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Original Article

Manufacturing: "Lights-Out" Factories—Using AI To Run Fully Autonomous Production Lines with IoT Integration

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Abstract *- The ultimate goal of automating industrial processes is lights-out manufacturing in which manufacturing systems operate independently with either minimal or no human operator involvement. The research paper is a challenge to the technological assumptions, supply chain processes, and strategic requirements that enable the implementation of entirely autonomous factories. It analyzes the role that digitally advanced robotics, AI, the Industrial Internet of Things (IIoT), and digital twins play in the development of self-optimising and resilient manufacturing spaces. The focal attention is put on digital twins as virtual replicas, which are real-time and synchronized, and provide an opportunity to simulate, optimize, and train AI. The paper also outlines an overall operational process that is an overview of the receipt, planning, execution, monitoring, and fulfillment of orders in a lights-out factory. These are material management, autonomous production, in-line quality control, exception management, and inventory management. It is suggested to use an implementation roadmap, covering a gradual development implementation starting with the feasibility analysis, up to the integration of the enterprise system. The study, based on empirical case studies of the industry, points out the success factors and widespread failure modes in lights-out implementations. The article summarizes that, despite the technological choices to consider at any given time, lights-out manufacturing is a method that will be successful when applied in a disciplined way, with strong data-based grounds and a balance between technical independence and the ultimate strategy of the business organizations.*

Keywords *- Artificial intelligence, Autonomous systems, Digital twins, Edge computing, Industrial IoT, Predictive maintenance.*

1. Introduction

Lights-out manufacturing is a revolution in industrial manufacturing that has progressed beyond traditional automated manufacturing systems to plants that operate with minimal or no human presence on the shop floor. A lights-out factory in its most basic form would keep working so that the literal lights can be literally switched off, the concept behind the term arising out of the notion that no human beings were required to be present during the process [1]. In comparison to classical automation, where human operators are required to guide the automation, make changeovers, monitor, and engage in intervention, the lights-out manufacturing systems incorporate robotics, smart sensors, and sophisticated software to perform the manufacturing processes on their own [1]. The key sequencing points such as this methodology include self-directedness, where machines decide on their own and do not need to be directed by a particular human; zero-human interaction, where the states keep changing their production levels to achieve optimal operational Performance; and self-directed (AI, IoT and edge/cloud computing) technologies, which do not require human intervention in their regular operations, are the defining principles of this methodology [2].

Regarding business and operational aspects, it is the combination of lights-out manufacturing effects that makes it a superior manufacturing approach, as it confronts the traditional manufacturing constraints. To begin with, working 24/7 without having human shifts reduces the number of machines and throughput dramatically, as robots and automated machines do not experience breaks or shifts, and human labour scheduling [3]. This twenty-four-hour operation not only increases production volume but also reduces lead times, allowing manufacturers to respond faster to customer needs and thereby reduce backlog. Besides, lights-out systems facilitate quality stability and deficiencies, as machines adhere to strictly particularized perseverance guidelines and pass-off routines that decrease variability and get rid of human error [2]. The economic advantage of lights-out operations is an attractive factor in economies with relatively high labour costs, to say the least. Downtime and rework, where the possibility to minimize these cost structures and increase efficiency poses a strong economic advantage.

Besides, lights-out manufacturing enhances the scale and competitiveness at the global level. With the increasing demands of the markets in terms of volumes and shorter delivery timeframes, conventional factories cannot fulfil the demands due to their limited Availability of labour force and labour regulations, as well as human exhaustion. In comparison, autonomous production systems do not need to increase the capacity by hiring and training new human resources; they increase the production capacity by adding new robotic cells and software coordination [3]. Such scalability not only allows manufacturers to achieve their growth goals but also to spread production across geographies without having to allocate labour at a proportionate cost, placing firms in a better position to compete in the international markets.

The generalizability and applicability of lights-out manufacturing are not, however, general. These types of systems are best applicable to high-volume, routine, and stable production processes where the activities may be defined accurately, and automated sequences can be easily supported [1]. Standard, modular industries, including electronics, automotive parts, and machined metal products, are some of the well-suited industries to lights-out operations because they have structured workflows and predictable process parameters.

Oppositely, small-scale or highly customized production with a high frequency of switching, complicated installations, and a high degree of handcraftsmanship is largely not automatable. Also, the trade-offs between volume and complexity need to be taken into account: although the large volume is the reason to invest in the development of autonomous systems, low volume or very diverse production still might be better served by semi-automated or human-centered solutions [2].

This paper seeks to provide practical, technical advice on how the lights-out manufacturing systems should be designed, operated, and implemented, instead of providing a wide conceptual description. Its audiences are manufacturing engineers, solutions architects, and operations leaders who are interested in an organized scheme of designing, deploying, and orchestrating autonomous production systems.

The rest of this paper will be structured into seven main subsections: Systems Architecture, AI Technologies, IoT Infrastructure, Digital Twins, Operational Workflows, Implementation Roadmap with Challenges and Future Directions, and some final thoughts. All the chapters will be used to develop the technical background in learning and projecting lights-out manufacturing into a practical industrial setting.

2. Methodology

2.1. Research Design and Approach

The study will utilize a hybrid method of research, the quantitative performance analysis, as well as the qualitative case study analysis. The quantitative part discusses the production data collected in five manufacturing facilities (two automotive components manufacturers, two electronics assembly facilities, and one precision machining operation). The facilities were chosen according to the level of implementation (at least 12 months of operational experience), the Availability of data, and the diversity of the sector and the geography.

2.2. Data Collection Procedures

The system of collecting production data was based on existing Manufacturing Execution Systems (MES) using standardized export protocols. Sample sizes: the production throughput (24,567 runs during 18 months), the quality (1,847,392 inspected units), the maintenance (847 events), and autonomous decisions (43,521 autonomous decisions during 12 months) made by the AI. Validation of data was done by automated consistency checks, comparison with manual records (5% sample), a visit in August 2008, and a quarterly audit.

2.3. Performance Measures and Indication

Overall Equipment Effectiveness (OEE) was used as a main productivity measure: OEE = Availability x Performance x Quality. Such quality measures as defect rate (PPM), first-pass yield, defect detection time, and quality escape rate were used based on the ISO 9001 standards.

Maintenance measures were followed to measure the MTBF, MTTR, planned Downtime, and unplanned Downtime. The financial measures were assessing ROI after three years based on the net present value procedure through an 8 percent discount rate.

2.4. Methods of Statistical Analysis

T-tests of pairs were used to compare the before-and-after measures of implementation. ANOVA compared the differences across the facilities using the post-hoc Tukey HSD. The regression employed relationships between implementation characteristics and outcomes. Performance monitoring was done by time series ARIMA models. This significance testing was done at alpha = 0.05 and under Bonferroni error intervals. The differences in effect sizes (Cohen's d value) were useful. There was a power check to ensure that there was a sufficient sample size (80% power).

