Environmental Risk Assessment and Management in Industry 4.0

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Contributor: Janaína Lemos, Pedro D. Gaspar, Tânia M. Lima

According to the International Labour Organization, occupational injury is a personal injury, disease, or death that results from an occupational accident. Occupational accidents, in turn, are unexpected occurrences, including acts of violence, arising out of or in connection with work and resulting in one or more workers incurring personal injury, disease, or death. Occupational diseases are acquired through personal exposure to environmental risks, such as physical, chemical, and biological agents in situations above the tolerance limits imposed by legislation or applicable standards. These diseases are caused or aggravated by specific activities, and are characterized when the causal link is established. between damage to the worker's health and exposure to certain work-related risks. Occupational diseases occur after various years of exposure, and in some cases, they can arise even after the worker is no longer in contact with the causative agent.

Keywords: : occupational risk assessment ; Industry 4.0 ; internet of things

1. Occupational Risks and Diseases in Industry 4.0

An occupational risk factor is an agent that can cause damage to a worker's health. The potential risk factor is called hazard. Occupational risk is the combination of the probability of an adverse effect (damage) on the worker's health and the severity of this damage, assuming that there is exposure within the work environment [1].

Examples of common occupational diseases include occupational asthma [1][2], vibration-related diseases [3][4][5], noise related diseases [6], pulmonary fibrosis [7], bronchopulmonary pleural fibrosis and damage caused by the inhalation of asbestos dust [8], and occupational cancer [9].

As mentioned above, in Industry 4.0 workplaces the presence of new technologies brings new opportunities and new risks. In addition to common occupational diseases, the nature of work in Industry 4.0 has the potential to contribute to the increasing frequency of other diseases, including mental disorders and diseases related to sedentary behavior. In Industry 4.0, several workers can often be involved in creative value-added tasks, while routine activities, as well as certain dangerous tasks, are often performed by robots. This scenario, along with early and continuous risk analysis and management based on various technologies, could make workplaces safer. On the other hand, semi-skilled employees could lose workplace opportunities because of potential difficulties in performing more complex tasks. At the same time, the use of digital tools to continuously monitor the performance of employees may become common, which could result in privacy invasion and psychological pressure [10][11].

In addition, the risks related to interactions between humans and machines have increased and greater connectivity makes it possible to work anywhere at any time. This scenario brings benefits such as flexibility, but also has the potential to impact individuals' work–life balance, which may in turn be harmful to mental health [12]. According to [11], depression is very common in workplaces compared to other mental disorders, and affects workers by reducing productivity, diminishing job retention, and increasing the risk of accidents at work. Another issue related to Industry 4.0 is the existence of many sedentary jobs, such as computer-based work. High levels of sedentary posture are associated with an increased risk of cardiovascular disease and type 2 diabetes, several cancers including lung and breast, and mental disorders such as depression. In addition, poor lighting conditions in workplaces (for example, store warehouses, since online commerce has been growing) can cause severe headaches and discomfort. Insufficient lighting makes it difficult to perceive the depth, shape, speed, and proximity of objects, and related accidents may often occur [13].

2. Organizational Culture as a Key Factor in Ooccupational Ssafety and Health (OSH)OS

According to [14], the occurrence of occupational diseases and accidents causes significant losses in companies' reputation and decreases their productivity. For example, a worker who becomes aware of a colleague's illness may become discouraged and start to produce less or may look for another job opportunity with better OSH conditions. To combat or significantly minimize these problems, it is necessary to perform preventive actions. The management of a company has an obligation to foresee, organize, and coordinate the organization of work, providing methods for preventing incidents and accidents in the workplace, through the effective management of occupational risks [15].

Risk perception depends on a variety of factors, including values and educational level [16][17]. Environments where workers feel pressured and overworked are in general quite prone to accidents. In addition, unqualified workers are generally more susceptible to accidents, because they often perform dangerous tasks. The low education of these workers tends to affect perception of risks present in the work environment and may make it difficult to understand the issues addressed in the health and safety training provided by companies. This issue demands special attention from professionals who plan and train these workers, to make sure that the topics covered are really understood [18].

Aiming to ensure the effectiveness of measures to prevent illnesses and accidents in the work environment, it is necessary that managers remain continuously engaged with the objective of promoting actions focused on the safety and well-being of workers. Improvements within a company should not happen only after an unwanted event has occurred, because this type of approach often means workers fail to take proper precautions after a time and even forget about them completely [14].

