

Article

Virtual Commissioning for Optimization of an Automated Brushless Stator Assembly Line

Florina Chiscop , Andrei Serban, Carmen-Cristiana Cazacu , Cicerone Laurentiu Popa 
and Costel Emil Cotet 

Robots and Production Systems Department, Faculty of Industrial Engineering and Robotics, National University of Science and Technology POLITEHNICA Bucharest, Splaiul Independenței 313, 060042 Bucharest, Romania; florina.chiscop@upb.ro (F.C.); andrei.serban1704@stud.fiir.upb.ro (A.S.); carmen.cazacu@upb.ro (C.-C.C.); costel.cotet@upb.ro (C.E.C.)

* Correspondence: laurentiu.popa@upb.ro

Abstract

This study applies to a virtual commissioning (VC) workflow with discrete-event simulation in WITNESS Horizon to diagnose and improve an automated brushless stator assembly line. A validated model of the full route—Stator Assembly Machine (SAM), Linear Transport System (LTS), Winding Machine (WM), Terminal Welding Machine (TWM), Inspection Machine (IM) and Electric Tester (ET)—was executed over a one-shift horizon (28,800 s). We compared the baseline configuration with an optimized scenario that retrieved robot tasks and refined LTS routing. Key performance indicators (KPIs) were resource utilization (Busy/Idle/Blocked) and completed operations. The results are quantitative and specific. Blocking at the SAM interface collapsed from 73.32% to 0% at PressPosition and from 80.64% to 0% at Robot2. LTS transitioned from 97.46% Blocked to 0%, with the share of Move/Running increasing to 14.76% (from ~0%). Line output—measured as completed assemblies at SAM—increased from 368 to 425 units per shift (+15.5%). Similar gains were recorded at other stations (e.g., WM1: 351 → 424 operations, +20.8%). These changes reflect the removal of the primary transfer bottleneck and a more balanced utilization across stations. The study demonstrates that VC can deliver actionable commissioning guidance. By quantifying where blocking occurs and testing alternative control strategies in a virtual environment, it is possible to raise throughput while maintaining stable operation. The modeling approach and metrics are reusable for related electromechanical assembly lines.

Keywords: automation; Lean manufacturing; smart manufacturing; virtual commissioning; simulation-based optimization



Academic Editors: Mengchu Zhou and Dan Zhang

Received: 22 September 2025

Revised: 10 November 2025

Accepted: 13 November 2025

Published: 24 November 2025

Citation: Chiscop, F.; Serban, A.; Cazacu, C.-C.; Popa, C.L.; Cotet, C.E. Virtual Commissioning for Optimization of an Automated Brushless Stator Assembly Line. *Processes* **2025**, *13*, 3793. <https://doi.org/10.3390/pr13123793>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Recent advances in virtual commissioning (VC) and digital-twin technologies reinforce their role as key enablers for reducing ramp-up time and validating control logic prior to factory deployment, including through concrete industrial components (e.g., RFID for VC) and through dual closed-loop architectures for process self-optimization [1,2]. Their integration enables virtual testing and validation of control systems before physical deployment, significantly reducing ramp-up time and the risk of unexpected errors [3]. For instance, Iyer et al. demonstrated the virtual commissioning of a reconfigurable assembly line using a synchronized digital twin, successfully validating a new module's integration with only ~1.3% timing deviation from the physical system [4]. Similarly, Scholz et al. applied a

digital-twin-based development approach to electric traction motors, enabling sustainability evaluation and early-stage design optimization of electromechanical systems [5]. These recent advances highlight the growing industrial relevance of VC and digital twins in improving the efficiency, flexibility, and reliability of modern manufacturing processes.

The present work is driven by a real industrial problem: an automated stator line whose initial implementation exhibited poor task sequencing, asynchronous robot handoffs, and severe blocking at the interface between the Stator Assembly Machine (SAM) and Linear Transport System (LTS). We adopted a VC workflow in WITNESS Horizon to reconstruct the line, diagnose bottlenecks over a one-shift horizon (28,800 s), and evaluate corrective scenarios before changes on the shop floor.

Our originality and contributions advance a virtual commissioning framework for a complete brushless stator line, integrating stations, SCARA robots, buffers, and a shuttle-based LTS with realistic interlocks and routing that reflect plant control. The core contribution is quantitative evidence over a one-shift horizon: the SAM interface removes blocking (PressPosition from 73.32% to 0%; Robot2 from 80.64% to 0%), LTS moves from 97.46% blocked to 0% with Move $\approx 14.76\%$, and line output rises accordingly (SAM 368 $\rightarrow$ 425; WM1 351 $\rightarrow$ 424). In parallel, we report explicit scenario-to-baseline deltas at the resource and conveyor levels (Empty/Move/Blocked), which provide a mechanistic account of how transfer-constraint removal redistributes activity and lifts throughput. We also discuss the implementation of factors, thermal conditions near TWM, and alignment-related transfer drifts, which explain deviations from nominal times and guide control retiming and buffer tuning. Overall, the paper moves beyond generic VC descriptions by delivering replicable, quantified indicators and an engineering rationale for the observed gains.

The remainder of the paper is organized as follows. Section 2 reviews related work and technological background. Section 3 details the methodological framework and VC setup. Section 4 describes the automated stator process flow and key interactions. Section 5 reports the simulation experiments and KPI analysis (baseline vs. optimized), including conveyor state results. Section 6 concludes the paper.

2. Related Work and Technological Background

Recent reviews and methodological papers clarify how virtual commissioning relates to digital twins and cyber-physical systems, mapping concepts, toolchains, and challenges in manufacturing contexts and outlining CPS architectures for Industry 4.0 [6–11]. Literature on Lean and digitalization presents integrated or complementary frameworks, often positioned as sustainable or resilient shop-floor strategies, and discusses the adoption of drivers and barriers, particularly for SMEs [12–19]. Work on automation and human factors introduces reference frameworks, full-scale or cell-scale demonstrators of adaptive assembly, and ergonomics-oriented guidance for work system design [20–24]. In the electric machines domain, DT-focused studies address modeling of permanent-magnet synchronous motors and online diagnosis of inter-turn faults in stator windings, illustrating quality and maintenance uses of high-fidelity models [25,26]. Proceedings and application papers report digital-twin and optimization practices in electromechanical equipment or component subsystems [27–31]. Across these sources, the explicitly stated gaps include the need for broader industrial validation, quantification of performance gains, and, in some cases, limitations intrinsic to cell-scale or platform-specific demonstrations [7–9,31].

Positioning and Gap

While prior work establishes VC/DT principles and shows Lean-digital synergies, most studies remain generic, tool-centric, or focused on isolated cells. Few quantify

blocked/idle time elimination at specific robot–conveyor interfaces or demonstrate shuttle-based LTS decoupling with line-level KPIs over realistic horizons. Moreover, limitations frequently include partial validation, small experimental scales, or qualitative outcomes without scenario-to-baseline deltas. The present study addresses these gaps by (i) modeling a complete brushless stator line (SAM → LTS → WM → TWM → IM → ET) with realistic interlocks; (ii) reporting quantified improvements (e.g., blocked time at SAM interface and LTS reduced to 0%, operations per shift increased at SAM/WM); and (iii) discussing implementation constraints (thermal and alignment) that explain deviations between model and plant, in line with best practices recommended by recent VC frameworks and reviews [7,9,31].

The literature, mentioned in Table 1, provides strong conceptual and architectural support for VC/DT integration [1–3,6–11], shows Lean–digital complementarities for flow and sustainability [12–14,16,17,21,28], and documents automation/ergonomic considerations for assembly [17–24]. However, few studies report station-level, scenario-to-baseline KPI deltas for blocked/idle/throughput at robot–conveyor interfaces or quantify LTS de-bottlenecking over full-shift horizons.

Table 1. Selected prior studies: methods and main contributions (ordered by the manuscript’s numbering).

Ref	Methods/Design	Main Contributions/Findings
[1]	Implements a digital component twin of RFID read/write units that models tag–reader behavior (read/write cycles, collisions, and error states) and uses it as a behavior model inside a VC simulation, interfacing with PLC/control logic to test scenarios without physical hardware.	Shows that component-level twins make RFID-dependent control code testable in VC, enabling realistic fault injection and parameter tuning; provides a reusable modeling approach for RFID devices within DT/VC workflows and illustrates it on an industrial case.
[2]	Proposes a DT dual closed-loop self-optimization framework (DT-DCS) for copper disc casting; formulates a CPMC optimization model; implements twin modules for data acquisition, state estimation, optimization, and feedback control; validated in an industrial case study	Establishes two closed loops: shop floor → DT (model updating) and DT → process (control optimization), achieving self-optimization during casting with improved process indicators in the case study; provides a generalizable architecture for similar continuous casting processes.
[3]	Summarizes synergies between VC and DT.	Highlights convergence trends and cites key reviews.
[4]	Develops a real-time synchronized digital twin to enable virtual commissioning of a modular, reconfigurable process line.	Demonstrates accurate pre-deployment validation with <1.3% deviation between digital and physical systems, highlighting VC’s effectiveness for modular integration.
[5]	Proposes a structured development framework using a digital-twin model that integrates mechanical, thermal, and lifecycle data for electric traction motors.	Enables early-stage sustainability assessment and design optimization by linking simulation with real-world feedback across the product life cycle.
[6]	Correlation and comparison between Digital Twins and CPS; conceptual synthesis.	Clarifies definitions and relationships between DT and CPS in smart manufacturing.
[7]	Analyzes scientific approaches to virtual commissioning and categorizes challenges.	Provides a state-of-the-art map and critical challenges and notes limited SME adoption.
[8]	Proposes a VC-based methodology to integrate DTs; validated via a flow shop case.	Shows stepwise DT design/integration using a virtual environment and demonstrates reactive scheduling.
[9]	Proposes “Virtual Commissioning House” framework; includes lab case study.	Provides guiding principles for VC and structured design steps.
[10]	Proposes CPS architecture layers for I4.0 manufacturing.	Defines the five-level CPS architecture widely cited.
[11]	Comprehensive review of intelligent manufacturing, IoT-enabled, and cloud manufacturing.	Synthesizes topics and research streams in the I4.0 context.
[12]	Develops an innovative agile model integrating smart–Lean–green for operational improvement.	Claims the model enhances operational performance within limited constraints.

