Reliability (HCR) and Human Error Assessment and Reduction Technique (HEART) assume that humans fail to perform tasks because of natural deficiencies [20]. This assumption prevents consideration of aspects of dynamic interaction with the work environment, both as a physical and social environment. In first-generation methods, HEP is usually assigned based on the characteristics of an operator's tasks and then adjusted by PSFs. Swain [70] criticizes that first-generation methods often lead HURA analysts to deliberately apply higher estimates of HEPs and larger uncertainty bounds to compensate for the drawbacks stated above. Despite the criticisms and shortcomings of these methods, they are widely used because of their ease of use and quantitative aspects [20].

Fig. 9 displays the analytical tool for the analysis of human reliability using the THERP method. The nodes in the event tree correspond

Table 6
Contributions utilizing BNs for reliability assessment.

Article	Summary and findings
Karaulova et al. (2012) [62]	• Introduce a framework for fault analysis in production processes using an extended Failure Mode and Effect Analysis (FMEA) approach. • The framework incorporates a fault classifier and Bayesian Belief Network (BBN) to classify faults and estimate FMEA parameters. • The framework enables companies to analyze production processes comprehensively and identify critical faults for efficient process improvement. • Highlight the effectiveness of using BBN for modeling process losses and evaluating the effectiveness of recommendations for process reliability improvement. • Future work includes the development of a reliability analysis module and its integration with an ERP system to estimate reliability for each manufacturing operation.
Görkemli & Ulusoy (2010) [63]	• Introduce a novel modeling approach for reliability and availability assessment of production systems that considers the hierarchy and all components of the system. • Employ a fuzzy Bayesian method to address uncertainties in the production environment and improve the accuracy of estimates. • Highlight the limitation of considering only machine reliability in calculations and emphasize the importance of considering all components for accurate reliability and availability assessments. • The proposed approach accounts for imprecision in data and provides more accurate estimates by considering the entire system and its components. • Future research directions include exploring non-exponential distributions for failure and repair times of sub-processes and investigating fuzzy multi-state reliability.
Jones et al. (2010) [64]	• Introduce the use of BNs for maintenance planning in manufacturing systems. • Apply the proposed methodology to a case study to determine the failure rate of a system and to optimize inspection intervals. • Consider influencing events and incorporate available data to update probabilities, leading to improved accuracy in failure rate estimation. • The study highlights that BNs provide insights into likely causes of failure and offer a more accurate method for establishing failure rate parameters. • The use of BNs in maintenance planning increases confidence in decision-making, reduces downtime, and improves overall system reliability.
Weber & Jouffe (2003) [65]	• Propose a methodology for developing Dynamic Bayesian Networks (DBN) to model complex manufacturing processes for optimal diagnosis and maintenance. • The DBN model is compared with the classical Markov Chain for reliability estimation using a small valve system. • Conclude, that the DBN approach is a powerful tool for decision-making aid in maintenance, providing more compact and readable models and for effectively modeling the dependency between failure modes and common modes. • Future research should focus on incorporating learning algorithms of BN to model the dynamics of system reliability and the behavior of parameters in manufacturing systems.

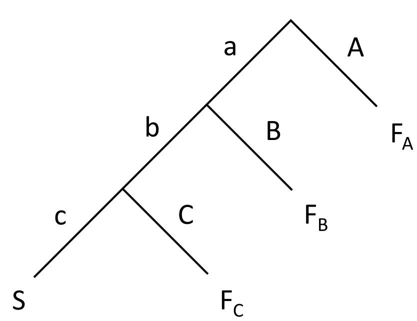

Fig. 9. Structure of a THERP event tree.

to all events that can occur within a system. The root node is the initiating event and the branches are consequences of the initiating event. Each node has two branches that correspond to either success (lowercase letter; Human Reliability) or failure (uppercase letter; HEP). By adding the probabilities for the individual events along each path, the likelihood of the various outcomes can be calculated such as success without any failures (i.e., S) or failure (e.g., F_B).

