ISSN 1980-5411 (On-line version)
Production, 33, e20220077, 2023
DOI: 10.1590/0103-6513.20220077

Thematic Section - Production Engineering leading the Digital Transformation

The impacts of inventory record inaccuracy and cycle counting on distribution center performance

Iuri Rafael Destro[a], Francielly Hedler Staudt[b], Karine Somensi[a*], Carlos Taboada[a]

[a]Universidade Federal de Santa Catarina, Florianópolis, SC, Brasil

[b]Universidade Federal de Santa Catarina, Joinville, SC, Brasil

*karinesomensi@hotmail.com

Abstract

Paper aims: The objectives of this paper are: (i) to analyze the impacts of Inventory Record Inaccuracy (IRI) on picking productivity (PP), lost sales (LS), and warehouse capacity utilization (WCU) for different warehouses; (ii) verify if the Cycle Counting (CC) implementation is sufficient to reduce IRI and (iii) the number of CC operators to maintain warehouse performance.

Originality: A causal loop diagram in detail of the IRI and CC variable's effects in receiving and picking processes is developed. IRI is separated into ghost and hidden inventory to represent the actual effects in WCU, LS, and PP.

Research method: A dynamic system model is built. Simulations are performed for the five categories of warehouse performance with different numbers of CC operators.

Main findings: IRI impacts in all warehouses simulated, so managers should monitor IRI besides employee productivity. CC can reduce IRI in all types of warehouses. The number of CC operators to be implemented is different for each warehouse.

Implications for theory and practice: Several implications for theory and practice are discussed. For example, IRI impacts more ADV and BIC warehouses without CC implementation. In TYP, ADV, and BIC warehouses CC is sufficient to reduce IRI. In MO and DIS warehouses, other improvements are needed.

Keywords

Warehouse performance. Simulation. Inventory management. Picking productivity. System dynamics.

How to cite this article: Destro, I. R., Staudt, F. H., Somensi, K., & Taboada, C. (2023). The impacts of inventory record inaccuracy and cycle counting on distribution center performance. *Production*, *33*, e20220077. https://doi.org/10.1590/0103-6513.20220077

Received: June 5, 2022; Accepted: Dec. 9, 2022.

1. Introduction

Warehouse operations are rapidly becoming more robotized to increase performance and cut costs, yet humans remain an essential part of operational performance (Pasparakis et al., 2021). Azadeh et al. (2020) comment that operations with human-robot collaborative picking, such as Autonomous Mobile Robots (AMRs), have become more common. However, the human factor is still present even with implementing Industry 4.0 technology in warehouses, such as Augmented Reality (AR) or AMR. One of the main problems related to human labor in warehouses is operational errors that turn into inventory disparity.

Inventory systems are dynamic, with complex interactions between processes, information systems, and employees (Barratt et al., 2018). One of the main challenges in inventory management is Inventory Record Inaccuracy (IRI), defined as the degree of the System Inventory Record (SIR) inaccuracy concerning the physical inventory of a specific item (Barratt et al., 2018; DeHoratius & Raman, 2008).

IRI results from errors in several underlying sales and inventory management processes (Best et al., 2022; Shabani et al., 2021). IRI is a severe problem that can significantly affect operational productivity and inventory management (Barratt et al., 2018; Rekik & Sahin, 2012; Rekik et al., 2019a). It can generate low productivity losses in corporate profits (Kang & Gershwin, 2005), low service level (Waller et al., 2006), increased costs (Waller et al., 2006), and lost sales (DeHoratius & Raman, 2008; Waller et al., 2006). In addition, IRI undermines decision-support tools such as automated replenishment (Hofstra et al., 2022). Therefore, IRI should be used to evaluate operational warehouse performance (Staudt et al., 2015) since the elimination of IRI reduce supply chain (SC) costs and the level of stock unavailability (Fleisch & Tellkamp, 2005).

In recent years, the topic of IRI has received increasing attention (Aguirre et al., 2021; Hofstra et al., 2022). The academic literature has adopted different approaches to investigate how inventory managers assess, monitor, and deal with IRI (Barratt et al., 2018; Best et al., 2022; Hofstra et al., 2022; Rekik et al., 2019a). One of the methods is the System Dynamics (SD) simulation, which formalizes and explores interactions within the dynamic inventory system and underlies structures that generate inferences about the ongoing dynamics of the same system (Barratt et al., 2018).

Several studies have been applying SD to studying IRI's problems, such as Agarwal et al. (2006), Barratt et al. (2018), and Hachem et al. (2016). However, few academic studies address IRI and warehouse operations (Barratt et al., 2018). Moreover, the effect of IRI in warehouses with different performance levels has not yet been explored. Studies on inventory issues have been concentrated in manufacturing and retail (Heese, 2007; Wang et al., 2016), and little attention has been paid to the impacts of IRI on warehouse inventory policies (Barratt et al., 2018). Furthermore, several traditional inventory models do not consider IRI, and those that do, address the issue as a random phenomenon, and fail to provide insights about its origin (DeHoratius & Raman, 2008). Thus, the first research question I (RQ1) proposed is: What is the impact of IRI on warehouse picking performance, lost sales, and warehouse capacity utilization for warehouses with different performance levels?

One of the policies to maintain inventory accuracy is cycle counting (CC) (DeHoratius & Raman, 2008). CC is a continuous planned count of a given set of items during a pre-defined period to identify and correct IRI (Gumrukcu et al., 2008). Authors such as Agarwal et al. (2006), Barratt et al. (2018), and DeHoratius & Raman (2008) argue that a higher frequency of CC can contribute to reduced IRI levels. However, it is time-consuming, generates labor costs, and can reduce operational efficiency (Hachem et al., 2016). It is possible to note that, even if the literature supports CC implementation, no research has evaluated the efficiency of CC operation to reduce IRI in a system dynamic model. Moreover, the number of cycle counters that should be deployed has not yet been studied for different warehouse conditions. In this context, the present study also aims to answer the following questions:

Research question II (RQ2): Is cycle counting implementation sufficient to reduce IRI in warehouses with different performance levels?

Research question III (RQ3): How many cycle counting operators are necessary to maintain warehouse performance?

To answer these questions, the paper aims to analyze the impacts of IRI on picking productivity, lost sales, and warehouse capacity utilization for five warehouse performance categories. In addition, it is verified if the CC implementation is sufficient to reduce IRI and the number of CC operators to maintain, increase or decrease performance in each warehouse category.

The research questions guide this study to fill a gap in the academic literature that seeks to understand the dynamic effects of employee interaction with the inventory system in a warehouse environment (Barratt et al., 2018). For that, this research considers that employee interaction - with human error - with the inventory in receiving and picking processes are also causing IRI (Kang & Gershwin, 2005), as well as CC operators (agents) working in the correction of divergences between physical and logical inventory through CC.

Previous studies using the SD model to address IRI and CC diverge from the present work in the following aspects:

- The warehouse operation simulated in the SD model considers receiving, CC, and picking processes;
- the impacts of IRI and CC on warehouse performance are evaluated through performance indicators such as picking, lost sales, and warehouse capacity utilization;
- simulations are performed for five warehouse categories established by WERC (Warehousing Education and Research Council): Major Opportunity (MO), Disadvantage (DIS), Typical (TYP), Advantage (ADV), and Best in Class (BIC), with different numbers of CC operators;
- this research considers the influence of Ghost stocks (when the logical inventory is greater than the physical inventory) and Hidden stocks (when the logical inventory is lower than the physical) separately, which are results of operational errors (Hachem et al., 2016).

