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LEAN PRINCIPLES FOR ORGANIZING ITEMS IN AN AUTOMATED STORAGE AND RETRIEVAL SYSTEM: AN ASSOCIATION RULE MINING – BASED APPROACH

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Abstract
The application of the 5S methodology to warehouse management represents an important step for all manufacturing companies, especially for managing products that consist of a large number of components. Moreover, from a lean production point of view, inventory management requires a reduction in inventory wastes in terms of costs, quantities and time of non-added value tasks. Moving towards an Industry 4.0 environment, a deeper understanding of data provided by production processes and supply chain operations is needed: the application of Data Mining techniques can provide valuable support in such an objective. In this context, a procedure aiming at reducing the number and the duration of picking processes in an Automated Storage and Retrieval System. Association Rule Mining is applied for reducing time wasted during the storage and retrieval activities of components and finished products, pursuing the space and material management philosophy expressed by the 5S methodology. The first step of the proposed procedure requires the evaluation of the picking frequency for each component. Historical data are analyzed to extract the association rules describing the sets of components frequently belonging to the same order. Then, the allocation of items in the Automated Storage and Retrieval System is performed considering (a) the association degree, i.e., the confidence of the rule, between the components under analysis and (b) the spatial availability. The main contribution of this work is the development of a versatile procedure for eliminating time waste in the picking processes from an AS/RS. A real-life example of a manufacturing company is also presented to explain the proposed procedure, as well as further research development worthy of investigation.

Keywords
lean management, AS/RS, Association Rules, Data Mining, Industry 4.0, 5S, shoe manufacturing.

Introduction

Warehouse management plays a vital role from an organizational point of view. Indeed, inefficiencies in this field may reflect on the whole downstream production processes. From a lean management point of view, reducing the time dedicated to non-adding value tasks during the picking process represents a waste reduction, and it is considered as a challenging research goal [1]. As noted by Tompkins et al. [2], the travel from the picking point is the most time consuming task during the picking process, followed by the search and the pick-up of the components. Hence, it is fundamental that the warehouse is well-organized, in order to avoid, or at least limit, these time wastes. In case of manual storage system there are several modifiable variables, such as modifying picking routes or the layout of the warehouse. In case of Automated Storage and Retrieval Systems (ASRS), instead, items' allocation to the most convenient storage location is the only settable parameter, together with the clustering of items frequently picked together. According to lean management requirements, 5S methodologies can be applied to improve the current state organization of a company's warehouse in order to reduce the wastes in the picking process. 5S methodology represents an interesting technique for smoothing the production process, aiming to embed values like organization, neatness, cleaning and standardization in companies' operations [3]. The five step characterizing the 5S methodology proposed by Osada [4] are:

- Seiri: sorting all the items in the workplace and eliminating the unnecessary ones;
- Seiton: place the items in the optimal location;
- Seiso: regularly clean the workplace;
- Seiketsu: standardize the process;
- Shitsuke: sustain the process, ensuring that the previous activities are regularly executed.

Considering the aforementioned definitions and the problem addressed in the current paper, it is noteworthy that 5S methodology is not only suitable for improving production processes' conditions, but also for space management issues like those faced in warehouse management, where space organization represents a focal point. Indeed, as noted by Khamis et al. [5], 5s practices are applied to obtain and maintain a quality environment, as required by the continuous improvement approach. Since current manufacturing environment is moving towards a 4.0 perspective, there is a growing focus on big data analytics techniques. Indeed, data understanding represents a key aspect for extracting useful knowledge and new information with the aim of taking advantage from them [6]. Thus, the application of Data Mining (DM) techniques surely supports the interpretation of the data provided by production processes and supply chain operations in order to increase company's efficiency [7]. Integrating the opportunities by DM techniques and the desire of efficiency growth, this research is directed to material management in AS/RS: a procedure for organizing the items in an AS/RS based on a well-known DM technique, namely the Association Rule Mining (ARM), is developed. Specifically, the historical data of the order picking processes are analyzed in order to determine the item categories frequently required together. Then, on the basis of the confidence of the rules mined, on the area required by each category and on the dimensions of the ASRS, items categories are assigned to the most convenient shelf of the storage system. In this way, the space and material management at the basis of the 5S philosophy is pursued.

The remainder of the paper is organized as follows: after this brief introduction and a review of the most relevant contributions on similar topics (Sec. 2), the procedure is developed in Sec. 3, additionally providing a description of the ARM. Moreover, in Sec. 4, the case of a shoe manufacturing company is presented to better clarify the application of the procedure. Lastly, in Sec. 5 the conclusions and future research directions are presented.

