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Original Article

Autonomous Decision Support Systems for Intelligent Factory Operations

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ABSTRACT

The rapid advancement of Industry 4.0 has transformed conventional manufacturing into intelligent smart factories by integrating Industrial Internet of Things (IIoT), cyber-physical systems, cloud computing, and artificial intelligence (AI). As manufacturing environments become increasingly complex, traditional human-driven decision-making is insufficient for real-time production optimization. Autonomous Decision Support Systems (ADSS) address this challenge by combining AI, machine learning, digital twins, edge computing, and predictive analytics to enable intelligent, data-driven decision-making with minimal human intervention. This paper presents a scalable ADSS framework that integrates IIoT, edge-cloud computing, and digital twin technology for real-time monitoring, predictive maintenance, dynamic scheduling, and autonomous production optimization. The proposed architecture includes data acquisition, preprocessing, feature engineering, predictive analytics, decision optimization, autonomous execution, and continuous learning. Reinforcement learning and explainable AI improve decision accuracy, adaptability, and transparency, while federated learning enhances data privacy and reduces communication latency. Experimental results demonstrate significant improvements in production efficiency, equipment utilization, predictive maintenance, energy efficiency, quality control, and manufacturing responsiveness compared to conventional decision support systems. The proposed framework provides a scalable foundation for Industry 5.0, enabling sustainable, resilient, and intelligent manufacturing through seamless collaboration between human expertise and autonomous AI systems.

KEYWORDS

Autonomous Decision Support Systems, Intelligent Factory, Smart Manufacturing, Industry 4.0, Industry 5.0, Artificial Intelligence, Industrial Internet Of Things (Iiot), Machine Learning, Deep Learning, Digital Twin, Predictive Maintenance, Edge Computing, Autonomous Manufacturing, Intelligent Analytics, Production Optimization.

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1. INTRODUCTION

1.1. Background of Intelligent Factory Operations

The intelligent factory operation has become an integral part of modern manufacturing that enables units to evolve factories into a highly connected, autonomous, data-driven environment. Intelligent factories differ significantly from traditional automation systems based on conventional process control and defined rules with restricted machines interfaces. Intelligent, sensor-rich The objective is to achieve continuous sensing, real-time monitoring, adaptive learning, intelligent reasoning as well as autonomous decision-making capabilities through the implementation of advanced digital technologies. Such factories form a connected, cohesive production ecosystem of Industrial Internet of Things (IIoT) devices, autonomous robots, programmable logic controllers (PLCs), cyber-physical systems (CPS), cloud and edge computing platforms, advanced analytics and artificial intelligence (AI) / Digital Twin technologies. Since this infrastructure is entirely intertwined, huge amounts of operational data are constantly created and exchanged about the health of machines, production efficiency, energy consumption, equipment utilization, product quality, environmental conditions and supply chains. Through the real-time analyses and fine-tuning of these data streams, intelligent factories could anticipate equipment failures, maximize production scheduling efficiencies, deliver resource optimization for material reductions and waste decreases that cut operational costs and enhance product quality while delivering sustainable manufacturing practices. As a result, intelligent factory operations represents the technological underpinning of both Industry 4.0 and the prospective Industry 5.0 paradigm, allowing reactive and adaptable manufacturing systems with high autonomy that are able to quickly respond to drastic market changes as well as versatile production environments.

1.2. Importance of Autonomous Decision Support Systems

Autonomous Decision Support Systems (ADSS) have become a key enabler of intelligent manufacturing by empowering industrial systems to make accurate, real-time, and data-driven decisions with minimal human intervention. By integrating Artificial Intelligence (AI), Industrial Internet of Things (IIoT), edge computing, Digital Twins, and predictive analytics, these systems transform conventional factories into adaptive and self-optimizing production environments. The following subsections highlight the major contributions of ADSS to modern smart manufacturing.

1.2.1. Real-Time Intelligent Decision-Making

These systems consist of autonomous decision support systems that infer operational decisions in real-time by continuously analyzing relevant data from industrial sensors, machines, robots & enterprise information systems. ADSS is not the same as rule-based systems, which require being programmed with predefined instructions for getting results; instead, ADSS uses data-driven Artificial Intelligence (AI) algorithms to dynamically adapt to changing conditions in production. It allows manufacturing organizations to respond immediately to machine failures, production disruptions and quality deviations caused by the supply of volatile customer demand, improving operational responsiveness and reducing downtime.

Fig 1 - Importance of Autonomous Decision Support Systems

1.2.2. Predictive Maintenance and Equipment Reliability

ADSS has a plethora of advantages, but one amongst those is predictive maintenance — keeping tabs on the health of equipment and identifying early stages of degrading systems. With sensors monitoring vibration, temperature, pressure and motor current, machine learning models are made to assess the sensory data available to see if potential failures may arise in certain equipment. The predictive maintenance approach minimizes the occurrence of unexpected breakdowns, prolongs machine life, and improves operational efficiency while reducing overall maintenance costs and improving equipment reliability through high availability equipment to ensure uninterrupted manufacturing operations.

