Time and space efficiency in storage systems: a diagnostic framework

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Abstract:

Warehouse management and optimization aim at improving relevant metrics of performances and associated costs. To meet these goals becomes hard when scarce data are available, and the supply chain is not vertically integrated. This is, often, the case of 3PL providers whose customers are not willing to share data. Nevertheless, storage managers always need benchmarks of warehouse time and space performances to identify whether a storage system is performing well. Benchmarking of a storage system is rarely considered in warehouse science, for this reason it is the focus of this paper.

This study aims at illustrating a decision support framework to (1) assess the behaviour of the storage system, to (2) quantify metrics and key performance indicators (KPIs), to (3) benchmark the nature of the storage system, and to (4) diagnose issues and criticalities even when a limited amount of data is available to storage managers. This framework is made of a set of tools that all lie on the picking data records, which are typically available at any warehousing system. The tools calculate KPIs easy-to-read by practitioners who want to investigate the behaviour of the SKUs and the criticalities of the storage system.

The framework is applied to evaluate KPIs in a 3PL case study. Each KPI is linked to a practical issue and gives advices to practitioners to address it. The framework is implemented using Matlab and its outputs are presented, described and discussed in the paper through graphical and numerical analysis aiming at the improvement of the storage system performance.

Keywords: Warehouse analysis, storage optimisation, performance benchmark, 3PL providers

1. Introduction

"We need more space!" or "We need more pickers!". These are common claims by practitioners committed to the management of warehousing systems. Nevertheless, the space can hardly be increased as well as the workforce. This paper takes inspiration from these two practical and very popular issues. Graphical methodologies are addressed to these problems to obtain the best allocation of space and workforce in a storage system.

Storage systems are the buffers of any supply chain, indispensable to balance customers demand and production flows. They are widely studied in the last decades with emphasis on design (Gu, Goetschalckx and McGinnis, 2010; Manzini, 2012), control (De Koster, Le-duc and Roodbergen, 2007; Gu, Goetschalckx and McGinnis, 2007; Manzini et al., 2015[b] and 2016, Accorsi et al., 2018[a]) and performance evaluation (Accorsi et al., 2012; Accorsi et al., 2017; Staudt *et al.*, 2015). Unfortunately, new purchasing channel (e.g. e-commerce) and lean thinking discourage production companies owning storage systems. This fact leads to a massive use of third-part-logistics (3PL) providers (Selviaridis and Spring, 2007) whose stock keeping units (SKU) are extremely various in volume and order profile. In addition, storage systems rapidly changes their behaviour in agreement with demand change, and 3PL provider usually sign short-term (i.e. 1-2 years) contracts to reduce the management risk (Aguezzoul, 2014). These companies should continuously benchmark and assess their performance and allocate the adequate picking workforce and storage infrastructure able to fulfil client's needs and to avoid contract penalties. The difficulty of such management task is further influenced by the lack of visibility on supply chain flows (e.g. production flows and customer demand) and other information. As a consequence, 3PL warehouses operates in extremely uncertain environments as this information asymmetry leads to bottlenecks and avoidable storage and transport costs (Accorsi et al., 2018[b]). For this reason, 3PL providers need tools to deal with uncertainty and continuously analyse the behaviour of their storage system.

Scholars develop many methods addressed to storage system issues as the location of SKUs, the allocation of space and the pickers routing. Such methods are typically problem-oriented and can be difficulty applied to other storage systems. For these reason, an original diagnostic framework enabling general and comprehensive analysis on different warehousing systems is proposed. This framework is flexible and can be applied to any storage system managed through a generic warehouse management system (WMS).

The diagnostic framework uses two classes of key performance indicators (KPI) to answer practitioners' issues:

- Volume-based KPIs (dm^3)

