Indoor positioning systems to digitalize manual production processes

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Abstract: Modern manufacturing companies operate at fast pace and their processes presents several in-plant interdependencies. In addition, human operators still play a pivotal role in particular for scenarios in which automation is not feasible or economically viable. Therefore, consistent decision-making processes are needed to reinforce in-plant performances at targeted levels. In this scenario, traditional tools of analysis are no more adequate to monitor such complex and variable environments. Recently, different digital technologies have been developed to acquire insightful and structured datasets of manufacturing processes. Among them, indoor positioning systems have gained interest due to their ability to accurately track any tagged moving asset within a certain coverage area. This paper proposes an original hardware and software architecture to autonomously and quantitatively monitor labor intensive job shops. The hardware consists in an Ultrawide-band based indoor positioning system, where tags are assigned to workers. The software counterpart leverages the acquired spatial and temporal data to enhance the visibility of production processes into different levels. On one hand, an automatically evaluated from to chart defines the rate of dependency among the geofenced areas of the job shop. Times spent within the storage areas are computed to evaluate the impact of replenishment routes for each worker. On the other hand, a Gantt chart displays times spent in each area along with the visiting sequence. By selecting a time interval equal to the cycle time of the job shop is possible to visualize how working times are divided into the different areas. From these valuable outputs, a re-layout of the entire job shop may be suggested and identified to increase the productivity of the process. The consistency and the resilience of this digital architecture is tested in a real manufacturing job shop which performs manual and automatic machining for the automotive industry.

Keywords: Indoor positioning systems, manufacturing re-layout, in-plant performances, manual processes, human factor

I. INTRODUCTION

In modern and globalised markets, manufacturing companies operates at fast pace and their processes present an increasing amount of internal and external interdependencies [1]. Therefore, long before the COVID19 pandemic, manufacturing companies were leveraging Industry 4.0 technologies to be more resilient to changing market conditions and increase their productivity [2].

In this scenario, automated machines and collaboratives robots have progressively replaced humans in performing repetitive and dangerous tasks. Consequently, human operators play a pivotal role in fulfilling experienced and extremely value-added tasks [3]. A relevant target of such labour-intensive industries is to smooth the mutual collaboration between automated resources and workers. Although automated processes are measurable and predictable through quantitative methods, the management of human centred production processes is usually a challenging task [4]. Hence, traditional tools of analysis along with a decision-making process solely based on personal experience are inadequate to reinforce required in-plant operational efficiencies [5].

The demanding need of structured datasets resulted in ubiquitous adoptions of another core digital solution brought by the fourth industrial revolution, e.g., Industrial Internet of Things (IIoT) technologies. As Internet connected devices, these heterogeneous sensors allow to collect and analyse vast amount of data in complex and variable manufacturing processes [6]. In particular, an accurate indoor positioning information of industrial assets have gained a tremendous importance in the latest years in manufacturing environments. While the Global Positioning System is mostly underperforming in non-line-of sights (NLoS) settings, indoor positioning systems (IPS) meet the requirement to accurately track industrial assets within an indoor coverage area defined by the displacement of anchors (ANs) at known positions of the production layout. For this purpose, different IPS-based framework were proposed in the manufacturing industry. Among all the possible applications, quantitative and automatic monitoring of in-plant performances gained relevant interest in different scenarios [7]. For instance, Tran et. al [8] described a valid path to increase the consistency and the reliability of the traditional lean management tools (e.g., spaghetti chart, value added working times, process traceability, etc.).

