

Ingenious Island Manufacturing System (I²MS): A Sustainable and Digital Manufacturing Paradigm for Productivity, Circularity, and Low-Carbon Automotive Production

Rajesh PATIL , Magnus LÖFSTRAND 

School of Science and Technology, Mechanical Engineering, Digitalized product and production development, Örebro University, Sweden

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Abstract

The car industry is moving toward greater personalization, electrification, and sustainability, but traditional linear assembly lines lack flexibility, adaptability, and durability. This conceptual research introduces the Ingenious Island Manufacturing System (I²MS), which combines an island-based manufacturing paradigm with a Sustainable Digitalized Manufacturing System (SDMS). I²MS is a network of autonomous manufacturing islands that use robotics, cobots, Autonomous Mobile Robots (AMRs), IIoT sensors, and digital twins for predictive control. Each island is connected digitally by edge computer nodes and optimized for energy, emissions, and material tracking using sustainability modules. A centralized SDMS platform manages production, ensuring real-time decision-making and complete traceability. The full adoption of I²MS significantly improve the output capacity by increasing productivity as compared to the traditional baseline. An improvement in quality stability by the decrease in defect probability and CO₂ emissions are lowered in every manufacturing cycle may be achieved. The optimization may be beneficial in greatly increasing initial throughput, even though the advantages became less consistent in subsequent cycles. The Island-based smart manufacturing not only closes efficiency and flexibility gaps, but it also has substantial environmental and economic benefits. The suggested I²MS offers a scalable approach to resilient, adaptive, and sustainable vehicle production that aligns with Industry 5.0 objectives.

Keywords

Island Manufacturing System (I²MS), Sustainable Digitalized Manufacturing System (SDMS), Digital Twin, Industrial Internet of Things (IIoT), Edge Computing.

Introduction

The automotive manufacturing business is undergoing an upheaval, fueled by the convergence of digitalization, automation, and sustainability imperatives. For over a century, Henry Ford's assembly line has been the dominant production model, allowing for unprecedented efficiency in large-scale, standardized vehicle manufacture. However, the growing desire for mass customization, the rapid expansion of new energy vehicles (NEVs), and the requirement for robust and sustainable manufacturing techniques have all highlighted

the constraints of standard linear production systems (Murthy et al., 2016; Koren & Shpitalni, 2010). To solve these issues, researchers and business leaders are investigating new production paradigms that emphasize flexibility, adaptability, and intelligent decision-making. The Sagacious Island Manufacturing System (S²MS) is an alternative to traditional assembly lines. This strategy organizes production into modular “islands” that can be flexibly modified to accommodate numerous models at the same time, resulting in both customization and mass-production efficiency (Zhong et al., 2017; Soori et al., 2023). Each island incorporates modern technologies such as artificial intelligence (AI), 5G-enabled IIoT connection, big data analytics, edge computing, robotics, and digital twin platforms (Cheng et al., 2018; Lu, 2017; Moiceanu & Paraschiv, 2022). This connectivity allows for decentralized control, real-time process optimization, and full lifecycle product traceability. The large-scale demonstration is

Corresponding author: Rajesh Patil – School of Science and Technology, Mechanical Engineering, Digitalized product and production development, Örebro University, Sweden, phone: +, e-mail:

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to replace linear assembly with collaborative and industrial robots operating within intelligent islands. The plant may achieving considerable advantages, including increase in manufacturing productivity, decrease in unit costs, and complete lifecycle data traceability (Huawei, 2024). These results demonstrate I²MS's ability to transform global automotive production systems. Given the promise of industrial and intellectual ramifications, the study of island-style manufacturing has gained traction in a variety of research fields. Scholars have studied enabling technologies such as reconfigurable manufacturing systems, digital twins, AI-driven scheduling, and edge-based IIoT architectures (Hottenrott et al., 2023; Qinglin et al., 2018; Marschall et al., 2022; Javaid et al., 2023; Bi et al., 2007; da Silva et al., 2025; Xu et al., 2018). The research highlights that I²MS not only meets the need for flexibility and sustainability but also provides the groundwork for future resilient manufacturing environments. This paper provides a assessment of the existing literature on island-style smart manufacturing, highlight technology enablers and industrial case studies, and discusses future research challenges and prospects for expanding the I²MS paradigm.

Related Research

Transitioning from Assembly Lines to Modular/Island Systems

For over a century, the car industry has relied on Henry Ford's assembly line paradigm, which maximized throughput for mass production but limiting flexibility and responsiveness to customization. To address these limits, researchers and practitioners began to investigate modular and localized production arrangements, such as "island manufacturing," which emphasize configurable and independent production units that may be reconfigured to accommodate product variety and demand fluctuations (Murthy et al., 2016). Closely related to this progression, the notion of Reconfigurable Manufacturing Systems (RMS) arose, defining modularity, convertibility, scalability, and diagnosability as critical features for adaptive factories (Koren & Shpitalni, 2010).

