Renewable Energy and Island Sustainability and Signal Processing Applications for the Smart Grid



KU Leuven
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REIS
RENEWABLE ENERGY & ISLAND SUSTAINABILITY

College of ENGINEERING
UNIVERSITY OF HAWAI'I AT MĀNOA

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Outline

- Introduction
  - Hawai`i Energy Landscape
  - University of Hawai`i, College of Engineering, REIS
- Research activities
  - Signal processing and machine learning applied to energy and smart grid problems

Introduction

Hawai`i Energy Landscape

- Energy costs: more than 10% of GDP
- Energy breakdown: roughly 1/3 electric grid, 1/3 ground transportation, 1/3 air transportation
- Most of energy comes from imported oil. For electricity production 71% from oil, 15% from coal
- Pay highest electricity prices in country > $.31 /kWH
- Each island has separate isolated grid
- Hawai`i Advantages:
  - Natural resources: sun, wind, waves, geothermal
  - Closed grid system: more amenable to analysis
  - Ahupua`a system: island sustainability

Hawai`i Energy Future

- Hawai`i Clean Energy Initiative (HCEI): MOU between Hawai`i and Department of Energy: By 2030 40% energy from renewable sources and 30% savings in energy efficiency
- Hawai`i government recently passed bill with a goal of attaining 100% renewable energy by 2045
- Hawai`i currently has highest penetration of residential solar in US (12% for residential households): for many distribution grid circuits solar penetration is greater than daytime minimum loads
- In Dec. 2014 Next Era Energy announced plans to buy Hawaiian Electric Industries

University of Hawai'i Manoa

- Founded in 1907
- Approximately 20000 students, 13500 UG students, 6500 graduate students
- Research extensive University with 11 colleges and 9 schools, 87 bachelor degree programs, 87 master degree programs, 55 doctoral degree programs
- University of Hawaii system includes, 4 year schools, and community colleges

College of Engineering Overview

Civil and Environmental Engineering	Electrical Engineering	Mechanical Engineering
Hawaii Center for Advanced Communicatios	Hawaii Space Flight Laboratory	Renewable Energy and Island Sustainability

54 faculty, 940 UG students, 300 pre-engineering students,
180 graduate students

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REIS Goals

- Develop REIS program to educate students in renewable energy and sustainability and provide work force for Hawaii, USA, and globally
- Multidisciplinary team formed to conduct cutting edge renewable energy and island sustainability research
  - Obtain sustained funding from (NSF, DOE, military)
  - Become internationally recognized program
- Work with state of Hawaii and industry to help with renewable energy and energy efficiency goals
- Work with other UH energy groups on joint education and research projects
- Develop experimental lab: UH campus, D^3
- Recruit undergraduates, K-12 students, underrepresented students into REIS program

REIS Summary

- Formed at the start of 2009 (2009 COE retreat on sustainability, Nov. 2008 energy workshop at ASU)
- REIS has 28 members from 8 colleges and 10 departments at UHM
- Won $1M seed funding from VCRGE sustainability competition in 2009, obtained more than $7.8M in funding from grants (i.e. DOE including $2.5M workforce training grant in STEPS , NSF)
- Developed graduate and UG curriculum in energy and sustainability (REIS graduate certificate approved)
- About 50 grad. and 100 UG students supported

REIS Educational Activities

- Student obtains (MS, PhD) in department plus REIS certificate
- Industry experience: students encouraged to work in Hawaiian energy and sustainability companies
- Collaborations with other institutions and international experience: we will set up faculty and student exchanges with our academic partners (including international institutions)
- Multidisciplinary research: Projects will be group oriented requiring multiple disciplines
- Undergraduate power systems, RE courses
- Undergraduate research projects
- Develop short courses (first course on wind energy, Apr. 2011, summer 2012 course on smart grids, solar thermal)
- Seminar series

