Abstract

Variability and uncertainty in power output is a major concern and forecasting is, therefore, a top priority. We propose a sensing infrastructure to enable sensing of solar irradiance with application to solar array output forecasting. This poster shows the potential of our prediction system as a low cost, high accuracy tool for short-term solar forecasting.

The deployment of our solar prediction system, is located near a 1 MW solar plant. Our prediction system is comprised of a wireless network of Solar Irradiance Motes (SIMs) measuring the current solar irradiance, a data processing system, and a prediction model. With a price of about $180, our SIM cost only a fraction of common solar observatory instruments.

Solar Irradiance Motes

Our sensor deployment functions as an early warning system for approaching clouds. Sensors record a cloud phenomenon 1-2 minutes earlier then the solar field. This gives our system an advantage for output power prediction.

Solar Energy Prediction System

Our prediction model is based on a Nonlinear Autoregressive with External Input (NARX) Neural Network (ANN) which predicts a series of n future values based on past sensor and solar plant output values.

\[
\hat{y}(t+1) = f(y(t), y(t-\Delta t), ..., y(t-n\Delta t))
\]

For training and validation data sets we are only considering data with a high variability of more than 100 kW per minute. For practical usage of solar energy, predicting times of high variability caused by open and closed cloud cover is a critical issue. The evaluation results show that our system is able the perform short-term prediction on high variability data 2-3 times better compared to a time series prediction model.

Prediction Evaluation

We compare the prediction results of our NARX ANN to a Nonlinear Autoregressive Neural Network with no external input (NAR) that predicts the solar field output only based on a time series of the solar plant energy trace.

\[
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The comparison metric we use involves a clear sky persistence model which predicts the next time step \(y(t+1)\) by comparing the measured irradiance to the clear sky irradiance. The clear sky persistence model is based on the data of a clear day without any clouds.

\[
P(t+1) = \frac{P(t)}{P_{cl}(t)}
\]

Solar irradiance at the ground level has a high variability which, mostly depends on the current solar position and the cloud coverage. We use a variability metric so that the diurnal variability is neglected.

\[
V = \frac{1}{N} \sum \left( \frac{P(t) - P_{cl}(t)}{P_{cl}(t)} \right)^2
\]

To take account of the uncertainty, we use a metric which is very similar to the Root Mean Squared Error but a normalization of the error is made in respect to \(P_{cl}(t)\).

\[
U = \frac{1}{N} \sum \left( \frac{P(t) - P_{cl}(t)}{P_{cl}(t)} \right)^2
\]

By determining the uncertainty \(U\) and the variability \(V\) we can calculate the metric \(s\) to evaluate the quality of forecast models.

\[
s = \frac{V}{U}
\]

A value of \(s=1\) means the prediction is perfect, a value of \(s=0\) means the variability dominates the forecast.

References: