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A Study on Industrial Process Optimisation and Predictive Maintenance using AI-mRL

Sridharan Ganesan
Research scholar, Department of Management Studies, Vels Institute of Science, Technology and Advanced Studies

Abstract: Industrial 4.0 automation environment integrates a combination of mechanical devices, process machinery, Inductive and resistive loads that are monitored and operated through sensors, PLCs, PAC and Industrial IOT (IIOT) devices for better process and efficient operations.

Creating a seamless operating environment requires a robust and most advanced technology integration and data mining environment. Our Research uses multiple fusion sensing hardware and embedded programming with Deep learning and AI algorithms to predict industrial process/machine failures using,

- ***An Embedded AI edge device (hardware).***
- ***Long distance Sub-GHz communication protocol.***
- ***AI agent to collect, analyse and tigger faults on local and cloud infrastructure.***

The hardware uses a micro controller with Wi-Fi communication to collect and transmit data. The system captures data on multiple sensing elements including Power, Vibrational and temperature for smart analytics to sense and report failure mode trigger to avoid process failures and machine breakdown.

The research will understand the industrial process efficiency and performance by collecting data from multiple sensors for a data driven approach using Machine learning and deep learning algorithm. "A fault trigger before the machine breakdown", that minimise the cost and improve the process efficiency using Machine Reinforcement Learning (mRL).

Keywords: Industrial 4.0, Automation, Sensors, PLC (Programmable Logic Controller, PAC (Programmable Automation Controller, Industrial IoT (IIoT), mrL etc

I. INTRODUCTION

A. Edge AI

The term AI is buzzing word in the tech industry now, but what make the AI better in term of computing is bringing the intelligence into the edge device, or embedded code with AI logic into the microcontroller. This approach changes the game of electronics and computing to the next level. Edge AI is basically the embedded deployment of AI applications and its logic into the device and create a network of connected device to create an actionable insights and deliverables. Usually with the recent advancement on the cloud computing and data collection from the device stores its data into the cloud or local storage for ML, deep learning or AI logics that can later pushed in to the hardware to act. This approach requires an uninterrupted, reliable internet connectivity with no latency. Now with Edge AI, computing is available on the edge device that can collect, store, compute and deliver results locally without any latency. The data collected and computed are then stored in the cloud for further finetune and data mining purposes.

B. Edge AI in Industrial Automation

AI at the edge is the next generation of connected device in industrial automation with local intelligence to the process. This adds better advantage of data collection to control system into a single platform with no latency. Process machines or industrial loads need PLC or PAC logics to perform operation which are preprogrammed. Now with the help of edge intelligence, the system can perform a more dynamic task at the greater speed to achieve better process efficiency and energy savings.

With Industrial IOT (IIOT) application with Edge AI can learn and adapt to new scenario on the process, the ML and deep learning framework can feed quality data sets.

1) Process efficiency can be improved using smart sensors, connected devices and AI application to understand Machine dependency, Machine idle time and TOU (time of use tariffs) to delivery better operational efficiency.
2) Preventive maintenance can be improved to the next level to create new standards for "Predictive maintenance". Understanding and feeding the historical data of machine or motor efficiency curve and its system failure to the AI model using Machine Reinforcement Learning (mRL) can deliver cost savings and better maintenance.

