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Real time locating system for a learning cross-docking warehouse

Francesco Pilati[a,*], Andrea Sbaragli[a], Alberto Regattieri[b], Yuval Cohen[c]

[a]*Department of Industrial Engineering - University of Trento, via Sommarive 9, 38123 Trento, Italy*

[b]*Department of Industrial Engineering - University of Bologna, viale del Risorgimento 2, 40136 Bologna, Italy*

[c]*Department of Industrial Engineering - Tel-Aviv Afeka College of Engineering, Mivtza kadesh St, 38 Tel Aviv, Israel*

Abstract

Real time locating systems (RTLS) represent today an established and reliable technology to identify, track and monitor, in real time with any human commitment, the dynamic evolution of the spatial location of tagged entities inside factory layout. This results in more effective and continuous monitoring of products, stock-keeping units (SKU), and vehicles of production plants or logistic facilities. This paper targets the adoption of such RTLS in warehousing systems focusing on the related learning opportunities to enhance the efficacy and the productivity of the storage process which have consistent externalities during the order picking. For this purpose, a cross-docking warehouse is equipped with an ultrawideband (UWB)-based RTLS to track any forklifts traveling activities and SKU dynamic locations. A set of relevant data is automatically generated by the interactions between the transmitters, which are installed on board of the forklifts and connected to the SKU barcode readers, and the receivers, which are displaced in fixed positions all over the warehouse layout for optimizing the data transmissions. Furthermore, to yield further insights into the performed storage and retrieval operations, the daily incoming and outcoming shipping orders are also considered at the detail level of every single SKU. All this relevant information is merged into a unique database that evolves in real time representing the dynamic evolution of the warehouse operations over time. A digital representation of the physical storage system is developed to leverage such relevant datasets through adequate data analysis algorithms. A set of quantitative key performance indicators is evaluated, and suggestions are automatically offered to the warehouse manager to improve the storage system efficiency. The implementation of such modification, through a feedback loop, is to offer the unique opportunity to such warehousing system to analytically learn by its process's underperformances, as well as to evaluate the efficacy and efficiency of the corrective actions suggested by the developed algorithms.

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1. Introduction

In the latest decades, the volume of traded goods all over the globe experienced a constant and remarkable increase determining a surge in transportation demand and logistics flows. For this purpose, according to data released in 2021 by the United Nations, imports and exports volumes in developed countries, between 2005 and 2019, faced both a surge higher than 20% [1]. Logistics companies face tremendous difficulties in handling the inbound and outbound flows of material from and to their warehouses. Moreover, important challenges are faced in the tracking procedures and tools concerning the stored items and, consequently, a significant efficiency and

* Corresponding author. Tel.: +39 0461282425
E-mail address: francesco.pilati@unitn.it

economic threat is posed by the dynamic management of storage locations and the related frequent tracking of goods stored in warehouses. For this purpose, traditional barcode systems are utterly inadequate due to their strong dependency on human accuracy and commitment. Consequently, real time locating systems (RTLS) or indoor positioning systems (IPS) widen their industrial applications. RTLS are wireless systems up to locate the position of a tagged item anywhere in a defined environment in real time. Since indoor environment, typically, have to rely on non-line-of-sight propagation (n-LOS) in which signals cannot travel directly in a straight path from an emitter to a receiver, among IPS based on short-range, RF technologies are the most promising due to a large penetration power, a wide coverage area, and affordable hardware costs[2]. Radio Frequency Identification (RFID) is a wireless non-contact radio system, whose main purpose is to track items in real time, as Stock Keeping Units (SKUs). Therefore, data, updated through the supply chain, provides insight into possible inefficiency concerning logistics and distribution. Furthermore, the autonomous reading of SKU-related information saves time and labor [3]. Among RF solutions, ultra-wideband (UWB) is widely considered the most performing technology concerning multipath resolution and accuracy [4].