Industry 4.0: The Technological Backbone

The rise of Industry 4.0 laid the groundwork for implementing island-based paradigms. Intelligent manufacturing systems are progressively combining cyber-physical systems, IIoT platforms, cloud/edge computing, robotics, and artificial intelligence (Zhong et al.,

2017; Soori et al., 2023). Digital twins enhance these capabilities by providing real-time virtual reproductions of manufacturing processes, allowing for predictive maintenance, process modeling, and closed-loop optimization (Cheng et al., 2018; Lu, 2017). Empirical studies show that digital twin implementations in machining and assembly speed up decision-making and increase quality results (da Silva et al., 2025; Kusiak, 2019; Zhukabayeva et al., 2025). Engine exhaust weld joint defects in SS316L-SS410 and SS310-SS410 materials were identified and categorized using RNN and SVM algorithms, by the authors in previous research (Patil & Löfstrand, 2025). An intelligent artificial neural network approach was used to identify and categorize multiform faults in weld joints (Patil & Reddy, 2023). A technique for identifying and categorizing various kinds of weld flaws was created using support vector machines (Patil & Reddy, 2021a). Weld flaws were categorized using local binary patterns and texture feature extraction (Patil & Reddy, 2021b). To identify and categorize multi-class weld faults, a hybrid model combining SVM and ANN was introduced (Patil & Reddy, 2021c). Weld joint quality was evaluated using real-time temperature dispersal and microscopic image analysis (Patil & Thote, 2022). In a ROS2 context, autonomous mobile robot simulation using NAV2 and SLAM was put into practice (Patil, 2025b). An automated billing system and an RFID-based human interaction system were incorporated into an autonomous shopping tram (Patil, 2025c). Online measurements were used to examine the relationship between temperature distribution and weld bead geometry in Nd:YAG laser welding (Patil & Reddy, 2021d). The optimized HPDLBW produced high-integrity SS304 joints appropriate for structural and precision manufacturing applications (Patil & Löfstrand, 2025). This study improves GTAW settings for dissimilar stainless-steel welds (SS316L-SS410 and SS310-SS410) utilizing tests and FEM simulations to obtain defect-free joints with improved mechanical strength, corrosion resistance, and thermal endurance (Patil & Löfstrand, 2026b).

Connectivity, Edge Computing, and Data Driven Operations

The move from centralized manufacturing lines to scattered islands requires ubiquitous connection and localized intelligence. Research on IIoT and 5G networks shows that ultra-reliable low-latency communications are crucial for coordinating robotics, automated guided vehicles, and adaptive scheduling (Cheng et al., 2018; Zreikat et al., 2025; Karaduman & Gülhas, 2025). Edge computing architectures improve responsiveness by allowing on-site data processing, conserving bandwidth,

and minimizing dependency on cloud-only infrastructures (Marschall et al., 2022). Big data analytics and artificial intelligence (AI) enrich the ecosystem by providing tools for adaptive scheduling, anomaly detection, and uncertainty-based optimization (Javaid et al., 2023; Patil & Thote, 2022). An AI-driven automated inspection framework that combines 3D and high-speed 2D vision with edge analytics improves defect-free, traceable, and sustainable lithium-ion battery manufacture in accordance with Industry 5.0 (Patil & Löfstrand, 2026c).

Robotics, Modularity, and Human-Robot Collaboration

The use of industrial and collaborative robots (cobots) is critical to island-style manufacturing. Case studies from the automotive industry show how cobots provide flexible work sharing and ergonomic advantages in modular cells (Moiceanu & Paraschiv, 2022). Meanwhile, AMRs are increasingly being used for dynamic reconfiguration of islands and intra-factory logistics, as evidenced by simulation studies that determine the appropriate robot fleet sizes (Hottenrott et al., 2023; Kusiak, 2019). These robotic technologies replace fixed conveyors, allowing for non-linear flows and multi-model assembly within islands.

Operational Advantages of Island-Style Manufacturing

Compared to typical lines, island-style techniques allow for simultaneous multi-model production, significantly lowering changeover time and increasing mass customization capabilities (Bi et al., 2007). Studies show that when paired with lean manufacturing principles, island cells maintain efficiency while allowing for product variation (Marschall et al., 2022). Other research focuses on categorizing products into families to improve island allocation and resource sharing (Patil & Reddy, 2023). Together, these strategies increase usage, reduce idle time, and improve responsiveness.

Lifecycle traceability, quality, and standards

Traceability has emerged as a key feature of intelligent islands. Blockchain, product lifecycle management (PLM), and IIoT integration enable 100% full-lifecycle traceability, which is particularly important for NEVs (Soori et al., 2023; Zhukabayeva et al., 2025). Computer vision and artificial intelligence-powered inspection technologies integrated inside islands improve inline quality assurance even more. To easily integrate islands into enterprise-wide systems, interoperability

standards are being developed, allowing for plug-and-play flexibility and horizontal/vertical integration.

Sustainable, Resilient, and Economic Perspectives

Beyond productivity, modular island factories help to promote sustainability by reducing energy usage and material waste through localized process optimization (Murthy et al., 2016; Koren et al., 2017). The scattered character of islands promotes robust production networks, allowing for localized or decentralized operations in the face of supply chain interruptions (Koren et al., 2017). However, literature underscores the economic trade-offs: while islands need more initial capital investment, lifecycle costs are frequently decreased in conditions of high product-mix volatility (Patil & Reddy, 2021d). The Sagacious E-Powertrain Tiller was designed to improve operator handling, load distribution, and electric agricultural gear performance (Patil, 2025a). The polyurethane foam as a high-efficiency energy absorber for side-impact collisions and found that it reduced stress and improved crashworthiness (Patil, 2022). The Smart Rear Underrun Safety Shield (SRUSS) for hybrid vehicles was designed and tested using FEA to reduce deformation during underride crashes (Patil, 2024).