II. REVIEW OF LITERATURE

The rising complexity and competitiveness of modern companies necessitates the use of innovative technology to improve operational efficiency and lower costs. Predictive maintenance has evolved as an important method that uses artificial intelligence (AI) and machine learning to predict equipment breakdowns and optimise maintenance schedules. Organisations may dramatically enhance forecast accuracy by combining numerous machine learning algorithms with anomaly detection, opening the path for more effective maintenance plans. However, the shift to AI-driven predictive maintenance is not without obstacles, such as the necessity for significant amounts of high-quality data, the complexities of installing machine learning systems, and the need for qualified individuals. Recent studies emphasise AI's disruptive potential in a variety of industries, including automotive and manufacturing, demonstrating major benefits such as decreased downtime, cost savings, and increased operational efficiency. Researchers emphasise the importance of data analytics in enabling pre-emptive interventions while admitting the challenges of data quality and the need for technical skills. Furthermore, the use of sophisticated techniques like multi-agent reinforcement learning and machine learning algorithms results in significant advancements in decision-making processes across many industrial settings. By examining key research findings, this paper aims to shed light on the critical components required for successful integration and identify future directions for research and practice in predictive maintenance strategies. This introduction sets the stage for a comprehensive discussion of the current landscape of AI-driven predictive maintenance, outlining both the benefits and challenges associated with its implementation.

III. PROBLEM STATEMENT

A. Data Collection And Data Mining In Manufacturing

The manufacturing process gathers many data sets from multiple sources and multiple processes. But these data are not put together for better understanding and actionable items.

Basic IOT applications gather data from feeders, sub-feeders, and motor levels for electrical parameters; these KWh, KVA, voltage, amps, PF, and THDs are not properly used for further energy optimization.

Similarly, industrial sensor data from the IOT platform delivering temperature, pressure, airflow, air quality, hazardous gases, etc. are only collected and reported. But taking the information to the optimization level is very critical. Similarly, collecting, capturing, and mining the data for quality data sets are quite challenging. The ML/deep learning algorithm can extract the relevant data set, which is useful for further analysis and decision-making.

There are several hardware platforms like PLC, PAC, RTU, SCADA, HMI, RFIDs, WiFi sensors, AI image processors through CCTV, and much more to gather raw data that can be either fed to the data network or edge device for further data processing and data mining activities to gather usable data sets for process optimization.

B. Challenges and impacts on process improvement

The key challenges around manufacturing data collection are these legacy systems with networks or communication protocols that are not compatible with modern data collection, data monitoring, data mining, and data computing methods. Many older machines on the factory floor don't have hardware compatibility, or the floor team doesn't have the extensive experience of integrating legacy equipment or hardware with the new set of hardware for data collection.

Even when there is hardware available that can be capable of understanding the data and creating an actionable insight, the control system on the legacy equipment is not capable of adapting to the new control algorithms. Replacing the equipment and its control systems is the nightmare for floor operators.

There should be two levels of expertise needed to achieve a better result: domain knowledge on the equipment, its hardware behaviors, and middleware communication between the legacy and new manufacturing data collection systems. The legacy of modern communication protocol is the key factor for a successful digital efficiency for an industrial process.

IV. RESEARCH APPROACH

Training the AI models by feeding quality data sets and deploying these models into the industrial process and operation at the edge devices makes a huge difference and adds value to the existing industrial 4.0 environment through connected equipment. Moreover, the hardware selected for the edge devices needs more computing capacity that can help deep learning and neural network algorithms. Currently, IOT-connected devices are mainly responsible for delivering the data volume at machines and sensors.

A. Technology Review

Recent development of GPUs (Graphics Processing Units) not only delivers graphics at the edge but also gives more computation power at the edge device for more data analytics and reasoning capabilities. Connecting the parallel GPUs is now common in the industrial environment to collect and run neural network logics to deliver a precise event trigger for process and operational efficiency. Deploying more sensors, cameras, and RPA (robotic process automation) frameworks at the floor and machine level will introduce an additional layer of intelligence to deliver improved efficiency. Now, with recent advancements in connectivity, speed, reliability, and data security, it's the best time to adopt and utilize the technical innovation into industrial infrastructure.

