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Comparative Study of Operational Handling Method Decision-Making in Simulated Processes and Signal Triangulation Reading

Santos R[a,b], Facin A. L. F.[a], Arruda M[a,b]

[a]*Paulista University, Rua Doutor Bacelar, 1212, São Paulo 04026-002, Brazil*
[b] *SENAI, Rua Santo André, 680, São Caetano do Sul, 09572-000, Brazil*

Abstract

This study provides a comparative analysis of two pivotal methodologies for evaluating operational handling in industrial environments: Discrete Event Simulation (DES) and Real-Time Locating Systems (RTLS). While the former leverages digital platforms to model production flows and mitigate bottlenecks through risk-free scenario testing, the latter employs signal triangulation for the dynamic tracking of asset trajectories, uncovering empirical inefficiencies through high-granularity spatial data. Our findings highlight a critical complementarity: DES offers a predictive framework for resource allocation and layout optimization, whereas RTLS provides the empirical validation necessary to refine these virtual models. By demonstrating the integration of digital twinning principles with real-time telemetry, this research contributes a robust framework for enhancing decision-making and operational excellence in complex manufacturing environments.

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1. Introduction

The global manufacturing landscape is currently undergoing a transformative shift, transitioning from the technology-centric paradigms of Industry 4.0 toward the human-centric and value-driven objectives of Industry 5.0 [1]. Whitin this evolution, sectors such as automotive and general manufacturing confront intensifying challenges, primarily driven by volatile customer demand and escalating product complexity. To sustain a competitive advantage, organizations are pivoting from rigid production models toward Reconfigurable Manufacturing Systems (RMS), capable of autonomous adaptation to product-driven lifecycles [2]. Consequently, the convergence of advanced

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mechatronic systems, robotics, and the Industrial Internet of Things (IIoT) has become a prerequisite for facilitating the real-time data exchange and decentralized decision-making essential to modern smart factories [3].

To navigate this heightened complexity, Discrete Event Simulation (DES) has solidified its role as a fundamental methodology for validating plant efficiency and optimizing spatial layouts [4]. Traditional manual planning is increasingly scrutinized as an obsolete, time-intensive process that frequently fails to capture the dynamic interdependencies inherent in the "factory of the future" [5]. Modern simulation-based frameworks now leverage high-fidelity tools, such as Siemens Tecnomatix Plant Simulation, to deliver robust graphical solutions for process optimization [6]. Furthermore, the state-of-the-art in layout planning is experiencing a paradigm shift toward the use of Artificial Intelligence (AI), where deep reinforcement learning and neural networks are deployed to forecast throughput and streamline material flow, significantly surpassing the efficacy of conventional heuristic methods [5].

However, a critical research gap persists regarding the systematic reconciliation of predictive simulation performance with the real-time empirical capabilities of Indoor Positioning Systems (IPS). While Autonomous Mobile Robots (AMRs) and AI-enabled intralogistics frameworks are revolutionizing the shop floor, established pathways to transition from foundational IPS research to context-aware, full-scale information delivery systems remain elusive [7]. Existing literature lacks a cohesive framework delineating the information trajectory from raw sensor acquisition to simulation-based strategic decisions [8]. Moreover, there is a urgent need to validate the scalability of these digital instruments for Small and Medium Enterprises (SMEs), particularly in harmonizing the discrepancies between simulated throughput projections and real-time operational status [9] [10].

Despite the technical maturation of IPS, current scholarship remains largely preoccupied with sensor precision and localized performance metrics, often relegating industrial applications to rudimentary tracking. This article addresses this shortcoming by investigating the integration of spatiotemporal indoor positioning data with simulated factory planning. We propose a methodology that transforms raw data into actionable intelligence, fostering robust, adaptive layout decisions aligned with the stochastic behavior of physical production system. By identifying the inherent trade-offs between virtual optimization and real-world execution, this study provides a framework to enhance the fidelity of "what-if" analyses through live data synchronization. Ultimately, this work advances a resilient, synchronized production-intralogistics architecture, aligned with the emerging imperatives of the Industry 5.0.

2. Review of Literature

Facility layout optimization remains central to production engineering, directly affecting logistics, resource utilization, and responsiveness to volatile demand. Within Industry 4.0, digital technologies have transformed this discipline by enabling advanced modeling, monitoring, and iterative refinement of configurations. The integration of Lean Manufacturing, Discrete Event Simulation (DES), and real-time tracking systems supports a shift from static planning to dynamic, data-driven industrial environments.