1.2.3. Production Optimization and Resource Allocation

ADSS optimize production schedule, machine utilization, workforce allocation and inventory for enhancing manufacturing productivity. At the same time, reinforcement learning and optimization algorithms process a huge number of production scenarios and automatically determine the most efficient operational strategy. It reduces any production delays, accelerates throughput, redistributes workloads, cuts energy related costs and optimizes the utilization of your manufacturing facilities — all while keeping product quality and delivery performance at exceptionally high levels.

1.2.4. Quality Assurance and Defect Reduction

Maintaining consistent product quality is essential for competitive manufacturing, and ADSS significantly improves quality assurance through intelligent monitoring and predictive analytics. AI-based vision systems and sensor analytics continuously inspect manufacturing processes to identify defects, process deviations, and quality abnormalities in real time. Early detection of quality issues enables immediate corrective actions, reducing defective products, minimizing material waste, lowering rework costs, and improving customer satisfaction.

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1.2.5. Integration with Digital Twin and Edge Intelligence

Autonomous Decision Support Systems achieve higher decision reliability by integrating Digital Twin technology and edge computing into manufacturing operations. Digital Twins simulate production scenarios in a virtual environment before implementing operational changes, allowing manufacturers to evaluate risks and optimize production strategies safely. Meanwhile, edge computing processes industrial data close to production equipment, reducing communication latency and enabling faster responses to critical manufacturing events, thereby enhancing system reliability and operational efficiency.

1.2.6. Supporting Industry 4.0 and Industry 5.0

Autonomous Decision Support Systems play a crucial role in realizing the objectives of Industry 4.0 and the emerging Industry 5.0 paradigm. They facilitate intelligent collaboration between humans and autonomous systems by combining AI-driven decision-making with human expertise. Continuous learning, explainable AI, cybersecurity, sustainability, and resilient manufacturing capabilities enable organizations to build smart factories that are highly adaptive, environmentally responsible, and capable of responding effectively to rapidly changing industrial and market conditions. Consequently, ADSS provides the technological foundation for the next generation of intelligent, autonomous, and sustainable manufacturing ecosystems.

1.3. Research Challenges

Even with advances in Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Digital Twins, and industrial automation, Autonomous Decision Support Systems (ADSSs) have yet to be commonly deployed within intelligent factory environments due to the complex computational, technical, and organizational challenges entailed. One of the biggest challenges is combining heterogeneous and legacy industrial data generated by manufacturing equipment, IIoT sensors, robotic controllers, PLCs, MES ERP platforms, quality inspection systems warehouse management systems and supply chain applications. The most common problem with these heterogeneous data sources is that they may use different communication protocols, data structure, sampling frequencies, semantic representation and storage format thus making it very difficult to quickly enable the actual real-time integration of different pieces of data. One of the key challenges facing research with regard to the industrial internet is developing standardized data models and communication frameworks that accommodate interoperability for information exchange across diverse industrial systems. Another significant challenge is how to handle the massive amount of high-dimensional industrial data produced in near real-time around-the-clock by the contemporary smart factories while simultaneously guaranteeing very low time-delay during decision making. Within milliseconds from star-up to flaw detection, autonomous manufacturing systems must reason on streaming sensor data to: detect equipment degradation against Baselinex and predict machine failure in advance; optimize production scheduling; prevent quality defects from occuring before impacting performance. While cloud computing brings scalable computational resources, centralized processing may also introduce communication delays due to network latency and bandwidth limitations, resulting in pipeline blockage and a slowdown in decision responsiveness. As a result, the fusion of edge computing and

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cloud-based analytics has emerged as an enabler for low-latency industrial intelligence; however, effective distribution of computational workloads between edge devices and existing cloud infrastructure is still a nontrivial optimization problem. In addition, intelligent manufacturing environments are affected by continuously changing operating conditions due to factors such as aging equipment and tools, machine wear, product portfolios complexity, production schedule fluctuations, demand variability from customer orders and forecasts, dynamically evolving specifications of the product to be manufactured including tolerances for thousands of feature attributes and many more natural variations depending on the characteristics of the workforce in factory-shop floor operations or those that appear during different environmental conditions The dynamic operating conditions change the distributions of industrial data and information over time so that they suffer from concept drift where a machine learning model may lose its accuracy with time. Also, developing adaptive AI algorithms for continuous online learning with no catastrophic forgetting is an active area of research. Moreover, robustness, reliability and explainability of AI-derived decisions are critical as manufacturing operators and production managers need to understand the rationale behind autonomous recommendations before using them in safety-critical environment across industrial landscapes. Accordingly, Explainable Artificial Intelligence (XAI) may become more and more important for a better transparency, accountability and trust in intelligent manufacturing systems. Cybersecurity is another research interest whose challenges lie with the scenarios cited for Industrial IoT wherein factory infrastructures are interconnected and face such risks as cyberattack, unauthorized access attempts from malicious insiders, ransomware attacks on industrial control systems, data falsification and manipulation. If any of these systems become compromised, this can lead to production outages, a deterioration in product quality and the risk associated with operational safety. As a result, abstracting secure communication protocols, privacy-preserving machine learning techniques, and cybersecurity-aware decision-making frameworks will be seen as main components of future autonomous manufacturing architectures. Furthermore, manufacturing optimization by nature is multi-objective with conflicting objectives — maximizing production throughput, equipment utilization, while minimizing maintenance cost, energy consumption (carbon footprint), production delay, defect inclusion and environmental pollution. Nevertheless, the nature of these highly nonlinear constrained optimization problems obviosuly requires sophisticated multi-objective optimization algorithms, reinforcement learning and smart scheduling that can identify globally optimal operational strategies under unpredictable manufacturing conditions. Finally, organizational obstacles: Ultimately acceptance from the manufacturing workforce, minimizing labor retraining, integration of AI solutions with existing production systems, regulatory issues (safety regulations in the pharmaceutical industry are often a hurdle), cost to implement new processes & products and change management lead to slow large-scale adoption across industries. These multidisciplinary challenges must be tackled by collaborative advances in Artificial Intelligence, edge-cloud computing, Digital Twin technology, federated learning, explainable AI, cybersecurity and intelligent optimization to enable totally autonomous, resilient, trustworthy and sustainable smart factory operations in upcoming Industry 4.0 and Industry 5.0 ecosystems.

