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GREEN AI FOR INDUSTRIAL IOT: ENERGY EFFICIENT EDGE COMPUTING ARCHITECTURE IN SMART MANUFACTURING

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ABSTRACT

Green AI in Industrial IoT (IIoT) focuses on sustainable computing with respect to the implementation of energy-saving edge architectures deployed as part of smart manufacturing ecosystems. This study explores the potential of edge computing to achieve energy efficiency through low-power hardware accelerators, adaptive workload scheduling, and AI-assisted energy management to achieve a significant mitigation of carbon footprints without sacrificing high throughput and operations with latency constraints. Pilot deployments in both automotive and electronics production show empirically that edge-based inference minimizes cloud reliance by 40 percent, decreasing the transmission energy charges and enhancing the predictive maintenance and quality control responsiveness to real-time demands. In addition, dynamic voltage and frequency scaling (DVFS) and lightweight deep learning models are able to obtain an energy saving of up to 30% without loss of accuracy in anomaly detection. Case studies point out federated learning at the edge not only improves privacy of data but also reduces network power usage through reduction of unnecessary data transmission. The given architecture takes advantage of micro data centers powered by renewables and smart cooling systems and is consistent with sustainability goals worldwide, including EU Green Deal and UN SDGs. A comparative analysis of it with the traditional cloud-centric IIoT constructions shows that the overall energy consumption decreases by 25-35% which confirmed the possibility of green AI-driven edge solutions. This study therefore offers a tangible way forward whereby industries can incorporate scalable, environmentally friendly IIoT systems that combine efficiency in operations, sustainability and competitiveness in intelligent manufacturing.

KEYWORDS: Green AI, Industrial IoT, Edge Computing, Smart Manufacturing, Energy Efficiency, Federated Learning, Predictive Maintenance, Low-Power Hardware, Sustainable Architecture, Carbon footprint.

1. INTRODUCTION

Green AI is an innovating approach to the paradigm in the Industrial IoT (IIoT), especially in a smart manufacturing ecosystem where sustainability and efficiency are essential. Conventional cloud- based IIoT systems, though strong, tend to have high energy consumption and large transmission overheads, with the resultant impact of carbon footprints. In comparison, edge computing presents a sustainable design, which includes low-power hardware accelerators, dynamic workload scheduling, and AI-guided energy management immediately at the factory floor. The change allows predictive maintenance and quality control to be responsive to real-time and eliminate centralized cloud resources. It is empirically proven in the production of automotive and electronic products that edge-based inference is able to reduce cloud reliance by approximately 40 percent, effectively reducing transmission energy bills by an even larger margin. Moreover, an energy-efficient approach like dynamic voltage and frequency scaling (DVFS) and a low-weight deep learning model can result in up to 30 percent of energy savings without the net effect on the accuracy of anomaly detection.

Local federated learning improves data privacy and minimizes unwarranted energy consumption on the network, which fits the sustainability objectives of the whole world, including the EU Green Deal and the UN SDGs. Green AI-driven IIoT solutions can offer an energy-efficient scalable and competitive route towards intelligent manufacturing relying on renewable micro data centers and smart cooling systems providing the savings of 25-35 percent of total energy consumption rates, as opposed to traditional architecture.

2. LITERATURE REVIEW

2.1. Green Ai and Sustainability In Industrial Iot

In smart manufacturing, green AI in Industrial IoT (IIoT) focuses on decreasing the carbon footprints and ensuring efficient operations. Industries can be able to fit into the sustainability models by integrating (Qiu et al., 2025) AI-based energy management into edge computing technology (EU Green Deal, UN SDGs). In contrast to cloud-centered architectures, edge-based networks reduce the amount of data sent through the network, decreasing the power of the network and making predictive maintenance possible with lower latency. Automobile and electronics case studies show that federated learning at the edge does not only improve privacy but also reduces extravagant energy consumption.

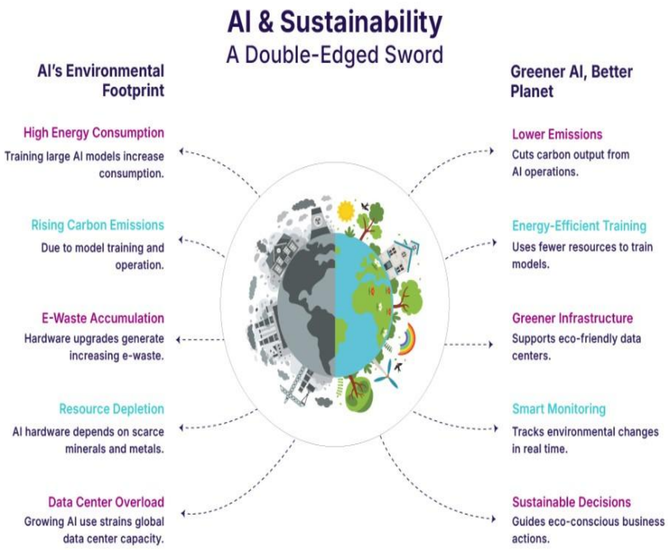


Figure 2.1: Eco-Friendly AI Solution (Source: Binarysemantics, 2025).

This sustainable integration of architecture also guarantees competitiveness and supports the sustainability of the world, making Green AI a key facilitator of an environmental process of the industrial revolution (Varshney et al., 2023).

