Contextual Approaches to Data-Driven Fault Detection in Solar Photovoltaic System

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***Abstract*—Renewable energy offers a sustainable solution to climate change and environmental degradation by reducing greenhouse gas emissions and pollution. Solar energy, in particular, is a promising source due to its global availability, environmentally friendly operation, and declining costs. However, faults in solar photovoltaic (PV) systems can diminish their efficiency and pose safety risks. Detecting and diagnosing these faults is crucial for optimizing performance, minimizing downtime, and ensuring safety in solar PV installations. Contextual data, widely used in fields like NLP, computer vision, and recommender systems, are not as prevalent in the domain of solar PV systems. This paper focuses on leveraging contextual information to enhance fault detection in PV systems using ML-based models. The objective is to explore methods for integrating contextual features into machine learning models for AC power prediction and fault detection in solar PV systems. Three strategies for handling contextual data are compared. The results showed that for AC power prediction, contextual expansion and contextual normalisation performed better than contextual model selection strategy.**

***Index Terms*—solar photovoltaic system, power prediction, fault detection, data-driven model, context**

I. INTRODUCTION

Renewable energy plays a pivotal role in addressing the escalating challenges of environmental degradation and climate change. As a sustainable alternative to fossil fuels, renewable sources such as solar, wind, hydro, and geothermal power offer a clean and inexhaustible means of generating electricity. Embracing these technologies not only reduces greenhouse gas emissions but also mitigates air and water pollution, fostering a healthier planet. Moreover, energy security is enhanced by shifting towards renewable energy, thereby, reducing dependence on finite resources by diversifying the energy mix, and promoting decentralized power generation. The importance of renewable energy is imperative for combating the impacts of climate change in order to achieve a sustainable future [1].

Solar energy is regarded as the most promising renewable energy source for extracting energy from the environment [1], [2]. The utilization of solar photovoltaic (PV) systems for electricity generation has witnessed a significant upsurge in recent years, attributed to several advantages offered by these systems. These advantages include the widespread availability of solar energy resources globally, environmentally friendly operation with zero pollution and noise, straightforward installation procedures, modular configuration options, and a reliable method for converting solar energy into electricity [3]. It is crucial to recognize that electricity remains the primary energy demand for consumers across various sectors [4]. Given the escalating energy requirements, the PV sector is poised for expansion, driven by several factors. These factors include the declining prices of PV modules and the associated balance of systems, advancements in manufacturing technologies, government incentives aimed at promoting solar energy adoption, and continuous enhancements in power converter technologies [5].

Over time, faults occur in PV systems, affecting their efficiency. These faults are primarily classified into three types: environmental faults, physical faults, and electrical faults. Environmental faults usually include shade faults due to cloud movement, tree shadows, bird droppings, and dust accumulation. Degradation faults, internal damage to PV cells, bypass diodes, and cracked and broken panels are classified as physical faults. Open-circuit faults,Line-to-line faults, short-circuit faults, MPPT (Maximum Power Point Tracking) faults, ground faults, arc faults, and islanding operations are classified as electrical faults [6]. Energy losses in solar PV systems primarily arise from faults that can severely impact system efficiency. The failure of a PV module not only results in a degradation of its output power but also diminishes the overall performance and reliability of the system, potentially leading to safety concerns [7]. Hence, fault detection and diagnosis in solar PV systems is imperative to safeguard investments, ensure optimal performance, minimize downtime, and enhance safety measures. To ensure the reliable and safe operation of solar PV installations, it is crucial to implement monitoring and fault diagnosis systems that can detect and address problems promptly [8].

Contextual data have been widely used in various areas such as Natural Language Processing (NLP) [9], computer vision [10], and recommender systems [11]. However, the use of context in the field of solar PV systems is not as prevalent as in these domains. In this paper, we emphasise the utilisation of contextual information while learning an ML-based model for fault detection in PV systems to enhance the performance of the detection model. Various studies have shown that seasonal variations have a significant impact on the performance of solar PV systems [12], [13]. Solar power or irradiance plays a crucial role in determining the output of photovoltaic (PV) panels. Several factors can influence solar irradiance, thereby affecting the performance of PV systems. These factors include location, time of day, weather, seasonal fluctuations, and solar position in the sky [14]. The objective of this paper is to investigate strategies for integrating such contextual information, in the form of contextual features, into machine learning-based models for the task of fault detection in solar PV systems.

The paper is organised as follows, in section II a brief overview of various existing data-driven PV fault detection approaches is presented, section III discusses the approaches used for handling contextual features. In section IV the proposed fault detection framework is discussed and section V presents the case study on 10 MW grid-connected PV plant. Finally in section VI the conclusion is provided.

