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Warehouse management system customization and information availability in 3pl companies

A decision-support tool

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Received 19 January 2018
Revised 7 April 2018
14 June 2018
Accepted 1 July 2018

Abstract

Purpose – The purpose of this paper is to illustrate an original decision-support tool (DST) that aids 3PL managers to decide on the proper warehouse management system (WMS) customization. The aim of this tool is to address to the three main issues affecting such decision: the cost of the information sharing, the scarce visibility of the client's data and the uncertainty of quantifying the return from investing into a WMS feature.
Design/methodology/approach – The tool behaves as a digital twin of a WMS. In addition, it incorporates a set of WMS's features based both on heuristics and optimization techniques and uses simulation to perform what-if multi-scenario analyses of alternative management scenarios. In order to validate the effectiveness of the tool, its application to a real-world 3PL warehouse operating in the sector of biomedical products is illustrated.
Findings – The results of a simulation campaign along an observation horizon of ten months demonstrate how the tool supports the comparison of alternative scenarios with the *as-is*, thereby suggesting the most suitable WMS customization to adopt.
Practical implications – The tool supports 3PL managers in enhancing the efficiency of the operations and the fulfilling of the required service level, which is increasingly challenging given the large inventory mix and the variable clients portfolio that 3PLs have to manage. Particularly, the choice of the WMS customization that better perform with each business can be problematic, given the scarce information visibility of the provider on the client's processes.
Originality/value – To the author's knowledge, this paper is among the first to address a still uncovered gap of the warehousing literature by illustrating a DST that exploits optimization and simulation techniques to quantify the impacts of the information availability on the warehousing operations performance. As a second novel contribution, this tool enables to create a digital twin of a WMS and foresee the evolution of the warehouse's performance over time.

Keywords 3PL, WMS, Information availability, Decision-support system, Digital twin, Warehousing operations
Paper type Research paper

1. Introduction

Third-party logistics (3PL) providers have come a long way since their dawning in 1980s. The types of services that companies entrusted to 3PL providers were limited to transport and storage operations. In the last decades, with the increasing trend to outsourcing, the

The authors would like to heartily thank the company Due Torri S.p.a. involved in this study. Especially in the name of Eng. Nicola Borghi, for his valuable inputs, his support and his willingness to cooperate in this research project.

Industrial Management & Data Systems
Vol. 119 No. 2, 2019
pp. 251-273

0263-5577
DOI 10.1108/IMDS-01-2018-0033

offer of value-added logistic services has grown (Langley, 2015; Shi *et al.*, 2016; Large *et al.*, 2011). These services widen the business opportunities for 3PL providers but require continuous review of the provided processes to meet the clients' requirements. Particularly in warehousing operations, enhancing efficiency and service level is increasingly challenging given the large inventory mix and the need to manage many clients simultaneously (Hilmola and Lorentz, 2011).

The warehousing operations are generally aided by the warehouse management system (WMS). This enterprise resource planning (ERP) module controls the flows of goods and information as well as the personnel tasks, supervising the operations within a warehouse (Ramaa *et al.*, 2012). The introduction of WMSs at the different levels of a supply chain facilitates the creation of information infrastructures that enterprises exploit even in procurement, production, storage and distribution activities (Tan, 2009).

In view of this, an increasing number of 3PL providers are investing in WMSs. The 19th annual report on the logistics outsourcing (Langley, 2015) shows that the 58 percent of companies have already purchased a WMS and the 33 percent have invested in WMS customization (e.g. functionalities for the labor management, analytics). Nevertheless, among the jungle bid of WMSs that sees hundreds of standardized solutions, the identification of the most suitable WMS customization for each specific business is challenging.

This choice is further complicated by the scarce information availability along the supply chain (Selviaridis and Spring, 2007; Karagiannaki *et al.*, 2011), which affects the visibility on the operations to be managed. Although the crucial role of the information in operations management is unanimously stated (Cantor and Macdonald, 2009; Mandal and Bagchi, 2016; Ruel *et al.*, 2017), the 3PL providers usually make decisions with partial visibility on the client's processes, especially during the tender of new clients. The competition among 3PL providers and the high turnover in their clients' portfolio reduce the opportunity for long-standing and trustworthy partnerships, and discourage data and information sharing. The schedule of the incoming trucks, the loads of these trucks, the changes in the inventory mix, and the orders forecasts are examples of this unknown information (Accorsi *et al.*, 2018a).

Three main issues in the design of WMS motivate this paper:

- Issue 1 – costs of information technologies (IT). Both scientific literature and industrial practice highlight the positive effects of IT on the 3PL provider's performance (Evangelista *et al.*, 2012). Nevertheless, four cost drivers should be taken into account (Chen and Tsou, 2007): the IT infrastructure, the alignment between the IT and the business strategies, the re-organization of the organigram and the communication procedures (e.g. activities coordination, communication rules, procedures) to meet the IT capabilities, the workers training.

- Issue 2 – partial information availability. The lack of visibility on the characteristics of the inventory (e.g. weight, volume, safe conservation conditions per each stock-keeping-unit SKU) or the clients' targets (e.g. demand forecast, products life cycle) limit the benefits resulting by a WMS.

- Issue 3 – uncertainty on the benefits. The long-term benefits resulting from the implementation of a WMS feature are hard to be predicted because of the level of achievable customization and the unexpected changes in the business operational conditions. This often discourages the 3PL providers to invest in WMS's features.

This paper aims to support the 3PL managers to design the proper WMS customization. To this purpose, we illustrate a decision-support tool (DST), named Store Simulator, that is intended to address Issue 3 in the first place. Particularly, the proposed tool is able to assess the long-term impacts resulting by implementing a WMS feature on a set of economic and logistic KPIs. Moreover, a second aim of this tool is to study and compare the effects of higher information availability on the warehouse performances, therefore addressing to Issue 2. For these reasons, we retain Store Simulator provides a valuable support to the investments assessment in the WMS design and customization, under the constraint derived by Issue 1.

The remainder of the paper is organized as follows. Section 2 illustrates the research background and the state-of-art of the literature. Section 3 introduces the approach of analysis and illustrates the architecture of the DST. Section 4 introduces the tool functionalities that virtualize the WMS features. Section 5 presents how the proposed tool performs in a 3PL provider warehousing system for pharmaceutical products, that represents the testbed for a what-if multi-scenario analysis. Section 6 discusses the paper results. Finally, Section 7 summarizes the conclusions and sets the goals for future developments.

2. Literature review

The WMS is a management information system that controls the physical and informative flows within the warehouse, involving both inbound and outbound processes (Shiau and Lee, 2010). A WMS gathers, stores and provides information on products, resources and processes, recording the transactions and transferring them to other modules of the company's ERP (Verwijmeren, 2004). Some technologies as Auto-ID Data Capturing or Radio-frequency identification may be integrated to support the data collection (Ramaa *et al.*, 2012). Faber and De Koster (2002) list the advantages from the introduction of a WMS: better space utilization, more accurate inventory, productivity increase and enhancement of the number and quality of services offered to clients. They even distinguish between Basic WMS and Complex WMS, which manages a network of warehouses, implementing integrated inventory management and picking policies. Furthermore, a Complex WMS offers value-added functionalities as data-driven planning, traceability, dock allocation, automated process supervision and control (automated guided vehicles or automated storage and retrieval system) (Roodbergen and Vis, 2009). Both practitioners and researchers recognize the role of the WMS in improving the warehouse performance (Faber *et al.*, 2013; Lam *et al.*, 2010; Staudt *et al.*, 2015). Tan (2009) and Shim *et al.* (2002) underline how the selection of the proper WMS features is crucial for a 3PL provider which operates with several clients and different items by characteristics and turnover.

