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Maintenance 5.0: Towards a Worker-in-the-Loop Framework for Resilient Smart Manufacturing

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Abstract: Due to the global uncertainty caused by social problems such as COVID-19 and the war in Ukraine, companies have opted for the use of emerging technologies, to produce more with fewer resources and thus maintain their productivity; that is why the market for wearable artificial intelligence (AI) and wireless sensor networks (WSNs) has grown exponentially. In the last decade, maintenance 4.0 has achieved best practices due to the appearance of emerging technologies that improve productivity. However, some social trends seek to explore the interaction of AI with human beings to solve these problems, such as Society 5.0 and Industry 5.0. The research question is: could a human-in-the-loop-based maintenance framework improve the resilience of physical assets? This work helps to answer this question through the following contributions: first, a search for research gaps in maintenance; second, a scoping literature review of the research question; third, the definition, characteristics, and the control cycle of Maintenance 5.0 framework; fourth, the maintenance worker 5.0 definition and characteristics; fifth, two proposals for the calculation of resilient maintenance; and finally, Maintenance 5.0 is validated through a simulation in which the use of the worker in the loop improves the resilience of an Industrial Wireless Sensor Network (IWSN).

Keywords: smart manufacturing; intelligent maintenance; human-in-the-loop; resilience; human-machine interaction

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1. Introduction

The appearance of the COVID-19 pandemic, the Ukraine War, the semiconductor crisis, and climatic factors such as extreme cold and other factors have caused great uncertainty in the world. Some have called it VUCA World [1]. To maintain their influence in society, companies need to have resilient processes. Uncertainty refers to the lack of knowledge of the causes that originate phenomena in the business environment [2]. It is important to achieve prompt detection of threats and mitigation of uncertainty in manufacturing processes, for which it is convenient to develop resilient assets. According to the World Economic Forum, the future of global trade requires real-time resilience [3]. Resilience is the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions [4]. In a business, resilience can be seen as the ability to predict and recover in a brief time from operational disruptions that threaten some element of the company's value chain, with minimal economic, social, and environmental impact. The business value chain indicates a firm's set of activities to create a profitable product or service for the market impact [2].

To solve these problems, in recent years some initiatives have emerged that bet not only on technological advances but also on human beings to strengthen industry and society and make them more resilient. First, Society 5.0 [5] is trying to achieve a super-intelligent people-centric society that solves social problems using intelligent technologies. It seeks, on the one hand, (a) high-level convergence between cyberspace and physical space, in addition to (b) balancing economic development with the resolution of social problems, which requires that this society be (c) human-centered. Society 5.0 will be made up of systems that will operate throughout society in an integrated manner to guarantee wellness, innovation, and comfort [6], going beyond ergonomics and providing comfort in all aspects of life, such as transportation, energy, care medical, shopping, education, work, industry, leisure, etc. [5,7]. Another initiative is Industry 5.0, which seeks to personalize company operations through cognitive collaboration between human beings and innovative technologies. The three Industry 5.0 main characteristics are [8]: (a) it seeks to improve the well-being of human beings, (b) they seek to solve social problems, and (c) they promote mechanisms to make industrial processes more resilient. Industry and society define the work ecosystem of the future. Work is transforming from paper to digital, from historical to real-time, as well as from productive to personalized.

The maintenance worker has had a historical process within industrial operations; according to P. N. Stearns [9], the first industrial revolution includes the changes that have occurred since the invention of the steam engine in the 1760s and enhanced by the invention of the mechanical loom. The Maintenance Worker 1.0 was an expert on the machine he was working on, and he was the one who knew best how to be more productive. The second industrial revolution started in 1880 when industrial processes adopted electric motors to move machines. Because Taylor divided labor, Worker 2.0 could now be a manager who coached other workers and demanded results. Since the 1950s, and until a few years ago, various technologies were developed that have driven the 3rd Industrial Revolution, where cost reduction and productivity are essential elements. Worker 3.0 used computers, robots, information systems, and various technologies to automate processes and conduct their daily activities was a person who had degrees and certifications and was a better solver of company problems. After 2011, by integrating the enabling technologies of Industry 4.0 and AI algorithms, various processes can be automated to increase productivity, replacing humans with robots. AI and Machine Learning (ML) are considered the driving force of the smart factory revolution [10]. According to the estimate made by Osborne and Frey [11], 47% of total US employment is at a high risk of being automated in the next two decades. Their model predicts that most workers in transportation, logistics, and production occupations and most office and administrative support workers are at risk. To face this trend, proposals have been made, such as worker 4.0 [12,13]. A worker 4.0 is an employee equipped with adaptive technology and technical skills [14]. The objective is to help the worker to be more productive and add value to companies.

The worker for industry 5.0 must be defined, characterized, and have certain digital skills, tools, and technologies to assist machines and physical assets maintain resilience in real-time. On one hand, the Wearable Artificial Intelligence (AI) Market size surpassed USD 35 billion with a demand of more than 150 million units in 2018 and is set to register a Compound Annual Growth Rate (CAGR) of around 30% from 2019 to 2025 [15]. On the other hand, the WSNs market size was USD 38.99 billion in 2018 and is projected to reach USD 148.67 billion by 2026, exhibiting a CAGR of 18.3% [16]. Some growing drivers of AI usage in wearables include (a) rising disposable income of consumers in emerging economies, (b) increasing sales of smartwatches, (c) growing focus on health monitoring, (d) technological advancement in consumer electronics, and (e) increasing smartphone and internet penetration [15].

The main purpose of maintenance is to ensure equipment functions at its original optimal level [17]. The objective of this publication is to show that smart manufacturing can become more resilient if it centers on the protection and maintenance of its assets on human-intelligent assets interaction. By complying with this, we can talk about Industry 5.0 since, in addition to increasing productivity, it also seeks to personalize manufacturing. According to the International Society of Automation (ISA) [18], the human-in-the-loop can be considered a human asset who possesses knowledge and skills associated with production activities.

Motivation

Since the market for Wearable AI sensors and WSNs is so promising, the author's motivation is to learn about its ecosystem to propose a human-in-the-loop maintenance reference framework that helps factories take a more holistic view that allows them to be resilient and direct them toward Industry 5.0. This approach can improve industrial communications networks to impact assets availability, reliability, security, evaluation of risks, and mitigating uncertainty.

The novel Maintenance 5.0 framework considers the contribution made by the worker in the company's value chain, as well as their digital skills with which they have a positive impact on the resilience of the physical assets that conform to the industrial process, meeting the objectives of Industry 5.0 [11]. According to the ISA, a physical asset is any physical component or group of components belonging to an organization [18]. A human-centric solution for maintenance is desired [19].

The work is organized as follows: first, in Section 2, a search is made for works related to trends in industrial maintenance. Section 3 presents the research methodology, where the research question, the variables, and the literature search methodology are raised. Then, in Section 4, the results are presented; first, a definition of Maintenance 5.0 and the elements of the framework are described; second, as Maintenance 5.0 is human-centric, a Worker 5.0 paradigm is introduced; finally, the resilience model is presented.

In Section 5 a use case is presented where Maintenance 5.0 is applied in IWSNs to verify if a human-in-the-loop approach could improve the resilience of the sensor network. The results and the use case are discussed in Section 6 and finally, the conclusions are provided in Section 7.

2. Related Work

The maintenance systems and their future development in Industry have been studied by J. Bokrantz [20], who theoretically proposed how maintenance could be conceptualized and operationalized within the framework of digital manufacturing, detecting dominant themes such as education and maintenance training, fact-based maintenance planning, intelligent work procedures, systems-perspective maintenance planning, and more. On the other hand, Algabroun, H. [21], proposed a theoretical reference framework for Maintenance for the factory of the future within the Industry 4.0 environment, but it has not been tested in the real world and does not take into account the human being. Rastegari, A. [22] proposes a maintenance strategy for decision-making through the implementation of condition-based monitoring (CBM) in the manufacturing industry, including a cost-benefit analysis. In developed countries, these maintenance systems are already being applied with new business models, and according to the World Economic Forum [23], predictive maintenance actions provide various benefits such as 12% reductions in repair times, reduction in up to 70% in failures of some machines, and a reduction in maintenance costs of 30%, among other benefits that investment in applied research of intelligent manufacturing systems brings. According to [24] maintenance's potential to improve the organization's robustness and resilience still need investigation, requiring a search for the main research gaps in industrial maintenance systems.

Like any industrial machine, modern technology needs to have a maintenance methodology that helps it optimize its useful life. A research gap analysis of the study of predictive maintenance at the system level is developed by Miller and Dobrawsky [25] pointing out the lack of incorporation of interactions between components as the main research gap, with two aspects: a. Reliability modeling and analysis, which is performed using Failure Modes and Effects Analysis (FMEA), Failure Modes, Effects and Criticality Analysis (FMECA), fault trees (dynamic), Bayesian networks (dynamic), and networks stochastic Petri; and b) the primary literature focused on complex assets, which often involves modeling the relationship between component detection and state and component-component interactions. The second research gap lies in the lack of attention given to maintenance effects. Maintenance censors' future failure events and maintenance actions can alter the state of latent degradation and its trajectory in trivial ways. Figure 1 shows the maintenance space state, within which are the different trajectories of degradation that a physical asset can suffer from the beginning of its life cycle until a failure occurs, either without preventive intervention or with preventive interventions, but reaching the failure boundary.

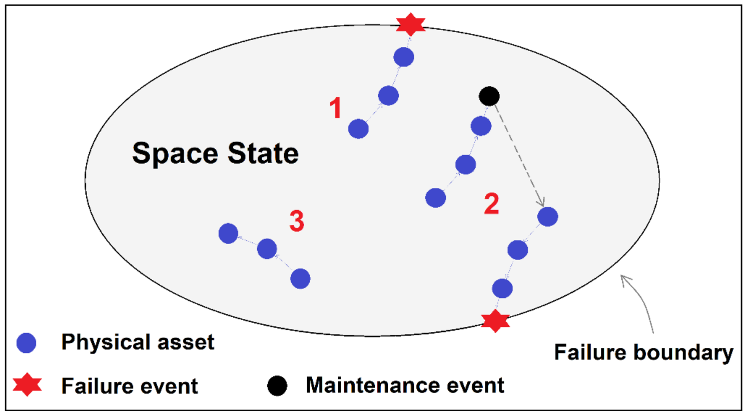

Figure 1. Maintenance Space State: (1) Asset life cycle without maintenance events, (2) Failure event with maintenance events, and (3) No failure events. Own elaboration inspired from [25].

A critical study of existing problems in manufacturing maintenance systems has been made by Alvanchi et al. [26] pointing out that the lack of synergy between humans and intelligent machines represents the principal gap. On the other hand, Bousdekis et al. [27] point out the importance of developing feedback mechanisms to improve decision-making algorithms. In another study, Bousdekis et al. [28] review data-based decision-making methods for Industry 4.0 maintenance applications, pointing out a research agenda with the use of enabling technologies, such as the use of Augmented Reality (AR) that serves as an interface with decision-making algorithms for maintenance applications, or the use of the Internet of Things (IoT) to eliminate uncertainty to avoid implementing inappropriate autonomous maintenance actions, as well as vertical and horizontal integration in industrial systems, or the use of cloud computing, big data, additive manufacturing, autonomous robots and simulation, which could all be embraced in a digital twin approach to predictive maintenance. Furthermore, Ensafi and Thabet [29] study the challenges and gaps in facility maintenance practices, showing the main problem as the loss of data, waste of time searching for information, lack of interoperability, etc.; they also point out that the lack of adequate approaches to decision-making and lack of maintenance planning can increase the cost of operation, which influences the quality of facility management. Meanwhile, Lepenioti et al. [30] reviews the literature and discusses the research challenges of using prescriptive analytics in the industry, highlighting the need to address the uncertainty introduced by predictions, incomplete and noisy data, and subjectivity in human judgment. To achieve the above, they propose current trends in data, such as big data and machine learning algorithms. Finally, human-machine connectivity and coexistence are gaining a lot of interest among the research community, as it is seen as the gateway to Industry 5.0 [31]. Uncertainty is slowing down decision-making in factories, so a new sustainable, resilient, and human-based [8] maintenance 5.0 [32] is needed.