II. Related Work

Fault detection models for solar PV systems can be broadly classified as physics-based models, and data-driven models which rely on Machine Learning (ML) methods [15]. In this section, we discuss briefly the data-driven approaches. For photovoltaic prognostics and health management, Riley and Johnson [16] introduced an ANN-based technique. They monitored two systems, each having a capacity of 1.1 kWp. Ambient temperature, wind speed, and solar irradiance were the model's inputs and predicted AC power was the model's output. They created a different ANN model for each of the systems. The power estimated by the ANN models is compared with the actual power measured by the monitoring system, and an alarm threshold of 10% was used to generate a warning. In [17] and [18] also, ANN-based models are used for fault detection and diagnosis.

Another commonly used ML approach for detecting faults in PV systems is support vector machine (SVM). Yi and Etemadi [19] proposed a method for line-to-line fault detection in PV arrays using SVM. Rezgui et al. [20] presented a method for detecting short circuit faults in a PV system using SVM along with K-NN algorithm. In [21] and [22], also SVM is used for detecting faults in grid-connected PV systems. A data-driven anomaly detection and classification model was presented for large-scale photovoltaic system anomalies at PV string-level in [23]. It used SCADA data for model development that consisted of two approaches. The first one was based on unsupervised learning, named as hierarchical context-aware anomaly detection method, whereas the second method applied supervised learning for anomaly classification. The anomaly detection module considers PV strings in the same combiner box as the context for detecting anomalous PV strings. The behaviours of both normal and anomalous PV strings are represented at the combiner box level using Gaussian Mixture Model.

Recently, deep learning-based methods have been applied for detecting faults in PV systems. Huuhtanen and Jung [24] applied convolutional neural networks (CNN) to monitor abnormalities in PV panels. The authors presented a method to detect malfunctioning of PV panel based on history data of power measurement of PV panels. The basic idea was to perform anomaly detection by comparing the actual power curve of a panel and the estimated power curve based on adjacent panels. In [25], CNN is used to detect faults from simulated PV array data. The proposed method was used to extract features from 2-D scalograms generated from PV system data using simulation. The authors considered five different faulty cases, namely, line-to-line fault (LL), high-impedance/series arc fault, partial shading (PS), open-circuit fault (OC), and faults in PS. In [26], three deep learning approaches, viz. Long-Short Term Memory (LSTM), Bidirectional LSTM, and CNN are compared for the task of fault diagnosis and detection in an emulated grid-connected PV system. The methods were validated under different operating conditions. According to the simulation results, the implemented classification methods were able to categorise the faults, however, they showed miss classification rates for certain circumstances, especially when CNN was used.

Although much work is being done on ML-based methods for PV system fault detection, there is a notable lack of emphasis on incorporating contextual data into the learning process of detection models in this domain. While some studies [23], take context into account, this context is created by the surrounding strings rather than contextual data from external sources.

III. Methods for Handling Context

The term *context* is widely used in various domains. First, we present the notion of context and contextual features from the perspective of ML as defined by Turney [27]. While learning a predictive model, the feature set can be categorised as: primary features, contextual features, and irrelevant features. Primary features are those that are effective for prediction on their own, without considering other features. Contextual features, on the other hand, only contribute to prediction when considered alongside other features. Irrelevant features do not aid in classification, either individually or in combination with other features. The set of contextual features defines the context. If subsets of the contextual features are considered, each of the subsets defines a context.

In [28], five strategies for handling explicit contexts for the task of classification are discussed, which are as follows: *contextual expansion*, *contextual normalisation*, *contextual weighting*, *selection of contextual classifier*, and *adjustment of contextual classification*. In contextual expansion, the feature space is expanded by incorporating contextual features alongside primary features. This expanded set of features, consisting of both primary and contextual features, is then utilised for learning. Contextual normalisation involves normalising context-sensitive primary features using contextual features such that the former's sensitivity to context is minimised. In contextual weighting, the primary features are weighted using the contextual features such that features that are more useful within a specific context are given more importance. The selection of contextual classifier strategy is a two-step process. Based on the contextual features, first, a specialized classifier from a group of classifiers is selected. Next, the specific classifier is applied to the primary features. In the adjustment of contextual classification, initially, classification is done based on primary features, and then contextual features are used to make some adjustments to classification.

