TASK 13: PERFORMANCE AND RELIABILITY OF PV SYSTEMS

Improving Efficiency of PV Systems Using Statistical Performance Monitoring

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Independently Motivated Development

Why? …it must be important…

09:00 AM 18:00 PM 01:00 AM
The Motivation

- To develop a method to closely monitor a PV system!
- PV must become more AVAILABLE
- PV must achieve it’s assumed efficiency
- PV must become PREDICTABLE
The Motivation

Utility Grade PV:

• High level of predictability
• High level of availability
The Motivation

Across Europe by Capacity:

28%
21%
19%
32%

2016

...but the story is residential
The Motivation
The Motivation

The joys of residential PV......
The Motivation
Current State of the Art
Statistical Performance Monitoring

• Smart Monitoring for Residential Solar

• Machine Learning for Fast Fault Recognition

• Fault Prediction Using Clustering Algorithms

• Fault Detection Using Artificial Neural Networks
Smart Monitoring for Residential Solar

- Monitor mounted in the household electrical panel
- Australian NWS ➜ Meteo data and satellite maps
Smart Monitoring for Residential Solar

System parameters:

- Location
- PV module type
- Inverter type
- PV module orientation
- PV module tilt
- String configuration
Smart Monitoring for Residential Solar

- Generation Estimation
- Real-time monitoring - day end evaluation
- Performance losses:
  - Shading
  - Inverter clipping
  - Power Factor correction
  - Degradation
  - String/Module faults
Smart Monitoring for Residential Solar

Finding faults in strings without string monitoring
Smart Monitoring for Residential Solar

Measured vs Expected Production

Inverter 1

Inverter 2

Measured Production

Inverter 1

Inverter 2

Daily Energy

Energy (kWh)

Measured Production

Expected Production

Inverter 1

Inverter 2

Daily Energy

Energy (kWh)
Smart Monitoring for Residential Solar

1 hour resolution

5 minute resolution
Smart Monitoring for Residential Solar

Power and Voltage: 5 second resolution

Power: 5 second resolution
Machine Learning for Fast Fault Recognition

- Prediction software
- No sensors
- No irradiation maps
Machine Learning for Fast Fault Recognition

- Temperature
- Humidity
- Barometric pressure
- Wind speed
- Dew point
- Rain
- Sky view

Hourly generated power +

No irradiance
## Machine Learning for Fast Fault Recognition

### Daily State of Health Score

<table>
<thead>
<tr>
<th>No</th>
<th>Inverter</th>
<th>Health Index</th>
<th>Relative Index</th>
<th>Production (kWh)</th>
<th>Prediction (kWh)</th>
<th>Self Health Relative</th>
<th>Revenue (NIS)</th>
<th>Normalized (kWh)</th>
<th>Installed (KWp)</th>
<th>Health History</th>
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<tr>
<td>1</td>
<td>2001451939</td>
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<td>59.37</td>
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<td>38.4</td>
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<td>A</td>
<td>60.05</td>
<td>60.74</td>
<td>0.99</td>
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<tr>
<td>3</td>
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<td>A</td>
<td>C</td>
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<td>1.02</td>
<td>60.3</td>
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<td></td>
<td>267.24</td>
<td>267.25</td>
<td>0.95</td>
<td>173.71</td>
<td>19.71</td>
<td>54.32</td>
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</tr>
</tbody>
</table>

**A = 100 to 97 %**

**B = 97 to 95 %**

**C = 95 to 90 %**

**D = 90 to 85 %**

**E = 85 to 80 %**

**F = less than 80 %**

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**Ratio between PREDICTED energy and PRODUCED energy**

**Previous week in daily SoH**
Machine Learning for Fast Fault Recognition

Regression Tree:

- **Dependent Variable**
  - Energy

- **Independent Variable**
  - Temperature
  - Humidity
  - Barometric pressure
  - Wind speed
  - Dew point
  - Rain
  - Sky view
Fault Prediction Using Clustering Algorithms

Clustering:

- **Dependent Variable**
  - AC Power

- **Independent Variable**
  - Weather parameters
  - All available inverter parameters
  - Yesterdays generation
  - Last hours generation
  - Trigonometric transformation
Fault Prediction Using Clustering Algorithms

1. Generate a clear data set
2. Choose an output value (dependent variable)
3. Add the following to each record
   1. Generation from previous hour
   2. Generation from this hour yesterday
   3. Day of the year expressed as:

\[
\sin \left( \frac{\text{dayofyear} \times 2 \times \pi}{365} \right), \cos \left( \frac{\text{dayofyear} \times 2 \times \pi}{365} \right)
\]

4. Develop an equation for each cluster with CI of 99%
5. Test with new data; output should match data by 0.001
6. All new data run through equation; should fall within CI
Fault Prediction Using Clustering Algorithms
Fault Prediction Using Clustering Algorithms
Fault Detection Using Artificial Neural Networks

Neural Network Algorithms

Three algorithms:

- LAPART - Laterally Primed Adaptive Resonance Theory
- SVM - Support Vector Machine
- GPR - Gaussian Process Regression
Fault Detection Using Artificial Neural Networks

LAPART:
Fault Detection Using Artificial Neural Networks

Support Vector Machine (SVM):

- Optimal Hyperplane
- Maximum Margin
Fault Detection Using Artificial Neural Networks

Gaussian Process Regression (GPR):

\[ f(x) = \text{GP}(\mu(x), k(x,x')) \]
Fault Detection Using Artificial Neural Networks

30 Days 1-min. data including 10,000 faults

LAPART
Fault Detection Using Artificial Neural Networks

PV array – 10.8kWp; 4x10 modules
SVM
Fault Detection Using Artificial Neural Networks

- **I-V Curve**
- **SVM + GPR**
Statistical Performance Monitoring

![Graph showing power output vs time]

![Scatter plot of DC power produced vs irradiance]

![Graph of I-V curve fault classification]

![Graph showing power actual vs estimated]

- TP=82, FN=0, TN=242
- $y=0.989x + 23.9$