2.1. The Role of DES in Dynamic Factory Planning

The complexity of modern manufacturing environments often exceeds the analytical capacity of static Lean tools. Discrete Event Simulation (DES) emerges as a critical computational approach for evaluating system performance under stochastic conditions, incorporating variables such as downtime, demand fluctuations, and capacity constraints [11]. As a virtual testbed, DES enables accurate sizing of WIP inventories and validation of layout resilience without the risks of physical implementation [12].

A key challenge in simulation modelling is defining the appropriate Level of Detail (LoD) and scope to align with strategic objectives. Recent research has incorporated metaheuristics and Artificial Intelligence (AI), particularly neural networks, to accelerate solution-space exploration. Simulation provides a virtual environment for hypothesis testing without physical implementation [13], enabling the management of dynamic and stochastic production systems and offering performance estimates often unattainable through static analytical methods.

Metaheuristic optimization methods have been extensively applied to the Facility Layout Problem (FLP), generating near-optimal solutions subsequently evaluated through simulation to assess KPIs under dynamic and stochastic conditions [12]. The integration of Artificial Intelligence (AI), particularly neural networks trained on

simulation data, enables rapid prediction of layout performance. This synergy between simulation and AI accelerates decision-making and enhances the exploration of near-optimal facility layout alternatives.

The practical implementation of optimized layouts requires monitoring mechanisms to ensure adherence to planned configurations. Indoor Tracking systems play a strategic role by employing technologies such as Ultra-Wideband (UWB), Bluetooth Low Energy (BLE), or RFID within Real-Time Locating Systems (RTLS) to collect movement data from operators, vehicles, and materials, transforming them into inputs for continuous improvement [14]. These data validate Lean planning assumptions and simulation outcomes, revealing hidden bottlenecks and deviations from standardized routes. Integrated into Digital Twin models, they enable factories to operate as cyber-physical systems (CPS), sustaining the logic of Digital Kaizen [15].

Digital Twins (DTs), a key element of Industry 4.0, connect physical and virtual worlds with high-fidelity representations of geometry, physics, behaviors, and functions. Virtual models simulate spatio-temporal states and interact with physical assets through real-time feedback, enabled by bidirectional mapping that integrates geometric, structural, and functional characteristics [15].

2.2. Indoor Positioning Systems Overview

The demand for fast delivery, quality, and customization drives the adoption of Industry 4.0 technologies, which integrate advanced communication, information, and intelligence systems to enhance flexibility and productivity [1]. A key element is the use of spatio-temporal data on resources and events, enabling precise planning, scheduling, and execution [16]. Indoor Positioning Systems (IPS) support asset and personnel tracking, safety, automation, and efficiency (Ayub et al., 2025). Technology selection is guided by cost, accuracy, robustness, and scalability [17].

Standardizing real-time resource representation is essential for visualization and interoperability among industrial stakeholders. This standardization enhances monitoring and enables rapid responses to emergencies such as collisions, anomalies, and risk detection. Spatio-temporal traceability supports the identification of bottlenecks from scheduling failures, layout inefficiencies, or material flow issues. Real-time identification further enables corrective actions like dynamic rescheduling, reducing costs and maximizing productivity [1].

In assembly lines, Work in Progress (WIP) buffers variations during peaks or interruptions. Its efficiency depends on storage distances and retrieval order, directly impacting time and cost [7]. Optimizing spatio-temporal resource coordination is therefore essential to achieving zero-inventory or zero-storage concepts.

Targeted research on Indoor Positioning Systems (IPS) and computer simulation is essential. Evaluations must align technologies and methods with process demands and precision requirements (area, orientation, location) [18]. Integrating advanced data processing and machine learning ensures consistent extraction and analysis of spatio-temporal data, mitigating resource complexity and interruptions. These mechanisms support the transition from technology-centered Industry 4.0 to value-oriented Industry 5.0 [19].

Cost includes hardware, software, deployment, maintenance, installation time, calibration, physical constraints, and required expertise [19]. Accuracy, expressed as mean error, is the key metric and must consider industrial challenges such as metallic structures, machinery, and electromagnetic interference. Resilient technologies and proper antenna planning help mitigate these effects [17].

