AI-based Autonomous Diagnostics and Maintenance System for Cyber Physical Systems

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***Abstract*— Cyber-physical systems (CPSs) have been deployed rapidly and widely for Industry 4.0. This work develops an AI-based autonomous diagnostics and maintenance system for CPSs to reduce operations & maintenance costs through detecting artefacts such as faults and equipment degradation, eliminating unnecessary downtime, and performing non complicated maintenance. This system is made possible by recent rapid technological advancements in robotics and computing to perform dynamic sensing and remote manipulation to reduce repetitive work and maintenance tasks, especially in harsh environments dangerous or hostile to humans. This autonomous system aims to: (1) uses mobile robots with portable sensors to dynamically sense in-the-field data, (2) uses machine learning (ML) and AI to analyze the integrated dynamic sensor data with sensor data from sensors installed in CPSs, and (3) accomplish ancillary maintenance tasks via robots. The current work progress includes a power plant simulation for robotic navigation and manipulation simulations, trajectory optimization and task planning algorithms development, and ML-based diagnostics system. This work also discusses the research challenges which need to be solved to achieve the proposed autonomous diagnosis and maintenance system.**

I. INTRODUCTION

As CPSs become ubiquitous in the Industry 4.0 era, diagnosis and maintenance of these systems should be improved through leveraging advanced AI and robots technologies. This research is developing an AI based autonomous diagnosis and maintenance system that can monitor, diagnose, and provide maintenance to CPSs without much human interaction. Specifically, the research is:

1) Developing a power plant digital twin to provide an operational environment for robotic simulations. A 3D plant layout is under development using the Robot Operating System (ROS) suite, and sensor data, such as temperature, pressure, and flow rate, will be integrated into the 3D environment using real-time telemetry from a full-scale power plant simulator.
2) Developing an AI-based diagnosis system with executive control over robotic tasking. This platform will autonomously detect faults, locate faults, evaluate the capability loss, and generate tasks to find and resolve the issue.
3) Developing a task planning and trajectory optimization algorithm to dispatch robots for in-field sensing, diagnosis, and online maintenance.

This system will serve as a foundation for future research in integrating robot and AI on improving the safety and efficiency of CPSs.

II. METHODOLOGY

Figure 1 shows the proposed autonomous diagnostics and maintenance system application to nuclear power plant (NPP) [1]. The decision-making system (DMS) receives data from both sensors installed in CPSs (or an NPP in this example) and robots to perform fault detection, diagnosis, and dynamic risk assessment using ML/AI. The robots can have various capabilities, depending on what sensors they carry, such as mounted thermal cameras, to confirm faults and augment diagnostic information. According to ML/AI diagnosis results, DMS dispatches robots through advanced task planning and trajectory optimization module. The system also allows operator intervention, as illustrated in Figure 1. This human in the loop system can improve this AI system and/or provide intervention as needed.

A. Real-time 3D environment development

In order to enable research in robot navigation, trajectory, and manipulation planning, a virtual environment must be developed which enables the rapid testing and iteration of algorithms before their implementation on real-world hardware. Since plants are complex, containing equipment such as pumps, steam generators, multi-stage turbines, condensers and other pieces of equipment, these items must also be modeled in the environment. This equipment, along with quadrapedal robots and their physical profile, will be simulated in a 3D environment using the ROS ecosystem. We will also project real-time sensor data from a power plant simulator to this environment, in order to simulate the physical environment under both normal operating conditions and faults. Examples of data to be projected into this environment include sensor data such as temperatures and flow rates and control parameters such as valve position.

