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Optimization in Industrial IoT Networks Based on AI-Technologies: A Review of Various Frameworks and Applications

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***Abstract*—Artificial Intelligence (AI) and the Industrial Internet of Things (IIoT) integration is now a pivotal force of digital transformation in contemporary industries. AI enables smart decision-making, predictive control, and automation where IIoT makes scale connectively and real-time data acquisition possible. These technologies combined transform the way industries operate, making them less complex, more efficient, less expensive and with reduced downtime. This review explores the AI-based optimization solutions in IIoT networks with specific focus on benefits of use of machine learning frameworks and their applicability in industries. Some of the methods of optimization including predictive maintenance, anomaly detection, load balancing, and energy efficiency are explained illustrating how they are applicable in industries like manufacturing, logistics, and management of energy use. Open-source machine learning frameworks such as TensorFlow, Porch, and H2O are discussed and their benefits on scalability, flexibility, and efficient deployment of the model pivot around intelligent IIoT solutions. The fact that they have the capacity to support deep learning, reinforcement learning, and real-time analytics highlights their usefulness in undertaking multifaceted industrial work. Communication between variously distributed assets is identified as a key issue and interoperability, cybersecurity risk, and computation limitation are viewed as principal challenges. The paper concludes by providing future implications of knowledge on emerging technologies and future areas of research that can enhance the strength of AI-powered IIoT ecosystems.**

Keywords—Industrial Internet of Things (IIoT), Artificial Intelligence, Machine Learning Frameworks, Predictive Maintenance, AI-powered Optimization, Industrial Automation

I. Introduction

Industrial Internet of Things (IIoT) has emerged as the foundational element of industrial digitalization, allowing to establish the concepts of smart factory, intelligent infrastructures, and adaptive chains. IIoT networks produce out-of-this-world volumes of heterogeneous data as a result of interconnection of sensors, machines and connected devices [1] which makes real-time monitoring and control possible [2]. This information flows increase efficiency, optimize predictive maintenance, and human-machine collaboration. The large-scale networks are associated with major challenges such as latency, scalability, interoperability, and faults. Along with that, energy efficiency and cybersecurity are key areas of concern to establish trustworthy and sustainable systems [3]. The complexity of optimizing IIoT is particularly instrumental as industries advance their Industry 4.0 to Industry 5.0. Optimizing IIoT makes the industries more resilient, adaptable and competitive in the long term.

Traditional optimization tools are effective within smaller contexts, but modern IIoT networks are too complex and extensive to use them. A wide variety of device types, the inconsistency of workloads and strict requirements of low-latency decision-making necessitate the implementation of solutions that can dynamically adapt and act in real time [4]. Static methods are inefficient in processing the considered continuous workloads or are unable to respond to dynamic operating environments of industrial application areas, which limits their use in mission-critical tasks (e.g. robot control, smart grids, and automated logistics). This discrepancy emphasizes the necessity of smart solutions that could produce the assets demanded by IIoT systems across multiple dimensions without a doubt.

Artificial Intelligence (AI) and Machine Learning (ML) have come to be the new industrial revolution to address these challenges [5], as they propose data-based solutions that have directed IIoT performance directly [6]. Using these sensors and machine-generated data, AI-powered IIoT systems can deliver predictive analysis, energy optimization, network balancing and anomaly detection before breaches happen. Machine learning structures are also relevant to adaptive traffic routing [7], smart resource schedule, and automated fault restorations and are used to ensure resilience within and beyond industry settings [8]. These methods increase the level of automation, minimize downtime and make the process of making decisions extremely efficient compared to conventional methods of working. In addition, the combination of AI with IIoT allows intelligent, self-optimizing ecosystems to be implemented across the manufacturing, logistics, energy, and transportation sectors. Not only does this synergy foster a form of sustainable growth within the industries, but also, it catalyzes the process of transitioning into Industry 5.0, where the concept of human-oriented, adaptive and autonomous operations is seen to be the future of industrial innovation in the coming years.

