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# Enhancing operator health and safety in manufacturing: an intelligent digital humanization approach

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**Abstract**

The manufacturing industry relies heavily on human labour, making the health and safety of operators paramount. Emerging technologies such as Human-Cyber-Physical Systems (HCPS) and Machine Learning (ML) have the potential to transform the approach to these critical issues. In fact, such technologies enable the creation of virtual replicas of tangible systems, providing innovative solutions for assessing operator safety. In this context, this work presents a digital humanization methodology designed to comprehensively evaluate the health and safety risks associated with operator involvement in production processes. Using cutting-edge sensors, advanced machine learning algorithms, and scenario simulations, such methodology generates real-time virtual representations of the physical condition and behaviour of the operator. These representations allow the risk characterization by estimating magnitude, priority, and occurrence, thereby facilitating early detection and preventive measures against potential hazards. A case study is considered to demonstrate the practical application of the proposed framework.

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*Keywords:* Health and safety; Human-cyber-physical system; Risk assessment; Social sustainability

## 1. Introduction

Industry 5.0, the forthcoming phase of industrial evolution, integrates the technological advances of Industry 4.0 with a sustainable, resilient, and human-centered approach [1]. The latter pillar repositions workers as valuable investments rather than costs, and promotes the development of technologies that serve people and societies. This paradigm shift responds to the growing market demand for technologies that leverage both human skills and machine precision. Furthermore, sustainability should encompass not only the environmental and economic issues, but also social sustainability [2], which (among other objectives) has to ensure the well-being of workers and foster a healthy working environment [3]. In this context, this research proposes an enhanced Human-Cyber-Physical System (HCPS) [4] to dynamically estimate the operator risks in manufacturing environments. The HCPS uses a variety of sensor data to accurately assess operator health risks. It integrates human physiology, environmental factors, and manufacturing variables to interpret complex patterns and interactions by using advanced data analytics techniques to process multi-dimensional data over time. The novelty of the proposed framework lies in the dynamic computation of risk priority using both an analytical model and Machine Learning (ML) fitting, extending the capabilities of the previous models developed by the authors [5, 6].

## 2. Framework and methodology

The proposed framework involves the development of a Human-Cyber-Physical System (HCPS) architecture aimed at assessing a risk priority index, both by using an analytical

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model and by performing a machine learning fitting to enable a priority risk characterization and related hotspots, triggering a series of mitigating and/or corrective actions.

### *2.1. System architecture*

According to Fig. 1, the physical layer includes sensing units that collect data on human health, working conditions, and manufacturing processes during work shifts. This data is sourced from a variety of sensors, for a total of 58 variables, belonging to three different categories [5, 6]:

- *Human health*: Captures the well-being of operators. It includes factors as age, BMI, mental health, pregnancy, gender, blood pressure, respiratory rate, heart rate, oxygen saturation, body temperature, posture, eye blink frequency and duration, body vibration, hand-arm vibration, and hydration levels [7].
- *Working Environment*: Measures workplace conditions that may affect operators and processes. It includes ambient ventilation, lighting, temperature, perceived indoor air quality (priority and volatile compounds), dust, humidity, oxygen deficiency, ultrasounds, infrasound, heat source, radiant heat flux, mechanical vibrations, current consumption, machine overload, various types of radiation [7].
- *Manufacturing*: Evaluates the performance and inherent characteristics of manufacturing processes. It includes ultrasound, infrasound, heat source, radiant heat flux, mechanical vibration, power consumption, machine overload, various types of radiation [8] that are specific to the manufacturing equipment and machinery and not to the broader work environment.

The ICT layer consists of a customized Information and Communication Technology infrastructure. This layer enables the communication between the various sensing units and the digital component of the system, and addresses storage-related challenges such as data volume, network bandwidth limitations, and latency issues [4]. Raw data is sent to a fog computing unit for preliminary processing, which includes triggering, re-sampling, filtering, and feature extraction. The subsequent phases of data processing, storage, mining, and access/visualization for system management and operators are performed within a cloud server [9].

