Assessing the short-term solar forecasting performance of popular machine learning algorithms

Presenter: Alex Dobbs ***Mentor:*** Anthony Florita

Accurate short-term solar forecasting is necessary for operating a reliable grid with high penetrations of solar energy. Machine learning techniques have shown promise for making more accurate short-term forecasts. In this study, a framework for assessing the solar forecasting performance of four popular machine learning algorithms is presented in conjunction with a range of numerical results using global horizontal irradiance (GHI) from the open-source SURFace RADiation data network. Training inputs include time series observations of GHI for a history of years, in addition to various other weather measurements, such that training sensitivities can be inferred. Prediction outputs include GHI forecasts up to four hours ahead of the forecast time. The suite of machine learning algorithms is compared according to a set of statistically distinct metrics and benchmarked against a landmark study and the persistence-of-cloudiness forecast. Results show significant improvement over the benchmark in most forecasting situations among the machine learning algorithms based on the spatial and temporal situations they are forecasting. Improved solar irradiance forecast can be combined with photovoltaic power and energy outputs to better understand power system impacts of integrating variable renewable energy sources.

NREL
NATIONAL RENEWABLE ENERGY LABORATORY

NREL is a national laboratory of the U. S. Department of Energy, Office of Energy Efficiency and Renewable Energy, operated by the Alliance for Sustainable Energy, LLC.

Situation dependent short-term solar forecasting

Performance of popular machine learning algorithms

Alex Dobbs[1,2], Tarek Elgindy[2], Bri-Mathias Hodge[2], Anthony Florita[2]

[1]Colorado School of Mines, [2]National Renewable Energy Laboratory

INTRODUCTION

Motivation:

- Integrating high levels of solar energy into the grid poses technical challenges for grid operators. Improvements in short-term solar forecasting will increase grid reliability and minimize economic losses.
- Machine learning (ML) approaches show potential for improving short-term solar irradiance forecasts. ML allows computers to learn and predict without being explicitly programmed. Use of Big Data creates more powerful models.

Research goal:

- Find optimal machine learning (ML) algorithm for predicting short-term solar irradiance (1, 2, 3, and 4 hours ahead) depending on the geographic location, time of year, and forecast horizon (*f.h.*) of each forecasting situation.

BACKGROUND

Terminology:

- **Global horizontal irradiance** (GHI^t): sum of instantaneous direct and diffuse solar irradiance measured in W/m^2.
- **Clear sky GHI** (GHI^t_{clear}): theoretical maximum GHI for an instantaneous point forecast assuming zero cloud coverage.
- **Clear sky index** (CSI^t): metric of cloud cover defined as the ratio between GHI^t and GHI^t_{clear}. CSI is the most indicative weather feature for GHI.

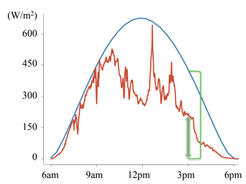

Fig 1: Ideal vs. actual time-series irradiance.

Machine learning methods:

(Various *hyper-parameters* are used to tune each model)

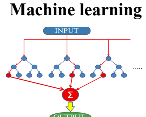

Fig. 2

- **Random Forests** (RFs) *average* the predictions across an ensemble of decision trees. Each tree directs input signals through a series of decision nodes to a final output.

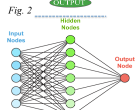

Fig. 3

- **Artificial Neural Networks** (ANNs) simulate the neural networks found in the brain. Input signals are assigned *weights* that activate nodes as they propagate through the network. Weights are then adjusted with back propagation.

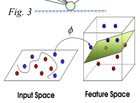

Fig. 4

- **Support Vector Machines** (SVMs) work by transforming a non-linearly separable input space into a higher dimensional feature space where variables can be separated by a 3-D *hyperplane.*

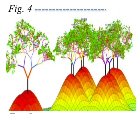

Fig. 5

- **Gradient Boosting** (GB) is a method similar to RFs, but instead adds new decision trees one at a time that are specifically built to correct for residual errors in the already trained ensemble of trees. This is opposed to RFs building and adding trees using random feature selection.