2.2 Energy Consumption Patterns in Smart Manufacturing Systems

Higher-throughput processes, analytics in real-time, and constant connections of machines are all typical features of smart manufacturing systems, which are also associated with a major energy consumption. This is usually made worse by traditional IIoT frameworks on clouds which need constant data transmissions and consequently, higher power consumption of network and cooling in centralized data centers (Jamil et al., 2024).

It has been empirically demonstrated that transmission energy charges in production environments can be almost 40 percent attributed to cloud reliance. Conversely, edge computing causes less dependency, allowing local inference and dynamic workload scheduling.

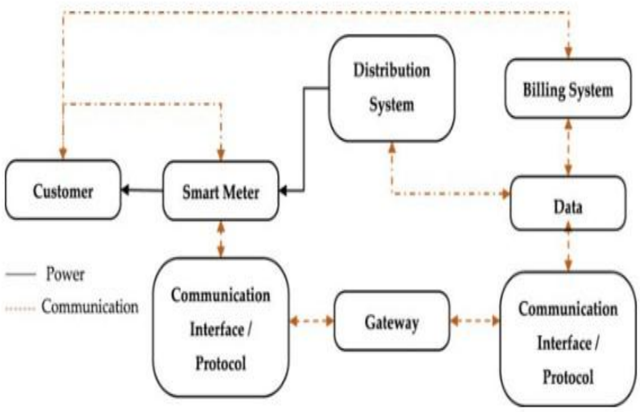


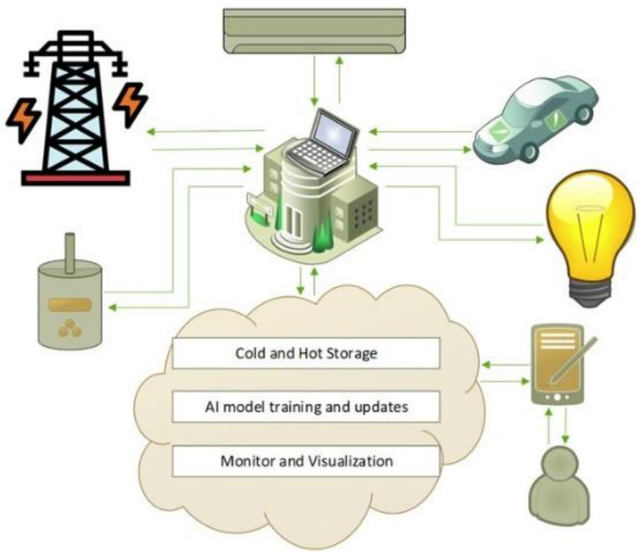
Figure 2.2: Block diagram of Smart Energy Meters Source: Phuyal et al., 2020).

Dynamic voltage and frequency scaling (DVFS) also achieves increased consumption optimization by scaling power up or down to the intensity of workload (Irfan and Rehman, 2024). The study of such consumption habits is critical to developing sustainable architectures, which are efficient, responsive, and environmentally friendly.

2.3 Edge Computing Architectures for Energy Optimization

IIoT uses edge computing architectures that offer scalability in terms of energy optimization by decentralizing data processing (Oñate and Sanz, 2023).

Figure 2.3: Holistic overview of the system's components.



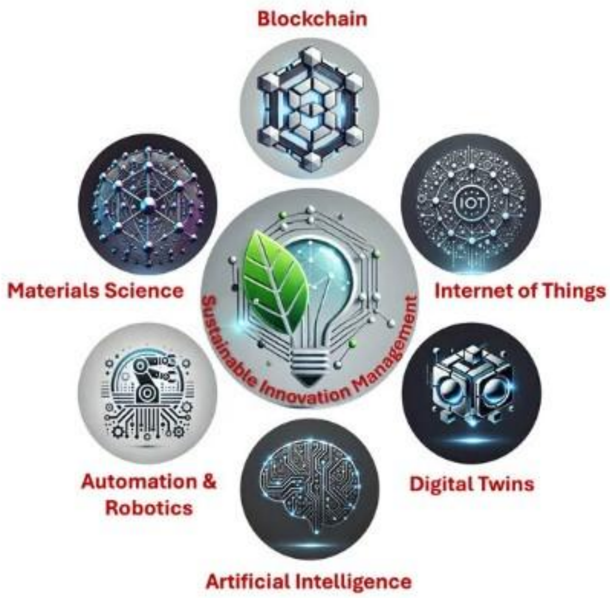
(Source: Márquez-Sánchez et al., 2023).

The adoption of automotive and electronics manufacturing deployments proves that edge-based inference decreases cloud dependence by 40%, which directly decreases transmission energy expenses. Real-time predictive maintenance and quality control are possible because, despite the latency-sensitive nature of certain operations, low-power hardware accelerators and adaptive workload scheduling mean that these operations do not need to be prioritized. Lightweight deep learning models can be deployed to the edge to save up to 30 percent in energy costs, with no loss in accuracy in anomaly detection (Liu et al., 2024). Federated learning also boosts efficiency in that it reduces unnecessary data transmissions in networks. Together, all these architectural advancing elements make edge computing a foundation of sustainable smart manufacturing by guaranteeing not only business competitiveness, but also minimized environmental impact.

