Business Process Optimization Using a Real-Time Locating System

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Abstract

Assessing the performance of intralogistics operations and real-time process optimization in manufacturing and warehouse facilities are crucial for promoting lean manufacturing in the fourth industrial revolution (Industry 4.0) context. Excessive travelling, out-of-schedule activities for picking, and inefficient routing are just shortfalls that should be optimized with the use of Information and Communication Technology (ICT) tools. The Internet of Things (IoT) provides technical solutions for monitoring the movement of assets at the facilities, and the development of sophisticated software tools enables the monitoring of intralogistics operations. This research contributes to the digital transformation of intralogistics operations and the interconnection with the physical world using ICT and Business Process Management tools. Specifically, the proposed framework analyzes how real-time locating systems can positively impact critical manufacturing flows: i) material; ii) process; and iii) information. Furthermore, the framework enhances transparency and sustainability. From the perspective of transparency, it interconnects the physical world and the processes of the company while focusing on the sustainability of the social, environmental, and economic dimensions. The social dimension is enhanced by creating a safer working environment for the employees while the environmental and economical dimensions are enhanced by minimizing the travelling distance of the moving vehicles and therefore the total energy consumption.

Keywords
RTLS, Information Technology, BPMN redesign, Operational Optimization, Autonomous Vehicles.

1. Introduction
Internet of Things (IoT) has provided a promising opportunity to build powerful industrial systems and applications by leveraging the growing ubiquity of radio-frequency identification (RFID), and wireless, mobile, and sensor devices (Xu et al., 2014). The Industrial Internet of Things (IIoT) is an innovative technology that accelerates the digital transformation in industries. During the fourth industrial revolution businesses changed dramatically from the perspective of information. While the third revolution focused on introducing automation in industries the fourth industrial revolution seeks new ways to optimize the processes in order to bust competitiveness. The goals of Industry

4.0 is to achieve a higher level of operational efficiency and productivity, as well as a higher level of automatization (Thames & Schaefer 2016). However, the digitization of industries is still in progress and there are several challenges that need to be tackled such as the coexistence of humans among robots, robotic arms and autonomous vehicles. In this direction, Industry 4.0 increases the digitization of manufacturing with Cyber Physical System (CPS), in which connected networks with human and robots interact synergistically (Furukawa & Shida 2015). In addition, the digital connectedness and information development and sharing may have impacts on economic, environmental, and social sustainability pillars (Kamble et al. 2020; Müller et al. 2018). Hence, some researchers elaborate on the deployment of smarter machines, devices and IoT to propose numerous solutions for increased manufacturing productivity, maximization of resource utilization, waste reduction and enhanced human-robot collaboration (Tortorella & Fettermann 2018).

Real-Time Locating Systems (RTLS) are used to localize assets in indoor areas. The primary function of a RTLS is similar to GPS, as it tracks a mobile unit while presenting it on a map with the support of a device that uses wireless signals (Hancock 1998). RTLS can be also used in indoor facility layouts, for following the unit's path. RTLS technology has been introduced in industries as a tool to acquire real-time information about the location of assets, employees, and vehicles. However, there is a connection between their location and the processes performed as within the industrial facilities there are predefined activities in every manufacturing cell and a specific order to execute the activities. A recent research examined how the information provided by a RTLS can be utilized in the digital transformation of flexible manufacturing (Tran et al. 2021). The authors elaborated on how to transform the information sources of value stream mapping and positioning data into key-performance indicators used in Lean Manufacturing.

This work proposes an algorithm that can extract processes by using the assets' historical positioning data. Assuming that a process execution from a specific asset requires its movement around a specific manufacturing cell, and hence at a specific area in the industrial facility, the algorithm can extract information about the processes that each asset executes. In the end, the algorithm was validated through a simulation in the AnyLogic software. The rest of the paper is structured as follows. Section 2 presents a literature review about business process management and the state-of-the-art RTLS implementations towards to automatic process identification in manufacturing facilities while Section 3 presents the developed algorithm and the experiment that was executed for the validation of the proposed algorithm. Finally, conclusions and further steps are presented in Section 4.

