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Industry 4.0: Some Challenges and Opportunities for Reliability Engineering

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Abstract

According to the development of Industry 4.0 and increase the integration of digital, physical and human worlds, reliability engineering must evolve for addressing the existing and future challenges about that. In this paper, the principle of Industry 4.0 is presented and some of these challenges and opportunities for reliability engineering are discussed. New directions for research in system modeling, big data analysis, health management, cyber-physical system, human-machine interaction, uncertainty, jointly optimization, communication, and interfaces are proposed. Each topic can be investigated individually, but this paper summarizes them and prepared a vision about reliability engineering for consideration and discussion by the interested scientific community.

Keyword: Reliability engineering, Industry 4.0, Challenges, Big data, health management, cyber-physical system, Human-machine interaction, jointly optimization, communication and interfaces

Introduction

The increasing integration of the digital, physical and human worlds makes a deep transformation in the industry and we are witnessing the fourth industrial revolution that it is called Industry 4.0. It provides opportunities to make the factories as an open platform and distributed systems with the dynamic structure that they are more efficient and faster, and more flexible and resilient the complex supply chains [1]. The term Industry 4.0 was first publicly introduced in 2011 as "Industries 4.0" to enhance the German competitiveness in the manufacturing industry [2,3]. The German federal government adopted the idea in its High-Tech Strategy for 2020. Today, this concept is becoming increasingly ubiquitous. Several researches have been performed to explain this idea and introduce its challenges and benefits, but more research in this field is necessary. In this study, some challenges and opportunities of industry 4.0 from the reliability engineering point of view is investigated.

The Industry 4.0 concept

According to change in the manufacturing environment and competition increasing among companies, we need a new concept to define and make manufacturing factory, because the future industrial factories need a new paradigm to work as resilience and flexible system with reasonable cost. In this section, the past industrial revolutions are reviewed to illustrate this new concept better.

In the eighteenth century, the first industrial revolution caused major changes in industries by utilizing steam power. Electric power and the assembly line for mass production made the second industrial revolution. Computers and information technology were integrated into manufacturing and the different computer-aided systems were produced in the third industrial revolution. Now, the fourth industrial revolution involves the heavy use of automation and data exchange in manufacturing environments. The new systems utilize the advanced technologies, such as cyber-physical systems, the Internet of Things (IoT), 3D printing, digital twinge, and advanced analytics, and cloud computing, and so on [4]. Fig. 1 shows the transformation that happens.

Therefore, industrial systems need to process digitalization, cyber-physical system integration and smart control on factory shop floors. Also, the efficiency increasing needs the integration of the supporting systems into the main system, such as maintenance, logistics and supply change.

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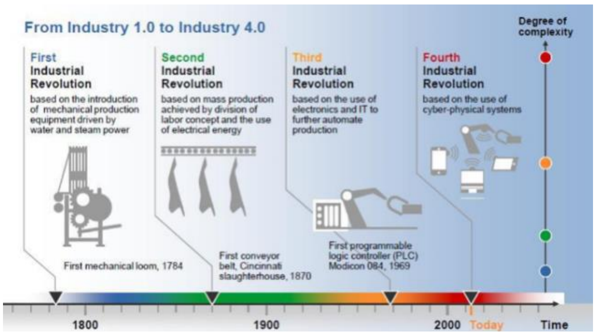

Fig. 1. Industrial revolution through the years [1]

In the other worlds, we deal with a smart system that it is a system of the systems with dynamic structure. This change in industry improves the manufacturing environment and increase system speed and flexibility. Thus, investment level in smart manufacturing and industry 4.0 has been rising rapidly and several countries attend to this topic. Also, several types of research have been conducted to introduce and analysis industry 4.0 and smart manufacturing systems. The brief review of industry 4.0 and smart manufacturing is presented as follows.

The first paper about industry 4.0 was published in 2012 [4] and the abstract level description of Industry 4.0 was given by Lasi et al. [5]. Stock and Seliger presented extensive background research on the development of Industry 4.0 [6]. They also discussed the macro and micro perspectives of Industry 4.0 with regard to sustainable manufacturing and provided future scope in this domain. Mueller et al. [7] extensively studied industry 4.0 and focused on the bottlenecks associated with the implementation of Industry 4.0. They proposed a modulated architecture constituted of products, system software, processing, and manufacturing process. Lee et al. [8] proposed the implementation of cyber-physical systems (CPSs) in industry 4.0. CPSs provide the framework for close connections between physical devices and the cyber world. Condry and Nelson [9] proposed a more secure and efficient model for the IoT approaches as compared to traditional models. Their model considered the challenges and threats in the real-world scenarios and modeled them in the smart IoT devices.

