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Manufacturing Process Impacts on Occupational Health: a Machine Learning Framework

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Abstract

The Operator 4.0 generation denotes a smart and skilled operator accomplishing 'cooperative work' with robots, machines and cyber-physical systems. In this taxonomy, a healthy operator is an operator equipped with wearable technology to monitor biometrics in a workplace to monitor and ideally prevent urgent threats to safety, stress in manufacturing and production quality. In a digitalized context, a cloud manufacturing platform for occupational health assessment, capable of collecting physiological, environmental and manufacturing process data can potentially enable prompt action to prevent fatalities. This paper proposes a novel machine learning-based framework and associated methods to classify physiological data acquired using wearable sensors during manufacturing work, to be utilized in a fuzzy-based expert system to determine the level and type of health risk for Operator 4.0. Classification algorithms are presented and a manufacturing case study is illustrated to exemplify the proposed methodology and to evaluate the industrial suitability.

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Keywords: Industry 4.0; Operator 4.0; cloud manufacturing; sustainable manufacturing; hazardous manufacturing context; fuzzy inference system

1. Introduction

In the Industry 4.0 framework, a new operator generation, defined as Operator 4.0, has been identified. This figure has been well defined and investigated by Romero et al. [1, 2], who initially defined it as "a smart and skilled operator who performs not only cooperative work with robots – but also – work aided by machines as and if needed – by means of human cyber-physical systems, advanced human-machine interaction technologies and adaptive automation towards human-automation symbiosis work systems". As such, Operator 4.0 represents the "operator of the future", who utilizes the benefits of Industry 4.0 key enabling technologies to improve sensorial, cognitive, physical and interaction capabilities. This smart operator enriches the real-world with virtual and augmented reality, uses a personal assistant and social networks, analyzes acquired data, wears trackers and works with robots.

As a whole, Industry 4.0 describes the modern, evolving, digital technology-based manufacturing paradigm characterised by notable advancements with respect to the previous industrial revolutions [3]. This paradigm considers the implications of computers and automation, enhanced by smart autonomous systems that can make simple and more complex decisions based on data. The underlying commonality is the data availability and usage to realize a smart manufacturing paradigm. Many studies have shown the impact of data-driven decisions within manufacturing, which fall under a variety of modern manufacturing categories such as cloud-based, Internet of Things (IoT), intelligent and cyber-physical systems manufacture [4, 5]. There are clear advantages for issues like stock location and control, as well as big data tracking and machine tool status monitoring for predictive maintenance.

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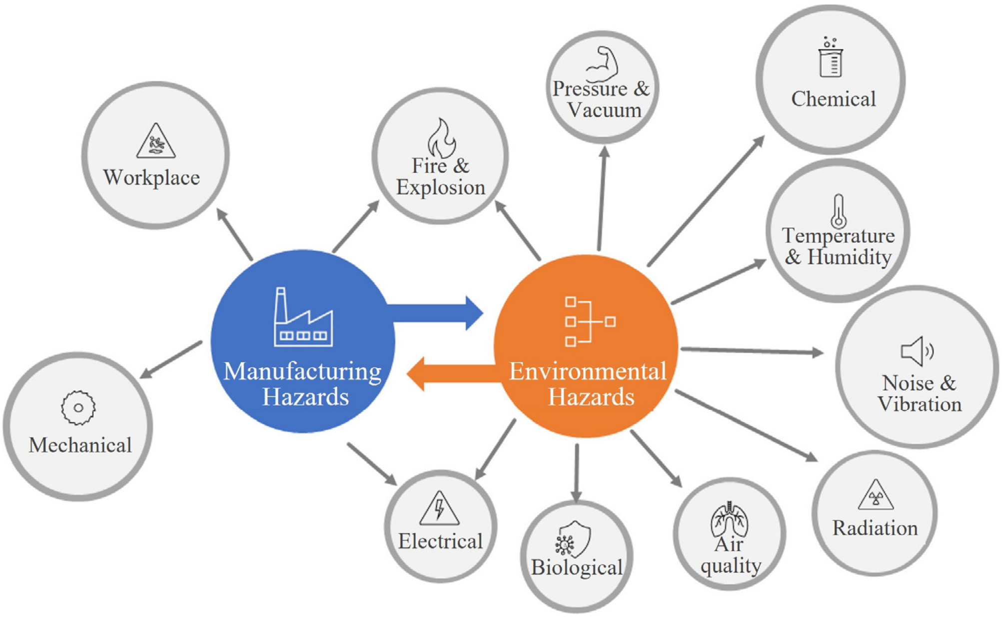

