A Post-processing Approach for Solar Power Combined Forecasts of Ramp Events

Mohamed Abuella

Supervised by:
Prof. Badrul Chowdhury

A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Electrical Engineering

Charlotte
October 1st, 2018

UNC CHARLOTTE
Energy Production and Infrastructure Center (EPIC)

Highlights

- A post-processing approach combines and improves solar power forecasts.
- The approach also adjusts the combined forecasts in terms of ramp events.
- A classification of all possible thresholds and classes of ramp event forecasts.
- A customized cost function for imbalanced classification of ramp events.
- Suitable metrics for the feature selection process and performance evaluation.
- An uncertainty analysis for probabilistic forecasts of solar power ramp events.

Motivation

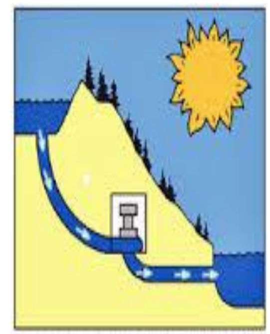
Why Forecast?

$$P_{Supply} = P_{Demand} + P_{Loss}$$

PV Solar Power Generations are Too Variable

Coordination with Operating Reserves and Energy Storage Systems

Reducing Cost and Pollution



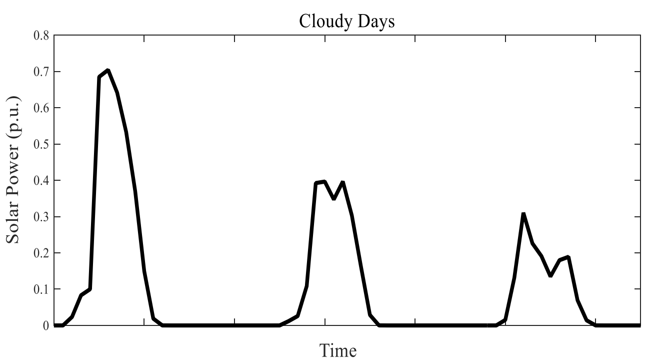
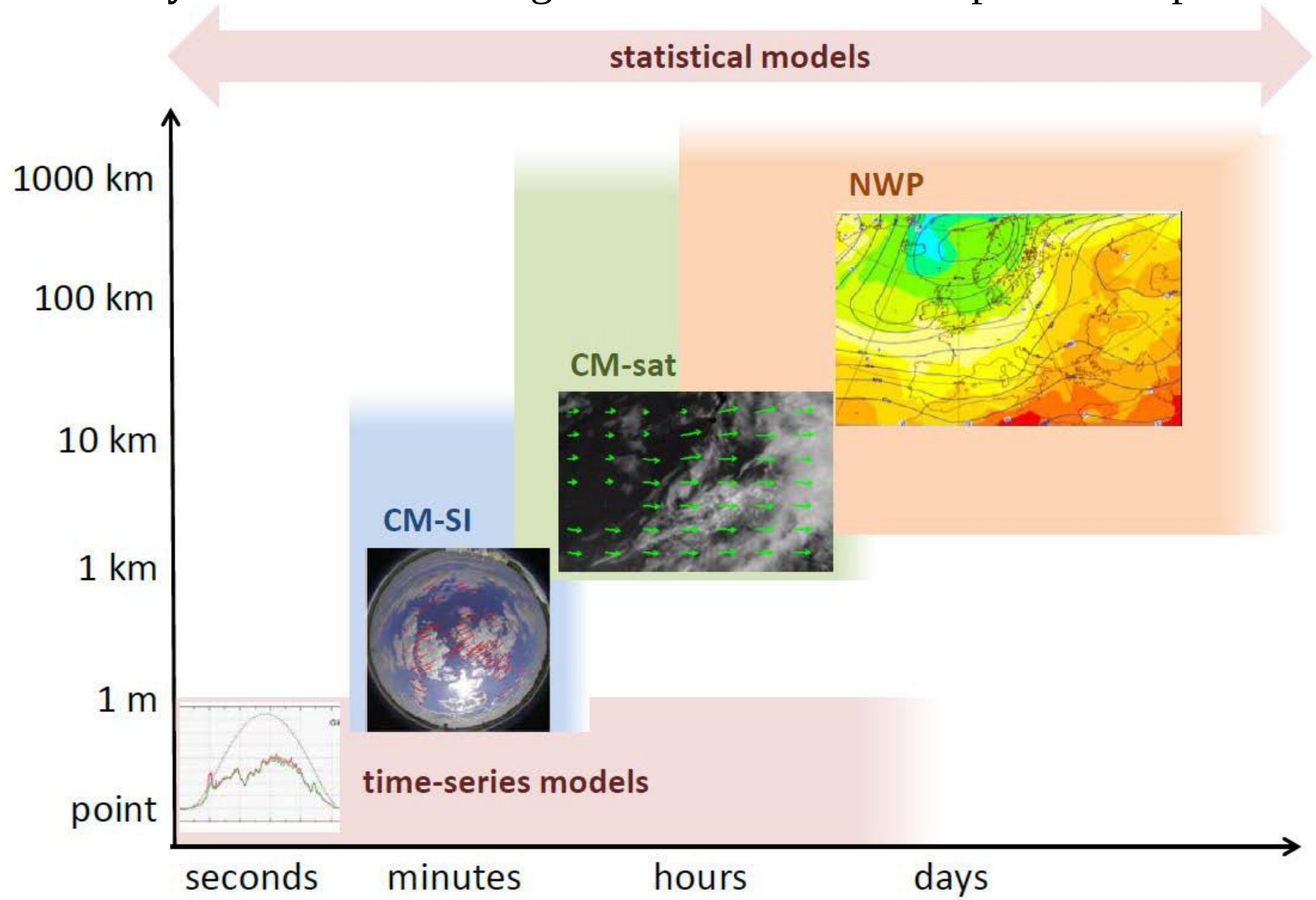


Illustration of the motivation of PV solar power forecasts

Literature Review

Taxonomy of solar forecasting methods based on temporal and spatial resolution#



CM-sat: cloud motion by satellite images;

CM-SI: cloud motion by sky-imagers

NWP: Numerical weather prediction Systems

Statistical models: blending and post-processing all of the methodologies.