Robustness is essential, requiring systems to withstand sensor failures, signal reflections, and adverse conditions [20]. Reliability is enhanced through multi-sensor fusion, adaptive filtering, fault-tolerant algorithms, and anomaly detection [21]. Scalability ensures performance as device numbers and coverage expand [8], demanding careful planning of reference density, antenna positioning, and network architecture [22]. In industry, the primary application of IPS is object tracking, covering products, materials, assets, and personnel. Technologies such as RFID, BLE, and UWB are applied in different contexts [23]. Passive RFID supports supply chain visibility and low-cost inventory management, while active RFID offers greater range and precision. BLE has been used for tracking molds and personnel, improving resource allocation and reducing idle time [24]. UWB provides superior performance in critical environments, overcoming multipath and NLoS issues to ensure precision under interference [20].

2.3. Factory Planning

Factory planning starts with demand and product specification analysis, guiding the sizing of machines, equipment, and human resources [25]. Layout arrangements must prioritize efficiency and flexibility, supported by methodologies such as the Theory of Constraints (ToC) for bottleneck identification and improvement prioritization. Time and motion studies remain essential for analyzing interactions among resources, materials, and operators [7].

Historically, analyses relied on tools such as paper layouts, spaghetti diagrams, and manual arrangements. While effective in context, these methods lacked precision and predictive capacity for dynamic scenarios. Advances introduced computer-aided design (CAD) and later discrete-event simulation, enabling the modeling of logistical flows, bottleneck identification, lead-time calculation, and value estimation [26].

Planning tools include Value Stream Mapping (VSM) for systemic analysis of inventories and waste, BPMN diagrams for administrative processes, and spaghetti diagrams to identify unnecessary movements. Line balancing studies gain precision through 3D simulations, which visualize configuration impacts [26]. In the Toyota Production System, material handling is a major source of waste and should be minimized before automation. Functional layouts often generate long displacements and intermediate inventories, while cellular layouts promote continuous flow, reduced WIP, and essential movements [27].

3. Materials and Methods

Experiments were conducted with a focus on improving process indicators, following the steps presented in Table 2. This study highlighted 14 organizations that exhibited process waste, including inventory accumulation between operations, waiting times due to material shortages, intuitive transport of raw materials resulting from inadequate planning, and excessive personnel movement caused by the unplanned distribution of assets.

Table 2. Process to layout improvement and monitoring.

Step	Project Phase	Key Activities	Deliverables (Outputs)
1	Diagnosis & Definition (Lean Input)	Define product families (up to 3 SKUs). Map process value aggregation (VA/NVA). Inventory stocks and convert to time.	Current State VSM 2D Plant Layout VA/NVA Ratios
2	Data Structuring	Map process-to-process flow matrix. List assets and human resources Define stochastic parameters (Cycle/Setup/Shifts).	Travel Matrix Capacity & Balancing Sheet Stochastic Data Profile
3	Model Construction (Digital Twin)	Import 2D layout and place 3D assets. Configure buffers and warehouse logic. Program resource priority and flow connections.	Functional Digital Twin 3D Simulation Environment Resource Logic Rules
4	Execution, Validation & Optimization	Run model for the planned period. Analyze OEE, occupancy, and spaghetti plots. Ideate and test "Future State" adjustments.	KPI & Performance Reports Digital Spaghetti Plot Validated Future State Model

The starting point is Lean Thinking, which establishes the logic of waste elimination and the creation of continuous flow as the foundation for any layout proposal. By mapping the value stream (VSM) and developing plans for every part (PFEP). The Lean Thinking defines not only the arrangement of operations but also the logistical parameters that ensure the supply of materials at the correct time and quantity. The expected outcome is the construction of a functional scheme capable of reducing work-in-process (WIP) inventory, avoiding unnecessary movements, and creating standardized routes that sustain the regularity of the production system.

The problem was defined and clear objectives were established. Priority was given to minimizing lead time, maximizing resource utilization, and reducing operational costs, while also seeking flexibility and the capacity for layout optimization. The analysis is enriched through the use of the Value Stream Map, which enables the identification of intermediate stocks, lead times, and activities that do not add value to the product. Process modeling in Business Process Model and Notation (BPMN) extends rationalization to administrative areas, where waste is often hidden.

