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Impact of operator health and safety on manufacturing process risk management

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Abstract

As manufacturing becomes increasingly digitalized and connected, new opportunities arise for monitoring operator health and safety risks. Addressing these risks by leveraging Industry 4.0 enabling technologies is strategic, as significant improvements in terms of social sustainability, such as the operator well-being, can positively impact manufacturing quality and productivity. In this context, this paper proposes a methodological framework that aims to leverage information derived from a variety of sensor data to provide actionable steps to support decisions to mitigate health and safety risks. A simulated case study to validate the suitability of the proposed framework is reported for relevant scenarios.

Keywords: Human-cyber-physical system; Safety; Sustainability

1. Introduction

According to the latest assessments from the International Labour Organization (ILO), an estimated 2.9 million workers die each year from occupational accidents and diseases, and at least 402 million workers are injured at work [1]. Work-related diseases are responsible for 81% of all work-related deaths, with fatalities due to occupational injuries accounting for 19%. In addition, addressing the health and safety needs of an aging workforce has become crucial as the number of people working at older ages increases [2].

Contextually, Industry 4.0 (which aims at the 5.0 paradigm [3]) exploits Cyber Physical Systems (CPS), which are integrated collaborating computational entities in intensive connection with the surrounding physical world and its ongoing processes, providing and using data-accessing and data-processing services available on the Internet [4]. Recent efforts have sought to incorporate human factors into CPS by developing Human Cyber Physical Systems (HCPS) to enhance human capabilities to dynamically interact with machines in the cyber and physical worlds, using human-computer interaction techniques designed to meet the cognitive and physical needs of operators [5]. HCPS enabling technologies involve sensing units, big data analytics [6], expert systems and machine learning [7].

The increasing availability of such technologies allows for an improved performance in addressing manufacturing-related occupational health and human factors (e.g., biometrics, ergonomics), the interactions between people and their work environments, and ultimately ensuring human well-being and preventing urgent safety hazards [8]. Recent research efforts focusing on human factors include manufacturing systems design [9], human-robot collaboration [10], fatigue recognition and musculoskeletal risk prevention [11] applied to assembly processes, but with limited application to transformation processes [12].

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Considering the challenges posed by all the criticalities of occupational health and safety, and the opportunities offered by the enabling technologies of Industry 4.0, this paper aims to develop an HCPS to assess the wide range of risks that operators face while performing their tasks in the complex environments of a production plant [13, 14]. The objective is to classify these risks based on a priority scale and to provide a methodical course of action that can be adopted to address the issues according to their priority, serving as a decision-support tool.

2. Framework and methodology

The proposed framework aims at identifying effective risk mitigation strategies for operators in a manufacturing context. The methodology follows the flowchart shown in Fig. 1 and builds upon a HCPS-based platform previously conceptualized in [13, 14]. This platform converts risk characterization into operational information to support data-driven risk management decisions in the manufacturing process. The framework takes as input a generic working configuration of the manufacturing system, defined here as a combination of resources (operators and workstations) within a specified time frame (e.g., a work shift).

2.1. Human-Cyber Physical System

Within an HCPS architecture, the physical layer consists of sensing units for comprehensive production context awareness [10]. It collects three categories of data: (*i*) human health, (*ii*) work environment, and (*iii*) manufacturing process data, collected from various sensors during shifts [7]. The complete list of variables that can be monitored is reported in Table 1.

