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Towards Secured Online Monitoring for Digitalized GIS Against Cyber-Attacks Based on IoT and Machine Learning

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ABSTRACT Recently, the Internet of Things (IoT) has an important role in the growth and development of digitalized electric power stations while offering ambitious opportunities, specifically real-time monitoring and cybersecurity. In this regard, this paper introduces a novel IoT architecture for the online monitoring of the gas-insulated switchgear (GIS) status instead of the traditional observation methods. The proposed IoT architecture is derived from the concept of the cyber-physic system (CPS) in Industry 4.0. However, the cyber-attacks and the classification of the GIS insulation defects represent the main challenges against the implementation of IoT topology for the online monitoring and tracking of the GIS status. For this purpose, advanced machine learning techniques are utilized to detect cyber-attacks to conduct the paradigm and verification. Different test scenarios on various defects in GIS are performed to demonstrate the effectiveness of the proposed IoT architecture. Partial discharge pulse sequence features are extracted for each defect to represent the inputs for IoT architecture. The results confirm that the proposed IoT architecture based on the machine learning technique, that is the extreme gradient boosting (XGBoost), can visualize all defects in the GIS with different alarms, besides showing the cyber-attacks on the networks effectively. Furthermore, the defects of GIS and the fake data due to the cyber-attacks are recognized and presented on the dashboard of the proposed IoT platform with high accuracy and more clarified visualization to enhance the decision–making about the GIS status.

INDEX TERMS Internet of things; machine learning; cyber-security; gas-insulated switchgear, partial discharge.

I. INTRODUCTION

Practically, gas-insulated switchgears (GISs) have a superior interruption and insulation performance compared to traditional air-insulated switchgears [1]–[3]. Specifically, GISs require low spacing while yielding decent environmental compliance, thereby extensively being the preferable option for main substation components [4]–[7]. Recently, the general electric system infrastructure has started to approve digital information technologies. Interestingly, the digital substation can provide reduce maintenance necessities and the need for long conventional cabling and other electrical apparatus [8], [9]. These benefits are achieved by combining the newest electrical gear with digital sensors as well as cloud computing. As a result of this digitalization trend, the cyber-physic system

(CPS) becomes essential to ensure the continued operation of GISs in a digitalized substation and so the entire power system [10], [11]. In this regard, it has become a worldwide tendency that power system equipment access to the cloud, with the growth of the Internet of Things (IoT) and cloud platform systems. Its main merit is to appreciate value-added services by online remote monitoring, smart operation, and effective maintenance and diagnosis strategies [12], [13]. In particular, the IoT arrangement contains several evolving technologies that empower wireless interconnections between physical components.

The collected data by digital sensors are passed to IoT components e.g. users, industrial equipment, and personal devices. In 2020, the number of intelligent devices that utilize IoT was estimated to be 30 billion globally [14], [15]. With the expansion of IoT, the massive dataset gathered by intelligent sensors are helpful to enhance the manufacturing procedures and the excellence of life [16]. Thence, this IoT topology is highly recommended as the most extraordinary technological advances in upcoming knowledge and got significant consideration because of its probable in empowering the fourth industrial revolution (so-called Industry 4.0) [17], [18]. The authors of [19] have identified various IoT attack models and learning-based IoT security methods which are shown to be efficient protection for the IoT. In power system applications, diverse power equipment has involved widespread consideration and is a distinctive application ground of IoT. Most importantly, GISs are considered the fundamental equipment for power system operation where they are the primary gear with the main amount of substation custom and the highest influence on the main electric network security. It is an important asset to guarantee the standard operation and security of GIS with advanced IoT topology.

In the literature, GIS and partial discharge (PD) diagnostics have intensively been investigated by diverse methods and applications to alleviate current limitations and to attain a better diagnosis and monitoring. PD examination has been achieved by machine learning-based approaches, e.g. support vector machine [20], random forests [21], artificial neural network [22], decision trees (DT) [23], and genetic algorithm [24]. Different partial detection methods have been investigated for condition monitoring [25]. In turn, other research studies have been directed to diverse features of GIS condition monitoring [26]. In [27], a novel deep-learning model has been proposed based on the combination of long short-term memory and self-attention mechanisms to categorize the PD patterns in GIS, which offers the advantages of simultaneous computation and selective focusing signals to categorize diverse GIS faults. In [28], an image analysis-based approach for PD analysis has been proposed, combined with a deep learning system, to decrease the complexity of finding features for GIS experiments. In [29], a fault diagnosis technique involving a feature selection approach has been proposed based on a genetic algorithm as well as density-based clustering of applications with noise. Further, a digital twin concept has been proposed to enhance the virtual-real integration of industrial IoT of GIS and has been demonstrated to be feasible [30]. Recently, a novel MobileNets convolutional neural network model has been proposed to identify the GIS-PD patterns [31]. The IoT topology shows promising impacts in improving the performance of digitalized GISs. However, its usage can introduce considerable risks that include cyberattacks that can affect the reliability of the entire power system, which is not yet investigated and still under development.

To cover the abovementioned gap in the literature, this study is aiming to propose a novel IoT topology for the online monitoring and defect diagnoses of GIS in an effective manner. The proposed topology is based on the concept of the cyber-physic system (CPS) which is a vital item in Industry 4.0. Nevertheless, the classification of the GIS defects, as well as cyber-attacks, characterize the key challenges for adopting IoT in the online monitoring and tracking of GIS health. Specifically, an advanced machine learning technique, which is extreme gradient boosting (XGBoost), is developed to detect cyber-attacks to perform the paradigm and the verification process, offering superior performance above three machine learning algorithms. Various test scenarios are simulated on diverse GIS defects that prove the efficiency and security of the proposed IoT topology. PD pulse sequence features are extracted for every defect to model the inputs for IoT topology. The merit of the proposed IoT is to visualize all GIS defects with diverse alarms and the cyber-attacks on the networks efficiently. The contribution of this paper can be summarized in the following points;

- Introducing intelligent online monitoring for the status of the GIS to diagnose various defects based on partial discharge pulse sequence features.
- Developing a new IoT architecture integrating an advanced machine learning technique.
- The proposed infrastructure can detect the GIS defects in order to ensure effective operation for the power system, keep the GIS in a healthy state, and avoid any possible failure for the GIS.
- The suggested machine learning technique can detect the cyber-attack and present it as fake data in the main dashboard of the IoT platform.
- A lot of experimental test scenarios are performed to confirm the effectiveness of the suggested smart system.
- The experimental results emphasize the superiority of the proposed IoT architecture integrating machine learning to monitor and diagnose partial discharges in GIS towards an effective, reliable, and securing power system.

II. PROPOSED IOT ARCHITECTURE OVERVIEW

In the modern manufacturing industry, following the trend of Industry 4.0, automation in GIS focuses on the usage of online condition monitoring systems which might be essential for increasing the safety of the power system. The system security