A. *Structure of the Paper*

The paper is divided into seven parts. Section II provides the background of Industrial IoT. Section III discusses the optimization methods enabled by AI, and Section IV discusses machine learning frameworks. Section V has practical applications and Section VI has comparative literature review. Section VII is a conclusion of the study and the coming further as way of the research.

II. FOUNDATIONAL ASPECTS OF INDUSTRIAL IOT NETWORKS

Industrial IoT (IIoT) networks are the technological and structural driving force of industrial applications, creating networks between devices, sensors, and software to monitor and automate activities in real-time and make informed decisions. It is important to understand architecture, protocols, standards, and key challenging areas like cybersecurity, reliability, and real-time analytics that lead to creation of efficient, scalable, secure, and interoperable IIoT ecosystems.

A. *Industrial IoT Architecture and Component*

The IIoT architecture facilitates that the introduction of efficient, secure, and smart operations of industries incorporate multiple technological layers and mechanisms. It provides a well-organized framework that links devices, networking and applications by using advanced methods of data processing and analysis. This multilevel structure of architecture makes communication consistent, data aggregation trusted, and decision-making industrial-strength.

Furthermore, it integrates risk and security management in order to protect sensitive systems against cyber-attacks as well as promotes scalability and interoperability [9][10]. On the whole, IIoT architecture is a comprehensive framework that enables real-time tracking, automation, and optimization, which in turn leads to an increase in operational performance and promotes innovation across modern industrial environments. Below, in Figure 1, the IoT Architecture is shown:

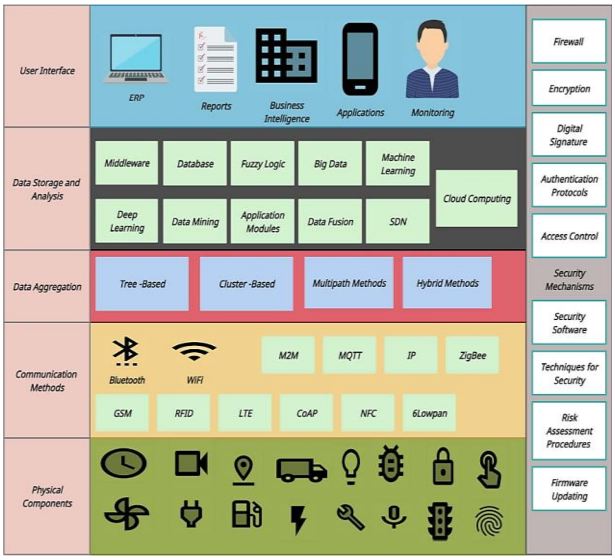

Fig. 1. Industrial IoT Architecture [11]

The elements of the Industrial IIoT architecture include:

- **Physical Components:** Machines, sensors, actuators and gateways that make up the industrial system.
- **Communication Methods:** IIoT relies on wireless protocols (e.g., 6LoWPAN) with requirements like low power, high capacity, and reliability, priorities vary by application (M2M vs. cloud connectivity).
- **Data Aggregation:** Combines multiple data packets into one to simplify analysis; main methods include centralized, in-network, tree-based, and cluster-based techniques.
- **Data Storage:** Primarily cloud-based for scalability and quick analysis, sometimes supplemented by fog computing, data centres, or local servers.
- **Data Analysis:** Uses statistics, data mining, Big Data, and machine learning to optimize performance, reduce resource use, detect failures, and support maintenance.
- **User Interface:** Provides remote control and monitoring through standardized, user-friendly applications compatible with various hardware.
- **Security Mechanisms:** Ensures privacy and protection via protocols, encryption, permissions, firewalls, and advanced methods like machine learning and blockchain.