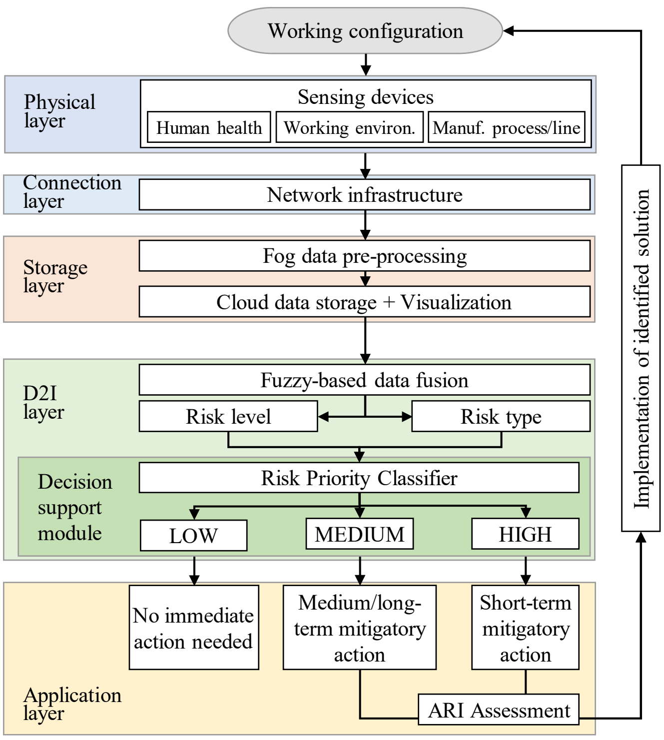

Fig .1 Framework flow chart

Table 1. List of sensing variables.

ID	Variable	ID	Variable
P1	Age	E10-16	VOCs
P2	BMI	E17	Ambient ventilation
P3	Medical history	E18	Ambient lighting
P4	Mental health	E19	Ambient temperature
P5	Pregnancy + Maternity	E20	Dust
P6	Gender	E21	Humidity
P7	Systolic blood pressure	E22	O_2 deficiency
P8	Diastolic blood pressure	E23-25	Ultrasound
P9	Respiratory rate	E26-28	Infrasound
P10	Heart rate	E29	Noise
P11	O_2 saturation	M1	Heat source
P12	Body temperature	M2	Radiant heat flux
P13	Sitting posture	M3	Mechanical vibrations
P14	Neck posture	M4	Power consumption
P15	Eye blink frequency	M5	Machine overload
P16	Eye blink duration	M6	Electromagnetic radiation
P17	Body vibrations	M7	Ultraviolet light
P18	Hand-arm vibration	M8	Blue light
P19	Hydration level	M9	Infrared light
E1-9	Priority compounds	M10	Ionizing radiations

The connection layer consists of a tailored Information and Communications Technology (ICT) infrastructure, required to allow the diverse sensing units to communicate with the cyber part of the system. As regards the storage layer, to address challenges like data volume, network bandwidth, and latency, raw data is sent to a fog computing unit for pre-processing. This involves tasks such as triggering, re-sampling, filtering, and feature extraction. The actual data processing, storage, mining, and access/visualization for system management and operators can be handled by a cloud server [15]. The Data to Information (D2I) layer (*i*) identifies the dependencies and correlations among the measured variables, (*ii*) progressively merges them into more complex variables, and (*iii*) provides an estimate and categorization of the risk. The criterion for merging is enabled by a comprehensive knowledge base, which includes ergonomics, occupational medicine and process engineering. The computational mechanism for the data fusion follows a fuzzy logic approach with the knowledge base being the expert system enabling the inference rules [16]. Such mechanism is extensively reported in [7, 17]. Fuzzy-based data fusion, consisting of fuzzification, inference and de-fuzzification, has to be applied progressively, starting from all the input variables, until all the complex variables converge to five risk categories, namely (*i*) physical, (*ii*) ergonomic, (*iii*) chemical, (*iv*) safety, and (*v*) mental risks [18]. Similarly, a final step is required to fuse the five risks into an overall risk. The process is graphically illustrated in Fig. 2. The input variables are preliminary normalized taking into account the exposure time, and then fused through the fusion steps.

In each fuzzy-based steps, three membership functions are considered, yielding to three risk classes, i.e., low, medium and high risk [16]. In this way, it is possible to estimate the risk level and the risk type as the input data are acquired and processed with a temporal resolution compatible with the hardware sampling capabilities. Within the D2I layer, a decision support module is embedded.