On the other hand, it is important to talk about the main characteristics of wearables. The term wearable devices refers to electronic and computing technologies that are incorporated into accessories or garments which can comfortably be worn in the user's body [33]. Wearables enable human-machine interactions (HMI), allowing humans to work collaboratively with machines; humans contributing their experience and common sense, and machines with optical, tactile, acoustic, bionic, motion technologies, etc. [34]. The wearables ecosystem is very broad since there are companies that sell consumer products for multiple applications and with multiple form factors such as wrist monitors, armbands, shirts, rings, smart scales, lightbulbs, tattoos, arm sleeves, contactless in-bed devices, epidermal patches, headphones, compression shirts, smart thermometers, tags attached to clothing, clipped on belt or bra, socks, helmets, glasses, etc. The market for artificial intelligence in wearables is expected to double from 2022 to 2025 [15]. In addition to the large transnationals, many other brands have emerged that sell these consumer products. Figure 2 shows some companies that are part of this growing ecosystem.

Figure 2. Wearable ecosystem.

Sensors are designed according to where they will be located on the human body as well as the type of bio signal they will measure. Lin et al. [35] note that the main surfaces and secretions used for in situ analysis include the skin and its secretions (sweat, interstitial fluid (IF), and wound exudate), saliva, tears, and breath. In addition, they point out that the most widely used sensor form factors currently are skin-interfaced sensors, which include tattoos, patches and bands, textiles, and clothing, but there are other mountable sensors, among which mouthpieces, contact lenses, glasses, shoes, etc. According to Ling et al. [36], there are two generations of wearables. Wearables 1.0 refers to currently used smart sensors installed in watches, glasses, rings, bands, etc. As seen in Table 1, the next generation of wearables 2.0, includes invisible, conformal to the skin, soft wearable devices, and gold nanowire tattoos. The wearable sensors can be classified into three groups based on the measured biological signals [36]: electrophysiological sensors, physical sensors, and chemical sensors.

Table 1. Wearable generations.

Type of Signal	Variable Measured	Type of Wearable 2.0
Electro-physiological	Electrocardiography (ECG), Electroencephalography (EEG), Electromyography (EMG).	Epidermal, sticky, graphene, silk-based
Physical	Pressure, displacement, temperature, light, sound, strain.	Tattoo, gesture detection, bending degree, limb movement, muscle training.
Chemical	Potassium and sodium ions, chloride ions, lactic ions, glucose.	Diagnosing cystic fibrosis, textile multi-ion sensor, hydration sensor, microfluidic sweat sensor, blood glucose.

The worker can use wearables to know the status of a signal but can also use them to monitor their performance. There are two big problems that workers face in their day to day that measure their resilience: stress and fatigue. These factors can influence ethical decision-making since they do not allow the worker to have a decent quality of life. It is possible to detect stress and other human emotions using signals from wearables. Zhang et al. [37] experimented with 123 participants, who walked using a Smart bracelet, which had an accelerometer; the result was the detection of neutral moods, happy or angry. Ragot et al. [38] shows that through machine learning, it is possible to recognize emotions using psychological signals. They demonstrate this by making a comparison between data sensed in a laboratory and data from wearables. Some psychological signals include ECG, PPG (photoplethysmography), GSR (Galvanic skin response), EDA (Electro-dermal activity), EDR (Electro-dermal response), SC (Skin conductivity), EEG, RSP (Breathing rate), and BT (Body temperature) [39]. In addition to stress, another major problem faced by the worker is fatigue. Papakostas et al. [40] uses EMG wearables and subjective use reports to detect fatigue; through machine learning, they obtain information to design scenarios for adaptive rehabilitation. On the other hand, Schmidt et al. [41] determined fatigue during a long sprint using Inertial Measurement Units (IMUs) attached close to the runner's ankle.

The business value chain indicates the set of activities that a firm performs to create a profitable product or service for the market impact [2]. The worker contributes value wherever he is in the company, so it is important to identify the impact that the application of the worker's knowledge has on the increase in the value of the finished product, or the service provided. Classically, Porter's value chain has been used as a reference framework to locate added value [42]. The value chain is horizontally composed of primary activities, such as inbound logistics, operations, outbound logistics, marketing, sales, and services. Other support activities include the firm infrastructure, human resource management, technology development, and procurement.

After having detected the need to mitigate resilience as the main research gap, having presented the ecosystem of wearables, the main tools to introduce the human being in control systems, as well as the main communication health care protocols, it will be proposed in the following section the methodology used.

3. Research Methodology

The analysis of intelligent maintenance research gaps has motivated the generation of the research question: Could a human-in-the-loop based maintenance framework improve physical assets' resilience?

In Industry, the physical asset definition includes a control system, physical network components, transmission media, conveyance systems, walls, rooms, buildings, material, or any other physical objects that are in any way involved with the control, monitoring, or analysis of production processes or in support of the general business [18].

A scoping literature review was made to understand the human and physical assets interaction in terms of maintenance and try to answer the research question [43]. Figure 3 presents how improved interaction could be the link between humans and physical assets' for better resilience in a maintenance system.

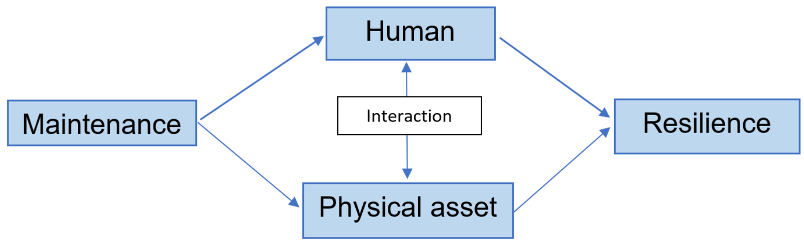

Figure 3. Research framework.

The research has been conducted by the PRISMA Statement because it is a method that helps to answer the research question using keywords and its use has been extended not only to the field of health but also to social sciences, engineering, and technology [44].

3.1. Search and Selection Process

To conduct the search and selection process, keywords from the research question were identified, which were classified into three groups, which are described in Table 2.

Table 2. Keyword groups.

Group	Description	Associated Keywords
A	The material object of the study: What is going to be studied?	*maintenance, smart, intelligent*.
B	It is the formal object of the study: Under what aspect is it going to be studied?	*human, machine, HMI, interaction, interface, human-in-the-loop*
C	Main study or dependent variable	*resilient, resilience*.

The review consists of three main phases: identification, screening, and final inclusion. Figure 4 shows the paper selection process.

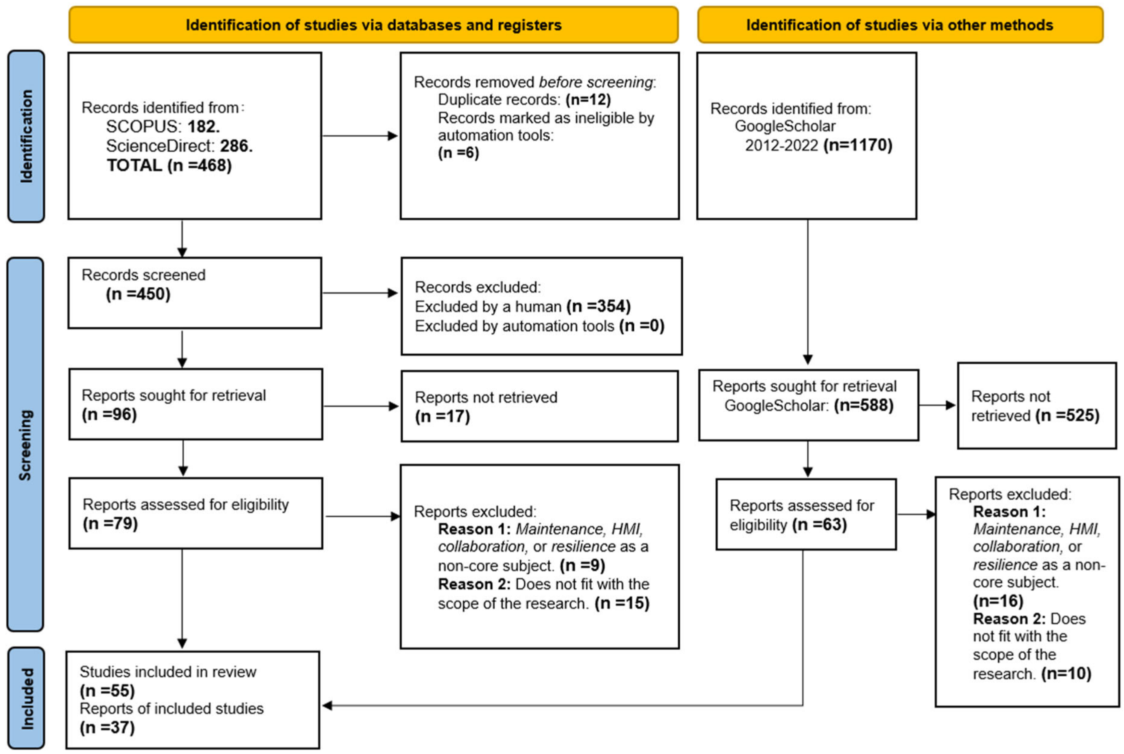

Figure 4. Flow diagram of search and selection process.

3.1.1. Identification

In the identification phase, SCOPUS and ScienceDirect were used for the database search section, while GoogleScholar was used in the section on alternative methods to identify studies. First, SCOPUS was chosen as the main database for this thesis since it is one of the largest databases of titles and abstracts and has a multidisciplinary approach with global coverage, in addition to allowing the database to be exported to a greater number of formats than other databases [45]. As a second option, the ScienceDirect database was taken, since it is a full-text scientific database that refers to more than 2500 peer-reviewed journals, as well as more than 11,000 books; In addition, ScienceDirect is part of SciVerse and is provided by the scientific publisher Elsevier [46]. It does not have all the options to export documents like SCOPUS, but it does offer various information filters that have been useful for this research. ScienceDirect integrates the search for abstracts and links them to other publishers' sites [47]. Finally, GoogleScholar was used for the stage of identification of studies via other methods, since this tool provides the researcher with results from different disciplines and academic sources such as articles, theses, books, international standards, patents, summaries of academic publishers, societies professionals, online repositories, universities, and other websites [46].

In all cases, a combination of the main keywords of this research was used as a search formula: ("maintenance") AND ("smart" OR "intelligent") AND ("human-machine" OR "HMI") AND ("resilient" OR "Resilience"). The following inclusion criteria shown in Table 3 were also used:

Table 3. Inclusion criteria for explorative literature review.