The commercial offer of WMSs includes a wide variety of solutions. Harris (2016) overviews the WMS's features proposed by the top vendors and software houses. He classifies these features into seven modules according to their purpose and function. Figure 1 shows the relationship between each module and the physical flows of products throughout a warehouse (extendedly referenced in Bartholdi and Hackman, 2013; Gu *et al.*, 2007).

A brief description of the operations involving these flows is given in Table I.

The purpose of selecting the set of features of a WMS has been already debated by Giannikas *et al.* (2013) which identify two decision drivers: the flexibility, i.e. reacting quickly to changes in customers demand and the adaptability, i.e. maintaining high service level when customers' requirements change. They also argue that the partial visibility on the processes bounds the level of reachable performance in the warehouse operations. Kearns and Lederer (2003) show the role of data sharing in strengthening and improving the operations between companies in the supply chain. Others accounts the related impacts on the bullwhip effect (Lee *et al.*, 1997; Cantor and Macdonald, 2009) and state how the upgrade

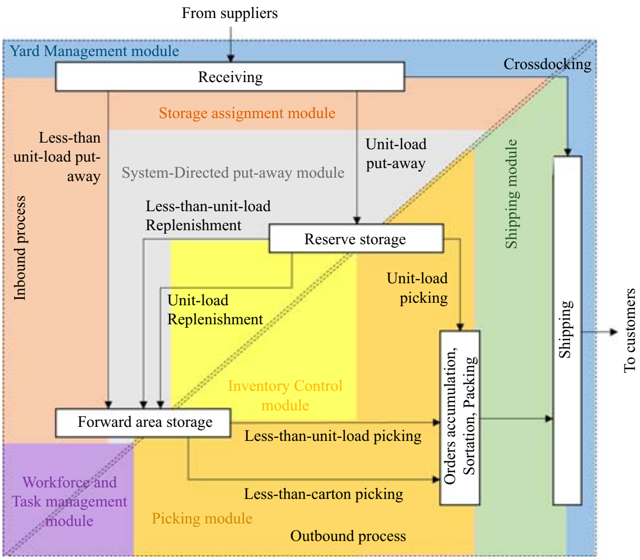

Figure 1.
The warehouse operations and the associated WMS management modules

Table I.
Warehouse operations description (for further details see [30, 43, 45-47])

Operation	Description	WMS module
Receiving	The incoming loads (i.e. pallets) are unloaded, checked, tracked in the system and prepared for put-away activities	Barcode reading/printing Yard management: doors allocation, arrival scheduling
Put-away	The loads are stored into the racks or assigned to a physical location within the storage system The loads can be stored into the reserve area or directly to the forward (picking) area A careful put-away reduces significantly the traveling during the retrieving activities (i.e. 55 percent of total warehouse costs)	Storage assignment: how to assign loads to the empty locations Replenishing policy: how to re-fill the forward area from the reserve
Picking	In response to the customer orders, picking lists are generated and devoted to the operators to perform the retrieving activities	Picking tour optimization (Picking list management) Inventory control Retrieving policy management: FIFO, LIFO, FEFO, FMFO (first-empty-first-out)
Sorting Packing Shipping	These include the loads preparation and the checkout activities. These activities are extremely labor-intensive since requires accurate control to avoid claims or back-orders	Shipping documentation printing Aided packing and cartonization: loading sequence suggestion Labor management

of ERPs and WMSs make companies more responsive to the changes of the customers' demand (Sambamurthy *et al.*, 2003; Comuzzi and Parhizkar, 2017).

Unfortunately, 3PL providers usually face the partial visibility on their clients' operations, on the products characteristics, on the variation of the turnover or the inventory mix. This limits the implementation of the so-called product intelligence paradigm in the 3PL warehousing operations (McFarlane *et al.*, 2013; Lu *et al.*, 2013). This paradigm exploits the interdependency between a physical entity (e.g. a product) and its informative content (Meyer *et al.*, 2009). For example, the use of some metrics (e.g. COI defined by Haskett, 1963), contributes to reduce the traveling for picking (Chan and Chan, 2011), but needs a set of information provided by the client, as the unit volume of the products and the number of orders (De Koster *et al.*, 2007).

In conclusion, a WMS provides knowledge and enables the improvement of the performance of the warehousing operations but requires input data, whose collection is constrained by several exogenous factors and is expensive. To avoid the "dog-chasing-its-own-tail" problem, the 3PL operations manager should consider carefully the adoption of a WMS and its customization in the view of the achievable benefits.

To the best of our knowledge, this paper addresses a still uncovered gap of the warehousing literature by illustrating a DST that exploits optimization and simulation techniques to quantify the impacts of the information availability on the performance of the warehousing operations, supporting decision making on the WMS features and customization. The tool allows to foresee the impacts of such choices on the warehouse performance over a time horizon, according to an approach already explored in the field of block-storage systems (Accorsi *et al.*, 2017). Since this tool virtualizes the dynamic behavior of a storage system, it behaves as a digital twin of a WMS (Grieves, 2014). In warehousing systems, a digital twin can be used to foresee the mid-term benefits of given logistics and operations decisions, thereby addressing to Issue 3. While digital twins are widely used in other sectors, such as aeronautics and mechatronics since the advent of the Industry 4.0 era (Tao *et al.*, 2018), to the authors' knowledge this is the first attempt in warehouse science.

Furthermore, it extends the limitations of the tool illustrated by Accorsi *et al.* (2014). This was intended to aid the design and management of effective storage systems from green field, and for the investigation on how to combine storage allocation and assignment policies in an existing facility with dedicated storage locations. Dedicated storage is indeed not suitable in 3PL warehouses, since the inventory mix changes continuously with demand seasonality and the clients' portfolio.

Simulation allows to study complex systems in an affordable way, by developing a model that replicates the behavior of the observed system and by varying the input parameters to evaluate the responses (Manzini *et al.*, 2005). Chan and Chan (2010) encourage the use of simulation to study the impact of the information sharing on the entire supply chains, and Dorigatti *et al.* (2016) propose a framework based on simulation to assess the benefits from collaboration and information visibility. Fleisch and Tellkamp (2005) use simulation to study the level of visibility on the inventory along the entire supply chain, while Ramanathan (2014) tests the impacts of supply chain collaborations.

The challenge of developing tools that reproduce the behavior of non-automated warehouses is widely recognized by the literature (Cagliano *et al.*, 2011), and few are the contributions on this topic. Table II shortlists some of these over the past two decades. It is worth noting how some scholars began exploring this topic quite early, while recent attempts are rare. The table classifies the tool with respect to the involved processes, the set of decision levers, the types of storage system (i.e. OPS or unit load warehouse), the tool scopes (i.e. the warehouse design or operations management), the measured performance indicators, the approach used in what-if multi-scenario analyses, the use of real input data and, lastly, the use of object-oriented programming languages. The check states if the contribution presents the specific characteristics, while the acronym "NS" indicates whether it is not specified in the text.