2. Literature review

Before being a well-established technology, RTLS faced different applications, to check their consistency and reliability to, at first, cope with the existent manufacturing environment and then to enhance its daily operations. According to the sophisticated mathematical model developed by Halawa et al. [5], RTLS provide a promising approach to reduce wasted time related to search assets in factories. During the actual era of "Industrial Internet of Things", a large volume of data is often collected by RTLS, sensors, gateways, etc. Consequently, in various industries, a current shift has been seen in the decision-making process towards digital data analysis rather than human experience. In this new technological environment, a disruptive path to improve industrial operations is enabled by the Digital Twin (DT) technology, the virtual and computerized counterpart of a physical system. As a result, factories and warehouses through iterative simulations can learn over time by themselves [6, 7]. Confirming this new trend, today numerous examples of industrial applications are focused on the role of digital data and the related learning process. During the era of low volume high-mix manufacturing, sensors and Industry 4.0 technologies offer real time status of manufacturing items. As a result, factories become more efficient due to early detections of damaged components and machines, a reduction in machines downtimes, a better leveling of the production, a more sensitive approach to ergonomic performances, a better in-plant supply of materials, etc. Cohen et al. [8] propose a road map to scale up the implementation these innovations in assembly system and then describe their impacts upon the operational, tactical and strategical level. At the same time, Zhou et al [9] propose in an RFID-based production process a manufacturing scheduler algorithm, aimed to continuously improve from its experience and applications. Another valid application is the digitalized in-plant milk run system which relies too on RFID technology [10]. In lean manufacturing, the milk-run is an effective approach to replenish those materials depleted in workstations through Kanban cards. Moreover, Löcklin et al. [11] propose an algorithm, upon data acquired by UBW-based RTLS, to smooth the mutual collaboration between workers and automated guided vehicles. Considering the mentioned scenario, the different configurations and types of RF technologies, even based on learning approaches, are well established in industrial environments. However, in literature, there are few applications focused on the learning process of a sensitized, UWB-based, warehousing system. For this purpose, data acquired by the IPS are mined in order to evaluate the efficacy of the storage process along with the externalities produced by non-performing activities monitored. The unique set of quantitative keys performing indicators, constitutes the core part to monitor in real time and then improve, through a closed feedback loop, the storage process over time. Moreover, the possibility to implement early warnings in real time enable to assess the root causes related with underperformances and, consequently, learn over the time by inefficiencies occurred. The paper is organized as it follows. The section 2 proposes a digital architecture for learning warehouses, divided in a hardware and software part, up to monitor the storage process. The section 3 presents the application of the architecture to a real case study while Section 4 discusses results and possible improvements to operations. Finally, section 5 ends the paper with conclusions and suggesting future research directions.

2. Digital architecture for learning warehouse

This section describes the original architecture developed to analyse performances of the storage process in warehousing systems upon data acquired by a specific IPS. Therefore, a software is proposed to develop a set of KPIs to evaluate the consistency and the efficiency of the storage process and, consequently, to trigger a quantitative and automatic learning process upon underperformances monitored. This learning aspect is outlined end emphasized in the Result section while analysing outcomes based on the proposed case study.

2.1. Indoor positioning system

The IPS adopted in this research is based on a pulsed UWB technology with a frequency range between 3 and 7GHz and a bandwidth of at least 500 MHz. The framework, featured by a maximum indoor range of 30 meters, is composed of anchors (AN), transponders (TN), gateways (GW), and a locating manager (LM). Each TN, placed on forklifts and SKUs, emits localization signals to ANs with a blink rate of 2Hz and, in relation to the asset, it stores either the SKU ID and the shipping ID or the forklift ID. ANs, to maximize the coverage area of the IPS, are place in the ceiling of the monitored warehouse and spaced up to 20 meters apart. Eventually, they can operate as GWs which transfer, through ethernet, wireless signals received to the LM. Both ANs and TNs have a maximum radio transfer rate equal to 850kbit/s. The LM software calculates the position of each TN by a method called Time Difference of Arrival (TDOA). At this point, accuracies, in such complex n-LOS environments, are increased down to 30 centimeters through the weighted nonlinear least-squares method.

2.2. Learning warehouse software

The learning warehouse (LW) software requires distinctive inputs to be effective. Data acquired from the IPS, once processed, are merged through a spatial SQL database in the location table (Tab.1). Each row represents, a time-dependent geometrical location $P_{i,j}$ of a tagged entity in 2 dimensions $\left(P_{i,j}^{x}; P_{i,j}^{y}\right)$, pinged by transponders inside the warehouse. In particular, the index i represents all points recorded during the route of the j^{th} SKU.

Table 1. Location table of tagged entities.