Literature review

Automated Storage and Retrieval Systems are widely used in manufacturing environment for storing raw material, semi-finished or finished products, and retrieving them when an order is required [8]. Remarkably, Chuang et al. [9] identify three different objectives pursued by the storage assignment policies developed in existing literature, that are, in general, dedicated to (a) improve the operating efficiency, (b) minimize storage costs and (c) minimize picking distances. The storage assignment problem can be addressed through different approaches, as originally identified by Hausman et al. [10] and Graves et al. [11]: the dedicated storage assignment, that mainly aims to increase the efficiency of the retrieval penalizing the utilization rate [8]; the random storage assignment, that is, instead, characterized by a high level of space utilization; other storage assignment criteria include the closest open location storage assignment, and full-turnover-based or class-based storage assignment. As noted by Dukic et al. [12], lean management philosophy promotes an efficient use of inventory systems, as well as the minimization of the picking times for production processes. In order to minimize picking distance and, thus, to reduce the time dedicated to this activity, Chuang et al. [9] proposed to store the most frequently picked items close to the picking point: they developed an approach to cluster products on the basis of their support and allocate them to the optimal storage location of a manual warehouse. In a similar perspective, Chen et al. [13] developed an algorithm for the picking of a number of order simultaneously, in order to achieve better productivity: the approach rely on the association rule mining and considers the support as the key performance indicator to define whether two items should be picked together. In Dotoli et al. [14], lean tools are applied to the analysis and optimization of a warehouse: specifically, Unified Modeling Language and Value Stream Mapping are applied to study material and information flows across the warehouse, while Genba Shikumi methodology is applied to rank the inefficiencies identified in the process. Dharmapriya and Kulatunga [15], instead, proposed a Simulated Annealing heuristic to optimize warehouse operations, relating its efficiency to items' allocation and to the picking route. A discrete event algorithm for items allocation is developed by Gopakumar et al. [16] that were able to quantify the improvement of the operations achieved through the application of the Value Stream Mapping. Also Chen et al. [17] benefits of Value Stream Mapping to study warehouse inefficiencies and integrates this approach with the introduction of RFID tags to control products flow and improve picking time.

According to existing literature contributions, there is a research gap involving the study of items organization in AS/RS; due to the wide amount of data nowadays available, the identified research gap could be addressed capitalizing on DM techniques.

Research approach

The current research approach aims at developing a procedure to organize items in AS/RS based on the Association Rule Mining and according to the space management aspect pursued by 5S methodology. Specifically, the reduction of the number and duration of picking processes is addressed.

Association Rule Mining

The Association Rule Mining (ARM) is a methodology that can be applied to extract interesting and hidden relations from large datasets with the aim of supporting the decisional processes. According to [18], through ARM attribute-value conditions that frequently occur together can be identified and provide a valuable contribution to the knowledge contained in a dataset. The remainder of the paragraph aims to provide a formal description of such method and the most widely applied metrics for ARs evaluation.

Let $B = \{b1, b2, ..., bn\}$ be the set of boolean data called items and $T = \{t1, t2, ..., tD\}$ be the set of all transactions, where each transaction ti contains an item-set (i.e., a set of items) selected from B. In the current work, $b1$ represents the picking of the item $i1$, and a transaction is the set of components that are picked during the same picking process.

An implication of the form $X \rightarrow Y$, where X and Y are item-sets such that $X, Y \subseteq B$, and $X \cap Y = \emptyset$, is called association rule (AR). X and Y are respectively named body and head of the rule.

The goodness of an association rule can be evaluated through several metrics, among whom Support and Confidence are the most important ones.

$\mathit{Support} = (\#\{X \cup Y\})/(\#\{T\})$: it measures the statistical significance of the rule [19] since it represents the probability of finding a transaction in the dataset T where X and Y appear simultaneously. Note that $\#\{T\}$ is the cardinality of the database, while $\#\{X\ U\ Y\}$ is the number of transactions containing both item-set X and item-set Y.

$\mathit{Confidence} = (\text{Support}\{X \cup Y\})/(\text{Support}\{X\})$. As suggested by [13], the confidence is a measure of the strength of the rule since it indicates the conditional probability of having Y in a transaction containing X.