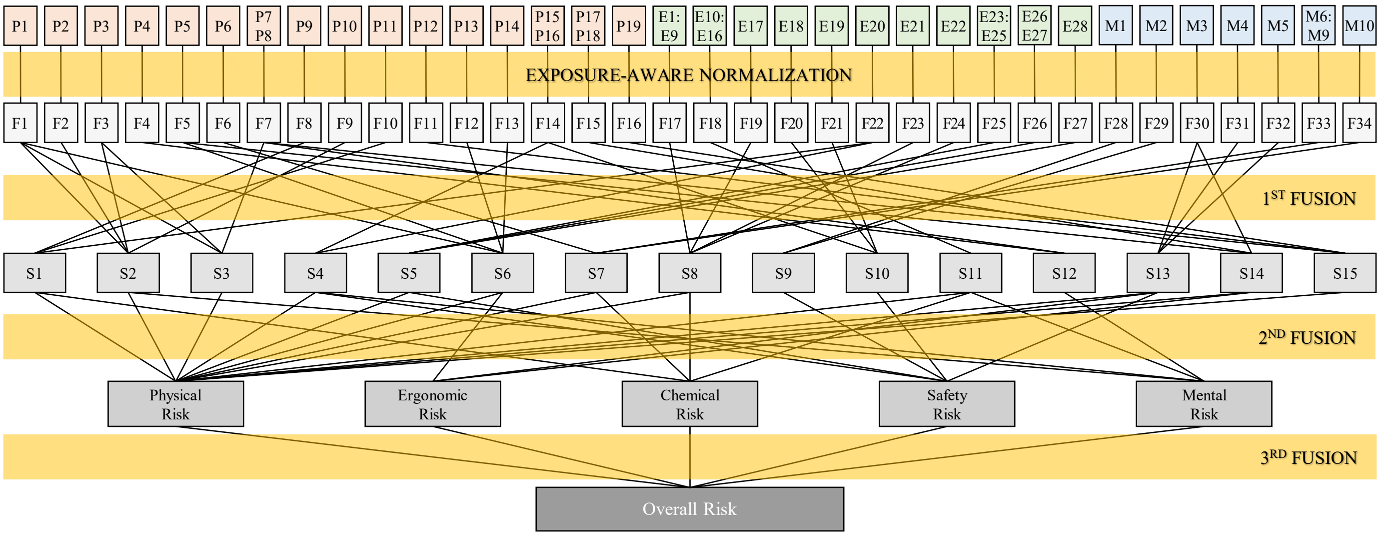

Fig. 2. Fuzzy-based fusion methodology

The goal of the module is to assign a priority to the risk based on the risk level and type distribution. Such a task can be configured as a classification problem and can be solved either by a knowledge base or, if enough data is available, by intelligent classifiers [7].

2.2. Risk classification

In this step, a machine learning-based automatic classifier, fed with the individual risk features extracted from operators' individual risk levels and types, automatically classifies the current configuration into three categories according to their priority:

- High Priority Risk Configuration (HPRC);
- Medium Priority Risk Configuration (MPRC);
- Low Priority Risk Configuration (LPRC).

Each of these categories indicates a different priority and requires a different course of action. A configuration classified as HPRC needs to be addressed as soon as possible because it poses major health and safety risks to the operators involved in the current shift. For example, a HPRC can be triggered by heat stress in the workplace that causes immediate harm to the operators [19]. High levels of heat stress from hot machinery, furnaces, or molten metal can, over time, lead to serious health consequences such as heart attacks and strokes. As a result, the HPRC classification requires immediate, short-term counter-measures to be implemented during the current shift or the next shift at the latest.

A configuration classified by the algorithm as an MPRC indicates a situation where the risk is not an urgent matter that must be addressed with the same urgency as a HPRC, but rather signals the possibility that the current configuration is susceptible to becoming a HPRC over an extended period of time. In order to prevent an MPRC to turn into a HPRC, the framework prescribes to analyze and assess the problem at hand and respond with counteractions apt to mitigate the risk within a broader time horizon than the shift. Examples of MPRC counteractions will be described in following paragraphs of this work. Finally, an LPRC confirms that the currently adopted configuration does not pose a significant risk to the operators involved, and therefore there is no need to take any short- or medium-term counteraction for risk mitigation.