Wang et al. [10] proposed a novel algorithm to perform the operations of the smart factory. They simulate intelligent manufacturing products that can communicate and cooperate with each other without human intervention. Further, this setup was made reliable, by preparing a better decision making environment to prevent deadlocks. The approach was validated through some numerical experimentations. Kadera and Novák [11] worked on the chilled water management system as an example to propose some key points to overcome the problems about communications between the interconnected devices in the industry.

Smart manufacturing is an essential component in Industry 4.0 paradigm which has fundamentally changed the production industry. Smart manufacturing has helped factories achieve productivity gains of 17–20% whilst simultaneously achieving quality gains of 15–20% [12]. Challenges and bottlenecks in smart manufacturing from the past to now should be discussed and the future researches and improvement are introduced [13]. Huang et al. [14] described the latest work in the growth of the community energy system planning (CESP) and discussed the basis of the smart industry techniques applied in CESP. They used a case study and declared that CESP is the next big thing for energy systems in the future industry for which they have developed a platform. Andrew Kusiak [15] described the fundamentals of smart manufacturing as a multi-thread perspective. He studied manufacturing resiliency and sustainability and explained their differentiators with smart manufacturing.

Several papers have been explained the industry 4.0 and smart manufacturing, but reliability engineering challenges, bottlenecks, and opportunities have received less attention. The lecture shows that Zio discussed challenges and opportunities in reliability engineering faced in big data [1]. He focused on knowledge, information and data application to analysis systems and only discussed the challenges of prognostic health management and degradation models. He extended his work and explained the framework for risk assessment in the new environment of industries [16]. This paper extends the previous study and covers other aspects of industry 4.0 challenges and opportunities for reliability engineers.

Industry 4.0 Challenges and Opportunities

All future factories should work based on Industry 4.0 paradigm. This concept was introduced based on manufacturing systems but this idea can be applied in different industries, such as oil and gas, chemical plants and power plants. Industry 4.0 has several benefits; increase production volume, fast response to customer requirement, production waste reduction. But, the implementation of industry 4.0 will need to satisfy several fundamental requirements for manufacturing [17]:

- Enterprise integration and interoperability
- Distributed organization
- Model-based monitoring and control
- Heterogeneous systems and environments
- Open and dynamic structure
- Cooperation and Collaboration
- Integration and interoperability of humans with software and hardware systems
- Agility, scalability and fault tolerance
- Interdependent networks
- Service-oriented collaborative manufacturing platforms

- Data-driven analysis, modeling, control, and learning systems for decision-making support.

Also, different types of technology should be set to build a smart factory [18-20]. These technologies include several software, advanced collaborative robotics, modular and adaptable configuration, high-speed systems for data transfer, and other. To obtain a fully smart system, we need smart supply chains, smart maintenance system, smart labor and so on. This type of system deals with several challenges from the technical point of view. Thus, some companies could not implement this idea and it is still a long way to go.

We know every manufacturing system should be reliable and its availability is reasonable. Also, security, safety and maintainability should be considered in the design, implementation and utilization steps. Thus, when a smart factory or industry 4.0 idea is studied, these challenges and opportunities from the reliability engineering view of point have to be considered. In the rest of the paper, the main challenges and opportunity are discussed.

Challenges and Opportunity for Reliability Engineering

Reliability engineering as a sub-discipline of system engineering includes the systematic application of the engineering principles and techniques throughout a product lifecycle so reliability should be considered from concept plan to wear out of the system/product. Reliability engineer defines reliability requirements, predict, analysis, assess and optimize system performance via reliability techniques.

Industry 4.0 makes the new opportunity for thought leaders and engineers to create new systems and innovate smart devices and instruments. These innovations facilitate infrastructures for industry development, but also generate new and unknown failure mechanisms, new and unknown economic, functional, technical and structural dependencies among system components, and eventually new and unknown hazards and risks. On the other hand, with complexity and dependence increasing, the implementation of new concepts, and the advancements in knowledge, methods and techniques, such as big data, internet of things and quick response to changes, make new opportunities for developing reliability engineering techniques and improve reliability prediction capability. In the rest of this study, some subjects related to reliability and industry 4.0 interactions are discussed.