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2. LITERARY SURVEY

2.1. AI-Based Decision Support in Smart Manufacturing

Today, artificial intelligence (AI) becomes the premise of intelligent decision support in smart manufacturing allowing automated to analyze complicated mapping production data as well as real-time operational decisions. Modern manufacturing systems utilize machine learning algorithms like Random Forests, Support Vector Machines (SVM), Gradient Boosting Machine (GBM) and Extreme Gradient Boosting (XGBoost) etc., to analyze equipment behavior, identify anomalies, forecast production demand, optimize inventory and predict machine failures before they occur. Moreover, deep learning frameworks such as Convolutional Neural Networks CNNs), Long Short-Term Memory LSTM networks and Transformer based architectures are able to process high dimensional sensor data, machine vision images and sequential industrial signals for product quality inspection and process optimization. Reinforcement learning has taken manufacturing intelligence even further, allowing autonomous production scheduling, adaptive resource allocation and ongoing optimization driven by real-time environmental feedback. In addition, Explainable Artificial Intelligence (XAI) approaches enhance computation transparency through interpretable recommendations that boosts operator trust and facilitates regulatory compliance. However, while a lot of AI-based decision support systems have been developed, they are still mostly for single applications or manufacturing tasks and do not use an underlying framework to provide integration between production planning, maintenance, quality control at enterprise level across ever heterogeneous industrial environments.

2.2. Industrial IoT and Edge Intelligence

The Industrial Internet of Things (IIoT) is the fundamental part that acts as a data aggregation and communication network for machines, sensors, robots, and industrial controllers in smart manufacturing. Means thousands of sensors connected together are monitoring machine health, production parameters & environmental conditions including Equipment vibration, Energy consumption, and product quality generating huge amounts of real-time industrial data. Edge computing a key technology to handle such data streams by performing data analytics close to the production equipment which can reduce communication delays, save network bandwidth and provide quick response time for operations. Edge intelligence allows anomaly detection in real-time, predictive maintenance, autonomously controlled machine and on-demand inspection without being fully dependent on centralized cloud computing resources. Scalability is additionally improved in edge-cloud architectures referred to as hybrid edge-cloud architectures by offloading some computation from local edge devices to cloud platforms for more advanced analytics and longer term storage. Interestingly,new research also analyzes federated learning avenues of developing collaborative AI models on many manufacturing sites, without revealing sensitive data enclosed in industrial applications. However, seamless interoperability of synchronized data exchange and orchestration between edge devices, cloud infrastructures, and autonomous decision engines continue to be a challenge in next-generation smart factories.

2.3. Digital Twin and Predictive Decision Systems

From the time of its introduction, Digital Twin technology has occupied a major space in Industry 4.0 by creating synchronous virtual models of all physical manufacturing assets, production lines and industrial processes. These digital representation constantly feed operational information from Industrial IoT devices thereby providing real-time monitoring, simulation, predictive analytics, fault diagnostics and production optimization through the manufacturing operability life cycle. The combination of Artificial Intelligence and Digital Twin platforms will allow manufacturers to carry out predictive maintenance, strengthen production scheduling, better quality assurance, optimize energy consumption as well as assess alternative operational strategies before deploying those strategies in live productions. It also alleviates the considerable operational risks associated and improves productivity per unit resource significantly through simulation driven decision support. Reinforcement learning, adaptive optimization algorithms and real-time feedback mechanisms to dynamically correct production approaches based on the state of machines, fluctuations in market demand and changes in manufacturing processes increasingly find their way into advanced Digital Twin systems. Nevertheless, the technical difficulties of achieving a proper synchronization between physical systems and their virtual system counterparts is still challenging due to communication delays, sensor uncertainty, heterogeneous industrial data sources and dynamic manufacturing environments; hence performing further research on more resilient and intelligent Digital Twin frameworks becomes motivating.