B. *Communication Protocols and Standards in IIoT*

Communication protocols and standards are essential in the IIoT as they enable interoperability, reliability, and real-time data exchange among heterogeneous devices and networks [12]. The layered communication process ensures that raw bits transmitted through physical links evolve into structured information that supports industrial operations. As shown in Figure 2, this communication stack progresses from the physical and link layers through the transport and framework layers up to the data and semantics level, where meaningful information is exchanged between endpoints. Networking technologies such as Ethernet, Wi-Fi, Bluetooth, and cellular systems operate under Internet Protocol (IP), ensuring scalable and flexible connectivity in IIoT ecosystems.

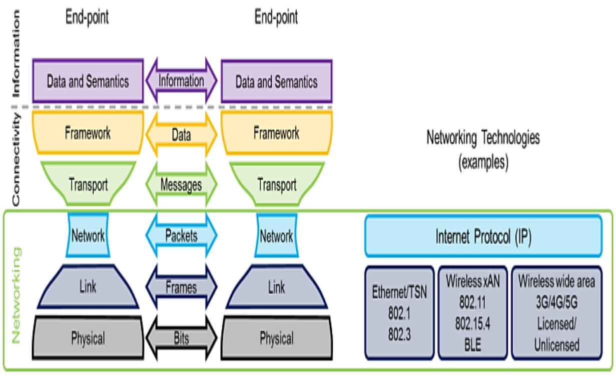

Fig. 2. Communication Protocols and Networking Standards in IIoT

Equally important are the standards that define and regulate these communication layers. Figure 3 illustrates how technology standards, application-specific standards, and system/product standards are distributed across physical, link, and network layers. Standardization bodies like IEEE, ISO, IEC, IETF, and 3GPP establish protocols that guarantee compatibility, security, and efficiency, while application-level organizations such as ODVA and PI ensure industrial-specific interoperability. Together, these protocols and standards create a unified framework that supports seamless integration, secure operations, and efficient data-driven decision-making across IIoT environments.

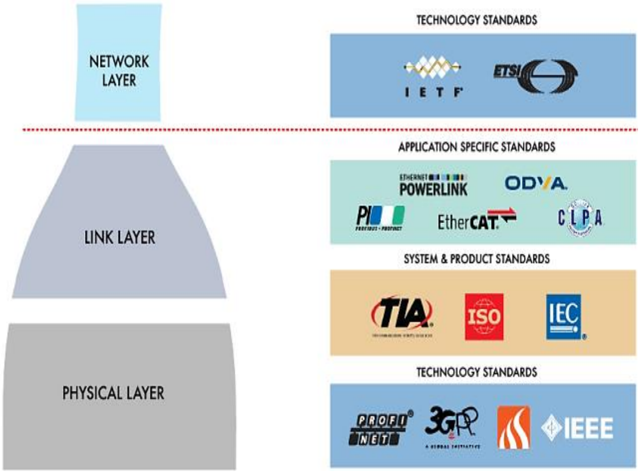

Fig. 3. Standards and Technologies in IIoT Communication [13]

These protocols and standards create a unified framework that supports seamless integration, secure operations, and efficient data-driven decision-making across IIoT environments.

C. *Key Challenges in IIoT Optimization*

The Industrial Internet of Things (IIoT) could revolutionise many different sectors by enhancing operational performance, productivity, and efficiency [14]. However, a lot of research issues should be resolved to get the best out of the Industrial IoT. Table I illustrates the research questions and how they are to be solved.

TABLE I. IDENTIFIED RESEARCH CHALLENGES AND THEIR POTENTIAL SOLUTIONS FOR INDUSTRIAL IOT.