After the preliminary definition of the layout, planning advances to time and motion studies that consider the interaction between equipment, people, and materials within the factory environment. This stage can be conducted using traditional methods, such as sketches on graph paper and manual diagrams, or digitally assisted design tools, which subsequently enable more complex computer simulations. These resources allow for the visualization of alternative scenarios, testing the feasibility of modifications, and anticipating bottlenecks even before the physical execution of the project.

To mitigate movement and transport problems, Discrete Event Simulation (DES) and lean manufacturing tools were utilized. The simulation process was conducted in phases, following the principles Synergetic Factory Planning, with an emphasis on the process perspective. The development of the computational model involved constructing the model logic within the simulation software. In this process, fixed points where entities are processed were defined, along with the Entities (items, people, or products being processed) and Resources (personnel or equipment required to perform actions, but not representing locations).

A conceptual structure of the system was developed, identifying events and elements. The conceptual model serves as the logical representation of the problem, mapping activities, inputs, outputs, controls, and system mechanisms, thereby facilitating the transition to the computational model. Data collection encompassed operation cycle times, equipment failure frequencies, material inter-arrival times, and variances.

After constructing the model, verification and validation were performed. Verification ensures that the model operates according to the modeler's intent through operation monitoring, event tracking, and logic debugging. Validation confirms that the model accurately reflected the behavior of the real system under study. This was achieved by comparing the model outputs to the historical performance of the real system using identical input data.

The model was subsequently employed to test alternative solutions. These tests were conducted through multiple replications (runs with varying inputs) to ensure the statistical validity of the results. Figure 1 illustrates the architecture of the Indoor Positioning System (IPS). To implement the real-time monitoring system, the Kaizen Digital application was employed. As a prerequisite for the platform's operation, it is necessary to upload a detailed factory layout drawing. Table 3 details the development workflow for the indoor positioning system, which is structured into six discrete phases. The sequence initiates with preliminary planning, proceeds through execution and commissioning, and terminates with the systematic validation of operational results. The antennas were mounted on tripods to facilitate the mobility of the solution across the monitored companies. UWB tags were attached to the assets that composed the production flow. Figure 2 illustrates the tags featuring the Decawave DWM1001 module, which were used on the monitored assets with a precision of 10cm.

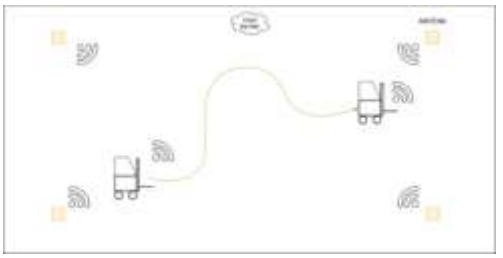

Figure 1 – IPS system applied to forklift monitoring

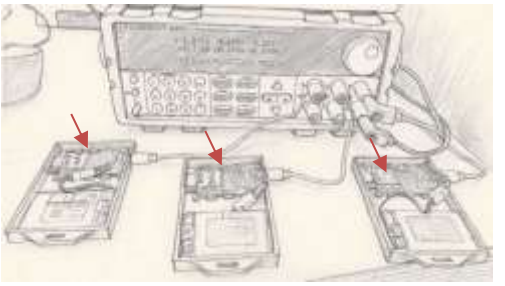

Figure 2 - Tags used in the asset movement monitoring solution.

Table 3. Process to develop the application

Step	Project Phase	Key Activities	Deliverables (Outputs)
1	Requirements & Feasibility	Define precision, range, and latency; Map layout areas for the Spaghetti Chart.	Technical Requirements Document & Business Rules.
2	Design & Architecture	Model physical-logical architecture (Tags > Antennas > Broker); Prototype UI/UX screens.	Architecture Diagram & Low-Fidelity UI Prototypes.
3	Hardware & Firmware	PCB Design (Electronics); BOM selection; Communication firmware programming.	PCB Prototype & Functional Firmware.
4	Software Development	Back-end (APIs) and Front-end (Interactive Map) coding; Database integration.	Integrated software system with simulated data.

5	Integration & POC	Physical installation in 100m² area; Real vs. Digital scale calibration; Andon testing.	Technical validation of on-site tracking accuracy.
6	Validation & Data	Generate movement and idle time reports; Compare physical vs. digital displacement.	Operational Performance Report & Final Spaghetti Chart.