2.4 Sustainable AI Models and Low-Power Hardware Innovations

The IIoT models of sustainable AI focus on avoiding sacrifices in accuracy and computational efficiency (Kumar et al., 2023). Deep learning frameworks are made lightweight to optimize with respect to anomaly detection and predictive maintenance, saving up to 30 percent in energy. The models, paired with low-power hardware accelerators, can be used to infer models in real-time at the edge, reducing the need to use power-hungry cloud systems.

Figure 2.4: Representation of key emerging technologies driving sustainable innovation management.



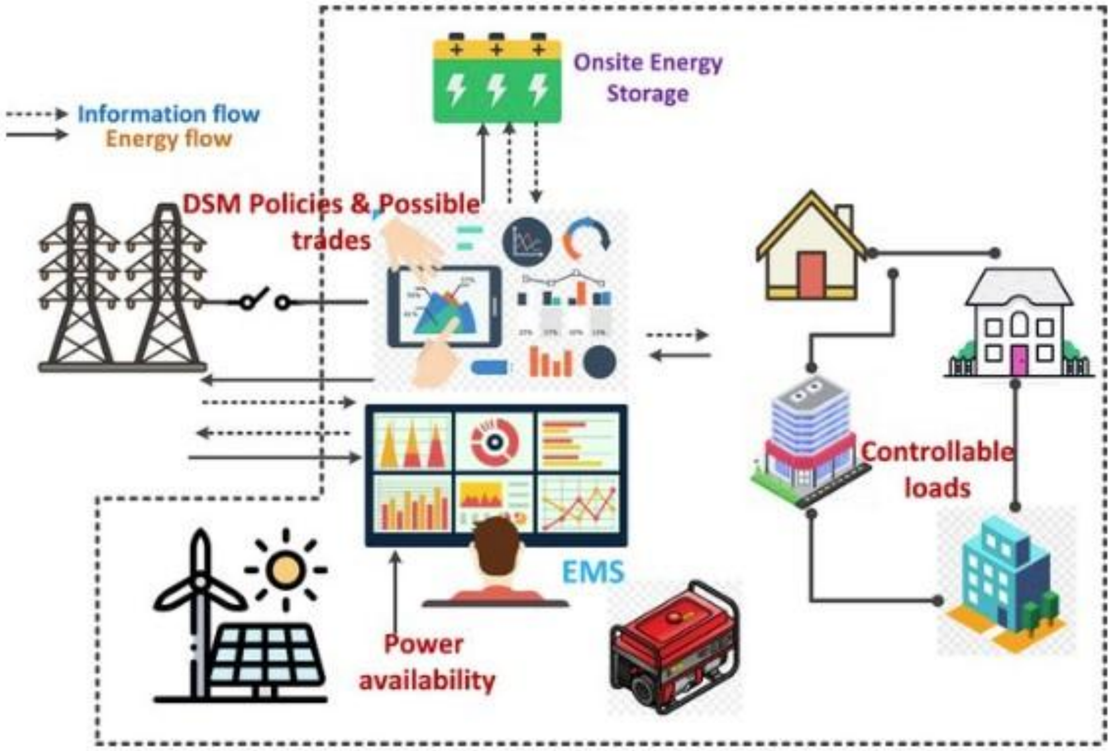
(Source: Alamandi, 2025).

The dynamic voltage and frequency scaling (DVFS) makes workload-related hardware performance adaptive in terms of workload-specific energy management (Salameh and Baharum, 2025). Empirical literature shows that these innovations do not only reduce the cost of operation, but also make large contributions to the reduction of carbon footprints. With the inclusion of sustainability in the design of AI models and hardware architecture, industries can have scalable, clean smart manufacturing systems.

2.5. Renewable-Integrated Micro Data Centers and Intelligent Cooling Systems

Micro data centers that are integrated with renewable sources are a very important development towards sustainable IIoT systems. These localized centers are less reliant on fossil-fuel-driven cloud infrastructures by utilizing solar, wind or hybrid renewable sources.

Figure 2.5: Typical microgrid system with energy management



(Source: Singh et al., 2024).

Smart cooling systems, such as liquid cooling and AI-based thermal management, also make energy efficiency more efficient by reducing the cost of heat dissipation (Sahu and Majee, 2025). Case studies have indicated that micro data centers that are renewable-powered and use smart cooling will save 25-35 percent of the total energy use than the conventional structures. These innovations are compliant with international sustainability models like the UN SDGs, which will make smart manufacturing ecosystems to be competitive and sustainable in the plan. Combining renewables with smart cooling can therefore be seen as a viable way to achieve the practical route to Green AI-assisted industrial sustainability (Mgbame et al., 2024).