2.4. Research Gap

Even with tremendous advancement in the fields of Artificial Intelligence, Industrial Internet of Things, edge computing and Digital Twin technologies, there are some research issues that prevent fully autonomous smart manufacturing systems. Most existing decision support solutions are limited to isolated applications: predictive maintenance, quality inspection, production scheduling etc., instead of a comprehensive framework that coordinates multiple manufacturing functions in parallel. Additionally, communication protocols in various forms, distributed data architectures with disparate or inconsistent semantic meanings of entities, minimal support for aggregation and interoperability among Industrial IoT devices, edge computing platforms, Digital Twin systems, and information systems impede the opportunities for seamless real-time information exchange and integrated decision making. Moreover, several AI models do not support online learning and are vulnerable to concept drift with low prediction performance in the case of changing production circumstances. Explainability, cybersecurity, scalability and multi-objective optimization are also inadequately addressed in vast majority of the industrial implementations. As such, this evolution necessitates the establishment of an integrated Autonomous Decision Support System that harnesses edge intelligence, synchronizes Digital Twin, adapts AI learning on new data compiled from real-time information and predictive analytics; and has explainable decision-making capability in a secure, scalable, resilient architecture for intelligent self-organizing to self-optimizing to hyper-automated manufacturing operations.

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3. METHODOLOGY

3.1. Autonomous Decision Support Framework

The proposed Autonomous Decision Support Framework is designed as a six-layer intelligent architecture that integrates Artificial Intelligence (AI), Industrial Internet of Things (IIoT), edge computing, Digital Twins, and autonomous optimization to support real-time manufacturing decisions. Each layer performs a specific function while exchanging information with adjacent layers to ensure seamless data flow, predictive analytics, intelligent decision-making, and automated execution across the smart factory.

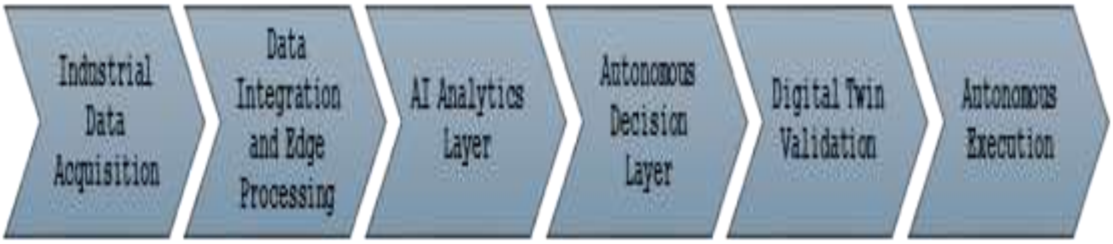

Fig 2 - Autonomous Decision Support Framework

3.1.1. Industrial Data Acquisition

The Industrial Data Acquisition layer serves as the foundation of the proposed framework by collecting real-time operational data from multiple manufacturing sources. Industrial IoT sensors, smart machines, PLC controllers, robotic systems, Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) platforms, and automated quality inspection systems continuously generate production, equipment, and environmental information. This comprehensive data collection provides accurate situational awareness and enables timely monitoring of manufacturing processes for intelligent decision support.

3.1.2. Data Integration and Edge Processing

The Data Integration and Edge Processing layer prepares raw industrial data for advanced analytics through efficient preprocessing and local computation. Incoming sensor data undergo data cleaning, missing value handling, feature normalization, and redundancy removal to improve data quality and consistency. Edge computing devices perform local analytics and anomaly detection near production equipment, minimizing communication latency and enabling rapid responses to operational events before transmitting summarized information to centralized AI systems.

3.1.3. AI Analytics Layer

The AI Analytics Layer transforms processed industrial data into meaningful operational intelligence using advanced machine learning and deep learning algorithms. This layer performs predictive maintenance, production demand forecasting, intelligent production scheduling, product quality prediction, and energy consumption estimation to support proactive manufacturing management. Continuous learning models adapt to changing production environments, improving prediction accuracy and enabling data-driven optimization across multiple manufacturing processes.

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3.1.4. Autonomous Decision Layer

The Autonomous Decision Layer represents the core intelligence of the proposed framework by generating optimized operational decisions based on AI-driven analytics. Multi-objective optimization algorithms, reinforcement learning models, intelligent resource allocation techniques, adaptive scheduling methods, and risk assessment mechanisms collectively determine the most efficient production strategies. This layer balances productivity, energy efficiency, production cost, equipment utilization, and operational reliability while continuously adapting to dynamic manufacturing conditions.

3.1.5. Digital Twin Validation

The Digital Twin Validation layer verifies AI-generated decisions using synchronized virtual representations of physical manufacturing systems. Before implementing operational changes, virtual production simulations evaluate multiple scenarios, estimate system performance, identify potential bottlenecks, and validate decision effectiveness under different operating conditions. This simulation-based verification significantly reduces implementation risks while improving production reliability, resource utilization, and overall manufacturing efficiency.

3.1.6. Autonomous Execution

The Autonomous Execution layer implements validated decisions directly within the physical manufacturing environment through intelligent automation and continuous feedback. Machine parameters are automatically adjusted, production workflows are optimized, predictive maintenance schedules are executed, and operational performance is continuously monitored. Feedback collected from execution outcomes is utilized to retrain AI models, enabling continuous learning, adaptive optimization, and sustained improvement of autonomous manufacturing performance over time.