REIS Research Activities

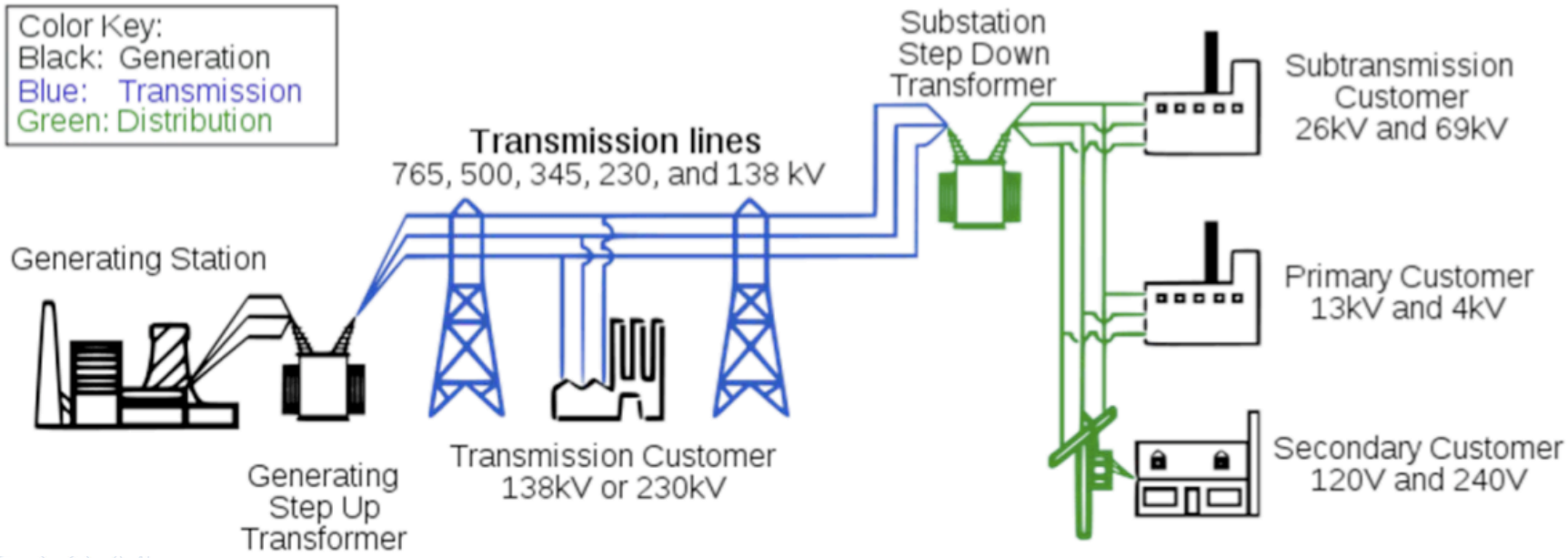
- **Multidisciplinary research in energy and sustainability topics**
  - **UH Campus Smart Sustainable Microgrids**
- **Topics**
  - **Smart grids**
  - **Energy harvesting**
  - **Renewable energy integration**
  - **Wave energy**
  - **Bio-energy**
  - **Renewable energy production and storage technologies**
  - **Energy economics and policy**

REIS Outreach

- **Goals:**
  - Create and maintain a pipeline of qualified (underrepresented, US) students to enter REIS related programs at UH Manoa (US PhD's in particular)
  - Gain more recognition and support from local community
- **Current/Future Activities:**
  - K-12 outreach on campus and off campus
  - Community Colleges outreach (through IKE and other programs)
  - Recruiting HI students from mainland colleges with NHSEMP
  - Reaching out to large HI energy users: military and hotel industry

Research Activities

Conventional Power Grid



Smart Grid


The Smart Grid Can Deliver
Market
$
MW
BENEFITS
• Enhanced energy security
• Reduced greenhouse gases
• Improved urban air quality
• Increased grid asset utilization
"Valley Filling"
(Energy for PHEVs)
kW
hours of day
PHEV
CO2 Emissions
Urban Emissions
Electricity Sales
Infrastructure Requirements
Utility Rates

Desired Characteristics of a Smart Grid

Energy Independence & Security Act 2007, Sec 1304 Smart Grid RD&D Highlights

- Enable *active participation* by consumers
- Accommodate *all* generation and storage options (including vehicles)
- Enable new tools, products, services and markets
- Provide power quality reliability for the digital economy
- *Optimize* asset utilization and operate efficiently
- Enable the *self-healing* grid to anticipate and respond to system disturbances
- Operate resiliently against attack and natural disaster