Table 1. *Cont.*

Ref	Methods/Design	Main Contributions/Findings
[13]	SLR of enabling technologies for smart manufacturing and circular business models (31 articles).	Identifies technologies/platforms that support resource optimization and circular models.
[14]	Reviews SGRL frameworks and future research directions.	Synthesizes integrated frameworks and proposes a research agenda.
[15]	Examine the adoption of digital technologies in smart manufacturing for SMEs.	Highlights drivers and barriers for SME adoption.
[16]	Synthesizes Lean manufacturing within the I4.0 context.	Positions Lean as a smart and sustainable manufacturing enabler.
[17]	Literature review of Lean–I4.0 relationship and path to Industry 5.0.	Finds positive and tech-oriented synergy and maps opportunities.
[18]	Discusses virtualization, decentralization, and network building impacts.	Provides I4.0 perspective and research streams.
[19]	Overviews Lean + automation examples and links to I4.0.	Illustrates practical combinations (Andon and CPS-Kanban).
[20]	Presents a framework and full-scale prototype of adaptive automation assembly systems.	Demonstrates adaptive automation concept at full scale with reference framework.
[21]	Designs and tests an adaptive automation assembly system.	Reports prototype performance and ergonomics-oriented design.
[22]	Guidance for designing work systems for optimal human performance.	Covers physical/cognitive/organizational ergonomics and case examples.
[23]	Explores a synergetic triad for resilient shop floors.	Proposes triad and discusses implications for pandemic resilience.
[24]	Empirical case on human factors.	Provides evidence from a case study on Logistics 4.0.
[25]	Surveys physics-based, data-driven, hybrid DT models for PMSM.	Identifies applications (real-time sim, fault detection, predictive maintenance).
[26]	Real-time DT compares measured and model currents to detect ITSC faults.	Demonstrates online detection and localization on induction motors.
[27]	Describes construction of a fully automated key production line; outlines workflow and implementation (per article page).	Presents a fully automated line and reports implementation details for key production.
[28]	Reports DT + intelligent algorithms in electromechanical equipment.	Shows application practice in the equipment context.
[29]	Structural optimization of a jet cooling device.	Demonstrates improved cooling outcomes for EV batteries.
[30]	Multi-constraint optimization and analysis.	Improved lifting efficiency via optimization.
[31]	Presents a method/tool enabling complete VC of robotic cells.	Demonstrates end-to-end VC workflow.
[32]	Discusses implementation approaches for shop-floor management.	Summarizes methods/approaches applied to shop-floor management.
[33]	Proposes sustainable methodology using Lean + smart; includes case evidence.	Reports productivity enhancement with cleaner shop-floor management using Lean–smart.
[34]	Reviews continuous improvement (CI) literature.	Summarizes CI principles and directions for future research.
[35]	Comprehensive reference on automation, production systems, and CIM.	Provides foundational definitions and architectures.

Our study contributes this missing link by (i) modeling the full stator line with realistic interlocks; (ii) reporting numerical improvements (e.g., blocked time $\rightarrow$ 0% at SAM interface/LTS; operations per shift +15–21% at key stations); and (iii) discussing plant-level constraints (thermal, alignment) that influence control retiming—thereby extending the practical guidance called for in recent VC/DT reviews [7,9,31].

3. Methodological Framework

This study adopts a virtual commissioning (VC) workflow, complemented by Lean principles, to analyze and optimize the stator assembly line. The research flow is summarized in Figure 1, which visualizes the inputs, the six methodological steps, the main outputs, and the iterative loop between optimization and re-diagnosis.

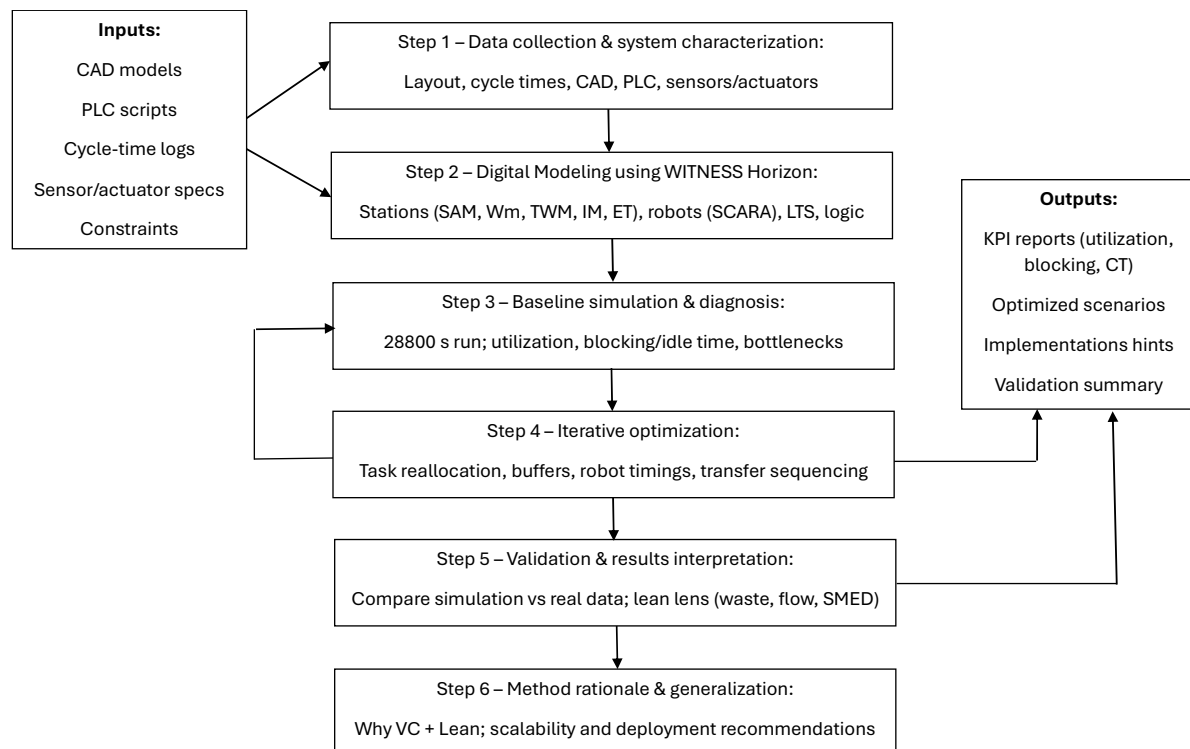


Figure 1. Methodological framework for VC-based optimization of the stator assembly line. The schematic shows inputs (CAD, PLC, cycle-time logs, and constraints), a six-step pipeline (Steps 1–6), main outputs (KPI reports, optimized scenarios, and validation summary), and an iteration loop from Step 4 back to Step 3 for model refinement.

1. **Collecting Data and Analyzing System Features:** We gathered the physical layout, cycle-time logs, CAD models, PLC/robot programs, and sensor/actuator specifications. Operational constraints (space, safety, takt, and quality) were recorded. Key performance indicators (KPIs) were defined: resource utilization, blocking/idle time, throughput, and work-in-process (WIP).
2. **Digital Modeling using WITNESS Horizon:** A discrete-event model was developed, including stations SAM (Stator Assembly Machine), WM (Winding Machines), TWM (Terminal Welding Machine), IM/VIM (Inspection/Visual Inspection), and ET (Electric Tester); SCARA robots; and buffers and Linear Transport System (LTS). Logical interlocks and routing rules were encoded to mirror real control behavior.
3. **Baseline Simulation and Performance Diagnosis:** The model was executed for 28,800 s (one shift) to establish a reference. KPI reports identified bottlenecks and quantified blocking/idle time and resource utilization across stations and transport segments.
4. **Iterative Optimization:** Scenario experiments modified job distribution across robots and stations, buffer capacities, robot timing/trajectories, and LTS transfer sequencing and logic. Each scenario was evaluated against the baseline utilizing the established KPIs, aiming for reduced blocking/idle time, balanced usage (achieving over 90% at important resources), and increased throughput while adhering to limits.

5. Validation and Result Interpretation: Simulation results were juxtaposed with plant measurements to verify accuracy (cycle times, utilization patterns, and queue lengths). Discrepancies informed model refinement. Results were analyzed through a Lean perspective (flow balance, waste reduction, SMED concerns) to formulate meaningful implementation suggestions.
6. Method rationale and generalization: VC enables safe, low-disruption testing of alternatives in systems with tight mechanical/robotic couplings and complex interlocks. The workflow generalizes to other electromechanical assembly lines by reusing the data → model → diagnosis → optimization → validation loop and the same KPI structure.

Implementation details:

Inputs and assumptions: CAD and PLC assets verified cycle-time logs, and equipment datasheets served as the ground truth for model parameterization. Initial assumptions regarding equipment calibration and ambient conditions were subsequently refined in line with validation results.

Simulation setup: The experiments covered a one-shift horizon of 28,800 s with warm-up trimming to remove transient effects. Multiple replications were executed wherever stochastic behavior was present, ensuring stable point estimates and confidence in comparative results.

Evaluation criteria: Primary KPIs comprised resource utilization, blocking/idle time, throughput, and work-in-process (WIP). Secondary diagnostics examined buffer-occupancy profiles, transfer waiting times, and the impact of station changeovers on flow stability.

Documentation: Results for each scenario are reported as KPI deltas compared to the baseline, along with a succinct implementation note detailing necessary layout and/or control modifications, anticipated downtime, and related risks to guide deployment decisions.

All simulations were performed in WITNESS Horizon, which provides a proprietary discrete-event simulation engine. The internal mathematical implementation is not publicly available, and this paper does not attempt to describe or derive that formulation. Instead, transparency is ensured by (i) specifying input parameters and operating rules, (ii) detailing experimental conditions and simulation horizon, and (iii) defining the reported indicators (e.g., utilization, blocking, and throughput). Our objective is to evaluate scenarios and quantify performance effects, not to develop a separate analytical model.

4. Automated Stator Line: Process Flow

The automated production line for brushless stators has a planned, modular route for the flow of materials. This route includes several interconnected workstations, robotic subsystems, and transfer systems. Every functional station does a certain task, and automatic handling makes sure that the transitions are always correct and consistent.

4.1. General Workflow Overview

The Stator Assembly Machine (SAM) starts the production process by putting together the main parts of the stator in a certain order: the bottom insulator, the lamination stack, and the upper insulator. Two four-axis SCARA robots put the parts in place, and a servo-driven pressing unit makes sure that the stator core stays strong. Robot2 takes the finished stator to the Linear Transport System (LTS), which is the most important part of the production line for moving materials.

