Metrics for Evaluating the Accuracy of Solar Power Forecasting
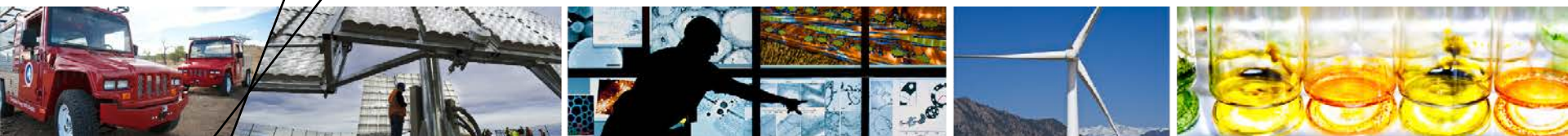
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Solar Power Forecasting

➢ Forecasting solar energy generation is a challenging task due to the variety of solar power systems and weather regimes encountered.

➢ Solar power generation presents different challenges for transmission and distribution networks:

  ▪ **On the transmission side:** solar power takes the form of centralized solar power plants, a non-dispatchable component of the generation pool.

  ▪ **On the distribution side:** solar power is generated by a large number of distributed panels installed on building rooftops, which changes the load profile without providing visibility to the system operator.

➢ Forecast inaccuracies of solar power generation can result in substantial economic losses and power system reliability issues.

Research Motivation and Objectives

Motivation

➢ Solar forecasting accuracy evaluation does not have a standard metric, because different forecasting stakeholders use different metrics.

➢ Establishing a standard set of metrics for assessing solar forecasting is:

- ▪ Critical to evaluating the success of a solar forecasting method.
- ▪ Useful for guiding the decision making of power system operators with a high penetration of solar power.

Research Objectives

- • Develop a suite of generally applicable, value-based metrics for solar forecasting for a comprehensive set of scenarios.

- • Analyze the sensitivity of the proposed metrics to different types of solar forecasting improvements.

Solar Power Data Summary

- The data was obtained from the Western Wind and Solar Integration Study Phase 2 (WWSIS-2).

- The 60-minute solar power plant output for 2006 is used as the actual data.

- Day-ahead (DA) solar forecasts are taken from the WWSIS-2 solar forecasts based on numerical weather prediction model simulations.

- One-hour-ahead (1HA) forecasts were synthesized using a persistence of cloudiness approach.

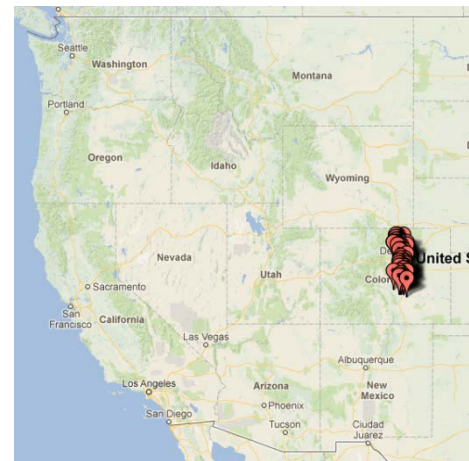**Western Interconnection**
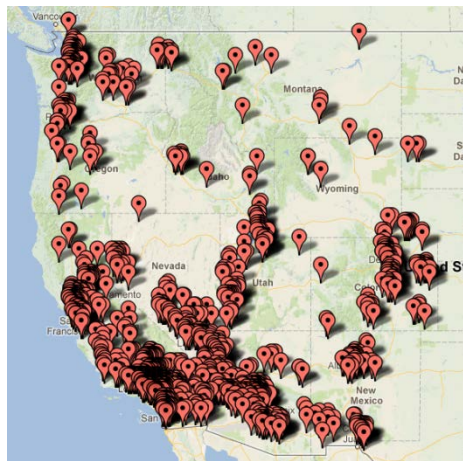
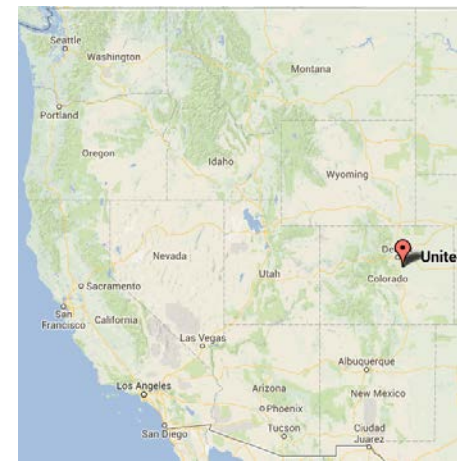**Colorado**
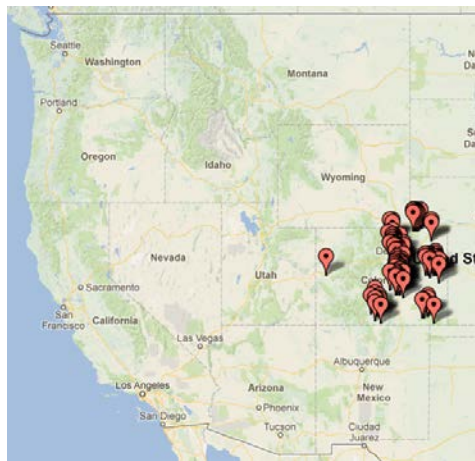
Denver

