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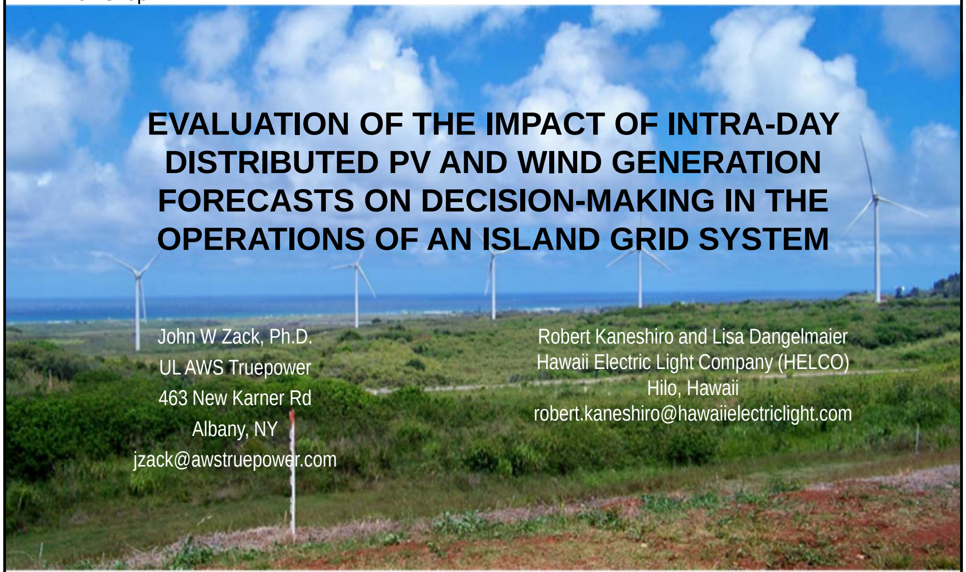
Tenerife, Spain



EVALUATION OF THE IMPACT OF INTRA-DAY DISTRIBUTED PV AND WIND GENERATION FORECASTS ON DECISION-MAKING IN THE OPERATIONS OF AN ISLAND GRID SYSTEM

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OVERVIEW

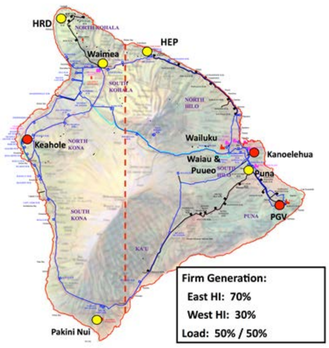
Objective: Develop and apply a forecast performance metric that provides a meaningful indication of the value of wind and solar forecasts to operational grid management decision-making

- System Overview: Hawaii Electric Light Company (HELCO) – Big Island
- Some Key Daily Operational Decisions Impacted by Renewable Generation
- Case Examples: Morning Peak Load Issues
- Traditional vs. Customized & Targeted Forecast Evaluation

BIG ISLAND/HELCO - THE CURRENT ISSUES: KILAUEA ERUPTS…



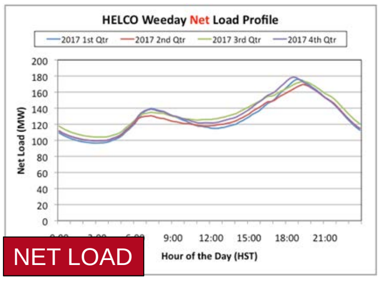

HELCO SYSTEM: GENERATION RESOURCES



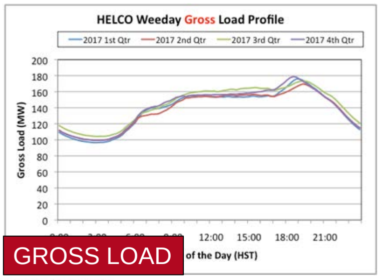
Renewable Resource	Capacity
Geothermal	38 MW
Hydro (3 gens)	16.2 MW
Wind (2 gens)	31 MW
PV (BTM distributed)	90 MW