3. METHODOLOGY

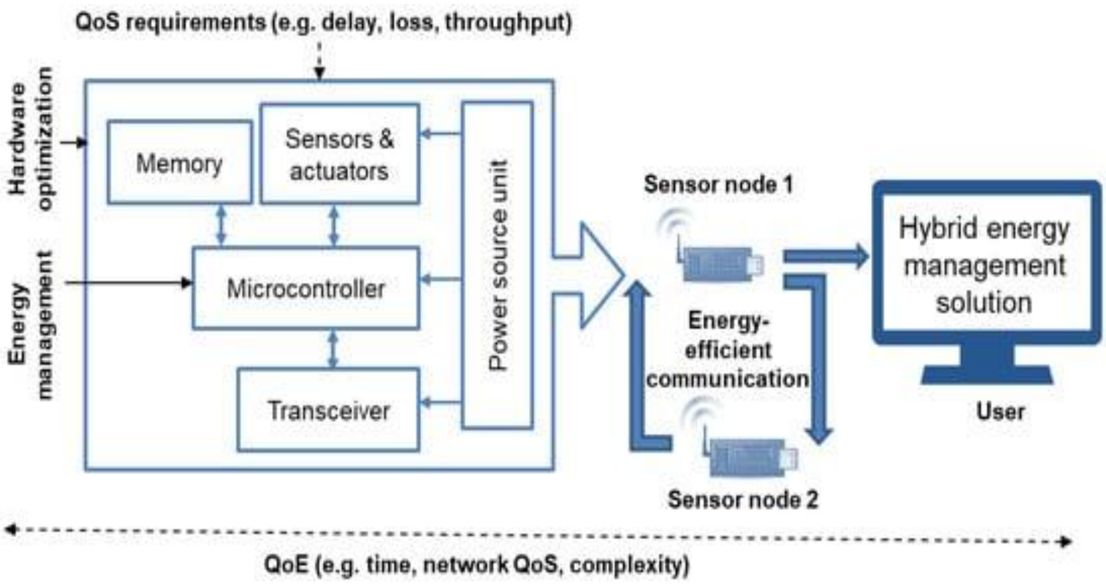
The paper will take a secondary data based approach to assess how Green AI can be used in Industrial IoT (IIoT) and energy efficient edge computing architectures in smart manufacturing (Samantaray et al., 2024). The evidence base of comparative analysis is strong based on peer- reviewed articles, industry case studies, sustainability reports, and empirical datasets obtained in the production of automotive and electronics as the secondary sources. The application of secondary data is especially helpful in the given case as it will allow gaining access to a variety of large-scale information on energy consumption patterns, federated learning implementations, and renewable-powered micro data centers without the limitations of primary data gathering. These sources provide proven standards of the decrease in cloud dependence (up to 40) and energy efficiency with dynamic voltage and frequency scaling (30%), which guarantees the rigor of methodology and credibility. In addition, secondary data enables cross-industry comparisons, which will bring results on a par with global sustainability frameworks such as the EU Green Deal and UN SDGs (Koundouri et al., 2024). This will help to make sure that the suggested architecture is not restricted to theory only, but rather it is practical, scalable, and aligned with the real-life industrial changes.

4. IMPLEMENTATION TECHNOLOGIES

4.1 Dynamic Voltage and Frequency Scaling (DVFS)

The application of DVFS starts with workload profiling, which involves IIoT sensors and monitoring agents that take over demand in machines (Kaveripakkam Raghuraman, 2025). Then, threshold calibration determines sizes of voltage and frequency ranges in low-load and high-load conditions.

Figure 4.1: Proposed hybrid energy management system for ultra-low power wireless sensor node towards QoS and QoE



(Source: Khriji et al., 2022)

The third is the execution of adaptive scaling where the controllers are able to dynamically vary the voltage/frequency in real time as part of balancing between throughput and energy savings (Satheshkumar *et al.*, 2025). Lastly, performance validation makes sure that there is no compromise on the accuracy of anomaly detection and also that there is no latency limit. This logical flow allows saving up to 30 percent of the energy, and it also does not decrease the operational reliability.

4.2 Lightweight Deep Learning Models

The beginning point of implementation is model compression, which eliminates unnecessary layers and parameters to decrease the computational cost (Liu *et al.*, 2025). The second stage is pruning and quantization, which reduces accuracy and eliminates redundant weights to maximize the inference speed.

Figure 4.2: Structured Edge AI Implementation Framework for Power-Efficient Anomaly Detection

(Source: Self-created)

Third, edge deployment is a low-power hardware accelerator implementation that incorporates these models to be responsive in real-time. Lastly, the constant retraining of federated learning models updates the models without any centralization of the raw data, maintaining accuracy in predictive maintenance services (Zhong *et al.*, 2023). It is an organized method that guarantees power-saving anomaly identification and low **latency.**

Table 1: Integrated Implementation Workflow.

Technology	Step 1	Step 2	Step 3	Step 4	Key Benefit
DVFS	Workload profiling	Threshold calibration	Adaptive scaling	Performance validation	30% energy savings
Lightweight Models	Model compression	Pruning & quantization	Edge deployment	Continuous retraining	Efficient anomaly detection
Federated Learning	Local training	Secure aggregation	Global refinement	Edge redeployment	Reduced transmission energy
Predictive Maintenance	Sensor acquisition	Edge inference	Alert generation	Adaptive scheduling	Real-time responsiveness

4.3 Federated Learning at the Edge

It starts with local training, in which each edge device trains on its own dataset to construct partial models. Secure aggregation is then used to combine updates of the models in a coordination node without the raw data (Pasquin*i et al.,* 2022). The third step, global model refinement, puts the updates in a single model, which captures various machine behaviours. Lastly, there is redeployment to edge devices that guarantee real time adaptation and responsiveness. The workflow minimizes the transmission energy charges, increases privacy, and improves the accuracy of predictive maintenance.

