In Field Predictive Maintenance

Abstract

Knowing in advance when an equipment will fail, avoids both unplanned and planned downtimes. Next-gen maintenance will increase equipment up-time by over 20%, reduce maintenance costs by 25%. A large part of industry 4.0 installation, machinery and vehicle operates in **austere environments with no access to internet or electricity**. Traditional solutions for predictive and diagnostic solutions fail without these two utilities.

AITS has developed an Agentic AI-based predictive maintenance solution that can be deployed directly on edge devices. This enables autonomous, low-power operation even without network connectivity, bringing advanced capabilities to in-field data.

Problem statement

American industries continue to spend over $1T in critical equipment maintenance costs that ballooned to over $2.1T by 2020. Somewhere between one-third and half of these maintenance $s were wasted through ineffective maintenance management methods. Industries can no longer absorb this level of inefficiency. The main reason for this level of inefficiency is lack of quantifying data based on which maintenance decisions and operations are scheduled. Maintenance has the potential to save the Department up to $5 billion annually [3]. This is based on AI analytics-based prediction and marks a new way of implementing maintenance at an industrial scale.

Industry 4.0 predictive maintenance solutions have been using data-center (internet or on-premise network) as a ready infrastructure. Traditional predictive maintenance approaches stop working on vehicles, equipment and machinery in motion without reliable connectivity. Moreover, a single application is deployed on thousands of machines disregarding the condition indicators of individual sites and machines.

Need & Background

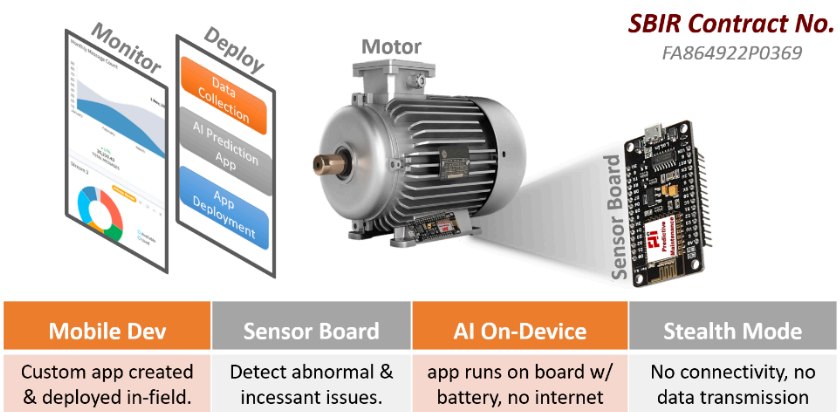
Typically, organizations do not track equipment performance, maintenance tasks performed, failure history or any of the other data that could, and should, be used to plan and schedule tasks that would prevent premature failures, extend the useful life of critical plant assets and reduce their life cycle cost. Instead, maintenance scheduling has been, and still is, determined by equipment failures or on the perceptions of potential failure by maintenance personnel who arbitrarily determine the type and frequency of routine maintenance.

In addition, the general opinion has been “Maintenance is a necessary evil” or “Nothing can be done to improve maintenance costs”. Perhaps these were true statements 10 or 20 years ago. However, the development of microprocessors, sensors and advancements in the field of Artificial Intelligence systems provide the means to optimize maintenance effectiveness.

Maintenance costs are typically a major portion of the total operating costs of most industrial plants. The industrial sector primarily uses either run-to-failure or preventive maintenance methods.

Solution

In Field Predictive maintenance - is a condition-driven preventive maintenance solution that is designed to work with low devices on equipment in situ at remote/electricity/internet devoid locations for the machinery and equipment. End to end "In Field Predictive Maintenance" solution includes a mobile device with touch screen and a sensor board. Sensor board is mounted on motor/equipment and connected to mobile devices to gather sensor data specific to the motor/equipment.



Mobile devices are connected to a sensor-board on motor/equipment with USB or BLE protocol to receive sensor data, train/test AI models, compile and deploy firmware to monitor health. Our solution provides high value to machinery and equipment operating in austere environments since it runs on battery and requires no Internet connection. By accurately predicting the actual failures, we can achieve maintenance cost reductions, increased productivity, and efficient utilization of budget and resources.

AITS solution uses machine learning to optimize maintenance schedules and provide analysis and recommendations at both a component and system level. It is capable of integrating historical structures (e.g., sensor reports) and datasets.