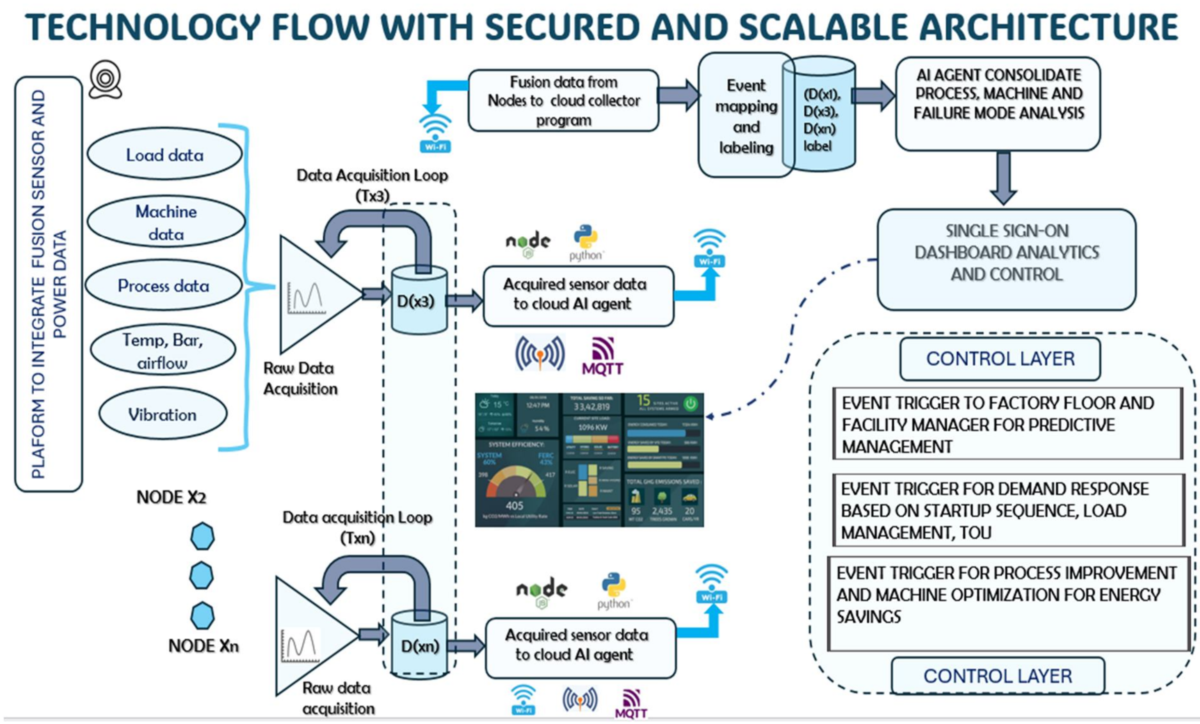

Figure 1: Node data flow integrated with AI-controlled smart processes using edge AI and cloud.

The research on quality data sets will help to understand the industrial process efficiency and performance by collecting data from multiple sensors for a data-driven approach using machine learning and deep learning algorithms. The mRL algorithm is used to feed a quality data set to teach the model for optimal output. The self-learning algorithm can help to optimize the process efficiency and deliver a seamless operation with reduced cost. The digital efficiency can help to create the most affordable smart factories using wireless edge devices.

V. BUSINESS CASE AND TECHNOLOGY ADOPTION

A. AI-controlled smart Processes and Digitalization

AI-based solutions with data-driven approach infrastructure are playing a vital role in smart factories to capture real-time data and compute a huge volume of data that includes programs from sensor-based process operations, smart machine vision, digital twin on process level, and machine-reinforced learning for better optimized output.

To achieve low latency, AI applications are run at the edge device rather than computing at the cloud level. This can create a whole next level of reduced storage and backup costs. Only quality datasets are retained at the edge level, and the rest can either be sorted or discarded at the cloud infrastructure. This AI edge framework plays a critical role in Industry 4.0 to digitalize and revolutionize the automation process to achieve data-driven insights.

The edge device and its computing power at the machine level thought the edge device could offer a solution for limitations in the cloud architecture. This approach can give more processing power to the edge devices and data storage closer to the machine/equipment, which can give better decision-making and enhanced security. The protection layer of a decentralized approach can eliminate the risk of cyber-attacks.

