5G-Enabled NetApp for Predictive Maintenance in Critical Infrastructures

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***Abstract*—Predictive Maintenance in critical infrastructure is a fundamental tool for predicting a failure in advance and for avoiding catastrophic equipment damage that can be prevented and the time-consuming repair scheduling can be executed in time. Artificial Intelligence (AI) based predictive maintenance utilises intelligent data for accurate predictions in order to make immediate interventions on critical assets. In this paper, we propose a 5G-enabled Network Application (NetApp) for predictive maintenance in energy-related critical infrastructures. The proposed NetApp consists of several containerised components responsible for retrieving time-series operational data from a power plant and detecting potential outliers/anomalies regarding the operation of energy generators. For the anomaly detection process, an autoencoder is used. The evaluation results demonstrate the efficiency of the proposed NetApp.**

***Index Terms*—5G, Artificial Intelligence, Network Application Autoencoder, Predictive Maintenance**

I. Introduction

Predictive Maintenance is a crucial maintenance tool based on the possibility of estimating the future values of some quantities that characterise a system (typically a machine, a plant, or a production process) through particular mathematical models in order to identify in advance the anomalies and potential faults. The predictive maintenance applications predict failure sufficiently ahead of time in order for the decision-makers to take appropriate actions, such as maintenance, replacement or even a planned shutdown. These applications promote savings on machine maintenance and increase productivity by guaranteeing the maximum uptime of machines. The manufacturing processes mostly adhere to an assembly line production, therefore any failure in the assembly line results in a domino effect, making it essential to evade any point of failure within the assembly line. By deploying predictive maintenance solutions, these failures can be evaded or at least minimised. However, for the most accurate and optimal prediction, it is required to gather and analyse large amounts of relevant data within a reasonable time frame. Consequently, big data analytics and stream processing technologies are key necessities for predictive maintenance solutions. Predictive maintenance applications are acknowledged as one of the fundamental data-driven analytical applications for large-scale manufacturing industries.

In this paper, we provide a Network Application (NetApp) for predictive maintenance in power plants, taking full advantage of containerisation, 5G and Artificial Intelligence (AI). In particular, the proposed NetApp adopts an autoencoder in order to recognise timely potential anomalies/outliers with respect to the functionality of industrial devices, paying special attention to electricity generators. For this purpose, operational data of the electricity generators are used. This kind of data is received through Programmable Logic Controllers (PLCs). Next, the autoencoder receives this kind of data and is responsible for the detection of anomalies.

The rest of this paper is organised as follows. Section II provides some relevant works in this field. Next, section III describes the architecture of the proposed NetApp. Next, section IV focuses on the evaluation of the autoencoder. Finally, section V concludes this report.

II. Related work

Several works investigate predictive maintenance applications and models in critical infrastructures, such as [1]–[5].

Each of the above works is further discussed below.

Sahal et al. [1] utilise a systematic methodology to review the strengths and weaknesses of existing opensource technologies for big data and stream processing to establish their usage for Industry 4.0 use cases. The authors aim to minimise the technological gap between the requirements of Industry 4.0 applications and the capabilities of available big data and stream analytics technologies for the use case of predictive maintenance. Several requirements were identified for the two selected use cases of predictive maintenance in the areas of rail transportation and wind energy. Considering use cases in the area of predictive maintenance, the requirements identified for a big data processing pipeline in the different phases of data processing can be described as data collection, analytics, querying, and storage. The mapping of these requirements establishes the capabilities of open-source technologies for big data and stream processing such as distributed queuing management, big data stream processing platforms, big data storage technologies and streaming SQL engines The outcome of this work is a comprehensive set of guidelines and technology combinations with a focus on open-source tools.

