High-Fidelity, Robust Forecast Engines for Variable Energy Production & Demand

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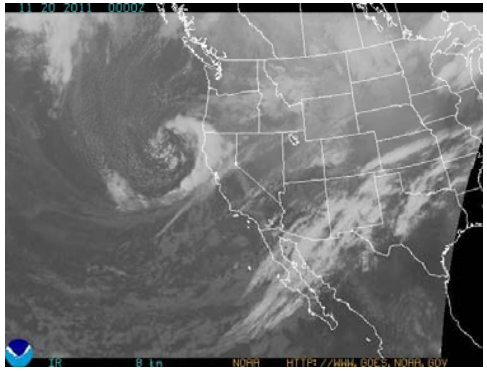
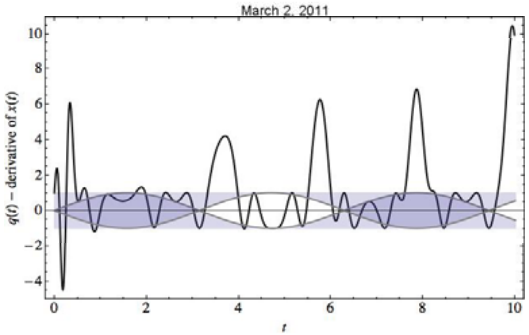
Forecast Engine Laboratory

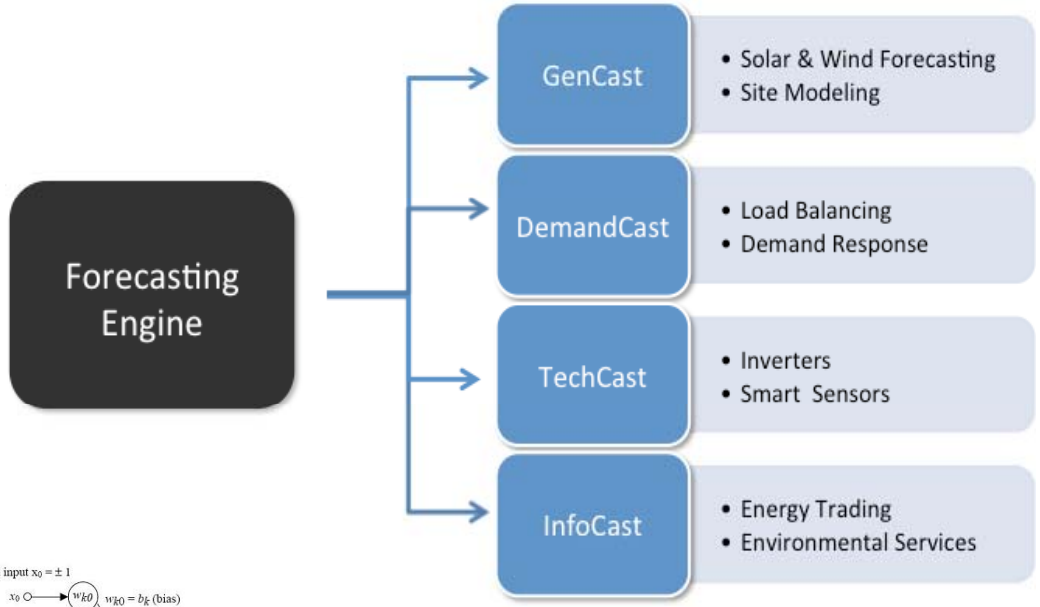
UC San Diego

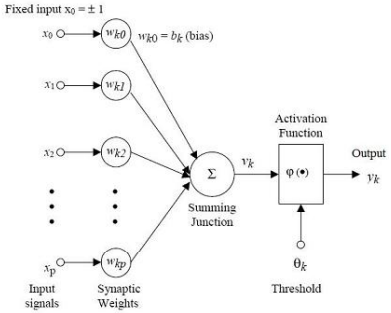


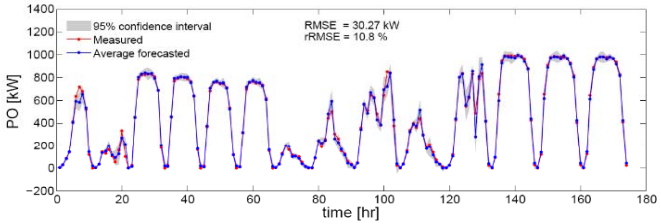
Multiple Inputs Generate High-Fidelity, Full Temporal Spectrum Forecasts