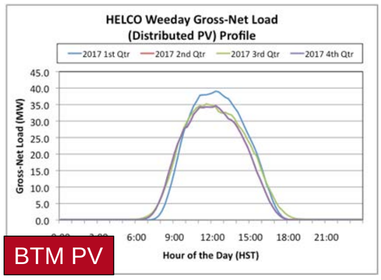
Base 24-hr Units
Hill 5 & 6 Steam Units
Keahole I1st CT in combine cycle (CC)
PGV (Geothermal)
Intermediate Units
Keahole 2nd unit in CC
HEP 1st and 2nd in CC
Peaking/Emergency Units
Kanoelehua CT-1
Keahole CT-2
Puna CT-3
Puna Steam Unit
12 Small Diesel Generators
As Available - Must Take
HRD Wind Farm (10.5 MW)
Pakini Nui Wind Farm (20.5 MW)
Walluku Hydro (12 MW)
Puueo Hydro (3.1 MW)
Waiau Hydro (1.1 MW)

HELCO: TYPICAL LOAD PROFILES



- Weekday Net load: 2 daily peaks
  - o Morning (~0800): 130-140 MW
    - Morning rise in gross load followed by morning rise in PV production
  - o Evening (~1800): 170-180 MW
- Weekday Net load: 2 daily minima
  - o Nighttime (~0300): 95-105 MW
  - o Daytime (~1200): 115-125 MW
    - Associated with peak of 35-40 MW of distributed PV production

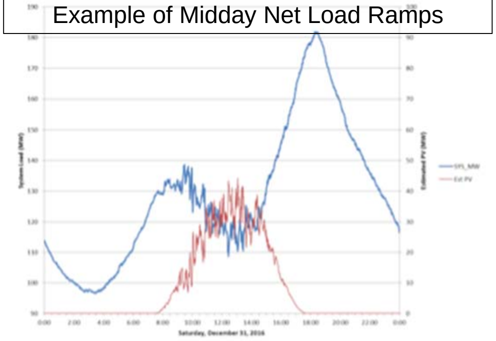




KEY DECISION-MAKING TIME FRAMES AND ISSUES

- 0500 HST: Preparation for morning peak and mid-day minimum
- 1000 HST: Midday net load ramps
- 1300 HST: Preparation for evening peak

Example of Midday Net Load Ramps

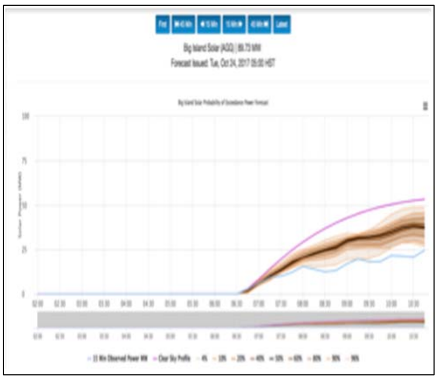


MORNING (0500 HST) DECISION-MAKING PERIOD

- System Management Issues
  - Will mid-day net loads be low enough to shutdown a unit after the morning peak?
    - o If YES: simple cycle CT that has no start/stop restrictions but less efficient can be used to serve the morning peak then shutdown when no longer needed.
    - o IF NO: more efficient combine cycle (CC) CT will be used throughout the day
    - o One CC plant has a start/stop restriction: no multiple starts in a calendar day
  - Will an excess energy situation occur due to high "as available" generation?
    - o Determine whether curtailment of the as-available renewable generation OR taking a unit offline will best address the situation
- Critical Forecast Questions
  - Will the distributed solar generation rise to its typical midday values or higher or will there much below normal solar generation?
  - Will the wind generation increase or decrease from its pre-sunrise level and thus either contribute to or offset a potential excess energy situation?

WIND AND SOLAR FORECAST SYSTEM: SWIFT

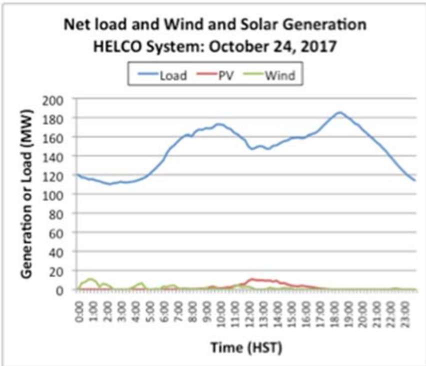
Example of a SWIFT Forecast Display



- Forecasts are produced from an ensemble of prediction-methods (physics-based and statistical)
- Two Forecast Time Frames
  - o Intra-day
    - 0-6 hrs ahead in 15-min time steps
    - 15-min updates
  - o Multiple Day
    - 0-7 days ahead in 1-hr time steps
    - 1 hr updates
- Probabilistic Format
  - o 10 Probability of Exceedance (POE) values
  - o 50% POE used as deterministic forecast
- Target Entities
  - o Utility-scale PV & wind generation facilities
  - o Substation aggregates of distributed PV
  - o Regional and system (island) aggregates