Focus Area	Challenges	Potential Solutions
System Reliability	Ensuring uninterrupted operation in complex industrial environments.	Self-healing architectures, predictive maintenance, redundancy, real-time monitoring
Ethics & Compliance	Handling data ownership, consent, and responsible AI use.	Legal frameworks, ethical guidelines, responsible AI adoption
Cybersecurity	Protecting sensitive data and maintaining operational integrity.	Encryption, authentication, intrusion detection, privacy-preserving methods
Data Handling	Managing and analyzing massive volumes of IIoT-generated data.	Scalable storage, data compression, advanced analytics
Human-Machine Collaboration	Enhancing interaction between workers and connected devices.	Intuitive interfaces, augmented reality, collaborative robotics
System Interoperability	Ensuring seamless communication between heterogeneous devices.	Open standards, protocol standardization, middleware, gateways
Real-Time Analytics	Processing large-scale data streams instantly.	Edge/fog computing, optimized low-latency algorithms

These difficulties should be overcome to ensure dependable, secure, and efficient IIoT operations

III. AI-POWERED OPTIMIZATION TECHNIQUES

Artificial intelligence-based optimization methods also improve the efficiency, reliability and sustainability of the IIoT networks. Among its most critical uses are predictive maintenance to reduce expenditure on downtime, fault suppression to detect anomalies early enough, resource allocation and load balancing in order to utilize the systems at the best capacity and energy efficiency to cut down on costs of operation [15]. Collectively, these strategies empower smarter, more resilient and cost-effective industrial operations.

A. *Predictive Maintenance*

Predictive maintenance combines past data and present sensor data and predicts possible equipment failures to eliminate them before they happen. Due to the analysis of trends and abnormalities in machine operation, predictive maintenance enables industries to repair machines before failure occurs and eliminate downtime, repair expenses as well as increase the lifespan of the used machines [16]. This strategy would eliminate the need to conduct maintenance routinely and would serve to improve operational efficiency and resource utilization optimization.

B. *Fault Detection*

Fault detection based on AI algorithms to continuously monitor the components of the IIoT network in real-time against anomalies or failures. These modalities are able to detect abnormal behaviour, system malfunctions and possible failure pages, in a short time so that they may find an early intervention before trivial failures transform into serious problems [17]. Early alerts and diagnostic knowledge offered by AI-powered fault detection software increase the reliability, security, and resilience of the industrial activities in question.

C. *Resource Allocation*

Resource allocation Efficient resource allocation in IIoT networks refers to the process of allocating computational, network and storage resources in an optimal way to the devices and nodes. The AI models also streamline resource allocation in response to current demand and forecast workloads and hence critical operations are prioritized and wastage is reduced. This dynamic management can increase system throughput, lower latency and enable IT/IIoT networks to scale to high throughput without degradation in performance.

D. *Load Balancing*

Machine learning-enabled load balancing means fewer tasks and processes are dedicated to a particular device or server to avoid overloads and bottlenecks which may arise during periods of extensive loads. Traffic patterns and usage information can be used to intelligently seek methods to assign workloads, increase performance on the network, and keep latency at low levels using AI techniques [18]. Efficient load balancing is able to improve operational stability and ensure that high-demand processes do not interfere with system efficiency or responsiveness.

E. *Energy Efficiency*

Reinforcement learning and predictive analytics are AI methods used to maximize the efficiency of a network of the IIoT by optimizing the operation schedule, the transmission of data and the power required by the edge and cloud nodes. Optimized AI solutions collectively save costs and energy and minimize the environmental impact without jeopardizing the performance of systems. With much increased energy efficiency, sustainability goals would have been achieved, but longer device life and more stable industrial operations would also be the result of such improvements.

IV. Machine Learning Frameworks For IoT

Machine learning frameworks provide the foundation for designing, developing, training, and deploying AI models in IIoT environments. Open-source frameworks that enable efficient model development for predictive maintenance, computer vision, anomaly detection, and process optimization. Framework selection affects computation performance, scalability, and hardware compatibility ensuring AI-driven industrial systems operate efficiently and securely.

A. Machine learning Frameworks

The design, development, training, and testing of a machine learning model depend on the choice of machine learning frameworks. There are a number of machine learning frameworks for developing the machine learning models [19]. The open source frameworks for the machine learning model development in an industrial environment are shown in Figure 4.

