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Indoor positioning systems to prevent the COVID19 transmission in manufacturing environments

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Abstract

Since the 11th of March 2020 when the World Health Organization declared the novel COVID-19 outbreak a global pandemic, it registered officially over 5 million deaths worldwide. According to the course of the pandemic, governments encouraged best practices and then ruled out temporary restrictions on daily lives. In this scenario, non-essential labor-intensive sectors were forced to put on hold operations producing massive temporary layoffs. In gradually restoring the economic activities, governments passed several laws to passively mitigate the pathogen transmission in indoor working environments. However, several COVID19-related injuries were filled by manufacturing companies. According to the outlined conditions, this paper proposes an original and advanced hardware and software architecture to prevent the COVID19 transmission in indoor production environments. The aim is to increase the safety of whichever indoor productive workplace through a contact tracing approach. Indoor positioning systems due to their ability to accurately track the movement of tagged entities compose the hardware part. For this purpose, human operatives are equipped with adequate wearable sensors. Raw data acquired are properly mined through advanced algorithms to quantitatively assess the degree of safety of any working setting. Indeed, having as a reference the epidemiological evidence the software part defines an innovative risk index along two correlated dimensions. While the first defines the risk of any worker getting infected during the shift, the other one expresses the degree of COVID19-safety of the shop floor defined by the displacements of the anchors. Benefitting from these targeted and quantitative hints, plant supervisors may redesign the production settings to lower the chances of COVID19 infection. This innovative digital framework is validated in a real case study in the North of Italy which performs manual mechanical processing for the automotive industry.

Keywords: safe workplace; indoor positioning systems; contact tracing; covid19 transmission prevention; manufacturing relayout

1. Introduction

The COVID19 global pandemic is posing tremendous threats to the globalized world under different viewpoints. At first, considering the health aspect, in November 2021 over 253 million confirmed cases and 5 million fatalities were officially recorded worldwide [1]. In this grim scenario, regional economies were disruptively hit. According to the statistic provided by Eurostat [2], the gross domestic product of the European area registered a slump of 5.9% in 2020. While public and private companies encouraged the work from anywhere approach, the labour-intensive industries at least during the first stages of the pandemic were forced to put on hold operations. Despite the massive activation of furlough schemes, the European Union lost 1.4% jobs in 2020 compared to the previous year [3]. The operative workers faced a tremendous burden in terms of occupational injuries. According to data surveyed by the Italian institute for insurance against labor accidents in February 2021, from the early days of the pandemic 156.766 work-related accidents were filled just in this country. In particular, 97,6% of the fillings are related to the private sector [4]. Governments worldwide fostered the social

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distancing approach in order to flatten the curve of COVID19 transmission. This passive measure to mitigate the contagion defines the degree of a safe interaction upon two independent variables which are the distance assumed by individuals and the time length of the interaction. In line with the guidelines ruled out by the World Health Organization (WHO), unsafe exposures are driven by face-to-face contacts with a probable or confirmed positive case within one meter and for more than 15 minutes [5]. Hence, the contact tracing (CT) platforms were believed a crucial tool to effectively curb the COVID19 contagion among individuals. Though, these platforms resulted mostly underperforming due to low adoption rates provided, among the others, by privacy concerns [6]. While CT platforms failed their purpose due to a lack of compliance by citizens, the outlined passive guidelines to prevent and mitigate the pathogen widespread resulted inadequate to preserve the health of workers. After having categorized ex-ante the degrees of COVID19 exposures related to specific occupations, the WHO action points gravitate mainly around the adoption of personal protective equipment, the need to lower the indoor occupancy loads and to adequately ventilate spaces [7]. Given the outlined limitations to proactively prevent the infection between individuals in particular in the manufacturing environment, this paper proposes a digital and unique hardware (HW) and software (SW) architecture called SHIELD4US. The aim is to increase the safety level of whichever indoor working environment. The HW architecture is represented by an ultrawide-band (UWB) based indoor locating system (IPS). While the displacement of anchors (ANs) defines the considered shop floor, employees wear an anonymous tag in a runner armband in order to monitor risky interactions among colleagues two distinctive levels. Complying with all privacy requirements, it is provided the personal risk of infection (PRI) connected to the anonymous TagID. Simultaneously, the cluster analysis yields the degree of safety of the monitored manufacturing system over the shift. The aim of these outputs is to provide to the management adequate and quantitative metrics to re-layout the job shop whether necessary. Therefore, any employee should achieve a benefit from this process and as a consequence there is no need to relate any metric to a known operator. This paper is organized as follows. The Section 2 describes the operative functioning of IPS along with their industrial application to preserve the health of human operators. The subsequent section defines the contagion risk index (CRI) to evaluate the degrees of safety of interactions among workers. The Section 4 analytically outlines the original SHIELD4US HW and SW architecture. The reliability and resilience of SHIELD4US are tested in an operative and real case study (Section 5). The obtained result over a monitoring of one week are properly discussed in the Section 6. Finally, conclusions and further research opportunities are outlined in the Section 7.

