

Integrated Model for Order Fulfillment: Standard Work with GenAI, SLP, WMS, and Augmented Reality in Distribution Operations

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Abstract - The low Order Fill Rate (OFR) remains one of the main logistical inefficiencies in distribution companies, directly impacting customer satisfaction and operational profitability. This paper presents an integrated methodology to optimize the OFR through the standardization of order management processes, improvement of internal warehouse flow, and automation of the picking process. The proposed solution integrates continuous improvement tools such as Standard Work (SW) and 5S, enhanced by generative artificial intelligence (GenAI), Systematic Layout Planning (SLP), and emerging technologies such as Warehouse Management Systems (WMS) and pick-by-vision augmented reality. The diagnosis identified a technical gap of 7.14% in the OFR, resulting in an annual revenue loss of 9.09%. Through simulation, significant improvements were validated in order preparation, product location, and customer coordination, approaching the target of 98% fulfillment. This methodology demonstrates that the integration of Lean approaches with digital technologies can significantly enhance operational efficiency in distribution processes.

Keywords: Order Fill Rate, Standard Work, Warehouse Management System (WMS), 5S, Systematic Layout Planning (SLP), Augmented Reality (Pick-by-Vision)

1. Introduction

In distribution systems, the efficiency of complete order fulfillment is a key factor in ensuring competitiveness, particularly in markets characterized by high turnover and fragmented demand. The Order Fill Rate (OFR), widely adopted in recent studies, has emerged as a critical metric for evaluating the quality of logistics services and the responsiveness of operations [1]. Poor OFR management not only affects the customer experience but also increases costs related to reprocessing, returns, and non-productive time [2].

The case study analyzed in this research pertains to a Peruvian distributor of fast-moving consumer goods, where a 7.14% gap was identified relative to the expected OFR benchmark of 98%. This deviation has led to economic losses equivalent to 9.09% of annual revenue, primarily due to picking errors, disorganized layout, and lack of standardized processes. These issues highlight the need for a comprehensive intervention that integrates physical design, task standardization, and digital support, as recommended by various hybrid models applied in high-turnover warehouse environments [3], [4].

Recent studies have shown that combining Lean methodologies—such as Standard Work, 5S, and Systematic Layout Planning (SLP)—with emerging technologies including generative artificial intelligence (GenAI), warehouse management systems (WMS), and augmented reality can yield significant improvements in accuracy, speed, and delivery performance [5]. However, the literature reveals a lack of integrated application of these tools in real-world distribution settings within emerging economies, reinforcing the relevance of this research [6].

This paper proposes an integrated methodology to optimize perfect order fulfillment by acting on the physical, procedural, and digital layers of the logistics system. The structure of the paper is as follows: Section 2 presents a literature review focused on the OFR indicator and the applied tools; Section 3 describes the methodological model; Section 4 covers the simulation-based validation process; Section 5 analyzes the results; and Section 6 summarizes the conclusions and operational contributions of the study.

2. Literature Review

2.1. Order Fill Rate

The Order Fill Rate (OFR) has become a key strategic metric for evaluating logistics performance, as it reflects the degree of complete and timely order fulfillment [7], [8]. Its optimization depends not only on inventory levels but also on the integration of processes such as picking, delivery synchronization, and demand management. Several studies highlight that approaches such as stochastic analysis, transshipment planning, and the use of decision support systems can significantly enhance OFR performance [9], [10]. Likewise, it has been shown that collaborative models, such as community logistics, and the integration of artificial intelligence can anticipate deviations and enable real-time corrective actions [11].

In summary, OFR is a variable highly sensitive to the quality of operational planning and the degree of technological integration. This underscores the need for hybrid models—such as the one proposed in this study—that combine traditional and digital solutions to optimize the supply chain.

2.2. Lean Tools in Logistics

Lean methodologies such as 5S and Standard Work have proven to be effective tools in logistics environments for reducing waste, stabilizing processes, and improving operational efficiency [12], [13]. Their systematic implementation reduces variability in repetitive tasks and reinforces a culture of continuous improvement. Studies in both industrial and agro-industrial sectors have reported productivity increases ranging from 15% to 25%, attributed to workspace organization, routine standardization, and the reduction of non-productive time [14]–[16].