M. Sengupta, A. Habte, C. Gueymard, S. Wilbert, and D. Renne, Best practices handbook for the collection and use of solar resource data for solar energy applications," Tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States), 2017

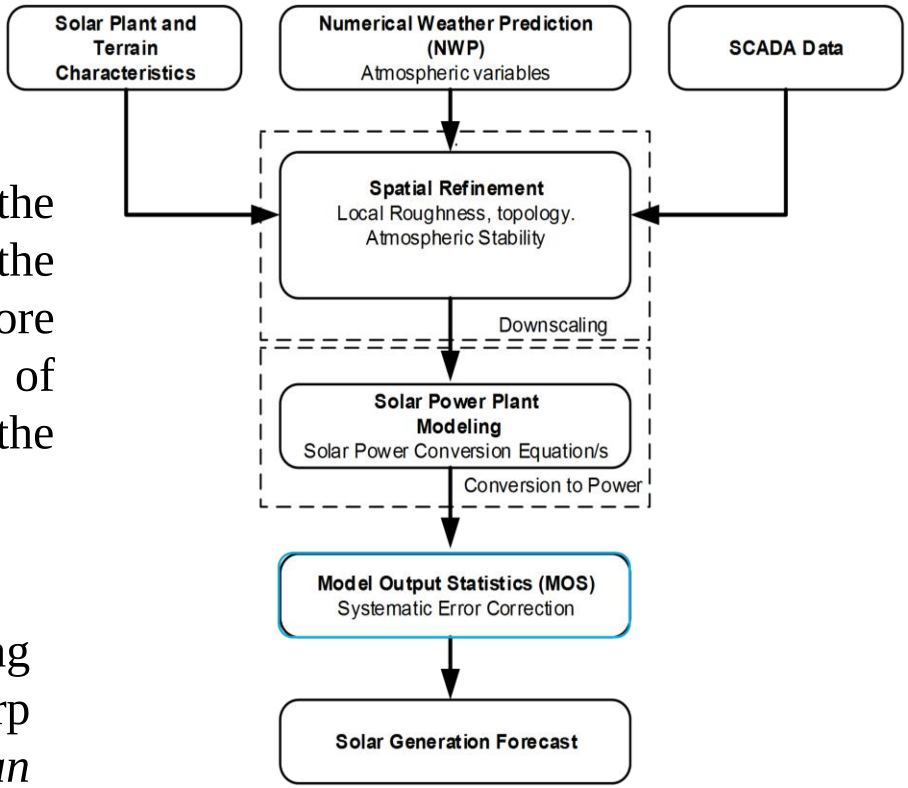
Yang, D., Kleissl, J., Gueymard, C. A., Pedro, H. T., & Coimbra, C. F. (2018). History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Solar Energy*. (**This review paper published in **2018,** and reviewing **1000** solar forecast studies).

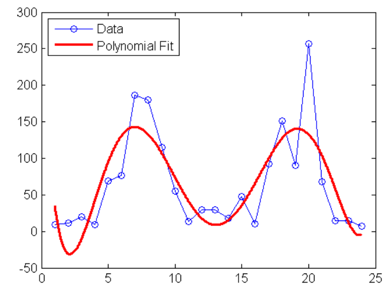
Problem Statement and Contribution

The Problem Statement

Combining of different forecasts can reduce the systemic bias of the individual models, boost the overall accuracy, and make the performance more robust, but it also smooths out the sharp changes of the forecasts, which leads to reduced accuracy of the combined forecasts for ramp events.

The post-processing methods (MOS) are affecting the ramp event forecasts by smoothing the sharp changes in the raw forecasts. (*Kleissl 2013; Inman et al. 2013*)





Kleissl, J. (2013). Solar energy forecasting and resource assessment. Academic Press.

Inman, R. H., Pedro, H. T., & Coimbra, C. F. (2013). Solar forecasting methods for renewable energy integration. Progress in energy and combustion science, 39(6), 535-576.

Problem Statement and Contribution

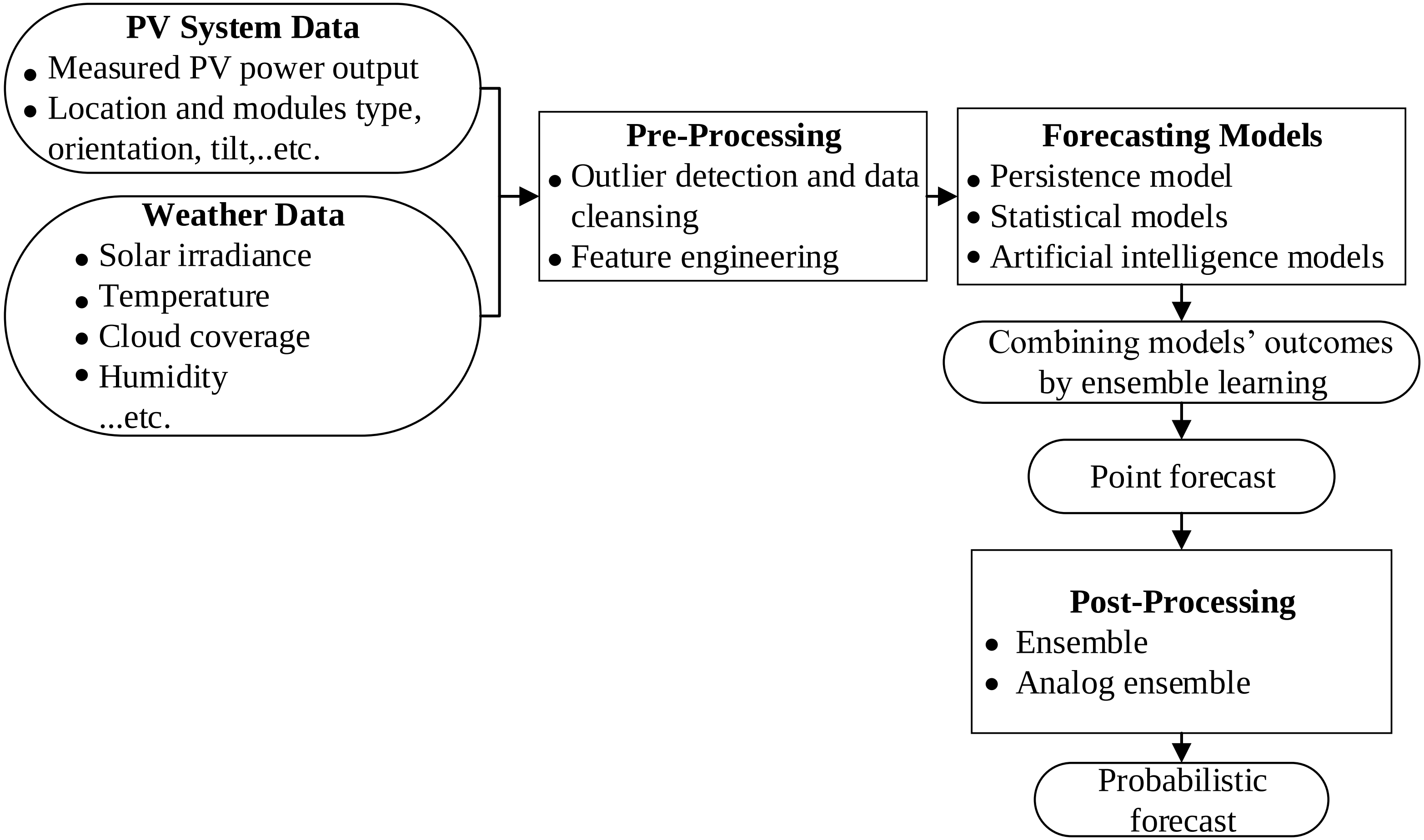
The Contribution

Due to the issue that was highlighted (*Kleissl 2013; Inman et al. 2013*), it is therefore, there is room for improvement by applying the proposed approach for adjusting the combined forecasts of solar power in terms of ramp events.