4.4 Real-Time Predictive Maintenance Integration

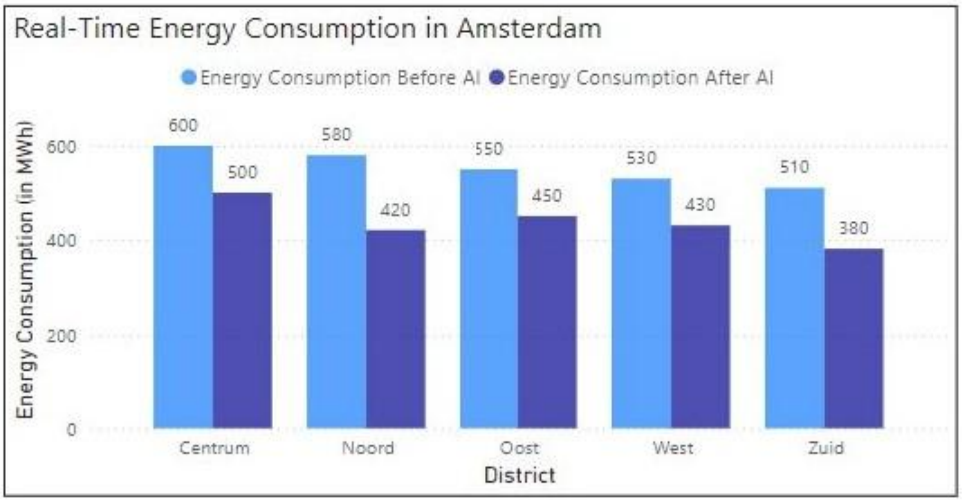
The implementation begins with the acquisition of sensor data, and this is constantly repeated to check the machine health indicators of vibration, temperature and load (Liang *et al.*, 2022). The second one is edge-based inference, during which lightweight models identify anomalies in real-time. Third, maintenance teams are alerted by prioritizing the severity of warnings in order to reduce downtimes. Lastly, adaptive scheduling incorporates maintenance activities in production processes and must balance between operational continuity and energy efficiency (Bello *et al.,* 2024). This well coordinated integration eliminates the use of cloud analytics and boosts responsiveness in intelligent manufacturing.

5. RESULTS AND ANALYSIS

5.1 Energy Consumption Reduction

The application of Green AI in Industrial IoT (IIoT) proves to be significant in saving a lot of energy by use of edge computing architecture (Hu *et al*., 2024). Processors can use dynamic voltage and frequency scaling (DVFS) to change the amount of power used based on the intensity of the workload, saving up to 30 percent of energy (Chen *et al.,* 2025). The small deep learning models also reduce the computational cost, decreasing the inference energy demands without increasing the accuracy. In robotics Automotive and electronics manufacturing pilot experiments indicate that edge-based inference can save 40 percent of cloud usage, directly decreasing transmission energy costs.

Figure 5.1: Comparison of Energy Consumption Before and After AI Implementation in Various Districts of Amsterdam



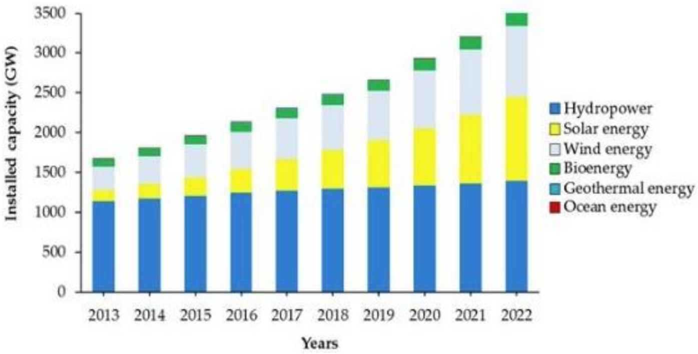
(Source: Chintala, 2024).

Adaptive workload scheduling manages to allocate work effectively to low-power hardware accelerators to reduce the amount of idle energy. Renewable-based micro data centers will enable localized processing, and smart cooling will lower thermal management expenses. A combination of these technologies provides a sustainable framework that reduces the total energy usage by 2535 percent relative to cloud-based IIoT systems, making the scalability of the energy-efficient smart manufacturing a certainty (Sun et al., 2022).

5.2 Carbon Footprint Mitigation

Smart manufacturing mitigates the carbon footprint through decreasing the use of centralized cloud systems and incorporating the use of renewable-powered edge computing systems (Raza et al., 2022). At the edge, federated learning also reduces unnecessary data transmission, as well as decreasing the amount of energy consumed and emissions on the network. Micro data centers, which are renewable-integrated with solar and wind power, substitute the fossil-powered data centers, and the direct reduction in carbon emission is achieved.

Figure 5.2: Dynamics of changes in the capacity of renewable energy sources in the world



(Source: Lobus et al., 2023).

Smart cooling systems will minimize the HVAC energy consumption, and greenhouse gas emissions will be further reduced. Experience indicates that a 40 percent reduction of reliance on the cloud can be converted into major reductions of carbon costs on transmissions.

