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Detecting surface discharge faults in switchgear by using hybrid model

Yaseen Ahmed Mohammed Alsumaidaee[1], Siaw Paw Koh[2,3], Chong Tak Yaw[2], Sieh Kiong Tiong[2], Chai Phing Chen[3]
[1]College of Graduate Studies (COGS), Universiti Tenaga Nasional (The Energy University), Kajang, Malaysia
[2]Institute of Sustainable Energy, Universiti Tenaga Nasional (The Energy University), Kajang, Malaysia
[3]Department Electrical and Electronics Engineering, Universiti Tenaga Nasional (The Energy University), Kajang, Malaysia

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ABSTRACT

Switchgear plays a crucial role in power systems, providing protection and control over electrical equipment. However, tracking (surface discharge) can lead to insulation degradation and switchgear failure, necessitating reliable and effective identification of tracking defects. In this paper, we propose a hybrid one-dimension convolutional neural network long short-term memory networks (1D-CNN-LSTM) model as a solution to this problem. Data from both time domain analysis (TDA) and frequency domain analysis (FDA) are utilized for model evaluation. The model achieved error-free accuracy of 100% in both TDA and FDA during the training, validation, and testing phases. The model's performance is further assessed using performance measures and the visualization of accuracy and loss curves. The results show that the hybrid 1D-CNN-LSTM model works well to accurately find and classify surface discharge tracking defects in switchgear. The model offers precise and dependable fault identification, which has the potential to significantly enhance switchgear functionality. By enabling proactive maintenance and timely intervention, the proposed model contributes to the overall reliability and performance of switchgear in power systems. The findings of this research provide valuable insights for the design and implementation of advanced fault detection systems in switchgear applications.

Corresponding Author:

Yaseen Ahmed Mohammed Alsumaidaee
College of Graduate Studies (COGS), Universiti Tenaga Nasional (The Energy University)
Jalan Ikram-Uniten, Kajang 43000, Selangor, Malaysia
Email: eng.yassin.ahmed@gmail.com

1. INTRODUCTION

In recent years, there has been a significant increase in electricity consumption, emphasizing the need for a reliable power distribution network to ensure a stable power supply for end-users [1]. A key component of this network is switchgear, which plays a crucial role in disconnecting and isolating specific buses to ensure the safety of maintenance personnel during repairs, component replacement, and fault monitoring [2]. Switchgear encompasses a range of devices, including switches, fuses, circuit breakers, isolators, relays, transformers, instruments, lightning arresters, and control panels, and is responsible for controlling and regulating electrical circuits within the power system [3], [4]. Switchgear can be classified based on insulation materials (air-insulated, oil-insulated, and gas-insulated) as well as voltage levels (low, medium, and high voltage) [5], [6]. To maintain a consistent and uninterrupted power supply, continuous monitoring and maintenance of switchgear's operational performance are crucial [7]. Malfunctioning switchgear can have severe consequences, leading to increased customer interruptions and regulatory assessments [8]. Common switchgear problems include surface discharges (tracking), corona, and arcing faults, which emit audible waves in the ultrasonic frequency range [9]–[11]. Surface discharge, specifically tracking, is a prevalent issue that can cause erosion and material deterioration due to conductive channels on the surface of materials [12], [13]. This phenomenon generates surface currents that dissipate energy as heat and degrade the material, eventually leading to complete electrical breakdown [14]. Although few researchers focus on the electrical tracking phenomena, most studies analyzing electrical tracking resistance primarily examine the material properties [15]–[18]. Significant contributions have been made in the field of switchgear defects and monitoring techniques. Fitton [19] conducted an extensive study on surface discharges in oil-insulated apparatus, providing valuable insights into the mechanisms of surface discharges in transformers. Lim and Bae [20] compared various SF6 candidate gases for surface insulation in eco-friendly gas insulated switchers (GIS) and solid insulated switchers (SIS), highlighting the effects of moisture and electric field intensity on surface flashover characteristics. Dai *et al*. [21] investigated creepage discharge experiments on power transformer insulating barriers, confirming the impact of moisture on flashover breakdown voltage. In a similar vein, Gu [22] developed a CNN-based algorithm for detecting partial discharge patterns, utilizing fractal theory for feature extraction and distinguishing defect types. Their proposed method showed promising results in assessing GIS insulation status and guiding maintenance decisions.

