Short-Term Solar Energy Forecasting Using Wireless Sensor Networks
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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.

Prediction System Infrastructure
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.

Components of a Solar Irradiance Mote:

Solar Irradiance Motes

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.

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.

Prediction Evaluation
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.

\[
\hat{y}(t+1) = \frac{1}{N} \sum_{i=0}^{N-1} P(t) \frac{P(t) - P(t+1)}{P(t)}
\]

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.

\[
V = \frac{1}{N} \sum_{i=0}^{N-1} \left( \frac{P(t) - P(t+1)}{P(t)} \right)^2
\]

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 \( P(t) \).

\[
U = \frac{1}{N} \sum_{i=0}^{N-1} \left( \frac{P(t) - \hat{P}(t)}{P(t)} \right)^2
\]

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:

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