Shin et al. [2] focus on image-based inspection, where visual images collected from various devices such as endoscopes and thermal imaging cameras are employed. The authors developed an AI model based on a deep learning algorithm, specifically a convolutional neural network (CNN), utilising the labelled endoscope image dataset. In this study, the authors' utilised AI model-assisted human inspectors in the tasks of detecting bearing faults for treatment. The effects of AI models are assessed by two-way ANOVA based on two factors existence of AI assistance and the level of task proficiency. The assessment was administered on both the performance and perception of the human inspectors. The performance was evaluated by establishing the results of the inspection tasks in terms of specificity, sensitivity, and time efficiency, and perceptions were evaluated using questionnaires in terms of cognitive load, intention to reuse, and usefulness. Even though the experiment was a classification task, areas under the receiver operating characteristics (AUROC) were not considered because they could not be calculated for human-involved experiments. The results demonstrate that all factors, specificity, sensitivity, and time efficiency, can be enhanced with AI assistance, for both the generalist group and specialist group. In fact, AI assistance aids the inspectors even when the performance of AI-only was worse than human performance. The perception effects investigated showed positive results.

In [3], the authors propose the use of predictive maintenance of operational battery energy storage systems (BESSs) as the next step in safely managing ESSs. Predictive maintenance comprises monitoring the components of a system for changes in operating parameters, which may be indicative of a pending fault. These changes depict the need for maintenance while the fault is still recoverable. Various industries, including utilities, utilise this maintenance approach for assets such as power plants, wind turbines, oil pipelines, and photovoltaic (PV) systems. However, this approach has yet to be fully explored and utilised for BESSs. Predictive monitoring can be interdependent to safer system designs, which are fundamental for the real-time mitigation of catastrophic failures. However, when enforced to BESSs, predictive monitoring can initiate actions that potentially prevent catastrophic failures from occurring. This article reviews current safety practices in BESS development by providing examples of predictive maintenance approaches in other industries while noting the key components of an effective approach and describes the methodologies utilised to identify leading fault indicators.

In [4], Y. Teoh et al. propose a Genetic Algorithm (GA) as the technique for resource management in assets management applications for Industry 4.0. The proposed system architecture contains five layers, including (1) assets, (2) perception, (3) network, (4) fog computing and (5) cloud computing. GA was assessed along with MinMin, MaxMin, FCFS and RoundRobin in FogWorkflowsim to demonstrate the effectiveness of the proposed technique. The performance metrics for the evaluation were execution time, cost and energy. An extensive simulation experiment established that GA outperformed MinMin, MaxMin, FCFS and RoudRobin in terms of having the lowest execution time, cost and energy. The execution time was increased by 0.48%, the cost was decreased by 5.43% and energy usage was 28.10% lower in comparison to the second-best results. Lastly, a model for equipment predictive maintenance had been deployed using a supervised machine learning algorithm, two-class logistic regression. The model was able to predict if the manufacturing equipment failing and produced an early warning alert for the production line. The training accuracy and testing accuracy for the model were 95.1% and 94.5% each.

Ahmad et al. in [5] focus on the utilisation of AI techniques in the energy sector. This study aspires to present a realistic baseline that allows researchers and readers to compare their AI efforts, ambitions, new state-of-the-art applications, challenges, and global roles in policy making. The authors covered three major aspects, 1) the use of AI in solar and hydrogen power generation; (2) the use of AI in supply and demand management control; and (3) recent advances in AI technology. This study investigated how AI techniques outperform traditional models in controllability, big data handling, cyberattack prevention, smart grid, IoT, robotics, energy efficiency optimisation, predictive maintenance control, and computational efficiency. Big data, the development of a machine learning model, and AI factor an important role in the future energy market. The authors demonstrate that AI is becoming a key enabler of the data-related energy industry, providing a key tool to enhance operational performance and efficiency. As a result, the energy industry, utilities, power system operators, and independent power producers require to concentrate more on AI technologies. Taking into account the development in information technology, AI and data analysis, regulatory approvals for new services and products can be enforced quickly and efficiently.

III. Proposed NetApp Architecture

As depictede in Fig. 1, the proposed NetApp is composed of six components: (a) On-Premises Apache Kafka Engine, (b) On-Premises Data Collector, (c) Edge Data Collector, (d) Edge Analytics Engine, (e) Cloud Data Collector and (f) Cloud Visualisation Engine. Each of the above components is provided in a container format, taking full advantage of `Docker`. Moreover, the containers are orchestrated by an application orchestrator based on `Kubernetes`. Each of the above components is further described below.

