Short-Term Solar Forecasting Performance of Popular Machine Learning Algorithms

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Outline

- Motivation
- Methodology
  - SURFRAD data and its preprocessing
  - Machine learning & forecasting methods
  - Situational dependent forecasts
- Validation Metrics
- Results
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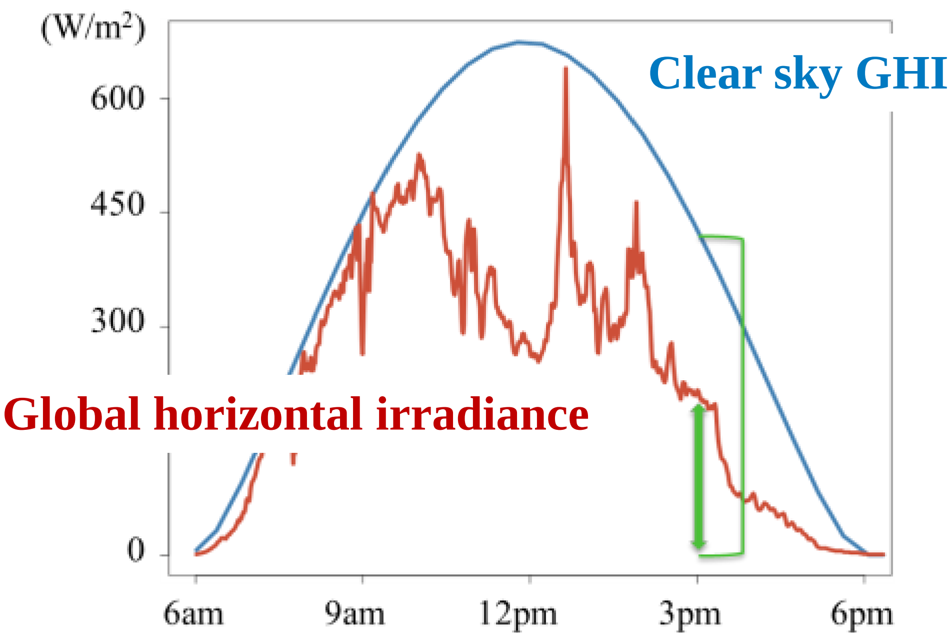
Motivation

Motivation

- Forecasting for solar PV increasingly important and can benefit from machine learning (ML):
  - Test popular methods available to researchers
  - Understand their sensitivities and tradeoffs
  - In the future, couple appropriate short-term (intra-day) ML methods with previous work in ML-aided numerical weather prediction (NWP) routines
- With an uncountable number of forecasting approaches available, need a performance testing framework
- Set solar forecasting performance benchmarks for point locations such that (any) advancements can be quantified

Methodology

Methodology – SURFRAD data



- Focus on global horizontal irradiation (GHI) using the Surface Radiation (SURFRAD) data network
  - Diverse US climates: NV, MT, CO, SD, IL, MS, and PA
  - 11 years of 1-minute weather measurement data
  - Clear-sky GHI calculated using the Bird model
- Use popular machine learning approaches to forecast at 1-, 2-, 3-, and 4-hour ahead horizons
- Independent variables = time, temperature, relative humidity, wind speed and direction, pressure, thermal infrared, GHI, GHI_cs, and (K) clear-sky indices

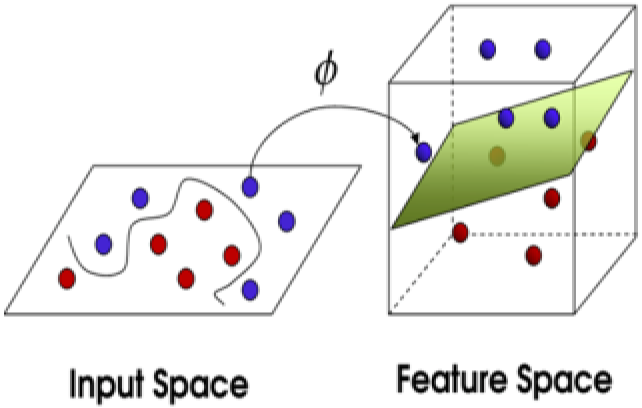
Methodology – SURFRAD data

- Training considerations:
  - Averaged, hourly clear-sky indices used as part of the GHI forecast – as a function of K and clear-sky GHI
  - Data scaled (standardized) according to min & max values for ML considerations
  - ML hyperparameters optimized using a grid search
- Data considerations:
  - Cleaned for missing data or obvious outliers
  - Partitioned by months for training and testing