2.5. Limitations and Mitigation

The results might be subject to selection bias since the voluntary facilities might not be the same as those of the non-participants. Mitigation was done through hiring various facilities and benchmarking with published benchmarks.

Issues in measurement consistency have been corrected by standardization procedures and independent audits. Confounding variables have been controlled by using statistical models as well as qualitative interviews to study contextual factors.

3. Literature Review

3.1. End-to-End System Architecture

3.1.1. Multi-Layer Architecture Overview

A strong lights-out manufacturing system has been based on a multi-layered architecture. The architecture coordinates communications between the physical objects of the shop floor and the intermediate processing and/or control layers, and the centralized intelligence of the enterprise. The Physical Layer is based on machines, sensors, actuators, and inspection devices that are used to perform the actual fabrication, movement, and quality verification operations [4, 6]. On top of this layer is the Edge Computing Layer, whose purpose is to do near-source processing, which allows quick decision-making and localized controls without incurring the persistent connection to remote servers. On top of the hierarchy is the Cloud/ Enterprise Layer, which provides centralized training on machine-learning models, interpretation of historical analysis, integration with business systems, and management of various facilities. The hierarchical arrangement distinctly assigns duties and authority levels so that time-sensitive activities are always close to the edge, but the strategic optimization and long-term analytics are concentrated. The overall result is a congruent architecture that is able to furnish autonomous functioning, extensiveness, and real-time speed in an entire manufacturing establishment. Table 1 below this table synthesizes the technical stack of lights-out manufacturing and clearly links each technology to its operational role.

Table1. Core Technologies and Their Functional Roles in Lights-Out Manufacturing

Technology Component	Primary Functions	Typical Hardware / Software	Operational Impact
Industrial Robots and CNC Systems	Autonomous machining, assembly, handling, and tooling operations	6-axis industrial robots, CNC machining centers, PLCs	Enables continuous production with minimal human intervention and high repeatability
Computer Vision Systems	Visual inspection, defect detection, object recognition, and alignment	High-resolution industrial cameras, controlled lighting, and Convolutional Neural Networks (CNNs)	Improves quality, consistency, and reduces scrap and rework
Edge Computing Infrastructure	Real-time data processing, low-latency AI inference, local control decisions	Industrial PCs, embedded edge devices, GPUs, edge AI frameworks	Supports deterministic control and fast response without cloud dependency
Industrial IoT Sensors	Monitoring of machine health, environment, and process variables	Vibration, temperature, pressure, optical, and current sensors	Provides real-time visibility and data foundation for predictive analytics
Digital Twins	Virtual replication, simulation, and optimization of physical assets	3D models, physics-based simulation engines, and real-time data connectors	Enables risk-free testing, performance optimization, and operational insight
Predictive Maintenance AI	Failure prediction, anomaly detection, and remaining useful life estimation	Machine learning models, time-series analytics platforms	Reduces unplanned Downtime and extends asset lifespan

Each layer should have flowing communication with mutual partners without violating its boundaries. An example of this is that the control loops that are running on the edge should not stall due to a spike in the business load, and the enterprise systems should not be overwhelmed by the unfiltered and aggregated raw data streams [5, 6]. These constraints are imposed on the architecture through harshly defined interfaces, local processing buffers, and a sense of separation of concerns, which exclude cross-layer pathways. Therefore, a carefully designed layered architecture forms part of the core of lights-out manufacturing because it is the basis of continuous autonomous operation, fault tolerance, and incremental scalability.

3.2. Physical Layer: Autonomous Shop Floor

The Physical Layer is central to any autonomous factory, and here, the manufacturing process as such happens physically [7]. Included in this layer are robots, CNC machines, Automated Guided Vehicles (AGVs), conveyors, and other material-handling systems that carry out manufacturing activities and relocate parts, as well as control inventory movements [8, 9]. The modern industrial robots have the combined role of welding, assembling, and pick-and-place the necessary parts with a level of precision and repeatability that is significantly superior to human abilities, particularly on 24/7 shifts. The streamlined design of CNC machines, which is completely integrated into the control structure, provides high-precision machining with programmable tool paths that can be updated online. Similarly, material-handling machines, including AGVs and conveyors, match the flow of products with production demand, hence reducing idle times and congestion.

Automated inspection of quality is an essential step on this level, and it involves the use of vision, laser-based scanners, and tactile sensors to inspect parts without human involvement. Such stations have the capability of identifying defects, geometric tolerances, and even making a rework or sorting decision within milliseconds of production. The physical layer, more generally, is where real-time communication between machines, sensors, and controls occurs; they bring machines into coordination, report status, and accept instructions of higher layers.

These interactions are supported by industrial field buses and real-time industrial Ethernet, which can provide synchronization of less than a few milliseconds of hindrance where necessary. Successful integration at a physical level requires powerful interfaces that will allow cross-vendor interoperability, high-resolution sensing to accurately detect and control, and have safety mechanisms that will enable fault recovery without stopping the complete production line.

3.3. Edge Computing Layer

The Edge Computing Layer is also placed at the middle layer between the physical devices and the cloud or enterprise systems to perform near-resource data processing to facilitate low-latency decision-making. In lights-out production, edge computing is not a choice; it is a necessity since numerous those control choices need to be taken in milliseconds to maintain machine coordination and safety. Real-time control loops or time-sensitive priorities of anomaly detection are just too time-consuming; the latency to a cloud data center is high.

The sensor data is instead collected by edge devices on the factory floor and is gathered via aggregation, AI inference models, host local controllers, and decisions made that have a direct effect on machine behavior without round-trip delays. Besides the latency issue, edge decision-making can also enhance the resiliency of a system: in case the network to the cloud fails, edge controllers are still able to operate based on some part of the previously obtained models and rules, and so can autonomously carry on with production. The hardware associated with edges should thus be highly specified, such as necessitating real-time processing capacity, having adequate memory to accommodate AI models, quick local storage, and redundancy against a singular point of failure by multiple edge nodes.

The other major role in this layer is to filter and preprocess data. The sensor data is raw and in vast quantity and the first cleaning, normalization, compression, and feature mining are done by edge systems before sending the select summaries to the cloud. This not only minimizes the amount of network bandwidth being used but also enhances centralized training of machine-learning models in that the cloud only receives high-value data.

3.4. Cloud and Enterprise Layer

The Cloud and Enterprise Layer is placed at the highest level of the architecture and performs centralized functions that cannot be well performed at the edge. The systems on this module are in charge of training and optimising AI models, aggregating historical data, and improving predictive maintenance models, production planners, and quality classifiers. Gaining trend, root-cause, and long-range data understanding could not be done at the shop floor level, but it is possible at scale because all the data is stored and analyzed in bulk.