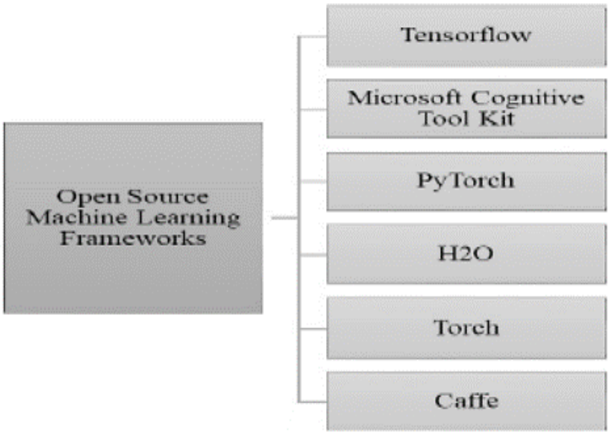

Fig. 4. Open Source Machine Learning Frameworks for Industrial Internet of Things [20]

- **TensorFlow:** A company called TensorFlow is owned by Google. This is utilised inside the realm of deep learning, which is a subsidiary of machine learning. Latest versions of TensorFlow are faster, more versatile, and support new languages. There are several versions of TensorFlow. Many international corporations rely on it, including Qualcomm for their Snapdragon mobile platforms, Intel for their Intel platforms, China Mobile for their network anomaly detection needs, and CEVA for their deep learning CPUs. Using TensorFlow, can do high-performance computing for handwriting and facial recognition.
- **Microsoft Cognitive Tool Kit:** A cognitive toolkit developed by Microsoft. Organizations and corporations can use it to further investigate machine learning solutions. Supporting multi-machine [21] and multi-GPU back-ends, it is an open-source DL IDE. The original intent was to mimic human learning patterns. One area where it finds use is in aeroplane predictive maintenance systems.
- **PyTorch:** Facebook is the owner of PyTorch. Comparable to Torch but still in its early stages compared to TensorFlow. Object-oriented programming is the foundation of PyTorch. Because of its built-in support for conditionals and loops, PyTorch makes it a breeze to write code. Big names in tech like Yandex, Facebook, and IBM all use PyTorch.
- **H2O:** Organizations and businesses rely on it as a major framework for building machine learning models, and it is open source. Water is used by the HORTIFRUT industry to process blueberries in the most efficient way possible. In order to maximize efficiency and minimize waste, Stanley Black & Decker optimizes and streamlines the manufacturing processes. For Intel's network traffic and intrusion detection purposes, they employ it [22].
- **Torch:** One open-source framework for building machine learning models is Torch. Who owns it? Facebook. The Torch is a set of tools for scientific computing, including a scripting language, a library, and a framework for GPU/CPU-based machine learning. Using a torch is simple and adaptable. Organizations like NVIDIA, Yandex, and Purdue utilised it.
- **Caffe (Convolutional Architecture for Fast Feature Embedding):** The Berkeley Vision and Learning Centre (BVLC) was designated as its developer. With the ability to process 60 million photos per day using just one GPU, it is among the quickest DNN systems. When training models, Caffe makes it straightforward to switch between using the GPU and the CPU. Computer vision, speech, and multimedia content analysis are some of Caffe's uses by organizations like Google and Pinterest. A Convolutional Neural Network (CNN) is trained to classify images using Caffe.

B. Advantages of ML frameworks in Industrial IoT

Machine Learning (ML) frameworks bring significant benefits to Industrial IoT (IIoT) systems by enabling intelligent, data-driven operations.