In addition to this introductory part, this study consists of the following sections: section 2 presents the theoretical background of IRI; section 3 states the methods used in the research, as well as the necessary steps for implementing the dynamic model; section 4 shows the results of implementing the dynamic inventory system; section 5 discusses the main results obtained; and finally, section 6, presents the main conclusions of the study with the future research directions.

2. Theoretical background

This section aims to present the IRI concept and its impacts and also discuss causes and solutions to IRI problems.

2.1. Inventory Record Inaccuracy (IRI)

Whereas the "physical inventory accuracy indicator measures the accuracy (by location and units) of the physical inventory compared to the reported inventory" (Staudt et al., 2015, p. 11), IRI is considered the inverse (DeHoratius & Raman, 2008). IRI measures the difference between the physical inventory (the actual inventory that physically exists in the warehouse) and the logical inventory, also called electronic, the one registered in the Warehouse Management System (WMS) or equivalent (Barratt et al., 2018; DeHoratius & Raman, 2008).

There are two kinds of inventory divergences studied in this research. The first one is the overestimated inventory, named in the literature as "Phantom inventory" or "Ghost inventory" (Hachem et al., 2016). The Ghost inventory occurs when the registered logical inventory is greater than the physical, existing only in the WMS or equivalent system (Drohomeretski & Favaretto, 2013; Hachem et al., 2016). The second divergence occurs when the registered logical inventory is lower than the physical one (underestimated inventory), called in this work "Hidden inventory" (Hachem et al., 2016).

Both divergences have an impact on warehouse efficiency differently. In the case of the Ghost inventory, as the WMS generates picking order tasks according to the logical inventory, if the item and quantity required in the pick list do not exist in that specific location where the logical inventory records exist, it results in wasted travel and time, impacting operational productivity. For the Hidden inventory, as the WMS records are lower than the actual physical inventory, false stockouts can occur, possibly causing lost sales, unnecessary location replenishment tasks, unnecessary resupply orders from suppliers, and spatial issues like warehouse overcapacity (Hachem et al., 2016).

Due to the many problems related to IRI, several researchers have been studying its effects and causes. Barratt et al. (2018) sought to explore the nature and existence of IRI in a multichannel environment. The authors conclude that IRI manifests itself in positive and negative errors, as more or less inventory is recorded than the existing ones. Agarwal et al. (2006) verified the impacts of Information Technology (IT) use in an automotive SC, concluding that IRI significantly impacts performance. Hachem et al. (2016) created an SD model to examine and confirm the substantial impact of error generation and IRI. The results show that even a tiny, undetected source of IRI can accumulate inaccuracies and eventually unbalance the system in a snowball effect, challenging the assumption that the information about inventory provided by the systems, like a WMS, is correct. Kang & Gershwin (2005) investigate problems related to information inaccuracy in the inventory systems, identifying that a small rate of items not detected by the WMS (1% of average demand) can lead to stockouts. In recent literature, Best et al. (2022) focus their work on positive inventory discrepancies in a retailing context. Shabani et al. (2021) identified store performance in terms of IRI. They provided managerial tools for assessing the prospects of IRI mitigation measures. Aguirre et al. (2021) identified the factors that cause IRI in retail companies and, using a mathematical model, worked to help retailers minimize the gap generated between physical audits and system records.

According to DeHoratius & Raman (2008), small values of IRI can result in substantial lost sales and cause significant losses in corporate profits (Kang & Gershwin, 2005). IRI can also impact other indirect areas, such as demand forecast, or promote intangible effects, such as loss of customer credit by delays in delivery or lack of items due to incorrect inventory information (Sahin, 2004).

2.2. Causes and solutions for Inventory Record Inaccuracy

The leading causes of inaccuracy in inventory cited by literature are human errors in the execution of tasks (such as receiving, picking, shipping, delivery, and scanning) and incorrect records (Barratt et al., 2018;

Best et al., 2022; Chuang & Oliva, 2015; Drohomeretski & Favaretto, 2013; Lei et al., 2018; Rekik et al., 2019a, b; Sarac et al., 2010), theft (Qin et al., 2017; Su et al., 2021; Waller et al., 2006) obsolescence (Kang & Gershwin, 2005), incorrect location (Brown et al., 2001; Raman et al., 2001), lack of training (Brown et al., 2001), long time between physical inventories (DeHoratius & Raman, 2008), damage (Rekik et al., 2019b), shrinkage (Chuang & Oliva, 2015; Lei et al., 2018; Wang et al., 2016), lack of clear procedures (Raman et al., 2001), low employee remuneration or motivation (DeHoratius & Raman, 2008), inaccessible inventory (Lei et al., 2018), lack of CC (Brown et al., 2001). Best et al. (2022) demonstrated that items' misplacement rate was one of the main drivers of positive IRI. Besides these causes, factors such as sales volume, product value, and product variety can also increase the IRI rate (DeHoratius & Raman, 2008)

To address and solve IRI issues, annual Full Inventory Counting (FIC) and CC can be performed as inventory audits (DeHoratius & Raman, 2008). In the case of an FIC, all inventory items are checked at once. The inherent problem of this practice is that error accumulates in inventory records until they are corrected and updated by the next FIC (DeHoratius & Raman, 2008). On the other hand, as CC is a systematic method that continuously counts small sets of items (Gumrukcu et al., 2008), it requires a team of operators working daily, carrying out an inherent cost related to the process. Despite the costs, CC can reduce IRI levels (DeHoratius & Raman, 2008; Barratt et al., 2018).

Although the benefits of CC have made annual FIC obsolete, some organizations, especially the ones with a small inventory, insist on annual FIC as the only action against IRI (Rajasekar & Sengupta, 2020) because it spends less time and costs (Hachem et al., 2016). Moreover, Kök & Shang (2007) emphasize that CC policies generally consider the ABC classification, which means that the counting periodicity is not the same for all items, which is a problem because the more significant the interaction between operators and items more opportunities for human error (Arnold et al., 2007).

To analyze the influence of these variables on IRI and the impacts of IRI and CC in the warehouse, this paper constructs an SD model. Through dynamic simulation, it is possible to formalize and explore interactions within the inventory system and underlying structures that generate inferences about the ongoing dynamics of an inventory system (Barratt et al., 2018). The construction of the dynamics system model is presented in the next section.

3. Methodology for the system dynamic model construction

Discrete-event simulation (DES) and System Dynamics (SD) are two of the most widely used modeling tools which underpin Decision Support Systems (DSS) (Tako & Robinson, 2012). Their study comparing DES and SD show that both simulation approaches have been used to model most logistics and Supply Chain Management (LSCM) issues, with DES being more used. However, the researchers found no evidence to support the belief that DES is used more for operational/tactical issues, whereas SD is for strategic problems (Tako & Robinson, 2012). Therefore, this research adopts an SD simulation for a warehouse operation with multiple analysis scenarios.

SD is a method for analyzing policies and solving complex problems using computer simulation models (Sterman, 2000; Cardiel-Ortega et al., 2017). Sterman (2000) states that dynamic complexity can arise even in simple systems. Using SD in simulations, policies can be incorporated as endogenous and exogenous variables and analyzed short, medium, and long-term from mental data and simulation software (Sterman, 2000).

SD helps to understand the general dynamics of the system, and the influence of different variables on the problem at hand, to support decision-making and test policies through simulations of various case scenarios. SD primarily investigates the structure of such cause-and-effect connections and how they evolve (Marco et al., 2012). Jay Forester initially used SD to solve issues related to the bullwhip effect. However, it has also been used in LSCM problems, as in the case of inventory planning and management (Tako & Robinson, 2012).