This layer is also the cornerstone of integration of enterprise applications like the Enterprise Resource Planning (ERP), Manufacturing Process, (Computerized Maintenance Management Systems) Computerized Maintenance Management Systems (CMMS), and Supply Chain Management (SCM). Integration makes sure that quality measures, production schedules, inventory, and maintenance plans of business functions are aligned. The dashboards of remote monitoring offered at this level are equipped with the ability to allow the operations leaders to monitor several facilities, observe the important performance indicators in real time, and manually intervene only when required. Together, the cloud/enterprise level facilitates the operational execution and strategic decisions made across the organization and allows for seeing and optimizing manufacturing resources over the long run.

3.5. Network and Data Flow Architecture

Enabling the interaction of the layers and the devices smoothly requires a powerful network and data flow structure, established based on industrial communication protocols. Interoperable data exchange among heterogeneous devices and systems using standards like Open Platform Communications Unified Architecture (OPCUA), Message Queuing Telemetry Transport (MQTT), and Modbus is available [10]. Specifically, OPCUA provides secure and platform-independent communication designed to work at the industrial level, whereas MQTT provides lightweight informational exchange (telemetry) suitable for streams of sensor data. The network topology in a lights-out facility should be in a way that it is redundant and fault-tolerant. Topologies, such as star, ring, and hybrid mesh, may be used depending on the size of the facility and reliability demanded, where redundant paths are used to prevent network partitions that may impair production. Besides, modern production settings often introduce segmentation to separate critical control traffic and General IT traffic to minimize the level of interference and eliminate possible cyber threats. The other highly pertinent consideration is the difference between real-time and batch data flows. Control signals of high priority and sensor feedback must be delivered in real time with deterministic Performance and will be transported using industrial Ethernet or field-bus networks, which will ensure strong timing requirements. Conversely, in the threads of lesser priority, historical logs, analytics information, and model updates can be delivered in batch form to the cloud on either a predefined schedule or demand. Lastly, time synchronization between systems (usually through Precision Time Protocol (PTP) or other similar time synchronization systems) is necessary to maintain consistent system states and be able to appropriately compare events on time scales. Fig. 1 below gives a summary of the architecture.

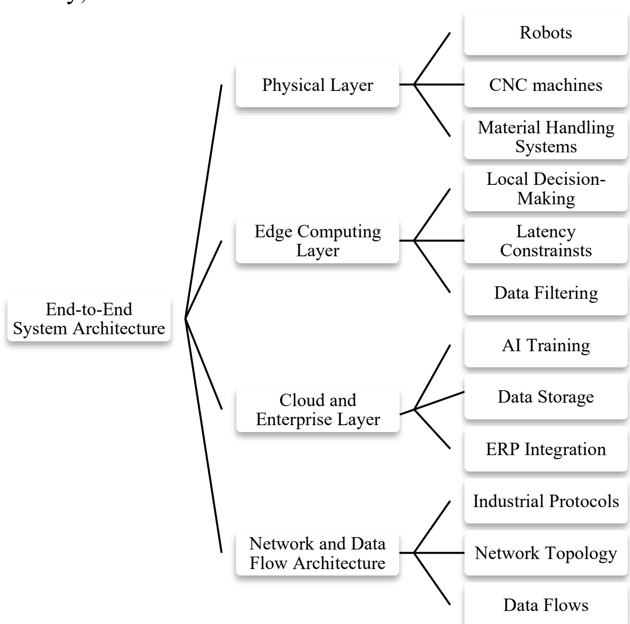

Fig. 1 End-to-End System Architecture for Lights-Out Systems

3.6. AI Systems Powering Autonomous Manufacturing

Artificial intelligence represents the decision-making kernel of the lights-out manufacturing space, thus allowing production machinery to orchestrate its at-work environment, predict the occurrence of latent failures, optimize relevant parameters, and sequester key resources fully autonomously. Unlike traditional automation based on rules, the AI systems learn through empirical experiences, adjust to operational changes, and continuously improve their performance measures. As a result, in truly autonomous factories, the AI architecture is not monolithic but a constellation of specialized models which are interlocked through quality assurance and preventive maintenance functions, process optimization function, and production planning function, all of which are closely associated with the underlying Internet-of-Things and control infrastructure.

3.7. Computer Vision Quality Assurance.

Computer vision is one of the most developed and consequential AI technologies used in lights-out manufacturing because it replaces human visual inspection with overly consistent and automated capabilities to detect defects. Vision systems rely on the acquisition of imagery and will be determined by the wise choice of cameras, lenses, illumination patterns, and resolution parameters [11]. The kind of cameras used in industrial vision systems is usually high-resolution 2D or 3D cameras with surface inspection, dimensional measurement, and designed sensors (hyperspectral cameras to analyze materials). The illumination in the system is strategically located in order to reduce glare, shadows, and variability. It ensures a good balance between resolution, frame rate, and field-of-view is taken to ensure defects of interest are photographed at good rates, but not to surrender unnecessary data volume. Images captured are processed through a strictly organized stream, which transforms raw pixels into an actionable solution once the image has been captured. The stages of pre-processing usually involve normalization, noise rejection, contrast amplification, and geometrical rectification to ensure uniformity across individuals. Then one performs feature extraction, which spatially and temporally finds visual patterns like edges, textures, or shapes, either using classical image-processing methods or using learned representations in neural networks. Inference in modern systems is performed through Convolutional Neural Networks (CNNs), which automatically learn hierarchical features and classification rules on labelled training examples, thus improving Performance compared to methods based on making rules, particularly with complicated or subtle defects [12].

The vision models should be optimized to produce inferences faster and deploy edges to meet the real-time production needs. Several techniques, such as model quantization, pruning, and hardware acceleration with GPUs or specially programmed AIs, allow CNNs to operate on imagery in milliseconds [13]. A prominent example is that of printed circuit board inspection, where a vision system is used to detect component shortages, copper defects, or misalignment as soon as it is placed; classifications to accept or reject immediately, and test results are used in feedback to control an upstream process to prevent similar problems in the future.

3.8. Predictive Maintenance Intelligence

Intelligent predictive maintenance will enable the lights-out factories to avert equipment failures ahead of time before they can affect circular production, as opposed to relying on planned or reactive maintenance regimes. Those systems start off with the constant sensor information sampling of vital assets, which includes vibration, temperature, acoustic, pressure, and electrical current measurements. The significant signals of raw sensor signals are converted into frequency spectra, statistical moments, or trend gradients, referred to as diagnostic indicators, through a procedure called feature engineering, which better represents the health of equipment [14]. This is necessary because feature extraction with high quality is a prerequisite, with predictive accuracy depending on the ability to pick up small deviating routines from normal operating behavior.