3. Technologies and Trends in OSH

3.1. Smart Personal Protective Equipment

According to [19], if an activity carried out by a worker involves a risk that cannot be reduced or eliminated by collective, technical, or organizational means, the use of personal protective equipment (PPE) allows that person to perform their activities without risk or with reduced risk of suffering injuries. In recent years the term 'smart PPE' has become more common. Every piece of smart PPE can interact with the environment and/or react to environmental conditions. This type of equipment combines traditional PPE with an electronic aspect, such as sensors, data transfer modules, or batteries. Sensors are used to monitor real-time hazardous factors for workers. In addition, the use of computer-based systems can facilitate OSH functions related to risk identification and management [20].

Aiming to assure that no new risks are added by the inclusion of electronic devices, tests must be performed designed for traditional PPE and related to electrical safety, such as surface temperature and battery safety. However, there are still no standards available for smart PPE, and standardization bodies must formulate requirements and procedures for testing this type of equipment. In Europe, there are some initial standardization projects in progress. Some of the challenges for the development of smart personal protective equipment are reliability, privacy, security, ergonomics, acceptance by users, applicable certifications, market surveillance, recycling, and the avoidance of additional risks [20].

3.2. Industry 4.0 Related Technologies and the Internet of Things (IoT) in OSH

Industry 4.0 can be defined as the Fourth Industrial Revolution, and encompasses a broad system of advanced technologies that are changing production and business models around the world. Industry 4.0 is related to the integration of the manufacturing process, aiming at continuous improvement, and avoiding waste [21][22].

The term Internet of Things (IoT), in turn, was introduced in the late 1990s by Kevin Ashton, a researcher at the Massachusetts Institute of Technology (MIT), referring to the connection of different objects to exchange data with other devices and systems over the Internet. IoT aims to supply a network infrastructure with interoperable communication protocols and software to connect this variety of devices. The term industrial IoT (IIoT) is related to the application of IoT technology in industrial environments [23].

IoT has been used in many OSH applications, including monitoring physiological variables of workers engaged in dangerous activities, as well as for sensors and alarm systems to prevent a variety of accidents. For example, Li and Kara [24] presented a methodology for monitoring factory conditions including temperature and air quality, by using wireless sensor networks and IoT. According to Awolusi et al. [25], wearable systems have been employed in construction sites to collect data to detect environmental conditions, and for determining whether people are close to danger. It was described how gyroscopes can verify the rotation of different parts of the body, while ultrasonic sensors can monitor muscle contractions. Described below are proposals for OSH that use Industry 4.0 and/or IoT-related technologies.

Aqueveque et al. [26] proposed a device to measure physiological variables including the electrocardiogram and respiratory activity of miners working at high altitudes. The proposed system's noninvasive sensors are embedded in a T-shirt. The device can monitor heart rate and respiration rate, and exchanges data with a central monitoring station.

Yu et al. [27] presented a wearable system involving physiological sensors embedded into firefighters' garments, assessing their physiological state by evaluating data collected from the sensors. The data was sent to the command center and the system evaluated the gravity of the risk scenario, sending messages, for example, to instruct that the action should be canceled because it is too dangerous. All collected data and messages were sent to the cloud.

Wu et al. [28] presented a hybrid wearable sensor network system for IoT-connected safety and health monitoring applications for outdoor workplaces. A local server processed raw sensor signals, displaying the environmental and physiological data, and triggered an alert if any emergency circumstance was detected. Temperature, humidity, Ultraviolet (UV) radiation, CO_2, heart rate, and body temperature were measured by the wearable sensors. The gateway pre-processed the sensor signals, displayed the data, and triggered alerts when emergency occurred. An IoT cloud server was used for data storage, web monitoring, and mobile applications.

Marques and Pitarma [29] proposed a real-time indoor quality monitoring system using a sensor to measure particulate matter (PM), temperature, humidity, and formaldehyde. The system included a mobile application for data consultation and notifications, and served a dataset to plan changes for improving indoor quality. The dataset can also support clinical diagnostics and correlate health problems with living environment conditions.

Balakreshnan et al. [30] proposed a system to check the safety of workers in the vicinity of machines. The solution used artificial intelligence and machine vision to identify use of safety glasses in areas where there are risks to the eyes, and can also detect the lack of other equipment. The system can initiate different control actions when safety violations occur.

Sanchez et al. [31] proposed a smart PPE using a sensor network located on a helmet and a belt, to monitor the worker and their environment. The system monitored biometrics risks and can detect external impact, shock, luminosity, gases, and environmental temperature, and provided real-time recommendations. Data were observable by the user on a tablet or a mobile phone. The device incorporated a flashlight that activated automatically if the worker was in poorly lighted areas, and a loudspeaker to assist the detection of audible alarms.