IV. Proposed Framework for Fault Detection

In this section, the details of fault detection in solar PV system is presented. Fault detection can be formulated as a classification task or regression-based task. In this work, we are considering a regression-based model for fault detection. The process of fault detection using regression models, typically involves two main steps:

- AC Power Estimation: The first step entails estimating the AC power using a regression model. This model is often constructed using ML approaches, leveraging only normal historical data and relevant features to predict the AC power output. The model's output provides an estimate of the expected AC power under normal operating conditions. In our case, we will be using a contextual approach for learning the predictive model.
- Fault Detection: In the second step, a comparison is made between the estimated AC power and the measured AC power. If the deviation between the estimated and measured values exceeds a predefined threshold, it indicates the occurrence of a fault. If such anomalous deviations persist for a specific duration of time, it triggers an alarm, indicating the presence of a fault or abnormal condition.

Fig. 1 shows a diagrammatic representation of this approach. To develop the data-driven predictive model, we used ML-based approaches with contextual information. We employed three strategies for handling the context data, viz., contextual expansion, contextual normalisation, and model selection strategy.

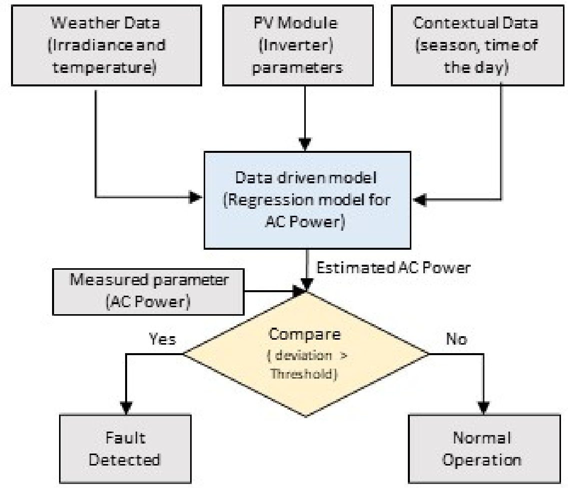

Fig. 1. Fault Detection Approach

V. Case study on 10 MW grid-connected PV plant

To test the performance of the proposed fault detection approach and compare various context handling strategies, we considered data from a 10 MW grid-connected PV plant located in the western region of India. In this section, first, the system description is presented followed by data description, data pre-processing, feature selection, model development, and finally the results.

A. System Description

The PV system under consideration is a 10 MW grid-connected PV plant operational in the western region of India. Fig 2 shows a simplified schematic of the PV plant. It consists of 16 inverters with 8 PV arrays connected to the inputs of each inverter through string monitoring boxes (SMBs). One PV array is connected to one SMB. A PV array consists of 5 PV strings with each PV string consisting of 19 PV modules connected in series. Five such strings are connected to one SMB which forms one Array. Eight of these SMBs are connected to a single 630kW inverter. Furthermore, a single transformer with a rating of 1300kVA is connected to two of these inverters.

B. Data Description

The dataset comprises SCADA data collected from inverter control rooms (ICRs) during a period of 11 months, from April 2019 to February 2020. Data is captured at 15-minute intervals each day, capturing 30 different characteristics like Date, Time, AC and DC Power, Current, Voltage, and Inverter Generation in kWh for a specific day. Along with this, each day's weather data which comprises of horizontal irradiation, tilt irradiation, ambient temperature, module temperature, and wind speed is also available. In addition, a record of the faults occurred in the inverters over the specified period is available as a separate file.

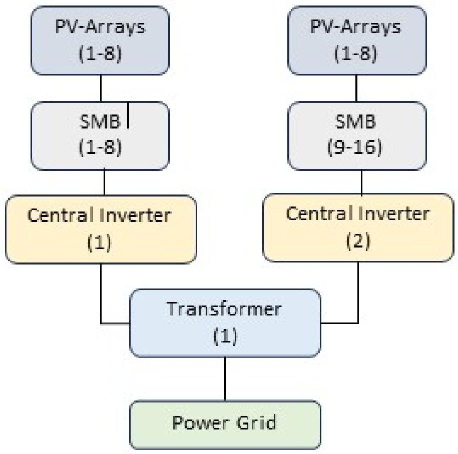

Fig. 2. A schematic diagram of a section of the layout.

