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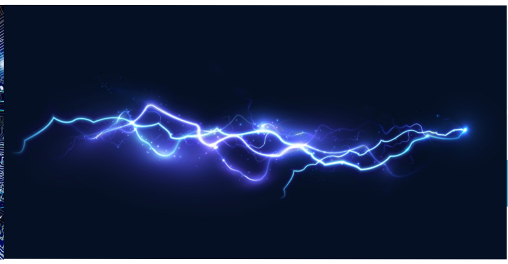
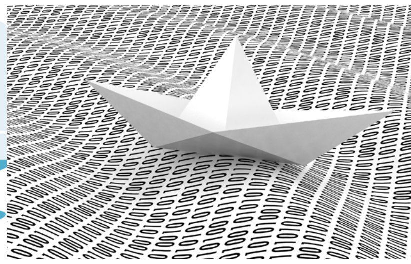
On Predictive Maintenance for Maritime Sector Using AI-Based Analysis of Partial Discharge



A prestudy carried out within the Swedish Transport Administration's industry program Sustainable Shipping, operated by Lighthouse, published in April 2025

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SWEDISH MARITIME COMPETENCE CENTRE

HÅLLBAR SJÖFART

On Predictive Maintenance for Maritime Sector Using AI-Based Analysis of Partial Discharge

This report presents a pre-study on the application of Partial Discharge (PD) and intermittent anomaly analyses for predicting failures in the power systems of the maritime sector.

Authors

Ebrahim Balouji, EcoPhi/Chalmers

Lucas Finati Thomée, DNV

In cooperation with

Chalmers University of Technology

Research Institute of Sweden, RISE

Minesto

Volvo Penta

ABB

Port of Gothenburg

A pre-study project carried out within the Swedish Transport Administration's industry program Sustainable Shipping, operated by Lighthouse

Summary

This report presents a pre-study on applying Partial Discharge (PD) and anomaly analyses for predicting failures in maritime electrical power systems. The maritime environment's elevated humidity, saltwater exposure, and mechanical stresses make electrical systems aboard vessels especially prone to insulation breakdown, which can lead to propulsion, distribution, and communications failures. In this context, PD—a localized dielectric breakdown—serves as a crucial early warning indicator of insulation deterioration.

Using test objects with simulated defects representative of maritime components, this study compiled 345,660 PD events that were categorized into 10 distinct types. Through advanced feature engineering, key attributes such as maximum PD amplitude, duration, inter-PD intervals, and the area under the PD curve were extracted and analyzed. Two machine learning architectures—an ensemble bagged Decision Tree and a Long Short-Term Memory network—achieved classification accuracies of 95.3% and 98.5%, respectively. These results indicate that PD-based predictive maintenance with machine learning can offer precise fault diagnosis and early warning before more severe electrical failures occur.

The findings show a robust predictive capability that links specific PD signatures to emerging electrical insulation faults. This high predictive accuracy not only reduces uncertainty in diagnosing potential electrical failures but also confers notable benefits regarding operational efficiency, safety, and sustainability. Early PD detection makes it possible to schedule proactive and timely repairs, thereby reduce unexpected downtime, minimize operational costs and repair expenses, and ensure the uninterrupted operation of essential activities. Furthermore, it decreases the likelihood of high-impact incidents at sea that can burden shipping companies with extensive direct and indirect costs, enhances safety for passengers and crew, and it also promotes sustainability by possibly preventing environmental hazards associated with the potential incidents. This approach also optimizes electrical system performance, leading to energy savings by avoiding inefficient operations caused by deteriorating components.

Building on these strong results, and through discussion with key maritime stakeholders in Sweden, the next proposed phase involves digitalization of substations and piloting the PD monitoring approach in a real Swedish maritime environment. The proposed pilot project will focus on integrating EcoPhi Merging Units and Centralized Monitoring Protection and Control (CMPC) or similar high-frequency devices on suitable vessels, enabling continuous monitoring of electrical components such as cables, switchgear, motors, and busbars. By deploying machine learning models for real-time PD classification, maintenance crews can receive early alerts and can prevent significant equipment deterioration. Throughout the pilot, it will be essential to gather data on reliability improvements, cost savings, and the overall impact on safety and operational performance. The pilot's outcomes will guide refining the solution, adapted to the specific conditions of Swedish maritime operations. Relevant rules and regulations will also be investigated in order to standardize frameworks and regulations for predictive maintenance that can ultimately be implemented throughout the industry.

Sammanfattning

Denna rapport presenterar en förstudie om hur partiella urladdningar (eng. Partial Discharge, PD) och anomali-analyser kan användas för att förutsäga fel i elektriska kraftsystem inom den maritima sektorn. Med tanke på de unika driftsförhållandena i marina miljöer – kännetecknade av hög luftfuktighet, exponering för saltvatten, och upprepande mekanisk stress – står elektriska system ombord på fartyg inför betydande tillförlitlighetsutmaningar och är särskilt utsatta för isolationsnedbrytning, vilket i sin tur kan orsaka fel inom fartygens framdrivning, elförsörjning och kommunikation. I detta sammanhang fungerar PD—en lokal dielektrisk urladdning—som en viktig indikator på tidiga isolationsskador.

I studien samlades 345 660 PD-händelser in från testobjekt med simulerade defekter som motsvarar vanliga maritima komponenter såsom kablar, ställverk, motorer och samlingsskenor. Händelserna kategoriserades i tio distinkta typer. Nyckelattribut som maximal PD-amplitud, varaktighet, tidsintervall mellan upprepade PD-händelser, samt area under PD-kurvan extraherades och analyserades. Två olika maskininlärnings-arkitekturer—en ensemble bagged Decision Tree och ett Long Short-Term Memory-nätverk—användes för att klassificera händelserna och lyckades nå klassificerings-noggrannheter på 95,3 % respektive 98,5 %. Dessa resultat indikerar att PD-baserat prediktivt underhåll kan erbjuda noggrann felsökning och ge tidiga varningar, innan allvarligare elektriska fel uppstår.

Studien visar på möjligheten att koppla specifika PD-signaturer till uppkommande elektriska isolationsskador. Detta förbättrar inte bara förståelsen för tillståndet och prestandan hos kritiska kraftsystemkomponenter, utan förbättrar också avsevärt träffsäkerheten i att förutsäga potentiella fel. Den höga träffsäkerheten minskar inte bara osäkerheten, utan medför också betydande fördelar med ökad drifteffektivitet, säkerhet och hållbarhet. Genom att upptäcka PD i ett tidigt skede, långt innan det resulterar i allvarliga fel, kan rederier och underhållspersonal planera förebyggande åtgärder, vilket kan reducera reparationskostnader och minimera oplanerade driftstopp, vilket i sin tur ökar säkerheten för passagerare och besättning. Det främjar också hållbarhet genom att minska sannolikheten för miljörisker i samband med kritiska elektriska fel och incidenter till havs. Det kan också öka energibesparingar genom att man undviker ineffektiv drift orsakad av föråldrade komponenter.

Utifrån förstudiens resultat och genom diskussioner med maritima intressenter i Sverige, är nästa föreslagna steg att genomföra ett pilotprojekt där PD-övervakning testas i en verklig svensk maritim miljö. Planen är att integrera EcoPhi Merging Units och Centralized Monitoring Protection and Control (CMPC) eller likvärdiga högfrekventa enheter på lämpliga fartyg, för att kontinuerligt övervaka elektriska komponenter såsom kablar, ställverk, motorer och samlingsskenor. Genom att tillämpa maskininlärningsmodeller för realtidsklassificering av PD kan underhållspersonal få tidiga varningar som kan förhindra allvarliga fel. Under pilotfasen kommer det att vara centralt att samla in data om hur tillförlitligheten förbättras, vilka kostnadsbesparingar som uppnås och hur säkerhet och drift påverkas totalt sett. Resultaten från piloten kommer att ligga till grund för att förfina metoden och anpassa den efter svenska förhållanden.

Relevanta regler och föreskrifter kommer också utredas för att kunna standardisera ramverk och regelverk för prediktivt underhåll som i förlängningen kan implementeras i hela branschen.

Contents

Abbreviations and key concepts used in the report

Artificial Intelligence (AI): The capability of computational systems to perform tasks typically associated with human intelligence, such as reasoning, learning, and problem-solving. In this report, it is techniques used to interpret complex partial discharge (PD) signals, extract features, and classify discharge patterns.

Adaptive Neuro-Fuzzy Inference System (ANFIS): A hybrid system that combines the learning capabilities of neural networks with the fuzzy logic principles of fuzzy inference systems. In this report, it is used to diagnose PD in gas-insulated switchgear, effectively managing uncertainties inherent in PD measurements.

Convolutional Neural Network (CNN): A deep learning model that is particularly effective for image and video recognition tasks. In this report, it is used to automatically identify PD patterns.

Decision Trees (DT): A non-parametric supervised learning method used to create a model that predicts the class of a target variable by learning decision boundaries inferred from the data feature.

Deep Belief Networks (DBN): A class of deep neural network composed of multiple layers of latent variables. When trained on a set of examples without supervision, a DBN can learn to probabilistically reconstruct its inputs and the layers then act as feature detectors and can be used for classification. In this report, it is used for unsupervised feature learning from raw PD data.

False Negative Rate (FNR): Measures the proportion of actual positive instances that are incorrectly classified as negative, ranging from 0 to 1. In this report, it is a measure used in the confusion matrix of PD classification.

Internet of Things (IoT): Devices combined with AI algorithms or with sensors, processing ability, software, and other technologies that connect and exchange data with other devices and systems over the Internet or other communication networks.