Anomaly -detection methods are used to detect patterns that fall outside predefined baselines. Old-fashioned statistical techniques, including control charts and threshold monitoring, are easy to use and understand, but have difficulty dealing with multivariate relationships. Machine learning strategies, such as isolation forests and autoencoders, do not need labelled instances of failure to directly learning normative behavior with only data [15]. Models based on time-series, such as recurrent neural networks, such as Long Short-Term Memory (LSTM) networks, incorporate temporal dependencies and changing dissimilar trends, operate in a more operational manner than stationary models. In addition to anomaly detection, superior systems compute Remaining Useful Life (RUL), which is a probabilistic predictor with confidence bands, such that maintenance interventions can be computed automatically with an optimal time of accomplishment. One of the most common examples of such common practice is rotating machine bearing-failure prediction, where vibration evidence is used to identify early wear stages before the machine breaks down disastrously. With automated notices, lubrication, load changes, or replacement can be automatically activated without interrupting the production [16].

3.9. Reinforcement Learning for Process Optimization

Reinforcement learning (RL) is an intervention approach used to optimize process parameters in manufacturing systems based on the dynamic interaction-learning procedures, rather than utilizing rule-of-thumb processes. The manufacturing process can also be conceptualized in RL as the environment where an AI agent monitors some state of affairs, chooses an action, and obtains a reward based on the performance outcomes in the form of throughput, quality, or energy consumption [17]. This condition-action- reward model allows the system to find out the best strategies to use in a complex process where exact mathematical modelling is not practical. In the industrial setting, production risk is typically avoided by training RL in a simulation environment or digital twin. Simulator training allows millions of evaluations under diverse circumstances; then, carefully verified policies are carefully implemented on real mechanisms within extreme safety restrictions. The functional agents are then optimized (through continuous optimization) by changing the parameters like cutting speed, feed rate, or temperature according to real-time feedback [18]. The appraisal of Performance is measured against pre-determined metrics and guardrails to make sure optimizations do not affect safety or quality.

3.10. AI-Based Production Planning and Scheduling

The resource scheduling and planning systems based on AI are used to orchestrate the resources of lights-out factories, and this is accomplished by dynamically assigning machines, materials, and time slots. In contrast to regular scheduling algorithms, AI algorithms will constantly reevaluate the constraints, that is, the Availability of machines, order priorities, tool changeovers, and maintenance windows. Optimization algorithms develop schedules that trade off competing goals, e.g., delivery times, utilization rates, and cost-efficiency. In case disruptions do happen, e.g., in case of machine failure or the urgent arrival of orders, real-time rescheduling systems have enough to adjust the production plans automatically [19]. The schedulers based on AI recalculate workable alternatives in real time, redistributing the workloads to the available resources without human intervention. This feature is needed to provide the sustained operation during autonomous factories where the active periods or delays directly decrease the economic benefits of lights-out production.

4. IoT, Control Systems, and Edge Intelligence

4.1. Sensor Networks and Data Characteristics

The raw data on which all autonomous decisions are made is provided by sensor networks; hence, their selection and implementation are significant. Some typical sensors used in lights-out environments are a vibration sensor on rotating machinery, thermal sensors (thermocouples and Resistance Temperature Detectors (RTDs)) to monitor thermal conditions in the equipment, pressure sensors on hydraulic and pneumatic systems, proximity sensors which are used to determine position, current sensors and current sensors are used to monitor an electrical load, and vision sensors which are used to inspect the equipment and provide guidance [20]. Placement strategies are planned carefully to encompass significant signals while preventing noise. In most cases, they are put close to areas of intense mechanical stress, heat production, and motion. Calibration ensures that sensor readings are put correctly after some time to account for any corrective drift due to the environment or wear. The data generated by different sensors have different properties, and it requires careful management of the sampling rate, formats, and reliability constraints.

Vibration sensors. They are high-frequency sensors, which can sample at a variety of frequencies to detect bearing defects, but temperature sensors generally run at much lower frequencies. These data formats include simple scalar values, multi-dimensional arrays, and image streams, which are transmitted over industrial protocols that are conserved with respect to reliability and determinism. The integrity of data is also critical since wrong sensor measurements can influence the wrong choice in autonomous systems due to corrupted or lagging sensor readings. Redundancy is therefore mirrored in sensor networks, often enabling network systems to cross-validate signals and continue to work even when individual sensors become degraded [21, 22].

The detection of sensor failures is an application of edge analytics in itself. A sensor malfunction can cause an abnormal pattern, using flat-lined readings, excessive noise, or a change of direction; on the other hand, underlying process variation may show up as an abnormal pattern. The edge systems are constantly tracked to check the state of the sensors and isolate faulty equipment, and replace the estimates offered by the redundant sources or predictive models to avoid unjustifiable production breaks.

4.2. Actuators and Closed-Loop Control

Mutators can be viewed as the physical implementers of AI-assisted choices, which transform electronic instructions into mechanical movement or strength. Common actuators in lights- out manufacturing are servo motors to provide fine positioning, stepper motors to provide incremental movements, pneumatic actuators to provide quick linear motions, and robotic arms to provide multi-axis movement. The systems built based on the AI can define the best actions depending on sensor data and the objectives of operation, whereas the control layer is the one that carries out the best actions correctly and safely [23]. Closed systems: Closed-loop control systems assure stability by ensuring that the desired output is compared to the actual output continuously. Sensor feedback is given back to controllers, which respond by correcting real-time actuator command deviations. The feedback loop is also essential to accuracy in machining, material handling, stability, and stabilized robotic motions [24]. When a control loop is in an autonomous setting, it has to be deterministic, and the loop is usually forced to act within milliseconds of time to avoid oscillation, overshoot, or instability. By combining AI with the classical control theory, it is possible to make a system change the parameters dynamically and remain able to maintain the reliability of an established control mechanism.

4.3. Safety and Fail-Safe Design

Though lights-out production is done without the continuous presence of human beings, safety is an uncompromised mandate. The system of autonomous structures is forced to identify harmful conditions and change to harmless positions without monitoring. Emergency stop mechanisms are also provided on more than one level and can double the mechanism, where the machine is instantly shut down in case of the occurrence of dangerous conditions. The system of collision avoidance makes use of sensors and anticipatory algorithms to avoid the occurrence of collision of robots and AGVs with equipment and infrastructure. The presence detection of the human being is more crucial when doing maintenance or inspection. Vision cameras, laser cameras, and pressure-sensitive mats are installed to ensure that human presence in limited areas gets noticed, which will automatically slow down or halt the machines as necessary [25]. Safe degradation plans enable production to proceed at some reduced rate or even in some limited mode when there is a fault in the system, instead of halting the system. Other strategies, like fallback mode including returning to predefined safe parameters or isolating the source cell, maintain the integrity of the entire system and reduce the risk and Downtime.