2. Literature Review

This section outlines the operative functioning of the indoor positioning systems along with their industrial applications to safeguard the health of operators.

2.1. Indoor Positioning systems state of the art

During the last decades, significant progresses were registered in the development of IPSs, especially aimed to develop a low-cost, accurate and local alternatives to Global Positioning System (GPS) for indoor environments [8][9]. IPSs can be categorized under multiple categories, mainly by computation approach, environment type or communication technology [10]. Among all possible communication protocols, UWB attracted increasing interest due to its excellent characteristics, such as robustness to multipath error, obstacle penetration, high accuracy, and low cost [11]. In the UWB localization systems, Time-of-Arrival (ToA) and Time-Difference-of-Arrival (TDoA) ranging techniques are commonly adopted. ToA approaches are based on the Time-of-Arrival of the signal, which allows to determine the distance between two entities starting from the radiofrequency (RF) wave propagation speed. The location information can be determined through for instance trilateration or multi-lateration algorithms (e.g., circle or sphere intersections) [12]. However, this approach is not performing for implementing a battery-powered CT platform, due to the large number of messages required to be exchanged between the ANs and the tag in order to complete a localization cycle. Indeed, to enable the capability of tracking simultaneously such multiple entities, TDoA is proposed. Similarly, to the ToA method, the distance estimation is based on the propagation speed. Though, exploiting the TDoA of the signal leads to a geometrical problem based on hyperbolas [13]. According to this, while tags solely needs to emit a single UWB signal, the ANs from the difference in reception times calculate the position of the mentioned dynamic entities with respect to a reference point [14]. With this method, the update rate of localization information is mainly determined by the number of tags to be tracked and theirs blinking duty cycle, leading to the energy optimization of the IPS infrastructure.

2.2. Industrial applications of indoor positioning systems for health safeguard

Modern manufacturing systems operate at a fast pace and many generally are distinguished by several interdependencies between multiple processes. Human operators still play a central role in such environments despite the adoption of automation [15]. Thus, the safety management aimed at safeguarding the health of operators represents a pivotal role in modern factories. According to this, IPSs are seen as a source of opportunity due to their ability to dynamically track whichever industrial asset. Different frameworks are proposed to exploit indoor positioning raw data providing enhanced visibility and traceability to whichever manufacturing process and entity [16]. While the monitoring of human activities may arise privacy issues, the adoption of proper approaches enable to fully safeguard the rights of workers producing positive externalities for their health [17]. For this purpose, Löcklin et al. [18] propose a quantitative model to predict in the short-term time horizon the location of workers to avoid dangerous collisions with automated guided vehicles. Benefitting from the Bluetooth low energy communication module, Zao et al. [19]