AITS In-Field Predictive Maintenance: A Modern Approach

AITS's solution marks a significant leap beyond traditional AI, evolving from human-assisted "co-pilot" tools to autonomous "autopilot" systems. This new paradigm, known as Agentic AI, describes self-sufficient systems designed to achieve complex goals with minimal human input, showing adaptability, advanced decision-making, and independence in dynamic environments.

To effectively function in industrial predictive maintenance, these general-purpose AI models require grounding in domain-specific knowledge. Our system achieves this through a unified industrial large knowledge model (ILKM) framework that integrates knowledge, data, and models for more effective and comprehensive solutions. By leveraging the latest AI capabilities, we validate our models with verifiable information from proprietary historical datasets, ensuring accuracy and traceability. This approach also mitigates "hallucination"—the generation of factually inconsistent content—using techniques like Retrieval-Augmented Generation (RAG).

The system's autonomous behavior is driven by advanced reasoning and prompting techniques, such as Chain-of-Thought, which enables the model to generate a series of intermediate steps to reach a solution. This is further enhanced by a Tree of Thoughts approach, allowing the model to explore multiple reasoning paths and self-evaluate its choices—crucial for complex tasks. Our system can also be viewed as a multi-agent system, where specialized agents collaborate on different sub-tasks, mimicking human expert teams.

The core value of our solution lies in shifting from diagnostics—identifying the cause of failure after it occurs—to prognostics, which proactively predicts future failures and a machine's remaining useful life. This enables optimized maintenance schedules and improved decision-making at both component and system levels.

Key Challenges and a Forward-Looking Roadmap

While the technological foundation for Agentic AI is robust, its widespread adoption faces significant non-technical and institutional challenges. These include issues related to accountability, trust, and integration with existing legacy systems, particularly in high-stakes fields like industrial manufacturing.

A primary technical challenge is the problem of **hallucination**, where a model generates content that is factually inconsistent or unfaithful to the user's input. The use of Retrieval-Augmented Generation (RAG) is a critical step in mitigating this issue by grounding the model in external, verifiable data sources. A related challenge is the complexity of **evaluation**. As Agentic AI systems become more capable, their assessment must move beyond simple task-level metrics to consider societal and ethical implications, such as bias and transparency.

To navigate these challenges, we propose a strategic, phased roadmap:

1. **Phase 1: Knowledge Integration.** The initial focus is on leveraging frameworks like RAG to ground general-purpose foundation models in proprietary, domain-specific information. This directly addresses the critical challenge of hallucination.
2. **Phase 2: Task Automation.** After a stable knowledge base is established, specialized AI Agents can be deployed to automate narrow, high-value tasks, allowing the organization to build internal expertise in model deployment.
3. **Phase 3: Autonomous Orchestration.** The final phase involves a transition to full Agentic AI, where multi-agent systems handle complex, multi-step workflows with minimal human intervention.

This phased approach, combined with a proactive investment in legal and ethical governance frameworks, is essential for building the trust required for large-scale deployment of autonomous systems.

Applications

Deep learning analysis of vibration's harmonic is critical to monitoring the health of many equipment including the ones shown in table below.

Air Pump	Turbine	Conveyor Belt	Air Conditioner	Boiler Burner
Generator	Air Filter	Transformer	Vibration Table	Brewing Engine
Air Compressor	Cold Room	Mixer	Vacuum	Elevator
Re-fusion Oven	Water Pump	Gearbox	Cryo Pump	…

Table: Equipment suitable for vibration based health monitor

It can detect faults like unbalance, misalignment, bearing issues, looseness, gear problem, bent shaft, cracked shaft, damaged rotor bar and many more.

Differentiators

The solution is designed for industry 4.0 machines and equipment installed in austere environments with no access to electricity and Internet.

1. Non tech users can deploy the solution with a few touch buttons in a matter of minutes.
2. End to end "In Field Predictive Maintenance" solution is created, deployed and used in the field.
3. Runs with no-cloud or no-Internet connection.
4. Sensor board firmware is customized for each motor/machine in the field leading to higher accuracy.
5. Low energy solution runs on battery for several months.

Conclusion

While traditional methods of predictive maintenance continue to reduce cost and improve schedules of machinery, last mile coverage of our “In-field Predictive Maintenance” technology is complementary. It not only enhances the value of existing tool-chain, it is much needed for mission critical and infrastructure operations without internet and electricity.

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