Fig. 1. Examples of manufacturing and environmental hazards that can impact operators.

When dealing with occupational health, relevant Industry 4.0 key enabling technologies are widely functional to deal with healthcare issues within manufacturing scopes. In this context, a 'healthy operator' is an operator equipped with wearable technology to monitor biometrics in a workplace and ideally prevent urgent threats to safety.

In manufacturing industry, the worker's health conditions may be affected by several environmental hazards (e.g. temperature, humidity, noise, vibrations, air quality, fire hazard) as well as manufacturing hazards (e.g. mechanical, electrical, workplace risk), see Fig. 1. The interaction between man and machine along with the harsh ambient conditions that can sometimes be present, pose particular challenges with respect to health and safety technology in manufacturing industry. Hence, monitoring of workers in hazardous or challenging environments is highly needed. Along with on-person sensing and monitoring, various sensors can monitor the surrounding environment and manufacturing process/system to operate within suitable human-centred operational boundaries.

Sensing units can be installed at the factory level to provide information about environmental parameters which are likely to affect the worker's health conditions, such as temperature, humidity, chemical and pollution, biological agents, radiations, noise, dust, vibration, poor ventilation, fire and smoke. In this way, it is possible to map critical environmental parameters.

As regards manufacturing hazards, hazard analysis should be carried out to characterize the mechanical hazards (e.g. heavy loads), the chemical and radiations hazards etc.

More and more sensors can be integrated in machine tools and equipment in order to provide relevant data to the users. Technologies like RFID, vision sensors, temperature sensors, pressure, force, torque, power, machine data, limit switches, encoders, etc. can be adopted to collect the required data.

The physical and cognitive interaction capabilities embedded in machines and production systems can support operators with health risk monitoring. Wearable trackers can measure human performance under stressful or difficult conditions analyzing them and sending warnings if needed.

Existing applications of smart healthcare monitoring include assisted living [6], patient self-assessment and monitoring [7], sensing and monitoring in harsh environments such as thermal power plants [8], hazardous waste [9], firefighting [10, 11] and asbestos removal [12]. Monitoring of humans has issues around effective real-time monitoring, data privacy and potential for poor application. However, these issues around developing Industry 4.0 practicalities can be outweighed by the benefits in in hazardous or challenging environments.

In such framework, the objective of this research work is the development of an intelligent decision-making support system based on machine learning for operator healthcare monitoring in an Industry 4.0 manufacturing context. This is part of the Cloud manufacturing platform able to collect and process physiological, environmental and manufacturing process data for occupational health risk assessment to enable prompt action and prevent fatalities [13]. A machine learning framework is then developed for input data classification as well as for the assessment of health risk level for the operator.

2. Industrial context

In order to illustrate the developed methodology, an industrial context which is suitable to highlight the manufacturing-related risks has been considered.

In particular, this framework relates to operators working on CNC machining employing cutting fluids. Cutting fluids used in machining operations, also called metal working fluids, perform the main functions of reducing the friction between the tool and the workpiece (lubrication), improving the heat dissipation (cooling), and facilitating the chip evacuation from the cutting zone (flushing). Conventional CFs are either entirely based on mineral oils or, in the case of water-based CFs, contain up to 10% mineral oils for the lubrication function. They are highly vulnerable to microbial contamination from bacteria and fungi which are potentially harmful for humans and for the environment [14].