Long Short-Term Memory (LSTM): A type of Recurrent Neural Network (RNN) architecture used for analyzing time-series data and predicting sequential patterns.

Machine Learning (ML): The field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instruction. In this report, it is used to enhance the effectiveness and accuracy of PD analysis.

Merging Unit (MU): A device of the process bus concept, enabling the digitization of analog, binary, and command information. In this report, it is used to capture and analyze PD and anomalies in maritime power systems.

Partial Discharge (PD): A localized dielectric breakdown of a small portion of a solid or fluid electrical insulation system under high voltage stress.

Principal Component Analysis (PCA): A linear dimensionality reduction technique with applications in exploratory data analysis, visualization, and data pre-processing. In this report, it is a technique used for feature extraction from PD signals before applying a neural network classifier.

Recurrent Neural Networks (RNN): A class of artificial neural networks designed for processing sequential data, such as text, speech, and time series. In this report, it is a type of neural network used for analyzing time-series PD data.

System Average Interruption Duration Index (SAIDI): An index used to evaluate the impact of PD monitoring on maintenance practices and the average duration of an interruption for the average system during a given time period.

System Average Interruption Frequency Index (SAIFI): An index used to evaluate the impact of PD monitoring on maintenance practices and the average number of times of interruptions for the average system during a given time period.

True Positive Rate (TPR): It represents the proportion of actual positive instances that are correctly classified as positive. A measure used in the confusion matrix of PD classification.

1 Introduction

In the challenging and dynamic environment of the maritime industry, ensuring the reliability and efficiency of electrical systems is paramount. Several significant blackout incidents on marine vessels have underscored the critical importance of predictive maintenance for electrical systems in the maritime industry. For instance, the *Carnival Triumph* suffered a complete loss of power in 2013 due to an engine room fire, leaving over 4,200 passengers and crew stranded in the Gulf of Mexico without propulsion or essential services [1]. Similarly, the *Costa Allegra* experienced a total power failure in 2012 after an engine room fire, causing the ship to drift in the Indian Ocean and necessitating a complex rescue operation [2]. The 2019 incident involving the *Viking Sky* further highlighted these vulnerabilities when the cruise ship lost engine power amidst rough seas off the coast of Norway, leading to the evacuation of hundreds of passengers [3]. More recently, the *MV Dali* experienced a complete blackout due to faulty electrical breaker operation, leading to the ship drifting and colliding with the Francis Scott Key Bridge in Baltimore in 2024 [4].

Figure 1: Viking Sky cruise ship in Norway. [Photo: Tore Sætre / Wikimedia]

The above mentioned incidents demonstrate the severe consequences that failures, directly or indirectly involving the electrical systems, at sea can have, including safety risks, environmental hazards, and substantial financial losses. Investigations into electrical system failure events on ships often reveal that insulation damage is a primary cause, accounting for approximately 80%[5]. This alarming statistic emphasizes the essential role that insulation integrity plays in maintaining the functionality of maritime electrical systems.

Predictive maintenance emerges as a vital solution in this context, with Partial Discharge (PD) analysis being particularly effective. PD refers to localized dielectric breakdown of a small portion of a solid or liquid electrical insulation system under high-voltage stress and these electrical discharges indicate insulation deterioration within high-voltage systems [6]. By monitoring and detecting PD activities, which is crucial for predictive maintenance because it serves as an early indicator of insulation deterioration and potential equipment failure, maintenance teams can identify defects at an early stage, allowing for timely interventions before catastrophic failures occur. Implementing PD analysis as part of a predictive maintenance strategy not only enhances the reliability and safety of marine vessels, and extends the lifespan of electrical equipment, but also optimizes maintenance resources by prioritizing repairs based on the severity of detected issues and can be used to optimize maintenance schedules and resource allocation [7, 8, 9, 10].

The integration of advanced PD monitoring systems, capable of high-frequency sampling and precise detection, provides actionable insights into the health of electrical equipment under real operating conditions. This proactive approach aligns with the industry's goals of reducing unexpected downtime, minimizing operational costs, and ensuring the uninterrupted operation of essential maritime activities. Considering the significant impact of insulation damage on electrical failures, the adoption of PD analysis is crucial for enhancing the resilience and sustainability of maritime operations.

1.1 Study aim

This feasibility study aims to explore the application of Partial Discharge and anomaly analysis as predictive maintenance tools in maritime power systems. Predictive maintenance is crucial for preventing unexpected failures and enhancing operational reliability, particularly in maritime applications where access to repair services is often limited.

1.2 PD analysis with deep learning

Artificial Intelligence (AI) has significantly advanced the analysis of PD data, enhancing predictive maintenance by enabling more precise fault detection and diagnosis. Researchers have employed various AI techniques to interpret complex PD signals, extract features, and classify discharge patterns. For instance, Abdi and Farasat utilized Support Vector Machines (SVM) for PD pattern recognition, demonstrating improved classification accuracy over traditional methods [11]. Similarly, Zhang et al. developed a Convolutional Neural Network (CNN) model to automatically identify PD patterns, achieving superior performance in handling nonlinear and high-dimensional data [12]. Moreover, Chen et al. proposed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to diagnose PD in gas-insulated switchgear, effectively managing uncertainties inherent in PD measurements [13].

Feature extraction is critical in PD analysis, and AI techniques have been instrumental in this area. Li et al. employed wavelet transforms combined with Principal Component Analysis for feature extraction from PD signals before applying a neural network classifier [14]. Sun and Wang introduced Deep Belief Networks for unsupervised feature learning from raw PD data, enhancing the efficiency and accuracy of the diagnostic process [15]. Additionally, He and Zhang investigated the use of Recurrent Neural Networks (RNNs) for analyzing time-series PD data, enabling better prediction of insulation failures [16]. Recent advancements have focused on integrating AI with other technologies. Wu and Chen explored the combination of Internet of Things (IoT) devices with AI algorithms for real-time PD monitoring and analysis [17]. Zhao and Xu applied transfer learning in PD analysis, allowing models trained on one equipment type to be adapted for others, reducing the need for extensive retraining [18]. Furthermore, Liu et al. proposed a hybrid model integrating machine learning with physical models of PD phenomena, enhancing the interpretability and reliability of diagnostic results [19]. These studies collectively demonstrate the significant impact of AI in advancing PD analysis, leading to more effective predictive maintenance practices.

1.3 Predictive maintenance and PD analysis in the maritime sector

Predictive maintenance of electrical systems in the maritime sector is a growing area of interest, driven by the need to enhance the reliability and safety of marine vessels and systems while reducing operational costs. The maritime environment poses unique challenges to electrical equipment due to factors such as saltwater corrosion, humidity, and constant vibrations. These conditions accelerate the degradation of electrical components, making effective maintenance strategies crucial. While predictive maintenance techniques are well-established in industries like manufacturing and power generation, their application in the maritime sector has been relatively limited.

Several studies have explored the implementation of predictive maintenance in maritime electrical systems using condition monitoring and advanced diagnostic techniques. For instance, Bhaduri and Battacharya discussed the use of condition-based monitoring for marine electrical equipment, highlighting the potential for reducing unexpected failures and maintenance costs [20]. Similarly, Zhang et al. investigated the application of vibration analysis and thermal imaging to monitor the condition of shipboard electrical machines, demonstrating improvements in fault detection [21]. Moreover, the integration of data analytics and machine learning for predictive maintenance in maritime electrical systems has been examined by authors like Kumar and Srivastava, who developed predictive models to anticipate equipment failures based on historical data [22].

Despite these efforts, the number of studies focusing specifically on predictive maintenance for maritime electrical systems remains limited. This scarcity can be attributed to several factors. First, the harsh and variable environment makes data collection and sensor installation more challenging compared to land-based settings. Second, the diversity of marine vessel types and operating conditions requires customized solutions, which can be resource-intensive to develop. Additionally, there is a lack of cross-competence knowledge related to the complex systems and for the people performing maintenance onboard, lack of knowledge and high rotation are also barriers. Lastly, there has been a traditional reliance on preventive maintenance schedules in the maritime industry, which may slow the adoption of predictive approaches.

The limited literature underscores the need for more research and development in this area. Advancements in sensor technology, data analytics, and remote monitoring systems offer opportunities to overcome existing barriers. By tailoring predictive maintenance strategies to the specific conditions of the environment, it is possible to enhance the performance and reliability of electrical systems on vessels, ultimately contributing to safer and more efficient maritime operations.

While PD analysis is a well-established method for predictive maintenance in industries such as power generation and transmission, its application in the maritime sector remains relatively limited. One recent paper [30] from the university of Athens, explains how analyzing partial discharge activity and coupling it with machine learning models, can detect early signs of insulation deterioration and potential electrical faults, but is has not been put to the test in the real-world. Seemingly two companies based in the UK; RB Marine and ModemTec claim to provide PD monitoring tools for maritime applications.

The unique challenges of the maritime environment affect both the performance of electrical insulation systems and the feasibility of implementing PD monitoring equipment. These factors can complicate the detection and interpretation of PD signals, making standard monitoring techniques less effective. Additionally, the integration of PD monitoring systems into existing vessels poses logistical and technical challenges, often requiring specialized equipment and installation procedures. As a result, there is a scarcity of literature focusing on PD analysis for predictive maintenance in maritime applications. This limited number of studies may be due to the traditional reliance on routine inspections and scheduled maintenance in the maritime industry, as well as the lack of standardized protocols for PD monitoring in this sector.