These tools also serve as a foundation for technological initiatives, such as automation or the use of AI in sequential tasks. Collectively, the literature validates that 5S and Standard Work not only improve physical and procedural performance but also act as key enablers for the integration of advanced technologies—aligned with the hybrid model proposed in this study.

2.3. Layout Optimization

Systematic Layout Planning (SLP) and ABC classification are essential tools for improving warehouse efficiency, as they help reduce travel times and reorganize critical zones based on product frequency and criticality [17], [18]. Recent studies have shown that combining SLP with relationship analysis and multi-criteria ABC classification can reduce travel distances by up to 30% in high-volume picking distribution centers [19], [20]. These techniques have also been validated in agro-industrial settings and are effectively complemented by methodologies such as FMECA, which help anticipate risks and design more resilient layouts [21].

Altogether, the integration of SLP and ABC provides a solid foundation for strategic decision-making in logistics management, aligning with this study's goal of optimizing internal warehouse flow.

2.4. AI-Based Standardization

Smart standardization combines Standard Work with Artificial Intelligence (AI) to eliminate operational inconsistencies and reduce errors in order management, by establishing consistent routines enhanced by advanced technology [22]. Recent studies have demonstrated that this synergy reduces cycle times, improves operational accuracy, and facilitates knowledge transfer through cognitive assistants that integrate tacit knowledge into digital instructions [23], [24]. These applications have achieved reductions of up to 21% in non-value-added tasks, validating their effectiveness across various industrial environments.

In summary, the combination of standardization and AI enhances operational execution and accelerates the adoption of continuous improvements, positioning itself as a key strategy for organizations aiming to align with Industry 4.0 principles [25].

2.5. Smart Warehouse Automation

The integration of Warehouse Management Systems (WMS) with augmented reality (AR) technologies—particularly through pick-by-vision interfaces—has proven effective in reducing picking errors, increasing execution speed, and improving the operator experience [26], [27]. These solutions project data directly into the user's field of view, eliminating the need for printed lists, and have achieved productivity gains exceeding 50% compared to traditional methods [28]. Additionally, the use of head-mounted displays (HMDs) has improved ergonomics and reduced training times [29]. Despite some operational limitations—such as visual fatigue or connectivity issues—studies in distribution and manufacturing support the notion that this technology enhances traceability and enables real-time control [30], [31].

Overall, the synergy between WMS and AR represents a viable strategy for optimizing high-volume logistics operations, aligning with the objectives of the present model in improving Order Fill Rate.

3. Methodology

This section outlines the proposed model, designed to address the main causes behind the low rate of complete order fulfillment. The model integrates advanced technologies with traditional tools to optimize logistics processes, reduce errors, and increase operational efficiency.

3.1. Problem Foundation

The proposed model is based on the need to reduce the 7.14% technical gap in complete order fulfillment (Order Fill Rate, OFR), currently at 90.86%, compared to the corporate standard of 98%. This shortfall negatively affects logistics efficiency and generates an annual revenue loss of 9.09%, primarily associated with reprocessing, idle time, and operational miscoordination. Causal analysis identified the main sources of error as incorrect picking preparation (38%), improper product placement in the warehouse (27%), and orders with incomplete data (34%), revealing both operational and structural deficiencies [3], [14], [27].

To address this issue, a hybrid methodology is proposed that combines Lean tools with digital technologies. Through this integration, the model aims to transform logistics operations in terms of efficiency, accuracy, and adaptability, aligning with smart logistics trends and Industry 4.0 principles. Unlike isolated interventions, this approach proposes an architecture that acts in a coordinated manner across the organization's physical infrastructure, operational procedures, and digital support systems [7], [24].

3.2. Integrated Model

The proposal is structured into three main components that act progressively on the identified root causes: standardization of order management, optimization of internal warehouse flow, and automation of the picking process. This organization enables incremental and sustained intervention, ensuring alignment between diagnosis, tools, and expected results.

Each component corresponds to a specific level of technical intervention. The procedural level includes tools such as 5S, Standard Work, and GenAI to establish consistent and adaptive routines [4], [5], [23]. The physical-spatial level is addressed through the Systematic Layout Planning (SLP) methodology and multi-criteria ABC classification, with the goal of reorganizing the warehouse and optimizing travel distances [3], [18], [21]. Lastly, the digital-operational level involves the automation of picking through the integration of a WMS with augmented reality (pick-by-vision), improving traceability and execution speed [10], [25], [27], [29].