With respect to the other contributions, this paper focuses on the impact of information visibility on the warehousing operations. The proposed tool quantifies multiple KPIs related to the receiving, the put-away, the storage, the picking processes, instead a single metric of a single process (Chen *et al.*, 2010), and involves the interdependencies between the storage and picking policies within a multiple-level order-picking system. In addition, a great deal of attention is devoted to data collection to enhance the robustness of the results in accordance

Contributions		This work	Accorsi *et al.* (2014)	Gagliardi *et al.* (2007)	Galè *et al.* (2002)	Lam *et al.* (2011)	Longo (2011)	Macro and Salmi (2002)	Medina *et al.* (2009)	Min (2009)	Yang (2008)
Processes	Receiving	✓	✓		✓		✓		✓		
	Put-away	✓	✓	✓	✓		✓	✓		✓	✓
	Storage	✓		✓				✓	✓	✓	
	Picking	✓	✓	✓	✓	✓	✓	✓			✓
	Sorting						✓				
	Packing						✓				
	Shipping				✓		✓	✓	✓		
Decision levers	Storage assignment	✓	✓	✓	✓			✓			
	Picking Policy	✓	✓			✓		✓			
	Order batching		✓								✓
	Routing policy		✓								
	Emptying policy	✓									
	Allocation strategy		✓	✓							
	Layout configuration	variable	variable	variable	fixed	variable	fixed	variable	ns	variable	variable
	Put-away policy	✓									
Type of storage system	Unit load warehouse	✓	✓	ns	ns		✓		ns	ns	
	OPS	✓	✓	ns	ns	✓		✓	ns	ns	✓
Objective	Design		✓					✓		✓	
	Operations management	✓		✓	✓	✓	✓	✓	✓		✓
Performance metrics	Single										
	Multiple	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Multi-scenario analysis	Setting-based	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Time-based	✓									
Real input data	Arrivals	✓	✓			✓		✓	✓	ns	
	Demand	✓	✓			✓		✓	✓		
Object-oriented language		✓	✓				✓				✓

Table II.
Literature overview

with the real-world instance. However, the main contribution presented by our DST regards the opportunity to foresee the evolution of the warehouse performance over time, behaving as a digital twin of the company's WMS. The building of the multi-scenario analysis is, therefore, obtained as a result of a combination of logistic choices (i.e. setting-based multi-scenario analysis), whose impact can be evaluated day-by-day (time-based multi-scenario analysis). Lastly, it is worth noting how the DST includes the opportunity to deal with several inbound decisions as the put-away policy to implement or the capacity of the staging area, i.e. buffer where to unload trucks and prepare the incoming unit loads for storage.

3. The decision-support tool

The DST manipulates a historical data set representing the available knowledge on the warehousing operations and simulates the behavior of the storage system over a given horizon (e.g. a year) according to the alternative WMS features and capabilities. These features control and affect the behavior of the warehouse. A set of features results in a specific release of the WMS (i.e. a management scenario). Thus, different sets correspond to multiple to-be scenarios. The to-be scenarios are compared with the benchmark (i.e. the *as-is* or current scenario) through a panel of performance indicators (i.e. traveling for picking, utilization of locations) which enables to identify the most performing management scenario. The implemented WMS's features include the management of both put-away and picking operations (see Table I), which together account for the 70 percent of the total operating costs (Bartholdi and Hackman, 2013).

Figure 2 shows the conceptual framework of the proposed tool, where the main functions are outlined through the use of pseudocode. These will be further explored at Section 4.2.

Framework of the progressive-adapting methodology implemented in the DST

(a) Import settings:
Buffer capacity: b
Step: m
Period (a day): t
Replenishing time: t_r where j is the last t_r in t
Simulation Periods: T
Assignment policy: k
Retrieving policy: n
Inventory snapshot: $s_{t_r, t}$
Unit load $= u$
Orders $= o$
Picklines $= pl$

(b) Import Data: import data from the database
(c) Simulation

while ($t \leqslant T$){

Set $s_{t_r=1, t} = s_{t_r=j, t-1}$
Set $L^{\mathrm{unitload}}_{t}$ as the list of incoming unit loads u in t
Calculate $\mathrm{pop}^{\mathrm{roll}}_{u, t, m}$ for each u in t according to m

Set $L^{\mathrm{orders\ imp}}_{t}$ as the imported list of orders o in t
Set $L^{\mathrm{pickline\ imp}}_{o, pl}$ as the imported list of pick line pl in o

for each t_r {

Perform the picking process according to n
Produce $s_{t_r, t}$
Produce $L^{\mathrm{orders\ sim}}_{t, t_r}$ as the simulated list of orders in t in (t_{r-1}, t_r)

}

Set $L^{\mathrm{orders\ sim}}_{t}$ as the simulated list of orders o in t

Solve the assignment problem according to k
Perform the put-away process
Update $s_{t_r, t}$
}
}
(d) Print results in the database

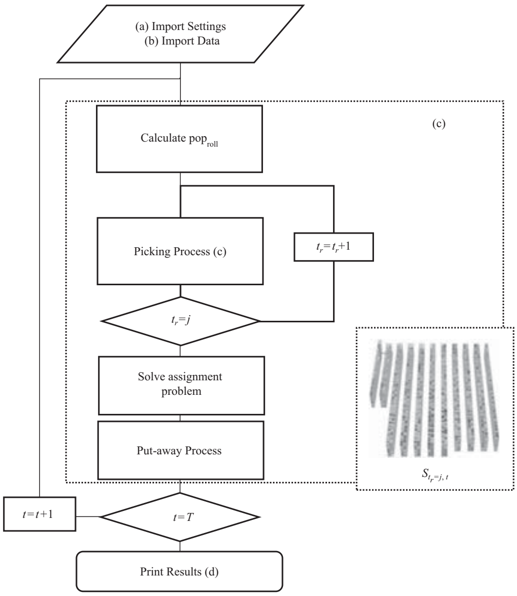

Figure 2.
Conceptual framework of the DSS

The proposed tool implements two key patterns described in the following:

(1) Progressive adaptation: starting from an initial inventory collecting the stored volume per each SKU, this tool progressively adapts to the introduction of new WMS features. Thus, the configuration of the storage system evolves during the day (i.e. within time batches called replenishing time), and along a time horizon according to inbound lines (i.e. incoming loads), the available empty locations, and the chosen management policy (i.e. that is the object of analysis). The replenishing time t_r is a batch within the day (e.g. 12:00–18:00—20:00) that decouples put-away from picking activities, and represents the instant when the inventory configuration is updated in the WMS. As a consequence, the inventory configuration at t_r is a combination of original frames (i.e. locations and held SKUs not yet visited) and adapted frames made by the storage locations visited at least once according to the selected management scenario (i.e. WMS's features). The adaptation of the storage system to a given WMS's feature is pursued progressively, at a ratio that depends by the average inventory's turnover.

(2) Adaptive assignment: in presence of variable demand the warehouse is the buffer that protects from stock-out and from bullwhip effects throughout the supply chain (Yingde and Smith, 2012). In such an environment, a storage assignment policy (i.e. the rule that assigns an incoming load to a location) built on a punctual time-dependent metric (e.g. popularity, turnover) is misleading. To avoid this problem, this tool implements an adaptive assignment approach (Chiang *et al.*, 2011) that exploits the historical data set to assess the dynamic behavior of a SKU (e.g. demand trend) and assigns it to a location accordingly. The time horizon considered for the assessment of the SKU's behavior is called step.

In order to implement the adaptive assignment, we use the rolling popularity metric as illustrated by Manzini *et al.* (2015) (see Figure 2). It is calculated in Equation 1 per each SKU i at period t as the number of pick lines cumulated within the previous time batch Δt, i.e. the step:

$$Pop^{roll}_{i,\Delta t}(t) = \sum_{t-\Delta t}^{t-1} Pop_i(t), \qquad (1)$$

where i is the SKU, Δt is the step (e.g. a week, a month expressed in term of periods).