In the broader perspective, the potential of machine learning within the maritime sector is recognized and there are relevant examples, e.g. from the The Swedish Maritime Administration's sea and air traffic control center JRCC in Gothenburg, Sweden for the application in sea and air rescue [31]. However, overall, in the maritime industry, the field is much in its infancy.

The gap in research and development highlights an opportunity for developing tailored PD analysis techniques that address the specific needs and conditions of the environment, which could significantly enhance the reliability and safety of maritime electrical systems.

This study is structured to provide a comprehensive literature survey on the current PD technologies utilized for predictive maintenance in the maritime sector. We cover the spectrum of methodologies, highlighting not only PD analysis but also other predictive maintenance techniques that are prevalent in maritime operations. Additionally, this survey delves into the Machine Learning (ML) methods currently employed to enhance the effectiveness and accuracy of PD analysis.

A significant focus is placed on comparing PD analysis techniques to other predictive maintenance methods. Through this comparison, we demonstrate why PD analysis, particularly when augmented with ML techniques, stands out as a superior choice. This approach offers distinct advantages in terms of early detection capabilities, the accuracy of fault localization, and the potential for automation, which are critical for maintaining the high-value assets typically found in maritime settings. By evaluating these aspects, the study provides actionable insights and validate the effectiveness of PD and anomaly analysis, reinforcing their place as essential components of an integrated predictive maintenance strategy.

1.4 Pre-study methodology

In this preliminary study, we focus on several key aspects to advance the application of PD analysis for predictive maintenance in the maritime sector.

- Data collection is performed using the EcoPhi Mu device, capable of sampling voltage and current up to 16 MHz. This high-frequency sampling enables precise detection and characterization of PD events, which is essential for accurate fault diagnosis.
- We concentrate on the detection and localization of PD within maritime electrical systems. Accurate identification of PD sources allows for targeted maintenance interventions, reducing the likelihood of unexpected failures.
- We explore the implementation of PD monitoring techniques specifically tailored to the maritime environment. This involves assessing both the benefits and risks associated with deployment, such as improved system reliability versus challenges posed by harsh operating conditions.
- We also address the difficulties associated with deploying PD monitoring systems on vessels. Factors such as limited space, electromagnetic interference, and the need for robust equipment are considered.
- An economic analysis is conducted to evaluate the impact of PD monitoring on maintenance practices. This includes the potential reduction in maintenance time and improvements in reliability indices like SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index). By minimizing downtime and maintenance frequency, significant cost savings can be achieved.
- Furthermore, we examine common problems associated with generators and electrical systems, including cost calculations related to repairs and operational losses due to outages. Understanding these costs underscores the value of predictive maintenance strategies.
- As the final step, recommendations and direction for the implementation in the specific Swedish context are discussed.

These highlights are elaborated upon in the following sections, where we provide detailed analyses and discuss the implications of the findings.

2 AI-based Partial Discharge Detection and Classification

This section describes the high voltage setup used to generate the waveform and measure the PD trace. Moreover, the initial AI based steps describing how to extract and engineer the PD features is addressed. Finally, the machine learning methods used for PD classification are explained.

2.1 Measurement of voltage and current

The experimental setup is designed to replicate a ship substation in a laboratory environment. It consists of four feeders connected to inverters or a generator, simulating the electrical distribution system commonly found on marine vessels. Figure 2 and Figure 3 illustrates the configuration of the substation model.

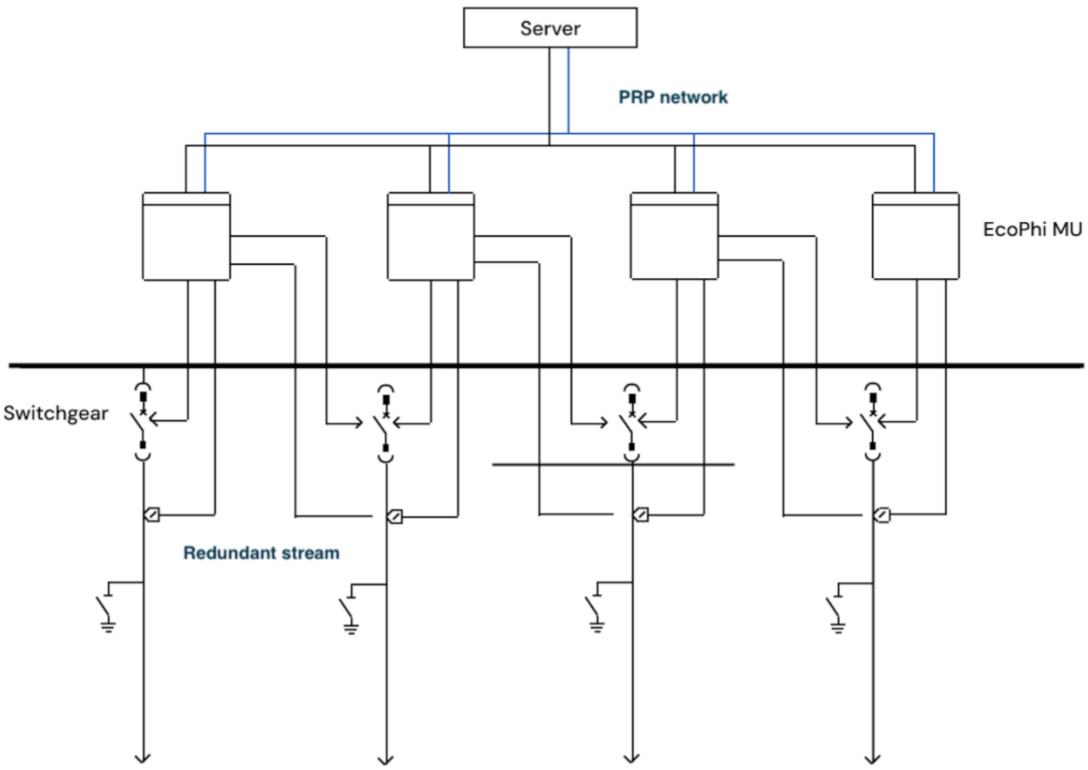

Figure 2: Schematic of Placement of merging units in four feeders and stream of real time sampled values of voltage and current to server

An EcoPhi Mu device, which is a device to capture and analyze PD and anomalies in power systems, is installed on each feeder to monitor voltage and current signals. These devices are capable of sampling at frequencies up to 16~MHz, which allows for precise detection and characterization of PD events. The collected data from each feeder is transmitted to a central server.

The central server hosts protection functions for each feeders in the case of short circuits, as well as the detection functions and the PD. By analyzing the high-frequency data from the EcoPhi merging units, the system can identify potential faults and degradation in the insulation of electrical components before they lead to failures. This setup enables real-time monitoring and diagnostics, enhancing the reliability and safety of the electrical system.

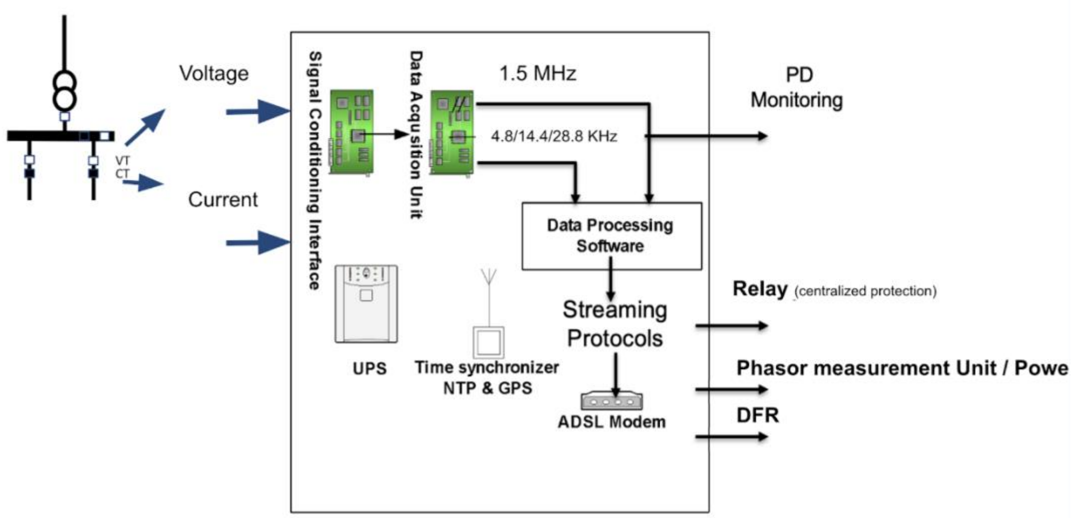

Figure 3: Architecture of merging unit for Estimation of Voltage and current as well as PD monitoring

2.2 PD Detection and initial signal processing

To obtain the information corresponding from the PDs and to sufficiently suppress the contribution from the applied voltage, a suitable PD detector circuit is connected capacitively to the test object. This approach facilitates calibration compared to contact-free methods. This circuit contains a Digital high pass filter to introduce transfer function resonances at higher frequencies. Two important aims with this circuit are both to amplify the PD magnitude with the resonance part of the spectra but also to sufficiently suppress the magnitude of the total voltage remnant to allow data capture with high quality. This enables the usage of appropriate AI based signal processing methods to obtain the PD information and remove contributions from the surrounding noise and the applied voltage. This results in a voltage remnant where PDs can be identified within the captured data by utilizing their stochastic nature to remove the stationary components, as will be discussed in the following.