System Modeling

Industry 4.0 integrates different engineering systems and disciplines. A system built based on this concept includes adaptive systems with differing levels of autonomy and all human activities are interconnected by a lot of communication systems at the moment [21]. This system often has multi-components, open, resilience and dynamic structure managed based on online data collection and analysis. The first challenge is the system modeling and the system definition for this type of system investigation. Although different researchers tried to system modeling via reliability engineering techniques, this type of system modeling and analyzing is an interesting topic for reliability engineers. Several advanced methods and techniques have been developed, such as dynamic fault tree [22], dynamic Bayesian [23], dynamic reliability block diagram [24], Markov chain [25] and Monte Carlo simulation [26]; but this topic needs more attention. The system that used in Industry 4.0 context consists of the new aspects and deal with the new challenges such as Cyber-Physical Systems (CPSs), reliance structure, supporting systems, multi-state components, distributed structure and so on. These challenges are discussed in the next sections.

Cyber-Physical Systems are electronic control systems that control physical machines, and the main structure of the industry 4.0 [17,27]. CPSs provide the framework for close connections between the cyber world and physical devices. Thus, modeling and analysis of CPS as an embedded system is very crucial.

Resilience system is the new types of engineering systems which have recently raised significant interest among both practitioners and researchers due to its role in reducing the risks associated with the inevitable disruption of systems [28]. Dinh et al. [29] identified six factors that enhance the resilience engineering of industrial processes, including minimization of failure, limitation of effects, administrative controls/procedures, flexibility, controllability, and early detection. Different definitions have been proposed for resilience systems [28], but most of them emphasize the system dynamic, adaptive control and recoverability. Adaptive control, online decision and re-configuration of the structure are essential portions of industry 4.0. In this condition, each sub-systems duty is defined based on its state and other sub-systems conditions. This dynamic dependence modeling is complicated and makes the big challenge for system modeling. A recent trend in resilience measures has been accounting for aleatory and epistemic uncertainty with stochastic approaches [28]. Also, addressing larger temporal and spatial scale, integrating more human and social aspects and employing more smart resources and solutions [30] and develop a new model to the time-dependent characteristic of system resilience are the new directions for resilience system modeling [31].

In industry 4.0, often, we deal with a system of systems that covers all aspects which impress system efficiency and performance. Then, system modeling is complex and different disciplines and supporting systems such as maintenance, spare parts inventory, logistics, warranty and after sale service, and others should be jointly considered. Supply chain and maintenance recently have been investigated by researchers [32-34]. Supplier selection, quality, logistics, storage management, spare parts inventory, and cost are studied and jointly optimization of supply chain and maintenance is considered. But study about the integration of maintenance, supply chain, and production planning is rare. When we talk about the factory for future, this necessity is being more highlighted.

A multi-state system is a kind of system **i**n which both the system and its components may display multiple performance levels, and it can be utilized to the modeling of the complicated and practical systems**.** Future engineering systems may use this scheme as a base structure or performance of this system according to the degradation of the system outcome is modeled by multi-state system techniques. When this structure is dynamic and includes software and hardware systems, the system complexity is increased and we deal with explosive states. Also, different components of the system have different behavior and follow a specified probability distribution. Thus, hybrid methods should be developed [35]. Study about the hybrid approaches especially hybrid Bayesian application as an advanced method to solve reliability problems is rare, and according to big data and a lot of evidence, Bayesian infer can be investigated more especially in reliability prediction, diagnosis and fault detection, and risk reduction of the system. A recent trend in the multi-state system has been accounting for dependence modeling among components [36-37].

Practical systems consist of the different components, so multi-component systems assessment recently receive more attention. Several dependencies can exist among the system components; the dependencies can be grouped into four types [38]: structural, resource, stochastic, and economic dependence. An optimal and reasonable plan to reliability assessment should consider these dependencies and the relations among the different components. Also, different levels of uncertainty in system components, different environment condition, exchange information among the components, the difference among components ages and different levels of technology are the main problems of the system. Recently, dependence modeling is a portion of the new researches about reliability engineering.

Today, companies attend to build new sites in other countries to optimize their performance, for instance, in developing countries. International cooperation is increased in business. Thus, we deal with the multi-national company and distributed system. In traditional form this relation is low, but when smartness is increased, the new problem and challenges appear. Today, the business model and supply chain management are studied [39]. Sub-systems are assumed as independent components, and arranged individually based on local regulation and requirements. But the factory of the future needs more integration. Security, dependency and reliability, the effective management of a diversified business, encompassing diversity in human resource, technical capacity, and technical problems are their challenges which must be navigated in ensuring business success.

Other challenges in system modeling are modeling tools and techniques, also interfaces among reliability engineering and other system engineering aspects such as safety, risk. Therefore, advanced methods especially Bayesian approaches [40] should be more considered and new concepts for system modeling is developed.