LTS, which comprises modular magnetic shuttles, allocates the stator to one of the five Winding Machines (WMs). In this setup, specialized SCARA robots meticulously position the component into the winding apparatus, where multi-phase coils are intricately

applied utilizing continuous copper wire. After finishing the process, the wound stator is sent back to LTS.

Subsequently, the Terminal Welding Machine (TWM) processes the wound stator to ensure accurate terminal joining. A SCARA robot is employed for part positioning, while the welding table incorporates servo motors and pneumatic grippers to ensure stable contact and precise execution of welds.

After welding, the stator is moved to the Inspection Machine (IM) for basic visual checks and to cut the wires. A final transfer to the Electric Tester (ET) takes place, during which electrical compliance is checked. Units that do not pass inspection are taken out of the workflow, while those that do pass proceed on to final packaging or the next steps.

4.2. Interactions and Transitions Between Modules

Figure 2 illustrates the principal interactions. SAM-to-LTS handoff is performed by Robot2 and lasts approximately 4 s, ensuring correct alignment and avoiding orientation errors. LTS then dispatches the part to an available WM. The full winding operation—covering robot pick-and-place to and from both LTS and the bobbin table—requires about 86 s. After winding, the stator returns to LTS and is directed to TWM; this transfer typically takes ~4 s. Terminal welding itself requires approximately 30 s. The welded part is placed on the IM conveyor in about 15 s, during which air cooling prepares the part for reliable testing. A four-axis robot at IM executes wire trimming in ~15 s, and the part is then handed to the ET robot in ~3 s. Electrical tests at ET last about 40 s, after which parts are routed according to the OK/NG result.

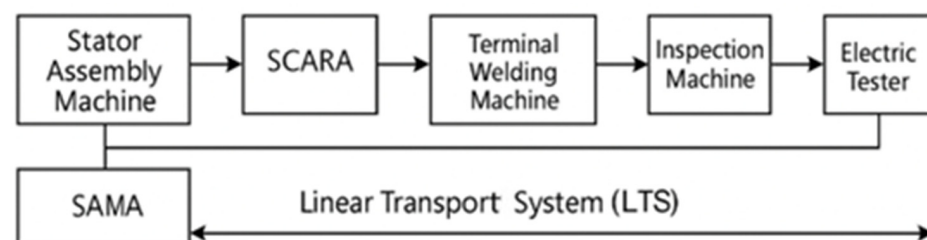


Figure 2. A diagram showing how materials go through the automated brushless stator assembly line. The process starts at Stator Assembly Machine A (SAMA), where important parts are put together. It then moves on to the Linear Transport System (LTS), Winding Machine (WM), Terminal Welding Machine (TWM), Inspection Machine (IM), and Electric Tester (ET). Using robotic handling makes it easier to move and place parts across modules exactly where they need to go. The layout shows how the process changes logically and functionally at each step.

Early tests showed that the flow was not consistent, notably at the points where SAM and LTS meet and between the winding and welding stations. There were delays and bottlenecks because robotic jobs and asynchronous handoffs overlapped, especially at Robot2 and the PressPosition unit, where blockage rates were above 70%. To fix this problem, the control logic was changed, buffer zones were added, and the robot's movements were recalibrated.

Furthermore, the cooling limitations associated with TWM modules were identified as factors leading to shuttle overheating and motor misalignment. Improvements in thermal management, such as adjusted cooling fan placements, were executed to minimize downtime.

Figure 3 depicts the comprehensive logistic flow of the automated brushless stator production line. The sequence of equipment involved in the assembly, winding, welding, inspection, and testing of electricity processes is illustrated, along with the interaction between robotic systems and conveyors.

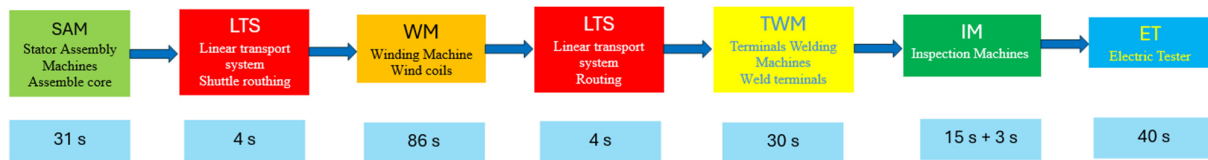


Figure 3. Brushless stator logistic flow.

For clarity, the principal cycle-time allocations used in the model are as follows: SAM assembly ≈ 31 s, SAM-to-LTS handoff ≈ 4 s, LTS exchange at WM ≈ 10 s, winding ≈ 86 s, LTS transfer to TWM ≈ 4 s, terminal welding ≈ 30 s, TWM-to-IM conveyor transfer and cooling ≈ 15 s, IM wire trimming ≈ 15 s, IM-to-ET transfer ≈ 3 s, and ET electrical testing ≈ 40 s.

4.3. Equipment Identification

4.3.1. Stator Assembly Machine (SAM)

The automated line begins with SAM equipment, which, using two four-axis SCARA robots and a servo-motor (used for pressing), assembles the insulators (top and bottom) together with the laminations, thus generating the raw stator.

Figure 4 presents the structural layout of the Stator Assembly Machine (SAM), highlighting the two four-axis SCARA robots and the servo-driven press. This configuration enables the automated assembly of upper and lower insulators together with the lamination stack into a stator unit, using predefined assembly components.

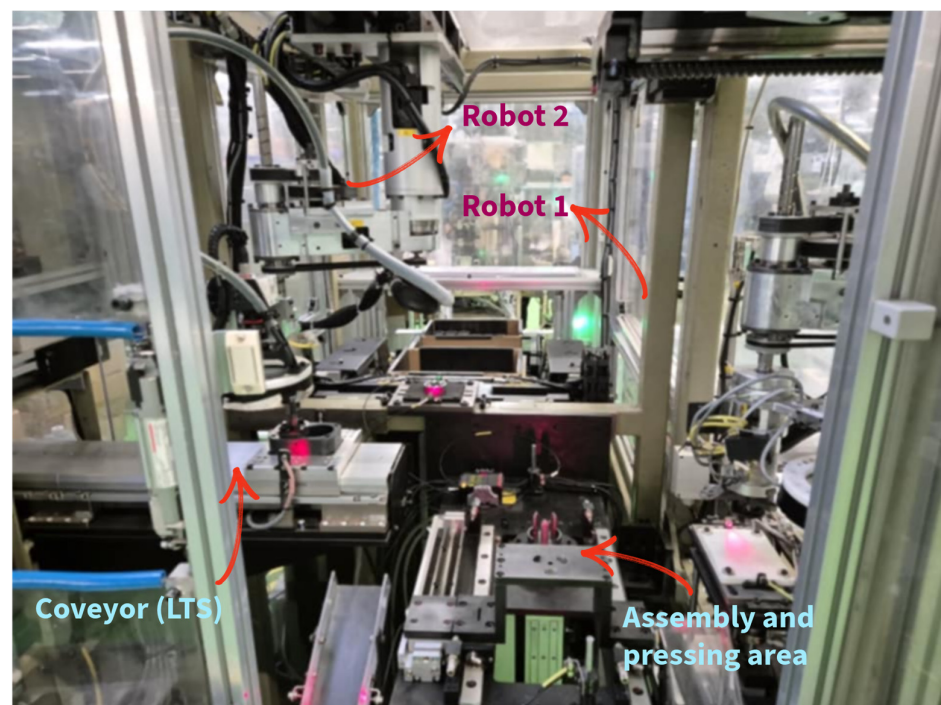


Figure 4. SAM equipment structure.

The stator unit, which comprises three components—upper insulator (c), lamination stack/core (b), and lower insulator (a)—is illustrated in Figure 5. Robot1 places the lower insulator (a) in the pressing area, after which Robot2 positions the lamination stack (b); this placement phase requires approximately 12 s. A servo-motor press and pneumatic jig then seat the components (~ 5 s). Robot1 places the upper insulator (c) (~ 6 s), and a second pressing cycle is executed (~ 5 s). The assembly cycle at SAM thus totals ~ 31 s. Robot2

completes the operation by retrieving the stator and loading it onto the LTS shuttle in ~4 s, yielding ~35 s from first pick to LTS dispatch.

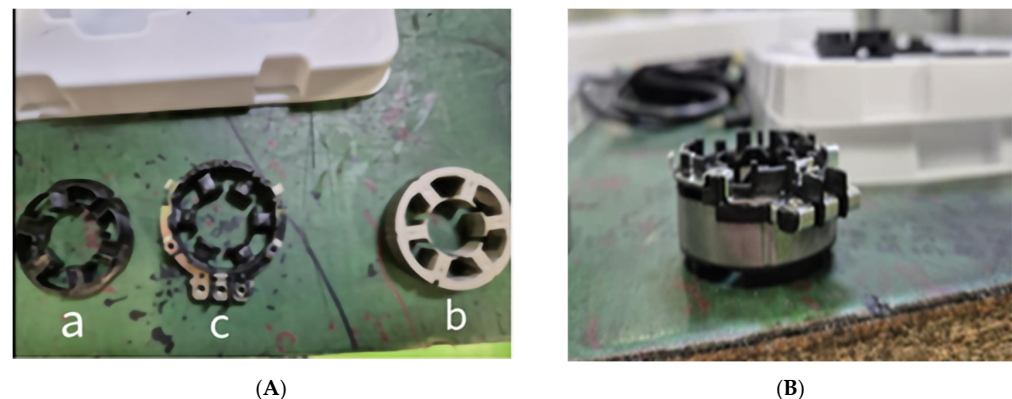


Figure 5. (A) Assembly components (upper and lower insulators and lamination stack); (B) assembled stator.

4.3.2. Linear Transport System

LTS consists of modular conveyor segments driven by magnetic shuttles—hence the term “modular conveyor.” While acceleration and deceleration are generated by coils within the modules, the system is not a full magnetic levitation (maglev) design. LTS provides precise positioning, high-speed transfers, and structural rigidity across stops and handoffs. Its modularity allows rapid isolation and replacement of affected segments during maintenance. As the primary handling link between SAM, WM, and TWM, faults at this level can halt production. Effective cooling via module-mounted fans is essential; the module adjacent to TWM is most exposed to welding residues that can impair airflow, so preventive cleaning and optimized fan placement are recommended.