Procedure

Definitions:

- I is a matrix containing the following information: [ID, A, F] ordered by F descending.
- ID: a vector of item categories i to be stored in the AS/RS;
- A: a vector of the areas occupied by each item category, i.e., the area required by all items of the same category;
- F: a vector of the picking frequencies of each item category.
- S: a vector containing the available area of each shelf of the AS/RS where the components have to be stored;
- $S_{\text{available}}$: the space available in each tray;
- K: a matrix of items categories that appear as head of the rules mined, the confidence of the rules and corresponding areas occupied by the maximum stock kept.

1) Input data and hypothesis definition:

The procedure requires as input the information contained in the matrix I and in vector S. Matrix I includes the id of the item, the area occupied by the item to allocate and the corresponding picking frequency, while in vector S the available area on each shelf of the AS/RS is reported. The information on the areas is of particular importance since they provide the principal constraint considered in the procedure. It is noteworthy that in the current research approach a fundamental hypothesis is formulated: the area required by each category of items is smaller than the area of an entire shelf. Considering this assumption, it is not necessary to define criteria for allocating each item category in two or more shelves. Moreover, it is reasonably hypothesized that all the shelves are characterized by an analog available area.

2) Picking frequency estimation:

The first step of the procedure requires the selection of the most-frequently picked category of items (i_1). According to the definitions provided in the previous subsection, the picking frequency can be calculated by determining the support of the item-sets composed of a single item category: indeed, the support represents the probability of selecting i_1 on the total of the considered picking. Moreover, even the first shelf (j) to be filled should be selected, considering at each iteration the closest to the picking point, in order to minimize the picking time of the most frequently required items. Then, the item is allocated to j: the available area of j is decreased on the bases of the space occupied by i_1.

3) Association Rule Mining and item categories allocation:

The following step of the procedure requires the mining of the association rules R: specifically, only the rules having i_1 as the body (R: $i_1 \rightarrow i_k \forall k = 2, ..., n$) are selected and are evaluated by their confidence. A matrix K containing the item categories appearing as head of the rules (i_k) and the area occupied by each of them is created, ordering them by descending confidence. At this point, the first element (e.g., i_2) of vector K is assigned to shelf j. If the available area of j can host the total amount of i_2, i_2 is removed from K and I, another item category (e.g., i_3) from K is selected. Else, j is saturated, i_2 is not removed from K, but its area is decreased by the amount allocated to j; i_1 is removed from I, and the analysis re-starts from the new first element contained in I.

The procedure ends if all the item categories have been assigned to a shelf. In Fig. 1, a complete representation of the process is reported.