The primary objective of the Data-to-Information (D2I) layer is to identify interdependencies and correlations among the measured variables. It progressively merges them into more complex variables, while also providing risk estimation and categorization. The criteria for merging are driven by and require a comprehensive knowledge base, encompassing fields such as ergonomics, occupational medicine, and process engineering. The computational mechanism used for data fusion follows a fuzzy logic approach, with the knowledge base serving as the expert system that enables inference rules [10]. The input variables are initially normalized, taking into account the exposure time, and then subjected to the fusion steps. This fuzzy-based data fusion process is applied progressively until all the complex variables converge into five distinct risk categories (listed in Table 1): (*i*) physical, (*ii*) ergonomic, (*iii*) chemical, (*iv*) safety, and (*v*) mental risks [6]. These risk categories are then aggregated into an overall risk indicator. In each of the fuzzy-based stages, three membership functions are considered, resulting in three risk classes: low, medium, and high risk. This approach allows for the estimation of a normalized risk level $R_{i,t}$ for each risk category $i$ as the input dataset is acquired and processed, with a temporal resolution $t$ that matches the sampling capabilities of the hardware. The D2I layer also includes an integrated decision support module that performs a machine learning-based fitting of the risk priority.

The application layer deploys the results of the previous layer by performing a priority risk classification in three classes (namely low, medium, and high priority) in order to determine the actions to be taken to mitigate and correct health- and safety-related issues. This is done by performing a root-cause analysis [11, 12]. Data and information related to risk priority and actions are used to create a database that can be used to configure predictive models in an if-then fashion. Such results are deployed for the risk priority modelling as reported in the following section. In addition, the implementation of these results initiates a feedback loop with the physical layer, that could allow the system to self-adjust and increase the accuracy of the risk priority modelling.

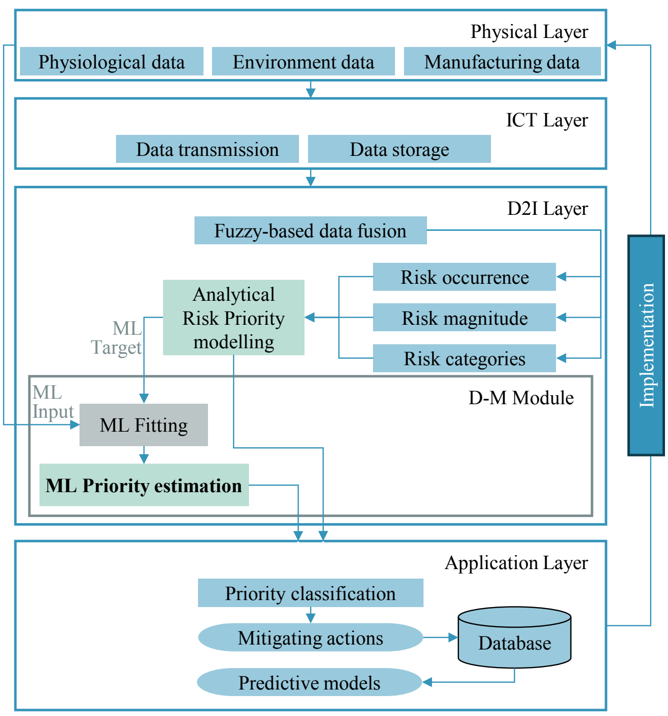


Fig. 1. General Framework

Table 1. Risk categories and related weights

| Risk type | $w_i$ | Description |
|---|---|---|
| Physical | 5 | Risk that could result in fatality. |
| Ergonomic | 2 | Risk that may cause complications in the distant future. |
| Chemical | 4 | Risk that could pose an immediate threat to the operator. |
| Safety | 5 | Risk that could cause irreversible damage. |
| Mental | 3 | Risk that is of significant importance in the medium term. |

### 2.2. Risk priority modelling

The risk priority modelling aims to calculate a dynamic Priority Index ($PI_{i,t}$) for each risk category $i$, using the information embedded in the risk levels estimated as described in the previous section. The first step is to assign a weight $w_i$ to each risk category in order to prioritize the risks that require timely action in a specific manufacturing setup. These weights (an example of which is suggested in Table 1 for illustrative purposes) should be determined through a qualitative analysis of the various risks and the response time needed to ensure the health, safety, and wellbeing of the operators. The selection of weight values should take into account the peculiar industrial context, the specific hazards, and the operator characteristics.