developed a tracking model to speed up the responsiveness of rescuing injured workers. The proposed algorithm notifies to the qualified personnel of prolonged motionless activities through appropriate warnings. The dynamism of IPS provides the possibility to target the same purpose by monitoring other industrial assets. For instance, Sun and Ma [20] tagged forklifts to evaluate the safety of the monitored storage system. The monitoring of forklifts accesses in restricted areas enables the management to redefine material flows within the system in order to prevent accidents. Considering the COVID19 outbreak, the experience gained in IPS applications to safeguard the health of workers lead to the development of robust indoor CT architectures. Upon acquired structured raw data, algorithms quantitatively detect and thus notify ex-post infective contacts and mass-gatherings between workers in the workplace over the shift [21]. Hence, there is a lack of applications aimed at proactively evaluating ex-ante the riskiness of any interaction between individuals in the workplace over the shift.

3. COVID19 transmission risk index

While national health authorities distinguished between risky and non-risky human interactions for COVID19 transmission, this section aims to extensively and analytically describe an original risk index upon which the safety against COVID19 spread in indoor working environments is evaluated. The developed CRI provides targeted and straightforward information on two distinctive levels. At first, it is evaluated the PRI for whichever human operator during relevant working interactions. Assuming g individuals, the PRI evaluates any contact that occurred between couples of them. Since the pathogen transmission takes place not solely on large and isolated droplets, Tab.1 associates to the specific i ranges of distances assumed between 2 workers different degrees of contagion risk [22].

Table 1. Contagion risk associated to ranges of distances.

i	Range of distance (m)	Risk index weight (r_i)
1	D<=0.4	1
2	0.4< D <=1.2	0.75
3	1.2< D <=1.7	0.5
4	1.7< D <2	0.25

However, to properly evaluate the riskiness of human contacts the temporal dimension has to be considered as well. For this purpose, the total time of the $d-th$ interaction occurred between the individuals g' and g'' ($T_d^{g',g''}$) is equal to the sum of the partial times ($t_{i,d}^{g',g''}$) spent by the working couple in a specific range of distance i. Consequently, $t_{i,d}^{g',g''}$ can also be expressed as the percentage of time ($w_{i,d}^{g',g''}$) spent in the aforedescribed $i-th$ range of distance. According to the outlined parameters, the risk of whichever interaction occurred $g'$and g'' is expressed in the following equation.

$$R_d^{g',g''} = \frac{\sum_{i=1}^{4}(w_{i,d}^{g',g''} * r_i) + \overline{RD_d^{g',g''}}}{2} \tag{1}$$

Where $\overline{RD_d^{g',g''}}$ defines the risk connected to the mean distance registered during the $d-th$ interaction ($\overline{D_d^{g',g''}}$). According to Tab.1, $\overline{D_d^{g',g''}}$ equal to 1.5 meters provides r_i and thus $\overline{RD_d^{t',t''}}$ equal to 0.5. The $R_d^{g',g''}$ computed through an arithmetic mean assigns to $\overline{D_d^{g',g''}}$ and $w_{i,d}^{g',g''}$ the same relevance. Despite the countless way in which individuals may interact, this framework considers relevant and infective contacts all the d interactions with a $T_d^{g',g''}$ not lower than 20 seconds as outlined by [23]. While the proposed equation (1) evaluates the COVID19 infection risk for whichever $d-th$ interaction between couple of colleagues, the second level of the analysis aims to assess the degree of safety of whichever indoor working environment. Considering the attention drawn by mass-gatherings which may result in super spreading events, this analysis takes into account clusters of workers. Given a set of individuals, they belong to the same cluster whether at least each one is spaced less than 2 meters apart from one of the others [7]. After having detected in specific timeframes the cluster composition, this risk index proposes a quantitative analysis about the occupancy load (OL) of the monitored clusters. For this purpose, it is assumed that individuals conceptually occupy 1-meter radius circles. The OL of each cluster is given by the total area defined by the circles' intersection divided by the number of individuals detected inside this region. Similarly, to the first level of the proposed analysis, tab.2 defines the contagion risk (s_j) connected to each j-range of OL according to [24].