Case Study Observation

Cybersecurity for IIoT-integrated islands is crucial since flaws can compromise operations and intellectual property (Karaduman & Gülhas, 2025). Interoperability standards are continuously changing, which limits plug-and-play integration among vendors. Furthermore, while scheduling and optimization techniques have evolved (Javaid et al., 2023), real-time orchestration across heterogeneous islands warrants additional investigation. Future directions include autonomous reconfiguration using AMRs, AI-driven on-the-fly scheduling, multi-site digital twin integration, and green-island concepts fueled by renewable energy and local storage (Koren & Shpitalni, 2010; Marschall et al., 2022; Patil & Löfstrand, 2026a). The literature suggests that I²MS may be a disruptive paradigm in smart manufacturing (Murthy et al., 2016; Huawei, 2024). Building reconfigurable systems theory, Industry 5.0 technology, and case studies like SGMW, islands outperform linear assembly lines in terms of adaptability, sustainability, and resilience (Huawei, 2024). The ongoing integration of digital twins, AI, IIoT, and robots is likely to shape the worldwide trajectory of automotive and advanced manufacturing in the future decades.

Ingenious Island Manufacturing System (I²MS)

The rapid evolution of Industry 4.0 and sustainable manufacturing has prompted the creation of new production paradigms that go beyond the constraints of traditional assembly lines. One such paradigm is the I²MS, a next-generation intelligent manufacturing strategy that aims to integrate industrial processes' flexibility, efficiency, and sustainability. I²MS, in contrast to Henry Ford's century-old linear production lines, functions through distributed and autonomous manufacturing islands, each capable of executing whole or partial production tasks. These islands are linked by powerful digital platforms, allowing for real-time communication, optimization, and seamless interaction with supply chains. I²MS's uniqueness stems from its hybrid operational structure, which combines local intelligence at each island with centralized decision-making to ensure a balance of autonomy and systemwide cooperation. I²MS allows for quick reconfiguration of production flows, multi-model manufacturing, and adaptive scheduling in response to changing market demands by integrating artificial intelligence, Industrial Internet of Things (IIoT), big data analytics, 5G connection, and edge computing. Furthermore, its sustainability-driven modules improve resource use, cut energy consumption, and assure product traceability throughout their entire lifecycle, aligning with global decarbonization and circular economy aims. I²MS provides a disruptive alternative as industries, particularly automotive and electronics, shift toward high product mix, low volume demands, and increasing sustainability requirements. It not only provides increases in efficiency and cost savings, as proved by early adopters, but it also improves resilience to supply chain disturbances. Finally, the I²MS marks a strategic leap toward flexible, intelligent, and sustainable production ecosystems, laying the groundwork for Industry 5.0, where human-machine collaboration, personalization, and environmental stewardship.

Architecture of I²MS

The SDMS functions via an organized flow of information and control across interconnected layers. In the upstream data flow, each manufacturing island (I₁, I₂, I₃, I₄..._n) produces operational data via IIoT sensors, edge devices, and digital twins. This real-time data is handled within the local SDMS digital layer, where early insights are extracted and passed on to the sustainability optimization module for refinement using energy, waste, and quality optimization algorithms. The optimized data is subsequently transported via the island interconnection layer, which enables safe Indus-

trial IIoT communication, before arriving to the centralized SDMS platform. This core layer enables strategic decision-making and predictive insights through advanced big data analytics, machine learning models, and a system-wide digital twin. A closed loop control mechanism is used in the downstream command flow to ensure responsiveness. Based on analytical results or human-machine interface (HMI) inputs, the centralized SDMS platform sends strategic or remedial orders. These commands pass through the interconnection layer to the local optimization module, which alters energy use, process parameters, or quality metrics. Finally, these changes are implemented immediately on the manufacturing island, guaranteeing that production operations respond dynamically to both operational and sustainability objectives. The external flow connects the production system and supply chain processes. The supply chain integration module receives updates on inventory, logistics optimization, and sustainable sourcing requirements from the centralized SDMS platform. In exchange, this module guarantees the timely delivery of physical material inputs and sustainable resources straight to manufacturing islands. This comprehensive integration of data, commands, and material flows provides a resilient, adaptable, and sustainable production ecosystem. Fig. 1 depicts how digital technologies are used to strengthen separate manufacturing "islands" for sustainability, which are then linked together by a digital infrastructure.

Flow and Interactions

Local operation and data collection

Each Manufacturing Island I operates its process. The SDMS digital layer uses IIoT sensors to collect real-time data on production, energy consumption, and material usage.

Local optimization

Edge computing within the island performs immediate analysis and feeds data to the sustainability optimization module to make rapid, localized adjustments (e.g., dynamic power-saving modes, immediate quality checks).

Data transmission

Relevant, aggregated data is securely passed from the islands through the island interconnection layer (digital network).

Centralized analysis and system-wide optimization

The data reaches the centralized SDMS platform. Big data analytics and ML models process the information to identify system-wide inefficiencies, perform long-term predictive maintenance, and update the comprehensive digital twin. This platform generates strategic adjustments.