Transponder ID	Type	Timestamp	Geometrical location (X;Y) [m]
bearerid_7684	SKU	2020/06/08 12:34:01.772	(1342775.251;57745513.951)
….	….	…	…
bearerid_7684	SKU	2020/06/08 14:18:56.347	(1342755.201;57745516.005)
zebra01	Forklift	2020/06/08 12:35:58.986	(1342769.174;57745520.223)
…	…	…	…
zebra01	Forklift	2020/06/10 13:01:58.649	(1342758.251;57745518.876)
…	…	….	…

Moreover, the WMS feeds automatically, in the LW software, the expected time in stock, E_j, for each j^{th} SKU. To evaluate the performance of the storage process, the warehouse layout should be divided in t-areas. According to the well-known and widely adopted Pareto criteria [12], the proposed LW software considers three distinctive areas. Each area has to store a set of products which spend a fixed range of time in the warehouse. In particular, the area closer to the inbound/outbound docks should be adopted to stock high rotational SKUs in order to reduce time and distances travelled by forklifts. Through a trivial combination of the aforementioned input data, it is possible to obtain a shipping table in which each row represents a static overview of the physical presence of the SKU considered (Tab.2). The creation and the delivery time correspond to the first and the last instant in which ANs detect the SKU inside the warehouse.

Table 2. Shipping Table.

SKU ID	Shipping ID	Creation Time	Delivery Time	Expected Time [h]
7684	4684	2020/06/08 14:18:56.294	2020/06/09 12:33:55.000	36.55
7602	4684	2020/06/08 14:19:05.000	2020/06/09 12:36:50.000	36.55
7723	4755	2020/06/09 09:51:01.000	2020/06/09 15:34:18.000	100.2
7584	4801	2020/06/09 09:47:58.000	2020/06/09 15:24:35.000	14.87
…	…	…	…	…

Based on these quite traditional data for a warehousing system, a novel heuristic algorithm is proposed to provide a punctual monitoring , in the preferred time-unit, of the storage process and an effective way to make the industrial environment learn upon its mistakes or inefficiencies over time (Fig. 1). At first, it is necessary to identify in which area each SKU is stored (SA_j) end then the ideal target area in which should be stocked (SA_j^*), in relation to the E_j and the time range of each area. Based on this comparison, the algorithm assesses the consistency of every performed storage activity categorized, at first, in matches (MT) and mismatches (MS). In case of misplacement, the algorithm updates the counter of actual and target SKU placements of the respective areas. For instance, S_B^* and S_A are both increased by one whenever a generic SKU is placed in A instead of B, the optimal area due to the aforementioned requirements. Therefore, since misplacements may have different magnitude on operations, the algorithm has to keep track of errors' typology. For example, with respect to the previous misplacement between A and B, T_3 is increased by 1. On the other hand, a right SKU allocation scenario results in an increase of both counters of stock in the same area. Once an SKU is delivered, the algorithm computes the distance travelled from the storage location to the outbound docks through the Euclidean method. Finally, for each storage area, it is evaluated the distribution of the distance travelled for SKU handling activity, upon its respective $d_{j,t}$.