B. ML based diagnostics system development

To develop a ML-based intelligent diagnostics system, data will be collected under all normal operations and abnormal scenarios such as malfunctions, physical faults, such as sensor drift, pipe leakage, pump degradation, and cyber-attacks such as false data injection. These faults are specifically aimed towards enabling the development of an integrated diagnostics system and robot platform, by simulating scenarios where robots can offer dynamic sensing in aiding diagnosis and temporary maintenance. Normal data will be utilized

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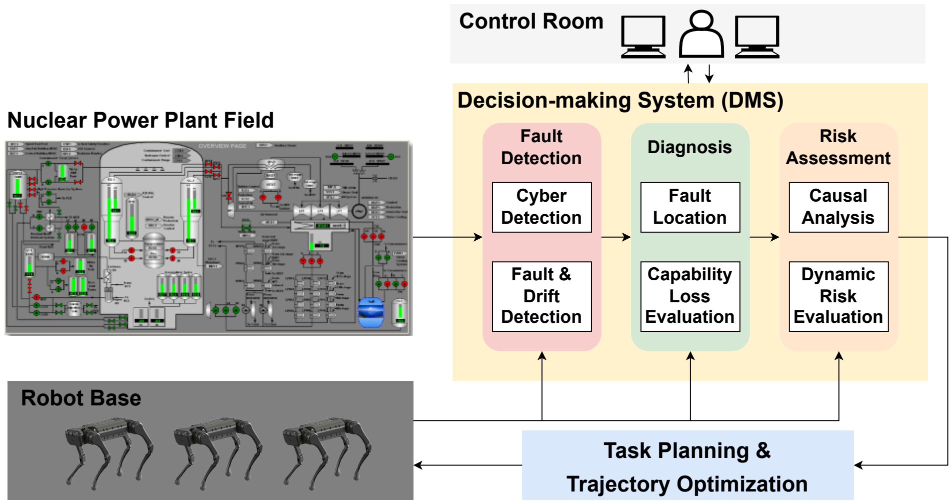

Fig. 1. AI-based autonomous diagnostic and maintenance system framework for CPSs[1]

as a baseline to build unsupervised and supervised ML monitoring models, while data under abnormal conditions will be utilized to build supervised models for fault detection and diagnosis. Supervised learning uses labeled data to train classification or prediction models based on previously collected historical patterns [2]. However, supervised learning cannot detect faults which are not in the training data. Unsupervised learning utilizes unlabeled data to discover hidden patterns in data without labeled examples, for applications such as clustering [3]. When applied to fault detection, these unsupervised models trained on fault-free data can be used to detect and flag deviation from normal behavior as a fault. An unsupervised deep neural network (DNN) model will be trained based on sensor data collected from the entire plant to detect anomalies which deviate from normal operations. DNNs can effectively leverage large amounts of data to capture complex and non-linear relationships, making them ideal candidates for modeling large sets of plant-wide time series data from many sensors [4]. Supervised models, including k-nearest neighbors (KNN), support vector machine (SVM), and ensemble regression models will also be built and used for select components including turbines, the steam generator, and main coolant pumps for fault detection and classification. The supervised models will also be able to take additional dynamic sensing variables, such as radiation level, for analysis. Metrics to evaluate the system effectiveness will include time-to-detection and false positive/negative rates for known/unknown faults.

C. Task planning and trajectory optimization algorithms development

Once a fault is detected by the diagnostics system from fixed sensors, the robots (multi-agents) need to visit several locations in a CPS to better diagnose it. The order in which the robot visits these locations is non-trivial since there are locations more likely to be the cause of specific faults versus others, or a certain sensing variable is more helpful than others to diagnose the fault cause. This can be modelled as having weights associated with each location. A trajectory optimization algorithm is developed that takes the sensing location preference into account.

III. CONCLUSIONS

This research aims to develop an autonomous diagnostics and maintenance system for CPSs using robots and ML. By using robots as a versatile and mobile sensing platform, combining with ML, this research improves the overall accuracy and effectiveness in identifying and resolving issues such as degradation and faults in CPSs, while reducing human labor and exposure to hazardous environment.

A novel trajectory optimization and task planning algorithm is developed to allocate the tasks to multi-agents. Current effort focuses on sensor priority selection for improving ML-based intelligent diagnostics system. Future work includes advanced ML/AI based diagnostics system and integration with robots manipulation.

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