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High-resolution data-driven anomalous event detection from solar farm data using clustering large applications based upon randomized search

Maitreyee Dey[1,2*], Soumya Prakash Rana[1], Clarke V Simmons[2], Sandra Dudley[1]

[1] School of Engineering, London South Bank University, London, UK

[2] Neuville Grid Data Limited, London, UK

ABSTRACT

Solar energy is a significant and fast-growing source of low-carbon electricity. The usual means of utility-scale solar farm condition monitoring is limited by poor measurement accuracy and low-resolution data collection rates. A micro-synchrophasor measurement unit (μPMU) has been adapted and integrated with a power quality monitor (PQM). This apparatus provides the high-resolution, high-precision, time-stamped data needed by analysts to make solar farms more cost-effective and to better understand decentralize grid behaviour. The resulting big data necessitates applying machine learning (ML) for automatic event forecasting, fault detection, and site maintenance. The limited availability of data knowledge, data volume, and performance issues drives the exploration of data-driven based unsupervised ML methods on this occasion. **C**lustering **L**arge **A**pplications based upon **RAN**domized **S**earch (CLARANS) algorithm has been employed owing to its suitability to categorise events from the big data. CLARANS has been performed to recognize inefficient voltage phase unbalance. The voltage and current waveforms and related issues such as, voltage dip or voltage sag and phase imbalance events have been considered among multiple data streams and various power distribution issues for this investigation. Ten consecutive days of empirical data have enabled this research. Altogether, 250.92 million power quality data points have been tested and validated.

Keywords: Renewable energy, solar photovoltaic, Smart grid, micro-synchrophasor measurement unit, Big data mining, Anomaly detection, Unsupervised machine learning.

1. INTRODUCTION

Stopping climate change motivates implementation of renewable energy sources such as wind and solar with much smaller carbon footprints. However, irregular their behaviour brings challenges for consistent operation in power distribution systems [1]. Utility-scale (>1 MW) solar farm owners suffer from significant plant failure rates, reduced equipment life, unplanned outages, and the replacement overheads [2]. These problems can be countered through better condition monitoring data collection and knowledge discovery to automatically understand issues and predict problems before they occur.

Today's industry standard Supervisory Control and Data Acquisition (SCADA) system systems do not have capability to detect anomalous behaviour, faults and failure modes that lead costly problems [5]. Improved monitoring tools are beginning to provide more granular and higher accuracy data capture together with precise timing information [5].

Our research assesses solar farm behaviour to reduce operating costs, prevent outages, and increase operational life. This is implemented by collecting and analyzing μPMU data alongside classic power quality measurements data from large UK solar sites, enabling appropriate machine learning techniques for remote and automatic plant anomaly detection.

2. BACKGROUND OF POWER GRID SYSTEM

Machine learning methods will play a crucial role towards making large scale systems such as cities and their power grid smarter and more sustainable. Several researchers have investigated the challenges to optimise energy performance of low carbon cities exploring

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artificial intelligence [3, 4]. In future power distribution system, μPMUs and similar devices will provide system operators fast, high-resolution, and accurate measurements. The gathered energy data will exhibit big data characteristics in terms of volume, variety and velocity [1]. In work by Yigit, Gungor, and Baktir [2], linear state estimation has been performed to improve parallel computation for big data screening, gathering, and processing, with the aim to provide intelligent grid monitoring via abnormal event detection. Several studies have been performed investigating big μPMU data to identify anomalous events in the power distribution network [5–10]. These methods focus on the data-driven approach employing machine learning algorithms to improve solar farm behavioural awareness [5]. Some of the methods perform statistical approaches, where the absolute deviation around median combined with dynamic window sizes have been used for event detection [6]. Other methods used supervised or semi-supervised machine learning for identifying different event, where the knowledge of the event already provided as a priori [7-9].

Data-driven unsupervised learning via an installed μPMU has been employed in this study to detect anomalous electrical event from the solar farm and connect power distribution system.

3. MATERIAL AND METHODS

Engineers at Neuville Grid Data have built a novel patent pending apparatus, the Grid Data Unit (GDU), for the specific purpose of high-resolution and accurate data collection from the sites. Data for this analysis comes from a GDU installed at the 8MWp Kenninghall Solar Farm in Norfolk England. The site connects to the UK Power Networks distribution system at 33kV. During 2016-2018 the site produced an average 7,112 MWh/yr.