The technique to identify PDs and suppress the remnant voltage originating from the applied voltage although the frequency content is overlapping can be performed by applying a time-based filtering approach. The main principle is then to identify stationary from non-stationary content. Each newly captured data-trace contains both PDs (when present) as well as remnants from the applied voltage (50Hz/400Hz), see Fig. 4. The difference between remnants from the voltage flank and actual PDs is that the latter appears stochastically in the data-trace. However, the contribution from the voltage flank remains the same. Thus, after each new waveform is captured, the non-stationary data containing PDs can be obtained and identified by subtracting the average waveform from the latest captured trace. After high pass filtering the signal the PD signals are more visible with much less interference from the voltage steps which facilitates further analysis. Data traces are recorded for 40Ms seconds independent from each other and each recording is referred to as a cycle of PDs in this paper.

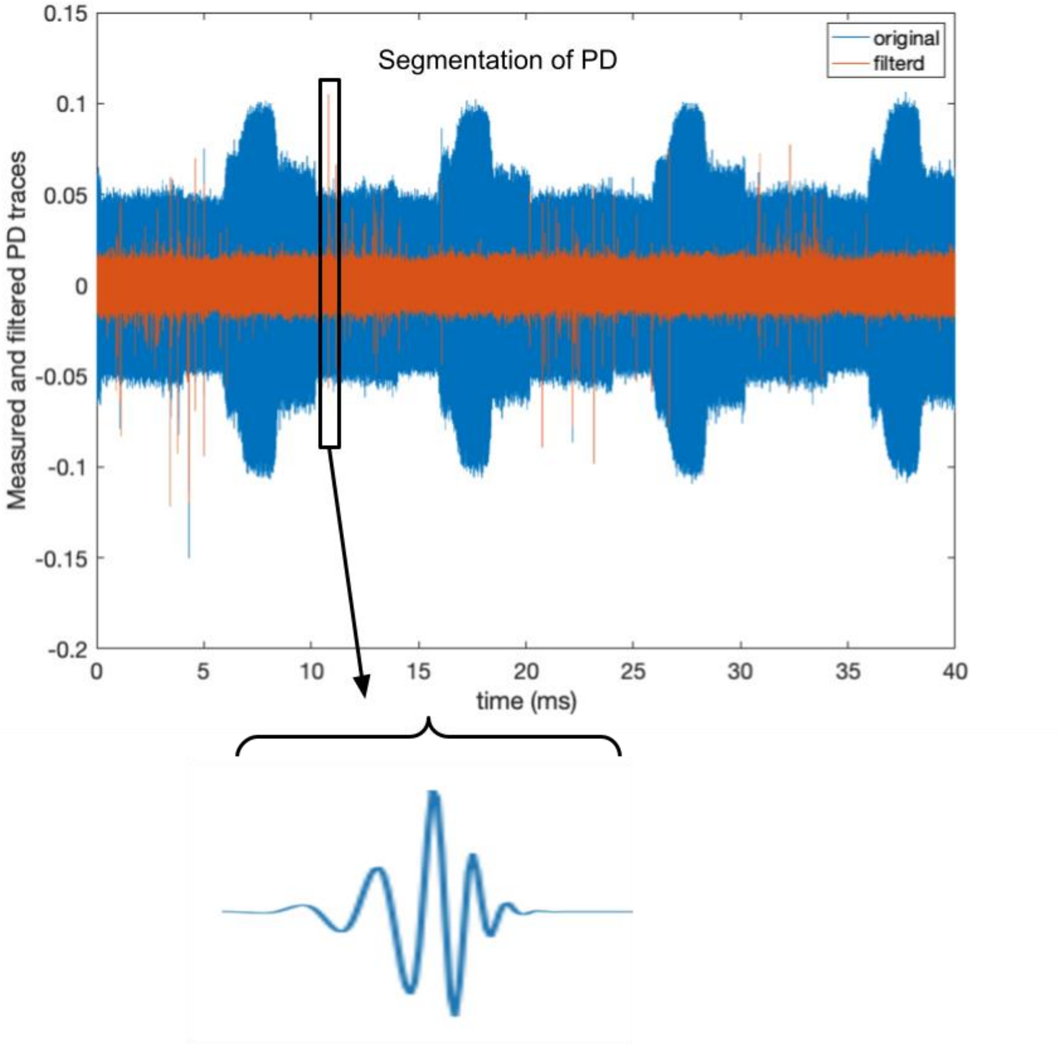

Figure 4: Illustration of initial signal processing, where the voltage remnant waveform averaged over 80 cycles is subtracted from a new trace (Voltage remnant) to obtain the PD information (PD trace). Note that the PD occurrence can be identified visually.

To experimentally generate different types of PDs, we have designed a test object shown in Fig. 5. The test object is made of three polycarbonate discs surrounded by two epoxy discs sandwiched between the two brass electrodes. One of the three polycarbonate discs has a drilled cavity with a diameter of 0.75 mm. Depending on the position of the cavity in the pack, the test object has two configurations. The Cavity disc is placed in the middle or the bottom. The voltage waveform is used with in this setup is two 50Hz and 400 Hz with 4 kV level. Finally, two more types of PDs are originated due to the cavity between the electrode and insulation disc. The collected PD traces are also divided into negative voltage flank (NF) excitation and positive voltage flank excitation (PF).

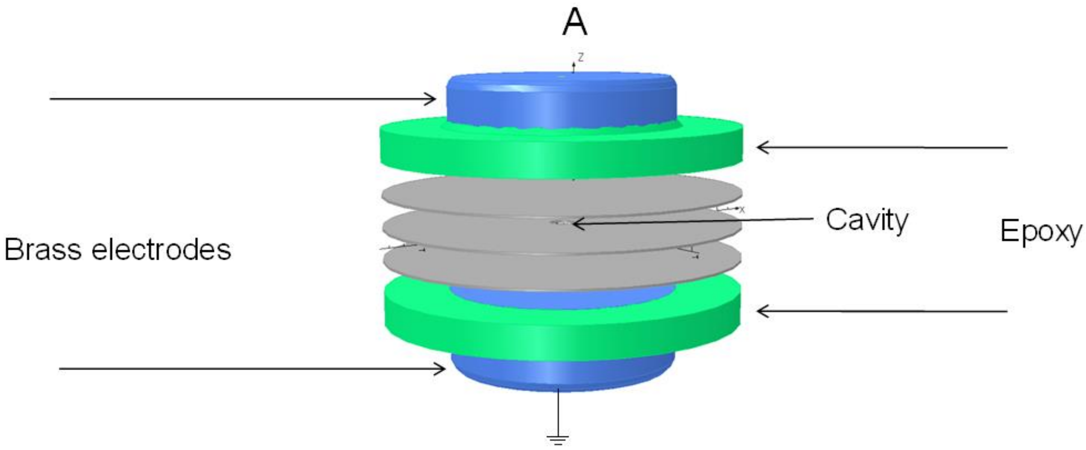

Figure 5: Test object is made of three polycarbonate layers surrounded by epoxi plates for creation of PDs

In Table 1 the experimental conditions for the 10 cases studied are summarized including the number of PDs measured for each test case.

Table 1: Information and distribution of the number of PDs in each class Individually. Abbreviations used on this table: C: class, B: bottom, M: middle, E: electrode.

Class	**C1**	**C2**	**C3**	**C4**	**C5**
# PD	32270	32270	35175	35175	35000
cavity position	B disk	B disk	B disk	B disk	M disk
frequency	400 Hz	400 Hz	20 μs	20 μs	400 Hz
flank type	positive	negative	positive	negative	positive
Classes	**C6**	**C7**	**C8**	**C9**	**C10**
# of PD	35000	35385	35385	35000	35000
cavity position	M disk	M disk	M disk	E and disk	E and disk
frequency	400 Hz	20 μs	20 μs	20μs	20μs
flank type	negative	positive	negative	positive	negative

Once the high pass filter is applied, the AI based segmentation method employed in EcoPhi MU can capture the PDs and stream to the server and this will help to avoid continuous stream of current waveforms with 15Mhz sampling rate. This can reduce the cost on the communication inference, and with fiber optic and normal Ethernet ports we can transfer the data and deploy AI based PD classification on the server which can reduce the computation burden from the EcoPhi MU. Another benefit of this approach is that we can have a model that can analyze the PD signals coming from all of feeders and reduce the training time and increase the accuracy of prediction.

2.3 Feature engineering

In this subsection, after AI based detection and segmentation of PDs, we extract the feature and process the PD trace into a lower-dimensional feature vector to mitigate noise and to provide domain knowledge for the ML-based algorithms. An example of a data segment PD trace with one PD is illustrated in Fig. 6.

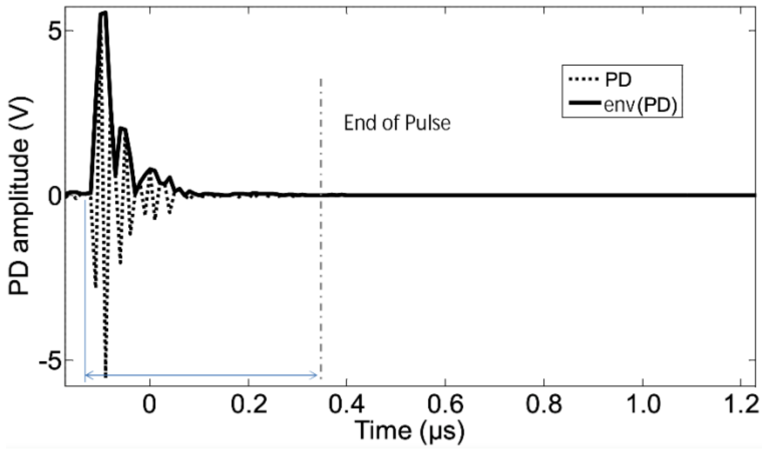

Figure 6: PD trace (dotted line) and envelop of the PD trace (solid line) for a segmented PD event with the indication of the time after which detection of a new PD becomes possible (End of Pulse).