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2.1. Metal working fluids: health & safety risks

Microbial contamination and proliferation represent a risk of health hazards for the machine operators (e.g. allergic reactions, irritation of the eyes, skin dermatitis and hypersensitivity pneumonitis).

There are several ways of workers' exposure to cutting fluids. For example, cutting fluids can enter the human body through contact with the skin, through cuts and abrasions, through the mouth. But most of the cutting fluid enters the human body through inhalation of the cutting fluid vapor or mist. CF mist is produced inside the CNC machine during machining. Severity of the exposure through inhalation depends on several factors, for example the operator-machine distance, operating parameters, machine enclosure, ventilation, etc. The inhalation of CF mist can cause lung diseases such as occupational asthma and hypersensitivity pneumonitis.

2.2. Local Exhaust Ventilation (LEV)

In general, oil mist local exhaust ventilation (LEV) systems are used for extracting the mist and fume generated from metal cutting processes (e.g. turning, milling, drilling, grinding)[15].

LEV systems protect employees from exposure to hazardous substances (e.g. vapour, mist, dust or other airborne contaminant) by containing or capturing them locally, at the emission point. Indicators may be used at the hood to show the system is performing correctly, e.g. by displaying the flow rate with colour-coded bands for acceptable ranges [16].

2.3. Severity of exposure: main influencing factors

The severity of the worker's exposure through inhalation depends on a number of factors, for example on the worker's health conditions. Workers who already have asthma and are then exposed to cutting fluid inhalation are at greater risk of aggravating their condition. Another factor is the LEV system airflow rate, because the CF mist produced inside the CNC enclosure during machining can escape if the LEV is not working properly. Other relevant factors are the cutting fluid pressure and flow rate: the production of vapour and mist can be minimized by controlling the volume and rate of delivery of the fluid. Moreover, the temperature of the cutting fluid and the ambient temperature are relevant: lowering the fluid temperature may discourage bacterial growth. The main influencing factors with respect to the health and safety risk of CF mist exposure through inhalation are summarized in Fig. 2.

3. Framework

The framework of the proposed system aims at combining three different types of data:

- *Physiological data*, coming from wearable sensors which provide for real time information on physiological parameters of the worker
- *Environmental data* are meant to provide additional information on the hazards, as particular environmental conditions can badly affect the worker's health, for example high temperature, high humidity, dust, pollution and noise
- *Manufacturing related data* coming from sensing units are embedded in the machines. Such kind of data indicate the nature of the hazard and potential health and safety issues during specific manufacturing processes.

All the data types have to be triggered, synchronized and preprocessed in order to be able to perform a classification. This classification can be carried out either via thresholding method or, when more complex data are available, using machine learning classifiers. The results of classification are then utilized as an input for a fuzzy inference-based decision-making system. Fuzzy inference consists in a mapping process from a set of fuzzy inputs to a crisp output based on fuzzy logic, which deals with vague and imprecise information. The fuzzy inference process includes membership functions, logical operations, and if-then rules [17]. In this respect, a number of rules have to be set to link the fuzzy input to a fuzzy output which is represented by the risk level and the risk type. Defuzzification is then carried out in order to quantify the output levels and take appropriate actions.

The overall framework for data collection, data classification and fuzzy inference decision-making is illustrated in Fig. 3.

3.1. Data classification

Simple data like environmental variables and manufacturing indicators, along with simple physiological data such as breath rate, blood pressure and heart rate can be easily classified using commonly recognised threshold values available in relevant handbooks or using occupational doctor expertise [18]. As regards complex physiological data, for example electrocardiogram (ECG), a tailored machine learning based classification procedure was carried out, as shown in Fig. 4. Such classification is implemented by accessing a pre-trained pattern recognition system. For this purpose, ECG data were acquired from open source dataset provided by PhysioNet [19].