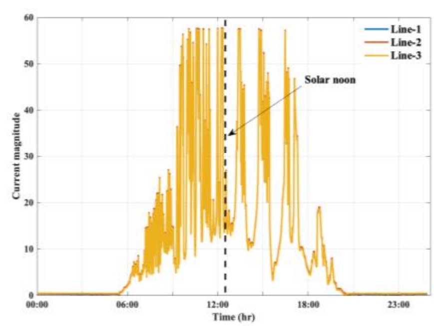
3.1 Designed Apparatus

The μPMU instrument is incorporated into the GDU (shown in Fig. 1). The GDU incorporates a power quality monitor (PQM), simultaneous global positioning system (GPS) based time-synchronization to sub-100ns, solid-state memory for data-buffering, and secure bidirectional 3G/4G cellular data telemetry equipment with the twice-per-cycle (100/120 Hz) data-reporting rate.

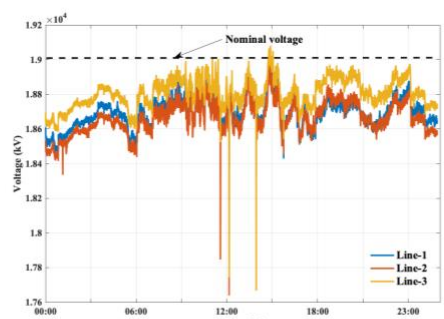
Fig 1 Grid Data Unit including μPMU.

3.2 Micro-synchrophasors Measurement Unit (microPMU) *Data Description*

Operating in the frequeuncy domain, the μPMU is used to collect data for each half cycle at 10 milliseconds reporting periods (100Hz in the UK). Fig. 2 shows the actual power measurement generated by the solar farm on a single day during summer (May) 2020. Fig. 2(a) depicts how the photovoltaic (PV) generated output current varies with solar irradiance being subject to intermittent cloud passage. Fig. 2 (b) depicts the simultaneous voltage measurements. In this figure, the



(a)



(2)

Fig 2 Collected μPMU solar farm data for a single day , (a) the cuurent measurements (b) voltage measurements.

large voltage drops are shown to occur over a number of occasions and their exhibition would not go unnoticed on slower rate systems. Possibly obscuring issues that need immediate attention.

3.3 Proposed Approach

The major difficulties in analyzing big data is to clean and prepare to tackle outliers. Here, CLARANS clustering algorithm has been applied as the type of any failures are not available in the μPMU. This data-driven method has been employed for anomalous event detection, described in the following subsections. The overall process flow has been shown in Fig. 3.

3.4 Clustering and Validation

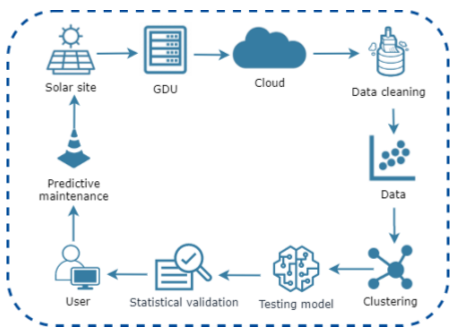


Fig. 3 Proposed flow diagram for μPMU data-driven based anomaly event detection.

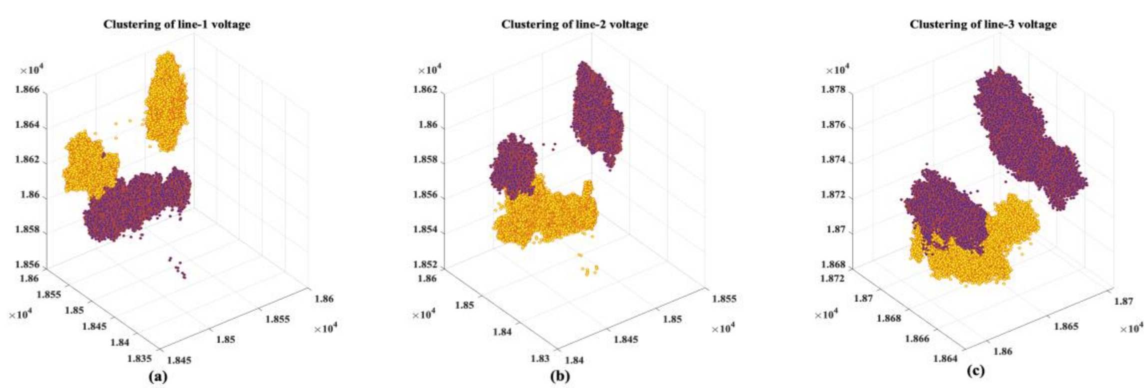


Fig 4 Clustering outcomes for three-phases voltage of a single day micro-PMU data.