While first-generation methods focus on human behavior, **second-generation HURA methods** aim for a more conceptual approach. Such methods focus on cognitive aspects of humans to explain their behavior, on the causes of errors rather than their frequency, and on the influence of the interaction of PSFs on the HEP [20]. The development of second-generation methods began in the 1990s. Popular methods are Cognitive Reliability and Error Analysis Method (CREAM) [21], A Technique for Human Analysis (ATHEANA) [71], Success Likelihood Index Methodology (SLIM) and the Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) [72]. Di Pasquale [20] argues that any attempt to understand human performance must include the role of human cognition, which is defined as an "act or process of knowing including both consciousness and judgment". To account for human cognition in HURA methods, a new error category, "cognitive error," was introduced. Such an error is defined both as a failure of a predominantly cognitive activity and as a derivative cause of a failed activity [21].

Several contributions address HURA of manufacturing systems (Table 8). Ellis et al. [73] focus on the impact of age of workers on manufacturing system reliability. Myszewski [7] proposes to apply the bathtub curve to describe human reliability during a work shift over time. Bubb [34], Aalipour et al. [74], Wang et al. [75], Angelopoulou et al. [36], and Torres et al..[76] apply HURA methods such as THERP, HEART, SPAR-H and BNs to several different manufacturing environments.

In summary, HURA studies in manufacturing emphasize the influence of age-related changes, time pressure, lack of experience, poor procedures, and other PSFs on HEP. Task analysis combined with knowledge of age-related changes helps identify potential challenges faced by older workers, while the integration of ergonomic measures, organizational measures, and education/training measures improves human reliability.

Simulation models for HURA in manufacturing systems consider the impact of human error in Industry 4.0, digitized manufacturing, and complex manual assembly. These models allow for the classification and quantification of human errors, identification of error modes, and

Table 7
Contributions utilizing a combination of modeling formalisms for reliability assessment.

Article	Summary and findings
Fazlollahtabar & Niaki (2018) [66]	• Propose an integrated FTA and RBD model for evaluating the reliability of a complex robot system used in advanced manufacturing systems. • The methodology is implemented in a complex advanced manufacturing system with autonomous guided vehicles (AGVs) as material handling devices. • The results demonstrate that the reliability of the system is highly dependent on the occupied paths by AGVs, and filtering these paths can significantly impact system reliability. • The FTA-RBD model provides a hierarchical representation of system components, facilitates fault detection, and enhances maintenance and repair programs. • The proposed model has the potential to be extended to more complex systems and can assist in making informed decisions about mission performance acceptability.
Yan et al. (2017) [67]	• Compare FTA and PN modeling for evaluating the mission reliability of AGV systems. • PNs are found to be effective in assessing AGV mission reliability by considering maintenance influence and dependencies within subsystems and across mission phases. • PNs are considered more suitable for complex systems with multiple mission phases, as FTA becomes slower and more complex with an increasing number of phases. • The results obtained from PN modeling were comparable to those obtained from FTA, indicating the effectiveness of PNs in evaluating mission reliability. • Suggest, that PN modeling can be a valuable alternative to FTA for assessing the mission reliability of AGV systems.
Coban et al. (2019) [68]	• Focus on the reliability analysis of assembly processes involving human–robot interaction in manufacturing. • Utilize RBDs and MMs to assess the probability of failure conditions in the supporting systems over a specific period. • An RBD is created to represent the system and determine its reliability value over time, and a MM is developed to identify fault conditions in the system and calculate the likelihood of their occurrence. • The analysis provides a comprehensive understanding of the reliability of assembly processes with human–robot interaction and enables the identification of potential failure conditions.
Chang (2019) [69]	• Introduce a novel Monte Carlo simulation approach based on stochastic production networks to estimate the system reliability of a stochastic production system with finite buffer storage. • The study demonstrates that assuming infinite buffer storage can result in an overestimation of system reliability. • The findings emphasize the significance of considering finite buffer storage in the evaluation of demand satisfaction and system reliability. • Suggest future research directions, including evaluating the exact system reliability, exploring buffer allocation strategies to maximize system reliability, and considering buffer storage size to minimize total cost while achieving the required system reliability.

evaluation of factors contributing to those errors. Recommendations include perceptually engaging assembly instructions, improved inspection processes, better operations tracking, feedback provision, and the integration of technology in assembly guidance systems.