4.3.3. Winding Machine (WM)

The line incorporates five winding stations, each comprising a winding unit and a four-axis SCARA robot. Coils are applied with an uninterrupted copper wire, so inter-coil connections are formed through upper and lower transitions. Because the wire is continuous, a surplus tail appears at one terminal; this feature motivates the subsequent trimming operation at IM. The total time for the winding stage, including robot interactions with both LTS and the bobbin table, is ~86 s.

4.3.4. Terminal Welding Machine

After a WM completes its cycle and exchanges the wound for the unwound stator, LTS delivers the part to TWM, where terminal welding is performed—typically on 3 to 6 terminals depending on the stator model—using paired electrodes (anode and cathode). Air cooling extends electrode life and maintains thermal stability. TWM comprises three functional zones:

Robot zone: A four-axis SCARA robot with a rotary cylinder executes three tasks. It receives the part from LTS, performs the exchange between the welded and unwelded stator at the table, and transfers the welded stator to the IM conveyor.

Table zone: The welding table provides the fixture for the stator and incorporates three servo motors—for front-back translation, vertical translation, and rotation—and one pneumatic cylinder that actuates the grippers to stabilize the workpiece during welding.

Welding zone: Independent motors drive the front-back translation of the anode and the cathode, while a pressing jig inserts the wire into the terminal prior to electrode advance to ensure repeatable weld quality.

The nominal welding time is ~30 s.

4.3.5. Inspection Machine (IM/VIM) and Electric Tester (ET)

IM (VIM) and ET share a common touch-panel interface and are therefore treated as a single workstation with distinct functions. Immediately after welding, the part is transferred to the IM conveyor in ~15 s, providing air cooling to stabilize the temperature before testing. A four-axis SCARA robot, assisted by a centering jig, aligns the wire surplus for trimming; the operation requires ~15 s and is necessary to ensure reliable electrical contact during testing. The part is then handed to the ET robot in ~3 s. ET applies to a suite of tests with spring-pin contacts—conductivity, resistance, and contact confirmation—over a ~40 s cycle. Wire surplus may interfere with the test pins; trimming at IM eliminates this source of measurement error.

5. Manufacturing Architecture Simulation

5.1. Preliminary System Simulation

The system simulation developed in WITNESS Horizon Version Release 23.0c (Build 3562) (Haskoning, Puteau, France) was executed over a 28,800 s horizon and comprised the following components: circulating entities (Ins1, Ins2, Tola, and Stator); storage systems (LowerInsulator, UpperInsulator, SheetBox, and Box); conveyor-type transport systems (LTS, VIMConveyor, and FinalConveyor); workstations (PressPosition, WM1, TWM, VIM, ET, and Inspection); and robot-type transfer systems (Robo1, Robot2, TWMRobot, VIMRobot, and ETRobot). Analysis of the results shows that the model faithfully reproduces the actual production scenario, confirming the required number of coilings (windings).

Figure 6 illustrates the sequential control and decision-making framework regulating the interaction between the LCM-X transport platform and the SCARA-based robotic subsystem within the simulation environment designed to optimize the stator assembly process. During execution, simulation parameters, including velocities, cycle durations, and positioning tolerances, are initialized, while sensors localize stations and components to facilitate accurate placement. LCM-X and SCARA controllers subsequently synchronize their communication handshakes to avert collisions and idle delays, after which the system performs the necessary SCARA procedures (pick, position, and fasten) in the specified order. Each operation is followed by automated verification that validates the outcome and, when successful, authorizes the transition to the next station. This control–simulation loop continues to iterate until the programmed production run reaches completion. This diagram helps illustrate how logical modeling and process synchronization are carried out in automated industrial environments. It serves as a key component for implementing a functional digital model and virtually testing production parameters.

Table 2 presents the simulation parameters of the model.

Figure 7 displays the initial simulation activity results, showing utilization levels and time distributions for each station and robot. The report highlights significant blockages and waiting times that helped identify inefficiencies in the unoptimized system.

Figure 8 indicates that the manufacturing line suffers from considerable operational imbalance, mostly due to recurrent bottlenecks and elevated waiting times in multiple subsystems. Essential elements like PressPosition, Robot2, and Robot1 have blockages for over 60–70% of the duration, indicating inadequate synchronization or excessive demand at these stations. Concurrently, facilities such as the Inspection Station and ETRobot exhibit approximately 100% waiting time, indicating significant underutilization attributable to upstream delays. LTS is obstructed 97.46% of the time, significantly disrupting production flow and underscoring an immediate necessity for optimizing control logic and process se-

quencing. The analysis emphasizes the need to recalibrate the entire production framework to eliminate fundamental inefficiencies.

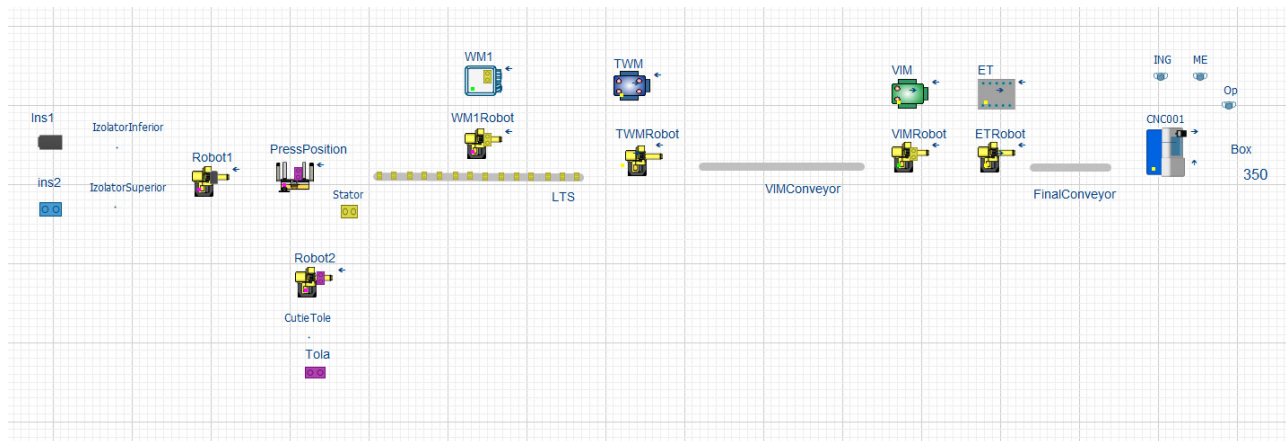


Figure 6. Preliminary system simulation.

Table 2. Simulation Model Parameters.

Item	Value/Setting
Horizon	28,800 s (one shift)
Circulating entities	Ins1, Ins2, Tola andStator
Buffers (capacity)	IzolatorInferior 1500; IzolatorSuperior 1500; CutieTola 1500; Box 1500
Conveyors	LTS, VIMConveyor, and FinalConveyor
Workstations	PressPosition (SAM press), WM1 (winding), TWM (terminal welding), VIM (inspection), and ET (electric tests)
Robots	Robot1, Robot2, WM1Robot, TWMRobot, VIMRobot and ETRobot
SAM assembly time	~31 s
SAM → LTS transfer	~4 s (Robot2 handoff)
LTS ↔ WM exchange	~10 s (SCARA exchange)
Winding cycle (incl. pick/place)	~86 s
LTS → TWM transfer	~4 s
Terminal welding time	~30 s
TWM → IM transfer and cooling	~15 s
Wire trimming (IM)	~15 s
IM → ET transfer	~3 s
Electrical testing (ET)	~40 s

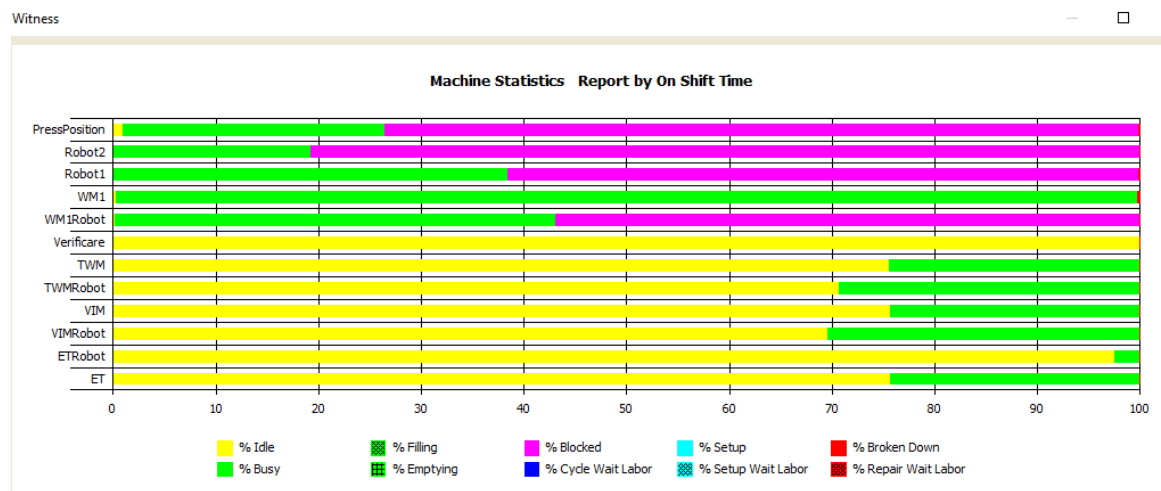


Figure 7. Initial simulation activity report for the preliminary production line.

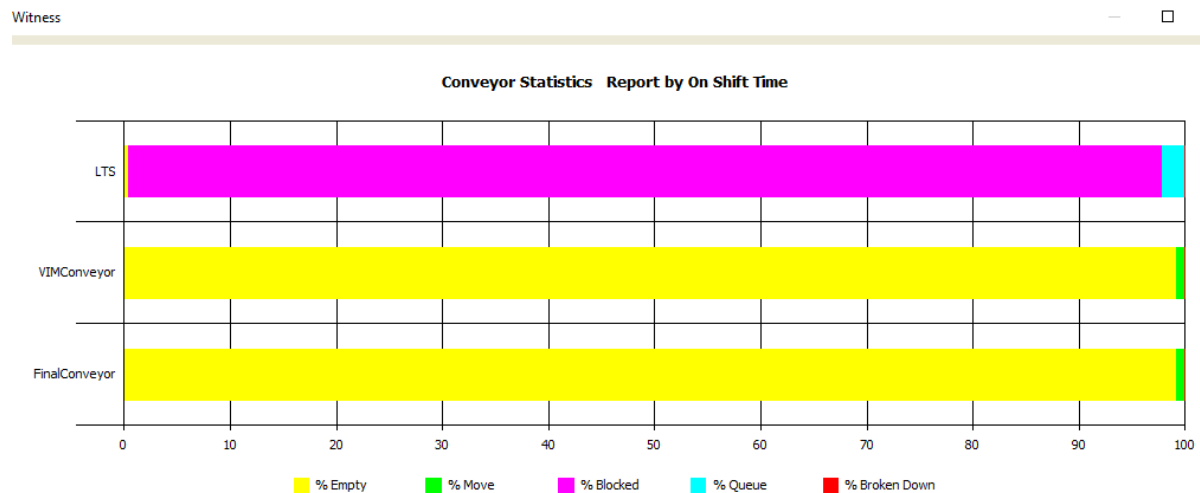


Figure 8. Activity reports after preliminary simulation.