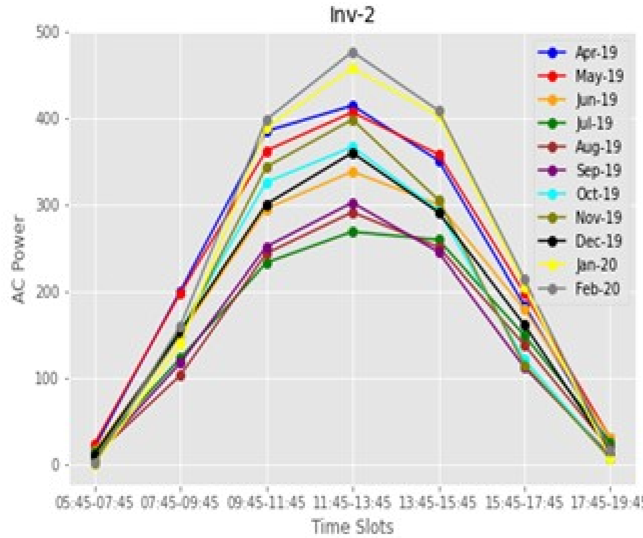

Fig. 3. Average (2 hourly) AC Power for Inv-2 for all months.

C. Data Analysis

A detailed analysis of this dataset was performed, however, we provide here only specific results which are required for the completion of this paper. The analysis involved the AC power of all 16 inverters. When average AC power is plotted for all the inverters for various months, it indicated that the plant was not productive in July, August, and September while production was high during April, May, January, and February. The highest number of faults occurred in July, followed by August and September, which can be one of the causes for the low output in that month [29].

We also plotted the average AC power of each inverter using two hourly averages for every month to see the seasonal variance. The plot for one inverter, Inv-2, is displayed in Fig. 3. The figure shows clusters of AC Power for certain months, for example, July, August, and September are all in one cluster. Additionally, the pattern of the AC power in January and February is similar. As expected, the figure shows that the time of day and season have an impact on AC power. This reaffirms the necessity of incorporating context (seasonal data and time of day) in the predictive model development process [29].

D. Data Preprocessing and Feature selection

To prepare the data for modelling, the data belonging to early and late hours are removed first, leaving only the data from 7:00 to 18:30. Further, the faulty samples are eliminated, so that data from the plant's regular operations can be used in the model's training. Following the initial preprocessing, a total of 96912 normal samples are retained. Three primary features are selected, Tilt Irradiation, Horizontal Irradiation, and Ambient Temperature, and the target is the AC power at a specified time step. Additionally, previous AC power is also considered as a primary feature. The features are selected based on correlation coefficients. Lastly, the season and time of day are taken into consideration as two contextual features. For contextual expansion, the seasons are represented as numeric where the first season is labelled as 1 and so on. For the time of the day, cyclical encoding is used where the time of the day is represented as cyclical feature using sine and cosine.

The data is preprocessed according to the context handling strategies. For all the strategies except contextual normalisation, the data is normalised using min-max normalisation. In the case of contextual normalisation, the data is normalised as follows [30]:

$$v_i = \frac{x_i - \mu_i(\mathbf{c})}{\sigma_i(\mathbf{c})} \tag{1}$$

where $\mu(\mathbf{c})$is the expected value x_i and $\sigma_i(\mathbf{c})$ is the expected variation of x_i, as a function of the context $\mathbf{c}$.

E. Model Training

To compare the context-handling strategies, we trained the following models: Linear Regression (LR), MLP (Multilayer Perceptron),Random Forest Regressor (RFR), Support Vector Regressor (SVR) and Long Short-Term Memory (LSTM) networks.

We trained the models considering three context handling strategies, the first model is trained with only primary features (Base model), the second model considers primary features with contextual normalised data, and the third model employs contextual expansion where contextual features are treated as primary features. Finally, we trained four models separately for each season (context) to implement the last context-handling strategy where a model will be selected based on the given context of the input data.

During training, the hyperparameters are tuned using the validation set to optimize the performance of the models. Table I shows the values of only a few selected hyperparameters. The results are discussed in the following sub-section.

TABLE I
MODELS AND SELECTED HYPERPARAMETERS

Model	Hyperparameters	Base model	Contextual Models
LR	Fit intercept	True	True
MLP	Hidden layer sizes	(50, 100)	(200,)
	Epochs	500	200
	activation	'relu'	'relu'
	optimizer	Adam	Adam
	Learning rate	Adaptive	Adaptive
SVR	Kernel	'rbf'	'rbf'
RFR	Depth	25	20
	# estimators	200	200
LSTM	Sequence length	5	10
	#layers	1	2
	Hidden units	50	200
	learning rate	0.0003	0.001
	Epochs	100	100
	Optimizer	RMSprop	Adam

TABLE II
MODEL PERFORMANCE (RMSE VALUES)

Model	Context-handling strategies			
	Base Model	***Contextual Normalisation***	***Contextual Expansion***	***Contextual Model Selection***
LR	0.1026	0.0932	**0.0860**	0.1010
MLP	0.0942	**0.08155**	0.0950	0.0949
SVR	0.0984	**0.0803**	0.0940	0.0935
RFR	0.0658	**0.0590**	**0.0589**	0.0665
LSTM	0.0811	0.09678	**0.0801**	0.1012

F. Results and Discussion

As mentioned earlier, for a given input, the AC power is first predicted and then compared with the measured AC power to identify faults.