2. Literature Review

Business Process Management (BPM) is the discipline that combines knowledge from information technology and management sciences and applies them to operational business processes to create more productive, effective, and cost-efficient operations (van der Aalst 2013). Also, the authors proposed a BPM life cycle which includes three phases (design, implement/configure and finally, execute and adjust). At the first phase (design) the Business Administration (BA) designs a process model based on the theoretical operational flow that has been approved for the development of the final product. Specifically, the BA designs the asset flows that are needed in order to create the predefined process flows and its overarching aim is to evaluate them based on the results from information flows. The second phase (implement /configure) transforms the designed model to make a process model executable while the third phase articulates the procedures for the model's execution and reconfiguration in order to create more effective and efficient operations.

The primary purpose of a business is to maximize profits while maintaining or enhancing corporate social responsibility. In this vein, industries are striving to minimize their costs with regards to the creation of more competitive products. The more complex the product the greatest the need for an optimized BPMN diagram to support industries' competitiveness and effectiveness. An optimization method based on big data analysis has been proposed and the authors state that data analytics could lead to efficient business processes as they tend to (i) optimize the process itself; and (ii) find commonalities in some processes (Li et al. 2019). Also, Massachusetts General Hospital (MGH) tried to optimize surgical equipment delivery with a RTLS tool and they observed that it managed to increase efficiency and save costs for the hospital (Troutner et al. 2020). Furthermore, some researchers analyzed how: (i) a RTLS could provide information about the current state of the production line, and (ii) it can locate the workstations by monitoring the asset flows that are moving around them within the industrial facility (Rácz-Szabó et al. 2020).
The uncertain environment and the continuous changes in customers' demand motivate the use of an optimization framework to optimize their business processes and easily adapt to the dynamic demand that is driven by the

customers' needs. For example, during the COVID-19 pandemic many shortfalls were observed in America since 43% of businesses were temporarily closed and employment had fallen by 40%, while some of the workers called to work remotely and the customers' demand changed dramatically (Bartik et al. 2020). In addition, some have argued that the adaptation of Information Systems is the key to move a step forward from the post-COVID era (Dwivedi et al. 2020). The above-mentioned issues force the use of Information Systems and Digitalization strategies in order to tackle the upcoming challenges.

In case of industries the Process Management is primarily connected with resource (vehicle, asset, and worker) management within the industrial facilities. Thus, the first priority is the optimization of the resources towards the creation of more efficient and effective industrial processes. A recent work shows that indoor positioning data could provide critical information in industries by classifying data points according to the total time spent in each spot in order to identify states and positions (Darányi et al. 2022). The authors state that they were in a position to export information about the utilization of the resources.

We can conclude that, in this constantly changing and demanding industrial environment there is a need for adopting Information Systems that enable fast and reliable business process mapping for effective and efficient business process management and reconfiguration. RTLS is a technology that can provide information that not only addresses real-time tracking issues but could additionally support stakeholders to automatically map their processes. The mapping of the real-world activities can help the BA layer on the business process optimization procedure in order to minimize the travelled distances of the employees, enhance the human-robot collaboration, and maximize the utilization of the resources.

3. Methodology

This section analyzes the proposed system. Firstly, the classification algorithm that can export real world processes based on historical positioning data is presented. Then, to validate the algorithm a simulation with the Anylogic software that demonstrates a real-world industrial environment is presented. Finally, the results about the assets' utilization and the process flows of the assets are analyzed.