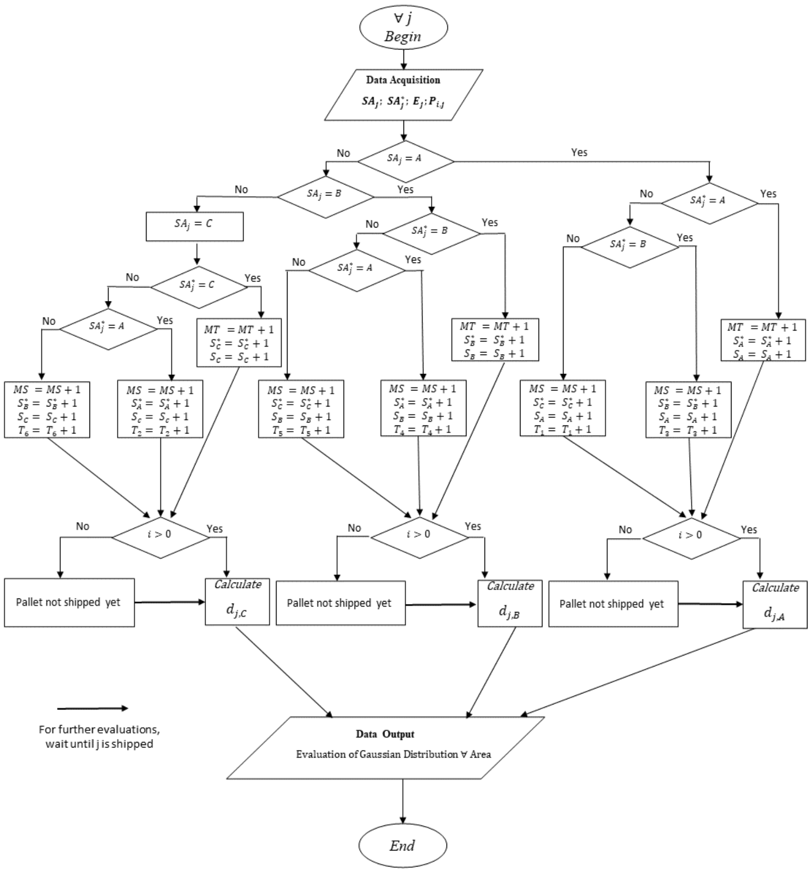

Fig. 1. Flow Diagram of the heuristic algorithm implementation in the LW software.

3. Case study

In this section, the developed digital architecture is adopted for a cross-docking warehousing system, located in Northern Italy, with a floor area of 1260 square meters. Cross-docking is a logistic approach in which unloaded SKUs from inbound carriers are transferred to outgoing carriers with short storage in between [13]. The analysis, aimed to improve an existing storage process, monitors the dynamic evolution of storage activities and their related performances over time [14]. The period considered is focused on a representative month during 2020 in which the warehouse operated 8 hours per shift, 5 days per week for a total of 4 weeks (Fig. 2a). According to the algorithm requirements, Fig. 2b. presents the warehouse layout and the related storage areas along with the displacement of the ANs. Area A, the closest to the outbound docks, has to store the so-called "fast deliveries" which spend less than 24 hours in stock. This "fast area" has a capacity of 176 SKUs. Up to 48 "slow freights" which spend more than 50 hours in stock, can be placed in C, the farthest from the outbound docks.

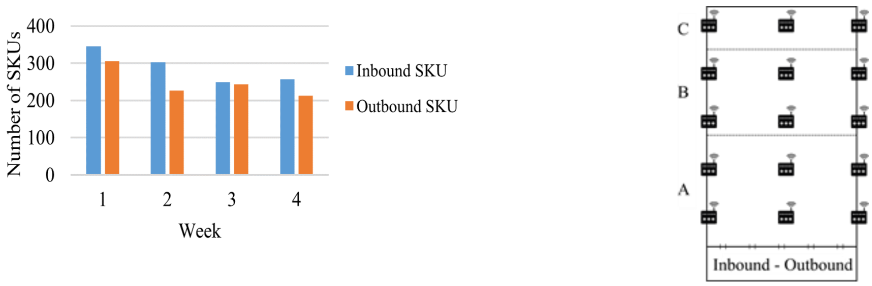

Fig. 2. (a) Inbound and Outbound SKUs; (b) Cross-docking layout.

Finally, area B, geographically and for storage time in between the two aforedescribed ones, can store up to 160 freights. Both forklifts and SKUs are equipped with TNs to reduce costs related to mismatches of SKUs and meters travelled to perform deliveries and, consequently, make the warehouse resilient towards stressful periods. Warehouse workers perform operations through a user-friendly tablet that displays in real time, each acquired information at the detail level of SKU. Once a delivery is ongoing, SKU by SKU the system also computes the shortest route from the current to the stored location.