Furthermore, the tool framework is built upon three basic assumptions. First, the flow of loads is one-directional, from inbound to outbound. Re-locating flows (i.e. SKUs moved among locations) are not allowed. Second, each storage location is single SKU and all the locations are devoted to picking (i.e. multi-level picking). Once a pallet of a generic SKU i is assigned to an empty location l, this remains occupied until the whole stock is retrieved. Third, the pallet received at day t is stored in day t and retrieving is allowed from day $t+1$ (see Figure 2).

4. Tool design and functionalities

According to Power and Sharda (2007), the proposed DST is classified as a model-driven decision-support system. Its architecture is made of multiple patterns for the simulation of the warehousing operations. The DST implements and solves even optimization problems for the storage assignment. Particularly, it can be interfaced with a generic commercial solver (e.g. Gurobi) for linear or multi-objective models that are written in AMPL. Store Simulator is written in C#. NET, using LINQ libraries, and is connected to a relational SQL database, which is described in the following sub-section. The DST is intended for users with poor informatics skills. Two user-friendly graphical user interfaces (GUIs) are developed and illustrated below. The proposed tool is highly customizable and can quickly incorporate new management scenarios (i.e. WMS's features) to be tested and assessed.

4.1 Database description

The designed database is inspired to the typical WMS's data architecture and tracks the warehouse's inbound and the outbound operations within a given horizon. The tables include required and auxiliary ones. The first set tracks the essential information that draws the storage system, the inbound flows, the demand orders. The auxiliary tables are involved case by case depending on the WMS's feature to be assessed. Table III further describes the characteristics of each table.

Both required and auxiliary tables are oorganized in the entity-relational diagram of Figure 3, which underlines the connection between input and output tables.

4.2 Simulation settings and graphic user interfaces

Two GUIs enable setting the simulation parameters and visualizing the KPIs resulting by each management scenario. Figure 4 summarizes the levers of analysis manageable through the GUIs and provides an exemplifying set of settings.

The first lever is the aforementioned replenishing time t_r. This reflects the typical work flow of the warehouse, as the working shifts, or the distribution of the truck arrivals over the day. High-frequency replenishing requires at least one (in small warehouse) operator entirely devoted to put-away activity. Low frequency replenishing concentrates put-away in a specific, generally longer, time batch.

Input tables	Data
Mandatory	
SKU	The SKUs' characteristics (e.g. SKU code, description, volume, weight, labeled temperature standard)
OrderList	The historical demand orders and the associated picking tours: date and time of the pick, SKU code and lot code, order code and picked quantity
Inventory	The initial inventory snapshot that reports per each SKU the cartons stored per location
InboundList	The historical records of the incoming unit loads, including the list of SKUs per pallet, the arrival time and the truck code
Location	The characteristics of the storage locations (e.g. distance from the I/O dock)
WH	Information on the warehouse, e.g. location, sizes and the number of aisles and bays
Auxiliary	
Temperature	Indoor temperature per unit time (e.g. hour, minute) within a selected period of time (e.g. a month, a year)
Weather	Outdoor temperature values (maximum, minimum) and humidity recorded during each day of the simulation
Output tables	Data
Mandatory	
SimulationOrderList	The picks list resulting from the simulation. This table has the same structure of ORDERLIST
SimulationSettings	Summarizes the user choices and the simulation settings
SimulationInventory	Inventory snapshot taken during each day of the simulation
SimulationStockBuffer	The list of pallets queued in the pre-storage buffer (i.e. inbound docks)
Auxiliary	
SimulationResults	Value of the objective functions used in the optimization of the assignment process
SimulationSolver	Results of the algorithm for the selection of the trade-off solution of the multi-objective optimization problem

Table III.
The database tables

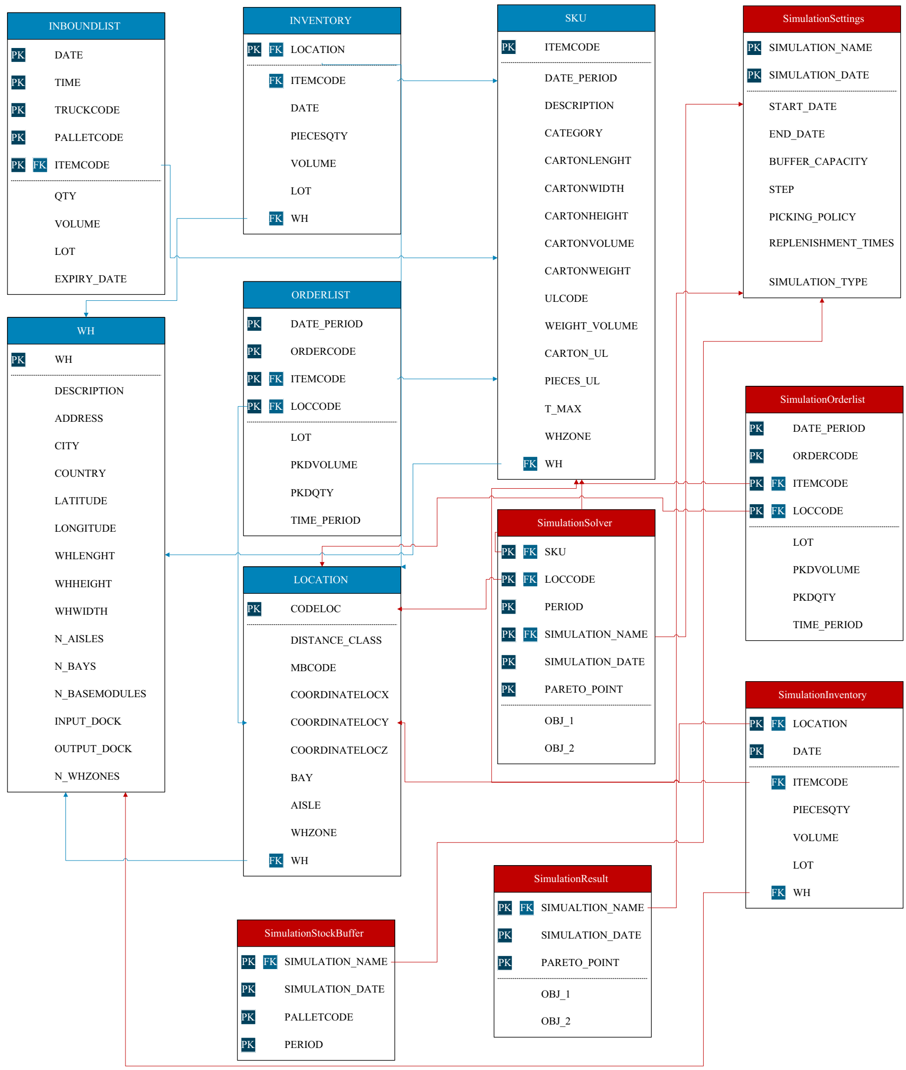

Figure 3.
Entity relationship (E-R) diagram

The capacity of the inbound buffer b is another lever of analysis. When, at time t_r, the empty locations are less than the incoming pallets the DST temporarily assigns the remaining loads to the buffer. The buffer is indeed the floor storage area placed at the inbound dock where the trucks are unloaded and the pallets wait for put-away. The larger the buffer capacity b, the less the storage volume utilization will be. Nevertheless, a larger buffer enables holding the incoming SKUs until adequate storage locations are again available. In view of this, the manager should carefully handle the relationship between the replenishing time and the buffer capacity.