From the PD trace corresponding to a single detected PD, we extract the following features: *a*: the maximum amplitude of the PD trace, *b*: the duration of the PD, *c*: the area under the envelope curve of the PD trace and *d*: the time distance to previously occurring PD as features. The scatter plot of the max amplitude for two randomly selected PD events for a given class is illustrated in Fig. 7.

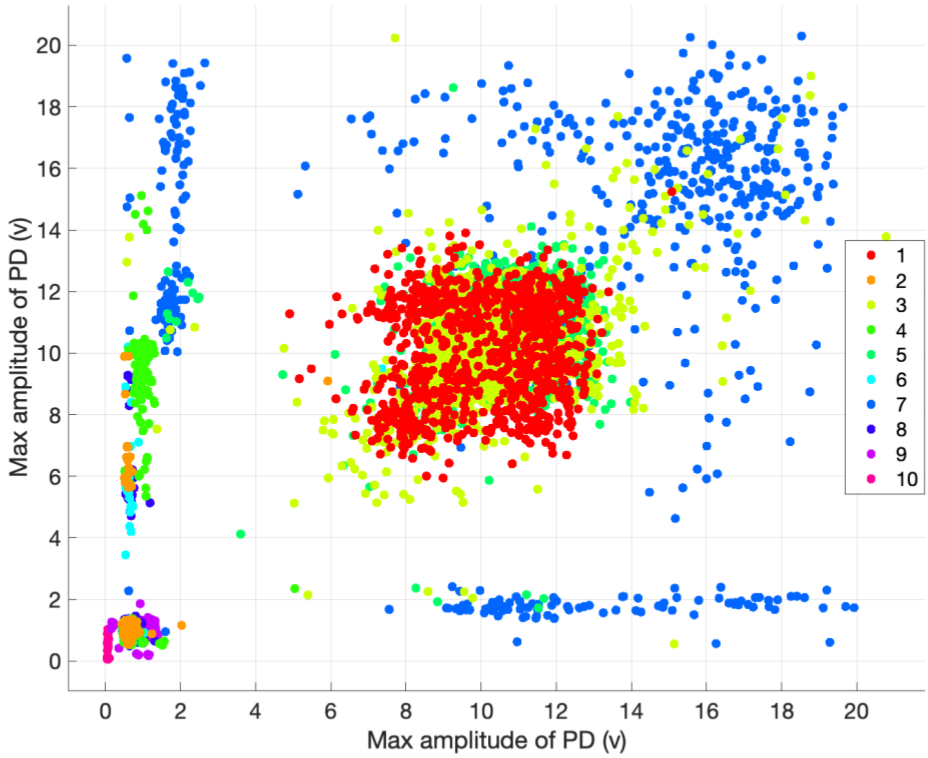

Figure 7: Scatter plot of the max amplitude for randomly selected PDs from different classes. The numbers from 1 - 10 represents each class of PD with different color.

From the scatter plot corresponding to Class 8 we notice evidence of a bimodal distribution of the maximum amplitude with one cluster around 2 and one around 18 which indicates that the underlying distribution is complex and might have a temporal dependence between consecutive PDs. Thus, in the classification process, if we take features from several consecutive PDs concatenate them, we might cover these distributions and increase the possibility of differentiating the PD classes.

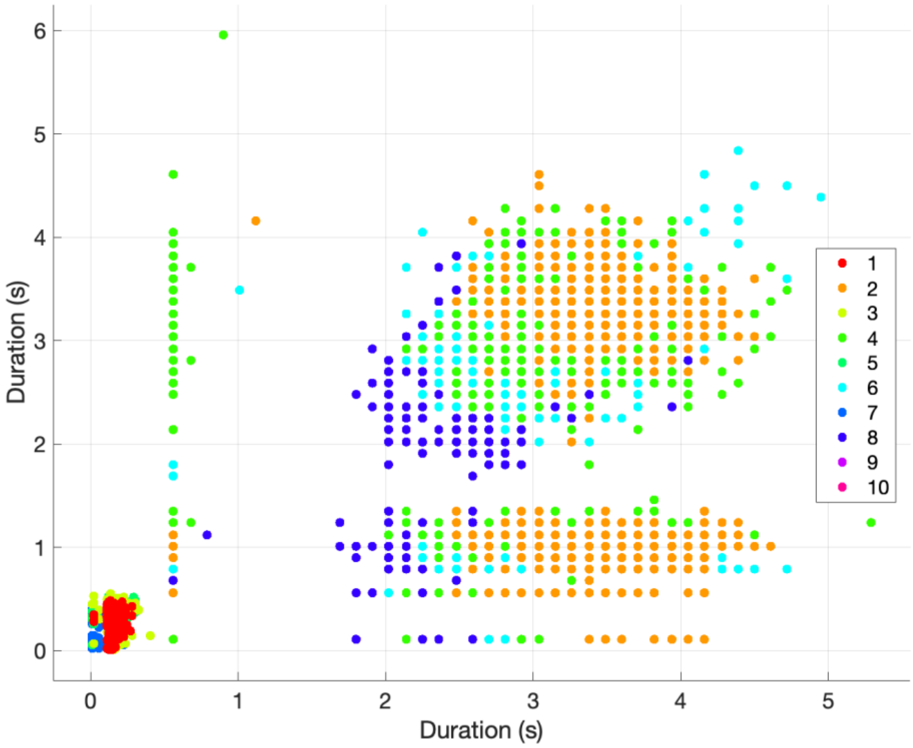

Figure 8: Scatter plot of the duration of randomly selected PDs from 10 classes scaled by $10^{(-6)}$. The numbers from 1 - 10 represents each class of PD with different color.

Similar observation can be seen for other features such as the duration of PDs (see Fig. 8). As such, using the max amplitude feature for classification might be in the range of other classes and can cause classification error. Another issue is that the value of these features varies a lot even within the same class of PDs. Therefore, we propose stacking the features of a number of consecutive PDs as the first step to create the sequences of the features into vector forms. An example of this is for instance the maximum amplitudes of PDs which can be defined as:

$$PD_{m.a} = \begin{bmatrix} a_1 & a_2 & a_3 & \dots & a_n \end{bmatrix} \quad (1)$$

where n is the total number of consecutive PDs which together form the vector of maximum amplitudes. The other feature sequences for duration, time distance and area under the graph can be defined as PD_d, $PD_{t.d}$ and $PD_{a.u}$ similar to Equation (1). In this paper we investigate different classifier architecture that uses some or all of the derived features. To capture the correlation between the sequence PDs, we base the PD classification of data from a total of n PD events. The data originating from a window of n consecutive PDs can hence be collected into a data matrix

$$PD_p = \begin{bmatrix} a_1 & a_2 & a_3 & \dots & a_n \\ b_1 & b_2 & b_3 & \dots & b_n \\ c_1 & c_2 & c_3 & \dots & c_n \\ d_1 & d_2 & d_3 & \dots & d_n \end{bmatrix} \tag{2}$$

where the matrix elements in each column corresponds to the features of a given PD and the columns corresponds to the different PDs in the analyzed data window.

2.4 Machine learning methods

Based on feature engineering steps explained in the previous subsection, this subsection aims to introduce two ML models developed for the classification of features of PDs.

We build classification models in two different ways. For the ensemble bagged Decision Tree (DT) architecture, we concatenate the features from the n individual PDs into a single feature vector. In the second architecture, we use a recurrent structure where the data vectors from the n PDs are feed sequentially to the network. For this approach, we use the Long short-term memory (LSTM) network structure. The process of using these models for classification can be formulated as learning a function F defined as:

$$y = F(x) \tag{3}$$

where x is PD_P defined in Equation (2) and y is corresponding class label predicted.

2.4.1 Ensemble Bagged Decision Tree (DT)

DT is a non-parametric supervised learning method to create a model that predicts the class of a target variable by learning decision boundaries inferred from the data features. The obtained decision boundaries will divide the feature space into regions $R_1 \dots R_i$. where $\hat{y}$ is the estimated label for each region. However, the drawback of the DT method is that it models the feature spaces based on variance estimation. This means that its performance can have a dramatic drop when new observations are added to the training.

One way to solve this is to increase the number of defined parameters. However, increasing the parameters can lead to overfitting problems. Thus, we use ensemble bootstrap aggregation (bagging) with Bayesian optimizer to randomly form K subsets of data from the original training data set and for each subset train a classifier model $M\_i(x)$, $i = 1 , \dots , K$. The class with a maximum number of votes will be elected as the label of x. The formula of extracting labels using majority votes can be described as:

$$M(x) = \arg\max_{y} \sum_{i=1}^{k} [M_i(x) = y] \tag{4}$$

The pseudo code of ensemble bagged DT is addressed in Algorithm 1.