Table 2. Contagion risk associated to ranges of occupancy loads (OL).

j	Range of OL (m^2/p)	Risk index weight (s_j)
1	OL<1.7	1
2	1.7<= OL <2.1	0.8
3	2.1<= D <2.5	0.6
4	2.5<= OL <2.9	0.4
5	2.9<=OL<=3.1	0.2

Considering the cluster analysis, the temporal dimension contributes to define the degree of risk of the monitored mass gathering. In this regard, as long as the composition of the cluster does not change, these timeframes define the total interaction time inside the $m-th$ cluster (T_m^c) during $c-th$ time window. Trivially, the sum of each partial time ($t_{j,m}^c$) spent by individuals in the aforementioned j-occupancy load ranges is equal to T_m^c. Furthermore, $t_{j,m}^c$ can be also expressed as the percentage of time ($w_{j,m}^c$) spent into a specific bound of occupancy loads. Hence, the risk of infection of a set of individuals grouped in $m-tj$ cluster during the $c-th$ time window (R_m^c) can be defined as follows.

$$R_m^c = \frac{\sum_{j=1}^{5}(w_{j,m}^c * s_j) + \overline{ROL_m^c}}{2} \tag{2}$$

Where $\overline{ROL_m^c}$ defines the risk connected to the mean occupancy load ($\overline{OL_m^c}$) of the $m-th$ cluster during T_m^c. According to Tab. 2, $\overline{OL_m^c}$ equal to 2.7 m^2/p results in a s_j and hence $\overline{ROL_m^c}$ equal to 0.4. The R_m^c is calculated through the mathematics mean for the same reason described for $R_d^{g',g''}$.

4. SHIELD4US architecture

Having as a reference the developed CRI, this section describes the original HW, and SW architecture developed to perform an effective COVID19 spread prevention in indoor manufacturing environments.

4.1. Hardware architecture

The developed HW infrastructure is composed of two macro entities. The six ANs deployed at know positions and the anonymous tags worn by the monitored workers. On one hand, the mentioned reference points are installed on the ceiling at 7 meters height approximately. Each anchor is based on a Raspberry 3 along with a Decawave DWM1001 UWB radio.

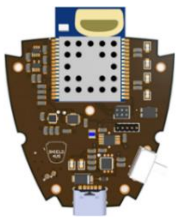

Fig. 1. Configuration of the wearable sensor.

While ANs are synchronized and connected using the Wi-Fi connection, the acquired data are shared and then stored in a spatial database exploiting the MQTT protocol. According to this, the engineered system can be straightforwardly retrieved and managed also by remote accesses. On the other hand, the wearable sensor depicted in Fig. 1 is based on a nRF521 low-power MCU from Nordic Semiconductors with integrated Bluetooth functionalities. The MCU is then connected using SPI communication protocol to a DMW1000 module, a fully integrated single chip UWB low-power and low-cost transceiver IC, compliant to IEEE802.15.4-2001 standard. The outlined modules are commercially available in a compact SoM developed by Decawave. Finally, the tag integrates a LiPo battery charger and a buck power module to provide a stable power stream to the moving sensor.