The measured positions from the RTLS of each asset are first classified. Assuming that each tracked asset has some recorded historical positioning data that represents the movement of the asset within the industrial facility during the working hours, we can conclude that each point is constructed as follows:

$$P_i(x_i\ ,\ \ y_i), \qquad \mathrm{i}\ =\ 0, \dots, \mathrm{n}$$

where n presents the number of samples for a certain asset that has been recorded and x_i, y_i represent the x and y coordinates of i-th sample. Thus, we need to classify the consecutive points that have a Euclidean distance smaller than the predefined threshold value. Thus, the algorithm creates some clusters based on the movement of the asset. If the asset moves a Euclidean distance, from the center of the latest class, greater than the predefined threshold, the algorithm creates a new class with center the point's coordinates. As cluster is defined as a number of m measurements:

$$Cluster_i = P_k, \dots, P_{k+m} \qquad \mathrm{i}\ =\ 0, \dots, \mathrm{n}_c$$

where n_c is the number of the created classes, k represents the position of the point from which the cluster starts to group the m points that are located within the circle of the defined threshold with the following restrictions k ≥ 0, m > 0 and k + m ≤ n. Assuming that the center of the Cluster is the first point that the algorithm adds in it, the center's coordinates of the cluster are:

$$Cluster_{center,x} = P_{k,x} \text{ and } Cluster_{center,y} = P_{k,y}$$

Thus, all the m samples that belong in the same cluster must satisfy the equation:

$$\sqrt{(Cluster_{center,x} -\ P_{j,x})^2 + (Cluster_{center,y} -\ P_{j,y})^2} \leq\ \mathrm{threshold}_{points}, \qquad \text{for each j in } [\mathrm{k}, \mathrm{k}+\mathrm{m}], m \geq 1$$

After the creation of the clusters the algorithm decides whether the cluster includes a significant number of points. For example, if a cluster has only one or two points it means that the asset just passed through this area while it was moving from one process to another. This has an added value if we are trying to identify the paths that a certain asset is following, for example the path of an employee. From the perspective of the business management the first priority is the identification of the processes, and the algorithm ignores these points and their classes. Thus, the algorithm deletes the classes that have less than a predefined number of points. The drawback of this method is that it provides information only about consecutive measurements, and it doesn't consider the location of the clusters that are identified on the same area. Hence, it creates many clusters at the same area that the asset visits at different time windows. Figure 1 presents the flowchart and the processes that the algorithm executes for the identification of the clusters.