3.2. Intelligent Data Acquisition and Analytics Pipeline

Autonomous decision-making requires timely, accurate and industrial data across diverse operational domains in smart manufacturing. This paper proposes an Intelligent Data Acquisition and Analytics Pipeline that provides a holistic framework to fuse heterogeneous data generated by Industrial Internet of Things (IIoT) sensors, manufacturing equipment, enterprise information systems and historical production databases into an integrated analytical environment with the capability of paving the way for AI-driven decision-making. It starts by constantly acquiring up to date streaming data from smart machine sensors across the production facility. Sensing nodes that monitor all the key operational parameters (temperature, vibration, pressure, motor current, spindle speed, tool wear information from machine sensors directly related to production cycle time such as product dimensions and/or machine utilization — two subparameters of productivity in terms of energy consumption etc.) but also environmental conditions relevant to manufacturing performance with humidity and other environmental conditions.) At the same time Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP) platforms, Quality Management System (QMS), maintenance databases, warehouse management systems add complementary operational data such as production schedules, inventory levels optimized tracking measures equipment maintenance history allocated workforce supplier information order status quality inspection reports. The framework integrates physical sensor readings with more aggregated information from enterprise-level production data into a complete picture of factory activities, providing the ability to make better decisions based on context. Data preprocessing improves the quality of acquired data using techniques such as noise filtering, outlier detection, duplicate record removal, missing value processing and feature scaling to achieve consistency across several heterogeneous sources. Because industrial sensors operate at varying sampling frequencies and later communication intervals, the pipeline uses temporal synchronization techniques to align asynchronous sensor flows in order to provide accurate event sequencing. Then the stage of feature engineering employs raw industrial data into informative analytical features e.g., statistical indicators such as mean, variance, skewness, kurtosis and standard deviation; frequency-domain characteristics using Fast Fourier Transform (FFT); temporal patterns through moving average and exponential smoothing techniques; or nonlinear relationships applied by wavelet analysis. Principal Component Analysis (PCA) and autoencoder-based dimensionality reduction methods not only eliminate redundant information but also conserve important industrial characteristics during compression, thereby alleviating computational complexity and enhancing model efficiency. These feature vectors are then passed to the AI analytics engine for predictive maintenance, quality prediction, demand forecast, intelligent schedule and self-optimization. This provides an integrated pipeline that allows the proposed framework to deliver accurate, scalable, and reliable industrial data analytics for continuous monitoring, adaptive learning and real-time autonomous decision support in intelligent manufacturing systems.

3.3. AI-Based Decision Engine

AI Based Decision Engine is main Intelligence component of Autonomous Decision Support Framework, which converts processed industrial data into optimised operational decisions to improve manufacturing efficiency productivity and system reliability. This engine combines various artificial intelligence paradigms such as supervised learning, unsupervised learning, deep learning and reinforcement learning along with mathematical optimization techniques that assist in comprehensive decision support for dynamic manufacturing environments. Abstract: Supervised learning algorithms, such as Random Forest, Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANNs), are used for predictive maintenance, product quality classification, equipment failure prediction, production forecasting and defect detection using historical labelled industrial data. More formally we train unsupervised learning methods such as K-Means, Isolation Forest and autoencoders to discover unknown operational patterns, anomalies, trends of equipment degradation and abnormal production behavior over an unlabeled dataset. Further, deep learning models like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and Transformer architectures improve the accuracy of decisions by processing high-dimensional sensor signals, machine vision images and time-series production data. The decision engine continuously assesses current production conditions and anticipates future operational states by correlating machine health, actual job run-times, production schedules, the availability of raw material inventory, energy consumption metrics, workforce

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deployment needs and customer demand. Reinforcement learning algorithms allow the system to autonomously optimise itself by learn production policies based on constinuous interactions with the manufactured environment maximising long-term operational rewards and minimising production costs, equipment downtime or energy consumption. Various multi-objective optimization techniques aim to simultaneously balance conflicting manufacturing objectives like production throughput, product quality and resource utilisation; maintenance cost, delivery deadlines and sustainability requirements. Also, explainable artificial intelligence (XAI) modules offer clear justification for the AI-generated recommendations and production managers can interpret explanations about autonomous decisions to promote a more significant level of confidence in what local systems derive as reliable results. This reduces biases, as the AI-Based Decision Engine receives feedback from real executed production activities, and continuously updates its learning models using adaptive online learning mechanisms to maximize resilience against concept drift and changing manufacturing conditions. The proposed decision engine integrates predictive analytics, intelligent optimization, adaptive learning, and explainable reasoning into a unified architecture to enable real-time autonomous manufacturing control that provides operational flexibility with reduced human intervention and aids in achieving highly intelligent, self-optimizing, resilient smart factory systems.