- **Real-Time Anomaly Detection:** ML frameworks identify unusual patterns in real time, preventing faults, safety hazards, or cyber threats.
- **Process Optimization:** Continuous learning from production data allows optimization of workflows, energy use, and resource allocation.
- **Scalability and Adaptability:** ML frameworks handle large-scale, heterogeneous data and can easily scale across devices, plants, or supply chains.
- **Improved Decision-Making:** Real-time insights support accurate forecasting, inventory management, and operational planning.
- **Cost Efficiency:** Automation of inspection, monitoring, and predictive tasks reduces labor costs and improves overall efficiency.
- **Security Enhancement:** ML detects suspicious activity and strengthens cybersecurity within IIoT networks.

By integrating ML frameworks, industries achieve smarter operations, reduced costs, and greater system resilience.

V. Applications Of Ai In Industrial Iot

Industrial IoT (IIoT) networks connect sensors, machines, and devices in order to capture a tremendous amount of operational data. AI is key to the analysis of this data to improve operational efficiency, cut time lost and make industrial processes efficient.

Predictive maintenance is one of the most important AI-based IIoT applications. Through reading sensor data on machinery and equipment, AI models are able to predict performance before it fails. This enables the industries, particularly manufacturing and heavy machinery to prevent complex maintenance hence avoiding interruption of operations leading to loss of money. Other companies, such as GE Digital, have successfully run predictive maintenance on their Predix platform, reporting noticeably better levels of disruption to operations [23].

Process optimization and energy optimization are also other applications. By using AI algorithms, production processes, real-time sensor data analyzing, production work process efficiencies, energy consumption, and plant efficiency in general, are optimized. As an example, industrial facilities driven by Siemens Mind Sphere and Schneider Electric Contribute use artificial intelligence to fine-tune operating conditions and minimize energy consumption as well as optimize product quality. Besides efficiency, AI enables monitoring of resource use, load-balancing, and reduction of wastage of resources, something that is paramount in sustainable industrial practices.

Quality inspection and defect detection Quality inspection and defect detection is the second area on which deep learning algorithms can start to automatically detect defects or deviations in products on the assembly line. This increases product quality, less manual inspection costs, and increases the safety standards compliance [24]. Bosch Connected Industry and its artificial intelligence solution provider have applied visual inspection systems in manufacturing lines and realized succeeding above and beyond the performance metrics of a manufacturing process yield and the defect rates.

AI is also used in supply chain and logistics activities within industrial networks [25]. Using the data of sensors installed in warehouses, vehicles, and units of production, the AI can predict demand levels, find the most effective methods of managing inventory, and plan delivery routes. This helps to attain timely delivery, saves on storage costs, and enhances the effectiveness of the supply chain. Solutions being driven by AI, in real-life production and logistics, have demonstrated that integrated IIoT improves decision-making, and there is reduced human error in operations.

The Table II tabulates the main AI applications in Industrial IoT, such as; predictive maintenance, process optimization, quality inspection, and supply chain management, and how AI can be used to improve efficiencies, minimize downtimes, and ensure operational reliability.

TABLE II. KEY AI APPLICATIONS IN INDUSTRIAL IOT NETWORKS

Industry	AI Application	Brief Description
Manufacturing	Predictive maintenance	AI analyzes sensor data to predict equipment failures and reduce downtime.
Energy & Utilities	Process & energy optimization	AI optimizes energy usage, load balancing, and operational efficiency in plants.
Automotive Manufacturing	Quality inspection	AI-driven visual inspection systems detect defects in production lines.
Logistics & Supply Chain	Inventory & route optimization	AI forecasts demand, optimizes inventory, and improves fleet routing.
Smart Factories	Real-time monitoring	AI analyzes IIoT sensor data to detect anomalies and improve operational decisions.

In summary, AI applications in Industrial IoT networks enable industries to enhance operational efficiency, minimize downtime, improve product quality, and optimize supply chains, paving the way for smarter, data-driven industrial ecosystems.

VI. LITERATURE REVIEW

The literature on AI-powered Industrial IoT highlights advancements in resource allocation, predictive maintenance, anomaly detection, hardware optimization, and integrated frameworks, demonstrating progress and challenges in real-time, sustainable industrial applications. Recent studies given below illustrate these developments.