Overall, the use of HURA in manufacturing systems is essential for understanding, predicting, and mitigating human errors, thereby improving system performance, safety, and efficiency.

5. Challenges and opportunities for reliability assessment of manufacturing systems

In this section, we highlight challenges and opportunities for reliability assessment of manufacturing systems based on the reviewed literature. Challenges and opportunities specifically for HWRA and HURA as well as for reliability assessment of manufacturing systems in general are presented. The emerging and promising research field of data-driven reliability assessment of smart manufacturing systems is covered separately in Section 5.4.

5.1. Challenges and opportunities for hardware reliability assessment

Challenges:

- **Data Availability and Quality**: Obtaining accurate and reliable data for HWRA can be a challenge. Manufacturing systems often generate large amounts of data on hardware components, but it may not always be readily available or of sufficient quality for meaningful analysis. Ensuring data completeness, consistency, and validity is crucial for accurate reliability assessment [63,64].
- **Uncertainty and Variability**: Manufacturing environments are inherently subject to uncertainties and variability in operating conditions, component behavior, and system dynamics. Accounting for these uncertainties and their impact on hardware reliability assessment can be challenging, requiring robust modeling and statistical techniques to handle the variability effectively [41,55,60,63].
- **Technological Advancements and Rapid Changes**: Manufacturing systems and associated hardware technologies are constantly evolving, with new technologies and advancements being introduced regularly. Keeping pace with these advancements and adapting reliability assessment methodologies to incorporate emerging technologies can be challenging but necessary for accurate and up-to-date reliability assessments [40,66,67].
- **Computational Complexity**: Some reliability assessment techniques, such as Monte Carlo simulation, can impose a significant computational burden, especially for large and complex manufacturing systems. Efficient algorithms and computational resources are required to handle the computational complexity and perform timely and accurate reliability assessments [43].
- **Limited Failure Data**: In some cases, there may be limited failure data available for specific hardware components or subsystems in manufacturing systems. Insufficient failure data can make it difficult to accurately estimate failure rates, probabilities, and other key parameters for reliability assessment.
- **Lack of Standardization**: The field of hardware reliability assessment in manufacturing systems lacks standardized methodologies, metrics, and evaluation criteria. The absence of standardized practices can make it challenging to compare and benchmark reliability assessments across different systems and industries.

Opportunities:

- **Integration of Multiple HWRA Methods**: Exploring the integration of multiple modeling formalisms, such as BNs, PNs, MMs,

Table 8
Contributions addressing human reliability assessment.