Big Data and Data Processing

Advanced instruments and facilities are applied in the smart systems and data at different stages of a product's life, such as raw materials, machines' operations, facility logistics, quality control, product utilization and warranty duration is collected and analyzed. This data's role in industry 4.0 and smart systems is crucial and big data empowers companies to utilize data-driven strategies to become more flexible and powerful for market competition. Data collected from manufacturing systems are very important and must be stored and analyzed. In the past, data was documented on paper, with industrial development and the integration of information technology and manufacturing, also computerized systems utilization, data is collected and saved on a machine. Recently, the capability of information technology is quickly grown up and advanced technologies (e.g., Internet of Things, cloud computing, big data analytics, and artificial intelligence) are introduced and simultaneously applied in industrial and business systems. Systems integration with IT leads to use of a new paradigm as industry 4.0. Fig. 2 shows the evolution of data in manufacturing systems, similar integration for other systems can be assumed.

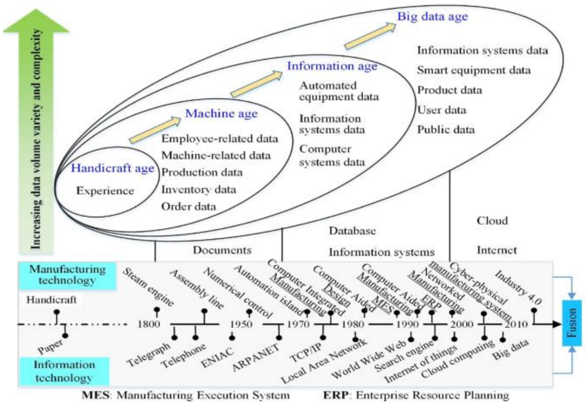

Fig. 2. Evolution of data in manufacturing systems [41]

Big data collected have to be processed and applied to improve system performance. This data consists of different type of parameters with different quality and form because several sensors and sources are applied. Some part of data may be collected as voice, video, image, electronic signal and other, these data should be pre-processed, processed and analyzed for application. Crude data is not useful and it may include noisy data, thus, this data should be translated into concrete information content and context that can be directly understood by users. Thus, we need advanced methods such as cloud computing, neural networks and deep learning [42].

Cloud-Based Big-Data processing techniques as an interesting topic have been investigated in the past decades, different computing models have been proposed based on different platform and focus, such as batch-based, stream-based, graph-based, directed acyclic graph based, Interactive-Based and Visual-Based processing [43].

Neural networks are a useful tool in reliability engineering, especially for remain useful lifetime prediction [43], Farsi and Hosseini used ANN to reduce noise effect and estimated a bearing lifetime [44]. Although ANN is a useful tool for data processing, deep learning is more effective. Deep learning benefits include reducing operating costs, keeping up with changing consumer demand, improving productivity and reducing downtime, gaining better visibility and extracting more value from the operations for global competitiveness [42]. Different models have been developed in manufacturing, as shown in the table below.

Table 1. The deep learning models and application in manufacturing [42].

Deep learning model	Application Scenarios
Convolutional Neural Network	Surface integration inspection Machinery fault diagnosis
Deep Belief Network	Machinery fault diagnosis Predictive analytics & defect prognosis
Auto Encoder	Machinery fault diagnosis
Recurrent Neural Network	Predictive analytics & defect prognosis

The advance in computing techniques and data processing impress design methods and computer-aided engineering systems, for example, different types of failures in the system can be modeled and evaluated by simulations. This capability increases knowledge about the failure mechanism to avoid them in the utilization stage. Reliability engineer can use these capabilities to improve reliability prediction of a new product in the design step. On the other hands, designers incorporate Artificial intelligence (AI) and deep learning into new products and in their own design processes. Design engineers will be challenged to use these tools in their own design processes to more quickly optimize final designs [45]. Xue et al. use deep learning to accelerated search for materials with targeted properties by adaptive design [46].

Another challenge in big data processing is the dynamic behavior of the system. The used model to system modeling should be adapted based on the system age, degradation behavior and condition. Because data collected real-time, may change the pre-defined model of the system. Therefore, model updating can be considered as an interesting topic in this field [1].

Big data and data-driven methods are almost applied to improve maintenance management. Maintenance is a method to keep a system or component in a good and acceptable state. Different maintenance disciplines are applied to avoid catastrophic and unexpected failure, for instance, condition based maintenance (CBM) is frequently applied in modern systems, such as locomotive engines, aircraft engines, aircraft bodies, dams, power distribution transformers, and wind turbines.

In CBM policy, critical components are monitored and controlled; data are collected and processed to make the best decision for system holding. In a CBM system degradation is monitored and controlled to decrease the degradation processes develop. Thus, degradation modeling is an important topic for reliability engineers so different models have been proposed about that. During the last two decades, a number of degradation models have been developed to analyze the degradation dynamics of a product. These models are categorized as follows [1]:

- Statistical models of time to failure
- Stochastic process models
- Physics-based models (PBMs)
- Multi-state models (MSMs).

