Preliminary Voltage Analysis and Explainable Hybrid LSTM-XGBoost Framework for Kualanamu Airport 20 kV Distribution Network

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Abstract

Voltage reliability in a 20 kV distribution network is important for maintaining airport operational continuity. This study uses ten MVDP 2 monitoring screenshots as preliminary observations and proposes an Explainable Hybrid LSTM-XGBoost framework for multi-horizon voltage-state prediction. The screenshots provide phase-to-phase voltage, three-phase current, frequency, and, in several observations, active power and power factor. The average line-to-line voltage across the ten observations ranges from 19.770 to 20.840 kV, with an overall mean of 20.355 kV, while frequency ranges from 49.93 to 50.22 Hz. Using the internal preferred operating band of 20.2-20.5 kV only as a preliminary descriptive label, 5 observations are classified as Low and 5 as High, with no Normal observation. The photographs are therefore useful as a pilot dataset and variable-feasibility evidence, but they are not sufficient for LSTM training or t+5, t+15, and t+30 prediction because continuous timestamps are unavailable. The main dataset should be obtained from timestamped SCADA/power-meter historical exports. Random Forest, XGBoost, LSTM, and Hybrid LSTM-XGBoost will subsequently be evaluated using walk-forward validation, macro F1-score, MCC, abnormal-class recall, and SHAP.

Keywords: SCADA; LSTM-XGBoost; multi-horizon prediction; voltage anomaly; Explainable AI; 20 kV distribution network

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Introduction

Electrical continuity is a critical supporting element of airport operations. Facilities related to terminals, communication, security, information systems, and operational services depend on a stable electrical supply. In the Energy & Power Supply environment at Kualanamu International Airport, the 20 kV distribution network is monitored through a digital power-monitoring interface that provides phase-to-phase voltage, phase current, frequency, power, power factor, and accumulated energy.

Field observations indicate that voltage does not remain at a single value. The operational team uses approximately 20.2-20.5 kV as a preferred internal operating band. Values below or above this band may trigger closer observation and operational coordination. This internal band is used in this paper only for preliminary descriptive labeling and should not be interpreted automatically as a regulatory limit.

The ten monitoring screenshots supplied for this study provide direct evidence that the available instrumentation contains variables suitable for machine-learning research. However, static screenshots alone cannot establish temporal dependencies because the exact timestamp and fixed sampling interval are not visible. This distinction is important: a collection of photographs can support exploratory analysis, whereas multi-horizon forecasting requires a chronological series in which each observation can be linked to future states at t+5, t+15, and t+30 minutes.

Previous studies have shown that Random Forest and XGBoost are effective for nonlinear tabular data, while LSTM is designed to learn sequential dependencies. A hybrid design can combine these strengths by using LSTM to extract temporal representations and XGBoost to perform final classification. Explainable AI, especially SHAP, is added so that operators can understand which variables contribute most strongly to each predicted condition.

Accordingly, this paper has two objectives. First, it presents a preliminary descriptive analysis of actual monitoring observations obtained from the MVDP 2 screen. Second, it refines the research design for a future timestamped dataset that will compare Random Forest, XGBoost, LSTM, and Hybrid LSTM-XGBoost across three prediction horizons.

1.1 Preliminary Operational Dataset

Ten screenshots were treated as ten pilot observations. Observation identifiers O1-O10 follow the order in which the images were supplied and do not represent verified chronological order. The average line-to-line voltage was calculated as the arithmetic mean of Voltage AB, Voltage BC, and Voltage CA. Average current was similarly calculated from phases A, B, and C. Where active power or power factor was not fully visible in the supplied image, the value is reported as not available rather than estimated.