4.2. Software architecture

Different MATLAB executable files mines acquired data from the adopted IPS to prevent the COVID19 transmission in indoor working environments. Data acquired from the UWB-based IPS are filtered through a median filter and a 2D constant velocity Kalman filter. Once processed, raw data with an accuracy of 35 cm and an average sampling time of 0.15 seconds are stored in a spatial database where each row represents a 2D time-dependent spatial location in metres (P_f^t) by each $g-th$ tag, worn by workers, during the $f-th$ timeframe recorded. Based on these data, a novel heuristic diagram is proposed to prevent the COVID19 transmission in whichever manufacturing system (Fig.2). In the preliminary step is computed the Euclidean distance between simple combination of the $g-th$ tag. Then, the analysis is structured on two distinctive levels. In line with the outlined CRI, the first step takes into account the PRI while the second one performs the cluster analysis. Starting from the PRI, at first it is evaluated the local risk of infection for any relevant $d-th$ interaction occurred over the shift. In particular, the duration of each $d-th$ interaction is given by the sum of all $f-th$ timeframes in which the distance between simple combination of tags is lower than 2 meters. Hence, it is computed $R_d^{g',g''}$ for any relevant interaction over the shift between workers. However, any monitored employee may interact with several others during the same $d-th$ interaction. For this purpose, the subsequent stage assesses the global risk of infection for each $g-th$ worker (GR_g) having as input the respective local risks $R_d^{g',g''}$. Plant supervisors can analyse, fulfilling all privacy requirements, GR_g and the distinctive $R_d^{g',g''}$ for whichever worker or simple combination of colleagues at the end of the shift, to assess preventively the COVID19 infection risk both at personal and global level and consequently implement corrective actions. On the second level, the safety of the considered shop floor is evaluated through the cluster analysis. Starting from the already performed Euclidean distances between simple combination of tags, each worker is allocated to a specific cluster. A cluster is a dynamic collector of tags that are characterized by a 2D geometrical position in a specific timeframe. For this purpose, timeframe over timeframe workers are allocated to clusters. The developed framework considers valid clusters which group at least two tags. The $c-th$ time window of any $m-th$ cluster lasts as long as the workers contained do not change. The centre of gravity of the $c-th$ time window for the $m-th$ cluster is computed having as input the f centres of gravity related to each frame. The obtained centres of gravity for each c time window are assigned to the dimensioned a sub-areas of the monitored job shop which have a plan area equal to 1 m^2. According to this, it is straightforward to evaluate for any m-cluster the relative visiting frequency connected to each a-area (vf_a^m) as proposed by (3).

$$vf_a^m = \frac{\sum_{c=1}^{C} x_m^{c,a}}{\sum_{a=1}^{A}\sum_{c=1}^{C} x_m^{c,a}} \tag{3}$$

Where $x_m^{c,a}$ is equal to 1 whether the centre of gravity of the $c-th$ time window belongs to the sub-area a, and 0 otherwise. However, high relative visiting frequencies over the shift are not necessarily related to worrisome chances of infection. For this purpose, it is evaluated R_m^c for any $m-th$ and $c-th$ time window. Benefitting from the centres of gravity computed for each valid cluster and defined time window, whichever R_m^c can be univocally related to a point and thus an a sub-area of the job shop. Furthermore, it may occur that the same cluster may take place in the same area over different time windows. Indeed, multiple R_m^c are connected to the same sub-region. The COVID19 riskiness of infection for each area and cluster is evaluated as it follows.

$$r_a^m = \frac{\sum_{c=1}^{C} R_m^c * x_m^{c,a}}{\sum_{c=1}^{C} x_m^{c,a}} \tag{4}$$

At managerial level, a dedicated dashboard displays cluster per cluster the vf_a^m and the r_a^m of the sub-areas. The proposed software is not limited to displaying follow-up information on potentially infective contacts among colleagues, but it may reduce the COVID19 work injuries while maximizing in-plant productivities.