SolAspect's Commercial Products





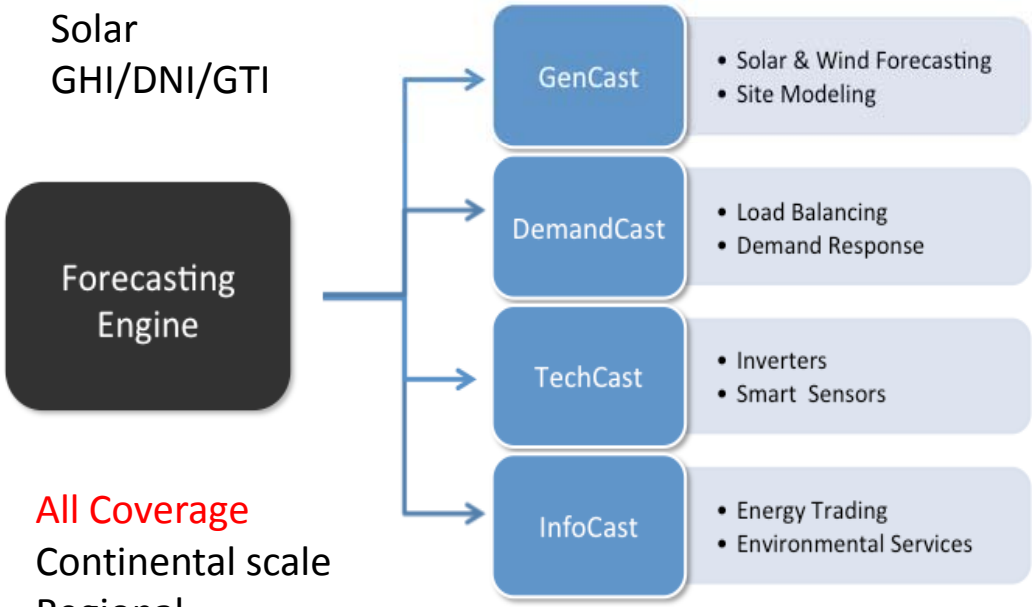




Full Spectrum Forecasting Engines

All Applications
Load
Wind
Solar
GHI/DNI/GTI

All Time Horizons
Intra-minute
Intra-hour
Intra-day
Intra-week



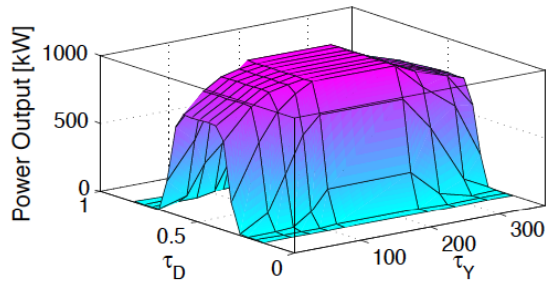
All Types of Data
No telemetry at all
Met time series
Forecast time series
Ground images
Satellite images

All Coverage
Continental scale
Regional
Substation level
Solar/wind farms
Sensor level

The Merced Testbed – 8.5 acres, 1 MW of TPV

1 hour ahead PV power forecasts with no telemetry and no image processing

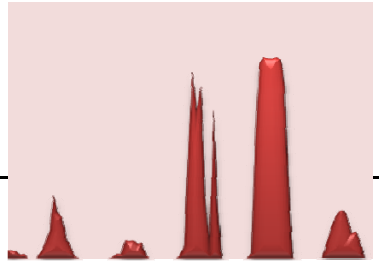
- Performance of "traditional" forecasting methodologies:
  - Persistent(Δt): PV(t+Δt) = PV(t)
  - S_Persistent(ω, CI): PV(t+Δt) = PV(t, ω, CI)
  - ARIMA
  - k-Nearest-Neighbors (kNN)



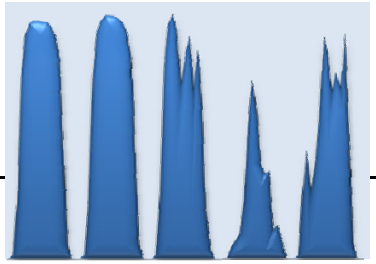
- No exogenous variables

	RMSE [kW]				R^2			
Method	Tot	P_1	P_2	P_3	Tot	P_1	P_2	P_3
Persistent	172.60	165.70	186.62	181.82	0.80	0.79	0.78	0.79
S_Persistent	**116.54**	129.18	124.09	**42.07**	**0.91**	0.87	0.90	**0.989**
$ARIMA_{413}$	123.06	**124.80**	**121.22**	120.01	0.898	**0.881**	**0.90**	0.90
kNN	126.47	139.79	133.66	52.58	0.892	0.851	0.882	0.981

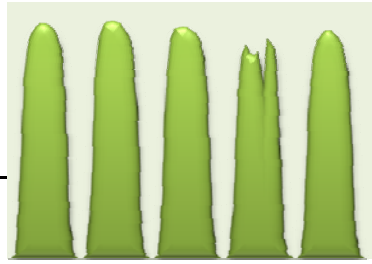
P_1: High variability



P_2: Intermediate variability



P_3: Low variability



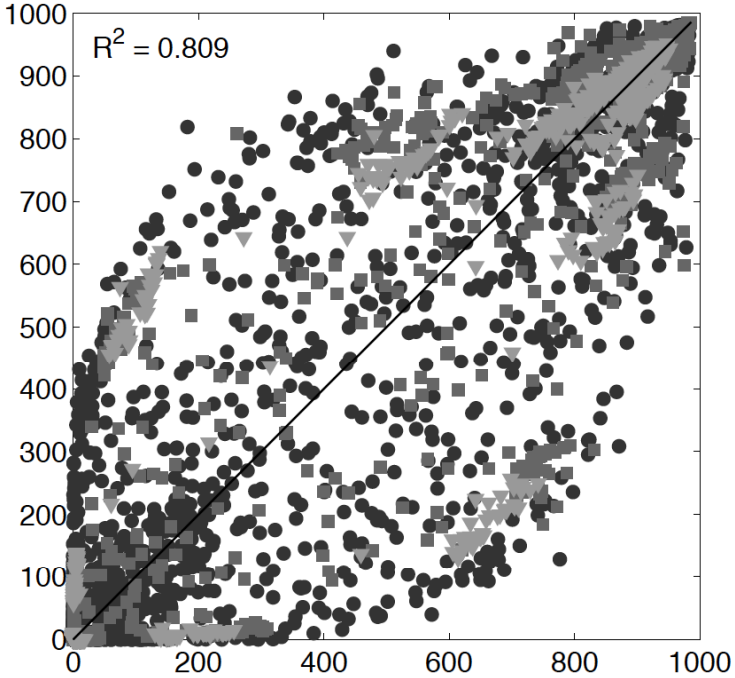
1 hour ahead PV power forecasts with no telemetry and no image processing (no exogenous variables)