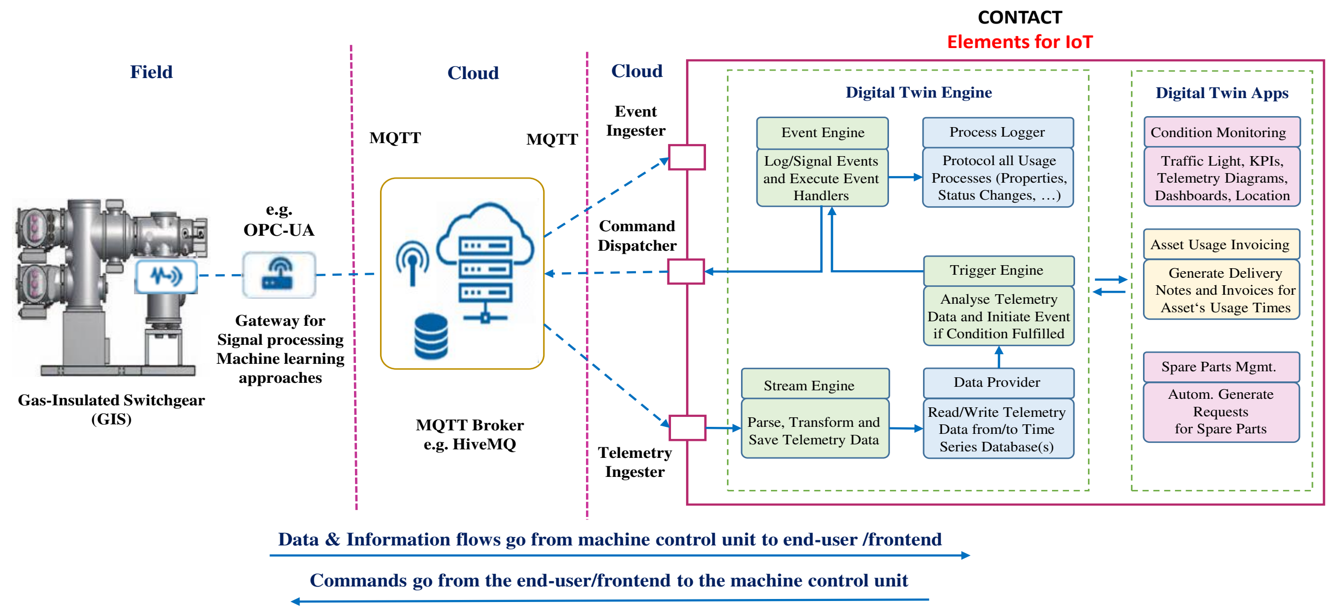

FIGURE 1. **Proposed IoT architecture for PD monitoring on the GIS.**

and the management of big data represent the big challenge in the context of condition monitoring. The goal of condition monitoring is to decide the correctness of the running states of physical assets and power system operation. Normally, whilst a propensity of equipment fault or failure is detected, highly skilled machine learning methods are capable of performing appropriate decisions to decrease the outage scenario of the power system. Next, appropriate action on the operating states of physical assets and power system processes is needed for mitigating failures.

The automatic identification of partial discharges (PDs) in GIS is the first task in designing an intelligent system to avoid failures. Further development of real-time GIS monitoring needs to be an intelligent system for PD diagnosis. Wherein, the monitoring approach should read the GIS information, gather and examine the sensor records, and send the manipulate command to the automated manage interface. Further, with the development of edge computing, 5G network, and IoT, it is become feasible to put in force this form of system in actual existence. Therefore, the implementation of the system for online PD monitoring on the shop floor is considered in this paper. The proposed IoT architecture consists of sensors for the measurement of PD pulse sequence features including phase appearance and its corresponding instantaneous voltage magnitude, which stands for the "physical" part.

Usually, there are various PD sensors that can be implemented with GIS to acquire PD pulses. These sensors are normally operating in the high-frequency range. The used sensors can be very high frequency/ultra-high frequency antenna that measures the radiated electromagnetic energy from PD events [32] or can be high-frequency current transformers that measure the induced currents from PD events [33]. The later one is preferred due to its lower attenuation and immunity to surrounding electromagnetic noises. Once a PD event is acquired, the instantaneous operating voltage and phase angle are recorded using voltage sensors and are sent to the data acquisition system.

This IoT platform has three components: connectivity, software, and a user interface. The hardware requires a way to send all the processed data to the cloud and requires a way to receive commands from the cloud. The WiFi, a short-range IoT connectivity, is considered as one of the best options for data-intensive speedy IoT systems operating within a small area. The IoT platform is responsible for storing and analyzing the vast amount of measured PD signals, and also for automatically identifying defects. Edge computing allows PD data from the IoT devices to be processed at the edge of the network before sending to the cloud. The data acquisition is carried out by utilizing interfaces such as Modbus, Open Platform Communications (OPC), and different network protocols like Hypertext Transfer Protocol (HTTP) and Message Queue Telemetry Transport (MQTT). A complete IoT platform needs a user interface. The contact elements for IoT are used for users to interact with the IoT platform as shown in Figure 1.

III. MACHINE LEARNING ALGORITHMS

A. OVERVIEW

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Recently, machine learning techniques have been applying in many fields, particularly for data analytics and data science in automated processes. The learning process of machine learning is to review historical events and to learn new skills and knowledge from that data [34]. The machine learning-based classifiers can be split into different categories such as supervised learning, unsupervised learning, reinforcement learning, and semi-supervised learning. A supervised learning method that the machine utilizes training dataset to learn what it should do [35]. For instance, if the manner is to classify images of puppies and cats, the machine utilizes a classified dataset approximately of puppy and cat sets to examine the variations among the puppies and cats. Unsupervised studying is applied to divided statistics organizations into similar categories [36]. For example, if the inputs of the system are sets of cats and puppies' photographs without any label of that is puppy or cat, the machine can divide those units of sets into a kind category primarily based on the similarities between images. In addition to supervised and unsupervised learning, reinforcement learning is one of three basic machine learning paradigms that describes how an agent operates in an environment to optimize the notion of cumulative reward using feedback [37]. While semi-supervised learning uses both labeled and unlabeled datasets, the semi-supervised algorithm falls between supervised learning and unsupervised learning algorithms [38].

Machine learning relies upon strategies named regression and classification. Regression is a forecasting approach utilized for continuous variables. On a different hand, the classification predicts the activities of distinct outputs, as an example, it can predict the day fame as be sunny or foggy. For example, the linear regression approach can be used to forecast continuous variables, even as the discrete variables can be predicted by using the logistic regression technique. There are lots of strategies utilized for machine learning, which include neural networks, decision trees, and random forests. Among those strategies, extreme gradient boosting (XGBoost) is a powerful approach that could perform both regression and classification. Furthermore, it may be applied for the prediction of both continuous and discrete outputs. The subsequent subsection discusses the XGBoost in extra detail.

B. EXTREME GRADIENT BOOSTING CLASSIFIER

Extreme Gradient Boosting, known as an ensemble technique of multiple classifications and regression trees, is a scalable end-to-end tree boosting system introduced by Chen et. al. [39]. It has been widely used for applied machine learning with great performance for fault classification problems [40], [41]. The XGBoost utilizes a gradient descent algorithm to create a new model that the error made by the previous model is computed and to be corrected by a succeeding model to make the final prediction. Interestingly, the XGBoost can push the limit of computations resources for boosted tree algorithms. Several calculations can be reduced, and the classification speed can be improved. Further, the XGBoost classifier also can avoid the overfitting problem by simplifying the objective functions. The iteration

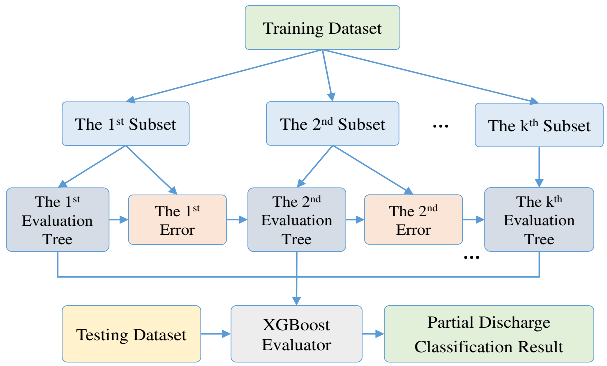

FIGURE 2. Scheme of extreme gradient boosting classifier for partial discharge diagnosis.

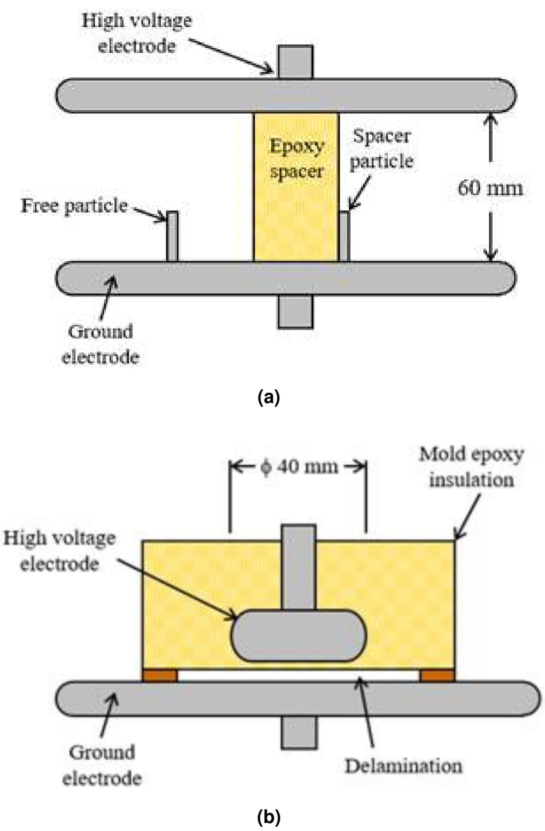

FIGURE 3. Experimental setup for most common PD defects in GIS; (a) free and spacer particle defects (MPG and MPS), (b) delamination (EID) defect.