The aforementioned step Δt, measured in periods (e.g. days), is a key driver of analysis. It represents the time batch used to quantify the dynamic behavior of a SKU and organize the storage assignment policy accordingly. Usually, the average turnover of a warehouse is a

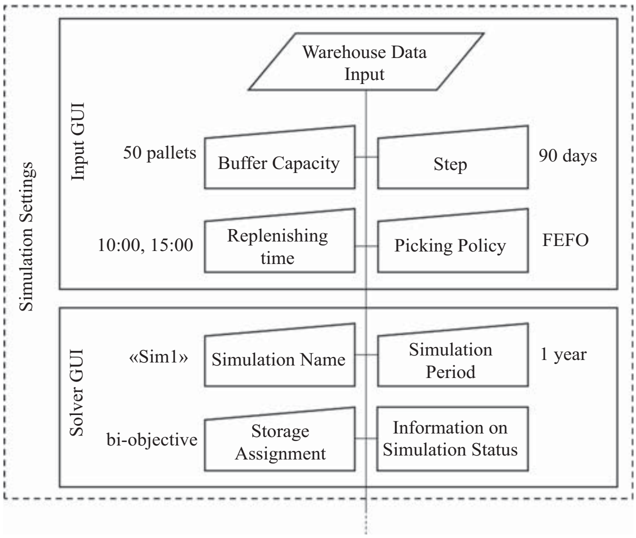

Figure 4. Graphic user interfaces (GUIs) functionalities

fair value to quantify this step. High values of step compared to the inventory turnover (e.g. 1 or 2 months) flatten the differences among the SKUs and smooth the seasonality. Conversely, short values (e.g. 1 day) may not reflect the erratic behavior of a SKU.

The storage assignment policy k is the rule to assign an incoming pallet to a storage location. The DST incorporates a wide set of assignment policies to cope with different 3PL companies and business. These base either on a sorting algorithm (i.e. ranking heuristics) (see for details Accorsi *et al.*, 2012), or on optimization techniques. The former, generally implemented through SQL scripts, are easier and require usually cheaper WMS's customization. The latter are more performant, but require a commercial linear solver, whose annual fee is expensive for low-margin business as 3PL, and also advanced mathematical and informatics skills generating higher software maintenance costs.

Through the DST, the user also decides for the picking policy to pursue. The fulfillment of the customers' orders requires the punctual analysis of the inventory configuration, in order to figure out where each SKU is located. Different picking policies generate different picking lists and consequently different configuration of inventory and empty locations. As example, a policy favors the minimization of the traveling for the picking tour (i.e. retrieving a SKU from the locations closer to the docks), another favors the emptying of the storage locations (i.e. retrieving a SKU from the locations with least residual stock), which particularly fits with 3PL companies that sell pallets locations to their clients. The developed GUIs are shown in Figure 5.

5. Proof of concept with a real-world warehouse

In order to showcase the DST's functionalities, this section illustrates its application to decide on the customization of the WMS for 3PL warehouse involved in the supply chain of biomedical products and devices. Given the wide inventory mix to manage and the reluctance of the clients in sharing information on the products, this case represents a valid testbed for the validation of the DST. In order to provide the input data set required by the tool, a prior extensive phase of data collection has been conducted. Data were collected through on-field observation and monitoring of the workers' tasks, but mostly by extracting and manipulating records from the company WMS.

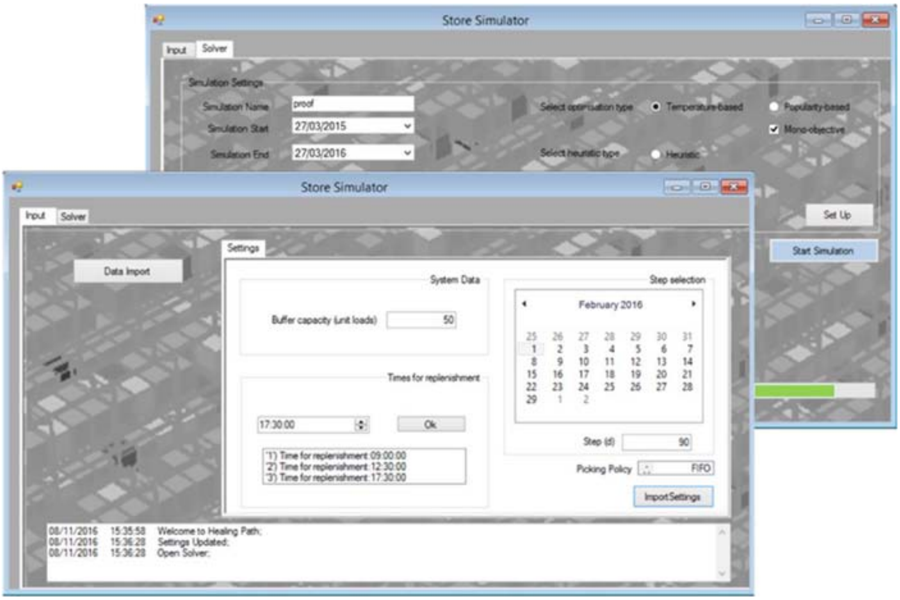

Figure 5.
Graphic users interfaces (GUIs)

The following sub-sections illustrate the main characteristics of this warehouse, and describe how the tool functionalities are used to perform a what-if multi-scenario analysis considering alternative WMS features.

5.1 Problem statement

We analyze a middle-sized warehouse of 5,088 locations devoted to products and equipment for dialysis of a renowned vendor of this sector. Figure 6 reports the main characteristics of the storage system (i.e. *as-is* scenario), including data on the storage infrastructure (i.e. racks) and the processes, the level of information visibility, and the *as-is* WMS's features.

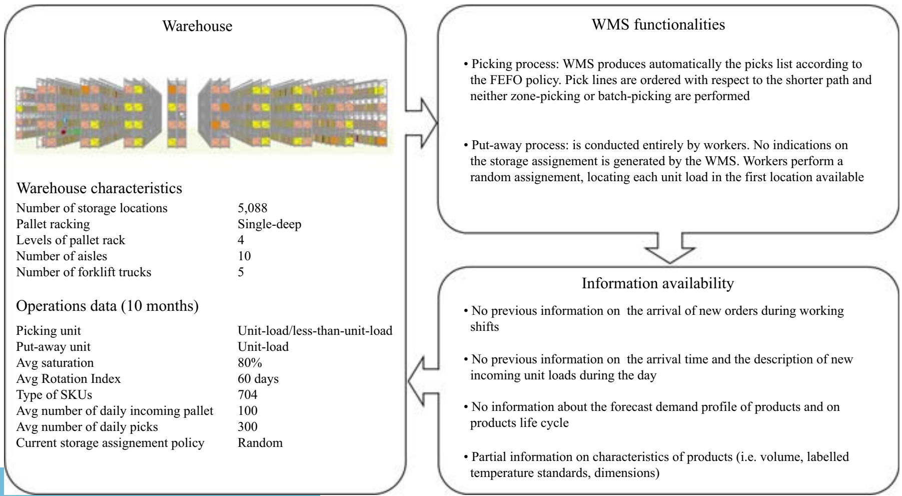

Figure 6.
Case Study

We consider an historical profile of about ten months (from March to December). The warehouse experiences high turnover and presents a wide variety of perishable products in the inventory mix. More than 700 SKUs are stored in the selective racks with an average turnover index of about 60 days. Despite the long-term partnership with the client, the provider has scarce information visibility on the variation of inventory mix. This complicates the planning of the warehousing activities and affects the fulfillment of the high standards of efficiency and service level required. The *as-is* put-away process is randomly performed by the workers who assign the incoming pallets to the first empty location they find. The random assignment policy does not require specific information about the SKUs and their behavior and avoids the costs for implementing dedicated WMS's functionalities. Nevertheless, given the typical high utilization of the locations in 3PL warehouses, the time spent for searching empty locations is not negligible. Furthermore, this policy locates fast-moving SKUs even far from the I/O dock, enhancing the traveling time for picking.