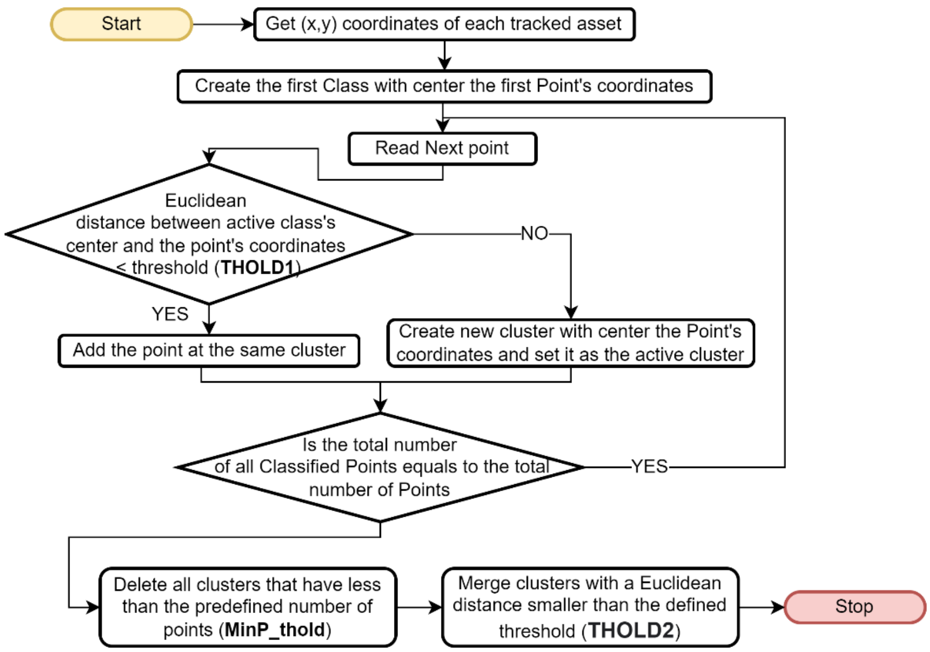


Figure 1. Flowchart of the proposed classification algorithm

Then as a second step, the algorithm merges the clusters that have a Euclidean distance between their centers smaller than the predefined threshold value for the classification of the clusters. This step is important in order to merge the classes that belong to the same industrial area, but the asset visits them at different time windows, which represents a high probability of the same process execution at the same manufacturing cell. Hence, the algorithm assumes that the tracked asset is executing the same process and connects this process with the process that identified first at this point. Thus, the new cluster will contain the points of all merged clusters. With this method, a new problem is created as the algorithm creates some clusters with multiple outputs as each cluster is not connected only with the next cluster. Hence, the second classification will create a multi-flow process diagram where a single process can lead to more than one process. With this technique, the algorithm creates a diagram that has the drawback of missing information about the next process that the asset will execute but creates a clearer representation of the processes that each tracked asset executes.

4. Validation

For the validation of the proposed system, a simulation experiment was conducted. In the experiment, the industrial facility had an Autonomous Ground Vehicle (AGV) and one employee. The vehicle was responsible for the transportation of the part from the arrival area to the machine 1 manufacturing cell, while the employee is responsible for: (i) the transportation of unprocessed parts to machine 1; (ii) the execution of the machinery process at machine 1; and (iii) the transportation of the item at the final station after the completion of the machinery process. Figure 2 showcases the 3d layout of the developed simulation model while in Figure 3 the stations that are included in the procedure are presented. Also, a random positioning error with uniform distribution in the range [-0.2m, +0.2m] is added to each positioning measurement to simulate the localization error of the RTLS hardware. During the execution of the simulation, the AGV and employee positions were recorded with a rate of 10 samples per second while the movement speed of the AGV was set at 1.5 m/s and the speed of the employee at 2 m/s. Moreover, for the first classification of the positioning data the threshold value of 1 meter was used, while for the classification of the clusters (2^{nd} classification procedure) the threshold value of 5 meters was used. Furthermore, for the acceptance of a cluster as a process (last step of the algorithm at Figure 1) a minimum number of 30 points (stay at a point for at least 3 seconds as we set the sample rate at 10 samples/sec) was defined.