5.2. Functional Remodeling System Optimization

A series of trials was conducted before finding an optimal solution.

After implementing flow optimization, Figure 7 reflects the updated simulation model of the production line. The results show a more balanced workload among the robots and workstations, with substantially reduced bottlenecks.

Figure 9 illustrates the simulation model of the production system after the implementation of various process optimizations designed to address the inefficiencies identified in the initial analysis. The enhancements comprise modifications in equipment sequencing, re-allocation of tasks among robots, and optimization of SCARA robot movement timing. Critical stations—namely PressPosition, Robot1, and Robot2—demonstrate nearly uninterrupted operation, with utilization rates surpassing 95%. Significantly, Robot2, which formerly experienced over 80% blockage time, now functions without any obstructions, demonstrating effective load balancing. The visualization emphasizes a more coordinated production flow, enhanced utilization of available resources, and a substantial decrease in system downtime. This simulation is essential for validating the efficacy of the proposed redesign prior to its implementation in the physical production environment.

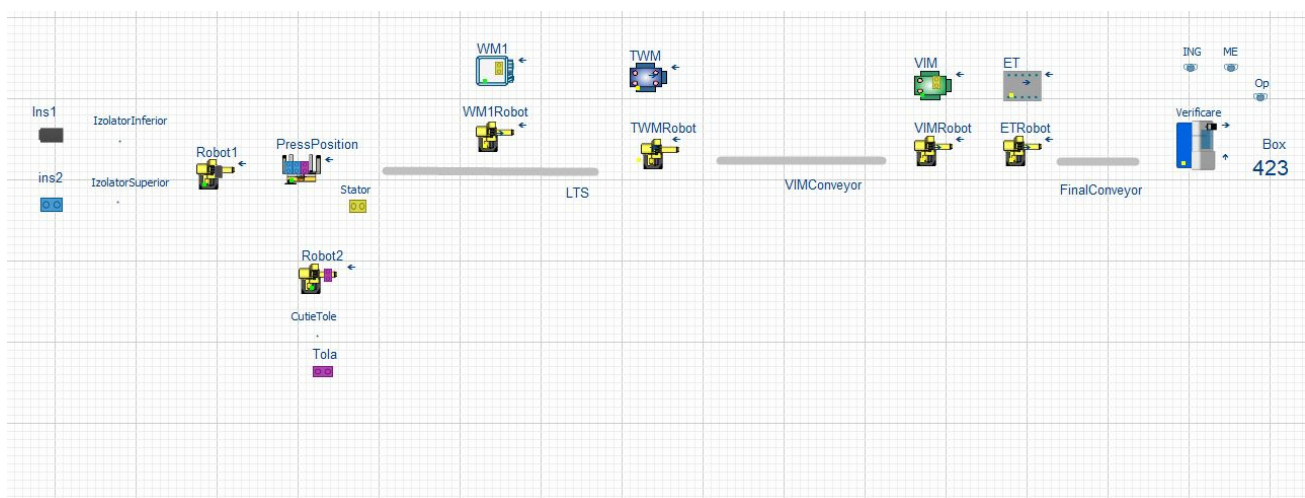


Figure 9. Simulation model of the production line after process optimization.

Figure 10 visualizes the enhanced system simulation after optimization. The updated digital model demonstrates a smoother material flow, reduced waiting times, and improved coordination across the entire line.

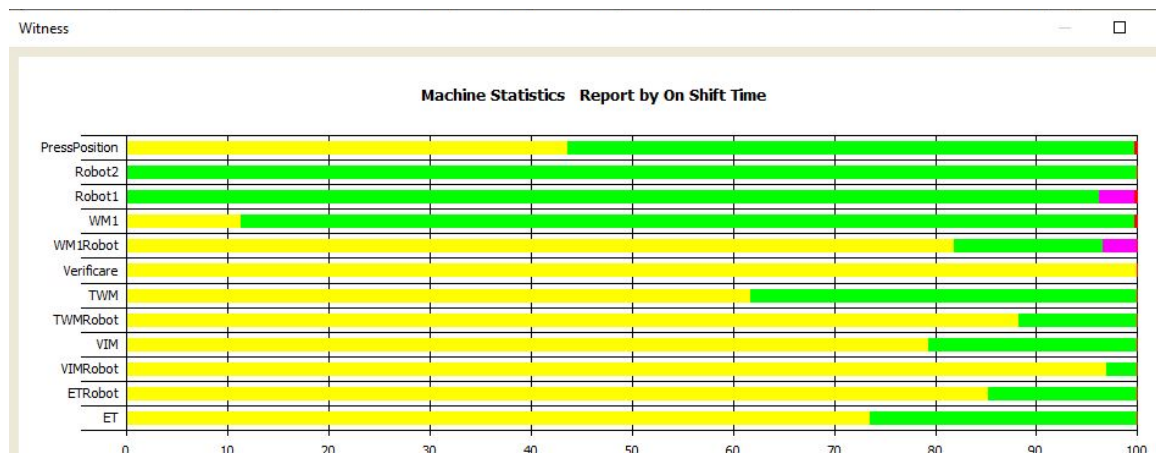


Figure 10. Visualization of the optimized system simulation for the brushless stator production line.

Figure 11 indicates a substantial improvement in the overall performance of the production line relative to prior values. Significant advancements encompass the substantial decrease in blockage durations for critical stations like PressPosition, Robot1, and Robot2, which now function within normal parameters for over 95% of the time. Significantly, Robot2 has eradicated blockages entirely (from 80.64% to 0%) and operates nearly continuously under excellent conditions.

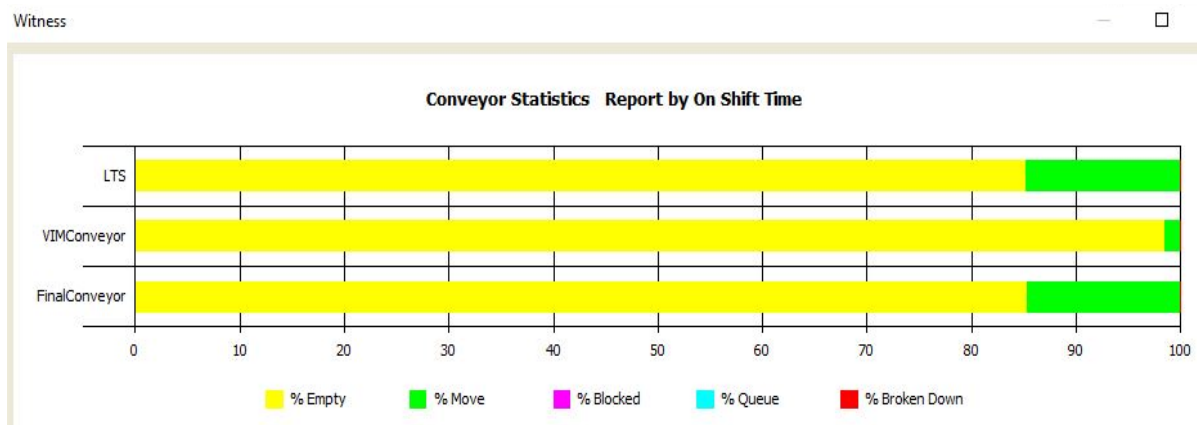


Figure 11. Activity reports following the optimized model simulation.

Subsequent research could investigate the incorporation of digital model feedback that loops directly into LTS and SCARA control algorithms. Embedding sensor data in simulation settings enables the application of model-predictive control (MPC) methodologies that dynamically modify system parameters in real-time. Such an approach would enable adjustable cycle times contingent upon real-world disruptions, such as mechanical degradation, heat variation, or operator inconsistency. Furthermore, the application of reinforcement learning algorithms in robotic decision-making may facilitate autonomous calibration and task allocation, enhancing throughput without necessitating manual reconfiguration. Furthermore, the incorporation of multi-objective genetic algorithms (MOGAs) could enhance optimizations for speed, efficiency, energy consumption, mechanical stress reduction, and ergonomic considerations. These methodologies correlate with the overarch-

ing objectives of Industry 5.0, guaranteeing that productivity and human-centered design continue to be essential performance metrics in next-generation smart factories.

5.3. KPI Analysis

This subsection reports the quantitative outcomes of the simulation over a 28,800 s horizon, contrasting the baseline and optimized configurations. Table 3 summarizes station- and robot-level KPIs (Idle/Busy/Blocked and number of operations).

Table 3. Station and robot KPIs under the baseline and optimized configurations (Idle/Busy/Blocked percentages and number of operations over a 28,800 s horizon).

Asset	Baseline—Idle %	Baseline—Busy %	Baseline—Blocked %	Baseline—No. of Operations	Optimized—Idle %	Optimized—Busy %	Optimized—Blocked %	Optimized—No. of Operations
PressPosition (SAM)	0.95	25.56	73.32	368	43.59	56.15	0.00	425
Robot1 (SAM)	0.01	38.44	61.38	369	0.01	96.22	3.51	426
Robot2 (SAM)	0.00	19.27	80.64	185	0.00	99.91	0.00	213
WM1 (winding)	0.31	99.48	0.00	351	11.24	88.44	0.00	424
WM1Robot	0.19	42.90	56.88	353	81.86	14.76	3.33	425
TWM (welding)	75.59	24.38	0.00	351	61.67	38.28	0.00	424
TWMRobot	70.75	29.25	0.00	351	88.22	11.78	0.00	424
VIM (inspection)	75.66	24.31	0.00	350	79.39	20.56	0.00	423
VIMRobot	69.58	30.38	0.00	350	97.00	2.94	0.00	424
ETRobot	97.53	2.43	0.00	350	85.26	14.69	0.00	423
ET (tester)	75.66	24.31	0.00	350	73.51	26.44	0.00	423

Compared with baseline, Figure 12, the optimized setup virtually eliminates blocked time at the SAM interface and conveyors while increasing completed operations across resources, indicating a clear throughput improvement and removal of the primary bottlenecks.