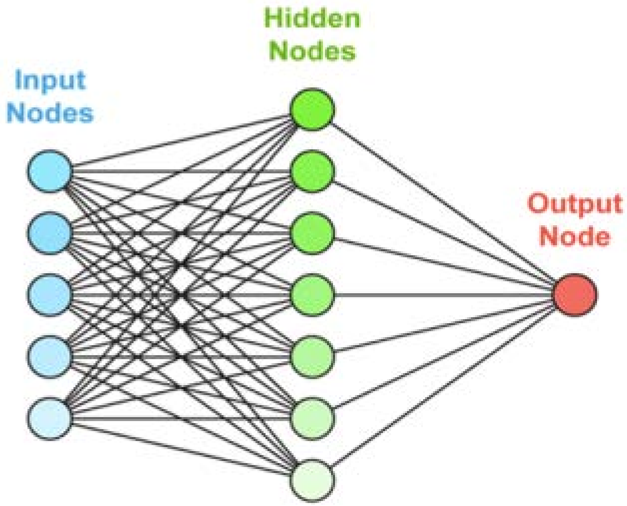
Methodology – Machine Learning & Forecasting Methods

1. Persistence of Cloudiness
   - Current cloud cover to predict future GHI
   - Adjustments for solar angles considered
2. Support Vector Machines
   - Transformation of a nonlinearly separable feature space into a multidimensional space in which variables can be separated by a hyperplane
   - Nonlinear radial basis function utilized
3. Artificial Neural Networks
   - Input/hidden/output nodes with architecture, activation, and learning function
   - Back-propagation learning methods utilized

Support Vector Machines

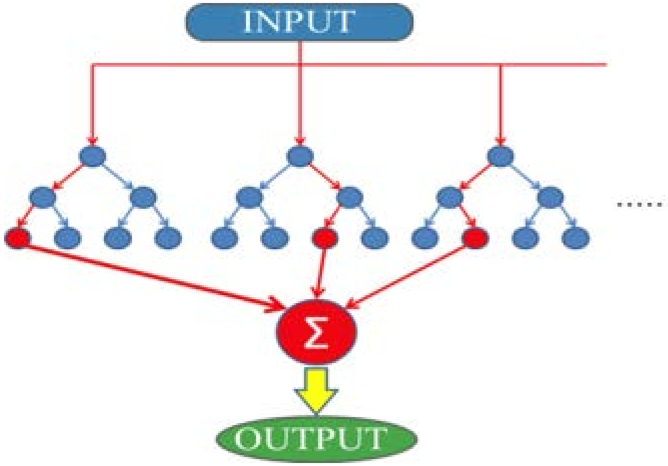


Artificial Neural Networks

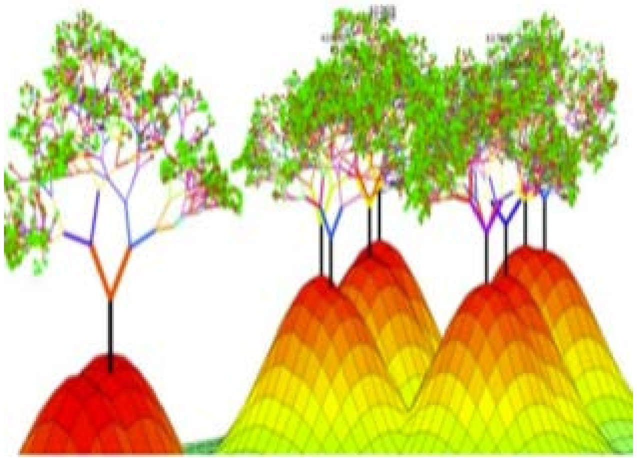


Methodology – Machine Learning & Forecasting Methods

Random Forests



Gradient Boosting Method



4. Random Forests
   - o Collection of single classification and regression trees
   - o Bagging algorithm utilized
5. Gradient Boosting Method
   - o Built ensemble of decision trees
   - o Gradient descent methods to determine structure
6. Situation Dependent, Multi-Model
   - o Utilize the best ML algorithm best on historic performance in unique weather regimes
   - o Blending not considered in this study