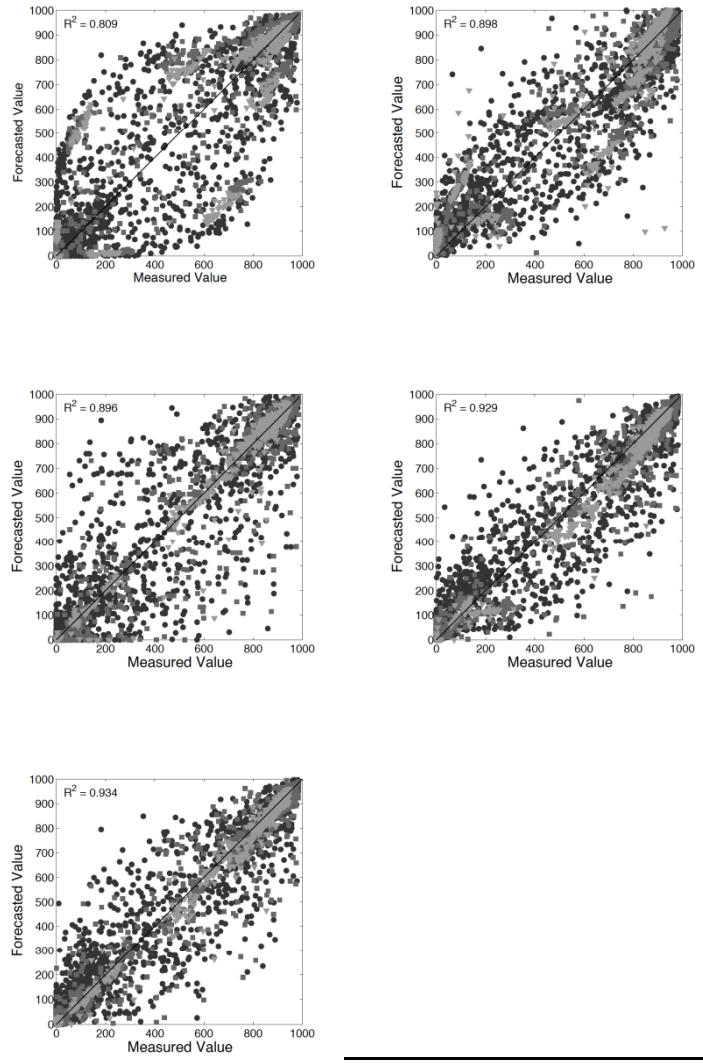
- More advanced forecasting techniques:
  - Artificial Neural networks (ANN)
  - ANNs optimized by Genetic Algorithms (GA/ANN)
  - GA/ANN with Fractional Order preprocessing (ENIO™)

	RMSE [kW]				R^2			
Method	Tot	P_1	P_2	P_3	Tot	P_1	P_2	P_3
Persistent	172.60	165.43	183.97	178.71	0.80	0.79	0.78	0.79
S_Persistent	116.54	129.18	124.09	42.07	0.91	0.87	0.90	0.989
$ARIMA_{413}$	123.06	124.80	121.22	120.01	0.898	0.881	0.903	0.9
kNN	126.47	139.79	133.66	52.58	0.892	0.851	0.882	0.981
ANN	104.3	114.54	107.53	56.15	0.927	0.9	0.923	0.978
GA/ANN	99.24	110.87	102.17	40.28	0.934	0.906	0.931	0.989
ENIO™	88.78	101.42	83.67	39.97	0.95	0.92	0.95	0.989

Scatter plots for 1 hour-ahead forecasts (4 seasons)

Persistent





Legend:

High variability period P_1

Intermediate variability period P_2

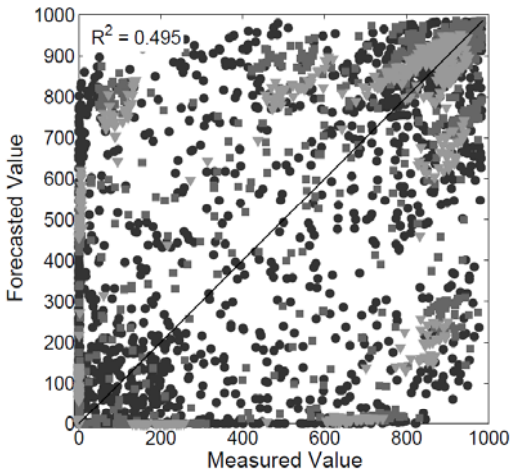
Low variability period P_3

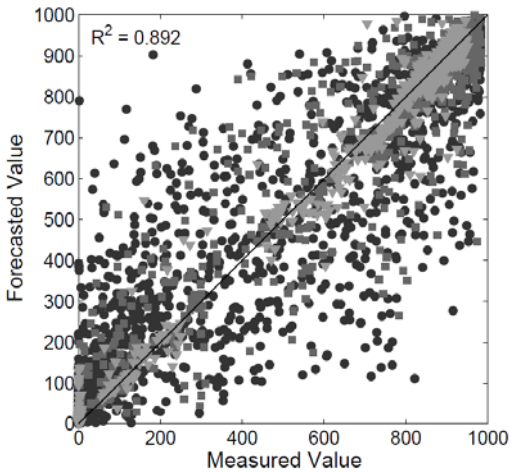
2 hours ahead PV output forecasts

(18 months of data)