The model follows an input-process-output transformation logic, targeting three root causes: Incorrect picking preparation, misplaced products and orders with incomplete data. These deficiencies are transformed into concrete operational results: accurate picking preparation, correct product placement and complete and validated order data.

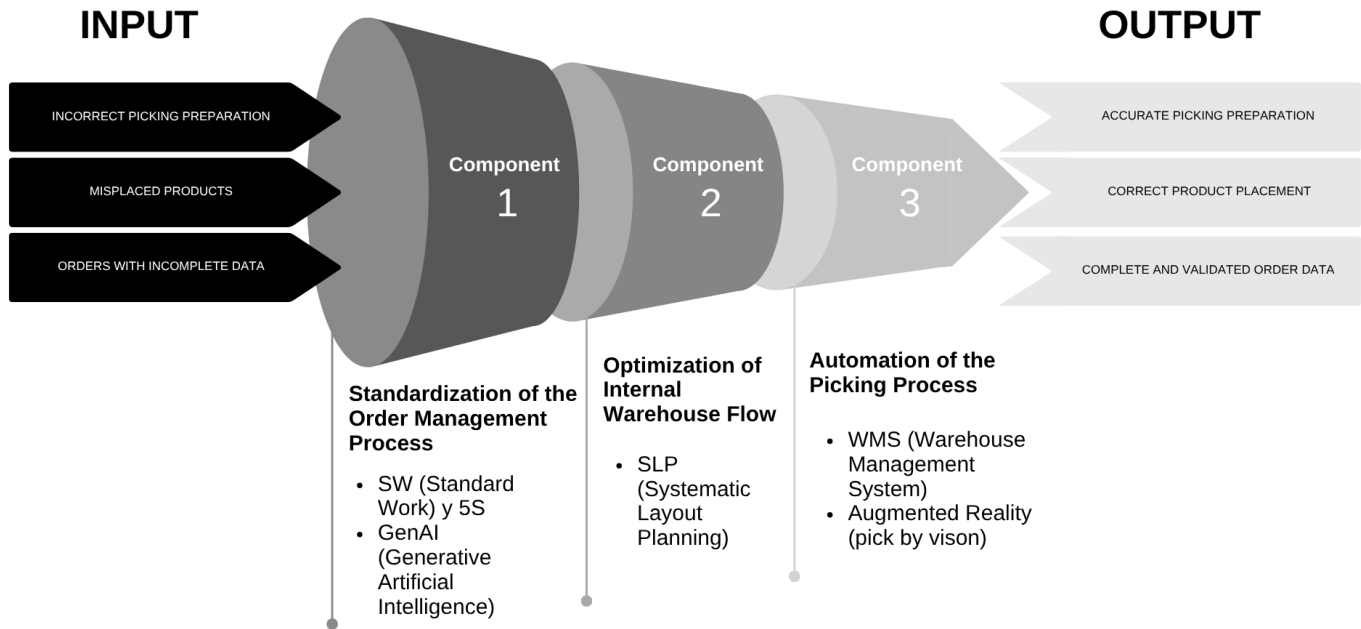


Fig. 1: Detailed solution model

3.3. Key Metrics

The key performance indicators of the model include the Order Fill Rate (OFR), which measures the proportion of correctly completed orders and projects an improvement of 7.14%; the Picking Error Rate, which tracks mistakes in order preparation with a projected reduction of 4.47%; the Order Operation Time, which assesses the average time spent on travel and picking activities with an expected 50% improvement; and the Incomplete Order Rate, which aims to reduce the proportion of orders with missing information by 30.43%. These indicators are summarized in the table below, reflecting the expected improvements following the implementation of the proposed model.