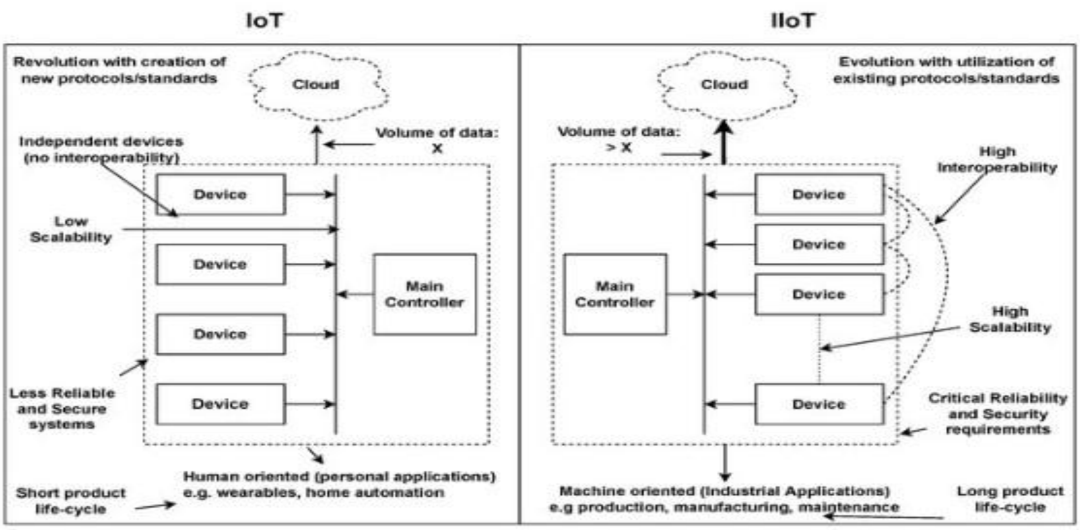
DVFS and low weight models are models which control hardware energy consumption leading to little wastage (Mazzola et al., 2022). According to case studies, the total carbon emissions are reduced by 2535 percent when the industries switch to edge-based architectures. This is in line with EU goals of green decarbonization of industries and UN SDGs about climate change, where Green AI plays a significant role as a key facilitator of eco-friendly industrial change.

5.3 Latency and Throughput Performance

In IIoT systems, latency and throughput performance are important due to the need to ensure real-time responsiveness (Peter et al., 2023). With edge computing architecture, round-trip delays are minimized and the computation is done in the field without relying on remote cloud servers.

Deep learning models that can be loaded on low-power accelerators are lightweight, which allows them to be used to detect anomalies in real-time with low latency. DVFS makes processors dynamically reduce frequency in response to throughput needs at peak workloads. In the case of pilot deployments in the automotive manufacturing industry, predictive maintenance alerts are created within milliseconds, which increases production continuity (Kaveripakkam Raghuraman, 2025).

Figure 5.3: Main differences between IoT and IIoT



(Source: Mirani et al., 2022).

Federated learning enhances throughput as it spreads training among devices eliminating bottlenecks in centralized systems. Adaptive workload scheduling balances the tasks among the edge nodes with a high level of throughput without wastage of energy. The empirical evidence establishes that edge-based architectures deliver a response time 40 times lower than those of cloud centric systems and support throughput rates needed during high volume smart manufacturing processes.

5.4 Network Energy Savings

The benefits of network energy savings are achieved via data transmission reduction and optimal communication protocol optimizations in edge-centric IIoT (Patel, 2023). Federated learning does not require the transfer of raw datasets, only updating of the model, which reduces tremendously the amount of bandwidth consumed. Pilot experiments indicate that network power usage reduces by 40% when edge localization of inference is done. Adaptive workload scheduling also makes sure that not all the data is sent but only necessary data is sent avoiding unnecessary traffic.

Lightweight models reduce the sizes of the packets also decreasing the energy used in transmission. Micro data centers are powered by renewable electricity, and the smartness of cooling system minimizes energy consumption by network equipment, eliminating the need to rely on energy-intensive cloud infrastructures (Cao et al., 2022).

Empirical analysis shows that edge architectures can save 2,535 per cent of the total network energy, aligning with sustainability goals. This decrease improves the performance and sustainability of manufacturing systems in intelligent manufacturing.