Single Plant

Proposed Metrics for Solar Forecasting

➢ **Statistical Metrics**

- Pearson's correlation coefficient
- (Normalized) root mean square error (RMSE)
- Maximum absolute error (MaxAE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean bias error (MBE)
- Standard deviation, skewness, kurtosis
  - ✓ Skewness: a positive (or negative) skewness of the forecast errors leads to a forecasting bias
  - ✓ Kurtosis: a measure of the magnitude of the peak of the error distribution and the thickness of the tails
- Kolmogorov–Smirnov test Integral (KSI)
  - ✓ KS test is to determine if two data sets differ significantly
  - ✓ The KSI is the integration of differences between the cumulative distribution function (CDF) for the two sets
- OVER
  - ✓ The OVER is also the integrated differences between the CDFs, but only for those in which a critical value V_c is exceeded

Proposed Metrics for Solar Forecasting

➤ **Variability Estimations**

- Different time and geographic scales
- Distributions of forecast errors: estimated using the kernel density estimation (KDE) method

➤ **Uncertainty Quantification**

- Standard deviation
- Rényi entropy: a larger Rényi entropy indicates a high uncertainty in forecasting

➤ **Ramping Metrics**

- Heat maps: allow the operator to simultaneously see the timing and magnitude of forecast errors
- Swinging door algorithm: extracts ramp periods in a series of power signals, by identifying the start and end points of each ramp
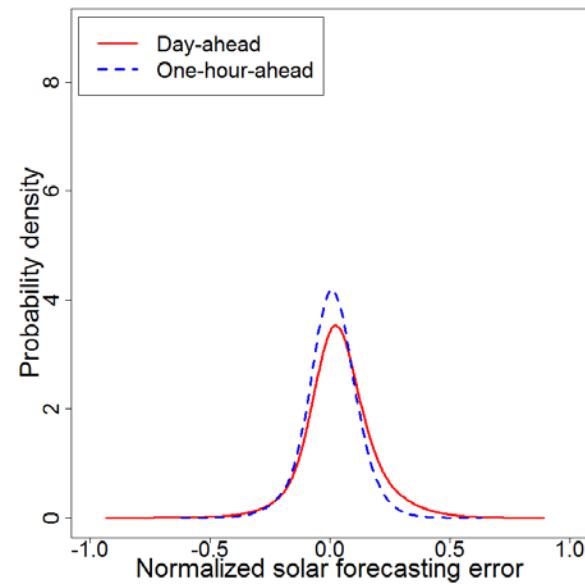
➤ **Economic Metrics**