Methodology - Situation dependent forecasts

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

= 1,344 models

Input

SURFRAD Sites
Boulder, CO
Bondville, IL
Goodwin Creek, MS
Fort Peck, MT
Desert Rock, NV
Penn State, PA >
Sioux Falls, SD

Month
Jan
Feb >
Mar
Apr
May
June
July
Aug
Sept
Oct
Nov
Dec

Forecast
1 hour
2 hour
3 hour
4 hour >

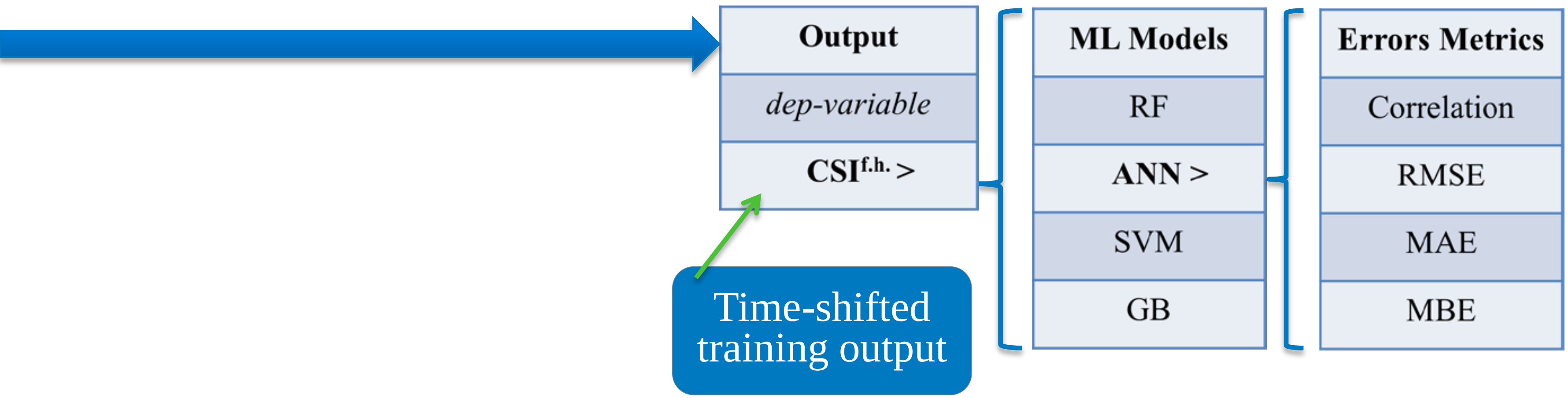
Input Vector
indep-variable
Time
Temp
Humidity
Wind Speed
Wind Direction
Pressure
Thermal IR
GHI^t
GHI^t_{clear}
CSI^t

Methodology - Situation dependent forecasts

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

= 1,344 models

Output



Validation Metrics

Validation Metrics

- Metrics chosen according to previous work showing the following metrics provide unique information:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(G(i) - (H(i)\right)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|G(i) - H(i)|$$

$$nRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left(G(i) - H(i)\right)}{\max(G(i))}\right)^2}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|G(i) - H(i)|}{\max(G(i))}$$