Year	2012–2022
Document Type	Article OR Review OR Book Chapter OR Conference paper
Subject area	Engineering OR computer science,
Language	English

The results were as follows: 182 records were identified from SCOPUS, 286 from ScienceDirect, and 1170 from GoogleScholar. The search and gathering process was conducted on 25 July 2022.

3.1.2. Screening

The screening process was performed based on two steps in this stage. First, duplicate records were removed, and some records deemed ineligible by the Mendeley software were discarded. The Mendeley tool was chosen because it allows the host of supplementary material, promotes discussion and debate, compiles and organizes references, extracts, and builds social networks [48]. Then, the researcher examined the titles and abstracts of the articles with the following exclusion criteria: (a) Maintenance, HMI, collaboration, or resilience as a non-core subject, (b) Does not fit with the scope of the research, and c) full text could not be assessed. After the screening, seventy-nine reports were assessed for eligibility from the SCOPUS and ScienceDirect databases, and another sixty-three were from GoogleScholar.

3.1.3. Final Inclusion

The reports evaluated for eligibility were further analyzed, reviewing the full-text papers, and looking for their contribution to the answer to the research question, leaving fifty-five studies from the SCOPUS and ScienceDirect databases and 37 GoogleScholar records.

3.2. Data Analysis Strategy

When analyzing the trend of the selected publications in the last ten years (see Figure 5), how more publications talk about the keywords that were used for the literature review is notorious; the foregoing indicates that the selected research gap is generating a lot of interest in recent years.

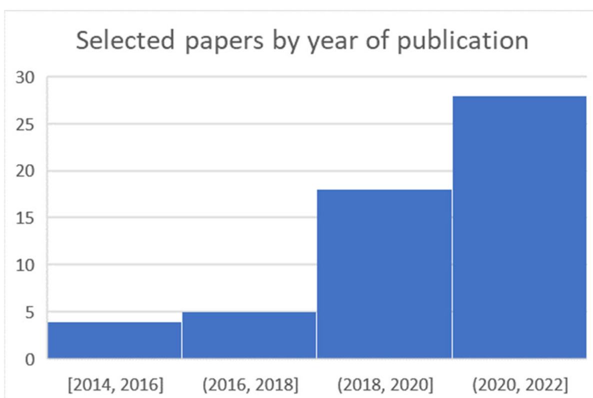

Figure 5. Selected papers by year of publication.

A second reading was made of the titles and abstracts to obtain new insights from this analysis that allow us to know the most specific area of knowledge in which it is necessary to deepen to answer the research question more deeply and extensively. The insights obtained (see Table 4) in Keyword Group A can be grouped as solutions provided by Industry 4.0 [1,34–[44–57] since they are tools like AI, IoT, and WSN technologies to increase the productivity and efficiency of a predictive maintenance system, while the insights obtained from Keyword Groups B and C are tools that contribute more to Industry 5.0 [8,11,24], whose main objectives are a *human-centered* [24,34,44,49– [58–81] approach, and *resilience* [69,72,77– [82–105].

Table 4. Insights from the literature scoping review.

Group	Keywords	Papers	Cluster
A: *maintenance, smart, intelligent*.	Artificial Intelligence (AI), predictive, Machine learning, Reinforcement learning, Assessment, Manufacturing control, Cyber-physical Systems, Industry 4.0, Knowledge-based approach, Prognosis, Prognostics and Health Management (PHM), Internet of Things (IoT), Industrial Internet of Things (IIoT), Maintenance policies, simulation, Wireless Sensor Networks (WSN), Machine tool, Maintenance 4.0	[1,34,44–57]	**Industry 4.0 (predictive maintenance system)**
B: *human, machine, HMI, interaction, interface, human-in-the-loop*	Work assistance, Augmented Reality (AR), Extended Reality (XR), Virtual Reality (VR), Situational Awareness, Digital Twins, Condition-based Maintenance (CBM), Human-centered approach, Collaborative systems, Industry 5.0, Sensemaking approach, *Supervisory control, and data acquisition* (SCADA), human-AI interaction, Human-robot Collaboration.	[24,34,44,49,58–81]	**Industry 5.0: "Human-in-the-loop" (worker-in-the-loop)**
C: *resilient, resilient*.	Security, Resilience of factories, social sustainability, Autonomous maintenance, Work, Adaptive Manufacturing, Retrofit, Training.	[69,72,77,82–105]	**Industry 5.0: Resilience and metrics**

While Industry 4.0 is technology-driven and productivity-centered [33], Industry 5.0 is considered value-driven and human-centered. Industry 5.0 does not replace Industry 4.0 but enhances it, broadening its horizons and adapting it to the new needs of continuous changes [106].

This search in the literature has served to elaborate the hypothesis: if physical asset maintenance had the human-in-the-loop, it would be possible to improve the resilience of physical assets. To make the proposal shown in the next section, the Keywords obtained in Table 4 were deepened by surveying experts in industrial maintenance forums. This publication is supported by a previous experiment carried out with IWSNs [107] that validates the detection part of the proposed Maintenance 5.0 framework. The results of this research are presented below.

4. Results

The search in the literature has helped the authors to have a clearer idea of the keywords that can be part of the maintenance framework that makes manufacturing more resilient. In this section, the definition, characteristics, and control loop of Maintenance 5.0 framework will be presented, as well as the maintenance worker 5.0 definition and characteristics and two novel methods to calculate resilience of physical assets.

4.1. Maintenance 5.0 Definition, Characteristics, and Control Loop

The theoretical proposal in which humans will have a greater role in the maintenance and smart manufacturing is presented below. Based on the objectives of industry and society 5.0 and seeking mutual understanding between machines and humans [108], we define Maintenance 5.0 as: A maintenance system that increases resilience of physical assets by increasing human-physical asset interaction. We answer the research question through the theoretical proposal of a maintenance 5.0 and a use case.

Table 5 shows the evolution that the industry has presented in terms of maintenance and concerning the worker. As can be seen, technological advances always generate the need to generate new maintenance methods and the duty to train workers in these new methodologies. The last column in Table 5 presents qualitative new contributions regarding how to adapt each element to Industry 5.0.

Table 5. Maintenance, Worker, and metrics development. Own elaboration.

Maintenance Work Characteristics					
Industrial Revolution	**First (1.0)**	**Second (2.0)**	**Third (3.0)**	**Fourth**	
				4.0	**5.0** [8] **(This Paper)**
Time	1760s	1880s	After World War II	S. XXI	*After 2021*
Technology enablers	Manpower and mechanical loop	Electric motors	Automation	Cyber-physical systems, IoT, Big Data, Cloud computing, 3D prints, etc. [109].	*Wearables, Cyber-physical human systems, Human-machine mutual learning, Body Area Networks, AI* [57,110].
Maintenance	Immediate corrective actions: "*Fix it when it breaks*"	Deferred corrective actions: "*I operate, you fix*"	Preventive (condition-based): "*Automation operates, you fix*"	Preventive (predictive analytics)	*Advanced analytics* [111] *and retrofit* [101] *with the human-in-the-loop* [112].
Metrics	Number of reparations	Availability, Longevity, Cost	Reliability, availability, maintainability, security	Productivity, offshoring	*Resilience* [113], *sustainability* [11], *impact on value-chain* [114]
Worker	Manual and cognitive worker skills	Manager worker assisting operators	Workers assisted by computers and robots	Augmented by technologies: exoskeletons, personal assistants, wearables, etc.	*Intelligent machine assisted by a human, connected.*

The performance metrics allow having enough data to be compared with the desired level of each of the signals; through the detection and mitigation algorithms, and the advice of the worker 5.0, an optimal solution can be obtained. Maintenance work is conducted on the physical asset, and it is then that the time and magnitude of the impact of the incident can be measured, so that resilience can be quantified. In addition, this resilience impacts an element of the company's value chain in which the physical asset provides its service. Table 6 presents definitions and descriptions of Maintenance 5.0 control loop elements.

Table 6. Definition of Maintenance 5.0 elements. Own elaboration.

World	Element	Definitions and Descriptions
Cyber	Setup	Gives the initial configuration to an asset, making available its signal to the system to be controlled.
	Detection algorithms	General algorithms [115]. Service that monitors and analyzes system events for finding, and providing real-time or near real-time warning of, attempts to access system resources in an unauthorized manner [18].
	Mitigation algorithms	Reinforcement learning and other artificial intelligence algorithms [58] mitigate risk. Mitigation controls are the combination of countermeasures and business continuity plans [18].
Real	Worker 5.0	The human-in-the-loop or "worker in the loop" can be considered as a human asset (people and the knowledge and skills that they possess associated with their production activities) [18].
	Risk event	The expectation of loss is expressed as the probability that a particular threat will exploit a particular vulnerability with a particular consequence. Risk = Likelihood * Impact [18].

Physical asset	*The most significant physical assets are those that make up the equipment that is under the control of the automation system*. [18].
Resilience	Disturbances can be deliberated attack types, accidents, or natural threats or incidents [4].
Value chain	The business value chain indicates the set of activities that a firm performs to create a profitable product or service for the market impact [2].
Performance metrics	Signals from Industrial Wireless Sensor Networks and Wearables

The main characteristics of maintenance 5.0 (see Figure 6) are that the worker is in the loop and that the detection and mitigation of the agents that generate risk and uncertainty is sought, thus increasing resilience. During the remaining useful life of a physical asset, inside the maintenance space state, different actions are conducted that put it at risk of reaching a catastrophic failure zone. The immunity level comes from the design of the product and refers to how well the configuration of the asset or machine that it already has from the factory protects it from a possible external or internal risk.

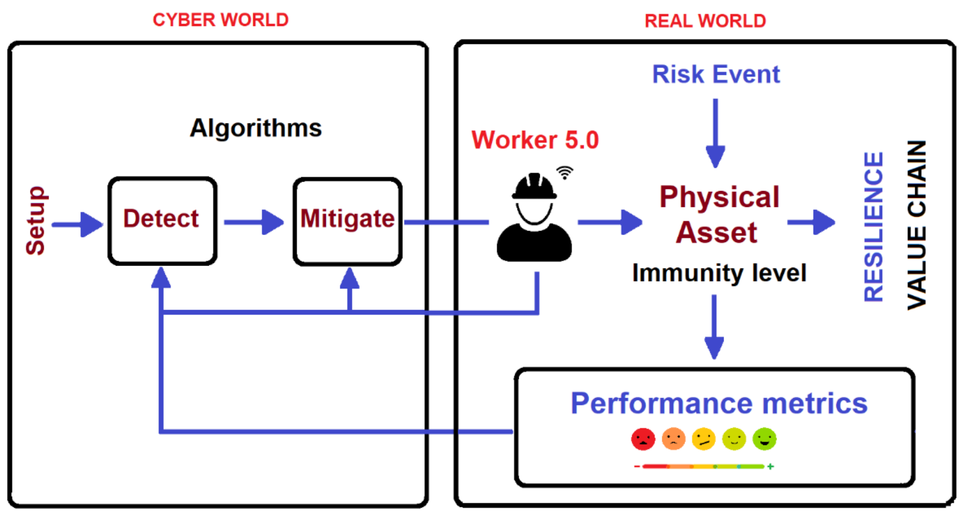

Figure 6. General human-in-the-loop control framework for maintenance 5.0.

The main input in the maintenance 5.0 control cycle is worker 5.0, whose detailed description is shown in the next section.