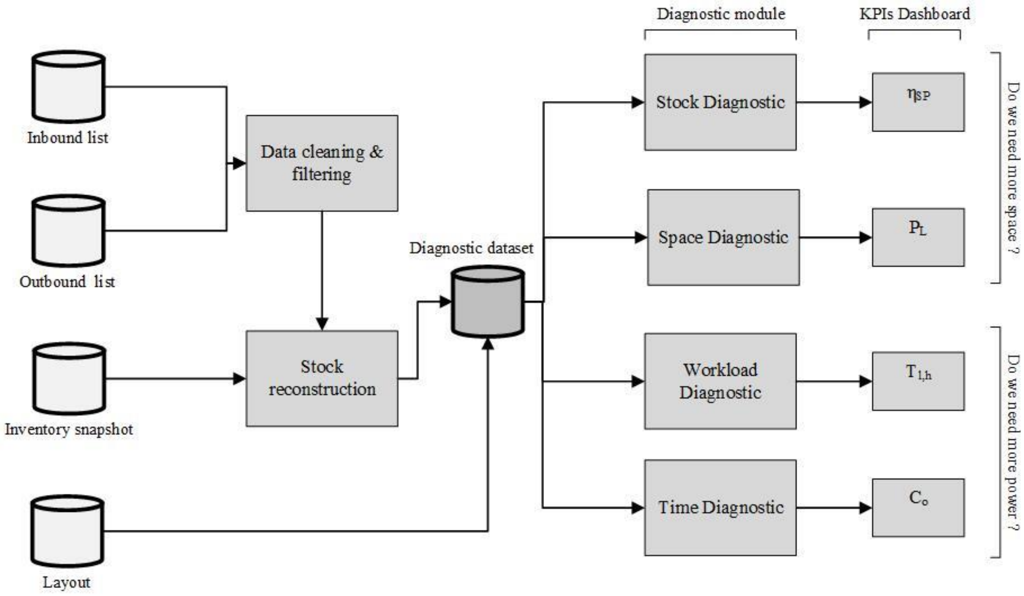

Figure 1: Proposed diagnostic framework data flow

- Popularity-based KPIs (N. of put-away/picking lines) (Manzini et al., 2015[a])

Starting from these two metrics, several KPIs are evaluated and presented to warehouse managers with graphic approaches. Volume KPIs are used to address the following tactical managerial questions:

- Warehouse seasonality and saturation. (Does it exist a seasonality trend? Is the warehouse currently saturated or not?)
- Time horizon for warehouse re-allocation/re-assignment. (Is re-allocation or re-assignment of SKUs needed? When is the best moment to do that?)
- The current use of the available space. (Are picking area concentrated near input-output (I/O) points?)

On the other hand, Popularity KPIs are used to check out:

- The handling power demanded by SKUs. (which SKUs generates more orders? Is the extant handling system properly designed?)
- The effect of handling on distances. (is the current routing policy efficient? Should it be re-designed?)

Typical research approaches use rigid and complex model to prescribe warehouse optimization. These models require large amount of data which are rarely available when the supply chain is not vertically integrated (e.g. in the case of 3PL provider). For this reason, the approach proposed in this paper is flexible and resilient and applicable to any storage system, in particular to these storage systems where outbound orders and inbound arrivals are not available in advance. The aim of the methodology is to give rapid and visual insights useful to briefly diagnose the behaviour of a storage system (Barbosa *et al.*, 2017). In addition to this, descriptive data is rarely used as a research methodology; this paper goes in the opposite direction aiming at reducing the gap between research activities and practical issues (Davarzani and Norrman, 2015), proposing smart and ready-to-implement KPIs.

The remainder of this paper is organized as follow: Section 2 presents the framework together with the data flows and data pre-processing. Section 3 discusses the analysing blocks through a case study from a 3PL storage system. Section 4 discusses the managerial implications of the framework and Section 5 concludes the work.

2. Diagnostic framework

This section illustrates the proposed framework. Special emphasis is given on data import, filter and manipulation The processed data are used to generate KPIs and to benchmark the storage system. The role of each of these KPIs is introduced and discussed in relation with the aforementioned managerial questions. The tactical level is the considered decision-making horizon. In particular, KPIs address decision related with the allocation of space and handling power in the storage system.

The framework includes four data source, two pre-processing procedure and four diagnostic routines used to generate KPIs.

The diagnostic framework needs four data sources:

1. Inbound list on time horizon $[T_0, T]$ (i.e. the list of all full-pallet replenishment).
2. Outbound list on time horizon $[T_0, T]$ (i.e. the list of all piece/carton/full-pallet picking).
3. Inventory snapshot at any time instant $t \in [T_0, T]$ (i.e. the inventory level for each SKU).
4. Storage system layout (i.e. the coordinates I/O, aisles and shortcuts between aisles).