Based on these statements, seven alternative management scenarios, likewise replicating different WMS features, have been simulated and compared to the *as-is* upon the performance of the picking activities (i.e. Traveling time). The analysis aims to identify the best management scenario and to aid the managers in assessing and quantifying the economic return from the WMS customization according to higher information visibility. It is worth noting that, among the wide set of warehousing KPIs, we assume the traveling time for picking as metric of performance since generally, the picking accounts for more than 55 percent of the whole warehousing costs (Bartholdi and Hackman, 2013).

Furthermore, each management scenario differs from the others for the level of the information availability as indicated in Table IV.

The what-if simulation analysis is conducted in agreement with a basic assumption: the demand orders and the trucks arrival are known at the beginning of each period (day) t. All the tested management scenarios share the settings of the buffer capacity (i.e. 150 pallets), of the step (i.e. 90 days), and of the replenishing times t_r (i.e. three per day at 11:00 a.m., 12:00 a.m., and 9:00 p.m.). They differ for the adopted storage assignment policy and the picking policy. Many researches and industrial applications demonstrate that the popularity-based assignment is an effective rule to reduce the picking traveling time (Thomas and Meller, 2015; Heragu *et al.*, 2007; Petersen and Aase, 2004; Tompkins and Smith, 1998; Wilson, 1977). For the first, three storage assignment policies based on the popularity index (Gu *et al.*, 2007) are thereby investigated. These are as follows: ($k=1$) a popularity-based rule, named in the following heuristic, ($k=2$) a class-based optimization model based on the popularity parameter, and ($k=3$) a bi-objective optimization model based on popularity and conservation temperature parameters, that aims at minimizing the temperature stresses during storage for the most sensitive SKUs.

For the second lever, two solutions are compared: the first-in-first-out (FIFO) and first-expiring-first-out (FEFO) policies that are commonly recommended to control the shelf-life of perishable products (Hertog *et al.*, 2014).

5.2 Tool functionalities

Per each period t, and replenishing time t_r, the tool calculates the rolling popularity $Pop^{roll}_{u_i,t,\Delta t}$ for the set of incoming SKUs $L^{ul}_{t_r,t}$ and implements the three alternative storage assignment policies (k: 1, 2, 3) as schematized in Figure 7.

The heuristic ranks the list of incoming SKUs ($L^{ulrnk}_{t_r,t}$) by the popularity rolling value and assigns them to the empty locations ($L^{elrnk}_{t_r,t}$) sorted by their distance from the I/O dock $d^{l}_{I/O}$. At each replenishing time t_r, the sorted lists SKUs and locations are matched, and the locations filled accordingly (i.e. SKUs with higher popularity rolling in the closer locations). The sorting process can be constrained by some parameters as the weight or the volume of

Simulation code	Simulation settings: common	Simulation settings: specific	Required information
1	Buffer capacity:150 pallets Step: 90 days Times for replenishment: 11:00, 15:00, 21:00 Simulation period: 27 March-23 December	Storage assignment technique: heuristic Item retrieval policy: FIFO Dimensional constraint: none	
2		Storage assignment technique: opt. mono-objective Item retrieval policy: FIFO Dimensional constraint: none	
3		Storage assignment technique: opt. bi-objective Item retrieval policy: FIFO Dimensional constraint: none	Information on products characteristics (i.e. labeled temperature conditions)
4		Storage assignment technique: heuristic Item retrieval policy: FEFO Dimensional constraint: none	Information on products characteristics (i.e. expiry date)
5		Storage assignment technique: opt. mono-objective Item retrieval policy: FEFO Dimensional constraint: none	Information on products characteristics (i.e. expiry date)
6		Storage assignment technique: opt. bi-objective Item retrieval policy: FEFO Dimensional constraint: none	Information on products characteristics (i.e. labeled temperature conditions, expiry date)
7		Storage assignment technique: heuristic Item retrieval policy: FEFO Dimensional constraint: weight	Information on products characteristics (i.e. expiry date, weight)

Table IV.
Required information for each simulation

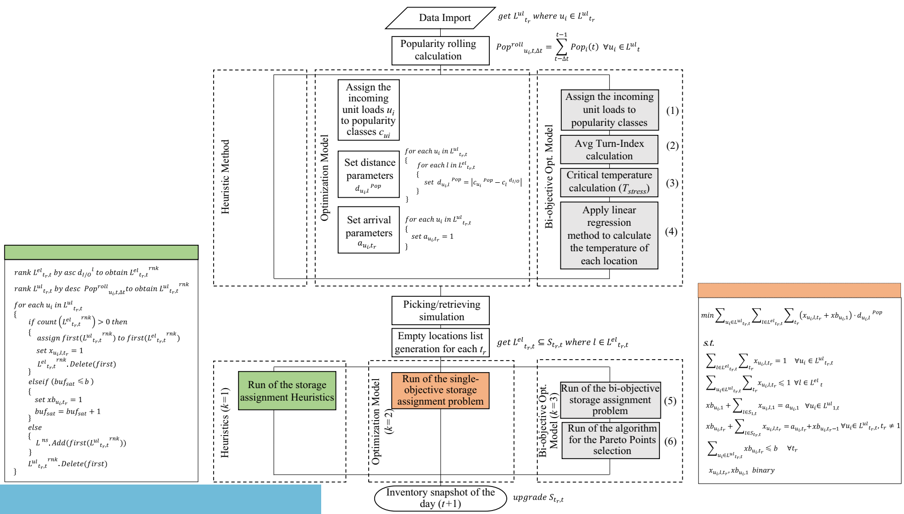

Figure 7.
Tool functionalities

the pallet, and the available location filtered accordingly. In this case, the tool implements also a weight constrained heuristic.

Two optimization models for the assignment problem are formulated and solved. The first linear integer model assigns a generic SKU of popularity class $c_{u_i}^{Pop}$ to a generic location of storage class $c_l^{d_{I/O}}$ (i.e. built upon the distance from I/O dock $d_{I/O}$) with the objective of minimizing the number of pallets stored out-of-their-class. As result, a unit load $u_i$of generic SKU i belonging to the first popularity class ($c_{u_l}^{Pop} = 1$) is assigned (i.e. $x_{u_i,l,t_r} = 1$) to an empty location l belonging to the first storage class ($c_l^{d_{I/O}} = 1$) whether available at time t_r.