Ye and Xie [5] have given an excellent review of this area. In the lecture, very few studies have considered degradation dependence in a system whose degradation processes are modeled by PBMs and MSMs, and several factors which can influence degradation evolution, thus, research about degradation modeling must be continued.

All these models need data and their accuracy depends on the data volume and quality. Industry 4.0 produces big data. Therefore, we can increase the prediction accuracy of these models. Also, big data helps to modify these models based on actual conditions or provide an opportunity to develop a new model as new directions of research.

Different types of components are used in a system, some components are critical and their role is crucial. The influence of some components on the system is low, and continuous monitoring isn't reasonable from technical or economical points of view. These are inspected or checked based on time tables. The optimal duration for inspection impresses data integrity as well as the cost. It is obvious that data integrity is very important and big data without integrity is not applicable. Therefore, determine optimal inspection times are important for holding the system at the desired level of reliability/availability and risk reduction. Several studies have been carried out in this field [47-48], recently dynamic framework for inspection has been received more attention [49], but we need more research in this field.

Sometimes system suddenly failed because of environmental conditions variation and excessive loading. Industry 4.0 improve system capability, but random failures can't be eliminated. Also, according to our lack of knowledge about a failure, we may not detect and prevent a failure. This event randomly occurs by external shocks same as mechanical, thermal or electrical shock. For example, the data in a computer system are frequently updated by adding or deleting them and are stored in secondary media. However, data files are sometimes broken by several errors due to human errors, incompatibility, noises, and hardware faults. According to the severity of the damage and its risk, research about these events modeling needs to be conducted. In a shock model, a system (or component) is subject to shocks occurring randomly in time. Over the past several decades, various shock models have been introduced and studied. Basically, those shock models fall into five categories [48]: Cumulative shock model, extreme shock model, run shock model, δ-shock model (delta-shock model) and mixed shock model. Recently, the healing ability of systems is considered by some researchers who study shock models. This topic includes 'curable' shock process and self-healing mechanism. The reliability modeling and assessment of multiple components and multiple self-healing abilities could be developed [50]. Mixed shock model [51], Joint optimization of maintenance policy and spare parts inventorying the system could also be further studied.

Prognostics and Health Management and big data

Prognostics and Health Management (PHM) is a field of reliability engineering that consists of the detection of the engineering component degradation, the fault type diagnosis, the failure time prediction and proactively managing of their failures. In other words, it is a process that predicts the future reliability for systems or products by determining the amount of the deviation or degradation of them from their expected normal situations. Remained useful lifetime (RUL) is the most important portion of PHM that it is estimated by the data-driven, physical model, experimental based and hybrid methods [52]. Most of these methodologies depend on data. In traditional PHM methods, data volume is limit because this data is collected from a single element or data acquisition isn't a continuing process. Then, these methods can not satisfy Industry 4.0 requirements and new and modern methods should be developed to use big data and predict system future, such as deep learning [53], health index similarity [54], on-line method [55]. Another problem is drift concept because we deal with a dynamic and resilience system and the relation between inputs and outputs of the system continuously changed. Thus, we need dynamic models updated using new input-output data collected in the new situations, especially, when there is multi dependence among components or failure modes. Several concepts are developed to drift detection and model updating [56-57], but it is necessary to more research in this field.

Another challenge for PHM methods is their capability to scale-up their results to the whole of the system. Fleet management deals with similar challenges to implement a distributed intelligent dynamic maintenance management system. Fleet maintenance programming is difficult [58] and different environment, different culture, oriented to mission reliability and different age of facilities and etc. increase this case complexity and make interesting topics for future research. On the other hand, the similarity in function and structure of this case cannot be ignored and data diffusion is an interesting subject for research.

Cyber-physical system

Since the decade 1950 that the first computerized machine was introduced and then software controlled a hardware (mechanical or electrical elements) [59], the interaction between hardware and software has appeared a challenge. This interaction has raised up with IT and cyber-physical systems (CPSs) developing so that today they are the foundation of Industry 4.0. The first definition that can be found about CPS dates from 2006, during a workshop with the American National Science Foundation (NSF). In the past decades, many types of research carried out about notions and concepts that have been at the origin of current CPS. Fig. 3 shows the principle of CPS. CPS promotes intensive connection and coordination between physical elements and computational software providing and using data accessing and data-processing services simultaneously. The main benefits that can be expected from the application of CPSs in manufacturing are summarized as [60-62]: optimization of production processes, optimized product customization, resource-efficient production, and human-centered production processes.