Table 1: Notation and KPIs formulae

Notation	KPIs Formulae
S, set of SKU s	$\eta_{SP} = \frac{1}{TC}\sum_{t=1}^{T}\sum_{s\in S}(V_{in,s,t} - V_{out,s,t})$
L, set of picking locations l	
T, set of days considered for the analysis (days)	
O, set of picking orders o	
$X_l; Y_l; Z_l$ Cartesian coordinates of location l	$P_l = \sum_{t=1}^{T}\sum_{s\in S} P_{out,l,s,t}$
$y_{s,o}$= 1 if SKU $s \in o$; 0 otherwise	
$w_{s,l}$= 1 if SKU s is located in location l	
$x_{l,h,o}$= 1 if arc between locations l,h is travelled in order o; 0 otherwise	
$V_{in,s,t}$ inbound volume of sku s at time window t (dm^3)	$T_{l,h} = \sum_{o\in O} x_{l,h,o}$
$V_{out,s,t}$ inbound volume of sku s at time window t (dm^3)	
C, capacity of the storage system (dm^3)	
$P_{out,l,s,t}$ number of pick of sku s from location l at time window t	
D_o travelled distance to perform order o (m)	$C_o = \left(\frac{\sum_{s\in S} y_{s,o}\, w_{s,l}\, X_l}{\sum_{s\in S} y_{s,o}}, \frac{\sum_{s\in S} y_{s,o}\, w_{s,l}\, Y_l}{\sum_{s\in S} y_{s,o}}\right)$

The inbound list is rarely considered in literature since the majority of costs are from outbound activities. Nevertheless, this study considers the inbound list to draw the storage trend and to characterize the storage system profile (Hackman *et al.*, 2001). Inbound list is used, as well, for handling benchmarking when inbound and outbound activities are similar (e.g. crossdocking storage system).

Pre-processing is used to check data consistency. Data cleaning is needed to remove useless records from the inbound and outbound lists: stock-stock movements, dummy storage location, and errors or null values are removed. In addition to this, the storage locations are georeferenced with the use of the layout from the WMS code into Cartesian coordinates to show visual KPIs.

At this stage, the inventory snapshot is used to build the inventory profile for each day in the time horizon $[T_0, T]$. Starting from the inventory date, inbound and outbound movements are summed to track the storage level day by day.

These data are consolidated into a diagnostic dataset, used to evaluate KPIs and assess the behaviour of the storage system. The whole framework is presented in Figure 1.

KPIs belongs to four different families, each of them generated by a different routine. The first two families address space issues; the others handling power issue. Each routine works independently to increase the contest of application of the framework. If some WMS does not embed the input data required by a routine, the others works independently and are capable to assess the KPIs. The following sections illustrate the KPIs and discuss their role in the tactical space and time allocation. These KPIs are chosen, among others, to measure the efficiency of the storage system in terms of time and space, which is the main efficiency metric for warehouse managers and 3PL providers. The characteristics of the stored products (type, weight, order frequency, turnover rate, etc.) are not considered because these data are hardly available when a supply chain is not vertically integrated, and it is even more rare to find such a supply chain nowadays. Table 1 introduces the notation and formulae used to calculate the KPIs.

2.1 Stock diagnostic

This module focuses on the utilization of the available space in a storage system. It performs analysis on the volume (dm^3) stored within a time horizon. The main insights are about:

- Inventory Seasonality
- Volumetric saturation of the storage system

This module uses the inventory level calculated per each day of the observed horizon during the pre-processing stage ($V_{in,s,t}$; $V_{out,s,t}$). The resulting trend identifies whether or not the storage system is subjected to high seasonality. An oscillation of this value identifies poor utilization of the available space with increasing depreciation cost per unit. Investigate seasonality helps understanding whether an adequate batch for SKUs relocation and house-keeping tasks exist (e.g. when the warehouse is under-saturated). In addition to this, η_{SP} is used as a measure of efficiency of space usage. This is useful for a 3PL provider to verify how much space is available for new customers.