Furthermore Yuan *et al*. [23] explored the use of visible images and machine learning (ML) for recognizing surface discharge states. They analyzed the chromatic, gray-scale, and morphological properties of visible images and employed clustering and spectrum correlation investigations to classify the images into four stages. Their findings demonstrated that ML techniques, particularly those based on chromatic characteristics, achieved high recognition accuracy in identifying surface discharge states. This approach holds potential for efficient and accurate fault recognition and localization. The existing literature highlights the need for comprehensive and accurate methods to detect and classify surface discharge (tracking) faults in switchgear. Currently, there is a lack of advanced techniques that combine the extraction of relevant features from the input signal and the capture of temporal dependencies in the data. Furthermore, real-time and reliable fault detection methods are needed to ensure the safe and efficient operation of switchgear systems. While these studies have contributed to the understanding of switchgear faults and monitoring techniques, there is still a need for advanced methods that can effectively detect and classify surface discharge (tracking) faults in real-time. This article addresses this gap by proposing a novel hybrid one-dimension convolutional neural network long short-term memory networks (1D-CNN-LSTM) model, which combines the strengths of convolutional neural networks (CNN) and long short-term memory networks (LSTM) to improve the accuracy and reliability of fault detection in switchgear systems.

The 1D CNN and LSTM have shown promising results in detecting faults in switchgear [24], [25]. The combination of 1D CNN and LSTM has been proven effective in detecting faults in switchgear [26]. The 1D CNN extracts relevant features from the input signal, while the LSTM captures the temporal dependencies in the data [27]. This combination allows for accurate and reliable detection of faults in switchgear. Several studies have reported successful applications of hybrid models in various fields [28]–[32].

The following summarizes the objectives of the research and its contributions:

- The objective of this study was to improved the overall safety and dependability of power systems. by improving the hybrid 1D-CNN-LSTM model for detecting tracking faults, also known as surface discharge, in switchgear.
- A novel hybrid approach has been developed in this study for detecting tracking faults, by leveraging the strengths of both 1D-CNN and LSTM models. The primary focus of this study was to apply the hybrid technique for the first time in detecting a tracking fault in switchgear.
- Evaluation of the hybrid 1D-CNN-LSTM model in the time domain analysis (TDA) and frequency domain analysis (FDA), a new approach not done before in similar studies using this technique.
- The effectiveness of the hybrid model has been proven in rapidly detecting and distinguishing tracking faults from other types of flaws, a hybrid approach is considered optimal for the detection of a tracking (surface discharge) fault in both domains.

The article follows a specific structure. Section 2 describes the methodology of the hybrid 1D-CNN-LSTM model, including the detailed description of the development process. The collected experimental data from switchgear systems will be analyzed using the proposed model. In section 3, the results and discussion will showcase the effectiveness of the hybrid model in detecting and classifying tracking faults. Finally, section 4 concludes the article by summarizing the findings and discussing the implications for enhancing the reliability and safety of power distribution systems.

2. METHOD

In this article, Figure 1 provides a visual representation of the various stages that the authors conducted in their study. The first crucial step involved acquiring sound data, which was carefully collected from switchgear systems. To extract meaningful information from the dataset, the authors employed the Mel-Spectrogram technique, a widely used method for feature extraction in audio signal processing. The dataset used in the study encompassed a comprehensive range of switchgear failures, including both tracking and non-tracking errors such as arcing, corona, mechanical faults, and normal operation.