To the best of our knowledge, this is the first attempt to tackle this issue of the combined forecasts for solar power ramp events.

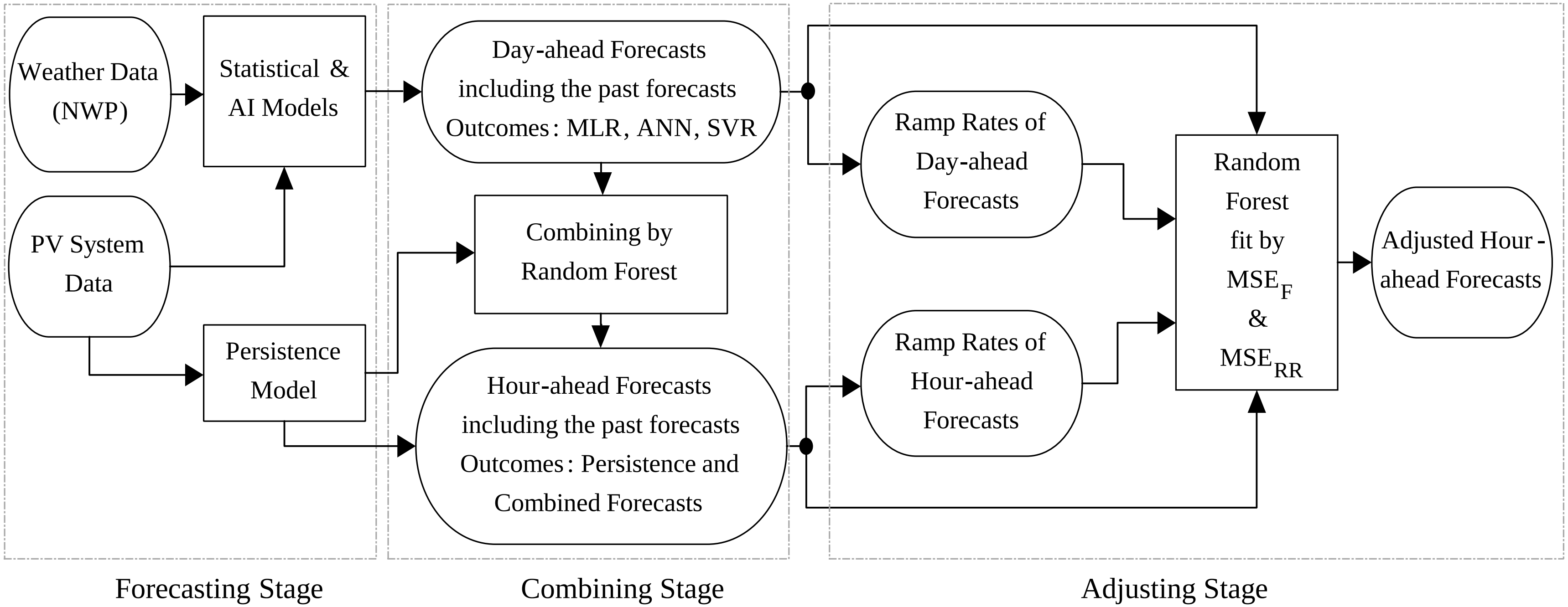
- A post-processing approach combines and improves solar power forecasts.
- The approach also adjusts the combined forecasts in terms of ramp events.
- A classification of all possible thresholds and classes of ramp event forecasts.
- A customized cost function for imbalanced classification of ramp events.
- Suitable metrics for the feature selection process and performance evaluation.
- An uncertainty analysis for probabilistic forecasts of solar power ramp events.

Graphical Abstract of the Proposed Adjusting Approach



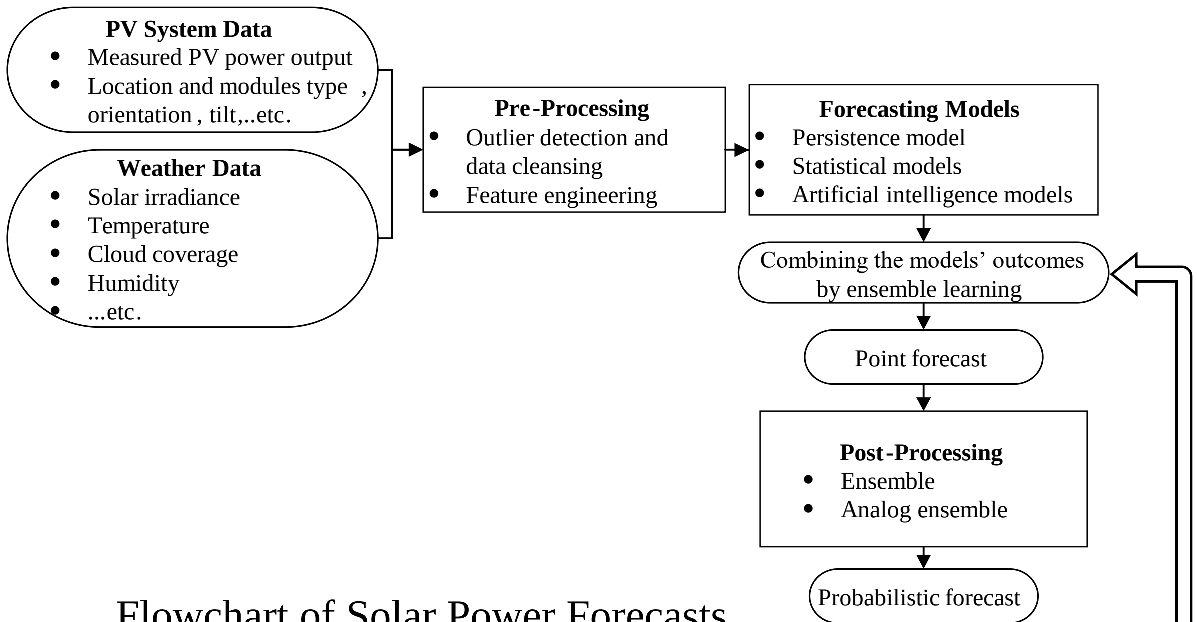
Flowchart of Solar Power Forecasts

Graphical Abstract of the Proposed Adjusting Approach

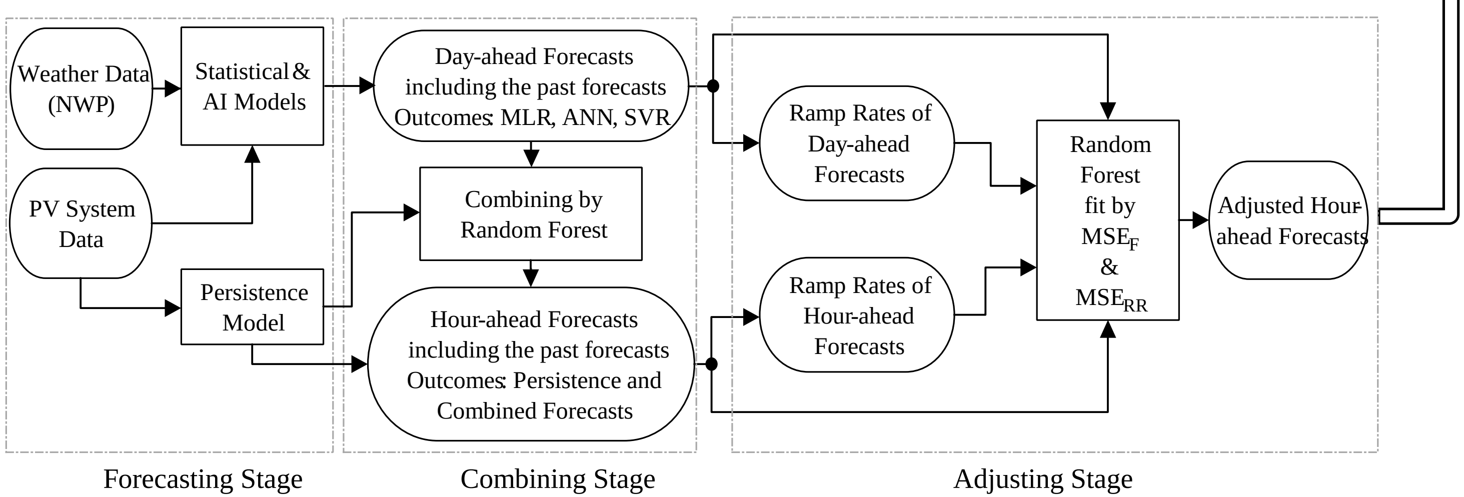


Block diagram of the adjusting approach

Graphical Abstract of the Proposed Adjusting Approach



Flowchart of Solar Power Forecasts

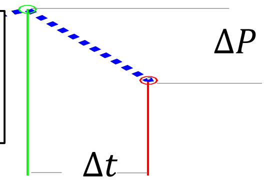


Block diagram of the adjusting approach

Solar Power Ramp Rates

Solar power ramp rate (RR) is *the change of solar power during a certain time interval.*

$$\boxed{Ramp\ Rate, RR(t) = \frac{dP(t)}{dt} = \frac{P(t+D)-P(t)}{D}}$$



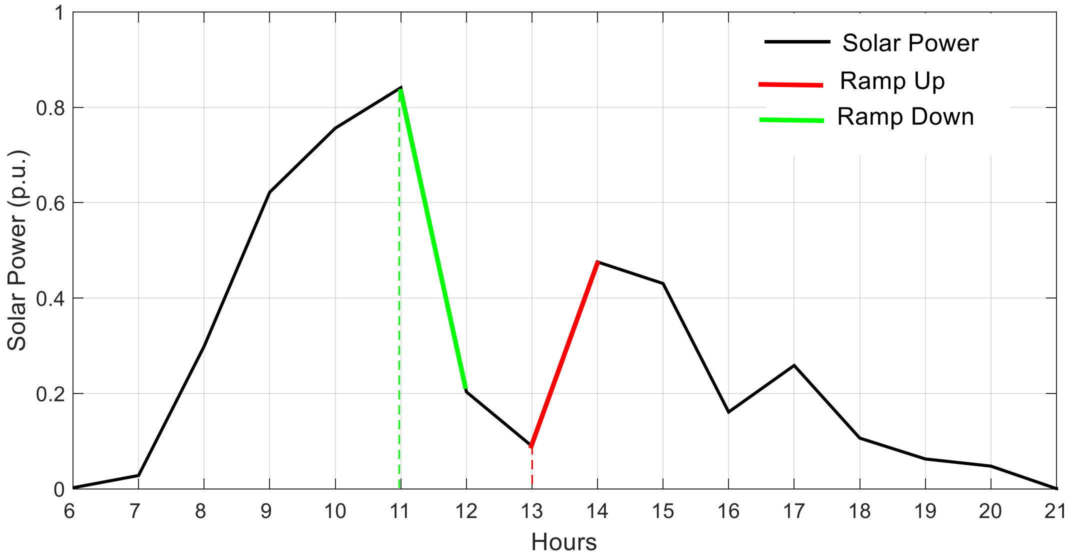
where P(t) is the solar power of the target hour, it can also be its forecast F(t); D is the time duration for which the ramp rate is determined.

For the illustrated cloudy day below:

Ramp rate, $\frac{\Delta P}{\Delta t} = \frac{0.2-0.85}{12{:}00-11{:}00} = -0.65\ (-65\%)\ ramp\ down\ of\ its\ normal\ capacity,\ (pu/hr)$

Ramp rate, $\frac{\Delta P}{\Delta t} = \frac{0.48-0.1}{14{:}00-13{:}00} = +0.38\ (+38\%)\ ramp\ up\ of\ its\ normal\ capacity,\ (pu/hr)$

Some ramps are with low rates, while others with high rates.



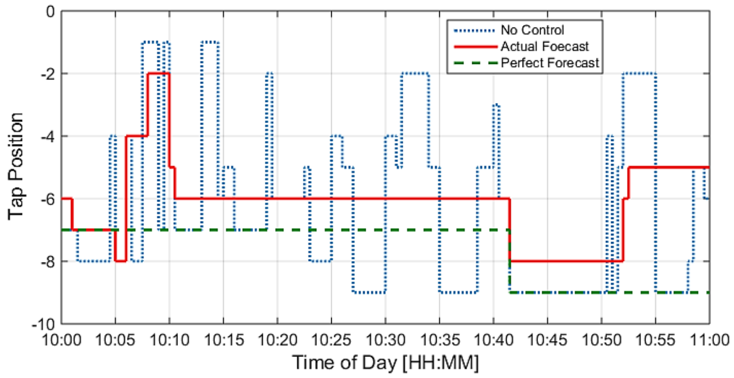
Ramp Events During a Cloudy Day

Potential Applications

There are several applications of power systems that rely on solar power ramp event forecasts

Distribution level:

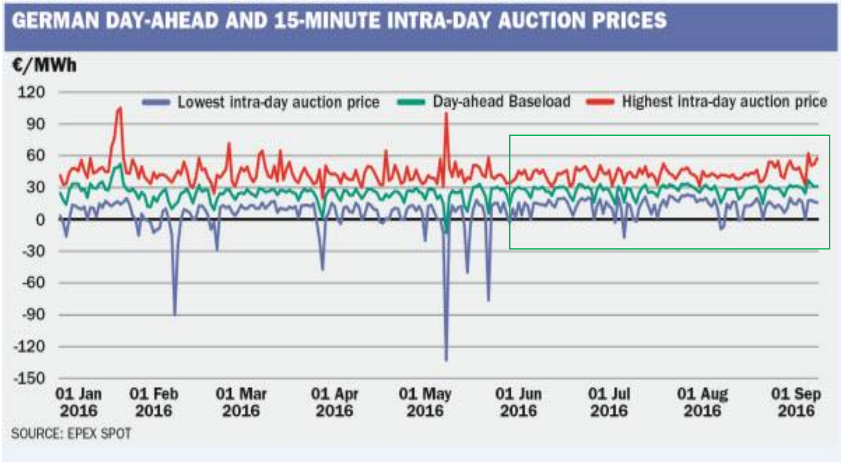
- Optimizing the voltage regulation equipment.
- Control schemes of energy storage systems.



Optimizing the Transformer's Tap Changer position sequences using the solar forecast

Transmission / bulk level:

- Trading & dispatching the operating reserve.
- Managing the ramp capability / system flexibility with high-level of renewable energy integration.



EPEX: European power exchange spot trading

Data Preprocessing

Data Description:

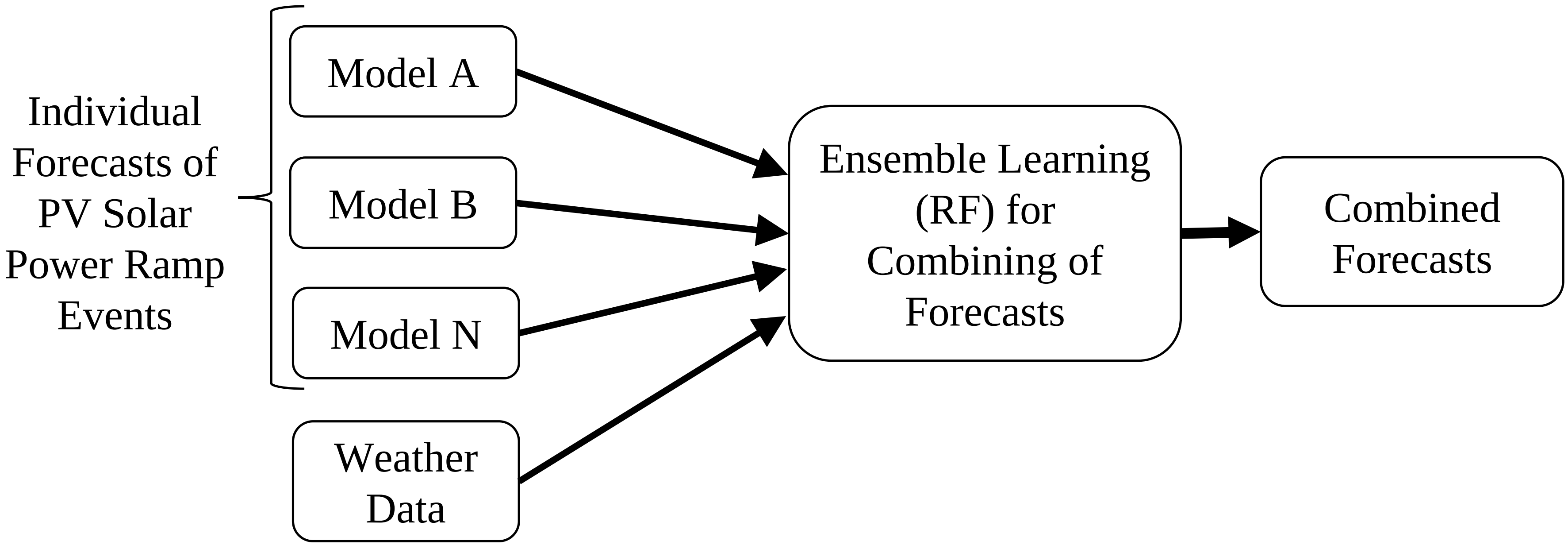
Dataset	Golden, CO	Cocoa, FL	Eugene, OR	Canberra
Country	USA	USA	USA	Australia
Climate type	Semi-arid	Subtropical	Marine coast	Oceanic
Latitude (°, -S)	39.74	28.39	44.05	-35.16
Longitude (°, -W)	-105.18	-80.46	-123.07	149.06
Elevation above sea (m)	1798	12	145	595
Number of panels	11	11	11	8
Panel tilt (°) from horizontal	40	28.5	44	36
Panel orientation (°) clockwise from North	180	180	180	38
Total capacity (W)	1252	1272	1290	1560
Time period of observations	Aug. 2012 to Sep. 2013	Jan. 2011 to March 2012	Dec. 2012 to Jan. 2014	April 2012 to May 2014
Data resolution	15min	5min	5min	1hr
Missing (% of observations)	18%	17%	10%	0%
Variability (data resolution) Std.Div.	(15min) 0.256 (1hr) 0.119	(5min) 0.251 (1hr) 0.164	(5min) 0.250 (1hr) 0.161	(1hr) 0.259

B. Marion, A. Anderberg, C. Deline, J. del Cueto, M. Muller, G. Perrin, J. Rodriguez, S. Rummel, T. J. Silverman, F. Vignola, et al., New data set forvalidating pv module performance models," in Photovoltaic Specialist Conference (PVSC), 2014 IEEE 40th, pp. 1362{1366, IEEE, 2014.

https://crowdanalytix.com/contests/global-energy-forecasting-competition-2014-probabilistic-solar-power-forecasting

Methodology

Ensemble Forecasts: Combining Various Models



General diagram of combining different models

$$F_{comb} = W_A * M_A + W_B * M_B + W_C * M_C \; \ldots . + W_N * M_N$$

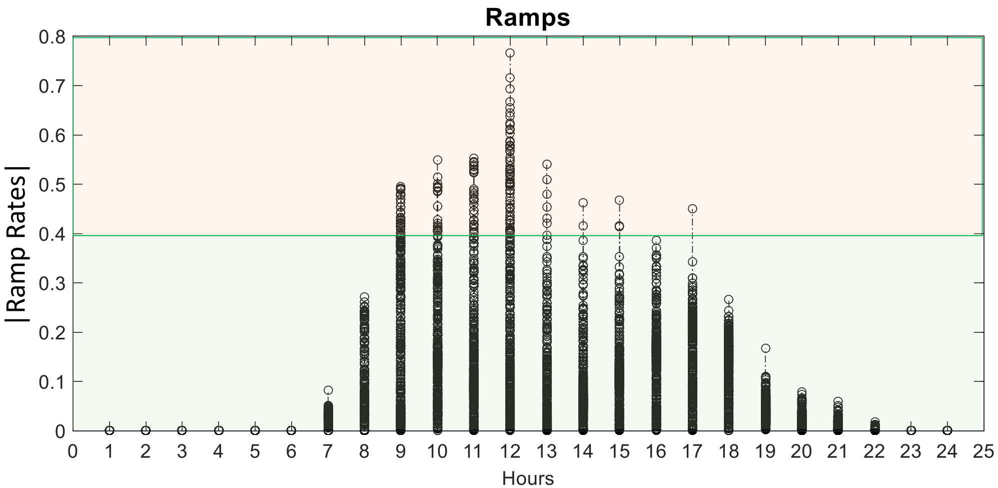
Method of Combining The Models

Random forest (RF) is chosen to be the ***ensemble learning*** method for combining the various models' outcomes.

T. Hastie, R. Tibshirani, J. Friedman, and others, *The elements of statistical learning*, 2nd Edition. Springer-Verlag New York, 2009.

Modeling and Results

Implementing several classification models to forecasts solar power ramp events



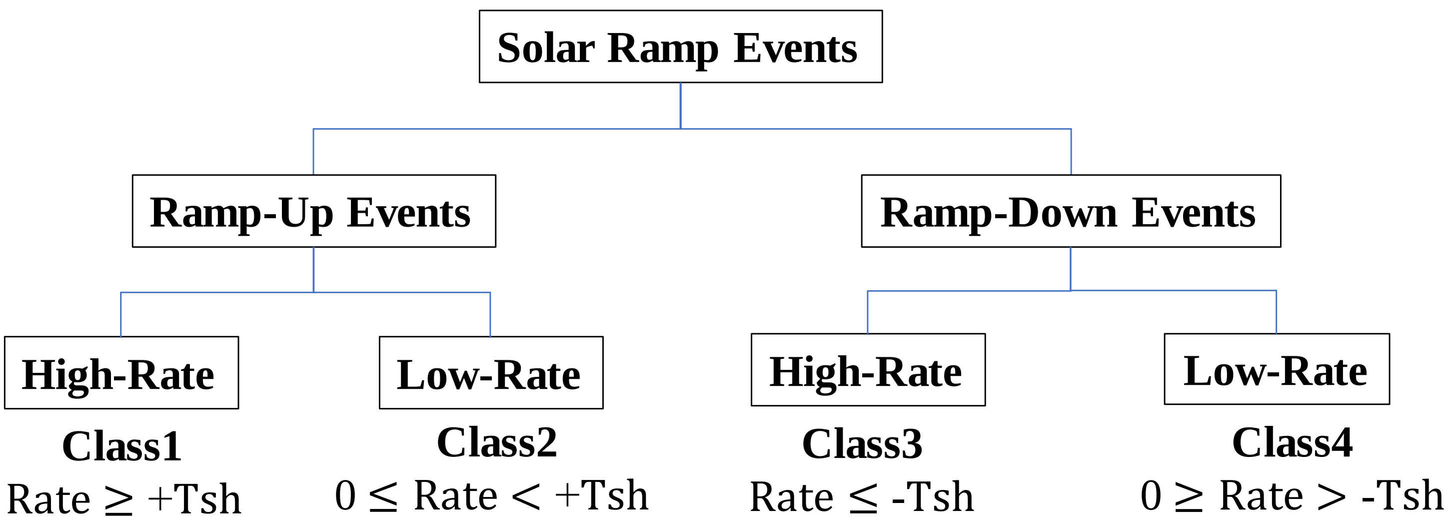
Classes of solar power ramp events in the case study

Objective: Increase the true events,
Decrease the false events.

True Events ↑ & *False Events* ↓

Ramp Classes as following:

Class1: Ramp up of high rate, |rate| ≥ Tsh
Class2: Ramp up of low rate, |rate| < Tsh
Class3: Ramp down of high rate, |rate| ≥Tsh
Class4: Ramp down of low rate, |rate| < Tsh



Distribution of the classes of solar power ramp events at threshold (Tsh) =0.4pu/hr.

Modeling and Results

Combined Forecasts of Ramps

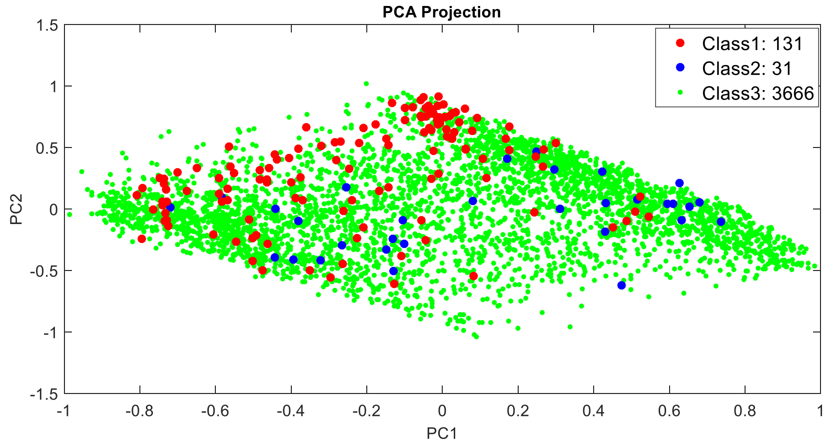
Data projection onto PC1 and PC2:

For clarity, low-rate classes (2&4) become as a one class, class3: ➔

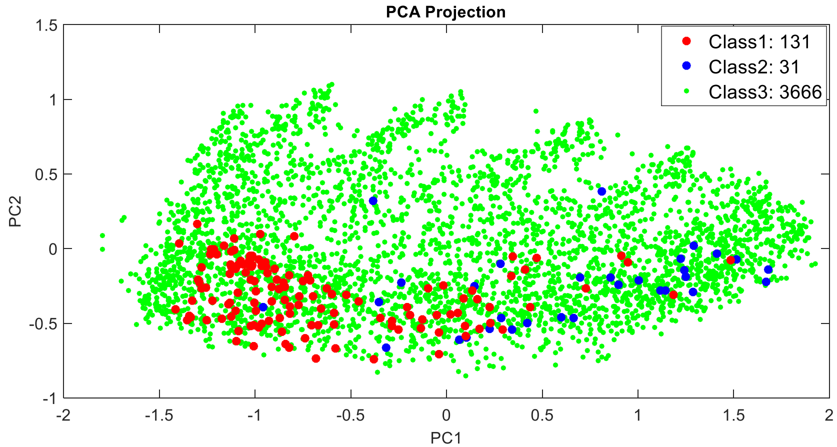
Threshold=0.4pu/hr

Class	Class1	Class2	Class3	Total
Samples	131	31	3666	3828

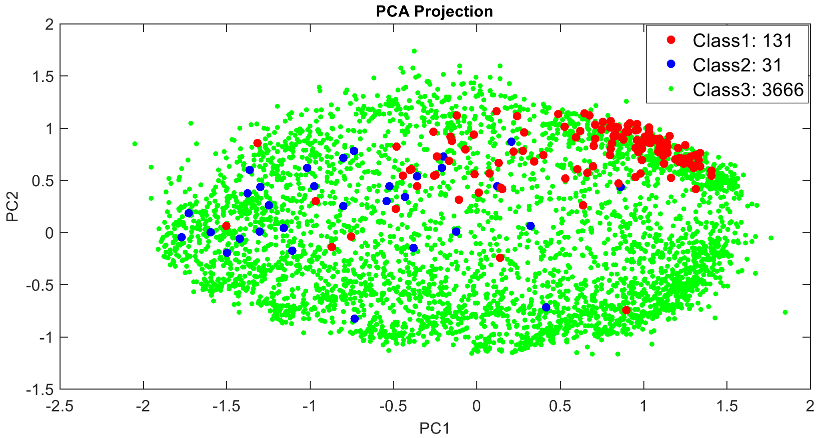
1) All 14 weather variables



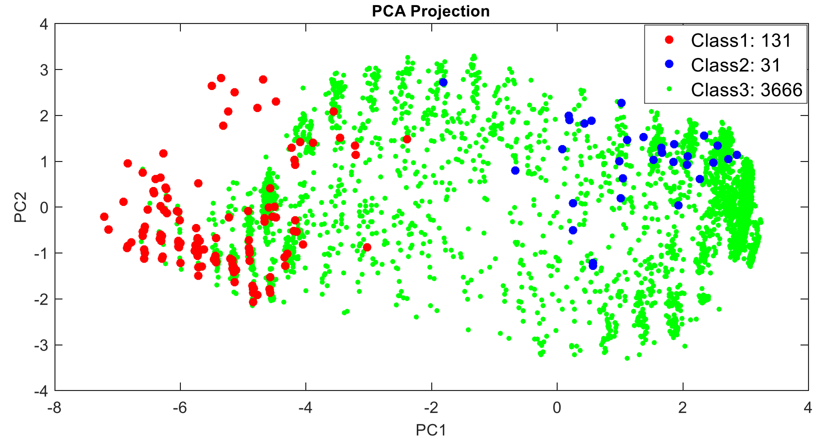
2) All 30 Features (*add solar power forecasts*)



3) All 50 Features (*add ramp rates of forecasts*)

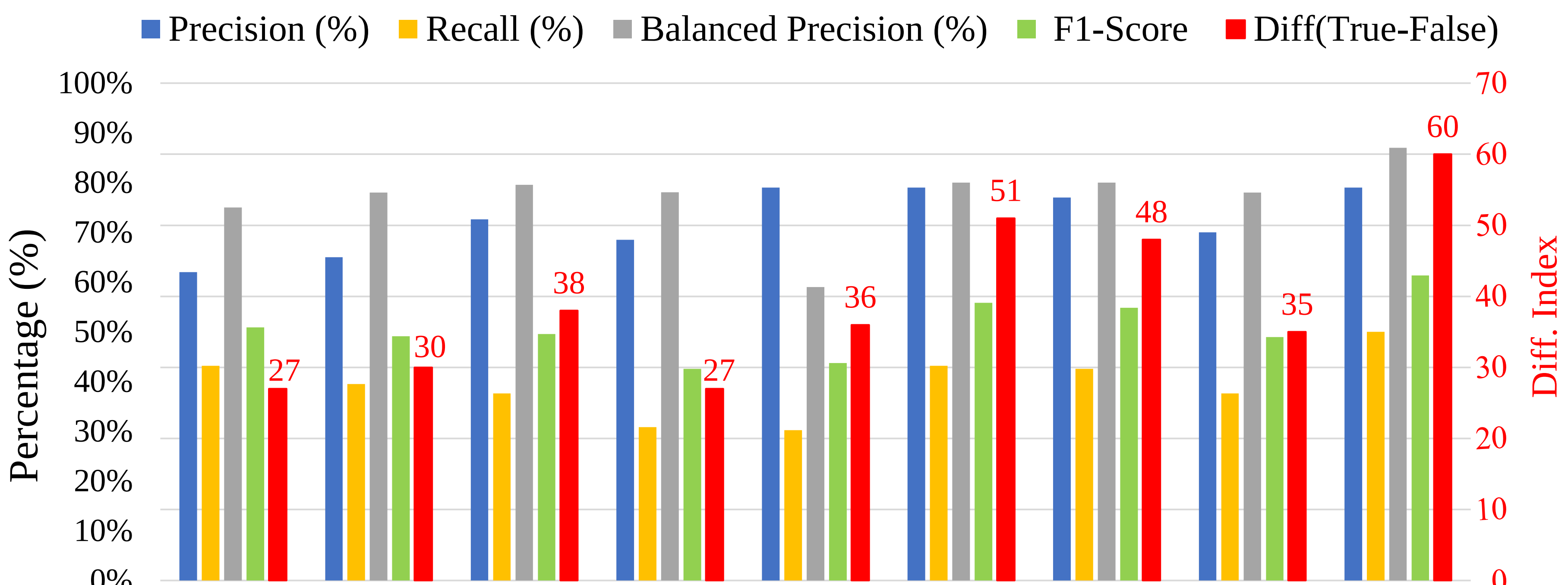


4) All 66 Features (*add class labels of forecasts*)