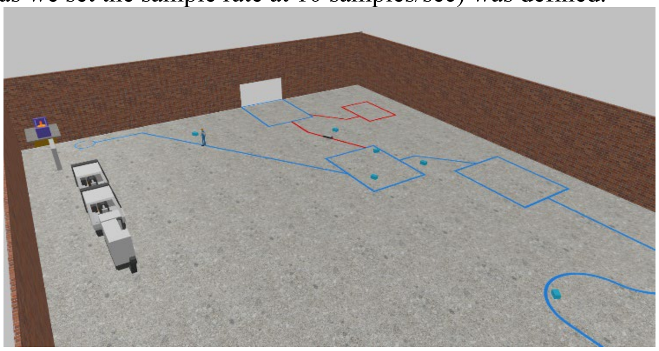


Figure 2. 3D simulation environment of AnyLogic software

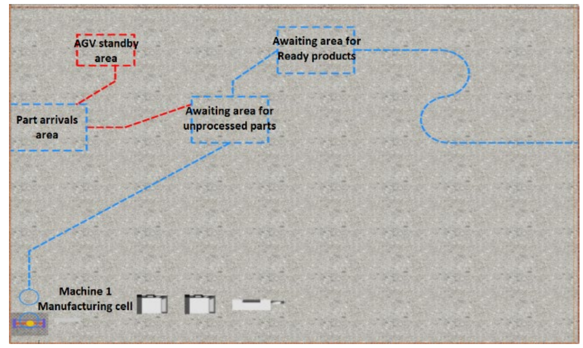
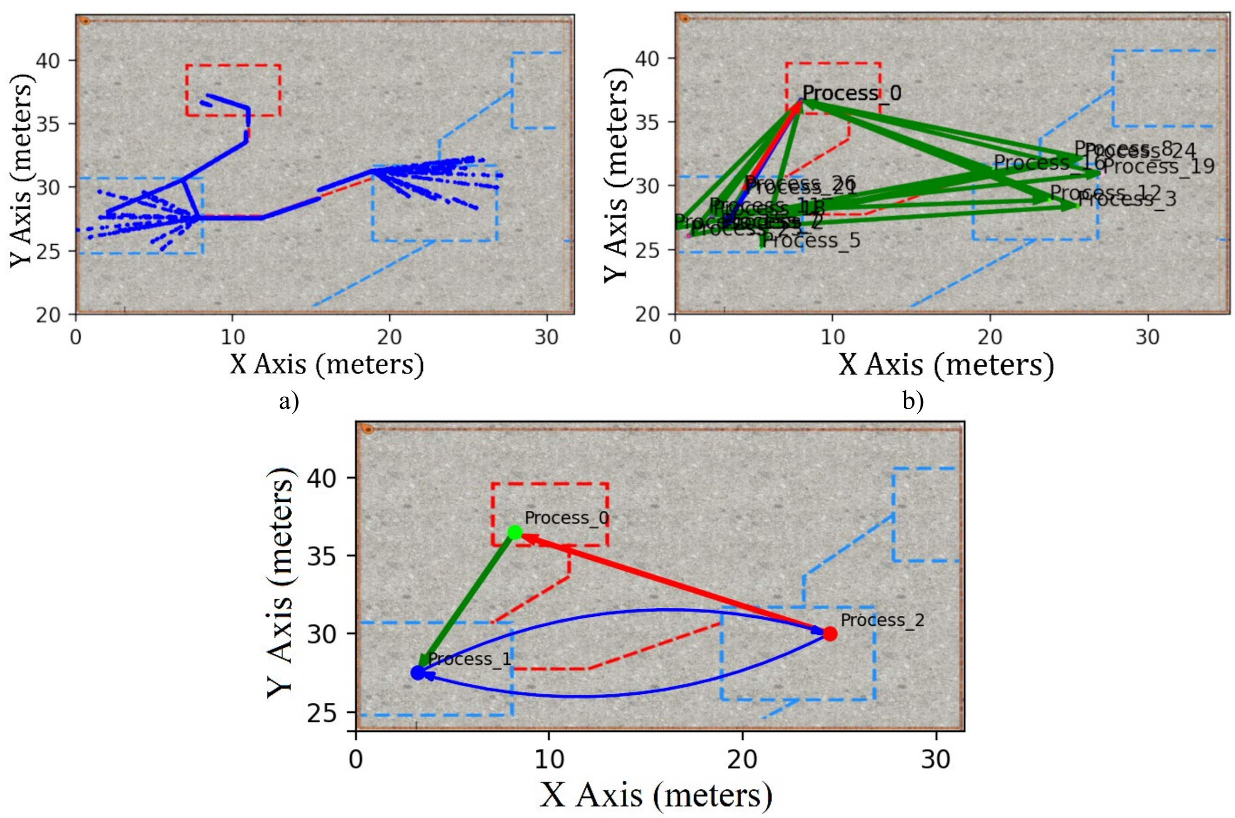


Figure 3. Top view of the industrial area and the available stations

Moreover, the arrival of the first part was set at the simulation time 0 and the simulation was executed in two stages. The first stage ran for approximately 10 minutes for the demonstration of the collected positioning data before the classification (Figure 4a) and after the first classification procedure (Figure 4b). Then the simulation continued until it reached one hour and collect more data for the final classification of the clusters. After the completion of the simulation, only the positioning data of the AGV and the employee were used for the exportation of the below results. It is crucial to state that in this research paper we resent the results for the algorithm's first step separately as the classification led to the creation of many clusters that was not feasible to represent in one image as shown on Figure 4b. Below in Figure 4, the results after the two above-mentioned algorithmic classification procedures are presented and the final diagram with the process flows is showcased (Figure 4c).



a) b) c)

Figure 4. Algorithms clustering results. a) AGV's unclassified positioning data, b) the extracted processes (clusters) from the algorithm after the first classification of the positioning data and c) the final processes that extracted after the classification of the clusters.