The SD model built in this work follows the four main steps proposed by (Sterman, 2000): (i) problem articulation, in which the dynamic problem, key variables, and simulation horizon are defined; (ii) dynamic hypothesis formulation, which explains the dynamics as endogenous consequences of the feedback structure, resulting in the Causal Loop Diagram (CLD); (iii) simulation model construction, detailing the premises, structure specification and initial conditions, (iv) testing, which evaluates model consistency and robustness and (v) policy design and evaluation, encompassing 'what if' analysis with the policies interaction. The following subsections elaborate on these steps to construct the SD model and results.

3.1. Problem articulation

Based on the literature, the dynamic problem developed in the simulation considers the IRI and CC variable's effects in the warehouse operations (Barratt et al., 2018; DeHoratius & Raman, 2008) simultaneously. While CC execution can decrease inventory inaccuracies, human and technical errors in warehouse operations (receiving, picking, and CC) generate ghost and hidden inventory and increase the IRI rate (Barratt et al., 2018; DeHoratius & Raman, 2008). In addition, the study investigates whether a higher frequency of CC, which can be achieved with more CC employees, contributes to reducing IRI levels. Besides that, the assessment of IRI and CC impact in warehouses with different levels of performance is also explored in the simulations. The simulation time is set to one year to allow the interaction of IRI and CC in the medium term.

3.2. Dynamic hypothesis formulation

The second step involves constructing a Causal Loop Diagram (CLD), a tool designed to help researchers visualize how distinct system variables are interrelated through endogenous consequences (Sterman, 2000). The Stella® software was used to build the SD simulation. Figure 1 shows the warehouse modeled with operational errors in receiving (inbound process), order picking (outbound process), and cycle counting (CC process) generating IRI (Kang & Gershwin, 2005).

The product flow inside the warehouse in Figure 1 is built as follows. The items arrive at the warehouse and are received by the receiving team, which makes the item quantity input in the WMS (Logical inventory) and moves the items to a specific warehouse location (Physical inventory). On the outbound side, the external demand (specified as a constant with 10,000 units/day) defines the number of pickings that should be done per day. The picking process is executed when a picking operator (picker) collects items/products from locations (according to a pick list) and delivers them to a shipping area (an operation related to the physical inventory). In the simulated scenario, the bathtub - the classic example used by Sterman (2000) to explain dynamic systems - of the SD model (Physical inventory measured by Warehouse Capacity in Figure 1) reflects the accumulation of items in the warehouse due to the picking issues related to IRI, considering that receiving and demand are constant.

The increase in IRI rates reduces picking efficiency, resulting in more delays in completing order fulfillment tasks (measured in the simulation as lost sales). On the other hand, the work of the CC team decreases the IRI since the divergences between the physical and logical inventory are reduced, improving picking productivity and warehouse capacity utilization. Figure 2 presents the CLD developed, highlighting each warehouse process.

Besides the Physical and Logical inventory, Figure 2 also presents the Ghost and Hidden inventory, which are generated from the difference between the Physical and Logical inventory. The proposed model measures the Ghost and Hidden inventory separately since they can impact the warehouse outputs differently.

Problems related to Ghost inventory in the proposed simulation are: (i) a stockout scenario, generating lost sales, (ii) waste in picker's movement with a longer lead time for order picking, reducing picking productivity, and (iii) possible order fulfillment delays, that also could generate lost sales. The main issues regarding Hidden

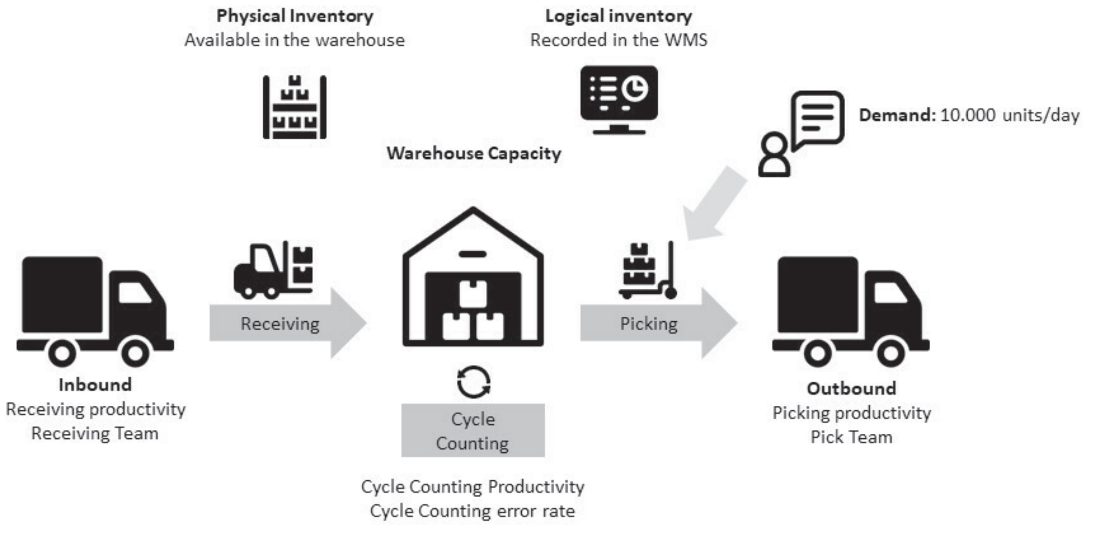

Figure 1. Warehouse activities in the dynamic system developed.

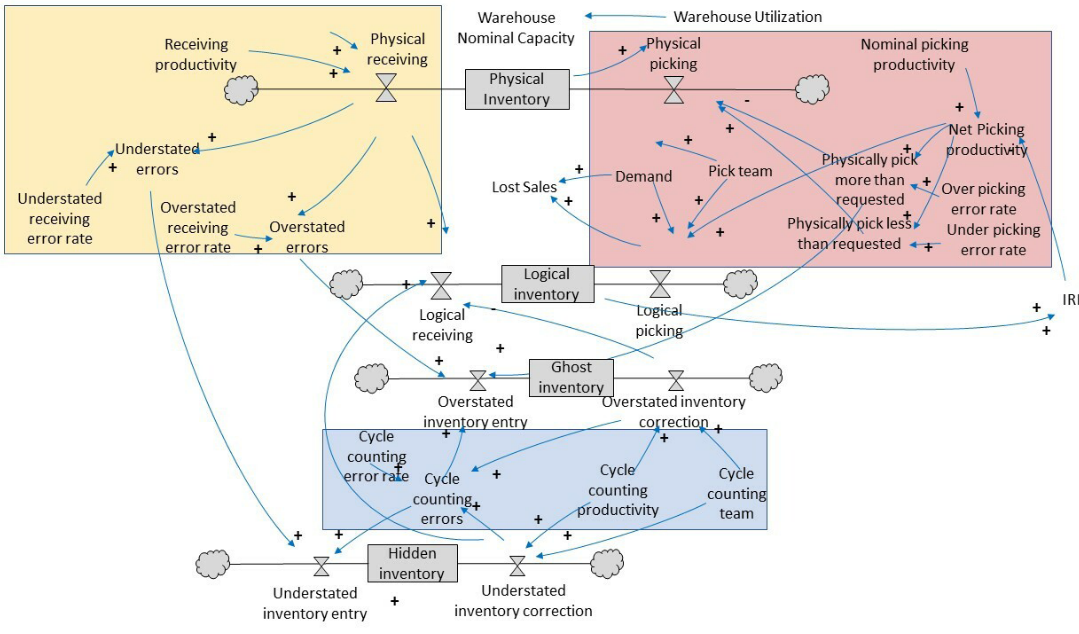

Figure 2. Causal Loop Diagram of the simulated warehouse.

inventory in the proposed scenario are: (i) ordering unnecessary replenishment from suppliers or unnecessary replenishments for forwarding picking locations directly impacting the warehouse capacity with overstock issues.