Clustering **L**arge **A**pplications based upon **RAN**domized **S**earch (CLARANS) [11] is a partitioning method discovered to overcome the limitations of K-medoids and K-means algorithms that operates on medoids for clustering the large database.

It presents a trade-off between the processing cost and effectiveness of obtaining clustering over samples. It calculates two parameters, the local minima and maximum neighbor. The higher the value of the latter, the closer will be CLARANS to PAM and the longer it will take to perform each search of the local minima. This is an advantage because the quality of the local minima is higher, and a smaller number of local minima are discovered returning a best local optimal as the final result.

4. RESULT ANALYSIS AND DISCUSSION

The proposed clustering approach has been experimented on three-phase voltage phasor data for 10 consecutive days (1st May – 10th May 2020 to categorise their functional behavior and detect anomalies on the power distribution system. Each day, 8.6 million voltage phasor data points are gathered per phase. The results have been shown here for 1st May 2020. Fig. 4 presents the CLARAS outcomes of the line-1 (first phase), line-2 (second phase), and line-3 (third phase) voltages. From this figure it has been seen that the shape of both clusters in each figure are spherical, thus depicts partitioning based method should work well to separate data patterns distinctly. Fig. 4(a), 4(b), and 4(c) shows the line-1 patterns, line-2 patterns, and line-3 patterns respectively where the outliers are clearly visible in both the clusters. This clustering grouped the data based on the magnitude variation of throughout the day, where one group comprises voltage magnitudes between ~1.85 to ~1.86 kV and the other group contains ~1.87 to ~1.88 kV respectively. The detected outlier events from the clustered data have been validated by the power quality measurement data and the abrupt event examples are shown in the Fig. 5. Figure 5 is a window showing 1.5 hours of data, where the exact voltage dip event along with its time and magnitude are displayed. It has found that the voltage dip (~11.15 am and ~12.56 pm) occurred two times during this period and reaches a magnitude of 1.76 kV, captured precisely by the clustering approach.

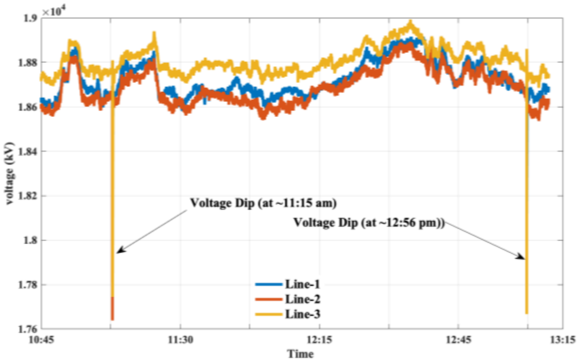


Fig. 5 Voltage dips of the μPMU data on the tested day.

Thus, the CLARANS shows useful performance grouping of high-resolution μPMU data for outlier detection. The experiment has been conducted employing MATLAB 2020a using the parallel processing mechanism on a 2.4 GHz 8-core i9 Macintosh computer with 64GB random access memory and 8GB Graphics processing unit (GPU).

5. CONCLUSION AND FUTURE WORK

This preliminary study combines empirical big data and machine learning to facilitate improved solar farm cost-efficiency through remote condition monitoring. The clustering of the high-resolution real data itself is a challenge in terms of cost, execution time and overheads. To overcome these limitations, we have successfully employed the first ever CLARANS on μPMU data to detect the outliers.

This research is encouraged by the fact that there is over 8 GW of underperforming utility-scale (>1 MW) solar capacity across approximately 1,200 sites hastily constructed in the UK during 2011-2017. The National Grid's Future Energy Scenarios 2020 report [12] projects 1.4GW of new UK solar installations every year through 2050.

We will continue to explore solar energy related data sets with machine learning approaches to automatically identify performance issues. This smart technology will assist in predictive site maintenance to avoid equipment failure and expend its operational life, providing macroscale distribution grid level data analytics and performance information as well as preemptive maintenance, improving performance across geographically dispersed sites.

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