2.2 Space diagnostic

This module analyses the put-away/picking workload (i.e. popularity KPI) allocated over the storage system's layout. The underlying idea is to identify whether the workload is distributed or concentrated in the area nearby the I/O. Two main suggestions result from this analysis:

- the effectiveness of the current storage assignment policy.
- The effectiveness of the extant routing policy

Two visual KPIs are hence provided. The first is useful to check where put-away/picking tasks occur and how much

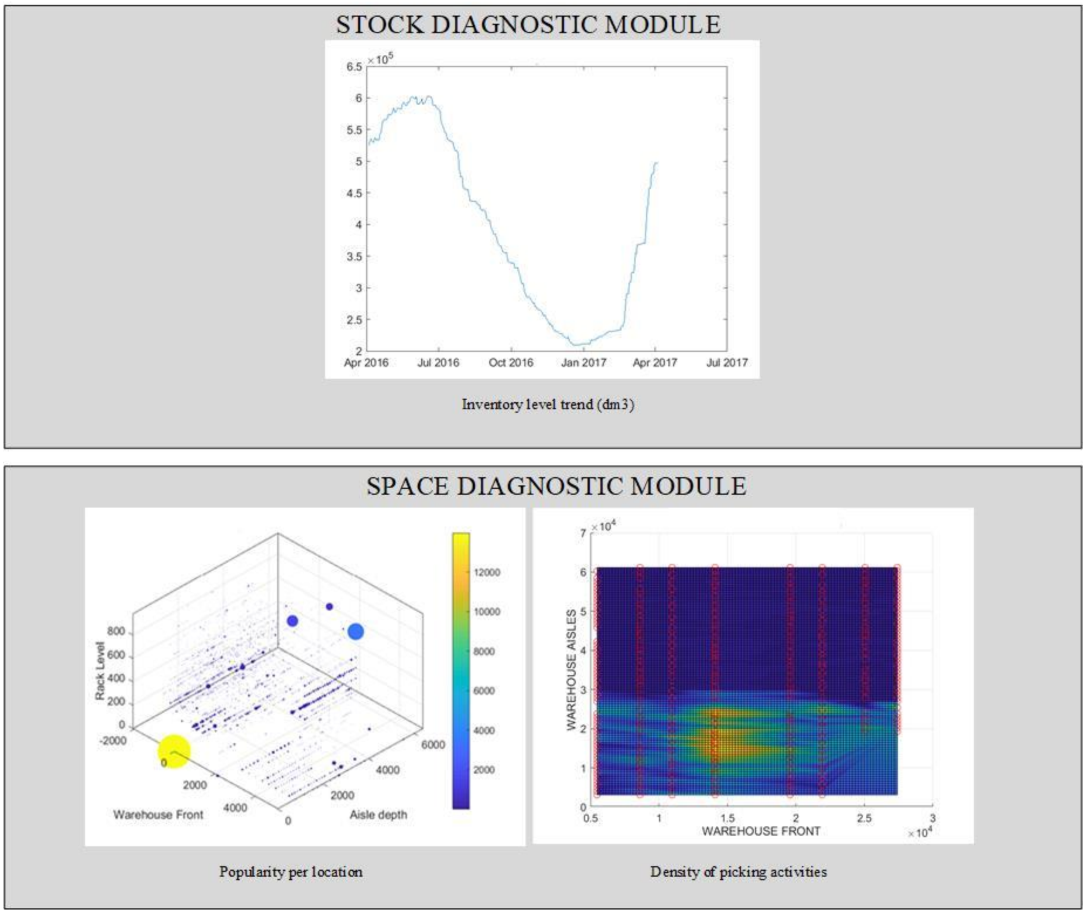

Figure 2: space efficiency dashboard

they are distributed over the storage layout. The KPI shows the value of P_l over a graph where *x*-axis and *y*-axis represent aisles and racks while *z*-axis represents the rack levels. With such view, the decision-maker easily identify if high flow SKUs are assigned to locations far from the I/O area suggesting relocation.

The second view defines the put-away/picking density based on P_l values on a 2-dimensional (plant) layout. This indicates which aisles, areas or zones are visited the most and allows managers to understand how the probability of access is distributed. Probability of access is represented as a continuous function which covers all the warehouse system area; red dots represents put-away/picking locations. Such view is useful to understand which routing policy is suitable for the warehouse. In addition to this, when separated areas are highlighted a zoning strategy may be considered to improve warehouse performance.

2.3 Workload diagnostic

This module aims at representing which SKUs request the most for handling activities. This information is crucial to adapt the storage assignment policy and to reduce the total travelled distance. The main insights of this analysis involve:

- SKUs ranking for storage allocation
- Picking activity allocation to picker

Many ranking indexes are provided: most of them are widely studied as popularity, volume, order completion (OC), cube-per-order index (COI), Turn. Other special purpose metrics are developed to investigate the impacts of pick lines and picked volumes on the processed orders. These indicators are represented via histograms and pareto curves. Other metrics are identified to investigate how the workload is assigned to handling resources (picking, forklift, AS/RS, etc.). These metrics are order-based and used to identify the workload associated to pickers and the number of pickers/asset needed to reach a certain level of productivity.

2.4 Time diagnostic

This module is focused on the calculation of travelled distance and associated time spent in operations. The aim of this analysis is to understand if picking missions are well organized and if it is possible to optimize them. The main insights are about:

- Total travelled distance
- Picking centroid for each order

The distance is obtained through a step counter algorithm inspired to (Zhang, 2016) which estimate vertical and horizontal distance in addition to distance to reach I/O. A

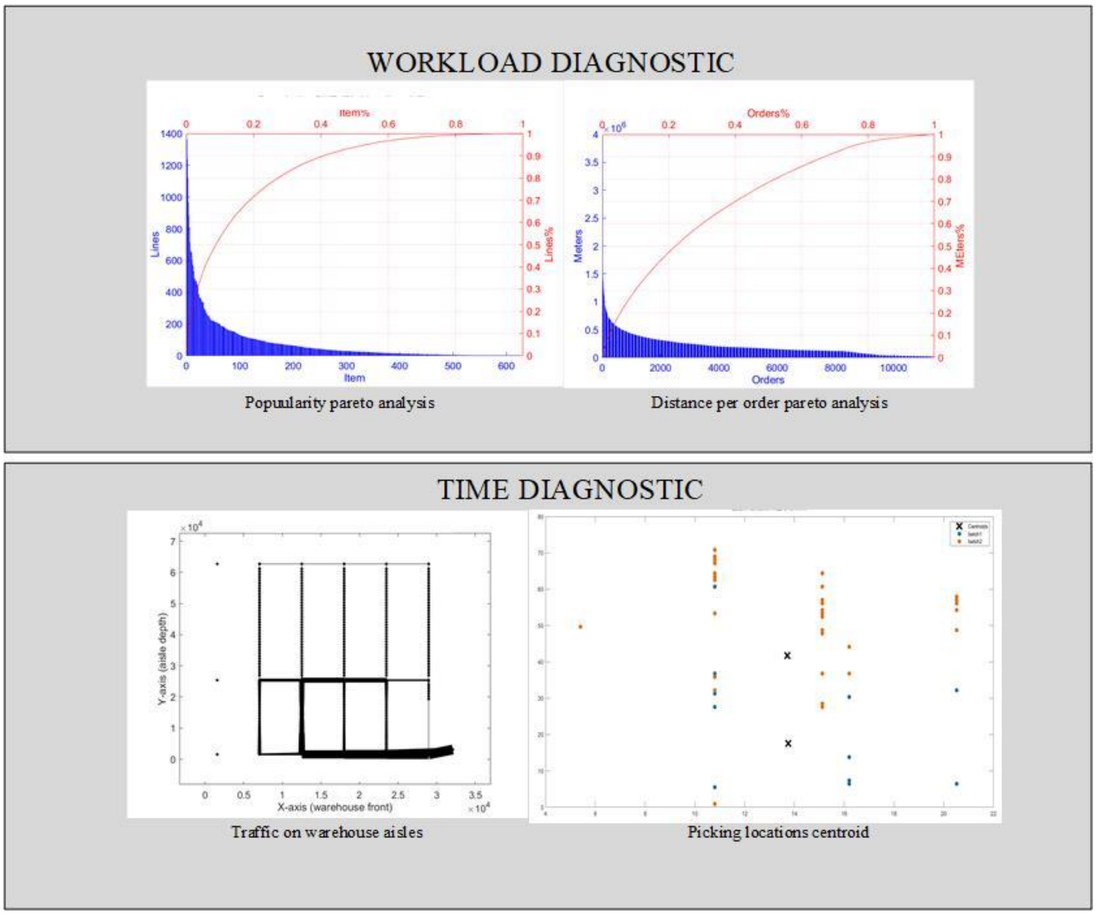

Figure 3: productivity dashboard

statistical distribution of this value is provided. This analysis visually represents T_{ih} with a traffic diagram which indicates which area is travelled the most and has a higher probability of congestion. The congestion is evaluated together with the number picker/forklift working in the storage system. A second analysis is performed on the picking mission: the centroid C_o of each mission is represented. Representing each mission with a different colour allows investigating whether or not order batching policy might be implemented with benefit.