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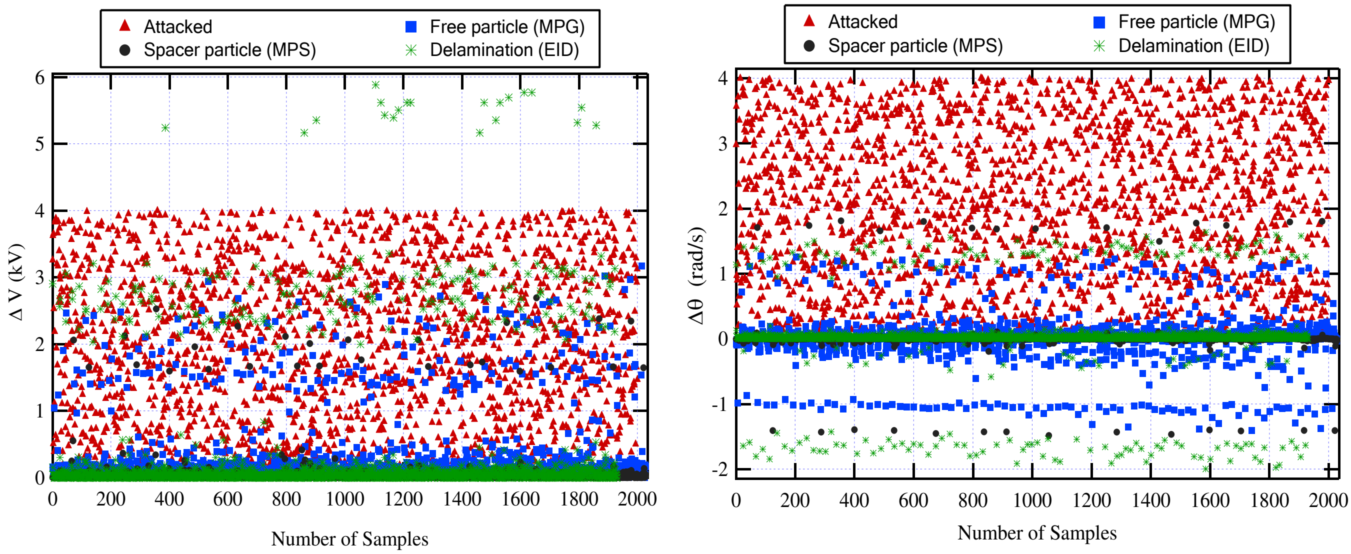

(a) (b)

FIGURE 4. Input datasets of the GIS and the corresponding classification; (a) The variation of voltage, and (b) The variation of angle.

of the XGBoost algorithm starts with the first learner which is fitted to the entire data. Then the error of the first learner will be fitted by the second learner. This process will continue the learning process and complete if a stopping condition is met. The workflow of the XGBoost classifier for partial discharge diagnosis is described in Figure 2.

Suppose the training data includes multiple features x_i to predict a target variable $\hat{y}_i$. The XGBoost model using k additive function to estimate the output can be described in Eq. (1).

$$\hat{y}_i = \sum_{j=1}^{k} f_j(x_i)\,, f_j \in F, \tag{1}$$

where the function space is defined as $F = \{f(x) = w_p\}(p: \mathbb{R}^n \rightarrow T,\ w \in \mathbb{R}^T)$, w represents the weight of the i^{th} leaf node, and the function f_k is corresponding to a p mapping and the score of its leaf nodes. The objective function of the XGBoost model, shown in Eq. (2), will be minimized to get a better learn of the final XGBoost model.

$$L(\theta) = \sum_i l(\hat{y}_i, y_i) + \sum_j \psi(f_j) \tag{2}$$

$$\psi(f) = \alpha T + \frac{1}{2}\beta\|w\|^2 \tag{3}$$

The objective function of XGBoost model has two parts, the first part is to measure the difference between the estimated class $\hat{y}_i$ and the real class y_i. The second term $\psi(f)$ is the regularization term which represents the complexity of the tree. It can be calculated using Eq. (3), where α is the regularization parameter of leaf number and β is the regularization parameter of leaf weight.

The second-order Taylor expansion is applied to the loss function shown in Eq. (4) for avoiding overfitting and enhancing the performance of the traditional gradient boosting tree.

$$L_j = \sum_i \left[l(\hat{y}^{j-1}, y_i) + g_i f_j(x_i) + \frac{1}{2} h_i {f_j}^2(x_i) \right] + \psi(f_j) \tag{4}$$

where g_i and h_i represent the first and the second-order gradient direction. The objective function is simplified by ignoring the constant term and obtain the simplified regularized objective function described in Eq. (5).

$$L_j^{\,*} = \sum_i \left[g_i f_j(x_i) + \frac{1}{2} h_i {f_j}^2(x_i) \right] + \psi(f_j) \tag{5}$$

IV. PD MEASUREMENT AND FEATURES EXTRACTION

In the present study, three different GIS defects were built experimentally as shown in Fig. 3. These defects are the most common defects that can be encountered in GIS [42], [43]. They include free metallic particles in the gas gap (called free particle, MPG), metallic particles adhered to the spacer surface (called spacer particle, MPS), and internal delamination at electrode/insulation interface (called delamination, EID). For free particle and spacer particle in Figure 3a, they have a length of 5 mm and a diameter of 0.25 mm, while for delamination defect in Figure 3b, it was sized 40 mm in diameter and 50 μm in depth. All these defects were sequentially implemented inside a pressurized GIS chamber, where a PD measuring process was performed using current pulse measurements. The PD pulses for various defects were acquired for a duration of 10 minutes and various PD features were extracted [44], [45]. The various PD features are phase appearance, amplitude, number of PD pulses, and instantaneous operating voltage. Regarding the PD amplitude, it usually needs proper calibration and it is

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dependent on the defect size. So, using PD amplitude for PD diagnosis can be misleading. Regarding the number of PD pulses, it requires statistical calculations for PD events. Instead, it is proposed in this paper to use pulse sequence features including phase appearance and voltage magnitude, which proved in previous researches their effectiveness in PD diagnosis [46], [47]. In addition, these pulse sequence features can be easily acquired using voltage sensors making them suitable to be used with IoT architecture.

V. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the XGBoost classifier is devoted to identifying four classes of partial discharge in gas-insulated switchgear including MPG, MPS, EID defect types, and cyber-attack cases. A real-time dataset is gathered from the GIS at several operation conditions for the training and testing of the XGBoost classifier. A cyber-attack dataset is combined with the real-time dataset of the GIS. The attacked data is labeled by 0 and the real data of the MPG, MPS, EID defects are labeled by 1, 2, and 3 respectively in order to train and test the XGBoost classifier. Figure 4 shows all samples of the inputs training dataset. The dataset includes 7986 samples with 4 features, of which the training dataset is 80% and the testing dataset is 20%. The training and testing models were processed using a PC computer with an Intel ® Core™ i7-8700 @3.20 GHz central processing unit and 8G RAM. In this paper, the grid search has been used to optimize the XGBoost hyper-parameters including estimators number, learning rate, maximum depth, min child weight, and objective of the model. The grid search approach scans the entire grid of hyper-parameter combinations in some order and also calculates the cross-validation loss to determine the optimal model parameters. The parameter, max_depth, is one of the Booster parameters that can define how deep each estimator is permitted to build a tree. The parameter max_depth is considered in the XGBoost classifier to avoid over-fitting. If max_depth is large, the model will learn very specific to a particular sample. In this study, the maximum depth was identified by tuning the hyperparameter of XGBoost using the grid search infrastructure. As a result, the optimal parameter of max_depth is set as 3. The grid search method is adopted to obtain the optimal parameters of the XGBoost model. The optimal parameters are listed in Table 1, in which the maximum number of iterations was optimized with “n estimators” of 600, the learning rate value is 0.1 which allow the learning speed is fast while remaining good performance of the model. The maximum depth of the tree is 3 that can control overfitting. The value of “min child weight” is 5. The learning process can be optimized using the objective function “multi: softprob”.