Connecting multiple edge devices to the local mesh network can allow multiple datasets from multiple devices and endpoints that can process large amounts of data in parallel to achieve actionable AI for automated decision-making capability.

For example, smart machine vision with sensors can deduce anomalies in processes to analyse and react to visual data processing at the machine level that reduces the lag when the data is sent, processed, and reacts from a cloud infrastructure.

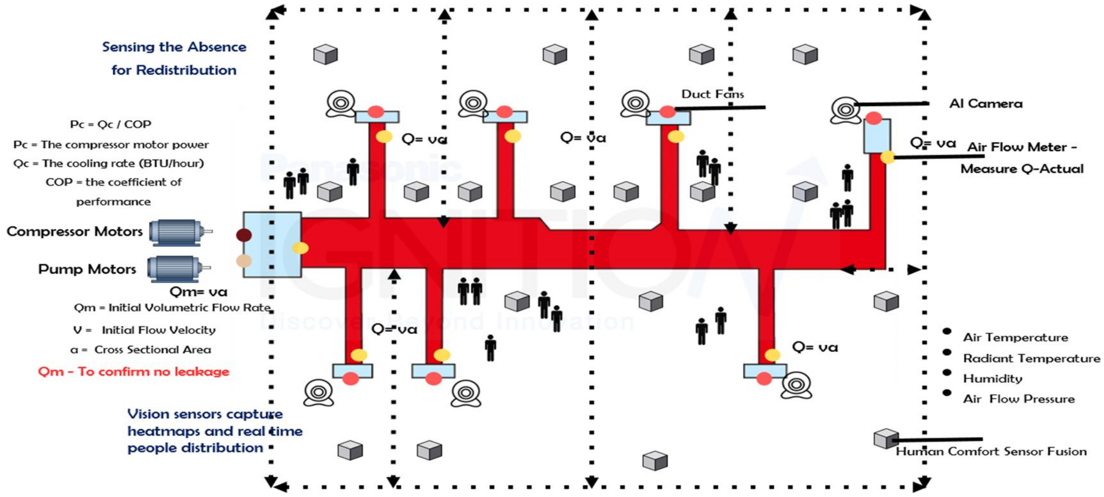

Figure 2: Process optimization on industrial HVAC using COP (coefficient of performance)

B. *Predictive Maintenance using AI-mRL*

The approach to real-time data analysis using machine learning to identify equipment anomalies is a starting point for AI-based machine reinforcement learning (mRL). The vulnerability or the change in load curve can help us predict the failure rate of equipment so the corrective maintenance can be even scheduled before the equipment failure. This involves data gathering at multiple sensors that includes vibration, electrical parameters, load curve, rated parameters of the asset, temperature, and operating conditions.

The predictive maintenance and corrective maintenance structure can be more cost-effective and can extend the life span of the equipment. At the same time, optimized data points arrived through the mRL algorithm can trigger the operating equipment to run at the optimal level to achieve energy savings and reduced breakdown.

The multiple benefits achieved through predictive maintenance and corrective actions are

- Increased production hours
- Reduced inventory in spares
- Eliminate unexpected downtime
- Increase system reliability
- Savings on repairs and maintenance costs