The next step is to calculate the magnitude of risk ($M_{i,t}$), which is a factor that takes into account the level of risk by assigning the appropriate importance to the timeliness of the action to be taken. This requires a threshold analysis involving relevant expertise, historical data and the industrial context in terms of health and safety issues. Specifically, the model needs the computation of a risk level-related factor $\lambda_t$ that is used to segment $R_{i,t}$ in three risk classes $C(R_{i,t})$ according to Eq. 1. This study adopts a power trend with threshold-based coefficients to assign greater importance to higher risk levels and less importance to lower risk levels.

$$\lambda_t = \begin{cases} 0 & R_{i,t} < 0.4 & C(R_{i,t}) = \text{Low} \\ 29.5 \cdot R_{i,t}^{11.7} & 0.4 \leq R_{i,t} < 0.75 & C(R_{i,t}) = \text{Medium} \\ 1 & R_{i,t} \geq 0.75 & C(R_{i,t}) = \text{High} \end{cases} \quad (1)$$

The determination of thresholds is also influenced by the specific industrial context. The nature of the industry and the materials it deals with may lead to the setting of higher thresholds, which in turn will affect the subsequent priority determination. The magnitude of the risk ($M_{i,t}$) can be computed analytically according to Eq. 2.

$$M_{i,t} = 1 + \lambda_t \quad \in [1; 2] \quad (2)$$

The model then requires the calculation of the Risk Occurrence ($O_{i,t}$), which indicates the sum of the times in which a given risk level has occurred during the time period under consideration. This approach allows to incorporate both real-time data and historical information stored in the database. The occurrence can be classified into two categories: continuous and intermittent. Continuous occurrence refers to a situation where a given level remains unchanged for a defined period of time. In contrast, intermittent occurrence considers all the data instances where a particular level is observed up to the current moment. The risk occurrence is taken into account in the priority modelling by computing, for a given timeframe $t$, the value $o_{i,t}$, i.e., the amount of time that the $C(R_{i,t})$ has occurred since the beginning of the shift. The computation of such occurrence enables the definition of an occurrence-related indicator, here referred to as $O_{i,t}$, which is defined based on the occurrence characteristics (intermittent or continuous) and value range. The analytical models for such computations are reported in Eqs. 3 and 4,

$$o_{i,t} = \sum_{\tau=0}^{t} [C(R_{i,t}) \equiv C(R_{i,\tau})] \quad (3)$$

$$O_{i,t} = \begin{cases} 1 & o_{i,t} = \begin{cases} (1, 1800] & continuous \\ (1, 3600] & intermittent \end{cases} \\ 2 & o_{i,t} = \begin{cases} (1800, 6300] & continuous \\ (3600, 8100] & intermittent \end{cases} \\ 3 & o_{i,t} = \begin{cases} > 6300 & continuous \\ > 8100 & intermittent \end{cases} \end{cases} \quad (4)$$

where $\tau$ represents the time index from the beginning of the work shift until the timeframe under consideration $t$. Continuous occurrence is more significant than intermittent occurrence and affects the categorization based on the predefined thresholds. Consequently, continuous values take precedence in determining the risk level, by using narrower threshold intervals [13]. At this point, it is possible to compute the Priority Index ($PI_{i,t}$), which is determined as the product of the three contributing factors mentioned above, according to Eq. 5.