TABLE 1. Optimum parameters of XGBoost model

Parameters	Values
estimators' number	600
learning rate	0.1
max_depth	3
min child weight	5
objective	Multi: softprob
thread number	1

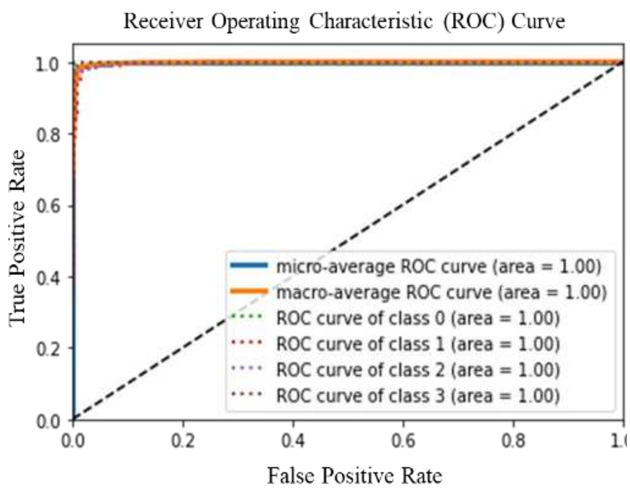

FIGURE 5. Receiver operating characteristic (ROC) curves of XGBoost classifier.

The final XGBoost model was obtained after training and parameter adjustment. The performance of the model is evaluated by Eq. (6). The best performance goes to the cyber-attack class with 99.75 % accuracy, which is followed by EID and MPG defect types, and the worst case is the MPS defect type with 97.01% accuracy. The average classification accuracy is 98.69% shown in Fig. 2(b).

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

where TP = true positive; TN = true negative; FP = false positive; FN = false negative.

Figure 5 performs the ROC curve of the proposed XGBoost classifier where the areas of different classes under different curves reach to 1. It shows that the balance of the dataset with multiple classes and the effective performance of the XGBoost model.

To further examine the effectiveness of the proposed XGBoost classifier for diagnosing PD in GIS, several machine learning classifiers such as artificial neural network

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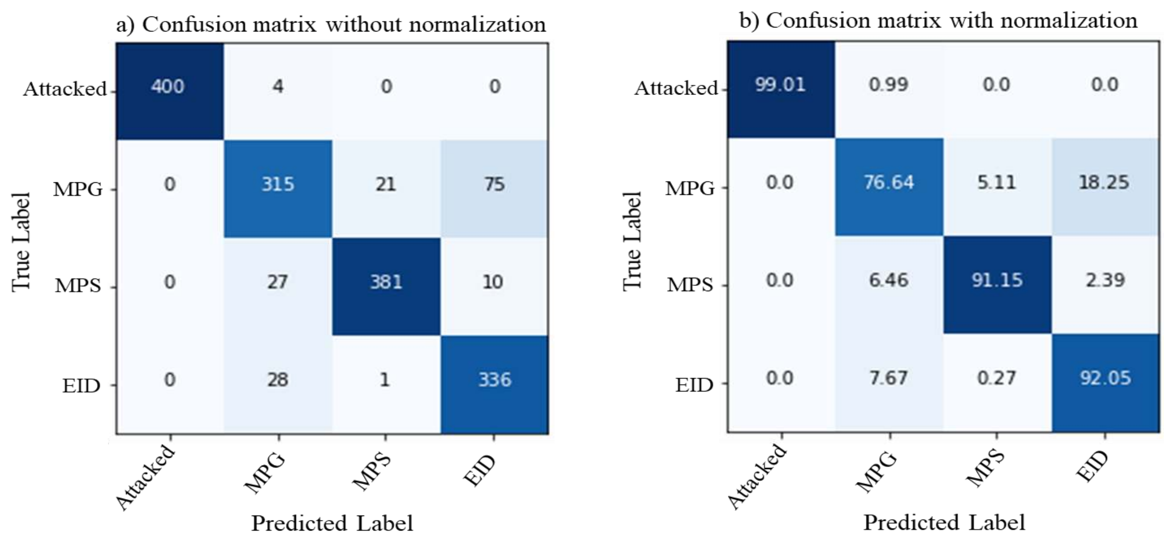

FIGURE 6. **Classification result from proposed ANN; (a) Confusion matrix without normalization, and (b) Confusion matrix with normalization.**

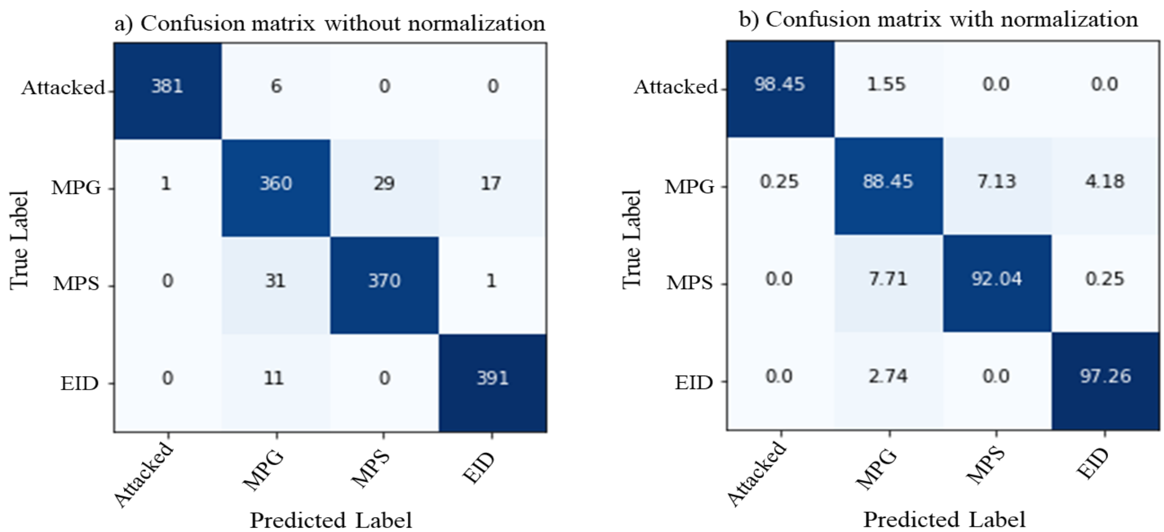

FIGURE 7. **Classification result from proposed DT; (a) Confusion matrix without normalization, and (b) Confusion matrix with normalization.**

(ANN), decision tree (DT), and random forest (RF) approaches were implemented for the classification. The ANN is a mathematical model that tries to simulate the functionality of the biological nervous system. The inputs of the model are assigned the specific weights and all the weighted inputs will be added with a bias term. In the end, the weighted inputs and the bias term will be transformed by an activation function to compute the output.

The ANN model has been widely used for PD pattern recognition. In this work, the ANN is using a backpropagation algorithm. The ANN consist of 4 input and 4 output representing 4 types of PD defects. The inputs go through with hidden neurons varied from 8 to 16. The activation function is rectified linear activation function. The DT approach is also one of the supervised learning algorithms that have a fast training process with low memory requirements. To estimate the class of the given dataset, first, the values of the root attribute are compared to the real dataset attribute. The algorithm continues to compare the attribute value with the other sub-nodes in the next node and moves further.