This diverse dataset allowed for a thorough evaluation of the hybrid model's performance across different fault types, ensuring its robustness and effectiveness in fault detection. To ensure the accuracy and reliability of the hybrid model, the dataset was partitioned into three distinct phases: training, validation, and testing. The training phase involved feeding the model with labeled data to learn the underlying patterns and characteristics of different fault types. The validation phase served as a checkpoint to fine-tune the model's parameters and optimize its performance. Finally, the testing phase was used to evaluate the model's effectiveness in detecting and classifying switchgear faults.

The key innovation of the proposed approach lies in the hybrid model, which combines two powerful deep learning (DL) architectures, namely 1D-CNN and LSTM. The 1D-CNN component enables the model to extract spatial features from the input data, capturing important patterns and correlations within the signal. The LSTM component, on the other hand, leverages its sequential processing capability to capture temporal dependencies and long-term patterns in the time series data. By integrating these two models, the hybrid approach achieves exceptional accuracy in detecting and classifying tracking errors in switchgear systems. This method plays a crucial role in identifying potential faults and mitigating major losses that can result from switchgear malfunctions. Moreover, it offers insights and actionable information to improve the overall performance and reliability of switchgear systems, ensuring their optimal operation and minimizing downtime.

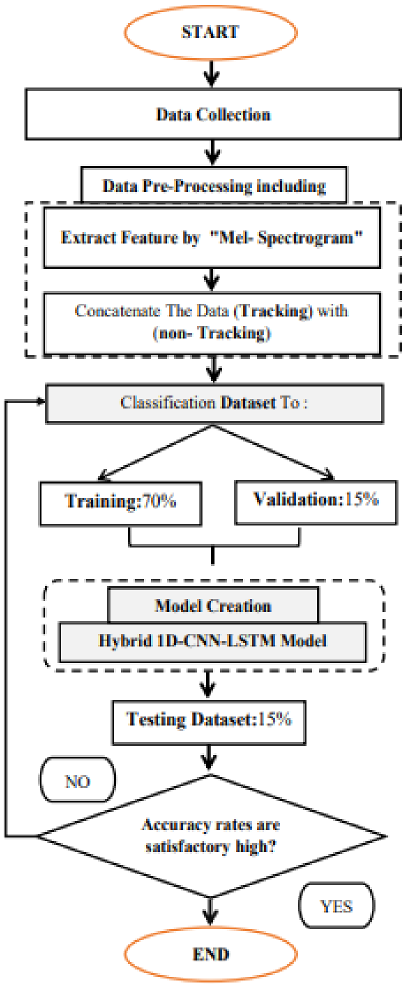

Figure 1. Flowchart outlining the research technique

2.1. Raw data collection

The authors of this article employed airborne ultrasonic test (AUT) equipment to gather data, which was subsequently saved in various file formats, including waveform audio (wav), moving picture experts group (MPEG), and mp3. To prepare the data for deep learning (DL) algorithms, a process known as data transformation was employed. This involved organizing and modifying the data into a suitable format, specifically a matrix structure compatible with the analytical software MATLAB. The dataset used in the study was collected from test results using four different models of ultrasonic testing equipment: the ultra transient earth voltage (TEV) plus, ultra TEV plus 2, ultra probe 9,000, and ultra probe 10,000. These devices provided valuable information for detecting surface discharge problems in switchgear. Table 1 presents a summary of the sample sizes and distributions of the tracking and non-tracking datasets related to the TDA and FDA. These datasets were crucial for training the hybrid 1D-CNN-LSTM model, which was specifically designed to detect and diagnose surface discharge issues in switchgear. By utilizing this data, the authors were able to assess the effectiveness of their proposed method and validate its capability to generate reliable findings for defect diagnostics. The application of this technique for switchgear fault detection and prevention has significant benefits. By effectively identifying and addressing switchgear problems, it becomes possible to minimize losses and enhance overall performance. The author’s approach holds promise for improved maintenance strategies and more reliable operation of switchgear systems.