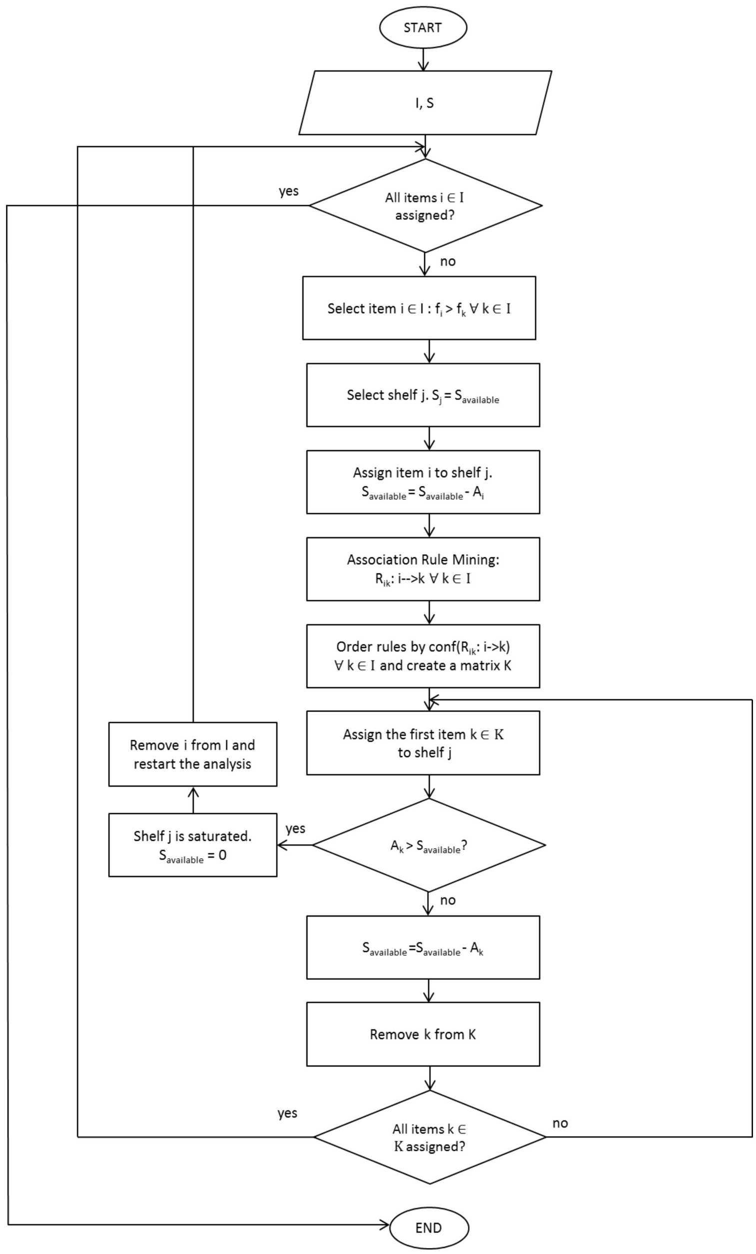

Fig. 1. Research approach developed.

Application

The proposed framework has been applied to the warehouse management of a manufacturing company as integration to 5S methodology during the transition towards an Industry 4.0 environment. Indeed, the organization under investigation is switching from a manual storage system to an automated one and it is focusing on making warehouse organization more efficient. Since the company is composed of three production lines for shoe manufacturing and has three separate warehouses, the pilot project has been implemented on the most critical one and it will be then extended to the whole organization. Before implementing the research framework, according to the 5S philosophy, the seiri step has been executed: all the unnecessary items have been removed from the analyzed warehouse. The muda identified have been classified into two categories:

- unnecessary and not re-usable items that were dumped or recycled;
- unnecessary items because belonging to other production processes. These items have been relocated in the right warehouse.

Through the procedure described reported in Fig. 1, instead, seiton and seiketsu steps have been implemented. Indeed, the former aspect requires putting each item in the optimal position for fulfilling its function. In this sense, the proposed framework assures that the items are allocated to the best shelf in order to limit the number of picking and, thus, the duration of the picking process. The latter, instead, regards the standardization of the activities to keep the warehouse sorted and ordered: the proposed procedure highlights this aspect since it indicates the steps to follow for shelves filling. The software chosen for the analysis is the open-source data mining platform RapidMiner. Specifically, Fig. 2 describes the whole process implemented: the dataset is read from Microsoft Excel. Then, through the operator "Filter Example", some filters are set, to exclude non-significant elements from the analysis. Through the "Generate Attributes", "Select Attributes", "Numerical to Binominal" and "Nominal to Binominal", data are arranged in the correct format. Lastly, FP-Growth and Association Rules respectively generate the frequent patterns and mine the Association Rules. In the next sub-sections, the details of the execution of the procedure will be explained.

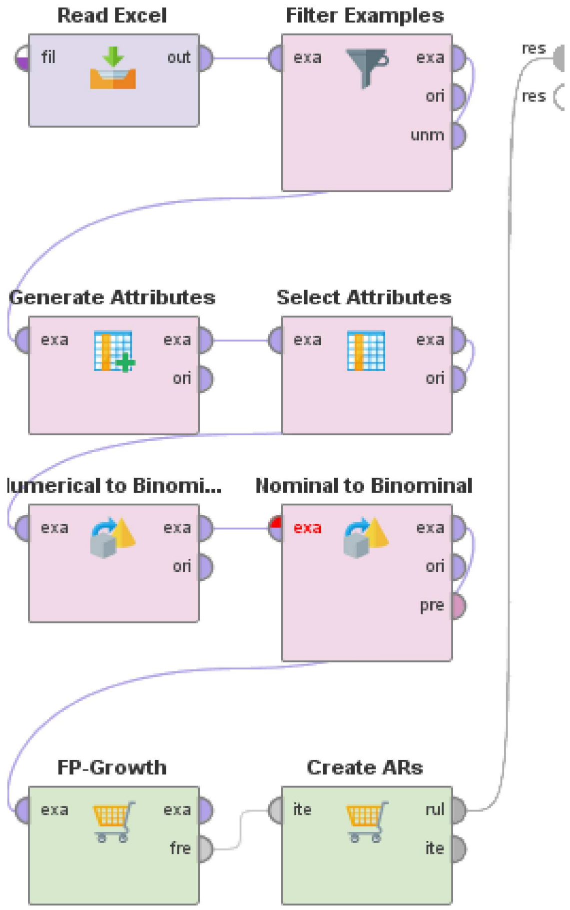

Fig. 2. Model of the process developed in RapidMiner.