Article	Summary and findings
Ellis et al. (1999) [73]	• The paper investigates the performance implications of older workers in technological manufacturing environments. • Task analysis combined with knowledge of age-related changes can help identify challenges faced by older workers and incorporate appropriate accommodations. • Aging is associated with a decline in various human performance measures, emphasizing the importance of qualitative task analysis in recognizing age as a PSF. • Techniques like THERP can be used to prioritize interventions and improve the working conditions for older workers. • Developing user-friendly manufacturing systems benefits all age groups, promoting independence and productivity among the older workforce.
Myszewski (2010) [7]	• The paper introduces a mathematical model of human error occurrence in manufacturing processes, considering continuous and discrete phenomena. • The model incorporates reliability concepts and the bathtub curve to represent learning, fatigue, and task accumulation in human work. • Inadequate time allocation for operations is linked to special causes of errors in industrial processes. • Improving the work environment, operator skills, and motivation is crucial for reducing error risk. • Graphical representations of error rate functions support intuitive interpretation, workflow organization, and risk analysis, emphasizing the need for proactive measures beyond operator motivation to address random and systemic mechanisms of error.
Bubb (2005) [34]	• The paper highlights the significance of human reliability in improving manufacturing quality. • Human actions and PSFs play a crucial role in HEP. • The THERP method is applied to manufacturing scenarios, and experimental research on error prediction is conducted. • Three primary measures for enhancing human reliability are identified: ergonomic measures, organizational measures, and education and training measures. • Financial considerations may influence the preference for education and training measures, despite their effectiveness in improving human reliability.
Aalipour et al. (2016) [74]	• The paper focuses on HURA in maintenance activities in the cable manufacturing industry. • Three HURA techniques (HEART, SPAR-H, and BN) are used to estimate HEP and assess their consistency. • Time pressure, lack of experience, and poor procedures are identified as the main causes of human errors during maintenance activities. • The estimated HEPs obtained through the three techniques demonstrate similar behavior and consistency. • Accurate estimation of HEP is crucial for efficient maintenance operations, and updated data and field evidence are needed to improve analysis robustness. The paper recommends evaluating HURA tools in different scenarios and using critical analysis to provide safety recommendations for procedures and equipment, aiming to reduce the risk of accidents.
Wang et al. (2019) [75]	• The paper focuses on using HURA and optimization techniques in manufacturing systems. • A BN model and Human Factors Experiments (HFEs) are utilized in a flexible intermediate bulk container manufacturing plant. • Physiological and psychological factors are considered as PSFs in the study. • The BN model is used to qualitatively describe the relationship between human factors and human errors and quantitatively assess their impact on system failures. • Workers' training based on fault diagnosis results leads to a significant decrease in errors and system failure rate. • The findings demonstrate the effectiveness of HURA and optimization using the BN model and HFEs in reducing system failures, with implications for future research and applications in other fields.
Angelopoulou et al. (2020) [36]	• The paper explores the impact of human error on Industry 4.0 systems and proposes a simulation model for HURA. • The study emphasizes the importance of considering the human factor in digitized manufacturing and automated processes. • The simulation model incorporates PSFs that influence human work in Industry 4.0 and quantifies human error in different scenarios. • The components and functionality of the simulation model are presented, highlighting the need for validation through real-world case studies. • The findings highlight the significance of integrating HURA in Industry 4.0 and suggest future work to improve the model's accuracy, expand the factors considered, and provide recommendations for error reduction.
Torres et al. (2021) [76]	• The paper focuses on classifying and quantifying human error in complex manual assembly within a manufacturing context. • HURA techniques, specifically SHERPA and HEART, are applied to identify and evaluate potential errors and contributing factors. • Analysis of critical assembly tasks reveals various error modes, with geometry-related assembly parts having the highest HEPs. • The findings highlight the importance of perceptually engaging assembly instructions, improved inspection processes, operations tracking, feedback provision, and technology integration in assembly guidance systems to reduce error probabilities and enhance overall performance. • The study emphasizes the significance of considering human errors in manufacturing and suggests the adoption of ergonomic analysis and HURA as crucial steps for improvement.

Table 9
Systematization of reviewed HWRA literature.