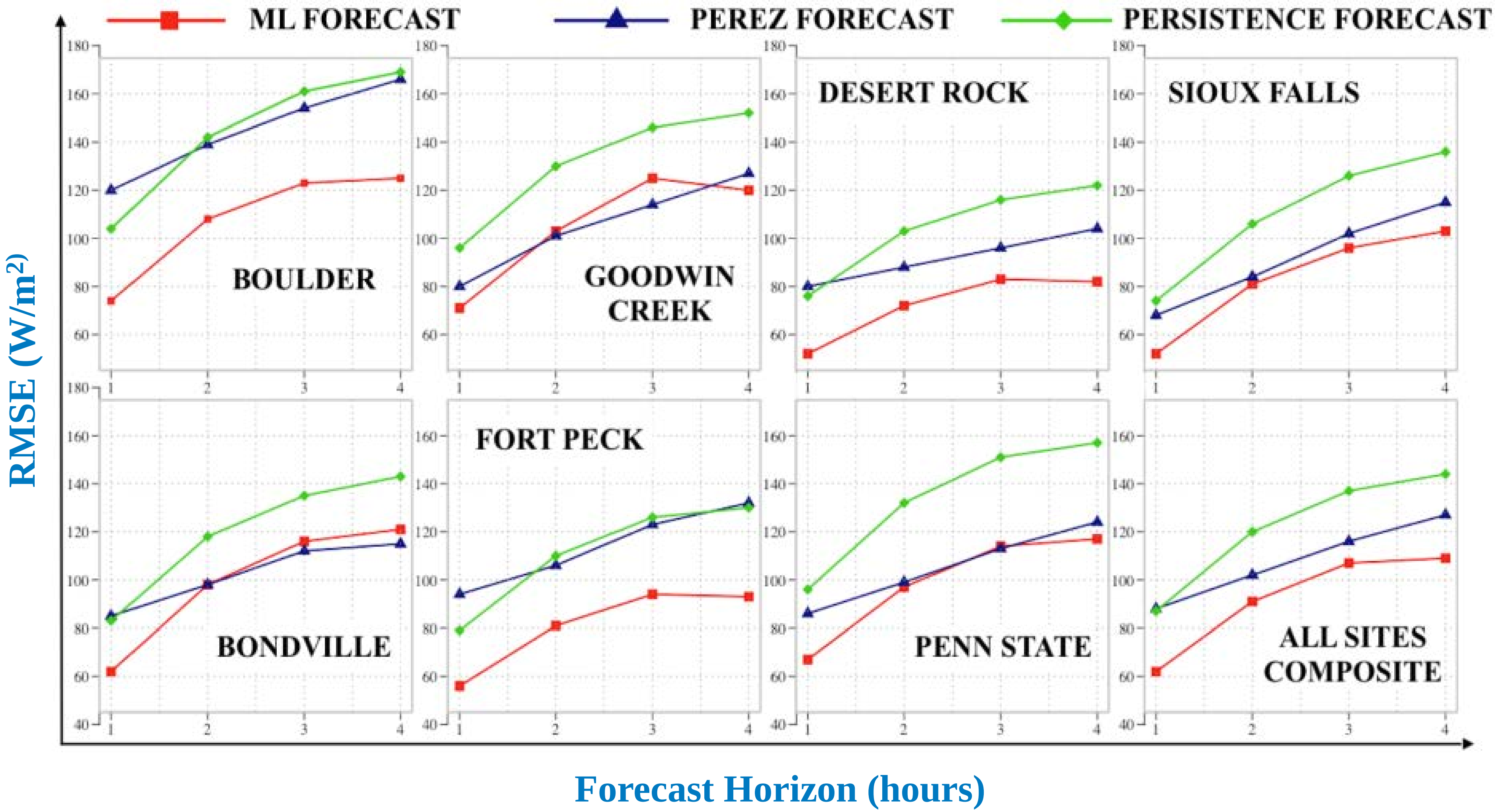
- RMSE for overall accuracy of the forecasts; penalization of large forecasting errors
- MAE for overall accuracy of the forecasts, no penalization large forecasting errors
- MAPE for normalization (of MAE) and batch comparisons
- NRMSE for normalization (of RMSE) and batch comparisons

Results

Results – RMSE values

	Forecast Horizon	Boulder			Bondville			Goodwin Creek			Fort Peck			Desert Rock			Penn State			Sioux Falls		
		ML	PC	PZ	ML	PC	PZ	ML	PC	PZ	ML	PC	PZ	ML	PC	PZ	ML	PC	PZ	ML	PC	PZ
ALL YEAR	1-hour	74	104	120	62	83	85	71	96	80	56	79	94	52	76	80	67	96	86	52	74	68
	2-hour	108	142	139	98	118	98	103	130	101	81	110	106	72	103	88	97	132	99	81	106	84
	3-hour	123	161	154	116	135	112	125	146	114	94	126	123	83	116	96	114	151	113	96	126	102
	4-hour	125	169	166	121	143	122	120	152	127	93	130	132	82	122	104	117	157	124	103	136	115
WINTER	1-hour	55	74	64	51	66	60	58	87	48	36	53	107	45	66	46	53	72	57	41	62	48
	2-hour	81	98	71	82	104	66	98	128	59	52	74	105	63	92	48	79	102	57	65	96	58
	3-hour	96	113	81	104	117	74	122	146	66	62	84	109	75	106	59	91	122	59	82	117	69
	4-hour	87	119	85	105	123	81	111	147	70	58	84	112	84	107	70	96	127	65	89	122	78
SPRING	1-hour	97	143	125	84	114	93	94	127	92	75	108	110	71	108	86	84	117	83	66	94	69
	2-hour	137	195	141	133	154	109	125	171	122	110	149	124	106	147	95	119	161	99	103	133	90
	3-hour	170	218	157	147	178	123	159	190	144	129	174	141	120	155	111	143	183	118	124	156	107
	4-hour	162	228	170	159	189	137	145	202	164	134	186	148	115	171	115	145	190	137	131	171	126
SUMMER	1-hour	96	136	143	76	97	100	88	119	92	81	101	91	48	71	99	88	125	112	67	90	80
	2-hour	137	185	175	111	134	115	121	151	113	110	143	109	64	85	110	122	170	127	99	129	98
	3-hour	144	211	189	135	153	129	135	168	120	125	164	129	70	105	111	140	194	142	112	155	120
	4-hour	175	222	204	138	169	138	139	175	129	122	173	142	74	118	124	138	208	152	118	168	129
FALL	1-hour	46	63	85	35	56	58	44	50	55	34	52	59	43	60	55	45	71	60	35	48	49
	2-hour	78	92	97	67	80	68	67	70	66	52	73	67	57	87	62	69	96	71	57	67	54
	3-hour	81	103	110	76	90	84	83	81	81	59	81	83	65	97	69	80	104	76	65	76	64
	4-hour	75	107	120	81	143	89	87	81	94	58	78	88	56	94	72	89	102	83	74	81	80