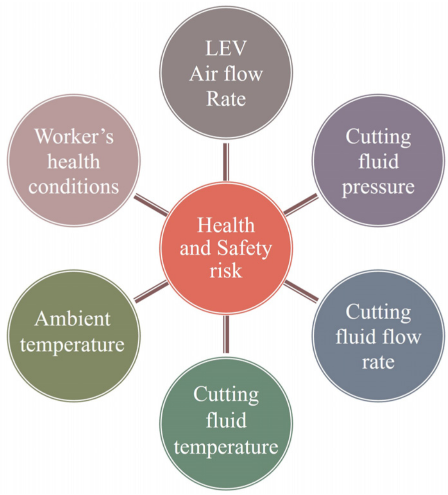

Fig. 2. Main factor influencing severity of the exposure through inhalation.

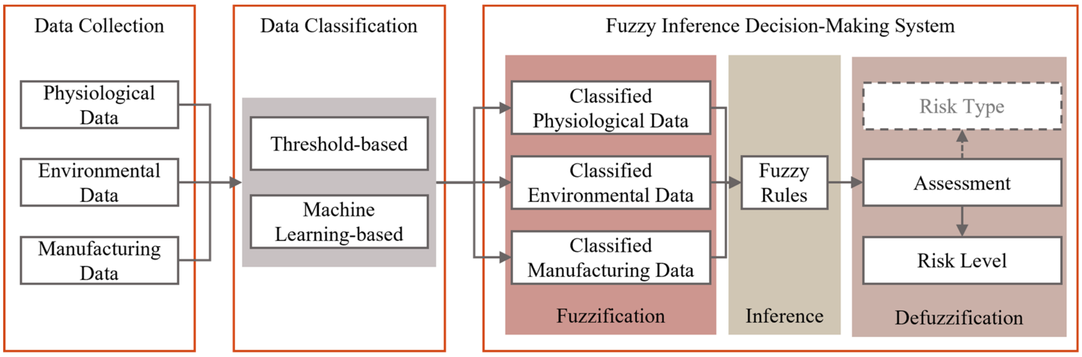

Fig. 3. Framework of the proposed system.

Based on the guidelines provided by American Association for the advancement of Medical Instrumentation (AAMI), ECG signal instances can be classified into the following categories [20]: normal beat (N), atrial fibrillation (AF), ventricular tachyarrhythmia (V), Congestive heart failure (C), Myocardial ischemia (ST) and apnoea (AP).

In this case, all ECG data are preprocessed through the use of various filtering operations, specifically a high pass filter (0.25 Hz), a low pass filter (49 Hz) and a gaussian filter (smoothing factor set to 0.25). Following the pre-processing, ECG signals were resampled to get 3000 sample points at 250 Hz, which means 12-second-long signals.

The features extraction is carried out via Continuous wavelet transform (CWT) [21] using a filter bank with 12 voices per octave, and a morse mother wavelet with skewness parameter $\gamma = 3$ and a time-bandwidth parameter $P = 60$.

The output of such procedure is a scalogram, i.e. a plot reporting the time on the x-axis, the frequency on the y-axis and the magnitude, i.e. the absolute value of the CWT coefficients of the signal. Fig. 5 shows two examples of clearly different scalograms of ECG signal instances. Fig 5(a) shows a scalogram related to a healthy ECG instance, while Fig. 5(b) shows a scalogram of a congestive heart failure ECG instance.

As concerns the ECG instances classification, this paper uses GoogLeNet [22] convolutional neural network (CNN). Such network consists in deep multi-layer neural network based on convolution, pooling and inception layers [21]. It utilises inception modules, which allow the network to choose between multiple convolutional filter sizes in each block. An inception network stacks these modules on top of each other, with occasional max-pooling layers with stride 2 to halve the resolution of the grid [22].