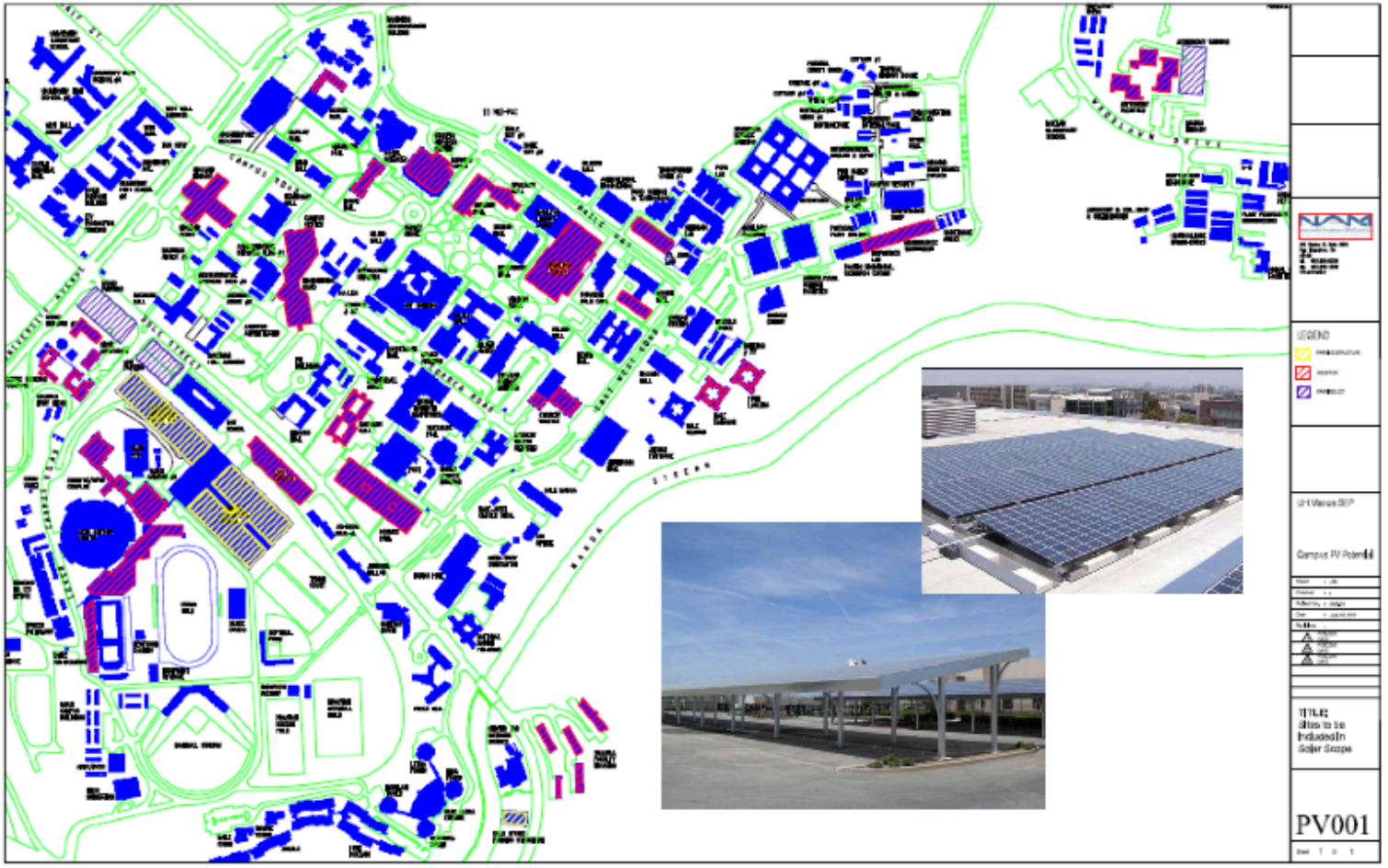
UH Campus Smart Sustainable Microgrid

Electricity costs have tripled in last dozen years

- **Energy efficiency: Demand response**
- **Integrate distributed renewable energy sources (PV), ancillary services**
- **Data gathering, analysis, decision making**