- Flexibility reserves are (i) primarily determined by net load forecast error characteristics and (ii) represented by using hourly time steps and 95th confidence intervals of solar power forecast errors
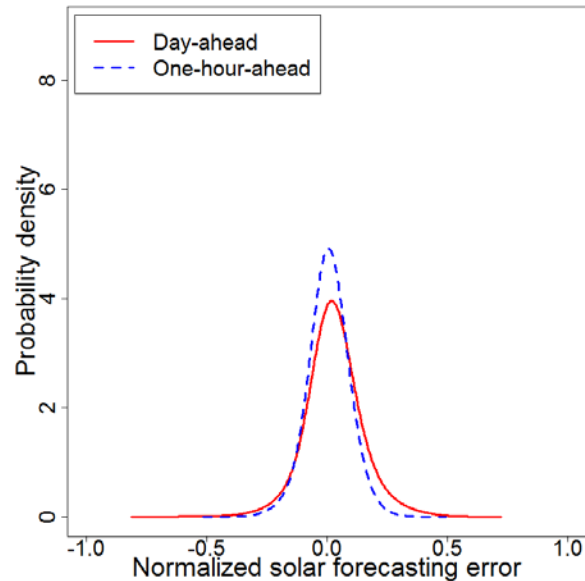
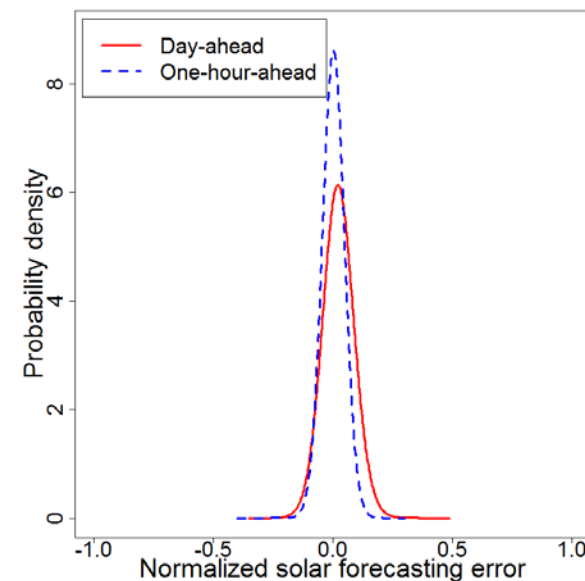# Distributions at Different Geographic Locations

One Plant
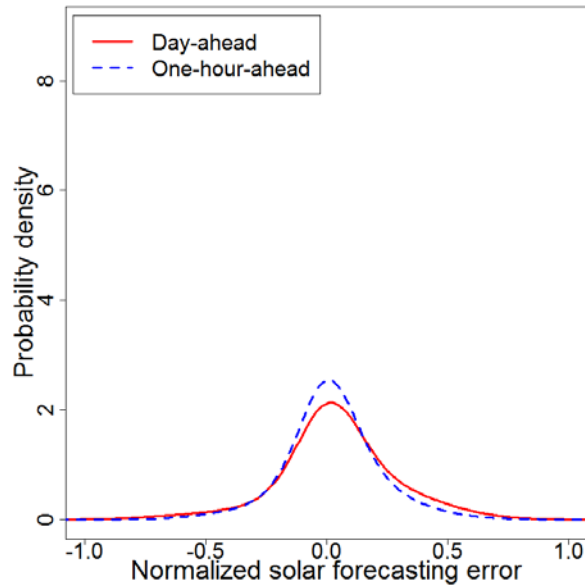
Denver

Colorado

Western Interconnection

Metrics Values Estimated by Using an Entire Year of Data

Metrics	One Plant		Denver		Colorado		Western Interconnection	
	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead
Correlation Coefficient	0.65	0.76	0.87	0.94	0.91	0.96	0.990	0.995
RMSE (MW)	22.07	17.12	438.25	284.36	624.19	378.65	2711.31	1488.28
NRMSE	0.22	0.17	0.13	0.08	0.10	0.06	0.04	0.02
MaxAE (MW)	84.10	74.33	2260.94	1304.73	3380.28	1735.24	17977.53	16127.32
MAE (MW)	14.81	11.34	286.65	191.17	413.11	256.69	1973.90	1064.52
MAPE	0.15	0.11	0.08	0.06	0.07	0.04	0.03	0.02
MBE (MW)	4.27	2.19	131.82	31.64	172.54	43.32	1497.29	132.13
KSIPer (%)	216.73	104.42	184.30	52.84	143.38	48.28	132.92	47.76
OVERPer (%)	136.36	28.16	94.43	0.77	54.65	0.37	41.43	0
Standard dev. (MW)	21.65	39.57	418.00	282.62	599.94	376.20	2260.09	1482.44
Skewness	-0.19	0.08	0.20	-0.20	0.18	-0.21	0.62	-0.23
Kurtosis	2.04	2.40	3.79	2.52	3.35	2.47	3.76	4.82
95th Percentile (MW)	50.59	39.57	990.66	637.45	1394.85	838.27	5652.60	3079.32
Capacity (MW)	100	100	3463	3463	6088	6088	64495	64495

Rényi Entropy at Multiple Spatial and Temporal Scales

- The length of the forecasting period affects the uncertainty in the forecasting.