$$PI_{i,t} = w_i \cdot M_{i,t} \cdot O_{i,t} \quad \in (0; \ 1] \quad (5)$$

The $PI_{i,t}$ is then normalized in a range between 0 and 1, where 0 indicates minimum priority and 1 indicates maximum priority. The resulting $PI_{i,t}$ is finally classified into three classes (namely low, medium and high priority), each triggering a specific set of actions. To achieve this, three different priority intervals are defined according to the thresholds shown in Table 2, here assumed to be uniformly distributed. The thresholds for the priority classification may vary depending on

the context and the preferences of the decision makers. One way to determine the thresholds is to use the mean and standard deviation of the $PI_{i,t}$ values across all risks, and then use a normal distribution to assign the probabilities of each priority class [14].

### 2.3. Machine learning data fitting

Given the complexity of priority modeling and the variability of thresholding methods, a machine learning approach [15] is proposed here to estimate the priority index $PI_{i,t}$. This approach uses input data from the physical layer and target data from the priority modeling. This is particularly useful in manufacturing scenarios where obtaining actual risk priority is challenging, expensive, and time consuming due to the expertise required and the dynamics of different activities. The goal is to train a model that can estimate the risk priority curve over time for each risk category, using input variables from the physical layer and targets from the priority modeling described in Section 2.2. This paradigm is illustrated in the flowchart in Fig. 2.

Table 2. Priority classification thresholds

| Interval | Priority classification of risk |
|---|---|
| (0, 0.33] | Low Priority |
| (0.33, 0.67] | Medium Priority |
| (0.67, 1] | High Priority |

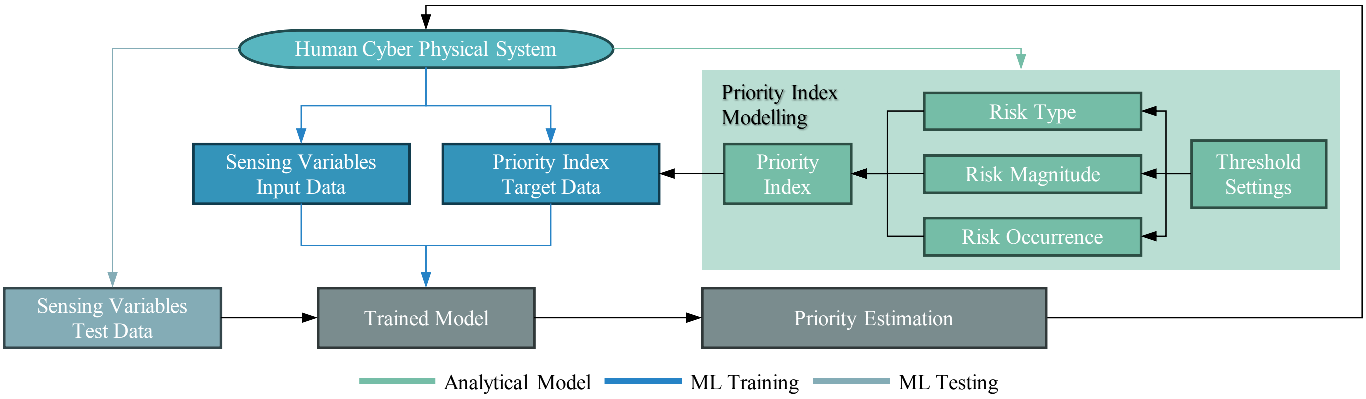


Fig. 2. Machine learning paradigm

### *2.4. Mitigating and corrective actions*

After classifying the $PI_{i,t}$, given the thresholds mentioned above, a study of the priority can be done in order to implement appropriate corrective/mitigating actions in the short and in the medium-long term, respectively. Short-term mitigation actions focus primarily on immediate measures to reduce the short-term impact of risks, often involving quick fixes and limited scope. These actions aim to temporarily mitigate the severity of the risk without a thorough investigation of the underlying causes. On the other hand, medium-to-long term corrective actions aim at addressing the root causes of risks to prevent their recurrence, requiring a more comprehensive and sustained approach. They imply in-depth analysis, substantial changes, and a focus on creating lasting and sustainable solutions that minimize the long-term impact of risks. To define the right actions to take, a multi-cause analysis is carried out based on a layer-by-layer backward analysis of the fuzzy-based fusion.