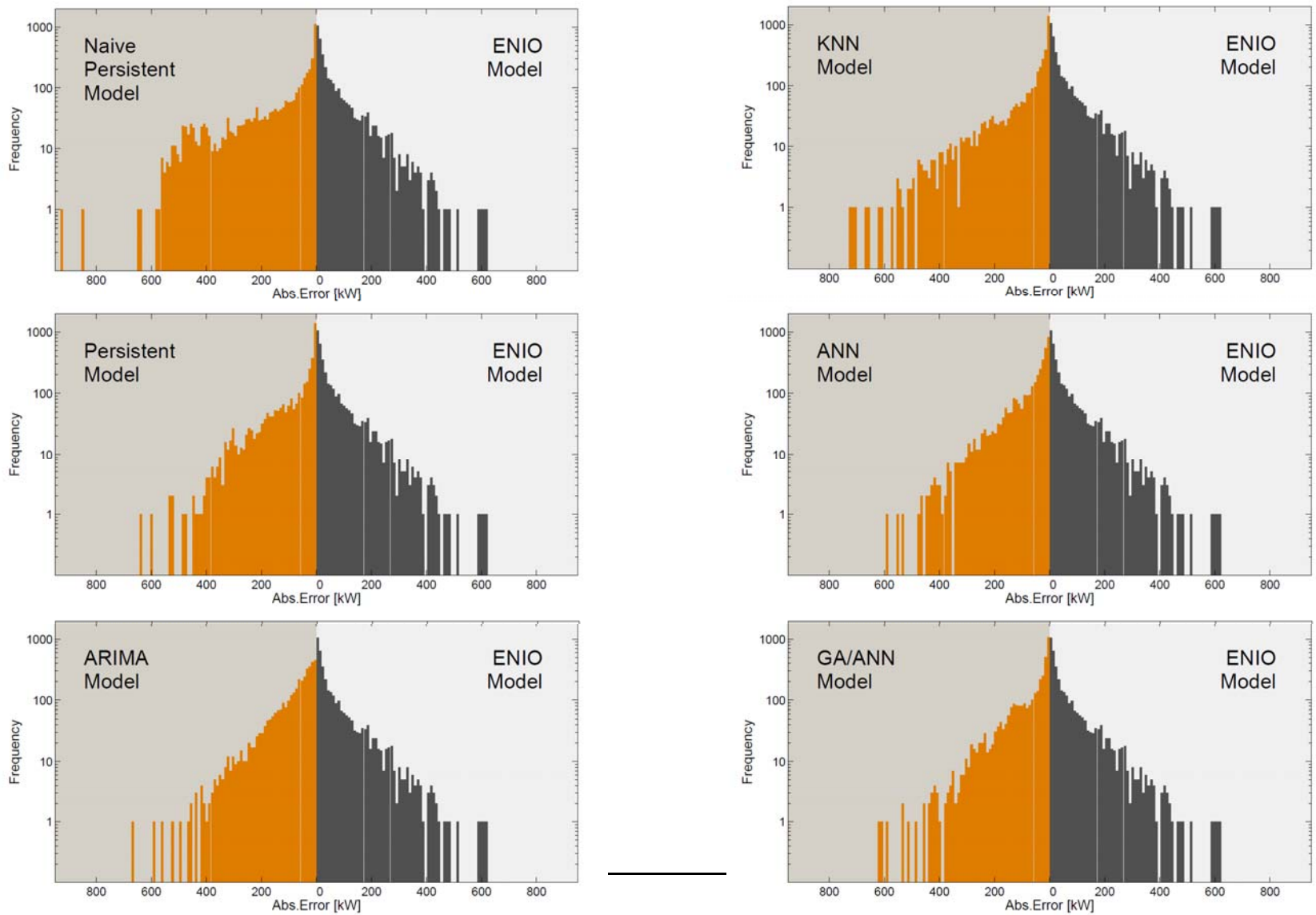
- The ENIO forecast for 2 hours ahead is much better than the 1 hour ahead forecast with traditional methods.

	RMSE [kW]				R^2			
Method	Tot	P_1	P_2	P_3	Tot	P_1	P_2	P_3
Persistent	296.9	277.7	320.0	322.0	0.40	0.41	0.32	0.28
ENIO	126.9	147.0	116.6	49.3	0.89	0.83	0.91	0.98





Comparison of Error histograms for the 1hr ahead Forecasting



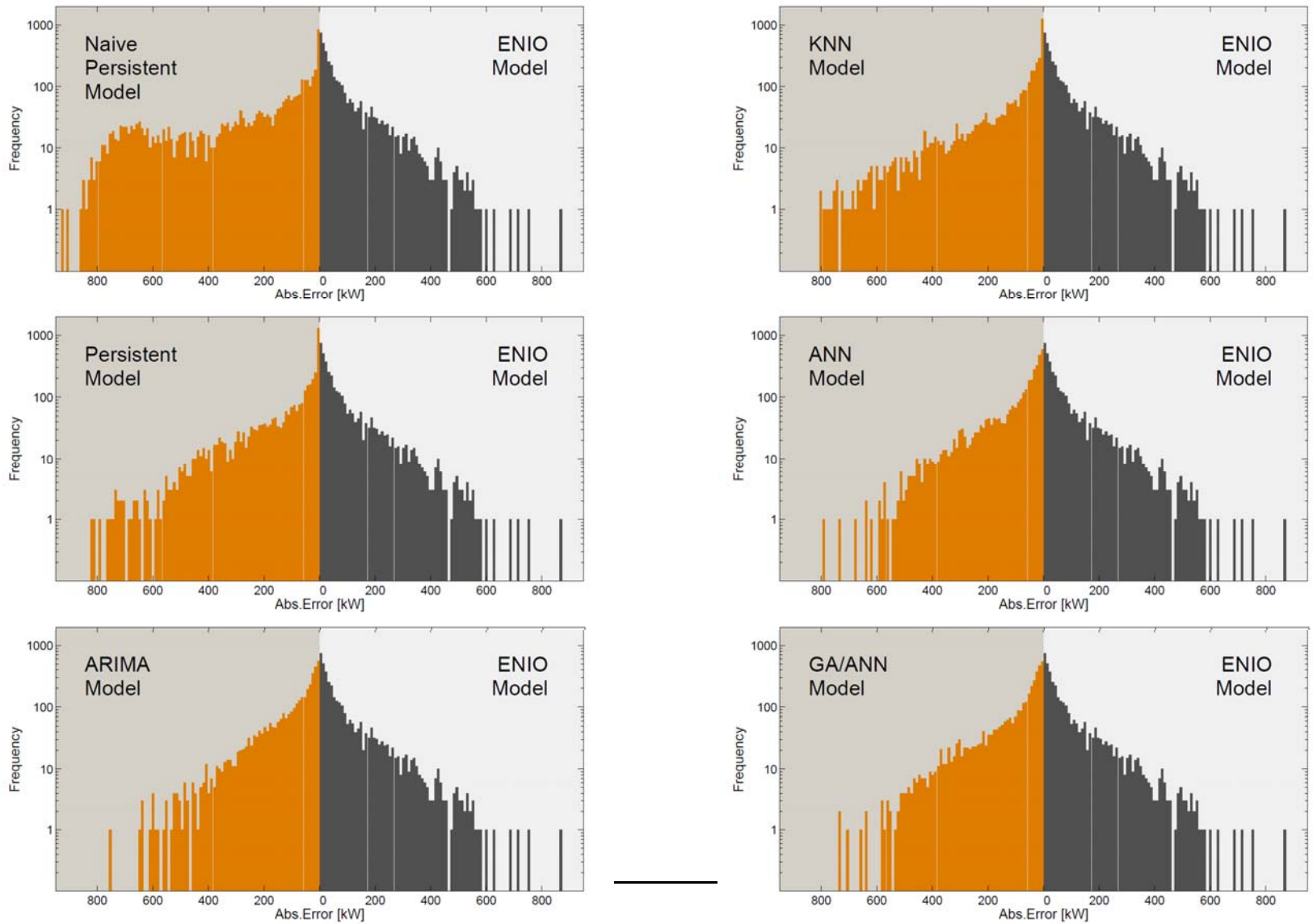
2 hours ahead PV power forecasting

(PO_{stat} + PO_{expect})