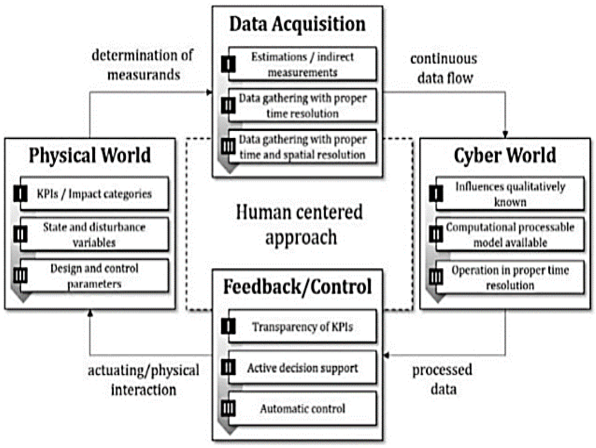

Fig. 3. The CPS principle [17]

CPS has three basic capabilities [62-64]: Intelligence (computation), Connectedness (communication), and Responsiveness (control). Each capability deals with challenges that should be solved and these capabilities need to be developed in future researches. IoT, FOG computing and high-speed networks have been developed, but the communication standards and increase data transfer capacity between different sub-systems need more research. From overview; grand-challenges for the manufacturing of the future and industry 4.0 implementation can be categorized as follows [17]:

1- CPPS-based Manufacturing Plant Control
2- Resilient digital manufacturing networks, collaborative control for Industry 4.0 and cyber-physical supply chains
3- Cyber-physical System-of-Systems interoperability
4- Interdependent networked systems and data analytics for decision support

These challenges influence reliability engineering. In manufacturing plant control as the lowest level of the system, we deal with hardware elements and sensors that collected data. So real-time communication and cooperation between humans, machines, smart equipment and sensors are important. Digital twin as a real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them [64], is created at this level of the system, and in the past, digital twin is mostly used for fault diagnosis, predictive maintenance and performance analysis [65-67]. Self-awareness, self-prediction and self-reconfiguration in the face of internal and external changes are also the system challenges. This concept helps the designer to increase the system reliability, but reliability assessment of this new context is difficult since interaction among physical and virtual items. Also, reliability, robustness and (cyber) security of data produced and consumed at the shop floor level with respect to control objectives are reliability engineering challenges.

The fourth industrial revolution is a customer base idea and CPPS increases system resilient and flexibility to satisfy customer requirements and needs. So, the system has a dynamic-complex configuration with different dependencies (structural, economic, stochastic and resource). In this situation, define the correct model of the system and communication networks, and supply chain management is essential. Also, the system includes different disciplines, machines, humans, data and software, and different types of flows exist in the system such as control flows, data flows, and physical flows. The need for these different types of flows increases the complexity of the models; on the other hands, this model should be flexible and dynamic. Thus, reliability modeling and assessment are interesting topics for research.

The factory of the future has an open platform with interdependency among components. Risk analysis and control for this dynamic system are necessary. Risk models and techniques developed until now often derived based on static state or simple dynamic condition. Therefore, increase dependencies and dynamic of the system lead to propose the new concept and tools for risk management and control. Zio [16] proposed a structure to risk analysis critical of infrastructures such as the electric power grid that this structure can be developed and used as an initial model for risk analysis.

Human role

Different concepts have been proposed for industry 4.0 and smart factory, these models involve human resource and need intervention. In industry 4.0 concept, the human role has been changed, but human as a significant portion of the system cannot be eliminated. Human Reliability (HR) and error impress the system reliability and safety; therefore, this subject should be more considered. Human education and training, resistance to change and his/her interaction with machine are the main challenges to industry 4.0 implementation from human resource aspect.

Human and human-machine interface is one of the challenges for future factory, because of human error and human safety. Human influence on quality management in the era of Industry 4.0 is also important. [68] According to the human role within the industry context, we need smart labors and operators. The human may be defined as a supervisor or human is guided by the CPS [62,68,69]. In these scenarios, it is the combination of calculation abilities of CPS and communication with human capacities that enable the enhancement of the performance of the cooperation system. Fig. 4 shows generic architecture with H-CPPS control loop.

The human-machine interface is changed from a simple push button to advance devices (touch interfaces, voice interfaces, gesture interfaces, and Virtual and augmented reality glasses). For instance, in maintenance and repair, an operator who uses smart VR/AR glasses is able to walk along a line of factory machines, see their performance parameters, and adjust each machine without physically touching it. These modern and smart devices strictly change human role in the industry, and increase the system complexity. On the other side, the reliability and availability of these modern devices are challenges that reliability engineers deal with that.