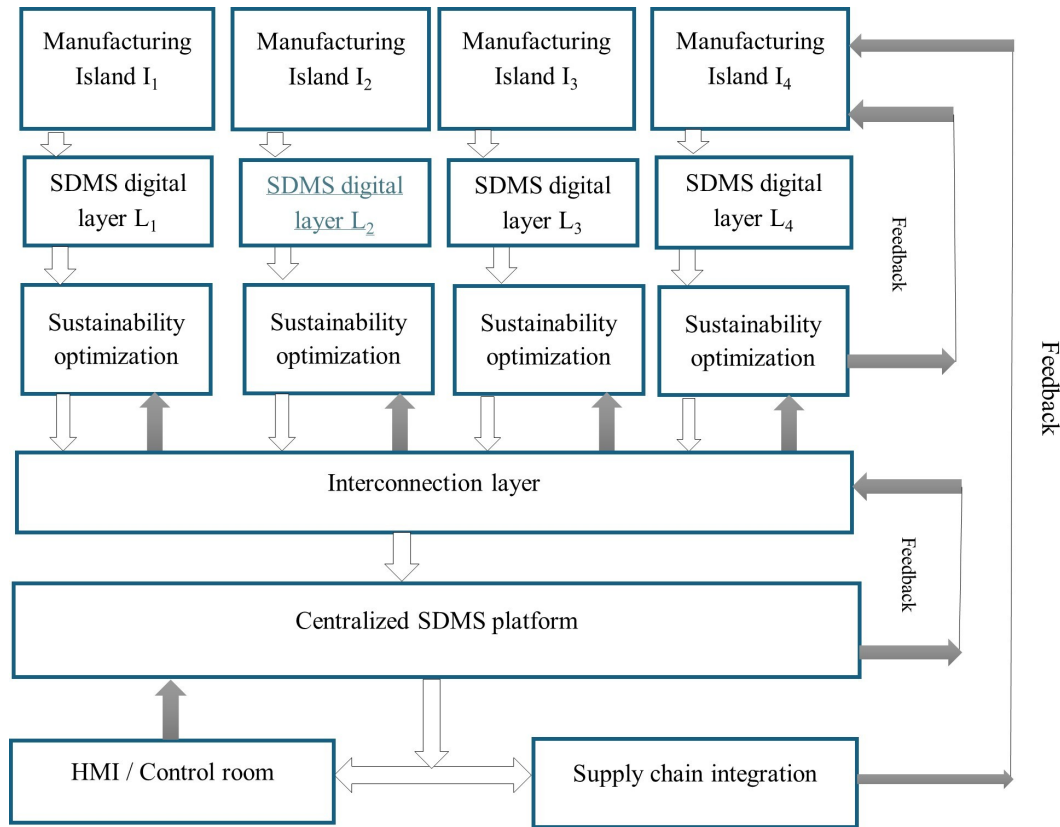


Fig. 1. Architecture of Ingenious Island Manufacturing Systems (I²MS)

External integration

The platform integrates with supply chain integration to ensure sustainable and timely material flow based on optimized production schedules.

Control and feedback loop

Operators use the HMI / control room to monitor the system's performance and manually or semi-automatically implement the strategic optimizations back to the individual islands, completing the closed-loop control system.

This structure allows the benefits of digitization (efficiency, data-driven decisions) to enhance the local, flexible nature of island-style manufacturing while embedding sustainability as a core operational goal.

Proposed Implementation of I²MS in manufacturing plants

As stated, the automobile industry is undergoing a paradigm transformation, fueled by the move to NEVs, sustainability imperatives, and the demand for mass customization. In response, firms are implementing island-based manufacturing systems, such as the ingenious Island Manufacturing System, which combines autonomous production cells, AI-driven opti-

mization, IIoT connection, and sustainability modules. Fig. 2 indicated a proposed architecture of I²MS in a manufacturing plant.

Mathematical Modelling of I²MS

The mathematical models for the I²MS serve as analytical tools and performance indicators, connecting the system's digital foundations to its observable operational benefits. The average cycle time equation is parallelized Island operations outperform sequential assembly lines in terms of production speed, as demonstrated by decreased cycle times in I²MS. Productivity increase and throughput equations capture gains in unit output, where decoupling bottlenecks and simultaneous processing across islands roughly doubles overall productivity. From a sustainability standpoint, energy per unit and carbon emissions per unit provide quantifiable metrics of eco-efficiency, emphasizing the reduced environmental impact obtained through AI-driven scheduling and adaptive resource allocation. The sustainability index combines productivity, energy efficiency, and emissions intensity to provide a single standard for balancing industrial success with envi-