Table 1. Switchgear fault datasets: tracking vs. Non-tracking in TDA and FDA

Fault	No. of Samples in TDA	No. of Samples in FDA
Arcing	54*20001	53 *10001
Corona	41*20001	39 *10001
Tracking	313*20001	40 *10001
Mechanical	17*20001	16 *10001
Normal	13*20001	12 *10001
Overall Size	17.5. MegaByte	11.3 MegaByte

2.2. Data pre-prpcessing

In this research, a crucial step was the pre-processing of the gathered data to transform it into a suitable format for the algorithms used. This involved combining or converting the data to meet the requirements of the MATLAB software. Additionally, the data was subjected to feature extraction using the Mel Spectrogram, which represents a sound signal in the frequency domain as a 2D image with time on the x-axis and frequency on the y-axis. The Mel scale was employed to approximate the non-linear frequency response of the human auditory system, providing valuable information about the signal's frequency content. The extracted features from the Mel Spectrogram were utilized to detect and classify tracking faults in switchgear. Relevant features were obtained from both the time domain, including the mean and variance of the signal envelope, zero-crossing rate, and root-mean-square (RMS) level, as well as the frequency domain, such as the mean and variance of the Mel Spectrogram and spectral centroid of normalized frames. By combining features from both domains, the hybrid 1D-CNN-LSTM model effectively identified tracking faults in switchgear that might not be distinguishable in either domain alone. During the preprocessing stage, the tracking and non-tracking data, encompassing various fault types like corona, arcing, mechanical, and normal, were combined. The dataset was then divided into three distinct phases: training, validation, and testing.

The majority of the dataset (70%) was allocated for training, while the remaining 30% was evenly split between the validation (15%) and testing (15%) stages. The Google Colab platform was utilized for preliminary data processing and model programming, ensuring proper data structuring for the DL algorithms' interpretation the successful translation of the data into a suitable format facilitated the accomplishment of the study's objectives, which included the precise detection of surface discharge flaws in switchgear, fault identification, and the prevention of significant losses.

2.3. Hybrid model

The hybrid 1D-CNN-LSTM model is a type of DL model that combines the strengths of two different neural network architectures: 1D-CNN and LSTM. The 1D-CNN is effective at extracting local features from time series data, while the LSTM can model temporal dependencies and long-term memory. By combining these two architectures, the 1D-CNN-LSTM model can effectively capture both local and temporal features from the Mel Spectrograms as shown in Figure 2. The feature extraction process involves passing the normalised Mel Spectrogram frames through a 1D-CNN, which applies a set of convolutional filters to the input, producing a set of feature maps. The feature maps are then passed through a max-pooling layer, which reduces the spatial dimension of the feature maps while preserving their most important features. The resulting features are then passed through a set of fully connected (FC) layers, which further process the features and prepare them for input into an LSTM layer. The LSTM layer processes the sequence of features generated by the 1D-CNN, modelling the temporal dependencies between them, and producing a final output that can be used for classification. The final output is then passed through a set of FC layers to produce the predicted class label. Figure 3. shows the layers that are used in the hybrid 1D-CNN-LSTM model in both domains.