Article	Method	Goal	Used data/expert knowledge	Metric	Manufacturing system type
Mubarok et al. [40]	RBD	Assess manufacturing service reliability in cloud manufacturing	Component and machine reliability	System reliability	Forklift manufacturing
Liu et al. [41]	RBD	Evaluation and analysis of mission reliability	Component reliability and maintenance times	Mission reliability	Radar manufacturing
Erozan [42]	RBD	Support restructuring decisions	Reliability of components	System reliability	Motor component manufacturing
Tont et al. [43]	RBD, MCS	Identify critical components in system	Failure times, repair times, maintenance times	System/component reliability/availability	Turbogenerator
Cheng et al. [47]	FTA	Increase inventory turnover rate	Probability of basic events	Probability of minimal cut sets/excess inventory	Aerospace parts manufacturing
Mhalla et al. [48]	(fuzzy) FTA	Increase system reliability	Probability of basic events	Probability of system failure (top event)	Milk bottling
Shu et al. [49]	(fuzzy) FTA	Identify most critical system component	Probability of basic events	Probability of system failure (top event)	Printed circuit board assembly
Kumar & Lata [50]	FTA	Increase system reliability	Probability of basic events	System reliability, risk reduction worth	Piston manufacturing
Relkar [51]	FTA, FMEA	Determine critical components, improve maintenance planning	FMEA insights from experts, probability of basic events	Probability of operation without failure (survival)	Car component manufacturing
Arena & Kiritsis [53]	PN (SPN)	Translate system knowledge into executable models for reliability assessment	System knowledge, failure and repair times of components	System and component failure probability	Automated assembly shop
Adamyan & He [54]	PN (SPN)	Analysis of sequential failures	Process/operation times, failure times	Probability of failure sequence	Automated machining and assembly
Adamyan & He [55]	PN (SPN)	Analysis of sequential failures	Process/operation times, failure times	Probability of failure sequence, system failure rate	Nitric acid cooler
Wang et al. [56]	(fuzzy) PN	Reliability evaluation/optimization	Machine and buffer capacity and initial reliability	System reliability	Oil pump manufacturing (flow-shop)
Nabi & Aized [57]	PN (CPN)	System optimization	Failure times, repair times, operating times	Buffer capacities, reliability, MTTR	Flexible manufacturing
Kharoufeh et al. [58]	MM (Markov chain, Markov process)	Better estimate component lifetime	Component degradation data	Component reliability	Generic complex systems
Che et al. [59]	MM (Markov process)	Identify factors that affect human error	Failure times, degradational states	System reliability	Generic man-machine systems
He et al. [60]	MM (ESFN)	Identify characteristics of multistate machines	Machine operational states	Mission reliability	Shifting unit manufacturing
Guo et al. [61]	MM (Markov process)	Better estimate reliability in multistage production systems	Failure rates, repair rates	System reliability and availability	Solar module manufacturing
Karaulova et al. [62]	BN (BBN), FMEA	Find optimal corrective actions for reduction of faults	Failure types and their severity and probability	Error probability	Machinery manufacturing
Görkemli & Ulusoy [63]	(fuzzy) BN	More accurate estimation of system reliability and availability	Failure rates, repair rates	Reliability and availability	Yarn production
Jones et al. [64]	BN	Improve maintenance planning	Component age, inspection intervals, operator competence, etc.	Failure probability	Carbon black production
Weber & Jouffe [65]	(dynamic) BN	Improve modeling of complex manufacturing processes	Failure rates	System reliability	Generic complex manufacturing processes
Fazlol-lahtabar & Niaki [66]	FTA, RBD	Improve maintenance and repair programs, reliability evaluation without excessive data requirements	Component reliability	System reliability	Material handling
Yan et al. [67]	PN, FTA, FMECA	Analysis of failure sensitivity for mission	Component failure rates	Mission reliability	Material handling
Coban et al. [68]	RBD, MM	Increase reliability of assembly process	Failure rates, repair rates	Process reliability	Hybrid (human–robot) assembly
Chang [69]	MCS, Stochastic Production Network	Improve buffer size and allocation	Reliability of components	System reliability	Printed circuit board production

Table 10
Systematization of reviewed HURA literature.

Article	Method	Goal	PSFs	Used data/expert knowledge	Metric	Manufacturing system
Ellis et al. [73]	THERP and others	Understand age as PSF; design systems that better accommodate needs of older people	Specific focus on age — for example, hearing, vision, reaction time, motor ability	Weights of PSFs	HEP	Generic
Myszewski [7]	Bathtub curve	Identify failure mechanisms of potential failures associated with human error	Rush, learning, fatiguing	Weights of PSFs	HEP	Generic
Bubb [34]	THERP	Quantify human error; indentify influence of PSFs on human error; suggest measures to improve human reliability	Instructions/training, ergonomics, workplace organization	Error probabilities of tasks	HEP	Electronics assembly bench
Aalipour et al. [74]	HEART, SPAR-H, BN	Identify main causes of human error during maintenance activities; compare different HRA techniques	Several, depending on method used	Weights of PSFs acquired from expert interviews	HEP	Cable manufacturing system
Wang et al. [75]	BN, HFE	Quantify positive effect of training on human reliability	Flexibility, coordination, memory, attention	Probability of individual ability shortage and human error	System failure	Bulk container manufacturing plant
Angelopoulou et al. [36]	Simulation (system dynamics)	Quantify human error in Industry 4.0 settings	e.g., standardized instructions, experience, equipment, safety culture	Weights of PSFs	HEP	Generic
Torres et al. [76]	HEART, SHERPA	Identify where and why manual assembly errors occur	e.g., System feedback, risk perception, testing of output, workforce moral	Error probabilities of assembly tasks	HEP	Manual assembly workstation