Considering the current trend of industries to shift the decision-making process towards data analysis, this paper proposes an original hardware (HW) and software (SW) architecture aimed at providing quantitative hints on labour intensive manufacturing job shops. While the adoption of IPS to monitor in-plant manufacturing operations is a research area deeply investigated, few contributions targets the monitoring of human operators working task. For this purpose, the HW part consist in an UWB-based IPS where workers wear in the preferred upper arm an anonymous tag. The SW counterpart leverage positioning data to provide two major quantitative outputs. First, a from to chart defines the rate of interdependencies among areas of the job shop. This key performance indicator is further narrowed to analyse the working patterns in the material storage areas. Second, a Gantt chart exploits the operator visiting sequence of job shop areas for any time window. Therefore, the main focus of this research is to perform an activity segmentation process of the working routine of human operators upon which, if necessary, trigger a re-layout of the entire job shop. By doing so, plant workers would be in the best conditions to perform their manual tasks in fast and dynamic production environments. The section 2 describes the operative functioning of the IPS along with their industrial applications to monitor in-plant manufacturing performances. Subsequently, it is outlined the developed digital architecture to enhance the visibility of manual production process (Section 3). Here, two dedicated subsections present the HW and SW architectures, respectively. Section 4 describes the real case study where the developed digital architecture is tested and thus validated. The obtained results bundled with an extensive discussion are outlined in the Section 5. Finally, Section 6 ends this work with the conclusions and further research opportunity.

II. Literature review

This section introduces different configurations of the IPSs along with geometrical methods to determine the tag position. Subsequently, different IPS-based manufacturing applications are investigated.

A. *Indoor positioning systems state of the art*

Over the few last years, different working industries developed the need to exploit indoor positioning information of their strategic assets. In such NLoS scenarios, the global positioning systems is mostly underperforming due to the obstructed direct connection between transmitters and receivers. Therefore, IPS were largely adopted in indoor settings to enhance the visibility of industrial processes [9].

Based on specific requirements, different means of short-range communications were proposed such as Ultrasonic ranging, Radio Frequency positioning, infrared radiations etc. Among them, Radio Frequencies technologies represent the most suitable solution for indoor environments mainly due to lower interference potential and large penetration power [10]. In addition, there are different protocols of communications distinguished by set-up requirements along with strengths and weaknesses. Although the Ultrawide-band (UWB) technology requires a dedicated hardware infrastructure, it is currently one of the most adopted solutions for its precise positioning accuracy (up to 30 cm). This is provided by a bandwidth at least equal to 500 MHz which prevent interferences with other systems and yield higher multipath resolutions [11].

In the UWB positioning systems, the geometric methods most commonly adopted to determine the unknown position of tags are the Received Signal Strength Indicator (RSSI), the Angle-of-Arrival (AoA), the Time-of-Arrival (ToA) and the Time-Difference-of-Arrival (TDoA) [12].While AoA accuracies decrease with increases in distances between tags and ANs and ToA has poor positioning accuracies in NLoS environments, the TDoA best meets the requirements to simultaneously track multiple tags. The TDoA exploits the distance between tags and ANs based on the signal propagation time. For a successful positioning estimation, this method requires at least three online ANs upon which determine the position on the tag based on the intersection of hyperbolas [13].

Despite the multitude of sectors (e.g., healthcare) were IPS are adopted, the following subsection outlines the adoption of such technologies to monitor industrial processes and thus reinforcing at target levels in-plant performances.

B. *Industrial applications of indoor positioning systems for process monitoring*

Over the last few years, the crescent need to enhance the visibility of manufacturing processes have resulted in vast adoption of different communication protocols of IPS in manufacturing environments. The area of applications in production and logistic can be broadly grouped into quality and safety management, and efficiency monitoring [7]. For the manufacturing processes in which the role of workers is still pivotal, the aforementioned applications have a strong interest. Although the process of tagging human operators gained little attention compared to other industrial assets, the scientific research offers different contributions to monitor in-plant performances through specific IPS hardware architectures [11].