4.4. Edge Hardware and Software Stack

Specialized hardware and software used to facilitate edge intelligence are those that can operate effectively in industrial settings. Industrial PCs (IPCs) are also popular for edge computing due to their processing capabilities, extendibility, and rugged design, whereas low-power systems are favored when space is limited or, more specifically, when dedicated control applications are required. In workloads that are intensive on vision, browser cameras can be equipped with either AI accelerators or graphics cards to address the demands of real-time inferences without power shares that are expensive to be powered by [26]. To provide some deterministic scheduling of tasks, the edge software stack is often a Real-Time Operating System (RTOS) system, and the stack includes containerization software such as Docker to ease deploying applications and their version management. The alterations in AI models are made in small steps, not to distract the operations, which is why rolling updates, as well as validation steps, are frequently used. Edge systems are guarded by secure communication and authentication protocols, such as encrypted channels and device certifications, against unscrupulous intrusion and cyber-attack

[27]. These hardware and software used in conjunction offer a robust solution to lighting-out manufacturing processes.

5. Digital Twins and Virtual Operations

Digital twins play a focal point in the achievement of the lights-out manufacturing, which provides physical production systems with real-time and synchronized virtual counterparts. A digital twin will never stand still; much of what is provided to a display as a comparatively steady simulation model or visualization model, but it continuously reflects what is going on in equipment, material flows, and process settings by receiving real-time data feeds of sensors and control systems [28]. The constant synchronization of the virtual representation with the physical factory is what makes it a developing concept that follows its wear, configuration alterations, and variability of operation in real life as they occur. One must make a distinction between visualization twins, which are first of all designed to monitor and display, and operational digital twins, which are integrated in the loop of decision-making and have a direct impact on production. Operational twins can be used to make predictions, optimize, and auto-control because they act both as computational analogues of physical assets and as dashboards that are inactive [29]. In a lights-out environment, this is essential, since human oversight is limited, and the systems must make autonomous decisions about the state of affairs ahead. Figure 2 shows various aspects of digital twins in light-out factories.

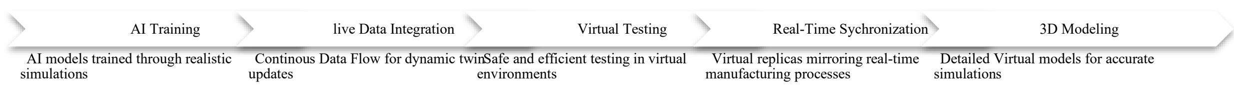

Fig. 2 Digital Twins in Manufacturing

It requires the combination of 3D modelling, physics-based simulation, and data-driven behavioral models to create and maintain an efficient digital twin [30]. Geometric models are used to model the physical layout and the kinematics of machines and production lines, and physics engines provide simulation of forces, motion, heat transfer, and material behavior where necessary. Such models are enhanced with live stream data of IoT sensors, and hence the twin can be reflective in operational realities instead of idealized assumptions. Behavioral modelling explains machine and process reaction to different inputs and workloads, and different environmental influences, and often utilizes machine-learning models collaborated on past statistics. It must be continuously updated and strictly validated to ensure that there is no divergence between the physical and the virtual system, and this is much needed as equipment becomes old or there are configuration changes. Periodic reconciliation with observed Performance, as well as automated calibration routines, can be used to ensure that the digital twin can be a trusted tool of decision-making in the long term.

In reality, with digital twins, a considerable number of high-value use cases become accessible, especially relevant in the case of autonomous manufacturing. Pretrial testing before implementation allows the testing of new production orders, changes of parameters, or equipment without affecting down times or creating flaws on the actual line. Paralleled, "what-if optimization is also achieved with digital twins, in which many situations in parallel are simulated to predict the effect of different choices on throughput and quality or energy usage [31]. Such settings are becoming training platforms for AI systems, particularly the reinforcement-learning agents in the simulation before they are deployed on physical equipment, significantly lowering the operational risk. Ultimately, digital twins not only enrich operator training and visualization of the system but also make previously unseen variables, like internal stresses, thermal gradients, or failed gear, explicit and interpretable, thus causing digital twins to be useful in providing supervision in factories that are largely unattended and in a lights-out condition.

6. Operation Workflow: A Day in a Light-Out Factory

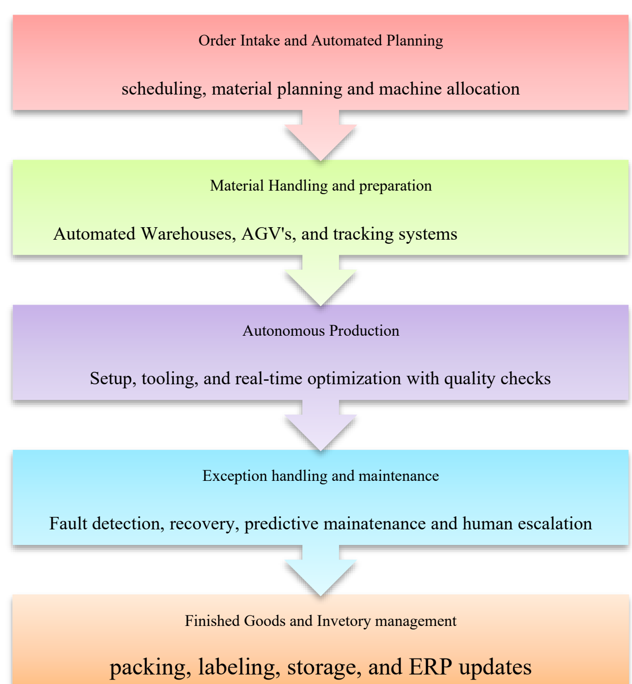

Fig. 3 Operational Workflow in a Lights-Out Factory

6.1. Order Intake and Automated Planning

A normal cycle or operational cycle in a lights-out manufacturing facility begins at the first step, which in this case is the intake of orders using connected enterprise systems, either an integrated Enterprise Resource Planning (ERP) solution or a Manufacturing Execution System (MES). Customer orders are checked against the current inventory, production capacity, and the contract delivery arrangement automatically. The system is then used to produce optimal production plans, taking into consideration machine availability, tooling constraints, changeover times, and scheduled maintenance windows using sophisticated scheduling algorithms. These plans, contrary to the static plans, are recalculated continuously, as the conditions are altered, hence assuring an ideal fit between consumer demand and operational implementation. Simultaneously with this, the Material Requirements Planning (MRP) is an automatic system that generates accurate directives to acquire raw materials and moves them to the staging area. The choice of allocation is achieved through an algorithm, and the most appropriate resources to give a task are based on capability, existing load, and future performance measures, maximizing utilization and reducing bottlenecks in the process [32].