Finally, the process reaches the leaf node of the tree. In addition to ANN and DT, the RF is also known as an effective method for fault diagnosis problems. The RF is an ensemble approach that uses tree-type classifiers. This method can enhance the performance of the model by using

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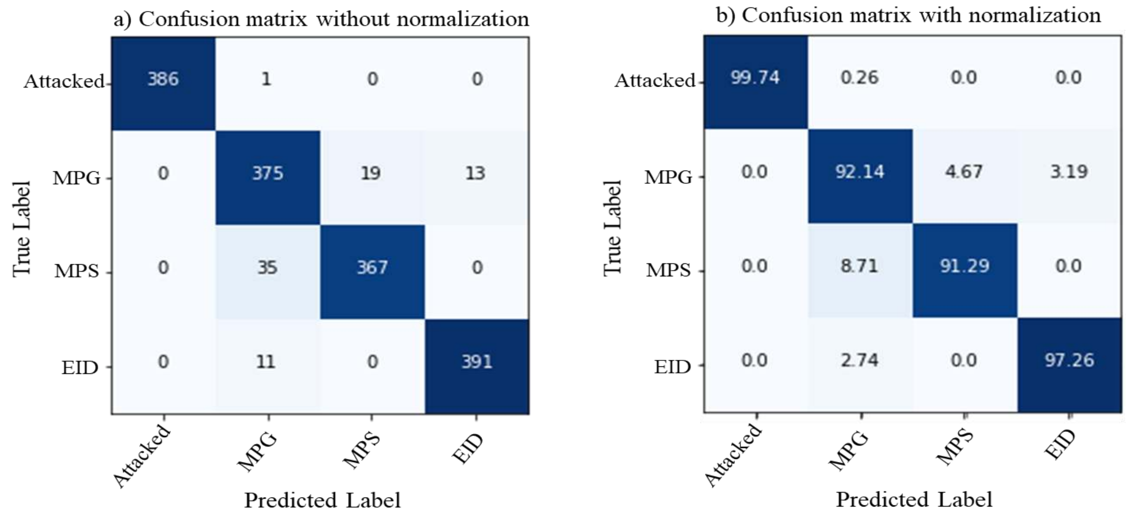

FIGURE 8. **Classification result from proposed RF; (a) Confusion matrix without normalization, and (b) Confusion matrix with normalization.**

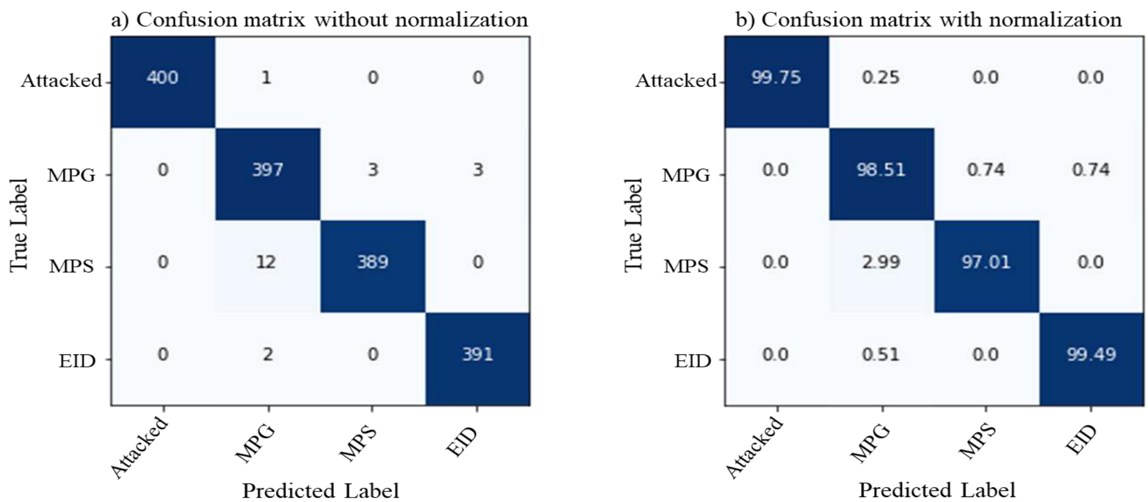

FIGURE 9. **Classification result from proposed XGBoost classifier; (a) Confusion matrix without normalization, and (b) with normalization.**

TABLE 2. **The accuracy of each machine learning method and the corresponding class.**

Class / Method	Attacked	MPG	MPS	EID	Total efficiency
ANN	99.01%	76.64%	91.15%	92.05%	89.71%
Decision Tree (DT)	98.45%	88.45%	92.04%	97.26%	94.05%
Random Forest (RF)	99.74%	92.14%	91.29%	97.92%	95.27%
Proposed XGBoost	**99.75%**	**98.51%**	**97.01%**	**99.49%**	**98.69%**

bagging to suppress over-fitting. The decisions of RF are based on the total votes of component predictors from each target. The classification results from all machine learning techniques are shown in Figures (6-9) and summarized in Table 2. The confusion matrix of the testing set shows that excellent classification accuracy can be achieved using the proposed XGBoost algorithm.

Figure 10 represents the classification accuracies obtained from different classifiers in the vertical bar plot for PD diagnosis in GIS. It shows that the proposed XGBoost classifier has the highest accuracy of approximately 99%. The ANN model has the lowest accuracy of approximately 90%. While the decision tree and random forest models

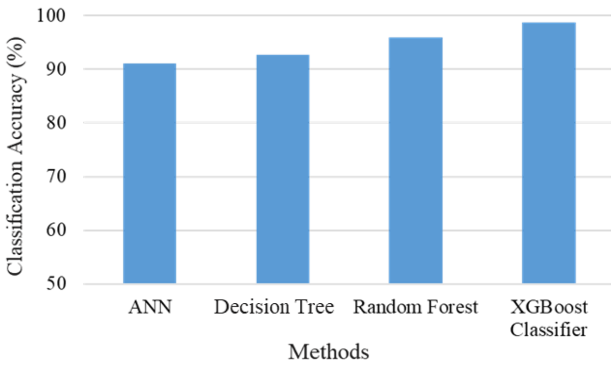

FIGURE 10. **Classification accuracy of different methods.**

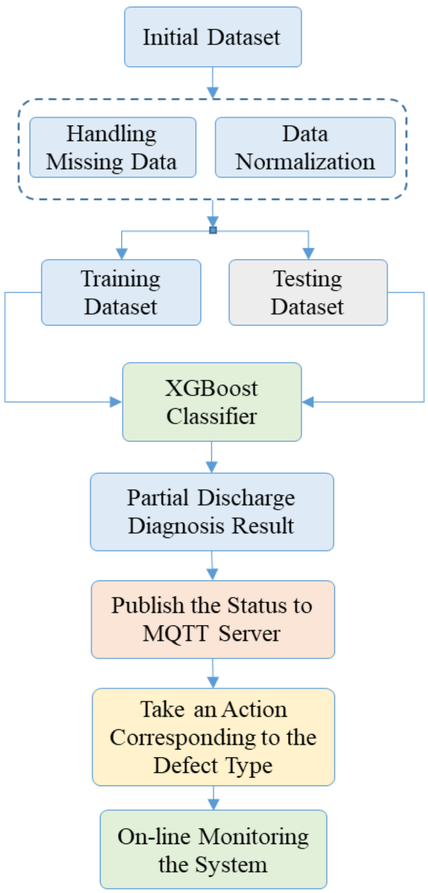

FIGURE 11. **Schematic of the proposed IoT architecture with the proposed XGBoost classifier.**

could provide better performance of the classification with the accuracy of approximately 94% and 95%, respectively.

After training and testing, the created model of the proposed XGBoost classifier is combined with the IoT architecture to categories the online reading of the GIS and present it through the IoT dashboard as described in the following test scenarios. The flowchart in Fig. 11 describes the total operation of data acquisition, validation, and visualization.

The current pulse measurements and the edge server for machine learning are the edge devices. The cloud server is MQTT server "HiveMQTT broker" with "Contact elements for IoT platform" and the data is transferred via MQTT protocol. The classifier is implemented at the edge server for machine learning. The following pseudo-code in Algorithm 1 summarizes the steps of the data acquisition, validation, and visualization based on the proposed IoT architecture and machine learning technique.

Algorithm 1. The pseudo-code of the proposed IoT architecture and machine learning technique

1: ***Read*** data from the current pulse measurements
2: ***Send*** data to the edge server for machine learning via MQTT protocol
3: ***Input*** the data to XGBoost model
4: ***Classify*** the GIS status by the XGBoost model
5: ***Connect*** to MQTT server
6: **elseif** the output XGBoost model==0
7: ***Publish*** that the GIS status is 'Fake data' and network status is 'Unstable network'
8: **if** the output of XGBoost model==1
9: ***Publish*** that the GIS status is 'MPG defect' and network status is 'Stable network'
10: **elseif** the output XGBoost model==2
11: ***Publish*** that the GIS status is 'MPS defect' and network status is 'Stable network'
12: **elseif** the output XGBoost model==3
13: ***Publish*** that the GIS status is 'EID defect' and network status is 'Stable network'
14: **else**
15: ***Publish*** that the GIS status is 'No defects' and network status is 'Stable network'
16: **end if**

A. SCENARIO 1: STABLE SYSTEM

This scenario is created to present the normal state of the system that represents the state of the GIS insulation and the proposed IoT architecture. The healthy or the normal state means that there are no defects in the GIS insulation and there is no cyber-attack on the internet network of the proposed IoT architecture. Figure 12 shows the GIS status and network status on the dashboard of the IoT platform. It is clear from this figure that the GIS does not has any defects and the internet network is stable which means there is no cyber-attack and the IoT system is secured. Besides, the traffic light is green which means the system works properly. Furthermore, the proposed IoT system monitor and visualize the GIS in an effective, clear and secure way instead of the traditional tracking methods that depend on the measurements and analysis and consume a long time and much costs.