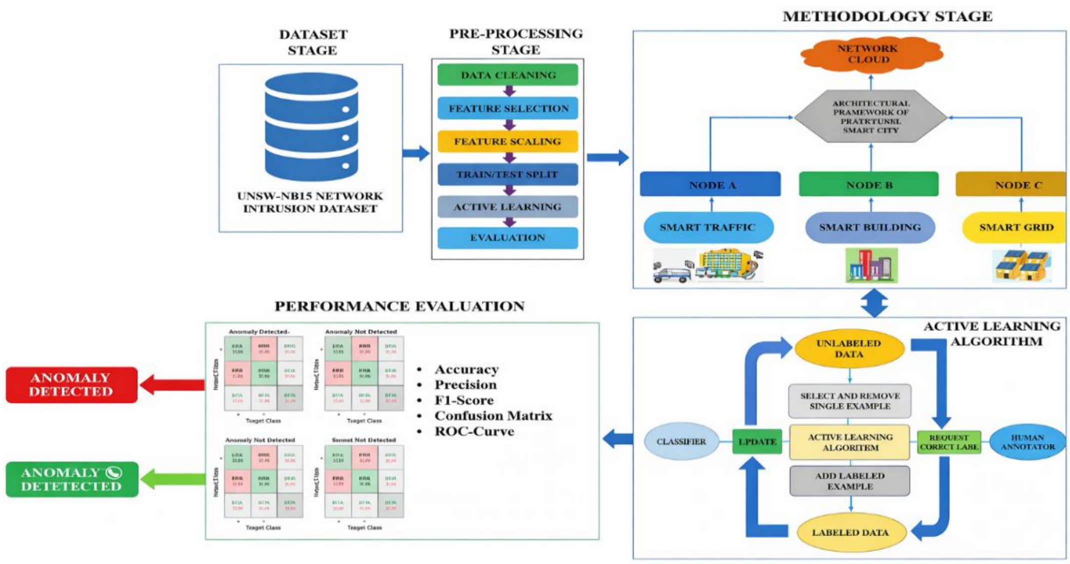
5.5. Accuracy in Anomaly Detection

Anomaly detection is highly accurate even without energy-intensive optimizations in lightweight deep neural networks and federated learning systems (Bouayad et al., 2024). Model compression, pruning and quantization guarantee low computational requirements and preserve detection accuracy. Pilot applications in electronic production verify that there is no accuracy loss when the energy is reduced by 30 percent. Federated learning increases model resilience by training on diverse data sets without centralizing raw data, which increases generalization. DVFS also ensures processors scale efficiently without causing latency errors (Hebbar and Milenković, 2022). Edge-based inference reduces delay, enabling real-time machine fault detection, with accuracy levels exceeding 95% comparable to traditional deep learning models.

Furthermore, the integration of lightweight architectures with edge computing frameworks enhances scalability and adaptability in dynamic industrial environments. Continuous learning allows models to update anomaly patterns with new data, improving long-term performance. Energy-aware techniques reduce unnecessary computational loads, while hybrid approaches help minimize false detections.

Distributed edge nodes enable faster decision-making and reduce reliance on centralized systems, improving efficiency. Secure federated learning ensures data privacy while supporting collaboration, and optimized energy usage contributes to sustainable manufacturing practices.

