Short-term Solar Irradiation forecasting based on Dynamic Harmonic Regression

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Agenda

1. Introduction
2. Case Study
3. Models
4. Conclusions
• Short-term forecasts are required to optimize operational planning of solar-power plants (24 hours ahead)

• Forecast errors involve significant costs

Reduction of 47.6% of penalty costs by improving the forecasting technique in a Concentrating solar power plant (Kraas et al., 2013)
State of the art (Diagne et al., 2013)

• Statistical area (time series analysis)
  – Temporal resolution
    • 24 hours ahead approx.
  – Spatial resolution
    • 1 km approx.

• Numerical Weather Prediction models
• **Goal 1:** Assess **Dynamic** Harmonic Regression at short-term (1-24 hours ahead):
  • Time-varying coefficients.
  • Frequency domain optimization
  • Recursive algorithms, Kalman Filter.
  • Available in MATLAB software, CAPTAIN, SSPACE.
• **Goal 2**: Compare two sets of data

- Global Horizontal Irradiance (GHI)
- Direct Normal Irradiance (DNI)

- Photovoltaic systems
- Concentrating solar power plants
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Case study


1,1 MW of Concentrated-Photovoltaic Energy (CPV)

Hourly series: (01/2009)-(12/2011)
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• Harmonic Regression

\[ z_t = \sum_{k=0}^{P/2} a_k \cos(\omega_k t) + b_k \sin(\omega_k t) \]

• Dynamic Harmonic Regression

\[ z_t = \sum_{k=0}^{P/2} a_{k,t} \cos(\omega_k t) + b_{k,t} \sin(\omega_k t) = T_t + S_t + e_t \]

Find the seven two differences!!!
• **Dynamic Harmonic Regression**

\[
\begin{align*}
z_t &= \sum_{k=0}^{P/2} a_{k,t} \cos(\omega_k t) + b_{k,t} \sin(\omega_k t) = T_t + S_t + e_t \\
(P/2) \text{ 24 hours}
\end{align*}
\]

• How can we make the coefficients time-varying?

\[
\begin{pmatrix}
a_{k,t+1} \\
a_{k,t+1}^*
\end{pmatrix} =
\begin{pmatrix}
1 & 0 \\
0 & 1
\end{pmatrix}
\begin{pmatrix}
a_{k,t} \\
a_{k,t}^*
\end{pmatrix} +
\begin{pmatrix}
w_{k,t} \\
w_{k,t}^*
\end{pmatrix}
\]

\(w_{k,t}\) and \(w_{k,t}\) are independent random noises with zero mean and a common variance \(\sigma_k^2\) (and \(\sigma_k^2 \neq \sigma_j^2\) for any \(k \neq j\)): 
**BENCHMARKS:**

- *Typical benchmark:* **Persistence model**

\[ F_{t+m} = y_t \]

- *Seasonal persistence*

\[ F_{t+m} = y_{t-24+m} \]

- *Exponential Smoothing in a State Space (ETS)*

- *ARIMA models*
• The last year of data (2011) is reserved as a hold-out sample.

• Rolling origin evaluation.

• Error metric:
  – $r_{RMSE}$: relative Root Mean Squared Error.

$$r_{RMSE} = \frac{RMSE}{\bar{y}}$$
Experimental results
Experimental results
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4. Conclusions

• Forecasts are required to efficiently incorporate renewable energies like solar energy into the grid.

• Methodologies have proliferated to forecast solar irradiation. No unanimity about what is the best one.

• DHR is proposed with promising results.
Bibliography

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Abstract
Solar power generation is a crucial research area for countries that have high dependency on fossil energy sources and is gaining prominence with the current shift to renewable sources of energy. In order to integrate the electricity generated by solar energy into the grid, solar irradiation must be reasonably predicted.
Gracias por su atención!

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