After the mapping of the processes the information extraction about the time windows that the tracked asset was occupied on each process is also feasible. Thus, based on the positioning data the algorithm extracts information about the asset's activities and the labor time windows for executing the processes. For example, in case of the AGV the algorithm extracts information about the activity that it executes by splitting the positioning data based on the locations of the extracted processes. The positioning data are splitting into the points that are: (i) outside of the AGV standby area (NOT working on Process_0); and (ii) inside the area. This categorization leads to the plot on Figure 5 that describes when the AGV was occupied. In addition, the algorithm extracts information about the AGV's utilization which in our experiment was measured approximately 64.59%. Thus, the proposed solution provides a complete report about the process flows, while it also provides information about the time that a certain resource was occupied.

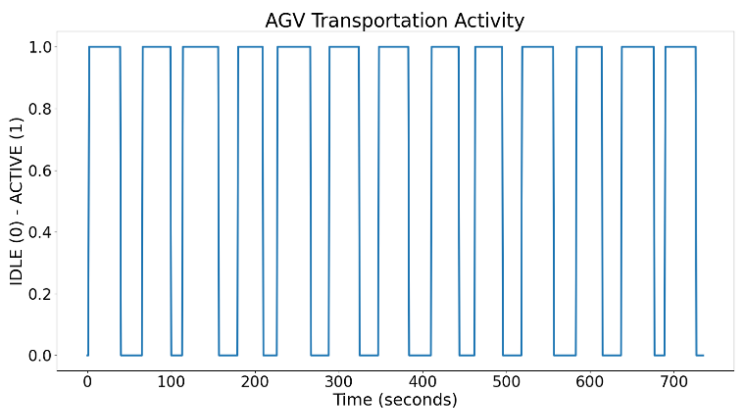
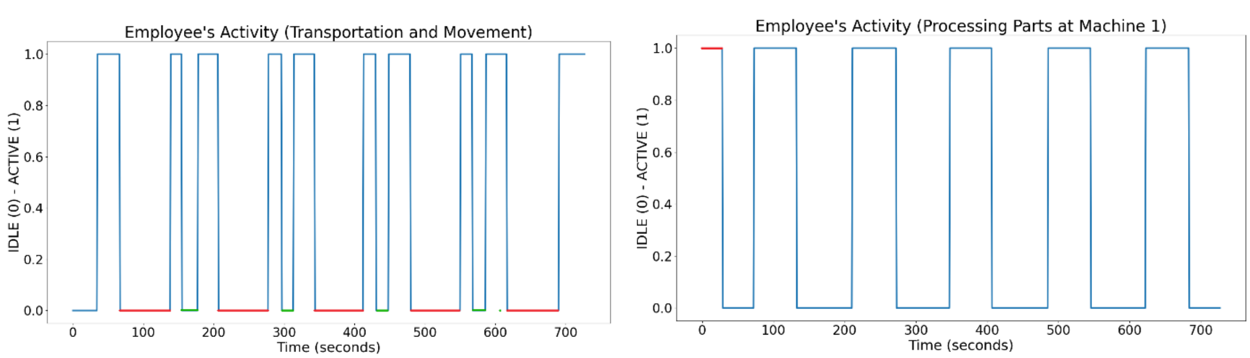


Figure 5. Transportation activity of the AGV

The case of the employee was a more complex scenario as he was executing transportation and machining processes. Thus, the algorithm should know where inside the industrial facility each process is executed. Based on the above-explained classification algorithm it was easy to identify each process area. In the end, by applying similar rules the algorithm was able to extract plots of each process. Below the time windows that the employee executes transportation tasks are depicted in Figure 6a, while in Figure 6b the time windows that the employee executes the machinery process at machine 1 are presented. It's easy to notice that we can export information about the average process time at machine 1 which is approximately 75 seconds, while in simulation the machine 1 processing time was set at 70 seconds.



a) b)

Figure 6. Metrics and analysis of positioning data for the employee: a) transportation and movement activities, b) processing times at machine 1.