4.2. The Maintenance Worker 5.0 Definition and Characteristics

The results of an AI system depend on three aspects: the mathematical model, the data with which the model is to be trained, and the human beings that interact with the algorithm [116]. Industry and society 5.0 seek to give an individualized touch to decisions in companies and see the human as an investment instead of just a resource, and this investment in the training of the human results in the well-being of the worker and economic benefits. In this work, the definition of Worker 5.0 is introduced as an employee who, through his cognitive skills and social leadership, is empowered with intelligent devices to maintain organizational well-being and the value he adds to the company, guaranteeing the resilience of the business in situations of uncertainty, as well as his social responsibility. The definition can be outlined using the proposed pyramid (see Figure 7) at the base of which is the work ecosystem where all business activities are conducted. At the next level is the business value chain, which is the place where the worker adds value to the company. Higher up are social leadership and emotional and volitional that influence the degree of influence that the worker wants and can have towards the other people and machines with which he interacts in his daily life. One step higher are smart technologies, which help you establish better communication with the machines and people around you through sensors, interfaces, and wearables, among others. At the top of the pyramid is the human being who works, who has cognitive abilities that help him, according to his intellectual training and his experience, to have greater participation of ideas to add value to his/her work.

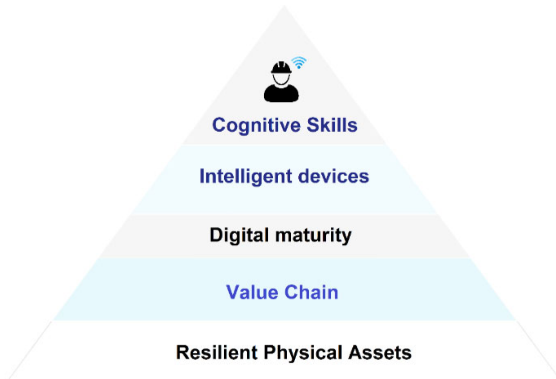

Figure 7. Worker 5.0 pyramid.

Looking at the pyramid from above, you can get an overview of how workers 5.0 manage to make their work environment more resilient based on their cognition and empowered through technologies such as artificial intelligence. Figure 8 presents some of the aspects that make up each of the levels of the worker 5.0 pyramid. A human-centric model is glimpsed where the worker 5.0 is the protagonist in the decisions but has technologies that help him not to make mistakes, proposing solutions to be applied in the department of the company where he works and can transform his environment and solve social problems.

Figure 8. Worker 5.0 ecosystem.

The elements that make up the worker 5.0 framework are described below, which help to implement the objectives of resilience and a social sense that industry and society 5.0 promote.

4.2.1. Human-in-the-Loop Cognitive Skills

The intention or motivation arises from the worker 5.0, as well as the experience of acting in different circumstances and the way of adapting to different environments. The worker has positive and negative experiences; has professional training to apply knowledge according to the context. One way we propose to implement the human-in-the-loop or for the worker to be part of the decisions of the system that controls a physical asset could be the use of reinforcement learning (RL), which, according to [117], is a machine learning (ML) paradigm that is capable of optimizing sequential decisions. According to Akalin y Loufty [118], there exists a large variety of approaches in RL; they can be most broadly distinguished as model-based and model-free. Model-free approaches can be further subdivided into value-based and policy-based approaches. Markov Decision Processes (MDPs) are mathematical models for describing the interaction between an agent and its environment [118]. Figure 9 presents a general setup for RL with a human in the loop and the relation between Environment M and Agent L.

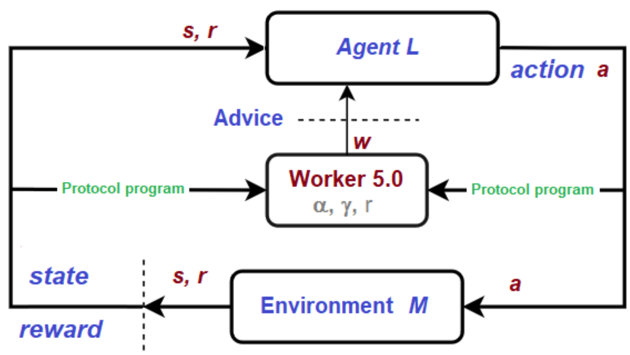

Figure 9. A general setup for RL with a human in the loop. Own elaboration, adapted from [119].

The environment M is a MDP specified by a tuple: $M = (S, A, T, R, \gamma)$, where S is the state space, A is the action space, $T : S \times A \times S \rightarrow [0,1]$ denotes the transition function, a probability distribution on states given a state and action, $R: S \times A \rightarrow \mathbb{R}$ is the reward function, which defines the learning goal and is a scalar value sent at each time instant by the agent to the environment; and γ is the discount factor. The model of the environment is the element that mimics the behavior of the environment and allows inferences to be made about it [120]. On the other hand, the agent L is a (stateful, potentially stochastic) function $L: S \times R \rightarrow A$. Finally, the human H is the Worker 5.0 who can receive and send advice information of flexible type, say X_{in}, X_{out}, so human can be expressed as (stateful, potentially stochastic) function $H: X_{in} \rightarrow X_{out}$[119]. Humans can intervene in the process since it is in interaction with the Protocol Program P, where the decisions of Agent M are validated, and the actions and rewards that come from Environment M are valued. Since the human represents a worker who is an expert on the subject, it is assumed in this model that the human is to add actions [121] in good faith and wants to help with their answers and knows how these answers will be used. The learning system includes a policy, which defines the behavior or action of the agent caused by a certain situation s in the environment and is composed of a set of rules or stimulus-response associations. A Q-learning algorithm could be used to deduct the an IWSN jammer behavior without the need of knowing the transition probability matrix [122]. A disadvantage of this algorithm is that it behaves poorly in some stochastic environments [123]; a similar mitigation approach has already been validated by Zhou et al. [55].

Human advice can be integrated into a reinforcement learning process. Najar, A. and Chetounai, M. [124] proposed a taxonomy of the different forms of advice that can be provided to a learning agent. Human advice can be (a) general, with general constraints and instructions, or (b) contextual, by bringing guidance with contextual instructions or by giving corrective or evaluative feedback. Another way to apply human-in-the-loop is by implementing human advice using wearable devices.

4.2.2. Connected Maintenance Worker 5.0

Worker 5.0 has wearables that help to promptly detect an unfavorable situation that leads to lower performance. Through an IIoT Architecture and the levels of the ISA-95 standard [125], the issue of maintenance and resilience of physical assets can be addressed from different levels (Figure 10): business level, manufacturing level, supervisory level, control level, and field level [126]. While the information technology (IT) worker connects and gives advice to the business and manufacturing levels, the operations technology (OT) worker connects and gives feedback to monitoring, control, and data acquisition systems.

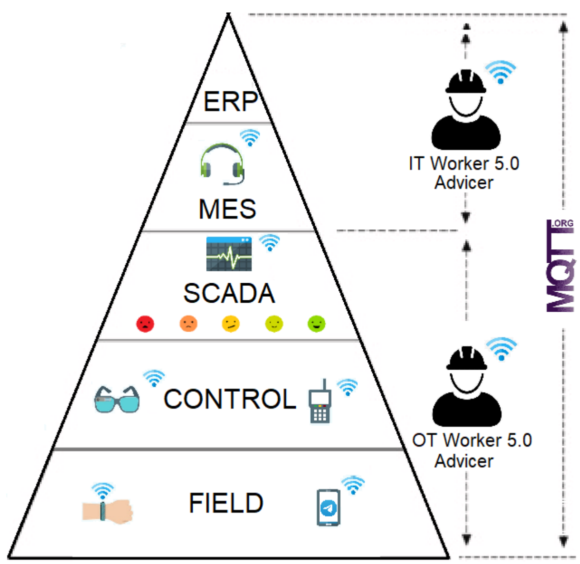

Figure 10. Connected worker 5.0 inside ISA 95.

Some wearable models that are used for emotion recognition like stress include the Empatica E4, Samsung Gear S, BodyMedia Sense Wear Armband, Neurosky MindWave, and XYZlife Bio-clothing [39]. All the data obtained from the wearable sensor is concentrated in a large data cloud, and big data can be transformed from personal situational awareness into collective awareness [127]. To establish communication in a collaborative or cooperative wireless sensor network (WSN) [107] and the wearables, Raad [33], points out that the most used protocol for IoT in the application layer is MQTT (Message Queuing Telemetry Transport); however, the Constrained Application Protocol (CoAP), the AMQP (Advanced Message Queuing Protocol) or the Extensible Messaging and Presence Protocol (XMPP) can also be used. For the transport layer, the User Datagram Protocol (UDP) protocol is used, while for the Network layer the IPv6, 6LoPAN, RPL, and thread protocols are used, and for the physical layer Wi-Fi, ZigBee, LoRa, BLE, and cellular. Signals can be pre-processed by using filtration, normalization, and winsonization methods; and features can be extracted by time or frequency domain methods, as well as statistical indices and nonlinear methods [39]. Finally, the security and privacy implications of implementing these solutions must be considered [128].

4.2.3. Digital Maturity Models

The digital maturity model for the worker 5.0 is similar to that of the worker 4.0. [12] which defines three competencies: The first group includes the digital and technical competencies, which are composed of the implementation of new digital technologies, the interaction with smart devices, making decisions in real-time supported by technological enablers, and solving problems using big-data. The second group of competencies is the personal competencies like creativity, initiative, leadership, negotiation, persuasion, planning, originality, organization, dynamic collaboration, diligence, change management, self-learning, self-organization, teamwork, flexibility, and resilience. Finally, the third group is composed of the socio-communicative competencies, which include effective communication through digital media, mastering digital jargon, and using digital gadgets in presentations.

As a result of the skills analysis, five maturity levels are presented. First, the (1) beginner is a worker who conceptualizes updated terms, identifies the current state, and plans strategic programs for worker development; second, the (2) managed implements training programs to develop skills and competencies for "smart" people. Third, the (3) proactive is a person who enhances the participatory culture through digital enablers for "smart" operations. Fourth, the (4) expert is a worker who becomes experienced, empowers talented workforce 4.0, and pursues continuous improvement. Finally, the (5) leader is a worker who transmits and promotes efforts in developing knowledge of the state of the art in Industry 5.0 objectives of resilience and human perspective.

4.2.4. Business Value Chain Impact

The places where the worker 5.0 can interact are many (see Figure 8); according to Raad [33], the internet of things (IoT) and Wearable Technology Enabled Applications include health-care, business, and well-being, sports, entertainment, gaming, pets, military, public safety, travel, tourism, aerospace, education, fashion, business, retail, logistics, industry (IIoT), home automation, smart living, smart grids, environment (pollution, climate), agriculture, baby diapers, person mood, etc. To the above list may be added vehicles [33] (autonomous driving, accident detection, driving behavior, location and tracking, infotainment and communication, maintenance services, safety, and insurance), and functional areas in a smart city [33]: Environment, governance, energy, education, health-care, transportation, homes and buildings, infrastructure, facilities, resources and services, living. Thanks to wearables and human-machine interfaces used daily, people have a greater awareness of the situation, being able to react more easily to an incident, that is, to be more resilient.