- The uncertainty in the forecasting of the whole year data is less than that in any of the other cases (January, July, 14:00, and 10:00 to 16:00).

Cases	One Solar Power Plant		Denver Region		Colorado Region		Western Interconnection	
	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead	Day-ahead	1-hour-ahead
Year	4.83	4.64	4.24	4.63	4.33	4.73	4.47	4.01
January	4.71	5.06	5.18	5.06	5.46	4.79	5.24	5.11
July	4.64	4.74	4.25	4.87	5.02	5.09	4.75	4.86
14:00	5.07	5.00	4.83	4.99	5.13	5.27	4.97	5.72
10:00 – 16:00	4.95	4.73	4.60	4.79	4.82	4.94	4.90	4.45

Ramping: Heat Maps of Mean Forecast Errors
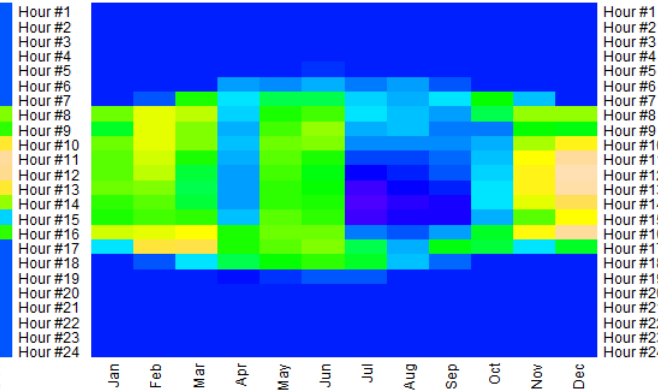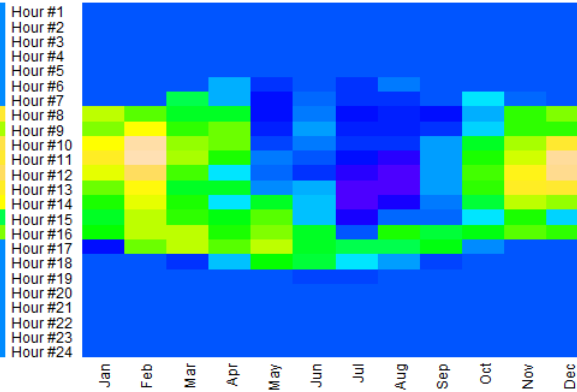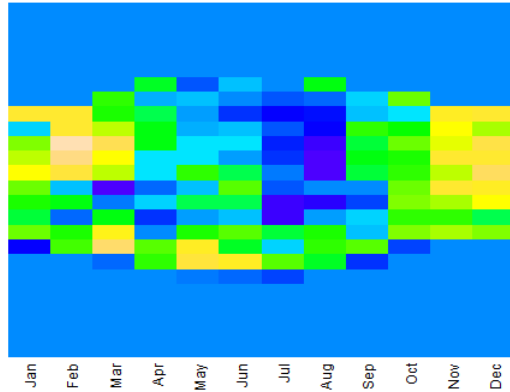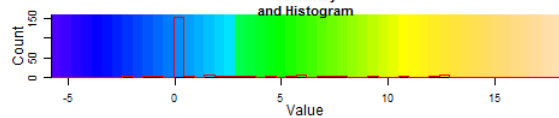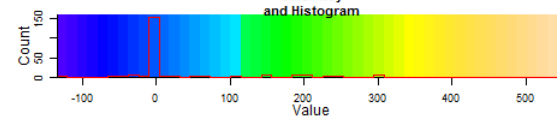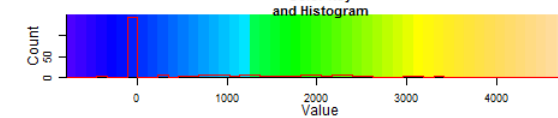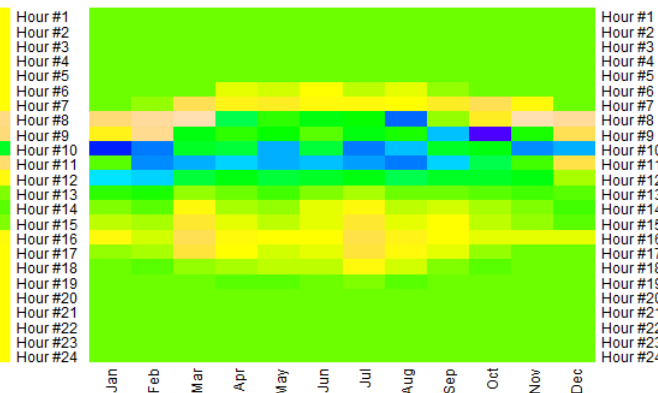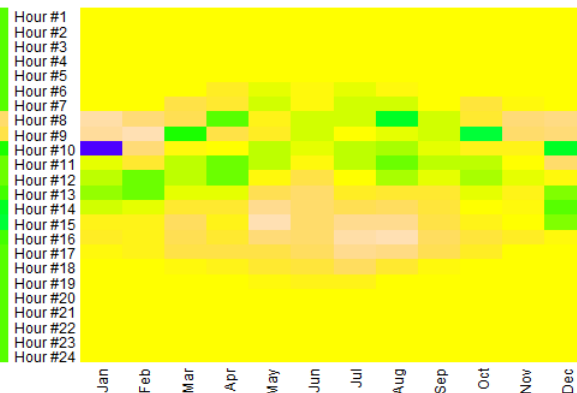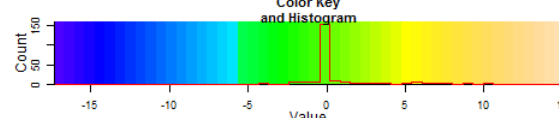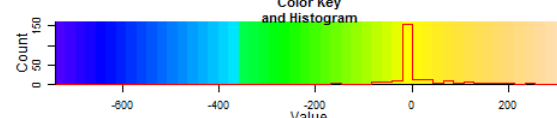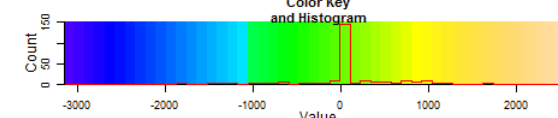
Solar Forecasting Improvement