Installing Distributed PV on UH campus

Proposed On-Campus Photovoltaic Roof-top and Car Canopy Sites



UHCSSM project areas

- Sensors and monitoring: Use and develop sensor technology to monitor the environment, renewable energy generation, power grid, and other networks
- Tools and models: data mining, modeling, analysis, and visualization. Observe sensor networks and simulate in hardware and software in SCEL
- Design, decision making, optimization and control: develop distributed optimization and control algorithm along with design procedures to create more sustainable UH campus
- Impacts and policy recommendations: Social, environmental, and economic impacts of moving UH to more sustainable energy practices

Research topics

- Signal processing & machine learning applications of energy and smart grids
  - Sensor placement problem
  - Solar forecasting using zenith angle and asymmetric cost functions
  - Distributed state estimation
  - Fault detection using online density estimators
  - Demand response for appliances using ADP
- UG projects
  - Environmental sensor network implementation

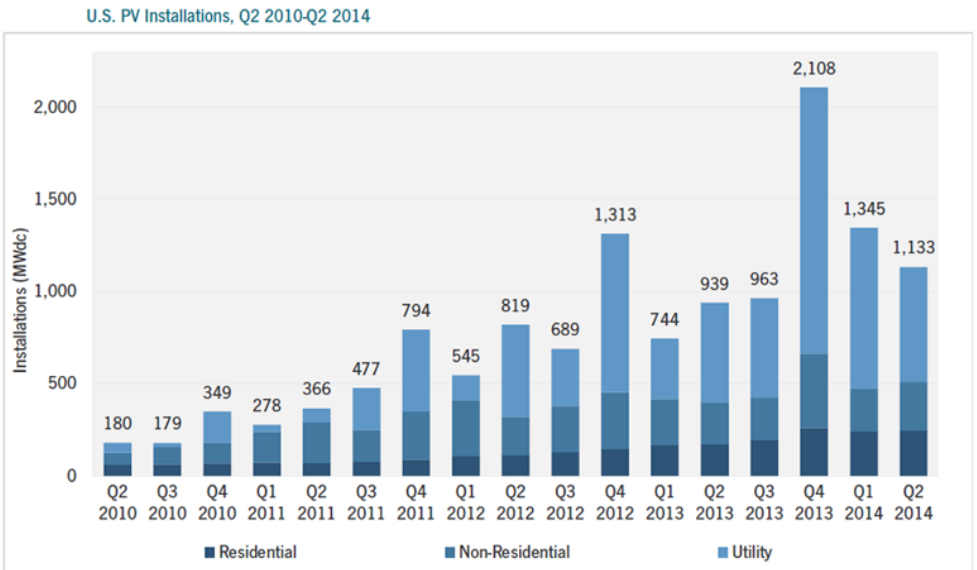
Solar forecasting using zenith angle and asymmetric cost functions

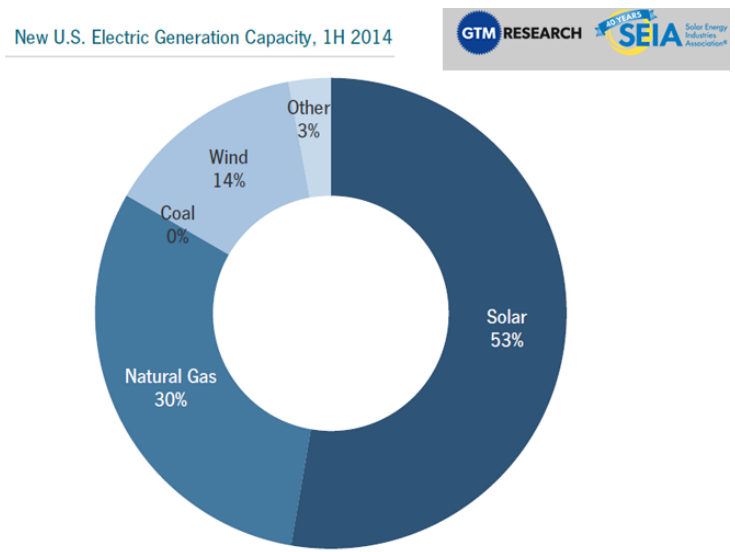
Outline

1. Motivation
2. Asymmetric Cost
   - Reliability Vs Cost
   - LinLin Cost Function
   - LinEx Cost Function
3. Forecasting Model
   - Zenith Angle - Def.
   - Zenith Angle and Radiation
4. Methods
   - Optimization Problem
   - Methods-LinLin
   - Methods-LinEx
5. Simulation Results
   - Simulation Results-LinLin
   - Simulation Results-LinEx
6. Conclusion

Motivation

- Transition from fossil fuel energy sources towards renewable energy sources is inevitable.
- Solar energy is abundant and clean.
- Price of installation of PV has decreased by about 50 %.
- 53% of new generation capacity is solar.
- Capacity of solar power continue to rise at a rapid rate.