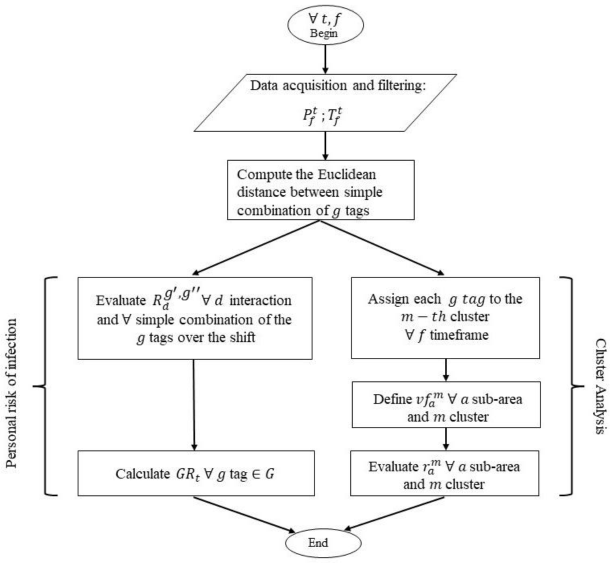

Fig. 2. Heuristic diagram of the SHIELD4US software architecture.

5. Case study

The SHIELD4US architecture is adopted to prevent the COVID19 transmission in a manufacturing plant located in the North of Italy which performs mechanical operations for the automotive industry. While the displacement of six ANs covers an area equal to 225 m^2, the involved operators wear an anonymous tag in a runner armband. Before starting the experimental campaign, several examples of raw data and outputs were shown to final users. The operators were fully complaint to be tagged given the focus of the architecture on preventing the COVID19 transmission and thus absenteeism. In addition, GDPR privacy modules were signed by each tracked operator. The workers perform loading and unloading activities in two stand-alone machines and set productive cycles in two automatic lathes (AL). Based on the SW architecture, the degrees of COVID19 safety are evaluated. On one hand, since the assignment of tags to human operators is random, the plant supervisors cannot univocally relate the PRIs to workers. However, employees achieve a quantitative measure of their COVID19 exposure during the working shift. On the other hand, the management has privileged insights on the most visited and risky zones of the considered job shop. This framework generates two consistent competitive advantages. At first, whether a positive COVID19 case is detected only its shift colleagues most exposed at COVID19 contagion may be effectively tested and, hence, quarantined. Secondly, the management might redesign the job shop layout in order to preventively safeguard the health of human operators.

6. **Results & Discussion**

This section presents the results obtained adopting the SHIELD4US digital architecture for the considered case study. The analysis to prevent the COVID19 transmission in the aforementioned real case study provides different degrees of detail. At first, $R_d^{1,2}$ is evaluated for whichever relevant $d-th$ interaction between the monitored workers throughout a shift. Fig. 3 depicts the dynamic values of $R_d^{1,2}$ from 10:15 to 10:30 on the 7th of December 2021. Furthermore, the proposed plot outlines the different percentages of time ($w_{i,d}^{1,2}$) spent into the four ranges of meters for any relevant interaction detected. What is worth noting is that $R_d^{1,2}$ values are affected by both $w_{i,d}^{1,2}$ and $T_d^{1,2}$. For instance, despite $T_1^{1,2}$ and $T_3^{1,2}$ are equal to 55 and 120 seconds respectively, $R_1^{1,2}$ is markedly greater than $R_3^{1,2}$ due to higher percentages of time spent into the riskiest bound of meters. Plant supervisors can autonomously set the time window through a dedicated and user-friendly slider in the proposed software in order to exploit the most unsafe period of the analyzed shift. On an aggregated standpoint, the GR_g static value for whichever g worker are evaluated. Since the monitored case study involves solely two operators, they share the same GR_g over the shift which is equal to 0.526. Secondly, the cluster analysis is performed to detect mass-gatherings of two tagged colleagues in the job shop throughout the shift. According to the outlined heuristic diagram, the visiting frequencies (vf_a^m) at the detail level of single sub-area a are evaluated. Overall, as expected, the vast majority of aggregation of colleagues takes place on the sub-areas adjacent to the two stand-alone machines in which workers performs loading and unloading activities and along routes to replenish raw parts or temporary store in stock keeping unit finished goods. In this region occurs also the highest visiting frequency of the entire job shop.