Input data: Gathering information on item categories (I) and shelves (S)

The AS/RS of the company is a vertical warehouse: it is composed of a mechanical structure moving between two columns of shelves for picking up and storing items. Each shelf is made up of trays that can be internally partitioned in order to be adapted to the specific characteristics and dimensions of the materials. Figure 3 reports the dimension of each tray (1807×807 mm) and an example of the internal partitioning. The entire structure of the AS/RS is enclosed by walls that isolate it from the rest of the company environment; the only openings are constituted by one loading bay through which the system makes trays available. A software controls the handling operations through the appropriate station at the bay. 777 item categories have to be stored in the trays: for each one, the identification code, an indication of the maximum stock, and the area occupied are recorded.

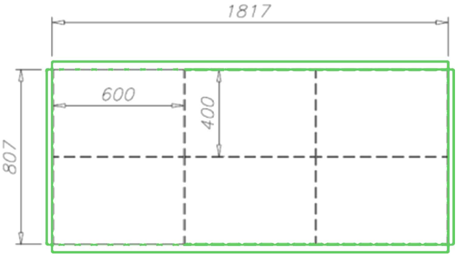

Fig. 3. Dimension of each tray and the example of internal partitioning.

Picking frequency estimation

In order to determine the picking frequency of each item category, the dataset employed contains information on the identification code, the aim of the picking (e.g., picking for manufacturing or item moving to another warehouse) and the quantity. The time interval considered in the current analysis is one year. Indeed, considering that shoe manufacturing refers to the fashion sector, enlarging the timeframe would include insignificant item categories, i.e., components no longer in stock because of production cessation. Through the FP-growth operator, as aforementioned, the frequent item-sets are determined. Then, the identification code (ID) of single items, together with their support (F) and the area occupied by each item category (A), is selected. This data is collected in the matrix I and the items are ordered by descending support (see Table 1 for an excerpt).

Table 1
Excerpt of frequency analysis.

ID	F	A [mm^2]
SPNCARL0508	0.081	66000
FDPARTYBLA02SMO	0.062	45000
SPCARTE0903	0.058	672000
SPSIMON0502	0.058	45000
FDPARTYBLA02SMO	0.057	143000
FDCARTEMC103XXX	0.05	180000
FDWILLIBLA01SMO	0.048	690000
SPCARTE0903	0.048	366000
FDWILLIBLA01SMO	0.044	705600
SPWILLI0501	0.044	51000
ISSIMON14012	0.034	162000
SPPOSI20801	0.034	143000
FDNCARLLA101FTM	0.034	45000
FDNCARLLA101FNE	0.03	1266000
SPYALTA0401	0.03	702000
FDGREGOBLA01SMO	0.03	375000
SPGREGO0501	0.03	345000
SPATLAN0401	0.03	120000
B*******	0.02	382800
A*******	0.02	1080000
K*******	0.01	585000

In order to be synthetic, only the items having a picking frequency higher than 0.01 have been reported.

Association Rule Mining and item categories allocation

Considering the proposed procedure, the first item to be allocated to S1 (i.e., the first tray) is SPNCARL0508, whose picking frequency is 8.1%.

Thus, the association rules having such item as a body are mined and matrix K is created (Table 2).

Table 2
Matrix I: ARs having SPNCARL0508 as body, confidence value and area required for the storage.

ID	Confidence	A [mm^2]
FDNCARLLA101FTM	0.43674	45000
FDNCARLLA101FNE	0.378345	1266000
B*******	0.178832	382800
K*******	0.175182	585000
FDNCARLLA305FTM	0.149635	920000
FDNCARLLA305FNE	0.149635	692250
A*******	0.139903	1080000
D*******	0.10219	943000

The area available in each tray is Savailable = 1458249 mm^2, but it has to be decreased by the area occupied by SPNCARL0508 (66000 mm^2). Hence, the maximum area available for the items listed in Table 2 is Savailable = 1392249 mm^2. According to the rules reported in Table 2, the first item assigned is FDNCARLLA101FTM (Savailable = 1392249 – 45000 = 1347249 mm^2), then, FDNCARLLA101FNE (Savailable = 1347249 – 1266000 = 81249 mm^2). Lastly, to saturate tray S1, part of item category B******* is also assigned. The total area required for B******* has to be decreased of the 81249 mm^2 allocated to S1 (382800 – 81249 = 301551 mm^2). Hence, items categories SPNCARL0508, FDNCARLLA101FTM, FDNCARLLA101FNE have to be dropped from matrix I and K, while for item category B******* only an update is required (in bold). An excerpt of the updated matrix I is reported in Table 3.