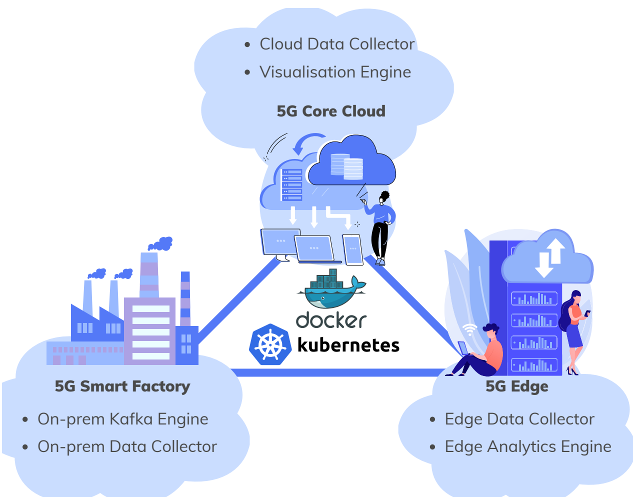

Fig. 1: NetApp Architecture

A. On-Premises Apache Kafka Engine

This component focuses on the deployment and preparation of the `Apache Kafka` service. Therefore, it plays the role of message bus, allowing the other components to communicate with each other in a more easy manner.

B. On-Premises Data Collector

This component is responsible for retrieving the operational data from the PLCs. To this end, the Modbus/Transmission Control Protocol (TCP) protocol is utilised. Next, this component publishes the operational data to the appropriate `Apache Kafka` topic created by the *On-Premises Apache Kafka Engine*.

C. Edge Data Collector

The Edge Data Collector is responsible for the data collection at the edge level. In particular, through `Apache Kafka`, it consumes the operational data stored by the *On-Premises Data Collector*. Next this data, is used by the `Edge Analytics Engine` for the anomaly/intrusion detection process.

D. Edge Analytics Engine

As illustrated in Fig. 2,the architecture of the *Edge Analytics Engine* consists of two main phases, namely (a) Training Phase and (b) Inference. During the training phase, *Edge Analytics Engine* is composed of three modules: (a) Pre-Processing Module, (b) Feature Engineering Module and (c) Training Module. The Pre-Processing Module normalises the time-series operational data, utilising various window sizes. Next, second module chooses the most informative data samples for the training procedure. Finally, the training module is responsible for the training process of the proposed autonecoder. In a similar manner, the *Edge Analytics Engine* consists of three modules. First, the Pre-Processing Module pre-process and normalises the time-series operational data. The Feature Selection Module, selects the appropriate feature based on the training process. Next, the Anomaly Detection Module applies the trained autoencoder and detects potential anomalies. The architecture of the proposed autoencoder is illustrated in Fig. 3. $ReLu$ was used as a hidden activation function, while $sigmoid$ was chosen as teh outpute activation function. Moreover, the mean squared error is used as a loss function and teh Adam optimiser was also chosen. Finally, the Response Module underatakes to publish an anomaly alert to the appropriate `Apache Kafka` topic established by the *On-Premises Apache Kafka Engine*.