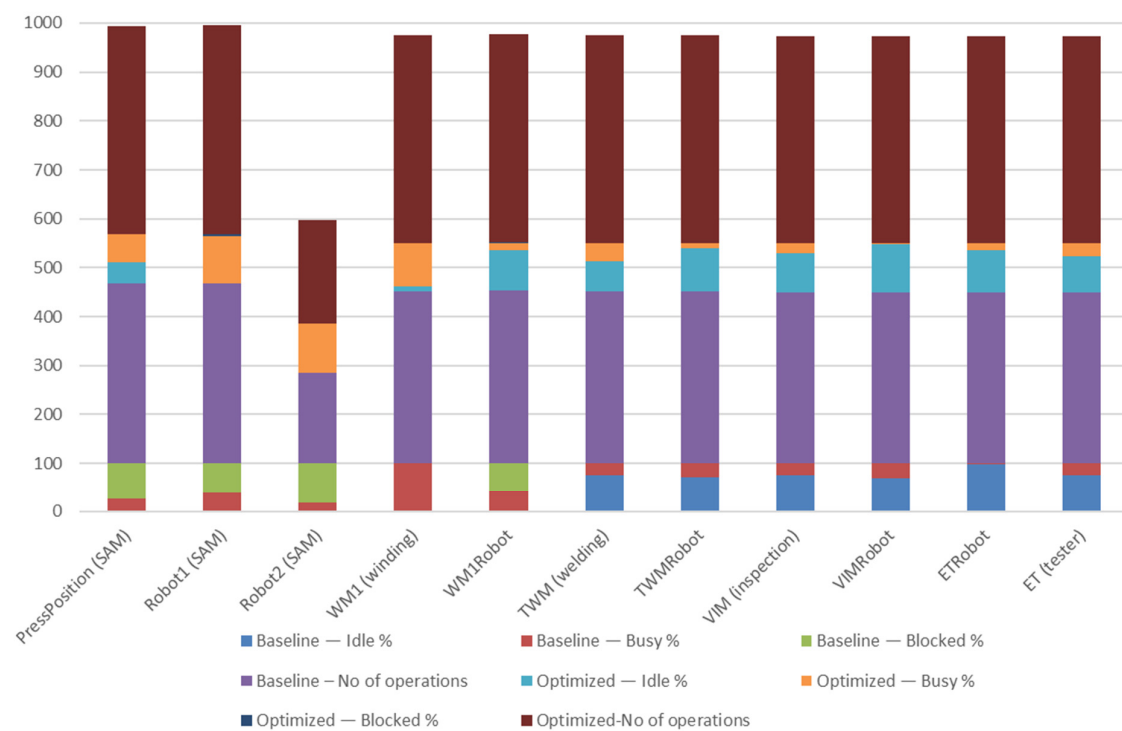


Figure 12. Baseline vs. optimized KPIs (Idle/Busy/Blocked and operations) by resource, 28,800 s run.

Table 4 reports conveyor states (Empty/Move/Blocked).

Table 4. Conveyor state distribution for LTS, VIMConveyor, and FinalConveyor (Empty/Move/Blocked, baseline vs. optimized).

Asset	Baseline— Empty %	Baseline— Move %	Baseline— Blocked %	Optimized— Empty %	Optimized— Move %	Optimized— Blocked %
LTS	0.37	0.07	97.46	85.24	14.76	0.00
VIMConveyor	99.19	0.81	0.00	98.53	1.47	0.00
FinalConveyor	99.19	0.81	0.00	88.31	14.69	0.00

Figure 13 compares the state distribution of the three conveyors across scenarios. Initially, LTS is predominantly Blocked (approximately 97.5%), establishing it as the transfer bottleneck; post-optimization, it is entirely unblocked (0% Blocked), with activity redistributed to Move (approximately 14.8%) and Empty (approximately 85.2%), signifying a seamless shuttle flow devoid of queues. VIMConveyor stays predominantly empty in both instances ($\approx 99\% \rightarrow 98.5\%$), exhibiting a minor increase in Move, indicating a brief, sporadic transfer. The Final Conveyor exhibits a significant rise in Move (about 0.8% to 14.7%) and a reduced Empty share (approximately 99% to 88%), indicating enhanced downstream throughput. Overall, optimization removes the transfer constraint from LTS and supports steadier, queue-free material flow.

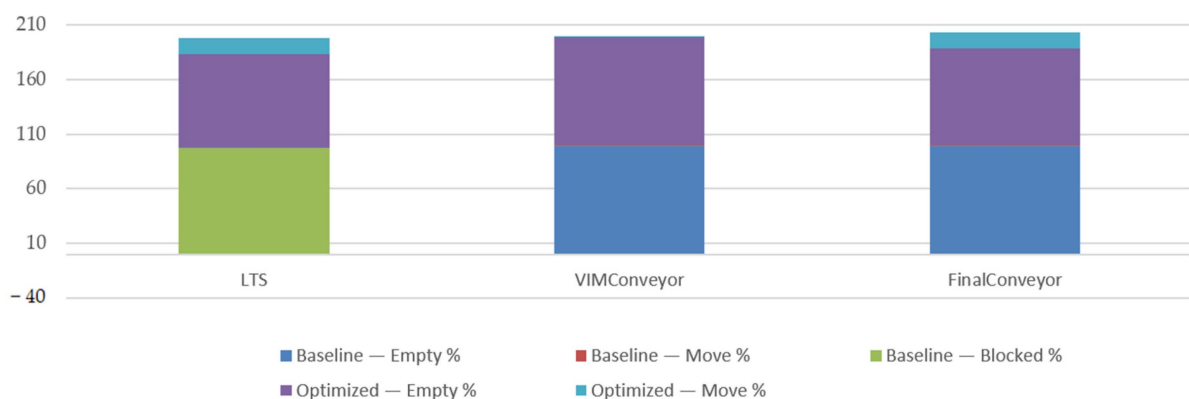


Figure 13. Conveyor states (Empty/Move/Blocked) for LTS, VIMConveyor, and FinalConveyor—baseline vs. optimized.

Table 5 and Figure 14 summarize the Δ KPIs between the baseline and the optimized configurations ($\Delta = \text{Baseline} - \text{Optimized}$), showing how idle, busy, and blocked time—and the number of completed operations—change for each resource over a 28,800 s run. Overall, the pattern is strongly favorable: blocked time collapses at the SAM interface (e.g., PressPosition and Robot2 show large positive $\Delta\text{Blocked}$), accompanied by higher busy time (negative ΔBusy) and more completed operations (negative $\Delta\text{No. of operations}$) across stations and robots. A few assets exhibit “mixed” behavior—slightly lower busy and higher idle despite higher output—indicating workload redistribution after the bottleneck removal rather than a performance regression. The final verdict column condenses these effects into an intuitive label (excellent/very good/good/mixed), clarifying where the optimization delivered the biggest gains.

Table 5. Baseline–optimized KPI differences by resource (Δ = Baseline – Optimized, pp = percentage points) and overall verdict for a 28,800 s run.

Asset	Δ Idle (pp)	Δ Busy (pp)	Δ Blocked (pp)	Δ No. of Operations	Interpretation ($\downarrow$ = Improved, $\uparrow$ = Worsened, $—$ = No Change)	Overall Verdict
PressPosition (SAM)	−42.64	−30.59	+73.32	−57	Idle $\uparrow$, Busy $\uparrow$, Blocked $\downarrow$, Ops $\uparrow$	Very good (bottleneck removed; throughput up)
Robot1 (SAM)	0.00	−57.78	+57.87	−57	Idle $—$, Busy $\uparrow$, Blocked $\downarrow$, Ops $\uparrow$	Very good
Robot2 (SAM)	0.00	−80.64	+80.64	−28	Idle $—$, Busy $\uparrow$, Blocked $\downarrow$, Ops $\uparrow$	Excellent (major de-blocking)
WM1 (winding)	−10.93	+11.04	0.00	−73	Idle $\uparrow$, Busy $\downarrow$, Blocked $—$, Ops $\uparrow$	Mixed (positive throughput, lower utilization)
WM1Robot	−81.67	+28.14	+53.55	−72	Idle $\uparrow$, Busy $\downarrow$, Blocked $\downarrow$, Ops $\uparrow$	Good (de-blocking, but higher idle/lower busy)
TWM (welding)	+13.92	−13.90	0.00	−73	Idle $\downarrow$, Busy $\uparrow$, Blocked $—$, Ops $\uparrow$	Good
TWMRobot	−17.47	+17.47	0.00	−73	Idle $\uparrow$, Busy $\downarrow$, Blocked $—$, Ops $\uparrow$	Mixed/minor improvement
VIM (inspection)	−3.73	+3.75	0.00	−73	Idle $\uparrow$, Busy $\downarrow$, Blocked $—$, Ops $\uparrow$	Mixed
VIMRobot	−27.42	+27.44	0.00	−74	Idle $\uparrow$, Busy $\downarrow$, Blocked $—$, Ops $\uparrow$	Mixed
ETRobot	+12.27	−12.26	0.00	−73	Idle $\downarrow$, Busy $\uparrow$, Blocked $—$, Ops $\uparrow$	Good
ET (tester)	+2.15	−2.13	0.00	−73	Idle $\downarrow$, Busy $\uparrow$, Blocked $—$, Ops $\uparrow$	Good