The UWB (Ultra-Wideband) antenna illustrated in Figure 3 facilitates ranging and localization with a precision margin of 10cm. This performance characteristic addresses the spatial resolution constraints inherent in narrowband protocols like Wi-Fi or Bluetooth. For system operation, the antenna is mounted on a tripod to establish a fixed spatial reference point. In addition to mapping the operational path, the application also provides heat map functionality, highlighting areas with the highest incidence of movement within the physical layout, as well as waiting times, continuous movement durations, restricted area access alerts, and dwell times in predefined zones.



Figure 3 - Method of attaching the tag to the tripod stand

4. Discussion of the results

With modeling, virtualization, and real-time process monitoring, significant productivity gains were achieved. Table 4 presents the global efficiency index of companies that planned the intralogistics flow of their processes using discrete element computer simulation.

Table 4 - Overall Efficiency Results in organizations that applied Computer Simulation for process improvement.

Company name	OEE - Future State	Productivity Increase	Company name	OEE - Future State	Productivity Increase
Company A	77,72%	28,66%	**Company H**	73,94%	12,65%
Company B	65,00%	10,00%	**Company I**	75,00%	21,24%
Company C	78,78%	48,15%	**Company J**	84,48%	52,11%
Company D	77,23%	77,08%	**Company K**	75,00%	67,92%
Company E	86,07%	10,69%	**Company L**	75,00%	10,51%
Company F	66,36%	70,00%	**Company M**	60,00%	10,00%
Company G	60,62%	12,28%	**Company N**	50,00%	20,00%

A key observation is the absence of a direct correlation between OEE and productivity gains. Company E achieved the highest OEE (86.07%) but only a 10.69% increase, while Company D reached a similar OEE (77.23%) with a much higher gain (77.08%). This discrepancy shows that the baseline of each organization determines improvement magnitude. Simulation bridges inefficiencies and theoretical capacity, independent of industrial maturity, while results reflect specific operational constraints [28][29]. Literature emphasizes the importance of modeling transferable layout strategies to achieve optimized future states [11]. Spaghetti diagrams revealed intersections and anchor points as opportunities for layout adjustments, with personnel movement directly impacting productivity greater movement correlating with lower performance.

The application was installed for 3 months in a metal-mechanical company, with antennas fixed in an area of up to 70 m². Table 5 shows the Overall Equipment Effectiveness (OEE) of companies using antenna triangulation. Results

range from 11.5% (Company N) to 55.6% (Company M). These gains indicate that precise resource tracking reduces downtime from misplaced tools and inefficient handling. Eight companies achieved OEE increases above 30%, reflecting greater stability in availability and performance. Company M's 55.6% improvement suggests that high variability in resource location was successfully mitigated through real-time tracking.

Productivity gains were consistently high, with all companies reporting increases above 55%, ranging from 55.6% (Company N) to 82.0% (Company C). These results highlight IPS as a key enabler of labour and flow optimization. By reducing search time and inefficient movements, effective working time per shift increases. The consistency across companies confirms IPS as a robust solution for improving throughput in complex indoor environments.

The integration of Indoor Positioning Systems (IPS) into Industry 4.0 explains the significant OEE and productivity gains observed, as these technologies provide essential data for synchronizing human-machine interactions and asset management. IPS enables detailed mapping of worker trajectories and identification of non-value-added activities, directly linked to productivity improvements [30]. Passive UHF RFID and IoT-enabled digital twins support real-time tracking and safety management [31], reducing variability and enhancing flow reliability [19][2][32]. Literature indicates that localization methods such as LMS and semi-supervised approaches are most valuable when transforming spatial data into actionable intelligence for process optimization [16][17]. Variations in OEE gains reflect different stages of digital maturity and specific localization challenges, including interference and tag density, common in modern warehouse and logistics environments [33].

Spaghetti diagrams, in both virtual and physical forms, revealed unnecessary displacements as a major source of waste in manufacturing. These movements stem from non-compliance or lack of standardization, showing that processes must minimize motion before automation or digitalization. The experiment enabled dynamic analyses of intralogistics flow [12], with simulations automatically calculating indicators such as distance traveled, machine occupancy, OEE, and performance graphs. This improved accuracy and accelerated decision-making, but effective planning required coherence between design and execution, supported by robust monitoring on the factory floor.

Table 5 - Overall Efficiency Results of Companies that used IPS for process improvement.