4. Results

This section presents the results obtained adopting the developed digital architecture for learning warehouse to the presented case study. This analysis, at first, focuses on general performances, and then it considers specifics errors occurred during storage and retrieval operations. The dualism between matches (MT) and mismatches (MS) in Fig. 3a. provides a general overview of how the warehousing system copes with storage requirements. MT and MS percentages, for each week, are given by the amounts of weekly placements and misplacement, respectively, divided by the amounts of weekly SKUs handled. The progressive convergence of MT and MS percentages week by week over the monitored time horizon suggests that the storage process increased autonomously both its efficacy and consistency. However, despite internal and external drivers which could have shaped placements over weeks, even at the fourth week roughly one out of two SKUs is misplaced. Since the operations are far apart from desirable performances, the warehousing system requires targeted suggestions to improve its storage routines. For this purpose, this first KPI enables to set the so-called minimum threshold of tolerance under which the system is underperforming. Unfortunately, this real time warning does not provide an accurate degree of detail about which areas are most affected by errors upon the others and the different typologies of misplacements. According to each MS type ($T_1, \ldots, T_6$), Fig. 3b. deepens this analysis by figuring out their frequencies over the four weeks. In addition, mismatch types are grouped in two main classes in relation to the magnitude of deviations involved. The blackout (BT) class includes T_1 and T_2 , misplacements that involve areas A and C, while the remaining fours, which involve mismatches between adjacent areas, belong to the Blurry Camera (BC) class. For this purpose, the BT groups the most disruptive errors whereas deviation in the BC class, potentially related to the full saturation of the target area, have a markedly lower impact on operations. Despite a remarkable reduction in SKUs misplacements over the considered period, the performance of the warehouse plunged as well. In fact, week by week the BC class accounts for a progressive reduction in deviations while the BT class keeps its levels constants. As a result, the share of the costliest class, given by the number of weekly BT errors discounted by the sum of weekly deviations of BC and BT classes, is doubled. For this purpose, the space in the "fast area" is unnecessarily occupied by "slow freights" and high priority SKUs travel higher distances before being loaded in outbound carriers. Consequently, in reducing errors, the warehousing system must prioritize the BT class, to significantly decrease the total distance travelled by SKUs and consequently by forklifts.

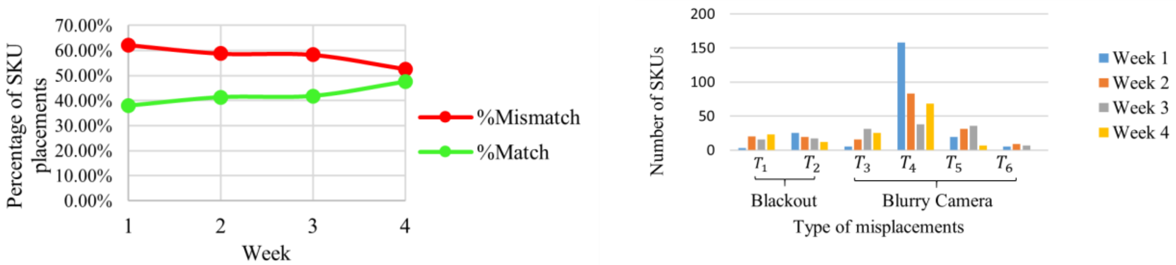

Fig. 3. (a) Mismatch and Match percentages; (b) Frequencies of different misplacements of SKUs.

To achieve this purpose, BT errors during the second and third week could be easily avoided since their respective T_1 and T_2 are at the same levels. Unfortunately, especially in stressful periods, deviations to best performances may be related to the full saturation of area A. In this scenario, the sub-optimal placement is somewhere in the BC class and there can be detected. For this indicator also, it is strongly suggested to set minimum thresholds for each storage class under which the warehousing system is too far apart from an acceptable functioning, therefore automatically emitting an alert to request a storage reorganization. Finally, a further relevant KPI is the evaluation of the distribution of the distance travelled by the different SKUs from each storage area to outbound docks. As presented in Fig. 4., misplacements result in both surge/plunge of expected range of meters to be travelled for the different areas and therefore unjustified and alarming occupancies of square meters. Consequently, this KPI enables to set ranges of acceptable distance travelled, for example equal to 95% of instances, to perform a delivery activity for each storage area.

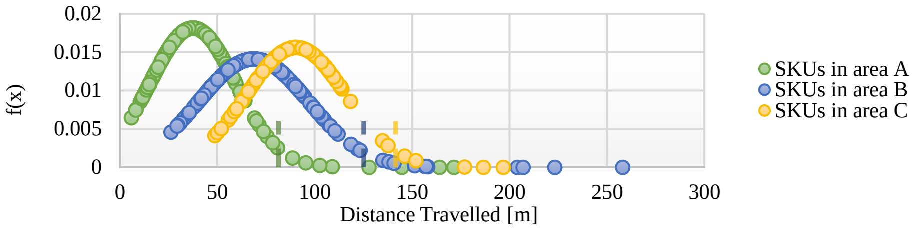

Fig. 4. Distribution of distance travelled x from each area to outbound docks.