2.3. Course of action

When classifying a configuration as HPRC, the solution considered in this paper involves swapping the operators with the highest and lowest Overall Individual Risk (OIR), taking into account the skills required for the process. This operator swap serves both as a short-term countermeasure and as a diagnostic tool to determine if the source of risk is man-related (operator health), machine-related (workstation conditions), or due to human-machine interaction. If the swap does not reduce the risk for the initially high-risk operator, the source of risk lies in the operator health condition, necessitating medical assistance. If the operator previously showing low risk now exhibits a high risk after the swap, it is fair to infer that the risk is machine-related or due to human-machine interaction, which requires further investigation.

In these situations, Lean Manufacturing principles [20], along with methodologies such as Six Sigma and World Class Manufacturing, can be utilized for the problem-solving. The framework advocates conducting a Root-Cause Analysis (RCA) by a cross-functional team, integrating risk information from the platform. RCA methodologies could include 5Whys, Ishikawa cause and effect, Fault Tree Analysis, Pareto Chart, and Is/Is not Analysis [21], all of which can better elucidate risk-contributing factors and aid in effective mitigation. Ideally, the RCA involves identifying the risk types that affect operator OIR at critical workstations, determining the parameters that cause anomalies in those risk types, and utilizing RCA tools to pinpoint and eliminate the root causes.

The HPRC course of action aims to swiftly reduce risk with short-term solutions. Operator swaps can effectively reduce the critical risk level that prompted the HPRC, creating a new configuration with a lower Overall Individual Risk. However, this new configuration may introduce increased risk levels for different types of risks. For example, while an operator swap reduces physical risk, it may result in slightly higher ergonomic risk for the other operator due to task unfamiliarity. To address this, additional interventions, like training, can be implemented alongside the solution.

At this point, a further assessment is made. In this respect, an Aggregated Risk Indicator (ARI) has been developed to assist decision-makers in identifying these situations. It exploits the platform risk data to yield an aggregate measure of risk for the configuration being used, and is intended to present an estimate of the risk level of the current configuration based on the data that the same configuration generated within the past work shift, considering each component of risk.

While the individual risk profiles give detailed information about the risk levels of each operator, this aggregate indicator is intended to provide a measure to compare the risk levels of each risk type across configurations. Its purpose is to provide a simplified summary of the risk level of each risk type by combining the individual risk profiles of all operators associated with the configuration. The ARI is an indicator of the risk of a configuration c as a whole in the form of a vector, according to Eq.1,

$$ARI_c = [\overline{PR}_c \quad \overline{ER}_c \quad \overline{CR}_c \quad \overline{SR}_c \quad \overline{MR}_c] \tag{1}$$

where PR refers to the physical risk, ER to the ergonomic risk, CR to the chemical risk, SR to the safety risk, and MR to the mental risk. Each element of the above vector is intended to express a high-level summary for each risk type. Analytically, a generic component $\overline{XR}_C$ of the ARI vector is computed as per Eq. 2,

$$\overline{XR}_C = \frac{1}{N}\sum_{i=1}^{N} \widetilde{XR}_i \tag{2}$$

where N is the number of operators in the configuration, and $\widetilde{XR}_i$ is the median value for the i-th operator in the current configuration. An MPRC configuration signals the possibility that the current configuration is likely to become an HPRC in the long term. In this case, the risk situation is addressed in a more structured way, following the PDCA methodology from the Kaizen approach [20].

3. Case study

To validate the proposed framework, a representative case study was simulated. The production process of an aircraft skin panel, which undergoes a series of manufacturing steps (i.e., heat treatment processes, cold forming processes, and chemical milling), is considered. The workpiece is a sheet of 2024-T3 aluminum alloy (overall dimensions: 1500 x 600 x 6 mm, mass: 15 kg) whose primary alloying element is copper.