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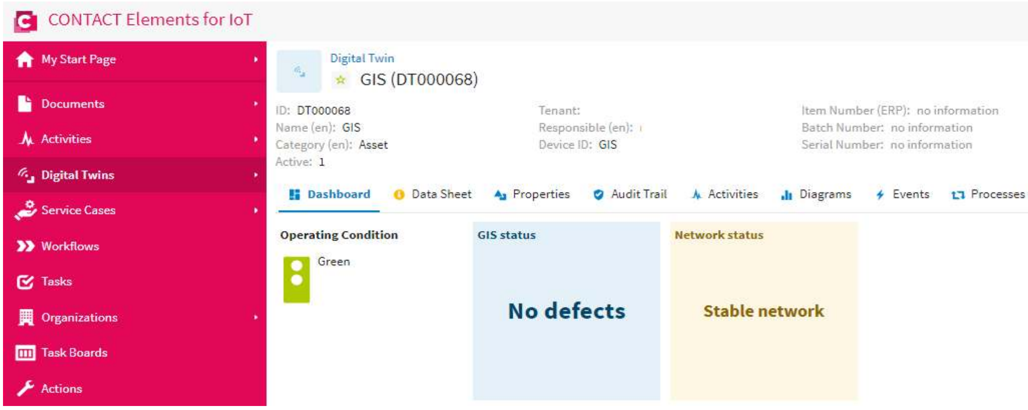

FIGURE 12. The GIS and network status in case of a normal case.

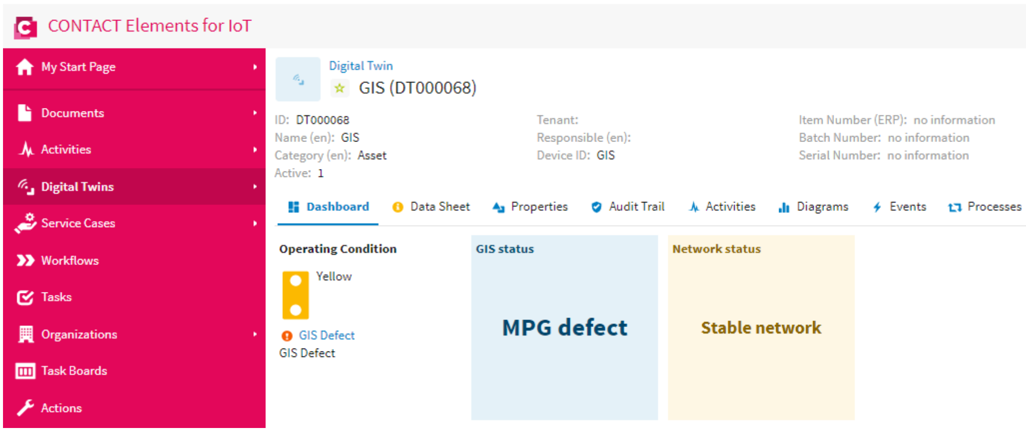

FIGURE 13. The GIS and network status in case of MPG defect.

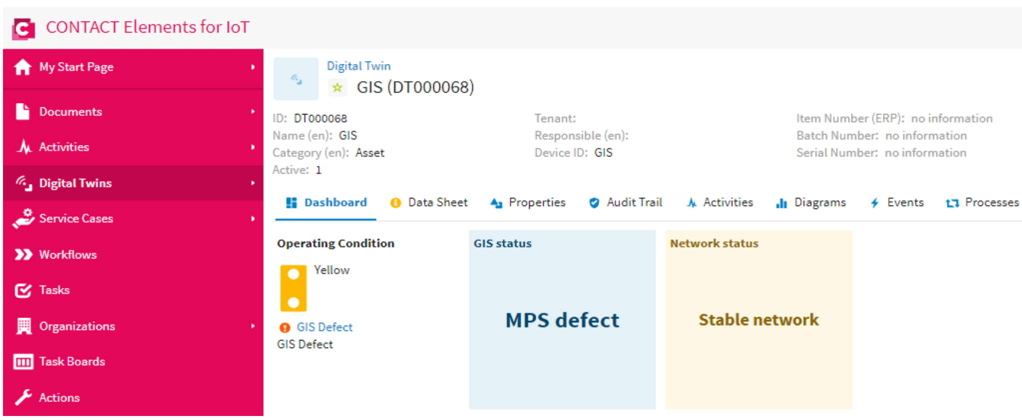

FIGURE 14. The GIS and network status in case of Scenario 3.

B. SCENARIO 2: MPG DEFECT

This test is carried out to validate the effectiveness of the proposed machine learning technique and the proposed IoT architecture to recognize and present the MPG defect. Figure 12 presents the GIS insulation status in case of the MPG defect. The system has MPG defect and the network is stable as clear in Fig. 13. Besides, the traffic light is changed to a yellow light to present an automatic alarm to the user about the defect state on the GIS in order to maintain the system. This test confirms that the proposed machine learning techniques and the IoT architecture work well and can recognize and visualize the MPG defect.

C. SCENARIO 3: MPS DEFECT

The MPS defect is created in this scenario as another class from GIS insulation defects. The proposed IoT platform presents the MPS defect and the network status in Fig. 14.

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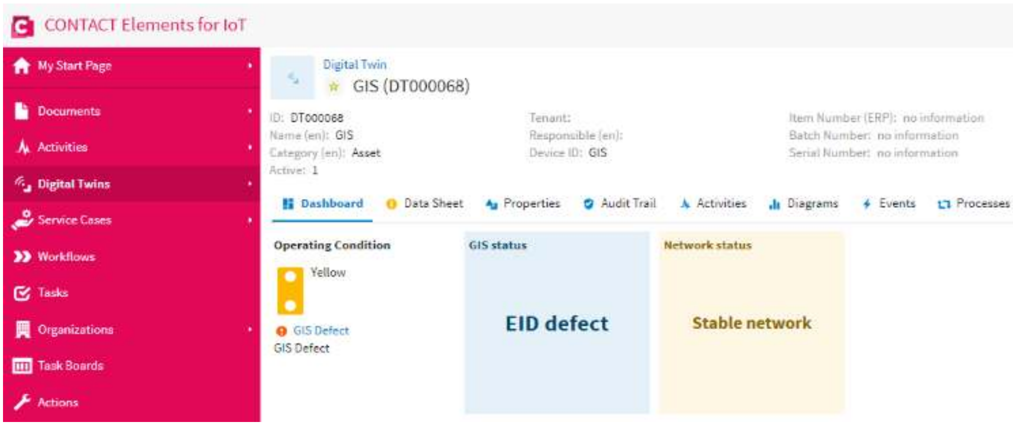

FIGURE 15. **The GIS and network status in case of EID defect.**

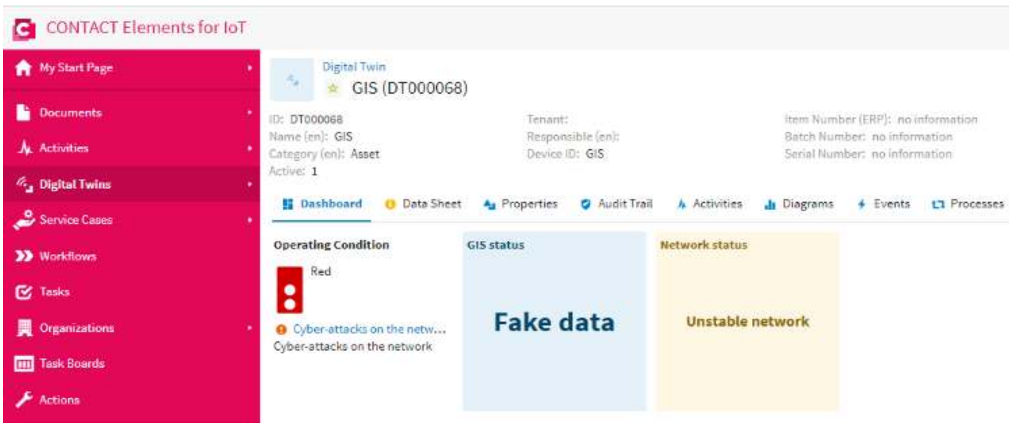

FIGURE 16. **The GIS and network status in case of cyber-attacks scenario.**

The IoT dashboard clear that the GIS insulation has MPS defect and the traffic light is changed to a yellow light to inform the user about the detected defect as shown in Fig. 14. Besides, the network is stable, and the transmitted data is secured that enhances the decision-making about the classified defect by the proposed machine learning technique.