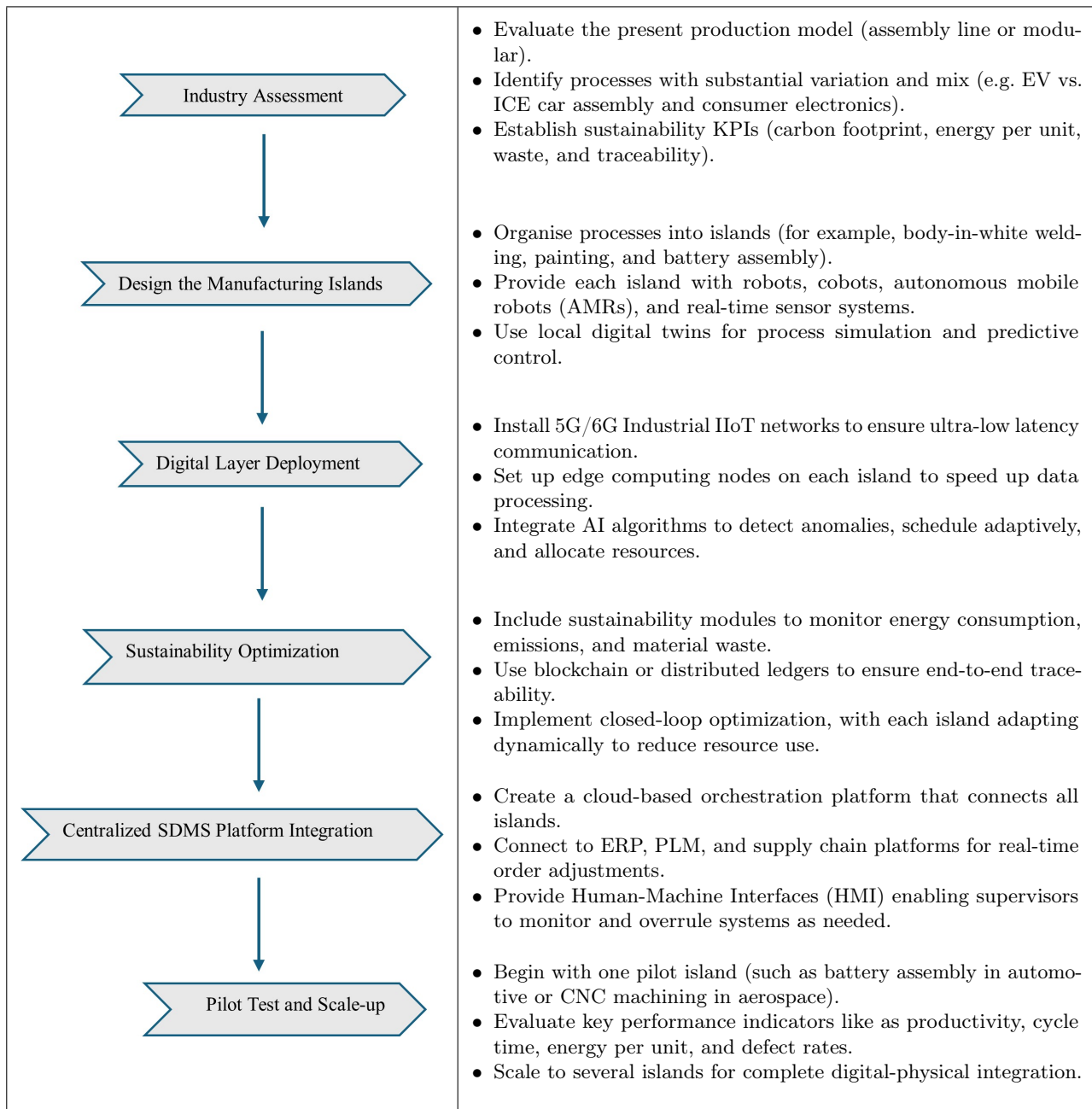


Fig. 2. I²MS implementation guidelines in manufacturing

ronmental responsibility. I²MS improves equipment reliability and minimizes idle time by intelligently distributing workloads, as measured by machine utilization and overall equipment effectiveness. Optimization methods such as linear programming for resource allocation and scheduling models for reducing work completion times strengthen lean and agile production features, ensuring client responsiveness. Finally, the use of dynamic state-space models and model predictive control formulations integrates predictive and

adaptive capabilities into the system, allowing it to retain stability and optimize performance under uncertainty. These equations provide a strong theoretical and quantitative foundation for I²MS, demonstrating that it improves productivity and flexibility while also achieving measurable sustainability outcomes aligned with Industry 4.0, Industry 5.0, and UN sustainable development goals. Equations (1-13) presents initial productivity, efficiency and optimization models.

Productivity and efficiency models

The average cycle time per unit is as follows:

$$T_{\text{avg}} = \frac{\sum_{i=1}^n T_i}{n} \quad (1)$$

The productivity advantage of I²MS over conventional systems can be represented as:

$$P_{\text{gain}} = \frac{P_{I^2\text{MS}} - P_{\text{conv}}}{P_{\text{conv}}} \times 100 \quad (2)$$

The system's Throughput is:

$$Q_t = \frac{N}{T_{\text{total}}} \quad (3)$$

Sustainability models

The energy consumption per unit is expressed as

$$E_{\text{unit}} = \frac{E_{\text{total}}}{N} \quad (4)$$

Similarly, carbon emissions per unit are computed as follows:

$$C_{\text{unit}} = \frac{C_{\text{total}}}{N} \quad (5)$$

A sustainability index (S) is defined as a weighted multi-objective function.

$$S = \alpha \cdot \frac{1}{E_{\text{unit}}} + \beta \cdot \frac{1}{C_{\text{unit}}} + \gamma \cdot Q_t \quad (6)$$

Subject to $\alpha + \beta + \gamma = 1$, $\alpha, \beta, \gamma \geq 0$

Reliability and utilization models

The machine usage factor is represented as follows:

$$U = \frac{T_{\text{busy}}}{T_{\text{total}}} \quad (7)$$

The commonly used Overall Equipment Effectiveness (OEE) statistics are:

$$\text{OEE} = A \times P \times Q \quad (8)$$

Optimization models

The resource allocation problem in I²MS is a linear programming (LP) optimization problem.

$$\max Z = \sum_{i=1}^N p_i x_i \quad (9)$$

The schedule optimization problem is expressed as follows:

$$\min \sum_{i=1}^n C_i, \quad i = 1 \dots N \quad (10)$$

Digital Twin and Predictive control models

A state-space model describes the dynamic behaviour of a production island:

$$x_{k+1} = Ax_k + Bu_k + w_k \quad (11)$$

$$y_k = Cx_k + v_k \quad (12)$$

The appropriate MPC cost function for optimization is:

$$J = \sum_{k=0}^{N-1} (\|x_k - x_{\text{ref}}\|_Q^2 + \|u_k\|_R^2) + \|x_N - x_{\text{ref}}\|_P^2 \quad (13)$$