Human Reliability Assessment (HRA) is a structured and systematic way of estimating the probability of human errors in specific tasks**.** Different approaches are proposed for traditional complex systems such as nuclear power plant, chemical plant, and air-traffic control. These approaches lie on the probability of human failure estimation such as THERP and HEART [70]. When dealing with CPSs or industry 4.0, firstly the integration level of human and system should be defined and then appropriated model and approach is driven. Because the human role can be varied from the supervision of the system (which is able to take all the necessary decisions without any intervention of the human) to the core of the system (he/she charge of all the decisions). Thus, the new generation may be created for HRA in this new context.

Recently, some researchers proposed operator 4.0 to discuss physical and cognitive interactions of operators and highlighting the role of a smart operator in manufacturing. Operator 4.0 was already divided into eight groups by Romero et al. [69, 71] as follows:

- Super-Strength Operator – operator uses his/her hands, foot, or another body organ (physical interaction),

- Collaborative Operator – a collaborative robot helps to operator (physical interaction),
- Virtual Operator – operator utilizes virtual reality (cognitive interaction),
- Augmented Operator – operator uses augmented reality (cognitive interaction),
- Smarter Operator – intelligent personal assistant, helps to operator (cognitive interaction),
- Social Operator – social networks are used by operator (cognitive interaction),
- Analytical Operator – big data analytics is used (cognitive interaction),
- Healthy Operator – operator uses a wearable tracker (physical and cognitive interaction).

Operator 4.0 needs advanced devices and technology to make interaction between machines and human, also smart and skilled operator. The simple case for operator 4.0 implementation is described by Iveta et al. [69], real and practical condition is more complicated than laboratory situation. This idea improves interaction among human and machines, but operator training and mistake reduction in a complex context are crucial.

On the other hands, labors and operators who work in a traditional factory should be employed and engaged in the factory of the future. Therefore, find a reliable method for smart labor training and draw a road-map for this matter is still a long way to go.

It should be mentioned that researches in some countries shown that for successful implementation of Industry 4.0, human resource constraints and parameters must be carefully considered [72].

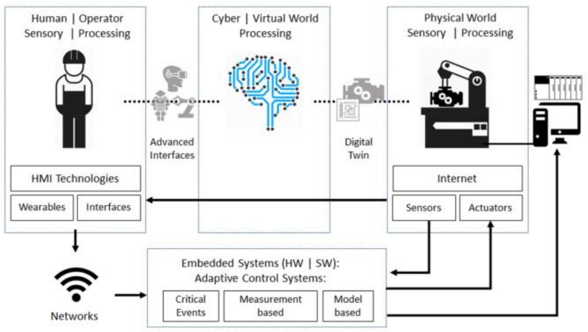

Fig. 4. Generic architecture with H-CPPS control loop [69]

Optimization

Optimization is defined by Merriam-Webster dictionary as an act, process, or methodology of making something (such as a design, system, or decision) as fully perfect, functional, or effective as possible [73]. Different optimization methods and algorithms have been proposed to find the optimal situation of a system/product, such as iterative methods, global convergence, heuristics. Heuristic algorithms recently have been more considered by researchers because of their speed to approximate the optimal situation [74]. Complex system reliability optimization is at the heart of reliability engineering [75], and the determination of optimal situation for real systems is necessary for Industry 4.0 implementation.

Recently, the advance in computational algorithm and computer science have helped to solve and optimize the complicated problem [76-77], but the number of parameters is finite and simulation time isn't acceptable for some of the real-time systems. Industry 4.0 context provides big data and on the other hands, dynamic and resilience structures need the real-time response; thus optimization algorithms must be improved. Moreover, different disciplines, hardware, and software are integrated into Industry 4.0, thus the modern complex systems reliability optimization deal with the following challenges [78]:

i. Integration and response to continuous streams of data proving new and updated information,
ii. Accounting for both aleatory and epistemic uncertainties within the decision-making framework of system reliability optimization,
iii. Cooperative optimization of multi-agent systems, with individual objectives to be optimized within an overall system optimization,
iv. Integrated optimization of reliability design, maintenance, spare parts inventory, and logistics management,
v. Dynamic optimization of evolving systems under changing conditions,

Also, on-line optimization needs high-speed computation and time-consuming reduction. Thus, these topics should be more considered for complex and resilience system optimization.

Interfaces and Compatibility

A system includes different elements from software to hardware. Interaction and interface among elements are the main challenges for system engineering, and at least 50% of problems occur at the interfaces among system elements [78]. To solve interface problems; firstly, system elements should be clearly defined and their input, output, and failure modes are described. Then, P-diagram, Function block diagram, fault tree, and interface matrix be used to manage the interfaces and reduce related failures.