Table 1: key performance indicators

Selected Indicators	Unit	AS IS	TO BE	Improvement
Fill Order Rate (OFR)	%	90.86	98.00	7.14%
Picking Error Rate	%	4.09	3.10	-24.20%
Order Operation Time	%	32	16	-50.00%
Incomplete Order Rate	%	4.10	0	-100%

In conclusion, this model combines advanced technologies with traditional tools to address the main causes behind low order fulfillment performance. The integration of WMS with augmented reality (pick-by-vision), SLP, and Standard Work and 5S enhanced with AI enables the optimization of operations, reduction of logistics costs, and establishment of a more efficient and Industry 4.0-aligned distribution system.

4. Simulation and Validation

To validate the proposed methodology, a discrete-event simulation model was developed using Arena software, replicating the real conditions of a distribution center operating six days a week, eight hours per day, with an average of 481

orders processed daily. The simulation model incorporated 29 entities, of which 28 were permanent and one was temporary (the order request). A total of 340 working days were simulated to capture annual variability.

The time distributions associated with each process were determined using Input Analyzer, ensuring statistical validity through Chi-square and Kolmogorov–Smirnov goodness-of-fit tests, with p-values greater than 0.1. Additionally, the model accounted for reprocessing caused by operational errors, such as incorrect order registration, misplaced products, and picking shortages.

Figure 2 illustrates the model of the current process (AS IS scenario), including service times, decision points, and error rates represented at each node.