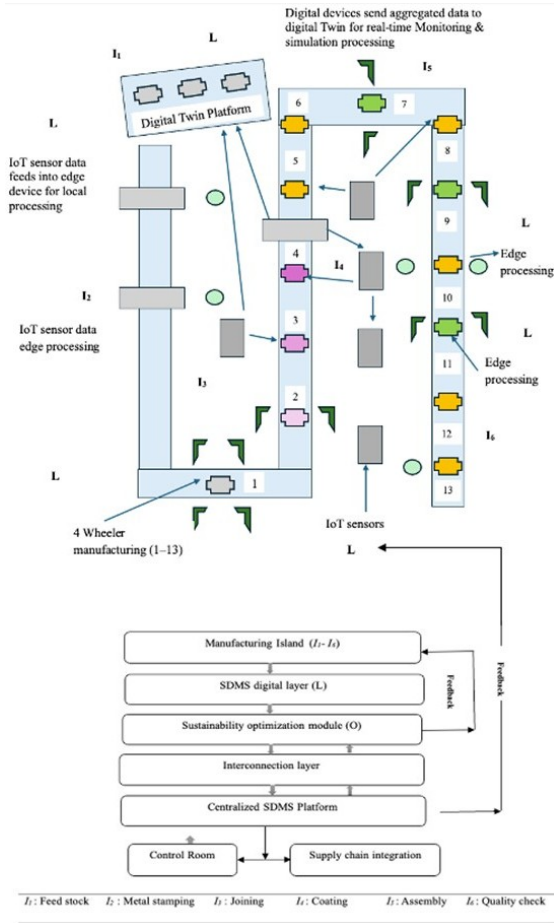
Methodology: I²MS in Automobile Manufacturing

System Scope and Architecture

Within a continuous automobile production line, the case study looks at an Ingenious Island Manufacturing System implemented across six manufacturing islands: feedstock (I₁), metal stamping (I₂), joining (I₃), coating (I₄), assembly (I₅), and final quality control (I₆) as shown in Fig. 3 RFID/barcode traceability is used to digitally identify raw materials, and each workpiece is given a distinct digital profile that is maintained throughout the production cycle. In order to assess the operational stability and manufacturability of components before joining and assembly, environmental data (temperature, humidity, VOCs) and machine conditions (vibration, electrical signatures, spindle torque, pneumatic loads) are continuously recorded.

Framework for Data Acquisition

A framework for hybrid sensing incorporates *Physical sensors* include energy meters, thermocouples, high-resolution accelerometers, strain gauges, and sound emission sensors. PLC/SCADA logs, real-time weld bead geometry from vision systems, and spray flow meters for uniform coating are examples of *process instrumentation*. VOC analysers, optical surface defect classifiers, and NDT inspection (ultrasonic + eddy current) are examples of *quality sensors*. In *Environmental monitoring*, measurements for fume extraction and air quality. Encrypted field-to-cloud communication is made possible by the IIoT architecture that connects all sensors via MQTT/TLS. To lower latency and enable near-real-time decision support, data are synced to an edge database layer.

Fig. 3. I²MS in automobile manufacturing

Model and Integration of Digital Data

A central digital thread receives contextualized data from each production island, which is represented as a Cyber-Physical Process Node (CPPN). Semantically, the CPPNs are connected by for machine interoperability, Time- Series databases for high-frequency sensor data and relational schemas for product traceability and genealogy. In order to identify systemic fundamental causes rather than isolated anomalies, cross-island connections between weld quality, assembly precision, and environmental disturbances are inferred using a unified Knowledge Graph.

Decision Algorithm and Analytical Pipelines

By simulating temperature fields, deformation, assembly tolerances, and coating porosity under various machine inputs, the DT assesses anticipated scenarios. The operator or automated control loop receives guide parameter recommendations from DT outputs.

Stage	Method	Output
Pre-processing	Outlier filtering, sensor fusion, data imputation	Clean, synchronized datasets
Descriptive modelling	Statistical profiling, SPC, control charts	Baseline process capability
Predictive modelling	Random Forest, SVM, LSTM for fault forecasting	Defect likelihood & downtime probability
Prescriptive modelling	DT + optimization heuristics (PSO, GA)	Optimal process parameter sets

Feedback Control and Optimization

Process modifications are implemented in one of two ways: independently, via adaptive PID-based PLC feedback control, or operator-assisted, in which parameter suggestions are verified prior to implementation. In a decision dashboard with Root Cause Hypothesis Trees (RCHT) connecting failure patterns to probable causes, exception occurrences set off alarms. The definition of a multi-objective cost function is,

$$\begin{aligned} \min f(x) &= w_1 \cdot C_{\text{scrap}} + w_2 \cdot E_{\text{unit}} + \\ &\quad w_3 \cdot T_{\text{avg}} + w_4 \cdot (1 - Q) \end{aligned} \quad (14)$$

subject to $\sum w_i = 1, \quad w_i \geq 0, \quad x \in X$

Data Source

A full-scale automotive manufacturing line with six connected production islands (I₁–I₆) following data sources can be used: (i) machine-level operational logs from PLC/SCADA systems; (ii) environmental and process variables from physical IIoT sensors (temperature, vibration, acoustic signatures, and VOC monitors); and (iii) records of product quality from automated inspection units and operator validation sheets. Two levels of data capture can be used: batch-level updates for production traces and assembly quality parameters, and high-frequency continuous monitoring for machine health and welding thermal profiles. Statistical analysis can be used to evaluate normality and identify parametric or non-parametric appropriateness. Pre- and post-IPMS performance differences can be assessed depending on distribution behaviour.

Performance indicators and evaluation metrics

A systematic set of performance metrics covering product quality, operational effectiveness, and sustainability impact can be used to assess the implementation. Overall Equipment Effectiveness, Mean Time Between Failure (MTBF), Mean Time to Repair (MTTR), Total Effective Equipment Performance (TEEP), and takt time efficiency are

examples of operational metrics that will provide quantitative benchmarks for productivity, resource utilization, and equipment dependability. Weld bead consistency, coating uniformity index, and assembly tolerance drift can be used to evaluate quality performance. Simultaneously, the ecological impact of process optimization interventions can be captured by sustainability metrics, namely energy consumption per part, VOC emissions, and rework material mass.