In such scenario, Gladysz et. al [14] benefitting from an UWB-based IPS tagged several forklifts to develop a dynamic spaghetti chart within the monitored system. Adopting a dynamic approach for monitoring forklifts provide several benefits to the decision-making process. For instance, while abnormal movements of forklifts are evaluated identifying the root causes, the utilization rate of resources and docks are quantitatively assessed. This dynamic and quantitative approach provides a structured path to the management to implement corrective actions to the scheduled scenario. Furthermore, in production settings, heterogeneous set of products (e.g., raw materials and WIP) can be tagged. In addition, to the unique ID each tag may store other information such as the type of product and the belonging batch. This approach provides a substantial competitive advantage at the production level. Dynamic and quantitative key performing indicators reflect under different viewpoints the efficiency of the ongoing process. This allows to detect bottlenecks and unexpected deviations from the planned state of the production process. Based on these quantitative outputs, the management achieves a better visibility on the monitored process and if necessary, modify the scheduling in terms of batches to be manufactured. Therefore, the optimal scenario is validated upon the quantitative data acquired by the adopted IPS [15][16]. A similar approach to reduce downtimes in production environments is proposed by Kelepouris et. al [17]. Considering that manufacturing environments typically deals with limited number of resources, several shared tools were tagged to reduce human operator searching times. The adoption of an IPS resulted in a daily saving time equal to 80 minutes to search six different tools. Although the mentioned quantitative approaches provide a valid path to enhance the visibility of manufacturing processes, in the literature there are few contributions aimed at achieving the same purpose by tagging human operators. Therefore, this paper proposes an UWB-based IPS HW architecture where the productive tasks of workers are anonymously monitored during the shift within an operating job shop. Subsequently, the SW counterpart leverages the acquired time-dependent geometrical data to generate quantitative metrics to improve the knowledge and efficiency of the monitored industrial process.

III. Digital Architecture

This section describes the developed HW and SW architecture to quantitatively and automatically analyse manual production processes.

A. Hardware architecture

The engineered HW architecture constitutes of distinctive components based on commercial Decawave modules. The six ANs has to be displaced in the ceiling of the monitored area at a height approximately between 3 and 7 metres. These reference points are based on a Raspberry Pi 3 along with a vertically polarized Decawave DWM1001 UWB-based radio technology. The outlined network is synchronized and connected exploiting the Wi-Fi. In addition, benefitting the MQTT protocol, acquired data are stored in a spatial database. Based on this network configuration, the entire infrastructure can be remotely accessed and managed. The tags worn by workers on the preferred upper arm in a runner armband (Fig. 1) represent the other main key component of the architecture. The anonymous sensor, developed by Nordic Semiconductors and powered by a LiPo, is based on a nRF521 low-power MCU with Bluetooth connectivity. Then, the MCU is connected through the Serial Peripheral Interface (SPI) communication protocol to a DMW1000 module. This module, compliant to IEEE802.15.4-2001 standard, is a fully integrated single chip UWB low-power and low-cost transceiver IC. At the end of the shift positioning data are downloaded in csv format and thus leveraged by the advanced algorithms that are extensively outlined in the following subsection.

Fig. 1. Tag worn by a worker

B. Software architecture

The SW architecture, developed in MATLAB R2021a executable files (.exe), leverages data acquired by the UWB-based IPS as depicted by the heuristic flow diagram in Fig. 2. For simplicity, the flow diagram is divided into three main steps. The first one evaluates any entrance and exit in strategic areas of the monitored layout for each active tagID. Once acquired, the positioning data for each t-th tag during the f-th frame (P^t_f) are filtered through a median filter and a 2D constant velocity Kalman Filter. Trivially, to each P^t_f raw array is related a specific timestamp T^t_f. This reliable and structured dataset has an average sampling time over the shift equal to 0.15 seconds. Subsequently, the monitored job shop has to be divided into N areas. Each n-th area (a_n) is either a regular or irregular polygon with known 2D vertices. At this point, the algorithm checks, for each t-th tag and f-th frame, whether P^t_f belongs to the n-th area with respect to the i-th visiting sequence($a^t_{n,i}$). The i-th visiting sequence groups at least one P^t_f which belongs to the related n-th area. In addition, the index i is incremented if and only if exists at least one positioning location related to a specific area. Once, a 2D geometrical positions is assigned to a specific $a^t_{n,i}$, P^t_f is assigned to the first empty row of the matrix $pa^t_{n,i}$. This matrix stores all P^t_f which belongs to the i-th visiting sequence in a defined n-th area. The same procedure is applied to determine the array of the timestamps related to the i-th visiting sequence for the t-th tag in a specific n-th area ($ta^t_{n,i}$). Trivially, $pa^t_{n,i}$ and $ta^t_{n,i}$ have the same length if the indexes upon which are subjected assume the same value.