- ➤ **Uniform Forecasting Improvement**
  - ▪ The uniform forecasting improvement is accomplished by examining the forecast error then essentially decreasing this error at each time period by a set percentage.

- ➤ **Ramp Forecasting Improvements**
  - ▪ The ramp extraction algorithm performs a piecewise linear approximation to the original signal (actuals and day-ahead forecasts).
  - ▪ Only ramps that exceed a threshold value (e.g., 20%) of the maximum plant capacity are modified in the improved forecasts.

- ➤ **Threshold Value:** percentage of the maximum wind power plant capacity
  - ▪ Range: 10% – 30%

Overall Structure of Metrics Analysis

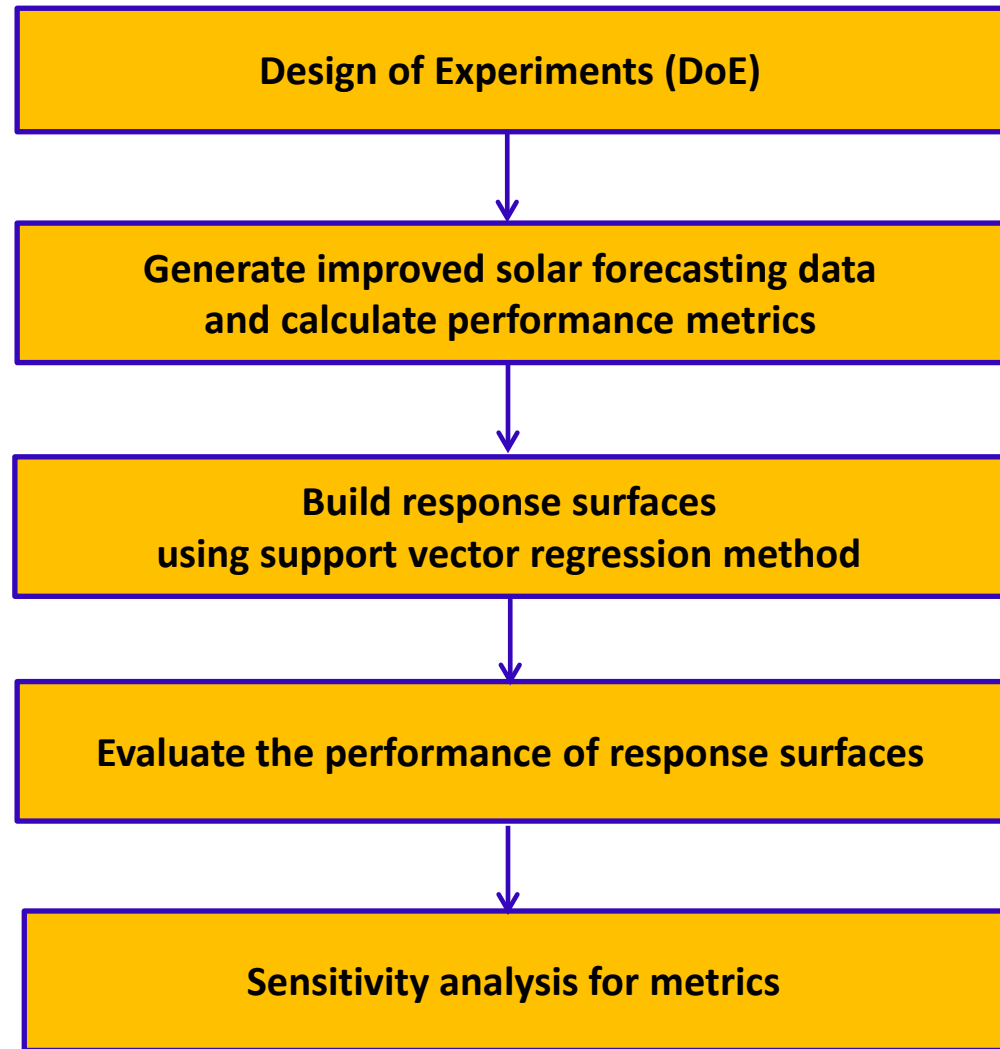- ➢ **Design of Experiments (DoE)**

  - ▪ Sobol's Quasi-random Sequence Generator

  - ▪ Sobol sequences use a base of two to form finer uniform partitions of the unit interval and reorder the coordinates in each dimension.

- ➢ **Surrogate Models**

  - ▪ Support Vector Regression

- ➢ **Sensitivity Analysis**

  - ▪ Extended Fourier Amplitude Sensitivity Test

Design of Experiments (DoE)

↓

Generate improved solar forecasting data and calculate performance metrics

↓

Build response surfaces using support vector regression method

↓

Evaluate the performance of response surfaces

↓

Sensitivity analysis for metrics

Surrogate Modeling Methods

- Surrogate modeling is concerned with the construction of approximation models to estimate the system performance and to develop relationships between specific system inputs and outputs.

- Support Vector Regression (SVR)

  - A regression method to construct smooth, nonlinear, regression approximations by formulating the surrogate model construction problem as a quadratic programming problem
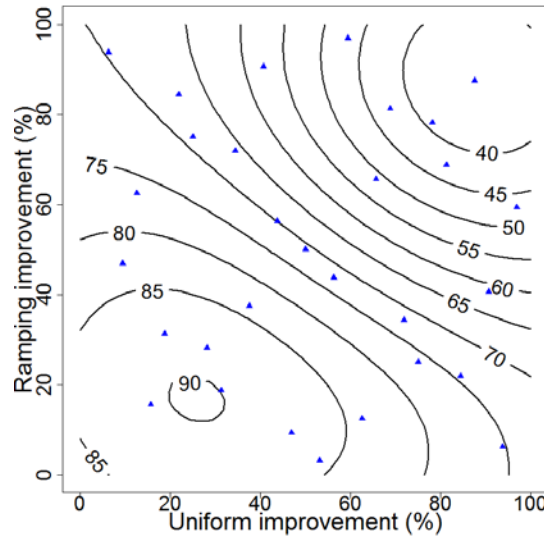
$$\tilde{f}(x) = \langle w, \emptyset(x) \rangle + b$$