Risk characterization is based on data from sensor units, considering machine, operator, and environmental factors. When high-priority risks are identified, immediate action is taken. Collective risks are addressed first, as they can potentially lead to plant evacuation and rapid issue resolution [16]. If no high-priority collective risks are present, the focus shifts to physical and mental priorities that affect operators. In both scenarios, the safety team conducts a thorough analysis to plan actions such as system upgrades. High physical or mental priority risks could be addressed, in the short term, by a priority-driven operator swap [17], where a SWAP coefficient could be calculated for each operator, at a given time frame $t$, using Eq. 6,

$$SWAP_j = k_1 \frac{\left(\sum_{i=1}^{5} PI_{i,j}\right)}{\max\left(\sum_{i=1}^{5} PI_{i,j}\right)} + k_2 \frac{d_j}{\max\,(d_j)} \quad \in [0,1] \qquad (6)$$

where $i$ represents the risk type, $j$ represent the operator ID, and $d_j$ the distance between the operator $j$ and the operator to be swapped. The SWAP coefficient can be adjusted by introducing two weights ($k_1$ and $k_2$) to adapt to specific scenarios. The SWAP coefficient is calculated for qualified operators at a given workstation. In the long term, corrective action may include a review of work assignments, to reduce overall plant risk and, for persistent problems, even a layout optimization to reduce distances from potentially problematic operators [18]. If, on the other hand, the high priority is machine- and/or equipment-related, extraordinary maintenance could be performed in the short term and equipment upgrades could be considered in the medium/long term. If no high priority has been detected for any of the risk categories, the HCPS analyzes the medium priorities and evaluates the causes that may increase the risk priority. Firstly, if the cause is environmental-related, a ventilation of the room/floor could be performed in order to mitigate the priority risk in the short-term, followed by a study of the further possible environmental causes in the medium/long-term [19]. If the cause is operator-related instead, an extra break could be advised to the operator, and a review of the assignments should be carried out in the medium/long-term if necessary. Then, if a machine-related risk is the principal cause of the medium priority, an extraordinary maintenance could be scheduled while in the medium/long-term an equipment upgrade is recommended. At the end of this action sequence, if none of the scenarios described above are present, the system continues to monitor the configuration and appends the data to the database.

## 3. Case study

To demonstrate the applicability of the framework described in the previous section, a case study is considered. It focuses on the simulation of a semi-automatic welding of a mechanical workpiece, which is subjected to various operations during the work shift by a single operator, including pre-weld parts inspection, electrode preparation, configuration of welding parameters, station setup, process monitoring, post-weld inspection, and part removal.

Table 3. Process cycle times [6]

| **Activity** | **Duration (min)** |
|---|---|
| Pre-welding inspection | 5 |
| Electrode preparation / grinding | 10 |
| Parameters configuration | 5 |
| Station setup | 15 |
| Welding #1 | 18.75 |
| Post-welding #1 inspection | 2 |
| Welding #2 | 18.75 |
| Post-welding #2 inspection | 2 |
| Removal | 10 |
| **Total** | **86.5** |

Table 3 details the average time required for each step in this process. The entire welding process is repeated 5 times during a work shift, with a 5.8-minute break at the end of each process and a 30-minute lunch break at the end of the third process. The simulations are performed considering two different scenarios. The first scenario is related to a young and fit operator who runs the process with the standard values of the input variables as an optimal case. The second scenario is related to an elderly and overweight operator with a more severe health background. Each scenario also takes into account a fatigue factor that increases incrementally throughout the working shift [20, 21]. For the ML Priority Index fitting, a neural network model was trained with 58 input nodes representing the 58 sensing variables from the physical layer, 116 hidden layer nodes, and a single output node representing the estimated Priority Index. Each dataset consisting of one work shift was divided into a training set (70% of the data samples), a validation set, and a test set (15% of the data samples each).