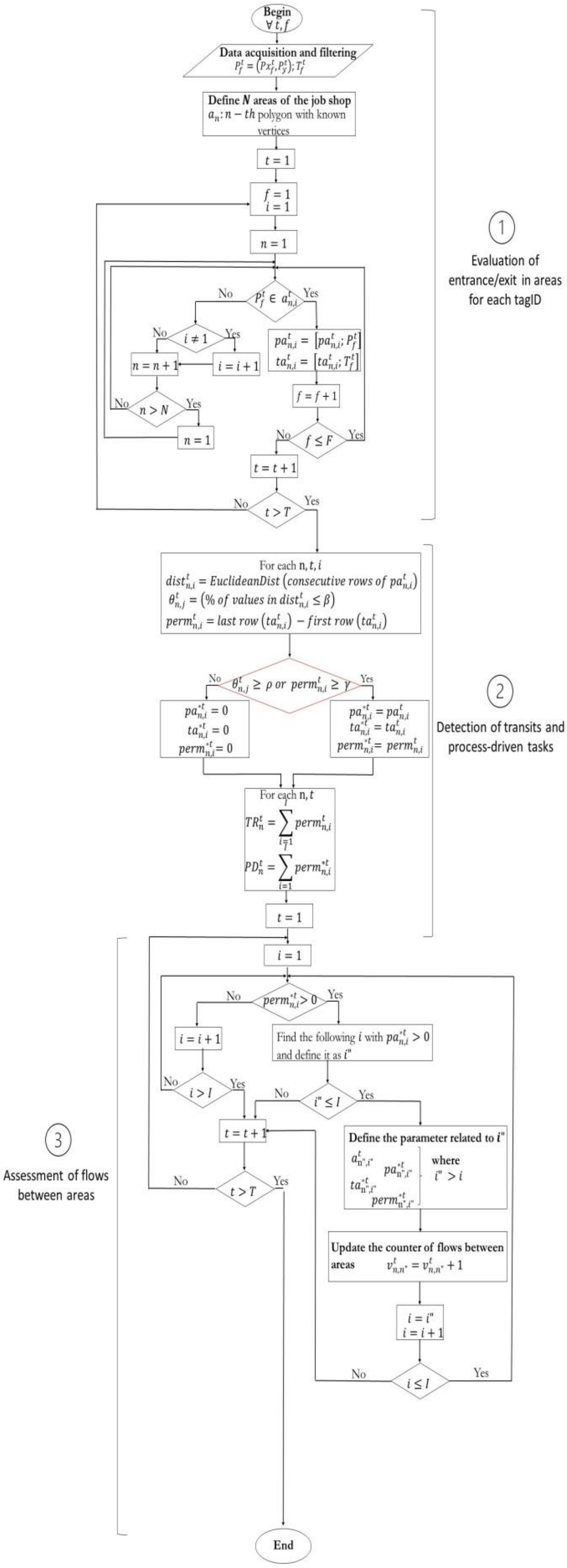

Fig. 2. Heuristic diagram of the software architecture

After assigned all P^t_f to the respective $a^t_{n,i}$, the second step of the flow diagram groups the visiting sequences into two categories. In this regard, the Euclidean distance is computed among consecutive rows of $pa^t_{n,i}$ for each i-th visiting sequence and t-th tag ($dist^t_{n,i}$). Of course, $dist^t_{n,i}$ is a real array with one row less than the respective $pa^t_{n,i}$. In each array of $dist^t_{n,i}$, it is evaluated the percentage of values ($\theta^t_{n,i}$) lower than a given threshold in meters (β). In addition, from each $ta^t_{n,i}$ is assessed the time spent during the i-th visiting sequence inside the n-th area ($perm^t_{n,i}$) as the difference between the last and the first timestamps of the array. These two introduced parameters, namely $\theta^t_{n,i}$ and $perm^t_{n,i}$, are strategic to assess whether the t-th tag during the i-th visiting sequence solely passed through the n-th area. For this purpose, the red rhombus checks if $\theta^t_{n,i}$ and $perm^t_{n,i}$ are greater than the related percentage (ρ) and unit of time (γ) thresholds. Whether this condition is verified, $perm^{*t}_{n,i}$, $pa^{*t}_{n,i}$ and $ta^{*t}_{n,i}$ are equal to $perm^t_{n,i}$, $pa^t_{n,i}$ and $ta^t_{n,i}$, respectively. Otherwise, the star parameters are equal to zero. Based on this condition-based assignment, the I visiting sequence in a given area is conceptually divided into transits and process-driven tasks. The process driven category groups value-added operations and withdrawal and deposit of materials (e.g., raw and finished). Therefore, comparisons between $perm^{*t}_{n,i}$ and $perm^t_{n,i}$ exploit the relevance of area transits during the working shift. On an aggregated viewpoint, TR^t_n and PD^t_n exploits the difference among the transits and the process-driven tasks for the entire shift.