The following section presents the simulation model specification, including more premises and initial conditions.

3.3. Simulation model construction

The simulation model construction specifies the structure and decision rules of the study (Sterman, 2000). According to the warehouse schema presented in Figure 1, it is necessary to define more premises and initial conditions to run the model. The premises comprehending the receiving, picking, and cycle counting productivity and warehouse capacity need to be provided. All the warehouse constants and variables considered in the SD model are presented in Appendix A.

The values of the warehouse constants are established based on the rationale explained as follows. The warehouse capacity is defined based on the inventory coverage rate. As in the model, the outputs are just impacted by IRI (other inventory losses such as obsolescence, accidents, or theft are not included), and coverage rates with more than 60 days are not considered. On the other hand, a reduced coverage rate can influence the results since once the warehouse capacity is 100%, no more products are received. Thus, the authors defined an inventory coverage rate of 37.5 days to determine the warehouse storage capacity as 375,000 units.

To better evaluate the causality among the endogenous variables, the receiving and picking processes' capacity are equal to demand, value arbitrarily established by the authors as 10,000 units/day. Receiving is supposed to be performed in pallets, whole picking in units, which changes an operator's productivity in each activity. The inbound team is defined with ten receivers (with a productivity of 1,000 units/man.day), and the outbound team has 100 employees (with a productivity of 100 units/man.day). The CC productivity is defined as 200 units/man.day, with a constant error rate of 1%, but the number of employees is variable. It is essential to highlight that these productivity rates are affected by the initial IRI, as shown in the equations of Appendix B.

The last premises are: (i) extra hours are not included in the model, and order fulfillment delays are measured only as lost sales; (ii) the CLD (Figure 2) considers the practical issue that, in the event of lost sales, managers considered unmet demand in lost sales to be subtracted from the amount received, to avoid overcapacity. The Physical Receiving equation in Appendix B implements this second rule.

Once the premises of the simulated scenario are established, it is necessary to define the input and output variables to be analyzed. The input variables for the simulation scenarios are IRI, receiving error rate, picking error rate, cycle counting team, and warehouse capacity utilization (WCU). The input values are defined according to the Warehousing Education and Research Council (WERC) annual report, presented in section 3.5. This report summarizes real data from warehouses of different companies sizes that participate in the study.

In the last 20 years, WERC has published a report containing a study on warehousing and distribution center demographics and challenges across the industry to create benchmarks on multiple statistics.

The simulation outputs analyzed in all scenarios are:

- WCU (%): the average warehouse capacity during simulation, calculated from the volume of all items in the warehouse divided by the building's storage capacity (Warehousing Education and Research Council, 2019).
- Picking productivity (%): the average order-picking productivity.
- Lost Sales (%): the ratio between the total number of lost sales units in simulation and the total annual demand.

3.4. Testing

According to Sterman (2000), some tests can be used to search for and correct flaws and improve models. To verify if the units of all parameters, variables, and constants of the model are right, this research performed a structural test to validate dimensional consistency using the dimensional analysis functionalities contained in Software Stella®, which presents the possibility of verifying the regularity in the units and equations. The test was positive, confirming that the model is consistent.

3.5. Policy design and evaluation

The policy design can refer to the strategies represented in the scenarios, and the evaluation relates to analyzing these policy effects (Sterman, 2000). Considering the proposed warehouse scenarios, three main results are evaluated: (i) to which extent IRI impacts the warehouse's outputs with different performance levels (RQ1); (ii) whether the CC is efficient in reducing IRI independently on the current performance of the warehouse (RQ2); (iii) the number of CC employees that managers should deploy to maintain or increase warehouse performance (RQ3). The WERC classification is adopted in the simulation to investigate the proposed strategies.

The WERC annual report traditionally classifies warehouses into five categories according to their performance indicators: order Receiving error rate, order Picking error rate, IRI, and WCU. The five warehouse categories are:

1. Major Opportunity (MO);
2. Disadvantage (DIS);
3. Typical (TYP);
4. Advantage (ADV);
5. Best in Class (BIC).

To facilitate inserting the initial values of the proposed dynamic warehouse, it was necessary to calculate the average value between the minimum and maximum values adopted by Warehousing Education and Research Council (2019) to classify warehouses within the performance indicators. For example, according to the report, a warehouse in the DIS category has IRI accounted for as more significant than 3% and less than 10%. Therefore, the authors adopt an average between the minimum and maximum values (6.5%, in the MO case) as the starting value for the scenario. The objective is to verify if the warehouse category would be downgraded or upgraded, as the dynamic scenario evolves. The same procedure was done with the other categories of warehouses for initial values.

Table 1 shows the input values adopted for each indicator measured in the SD model, taken from the Warehousing Education and Research Council (2019) report (Appendix C).

As seen in the SD model equations (Appendix B), receiving and picking error rates must be divided between under and over-error rates (Table 2) to generate Hidden and Ghost inventory. There is no such proportion rate in the literature. So, this research considered it as 90/10, supporting their decision by the research of Hachem et al. (2016) when the authors stated that larger volumes in receiving (quantity per operator) imply more chances of human errors affecting the physical inventory negatively. According to this rationale, since the receiving error

Table 1. Values adopted in the simulations for each warehouse category.

Indicator / Category	MO	DIS	TYP	ADV	BIC
Order Receiving Error rate	10.00%	7.50%	3.50%	1.50%	1.00%
Order Picking Error rate	2.00%	1.50%	0.70%	0.25%	0.11%
IRI	10.00%	6.50%	1.95%	0.54%	0.10%
Average WCU	75.00%	77.50%	82.79%	89.06%	92.54%

Source: based on Warehousing Education and Research Council (2019).

Table 2. Initial values for error rates for each warehouse scenario.

Input variables	Scenario 1: MO	Scenario 2: DIS	Scenario 3: TYP	Scenario 4: ADV	Scenario 5: BIC
Under Receiving Error Rate	9.00%	6.75%	3.15%	1.35%	0.90%
Over Receiving Error Rate	1.00%	0.75%	0.35%	0.15%	0.10%
Under Picking error rate	1.80%	1.35%	0.63%	0.22%	0.10%
Over Picking error rate	0.20%	0.15%	0.07%	0.02%	0.01%
Initial IRI	10.00%	6.50%	1.95%	0.54%	0.10%
Initial Warehouse Capacity Utilization	75.00%	77.50%	82.79%	89.06%	92.54%
Cycle Counting Team	0 to 20	0 to 15	0 to 10	0 to 6	0 to 6

rate for the MO warehouse in Warehousing Education and Research Council (2019) is 10%, it is converted to 9% under Receiving Error Rate and 1% over receiving error rate. Then, the input variables of Table 1 are converted, using the model equations (Appendix B), into the initial values of physical inventory, available logical inventory, hidden inventory, and ghost inventory.

The number of cycle count operators (Table 2) varies for each warehouse category to answer RQ3. The scenarios with no cycle counter operator represent that any formal procedure to correct inventory divergencies is adopted in the warehouse. In contrast, the scenarios with one or more operators correspond to the cycle counting activity. Therefore, several simulations are carried out for each warehouse category, modifying the number of operators in the cycle counting team. The results are presented in section 4.

4. Results

The simulation results are presented in Figure 3. Figure 3a-3c demonstrate lost sales (in bars, left y-axis) and picking productivity (in lines, right y-axis) according to the number of CC operators simulated (x-axis). Figure 3a illustrates results for MO and DIS warehouses, whereas Figure 3c for ADV and BIC, due to the similarity of the indicators outputs. Figure 3d shows the WCU for MO, DIS, TYP, ADV, and BIC according to the number of CC operators (x-axis).

