Short-Term Solar Power Forecasting Using a Distributed Sensor Network

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Abstract

Solar Photovoltaic (PV) power generation continues to grow in popularity as prices for the technology continue to fall. This trend has made solar energy increasingly attractive in smaller, electrically isolated Alaskan communities where fuel and electricity costs are high. Unfortunately, solar PV is also highly variable due to weather effects such as clouds. Being able to forecast solar power production a few minutes into the future is very useful for ensuring electric grid stability[1].

Here, we present preliminary results from a recently installed array of cloud-detecting light sensors deployed around a grid-scale solar array in Kotzebue, Alaska, including a comparison of forecasting models using data from the sensors and discussions on future applications.

Introduction

Solar power generation is highly variable due to clouds.

- Sudden surges or dips can destabilize electric grids.
- Smaller, electrically isolated grids are particularly vulnerable.
- Alaska has over ***150 such grids.***

Diesel generators are the most common solution

- These provide fast-response power to accommodate sudden changes. They can range from 30 kW to over 1 MW in Alaskan communities.
- Diesel fuel is particularly expensive in these communities.
- Generators cannot be turned on or off quickly and typically take ***1 to 2 minutes*** to start from off[2], so they must be kept running even if solar power production is high, just in case.

What if we knew what the solar array was going to do in time to turn on a generator?

- Could money and/or emissions be saved by leaving them off more often?

What options exist for solar power prediction

- Numerical weather prediction (not suitable for short-term forecasts)
- Satellite imaging (needs large amounts of bandwidth, poor coverage over Alaska)
- Sky cameras (expensive, difficult to maintain)

The Sensor Network

An inexpensive solution for short-term forecasting

Figure 1 – Sensor deployed in Kotzebue

- Network of 10 light sensors surrounding the Kotzebue Electric Association (KEA) solar array to detect clouds
- Installed summer of 2022
- Powered by solar with a small backup battery
- Designed for Arctic environments
- Use LoRa radio communication
- Data is transmitted live
- Around **$450 per sensor**

Figure 2 – ACEP's sensor network

Forecasting Models

A wide variety of models exist for prediction

- ARIMA
- Exponential Smoothing
- Neural Networks

Two models used in this analysis

- Long short-term memory (LSTM) neural networks: one only using the data from the solar array and the other also using the sensor data

Metrics and Results

How do we know our models work?

The models were evaluated using standard metrics:

- Mean-Square Error (MSE)
- Root-Mean Square Error (RMSE)
- Mean Absolute Error (MAE)
- Mean Bias Error (MBE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)$$

Comparing to a reference

A common model to use as a reference for these types of forecasts is a "persistence" model which simply assumes that the forecast at any given time is simply equal to the last measured data point. This is surprisingly difficult to beat at short timescales.

We can define a metric called Forecast Skill (FS) to compare our models to the persistence model.

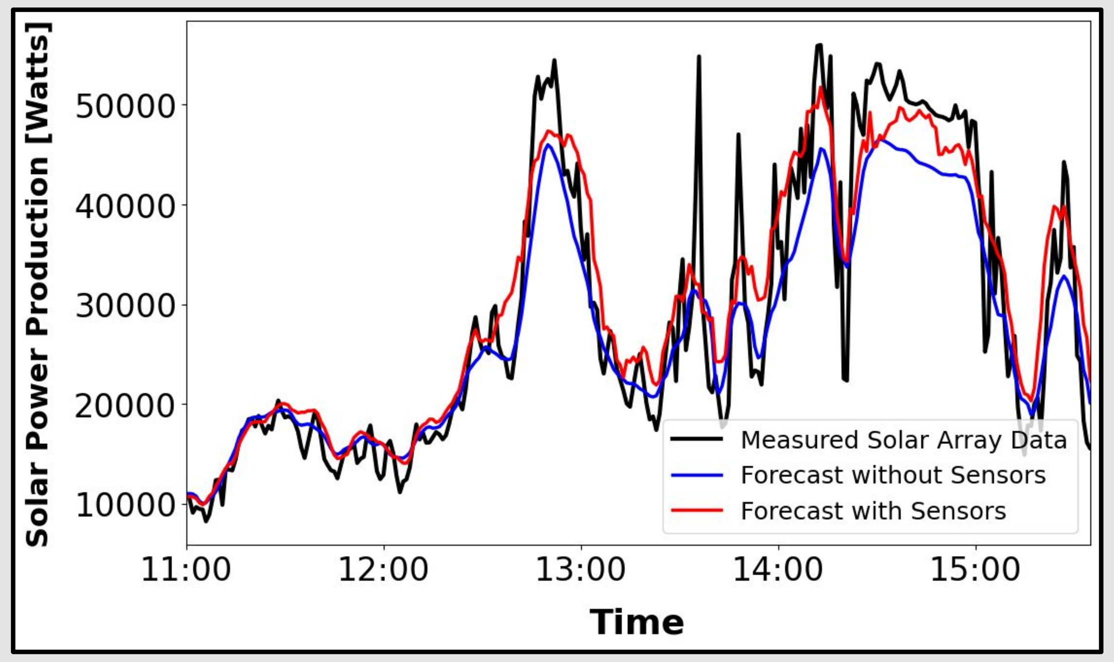
$$FS = 1 - \frac{RMSE_{forecast}}{RMSE_{persistence}}$$

Table 1 – Normalized model evaluation metrics for 1 month of testing data (October, 2022)

	MSE	RMSE	MAE	MBE	FS
Persistence	N/A	0.522	1.889	N/A	N/A
Without Sensors	0.310	0.548	0.393	0.254	-0.050
With Sensors	0.242	0.490	0.372	-0.123	0.061

The sensor model has a ***10.6%*** better RMSE

Figure 3 – Neural network (LSTM) models forecasting Kotzebue Electric Association's solar array production (Oct. 10th, 2022)



Conclusion

It is apparent from Figure 3 that neither model can fully forecast the peaks and valleys present in the dataset.

The improvement of the model which used the sensor data is modest to be sure, but its gain over the model which only used the solar production data shows that the sensors can detect clouds in a meaningful way.

The abilities of this current model are severely limited by a lack of sensor data. These preliminary results were generated using only 2 months of data as a training set. More data will undoubtedly help to improve forecast accuracy.

Future Work

- Parameter tuning to improve model performance
- Perform a more exhaustive study of potential model structures.
- Test different combinations of sensors to study the influence of geographic distribution on model accuracy.
- Implement metrics to see how many sudden changes of a certain size our models are missing.
- Test other models such as ARIMA, Exponential Smoothing, TBATS, etc. with the sensor data.
- **Collect more data.**

References

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Acknowledgements

We give our deepest appreciation to the Kikiktagruk Inupiat Corporation for generously allowing the sensors used in this research to be placed and maintained on their land as well as to Kotzebue Electric Association for all their continued logistical support. This work would not have been possible without your help!

The project is part of the Arctic Regional Collaboration for Technology Innovation and Commercialization (ARCTIC) Program, an initiative supported by the Office of Naval Research (ONR) Award # N00014-18-S-B001.