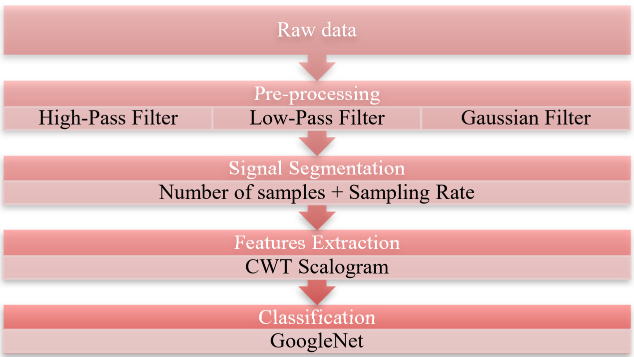

Fig. 4. ECG signal classification procedure.

The input of a GoogLeNet is an array of 224 x 224 x 3, matching the RGB image of the scalogram computed for each signal instance. The architecture consists in 27 layers, i.e. three shallow convolution layers, three activation layers, five pooling layers, two normalization layers, nine induction modules, one dropout layer, one fully connected layer, one softmax layer, one input layer and one output layer. A detailed description of the GoogLeNet architecture and parameters configuration can be found at [23]. The GoogLeNet classification performance is reported in Table 1 for the six ECG classes.

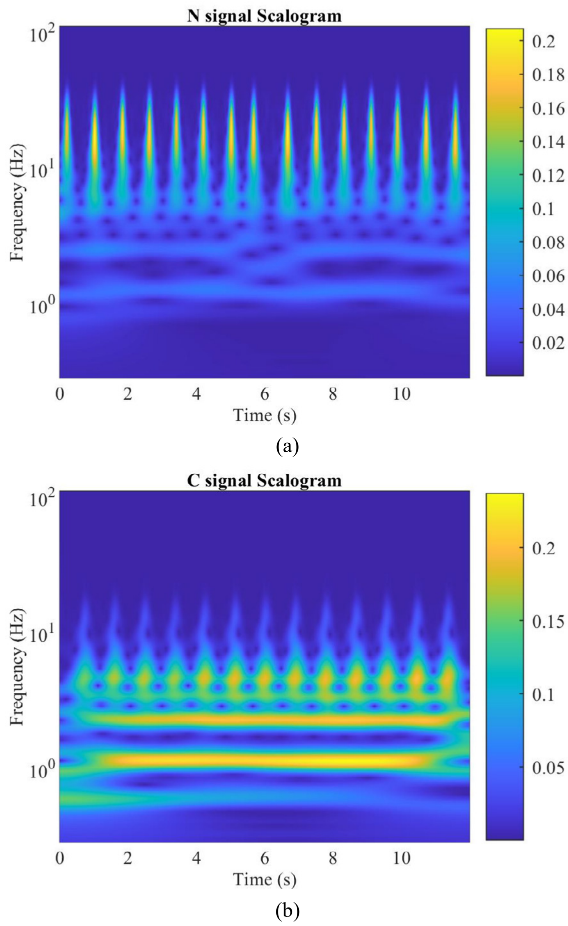

Fig. 5. Scalograms (a) normal, (b) congestive heart failure.

Table 1. ECG classification results

	AF	AP	C	N	ST	V
Training	99..5%	100%	100%	100%	99.9%	100%
Testing	99.4%	99.9%	99.8%	100%	100%	100%

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4. Case study

To validate the effectiveness of the proposed platform, a simulated case study is reported. The context is a CNC machining process in which a particularly demanding material is considered. This means high values in terms of cutting fluid flow rate and cutting fluid pressure. The simulated location is Shantou, which is in the South China, where in summer the indoor temperature in a factory workshop can easily reach over 30 °C. The machining process is here characterized by high coolant temperature, high but still included within acceptable limits. The simulated scenario consists in a damage to the Local Exhaust Ventilation (LEV) system. The exposure time to cutting fluid mist can be modelled by a short manufacturing time and a high number of products. This scenario configures a prolonged exposure to cutting fluid vapors due to the high number of changeovers.