Before analyzing the results, it is essential to remember that the initial IRI is different for each warehouse (e.g., the MO warehouse is 10%, whereas for the BIC warehouse is 0.10%, see Table 2). Also, all picking productivity issues are converted into lost sales, and the most relevant variable for productivity losses is IRI. For this reason, the final values of IRI and lost sales are very close.

It is possible to verify, when comparing Figure 3a-3c, that in warehouses with no CC implementation, the final IRI is much higher than the initial in all types of warehouses, demonstrating that IRI needs to be carefully controlled by warehouses' managers. In addition, the increase in the number of cycle counters reduces the IRI to a certain inflection point, and after that, the lost sales stabilize for all warehouses' scenarios.

The MO and DIS warehouses, Figure 3a, attain high lost sales levels with no CC implementation (approximately 45% and 35%, respectively) and just 55% and 65% of picking productivity. The CC implementation with few employees (5, for example) does not seem to solve the problem for MO and DIS warehouses, which remain very unproductive, with the lost sales becoming unmanaged (almost 30% for a MO warehouse). Suppose a MO warehouse wants to reduce lost sales in the short term with CC implementation and without process changes. In that case, it is possible with at least 15 counters, considering our simulation conditions. The result suggests that MO warehouses, Figure 3a, cannot upgrade to a BIC warehouse performance by just implementing the CC operation since the number of CC employees needed to reach IRI equal to 0.10% is greater than 20% of the total number of warehouse employees (according to our simulation conditions). In the case of DIS warehouses, with ten counters, the IRI stabilizes below 2%, promoting the warehouse to a TYP category, with 2% of lost sales and 98% of picking productivity.

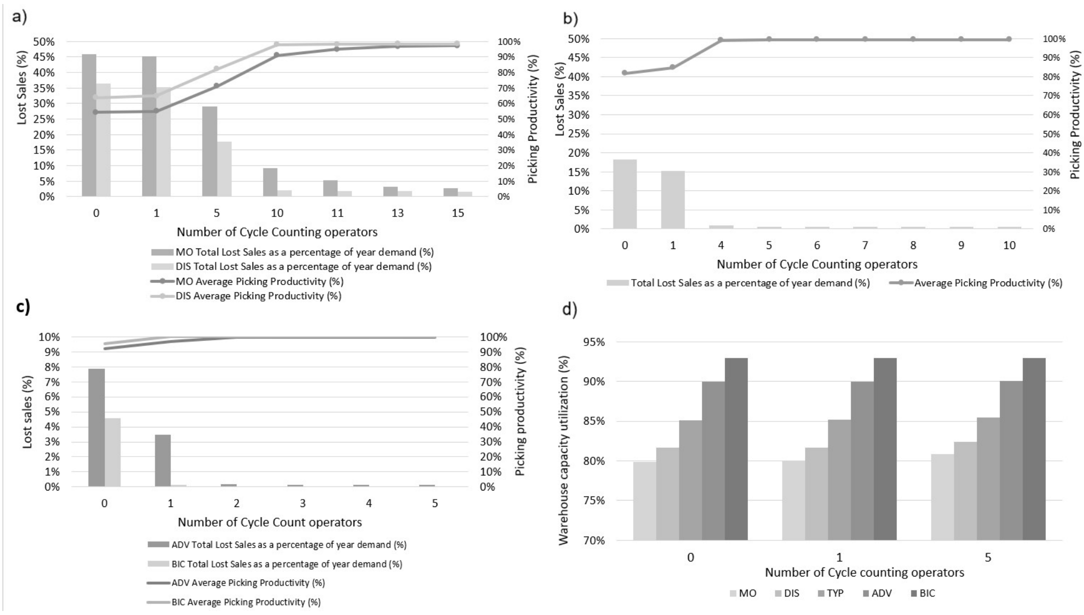

Figure 3. Simulation results for lost sales and picking productivity in a) MO and DIS warehouses; b) TYP warehouse; c) ADV and BIC warehouses; and d) WCU for MO, DIS, TYP, ADV, and BIC warehouses.

For TYP (Figure 3b) ADV and BIC warehouses (Figure 3c), it is possible to note that CC implementation with just a few counters vastly improves the warehouse's outputs. With an initial IRI of 0.54% and without cycle counters, lost sales of the ADV warehouse reached 7.85% at the end of the year. With only one counter, the lost sales reduced to 3.46%, with picking productivity of 96.5%. With two counters, the average IRI stabilizes below 1%. Thus, the results reveal that IRI and CC impact warehouse outputs in different proportions, and this variation is related to their current performance.

Regarding WCU, in Figure 3d, the result suggests that the CC implementation has little impact on WCU. The reasons for this result and other conclusions are presented in the next section.

5. Discussion

This section discusses the five warehouse scenarios in terms of theoretical and practical implications regarding the three research questions introduced in section 1.

Table 3 shows the results for each warehouse scenario without cycle counting implementation and with cycle counting implementation (1 and 5 counters) to answer RQ1 and RQ2. Besides the output indicators (Lost sales, Picking Productivity – PP, Warehouse Capacity Utilization – WCU), it is also presented the number of times IRI increases (or decreases) at the end of the simulation.

Concerning RQ1, the first conclusion is that IRI negatively impacts all warehouse outputs simulated in warehouses without CC implementation. Besides, IRI affects differently the outcomes depending on the current warehouse performance. One unexpected aspect of the results without CC is that IRI increases substantially in warehouses with superior performances (ADV and BIC). On the other hand, the impact of IRI in ADV and BIC warehouses with CC implementation is substantially reduced with one counter or eliminated for more than two counters.

Regarding the WCU, it is possible to note that IRI negatively impacts WCU, i.e. higher IRI values generate an increase in warehouse capacity utilization. In this work, a high level of warehouse utilization means high levels of hidden inventory. On the other hand, the WERC report relates higher WCU levels to better warehouse performance. Thus, the main conclusion is that the WCU indicator should be analyzed carefully, and picking productivity and lost sales must also be monitored. If these two indicators worsen, the WCU may increase with no improvements in the warehouse's performance.

In terms of the CC impact in WCU outputs, it does not differ substantially among the warehouse types. The main reason is that the feedback implemented in the SD model ensures that the warehouse continues to operate during all the simulation days. So, even in the MO warehouse, WCU does not reach 100%.

Table 3. Output for each warehouse category without and with cycle counting implementation (1 and 5 counters).

Outputs No cycle counting (360 days)				
Scenario	Lost Sales	PP	WCU	IRI increase
MO	45.80%	54.30%	79.90%	3.6x
DIS	36.40%	63.70%	81.65%	4.6x
TYP	18.30%	81.80%	85.12%	8.3x
ADV	7.80%	92.20%	89.97%	13.5x
BIC	4.60%	95.50%	92.96%	44.5x
Outputs 1 counter (360 days)				
Scenario	Lost Sales	PP	WCU	IRI increase
MO	45.23%	54.90%	79.92%	3.5x
DIS	35.22%	64.88%	81.69%	4.4x
TYP	15.32%	84.73%	85.18%	6.8x
ADV	3.47%	96.54%	90.00%	5.4x
BIC	0.13%	99.87%	92.97%	0.3x
Outputs 5 counters (360 days)				
Scenario	Lost Sales	PP	WCU	IRI increase
MO	29.00%	71.08%	80.82%	1.9x
DIS	17.81%	82.24%	82.41%	1.7x
TYP	0.58%	99.42%	85.46%	-0.7x
ADV	0.15%	99.85%	90.02%	-0.7x
BIC	0.05%	99.95%	92.97%	-0.5x

As seen in Table 3, a daily CC policy reduces IRI levels, consequently preventing lost sales and optimizing WCU. However, it is crucial to monitor warehouse performance indicators regarding transactional errors and drive them to better numbers. The CC works better if it is followed by the reduction of operational errors and improvement of picking and receiving accuracy: a MO warehouse with a team of 10 counters has more lost sales in a year than a BIC warehouse without any counting at all.