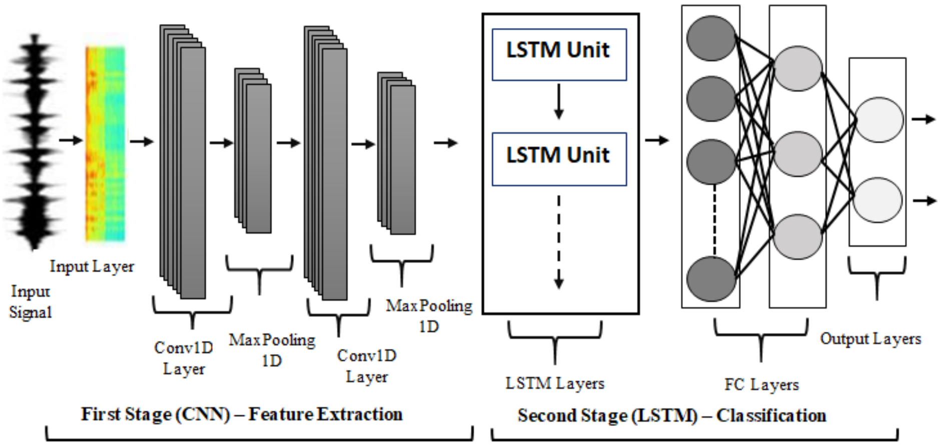

Figure 2. Diagram of a combined 1D-CNN and LSTM model

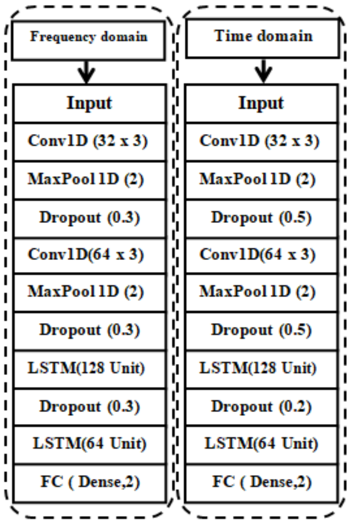

Figure 3. Illustration of a model for detecting tracking and non-tracking faults in switchgear in both domains

The equations for the 1D-CNN model and the LSTM model that are utilized in the hybrid 1D-CNN-LSTM model are as:

- For the 1D-CNN Model, as shown in (1):

$$Y_i = ReLU(W * X_i + b) \tag{1}$$

where X_i is the input at position i, W is the convolutional filter matrix, b is the bias vector, and $ReLU()$ is the Rectified Linear Unit activation function. Y_i is the output at position i.

- For LSTM layer as (2)-(7):

$$i_t = \sigma(x_t U^i + h_{t-1} W^i + b_i) \tag{2}$$

$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f + b_f \right) \tag{3}$$

$$O_t = \sigma(x_t U^o + h_{t-1} W^o + b_o) \tag{4}$$

$$C_t = \sigma\left(f_t \odot C_{t-1} + i_t \odot \check{C}_t U^i + b_c \right) \tag{5}$$

$$\check{C} = tanh(x_t U^g + h_{t-1} W^g) \tag{6}$$

$$h_t = tanh(C_t) \odot O_t \tag{7}$$

where x_t is the input at time t, h_t is the hidden state at time t, C_t is the cell state at time t, W^f, W^i, W^g, and W^o are weight matrices for the forget gate, input gate, cell input, and output gate, respectively, b_f, b_i, b_c, and b_o are bias vectors for the same gates, and $\sigma()$ and $tanh()$ are the sigmoid and hyperbolic tangent activation functions, respectively.

3. RESULTS AND DISCUSSION

In order to analyze the suggested model, Table 2 was utilized. This table displays a confusion matrix, in which the values 0 and 1 respectively indicate tracking and non-tracking states in both the time and frequency domains. The performance of the model was evaluated using a number of different indices, including categorization, reliability, dependability, sensitivity, and the F1 measure, as can be seen illustrated in (8)–(11). To determine how correctly relevant samples were recognized and retrieved from the data, respectively, the recall and precision metrics were utilized for the evaluation. As demonstrated in (11), cross-entropy loss was also used to evaluate how well the model's predictions matched the target data. This evaluation was carried out using the model.

$$Accuracy\ (\%) = 100 \times \frac{TP+TN}{TP+FP+FN+TN} \tag{8}$$

$$Error\ Rate\ (ERR)(\%) = 100 \times \frac{FP+FN}{TP+TN+FN+FP} = 100 \times \frac{FP+FN}{P+N} \tag{9}$$

$$Recall\ (Sensitivity)(\%) = 100 \times \frac{TP}{TP+FN} \tag{10}$$

$$Precision\ (Dependability)(\%) = 100 \times \frac{TP}{TP+FP} \tag{11}$$

$$F1\ measure\ (\%) = 100 \times 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{12}$$

Table 2. Confusion matrix for tracking and non-tracking faults in both domains

	Predictive tracking (0)	Predictive non-tracking (1)
Actual tracking (0)	TP	FP
Actual non-tracking (1)	FN	TN

Where false positive (FP) and false negative (FN) refer to inaccurate predictions, while true positive (TP) and true negative (TN) refer to accurate ones.