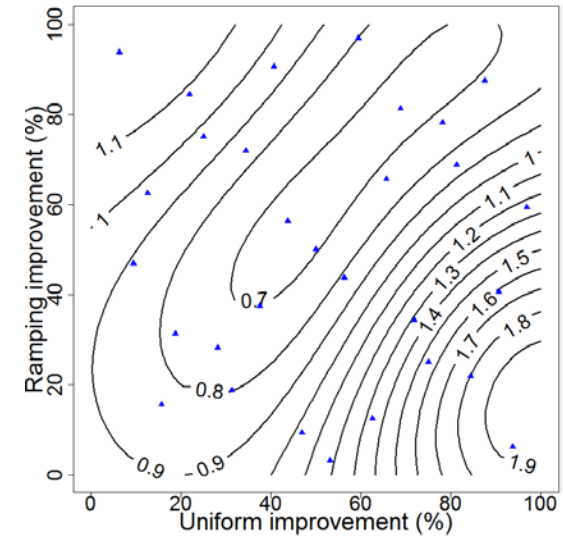# Surrogate Models of Multiple Metrics
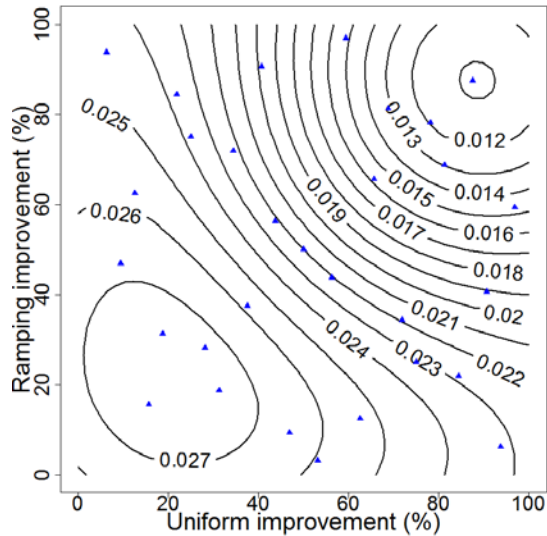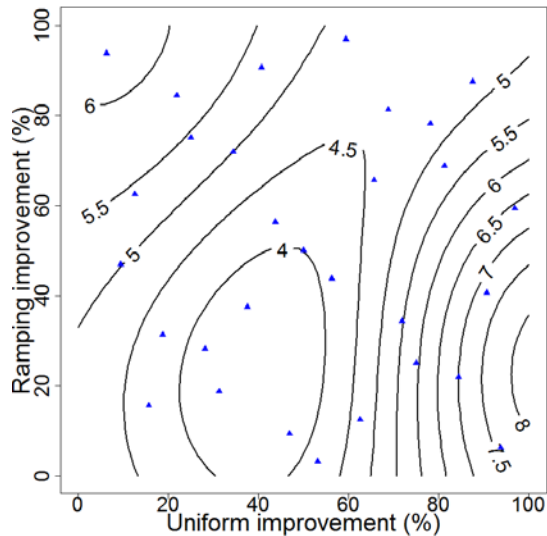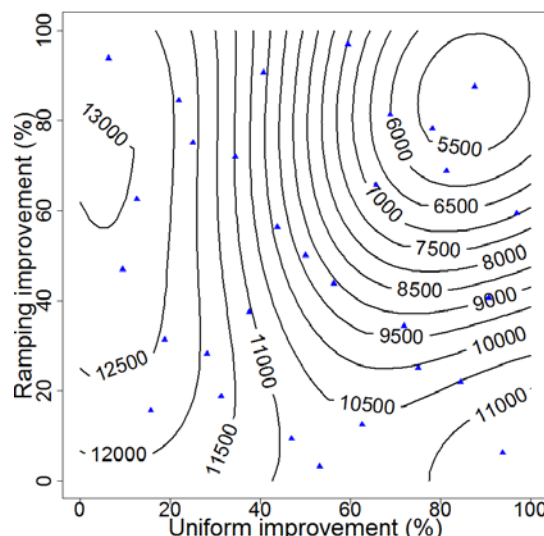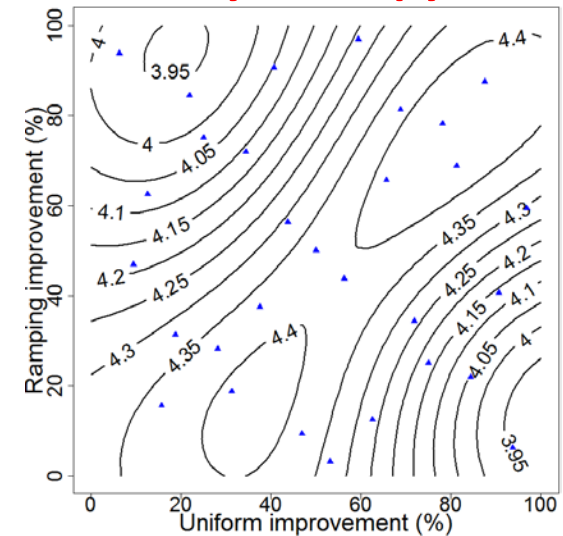
Sensitivity Analysis