Procedure reiteration

Having saturated the first tray, a reiteration of the procedure is required. The new item category to be assigned is FDPARTYBLA02SMO, that is characterized by a picking frequency of 6.2%. The item categories to be assigned to S2 are reported in Table 4. Considering the available area constraint, it is possible to allocate the totality of item FDCARTEMC103XXX (Savailable = 1458249 – 180000 = 1278249 mm^2), the totality of B*******

(Savailable = 976698 mm^2), and part of A******* (Savailable = 0 mm^2; New area required for the complete storage of A******* = 103302 mm^2). In Table 5, matrix I updated after the second reiteration of the procedure is reported.

Table 3
Matrix I after the first update.

ID	F	A [mm^2]
FDPARTYBLA02SMO	0.062	45000
SPCARTE0903	0.058	672000
SPSIMON0502	0.058	45000
FDPARTYBLA02SMO	0.057	143000
FDCARTEMC103XXX	0.05	180000
FDWILLIBLA01SMO	0.048	690000
SPCARTE0903	0.048	366000
FDWILLIBLA01SMO	0.044	705600
SPWILLI0501	0.044	51000
ISSIMON14012	0.034	162000
SPPOSI20801	0.034	143000
SPYALTA0401	0.03	702000
FDGREGOBLA01SMO	0.03	375000
SPGREGO0501	0.03	345000
SPATLAN0401	0.03	120000
B*******	0.02	**301551**
A*******	0.02	1080000
K*******	0.01	585000

Table 4
Item categories to be assigned to S$_2$.

ID	Confidence	A [mm^2]
FDCARTEMC103XXX	0.827044	180000
B*******	0.210692	301551
A*******	0.163522	1080000
K*******	0.146226	585000

Table 5
Matrix I after the second update.

ID	F	A [mm^2]
FDPARTYBLA02SMO	0.062	45000
SPCARTE0903	0.058	672000
SPSIMON0502	0.058	45000
FDPARTYBLA02SMO	0.057	143000
FDWILLIBLA01SMO	0.048	690000
SPCARTE0903	0.048	366000
FDWILLIBLA01SMO	0.044	705600
SPWILLI0501	0.044	51000
ISSIMON14012	0.034	162000
SPPOSI20801	0.034	143000
SPYALTA0401	0.03	702000
FDGREGOBLA01SMO	0.03	375000
SPGREGO0501	0.03	345000
SPATLAN0401	0.03	120000

Discussion and conclusion

Managing inventory is one of the most vital and yet wasteful tasks in manufacturing. Labor is a large cost of warehouse operations. The more times one item is handled, the higher the costs associated with the item. In this work, a new approach has been proposed, based on Big Data Analytics methods, for reducing waste time during storage and retrieval activities of components and finished products. In existing contributions (e.g., [9, 13]), an application of ARM to material clustering in manual warehouses has been proposed, using the support of the rule as a driver for components' allocation. Our approach, instead, develops a procedure for material management in an AS/RS and prefers confidence as a driver metric. Specifically, the aim of the proposed algorithm allows minimizing picking time when operators have to prepare an assembly kit. In particular, it approach can be used during the implementation of 5S methodology since it helps assigning items to the shelf, removing items that are no longer needed (sort), organizing the items to optimize efficiency and flow (straighten), and developing behaviors that keep the workplace organized over the long term (sustain). Both manufacturing automation and lean manufacturing have the same goals: to satisfy customers at the lowest possible cost. To achieve these goals, both disciplines address removing low-value or nonvalue activities, reducing waste and producing predictable quality. Big Data Analytics methods showed their potential to facilitate the communication between automation systems and lean production approach in order to reach common objectives. Surely, the proposed method will be furtherly validated including an analysis based on simulation techniques (e.g., Montecarlo method). Further research directions worthy of investigation may also regard the introduction of the volume in the algorithm and the differentiation among stackable and not stackable items. Moreover, the implementation to specific case studies belonging to different industrial sectors and, thus, characterized by different items, should be carried out and compared.

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