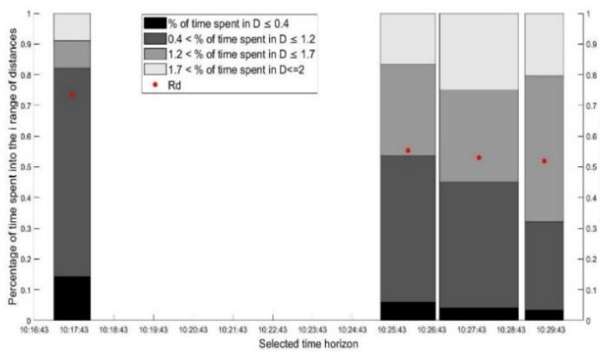

Fig. 3. $R_d^{1,2}$ values from 10.15 to 10.30 on the 7th of December.

In particular, the 58th sub-area which range from 2 to 3 meters and from 3 to 4 meters in the x and y axis respectively, has a vf_{58}^1 equal to 0.26. However, not necessarily the most visited areas are related to worrisome risks of infections as depicted in Fig.4. For instance, while the f_{147}^1 is equal to 0.0018, the risk of infection connected to the mass-gathering of the 147th area (r_{147}^1) next to the AL is the highest registered and it accounts for 0.8. Compared to r_{58}^1 which is equal to 0.36, r_{147}^1 is dramatically higher. Despite the r_a^m and f_a^m values serve different purposes, their combination may be extremely useful at the managerial level. On one hand, the relevant r_a^m values registered in the material storage next to the stand-alone machines not lower than 0.2 may be effectively reduced by designing worker-dedicated material storage apart from each other. The same approach may be applied to the distance between the stand-alone machines. On the other hand, the widely adopted visual management approaches should encourage best practices related to COVID19 with a privileged attention to mind the distance between colleagues. This may dramatically reduce high r_a^m in areas hardly visited during the shift as seen for the 147th. Finally, since the multitude of parts to be manufactured in this job shop may be stored in different positions by forklifts, the coloring pattern of the following figure may vary from shift to shift.

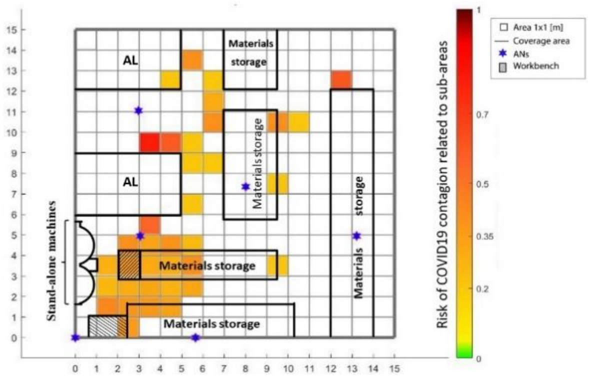

Fig. 4. Risk of COVID19 infection r_a^1 in the job shop from 7.00 to 14.00

7. Conclusions & further research

This paper proposes an original digital architecture aimed to prevent the COVID19 transmission in whichever indoor manufacturing shop floor. The UWB-based HW is developed to track any dynamic position assumed workers during the working shift. Data acquired by the adopted IPS feeds the SW part to evaluate the degree of safety of the monitored setting upon two distinctive levels. For this purpose, a novel heuristic diagram is proposed to analytically assess the global and local PRI and the most visited and risky zones cluster per cluster. The consistency and the resilience of the aforementioned architecture is tested in a real and operating manufacturing job shop. The yielded outcomes provide a structured path to safeguard the health of human operators over the working shift. Further research should include in the CRI the impact of the airborne transmission in COVID19 infections. For this purpose, the environmental parameters may be dynamically monitored through adequate internet of things sensors. Finally, the UWB tag may be equipped with a three-axis magnetometer to assess the orientation of any interaction.

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