In this case study, three types of physiological data have been taken into account, namely ECG, heart rate and respiration rate (i.e. breath rate). Only one environmental variable was utilized, corresponding to the ambient temperature. Manufacturing data coming from sensing units embedded in the machines in this case are the LEV airflow, the cutting fluid pressure, the cutting fluid temperature and the cutting fluid flow rate.

Fuzzification of numerical data is carried out according to predefined value ranges, company guidelines, government regulations and health and safety standards [18]. As regards the categorical data (e.g. ECG data), the fuzzification is actually the result of the probabilistic classification carried out by machine learning classifiers. An example of the fuzzification is reported in Fig. 6 respectively for numerical data and for categorical data.

In this case study the scenario was simulated with the following crisp input values. As regards the physiological data, a healthy operator was modelled with no heart disease, so a normal ECG. However, this operator presents a high heartbeat rate, 120 bpm, and a very short breath of 25.8 bpm.

The environmental conditions are modelled with an ambient temperature of 30° C. As regards the manufacturing related data, the LEV malfunctioning was simulated with a reduced airflow corresponding to 1150 m^3/h. The demanding machining conditions were instead simulated with a cutting fluid temperature of 40°C, cutting fluid pressure of 140 bar, cutting fluid flow rate of 62.7 l/min. The fuzzy rules are modelled according to literature survey, company policy and medical guidelines. The logical operator, in this case AND, is set in order to take into account the overlapping of the effects.

In this case study, all the weights were set to 1, giving all the variables equal impact to the risk level assessment. Considering the 8 input variables and their corresponding membership functions, a total number of 21 inference rules was set. Fig. 7 shows all the rules impacting on the health risk level along with the crisp values selected for this case study. The defuzzification was carried out using the centre of gravity (COG) method [17].

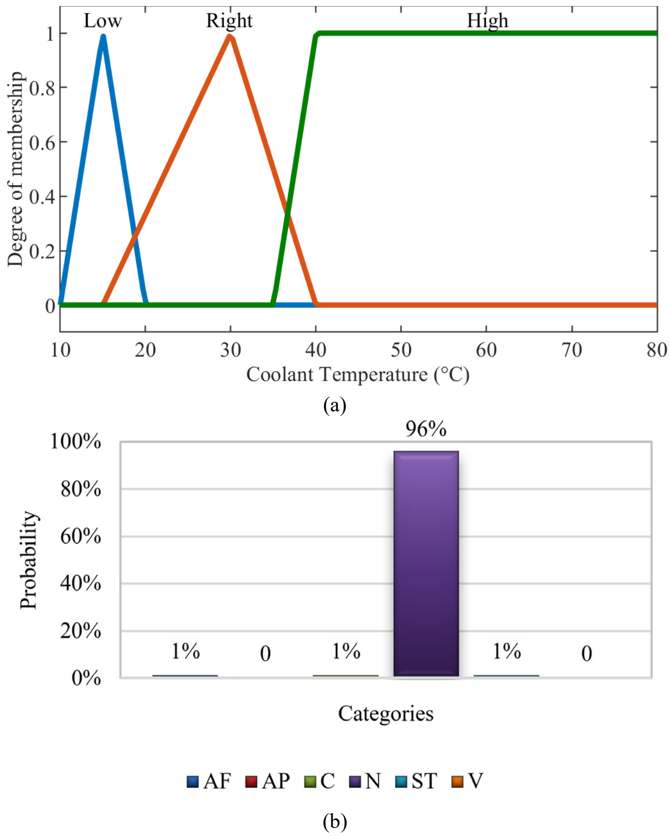

Fig. 6. Fuzzification (a) numerical data; (b) categorical data

5. Results and discussion

The last column on Fig. 7 shows that the fuzzy inference system output was a crisp value of 0.857, corresponding to a high risk level. This output is the result of the combination of several unfavorable conditions. Specifically, the LEV damage reduces the airflow and the cutting fluid mist is not drained out. The high ambient temperature increases the cutting fluid mist generation, and the cutting fluid temperature, pressure and flow rate negatively affect the cutting fluid hazard. Repeated machine opening to extract the finished product also increase the exposure to the cutting fluid. As a consequence, both heart rate, tachycardia and breath rate, hyperventilation, increase. As regards the risk type, this case study involves a respiratory related risk due to the cutting fluid exposure following the LEV malfunctioning.