Motivation- Integrating Large Share of Renewables to Grid

- For stability of electric grid at any moment, sum of generation should be equal to sum of consumption.
- Solar and wind energy sources are intermittent.
- Four ways for integrating large share of renewables to grid:
  - ✓ Having enough spinning reserves
  - ✓ Forecasting of renewable energy generation
  - ✓ Storage
  - ✓ Demand response

Motivation: for Hawaii

- Hawaii pays the highest cost for electricity in the US (about $.35 per kilowatt hour in Oahu and higher rates on outer islands)
- With reductions in solar PV costs and tax incentives HECO customers have the highest density of penetration of distributed solar PV in US (about 10%).
- HECO concerned about stability of the grid during the day more energy is generated on certain feeder lines from distributed solar PV than is being consumed (back flow of energy).
- HECO is restricting installation of new solar in certain areas and considering different options.
- This motivates the need for forecasting, storage, and demand response.

Motivation

- PV generation is intermittent and forecasting is efficient way to integrate large share of PV to the grid.
- Many researchers studied the solar radiation forecasting using symmetric criteria like root mean square error (RMSE) or mean absolute error (MAE)to find unbiased predictor.
- However grid operations are based on asymmetric costs. Load shedding is much more costly than curtailing.
- It is necessary to investigate forecasting methods under asymmetric loss functions which are a better fit to grid costs.

Reliability Vs Cost

- Reserves cost about 20% of per unit price of energy.
- If there is not enough reserve available during operation, the power system operator forces to cut power of some customers in order to maintain stability (Load shedding operation).
- The cost of energy not delivered to the customer due to load shedding is called Value of Lost Load (VOLL).
- VOLL is difficult to assessed and is reported to be around \$8/kWh to \$24/kWh for different cities. For this study we assume VOLL to be \$10/kWh.

LinLin Cost Function

$$LinLin(\epsilon) = \begin{cases} C_1\epsilon & \text{if } \epsilon > 0 \\ -C_2\epsilon & \text{if } \epsilon \leq 0 \end{cases}$$

- LinLin cost function introduced by Granger in 1969.
- The simplest piecewise linear asymmetric cost function.
- Per unit cost does not depend on magnitude of error.
- For power systems simply assume C_1 is equal to per unit cost of reserves and C_2 is value of lost load (VOLL).

LinEx Cost Function

$$LinEx(\epsilon) = b(e^{a\epsilon} - a\epsilon - 1)$$

- LinEx cost function introduced by Varian in 1975.
- Comprehensively discussed by Zellner in 1986.
- The a and b constants are called shape factor and scale factor respectively.
- The shape and scale factor are selected so that they are consistent with LinLin for underestimation errors and exceeds the LinLin cost for overestimation errors more than a predetermined value for example 25%.
- The power system usually is robust and can tolerate small errors. For this cost function load shedding results in small errors and generation shortage result in costs that increase exponentially.