Fig. 3 shows the manufacturing process flow. Tables 1-3 detail the activity breakdown and times for the relevant processes selected in this research for the analysis and scenario construction (namely, the deep drawing and the chemical milling, the latter further subdivided into preparation/finishing and etching). These production processes involve a wide variety of risks for operators, which allows for the simulation of a plausible setting for manufacturing industries.

The case study examines the pathways leading to the four possible outcomes defined by the framework, simulating the different risk scenarios. Furthermore, it is useful to analyze the countermeasures proposed to mitigate the identified risk from a practical standpoint. It is worth remarking that the process times are indicative and set here for proof-of-concept purposes. Specifically, two scenarios are modelled in this case study:

- An MPRC Scenario concerning the operator ‘Op2’, who is working on the deep drawing with a malfunctioning equipment. Specifically, this scenario is modelled by simulating anomalous levels of mechanical vibrations and noise. Such a problem occurs for a relevant time interval during the shift, but it does not have significant impact on the overall workflow of the manufacturing process.

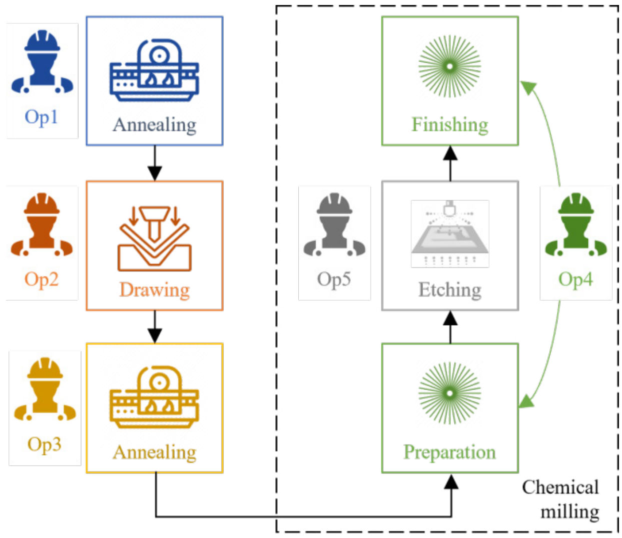

Fig. 3. Manufacturing cycle.

Table 2. Deep drawing process activity breakdown.

Activity	Time (min)
Manual handling of sheets (from buffer area)	5
Forming (incl. setup, configuration, and aux. activities)	15
Manual handling of manufactured parts (to buffer area)	5

Table 3. Chemical milling (preparation and finishing) activity breakdown

Operation	Time (min)
Part manual handling (from buffer area)	5
Cleaning + masking	20
Part manual handling (to scribing shop)	5
Scribing	60
Part manual handling (to inspection shop)	5
Demasking + repairing activity	30
Part manual handling (to buffer area)	5

Table 4. Chemical milling (etching) activity breakdown

Operation	Time (min)
Part manual handling (for positioning)	5
Etching + inspection	35
Rinse + inspection	15
Desmut + inspection	15
Rinse + inspection	15
Part manual handling (to buffer area)	5

In this respect, sensible changes in sensor data have been simulated for body vibrations, hand-arm vibrations, noise, and mechanical vibrations.

- An HPRC Scenario concerning the operator 'Op5', who is working on the etching process. Such scenario consists of simulating poor health conditions for the operator while working on an unsuitable process. 'Op 5' is assumed to be an elderly and overweighted operator with an underlying respiratory health condition. The activities related to etching are physically demanding in terms of internal logistics (loading/unloading of workpieces onto/ from the crane system). In contrast, the chemical milling preparation and finishing operations are assumed to be less physically demanding. In this respect, significant variations in sensor data have been simulated for 'Op5' in terms of age, BMI, heart rate and respiratory rate. The mitigating action to be taken is an operator swap with 'Op 4', as they are assumed to have similar skills and competences for chemical milling processes.