4.3. Maintenance 5.0 Metrics: Resilient Physical Assets

According to Parida et al. [129], the most recurrent indicators to measure maintenance performance and impacts are maintenance cost, Overall Equipment Effectiveness (OEE), availability, maintenance quality, Mean Time Between Failure (MTBF), Mean Time To Repair (MTTR), Mean Time to Failure (MTTF), downtime, number of failures, productivity, number of maintenance personnel, and number of safety, health, and environmental incidents. This publication proposes the calculation of resilience in two possible cases using real-time data and using historic data.

4.3.1. Resilience Using Real-Time Data

Resilience is defined as the area between the metric used to control the process in normal behavior and the variation that said metric undergoes due to random causes, unrelated to the process. The resilience area includes the three typical steps of variance behavior (see Figure 11): (1) increasing the value of the process metric where symptoms that a variance exists are detected; (2) stabilization of the value of the process metric, where the maximum value of the variation is detected and (3) decrease in the value of the process metric, where the variation is mitigated. We use a cycloid function with initial and final slopes equal to zero to show a smooth variation of the metric rising or falling, also known as raised cosine [130,131].

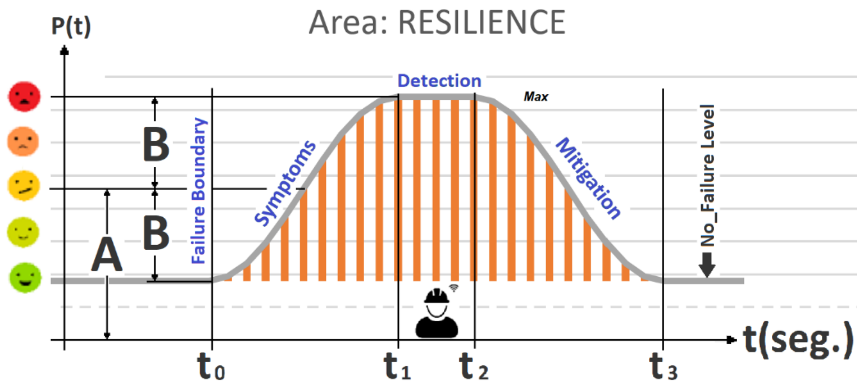

Figure 11. Resilience for real-time data. A is the *No_Failure Level* plus B, where B is the cosine amplitude.

$$P(t) = A + B\cos(\omega t + \varphi)\,;\, Rised\ Cosine \tag{1}$$

The maximum performance value curve (raised cosine) is shown in Equation (1). It can be applied to the symptoms, detection and mitigation intervals as follows: (a) $P_{Symptoms}(t) = A + B\cos(\omega t + \varphi)\,;\, Rised\ Cosine$; (b) $P_{Detection}(t) = A + B;\, Maximum\ Value$; and (c) $P_{Mitigation}(t) = A + B\cos(\omega t + \varphi)\,;\, Rised\ Cosine$; where B is the cosine amplitude expressed as: B= $(Max - No\_failure\ level)/2$; A is the raised cosine and is expressed as $A = No\_failure\ level + B$; the angular frequency is $\omega = \pi/(t_1 - t_0)$ and the phase angle is $\varphi = \pi t_1/(t_1 - t_0)$. The formula for calculating resilience in real time is presented in Equation (2) (area between the variation curve and the level of normal behavior.

$$\begin{aligned} Resilience = &\int_{t_0}^{t_1} \left[P_{Symptoms}(t) - P_{No\_failure\ level}(t)\right]dt \\ &+ \int_{t_1}^{t_2} \left[P_{Detection}(t) - P_{No\_failure\ level}(t)_n\right]dt \\ &+ \int_{t_2}^{t_3} \left[P_{Mitigation}(t) - P_{No\_failure\ level}(t)\right]dt \end{aligned} \tag{2}$$

Figure 12 presents other maintenance performance metrics that are related to resilience calculation. *N* corresponds to the number of failures in an interval: $(t_{33} <= \text{t} <= t_{01})$

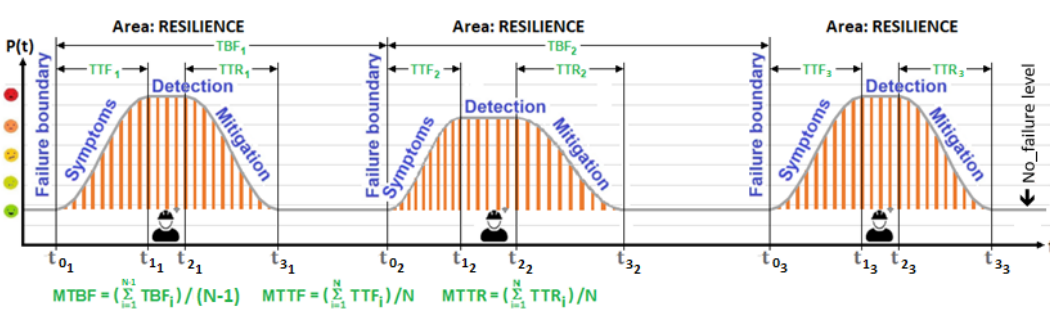

Figure 12. MTBF, MTTF and MTTR maintenance metrics.

On one hand, Figure 12 presents $MTBF = \frac{\sum_{i=1}^{N-1} TBF_i}{N-1}$ in the interval $(t_{0b} - t_{0a})$, has an $N = 3\ (N-1 = 2)$ with two intervals: $(t_{02} - t_{01})\ y\ (t_{03} - t_{02})$. On the other hand, $MTTF = \frac{\sum_{i=1}^{N} TTF_i}{N}$ in the interval $(t_{1a} - t_{0a})$ has an $N = 3$, with three intervals: $(t_{11} - t_{01}), (t_{12} - t_{02})\ y\ (t_{13} - t_{03})$. Finally, $MTTR = \frac{\sum_{i=1}^{N} TTR_i}{N}$ in interval $(t_{3a} - t_{2a})$, has an $N = 3$, with three intervals: $(t_{31} - t_{21}), (t_{32} - t_{22})\ y\ (t_{33} - t_{23})$.

4.3.2. Resilience Using Historic Data

This calculation can be used when an industrial machine completes its total period of useful life from its start-up ($\beta < 1$) to the end of its remaining useful life (RUL) ($\beta > 1$). The performance of a signal coming from a machine can be classified according to its transmission quality as $P_1(t)$, where normal operation is found in $P_2(t)_A$ and decreases until there is a catastrophic fault in $P_2(t)_D$. Inside the Maintenance 5.0 control loop, technological tools are used in each of the stages that an incident causes: normal operation, risk events, symptoms, detection, mitigation, and output (see Figure 13).

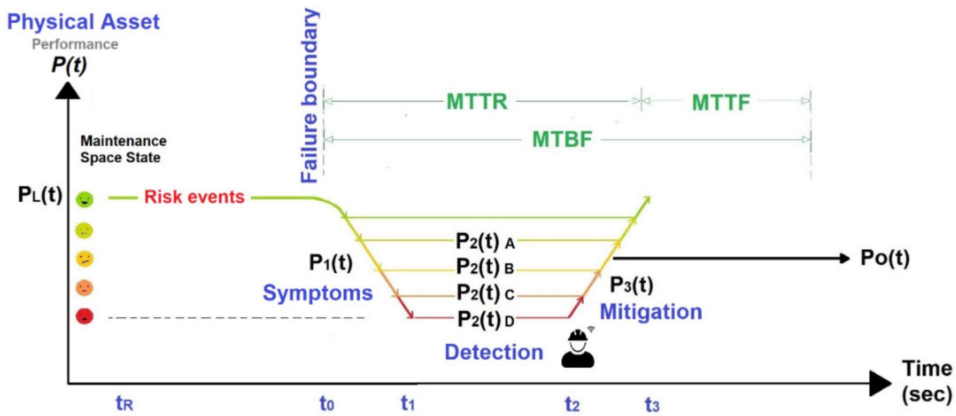

Figure 13. Resilience configuration.

In this work, resilience is defined as the area that includes the change in the performance of a signal coming from a machine and the identification time, which is the time in which the signal remains outside the desired levels.

Weibull distribution bathtub curve (Equation (3)) can be applied for resilience analysis:

$$P_n(t) = \frac{\beta}{\theta}\left(\frac{x-\delta}{\theta}\right)^{\beta-1} \tag{3}$$

In which the three parts of the curve correspond to symptoms, detection, and mitigation. A description of the Weibull distribution applied to maintenance is presented in Table 7.

Table 7. Weibull distribution bathtub curve for maintenance.

Stage	Description	Time	n Value	Performance $P_n(t)$	β
Symptoms	The incident gives rise to a state of deteriorating circumstances.	$t_1 - t_0$	$n = 1$	$P_1(t)$	$\beta < 1$
Detection	Struggle to overcome the degradation obtained by the incident.	$t_2 - t_1$	$n = 2$	$P_2(t)_m$ $m = A, B, C, D, E$	$\beta = 1$
Mitigation	Procedures for recovering from and overcoming incidents.	$t_3 - t_2$	$n = 3$	$P_3(t)$	$\beta > 1$

Resilience is the area between the maximum performance value line and the performance in the three stages of the Weibull distribution bathtub. $P_L(t)$ is the maximum performance value line, presented in Equation (4):

$$P_L(t) = \frac{P(t_3) - P(t_0)}{t_3 - t_0}(t - t_3) + P(t_3) \tag{4}$$

The resilience calculation formula for use cases with historic data is presented in Equation (5):

$$\begin{aligned} Resilience = \int_{t_0}^{t_1} [P_L(t) - P_1(t)]dt + \int_{t_1}^{t_2} [P_L(t) - P_2(t)_n]dt \\ + \int_{t_2}^{t_3} [P_L(t) - P_3(t)]dt \end{aligned} \tag{5}$$

In Equation (5), performance changes over different time intervals. $(t_1 - t_0)$ is the apparition of symptoms interval, $(t_2 - t_1)$ is the detection time, $(t_3 - t_2)$ is the mitigation time, t_3 is the repairs completed time, and $P_0(t)$ is the desired signal; finally, $P_2(t)_m$ is the signal obtained after an incident occurs and it can adopt $m = A, B, C, D, E$ value. The result of the Equation (5) represents the resilience; the smaller the area obtained, the greater the resilience of that signal. The foregoing implies that the maintenance system executes the control loop quickly and both the technologies and the human being are acting in symbiosis. Table 8 shows the impact that each of the performance levels observed in the system has on the performance metrics, as well as the enabling technologies that can be used within each of the maintenance stages.

Table 8. Performance analysis.