- Forecasting techniques:
  - Naïve Persistent, Persistent, ARIMA, kNN
  - Artificial Neural networks (ANN)
  - Optimized ANNs with Genetic Algorithms (GA/ANN)
  - GA/ANN with Fractional Order preprocessing (ENIO)

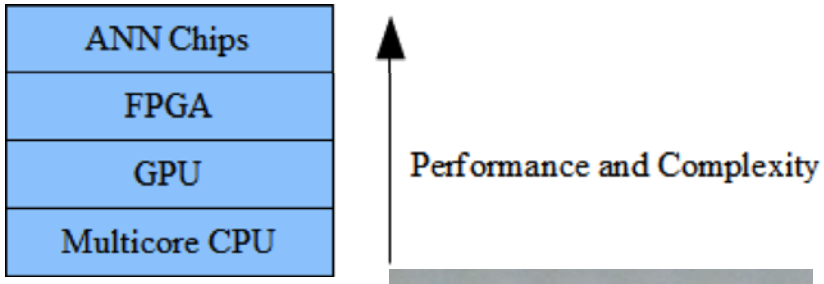
	RMSE [kW]				R^2			
Method	Tot	P_1	P_2	P_3	Tot	P_1	P_2	P_3
Persistent	296.9	277.7	320.0	322.0	0.40	0.41	0.32	0.28
S_Persistent	160.79	164.33	160.93	149.29	0.83	0.79	0.83	0.85
$ARIMA_{18,1,19}$	136.21	153.38	133.57	65.38	0.88	0.82	0.88	0.97
kNN	162.37	182.39	167.56	55.56	0.82	0.75	0.82	0.98
ANN	142.70	154.05	148.51	88.97	0.86	0.82	0.85	0.95
GA/ANN	143.22	152.97	149.46	96.73	0.86	0.82	0.85	0.94
ENIO	120.10	142.92	124.18	51.91	0.89	0.84	0.90	0.98

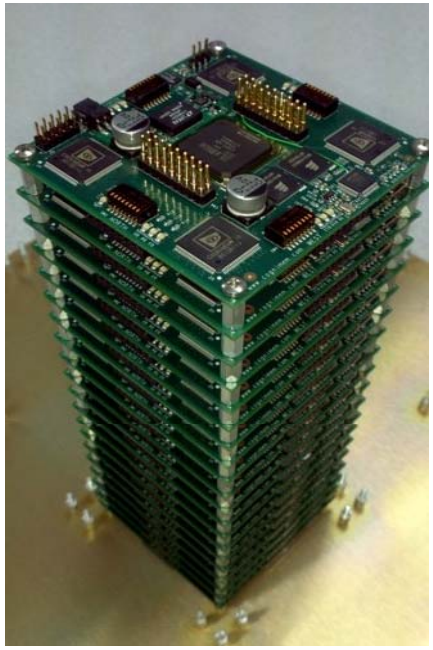
Comparison of Error histograms for the 2hr ahead Forecasting



Neurochip Board (1024 Neurons) and Neurostacks (up to 1M Neurons)
A Natively Parallel Platform Dedicated to Real-Time Forecasting
With the ENIO™ Algorithm:
Hardware Meets Software for Performance

SolAspect's Cloud Tracker™ Board Includes a Field Programmable Gate Array (FPGA), a Neurochip board and a high-resolution CCD Camera with fisheye lenses + filters





A NeuroStack with 50,000+ neurons (Global Sensing/CogniMeM™)

Forecasting with Exogenous Variables

- Intra-hour forecasting of DNI using sky images or intra-day forecasts using satellite images, telemetry, NSW, NDFD, etc.
  - Use high frequency images taken with total sky imagers
  - Images are processed and converted into numerical datasets and fed to ENIO algorithm
  - High-fidelity forecasts are produced by single pass through ENIO™ forecasting engine, which enhances accuracy of image translation