Lee et al. (2025) introduced a hardware-based 5G test-bed that emulates dynamic slicing and large-scale sensor data processing using AI-powered resource optimization. Taking advantage of current 5G infrastructure and surrogate sensor data generation, system enables realistic big data analytics in industrial environments. An AI-based decision tree model dynamically assigns network slices, optimizing throughput costs. Surrogate data provides good quality supplemental sensor data, preserving key statistical and spectral properties, enhancing sensor-driven big data applications. Experiments show improved data transfers, adaptive network slicing and scalable big data processing. This offers a cost-effective solution for small/medium-sized enterprises (SMEs) and research/development (R&D) teams [26].

Li (2025) highlights the importance of the Industrial Internet of Things (IIoT) in the fourth industrial revolution and automated manufacturing. The Digital Twin can monitor equipment status, predict failures, and optimize production distances. However, the dynamic changes, limited spectrum resources, and high security requirements pose challenges. The paper proposes a resource optimization for short packet communication (SPC) using deep reinforcement learning method. The total power minimization problem is constructed, considering security capacity and total bandwidth constraints. A dual-depth Q network and a power resource optimization network are designed, with simulation results showing that the intelligent resource optimization algorithm can effectively reduce the total power of SPC and ensure secure data transmission. [27]

Kumar et al. (2024) proposed AI-optimized hardware design leverages the latest advancements in semiconductor technology and integrates specialized processing units for efficient execution of machine learning tasks. The architecture is designed to meet the limitations of IoT devices, tight size requirements and real-time processing. Important parts of the design are low-power processors, hardware accelerators and memory hierarchies optimized to run AI workloads. The presented AI-optimized hardware design is simulated and tested experimentally, where it outperforms other conventional designs, in all regards of energy use, computing speed, and scalability. The paper prospective the possibility of the developed hardware in the disclosure of new opportunities of the application of AI in the various IoT arrangements, including smart cities and industrial automation, hospital and ecological observing, etc [28]

Deepan et al. (2024) explore the application of AI in predictive conservation of Industrial IoT systems and how it would enhance functionality, performance, and reduce time-out. Through predicting the defects that may compromise the functionality of equipment, ICA can prevent failures before they eventuate resulting in actionable interventions at a reasonable cost. Such a method prolongs the ministry's existence and enhances the legacies of planned conservation regimes and allocation. The paper also talks about implementation issues and successful implementations in the different colours and how the community of AI and the Internet of Things can change the character of traditional conservation activities and bring substantial changes in reliability and efficiency. The results highlight the opportunities of AI in increasing conservation practices.[29]

Chahed et al. (2023) introduce AIDA, a new framework for networks and processing that is driven by artificial intelligence, enabling dependable data-driven real-time industrial Internet of Things devices. To facilitate the real-time feeding of data into an observable edge/cloud continuum powered by artificial intelligence, the framework manages and configures Time-Sensitive Networks (TSN). Timely decisions are made for a variety of industrial IoT applications and the infrastructure as a whole by means of robust and pluggable ML components. There aren't enough frameworks for programming and integrating computing and networking infrastructures to make it easy to integrate time-sensitive networks with dependable data input and processing environments. The AIDA architecture is presented, demonstrated, and two use cases are used to illustrate it [30].

Wang and Lin (2023) highlight the importance of Artificial Intelligence of Things (AIoT) technology in the industrial revolution, particularly in achieving Industry 4.0 goals. They argue that effective implementation of AIoT solutions is crucial for sustained investments in manufacturing sustainability. However, previous studies have developed frameworks for industrial performance measurement, but practical implementation of AIoT solutions is still lacking. This paper examines the benefits of AIoT and how to turn them into a financial justification, focusing on the overall engineering framework. It introduces several benefit estimation methods for AIoT solutions that have not been officially installed on the production line. The case study presents two real-world AIoT-related manufacturing examples, exploring complex process KPIV and computer vision. Manufacturing practitioners can use the report as a tool to promote the values of AIoT [31].