and FTs, can enhance the accuracy and flexibility of HWRA in manufacturing systems [66–69].
- **Dynamic Reliability Modeling**: Developing dynamic reliability models that capture the evolving nature of manufacturing systems can provide a more realistic representation of system behavior, considering factors such as degradation, aging, maintenance actions, and environmental conditions [40,42,56,57,65].
- **Human–Machine Interaction**: Incorporating human factors and human-machine interaction in hardware reliability assessment can help identify potential failure points and design system improvements to enhance reliability in manufacturing environments involving human operators [59,68].
- **Uncertainty Quantification**: Advancing methods for quantifying and managing uncertainties in hardware reliability assessment, such as fuzzy logic, probability theory, and Bayesian approaches, can provide more robust and accurate reliability estimates [42,48,49,56,60,62–65].
- **Consideration of Dependencies and Interactions**: Manufacturing systems often consist of interconnected components and subsystems. Future research can focus on modeling and assessing the reliability of interconnected components, taking into account the dependencies and interactions between them, to provide a more realistic evaluation of hardware reliability [59,61,67].

5.2. Challenges and opportunities for human reliability assessment

Challenges:

- **Interaction with Automation**: The integration of automation and advanced technologies in manufacturing systems introduces challenges in understanding the interactions between humans and machines, as well as assessing the potential for human errors in these hybrid environments [36,59,68].
- **Real-time Decision Making**: Manufacturing systems often require workers to make quick decisions in dynamic and time-sensitive situations, increasing the risk of human errors due to time pressure and cognitive overload [37].
- **Workforce Diversity**: Manufacturing systems may have a diverse workforce in terms of age, experience, cultural background, and skill levels. Assessing the impact of these diverse factors on human reliability requires careful consideration [73].
- **Lack of Data and Evidence**: Obtaining updated and reliable data for HURA in manufacturing systems can be a challenge, as real-world case studies and empirical evidence are often limited [73,74].
- **Financial Considerations**: Implementing recommendations and interventions identified through HURA may require significant financial investments, which can be a barrier for organizations in adopting and implementing them fully [34].

Opportunities:

- **Human Factors Integration**: Incorporating human factors and PSFs that affect modern technologies such as lack of standardized procedures, lack of experience and/or previous training, insufficient equipment, ergonomics, lack of safety culture, stress, complexity, and population demography can enhance human reliability [34,36]
- **Training and Skill Development**: Providing comprehensive training programs that focus on human factors, task-specific skills, and error prevention techniques can enhance the capabilities and performance of workers, reducing the likelihood of human errors [7,34,75].

5.3. Challenges and opportunities for reliability assessment in general

Challenges:

- **Complexity of Manufacturing Systems**: Manufacturing systems can be highly complex, involving numerous interconnected components and subsystems. Assessing the reliability of such systems requires capturing the interactions and dependencies among various hardware, human, and software elements, which can be challenging due to the complexity and scale of the systems [40,43,55,58,60,61,65–67,76].

- **Model Accuracy**: The accuracy of reliability models depends on the accuracy of the input data, such as failure rates and probabilities. Obtaining accurate data can be challenging, as it may require extensive testing and analysis.
- **Model Maintenance**: Manufacturing systems are dynamic, with components and subsystems constantly changing. Updating a reliability model to reflect these changes can be challenging and time-consuming.