Modeling and Results

Combined Forecasts of Ramps

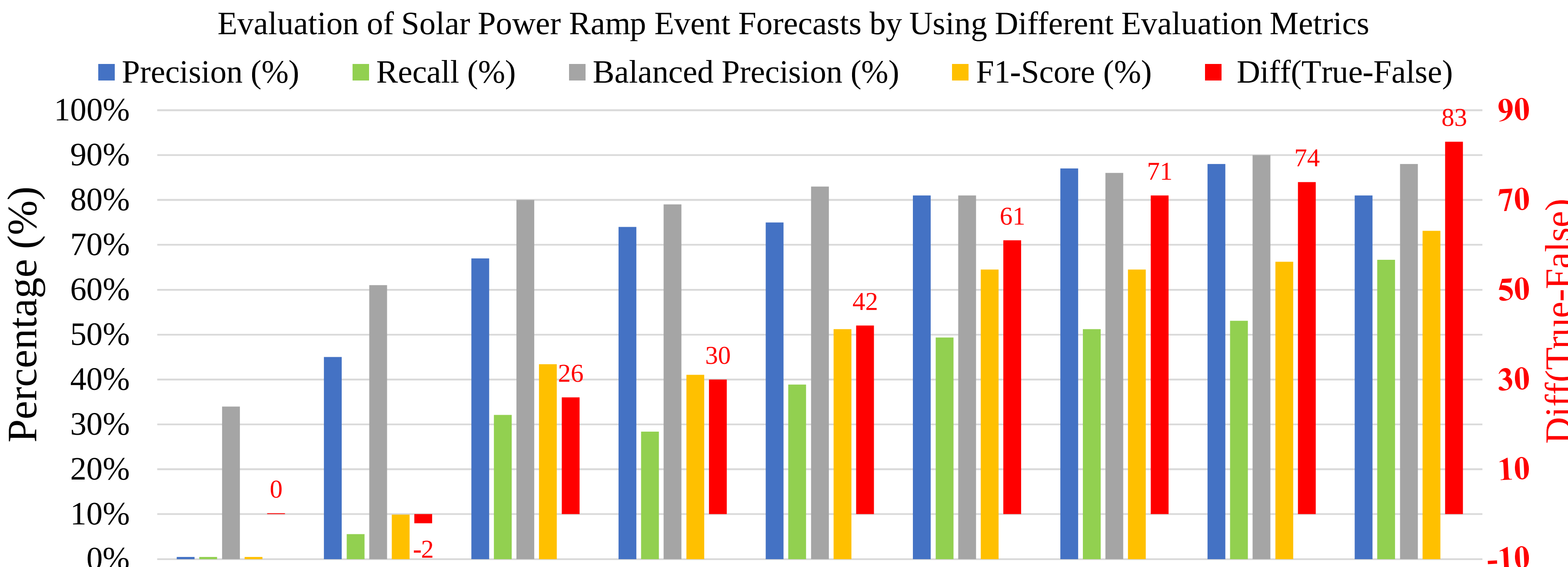


Method	Naïve Bayes	LDA	Decision Trees	kNN	Logistic Regression	Random Forest	SVM	ANN	Combined Classifiers
Precision (%)	62%	65%	73%	68%	79%	79%	77%	70%	79%
Recall (%)	43%	40%	38%	31%	30%	43%	43%	38%	50%
Balanced Precision (%)	75%	78%	80%	78%	59%	80%	80%	78%	87%
F1-Score (%)	51%	49%	50%	43%	44%	56%	55%	49%	61%
Diff. Index	27	30	38	27	36	51	48	35	60

Solar power ramp event forecasts of the high-rate ramp events, ($|Rate| \geq 0.4$ *pu/hr* = 162 events) by the classification techniques.

Modeling and Results

Implementing the ***adjusting approach*** to forecasts solar power ramp events



	Persistence, PV1	NARX	Simple Average (NARX, MLR, ANN, SVR)	Combined (Pers.1, MLR, ANN, SVR)	Adjust Approach (Pers.1, MLR, ANN, SVR)	Combined (Pers.1&3 +NARX, Clouds, MLR, ANN, SVR)	Adjust Approach (Pers.1&3 +NARX, Clouds, MLR, ANN, SVR)	Probabilistic Forecasts (Q1 to Q99)	Probabilistic Forecasts (Q25 to Q75)
Precision (%)	0%	45%	67%	74%	75%	81%	87%	88%	81%
Recall (%)	0%	6%	32%	28%	39%	49%	51%	53%	67%
Balanced Precision (%)	34%	61%	80%	79%	83%	81%	86%	90%	88%
F1-Score (%)	0%	10%	43%	41%	51%	64%	64%	66%	73%
Diff(True-False)	0	-2	26	30	42	61	71	74	83

Solar power ramp event forecasts of the high-rate ramp events, ($|Rate| \geq 0.4\ pu/hr$ = 162 events) by the ***adjusting approach***

Modeling and Results

Comparison the hourly forecasts of solar power by the adjusting approach with different datasets

Location	Australia	Golden, CO	Cocoa, FL	Eugene, OR
RMSE	0.0523	0.0453	0.0420	0.0411
Pinball	0.0084	0.0124	0.0109	0.0106

Specifications of solar PV systems and data statistics

Dataset	**Golden, CO**	**Cocoa, FL**	**Eugene, OR**	**Canberra**
Country	USA	USA	USA	Australia
Climate type	Semi-arid	Subtropical	Marine coast	Oceanic
Latitude (°, -S)	39.74	28.39	44.05	-35.16
Longitude (°, -W)	-105.18	-80.46	-123.07	149.06
Elevation above sea (m)	1798	12	145	595
Number of panels	11	11	11	8
Panel tilt (°) from horizontal	40	28.5	44	36
Panel orientation (°) clockwise from North	180	180	180	38
Total capacity (W)	1252	1272	1290	1560
Time period of observations	Aug. 2012 to Sep. 2013	Jan. 2011 to March 2012	Dec. 2012 to Jan. 2014	April 2012 to May 2014
Data resolution	15min	5min	5min	1hr
Missing (% of observations)	18%	17%	10%	0%
Variability (data resolution) Std.Div.	(15min) 0.256 **(1hr) 0.119**	(5min) 0.251 **(1hr) 0.164**	(5min) 0.250 **(1hr) 0.161**	**(1hr) 0.259**

Conclusions

- ✓ The adjusting approach improves the combined forecasts.
- ✓ The approach is simple vs. the classification techniques.
- ✓ Ramp classes more separable with features: forecasts, ramp-rates, clouds, neighboring PVs.
- ✓ Most effective weather variables:
  - Cloud information: cloud type, height and cloud formation.
  - Clear-sky solar irradiance / Top solar irradiance at Earth's atmospheric layer.
- ✓ Diff. Index of high-rate ramps is efficient for the imbalanced classification.
- ✓ Probabilistic forecasts as a tool of situational awareness.

Thanks for Your Listening

Any Question?

A Post-processing Approach for Solar Power Combined Forecasts of Ramp Events

Mohamed Ali Abuella
mabuella@uncc.edu

https://epic.uncc.edu

Energy Production and Infrastructure Center
University of North Carolina at Charlotte

UNC CHARLOTTE
Energy Production and Infrastructure Center (EPIC)