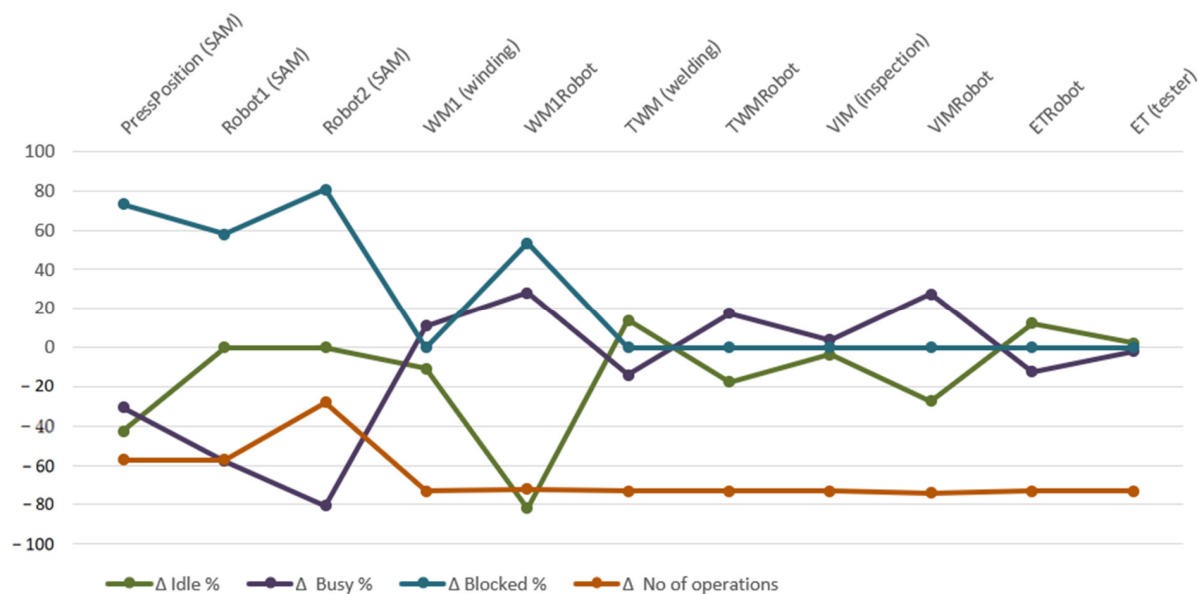
**Figure 14.** Δ KPIs by resource (Δ = Baseline – Optimized): Idle, Busy, Blocked (pp), and No. of operations (units) over a 28,800 s run.

Table 6 and Figure 15 compare the state distribution of the three conveyors using Δ = Baseline – Optimized. LTS shows a very large positive Δ Blocked (+97.46 pp) together with negative deltas for Empty and Move (meaning both Empty and Move increased in the optimized case), demonstrating that the shuttle system is no longer congested and now alternates between moving and free capacity. The VIMConveyor changes are negligible (slight rise in Move with Blocked unchanged at 0%), consistent with a short, intermittent transfer. The FinalConveyor exhibits a strong increase in Move and a reduction in Empty, reflecting the higher throughput delivered by the optimized line while keeping blockage at zero.

Table 6. Baseline–optimized differences for conveyor states (Δ = Baseline – Optimized, pp = percentage points).

Asset	Δ Empty (pp)	Δ Move (pp)	Δ Blocked (pp)	Interpretation ($\uparrow$ Increased, $\downarrow$ Decreased, — No Change)	Overall Verdict
LTS	−84.87	−14.69	+97.46	Empty $\uparrow$, Move $\uparrow$, Blocked $\downarrow$ (to 0%)	Excellent—constraint removed
VIMConveyor	+0.66	−0.66	—	Empty $\downarrow$ slightly, Move $\uparrow$ slightly, Blocked —	Stable/slight improvement
FinalConveyor	+10.88	−13.88	—	Empty $\downarrow$, Move $\uparrow$, Blocked —	Good—higher downstream flow

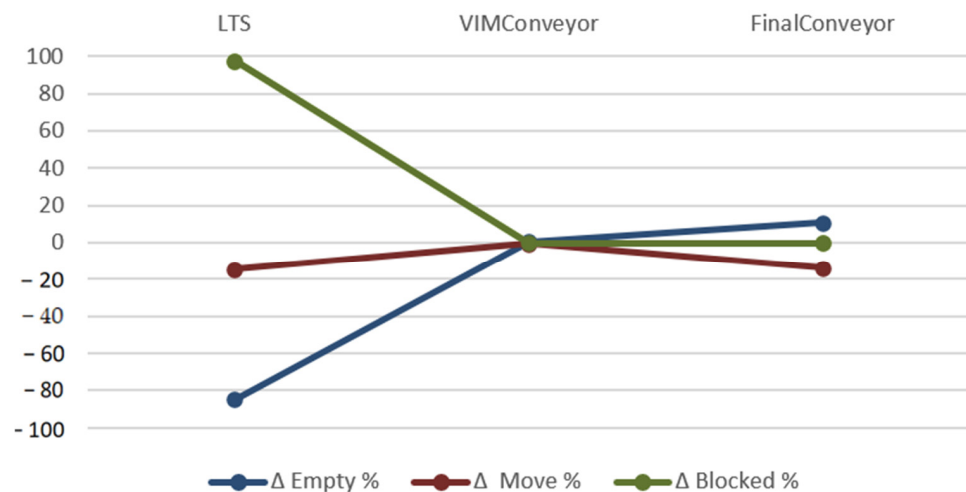


Figure 15. Δ KPIs by conveyor (Δ = Baseline – Optimized): Empty, Move, and Blocked (pp) over a 28,800 s run.

6. Conclusions

This study implemented a virtual commissioning (VC) workflow utilizing WITNESS Horizon to analyze and enhance an automated brushless stator production line. The initial simulation faithfully replicated the process logic and identified critical synchronization issues at the interface between SAM (Stator Assembly Module) and LTS (Linear Transport System), particularly during WM (Winding Module) to TW (Testing and Winding Module) handoff. It was observed that PressPosition, Robot1, and Robot2 were obstructed or idle for over 60–70% of their operational time, while LTS faced an alarming block rate of 97.46%, thus confirming it as the primary transfer bottleneck. Following iterative modifications to task allocations, robot timing, and LTS routing strategies, the optimized model demonstrated a significantly improved flow. The blocked time at the SAM interface was nearly eradicated, allowing critical resources to function within normal operational parameters for over 95% of the shift. The throughput improvements were evident in the operation counts across various stations: PressPosition increased from 368 to 425 operations (+15.5%), Robot1 from 369 to 426 (+15.4%), Robot2 from 185 to 213 (+15.1%), and WM1 from 351 to 424 (+20.8%). Similarly, LTS showed substantial improvements, with blocked time dropping from 97.46% to 0%, while the “Move” state was approximately 14.76%, and the “Empty” state was around 85.24%. The FinalConveyor also exhibited a change in “Move” time, rising from approximately 0.81% to about 14.69%, indicating a significant reduction in queue-related delays in downstream material flow. Despite these successes, some residual inefficiencies persisted. WM1Robot, VIMRobot, and TWRobot exhibited excessively high waiting periods (often exceeding 80–90%), indicative of potential overcapacity or coordination deficits with proximal stations, issues that necessitate further timing

adjustments and slight buffer modifications. Overall, the overarching outcome is favorable, highlighting a significant reduction in blockages at the SAM interface and along the conveyor systems, increased active time at critical stages, and a uniform rise in completed operations throughout the line. The study also emphasizes the vital need for ongoing calibration between the digital model and actual plant conditions. Real-world equipment introduces variances that idealized models may not capture, such as transfer times that can exceed nominal values by 30–40% due to alignment, sensing discrepancies or thermal influences. Variations in winding time relative to the 86 s benchmark and fluctuations in welding or testing durations attributable to fixture wear and temperature were also noted. Additionally, thermal management considerations near TWM have a tangible effect on LTS performance. Continually reconciling these real-world factors with the digital model facilitated a more effective balance of speed, reliability, and quality, sometimes necessitating slightly extended cycle times to mitigate defects and extend machinery longevity.

6.1. Limitations

The VC model was calibrated on a single product flow and over a one-shift horizon (28,800 s), with deterministic assumptions for part of the cycle times and without a human-in-the-loop coupling. Validation was performed via KPI agreement and nominal station-level cycle times; we have not yet integrated real-time closed-loop feedback or stochastic variability due to wear/temperature. The study is also single-plant and single-assembly in scope (we did not address disassembly lines).

6.2. Future Research

Future work will extend toward Industry 5.0 by embedding Human–Cyber–Physical Systems (HCPSs), with the operator in the loop alongside ergonomic–cognitive analysis and operational risk assessment [36]. We will address stochastic processing times and rare events via multi-objective scheduling in a hybrid flow shop—maximizing processing quality while minimizing total tardiness, implemented as a scheduling layer on top of VC [37]. The methodology will be transferred to multi-factory disassembly lines, with optimization that accounts for operator posture and ergonomic constraints, which is directly relevant to the circular economy [38]. Finally, we will integrate a dual closed-loop digital-twin pipeline (sensors → simulation → control) for online tuning of LTS/robot routing and for MPC- and reinforcement-learning-based task allocation [2].

Implementing these directions is compatible with our VC framework and the already defined KPIs (utilization, blocked/idle time, and throughput); we expect robust gains in performance under variability and improved human–machine compatibility.

In conclusion, the validated optimization process demonstrates that virtual commissioning provides insightful, low-risk strategies for system commissioning: it alleviates critical transfer bottlenecks, enhances effective utilization at essential stations, and boosts shift-level output while also providing a replicable framework to apply this approach across similar electromechanical assembly lines.

Author Contributions: Conceptualization, F.C.; methodology, F.C., A.S. and C.L.P.; software, F.C., A.S. and C.-C.C.; validation, C.L.P. and C.E.C.; formal analysis, C.-C.C., C.L.P. and C.E.C.; investigation, F.C., A.S. and C.-C.C.; resources, F.C., A.S., C.-C.C., C.L.P. and C.E.C.; data curation, F.C., A.S. and C.-C.C.; writing—original draft preparation, F.C., A.S. and C.-C.C.; writing—review and editing—C.L.P. and C.E.C.; visualization, C.-C.C., C.L.P. and C.E.C.; supervision, C.L.P. and C.E.C.; project administration, F.C.; funding acquisition, F.C. All authors have read and agreed to the published version of the manuscript.