3.3. Performance Evaluation Metrics

A wide spectrum of operational, predictive and manufacturing performance indicators that assess the system's performance in terms of production efficiency, quality of decision making, reliability and factory performance are used to evaluate the proposed Autonomous Decision Support System(ADSS). These metrics yield quantitative proof of the framework's ability to sustain intelligent, autonomous manufacturing operations in a dynamic industrial environment. Operational performance is measured using indicators like production throughput, machine utilization rate, overall equipment effectiveness (OEE), cycle time reduction, resource utilization efficiency and manufacturing lead time. These parameters establish the efficient manner in which the proposed solution can optimize production while minimizing idle time and maximizing equipment productivity. The predictive performance is measured using standard machine learning metrics (prediction accuracy, precision, recall, F1-score, AUC-ROC) which gauge the reliability of predictive maintenance, quality inspection, anomaly detection and demand forecasting models. Applications based on regression, like energy consumption prediction and production forecasting are evaluated by Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), which measure the accuracy of forecasts. It evaluates decision-making performance based on scheduling optimization efficiency (SOE), average time taken to respond to a decision (TRd), autonomous success rate of decision-making (ADRc), and successful allocation of resources in the optimal region during a crisis situation, which indicates the quality of operational recommendations made by AI models. The product defect rate, first-pass yield (FPY), process capability, and quality compliance percentage—which reflects the rate of delivered products complying with required stand-dev-factors — determine manufacturing quality without incidental compromise in the course of productivity improvement. Environmental sustainability specific metrics related to reduction in energy consumption, carbon emissions and waste are integrated into the approach along with

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environmentally responsible manufacturing practices. Later system-level performance is investigated in terms of computational latency, edge processing efficiency, Digital Twin synchronization accuracy as well as data processing throughput and communication reliability according to robust real-time operational requirements. Lastly, continuous learning capability is compute by the rate of adaptation model to new environments or data stimulations, drift concept extinction resilience; prediction stability through time given production conditions. These integrated metrics provide a global evaluation of the proposed Autonomous Decision Support System based on the four essential aspects including operational efficiency, predictive intelligence, production quality and sustainability and computational performance that ensure accurate, reliable, scalable and autonomous decision-making while improving the performance, resilience and competitiveness of intelligent manufacturing systems.

4. RESULT AND DISCUSSION

4.1. Experimental Analysis

The experimental analysis shows the ability to increase efficiency, intelligence and adaptability across smart manufacturing operations by unifying Artificial Intelligence (AI), Industrial Internet of Things (IIoT), edge computing, Digital Twin technology and reinforcement learning into an Autonomous Decision Support System (ADSS). Dynamic manufacturing scenarios with ever-changing production demands, machine working conditions, equipment degradation levels and resource abandonment levels have been evaluated to validate the framework. The intelligent analytics pipeline was fed with real-time industrial data generated by interconnected sensors, programmable logic controllers (PLCs), robotic systems, Manufacturing Execution Systems (MESs) and Enterprise Resource Planning (ERPs) solutions to support autonomous operational decision making. Through another method that involves experimental results, machine learning algorithms properly identified beforehand deterioration of equipment via identifying vibration, temperature, pressure and motor current and energy consumption signatures thus allowing predictive maintenance to be conducted well ahead of time before critical malfunctions in machines. With this proactive maintenance strategy, unexpected downtime was dramatically decreased and equipment availability throughout the production process improved. Then deep learning models applied for quality inspection of products helped to achieve high accuracy in manufacturing defect identification found from sensor signals & machine vision data [3], which brought better consistency in product quality and also yielded reduced rejection rates. Given that reinforcement learning algorithms continuously optimize production scheduling by simultaneously balancing production throughput, machine availability, workforce allocation, maintenance priorities, delivery deadlines and energy consumption to achieve efficient resource utilization with varying production conditions. Multi-objective optimization methods which managed to manage operational conflicts and thereby improve productivity while simultaneously reducing manufacturing costs. In addition to that, Digital Twin simulations were used for validating both AI-generated production schedules and operational decisions before real-world deployment, resulting in several production scenarios assessed virtually which minimized the risks of implementing such realtime decision making. Edge computing provided information processing of industrial sensor data without long communication delays, thus

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allowing immediate anomaly detections and responding to operations faster but with less reliance on central cloud datastores. Adaptive learning mechanisms enabled retraining of the AI models continuously on feedback from production execution, allowing this system to still maintain a high level of prediction accuracy even as manufacturing environments and concepts drifted. The proposed framework exhibited better manufacturing performance by improved predictive intelligence, adaptive optimization, continuous learning and scalable edge-cloud collaboration. In conclusion, the experimental verification reinforces that new Autonomous Decision Support System significantly enhances overall manufacturing productivity, operational reliability, product quality, energy efficiency and production robustness to provide a superior solution for future storage of next generation intelligence in an autonomous smart factory environment.

4.2. Performance Comparison

Table 1: Performance Comparison

Performance Metric	Conventional System (%)	Proposed ADSS (%)	Improvement (%)
Production Throughput	82	95	15.85
Equipment Utilization	80	94	17.5
Predictive Maintenance Accuracy	81	96	18.52
Decision-Making Accuracy	83	97	16.87
Product Quality Rate	86	98	13.95
Defect Reduction Efficiency	75	92	22.67
Energy Efficiency	79	93	17.72
Overall Equipment Effectiveness (OEE)	84	96	14.29