6. Conclusions

In this work, an intelligent decision-making support system based on machine learning was developed for manufacturing operator healthcare monitoring in an Industry 4.0 context. This system is integrated within a cloud manufacturing platform able to collect and process on-line data coming from various sensors and manufacturing equipment for occupational health risk assessment to enable prompt action and prevent fatalities. Three different data types are combined in the proposed framework: physiological data, manufacturing related data and environmental data.

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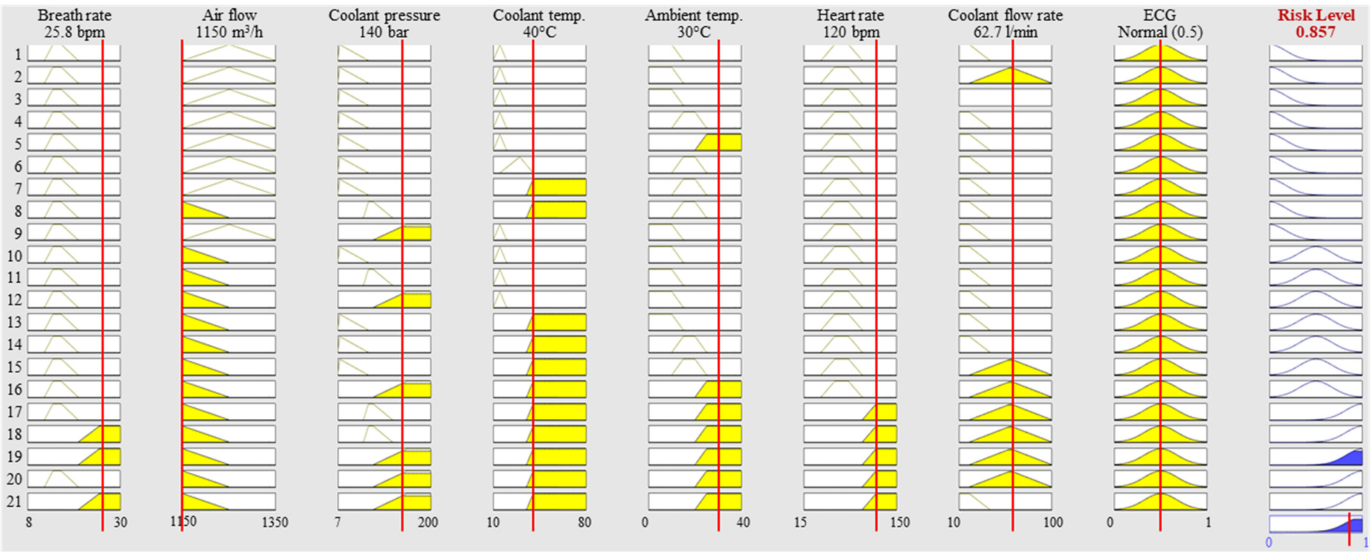

Fig. 7. Fuzzy rules impacting on the health risk level.

A machine learning-based methodology was developed for complex input data classification via GoogleNet deep learning network as well as for the assessment of health risk level via a fuzzy logic inference system.

To validate the effectiveness of the proposed platform, a simulated industrial case study involving manufacturing-related risks in CNC machining processes using cutting fluids was reported. The fuzzy inference system was able to process 8 different inputs including environmental, physiological and manufacturing data and provide as output the associated risk level, which in this specific case was a high risk level related to a respiratory hazard due to the cutting fluid exposure following LEV malfunctioning. Further elaboration is then required to link the machine data to a diagnostic system for medical checkup and for equipment diagnosis for maintenance.

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