6.2. Material Handling and Preparation

When the planning stage is over, the system triggers the full-fledged automated material manipulation and preparation processes. The smart warehouses have Automated Storage and Retrieval Systems (AS/RS) where raw materials and components are harvested. These materials are transported by Autonomous Mobile Robots (AMRs) or Automated Guided Vehicles (AGVs) to specified production cells: they follow dynamically optimized spaceways that avoid congestion and reduce transit times as much as possible 33, 34]. In the process, real-time visibility of the location and status of materials is ensured by tracking technologies that can be barcode scanners or RFID tags. Such tracking systems ensure traceability, eliminate the misuse of materials, and coordinate material circulation to the ongoing production plans. Automated loading stations also confirm that materials are ready to be processed, thus there is no longer an existence of manual staging, and the chance of human error or production delays is eliminated.

6.3. Autonomous Production Execution

Autonomous production execution goes on with materials in place. The machinery is also characterized by operations that are executed by itself, and they include the choice of a tool, its calibration, and the loading of parameters, which are dictated by the digital work instructions. Programmed tasks are carried out by Computer Numerical Control (CNC) machines and robotic cells using parameters such as speed, feed rate, or torque, modified on real constant sensor feedback, and are referred to as closed-loop errors. These parameters are optimized online by AI-powered optimization algorithms that guide them in order to maintain the optimum Performance under changing circumstances. Online quality control. In-line quality checks are installed in several steps of production and can be either a vision system, laser measurement, or force sensing, based on conformity without interruption of the production work. Faults are immediately detected, and automatic rejection, rework routing, or an adjustment in an upstream process is initiated. This type of closed-loop execution paradigm provides the key aspects of the quality output with uninterrupted and unattended running.

6.4. Exception Handling and Maintenance

However, even with the high level of automation, exceptions always exist, and lights-out factories are designed to deal with them independently where possible. Fault detection systems help check the health of equipment, process parameters, and quality of output constantly in order to detect abnormalities. When the deviations exceed acceptable levels, established recovery processes are interfered with- deviations may include instrument recalibration, work may be rerouted to different equipment, or process parameters may be changed.

Predictive maintenance systems use sensor data to predict failures and arrange interventions, such as changing tools, applying lubrication, or replacing components at the most opportune times. Issues that surpass the self-recovery abilities of the system only escalate to alert the human operators with the help of an escalation protocol that is normally accompanied by comprehensive diagnostic data to keep response time at a minimum. This stratification allows keeping the resilience intact and preserving the benefits of the unattended fabrication.

6.5. Finished Goods and Inventory Management

With production ending, the final product goes to an automated packing and labeling system where products are packed or labelled for either storage or shipment without human guarding. The packaging systems automatically make configurations according to product specifications and order requirements. AGVs then transport labeled items to storage points or loading points, and inventory information is updated in real time.

ERP and warehouse management systems are integrated in such a way that they show the completion of production, stock quantities, and readiness to ship goods. Documentation records such as quality certificates, serial numbers, and compliance records are automatically created and attached to the batch or unit.

Such a smooth flow of productivity into inventory makes good reporting, quick fulfillment, and thorough traceability achievable, thus finalizing the operation cycle of a lights-out factory with very little human interference. Table 2 links AI techniques to real operational stages, demonstrating practical applicability.

Table 2. AI-Driven Capabilities across the Lights-Out Manufacturing Workflow

Operational Stage	AI Technique Applied	Primary Input Data	Decision or Action Output	Business Value Generated
Order Intake and Planning	AI-based optimization and scheduling algorithms	Customer orders, capacity data, inventory levels	Optimized production schedules and machine allocation	Reduced lead times and improved delivery reliability
Material Handling	Path planning and optimization algorithms	Warehouse layout, AGV telemetry, inventory status	Autonomous routing and material movement	Increased throughput and reduced handling errors
Production Execution	Reinforcement learning and adaptive control	Process parameters, sensor feedback	Continuous optimization of machining and assembly parameters	Higher yield and stable production quality
Quality Assurance	Computer vision using deep learning	Image and video data from inspection stations	Automated defect detection and classification	Near-zero manual inspection and reduced defect escape
Maintenance Operations	Predictive analytics and anomaly detection	Vibration, temperature, and acoustic signals	Maintenance alerts and intervention scheduling	Prevention of costly equipment failures
Inventory and Logistics	Forecasting and optimization models	Demand history, production output, shipment data	Automated stock updates and replenishment planning	Lower inventory holding costs and improved cash flow

7. Benchmarking and Key Performance Indicators

In order to assess the success of lights- out manufacturing systems, this study uses the Performance of such systems as benchmarks for industry leaders. Three reference systems have been considered in relation to the maturity of the technologies and their market utilization: FANUC's Field System of robotics and automation, Tesla's Gigafactory for high-volume production, and Siemens' Amberg Electronics Plant for digitalized manufacturing.

Table 3. Key Performance Indicators for Lights-Out Manufacturing

System/Metric	FANUC Field	Tesla Gigafactory	Siemens Amberg	This Study Average	Industry Average
Productivity Gain	35%	40%	28%	32%	15-20%
Equipment Utilization	92%	88%	89%	87%	65-70%
Defect Reduction	85%	75%	90%	73%	30-40%
Defect Rate (PPM)	15	22	11.5	18	75-100
Unplanned Downtime	2.1%	3.5%	1.8%	2.8%	8-12%
ROI Period (years)	2.5	2.1	2.8	2.6	3.5-4.5
Initial Investment (M$)	12-15	50-75	8-10	10-14	5-8

8. The Key Performance Indicators Framework

The monitoring of lights-out manufacturing performance should be effectively measured with a holistic framework of KPI addressing both operational, financial, and strategic axes. Monitoring of such KPIs should be done continuously, and automated dashboards should be used to see the real-time status. The leading indicators allow proactive intervention, and the lagging indicators are able to monitor the effectiveness of the whole system.