Table III represents a comparative review of recent studies on AI-powered optimization in Industrial IoT, highlighting their focus, contributions, industrial domains, limitations, and future directions in advancing Industry applications.

TABLE III. RECENT STUDIES ON AI-POWERED OPTIMIZATION TECHNIQUES FOR INDUSTRIAL IOT APPLICATIONS

References	Focus / Application	Key Contributions	Industrial Domain	Limitations	Future Directions
Lee et al. (2025)	AI-powered resource optimization in 5G-enabled industrial networks	5G test-bed, dynamic network slicing, surrogate sensor data, AI decision tree for throughput optimization	General Industrial IoT, SMEs	Limited real-world deployment; mainly test-bed simulations	Real-world deployment in large-scale industrial networks; integration with broader IIoT applications
Li (2025)	Resource optimization for secure short-packet communication in IIoT	Dual-depth Q network for bandwidth allocation, DDPG for power optimization, secure and energy-efficient communication	Smart Manufacturing, IIoT Networks	Focused on short-packet communication; simulation-based results	Multi-objective optimization under heterogeneous IIoT devices; real-world validation
Kumar et al. (2024)	AI-enhanced hardware for Internet of Things devices	Low-power processors, hardware accelerators, memory hierarchies for real-time AI execution	Smart Cities, Industrial Automation	Hardware-level optimization; limited network integration	End-to-end AI-optimized IIoT systems combining hardware, network, and software
Deepan et al. (2024)	Predictive maintenance in IIoT	Real-time failure prediction, optimized maintenance schedules, resource allocation	Manufacturing, Industrial Equipment	Focused mainly on maintenance; network optimization not addressed	Holistic AI frameworks combining predictive maintenance and network optimization
Chahed et al. (2023)	Real-time AI-driven IIoT framework for Industry 4.0	Introduced **AIDA**, an AI-driven holistic network + processing framework with TSN support, pluggable ML, and edge/cloud continuum	Real-time IIoT, edge-cloud AI, process optimization	Framework still conceptual; limited validation through use cases	Expand AIDA to industrial-scale pilots, integrate cross-industry ML pipelines
Wang & Lin (2023)	Industrial AIoT performance measurement	Case studies on AIoT deployment, framework for operational & financial benefits	Manufacturing, Industry 4.0	Mostly theoretical; limited practical implementation	Real-time industrial deployment; performance optimization frameworks for AIoT

VII. CONCLUSION AND FUTURE WORK

The integration of AI with the Industrial Internet of Things is bringing about a paradigm shift in industrial systems, opening the door to new possibilities in process optimization, autonomous decision-making, and predictive analytics. Predictive maintenance, problem detection, energy management, and supply chain optimization are just a few examples of applications that have proven to be highly beneficial. These include more efficiency, less downtime, and better sustainability. Machine learning frameworks such as TensorFlow, PyTorch, and H2O provide strong advantages in Industrial IoT by offering scalability, flexibility, and compatibility with diverse hardware and software environments. These frameworks simplify model development, enable efficient training and deployment, and support advanced techniques like deep learning and reinforcement learning, making them central to the realization of intelligent and adaptive IIoT solutions. Practical implementations across manufacturing, logistics, and energy sectors highlight the transformative impact of AI-powered optimization, improving product quality, operational resilience, and resource utilization.

Despite these advances, industries still face persistent challenges related to interoperability, cybersecurity vulnerabilities, and the high computational costs of large-scale AI integration. Addressing these issues is crucial for widespread adoption and unlocking the full potential of AI in industrial ecosystems. Looking ahead, future research should focus on explainable and trustworthy AI, lightweight models for constrained devices, standardized frameworks, and emerging paradigms such as 6G-enabled IIoT, blockchain-based security, digital twins, and sustainable AI practices to advance Industry 5.0.

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