Table 1. Preliminary observations transcribed from the supplied MVDP 2 monitoring screenshots

Obs	Vavg (kV)	Iavg (A)	Freq. (Hz)	V spread (V)	P (MW)	PF	Prelim. label
O1	19.951	176.66	50.07	290.01	6.051	0.9914	Low
O2	20.752	120.04	50.01	303.75	4.286	0.9934	High
O3	19.938	150.72	50.22	285.44	5.190	0.9972	Low
O4	20.757	153.89	50.13	337.69	-	-	High
O5	20.840	123.06	49.93	296.54	-	-	High
O6	20.003	158.05	50.10	278.18	5.454	0.9960	Low
O7	20.005	172.60	50.00	260.74	5.927	0.9910	Low
O8	20.777	194.92	50.09	306.80	-	-	High
O9	20.753	125.74	50.16	344.93	4.489	0.9933	High
O10	19.770	172.63	50.11	297.08	5.888	0.9960	Low

Across the ten observations, average line-to-line voltage ranges from 19.770 to 20.840 kV and has a mean of 20.355 kV. Average phase current ranges from 120.04 to 194.92 A. Frequency remains within 49.93-50.22 Hz in the supplied observations. The phase-to-phase voltage spread ranges from 260.74 to 344.93 V. Using the internal preferred band only as a descriptive threshold, five observations fall below 20.2 kV and five exceed 20.5 kV. No screenshot represents the Normal

class. Therefore, these ten observations should not be used to estimate class prevalence or to train a three-class predictive model.

Table 2. Suitability of the screenshot data for machine-learning use

Purpose	Suitable?	Reason	Required next step
Evidence of real variables	Yes	Voltage, current, frequency, power and PF are visible	Document variable definitions and units
Descriptive/pilot analysis	Yes	Ten valid snapshots can be tabulated	Use only as preliminary observations
Random Forest/XGBoost training	Not yet	Ten rows are far too few and class coverage is incomplete	Export a much larger timestamped history
LSTM training	No	Sequential order and fixed intervals are unavailable	Obtain continuous time-series data
t+5/t+15/t+30 prediction	No	Future labels cannot be linked without timestamps	Use regular timestamped samples
Three-class Low/Normal/High model	No	No Normal sample exists in the ten screenshots	Collect representative Normal observations

Research Methodology

The empirical study will use historical exports from the SCADA or power-meter system rather than photographs as the primary training source. Each row should contain a timestamp, Voltage AB, Voltage BC, Voltage CA, Voltage L-L Average, Current Phase A, Current Phase B, Current Phase C, Frequency, Real Power, Reactive Power, Apparent Power, True Power Factor, and other available operating variables. The screenshots confirm that most of these fields are already measured by the monitoring system.

Data will be synchronized to a fixed interval and ordered chronologically. Missing values, duplicate timestamps, and sensor anomalies will be reviewed before feature generation. Derived predictors will include voltage and current lags, rolling mean, rolling standard deviation, rate of change, phase-to-phase voltage spread, and time-of-day features.

The output is defined as the operational voltage state at t+h. Three horizons are planned: t+5, t+15, and t+30 minutes. The preliminary internal band of 20.2-20.5 kV will be reviewed against company operating procedures before final labeling. The study will distinguish internal operating categories from regulatory compliance categories.

Four models will be evaluated under the same data splits: Random Forest, XGBoost, LSTM, and Hybrid LSTM-XGBoost. In the hybrid model, LSTM learns a latent representation from a historical sequence. The latent vector is fused with engineered features and passed to XGBoost for multiclass classification.

Walk-forward validation will be used so that training data always occur before validation data. The final chronological period will remain untouched as a test set. Class imbalance will be handled by class/sample weighting or other time-series-safe cost-sensitive methods, rather than randomly oversampling the entire series.

Model performance will be compared using macro F1-score, balanced accuracy, Matthews Correlation Coefficient, recall for Low and High classes, ROC-AUC, and confusion matrices. SHAP will be used to identify global feature importance and provide local explanations for individual warnings.