Due to the absence of relevant historical data to train a machine learning model, an algorithm based on conditional logic was adopted to classify the risk pattern of each operator:

- *High-risk pattern*: if, during the 8-hour work shift, the operator Overall Individual Risk is greater than 0.75 for 30 consecutive minutes, or if it accumulates non-consecutive 60-minute periods above this threshold;
- *Medium-risk pattern*: if no high-risk pattern is shown and, during the 8-hour work shift, the operator Overall Individual Risk is between 0.40 and 0.75 for 60 consecutive minutes, or if it accumulates non-consecutive 120-minute periods above this threshold;
- *Low-risk pattern*: if the operator Overall Individual Risk does not show either a high-risk or a medium-risk pattern.

Then, if at least one operator within the configuration has a high-risk pattern, the configuration is classified as HPRC. According to this simplified algorithm, other operators who exhibit medium-risk patterns are put-on-hold because HPRC is considered a priority. If none of the operators exhibit a high-risk pattern and at least one exhibits a medium-risk pattern, then the configuration is classified as MPRC. In all other cases the configuration is classified as LPRC. All the thresholds and the timespans are intended to be set for proof-of-concept purposes in this research.

4. Results and discussion

The scenarios described in the previous sections were simulated and compared to a best-case scenario, which is a theoretical situation consisting of ideal human health, environmental conditions, and process-related variables. The chart reported in Fig. 4 shows the results for the MPRC scenario, before and after the corrective action, which are both overlapped to the best-case scenario.

The MPRC scenario shows a higher overall risk than the best case for 388 minutes, which is the entire length of the work shift (excluding the two breaks). In particular, the MPRC risk is on average 2.8 times higher than the best case. Following the mitigatory action, the overall risk decreases, resulting to be only 1.9 times higher than the best case. This represents a reduction in the overall risk from MPRC to the mitigated scenario of 31.4%.

For the HPRC scenario, Fig. 5 shows the overall risk for 'Op4' on the chemical milling preparation/finishing process and 'Op5' on the etching process, which is here assumed to be more physically demanding, and therefore more hazardous. The difference in the results is amplified by the poor health conditions of 'Op5', resulting in a higher overall risk than 'Op4' for 370 minutes, representing a large proportion of the working shift. In particular, 'Op5' is exposed to critical overall risks (above 0.75) for 192 minutes. Such a situation triggers an HPRC course of action, which consists in swapping 'Op4' with 'Op5' (as described in Section 3). Following the operator swap, it is possible to observe in Fig. 6 how the 'Op5' has reduced the overall risk to an extent that it never goes beyond the critical threshold. This is due to the less physical effort required by the preparation/finishing process.

At the same time, it is possible to observe an increase of the overall risk for 'Op 4', now on the etching process. Such increase is higher than the critical threshold for 46 non-consecutive minutes only, and within the range [0.40-0.75] for 122 minutes in total. This configures a new priority scenario for this configuration, decreasing the priority from an HPRC to a MPRC. The bar chart in Fig. 7 shows the ARI values before and after the operator swap.

