



Short-Term Solar Energy Forecasting Using Wireless Sensor Networks

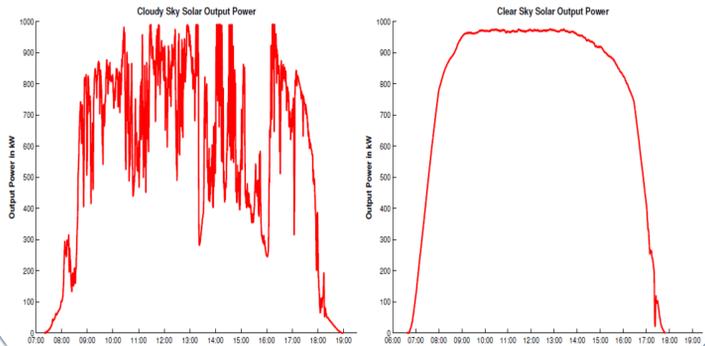
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Abstract

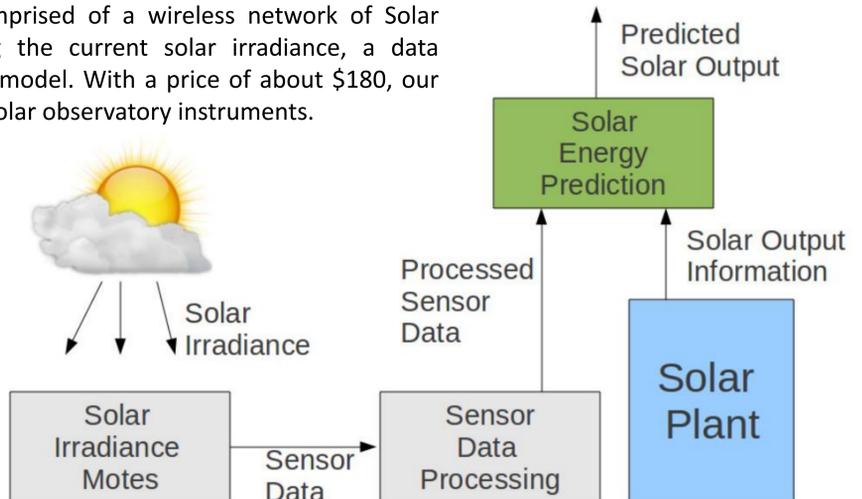
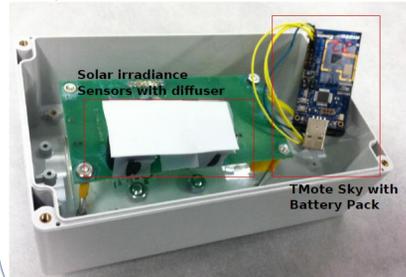
Variability and uncertainty in power output is a major concern and forecasting is, therefore, a top priority. We propose a sensing infrastructure to enable sensing of solar irradiance with application to solar array output forecasting. This poster shows the potential of our prediction system as a low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



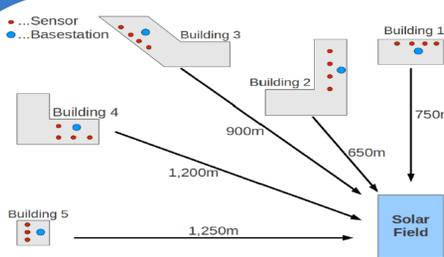
Prediction System Infrastructure

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.

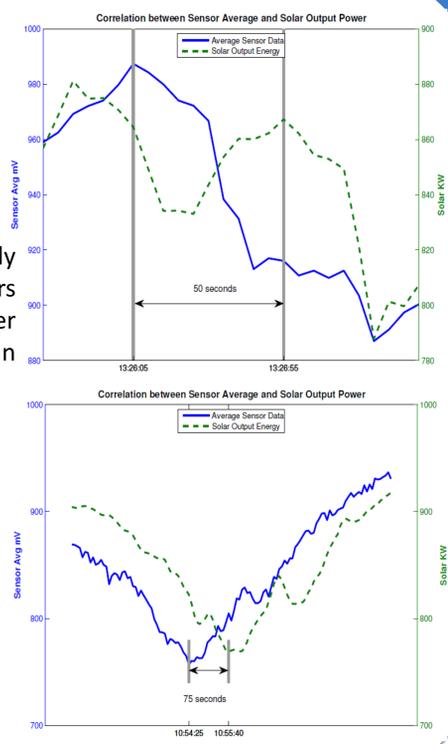
Components of a Solar Irradiance Mote:



Solar Irradiance Motes



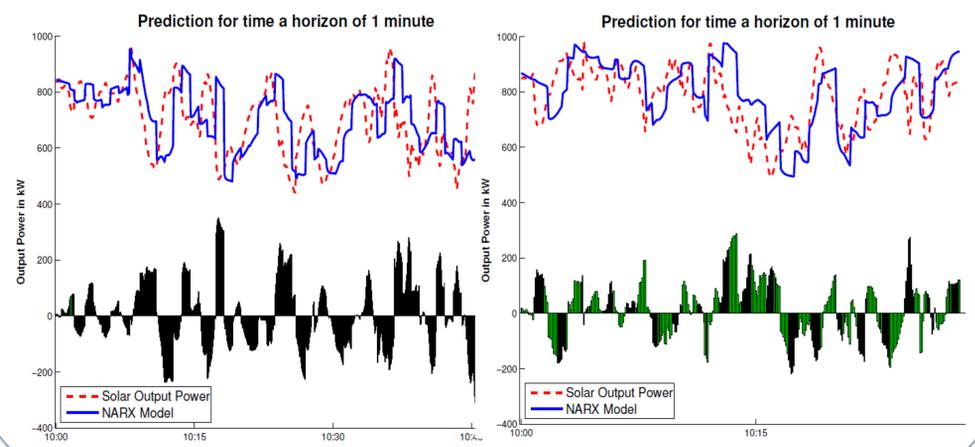
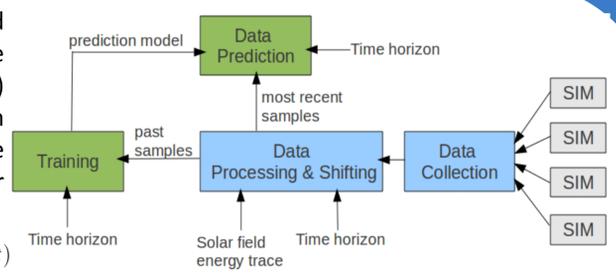
Our sensor deployment functions as an early warning system for approaching clouds. Sensors record a cloud phenomenon 1-2 minutes earlier than the solar field. This gives our system an advantage for output power prediction.



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.

$$\hat{y}(t + \Delta t) = f(y(t), y(t - \Delta t), \dots, y(t - n\Delta t), x(t - \Delta t), \dots, x(t - n\Delta t))$$

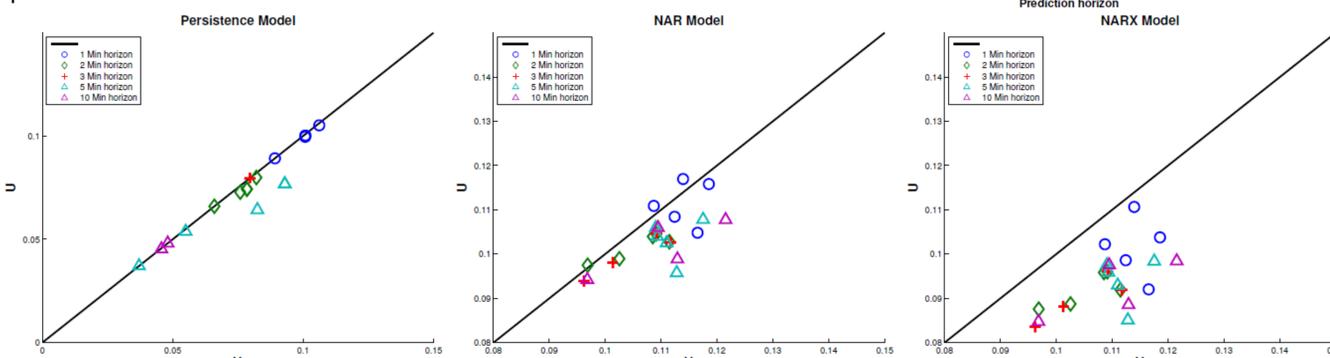


Prediction Evaluation

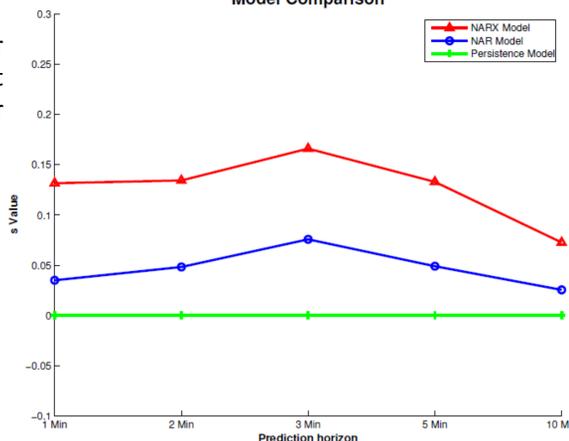
We compare the prediction results of our NARX ANN to a Nonlinear Autoregressive Neural Network with no external input (NAR) that predicts the solar field output only based on a time series of the solar plant energy trace.

$$\hat{y}(t + \Delta t) = f(y(t), y(t - \Delta t), \dots, y(t - n\Delta t))$$

For training and valuation 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 to perform short-term prediction on high variability data 2-3 times better compared to a time series prediction model.



Model Comparison



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.

$$P(t+1) = P_{clr}(t+1) \frac{P(t)}{P_{clr}(t)}$$

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.

$$V = \sqrt{\frac{1}{N} \sum_{t=1}^N \left(\frac{P(t)}{P_{clr}(t)} - \frac{P(t-1)}{P_{clr}(t-1)} \right)^2}$$

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 $P_{clr}(t)$.

$$U = \sqrt{\frac{1}{N_w} \sum_{t=1}^{N_w} \left(\frac{\hat{P}(t) - P(t)}{P_{clr}(t)} \right)^2}$$

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

$$s = \frac{V - U}{V}$$

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