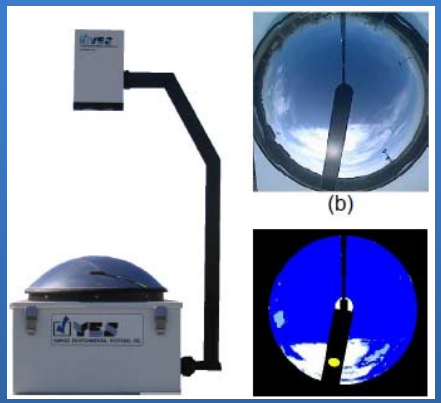
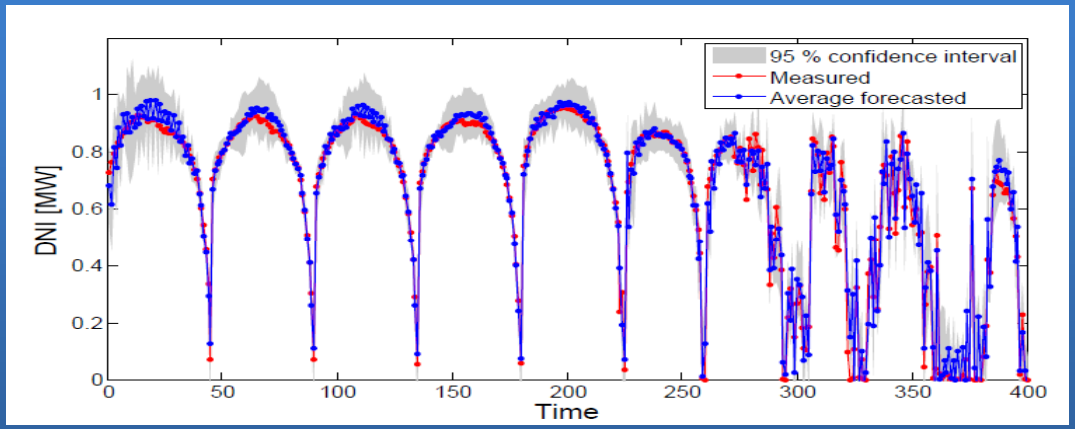
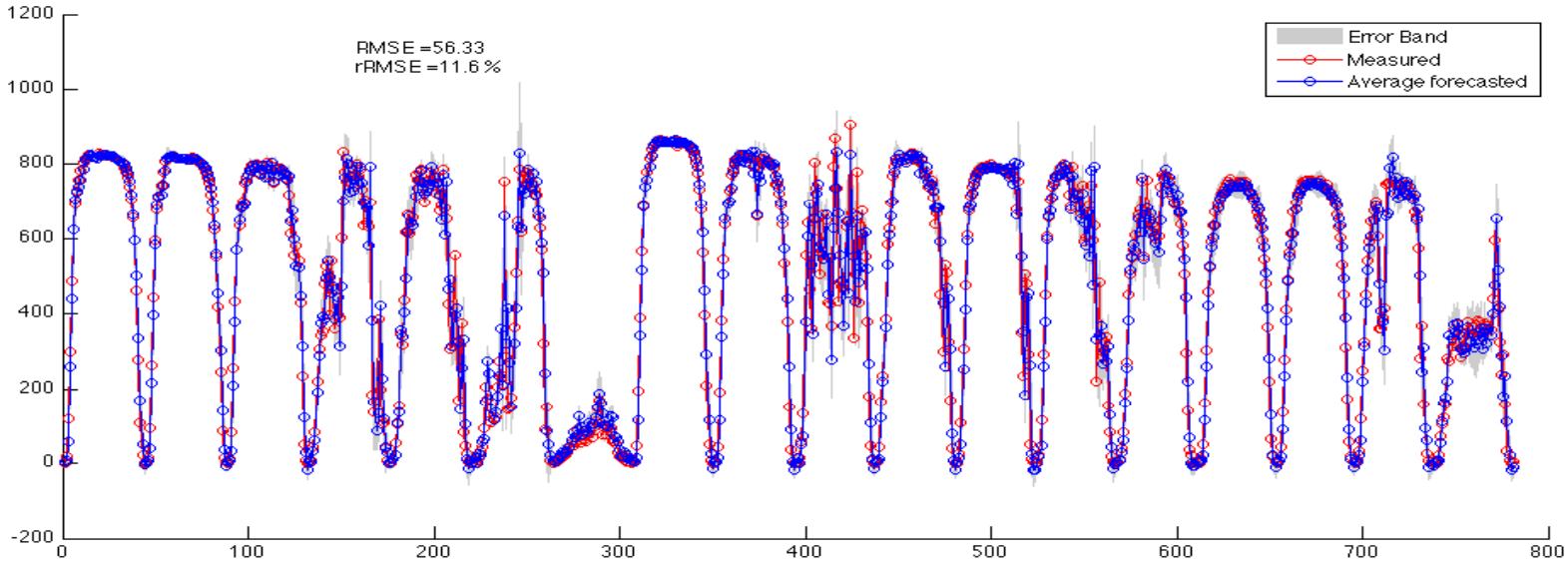
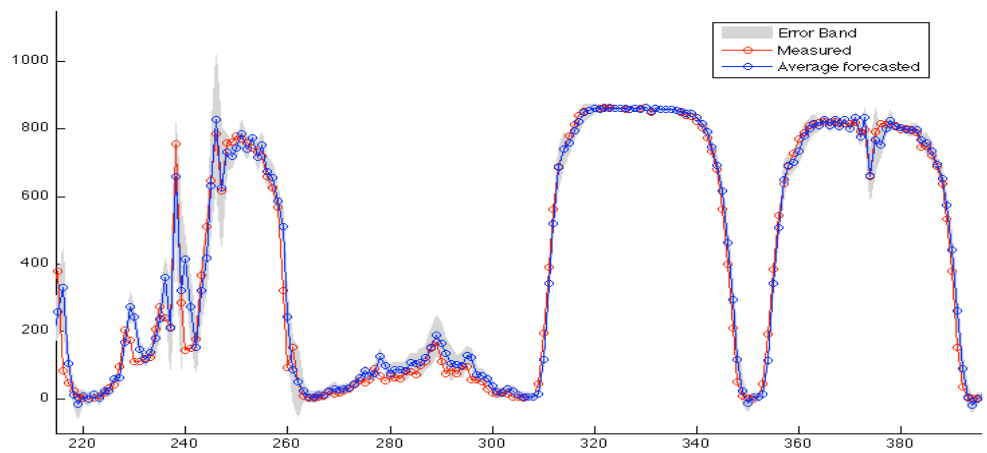