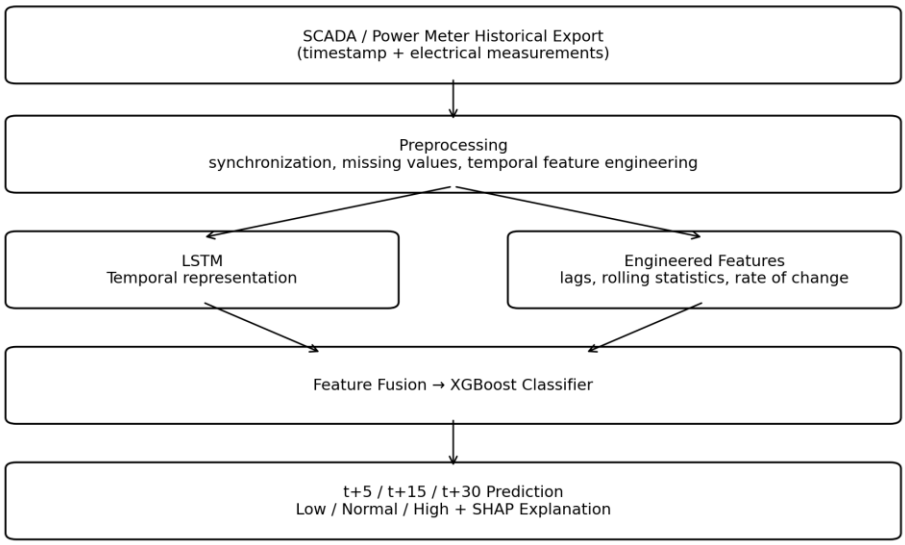


Figure 1. Revised data and modeling workflow for the proposed study

Results and Discussion

The preliminary observations demonstrate that the monitoring system provides a sufficiently rich set of electrical variables for a machine-learning study. Voltage, current, frequency, active power, reactive power, apparent power, and power factor can be observed directly on the MVDP 2 interface. This is an important feasibility finding because the proposed model does not have to rely on voltage alone if the historical export contains the same variables.

The ten pilot observations show two clearly separated operating groups when the internal 20.2-20.5 kV preferred band is used descriptively. The lowest average observed voltage is 19.770 kV, while the highest is 20.840 kV. Five observations are below the preferred band and five are above it. The absence of Normal examples means the current sample is intentionally treated as exploratory evidence rather than a representative training dataset.

Current also varies across the observations, with average three-phase current ranging from 120.04 A to 194.92 A. Frequency varies only from 49.93 to 50.22 Hz in the supplied sample. At this stage, no causal conclusion should be drawn from these values because the observations are not time-aligned and the operating context of each screenshot is not fully documented.

The main limitation is temporal information. LSTM and multi-horizon prediction require a continuous sequence with known intervals. Without timestamps, the photographs cannot determine whether one measurement occurred five, fifteen, or thirty minutes before another. For this reason, confusion matrices, F1-score, MCC, and SHAP values must not be calculated from the ten screenshots. These metrics will become valid only after a sufficiently large timestamped dataset has been exported and separated into training, validation, and test periods.

The revised research design therefore uses the photographs as preliminary operational evidence and shifts the core experiment to the historical SCADA/power-meter export. This approach strengthens the scientific validity of the paper because it avoids fabricating model performance while still grounding the proposed framework in actual field variables.

Table 3. Recommended structure of the main timestamped dataset

Field	Type	Unit	Role
timestamp	datetime	-	Temporal index
voltage_ab, voltage_bc, voltage_ca	numeric	V	Raw voltage features
voltage_ll_average	numeric	V/kV	Primary voltage feature

current_a, current_b, current_c	numeric	A	Load-related features
frequency	numeric	Hz	Power quality feature
real_power	numeric	MW	Load/power feature
reactive_power	numeric	MVAr	Reactive loading feature
apparent_power	numeric	MVA	Apparent loading feature
true_power_factor	numeric	-	Efficiency/phase feature
label_t+5, label_t+15, label_t+30	categorical	-	Prediction targets

Conclusion

The supplied MVDP 2 screenshots can be used as a preliminary dataset, but not as the final dataset for machine-learning training. They provide ten real operational observations and confirm the availability of voltage, current, frequency, power, and power-factor variables. Preliminary descriptive analysis identifies five Low and five High observations relative to the internal preferred band of 20.2-20.5 kV, with no Normal observation. Because the screenshots do not provide a verified continuous timestamp sequence, they cannot support LSTM training or t+5, t+15, and t+30 prediction. The revised study therefore treats the photographs as feasibility evidence and requires timestamped historical exports as the main dataset. Once the historical data are available, Random Forest, XGBoost, LSTM, and Hybrid LSTM-XGBoost can be evaluated using walk-forward validation, macro F1-score, MCC, confusion matrices, and SHAP explanations.

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