The second assignment problem is formulated through a bi-objective optimization model that combines the first objective with the minimization of the temperature stresses experienced by the stock. The second objective function considers the temperature measured within the storage system and requires thus other information (as indicated in Table IV). These are the outdoor and indoor temperatures measured at every storage location l during a time horizon obtained by a thermal monitoring campaign (see Table III). The associated WMS's feature manipulates the temperature records to identify the highest stress (T_{stress}) (3) that an incoming pallet u_i experiences during its average turnover (2). Then, the tool uses linear regression (4) to estimate the temperature achieved by each location in the worst case (T_{stress}) during the observed time horizon. Since each SKU has a safe temperature conservation range, optimization minimizes the number of pallets located out-of-their-safety-class (4). The tool solves the bi-objective assignment problem and obtains the trade-off solutions once the Pareto frontier is drawn through the ε-constrained method (Khalili-Damghani *et al.*, 2012) (5). A properly developed algorithm is then applied to obtain the best assignment solution among the Pareto points (6). Since the bi-objective formulation and its associated solving algorithm represent just an alternative management scenario, their formal and rigorous definition and description are not object of this paper, which conversely illustrates a tool for the comparison and assessment of multiple warehouse management scenarios. The bi-objective formulation is extendedly proposed and discussed in Accorsi *et al.* (2018b).

The computation time to assess each scenario varies with the assignment policy and the observed time horizon. Obviously, this time is higher for the optimization techniques than for the heuristics. Each run of the solver (i.e. one per replenishing time t_r and period t and more in case of the bi-objective problem) takes few seconds (between 1 and 5 seconds). This time is the same that the WMS feature would require in a real application, and allows understanding the feature responsiveness to the operational tasks.

5.3 Results

The what-if simulation analysis quantifies a set of KPIs that allows the assessment of management scenarios. This panel includes the overall traveling distance for picking, the average warehouse utilization percentage, the buffer utilization, the average pick lines per day, and whether or not the temperature stresses affect the management scenario. It comes out that all the to-be scenarios reduce the traveling time for picking compared to the *as-is* (see Figure 8).

The scenarios characterized by the FEFO picking policy (i.e. scenarios 4, 5 and 6) better perform in term of traveling reduction than those ruled by the FIFO policy (i.e. scenarios 1, 2 and 3). The scenario 4 implements the heuristic-driven storage assignment and obtains the highest traveling saving. Nevertheless, the FEFO-based scenarios require additional details from the client, which must track the expiration date of each pallet. On the contrary, the FIFO-based scenarios guarantee good performances requiring just the records of truck's arrival. Notwithstanding with the convenience for the 3PL provider, the picking policy is often negotiated with the client and is influenced by the sector, the demand seasonality, the products' turnover, the characteristics of the inventory mix and the information availability.

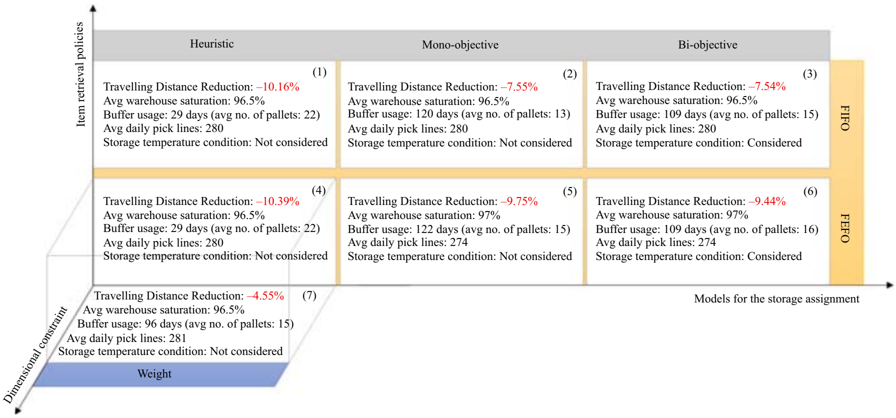

Figure 8.
Simulations results

Dealing with the comparison between the storage assignment policies, the saving in the picking traveling decreases from the heuristic to the bi-objective policy, while the buffer utilization increases. Indeed, the scenarios 2, 3, 5 and 6 utilize the buffer for more days than the scenarios 1 and 4. This leads to two considerations. First, the optimization technique exploits the buffer to organize (and eventually postpone) the put-away activities for assigning each SKU to its proper storage class. Second, the capacity of the buffer (i.e. the floor storage area besides the docks) has to be accurately designed, since it affects the assignment process and the resulting storage configurations. In response to the input data set and the simulated inbound and outbound profiles, the optimization policy is not convenient as expected, and its implementation as WMS's feature is not recommended.

Although the scenarios 3 and 6 account for higher traveling distance, the bi-objective assignment policy better complies with the safe storage temperature requirements. Nevertheless, the adoption of this WMS feature compels the visibility of the provider on the safe temperature ranges of each SKU.

Lastly, the scenario 7 represents the worst case in term of traveling minimization. Nevertheless, it allows to comply with the work safety standards that recommend to store the heavy loads at the bottom (i.e. low levels) of the racks.

Figure 9 focuses on the monthly trend of the average traveling time per pick line for each scenario. This is a well-known metric of performance for 3PL providers, since the clients commonly pay the storage service in terms of fulfilled lines.

It is worth noting that a significant difference between the worst and the best scenarios is quantified. This changes month by month and achieves four seconds and half per line at Month 7. Such a saving is multiplied for the monthly number of lines and results in about 6–7 percent reduction of the required labor time. The obtained result aids the 3PL managers to quantify the return on investment of each management scenario in comparison with the *as-is*, and to evaluate the payback of the associated WMS customization.

The bottom chart of Figure 9 highlights how the number of fulfilled pick lines slightly varies scenario by scenario over the time horizon. This is caused by the combination of the storage assignment and picking policy which might affect, and sometimes double, the number of locations to visit for fulfilling a pick line. As a consequence, the operators could save time to perform other activities as put-away, replenishment, stock consolidation, cycle-counting, thereby increasing the overall warehouse throughput and efficiency.

Some last considerations arise by observing Figure 10, which illustrates the multi-scenario comparison of the storage layout bird's views, as appear at the last period t of the time horizon (i.e. ten months). The three-dimensional layouts have been obtained through a

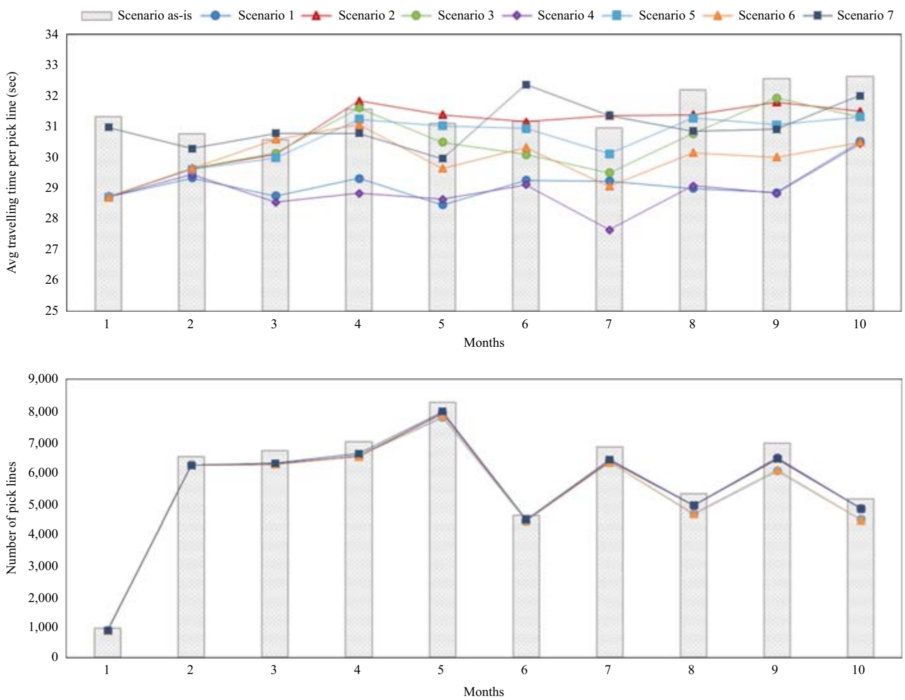

Figure 9.
Metrics comparisons from the multi-scenario analysis

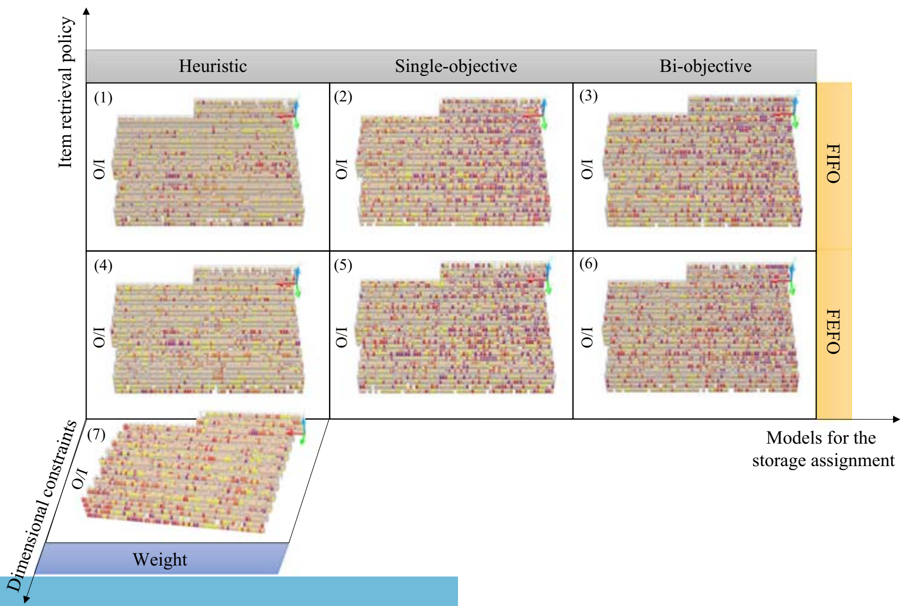

Figure 10.
Multi-scenario comparison of the layout bird's views

script written in AutoLISP and a developed interface through the AutoCAD® Software that is included into the DST. This comparison highlights how the scenarios (i.e. 1 and 4) that reduce the picking traveling the most, assign the fast-moving SKUs (i.e. the darkest unit loads) to the lowest levels of the rack and close to the I/O docks. The heuristics performs better than both the optimization policies, while the constrained-heuristics is affected by the weight of the incoming unit loads and is the worst performing. This result can be influenced by the distribution of the truck arrivals along the day, and the number and type of incoming unit loads u_i received by each truck.

Furthermore, the comparison underlines the complexity faced by a manager in understanding and foreseeing the dynamic behavior of a combination of storage and picking policies over the time. After ten months different daily management scenarios result in extremely different storage configurations, and this reflects the uncertainty of the managers to decide on the implementation of a specific WMS's feature.

6. Discussion

Through the DST, managers observe the variation of the warehouse performance over the time in order to assess how different scenarios respond to variation in the demand and the inventory mix. By implementing a dynamic and adaptive approach, this tool extends the contribution by Accorsi *et al.* (2014), which was intended to design a warehouse from green field, and to support the re-warehousing through a combination of storage allocation and assignment rules. For these reasons, we believe that the proposed DST contributes both to the literature and to the industrial practice. As stated in Section 2, the DST addresses to an extant gap providing a digital twin of the WMS able to virtualize the warehouse behavior in case of potential changes in the operations management. In other words, it tests the responsiveness and resilience of the management policies to the inventory mix variations and demand seasonality over time.

Ample opportunities exist for the development of new functionalities to explore other research topics concerning the impact of supply chain issues on the warehouse performance. Among these: the delivery policies (Accorsi *et al.*, 2018a), promotional campaigns, and the variations in the clients' portfolio.

Furthermore, we retain that this DST provides a valuable support to 3PL warehouse's managers in the decision making on how to address to specific instances from clients. Specifically, the main contribution to practitioners involves the opportunity of exploring the evolution of the inventory over a time horizon. As it is shown in Figure 11, this tool provides detailed inventory snapshots over time with an accuracy of a replenishing time.

However, two main limitations have to be claimed. First, the tool bases on specific data architecture that need to be fueled by precise data. The more precise the data set, the more reliable the decisions resulting from the analysis will be. As a consequence, the 3PL company has to involve their clients on an overall and long-term project of data gathering

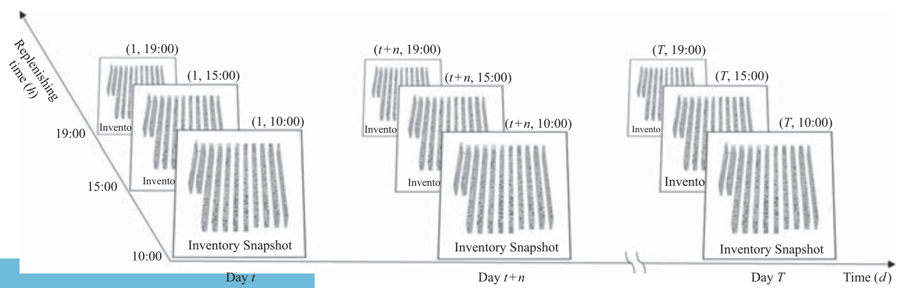

Figure 11.
Generation of inventory snapshots over the time horizon

and sharing. Second, a logistic specialist is required to design and propose the alternative WMS's features to try, as well as to interpret the results. Therefore, we retain that the development of further interfaces between the DST and the company ERP would facilitate the data import and the interaction with the managers' decision making.

7. Conclusion

This paper illustrates an original DST, named Store Simulator, which aids a 3PL manager to decide on the WMS's feature to implement in order to meet the client's requirements. This tool utilizes heuristics, optimization, and simulation techniques to virtualize the behavior of a specific storage or picking policy and assesses the short and mid-term impacts resulting by the implementation of that WMS' features. Fueled by a relational SQL database, the tool provides GUIs that lead the manager through a data-driven what-if multi-scenario analysis. This allows addressing three critical issues affecting the design and customization of WMS in 3PL warehouses. First, it quantifies the short- and mid-term impacts resulting by the implementation of a new WMS's feature (Issue 3), leading the manager to identify the proper management scenario that mostly enhances the efficiency, reduces the storage and picking costs, and has the shortest payback (Issue 1). Lastly, the DST, behaving as a WMS digital twin, aids the 3PL in establishing trustworthy added-value relationships with their clients based on increased awareness and higher visibility (Issue 2) in the era of Industry 4.0. In order to validate the proposed tool a proof of concept from a real-world warehouse is illustrated. The tool enables to benchmark seven scenarios resulting from seven different combinations of logistics choices. Future research developments will focus on extending the boundaries of analysis, and design new tools aimed to assess the impact of higher information availability and visibility on the economic and environmental performance of transport and distribution operations throughout the whole supply chain according to the Internet-of-Things paradigm.

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