LinLin and LinEx Cost Functions

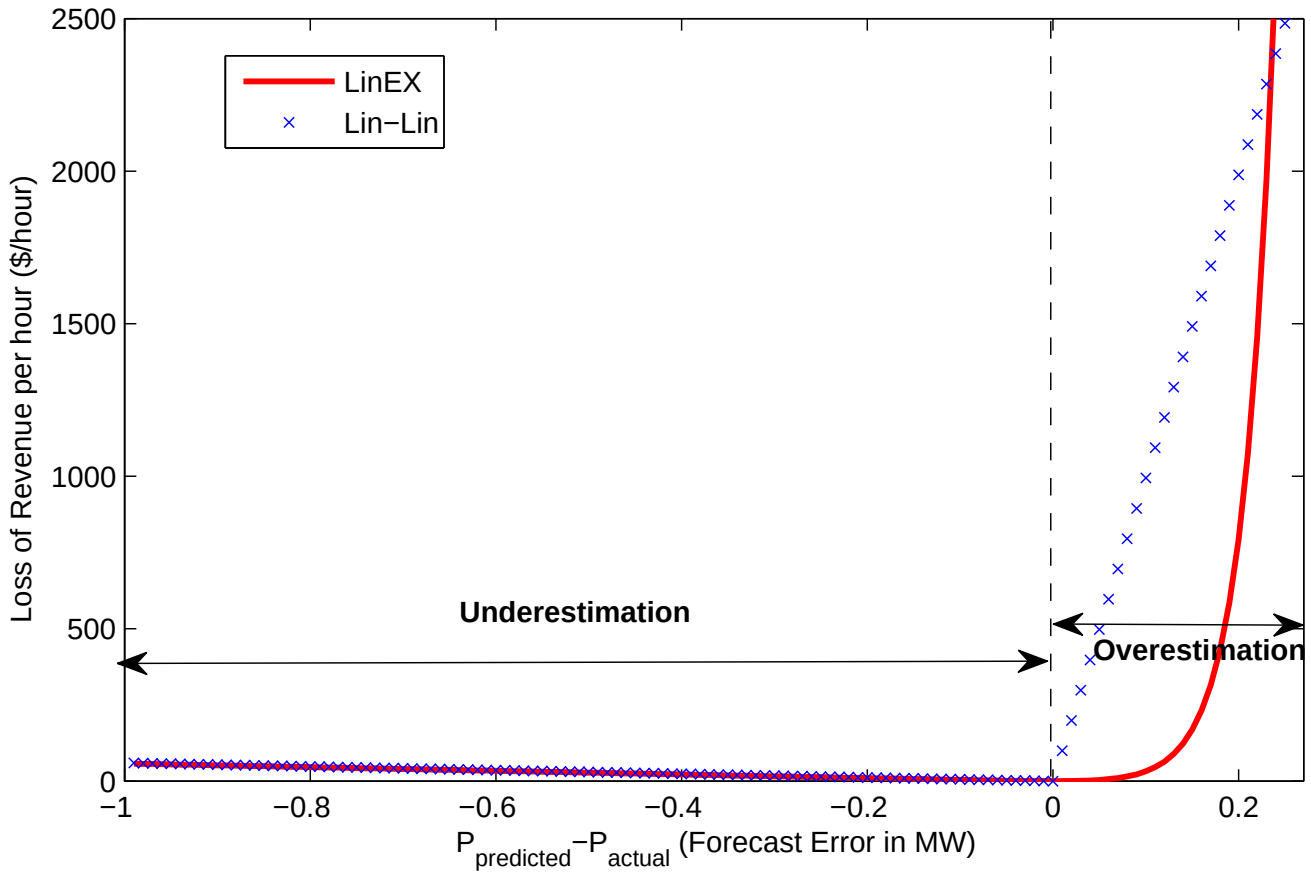


Figure: LinLin ($C_1 = \$10/kWh$, $C_2 = \$0.06/kWh$) and LinEx ($b = \$2/h$, $a = 0.03/kW$) cost functions

Zenith Angle - Def.