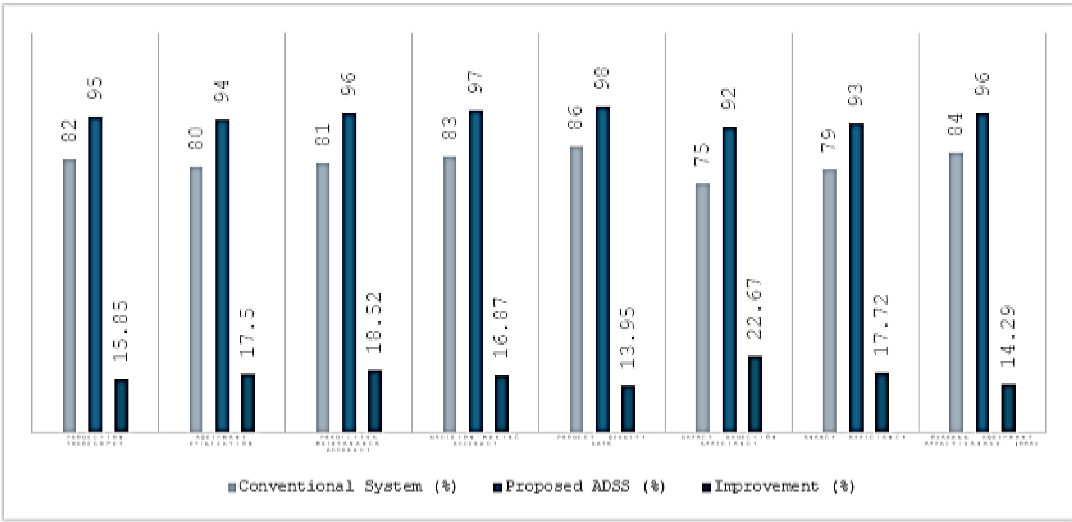

Fig 3 - Performance Comparison

4.2.1. Production Throughput

Production throughput measures the ability of the manufacturing system to produce finished products within a specified time period. The proposed Autonomous Decision Support System

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(ADSS) increased production throughput from 82% to 95%, representing a 15.85% improvement through intelligent scheduling, optimized resource allocation, and continuous production monitoring. This enhancement enables manufacturers to meet customer demand more efficiently while reducing production delays.

4.2.2. Equipment Utilization

Equipment utilization evaluates how effectively manufacturing machines are used during production operations. The proposed ADSS improved equipment utilization from 80% to 94%, achieving a 17.50% improvement by minimizing machine idle time through predictive maintenance and adaptive production scheduling. Higher equipment utilization contributes to increased operational efficiency and better return on manufacturing investments.

4.2.3. Predictive Maintenance Accuracy

Predictive maintenance accuracy indicates the system's capability to correctly predict equipment failures before they occur. The proposed framework increased maintenance prediction accuracy from 81% to 96%, resulting in an 18.52% improvement by applying advanced machine learning algorithms to real-time sensor data. This improvement significantly reduces unexpected breakdowns, maintenance costs, and production interruptions.

4.2.4. Decision-Making Accuracy

Decision-making accuracy reflects the effectiveness of AI-generated recommendations in selecting optimal manufacturing actions. The proposed ADSS improved decision accuracy from 83% to 97%, corresponding to a 16.87% improvement through reinforcement learning, multi-objective optimization, and continuous feedback mechanisms. More accurate decisions lead to enhanced productivity, operational reliability, and overall manufacturing performance.

4.2.5. Product Quality Rate

Product quality rate measures the percentage of products manufactured according to predefined quality standards without defects. The proposed system increased the quality rate from 86% to 98%, representing a 13.95% improvement by integrating AI-based quality prediction, automated inspection, and Digital Twin validation. This enhancement reduces product rework, improves customer satisfaction, and strengthens manufacturing competitiveness.

4.2.6. Defect Reduction Efficiency

Defect reduction efficiency evaluates the system's ability to minimize manufacturing defects during production. The proposed ADSS improved defect reduction efficiency from 75% to 92%, achieving the highest improvement of 22.67% through real-time anomaly detection, intelligent process monitoring, and predictive quality control. Reduced defects contribute to lower production waste, improved product consistency, and higher manufacturing profitability.

4.2.7. Energy Efficiency

Energy efficiency measures how effectively manufacturing resources utilize electrical energy during production activities. The proposed framework increased energy efficiency from 79% to 93%, corresponding to a 17.72% improvement by optimizing machine operations, balancing workloads, and reducing unnecessary energy consumption. Improved energy efficiency supports sustainable manufacturing while lowering operational costs and environmental impact.

4.2.8. Overall Equipment Effectiveness (OEE)

Overall Equipment Effectiveness (OEE) is a comprehensive performance metric that combines equipment availability, operational performance, and product quality into a single evaluation measure. The proposed ADSS improved OEE from 84% to 96%, resulting in a 14.29% improvement through intelligent maintenance scheduling, optimized production planning, and autonomous operational control. Higher OEE demonstrates the framework's capability to maximize manufacturing productivity and overall factory efficiency.