We first discuss the results of the regression models used for AC power prediction.Table II shows the results obtained from all the models. Note that the results are for normalised data. The LSTM-based regression model is used for one time step (15 minutes) ahead AC power prediction. It is apparent from the table that RFR performed the best and both contextual normalisation and contextual expansion well. Also, in all the models contextual normalisation and contextual expansion strategies provided slightly better results. We also observed that the context-handling strategies did not significantly improve the performance with this data. Considering the results from RFR, it is further employed for fault detection.

The detection process requires a threshold value to check the deviation between predicted and measured AC power. Here, the threshold value is determined using the training error. The training error is fitted with Gaussian distribution to identify the mean (μ) and standard deviation (σ). We considered 2σ and 3σ as the threshold and compared the results. We observed that 2σ is better because it resulted in fewer false negatives and false positives. Further, to reduce false positives, a fault is triggered after 4 consecutive samples have deviations more than the specified threshold.

Over the period of 11 months, faults occurred in 9 inverters out of 16 inverters. The entire day data in which a fault occurred in a particular inverter and two days prior and two days after is considered for testing. So, the test data consists of both normal and fault data samples. We compared the time of occurrence of the actual faults and the time when the faults were detected by the models. The aim is to see if the system can perform early fault detection which is desirable for PV systems. Table III compares the occurrence time of actual faults and detected faults. It also shows the corresponding models. For example, in Inv-3 first fault occurred at 14:00 and both contextual model selection strategy and contextual expansion strategy detected the first fault at 11:00. The occurrence time when the system detected a fault early is highlighted in red.

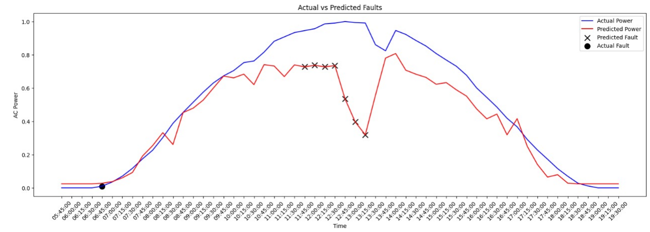

Fig. 4. Actual and detected faults for Inv- 4 (Contextual Model selection).

We observed that out of 13 faults, the system could detect 6 faults early and the remaining 7 faults were detected late. The late detections are primarily the faults that occurred early morning. Figure 4 shows a representative case for late fault prediction. During the morning hours, there is almost no deviation in the predicted power from the actual power. Also, in the figure the power is gradually increasing during the early morning hours, which is a normal trend. Due to this, the model could not detect the faults during these hours. In the future work, we will address this issue where faults occur early morning.

VI. CONCLUSION

In this paper, we utilized contextual data to enhance fault detection in solar PV plants. We assessed three approaches for managing context: normalisation, expansion, and model selection. Our findings indicate that integrating contextual information improved the predictive model's performance, although not significantly. Our proposed fault detection method demonstrated the capability for early fault identification. In this work, we have not employed deep learning models due to the limited size of the dataset. However, in future when more data will be available from the PV plant, we aim to explore their integration along with contextual attributes.

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TABLE III
Comparison of Time of Occurrence of Faults

Inverter	Fault day	Actual fault- ToC	Predicted fault- ToC	Model/Strategy
Inv-3	05-07-19	14:00	**11:00**	Model selection and Contextual expansion
	01-10-19	07:00	10:45	Contextual expansion
Inv-4	04-10-19	06:45	8:30	Contextual Normalisation
Inv-5	18-09-19	14:45	**11:45**	Model selection, Contextual expansion and Contextual Normalisation
Inv-6	26-06-19	14:30	**11:00**	Contextual expansion
Inv- 7	10-08-19	7:45	08:30	Model selection
	16-09-19	14:45	**11:45**	Model selection
Inv- 8	10-08-19	7:00	08:30	Model selection
	25-9-19	08:00	08:30	Model selection, Contextual expansion and Contextual Normalisation
Inv-9	09-07-19	6:30	12:00	Model Selection
Inv-14	07-07-19	6:15	08:00	Contextual Expansion Contextual Normalisation
Inv-15	23-10-19	15:30	**9:00**	Contextual Expansion
	07-02-20	12:00	**10:15**	Contextual Expansion and Contextual Normalisation

[a]Time of Occurrence.

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