Funding: Own financial resources.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

VC	Virtual Commissioning
IoT	Internet of Things
SMED	Single-Minute Exchange of Dies
DT	Digital Twin
SCARA	Selective Compliance Assembly Robot Arm
SAM	Stator Assembly Machine
WM	Winding Machine
LTS	Linear Transfer System
TWM	Terminal Welding Machine
ET	Electric Tester
IM/VIM	Inspection Machine
MOGA	Multi-Objective Genetic Algorithms
MPC	Model-Predictive Control
KPI	Key performance indicators

References

1. Komma, P.; Vogelbruch, M.; Jung, M. Digital Twins in Industrial Automation: A Closer Look on RFID Read/Write Components for Virtual Commissioning. In Proceedings of the 2024 IEEE 22nd International Conference on Industrial Informatics (INDIN), Beijing, China, 17–20 August 2024; pp. 1227–1234. [\[CrossRef\]](#)
2. Jiang, Z.; Xu, C.; Liu, J.; Luo, W.; Chen, Z.; Gui, W. A Dual Closed-Loop Digital Twin Construction Method for Optimizing the Copper Disc Casting Process. *IEEE/CAA J. Autom. Sin.* **2024**, *11*, 581–594. [\[CrossRef\]](#)
3. Tanegue, H.B.D.; de Paula Ferreira, W.; de Assis, R.F.; Brodeur, D. Synergies Between Virtual Commissioning and Digital Twins. *Eng. Proc.* **2025**, *89*, 12. [\[CrossRef\]](#)
4. Iyer, S.V.; Sangwan, K.S.; Sangwan, D. Digital Twin-Based Virtual Commissioning for Evaluation and Validation of a Reconfigurable Process Line. *IET Collab. Intell. Manuf.* **2024**, *6*, e12111. [\[CrossRef\]](#)
5. Scholz, J.; Klein, N.; Kößler, F.; Fleischer, J. Systematic Digital Twin-Based Development Approach for Holistic Sustainable Electric Traction Motors. *Sustainability* **2025**, *17*, 2518. [\[CrossRef\]](#)
6. Tao, F.; Qi, Q.; Wang, L.; Nee, A.Y.C. Digital Twins and Cyber-Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. *Engineering* **2019**, *5*, 653–661. [\[CrossRef\]](#)
7. Striffler, N.; Voigt, T. Concepts and Trends of Virtual Commissioning—A Comprehensive Review. *J. Manuf. Syst.* **2023**, *71*, 664–680. [\[CrossRef\]](#)
8. Barbieri, G.; Bertuzzi, A.; Capriotti, A.; Ragazzi, L.; Gutierrez, D.; Negri, E.; Fumagalli, L. A Virtual Commissioning-Based Methodology to Integrate Digital Twins into Manufacturing Systems. *Prod. Eng.* **2021**, *15*, 397–412. [\[CrossRef\]](#)
9. Korpai, R.; Szántó, N.; Csapó, Á.B. A Framework for Effective Virtual Commissioning: Guiding Principles for Seamless System Integration. *J. Manuf. Mater. Process.* **2024**, *8*, 165. [\[CrossRef\]](#)
10. Lee, J.; Bagheri, B.; Kao, H.-A. A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems. *Manuf. Lett.* **2015**, *3*, 18–23. [\[CrossRef\]](#)
11. Zhong, R.Y.; Xu, C.; Klotz, E.; Newman, S.T. Intelligent Manufacturing in the Context of Industry 4.0: A Review. *Engineering* **2017**, *3*, 616–630. [\[CrossRef\]](#)

12. Tripathi, V.; Chattopadhyaya, S.; Mukhopadhyay, A.K.; Sharma, S.; Singh, J.; Pimenov, D.Y.; Giasin, K. An Innovative Agile Model of Smart Lean–Green Approach for Sustainability Enhancement in Industry 4.0. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 215. [\[CrossRef\]](#)
13. Cioffi, R.; Travaglioni, M.; Piscitelli, G.; Petrillo, A.; Parmentola, A. Smart Manufacturing Systems and Applied Industrial Technologies for a Sustainable Industry: A Systematic Literature Review. *Appl. Sci.* **2020**, *10*, 2897. [\[CrossRef\]](#)
14. Touriki, F.E.; Benkhathi, I.; Kamble, S.S.; Belhadi, A.; Ffezazi, S.E. An Integrated Smart, Green, Resilient, and Lean Manufacturing Framework: A Literature Review and Future Research Directions. *J. Clean. Prod.* **2021**, *319*, 128691. [\[CrossRef\]](#)
15. Ghobakhloo, M.; Ching, N.T. Adoption of Digital Technologies of Smart Manufacturing in SMEs. *J. Ind. Inf. Integr.* **2019**, *16*, 100107. [\[CrossRef\]](#)
16. Rahardjo, B.; Wang, F.-K.; Yeh, R.-H.; Chen, Y.-P. Lean Manufacturing in Industry 4.0: A Smart and Sustainable Manufacturing System. *Machines* **2023**, *11*, 72. [\[CrossRef\]](#)
17. Moraes, A.; Carvalho, A.M.; Sampaio, P. Lean and Industry 4.0: A Review of the Relationship, Its Limitations, and the Path Ahead with Industry 5.0. *Machines* **2023**, *11*, 443. [\[CrossRef\]](#)
18. Brettel, M.; Friederichsen, N.; Keller, M.; Rosenberg, M. How Virtualization, Decentralization and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective. *Int. J. Mech. Ind. Sci. Eng.* **2014**, *8*, 37–44.
19. Kolberg, D.; Zühlke, D. Lean Automation Enabled by Industry 4.0 Technologies. *IFAC-PapersOnLine* **2015**, *48*, 1870–1875. [\[CrossRef\]](#)
20. Bortolini, M.; Faccio, M.; Galizia, F.G.; Gamberi, M.; Pilati, F. Adaptive Automation Assembly Systems in the Industry 4.0 Era: A Reference Framework and Full-Scale Prototype. *Appl. Sci.* **2021**, *11*, 1256. [\[CrossRef\]](#)
21. Bortolini, M.; Faccio, M.; Galizia, F.G.; Gamberi, M.; Pilati, F. Design, Engineering and Testing of an Innovative Adaptive Automation Assembly System. *Assem. Autom.* **2020**, *40*, 531–540. [\[CrossRef\]](#)
22. Berlin, C.; Adams, C. *Production Ergonomics: Designing Work Systems to Support Optimal Human Performance*; Ubiquity Press: London, UK, 2017.
23. Afonso, T.; Alves, A.C.; Carneiro, P. Lean Thinking, Logistics and Ergonomics: Synergetic Triad to Prepare Shop Floor Work Systems to Face Pandemic Situations. *Int. J. Glob. Bus. Compet.* **2021**, *16*, 62–76. [\[CrossRef\]](#)
24. Cimini, C.; Lagorio, A.; Pirola, F.; Pinto, R. Exploring Human Factors in Logistics 4.0: Empirical Evidence from a Case Study. *IFAC-PapersOnLine* **2019**, *52*, 2183–2188. [\[CrossRef\]](#)
25. Lukman, G.F.; Lee, C. Towards Digital Twin Modeling and Applications for Permanent Magnet Synchronous Motors. *Energies* **2025**, *18*, 956. [\[CrossRef\]](#)
26. Chen, Y.; Zhao, L.; Li, L.; Liu, K.; Ye, C. Digital Twin-Based Online Diagnosis Method for Inter-Turn Short Circuit Fault in Stator Windings of Induction Motors. *Energies* **2025**, *18*, 3063. [\[CrossRef\]](#)
27. Lee, G.-C.; Chiu, Y.-H.; Lee, K.-C. Construction of Fully Automated Key Production Line. *Eng. Proc.* **2025**, *92*, 83. [\[CrossRef\]](#)
28. Sun, D.; Li, W.; Shen, Y.; Chen, H.; Tan, Z.; Ding, X. Application practice of intelligent algorithm and digital twin in electromechanical equipment. *U.P.B. Sci. Bull. Ser. D* **2024**, *86*, 235–256. Available online: https://www.scientificbulletin.upb.ro/rev_docs_arhiva/full82f_322545.pdf (accessed on 9 February 2025).
29. Zhang, Z.; Li, X.; Peng, S. Structural Optimization Design of Jet Cooling Device for Lithium Batteries of New Electric Vehicles. *U.P.B. Sci. Bull. Ser. D* **2025**, *87*, 103–120. Available online: https://www.scientificbulletin.upb.ro/rev_docs_arhiva/full3a6_85968_2.pdf (accessed on 12 February 2025).
30. Wu, P. Optimization and Analysis of Lifting Efficiency for Power Catwalk Under Multi-Constrain Conditions. *U.P.B. Sci. Bull. Ser. D* **2025**, *87*, 269–280. Available online: https://www.scientificbulletin.upb.ro/rev_docs_arhiva/rezc13_771664.pdf (accessed on 15 February 2025).
31. Raffaeli, R.; Bilancia, P.; Neri, F.; Peruzzini, M.; Pellicciari, M. Engineering Method and Tool for the Complete Virtual Commissioning of Robotic Cells. *Appl. Sci.* **2022**, *12*, 3164. [\[CrossRef\]](#)
32. Tripathi, V.; Saraswat, S.; Gautam, G.D. A Study on Implementation of Various Approaches for Shop Floor Management. In *Advances in Energy Technology*; Lecture Notes in Electrical Engineering; Springer: Singapore, 2021; Volume 766, pp. 371–387.
33. Tripathi, V.; Chattopadhyaya, S.; Mukhopadhyay, A.K.; Sharma, S.; Li, C.; Di Bona, G. A Sustainable Methodology Using Lean and Smart Manufacturing for the Cleaner Production of Shop Floor Management in Industry 4.0. *Mathematics* **2022**, *10*, 347. [\[CrossRef\]](#)
34. Singh, J.; Singh, H. Continuous Improvement Philosophy—Literature Review and Directions. *Benchmarking Int. J.* **2015**, *22*, 75–119. [\[CrossRef\]](#)
35. Groover, M.P. *Automation, Production Systems, and Computer-Integrated Manufacturing*, 4th ed.; Pearson: Boston, MA, USA, 2015; ISBN 13: 978-13-349961-2.
36. Lou, S.; Hu, Z.; Zhang, Y.; Feng, Y.; Zhou, M.; Lv, C. Human-Cyber-Physical System for Industry 5.0: A Review from a Human-Centric Perspective. *IEEE Trans. Autom. Sci. Eng.* **2024**, *22*, 494–511. [\[CrossRef\]](#)

37. Fu, Y.; Wang, H.; Wang, J.; Pu, X. Multiobjective Modeling and Optimization for Scheduling a Stochastic Hybrid Flow Shop with Maximizing Processing Quality and Minimizing Total Tardiness. *IEEE Syst. J.* **2021**, *15*, 4696–4707. [[CrossRef](#)]
38. Guo, X.; Chen, L.; Qi, L.; Wang, J.; Qin, S.; Chatterjee, M.; Kang, Q. Multifactory Disassembly Process Optimization Considering Worker Posture. *IEEE Trans. Comput. Soc. Syst.* **2025**, *12*, 3049–3061. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.