## 4. Results and discussions

The simulations were performed for the two scenarios, and the five risk levels were output for each risk category. However, for the sake of brevity, this section will focus only on the physical risk, which is one of the most important for the priority characterization. Here, the results are presented and discussed in terms of the Priority Index ($PI$) and the machine learning fitting capabilities for the two operators. Regarding the $PI$, the graph in Fig. 3 shows how the younger operator remains in the low class for most of the shift and then, during the last process batch, the priority increases to a medium class, likely due to fatigue. For the elderly operator (Fig. 4), the $PI$ starts to increase during the second batch, as the input variables indicate that the physiological conditions of the worker are not optimal compared to the younger one; the priority then exceeds the medium class threshold during the third cycle of the process. Moreover, the $PI$ shows some peaks that represent the most interesting hotspots to focus on in order to optimize the process configuration. From the graphs in Figs 3 and 4, it is possible to visualize the correlation between the risk level and its associated $PI$. Regarding the younger operator, the priority index does not provide any additional information compared to the risk level, as the pattern is generally flat. However, for the elderly operator, the patterns of the two indicators show noticeable differences that are helpful to understand how to support the identification of appropriate actions to be taken in case of higher risk situations. Specifically, for the elderly operator, the $PI$ in Fig. 4 consistently indicates medium class peaks during the electrode grinding process. Similar peaks are also noted during station setup, which involves tooling activities such as clamping and aligning jigs and fixtures, as well as during the removal of the workpiece, highlighting these tasks as more physically demanding. No collective risks were identified, and other concerns fall below the High Priority ($HP$) threshold. As a result, the recommendation is to implement corrective actions such as improving the gas supply system, enhancing electrode monitoring, and upgrading the ventilation system, as well as making ergonomic adjustments and automating workpiece removal to reduce the physical risks.