Signal State	Performance	Resilience Metrics	Technologies Used
Normal operation $(t_0 - t_R)$	P_o (t)	Security, access control, segmentation, risk level, resourcefulness	IWSN, IBAN (wearables), IIoE, edge computing, 5G, 6G, blockchain, holography
Symptoms appear $(t_1 - t_0)$	Decrease from P_0(t) to P_1(t)	MTTR, redundancy	Cloud and green computing, Advanced Simulations, Big Data Analytics
Detection $(t_2 - t_1)$ if failure is simple, complex, complicated, or catastrophic	$P_2(t)_A$ (Simple)	MTTR, downtime, network traffic, network topology, resourcefulness, latency, quality of service	Cognitive and prescriptive analytics performed by H-CPS, AI, digital twins, softbot
	$P_2(t)_B$ (Complex)		Prescriptive and predictive analytics performed by H-CPS, AI, digital twins, softbot
	$P_2(t)_C$ (Complicated)		Preventive and Corrective actions programmed by H-CPS, AI, digital twins, softbot
	$P_2(t)_D$ (Catastrophic)		Corrective technologies programmed by H-CPS, AI, digital twins, softbot
Mitigation procedure $(t_3 - t_2)$	Increase from the $P_2(t)_n$ to $P_3(t)$	Reliability, MTBF, availability, MTTF, restoration delay	Additive manufacturing, cobots, renewable resources, fintech, bionics, Immersive technologies (XR: AR, VR, MR), drones, exoskeletons, the digital assistant
Normal operation	Maintain $P_3(t)$ in steady state P_0	Resilience, learning metrics	H-CPS, AI, digital twins, softbot

In the next section, the maintenance 5.0 framework will be implemented through a use case of an IWSN that is unexpectedly attacked by a jammer, causing the nodes to consume more energy. Network resiliency results will be displayed when a human gives advice and will be compared to the results when there is no human-in-the-loop.

5. Use Case: IWSN Resilience Using Maintenance 5.0

The contributions of the use case in this work which validate the proposed model are the following: first, a brief jamming mitigation simulation of Q-learning algorithm using python language, second, a comparison of mitigation times with and without Worker 5.0; third, the previous experiment [107] has been carried out again but now measuring the detection and mitigation times, in order to calculate resilience; fourth, resilience has been calculated using the maintenance 5.0 framework demonstrating that a human-in-the-loop maintenance framework could improve physical assets' resilience. A deeper validation of the jamming mitigation will be performed in future work. The role played by worker 5.0 in jamming detection and mitigation is shown in Figure 14.

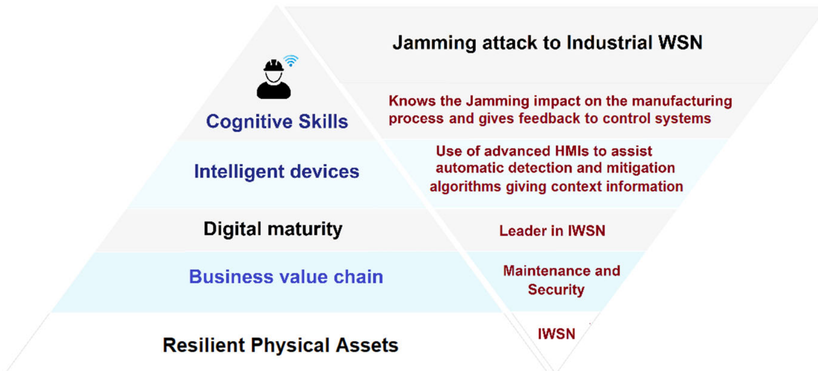

Figure 14. Worker 5.0 collaboration in Jamming Detection and Mitigation.

5.1. Use Case Background

This publication is supported by a previous use case experiment carried out with IWSNs [107] that validated only the detection part of the proposed Maintenance 5.0 framework, answering the question: which configuration helps more to protect an IWSN from uncertainty? As seen in Figure 15, the experiment consisted of 12 homogeneous sensor network nodes in an area of 500 m^2, sending data from seven days to a sink node located in the center of the grid. The Node RAM of the sensor nodes is 128 KB, and the nodes work with a voltage range from 1.8 V to 3.8 V

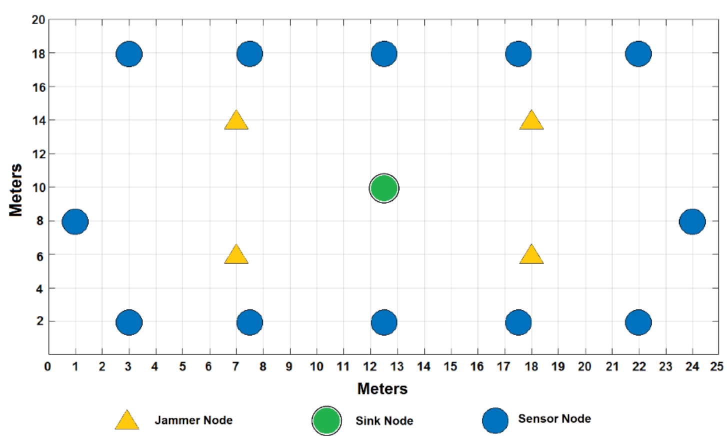

Figure 15. Distribution of the IWSN nodes of the experiment. Image obtained from [107].

The CC2530 sensor node has been used for the gateway. This node is good in system-on-chip solutions for Zigbee and 2.4 GHz IEEE 802.15.4, optimum for industrial control and monitoring, building automation, and low-power WSNs. On the other hand, the CC2650 SimpleLink sensor node has been used for sensor nodes. It supports Multi-Standard Wireless MCU: Bluetooth, Zigbee, 6LowPAN, and IPv6, and offers low-power consumption supporting low-power sensors such as ambient light, infrared temperature, ambient temperature, accelerometer, gyroscope, magnetometer, pressure, humidity, microphone, magnetic sensor, etc. Six nodes of the experiment are based on the Zigbee protocol and the other six are based on the Lora protocol [107]. The jammer nodes imitated the constant jamming attacks to put noise into the network and distort communication. Three performance metrics were sampled using cooperative and collaborative network schemes: the Packet Delivery Ratio (PDR), the Receive Signal Strength Indicator (RSSI), and the Energy. The experiment's results for Energy (J) metric are shown in Table 9.

Table 9. Jamming experiment results. Data obtained from [107].

Jamming	Energy (J)	
	Cooperative	**Collaborative**
Constant jamming	0.37	0.32
No Jamming	0.09	0.07

These results have shown that in the event of a drop in performance metrics due to the presence of a jammer, a collaborative scheme can be used to mitigate part of the damage.

Jamming Detection algorithm. Upon receiving a jamming attack, the IWSN has the current levels of its performance metrics (Energy, PDR, RSSI), which feed into the jamming detection algorithm shown in Figure 16. The performance metrics-based algorithm uses cooperative and collaborative schemes for any density of nodes is based to detect constant, deceptive, random, and reactive jamming.

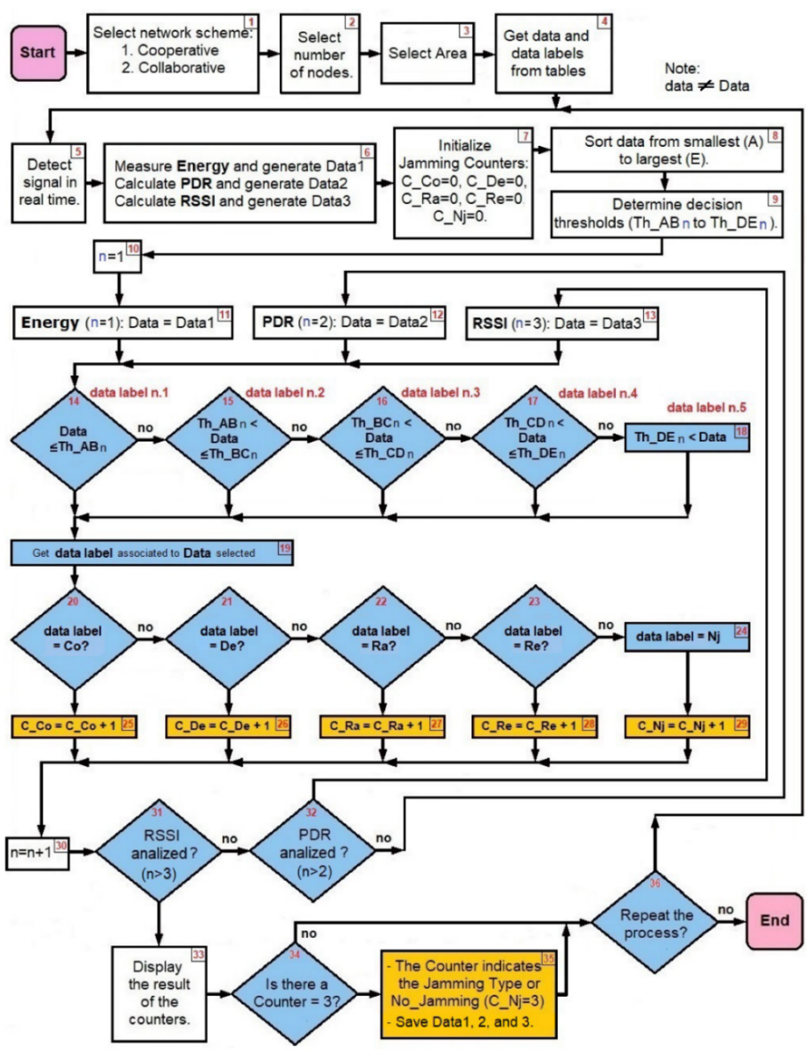

Figure 16. Jamming Detection Algorithm. Image obtained from [107].

For the detection of jamming, the measurements of the analyzed metric are ordered from the smallest to the largest and the thresholds are calculated. Thresholds are then compared with the real-time measurement. For the algorithm to return the presence of Jamming, a Counter $(C_{CO}, C_{DE}, C_{RA}, C_{RE}\ or\ C_{NJ})$ must be equal to three.

5.2. Applying Novel Maintenance 5.0 to Previos Study

When instantiating the maintenance 5.0 cycle to use case, performance metrics, the IWSN configuration, and the possible jamming attacks are monitored to perform the detection and mitigation algorithms, assisted by a human worker 5.0. This section will mention the application of the maintenance 5.0 aligning IIoT and ISA-95 to improve maintenance [125] and resilience at a manufacturing level, at a control level, and at a physical asset level (field).

5.2.1. Manufacturing Level

At a manufacturing level, as a means of training and improving worker skills for IWSNs security, remote experts, softbots, or AI systems can seamlessly connect with field technicians to help get machines back online faster improving availability, which is one important factor to OEE metric.

Manufacturing engineers could use a smart phone, smart glasses, or a head-mounted wearable, such as the HMT-1Z1, with which the other remote expert can see the environment situation and give advice or precise instructions on the best way to recover the process and continue with the production. Another possibility is the communication of an AI system with the worker to give feedback through a virtual assistant or a Telegram Bot. In an IWSN, repair and maintenance service metrics are improved by the increase in network availability (RSII) and reliability (PDR) and the decrease in Energy consumption.

5.2.2. Control Level

At a control level (see Figure 17), after setting up the network there are no need to detect of mitigate jamming attacks; in this time interval $(t_0 - t_R)$ the wireless sensors communicate with the gateway through Zigbee and LoRaWAN protocols, and the sniffer provides real-time Energy (J) performance metric at their optimal level $P_1(t)$, saving data history in a ".csv" file. After this, the IWSN works correctly until time t_0, which is when a jammer (in this case is a constant jammer) appears and distorts the energy (J) performance; after some time $(t_1 - t_0)$ the skewed metrics $P_2(t)_n$ will be in a steady state while the detection and mitigation algorithm runs, and repair changes are applied. The detection algorithm provides the status of the algorithm counters $(C_{CO}, C_{DE}, C_{RA}, C_{RE}, C_{NJ})$ (Figure 16) as well as the detection algorithm processing time $(t_2 - t_1)$.