Moreover, a pattern at transportation activities is recognized in Figure 6a. It's easy to observe that the time windows with red color in Figure 6a corresponds to the active status in the Figure 6b as the employee in these time windows executes the process at machine 1, while the time windows with green color represent the time that the employee needs to release the part at the "Ready products" awaiting area. Also, in the Figure 6b there is a false identification of the employee's activity as the initial point of the employee at the start of the simulation was at the machine 1 position and the algorithm recognized it as a process at Machine 1.

For the calculation of the resource utilization, a comparison table between the reported results from the algorithm and the AnyLogic software is represented. As the AnyLogic software does not provide the utilization percentages about the identified sub-processes, in the case of the employee the summation of the three processes was used for the calculation of the utilization. As a result, we observed a difference of 4.41% for the utilization of the AGV and a difference of 2.54% for the utilization of the employee. Thus, the results show that the calculations from the developed algorithm based on the RTLS provides acceptable metrics with an added value on the utilization of the resources that are being tracked. Considering that the proposed algorithm is using only the positioning data without any other information we conclude that the accuracy is at a high level in comparison with the AnyLogic software which calculates the utilization of the resources based on real-time resource's data which are not available in real-world industrial facilities.

Table 1. Utilization results between AnyLogic and RTLS positioning data calculations

	AGV utilization		**Employee utilization**	
Activities	AnyLogic	RTLS positioning data	AnyLogic	RTLS positioning data
Transportation	69%	64.59%	94%	35.57%
Machine 1	-	-		45.47%
Release at Output Area	-	-		10.42%
Total utilization	69%	64.59%	94%	91.46%

Finally, a last comparison about the total travelled distance that the proposed algorithm provides and the actual travelled distance that AnyLogic calculates is presented on Table 2. The distances on the proposed algorithm were calculated based on the Transportation Activity diagrams from Figure 5 and 6a. The estimations show that even without the movement activities inside the manufacturing cell (case of the employee) and the AGV standby area (case of AGV) the algorithm was able to estimate the travelled distance with high accuracy.

Table **2**. Travelled distances calculations (1hour of simulation)

	AGV		**Employee**	
	AnyLogic	RTLS positioning data	AnyLogic	RTLS positioning data
Total travelled distance	5378m	5189m	3842m	3711m

From all the above results we conclude that the RTLS provides crucial information about Business Process Management. In our case through that information the business administration layer could be able to identify the processes and readjust the industrial facility layout in order to move these processes closer to each other and maximize the resource utilization. Moreover, the minimization of the transportation activities could be achieved.

5. Conclusion

The road map towards the smart factories of the future includes new challenges for industries as well as for young engineers. While the primary aim of Industry 4.0 is the development of fully automated processes this accomplishment is still a far-reaching target for most of the industries. Information Technology Tools provide a basis for enhancing industrial activities. This research work proposes an algorithm that extracts crucial information about the operational processes of assets in a facility layout. Through a simulation experiment we conclude that the algorithm can effectively use asset's positioning data to extract information about resource utilization, total distance travelled, and the undertaken processes. Moreover, this tool prevents collisions and accidents between the tracking assets within the industrial area. As a conclusion, RTLS supports business process management on industries, especially by focusing on the business administration layer and by monitoring in real-time the ongoing activities in the industrial facility.

As a future step, the authors will improve the classification capabilities of the proposed algorithm by including information about the layout of the facility. In this way, more information about the processes could be extracted as there is a connection among the positioning data and the industrial manufacturing cells. Moreover, an algorithm that creates metrics about the flows and the percentages that the asset spends in each one of them could be developed.