- The Extended Fourier Amplitude Sensitivity Test

    - It is a variance-based sensitivity analysis method.

    - The sensitivity value is defined based on conditional variances that indicate the individual or joint effects of the uncertain inputs on the output.

    - *Main effect index*: measures the contribution of X_i alone to the uncertainty (variance) in Y

    - *Total effect index*: gives the total variance in Y caused by X_i and its interactions with any of the other input variables

Sensitivity Analysis of Metrics to Forecasting Improvements

Metrics	Uniform Improvement		Ramp Improvement		Ramp Threshold	
	Main effect	Total effect	Main effect	Total effect	Main effect	Total effect
R²	0.913	0.974	0.009	0.043	0.001	0.065
RMSE	0.883	0.958	0.016	0.060	0.000	0.088
NRMSE	0.883	0.958	0.016	0.060	0.000	0.088
MaxAE	0.899	0.977	0.011	0.063	0.002	0.057
MAE	0.896	0.955	0.016	0.056	0.003	0.077
MAPE	0.896	0.955	0.016	0.056	0.003	0.077
MBE	0.844	0.923	0.032	0.090	0.002	0.112
KSIPer	0.843	0.921	0.033	0.092	0.003	0.111
OVERPer	0.872	0.942	0.014	0.069	0.016	0.097
Standard Dev.	0.897	0.969	0.012	0.052	0.001	0.075
Skewness	**0.305**	**0.686**	**0.126**	**0.473**	**0.161**	**0.343**
Kurtosis	**0.394**	**0.858**	**0.041**	**0.169**	**0.081**	**0.207**
95th Percentile	0.886	0.965	0.013	0.060	0.002	0.082
Rényi Entropy	**0.120**	**0.624**	**0.071**	**0.599**	**0.260**	**0.463**

Concluding Remarks

➢ This paper proposed a suite of metrics for evaluating the performance of solar power forecasting.

  ▪ The performance of the proposed metrics was evaluated using the actual and forecast solar power data from WWSIS-2.

  ▪ The distribution of forecast errors indicates that relative forecast errors are smaller for a large geographic area.

➢ The results showed that the developed metrics can successfully evaluate the quality of a solar forecast.

  ▪ More over- than under-forecasting events were observed for the 1-hour-ahead solar forecasting; whereas the day-ahead forecasting tended to be under-forecast in summer.

➢ A sensitivity analysis methodology was developed based on a design of experiments and response surfaces approach:

  ▪ All proposed metrics were sensitive to solar forecasts with uniform forecasting improvements.

  ▪ The metrics of skewness, kurtosis, and Rényi entropy were also sensitive to solar forecasts with ramp forecasting improvements and ramp forecasting threshold.

Future Work

Future Work

- Determine baseline values and achievable target values for the metrics for independent system operators and utilities.

- Develop a suite of probabilistic solar forecasting metrics.

Acknowledgement

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Questions?