The final step of the proposed software leverages the parameters in which the i-th visiting sequence does not involve a transit in the n-th area. The target is to determine the number of flows between areas solely for the process-driven tasks. Therefore, given a $perm^{*t}_{n,i}$ greater than zero, the algorithm looks for the following i-th visiting sequence with a time spent inside the n-th area greater than zero as well. To avoid confusion, the second detected $perm^{*t}_{n,i}$ changes its indices from i and n to i" and n", respectively. Of course, i" still belongs to the set I and is greater than i. The same reasoning can be applied for n". After changing the indexing, the relevant parameters are updated accordingly (e.g., $a^t_{n",i"}$, $pa^t_{n",i"}$, $ta^t_{n",i"}$ and $perm^t_{n",i"}$). Finally, the algorithms increases by one the counter of the flows between the area n and n" ($v^t_{n,n"}$). These $v^t_{n,n"}$ form a widely adopted decision-making tool in manufacturing, the from to chart table of material flows handled by human operators in the monitored job shop. Benefitting from the rate of interdependencies among areas, plant supervisors may trigger a re-layout process aimed at placing close to each other areas with the highest $v^t_{n,n"}$.

IV. CASE STUDY

The described HW and SW architecture is validated in a manufacturing company in the North of Italy which performs mechanical operation for the automotive industry. The layout of the monitored job shop is outlined below in Fig. 3. For an effective implementation, six ANs were deployed in the layout at an height of 7 meters to cover a plan area approximately equal to 236 m^2. Before starting the experimental campaign, examples of acquired data and beta quantitative metrics were shown to human operators. In addition, 6 tags with a progressive ID were placed in the shared locker room of the mentioned final users. Therefore, they were able to autonomously wear the choosen tag in a runner armband on the preferred upper arm. Last, to be consistent with the right of privacy, workers were fully compliant to sign GDPR modules due to the anonymous monitoring process the clear target of the experimental campaign.