Márquez-Sánchez et al. [32] presented a system for the detecting anomalies in workplaces using a helmet, a belt, and a bracelet. Intelligent algorithms are applied to collected data through edge computing, in which processing takes place closer to the data source, providing faster services. The system early predicts and notifies anomalies detected in working environment. Then, data is sent to the cloud, where deep learning models verify possible anomalies because of the training of the set of data inserted previously.

Shakerian et al. [33] the authors proposed and examined an assessment process to evaluate workers' bodily responses to heat strain, to continuously and non-intrusively collect and evaluate workers' physiological signals acquired from a wristband-type biosensor. The proposed process assesses heat strain exposure through the collective analysis of electrodermal activity, photoplethysmography, and skin temperature biosignals. The physiological signals are uploaded to a cloud server, decontaminated from noise, and the measurable metrics are extracted from the signals and interpreted as distinct states of workers' heat strain by employing supervised learning algorithms.

Kim et al. [34] proposed an IoT-based system to monitor construction workers' physiological data using an off-the-shelf wearable smart band. The platform was designed for construction workers performing at high temperatures, to collect a worker's physiological data through a wearable armband that consists of three sensors—photoplethysmography (for heart rate monitoring), a temperature sensor, and an accelerometer, which provides the current position of a worker. The acquired data reflect a worker's current physiological status, sent to the web and to a smartphone application for visualization.

Yang et al. [35] conducted a study to monitor the level of physical load during construction tasks, to assess ergonomic risk to an individual construction worker. By using an ankle-worn wearable inertial measurement unit to monitor a worker's bodily movements, the study investigated the feasibility of identifying various physical loading conditions by analyzing a worker's lower body movements. In the experiment, the workers performed a load-carrying task by moving concrete bricks. A classification model to detect different physical load levels, using Bidirectional long short-term memory (Bi-LSTM) was developed and evaluated.

Marques and Pitarma [36] presented a real-time acoustic comfort monitoring solution suitable for occupational usage. The system was designed to be easy to install and use, incorporating a device for ambient data collection called iSoundIoT, and including Web/mobile data access based on Wi-Fi communication. The solution includes a notification feature to alert people when poor acoustic comfort scenarios are verified, and continuous real-time data collection enabling the generation of reports containing sound level values and alerts.

Mumtaz et al. [37], motivated by the COVID-19 outbreak, proposed an IoT-based system for monitoring and reporting air conditions in real time with the data sent to a web portal and mobile app. The solution can monitor multiple air pollutants, including carbon dioxide (CO2), particulate matter (PM) 2.5, nitrogen dioxide (NO2), carbon monoxide (CO), and methane (CH4), as well as temperature and humidity. The system generates alerts after detecting anomalies in the air quality. Various machine learning algorithms were employed to classify indoor air quality, and long short-term memory (LSTM) was applied for predicting the concentration of each air pollutant and predicting the overall air quality of an indoor environment.

Zhou and Ding [38] presented an IoT-based system to generate early warnings and alarms as dynamical safety barriers for different types of hazards on underground construction sites. Their solution was able to collect, analyze, and manage multisource information, automate monitoring and warning, and minimize the hazard energy coupling by using IoT. The data-sensing layer included an IoT reader, IoT tag with warning device, ultrasonic detector, and infrared access device, achieving about 1.5 m locating accuracy in underground workspaces. The portable warning device, designed with RFID-based positioning technology, was installed on the safety helmet. Each IoT tag consisted of a RFID chip and a wireless antenna, and stored information about the worker wearing it. In case of accident, the proposed system can be used also for investigation purposes.

Zhan et al. [39] proposed a monitoring system for cold storage based on Industrial IoT, to identify abnormal stationary and acquire the spatial-temporal information of workers in real time. In these workplaces, an abnormal stationary position is a sign of danger, such as falling or fainting. A deep neural network was applied to learn specific features involving location and vibration for anomaly detection. The Bluetooth low energy (BLE) and a log-distance path loss model were used to fulfill indoor localization to allow rapid responses to an incident on site. In addition, digital twin technology that mirrors physical objects in cyberspace can be used to enhance spatial-temporal traceability and cyber-physical visibility to enforce safety monitoring by managers. Cloud and edge computing can be used to improve overall computational efficiency and system responsiveness.

Campero-Jurado et al. [40] proposed a smart helmet prototype that monitored the conditions in the workers' environment and performed a near real-time evaluation of risks. The data collected by the sensors was sent to an AI-driven platform for analysis, where different intelligent models were evaluated by the authors. The design is intended to protect the operator from possible impacts, while monitoring the light, humidity, temperature, atmospheric pressure, presence of gases, and air quality. Alerts can be transmitted to the operator by means of sound beeps. For visualization of environmental data, through color codes an LED strip deployed on the helmet can notify the worker of anomalies in the environment.