Regarding RQ2, in the scenario without CC implementation, all warehouse outputs are worse than the initial values, demonstrating that CC should be implemented in warehouses with any performance. Even in the BIC warehouse, its IRI increases from 0.10% to 4.55% without CC. The CC implementation is sufficient to maintain its BIC status with just one counter (IRI reduces to 0.13%). The situation is similar to the ADV and TYP warehouses, for two and three counters, respectively, in which IRI remains the initial value. However, for MO and DIS warehouses, the CC implementation with five counters is insufficient to avoid IRI impacts, indicating that other improvements in the process should be made.

Regarding RQ3, Table 4 demonstrates the number of cycle counters to maintain, decrease or increase the warehouse category according to the IRI indicator in the simulated conditions, considering the WERC performance standard.

In the case of the MO warehouse, up to nine counters do not upgrade the warehouse category; a ten to fourteen counters team must decrease the IRI level to the DIS category and fifteen plus to improve TYP levels. As in all simulations there are 100 workers in picking and 5 in receiving, the warehouse manager needs to improve their workforce in 10% to maintain or improve its performance. In the same way, up to 5 counters in a DIS warehouse is not enough to keep IRI down: six to eight counters are necessary to remain in a DIS category, and nine plus to increase the category.

Just TYP, ADV and BIC warehouses can control IRI with few counters (at least two). Actually, less than two counters decreases their warehouses performance categories. So, CC is imperative to maintain their performance standards. On the other hand, it is interesting to highlight that TYP and ADV warehouses do not upgrade to BIC standard increasing the number of counters. Finally, the simulated results of Table 4 show that there is a limit to CC operators making an impact over IRI, and adding more counters will only increase labor costs.

Therefore, the main managerial practical implications issued from the study are presented as follows.

(i) Employee productivity should not be the only performance indicator observed by DC managers. They should monitor IRI because it has a significant impact on warehouse performance.

Table 4. The number of CC operators to maintain or improve the warehouse performance based on IRI levels.

Category	Decrease category	Maintain	Increase category
MO	-	1 to 9	10 to 14 (DIS), 15+ (TYP)
DIS	0 to 5 (MO)	6 to 8	9+ (TYP), does not upgrade to ADV
TYP	0 to 1 (MO)	2 to 3	4+ (ADV), does not upgrade to BIC
ADV	0 to 1 (TYP)	2+	Stabilize at 0.151% regardless of more counters
BIC	0 (TYP), 1 (ADV)	2+	Stabilize at 0.046% regardless of more counters

(ii) CC, even with a small team, proved to be effective in maintaining the performance of BIC warehouses and improving the performance of TYP and ADV warehouses.

(iii) In lower-performance warehouses (MO and DIS), CC reduces the impacts of IRI, but a small team of counters may be insufficient to improve its performance regarding IRI. Evaluating the number of CC operators is necessary since large CC teams are expensive and difficult to manage. In these cases other improvement tools should be implemented to reduce operational errors in receiving and picking.

(iv) The results discourage the adoption of annual FIC as the only IRI reduction practice. Even ADV and BIC warehouses would have problems without adopting a single counter, confirming that CC should be implemented regardless of the warehouse category.

(v) Managers should be concerned with the IRI and keeping close track of operational errors, especially in receiving and picking tasks, by monitoring and acting to suppress them with training, better recruiting, etc.

6. Conclusion

Inventory Record Inaccuracy (IRI) is defined as the degree of the System Inventory Record (SIR) inaccuracy concerning the physical inventory of a specific item. The literature reports IRI as one of the main challenges in inventory management and warehouse performance. To reduce IRI, the literature suggest the implementation of the cycle counting (CC) procedure. However, the literature does not have explored the quantitative relationship between IRI and CC regarding the warehouse's outputs. To fill this gap, this work built an SD model to analyze the influence of IRI and CC on the following warehouse outputs: picking productivity, lost sales, and warehouse capacity utilization. The SD model simulates the warehouse's processes of receiving, cycle counting and picking, which has not been reported in other works. To evaluate the IRI impact in warehouses with different performance levels, the WERC standard is used for each warehouse scenario (MO-major opportunity; DIS-disadvantage; TYP-typical; ADV-advantage; BIC-best in class). Three research questions guide the objectives of this paper: (i) to analyze the impacts of IRI on the warehouse outputs such as picking productivity, lost sales, and warehouse capacity utilization for warehouses with different performances, (ii) to verify the efficiency of the Cycle Counting (CC) implementation to reduce the IRI and (iii) the number of CC operators to maintain warehouse performance.

In general terms, the simulated scenarios show the dynamic behavior in the proposed system and quantify the IRI affect in the warehouse outputs. The results show an imbalance that leads to a drop in picking productivity, an increase in lost sales, and inventory build-up, hindering the warehouse capacity levels.

Regarding each warehouse category simulated, it is interesting to highlight some points. For MO and DIS warehouses, other improvements are needed in addition to the IRI correction, as it would require numerous cycle counters, which implies a high operational cost. For these warehouses, CC works better if it is combined with actions that reduce operational errors and improve picking and receiving accuracy. However, the CC implementation in TYP, ADV, and BIC warehouses is enough to reduce IRI. Concerning the WCU, the warehouse performance (lower IRI values), less the WCU was impacted by the inventory policy.

In practical terms, the simulated scenarios show that managers responsible for planning and controlling inventory should be concerned with IRI since it directly affects productivity in order fulfillment. Moreover, managers should pay close attention to transaction errors by monitoring inbound and outbound tasks and promoting actions such as CC, training, and better recruitment. Performance indicators concerning operational errors must be closely monitored, especially in receiving and picking, to reduce the impact in the warehouse system's dynamic.

Regarding the theoretical contributions, the results confirm the thesis of Barratt et al. (2018) that employee productivity should not be the only indicator evaluated by DC managers. As human transaction errors from operators feed the IRI, which, in turn, decreases productivity in order fulfillment. Also, Rajasekar & Sengupta

(2020) remarked that some small warehouses still use annual FIC instead of CC, despite the extensive studies assuring the latter's benefits. Warehouses that do not perform daily CC have considerable lost sales and high average IRI compared to those that perform CC.

This study has some limitations: (i) The constants of the simulated warehouse scenario are fictitious, (ii) the IRI is the only error considered in the warehouse processes, (iii) only the CC implementation were evaluated, (iv) the impacts of ghost and hidden inventory were evaluated just in WCU indicator. Some suggestions for future works are studies that consider more endogenous and exogenous variables, such as top-down pressure for results affecting the pace of tasks, workforce motivation, the impact of employee turnover and its consequences on the learning curve of new staff, employee fatigue due to overtime, etc. Also, the insertion of the operational cost of order fulfillment and cycle counting tasks as variables is another possible aspect to be investigated. Other works can simulate more warehouse processes as inventory movimentation from bulk to picking areas. The impacts of the ghost and hidden inventory in warehouse outputs can be further investigated. Finally, studies can analyze how digital technologies will impact IRI in each warehouse process, and the main tools to control IRI in warehouses 4.0.

References

Agarwal, A., Shankar, R., & Mandal, P. (2006). Effectiveness of information systems in supply chain performance: a system dynamics study. *International Journal of Information Systems and Change Management*, *1*(3), 241-261. http://dx.doi.org/10.1504/IJISCM.2006.011198.

