Anomaly Detection and Classification for Photovoltaic Systems

Master's Thesis –

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KEY TAKEAWAYS

Main Principle:

 Leverages data from neighboring PV systems to estimate daily production.

Universal Anomaly Detection Method:

 Operates without the need for meteorological data or additional sensors.

Promissing Results:

- Estimate daily production with a Mean Absolute Percentage Error (MAPE) of 4.35%.
- Detect simulated anomalies with 97.4% accuracy.

INTRODUCTION

- The number of residential PV systems in Switzerland is rapidly increasing.
- Detecting anomalies is crucial to reduce Mean Down Time (MDT), increase solar production, and minimize economic losses.
- Each residential PV system varies in configuration and available data.
- However, daily energy production is a commonly available metric.

OBJECTIVES

 Develop a universal method to detect and classify anomalies in PV systems, using only energy production measurements.

TARGET GROUP

Companies monitoring residential/small-scale PV systems.

USED DATA

- Daily energy production data from 326 PV systems in Switzerland over approximately 400 days.
- Characteristics of each system (location, orientation, size).



Detecting Anomalies in Solar Panels? Look no further than their Neighbors.







METHODOLOGY

The production of a PV system is influenced by three main types of factors:

Anomalies are detected by isolating their impact from system-specific and regional factors through: Normalizer: A physics-based simulator that accounts for System-Specific INPUT INPUT Measurements of the Measurements of Factors. It normalizes data to enable the Monitored System Neighboring Systems comparisons between neighboring * * * Physics-Based NORMALIZER Physics-Based NORMALIZER systems with different characteristics. Half-Sibling Regression: A Machine HALF-SIBLINGS Learning model that account for REGRESSION Regional Factors. It estimates the Expected Measured Production expected production, by comparing COMPARATOR production from neighboring systems. Comparator: Compares expected Under-Production production with actual production to Rule-Based DETECTOR estimate underp-production. **Detector**: Use statistics and predefined OUTPUT rules to flags days with abnormal **Detected Anomalies** underproduction as anomalies.

RESULTS

Daily, our monitoring tool:

- Performance.

To do this, our monitoring tool needs:

• At least 7 days of historical data.



LIMITATIONS

• We use only daily data, limiting our method accuracy and restricting monitoring to a daily frequency.

FUTURE DEVELOPMENT

To put our method into practice, we recommend the following: Develop a prototype in real-world conditions.

- automatic classification.

1. System-Specific Factors (location, orientation, size, losses, ...) 2. Regional Factors (primarily weather conditions) **3. Anomalous Factors** (which we aim to detect)

• Estimates Expected Production (with a MAPE of 4.35%). • **Detects nomalies** (with 97.4% accuracy on simulated anomalies). Provides the Maximum Daily Production and the System

• At least **2 neighboring** systems within a 3 km radius.

• No classification of detected anomalies is made, requiring its manual analysis to determine the cause.

Gather user feedback for continuous improvement.

• Enhance detection algorithms based on the feedbacks.

• Label anomaly types as they occur, to enable the development of

Develop an automatic anomaly classification.