5. Conclusions and further research

This paper proposes an original digital architecture aimed to present an innovative approach to monitor and then enhance storage activities in whatsoever warehousing system embracing a learning approach. The hardware adopted is represented by UWB-based RTLS, and it is designed to track in real time the movements of SKUs and forklifts in any n-LOS environment. The combination of the data acquired from the IPS and the WSM constitutes input data for the LW software. As a result, through a unique heuristic algorithm, the presented software keeps track of the storage performances and provides a valid basis to learn analytically upon the warehousing system underperformances. To test the consistency of the proposed architecture, an experimental application is performed in a real and operating cross-docking warehouse. The obtained outcomes show not only the reliability of the architecture but also a feasible path to improve the storage operations of the warehouse. Further research should enable the developed architecture to keep track of the route travelled before having placed the carried SKU. In this case, considering the same division of areas, the geographical position of the "fast area" has to minimize the sum of the placement route, from the inbound carrier to the storage position, and the delivery route, from the placement position to the outbound docks, further improving the learning possibilities determined by the adoption of such architecture. Moreover, the LW software should be able to identify different workers during the shift and to provide the same set of statistics for each of them. The ambition could be spreading best practices and gamification in a warehousing system fulfilling all privacy requirements.

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References

[1] United Nations, Conference on Trade and development, Key Statistics and trends in International Trade 2020

[2] Alarifi, Abdulrahman; Al-Salman, AbdulMalik; Alsaleh, Mansour; Alnafessah, Ahmad; Al-Hadhrami, Suheer; Al-Ammar, Mai A.; Al-Khalifa, Hend S. 2016. "Ultra Wideband Indoor Positioning Technologies: Analysis and Recent Advances" *Sensors* 16, no. 5: 707.

[3] Wang, K. (2014). Intelligent and integrated RFID (II-RFID) system for improving traceability in manufacturing. Advances in Manufacturing, 2(2), 106-120.

[4] Mazhar, F., Khan, M.G. & Sällberg, B. Precise Indoor Positioning Using UWB: A Review of Methods, Algorithms and Implementations. Wireless Pers Commun 97, 4467–4491 (2017).

[5] Farouq Halawa, Husam Dauod, In Gyu Lee, Yinglei Li, Sang Won Yoon, Sung Hoon Chung, Introduction of a real time location system to enhance the warehouse safety and operational efficiency, International Journal of Production Economics, Volume 224, 2020, 107541

[6] Werner Kritzinger, Matthias Karner, Georg Traar, Jan Henjes, Wilfried Sihn, Digital Twin in manufacturing: A categorical literature review and classification, IFAC-PapersOnLine, Volume 51, Issue 11, 2018, Pages 1016-1022

[7] Bortolini, M., Gamberi, M., Pilati, F., Regattieri, A. Automatic assessment of the ergonomic risk for manual manufacturing and assembly activities through optical motion capture technology. Procedia CIRP, 72, 81-86. (2018)

[8] Cohen, Y., Naseraldin, H., Chaudhuri, A., Pilati, F., "Assembly systems in Industry 4.0 era: a road map to understand Assembly 4.0. " Int J Adv Manuf Technol 105, 4037–4054 (2019).

[9] T. Zhou, D. Tang, H. Zhu and L. Wang, "Reinforcement Learning With Composite Rewards for Production Scheduling in a Smart Factory," in *IEEE Access*, vol. 9, pp. 752-766, 2021

[10] Sascha Gotthardt, Maria Hulla, Matthias Eder, Hugo Karre, Christian Ramsauer, Digitalized milk-run system for a learning factory assembly line, Procedia Manufacturing, Volume 31, 2019, Pages 175-179, ISSN 2351-9789,

[11] A. Löcklin, T. Ruppert, L. Jakab, R. Libert, N. Jazdi and M. Weyrich, "Trajectory Prediction of Humans in Factories and Warehouses with Real-Time Locating Systems," *2020 25th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, Vienna, Austria, 2020, pp. 1317-1320

[12] Y. Chen, K. W. Li and S. Liu, "A comparative study on multicriteria ABC analysis in inventory management," *2008 IEEE International Conference on Systems, Man and Cybernetics*, Singapore, 2008, pp. 3280-3285

[13] Jan Van Belle, Paul Valckenaers, Dirk Cattrysse, Cross-docking: State of the art, Omega, Volume 40, Issue 6, 2012, Pages 827-846

[14] Eberhard Abele, Joachim Metternich, Michael Tisch, George Chryssolouris, Wilfried Sihn, Hoda ElMaraghy, Vera Hummel, Fabian Ranz, Learning Factories for Research, Education, and Training, Procedia CIRP, Volume 32, 2015, Pages 1-6, ISSN 2212-8271