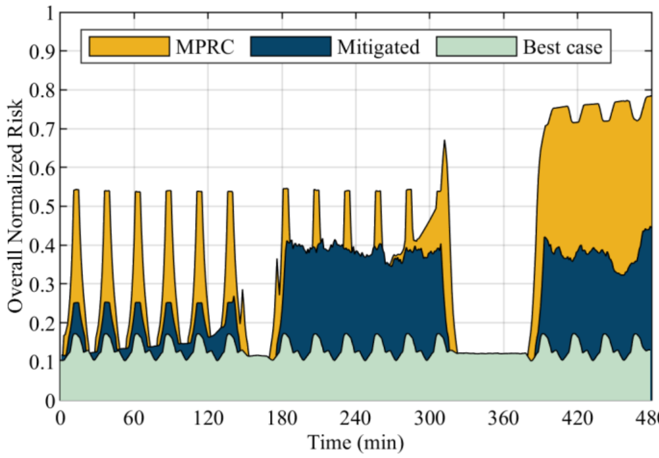

Fig. 4. Overall risk for Op2: best case, MPRC and mitigated scenario

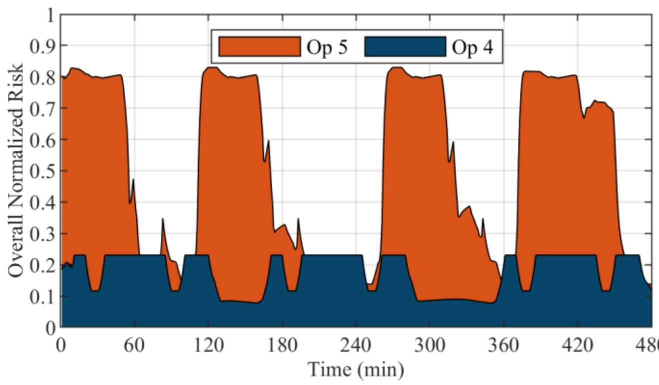

Fig. 5. Overall risk for Op4 and Op 5 before swap

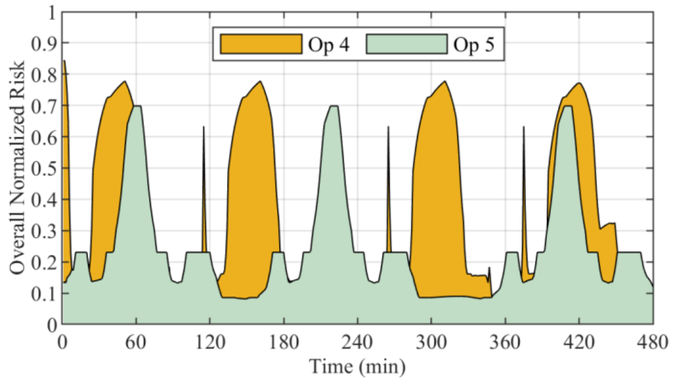

Fig. 6. Overall risk for Op4 and Op5 after swap

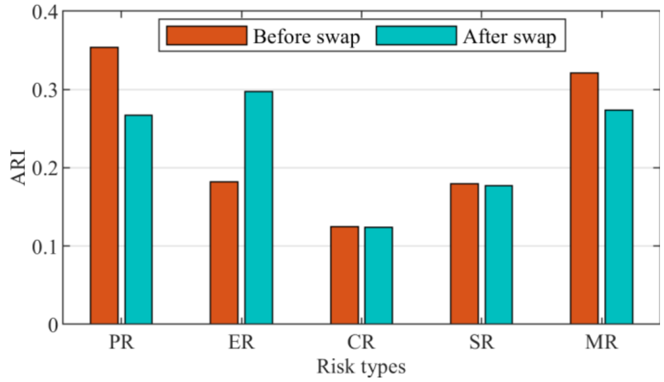

Fig. 7. ARI before and after the swap

It is possible to observe how the highest risk components, i.e., the physical and the mental risks, have been successfully reduced. However, there's a notable increase in ergonomic risk post-swap due to potential incorrect postures from workspace arrangements, necessitating adjustments or additional training for ‘Op 4’ to optimize task performance and posture. The bottom line of the ARI assessment is that, after promptly addressing the immediate and high-impact physical risk, the primary risk that remains is the ergonomic one. This risk can be addressed in the long term by implementing measures such as upgrading equipment to be more ergonomic-friendly.

5. Conclusions

An HCPS has been developed to perform a sensor-driven operator health and safety risk assessment based on the risk priority, and to provide a tailored course of action for each priority class to mitigate the identified risks.

The application of the proposed methodology has been validated as a proof of concept on a simulated case study with limited processes and scenarios. On-field trials are required to select the appropriate sensing variables, and the fuzzy inference system needs to be tuned taking into account the relevant health and safety hazards, which are case-specific. However, the main strength of such a methodological framework is its versatility in terms of application to a wide variety of manufacturing routes. Further research activities should focus on the automatic classification of risk priority via machine learning as well as the suitability of the proposed approach to be embedded in an environmental management system to assess the health and safety impacts of environmentally oriented policies.

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