Results – Annual RMSE Averages for all SURFRAD sites



Results – ML Methods' Performance

RMSE

Forecast Situation	RF	SVM	ANN	GBM
1-hour ahead	8%	31%	**42%**	19%
2-hour ahead	22%	20%	**38%**	20%
3-hour ahead	25%	13%	**45%**	16%
4-hour ahead	29%	20%	**38%**	13%
Winter	20%	22%	**38%**	20%
Spring	15%	25%	**40%**	20%
Summer	24%	17%	**47%**	12%
Fall	25%	23%	**38%**	14%
Boulder	27%	15%	**43%**	15%
Bondville	21%	21%	**35%**	23%
Goodwin Creek	21%	23%	**39%**	17%
Fort Peck	23%	**31%**	**31%**	15%
Desert Rock	15%	31%	**42%**	12%
Penn State	25%	15%	**45%**	15%
Sioux Falls	15%	12%	**50%**	23%
All Situations	20.8%	21.1%	**41.1%**	17.0%

MAE

Forecast Situation	RF	SVM	ANN	GBM
1-hour ahead	7%	**65%**	17%	11%
2-hour ahead	15%	**44%**	26%	15%
3-hour ahead	14%	**36%**	**36%**	14%
4-hour ahead	23%	**32%**	26%	19%
Winter	17%	**41%**	25%	17%
Spring	6%	**60%**	19%	15%
Summer	21%	**38%**	25%	16%
Fall	12%	**40%**	35%	13%
Boulder	10%	**48%**	25%	17%
Bondville	8%	**52%**	17%	13%
Goodwin Creek	23%	**35%**	19%	23%
Fort Peck	21%	**42%**	27%	10%
Desert Rock	21%	**48%**	19%	12%
Penn State	8%	**42%**	40%	10%
Sioux Falls	10%	**44%**	27%	19%
All Situations	14.6%	**44.3%**	26.2%	14.9%

Conclusions & Future Work

Conclusions

- Assessed the performance of ML techniques for short-term solar forecasting:
  - Lower average RMSE values than a cloud motion forecasting method for all 7 sites
  - Largest improvements for the 3 sites at the highest elevations and westernmost locations in the SURFRAD network
  - Outperformed the persistence-of-cloudiness forecasts at all 7 sites
  - Greatest improvements at the four locations of Boulder, Desert Rock, Penn State, and Fort Peck
- Testing the 4 ML algorithms against each other did not reveal any strong situation-dependent sensitivities
- SVMs or ANNs most often led to the lowest forecasting errors depending on the error metric used

Future Work

- Further work (in progress) is needed to fine-tune the approach:
  - Increase resolution from hourly to 5-minute increments
  - Optimize ML hyperparameters for each situation-dependent forecast
  - Facilitate higher penetrations of solar energy into the grid through data feedback schemes, e.g.
    - Coupling of day-ahead, intraday, and short-term forecasts
    - Forecast power vs actual power residuals minimized through site-specific learning mechanisms
    - Combine approach with cloud-sky imager

Questions?

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