Image capture

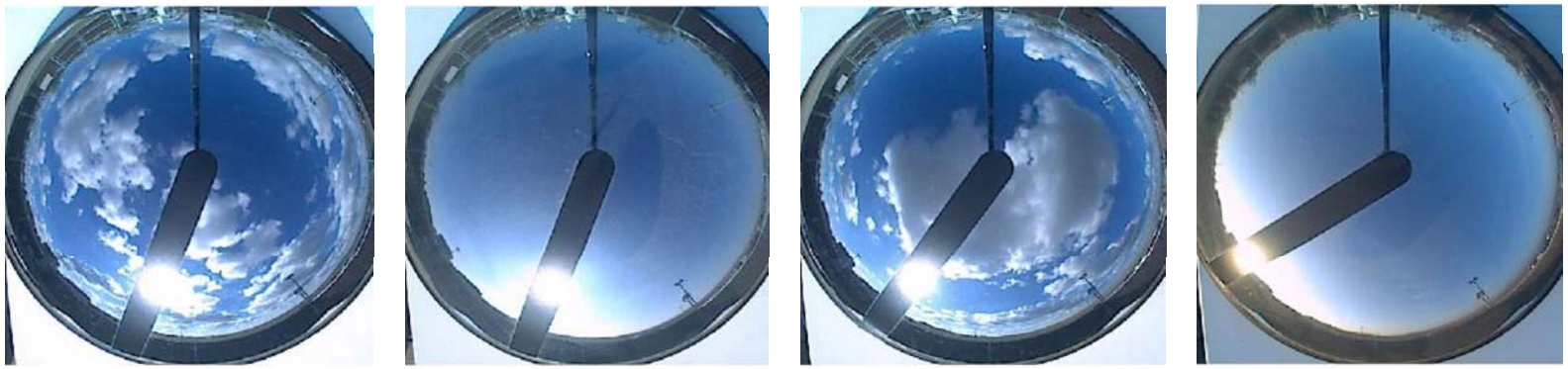


ENIO™ 15 minutes ahead for GHI



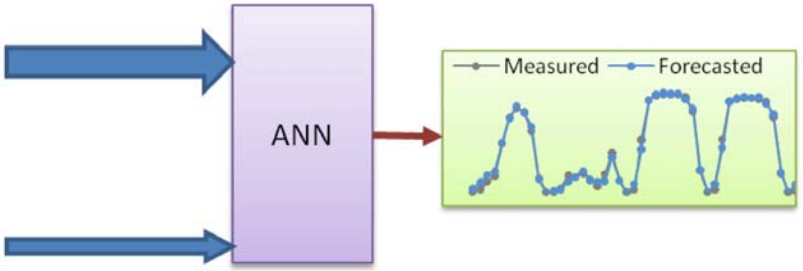


Tracking Method for TSI/Satellite Image Processing as Time Series Inputs to ENIO™



Inputs:

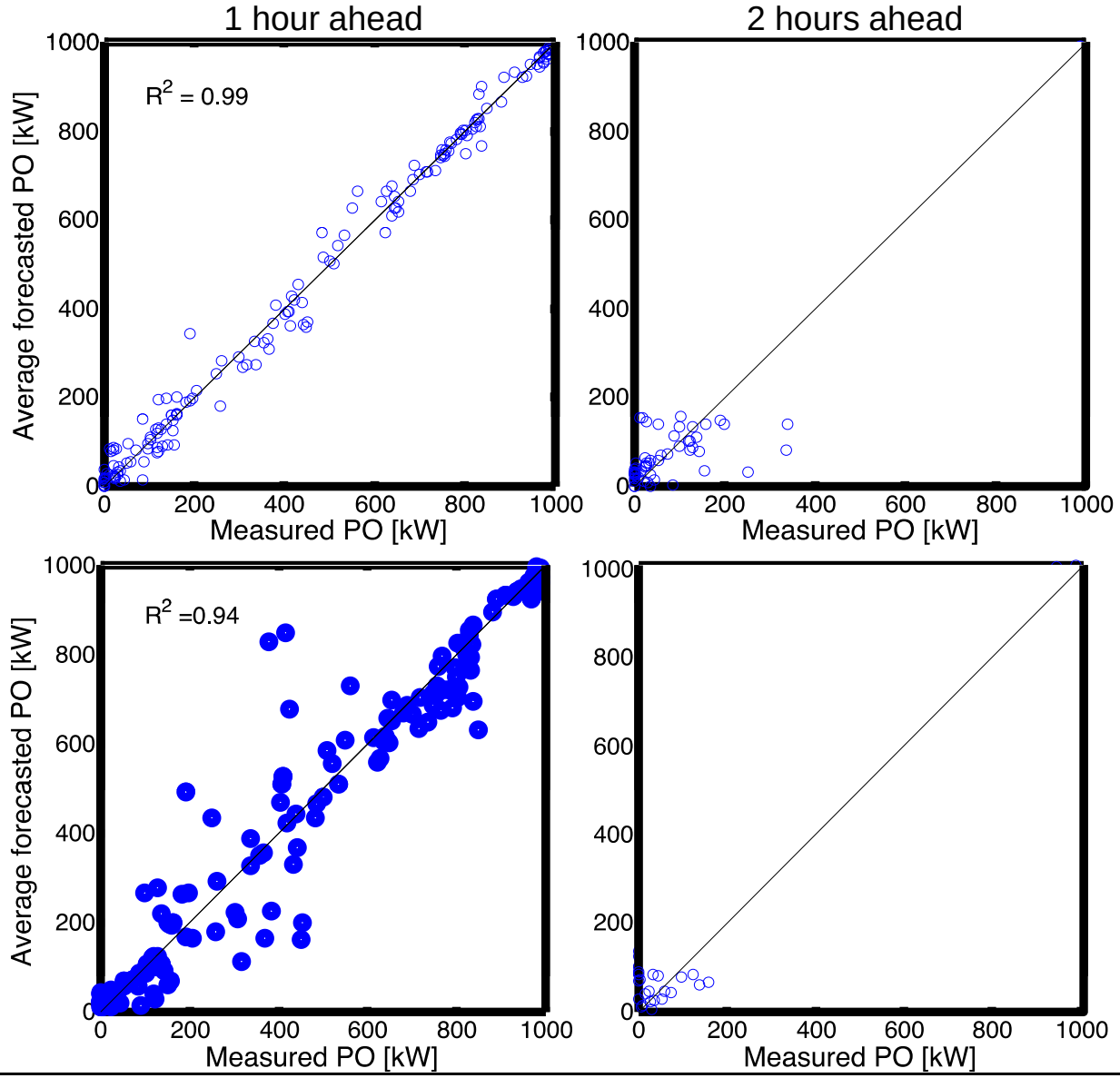
- Present and past values of radiation (DNI, GHI, etc)
- Present and past values of meteorological variables
- Cloud cover imaging