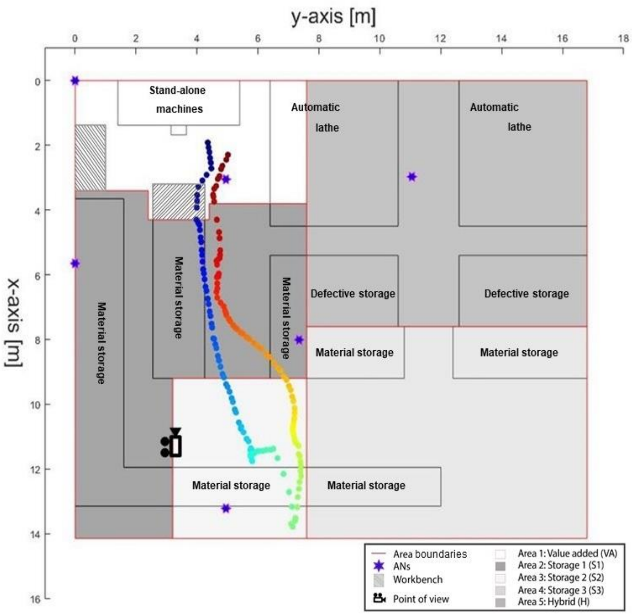

Fig. 3. Time dependent Spaghetti chart in the monitored industrial job shop

As depicted in Fig. 3, the two job-shop dedicated workers per shift perform their tasks in five conceptually different areas. In the value-added (VA) area, human operators perform loading and unloading activities in two stand-alone machines. In addition, two workbenches serve specific purposes in the productive cycle. While the left one is dedicated to manual rectifications, the workbench behind the machines is used for manual deburring. The second area labelled as storage 1 (S1) stores both raw materials and finished goods in dedicated stock-keeping-units (SKU). On the contrary, the third area (S2) solely stocks raw materials. Depending on the batch to be processed, SKUs of raw materials in S2 may be moved by manual transpallet in S1 to reduce the replenishment time. The bottom right area of the layout (S3) stores raw materials and full SKU of finished goods moved by manual transpallet from S1. At the end of the shift, forklifts move these full SKU, depending on the batch, to other in-plant job shops for further processing. The same is true for moving in S1 the batch to be processed. The fifth area (H) is hybrid because it stores defective materials and two interfaces of the automatic lathes (AL) where to set batch-based processing sequences. Since positioning accuracies around the AN of this area are quite underperforming, in this stage of the research was not feasible to further divide H. The time-dependent spaghetti chart in Fig. 3 represents an example of interdependencies between the previously described areas. The different colours associated to each geometrical position represent the temporal sequence from 11:46:27 to 11:46:46 of a manufacturing activity performed by the tagID2 on the 15th of February 2022. In particular, blue and red dots describes the start and the end of the travelling, respectively. Based on the aforedescribed method to detect transits in areas for the I visiting sequences, the relevant threshold are set with respect to this specific case study. The $\theta^{t}_{n,i}$ assess the percentages of values in the respective $dist^{t}_{n,i}$ lower or equal to 0.1 meters (β). In addition, ρ and γ are equal to 31% and 5 seconds, respectively. At this point, the proposed algorithm enhances the knowledge about the travelling activity depicted by the spaghetti chart (Fig. 3). The operator that wears the tagID 2 is detected twice within S1 in the considered 21 seconds. While during the outward travelling $perm^{2}_{S1,i}$ and $\theta^{2}_{S1,i}$ are equal to 2.88 seconds and 7,4%, during the return travelling these two parameters are equal to 4.37 seconds and 27%, respectively. Therefore, these travelling activities are labelled as transit in S1 and their respective parameters (e.g., $perm^{*2}_{S1,i}$, $pa^{*2}_{S1,i}$, $ta^{*2}_{S1,i}$, etc.) are set equal to zero. The same is not valid for the i-th visiting sequence in S2. Here, $\theta^{2}_{S2,i}$ and $perm^{2}_{S2,I}$ are equal to 40% and 8.3 seconds. Indeed, this activity belongs to the process-driven tasks. Considering that S2 stores solely raw materials, the journey of the tagID started in VA to pick-up at greatest two raw materials in S2 to be loaded in one of the stand-alone machines in VA. Consequently, $v^{2}_{VA,S2}$ and $v^{2}_{S2,VA}$ are both incremented by one. To not burden the Fig. 3, the points in VA are only a subset of the actual ones acquired for this replenishment route. Moreover, since different operations are performed in VA, the i-th visiting sequences in this area always verify the red condition in the developed algorithm (Fig. 2). Finally, based on the viewpoint placed in Fig.3, the Fig.4 illustrates the layout of the areas S1 and VA in the monitored job shop. Trivially, each SKU stores a variable number of WIP materials or finished good products related to a specific batch. The other storage areas are similarly designed.