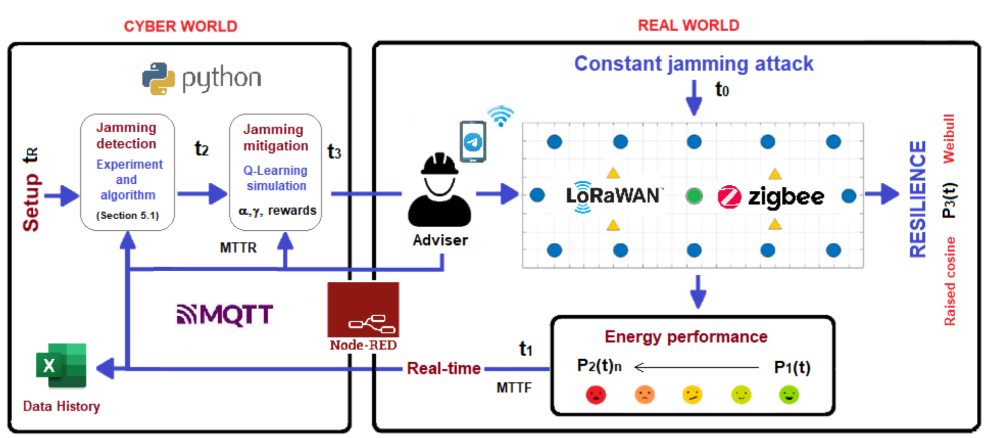

Figure 17. The worker-in-the-loop jamming attack control mechanism.

During the time span $(t_3 - t_2)$ a Q-learning mitigation algorithm is executed in python verifying the optimal route in which the data packets could arrive from a node to the coordinator. Resilience can be reached a) by switching collaborative and cooperative network schemes and b) by looking for the best route for data packets; In both cases, worker 5.0 acts as an adviser. As seen in Figure 18, to communicate worker 5.0 with the cyber world and with the real world, a Telegram Bot has been implemented, which communicates through an MQTT Broker and Node-RED [132,133].

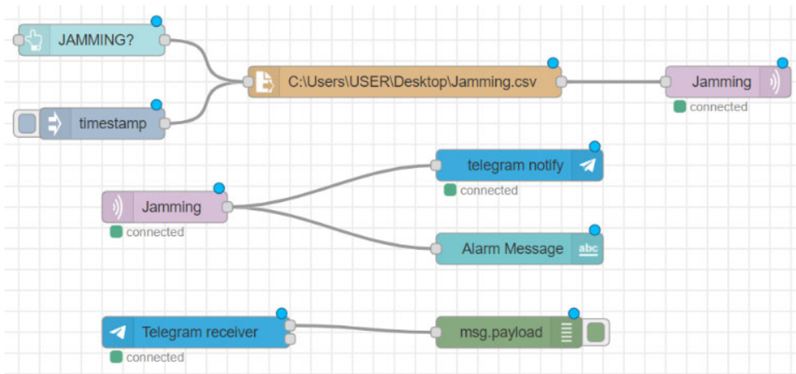

Figure 18. Node-red: Communication to Telegram Bot and Historic data through MQTT protocol.

Two approaches taken to measure asset resilience without human intervention versus human advice are shown in the next subsection.

5.2.3. Field Level (Physical Assets)

At the *physical asset* level, energy consumption was analyzed and used for constant jamming mitigation through asset configuration changes. Once the jammer is detected, it is up to the mitigation algorithm to recover the appropriate level of PDR, RSSI, and Energy of the network in the shortest possible time. In this case calculations are made only for Energy. The IWSN *resilience* has been approached in two ways:

(a) Cooperative and collaborative schemes. According to a previous study [107], resilience can be achieved by using a collaborative scheme between network nodes when a jamming attack of any kind appears. Greater availability is obtained in an IWSN when greater quantity of the available routes is found, reducing transmission latency, and reducing energy consumption. In this resilience approach, the method proposed in Section 4.3.1 and Figure 19 will be used, since it deals with signals with real-time data. Resilience is the area between the Energy (J) with No_Jamming and the Energy (J) with constant jamming in the three stages of the $P_L(t)$: 1) symptoms, 2) detection and 3) mitigation, presented in Equation (1) and Figure 11. From the data obtained in a previous experiment (see Table 9), the energy metric in a normal cooperative scheme operation had a value of 0.09 J, and when there was a jamming attack, the value goes up to 0.37 Joules. In this example, time $t_0 = 0.6$ sec, $t_1 = 1.6$ sec, $t_2 = 2$ sec, and $t_3 = 3$ sec, were randomly taken.

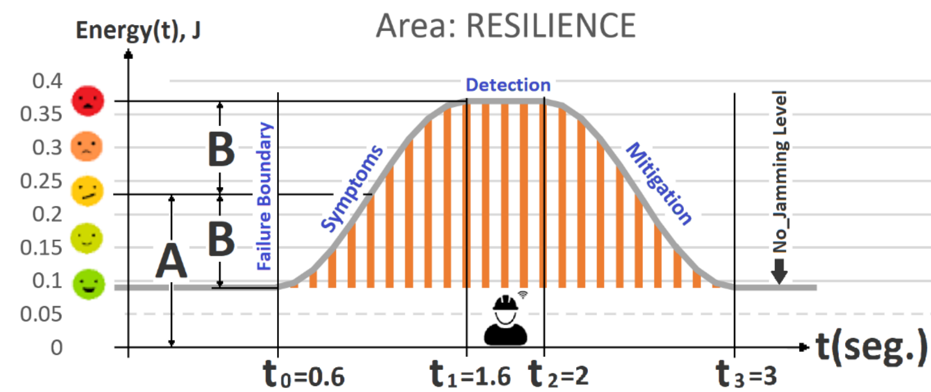

Figure 19. Resilience analysis for IWSN Jamming attack.

Calculations of the parameters A, B, ω and α have been carried out using trapezoidal integration with sampling every 0.1 s; the following values were obtained: $B = \frac{0.37-0.09}{2} = 0.14$; $A = 0.09 + 0.14 = 0.23$; $\omega = \frac{\pi}{16-6} = 0.31416$; $\varphi = 16\frac{\pi}{16-6} = 5.0265$. With those values, performance functions can be calculated. The raised cosine for the symptoms interval: $P_{Symptoms}(t) = 0.23 + 0.14\cos\left(\left(\frac{\pi}{10}\right)t - \left(\frac{16\pi}{10}\right)\right)$; the maximum value for the detection interval: $P_{Detection}(t) = 0.23 + 0.14 = 0.37$, and the raised cosine for mitigation: $P_{Mitigation}(t) = 0.23 + 0.14\cos\left(\left(\frac{\pi}{10}\right)t\right)$. The resilience calculation formula is calculated with Equation (6):

$$Resilience = \int_{t_0}^{t_1}\left[P_{Symptoms}(t) - P_{No\_Jamming}(t)\right]dt + \int_{t_1}^{t_2}\left[P_{Detection}(t) - P_{No\_Jamming}(t)_n\right]dt + \int_{t_2}^{t_3}\left[P_{Mitigation}(t) - P_{No\_Jamming}(t)\right]dt \quad (6)$$

Giving the following resilience result for Energy (J) performance metric: $Resilience = 0.608\ J \bullet s$. Figure 20 presents a graph of the use of the maximum performance value curves for real-time data showing MTBF, MTTF and MTTR metrics which are respectively associated with the stages of symptoms, detection, and mitigation of jamming attacks.

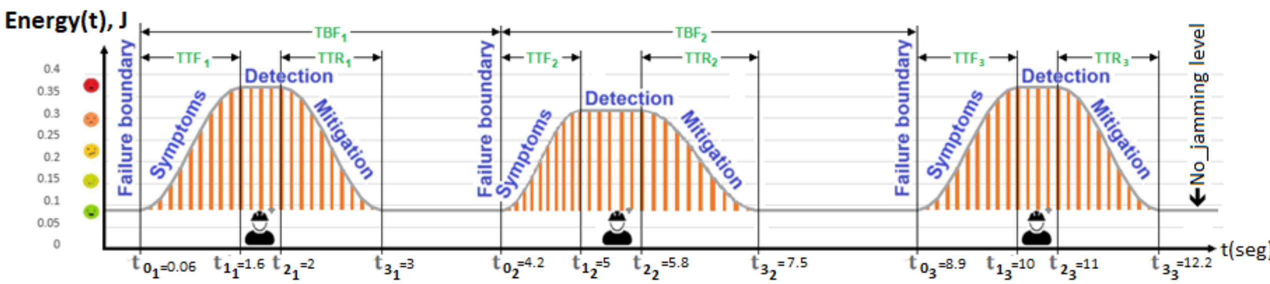

Figure 20. MTBF, MTTF y MTTR calculation.

As $N = 3$ (failures in interval $12.2 \leq t \leq 0.06$), First, $MTBF = \frac{[(4.2-0.06)+(8.9-4.2)]}{2} = 4.42\ s$; $MTTF = \frac{[(1.6-0.06)+(5-4.2)+(10-8.9)]}{3} = 1.147\ sec$; and finally, $MTTR = \frac{[(3-2)+(7.5-5.8)+(12.2-11)]}{3} = 1.3\ sec$.

By repeating the procedure with the intervention of the human, who received a message when the detection algorithm counters $(C_{CO}, C_{DE}, C_{RA}, C_{RE}, C_{NJ})$ had a value of one or two. The worker was able to advise about possible causes that existed in the environment and could be causing the noise (like unintentional jamming that includes environmental noises transmitted by motors, power circuits, inverters, contacts, electrostatic devices, thermostats, welding machines, frequency converters, etc.). Worker 5.0 then gives preventive advice on switching to a collaborative network configuration. By simulating random human advice times, the result of the resilience calculation was now $0.571\, J \bullet s$, which is smaller than the previous result, $0.608\, J \bullet s$, implying higher resilience.

(b) Q-learning algorithm simulation: Reinforcement learning algorithms [134–137] are suitable to defend a WSN by increasing the availability and optimal routes in a network. According to [118] interactive RL makes use of human feedback in the learning process in combination with or without environmental reward. As seen in Figure 21, Worker 5.0 gives advice to the agent [124], so the agent considers the human experiences to decide the action to be accomplished in the environment. The human engineer gives advice and changes the rewards given by some fixed reward function to influence an agent's learning [119]. The feedback can be evaluative, corrective, or just guidance.

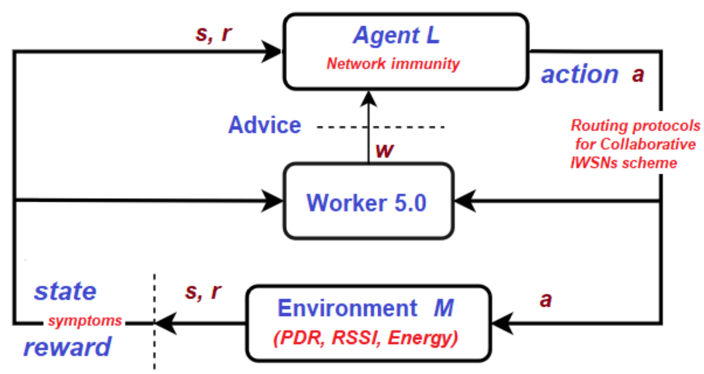

Figure 21. Worker 5.0—IWSN interaction in Reinforcement Learning.

Equation (7) shows the Q-learning algorithm, where an episode (or trial) describes a sequence from the initial state to the terminal state, and α specifies de learning rate [118].