Opportunities:

- **Improved Reliability**: Reliability assessment can help identify potential failure points in a manufacturing system, allowing for proactive maintenance and repairs. This can improve system reliability and reduce downtime.
- **Cost Savings**: By identifying potential failure points and implementing proactive maintenance and repairs, reliability assessment can help reduce the overall cost of maintaining a manufacturing system.
- **System Optimization**: Reliability assessment can help identify areas for improvement in a manufacturing system, allowing for optimization of system performance and efficiency.
- **Integrated Assessment**: Integrating hardware, software, and human reliability assessments can improve the accuracy and comprehensiveness of system evaluations [59].
- **Big Data Analytics**: Harnessing the power of big data analytics to analyze vast amounts of sensor data, maintenance records, and historical failure data can uncover hidden patterns and correlations, enabling more accurate reliability assessments and proactive decision-making.
- **Condition Monitoring and Predictive Maintenance**: Implementing advanced condition monitoring techniques, such as IoT sensors and predictive maintenance algorithms, can enable real-time monitoring of hardware health, early detection of potential failures, and optimized maintenance strategies.
- **Collaborative Reliability Assessment**: Encouraging collaboration and knowledge sharing among researchers, industry practitioners, and equipment manufacturers can foster innovation and best practices in reliability assessment for manufacturing systems.

5.4. Data-driven reliability assessment

The development of the industrial Internet of Things (iIoT) has brought about significant advancements, offering numerous opportunities for analyzing and assessing the reliability of manufacturing systems [77]. The iIoT enables the extensive collection of data throughout all stages of product production, including planning, procurement, assembly execution, and distribution. Furthermore, enterprise information systems such as ERP, MES, and SCM generate data that is relevant for reliability assessment. Data-driven reliability assessment (DDRA) aims to leverage this wealth of data to automate or support the process of reliability assessment [78,79].

For example, Lu et al. [80] propose a Bayesian approach for DDRA of manufacturing systems. Alsina et al. [81] utilize machine learning techniques and manufacturing component data to predict reliabilities. Zou et al. [82] present a novel data-driven stochastic manufacturing reliability model that describes production dynamics and identifies causes of persistent production failures in both deterministic and stochastic scenarios. Lugaresi et al. [83] employ Process Mining for automated manufacturing system discovery and digital twin generation. In our work [84] and [85], we propose an approach for data-driven reliability modeling of smart manufacturing systems using Process Mining and SPNs. Additionally, in another sequence of contributions [86–88], we present an approach for data-driven FTA based on time-series data of a system. These methods combine various data sources with knowledge about the physical characteristics of a manufacturing system. Such approaches facilitate self-diagnosis of a system and offer users a deeper understanding of the relationships between system status and performance, enabling real-time production control and decision-making support.

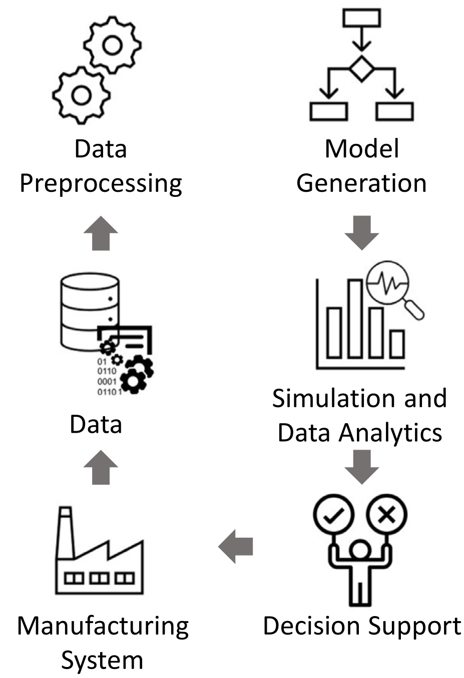

Fig. 10. Data-driven reliability assessment feedback loop.
Source: Adopted from [77].