Company name	OEE - Increase	Productivity Increase	Company name	OEE - Increase	Productivity Increase
Company A	**33,0%**	**66,5%**	**Company H**	**32,0%**	**64,5%**
Company B	**23,6%**	**61,9%**	**Company I**	**20,7%**	**59,3%**
Company C	**47,5%**	**82,0%**	**Company J**	**27,4%**	**66,0%**
Company D	**31,1%**	**62,7%**	**Company K**	**39,7%**	**56,0%**
Company E	**41,4%**	**69,0%**	**Company L**	**15,7%**	**57,8%**
Company F	**37,1%**	**63,2%**	**Company M**	**55,6%**	**60,0%**
Company G	**15,0%**	**57,5%**	**Company N**	**11,5%**	**55,6%**

The elimination of wastes classified as *muda*, *mura*, and *muri* remains central to production planning. Despite advanced digital tools, a gap persists between planning quality and execution effectiveness. The PDCA cycle remains relevant, emphasizing continuous improvement through planning, doing, checking, and acting. Without organizational culture and disciplined follow-up by trained professionals, even sophisticated planning risks being lost in daily execution, leading to extra costs, quality failures, and threats to business viability.

Although digitalization provides significant gains [34], such as automated calculations of distances, machine occupancy, and performance indicators, its integration with traditional methodologies like Lean Manufacturing, the Toyota Production System, WCM, and the Theory of Constraints remains essential. Ultimately, the most efficient process is not the most technologically sophisticated, but the one that is simple, lean, and oriented toward customer-perceived value.

The convergence of Lean, Simulation, and Indoor Tracking creates an iterative cycle in which each technology plays a complementary role. Lean guides waste elimination and flow design; Simulation enables experimentation and optimization under realistic conditions; and Indoor Tracking ensures adherence and continuous feedback to sustain improvements. This synergy enhances efficiency and prepares organizations for the complexity and adaptability required in Industry 4.0.

Even with Simulation and IPS integration, work standardization remains essential, as its absence generates variability and flow instability. Combined, simulation and IPS monitoring form a cyber-physical approach that closes the PDCA cycle, ensuring continuous feedback between planning and execution. Integrating traditional methodologies with digital tools enhances efficiency and adaptability to demand changes. Future developments point to algorithms capable of suggesting optimal layouts, anticipating bottlenecks, and supporting continuous decision-making. Ultimately, simplicity and customer-perceived value remain the core of production excellence.

5. Conclusion

The comparison of simulated operational movement systems with real-time monitored data using antenna triangulation demonstrated that companies adopting process virtualization integrated with operational flow programming logic achieved an overall efficiency index of until 86%. Metrics such as lead time, movement, and operational availability were measured.

The Indoor Positioning System (IPS) provided data for dynamic process control, real-time scheduling, and bottleneck identification, which promoted an efficiency index of until 47% and a reduction in delays. It prevented collisions in high-risk areas, allowing for the proper handling of intuitive movements within the process.

IPS and Computer Simulation were used to identify inefficient routes, internal traffic, and the time materials and employees spend on non-value-added activities, such as waiting or inefficient transport. The use of IPS tracking technologies represented a crucial advancement. Through tags installed on assets, tools, and materials, it was possible to track movement within the plant in real-time and manage the planned (simulated) flow against the executed flow. This integration enabled for the identification of deviations, reduction of transport waste, and the dynamic reconfiguration of the factory layout.

In the context of Industry 4.0, production systems must improve efficiency, adaptability, and collaboration to enable mass customization. Organizations must achieve higher levels of automation and process flexibility to expand internal production capacity and handle external uncertainties, meeting customer expectations for high-quality, personalized products. In highly dynamic factory environments, marked by fluctuating orders and variability in resource availability, conventional scheduling strategies and heuristic algorithms are insufficient to solve production planning and control challenges.

Layout choices also directly influence results. Process-based arrangements emphasize the intensive use of equipment but can generate intermediate stocks and excessive movement. The cellular layout, in turn, is recognized as the most favorable for continuous flow, as it reduces movement, minimizes work-in-process, and aligns the production rhythm with the demand takt time. This choice, however, must consider the nature of the orders. Large batches reduce setups but increase lead time and inventories, while smaller batches favor flexibility, even though they require greater balancing discipline.

Challenges include a lack of standardization, signal degradation, energy consumption, and integration with digital twins. Hybrid systems, AI, global standardization, and self-recovery are the future perspectives. IPS are no longer isolated systems; they have become strategic, sustaining intelligent and resilient industrial ecosystems.

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