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \underset{a}{max}\, Q(s_{t+1}, a) + Q(s_t, a_t) \right] \tag{7}$$

In this work, a brief simulation of the Q-learning algorithm has been carried out using a Python language program with which it has been evaluated which would be the optimal routing to send the data packets to the WSN coordinator, avoiding the areas of the network affected by a constant jammer. Worker 5.0 gives advice like corrective feedback, guidance and instructions [124]. In this simulation, the α and γ parameters from Equation (7) are instructions given by the human worker. In addition, Worker 5.0 gives corrective feedback by informing Agent L about the optimal action. Figure 22 shows the network generated by the python code [138], which simulates the distribution of Figure 15.

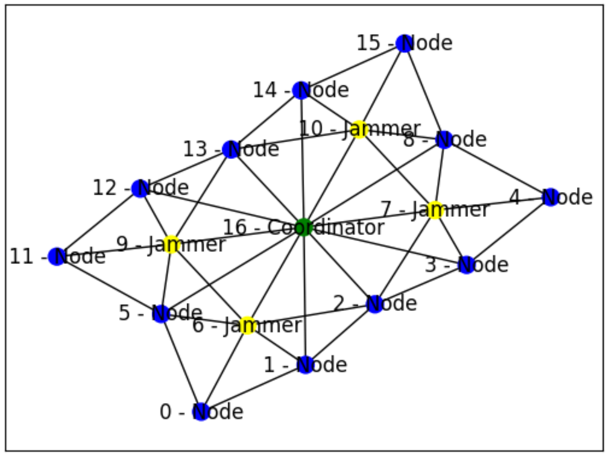

Figure 22. Network simulated.

On one hand, a gamma discount factor (γ = 0.2) has been chosen since, due to the environment of uncertainty that exists in the network, it is desired to hold on to current or tangible rewards, which resembles a collaborative network scheme [107]. On the other hand, despite the fact that an IWSN traditionally presents a deterministic scenario, due to the fact that the changes are unexpected and that it is a highly uncertain scenario, although alpha values close to one are usually used in stochastic scenarios, as shown in If you want the agent to use more recently acquired information (due to high uncertainty), a learning rate ($\alpha = 0.1$) has been used. The score in Figure 23 denotes the average number of goals achieved by the agent for the tasks in the test set [139].

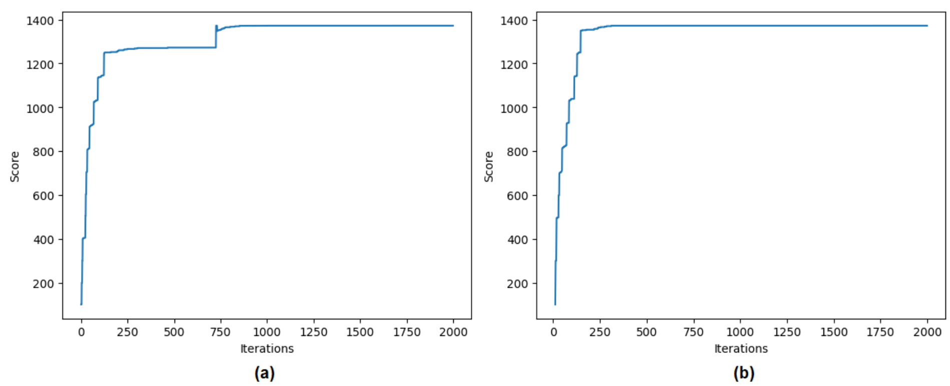

Figure 23. Simulation results: Iterations vs. Score. (a) No human, (b) Human.

The results show that the number of iterations can be reduced from 750 to 250 by human advice; worker expertise uses his/her long-term experience to give feedback and give rewards. Some other results are presented in Table 10. In one case, the optimal route obtained was $[0, 5, 16]$, and in the other case was $[0, 1, 16]$; on the other hand, since the rewards are different when a human acts according to the context that he knows, the execution time of the algorithm was shorter because it converges in fewer iterations.

Table 10. Jamming routing simulation for mitigation results.

	Human	**No-human**
Reward	10	1
Most efficient nodes path to arrive to coordinator	[0,5,16]	[0,1,16]
Iterations to converge to a solution	750	250

Zigbee protocol mitigation time [140]	2.456 s	
Lora protocol mitigation time [140]	2.332 s	
Time elapsed during the whole algorithm execution (routing time)	1.875 sec	1.9375 sec
Agent score	1372.48	1372.48

With the mitigation times obtained with the simulation and those already available from previous studies, as well as a random input for the appearance of symptoms (since it is precisely the uncertainty that is of interest to mitigate in this study), the calculation of resilience with the raised cosine method (SubSection 4.3.1) using Equation (2). As can be seen in Table 11, resilience has a lower value when a human intervenes by giving advice than when it does not intervene. Furthermore, it is confirmed that the LoRa protocol is more resilient than the Zigbee protocol.

Table 11. Energy resilience calculation from simulation data.

Protocol	Symptoms times $(t_1 - t_0)$ *(random)*	Detection times $(t_2 - t_1)$ From algorithm in Figure 16	Total Mitigation times $(t_3 - t_2)$ from Table 10		Resilience $(J \bullet s)$ (From Equation (2))	
			Human	No human	Human	No human
Zigbee	2.1	0.39453125	2.456 + 1.875 = 4.331	2.456 + 1.9375 = 4.3935	0.752	0.761
LoRa	2.1	0.37109375	2.332 + 1.875 = 4.207	2.332 + 1.9375 = 4.2695	0.728	0.737

Finally, Figure 24 shows how the behavior of resilience is seen in the different time intervals according to the data considered in the simulations.

Figure 24. Resilience with simulated data.

A more detailed experiment on jamming mitigation using this approach will be implemented in future work answering questions regarding costs, robustness, subjectivity, and reliability of human-in-the-loop. In the following sections, the results will be discussed considering the research question.

6. Discussion

Based on an analysis of research gaps in industrial maintenance, as well as knowledge of market trends regarding emerging technologies such as the Internet of Things, wireless sensor networks, AI Wearables, and advanced data analysis techniques such as big data and AI algorithms, the importance of implementing the new Industry 5.0 proposals have been found. The objectives of Industry 5.0 refer in the first place to the leading role of the human being to move from a productivity model to one of personalization, betting on the worker as an investment and not as an expense; secondly, it seeks to mitigate uncertainty by increasing resilience; and thirdly, it seeks to have an impact on society. According to the needs of the industry explored, the research question was formulated: could a human-in-the-loop based maintenance framework improve physical assets' resilience?

A review of the literature was then conducted, which helped to group the keywords into three clusters: a) Industry 4.0: predictive maintenance systems, b) Industry 5.0: human-in-the-loop and c) Industry 5.0: resilience and metrics. With the collected literature and complemented with related literature and the experience of the authors, a proposal was made for an intelligent maintenance reference framework inspired by the objectives of Industry 5.0, and it was called Maintenance 5.0.

Maintenance 5.0 seeks to answer the research question through the following hypothesis: if physical assets maintenance had the human-in-the-loop, would be possible to improve the resilience of a manufacturing system. An important contribution is the determination of a control cycle for maintenance 5.0, within which Worker 5.0 plays a significant role, who is the person who participates in maintenance decisions and gives feedback to control systems. Another contribution of this publication is the definition and description of the connected worker 5.0, which is the person who makes Industry 5.0 a reality, and who uses AI wearables to be connected to control systems. Due to its holistic vision, professional experience, and ability to understand the context, worker 5.0 assists artificial intelligence in decisions to detect and mitigate risks present in physical assets. The degree of human-in-the-loop involvement (independent variable) must impact the resilience (dependent variable) of the physical asset that is being maintained; the foregoing is achieved by reducing symptom reading times, the rapid application of detection and mitigation algorithms, as well as the change in the configuration of the assets.

In the presented use case, the increase in resilience in an IWSN is achieved through a change in the routing protocols of the nodes belonging to the IWSN, which changes from a cooperative scheme to a collaborative one, which was demonstrated in a previous study [107] that it is an effective strategy to achieve resilience when subjected to a jamming attack.

In addition, the influence that worker 5.0 can have on artificial intelligence algorithms such as the Q-learning algorithm was presented; This was achieved through a simulation, in which the resilience of an IWSN subject to a jamming attack was measured in two scenarios: a) when the control systems act without human intervention, and b) when there is human intervention. -in-the-loop that provides advice or feedback to control systems. The results showed that the intervention of a human can improve the resilience of physical assets, which answers the research question.

Despite having obtained a satisfactory result, to strengthen the proposal it is important to subject the maintenance system to other types of use cases, where other types of physical assets, other software and other algorithms can be used.

With the description of the maintenance 5.0 framework and its impact on resilience through the worker 5.0 advice, two of the three objectives of Industry 5.0 are met: human-in-the-loop, and increase in resilience; however, the impact on society has been presented conceptually from the point of view of the worker 5.0, which is aware of the impact of its decisions on the company's value chain and business metrics.

7. Conclusions

Could a human-in-the-loop based maintenance framework improve the resilience of physical assets? This work helped to answer this question through the following contributions: first, a search for research gaps of maintenance; second, a scoping literature review of the research question; third, the definition, characteristics, and the control cycle of Maintenance 5.0 framework; fourth, the maintenance worker 5.0 definition and characteristics; fifth, two proposals for the calculation of resilient maintenance; and finally, Maintenance 5.0 is validated through a simulation in which the use of the worker in the loop improves the resilience of an Industrial WSN.

The biggest challenge that Industry 5.0 brings to engineering is the transformation of the Industrial sector through the design of robust, secure, scalable, and human-centered systems; these solutions will be based on IIoT and cognitive computing. There is currently a great interest in materializing Industry 5.0, since it is a change in mindset that not only increases the productivity of processes but also combats uncertainty, keeping physical assets within the maintenance space state.

Maintenance 5.0 is a novel proposal that must be deepened and validated in each of its elements; however, in this study, it has been possible to establish a solid start that allows increasing the reliability, availability, maintainability, and security of physical assets in smart factories, keeping their performance metrics at acceptable levels, increasing resilience. In this study, a simulation was conducted at the control and field level with IWSNs, but future simulations and experiments can be carried out at the business, manufacturing, and supervisory levels to validate the model with other physical assets such as mechanical elements of machinery, electronic cards, numeric control machines, robots, electronic elements, etc.

Some future works include the experimentation of jamming mitigation in an IWSN through the application of routing protocols that may be inspired by reinforcement learning; In addition, the impact on society could be demonstrated through the impact on the value chain of the decisions made by the human worker-in-the-loop 5.0, which gives rise to future studies of the impact of AI on sustainable industrial solutions.

A pillar with which Industry 5.0 will be able to achieve the inclusion of humans in decisions will be AI algorithms; This tool will be essential for Industry 5.0 solutions to be more robust, ethical, and safe. The development and maintenance of AI systems have many similarities with the development of software systems, so future work should pay attention to the challenges that AI has at each stage of software development.

Some other questions that need to be answered in future work include: what types of user interfaces (HMIs) and displays (SCADA) cause humans to perform the most useful actions in response to a request from an intelligent maintenance system? How should we guide humans on where and when to intervene by adding actions? The interaction between humans and machines will bring with it the personalization of manufacturing through the deployment of collaborative robots; the human being will be able to delegate to machines unsafe, routine tasks that require mechanical effort; In addition, higher quality in the production chain and faster production will be achieved.

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