Aguirre, J. A. E., Peña, M., Jadan-Avilés, D., & Llivisaca, J. (2021, October 27-29). Relevant factors in the inventory record inaccuracy for retail companies: a study in food retail industry. In M. Botto-Tobar, S. M. León, P. Torres-Carrión, M. Z. Vizuete & B. Durakovic (Eds.), *International Conference on Applied Technologies (ICAT 2021)* (pp. 552-564). Cham, Switzerland: Springer.

Arnold, J. R. T., Chapman, S. N., & Clive, L. M. (2007). *Introduction to materials management*. Hoboken: Pearson Prentice Hall.

Azadeh, K., Roy, D. & Koster, M. B. M. R. (2020). Dynamic human-robot collaborative picking strategies. *SSRN Electronic Journal*, 3585396. Online. http://dx.doi.org/10.2139/ssrn.3585396.

Barratt, M., Kull, T. J., & Sodero, A. C. (2018). Inventory record inaccuracy dynamics and the role of employees within multichannel distribution center inventory systems. *Journal of Operations Management*, *63*(1), 6-24. http://dx.doi.org/10.1016/j.jom.2018.09.003.

Best, J., Glock, C. H., Grosse, E. H., Rekik, Y., & Syntetos, A. (2022). On the causes of positive inventory discrepancies in retail stores. *International Journal of Physical Distribution & Logistics Management*, *52*(5-6), 414-430. http://dx.doi.org/10.1108/IJPDLM-07-2021-0291.

Brown, K. L., Inman, R. A., & Calloway, J. A. (2001). Measuring the effects of inventory inaccuracy in MRP inventory and delivery performance. *Production Planning and Control*, *12*(1), 46-57. http://dx.doi.org/10.1080/09537280150203979.

Cardiel-Ortega, J. J., Baeza-Serrato, R., & Lizarraga-Morales, R. A. (2017). Development of a system dynamics model based on six sigma methodology. *Ingenieria e Investigacion*, *37*(1), 80-90. http://dx.doi.org/10.15446/ing.investig.v37n1.62270.

Chuang, H. H. C., & Oliva, R. (2015). Inventory record inaccuracy: causes and labor effects. *Journal of Operations Management*, *39-40*(1), 63-78. http://dx.doi.org/10.1016/j.jom.2015.07.006.

DeHoratius, N., & Raman, A. (2008). Inventory record inaccuracy: an empirical analysis. *Management Science*, *54*(4), 627-641. http://dx.doi.org/10.1287/mnsc.1070.0789.

Drohomeretski, E., & Favaretto, F. (2013). Different types of inventory control in Brazilian companies. *International Journal of Industrial Engineering and Management*, *4*(3), 131-140.

Fleisch, E., & Tellkamp, C. (2005). Inventory inaccuracy and supply chain performance: a simulation study of a retail supply chain. *International Journal of Production Economics*, *95*(3), 373-385. http://dx.doi.org/10.1016/j.ijpe.2004.02.003.

Gumrukcu, S., Rossetti, M. D., & Buyurgan, N. (2008). Quantifying the costs of cycle counting in a two-echelon supply chain with multiple items. *International Journal of Production Economics*, *116*(2), 263-274. http://dx.doi.org/10.1016/j.ijpe.2008.09.006.

Hachem, W., Harik, R., & Khoury, J. (2016, July 11-13). Error generation, inventory record inaccuracy (IRI) and effects on performance: a dynamic investigation. In R. Harik, L. Rivest, A. Bernard, B. Eynard & A. Bouras (Eds.), *IFIP International Conference on Product Lifecycle Management: Product Lifecycle Management for Digital Transformation of Industries* (pp. 642-651). Cham, Switzerland: Springer. http://dx.doi.org/10.1007/978-3-319-54660-5_57.

Heese, H. S. (2007). Inventory record inaccuracy, double marginalization, and RFID adoption. *Production and Operations Management*, *16*(5), 542-553. http://dx.doi.org/10.1111/j.1937-5956.2007.tb00279.x.

Hofstra, N., Spiliotopoulou, E., & Leeuw, S. (2022). Ordering decisions under supply uncertainty and inventory record inaccuracy: an experimental investigation. *Decision Sciences*, 1-16. In press. http://dx.doi.org/10.1111/deci.12564.

Kang, Y., & Gershwin, S. B. (2005). Information inaccuracy in inventory systems: stock loss and stockout. *IIE Transactions*, *37*(9), 843-859. http://dx.doi.org/10.1080/07408170590969861.

Kök, A. G., & Shang, K. H. (2007). Inspection and replenishment policies for systems with inventory record inaccuracy. *Manufacturing & Service Operations Management*, *9*(2), 185-205. http://dx.doi.org/10.1287/msom.1060.0136.

Lei, Q., Zhang, Y., & Zhou, L. (2018). Supply chain coordination under inventory inaccuracy with RFID technology. *Mathematical Problems in Engineering*, *2018*, 1-13. http://dx.doi.org/10.1155/2018/4686531.

Marco, A., Cagliano, A. C., Nervo, M. L., & Rafele, C. (2012). Using system dynamics to assess the impact of RFID technology on retail operations. *International Journal of Production Economics*, *135*(1), 333-344. http://dx.doi.org/10.1016/j.ijpe.2011.08.009.

Pasparakis, A., Vries, J., & Koster, M. B. M. R. (2021). In control or under control? Human-robot collaboration in warehouse order picking. *SSRN Electronic Journal*, 3816533. Online. http://dx.doi.org/10.2139/ssrn.3816533.

Qin, W., Zhong, R. Y., Dai, H. Y., & Zhuang, Z. L. (2017). An assessment model for RFID impacts on prevention and visibility of inventory inaccuracy presence. *Advanced Engineering Informatics*, *34*, 70-79. http://dx.doi.org/10.1016/j.aei.2017.09.006.

Rajasekar, D., & Sengupta, G. (2020). Annual physical inventory stock taking lead time reduction a case study. *International Journal of Management IT & Engineering*, *10*(11), 70-88.

Raman, A., DeHoratius, N., & Ton, Z. (2001). Execution: the missing link in retail operations. *California Management Review*, *43*(3), 136-152. http://dx.doi.org/10.2307/41166093.

Rekik, Y., & Sahin, E. (2012). Exploring inventory systems sensitive to shrinkage - analysis of a periodic review inventory under a service level constraint. *International Journal of Production Research*, *50*(13), 3529-3546. http://dx.doi.org/10.1080/00207543.2012.670919.

Rekik, Y., Syntetos, A. A., & Glock, C. H. (2019a). Modeling (and learning from) Inventory Inaccuracies in e□retailing/B2B contexts. *Decision Sciences*, *50*(6), 1184-1223. http://dx.doi.org/10.1111/deci.12367.

Rekik, Y., Syntetos, A. A., & Glock, C. H. (2019b). *Inventory inaccuracy in retailing: does it matter?* Retrieved in 2022, December 9, from https://www.cardiff.ac.uk/__data/assets/pdf_file/0003/1729236/84486-ECR-Inventory-Inaccuracy-Report-v12.pdf

Sahin, E. (2004). *A qualitative and quantitative analysis of the impact of the Auto-ID technology on supply chains* (Doctoral dissertation). Châtenay-Malabry: École Centrale Paris.

Sarac, A., Absi, N., & Dauzère-Pérès, S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics*, *128*(1), 77-95. http://dx.doi.org/10.1016/j.ijpe.2010.07.039.

Shabani, A., Maroti, G., Leeuw, S., & Dullaert, W. (2021). Inventory record inaccuracy and store-level performance. *International Journal of Production Economics*, *235*, 108111. http://dx.doi.org/10.1016/j.ijpe.2021.108111.