Fig. 4. Layout of the real production job shop from a static point of view

V. RESULTS & DISCUSSION

This section presents the results achieved adopting the proposed digital architecture for the mentioned industrial job shop. With respect to the developed SW part, the analysis provides quantitative metrics to enhance the visibility of the production process with different degrees of detail. At first, from an aggregated viewpoint, two from to chart tables (Table I and Table II) exploit the rates of interdependencies between areas for each tagID from 10:00:00 to 12:30:00 on the 15th of February 2022. These rates are expressed in travelling activities from a given area to a specific one. Of course, both tables have the main diagonal equal to zeros because is physically and conceptually impossible travelling from an area to the same one. In addition, as a reminder, a specific $v^t_{n,n”}$ is incremented by one whether consecutives areas ($a^t_{n,i}$ and $a^{*t}_{n”,i”}$), belonging to the areas n and n” during the visiting sequences i and i", have $perm^{*t}_{n,i}$ and $perm^{*t}_{n”,i”}$ greater than zero. Therefore, since tables are updated solely with flows among areas with the visiting sequences that belongs to the process-drive tasks, they may be not symmetric.

TABLE I
FROM TO CHART OF THE TAGID 1 FROM 10.00.00 TO 12.30.00 ON THE 15TH OF FEBRUARY 2022 [NUMBER OF TRAVELLING ACTIVITIES]

	VA	**S1**	**S2**	**S3**	**H**
VA	*0*	*18*	*0*	*0*	*3*
S1	*20*	*0*	*0*	*2*	*0*
S2	*0*	*0*	*0*	*0*	*0*
S3	*0*	*1*	*0*	*0*	*0*
H	*1*	*2*	*0*	*0*	*0*

Despite the difference in terms of absolute number of flows among the tagID (Table I and Table II), the pattern of travelling activities are fairly similar. It emerges a strong rate of interdependency between VA and S1. This may be also affected by a strong commitment by in-plant workers. For instance, $v^2_{S1,S3}$ equal to 3 flows and $v^2_{S3,S1}$ equal to 4 flows suggest that full SKU of finished goods material are moved from S1 to S3 and replaced by empty ones. The same reasoning may be applied with raw materials and other areas based on what kind of goods stock. It is worth noting that this is solely a hypothesis due to the adoption of one kind on sensor. For this purpose, in these cases may happen also a single picking or deposit of raw materials or finished goods, respectively.

TABLE II
FROM TO CHART OF THE TAGID 2 FROM 10.00.00 TO 12.30.00 ON THE 15TH OF FEBRUARY 2022 [NUMBER OF TRAVELLING ACTIVITIES]

	VA	**S1**	**S2**	**S3**	**H**
VA	*0*	*46*	*1*	*0*	*3*
S1	*47*	*0*	*3*	*3*	*2*
S2	*1*	*2*	*0*	*1*	*0*
S3	*0*	*4*	*0*	*0*	*0*
H	*2*	*4*	*0*	*1*	*0*

However, the developed from to chart are static and thus do not exploit the time-dependent pattern for the occurred visiting sequence. Therefore, to enhance the consistency of the decision-making process the Gantt chart in Fig. 5 exploits the visiting pattern within the different areas of the monitored industrial jobshop from 10:00:00 to 12:30:00 on the 15th of February 2022. Similarly to the previously analyzed $v^t_{n,n”}$, this managerial tool considers solely the visiting sequence with $perm^{*t}_{n,i}$ greater than zero. As depicted in Fig. 5, both tagID spend the vast majority of time within VA. In addition, as expected, the vast majority of flows from VA goes to S1 and then return in VA.