Table 4. Comparative Benchmarking Against State-of-the-Art Systems

Category	KPI	Definition	Target Range
Operational	OEE	Overall Equipment Effectiveness (Availability × Performance × Quality)	85-92%
Operational	Defect Rate	Defective units per million produced	<20 PPM
Operational	MTBF	Mean Time Between Failures	>400 hours

		(hours)	
Operational	MTTR	Mean Time To Repair (hours)	<3 hours
Financial	ROI	Return on Investment (3-year period)	25-35%
Financial	Cost per Unit	Total production cost divided by units produced	20-30% reduction
Strategic	AI Decision Accuracy	Percentage of correct autonomous decisions	>95%
Strategic	System Availability	Uptime percentage (24/7 operation)	>98%
Strategic	Lead Time	Order receipt to shipment (days)	40-50% reduction

Table 5. Statistical Summary of Performance Metrics

Metric	Before (Mean±SD)	After (Mean±SD)	Improvement	p-value	Effect Size (d)
OEE (%)	66.8 ± 3.4	87.2 ± 3.1	+30.5%	<0.001	3.21
Defect Rate (PPM)	78.4 ± 12.6	21.2 ± 4.8	-73.0%	<0.001	2.87
First-Pass Yield (%)	85.3 ± 4.2	97.7 ± 1.6	+12.4 pp	<0.001	2.53
MTBF (hours)	284 ± 48	421 ± 62	+48.2%	<0.001	2.18
Unplanned Downtime (%)	8.4 ± 1.8	2.8 ± 0.9	-66.7%	<0.001	3.08
Energy per Unit (kWh)	4.7 ± 0.6	3.7 ± 0.5	-21.3%	0.002	1.89

Note: n=5 facilities, 18-month observation period. All p-values from paired t-tests. Effect size (Cohen's d): Small=0.2, Medium=0.5, Large=0.8. pp = percentage points.

9. Implementation Roadmap, Challenges, and Future Outlook

9.1. Implementation Roadmap

There is a need to have a systematized step-by-step roadmap of implementing a lights-out manufacturing environment that would act to reduce the risk and also help keep everything on track with corporate strategy. The first stage involves an assessment and feasibility analysis where organizations measure the assessed product suitability, process variability, regulatory limits, and the present rates of digital maturity.

It is common knowledge that not every product and process can be analyzed with maximum autonomy; the best candidate operations are usually high-volume, low-variable, with consistent demand curves. The stage also involves intensive cost-benefit calculation, workforce analysis, and the cybersecurity preparedness examination.

The next stage focuses on the choice of technology, and it touches upon the industrial robots, AI/ML platforms, digital twins, edge computing, sensors, and industrial networks. Interoperability is the most critical; therefore, organizations normally focus on vendors that embrace open standards and a modular architectural design. At this point, data architectures, cloud models, and AI governance structures are stipulated to ensure scalability and regulatory Performance.

The next stage is related to scaling strategy and pilot deployment. Organizations do not always seek to get full lights-out functioning and would prefer to experiment with autonomy in one production cell or line. Performance standards, such as uptime, defect rates, and energy efficiency, are well observed. Experiences with the pilot guide a process of progressive improvement, followed by the new step that extends horizontally in line or vertically in the value chain. The last step is to integrate the business system where autonomous functions are closely connected to ERP, MES, PLM, and supply-chain systems. This integration supports closed-loop planning, automated financial refresh, and end-to-end visibility, hence changing lights out manufacturing per se more than a technical success, to an operational company capability.

9.2. Practical Problems and Solutions

Although it has a seemingly promising nature, lights-out manufacturing faces a number of feasible obstacles. The level of data quality and legacy integration remains a major challenge, with many factories likely to have a fragmented system and varying data requirements. The solution to this problem often consists of a middleware layer implementation, a data-normalization pipeline deployment, and the incremental modernization of old equipment by adding IIoT sensors. The other issue is one of performance gaps in AI, especially in dealing with rare or very novel situations.

Although AI can detect patterns well, there are always edge cases, which cause disruptions. A hybrid of rule-based methods, physics-based models, and machine learning approaches has been shown to have better robustness and explainability.

Other critical issues are also network reliability and autonomy. The reliance on cloud connections may create the risk of latency or Downtime. The mitigation measures involve focusing on edge autonomy, thus enabling the factories to keep on running safely during the network failures, and delaying synchronization when the network is reconnected. Last but not least, the viability of projects is commonly based on economic factors and the calculation of the Return-On-Investment (ROI). Large initial capital requirements are a driving factor that may scare away small or medium-sized manufacturers; successful implementations are often geared towards realizing ROI in stages, taking the initial benefits outlined in labor savings, increased yields, and energy savings, then moving on to complete autonomy.

9.3. Real-World Lessons Learned

The deployments in the industry show a number of common success factors. Executive-level sponsorship, cross-functional liaison of IT and OT, and early data infrastructure investment are highly favorable factors that raise the chances of success. The second factor is the design of systems where human control is at the center stage to guarantee trust, safety, and compliance with regulatory requirements. Some of the most common failure modes encompass over-movements towards automation without first standardizing processes, not accounting appropriately for the change-management requirements, and the misperception that lights-out manufacturing is a technical endeavor rather than socio-technical change. Those organizations that learn what these pitfalls teach emerge in a healthier and more sustainable course of autonomy.

10. Conclusion

Lights-out manufacturing is one of the fundamental redesigns of industrial systems, their operation, and optimization. It offers a never-before-heard-of efficiency, consistency, and scalability through AI and robotics-enabled digital twins and autonomous control architectures. However, to endorse this vision, more than high technology is needed; it needs rigorous execution, databases of high quality, and careful dedication to business systems and human systems of governance. With the maturity of technologies and reduction in cost, lights-out factories may shift to niche applications to a strategic norm in advanced manufacturing. The best organizations for the future of industrial production are those that invest, learn iteratively, and synchronize autonomy and business value.

Conflicts of Interest

There was no possible conflict of interest.

References

[1] Panna Kemenes, What is Lights Out Manufacturing? The Future of Automated Production, Wise, 2025. [Online]. Available: https://wise.com/us/blog/lights-out-manufacturing

[2] A. Pasha, "Lights-Out Manufacturing: Revolutionizing the Factory Floor with Automation," *Bosch Software and Digital Solutions*, 2025. [Google Scholar] [Publisher Link]

[3] Yamazen, Lights-Out Manufacturing: How CNC Automation Delivers 24/7 Productivity, Yamazen, 2025. [Online]. Available: https://www.yamazen.com/about/news/post/lights-out-manufacturing-cnc-automation