Finally, after the simulation, the algorithm should be tested in real-world scenarios and in numerous industrial facilities for the validation of the process extraction procedure.

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References

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C.,The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences of the United States of America*, vol. *117, no.30,* pp. 17656–17666, 2020. https://doi.org/10.1073/pnas.2006991117

Darányi, A., Dörgő, G., Ruppert, T., & Abonyi, J. , Processing indoor positioning data by goal-oriented supervised fuzzy clustering for tool management. *Journal of Manufacturing Systems*, *63*(February), 15–22, 2022. https://doi.org/10.1016/j.jmsy.2022.02.010

Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N., Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management*, *55*(July), 102211,2020. https://doi.org/10.1016/j.ijinfomgt.2020.102211

Furukawa, K., & Shida, S. , A Practical Comparison between Nitrous Oxide Dosimetry and Fricke Dosimetry for the Estimation of γ-RayEnergy absorbed in Gaseous Media. *Journal of Nuclear Science and Technology*, vol. *3, no.1,* pp. 41–42, 2015. https://doi.org/10.1080/18811248.1966.9732270

Hancock, P. L. , *MOORES, E. M. & TWISS, R. J. 1995. Tectonics. ix + 415 pp. New York: W. H. Freeman. Price £29.95, US $59.95 (hard covers). ISBN 0 7167 2437 5. 135*, 143–158, 1998.

Kamble, S., Gunasekaran, A., & Dhone, N. C., Industry 4.0 and lean manufacturing practices for sustainable organisational performance in Indian manufacturing companies. *International Journal of Production Research*, vol. *58, no.5,pp.* 1319–1337, 2020. . https://doi.org/10.1080/00207543.2019.1630772

Li, T., Xiong, L., Dong, A., Liu, Z. S., & Tan, W., Optimization method based on big data in business process management. *Cluster Computing*, *22*(s3), 5357–5365, 2019. https://doi.org/10.1007/s10586-017-1243-3

Müller, J. M., Kiel, D., & Voigt, K. I., What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability. *Sustainability (Switzerland)*, vol. *10, no.* 1, 2018. https://doi.org/10.3390/su10010247

Rácz-Szabó, A., Ruppert, T., Bántay, L., Löcklin, A., Jakab, L., & Abonyi, J., Real-time locating system in production management. *Sensors (Switzerland)*, vol. *20, no.23,* pp. , 1–22, 2020. https://doi.org/10.3390/s20236766

Thames, L., & Schaefer, D., Software-defined Cloud Manufacturing for Industry 4.0. *Procedia CIRP*, vol. *52*, pp. 12–17, 2016. https://doi.org/10.1016/j.procir.2016.07.041

Tortorella, G. L., & Fettermann, D., Implementation of industry 4.0 and lean production in brazilian manufacturing companies. *International Journal of Production Research*, vol.56, no.8, *pp.* 2975–2987, 2018. https://doi.org/10.1080/00207543.2017.1391420

Tran, T. A., Ruppert, T., & Abonyi, J., Indoor positioning systems can revolutionise digital lean. *Applied Sciences (Switzerland)*, vol. *11, no.11,* pp. 1–14, 2021. https://doi.org/10.3390/app11115291

Troutner, J. C., Harrell, M. V., Seelen, M. T., Daily, B. J., & Levine, W. C. , Using Real-Time Locating Systems to Optimize Endoscope Use at a Large Academic Medical Center. *Journal of Medical Systems*, vol. *44, no.4*, 2020. . https://doi.org/10.1007/s10916-020-1540-x

van der Aalst, W. M. P., Business Process Management: A Comprehensive Survey. *ISRN Software Engineering*, *2013*, 1–37, 2013. . https://doi.org/10.1155/2013/507984

Xu, L. Da, He, W., & Li, S., Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics*, vol. *10, no.4,* pp. 2233–2243, 2014. https://doi.org/10.1109/TII.2014.2300753

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