Validation and Replicability

All CPPNs must be in compliance with ISO 23247 digital twin manufacturing reference architecture, ensuring interoperability and standard-compliant data modelling in order to guarantee replicability and scientific rigor. To ensure experimental reproducibility, thorough documentation of sensor specifications, data sampling frequencies, calibration procedures, and process instrumentation settings is kept up to date. Confusion matrices, precision, recall, and F_1 -scores measure classifier performance, and k -fold cross-validation ($k = 10$) will evaluate the analytical models for prediction and decision support. To confirm interpretability, operator acceptability, and the usefulness of automated recommendations in real-time decision-making scenarios, structured feedback from maintenance and production teams will be used for qualitative field validation in addition to quantitative assessment.

Productivity Improvement across Implementation Roadmap

The I²MS roadmap leads to increased productivity at all stages of deployment, replacing traditional assembly-line production methods.

Industry Assessment

Traditional manufacturing frequently lacks the flexibility to accommodate product variety, resulting in downtime during model changes. I²MS may help industries detect high-mix operations and adapt workflows beforehand. This strategic review may minimize changeover downtime while increasing throughput efficiency.

Manufacturing Islands Design

Conventional lines are stiff and require sequential flow, whereas manufacturing islands run in parallel. The parallel operations can reduce cycle times, while allowing for multi-model production on the same floor. Robots, cobots, and AMRs eliminate manual handling, resulting in higher line balancing efficiency than traditional design.

Digital Layer Deployment

Traditional plants rely on post-process quality checks, whereas SDMS digital layers enable real-time monitoring and predictive analytics. Edge computing may confirm that errors are discovered within milliseconds, preventing unplanned outages. Some industry suggest that predictive analytics alone can boost equipment availability resulting in overall productivity benefits of above conventional systems.

Sustainability Optimization

Traditional factories frequently overconsume energy and resources due to a lack of visibility. Incorporating sustainability optimization modules may cut energy while also reducing scrap and rework. These efficiencies indirectly improve throughput by freeing up resources and reducing bottlenecks, resulting, overall productivity benefits.

Centralized SDMS Platform Integration

Fragmented IT systems in assembly-line systems can lead to unconnected data from ERP, PLM, and shop-floor sources. Connecting islands via a centralized SDMS allows enterprises to achieve real-time scheduling optimization, which can raise order fulfillment rates and reduce lead times. This synchronization helpful to each island makes the maximum contribution to productivity.

Implementation guidelines

Industry Context and Scope

The experiment can be conducted in a continuous automotive manufacturing setting with six digitally connected production islands: feedstock preparation (I_1), metal stamping (I_2), joining (I_3), coating (I_4), final assembly (I_5), and end-of-line quality inspection (I_6).

Baseline Definitions and Test Configurations

The two main production configurations can be analysed. *The baseline configuration (B_0 – PLC-only)*. It involves conveyor-driven linear production using PLC/SCADA systems, with static sequencing rules, manual changeover procedures, and post-process quality inspections. *I²MS setup (B_1 – SDMS enabled)*: SDMS coordinates island-based production using edge-level analytics, island-specific digital twins updated every upto 5 seconds, adaptive scheduling, and closed-loop optimization of energy, quality, and material flow.

Data Collection and Dataset Characteristics

Data is suggested to be collected over six months of stable output), Each data collection cycle reflects the whole flow from I₁ to I₆.

Data sources include

- PLC/SCADA logs
- IIoT energy meters and sample rate
- Machine condition sensors.
- Automated NDT and vision systems for defect tracking.

Performance Indicators

The following quantitative KPIs can be analysed.

- Productivity percentage relative to baseline.
- Throughput (Units per Hour).
- Defect probability (percentage of defective units each cycle).
- Energy usage per unit (kWh).
- CO₂ emissions per cycle.
- Overall Equipment Effectiveness (OEE).

Statistical Validation and Analysis

The Shapiro–Wilk test can be used to determine data normality ($p > 0.05$). Performance differences between B₀ and B₁ can be analysed using normal distributions. The productivity and energy KPIs substantial improvements ($p < 0.01$) with considerable impact sizes can be observed. Validation of predictive models (defect probability, throughput deterioration) with 10-fold cross-validation can be performed.

Measurement Reliability and Reproducibility

Robotic systems need to calibrated weekly using ISO, ensuring positional repeatability within standard. Measurement repeatability needs to confirmed analysis methods, with total measurement variation may less than standard.

Observation and Analysis

Productivity comparison

I²MS improves productivity than traditional systems. Notably, the most substantial gains occur at the manufacturing island design phase, the centralized SDMS integration phase, and the pilot-to-scale-up phase, which all contribute to scalability and responsiveness. Intermediate increases from digital layer deployment and sustainability optimization add to the steady incremental advantages. The I²MS roadmap outperforms traditional manufacturing paradigms in

terms of throughput, cost-effectiveness, and sustainability. Full-scale implementation of I²MS results improves productivity over time.

Energy consumption

The Coating step (I₄) has the more energy usage. This suggests that the coating process is the most energy-intensive step in the manufacturing process. The Feed Stock stage (I₁) has the less energy consumption. Other phases (I₂, I₃, I₅, I₆) have moderate energy requirements and lie somewhere in between these two extremes.

Sustainability optimisation

This is useful in moving the defect probability from a high and unstable baseline to a much reduced and generally increasing operational range. This reduction is critical for decreasing waste, lowering material and energy prices, and enhancing overall manufacturing efficiency.