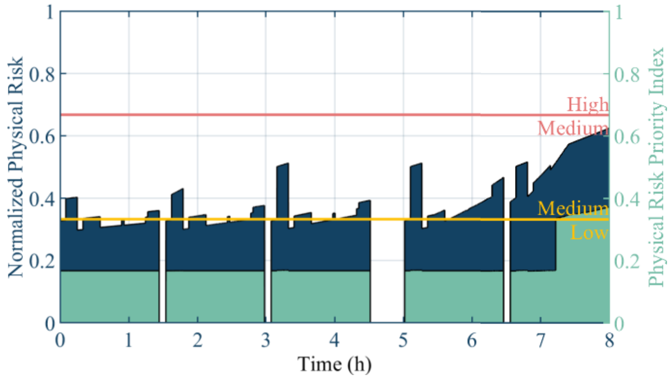


Fig. 3. Physical risk and Priority Index - Young operator

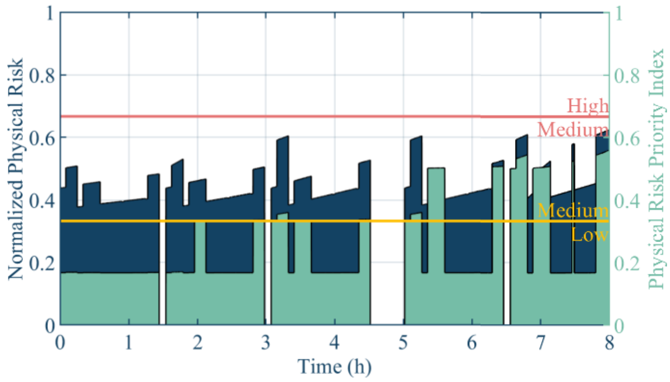


Fig. 4. Physical risk and Priority Index - Elderly operator

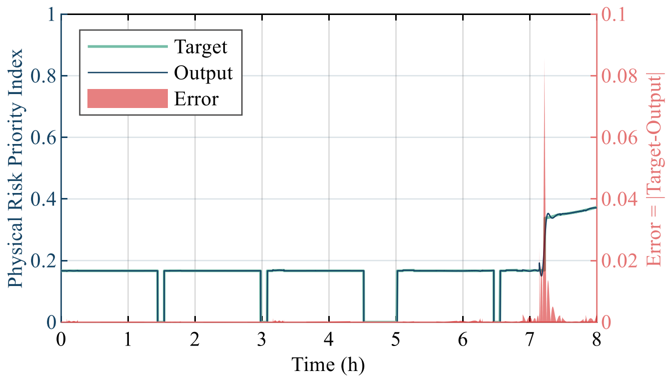


Fig. 5. Machine learning fitting performance - Young operator

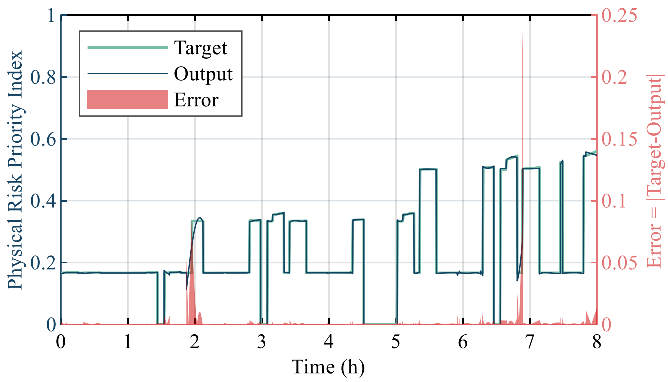


Fig. 6. Machine learning fitting performance - Elderly operator

Table 4. Machine learning fitting results

| Operator | Dataset | N. of Samples | MSE | R |
|---|---|---|---|---|
| | Training | 20160 | 1.78e-05 | 0.9989 |
| **Young** | Validation | 4320 | 1.72e-05 | 0.9986 |
| | Test | 4320 | 1.41e-05 | 0.9986 |
| | Training | 20160 | 1.19e-05 | 0.9996 |
| **Elderly** | Validation | 4320 | 1.37e-05 | 0.9995 |
| | Test | 4320 | 1.49e-05 | 0.9995 |

Based on the assumptions considered here in the case study simulation, a more operator-friendly redesign of the activities in the plant could be identified as a medium/long-term action. Therefore, although the current physical risk level for the elderly operator is manageable, it could be recommended to adopt measures and re-structure tasks to further improve safety and efficiency. Regarding the machine learning priority fitting, Figs. 5 and 6 show the estimated *PI* outputs and the computed *PI* targets for the young and elderly operator, respectively, along with the absolute value of the errors (defined as the difference between the target and the output), demonstrating satisfactory learning capabilities of the ML-trained model. Table 4 reports the fitting results for the two scenarios in terms of mean square error (MSE) and Pearson correlation coefficient $R$, showing consistently low MSE and R values very close to 1 across all datasets.

## 5. Conclusions and outlooks

The objective of this research was to propose a methodology to dynamically estimate the risk priority for an operator by using a human-cyber-physical approach. On the one hand, an analytical model was developed to compute a risk priority index for each risk category in an industrial context. On the other hand, an alternative machine learning fitting model was provided to by-pass the complex computations while still achieving a consistent result. A limitation of the proposed approach lies in the threshold definition process, which is subjective and requires manyfold expertise. In addition, the fine-tuning of the fuzzy inference can be burdensome and prone to bias. The simulated case study, although necessarily simplified for the sake of clarity, served as a proof of concept for the risk estimation methodology proposed here, emphasizing the need for experimental validation in real industrial settings to confirm its practical effectiveness. A certain flexibility is provided by the possibility to adjust thresholds and to consider exceptions in the calculation of the Priority Index. The methodology is scalable and allows for the integration of additional sensing units, facilitating adaptation to different operational needs and sizes without significant customization difficulties. Next developments may include the modelling of risk awareness, which may influence the risk perception and, hence, its estimation.

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