CASE EXAMPLE #1: OCTOBER 24, 2017
HIGH DAYTIME NET LOAD

Hot, humid, cloudy & very light winds

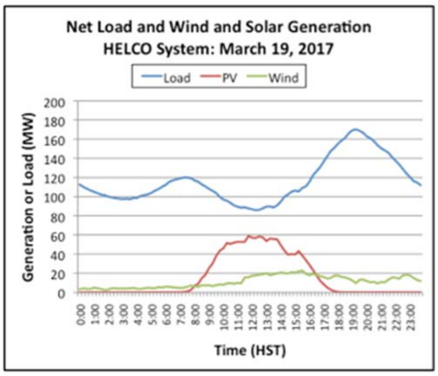


- Unusually high mid-day gross load
  - o Warm and humid -> high AC load
  - o Not anticipated – no weather dependent load forecast available
- Very low distributed PV production
  - o Much more cloudiness than typical
  - o SWIFT indicated a cloudy day but underestimated magnitude
- Near-zero wind production
  - o Was near zero before sunrise and remained at that level
  - o SWIFT predicted a rise in wind production that did not happen

OUTCOME: system had to rely on less economical fast starting simple cycle combustion turbines and quick start diesels. Had high net loads been anticipated, a combine cycle combustion turbine would have been utilized

CASE EXAMPLE #2: MARCH 19, 2017
EXTREMELY LOW DAYTIME NET LOADS

Cool, clear & increasing wind

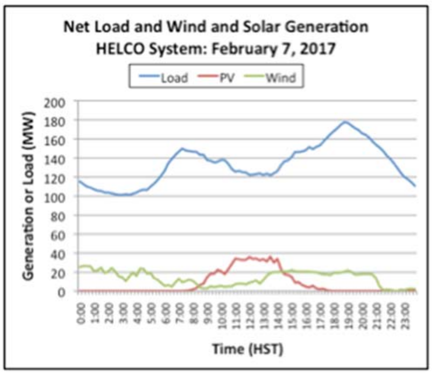


- Daytime minimum (85 MW) was below nighttime minimum (100 MW)
- Low mid-day gross load
  - o Cool and dry conditions
- Very high distributed PV production
  - o Almost 60 MW at mid-day,
  - o SWIFT accurately forecasted this
- Wind production had sig morning increase
  - o 15 MW increase: 0500 -> midday
  - o SWIFT accurately forecasted this

OUTCOME: Based on the forecasted high PV and increasing wind production operator took a combine cycle unit offline to avoid curtailment of the as-available renewable generation

CASE EXAMPLE #3: FEBRUARY 7, 2017
LARGE MORNING DECREASE IN WIND PRODUCTION

Warm, hazy and decreasing winds



- Typical mid-day gross load
- Typical morning rise in PV production
  - 35-40 MW
  - Well forecasted by SWIFT
- Significant decrease in wind production
  - -16 MW change: 0500 -> late morning
  - SWIFT erroneously predicted a continuation (i.e. no change) of the relatively high pre-sunrise wind production

OUTCOME: Wind forecast error caused stress but fortunately the operator was able to start a combine cycle unit early enough and had fast start units available to handle the change in wind generating capability.

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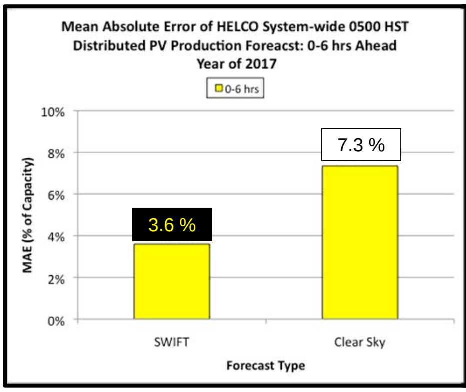
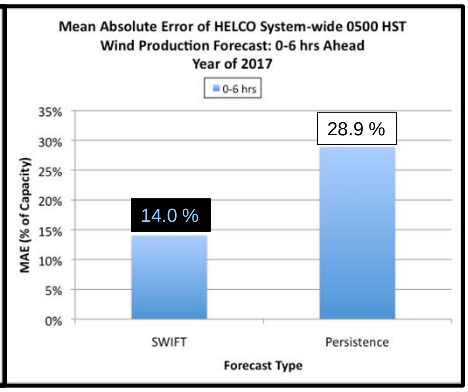
2017 TRADITIONAL FORECAST EVALUATION:
MORNING DECISION PERIOD (0500-1100 HST)