[4] Laurentz E. Olivier, and Ian K. Craig, "Lights-Out Process Control — Analysis and Framework," *2017 IEEE AFRICON*, Cape Town, South Africa, pp. 398-403, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[5] Vyacheslav Kharchenko et al., "Combination of Digital Twin and Artificial Intelligence in Manufacturing using Industrial IoT," *2020 IEEE 11th International Conference on Dependable Systems, Services and Technologies (DESSERT)*, Kyiv, Ukraine, pp. 196-201, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ruikang Wang, Yifei Tong, and Cunbo Zhuang, "Lights-out Factories: Review and Prospect," *Proceedings of the Institution of Mechanical Engineers Part B Journal of Engineering Manufacture*, vol. 239, no. 14, pp. 1983-1993, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Nejc Rožman et al., "Autonomous Production Unit: An Architecture for Blockchain-based Shared Manufacturing," *Robotics and Computer-Integrated Manufacturing*, vol. 96, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] C. Deepika, N. Khamar Taj, and N. Parashuram Bedar, "Automation in Production Systems: Enhancing Efficiency and Reducing Costs in Mechanical Engineering," *Nanotechnology Perceptions*, vol. 20, no. 5, pp. 1436-1447, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Industrial Quick Research, Factory Automation: Everything you need to know about Systems and Uses. [Online]. Available: https://www.iqsdirectory.com/articles/factory-automation.html

[10] Murilo Silveira Rocha et al., "On the performance of OPC UA and MQTT for Data Exchange Between Industrial Plants and Cloud Servers," *ACTA IMEKO*, vol. 8, no. 2, pp. 80-87, 2019. [Google Scholar]

[11] Svetlana N. Khonina et al., "Eyes of the Future: Decoding the World Through Machine Vision," *Technologies*, vol. 13, no. 11, pp. 1-37, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Yung-Tsan Jou et al., "Enhancing Integrated Circuit Quality Control: A CNN-based Approach for Defect Detection in Scanning Acoustic Tomography Images," *Processes*, vol. 13, no. 3, pp. 1-28, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] Li Gao, Zhongqiang Luo, and Lin Wang, "Convolutional Neural Network Acceleration Techniques based on FPGA Platforms: Principles, Methods, and Challenges," *Information*, vol. 16, no. 10, pp. 1-59, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Valerio Antonini, Alessandra Mileo, and Mark Roantree, "Engineering Features from Raw Sensor Data to Analyse Player Movements during Competition," *Sensors*, vol. 24, no. 4, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Katlego Ratsheola et al., "A Hybrid Artificial Intelligence for Fault Detection and Diagnosis of Photovoltaic Systems using Autoencoders and Random Forests Classifiers," *Eng*, vol. 6, no. 10, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[16] Eduardo Quiles-Cucarella et al., "Optimizing Bearing Fault Diagnosis in Rotating Electrical Machines using Deep Learning and Frequency Domain Features," *Applied Sciences*, vol. 15, no. 6, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Marco Antonio Paz Ramos, and Axel Busboom, "Systematic Review of Reinforcement Learning in Process Industries: A Contextual and Taxonomic Approach," *Applied Sciences*, vol. 15, no. 24, pp. 1-32, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Akshay Paranjap et al., "Reinforcement Learning Agent for Multi-Objective Online Process Parameter Optimization of Manufacturing Processes," *Applied Sciences*, vol. 15, no. 13, pp. 1-24, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] Ajay Surendrarao Bhongade et al., "Managing Disruptions in a Flow-Shop Manufacturing System," *Mathematics*, vol. 11, no. 7, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Renkeer, Types of Industrial Sensors for Automation, Renke, 2026. [Online]. Available: https://www.renkeer.com/types-of-industrial-sensors-for-automation/

[21] Amer Kajmakovic et al., "Degradation Detection in a Redundant Sensor Architecture," *Sensors*, vol. 22, no. 12, pp. 1-25, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Nicolas P. Winkler et al., "Using Redundancy in a Sensor Network to Compensate Sensor Failures," *2021 IEEE Sensors*, Sydney, Australia, pp. 1-4, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Minahil Khurram et al., "Artificial Intelligence in Manufacturing Industry Worker Safety: A New Paradigm for Hazard Prevention and Mitigation," *Processes*, vol. 13, no. 5, pp. 1-57, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Jalal Taheri Kahnamouei, and Mehrdad Moallem, "Advancements in Control Systems and Integration of Artificial Intelligence in Welding Robots: A Review," *Ocean Engineering*, vol. 312, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Juraj Slovák et al., "Vision and RTLS Safety Implementation in an Experimental Human—Robot Collaboration Scenario," *Sensors*, vol. 21, no. 7, pp. 1-27, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[26] Navdeep Singh Gill, GPU vs CPU for Computer Vision: AI Inference Optimization Guide, Xenonstack, 2026. [Online]. Available: https://www.xenonstack.com/blog/gpu-cpu-computer-vision-ai-inference

[27] Alaa Omran Almagrabi, and Rafiq Ahmad Khan, "Optimizing Secure AI Lifecycle Model Management with Innovative Generative AI Strategies," *IEEE Access*, vol. 13, pp. 12889-12920, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[28] N. Kshetri, *Amplifying the Value of Blockchain in Supply Chains*, Blockchain and Supply Chain Management, Elsevier, pp. 67-88, 2021. [Google Scholar] [Publisher Link]

[29] Muhammad Qamar Khan et al., "Impact of Digital Twins on Real Practices in Manufacturing Industries," *Inventions*, vol. 10, no. 6, pp. 1-26, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[30] Fan Feng et al., "An Effective Digital Twin Modeling Method for Infrastructure: Application to Smart Pumping Stations," *Buildings*, vol. 14, no. 4, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[31] Moones Keshvarinia, Cameron A. MacKenzie, and Zhuoyi Zhao, "A Simulation-based Digital Twin Model for Data-Driven Decision Optimization," *Decision Analytics Journal*, vol. 17, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[32] Ying Cheng et al., "Task Allocation in Manufacturing: A Review," *Journal of Industrial Information Integration*, vol. 15, pp. 207-218, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[33] Zeenat Khan, and Mohsin Bilal Ahmed, "Advancements in Automated Storage and Retrieval Systems: A Comprehensive Review," *Robotics and Automation Engineering Journal*, vol. 6, no. 2, pp. 1-10, 2025. [Google Scholar]

[34] Iveta Kubasakova et al., "Implementation of Automated Guided Vehicles for the Automation of Selected Processes and Elimination of Collisions between Handling Equipment and Humans in the Warehouse," *Sensors*, vol. 24, no. 3, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[35] Cademix Institute of Technology, Design, Programming, and Commissioning of Industrial Control Software using PLC Systems: A Practical Guide for Engineers, Cademix Institute of Technology, 2024. [Online]. Available: https://www.cademix.org/programming-of-industrial-control-plc-systems/

[36] Pedro Ramos Brandao, "The Impact of Artificial Intelligence on Modern Society," *AI*, vol. 6, no. 8, pp. 1-29, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[37] Rohit Salwan, Edge Computing Meets the Cloud, TechAhead, 2025. [Online]. Available: https://www.techaheadcorp.com/blog/edge-computing-meets-the-cloud/