METHODS

Process:

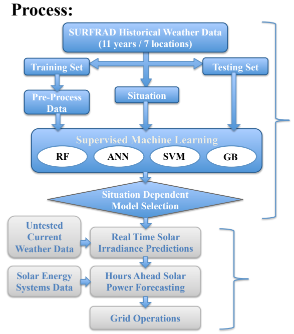

Fig. 6: Big data flow from historical observations, to optimized ML models, to real time grid *operations*.

- Relevant weather features from 11 years of data at 1 or 3 minute resolutions.
- Split: 10 years = training; 1 year = testing.
- Preprocess: clean data, time-shift future GHI values, tune ML *hyper-parameters*, etc.
- Train then test 4 ML models for each temporal and geographic situation.
- Use validation metrics to discover the best ML model to use per situation.

***Process for future applications**:*

- The trained ML models are then ready for use with real time weather observations. This allows for more accurate solar power forecasting for grid operators.

Time-shifted GHI forecasts:

- Rather than training on *instantaneous* GHI values 1, 2, 3, or 4 hours ahead, which may not be representative of the *most probable* $GHI^{f.h.}$, ML models train on the average CSI for the hour ending at the forecast horizon (*f.h.*), which is then multiplied by $GHI^{f.h.}{}_{clear}$ to produce a *most likely* GHI forecast.

$$GHI^{f.h.}_{prediction} = \frac{\sum_{t=f.h-60}^{f.h} CSI^t}{60} \bullet (GHI^{f.h.}_{clear})$$

Ex: Input training instance for 3 hour ahead forecasts. Time shifted training output

Time	Temp	Humidity	Wind Speed	Wind Direction	Pressure	Thermal IR	GHI^t	GHI^t_{clear}	CSI^t	⇨	$CSI^{f.h.}_{average}$
1200	20.7	71.3	5.2	54.6	838	403.4	816.3	870.4	.9378		.4407
…											…
…											…
…											…
1400	18.3	74.1	5.6	48.7	834	401.4	438.7	816.8	.5371		.392
…									…		…
…									…		…
…									…		…
…									…		…
…									…		…
1500	17.8	76.5	5.5	49.7	832	401.1	270.7	786.3	.3443		…

f.h. – 60 min.

Mostly sunny weather

60 minutes of mostly cloudy weather

$$CSI^{3:00pm}_{average} = \left[\sum_{t=2:00pm}^{3:00pm} CSI^t\right] \div 60 = .4407$$

f.h.

Fig 7: Example of time series weather observations. The last column is the time shifted *y*-variable; the forecast horizon's clear sky index.

$$GHI^{3:00}_{prediction} = \sim 786.3\ W/m^2 \bullet .4358 = 342.7\ W/m^2$$

1200	21.4	72.0	4.3	52.6	838	403.9	811.4	871.9	.9306	?	.4358

Ex: Unseen testing vector. ML models take input and make a prediction for output

Situation dependent forecasts:

(7 sites) • (12 months) • (4 forecast horizons) • (4 ML models) = 1,344 models

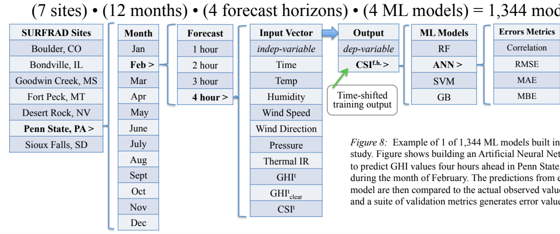

Figure 8: Example of 1 of 1,344 ML models built in this study. Figure shows building an Artificial Neural Network to predict GHI values four hours ahead in Penn State, PA, during the month of February. The predictions from each model are then compared to the actual observed values and a suite of validation metrics generates error values.

RESULTS

- **Error Metric: Root Mean Square Error (RMSE) = W/m^2**

(Results still being produced for four of seven locations)

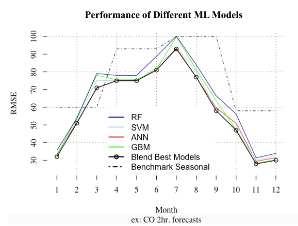

Fig. 9: The ML models perform differently depending on the time of year, location, and forecast horizon. Having a selection of models lowers overall yearly prediction errors.