Algorithm 1: Ensemble Bagged Tree

Training
for $i = 1, 2, \ldots, K$ *(number of DT models)* **do**
  - generate S_i by bootstrapping 60% of samples from training data-set
  - Build a DT classifier M_i using S_i
end
Classification
Run $M_1, \ldots, M_K$ on test data (x)
$M(x) = \arg\max_y \sum_{i=1}^{K} [M_i(x) = y]$

2.4.2 Long short-term memory (LSTM)

Different from ensemble bagged DT which divides the feature space into several regions, LSTM analyze the PD_p sequentially. Features are fed to LSTM networks in a sequence of vectors x_i, $i=1, \ldots, n$ where $x_i=a_ib_ic_id_i$ from Equation (2). With this style, it can create a model of the sequential patterns. The process of using the LSTM method is addressed in Algorithm 2 and illustrates the basic schema of LSTM Cells.

Algorithm 2: LSTM

W and U are symbols for weights
Take PD_p as input x to LSTM
$d = 0$
while $d < D$ *(number of created PD_p)* **do**
  $d \leftarrow d + 1$
  $j = 0$
  while $j < n$ *(length of PD_p in Equation (2))* **do**
    First LSTM layer:
      $j \leftarrow j + 1$
      $i_j^1 = \sigma_g(W_i x_j^1 + U_i h_{j-1}^1 + b_i)$ ▷ input gate
      $f_j^1 = \sigma_g(W_f x_j^1 + U_f h_{j-1}^1 + b_f)$ ▷ forget gate
      $o_j^1 = \sigma_g(W_o x_j^1 + U_o h_{j-1}^1 + b_o)$ ▷ output gate
      $\tilde{c}_j^1 = \tanh(W_c x_j^1 + U_c h_{j-1}^1 + b_c)$
      $c_j^1 = f_j^1 \circ c_{j-1}^1 + i_j^1 \circ \tilde{c}_j^1$ ▷ cell information
      $h_j^1 = o_j^1 \circ \tanh(c_j^1)$ ▷ state goes to next layer
      ⋮
    3^{rd} LSTM layer:
      $i_n^1 = \sigma_g(W_i h_j^2 + U_i h_{j-1}^3 + b_i)$ ▷ input gate
      $f_j^3 = \sigma_g(W_f h_j^2 + U_f h_{j-1}^3 + b_f)$ ▷ forget gate
      $o_j^3 = \sigma_g(W_o h_j^2 + U_o h_{j-1}^3 + b_o)$ ▷ output gate
      $\tilde{c}_j^3 = \tanh(W_c h_j^2 + U_c h_{j-1}^3 + b_c)$
      $c_j^3 = f_j^3 \circ c_{j-1}^3 + i_j^3 \circ \tilde{c}_j^3$ ▷ cell information
      $h_j^3 = o_j^3 \circ \tanh(c_j^3)$ ▷ state goes to FC layer
  end
  First FC layer:
  $FC^1 = W_F.(h_1^3, h_2^3, \ldots, h_j^3)$
  Second FC layer:
  $\mathbf{y}_d = \text{SoftMax}(FC^1)$
end

Each cell has a stateful operator h that is obtained from x_j at index j, and h_{j-1} and information of previous cells C_j. The cell has three gates to control the information flow. The forget gate f_j controls if the previous state of the cell should be erased or kept. The input gate, i_j controls how much information from other cells should be added to the current cell. Output gate, o_j controls the information that goes to the next cells. Note that the computed states h are fed as inputs to the next LSTM cells in the next LSTM layer.

The obtained states h_i, $i=1, \ldots, n$ from the first *while* loop of Algorithm 2 in the last layer of LSTM are fed to a network with fully connected layers (FC). In the fully connected network, these extracted states ($h_1, h_2, \ldots, h_j$) are used to obtain the probability of belongingness of the data sample to a certain class using *SoftMax* classifier. It is noteworthy that, different from ensemble DT, in the LSTM method, the feature variations are modeled using weights, and classification is done on extracted states.

3 Results and Discussion

This section will discuss the results of the proposed feature engineering methods applied on the PD data using ensemble bagged DT and LSTM approaches. The proposed methods are implemented in a *Python* software environment using a workstation with an Intel i7 3.40GHz CPU, 48GB RAM, and an NVIDIA Titan XP 12GB GPU. The training is performed on 80% of the PD data and tested on the rest (20%).

3.1 Results of Ensemble bagged DT and LSTM

In the case of creating the ML methods and preprocessing of data, we need to define the model architecture and select optimal hyperparameters. Thus, we let the ML method explore these hyperparameters within a specific range and select an optimal model. This process is called hyperparameter tuning and its result for ensemble bagged DT and LSTM are shown in Table 2.

Table 2: Investigation of the effect of the hyperparameter tuning and their results for the proposed methods. Abbreviations used on this table: parameters (P), methods(M), accuracy (Acc.), variation (Var.), average (Avg.) learning rate (lr)

M \ P	hyperparameters	best value	Acc. Var.(%)
Ensemble Bagged DT	n in PD_p(10:5:50)	35	32
	# of subsets (1:5:100)	55	8
	bootstrap (20%:5:100%)	60%	9
	Avg. vs majority vote	majority	5.5
	lr (0.00001:0.05:0.5)	0.1	14.4
	optimizer (Bayesian, Grid and Random search)	Bayesian	4
LSTM	n in PD_p(10:5:50)	35	35.8
	LSTM layers (2:1:4)	3	9
	FL layers (1:1:3)	2	8
	batch size (16:16:512)	64	5
	lr (0.00001:0.05:0.1)	0.01	15
	optimizer (SGD, Adam, Adagrad, RMSProp)	Adam	3

Column two shows the explorations for each hyperparameter based on the defined steps. Note that these explorations are carried out for classification of all the features, i.e. PD_p defined in Equation (2). Column three is the selected hyperparameter values that resulted in the highest classification accuracy for each method. The accuracy variations due to choosing hyperparameters in the given range in column two are stated in column four. The highest accuracy variation for both ensemble bagged DT and LSTM are observed for hyperparameter n in Equation 2 and learning rate (*lr*) with almost 30% and 15% effect respectively. The optimal value for n is 35 and led to a creation of a new distribution for PD data as illustrated in Table 3.

Table 2: The distribution of number of compound PDs feature vectors PDp obtained for each class.

Class	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
PD_p No	922	922	1005	1005	1000	1000	1011	1011	1000	1000

The overall results of the proposed different feature engineering methods and ensemble bagged DT together with LSTM are shown in Table 4.

Table 3: Investigation of results of proposed methods respect to using different feature engineering. Abbreviations used on this table: training data (D), feature engineering (FE), Method accuracy (M_{Acc}), maximum (Max.), amplitude (Amp.)

D / M_{Acc}	**Max. Amp.**	**Duration**	$\mathbf{PD_{m.a}}$	$\mathbf{PD_d}$	$\mathbf{PD_p}$
Ensemble Bagged DT (%)	56.8	59.9	82.2	82.1	**95.3**
LSTM (%)	53.1	59.3	80.5	81.6	**98.5**

Rows two and three show the accuracy of the classification of Max. amplitude and duration features of PD data without any concatenation. Without feature concatenation, the accuracy of classification is approximately between 53% and 60%. By creating sequences of information from extracted features, as explained in the methodology section (see Equation (1)), the classification accuracy has increased to almost 80% when we are using $PD_{m.a}$ or PD_d. Finally, the stacking the concatenated features ($PD_{m.a}$, PD_d, $PD_{t.d}$ and $PD_{a.u}$) and create PD_p (see Equation (2)) has increased the classification accuracy to 95.3% and 98.5% for ensemble bagged tree and LSTM respectively.

To see if the proposed methods have robust classification on all classes, the confusion matrix of classification of the test data set is obtained and illustrated in Fig. 9 and Fig. 10 for both ensemble bagged DT and LSTM respective. According to these confusion matrices, the lowest classification accuracy for the ensemble bagged DT is 89.1% for class C_6 and the lowest classification accuracy for LSTM is 92% for class C_5. The ensemble bagged DT has a small classification error between classifying C_5 from C_6 and C_7 from C_8. In overall, LSTM has fewer class-specific errors which are shown with the false negative rate (FNR) as illustrated at the right side of the confusion matrices in Fig. 9 and Fig. 10.

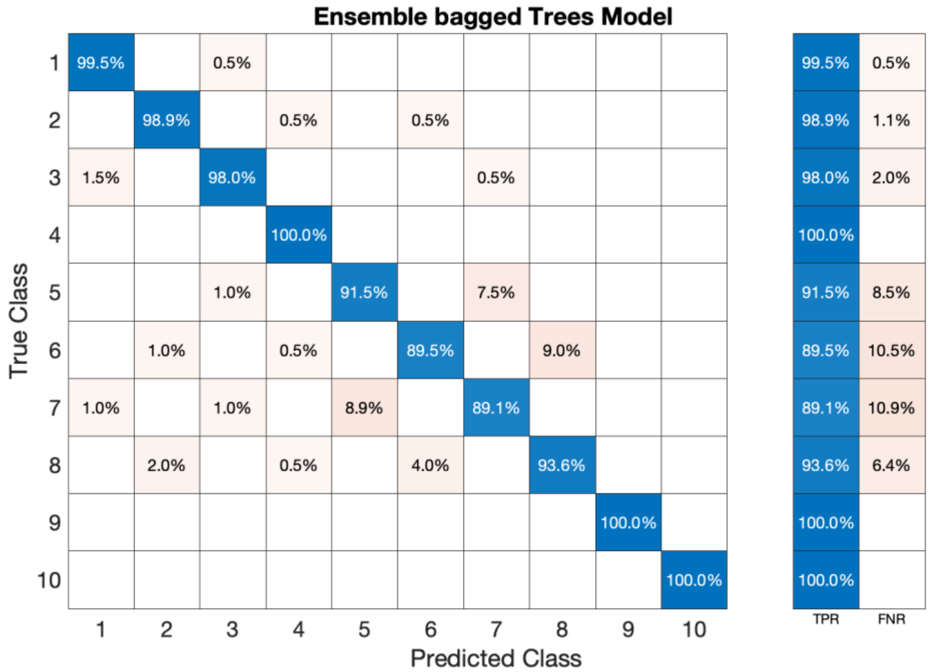

Figure 9: Confusion matrix of PD classification using ensemble bagged DT method. TPR and FNR stands for true positive rate and false negative rate.