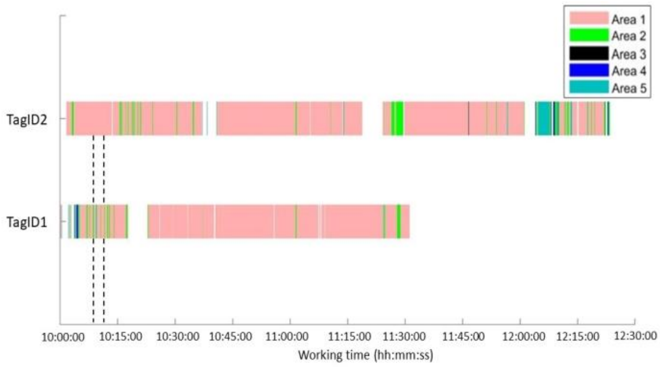

Fig. 5. Gantt chart of workers activities from 10.00.00 to 12.30.00 on the 15th of February 2022

Of course, this tool offers to plant supervisors the possibility to narrow the time window and hence the analysis. Based on the dashed lines in Fig.5, the following Gantt in Fig. 6 depicts the process-driven visiting sequences from 10.08.31 to 10.10.35. Despite it is difficult to assess what activity is performed in a particular region of the job shop, the description of areas and the time spent within them reduce a few the uncertainty. While the flows between VA and S1 suggest a picking or a deposit of material, the flow from VA to H along with a $perm^{*2}_{H,i}$ equal to 12 seconds advise a deposit of defective materials. In addition, the following travelling activities may suggest a picking of raw materials to be loaded in the stand-alone machines in VA.

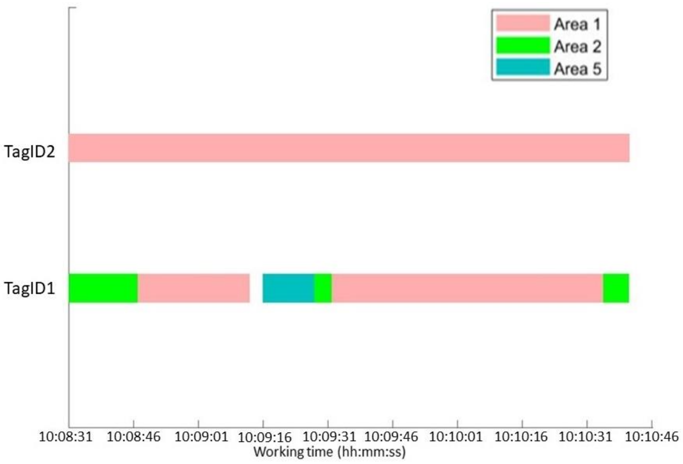

Fig. 6. Gantt chart of workers activities from 10.08.31 to 10.10.35 on the 15th of February 2022

To conclude, plant supervisors may integrate the presented structured output with process data (e.g., pieces manufactured per shift, machines failure, etc.) to achieve a deeper visibility on the process functioning. In this regard, optimization models may be leveraged to quantitatively schedule the batch sequencing and trigger a re-layout process.

VI. Conclusion & Further Research

This paper describes an original digital architecture aimed at monitoring manual production processes. While the HW part acquires time dependent positioning data, the software part leverages values inside them. Therefore, the defined from to chart table of material flows performed by human operators defines the rate of interdependencies between the areas. In addition, the Gantt chart exploits an activity segmentation of workers routines within a selected time window. These outputs provide to decision-making processes a quantitative path upon which trigger a tailored re-layout process. Further research should increase the reliability and accuracy of acquired data in the mentioned underperforming areas with structured tracking filters outlier detection techniques. Besides, a sensor fusion-based approach may be adopted to further reduce the uncertainty of the monitored activities. Benefitting from other parameters, the detection of process-driven tasks would be further enhanced. On the production analysis level, a weighted from to chart for loading and unloading activities and advanced techniques to forecast travelling among areas on the short term may be proposed.

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