Solar Power Forecast: Mean Absolute Error



Wind Power Forecast: Mean Absolute Error



But how useful is the forecast information in the morning decision-making process?

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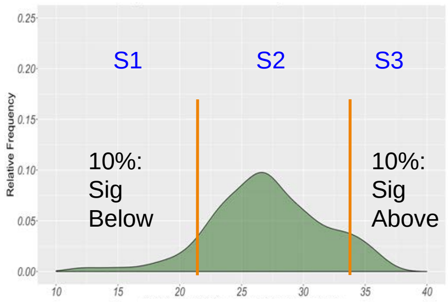
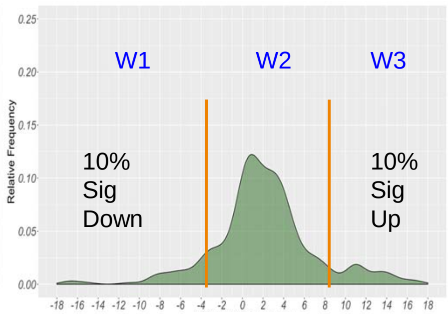
ALTERNATIVE FORECAST EVALUATION: DECISION-RELEVANT CATEGORIES

2017 Variability Distribution:
Morning (08-11) Increase in PV Production



2017 Variability Distribution:
Morning (05-11) Change in Wind Generation



Cat Label	Solar Event (08-11 HST)
S1	PV ramp rate sig below normal
S2	PV ramp rate in normal range
S3	PV ramp rate sig above normal

Cat Label	Wind Event (05-11 HST)
W1	Wind gen significantly decreases
W2	No significant change
W3	Wind gen significantly increases

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CATEGORY-BASED EVALUATION SYSTEM: BASIC

Category #	Forecasted			
Observed	Category	Below	Typical	Above
	Below	1	2	3
	Typical	4	5	6
	Above	7	8	9

- Ratios of Correct and Incorrect Outcomes
  - o Hits (H) = Cat #1 + Cat #9
  - o Misses (M) = Cat #2 + Cat #3 + Cat #7 + Cat #8
  - o False Alarms (FA) = Cat #4 + Cat #7 + Cat #3 + Cat #6
  - o Critical Success Index (CSI) = H / (H + M + FA)
- Issues
  - o Does not account for multiple category errors
  - o Does not consider relative frequency of outcomes: could provide hedging incentive
  - o Does not weight relative cost of errors
    - Does a miss of a "below" event cost the same as a miss of an "above" event?
    - Is the cost of a "miss" the same as a "false alarm"?

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CATEGORY-BASED EVALUATION SYSTEM: ADVANCED

- General Skill Score (GS)
  - o Measures skill relative to a random forecast of categories considering the relative frequencies of outcomes (0= same as a random forecast, 1= perfect)
  - o Can be formulated to have relative weighting for errors
  - o All of this accomplished through a scoring matrix: s_{ij}

$$GS = \frac{1}{N}\sum_{i=1}^{K}\sum_{j=1}^{K} n(F_i, O_j)\, s_{ij}$$

N = Total # of fcst-outcome pairs
n(F,O) = # of pairs in each fcst-outcome bin
S = Scoring matrix (score for each bin)
K = # of forecast categories

- Example of a Scoring Matrix (s_{ij})
  - o Based on a 10%, 80%, 10% (below, typical, above) frequency of outcomes
  - o 2-category errors are penalized twice as much as a 1-category errors
  - o All other errors have the same weighting (misses, false alarms etc.)