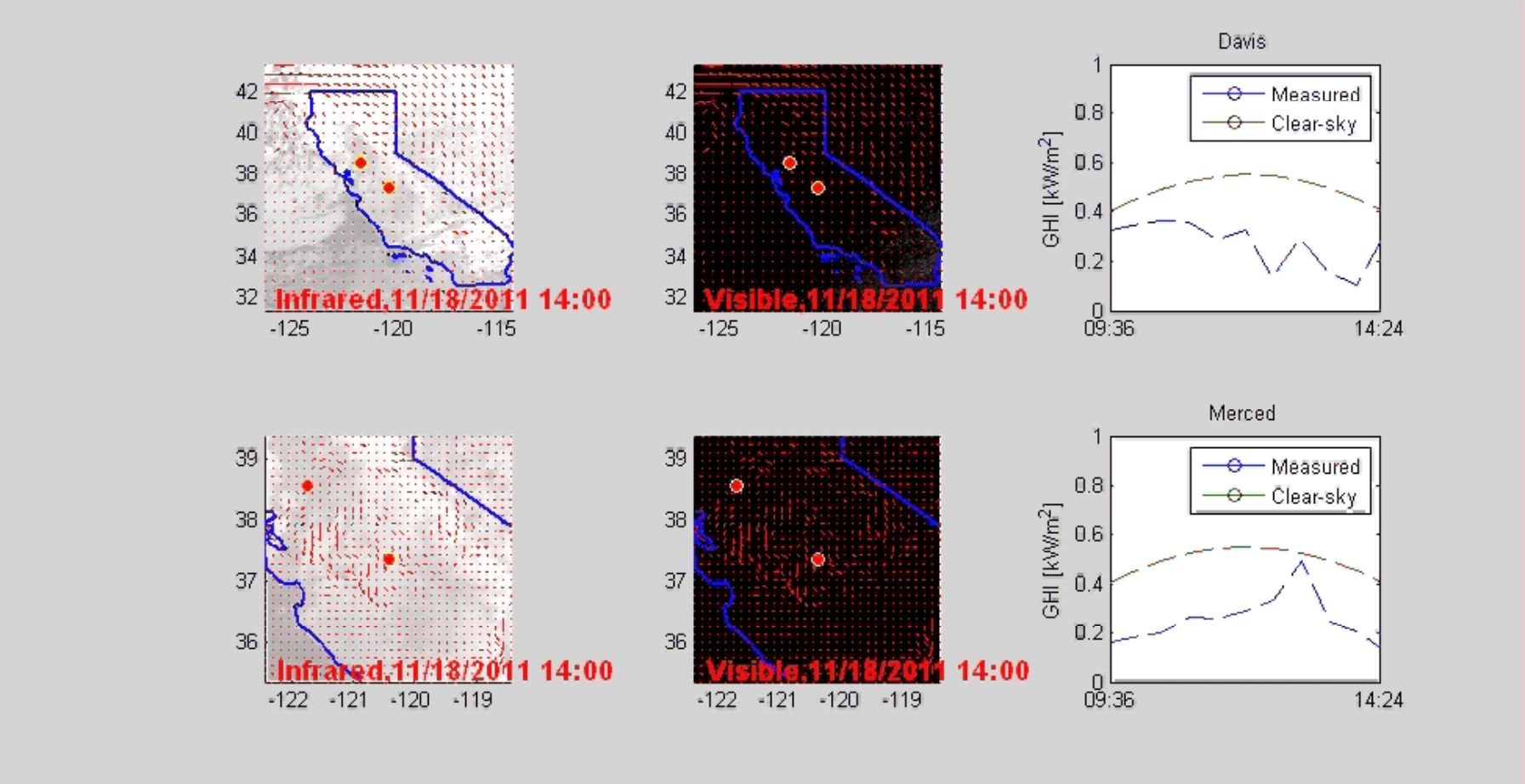
Head-to-Head Comparison for 2 Weeks of High-Variability Weather

SolAspect's ENIO™

Best GA/ANN



Cloud Image Velocimetry for 1-6 Hours Ahead: Continental Scale



Accurate Tracking of Cloud Speed in the Projection of the Sun

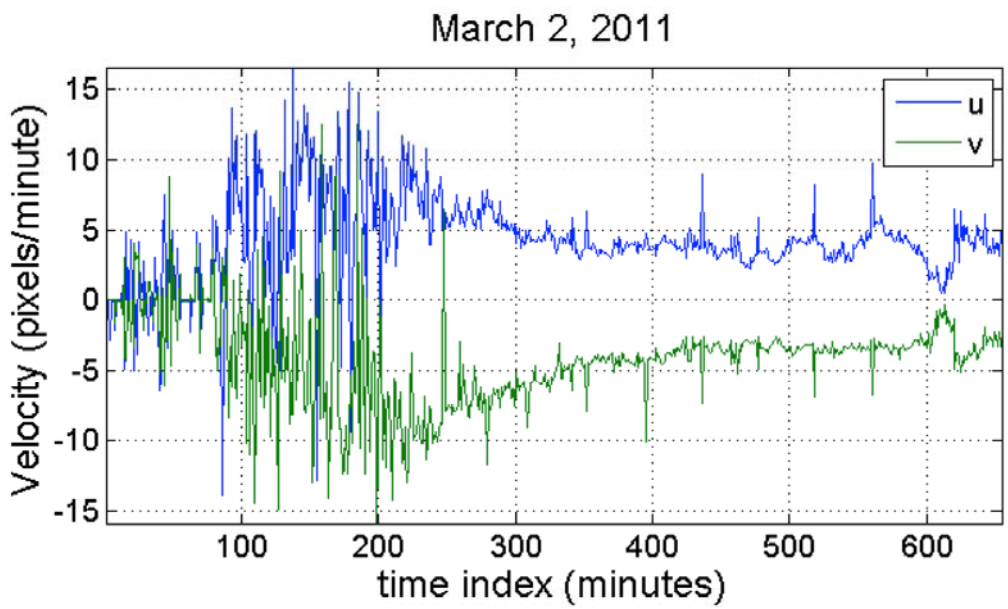


Figure 3.2. Time series of representative velocity components for each image gathered for March 2, 2011. The representative velocity components are obtained from clustering of the velocity vector fields.

Image Translation to Produce Forecasts

Image Translation Pass Through Forecasting Engine for Pattern Learning

Points Worth Mentioning

- The Evolutionary Non-Integer Order (ENIO™) algorithm offers unprecedented robustness and forecasting skills using the most diverse sets of inputs (no exogenous variables, no telemetry, with or without image processing, remote sensing and/or meteorological inputs, etc.)

- One of the most difficult tests for a forecasting engine is the uni-variate forecast (no exogenous inputs), for which the ENIO™ method outperforms all other methods, including very sophisticated and much slower GA/ANN algorithms that scan the whole space of solutions for optimal parameters.

- ENIO's flexibility in handling different inputs, and its continuous learning capability make it a perfect forecasting/modeling engine to reduce translation errors from deterministic models in real-time.

- The ENIO algorithm has been productized by SolAspect for solar, wind and load forecasting, and is ready to interact with other models and inputs.