Staudt, F. H., Alpan, G., Mascolo, M., & Rodriguez, C. M. T. (2015). Warehouse performance measurement: a literature review. *International Journal of Production Research*, *53*(18), 5524-5544. http://dx.doi.org/10.1080/00207543.2015.1030466.

Sterman, J. D. (2000). *Business dynamics: systems thinking and modeling for a complex world*. Boston: McGraw-Hill.

Su, H.-C., Rungtusanatham, M. J., & Linderman, K. (2021). Retail inventory shrinkage, sensing weak security breach signals, and organizational structure. *Decision Sciences*, 1-21. In press. http://dx.doi.org/10.1111/deci.12524.

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, *52*(4), 802-815. http://dx.doi.org/10.1016/j.dss.2011.11.015.

Waller, M. A., Nachtmann, H., & Hunter, J. (2006). Measuring the impact of inaccurate inventory information on a retail outlet. *International Journal of Logistics Management*, *17*(3), 355-376. http://dx.doi.org/10.1108/09574090610717527.

Wang, F., Fang, X., Chen, X., & Li, X. (2016). Impact of inventory inaccuracies on products with inventory-dependent demand. *International Journal of Production Economics*, *177*, 118-130. http://dx.doi.org/10.1016/j.ijpe.2016.04.019.

Warehousing Education and Research Council – WERC. (2019). *DC measures annual report*. Retrieved in 2022, December 9, from https://cdn2.hubspot.net/hubfs/476052/2019_WERC_DC_Measures 2019_Handout.pdf

Appendix A. Warehouse constants adopted for calculations.

ID	Warehouse Constants	Unit	Value
A	Warehouse Working Hours by day	hours/day	8
B	Warehouse Nominal Capacity	units	375,000
C	Demand	units/day	10,000
D	Physical Inventory (initial)	units	300,000
E	Receiving team	man	5
F	Receiving Productivity	units/man.hour	250
G	Cycle Counting Productivity	units/man.hour	25
H	Cycle Counting Error Rate	%	1%
I	Picking Team	man	100
J	Picking Productivity	units/man.hour	12.5
ID	**Warehouse variables**	**Unit**	
K	Under Receiving Error Rate	%	
L	Over Receiving Error Rate	%	
M	Cycle Counting Team	man	
N	Over Picking Error Rate	%	
O	Under Picking Error Rate	%	
P	Hidden inventory (initial)	units	
Q	Ghost inventory (initial)	units	
R	Available Logical Inventory (initial)	units	
S	IRI (initial)	%	

Appendix B. Equations and syntaxes adopted for calculations.

Variable	Equation/Syntax	ID
Under Receiving Errors	$\text{Under Receiving Errors} = \text{Physical Receiving} \times \text{Under Receiving Error Rate}$	1
Over Receiving Errors	$\text{Over Receiving Errors} = \text{Physical Receiving} \times \text{Over Receiving Error Rate}$	2
Hidden Inventory Correction	$\text{Hidden Inventory Correction} = \text{IF}\left(\text{Cycle Counting} / 2 \geq \text{Hidden Inventory}\right)\text{THEN}\left(\text{Hidden Inventory}\right)\ \text{ELSE}\left(\text{Cycle Counting} / 2\right)$	3
Ghost Inventory Correction	$\text{Ghost Inventory Correction} = \text{IF}\left(\text{Cycle Counting} / 2 \geq \text{Ghost Inventory}\right)\text{THEN}\left(\text{Ghost Inventory}\right)\text{ELSE}\left(\text{Cycle Counting} / 2\right)$	4
Pick Less than Requested in Physical	$\text{Pick Less than Requested in Physical} = \text{Picking} \times \text{Over Picking Error Rate} \times \text{Picking Team}$	5
Pick More than requested in Physical	$\text{Pick More than requested in Physical} = \text{Picking} \times \text{Under Picking Error Rate} \times \text{Picking Team}$	6
Under Receiving Entry	$\text{Under Receiving Entry} = \text{Under Receiving Errors} + \text{Pick Less than Requested in Physical} + \left(\text{Cycle counting errors} / 2\right)$	7
Over Receiving Entry	$\text{Over Receiving Entry} = \text{Over Receiving Errors} + \text{Pick More than requested in Physical} + \left(\text{Cycle counting errors} / 2\right)$	8
Cycle Counting Errors	$\text{Cycle Counting Errors} = \text{Demand} \times \text{Cycle Counting Error Rate} + \text{Hidden Inventory Correction} \times \text{Cycle Counting Error Rate}$	9
Physical Receiving	$\text{Physical Receiving} = \text{IF}\left(\left(\text{Receiving Productivity} \times \text{Receiving team} \times \text{Warehouse Working Hours by day}\right) \geq \text{Logical Picking}\right)\text{THEN}\left(\text{Logical Picking}\right)$ $\text{ELSE}\left(\text{Receiving Productivity} \times \text{Receiving team} \times \text{Warehouse Working Hours by day}\right)$	10
Logical Receiving	$\text{Logical Receiving} = \text{Physical Receiving} - \text{Under Receiving Errors} + \text{Over Receiving Errors} + \text{Hidden Inventory Correction} - \text{Ghost Inventory Correction}$	11
Cycle Counting	$\text{Cycle Counting} = \text{Cycle Counting Productivity} \times \text{Cycle Counting Team} \times \text{Warehouse Working Hours by day}$	12
Lost Sales	$\text{Lost Sales} = \text{Demand} - \text{Logical Picking}$	13
IRI	$IRI = \text{ABS}\left(\frac{\left(\text{Available Logical Inventory} - \text{Physical Inventory}\right)}{\text{Physical Inventory}}\right)$	14
Picking	$\text{Picking} = \left(\text{Picking Productivity} - \text{Warehouse Working Hours by day}\right) - \left(\text{Picking Productivity} \times \text{Warehouse Working Hours by day} \times \text{IRI}\right)$	15
Physical Picking	$\text{Physical Picking} = \text{Logical picking} - \text{Pick Less than Requested in Physical} + \text{Pick More than requested in Physical}$	16
Logical Picking	$\text{Logical Picking} = \left(\text{Picking Team} \times \text{Picking} \geq \text{Demand}\right)\text{THEN}\left(\text{Demand}\right)\text{ELSE}\left(\text{Picking} \times \text{Picking Team}\right)$	17
Warehouse Utilization	$\text{Warehouse Utilization} = \left(\text{Physical Inventory} / \text{Warehouse Nominal Capacity}\right) \times 100$	18

Note: absolute value (ABS).

Appendix C. Warehouse classification according to metrics.

Warehouse Metrics	MO	DIS	TYP	ADV	BIC
Average WCU	Less than 75.00%	More or equal to 75.00% and less than 80.00%	More or equal to 80.0% and less than 85.58%	More or equal to 85.58% and less than 92.54%	More or equal to 92.54%
Peak WCU	Less than 85.80%	More or equal to 85.8% and less than 92.00%	More or equal to 92.0% and less than 95.0%	More or equal to 95.0% and less than 100.00%	100.00%
Inventory Count Accuracy	Less than 90.00%	More or equal to 90.00% and less than 97.00%	More or equal to 97.0% and less than 99.01%	More or equal to 99.01% and less than 99.90%	More or equal to 99.90%
Order Picking Accuracy	Less than 98.00%	More or equal to 98.00% and less than 99.00%	More or equal to 99.0% and less than 99.60%	More or equal to 99.60% and less than 99.89%	More or equal to 99.89%
Percent of Supplier orders received with correct documents	Less than 90.0%	More or equal to 90.00% and less than 95.50%	More or equal to 95.5% and less than 98.00%	More or equal to 98.0% and less than 99.7%	More or equal to 99.89%

Source: Warehousing Education and Research Council (2019).