3. Case Study

A real-world application is presented to showcase the impact and potentials of the presented framework. The aforementioned modules of analysis are applied to a 3PL warehouse operating in the field of beverage and located in northern Italy. Table 1 presents the input data of the case study which has been implemented in several scripts developed in Matlab environment.

All the figures here represented consider the picking (i.e. outbound) activities but, as stated in the previous section, the framework can be applied to the inbound activities as well. Figure 2 presents the space efficiency dashboard and shows the results of stock and space diagnostic modules (1,2). The stock diagnostic modules identify the inventory trend expressed in units of volumes (dm^3). The graph pinpoints a high seasonality since during the spring-summer the inventory level is more than double compared to the winter months. The space diagnostic tool highlights where the workload is located. In particular, the first graph is a 3d-view of the warehouse and each bubble represents the popularity (i.e. number of access) to a specific location. This analysis highlights that some locations on the top rack levels accounts for a significant fraction of the accesses. A re-location of the SKUs in those positions is suggested to reduce retrieval times and handling costs. The second graph is a layout view which considers the density of picking activities distributed over the storage system. The areas with the most of picks are highlighted as well as if storage classes are respected (e.g. ABC). The red dots represent the storage locations. The analysis shows that a higher density exists in the front of the warehouse, so that picking costs are under control.

Table 2: input data

Input data	
Location	Northern Italy
Storage area	2400 sqm
Storage locations	4000
Aisles	5
Racks	9
Bays per rack	66
Analysis time horizon	8 months
Number of pickers	3 per shift
Outboud rows	44650
Number of SKUs	630

Figure 3 presents the productivity dashboard that focuses on the workload for retrieval and picking missions. The workload diagnostics module showcases that 20% of the SKUs accounts for about 75% or the popularity. This is a fundamental information to identify the space devoted to fast-moving and slow-moving SKUs. The following shows that 50% of orders accounts for 80% of the travelled distance. A routing policy is effective when the most of orders accounts for a small percentage of travelling distances since fast moving SKUs are located close to the I/O point. The time diagnostic modules identify troubles with the organization of retrieval missions. In particular, through a traffic analysis, it comes out that the second aisle from the left corner presents a higher traffic frequency than the others. This results from an incorrect assignment policy which locates frequently picked SKUs in an aisle far from the I/O point (i.e. located in the bottom-right corner). The second chart analyses the picking activities over a specific time horizon identifying the centroids of picking location. In this case the two centroids of the two picking missions are close to the centre of the warehouse, and this is due to an equiprobability distribution on the *x*-axis of the location popularity. When the picking process is intense, one may consider assigning a single order to multiple pickers aiming at reducing the time spent for retrieval.

4. Discussion

The proposed diagnostic framework organizes a series of indicators and analyses that elicit insights for practitioners and warehousing managers. The assessment of the behaviour of the storage system is reached through KPIs inspired by the literature and implemented with graphical view which requires no academic skills to be understood. There are many relevant managerial implications related to the implementation of this framework in 3PL providers. The framework enables the practitioners to analyse the current configuration of the storage system with a rigorous and clinic approach. This approach is flexible: it is applicable to any storage system and its results are comparable. Practitioners can identify criticalities based on quantitative data and reliable analysis. In addition to this, a continuous use (e.g. 2-3 months) of such a framework helps manager to understand the behaviours of their storage system from a tactical point of view and organize the operations consequently. This framework helps inidentifying performance benchmark of the storage processes. This is an important outcome to properly set the cost-per-line processed. The problem of costs is relevant in 3PL logistics where customers looks for the cheapest provider, without taking into account the offered level of service. Particularly, 3PL's managers can use such metrics to properly tender services and targets with their clients and show how their storage system is managed, controlled and optimized. Furthermore, this framework is scalable and may embed many other KPIs and analysis to support managers of a storage system.

5. Conclusion

This paper presents an original framework for the analysis of a storage system. The framework is based on few input data available from almost all WMS. Data are pre-processed and a part of them is considered to calculate quantitative and visual KPIs on space and time efficiency. This indicator are used from a tactical decision maker to identify if optimization (e.g. re-assignment of SKU) is needed. The framework is implemented into a series of Matlab scripts, one for each block of the framework, answering separate issues of warehouse managers. A case study from 3PL logistics is proposed to investigate the values of KPIs in a real case and to showcase the potential of the framework. Further research will identify best practices for the control and optimization of a warehouse solely using visual analysis without the use of complex decision support systems.

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