In system modeling, system boundaries and material, dependencies, data and energy flows must be clearly defined. Compatibility among system elements is a crucial problem that impresses the system outcome. Different elements use different protocol and standard for data, material and energy production or consumption. These elements are made by different factories with different capability and experiment. When they are integrated into a system, compatibility and their influence on others are very important, because of compatibility weakness. For example, two elements work perfectly, when they are jointed, an element impresses others and make instability in its work by Electromagnetic interference (EMI) and electromagnetic compatibility (EMC) effects. Thus, compatibility and interface control is very important for reliability engineering and physical based model and finite element methods are very effective to better understand and control incompatibility among different types of hardware [79-81]. Compatibility between mechanical elements is usually covered by design for assembly scheme. But, compatibility between electrical elements is more complex. Compatibility for software engineers is crucial, and several tests are performed as the type of non-functional testing. These tests control compatibility with hardware, operating system element, communication network, other software, versions, and human-interface device.

The lecture shows that interfaces among components, especially electrical components in Nano and Microscale needs to be continued for reliability improvement for the future industry.

Uncertainty

Uncertainty is one of the main challenges in both computational and real-world applications. Uncertainty cannot be eliminated because of knowledge lack and uncontrollable processes, but it can be managed. When a new problem or system created, our knowledge about that can be classified into types: Known and unknown. Each of them also categorized into two states; known (cognizable) and unknown (in-cognizable). When our knowledge state is known-known, we face a good state and we can overcome the problems. When it is known-unknown; we have a problem and try to solve that by increase knowledge and prepare evidences by sensors installation and data collection. In some cases, we deal with different data and information, but we are confused and cannot utilize these, this state is called unknown-known. In this situation, if the problem is restudied or reconstructed, the challenges would be reduced. In the worst state: unknown-unknown. It is a weakness or vulnerable point of the system and can make a significant risk. Risk assessment is necessary, and the new framework should be applied for this [16].

Uncertainty is the main portion of our unknown knowledge. Uncertainty can be accounted for models, computation, and measurement in various contexts. The sources of uncertainty are different and often is produced by parameter, parametric variability, algorithms and techniques, structural, experimental, interpolation and extrapolation [82].

Uncertainty analysis involves identifying and studying the sources of uncertainty and propagating the effects onto the output of the model. Uncertainty analysis is considered to obtain a system with large confidence and low uncertainty in the estimation. Thus it must be conducted to system optimization.

Industry 4.0 prepares different types of data as big data; this can provide an opportunity for uncertainty reduction because it can increase our knowledge and the domain of the known. But, some of the uncertainty sources are increases or remained. System resilience and dynamic behavior are the main challenges and when uncertainty is integrated into them, challenges are raised up. Also, the new devices, instruments, and software have been added to the system, new failure mechanisms and fault states appear. These may increase our unknown domain and make a new risk. Thus, increase knowledge, develop traditional methods and create a new paradigm for uncertainty analysis and risk assessment are necessary.

Miscellaneous

Sustainable development [6] and zero carbon [83], and so on, which recently introduced impress the future industry. Thus, the fourth revolution of the industry must consider these agreements. Their requirements are added to a system as regulations, constraints, and goals. For example, energy saving and environment effect have been studied by several researchers and they attended to make the system with maximum energy efficiency. Supply change, spare parts, and maintenance policies have good potential for optimization based on these criteria [83-85]. Industry 4.0 and related technologies influence the sustainability of manufacturing systems and this topic has been considered by different researchers [6,86-89]. Develop a new risk framework and define the reliability of the system based on sustainability characters can be considered as the new directions of research.

From the past decade, these subjects have been considered, but it is necessary to more research in these fields.

Conclusion

The fourth generation of the industry prepared an opportunity for reliability engineering to increase the system reliability by making big data, internet of things and quick response to changes. On the other hand, complexity increment, dependencies and interconnects among components, dynamic behavior, advanced components such as CPS and sensors, and so on make challenges for reliability engineering. Traditional methods must be updated and a new framework for reliability, risk, safety, and security must be developed. In this paper, Industry 4.0 is introduced and some opportunities and challenges are discussed. It is not pure or perfect review, or not focuses on specified aspects of industry 4.0 and reliability engineering, but we attend to make a perspective about these topics. Some interesting subjects same as system modeling, big data, CPS, uncertainty, interface problem, human-machine interaction, optimization and miscellaneous are considered. In each section, the principle of the object is explained and some of the new directions of research are proposed. In conclusion, today multi-component system modeling, dependence among them, jointly optimization of the supply chain, maintenance and production, and resilience modeling have been received more attention.

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