The proposed model was created to detect tracking faults of switchgear in the TDA. The model was trained, validated, and tested on a dataset consisting of 438 samples, as shown in Table 3. The evaluation results revealed a 0% error rate in tracking detection and 100% accuracy. Table 4 presents the outcomes of the 1D-CNN-LSTM model that was trained, validated, and tested in the TDA with a total of 306 datasets being used for instruction. In the training phase, the model was able to accurately identify 85 situations of tracking and 221 situations of non-tracking, yielding an accuracy of 100% and an error rate of 0%. This resulted in a perfect accuracy rating. During the validation phase, a total of 66 datasets were analyzed, and out of them, 25 situations of tracking and 41 situations of non-tracking were successfully recognized. This resulted in an accuracy rating of 100% overall and a rate of 0% for errors. During the testing phase, a total of 66 datasets were utilized, 15 of which were determined to be tracking and 51 of which were determined to be non-tracking. In this phase as well, the model was successful in that it attained a perfect accuracy of 100%

with a zero-error rate, indicating its usefulness in TDA. The classification of tracking faults in the FDA was conducted using a total of 160 samples, and the results are presented in Table 5. The analysis showed that the classification of tracking faults achieved an accuracy of 100% with a 0% error rate.

Table 3. Classification outcomes for tracking fault by using a hybrid model in the TDA

	Time domain		
	Training	Validation	Testing
Samples	306	66	66
Accuracy rate	100%	100%	100%
Error rate	0%	0%	0%
Feature number		20001	
Output number		2	

Table 4. TDA Results for tracking faults: training, validation, and testing phases

Hybrid model		
Training phase		
	Tracking	Non-tracking
Actual tracking	85	0
Actual non-tracking	0	221
Validation phase		
	Tracking	Non-tracking
Actual tracking	25	0
Actual non-tracking	0	41
Testing Phase		
	Tracking	Non- Tracking
Actual tracking	15	0
Actual non-tracking	0	51

Table 5. Classification outcomes for tracking fault by using a hybrid model in the FDA

	Frequency domain		
	Training	Validation	Testing
Samples	112	24	24
Accuracy rate	100%	100%	100%
Error rate	0%	0%	0%
Feature number		10001	
Output number		2	

The outcomes of the FDA are summarized in Table 6, which contains 112 data samples that were used in the training phase. The model identified 26 situations of tracking and 86 situations of non-tracking, achieving a perfect score of 100% accuracy with no instances of tracking being missed. During the phase of validation, a total of 24 data samples were employed, which led to an accuracy rate of 100% and an error rate of 0%. A total of 7 situations of tracking and 17 situations of non-tracking were found. During the testing phase, a total of 24 data samples were used, and the results showed an accuracy of 100% with a zero-error rate. Additionally, 7 situations of tracking and 17 situations of non-tracking were found. Table 7 exhibits the performance metrics for both tracking and non-tracking cases, indicating similar values for the metrics in both cases. This suggests that the model's performance was consistent in both scenarios.

Table 6. FDA results for tracking faults: training, validation, and testing phases

Hybrid model		
Training phase		
	Tracking	Non-tracking
Actual tracking	86	0
Actual non-tracking	0	26
Validation phase		
	Tracking	Non-tracking
Actual tracking	17	0
Actual non-tracking	0	7
Testing phase		
	Tracking	Non-tracking
Actual tracking	17	0
Actual non-tracking	0	7

Table 7. Metrics assessment for hybrid 1D-CNN-LSTM method in tracking and non-tracking fault diagnosis across TDA and FDA