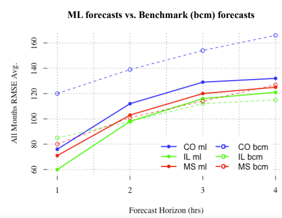

Fig. 10: Forecasting is improved in all situations in CO against a benchmark, and is improved under certain forecast horizons in other locations.

Frequency	RF	SVM	ANN	GBM
1 hour	3	10	**15**	8
2 hour	7	8	**12**	9
3 hour	9	4	**17**	6
4 hour	**14**	6	13	3
Winter	3	0	**6**	3
Spring	0	2	**9**	1
Summer	2	3	**5**	2
Fall	**3**	**3**	**3**	**3**
CO	13	7	**21**	7
IL	10	10	**17**	11
MS	10	11	**19**	8

Fig. 11: Table shows the frequency of each ML model in forecasting the lowest RMSE across all permutations of certain situations. Artificial Neural Networks out perform the other three models in the tests run so far.

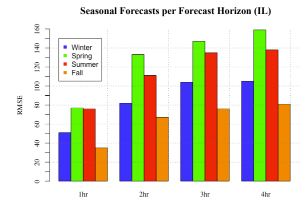

Fig. 12: Forecasting errors increase with increasing short-term forecast horizons, and Spring and Summer months tend to be the hardest to forecast. All months, sites, and forecast horizons will be compared when current tests produce results for other four sites.

CONCLUSION

Discussion:

- Results show a ~25% forecasting improvement over the benchmark in Boulder.
- Forecasts benefit from the availability of a selection of 4 ML methods, as the individual ML algorithms perform differently depending on the geographic and temporal forecasting situations.
- Artificial Neural Network is the newest ML method being employed and is producing the best results in this study. Results may be further improved by optimizing *hyper-parameters* specific to the different forecasting situations.
- A ML approach using ground measured weather observations can help advance short-term solar irradiance forecasting accuracy. Improved forecasts will help facilitate higher penetrations of solar energy into the grid.

Future work:

This solar power forecasting methodology can be extended by increasing the forecast horizon resolution from hourly increments to 5 minute increments, giving grid operators more dynamic information about upcoming ramping events. Further work should also look into optimizing ML hyper-parameters for each situation dependent forecast.

U.S. DEPARTMENT OF ENERGY | Office of Science

COLORADO SCHOOL OF MINES
EARTH • ENERGY • ENVIRONMENT

RED ROCKS COMMUNITY COLLEGE

Acknowledgments:

I would especially like to thank Anthony Florita for his guidance in this project and for entrusting me to contribute to the team's research. I would also like to thank Bri-Mathias Hodge, Tarek Elgindy, the Community College Internship (CCI) program, and the entire workforce development team at NREL.

Fig. 1: TJO (2015, June 4). Machine learning for package users with R (5): Random Forest. *Data Scientist TJO in Tokyo.* Retrieved July 31st, from http://tjo-en.hatenablog.com/entry/2015/06/04/190000

Fig. 2: Schutter, E. (2008, May). What are computational neuroscience and systems biology so separate? *PLOS Computational Biology.* Vol. 4 (5) Retrieved August 1st, 2017, from https://neuwritesd.org/2017/03/31/golden-retrievers-terriers-and-artificial-neural-networks/

Fig. 3: Dante (2017, March 13). Kernel trick explanation. *Stack Exchange: Data Science.* Retrieved August 1st, 2017, from https://datascience.stackexchange.com/questions/17536/kernel-trick-explanation

Fig. 4: George, D. (2015, December 20). Decision tree ensembles: bagging, random forest, and gradient boosting machines. *Machine Learning Lecture, Indian Institute of Management, Bangalore.* Retrieved August 1st, from, https://www.slideshare.net/DeepakGeorge5/decision-tree-ensembles-bagging-random-forest-gradient-boosting-machines

SULI POSTER SESSION
NREL - Golden, Colorado
August 9, 2017