D. SCENARIO 4: EID DEFECT

This scenario is created to demonstrate the last defect of the GIS insulation. The EID is one of the GIS insulation defects that must be recognized by the machine learning technique. Figure 14 shows the dashboard of the proposed IoT platform that presents the GIS status and the network status in a clear and effective presentation for the user. It is clear in Fig. 15 that the GIS insulation has EID defect. Besides, the IoT platform creates an alarm to hint the user about the abnormal state and changed the light of the traffic indicator to yellow light. Furthermore, the network status is stable that confirms the reliability of the transferred data about the GIS. This test confirms the effectiveness of the proposed machine learning technique to detect the EID defect and recognize the network status.

E. SCENARIO 5: ABNORMAL INTERNET NETWORK

The reliability of the internet network represents the main challenge against the implementation of the IoT architecture. Therefore, this test is carried out to confirm the superiority of the proposed machine learning technique to detect cyber-attacks on the internet network. This scenario represents a serious case in the system. Figure 16 shows that the internet network unstable that means the IoT system exposes to cyber-attacks. In this case, the transmitted data about the GIS is fake. Besides, the proposed IoT platform changed the traffic indicator to red light to inform the user about the abnormal case of the cyber-attacks to maintain the internet network and the IoT server. This test emphasis that the proposed machine learning technique and the IoT architecture can recognize the cyber-attacks and inform the user effectively. Furthermore, the proposed IoT is more reliable to track the GIS insulation status.

F. DISCUSSIONS

The following points summarize the main results of the above scenarios,

- The normal state of the GIS insulation and the internet network is visualized by the proposed IoT platform in a clarified dashboard in the first test scenario. It confirms that the GIS insulation does not have any defects and the internet network is stable.
- The second scenario demonstrates the effectiveness of the proposed IoT architecture and the proposed machine learning technique to detect and visualize the MPG defect of the GIS insulation. Besides, the proposed IoT platform created an alarm and changed the light of the traffic indicator from the green light to the yellow light in order to inform the user about the defect on the GIS.
- The third and fourth scenarios present the MPS and EID defects and confirm that the superiority of the proposed IoT architecture and the proposed machine learning technique to detect these defects and visualize them effectively.
- The last scenario emphasizes the effectiveness of the proposed machine learning technique to detect cyber-attacks on the network. Besides, the proposed IoT platform shows that the transmitted data about the GIS is fake which enhances the decision-making about the GIS. Furthermore, the IoT platform changed the light indicator to red light in order to inform the user about the cyber-attacks on the network.

VI. CONCLUSIONS

This paper presents new online monitoring and tracking for GIS defects based on a novel IoT architecture and machine learning technique. The defects of the GIS are classified based on effective new machine learning techniques. Besides, the proposed IoT architecture can recognize the cyber-attacks of the internet network based on the utilized machine learning techniques in order to provide reliable and secured monitoring for the GIS status. Further experimental scenarios are carried out to emphasize the superiority of the proposed IoT architecture. The results confirm that the proposed IoT topology with machine learning can detect and present the defects of GIS with high accuracy and effectiveness. Besides, the proposed IoT architecture based on the machine learning technique can detect the cyber-attacks on the internet network to provide the user with reliable data about the GIS status in order to support the decision-making. Furthermore, the proposed IoT platform can present the GIS defects and the network status in a more clarified visualization with different alarms about the GIS defects and cyber-attacks. The proposed IoT architecture solves the cyber-attack issue that provides a promising solution to be implemented on other power system applications in future work.

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REFERENCES

[1] M. Dsouza, R. S. Dhara, and R. C. Bouyer, “Modularization of High Voltage Gas Insulated Substations,” *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 4662–4669, Sep. 2020.

[2] H. Zhou *et al.*, “Review of charge accumulation on spacers of gas insulated equipment at DC stress,” *CSEE J. Power Energy Syst.*, vol. 6, no. 3, pp. 496–517, Sep. 2020.

[3] A. Darwish, S. S. Refaat, H. A. Toliyat, and H. Abu-Rub, “On the Electromagnetic Wave Behavior Due to Partial Discharge in Gas Insulated Switchgears: State-of-Art Review,” *IEEE Access*, vol. 7, pp. 75822–75836, 2019.

[4] J. Wang, W. Ding, Y. Liu, Z. Zheng, and C. Ge, “Application of x-ray inspection for ultra high voltage gas-insulated switchgear,” *IEEE Trans. Power Deliv.*, vol. 34, no. 4, pp. 1412–1422, Aug. 2019.

[5] A. H. Khawaja, Q. Huang, and Y. Chen, “A Novel Method for Wide Range Electric Current Measurement in Gas-Insulated Switchgears with Shielded Magnetic Measurements,” *IEEE Trans. Instrum. Meas.*, vol. 68, no. 12, pp. 4712–4722, Dec. 2019.

[6] S. Wu, F. Zeng, J. Tang, Q. Yao, and Y. Miao, “Triangle Fault Diagnosis Method for SF6 Gas-Insulated Equipment,” *IEEE Trans. Power Deliv.*, vol. 34, no. 4, pp. 1470–1477, Aug. 2019.

[7] F. Zeng *et al.*, “Fault Diagnosis and Condition Division Criterion of DC Gas Insulating Equipment Based on SF6 Partial Discharge Decomposition Characteristics,” *IEEE Access*, vol. 7, pp. 29869–29881, 2019.

[8] J. Sanchez-Garrido, A. Jurado, L. Medina, R. Rodriguez, E. Ros, and J. Diaz, “Digital Electrical Substation Communications Based on Deterministic Time-Sensitive Networking over Ethernet,” *IEEE Access*, vol. 8, pp. 93621–93634, 2020.

[9] B. Fardanesh, A. Shapiro, P. Saglimbene, R. Dasilva, G. Stefopoulos, and A. Esmaeilian, “A Digital Transformation at New York Power Authority: Using Innovative Technologies to Create a More Efficient Power System,” *IEEE Power Energy Mag.*, vol. 18, no. 2, pp. 22–30, Mar. 2020.

[10] K. Yamashita, C. W. Ten, Y. Rho, L. Wang, W. Wei, and A. Ginter, “Measuring Systemic Risk of Switching Attacks Based on Cybersecurity Technologies in Substations,” *IEEE Trans. Power Syst.*, vol. 35, no. 6, pp. 4206–4219, Nov. 2020.

[11] R. Zhu, C. C. Liu, J. Hong, and J. Wang, “Intrusion Detection against MMS-Based Measurement Attacks at Digital Substations,” *IEEE Access*, vol. 9, pp. 1240–1249, 2021.

[12] J. A. Jiang *et al.*, “A Novel Sensor Placement Strategy for an IoT-Based Power Grid Monitoring System,” *IEEE Internet Things J.*, vol. 7, no. 8, pp. 7773–7782, Aug. 2020.

[13] G. Bedi, G. K. Venayagamoorthy, R. Singh, R. R. Brooks, and K. C. Wang, “Review of Internet of Things (IoT) in Electric Power and Energy Systems,” *IEEE Internet of Things Journal*, vol. 5, no. 2. Institute of Electrical and Electronics Engineers Inc., pp. 847–870, 01-Apr-2018.

[14] S. K. Datta and C. Bonnet, "MEC and IoT Based Automatic Agent Reconfiguration in Industry 4.0," in *International Symposium on Advanced Networks and Telecommunication Systems, ANTS*, 2018, vol. 2018-December.