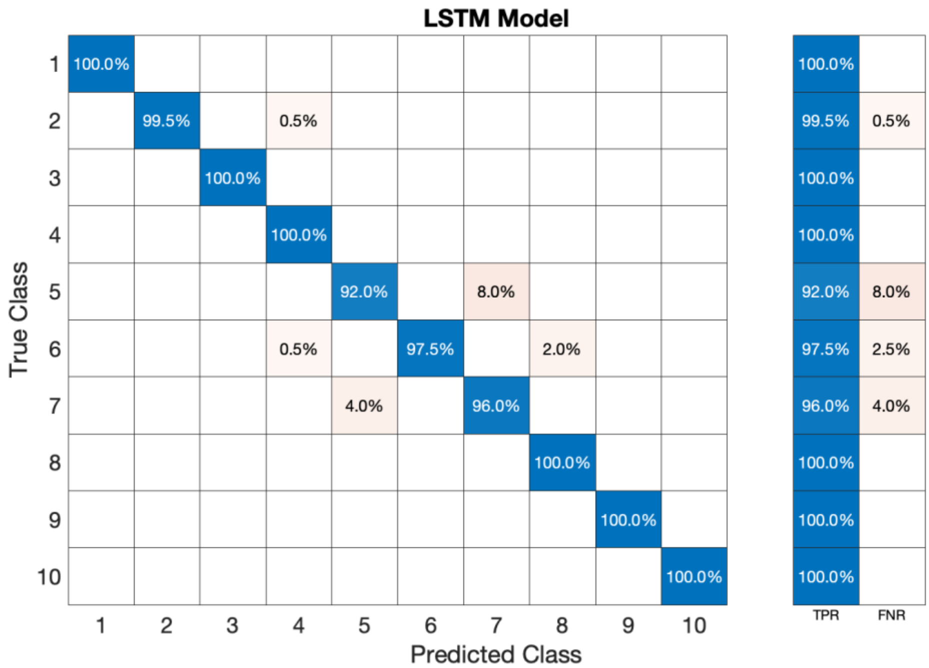

Figure 10: Confusion matrix of PD classification using LSTMT method. TPR and FNR stands for true positive rate and false negative rate.

3.2 Discussion on the results

In this subsection, we will discuss and address reasoning around the obtained results in the previous subsection.

3.2.1 The effect of hyperparameters

As we observed in the result subsection, the n in Equation (2) and lr has had the highest effect on the classification accuracy. In theory, the higher value for n can give a better result, however, it depends on the limitation of the number of PDs captured in each cycle of data recording and also the computational capacity of ML methods where the larger patterns can lead to saturation on feature learning. In the case of lr, we can state that when we choose a very low value for lr, the convergence time of an ensemble bagged DT and LSTM to reach the optimal point can significantly increase and we do not reach high accuracy in the defined number of running epochs whereas a value too large may result in learning a sub-optimal set of weights too fast or to an unstable training process.

3.2.2 The importance of feature engineering for PD classification

In this research work, as the first step we aimed for classifying raw PD segments illustrated in Fig. 6. This experiment resulted in around 55% accuracy using both ensemble bagged DT and LSTM. This is because, without feature engineering, the influence of various noise sources such as oscillation from the waveform is too high so that the methods fail to learn the characteristics of the PDs. As a second attempt, we aimed for concatenation of segments of PD to help methods to be less sensitive to noises. However, since the sampling rate of PD recording is very high, both methods failed to handle and analyze such long segments on the computer workstation system mentioned at the beginning of this section. This is because, from the computational point of view, complexity, size of the LSTM network, the number of branches in DT increases significantly with the number of samples on sequences.

3.2.3 Challenges and benefits of feature engineering

The reason for the low classification accuracy when using only one feature for one PD trace can possibly be explained by the non-Gaussianity of the distribution of the values of the feature. It is observed that the value of features varies a lot also within the class. Thus, they can have values closer to other classes of PDs. Therefore, it becomes harder to separate the classes based only on features from a single PD trace. Thus, using features from consecutive PD traces as seen in Equation (1) create an input pattern which is more informative for the classification task employing ML methods. Furthermore, the accuracy further increased, when using all extracted features (see Equation (2)). It can be concluded that each extracted feature has a useful piece of information that relates to the PD class. Thus, concatenation of them helps the ML-based methods to identify different angles of analysis and learn the specification of PDs better and classify them more accurately.

3.2.4 Discussion on confusion matrices

The reason for the higher FNR in some classes for ensemble bagged DT is due to the thresholds which settings are based on the distribution of the features characterizing each class. Thus, it can end up miss-classifying the classes that can have some similarity in the range of feature values and distribution. For example, both C_7 and C_8 are PD due to the cavity placed in the lower layer of the insulation disk originating from the PF and NF of the waveform, respectively. These classification errors are lower in the LSTM methods and perform slightly better than ensemble bagged DT. The reason for that can be the ability of the LSTM method to build a better model for sequential data thanks to the possibility to control the information flow by the gates and states as explained in the methodology section. LSTM can simply build a relation among indexes in sequences of PD_p. Also, this makes it possible to train LSTM with less data which reduces the sensitivity to noise and outliers.

It can be concluded that both methods have pros and cons. LSTM results in higher classification accuracy with less FNR compared to the ensemble bagged DT. On the other hand, it has more hyperparameters to tune and needs more sophisticated processors such as GPU to efficiently train the network. Ensemble bagged DT is easier to implement and needs less computational power. The proposed feature engineering method shows a significant improvement in the classification accuracy for both methods.

4 Additional discussion

4.1 Economic Impact and Potential Savings

Implementing predictive maintenance through PD monitoring in maritime electrical systems can have a significant economic impact. The maritime sector often faces high operational costs due to unexpected equipment failures, leading to unplanned downtime, costly repairs, and potential safety hazards. By adopting predictive maintenance strategies, these issues can be mitigated, resulting in substantial cost savings and efficiency improvements.

A recent incident highlighting the severe consequences of electrical failures is the collision of the *MV Dali* ship with the Francis Scott Key Bridge in Baltimore in 2024 [23]. The ship experienced an electrical fault that led to a loss of control, resulting in a collision that caused significant damage to both the vessel and the collapse of the bridge. The incident led to several deaths, substantial repair costs estimated in the billions of dollars, legal liabilities, and disruption of maritime and vehicular traffic. It also raised safety concerns and prompted regulatory scrutiny over the vessel's maintenance practices[4,24].

Electrical failures leading to blackouts on vessels have profound economic repercussions, affecting not only the shipping companies but also passengers, cargo owners, and the broader maritime industry. These incidents result in direct costs such as repairs, compensation, and operational losses, as well as indirect costs including legal liabilities, increased insurance premiums, and reputational damage.

Several other notable incidents illustrate the significant economic impact due to electrical failures (both direct and indirect):

- In February 2013, the *Carnival Triumph* cruise ship experienced an engine room fire caused by a fuel leak, which led to a complete loss of power [1]. The vessel was left adrift in the Gulf of Mexico with over 4 200 passengers and crew on board. The economic impact included compensation costs exceeding 49 million SEK, operational losses of approximately 378 million SEK due to the ship being out of service, repair costs around 105 million SEK, and additional legal and reputational costs [25].
- The *Costa Allegra* suffered a total power failure in February 2012 after an engine room fire [2]. Compensation costs were estimated around 16 million SEK, rescue and towing operations cost about 21 million SEK, and revenue losses from canceled voyages were about 50 million SEK.
- In March 2019, the *Viking Sky* cruise ship lost engine power off the coast of Norway [3]. Compensation costs exceeded 105 million SEK, with additional costs from rescue operations, inspections, repairs, and lost revenue.
- The *Maersk Honam* container ship caught fire in March 2018 [26], leading to a blackout that complicated firefighting efforts. The economic impacts included cargo losses exceeding 1.05 billion SEK and repair costs estimated at 315 million SEK.

The economic impact of unplanned downtime due to equipment failures can be substantial. Shipping companies may incur costs up to 525 000 SEK per day in lost revenue and operational expenses [27]. Major accidents can result in repair costs exceeding 105 million SEK, alongside legal liabilities, environmental fines, and reputational damage that can affect future business.

Implementing predictive maintenance strategies, such as PD monitoring, can help prevent critical failures by detecting issues before they escalate into major incidents and it can yield substantial economic benefits:

- **Reduced Maintenance Costs**: Predictive maintenance can lower maintenance expenses by up to 30%, optimizing resource utilization [28].
- **Minimized Downtime**: Proactive fault detection reduces unplanned outages, saving up to 525 000 SEK per day [27].
- **Extended Equipment Lifespan**: Early intervention can prolong the life of electrical components, delaying capital expenditures.
- **Accident Prevention**: Avoiding major incidents can save millions in repairs and liabilities.
- **Material Savings**: Implementing advanced PD monitoring systems can reduce copper wiring needs by up to 95%, leading to substantial material cost savings. With copper prices around 95 000 SEK per metric ton [29], this reduction is economically significant.