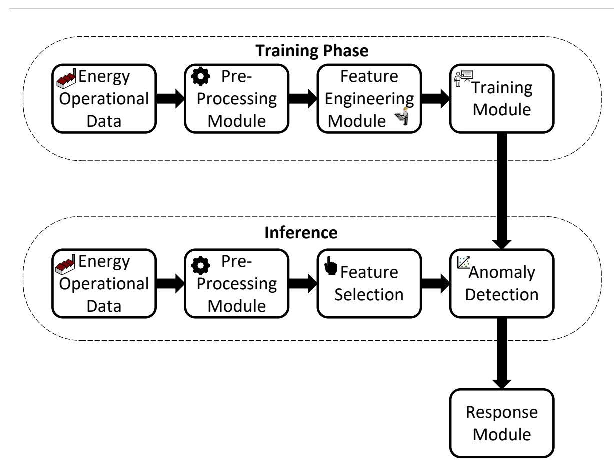

Fig. 2: Architecture of the Edge Analytics Engine

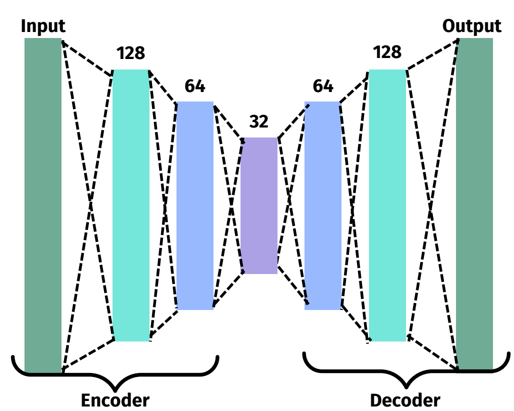

Fig. 3: Autoencoder Architecture

E. Cloud Data Collector

The *Cloud Data Collector* receives the anomaly alerts published by the Response Module of the *Edge Analytics Engine*. In particular, it consumes the alerts from the appropriate `Apache Kafka` topic established by the *On-Premises Apache Kafka Engine*.

F. Cloud Visualisation Engine

The *Cloud Visualisation Engine* visualisation engine receives the anomaly alerts and visualises them in a table format. Moreover, it is responsible for providing and visualising relevant statistics.

IV. Evaluation Results

This section is devoted to the evaluation analysis of the proposed NetApp for predictive maintenance in power plants. Before presenting the evaluation results, the relevant evaluation metrics should be first introduced. More information about them is given in [6].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{4}$$

Table I and Table II summarise the evaluation results of the proposed autoencoder compared to other anomaly/outlier detection methods, such as Local Outlier Factor (LOF), Isolation Forest, One-Class Support Vector Machine (OneClassSVM), Principal Component Analysis (PCA), Angle-Based Outlier Detection (ABOD), Stochastic Outlier Selection (SOS). Several choices of the window-size were tested. However, the best performance of the proposed autoencoder is achieved with window size: 40. Thus, based on the above evaluation metrics, the proposed autoencoder achieves the performance, while the worst performance is accomplished by ABOD.

TABLE I: Evaluation Results: Anomaly/Outlier Detection based on Energy Operational Data with Window Size 20

AI Model	**Accuracy**	**TPR**	**FPR**	**F1**
LOF	0.301	0.303	0.434	0.299
Isolation Forest	0.434	0.432	0.499	0.382
OneClassSVM - Linear	0.428	0.421	0.422	0.421
OneClassSVM - RBF	0.443	0.438	0.455	0.439
PCA	0.527	0.532	0.498	0.501
ABOD	0.188	0.187	0.243	0.122
Proposed Autoencoder	**0.865**	**0.866**	**0.323**	**0.861**
SOS	0.544	0.505	0.443	0.502

TABLE II: Evaluation Results: Anomaly/Outlier Detection based on Energy Operational Data with Window Size 40

AI Model	**Accuracy**	**TPR**	**FPR**	**F1**
LOF	0.421	0.402	0.333	0.329
Isolation Forest	0.494	0.448	0.455	0.442
OneClassSVM - Linear	0.422	0.422	0.401	0.421
OneClassSVM - RBF	0.421	0.432	0.413	0.420
PCA	0.545	0.547	0.349	0.522
ABOD	0.187	0.187	0.242	0.117
Proposed Autoencoder	**0.866**	**0.867**	**0.346**	**0.862**
SOS	0.549	0.515	0.439	0.532

V. Conclusions

In this paper, we present a 5G-enabled NetApp for predictive maintenance in critical infrastructures. In particular, the proposed NetApp was applied and tested in a power plant environment in Greece, utilising time-series operational data. The goal of the NetApp is to predict anomalies/outliers related to electricity generators. To this end, an autoencoder is adopted and Incorporated in the context of the Edge Analytics Engine. The evaluation analysis demonstrates the efficiency of the proposed NetApp.

Acknowledgment

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101016941.

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