For the design of IoT systems and devices for OSH, such as those described above, various low-cost devices and free software allow the implementation and use of IoT-based systems by small and medium-sized companies. Some of these technologies are described below.

3.3. IoT Devices

According to Lacamera [41], embedded systems consist of a class of systems that run on an architecture based on microcontrollers, that offer constrained resources. A microcontroller or microcontroller unit (MCU) is a device made of a dedicated processor for the purpose of running a specific application, unlike general purpose computers. These devices are often designed to be inexpensive, low-resource, and low-energy consuming. These devices can be used in factories and for several IoT applications. They are often used as sensors, actuators, or smart devices and may form networks. Below, the Arduino and ESP32 platforms are described, which are each widely used in IoT applications.

Arduino is an open platform for prototyping, based on free software and low-cost hardware, where the programs are written in the simplified C++ language. Arduino Integrated Development Environment (IDE) is used to write code and upload it to the board. The hardware consists of an open hardware design with a microcontroller manufactured by the Atmel Microchip company. The boards are sold preassembled, but hardware design information is available for people who want to build or modify them [42]. There are various types of Arduino boards supporting different features, such as Wi-Fi [43], Bluetooth, Bluetooth Low Energy (BLE) [44] and Global System for Mobile Communication (GSM) [45].

ESP32 is a series of low-cost and low-power microcontrollers and is a system-on-a-chip (SoC) with integrated microcontroller, Wi-Fi, and Bluetooth. ESP32 is a dual-core system and be used as a standalone system or can serve as a slave device to a host microcontroller. ESP32 is commonly used for academic and industrial purposes, especially in IoT. It can be programmed by ESP-IDF, which is a framework developed by ESPRESSIF, or by the Arduino Integrated Development Environment (IDE), which is the easiest way to start writing code for this platform [46].

3.4. Protocols for IoT

Below are described two protocols widely used in IoT, the Constrained Application Protocol (CoAP) and the Message Queue Telemetry Transport (MQTT). According to Shelby et al. [47], Constrained Application Protocol (CoAP) is suitable for resource-constrained environments, including those with power-constrained devices, low-bandwidth links, and lossy networks. In this protocol, the network nodes interact through a request–response model and support the built-in discovery of services. CoAP is very similar to the client–server model of Hypertext Transfer Protocol (HTTP), the widely used protocol that allows contents to be requested and transmitted between browsers and web servers via the Internet. However, CoAP implementations can often act in client and server roles. A client sends a request using a method code on a resource (identified by a URI—Universal Resource Identifier) on a server. The server, in turn, sends a response with a response code. CoAP executes these interchanges asynchronously using User Datagram Protocol (UDP). The messages support optional reliability, and CoAP supports secure messages using Datagram Transport Layer Security (DTLS), described in [48].

By other hand, MQTT provides asynchronous communication between devices [49]. This protocol uses a message publishing and signature model, and was invented by the IBM company in the late 1990s. MQTT was originally designed to link oil pipeline sensors to satellites. It is a lightweight protocol that can be implemented on devices with many restrictions, such as low computational power, and in networks with limited bandwidth and high latency. These features make MQTT suitable for several applications in IoT; publish–subscribe is the standard model for exchanging messages in MQTT. MQTT comprises two entities: a broker and the clients, where the message broker is a server receiving messages from clients and then sending these messages to other clients, that can subscribe to any message topic. Clients must publish their messages on a topic and send the topic and the message to the broker. The broker then forwards the message to all clients who subscribe to that topic. Clients can connect to the broker through simple TCP/IP connections or encrypted TLS connections.

3.5. Machine Learning

As described by Abiodun et al. [50], machine learning (ML) is a branch of artificial intelligence (AI) that uses computers to simulate human learning. In ML, computers can autonomously modify their behavior based on their own experience (training). ML algorithms are classified based on the approach used in the learning process.

In supervised learning, the learning algorithm aims to predict how a given set of inputs conducts to the output. The algorithm receives labeled data and learns from this data. In unsupervised learning the algorithm does not receive labels. This type of algorithm is mainly focused on finding hidden patterns in data. Semi-supervised learning algorithms have an incomplete training set, often with many target outputs missing, from which they must learn. Finally, the algorithm used in reinforcement learning learns from the external feedback received in terms of punishments and rewards [51].

Below are described recommender systems [51][52][53][54], anomaly detection, [55][56] and long short-term memory (LSTM) [57][58][59][60][61], which have each been applied in a variety of systems, and more recently have been suggested for use in IoT, healthcare, and OSH solutions.

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