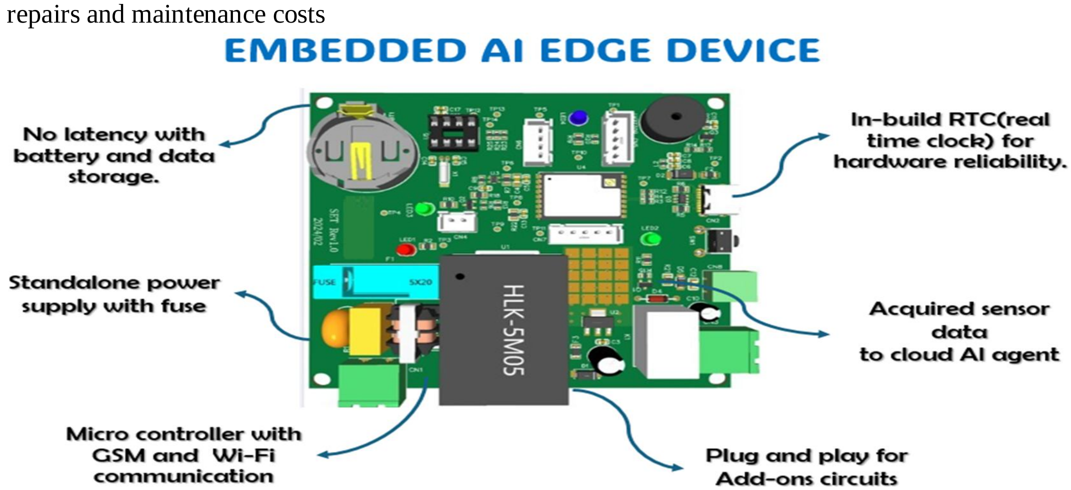

FIGURE 3: AI edge device capable enough to collect, analyse, and create an actionable AI

C. Deliverable

- "A fault trigger before the machine breakdown" that minimizes the cost and improves the process efficiency using machine reinforcement learning (mRL).
- AI-based process improvement and energy efficiency on utility and process load using particle swamp optimization (PSO) for every savings.

VI. DIGITAL TWIN IN INDUSTRIES

A. Process Digitalization Using Digital Twin

The real-time data collection thought IOT devices can give better insights but consistent visualization in an integrated environment where analytics and learning happening in parallel to trigger events and control the outcomes are the key factors. Digital twin, or DT, is one such infrastructure for combining multiple technology and data sources where we replicate the physical assets into a digital format with real-time data analytics where the plant management system can be operational remotely with 24/7 support for effective plant operations.

A virtual plant operation that can be monitored, controlled, and managed through a visual and digital infrastructure. There are few challenges faced by the technology team to adopting a full-fledged DT on a facility scale, but the advanced machine learning and big data infrastructure help to create an enterprise-level digital twin. This approach can create a much more interactive and simulative environment for facility management to try process improvements on a virtual setup before implementing in a physical environment.

Digital twin allows the next generation of automated flow shop that can be monitored and controlled to deliver an optimization on the process load, and there can be a lot of improvisation for future simulation and data visualization in real time. The most challenging part is to handle both graphic infrastructure and process lifecycle. The process should involve a high frequency of data exchange between smart devices and graphical rendering technologies for faster layout rendering.

B. Replicate Process Flow Using Edge Devices And Graphical Rendering

Digital twins can consider more of an AI system that has the potential to create a more automated industrial environment. Simulating the automated system requires a large volume of data from multiple sources and devices with parallel computing. Basically, integrating individual edge devices to create a sub-DT and then stitching it to a single model for further simulation. The data visualization before the action trigger can help to roll back actions at any point in time. The best data set can be retained in the Edge device, where the subset can be sent to the cloud for further fine-tuning. This model can replicate the process flow using edge devices and DT infrastructure.

VII. CONCLUSION

In conclusion, the integration of advanced technology such as AI, deep learning algorithms, and edge devices into the industrial environment has enabled the prediction of process failures and the optimization of machine efficiency through predictive maintenance. By leveraging quality data sets and machine reinforcement learning, this approach not only minimizes costs and prevents machine breakdowns but also improves process efficiency and energy savings. The utilization of AI-controlled smart processes and digitalization, along with the development of digital twin technology, allows for real-time data analysis, better decision-making, and enhanced operational efficiency in industrial automation. Moreover, the implementation of predictive maintenance using AI-MRL enhances production hours, reduces downtime, increases system reliability, and saves on maintenance costs. Overall, the adoption of edge AI and advanced technologies offers a transformative solution for achieving seamless and efficient industrial processes while paving the way for smart factories and automated decision-making capabilities.

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