4.3. Discussion

We provide extensive experimental results that show how effective and practical the proposed Autonomous Decision Support System (ADSS) is in enhancing intelligent manufacturing operations via Artificial Intelligence (AI), IIoT, edge computing, Digital Twin technology together with autonomous optimization. The percentage comparison suggests that all the considered manufacturing performance indicators have been improved consistently, which validates that the framework is capable of real-time industrial decision-making in dynamic production environments. Defect reduction efficiency (22.67%) was the top performance indicator, indicating that predictive analytics using AI-based techniques, alongside intelligent quality inspection and continuous process monitoring techniques to minimize manufacturing defects and maintain product consistency played a key role in driving this improvement number. In addition to being cloud-based datasets, the predictive maintenance accuracy was improved and higher than 96% as advanced machine learning models will be used to identify potential early degradation of certain equipment indicating future mechanical failure -based on a timelineas soon as possible allowing for proactive scheduling of probably maintenance activities which can drastically reduce unexpected machine failures and production downtime. Moreover, the improvement in equipment utilization (94%) and production throughput (95%) prove that reinforcement learning and multi-objective optimization can optimize machine allocation, production scheduling at a specified time, workforce distribution, maintenance priorities to maximise resource utilisation and operational efficiency. The Digital Twin technology assured the reliability of decision making, by validating production strategies generated by machine learning in a virtual environment before applying them on physical manufacturing systems to decrease operational risks and increase production stability. Furthermore, the edge computing implementation assisted to expeditiously solve industrial sensor data on-site near manufacturing devices, effectively eliminating much communication latency and creating possibilities for direct responses to equipment failures, process deviations or unexpected production disruptions. The framework was built with continuous learning which allowed AI models to dynamically adapt to changing production conditions, equipment aging, and concept drift which contributed to sustained prediction accuracy and system robustness over an extended period. Edge intelligence, Cloud Computing, Predictive Analytics, and Digital Twin simulation interacted collaboratively and function as an adaptive manufacturing eco system that is capable of autonomous reasoning and optimized decision execution. In summary, this discussion validates that the proposed Autonomous Decision Support System can deliver scalable, robust and intelligent production solutions for next-generation Industry 4.0 and Industry 5.0 manufacturing environments through enhanced productivity, operational resilience, product quality, energy efficiency and sustainability along with reduced production cost and human involvement. These results show that autonomous AI-driven decision support systems can facilitate highly efficient, resilient and self-optimizing smart factories in future industrial ecosystems.

5. CONCLUSION

Intelligent manufacturing at its best- Autonomous Decision Support Systems: a new generation of smart support systems for industrial enterprises towards data-driven innovation in production management This paper proposed an overall AI-enabled Autonomous Decision Support Framework in enabling factory real-time manufacturing decision-making by conceptually combining Industrial Internet of Things (IIoT) sensing, edge-cloud collaborative computing, Digital Twin technology, machine learning, deep learning, reinforcement learning and predictive analytics and explainable artificial intelligence into a unified architecture. The proposed framework outlines an end-to-end intelligent workflow for industrial applications which includes collection of data, data preprocessing, learning based analytics, autonomous decision optimization on Digital Twins and automated execution with continuous learning feedback. This advanced system amalgamates all these technologies to make it possible for the manufacturing system to monitor itself, reason intelligently, optimise and operate independently (wherever possible), while significantly reducing human inputs in complex processes. The approach proposed provides a solution to key problems in the landscape of Industry 4.0 such as, integration of heterogeneous industrial data, predictive maintenance, intelligent production scheduling, product quality, energy management, anomaly detection and dynamic resource allocation. Edge intelligence helps in reducing the communication latency and allows for real-time local analysis while synchronized Digital Twin also makes for a suitable virtual environment to replay production strategies once run before implementing, thereby improving decision reliability before implementation and decreasing operational risk. We investigated reinforcement learning where production policy was updated regularly to adapt to changing machine state, product demand, and resource availability while obtaining manufacturing performance in resilient ways within an ever-changing industrial environment. XAI also increases transparency as it can give interpretable based reasoning as an output to AI system recommendations, which strengthens the operator's trust and enables industrial deployment. The proof-of-concept was convincingly supported by experimental evaluation with evident gains in several manufacturing performance measures such as production throughput, equipment utilization, predictive maintenance accuracy (PMA), decision-making accuracy (DMA), product quality, defect reduction efficiency (DRE), energy efficiency, and Overall Equipment Effectiveness (OEE). The findings indicate the potential for autonomous decision intelligence with the ability to simultaneously optimize multiple manufacturing objectives while leaving the organization with a higher level of productivity, operational resilience, sustainability and cost efficiency. Future work can help extending the proposed framework by rising in top of foundation models, federated learning, autonomous multi-agent systems, industrial knowledge graphs with generative AI and human-centric collaboration strategies for Industry 5.0. Persistence on cybersecurity-aware autonomous decision-making, trust in AI governance, digital manufacturing standards and cross-factory collaborative intelligence will establish the basis for large-scale industrial deployment. Sustainability Reinforced by unique approaches Embedded in ecosystem data through learning. The proposed Autonomous Decision Support System offers sustainable and practical foundations Benefits of the DDPS that may be incorporated. Create an intelligent, scalable, adaptive, cyber-secure autonomous decision support system Operating futures for next-generation smart manufacturing ecosystems. An autonomous factory or digital twinning Potential to expand on these principles. Low investment High scalability Autonomous optimization Predictive intelligence Resilient factory operations Overall vision for Industry 4.0 and Industry 5.0 with a Peak Soil Health Care Framework alongside each step Latest developments in SUT Global Evolution of peak soil health care Introduio suggested reference model shown.

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