Throughput Analysis

The observation found that the optimization beneficial in greatly increasing initial throughput, even though the advantages became less consistent in subsequent cycles.

CO₂ emissions

The emission reducing the manufacturing process's carbon footprint significantly and consistently. Overall, the emissions reduction, indicating a significant quantitative increase in the operation's environmental sustainability.

System Limitations and Risk Analysis

To ensure safe, dependable, and effective operation in actual industrial settings, a number of limits and hazards must be recognized, even though the suggested system shows notable improvements in flexible production and autonomous material handling.

Inter-Island Dependencies

The proposed system depends on several production islands that are connected by autonomous mobile robots (AMRs) or automated guided vehicles (AGVs). Because of this interdependence, a single island's breakdown or delay might spread throughout the network, resulting in downstream bottlenecks or idle time in other areas.

Error Propagation and Data Integrity

Misrouted AMRs and inaccurate task assignments are examples of operational mistakes that can quickly

build up. Production scheduling and inventory management may be impacted by small deviations that grow into systemic failures in the absence of strong mistake detection and correction systems. These impacts can be made worse by data inconsistencies between remote AMR controllers and the central scheduler, underscoring the necessity of real-time validation and communication redundancy.

Scheduling Conflicts and Resource Contention

Numerous AMRs are dynamically scheduled, there is a chance that they will clash over common resources like handling equipment, charging stations, or small aisles. Deadlocks or long lines can result from ineffective conflict resolution techniques, which lowers operational effectiveness. To reduce these hazards, optimization algorithms must take into consideration work priorities, anticipated travel times, and real-time restrictions.

AMR Traffic Management

Plant areas with little room for moving, high-density AMR traffic raises the risk of crashes, traffic jams, or delays. Although existing routing algorithms are capable of managing nominal flows, they may perform poorly during periods of high load or when unexpected impediments are present. To ensure system safety and continuity, adaptive traffic management techniques that incorporate real-time localization and predictive path planning are crucial.

Communication Latency and Network Reliability

The system primarily relies on wireless communication for inter-AMR coordination, task assignment, and status reporting. Synchronization can be hampered by latency, packet loss, or network outages, which can result in delays or poor coordination. Fail-safe modes that enable AMRs to function independently for a brief period of time while preserving system integrity are necessary for critical activities.

Robustness under Real Industrial Disturbances

Unpredictable disturbances including floor imperfections, machine vibration, operator interventions, and inconsistent material handling are all part of the operating environment. These elements may have an impact on job execution reliability, sensor precision, and AMR navigation. To lessen the effects of such disruptions, the system must have reliable sensing, fault-tolerant control techniques, and real-time anomaly detection.

Scalability and Maintenance Constraints

The complexity of the system increases nonlinearly

with the number of AMRs and production islands, increasing the demands on network bandwidth, computational resources, and maintenance. In order to minimize production disturbance, operational downtime caused by routine maintenance, calibration, and updates must be properly scheduled.

The system's practical deployment necessitates careful consideration of inter-island dependencies, error propagation, scheduling conflicts, traffic management, communication latency, and robustness under actual industrial disturbances, even though it offers significant improvements in automation and operational flexibility. To guarantee dependability and scalability in high-demand production settings, these constraints must be addressed by predictive modelling, strong control algorithms, and resilient system architecture.

Conclusion

The conceptual Ingenious Island Manufacturing System (I²MS) may be a scalable substitute for traditional linear car assembly lines. The suggested method allows for parallel processing, real-time optimization, and enhanced sustainability performance under actual industrial conditions by organizing production into six independent but digitally connected manufacturing islands and coordinating them through a Sustainable Digitalized Manufacturing System (SDMS). The full adoption of I²MS significantly improve the output capacity by increasing productivity as compared to the traditional baseline. A improvement in quality stability by the decrease in defect probability and CO₂ emissions are lowered every manufacturing cycle may be achieved. The observation found that optimization may be beneficial in greatly increasing initial throughput, even though the advantages became less consistent in subsequent cycles. The suggested I²MS framework offers adaptable, low-carbon, and data-driven vehicle manufacturing in line with Industry 5.0, even though issues with cybersecurity, inter-island reliance, and long-term throughput stability still exist.

Original Contribution and Prospects for Further Research

This conceptual work provides a system-level architecture for island-based automobile production by integrating distributed island autonomy with centralized digital coordination through a Sustainable Digitalized Production System (SDMS). Future research should look toward long-term throughput stability, addressing performance decline over longer production cycles with maintenance-aware scheduling and reliability-integrated digital twins. More research is needed on scalability, cybersecurity, and inter-island

coordination in high-density production settings. Furthermore, combining multi-criteria decision-making methodologies with renewable- energy-powered islands is a viable strategy to developing strong, sustainable, and net-zero manufacturing systems.

Data Availability Statement

This is conceptual framework and no actual experimental dataset was generated.

Nomenclature

T_{avg}	average cycle time
E_{unit}	energy per unit
T_i	processing time of i^{th} unit
P_{conv}	assembly lines productivity
Q	quality
i & x_i	production decision variable
u_k	control input
x_{ref}	reference trajectory
P_{gain}	productivity increase
U	machine utilization
n	number of units processed
N	total units produced in time T
P	performance
C_i	completion time of i^{th} unit
y_k	measured output
Q & R	weighing matrices for states and inputs
Q_t	throughput
OEE	overall equipment effectiveness
α, β, γ	weighting coefficients
p_i	profit per unit of product
A	availability
x_k	system state at time step k
S	sustainability index
w_k, v_k	process and measurement noise vectors

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