Fig. 10 illustrates the feedback loop enabled by DDRA of manufacturing systems. Data capturing manufacturing processes is extracted from the manufacturing system, utilizing potential data sources such as ERP, MES, or SCM systems. This data can include information about material flow, resource states and conditions, or manufactured products. The extracted data undergoes preprocessing to detect key reliability-related events (e.g., fault occurrences, repair start and completion times) and convert it into a format suitable for model generation algorithms. Next, the data is utilized to generate reliability models, with the choice of model (e.g., RBD, FT, PN) influencing the preceding steps. Once a model is extracted, simulation and data analytics support decision-making processes related to system configuration, purchase decisions, or maintenance scheduling [77,78].

DDRA offers several advantages and disadvantages compared to knowledge-driven reliability assessment of manufacturing systems. A data-driven approach allows for the creation of more realistic models that better reflect the evolving behavior of manufacturing systems throughout their lifetimes. Furthermore, data-driven reliability models can be used to validate or calibrate existing knowledge-driven models. DDRA also provides manufacturers with deeper insight into the root causes of failures [78]. Ultimately, data-driven reliability modeling can assist decision-makers in maintenance planning, machine purchasing, and plant layout configuration, leading to more efficient resource allocation [89]. However, a key disadvantage of DDRA is the requirement for available data. The actual data collected by manufacturers varies depending on the level of digitization and commitment to the iIoT concept. Additionally, integrating and combining data from heterogeneous sources poses a significant challenge, necessitating the development of methods to incorporate such data into reliability model generation algorithms [78].

6. Conclusion

In this article, we provide a comprehensive overview of the most significant advancements and trends in the assessment of manufacturing system reliability. We review relevant publications addressing reliability assessment of manufacturing systems, distinguishing between HWRA, SWRA, and HURA. We, furthermore, derive challenges and opportunities for future research on reliability assessment of manufacturing systems based on the reviewed literature.

We identified a notable research gap in the field of SWRA, which can be attributed to the historical emphasis on hardware and human reliability within manufacturing systems. Software, being a relatively newer component, has received less attention in terms of reliability assessment. Moreover, limited understanding of software reliability in manufacturing further contributes to this gap. The assessment of software reliability in manufacturing systems requires a comprehensive understanding of both software engineering and manufacturing processes. The interdisciplinary nature of this task poses challenges, as researchers and practitioners may possess expertise in either software engineering or manufacturing, but not both.

In contrast, HWRA and HURA benefit from numerous established methods that are continuously being extended. Popular formalisms for HWRA include Reliability Block Diagrams, Petri Nets, and Markov Models. Similarly, HURA relies on formalisms such as Technique for Human Error Rate Prediction, Human Error Assessment and Reduction Technique, and Bayesian Networks. Furthermore, some publications highlight the potential of integrating HWRA and HURA to enhance reliability assessments.

Our review methodology classifies manufacturing system components into three categories: hardware, human, and software. This classification can be extended using the *5M1E* theory which considers Men, Machine, Material, Method, Measurement and Environment as influencing factors for reliability [8]. In this review, we have captured the factors Men (HURA), Machine (HWRA), Method, and Measurement (SWRA), but lack the factors "Environment" and "Material". In upcoming work, we plan to address these gaps to present a more comprehensive overview of the factors affecting manufacturing system reliability.

Another important approach to holistically assess manufacturing systems is mission reliability assessment. While conventional reliability assessment of a manufacturing system looks at its overall dependability, mission reliability assessment is focused on ensuring that the system can achieve specific mission-related goals and objectives. Both approaches are essential for maintaining efficient and dependable manufacturing operations. While we mostly focus on conventional reliability assessment in this article, a state-of-the-art review of mission reliability assessment methods would be beneficial to the research community.

Lastly, we recognize data-driven reliability assessment as a promising approach that complements conventional, primarily expert-based methods. The wealth of data available in today's manufacturing systems can be leveraged to support and enhance reliability assessments. This data-driven approach opens up new opportunities for improved understanding and evaluation of manufacturing system reliability.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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