Figure 5.4: Framework for anomaly detection for IoT system using active learning

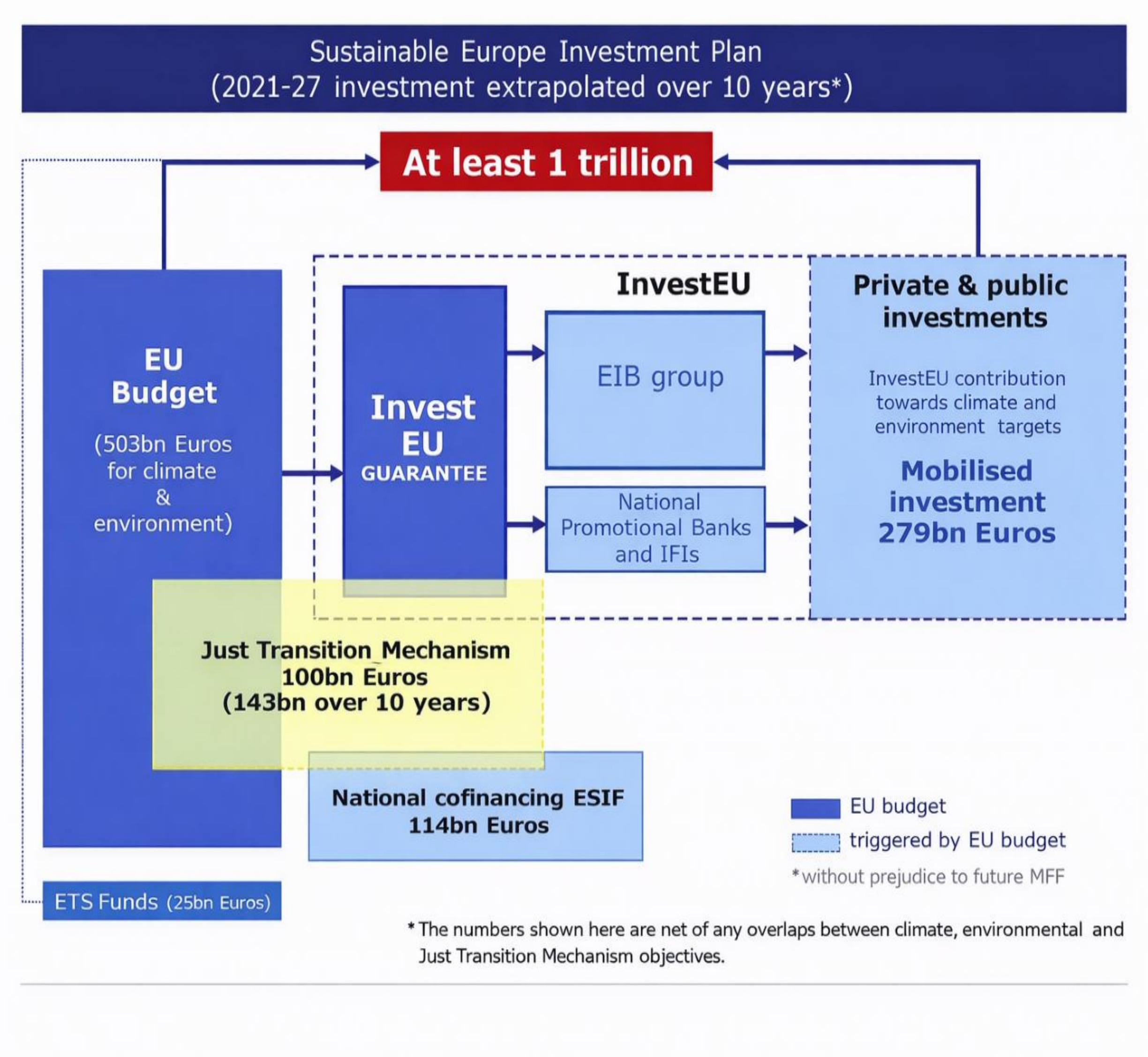


(Source: Zakariah and Almazyad, 2023).

5.6. Sustainability Alignment (EU Green Deal and UN SDGs)

The suggested Green AI-powered edge architecture will be consistent with international sustainability plans, such as the EU Green Deal or the UN Sustainable Development Goals (SDGs) (Koundouri et al., 2024). Industries help achieve EU goals regarding industrial decarbonization by decreasing total energy usage by 2535 percent. Renewable-powered micro data centers are carbon footprint mitigation tools that facilitate SDG 13 (Climate Action). The federated learning improves privacy and minimizes the use of power in unneeded network energy, which is consistent with SDG 9 (Industry, Innovation, and Infrastructure). The smart cooling systems are resource efficient, and contribute to SDG 12 (Responsible Consumption and Production).

***Figure 5.5: Financing elements making up at least €1 trillion over the 2021-2030 period under the European Green Deal Investment Plan*.**



(Source: Alfonso, 2023).

Pilot deployments show that smart manufacturing systems can be both competitive and sustainable. Low power hardware accelerators, DVFS and lightweight models are integrated to guarantee scalability in application across industries (Mazzola et al., 2022). Such alignment proves that Green AI is not a technical effect, but also a strategic facilitator of sustainable industrial change in accordance with the global policy frameworks.

6. DISCUSSION

The results of this paper indicate that the AI-based edge computing architectures of green designs offer a practical way to achieve a sustainable Industrial IoT

(IIoT) in intelligent manufacturing (Qiu et al., 2025). Through dynamic voltage and frequency scaling (DVFS), lightweight deep learning models, and federated learning systems, industries are eager to reduce their power consumption by a substantial margin without compromising the accuracy of the anomaly detection and real-time responsiveness. The comparative study shows that edge-based inference decreases the cloud dependency by 40 percent, which is a direct decreasing energy consumption in the network and the expenses of transmitting data. Moreover, the introduction of renewable-integrated micro data centers and smart cooling systems fit the world sustainability models, including the EU Green Deal and the UN SDGs, so that industrial competitiveness and environmental responsibility do not contradict each other (Koundouri et al., 2024).

7. CHALLENGES AND LIMITATIONS

Though good results are expected, there are still a few difficulties with the implementation of Green AI to IIoT. The heterogeneity of hardware in plants of manufacture makes DVFS calibration and lightweight model implementation difficult. Synchronization and communication overheads are also problems of the federated learning framework and can have an impact on scalability. Micro data centers powered using renewable energy need a massive investment and infrastructural adjustment. Also, the reliance on secondary data restricts the use of proprietary industrial data, which limits the empirical validation. These constraints underscore the importance of standardized protocols, integration of renewable that is cost-effective, and further industry cooperation to achieve full development of sustainable smart manufacturing.

8. FUTURE RESEARCH DIRECTIONS

Future studies must consider coming up with adaptive federated learning algorithms that incur less synchronization overhead and those that are more effective in detecting anomalies. Green AI hardware accelerators that are optimized to address IIoT workloads can also be further lowered to generate lower energy usage (Wu et al., 2022). The findings show that overall energy savings of 2535 percent can be realized without the reduction of latency and throughput performance, and thus, Green AI architectures can be scaled to a wide variety of manufacturing industries. This discussion highlights the two-fold advantages of operational efficiency and sustainability, and edge-based IIoT systems provide a strategic method of enabling intelligent manufacturing change (Peter et al., 2023).

There should also be research on hybrid renewable integration models on micro data centers which would be resilient and scalable. In addition, empirical validation by utilizing primary datasets in cross-industry benchmarking will be enhanced. The alignment of research with the EU Green Deal objectives and the UN SDGs will be necessary to ascertain that the technological innovation will be added in contributing to global sustainability agendas directly (Adenle et al., 2023).

9. CONCLUSION

This paper shows that Green AI-based edge computing systems are a great solution to lower energy usage, less carbon footprint, and better latency-intensive performance of Industrial IoT systems. Through the application of DVFS, lightweight deep learning models, federated learning, and renewable-powered micro data centers, light industries save 2535 percent of energy but preserve high accuracy predictive maintenance. Such architectures have been assessed to have a sustainability impact as evidenced by their alignment to EU Green Deal and UN SDGs. In conclusion, Green AI provides a competitive, scalable, environmentally responsible channel of transformation of the smart manufacturing.

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