SCORING		Forecasted		
	Category	Below	Typical	Above
Observed	Below	1	-4	-1
	Typical	0	1	0
	Above	-1	-4	1

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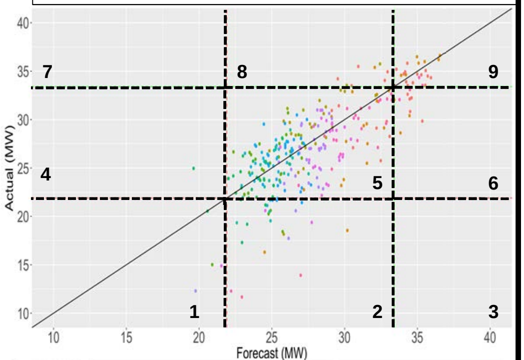
ALTERNATIVE FORECAST EVALUATION: 2017 CATEGORY-BASED SOLAR PERFORMANCE

2017 Daily Forecast vs. Actual of Morning (08-11) Increase in PV Generation



COUNT		Forecasted			
	Category	Below	Typical	Above	Obs Freq
Observed	Below	4	27	0	10.1%
	Typical	1	232	11	79.5%
	Above	0	8	24	10.4%
	Fore Freq	1.6%	87.0%	11.4%	100.0%

- Ratios: CSI=37.3%
  - o Hits are 37% of observed and forecasted events

Ratios	H	M	FA	Total	CSI
Below	4	27	1	32	12.5%
Above	24	8	11	43	55.8%
Total	28	35	12	75	37.3%

- General Skill Score: GS=39.1%
  - o 39% of the way from random to perfection

GS	F-Below	F-Typical	F-Above	Sum
O-Beloe	4	-108	0	-104
O-Typical	0	232	0	232
O-Above	0	-32	24	-8
Sum	4	92	24	120
Total Cases				307
GS				39.1%

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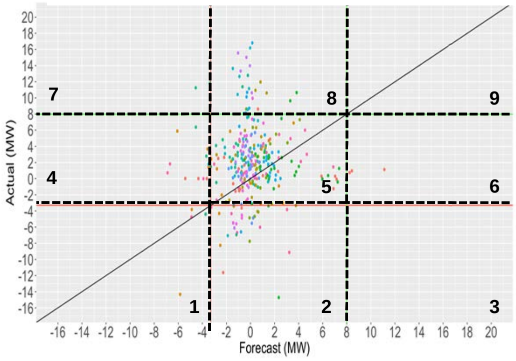
ALTERNATIVE FORECAST EVALUATION: 2017 CATEGORY-BASED WIND PERFORMANCE

2017 Daily Forecast vs. Actual of Morning (05-11) Change in Wind Generation



COUNT	Forecasted				
Observed	*Category*	Down	No Change	Up	Obs Freq
	Down	4	29	0	10.3%
	No Change	13	243	3	80.7%
	Up	2	27	0	9.0%
	Fore Freq	5.9%	93.1%	0.9%	100.0%

- Ratios: CSI=5.0%
  - Hits are 5% of observed and forecasted events

Ratios	H	M	FA	Total	CSI
DOWN	4	29	15	48	8.3%
UP	0	29	3	32	0.0%
Total	4	58	18	80	5.0%

- General Skill Score: GS=6.5%
  - 6.5% of the way from random to perfection

GS	F-Down	F-Typical	F-Up	Sum
Obs-Below\	4	-116	0	-112
Obs-Typical	0	243	0	243
Obs-Above	-2	-108	0	-110
Sum	2	19	0	21
Total Cases				321
GS				6.5%

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SUMMARY

- Identified the key operating decisions and time frames of the Hawaii Electric Light Co (HELCO) system that are dependent on wind and solar variability
- Formulated a customized categorical forecast evaluation scheme to measure the aspects of forecast performance that are critical to decision-making
- Developed a customized but structurally similar categorical scheme for each type of key operational decision-making situation (morning peak, mid-day net load ramps etc)
- Designed and implemented a customized categorical forecast performance metric
- Results:
  - Traditional forecast metrics (e.g. MAE, RMSE) indicate the wind and solar forecasts for the HELCO system achieve state-if-the-art forecast performance
  - Customized Category-based metrics based operational decision-making scenarios indicate that forecasts are biased to the prediction of typical conditions and do not have adequate skill in forecasting operationally significant atypical conditions
- Next steps: Optimize forecast systems to achieve best performance for customized category-based metrics (i.e. predicting atypical conditions)

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