Time domain			
Scenario Tracking (0)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100
Scenario Non-tracking (1)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100
Frequency domain			
Scenario tracking (0)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100
Scenario Non-tracking (1)			
Accuracy	Sensitivity	Dependability	F1-Measure
100	100	100	100

4. CONCLUSION

Switchgear is an essential component of the power system that guards against damage and preserves the operation of the equipment. Switchgear, however, is vulnerable to surface discharge tracking, which, if ignored, can seriously harm the electrical system. In this study, a hybrid 1D-CNN-LSTM model for surface discharge tracking detection in switchgear has been presented. It can be inferred from the outcomes of using the hybrid 1D-CNN-LSTM model that this method is very successful for identifying surface discharge tracking in switchgear. Impressive results were obtained in all three phases of the study—training, validation, and testing—in both the Time and frequency domains. The model had 100% accuracy and 0% error rate for tracking fault classification in the time domain, while in the frequency domain, it had 100% accuracy and 0% error rate for all phases. The results of this study have significant ramifications for enhancing the functionality and dependability of switchgear systems since early surface discharge tracking detection can reduce system failures and associated risks. Future study in this field is advised to make use of the hybrid 1D-CNN-LSTM model, and more investigation is required to fully assess its potential in related fields. Overall, this research adds to the expanding body of knowledge in the area of electrical power systems and offers an important tool for managing and maintaining switchgear.

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BIOGRAPHIES OF AUTHORS

Yaseen Ahmed Mohammed Alsumaidaee is currently a Ph.D. student in Electrical and Computer Engineering at Universiti Tenaga Nasional (UNITEN) in Malaysia. He obtained his MSc degree in Electrical and Computer Engineering in 2019 from Altinbas University in Turkey.his B.Sc. degree in Software Engineering at Northern Technical University in 2011. His areas of interest include machine learning deep learning and renewable energy. He can be contacted at email: eng.yassin.ahmed@gmail.com.

Siaw Paw Koh is currently a Professor in the Institute of Sustainable Energy in Universiti Tenaga Nasional. He received Bachelor degree (1st Class Honour) in Electrical & Electronic Engineering (2000), M.Sc degree (2002), and Ph.D. degree (2008) from Universiti Putra Malaysia. His areas of interest are in machine intelligence, automation technology, and renewable energy. He can be contacted at email: johnnykoh@uniten.edu.my.

Chong Tak Yaw received his bachelor's degree with honours from Universiti Tenaga Nasional (UNITEN), Malaysia in electrical and electronics engineering in 2008. He received his master's degree with honours from UNITEN in electrical and electronics engineering in 2012. He earned his Ph.D. in 2019 from UNITEN in artificial neural network. His research interests include artificial neural networks and renewable energy. Currently, he is working as a post-doctoral researcher at Institute of Sustainable Energy in UNITEN. He can be contacted at email: chongty@uniten.edu.my.

Sieh Kiong Tiong is currently a professor in the College of Engineering. He is also the Director for Institute of Sustainable Energy (ISE), Universiti Tenaga Nasional. He received his B.Eng. (Hons), MSc and Ph.D., in Electrical, Electronic and System Engineering from the Nasional University of Malaysia (UKM) in year 1997, 2000 and 2006 respectively. His research interests are renewable energy, artificial intelligence, data analytics, microcontroller system and communication system. He is currently a Professional Engineer registered with the Board of Engineers Malaysia (BEM). He is also a Member of the Institute of Electrical and Electronic Engineers (IEEE). He can be contacted at email: siehkiong@uniten.edu.my.

Chai Phing Chen is a senior lecturer in Universiti Tenaga Nasional (UNITEN), Malaysia. She has been associated with technical education for more than ten years and actively participated in various UNITEN project which involve machine learning. Her project field contains predicting for gas emission from power plant; prediction for short- term wind speed; health condition analysis for HV circuit breaker; fault detection for switchgear; fault detection for transformer; heat waste recovery system via thermoelectric generator and non-technical losses detection. She can be contacted at email: chencp@uniten.edu.my.