[15] M. Elsisi, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Reliable Industry 4.0 Based on Machine Learning and IoT for Analyzing, Monitoring, and Securing Smart Meters," *Sensors*, vol. 21, no. 2, p. 487, Jan. 2021.

[16] F. Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm," in *IEEE International Conference on Industrial Engineering and Engineering Management*, 2014, vol. 2015-January, pp. 697–701.

[17] I. Lee and K. Lee, "The Internet of Things (IoT): Applications, investments, and challenges for enterprises," *Bus. Horiz.*, vol. 58, no. 4, pp. 431–440, Jul. 2015.

[18] M. Elsisi, M.-Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Deep Learning-Based Industry 4.0 and Internet of Things towards Effective Energy Management for Smart Buildings," *Sensors*, vol. 21, no. 4, p. 1038, Feb. 2021.

[19] L. Xiao, X. Wan, X. Lu, Y. Zhang and D. Wu, "IoT Security Techniques Based on Machine Learning: How Do IoT Devices Use AI to Enhance Security?," in IEEE Signal Processing Magazine, vol. 35, no. 5, pp. 41-49, Sept. 2018, doi: 10.1109/MSP.2018.2825478.

[20] G. Robles, E. Parrado-Hernández, J. Ardila-Rey, and J. M. Martínez-Tarifa, "Multiple partial discharge source discrimination with multiclass support vector machines," *Expert Syst. Appl.*, vol. 55, pp. 417–428, Aug. 2016.

[21] Y. B. Wang, D. G. Chang, S. R. Qin, Y. H. Fan, H. B. Mu, and G. J. Zhang, "Separating multi-source partial discharge signals using linear prediction analysis and isolation forest algorithm," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 2734–2742, Jun. 2020.

[22] A. Krivda and E. Gulski, "Neural networks as a tool for recognition of partial discharges," in *IEE Conference Publication*, 1993, no. 378, pp. 84–85.

[23] Q. Khan, S. S. Refaat, H. Abu-Rub, and H. A. Toliyat, "Partial discharge detection and diagnosis in gas insulated switchgear: State of the art," *IEEE Electr. Insul. Mag.*, vol. 35, no. 4, pp. 16–33, Jul. 2019.

[24] W. Ziomek, M. Reformat, and E. Kuffel, "Application of genetic algorithms to pattern recognition of defects in GIS," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 7, no. 2, pp. 161–168, 2000.

[25] M. Wu, H. Cao, J. Cao, H. L. Nguyen, J. B. Gomes, and S. P. Krishnaswamy, "An overview of state-of-the-art partial discharge analysis techniques for condition monitoring," *IEEE Electr. Insul. Mag.*, vol. 31, no. 6, pp. 22–35, Nov. 2015.

[26] Y. Han and Y. H. Song, "Condition Monitoring Techniques for Electrical Equipment: A Literature Survey," *IEEE Power Eng. Rev.*, vol. 22, no. 9, pp. 59–59, Jul. 2008.

[27] V.-N. Tuyet-Doan, T.-T. Nguyen, M.-T. Nguyen, J.-H. Lee, and Y.-H. Kim, "Self-Attention Network for Partial-Discharge Diagnosis in Gas-Insulated Switchgear," *Energies*, vol. 13, no. 8, p. 2102, Apr. 2020.

[28] F.-C. Gu, "Identification of Partial Discharge Defects in Gas-Insulated Switchgears by Using a Deep Learning Method," *IEEE Access*, vol. 8, pp. 163894–163902, Aug. 2020.

[29] Y. Yang, M. Suliang, W. Jianwen, J. Bowen, L. Weixin, and L. Xiaowu, "Fault Diagnosis in Gas Insulated Switchgear Based on Genetic Algorithm and Density- Based Spatial Clustering of Applications with Noise," *IEEE Sens. J.*, vol. 21, no. 2, pp. 965–973, Jan. 2021.

[30] Z. Jiang, Y. Guo, and Z. Wang, "Digital twin to improve the virtual-real integration of industrial IoT," *J. Ind. Inf. Integr.*, vol. 22, p. 100196, Jun. 2021.

[31] Y. Wang, J. Yan, Q. Sun, J. Li, and Z. Yang, "A MobileNets convolutional neural network for gis partial discharge pattern recognition in the ubiquitous power internet of things context: Optimization, comparison, and application," *IEEE Access*, vol. 7, pp. 150226–150236, 2019.

[32] X. Han, J. Li, L. Zhang, P. Pang and S. Shen, "A Novel PD Detection Technique for Use in GIS Based on a Combination of UHF and Optical Sensors," IEEE Transactions on Instrumentation and Measurement, vol. 68, no. 8, pp. 2890-2897, Aug. 2019.

[33] A. Rodrigo Mor, L. Castro Heredia, and F. Muñoz, "A Novel Approach for Partial Discharge Measurements on GIS Using HFCT Sensors," Sensors, vol. 18, no. 12, p. 4482, Dec. 2018.

[34] K. R. Dalal, "Review on Application of Machine learning Algorithm for Data Science," in 2018 3rd International Conference on Inventive Computation Technologies (ICICT), 2018, pp. 270-273.

[35] N. Andrew, Machine Learning Yearning. Online Draft, 2017.

[36] Z. Ghahramani, "Unsupervised Learning," in Advanced Lectures on Machine Learning: ML Summer Schools 2003, Canberra, Australia, February 2 - 14, 2003, Tübingen, Germany, August 4 - 16, 2003, Revised Lectures, O. Bousquet, U. von Luxburg, and G. Rätsch, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2004, pp. 72-112.

[37] R. Nian, J. Liu, and B. Huang, "A review On reinforcement learning: Introduction and applications in industrial process control," Computers & Chemical Engineering, vol. 139, p. 106886, 2020/08/04/ 2020.

[38] Z. Ge, Z. Song, S. X. Ding, and B. Huang, "Data Mining and Analytics in the Process Industry: The Role of Machine Learning," IEEE Access, vol. 5, pp. 20590-20616, 2017.

[39] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, vol. 13-17-August-2016, pp. 785–794.

[40] D. Zhang, L. Qian, B. Mao, C. Huang, B. Huang, and Y. Si, "A Data-Driven Design for Fault Detection of Wind Turbines Using Random Forests and XGboost," *IEEE Access*, vol. 6, pp. 21020–21031, Mar. 2018.

[41] Z. Wu, X. Wang, and B. Jiang, "Fault Diagnosis for Wind Turbines Based on ReliefF and eXtreme Gradient Boosting," *Appl. Sci.*, vol. 10, no. 9, p. 3258, May 2020.

[42] D. E. A. Mansour, K. Nishizawa, H. Kojima, N. Hayakawa, F. Endo, and H. Okubo, "Charge accumulation effects on time transition of partial discharge activity at GIS spacer defects," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 17, no. 1, pp. 247–255, Feb. 2010.

[43] D. E. A. Mansour, H. Kojima, N. Hayakawa, F. Endo, and H. Okubo, "Partial discharge detection at delamination of electrode/epoxy interface in GIS spacers," in *Annual Report - Conference on Electrical Insulation and Dielectric Phenomena, CEIDP*, 2009, pp. 11–14.

[44] D. E. A. Mansour, H. Kojima, N. Hayakawa, M. Hanai, and H. Okubo, "Physical mechanisms of partial discharges at nitrogen filled delamination in epoxy cast resin power apparatus," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 20, no. 2, pp. 454–461, 2013.

[45] D. E. Mansour, H. Kojima, N. Hayakawa, F. Endo, and H. Okubo, "Partial discharges and associated mechanisms for micro gap delamination at epoxy spacer in GIS," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 17, no. 3, pp. 855–861, Jun. 2010.

[46] D. A. Mansour et al., "Comparison of partial discharge characteristics for different defect types in SF6 gas insulation system," 2008 12th International Middle-East Power System Conference, Aswan, Egypt, pp. 85-89, 2008.

[47] P. Wenger, M. Beltle, S. Tenbohlen, U. Riechert and G. Behrmann, "Combined Characterization of Free-Moving Particles in HVDC-GIS Using UHF PD, High-Speed Imaging, and Pulse-Sequence Analysis," IEEE Transactions on Power Delivery, vol. 34, no. 4, pp. 1540-1548, Aug. 2019.

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