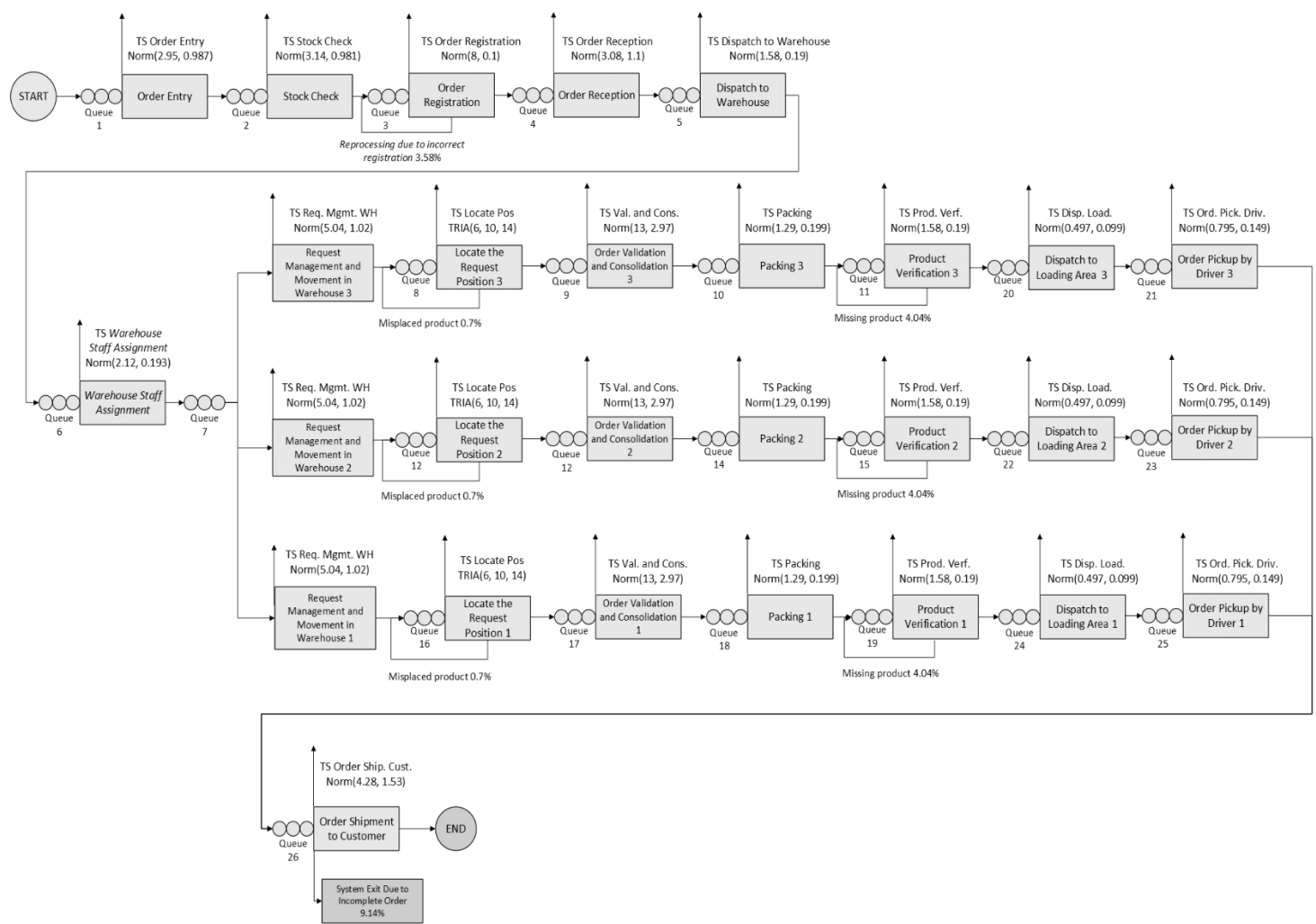


Fig. 2: Representation of the distribution process system for a single order request

This model enabled the simulation of both complete and incomplete order flows, allowing the measurement of key indicators such as the Order Fill Rate (OFR), picking error rate, incomplete data rate, and order operation time. Based on the results of this baseline (AS IS) scenario, a comparison was then made with the improved model (TO BE) to validate the feasibility and effectiveness of the proposed solution.

5. Results and Analysis

The validation of the proposed model was conducted through a quantitative comparison between the AS IS and TO BE scenarios, both in the actual implementation and in the simulations performed using Arena. The four evaluated indicators serve to measure operational efficiency and the quality of the distribution process.

Table 2 summarizes the results obtained for the Order Fill Rate (OFR), picking error rate, order operation time, and incomplete order rate.

Table 2: Comparative Results Table Based on Simulation Outputs

Indicators	AS IS	Simulation	Variation	TO BE	Simulation	Variation
Fill Order Rate (OFR)	90.86%	90.96%	0.11%	98.02%	97.89%	-0.13%
Picking Error Rate	4.09%	4.30%	4.78%	3.10%	3.22%	3.72%
Order Operation Time	32.0%	31.00%	-2.56%	16.00%	16.57%	3.44%
Incomplete Order Rate	4.10%	4.30%	4.42%	0.0%	0.0%	0.00%

The analysis demonstrates that the implementation of the proposed model led to substantial improvements. The Order Fill Rate (OFR) increased by more than 7 percentage points, reaching 98.00% in the theoretical target and 97.89% in the simulation, thereby validating the model's positive impact on order completeness.

Similarly, the picking error rate decreased from 4.09% to 3.10% in the field and 3.22% in the simulated environment. This improvement aligns with the integration of technologies such as pick-by-vision augmented reality, which provides real-time visual support to warehouse operators.

Order operation time per order also showed a significant 50% reduction—from 32% to 16%—as a result of the layout redesign using Systematic Layout Planning (SLP) and the implementation of optimized picking routes through multi-criteria ABC classification.

Finally, errors due to incomplete order data were fully eliminated thanks to the digitalization of the order registration and validation process using Generative AI (GenAI). This contributed to a robust and standardized information flow throughout the distribution system.

6. Conclusions

The proposed methodology effectively closed the technical gap in the Order Fill Rate (OFR), raising the indicator from 90.86% to 98.00% in real-world implementation and to 97.89% in simulation. This substantial improvement was achieved by integrating Lean tools (5S, Standard Work, and Systematic Layout Planning – SLP) with emerging technologies such as Generative AI (GenAI), Warehouse Management Systems (WMS), and pick-by-vision augmented reality.

The results demonstrate that smart standardization through GenAI eliminated registration errors in order intake, while layout redesigning significantly reduced travel time, and picking automation optimized execution accuracy. Collectively, these improvements led to a 50% reduction in order operation time, a 24% decrease in picking errors, and a complete elimination of orders with incomplete data.

Furthermore, statistical validation using Arena simulation showed strong consistency between the TO BE model and empirical data, with variations below $\pm 5\%$, supporting the reliability of the results obtained.

In conclusion, the integrated model presented here constitutes a viable and replicable solution aligned with the principles of Industry 4.0. Its progressive architecture enables simultaneous intervention across the physical, operational, and digital dimensions of the logistics chain, positioning it as an effective tool for enhancing the efficiency and competitiveness of distribution companies in emerging markets.

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