These potential savings underscore the value of integrating predictive maintenance strategies into maritime electrical systems. By preventing equipment failures and optimizing maintenance practices, shipping companies can enhance safety, reliability, and profitability.

4.2 Potential challenges and solutions in predictive maintenance of maritime electrical systems

Implementing predictive maintenance for electrical systems in the sector presents a set of challenges due to the operating environment, technical complexities, and human factors. However, by identifying these challenges and developing effective solutions, the maritime industry can overcome obstacles to enhance safety, reliability, and operational efficiency.

One of the primary challenges is the **harsh operating environment**, which significantly impacts the performance and reliability of both the electrical systems and the monitoring equipment. Marine vessels are exposed to high humidity, saltwater corrosion, temperature fluctuations, and mechanical stresses from waves and vibrations. These conditions accelerate the degradation of electrical insulation materials and can impair the functionality of sensors and diagnostic devices used in predictive maintenance. To address this, monitoring equipment must be designed with robust, maritime-grade materials and protective enclosures that can withstand corrosive environments. For example, Redundant monitoring of each feeder with the EcoPhi MU that can monitor two feeders at the same time can ensure the hardware capable of operating reliably under harsh conditions, ensuring continuous monitoring of electrical systems (See Figure 2).

Another significant challenge is the **integration of advanced monitoring technologies** into existing shipboard systems. Many vessels, particularly older ones, are equipped with legacy electrical systems that were not designed with modern predictive maintenance technologies in mind. Retrofitting these ships with advanced sensors and data acquisition systems can be technically challenging and costly. Compatibility issues may arise, necessitating custom solutions to interface new monitoring equipment with existing systems. To overcome this, modular and scalable monitoring solutions can be developed. The EcoPhi MU, for instance, offers flexible integration by utilizing standardized communication protocols and interfaces, allowing it to connect with various types of equipment without extensive modifications.

The **collection and management of data** is also a critical challenge. Predictive maintenance relies on the continuous monitoring and analysis of large volumes of data to detect patterns indicative of impending failures. Implementing such data-intensive systems requires robust onboard data processing capabilities or reliable communication links to transmit data to onshore facilities for analysis. Maritime communication systems often suffer from limited bandwidth and high latency, making real-time data transmission difficult, although improvements are seen lately with the introduction of satellite internet provision from Starlink and the likes of Amazon's Project Kuiper [32]. A potential intermediary or complementary solution is to perform edge computing on-board, where data is processed locally by the monitoring units to reduce the amount of data that needs to be transmitted. Edge based data analytics, enables preliminary processing and anomaly detection without relying solely on external communication (see Figure 1: server).

Ensuring the security and integrity of the data is essential to prevent cyber threats, which adds another layer of complexity. Implementing robust cybersecurity measures, such as encryption and secure authentication protocols, can protect the monitoring systems from unauthorized access. Regular security updates and compliance with international cybersecurity standards are also crucial.

Human factors should be viewed as an integral part of the design and implementation process. The successful implementation of predictive maintenance depends on the expertise of the crew and maintenance personnel. There is often a need for specialized training to operate and interpret advanced monitoring systems effectively. High turnover rates in maritime staffing can lead to a loss of expertise, requiring continuous training efforts. To mitigate this, user-friendly interfaces and automated reporting can reduce the reliance on specialized skills.

Economic considerations cannot be overlooked. The initial investment required for implementing predictive maintenance systems can be substantial, encompassing the costs of equipment, installation, training, and potential modifications to existing systems. Shipping companies may be reluctant to make such investments without clear evidence of return on investment (ROI). Demonstrating the long-term cost savings from reduced downtime, extended equipment life, and avoidance of major failures is essential. Pilot programs and phased implementation can help prove the effectiveness of predictive maintenance systems, encouraging broader adoption.

Regulatory and compliance issues also pose challenges. Maritime regulations concerning the installation and operation of electronic equipment are stringent to ensure safety at sea. Gaining approval for new monitoring systems can be a lengthy and complex process. Collaborating with regulatory bodies and adhering to established standards can facilitate approval. Additionally, contributing to the development of industry-wide guidelines for predictive maintenance can promote standardization and ease compliance hurdles.

Lastly, **data interpretation and decision-making** present challenges. The effectiveness of predictive maintenance relies on accurate analysis of diagnostic data to make informed decisions about maintenance actions. Developing algorithms and models that can reliably predict failures in the complex and variable conditions of the maritime environment is non-trivial. Incorporating machine learning and artificial intelligence can enhance the accuracy of predictions.

5 Conclusions

This study demonstrates the feasibility and effectiveness of applying Partial Discharge (PD) and anomaly analysis for predictive maintenance in maritime power systems. By utilizing high-frequency sampling with the EcoPhi Merging Unit (MU) and employing advanced machine learning techniques such as ensemble bagged Decision Trees (DT) and Long short-term memory (LSTM) networks, we achieved high classification accuracies of PD events, with 95.3% and 98.5% respectively. The successful classification of PDs and association with potential failures in specific components significantly enhances our ability to predict which parts of the maritime electrical systems are most susceptible to failure.

The results also highlight the substantial economic benefits of implementing predictive maintenance strategies in the maritime sector. Electrical failures leading to blackouts have profound economic repercussions, including costly repairs, operational losses, legal liabilities, and reputational damage. By proactively detecting and addressing insulation deterioration and other electrical anomalies, shipping companies can reduce maintenance costs by up to 30%, minimize downtime by up to 45%, extend equipment lifespan by 20%, and prevent costly accidents that can result in damages exceeding 1.05 billion SEK [4, 28].

By adopting advanced PD monitoring systems, the maritime industry can significantly reduce unexpected downtime, minimize operational costs, and ensure the uninterrupted operation of essential activities. This approach not only enhances operational efficiency but also promotes sustainability by reducing energy losses and preventing environmental hazards associated with electrical failures. From a reliability standpoint, integrating PD monitoring and predictive maintenance ensures the continuous operation of critical maritime systems, enhancing safety for passengers and crew. This approach also optimizes electrical system performance, leading to energy savings by avoiding inefficient operations caused by deteriorating components.

Furthermore, this proactive strategy improves the reliability and safety of vessels while supporting the transition to future autonomous ships by providing real-time insights into the health of the electrical systems.

5.1 Recommendations for next steps

Deploying the proposed PD monitoring and analysis system in an actual maritime environment through a pilot program in Sweden is a critical next step because it allows for direct testing and refinement of the technology under real operating conditions. While laboratory simulations provide valuable early insights, they cannot fully replicate the combined effects of saltwater exposure, vibration, humidity, and unpredictable load variations that ships encounter at sea. By integrating the system into an operational vessel, developers can gather high-quality data to fine-tune sensor configurations, validate machine-learning models, and address practical challenges of onboard implementation.

The pilot also enables close collaboration with maritime stakeholders—crew, maintenance teams, and regulators—ensuring that the technology is shaped to fit real-world routines and constraints. Through this hands-on approach, the PD monitoring solution moves from a proof-of-concept stage to a mature, reliable technology readily adaptable across the maritime industry.

Pilot projects can also help in refining the machine learning models with data from actual operating conditions, further improving prediction accuracy. Moreover, advancements in machine learning algorithms, such as incorporating deep learning and transfer learning techniques, can enhance the system's ability to predict PDs in increasingly complex scenarios. The development of edge computing capabilities within the EcoPhi MU can allow for real-time analysis and decision-making on board, reducing the reliance on data transmission and enhancing responsiveness.

More detailed next steps are:

1. **Engaging Key Stakeholders**: Initiate discussions on a pilot project with key Swedish maritime stakeholders, including the Swedish Transport Administration, shipping companies, and maritime technology providers. This will help in understanding their specific needs and gaining their support for the pilot project. The Lighthouse annual conference 20th March will be the first step to gain further traction.
2. **Continued Collaboration with Research Institutes**: Work with research institutes such as Chalmers University of Technology and the Research Institute of Sweden (RISE) to leverage their expertise in PD analysis, machine learning and other related or cross-functional research domains.
3. **Pilot Project Planning**: Develop a detailed plan for a pilot project that includes objectives, scope, timeline, and resource requirements. The pilot project should aim to test the application of Partial Discharge (PD) and anomaly analysis in real-world maritime settings in Sweden, e.g. centered around the port of Gothenburg with access to several key stakeholders.
4. **Technology Integration and Data collection**: Work on integrating the EcoPhi Merging Unit (MU) and other monitoring technologies into existing maritime electrical systems. This may involve retrofitting older vessels with new sensors and data acquisition systems. Collect data from the pilot project and analyze it using the machine learning models developed in the study. This will help in validating the effectiveness of the PD monitoring system in predicting failures and improving maintenance practices.
5. **Training and Capacity Building**: Provide training to maritime personnel on the use of PD monitoring systems and the interpretation of diagnostic data. This will ensure that the crew can effectively operate and maintain the new systems.
6. **Regulatory Compliance**: Investigate relevant rules and regulations to ensure that the pilot project complies with Swedish maritime regulations and standards. Collaborate with regulatory bodies to facilitate the approval process for new monitoring systems onboard.
7. **Evaluation and Scaling**: Evaluate the results of the pilot project and identify areas for improvement and the impact on such implementation. Based on the findings, develop a plan for scaling up the implementation of PD monitoring systems across the Swedish maritime sector.

Through these proposed steps, the findings of the report can be effectively implemented in the Swedish context, ultimately leading to improved reliability and safety of maritime electrical systems, improve fuel and emission performance, and achieve cost efficiency.

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