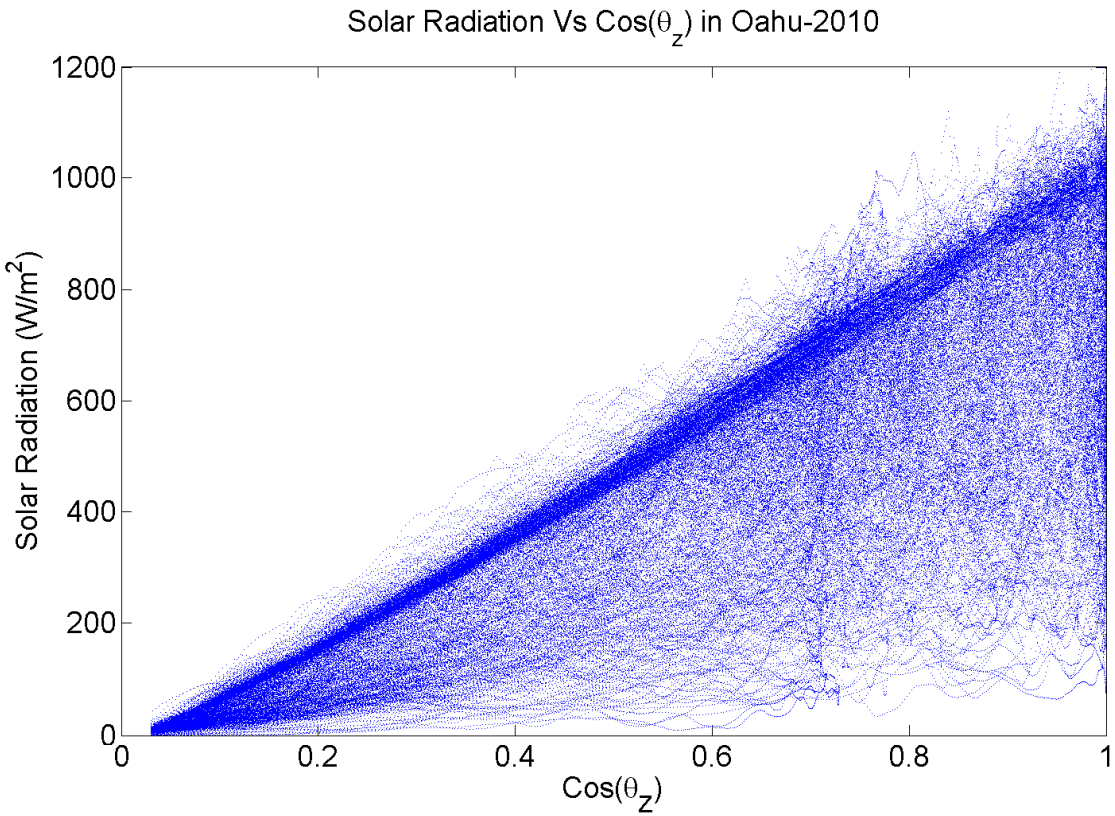
- Zenith angle,θ_z is the angle between sun beam and perpendicular line on horizontal surface.
- Every day starts with sunrise when $\theta_z = 90°$ and ends with sunset when θ_z again is 90°. Zenith angle is minimum at solar noon.
- Zenith angle computed from:

$$\cos\theta_z = \cos\phi\cos\delta\cos\omega + \sin\phi\sin\delta$$

where ϕ is latitude; ω is sun time which is negative in mornings, zero at noon and positive in afternoons, and changes by 15°/hour rate; and $\delta = -23.45° \cos\frac{360(d+10)}{365}$ where d is day of year

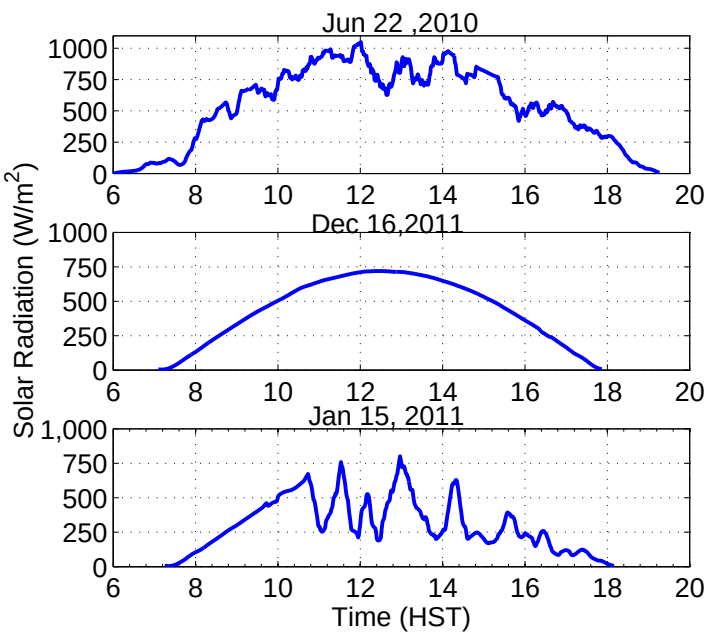
Zenith Angle and Radiation

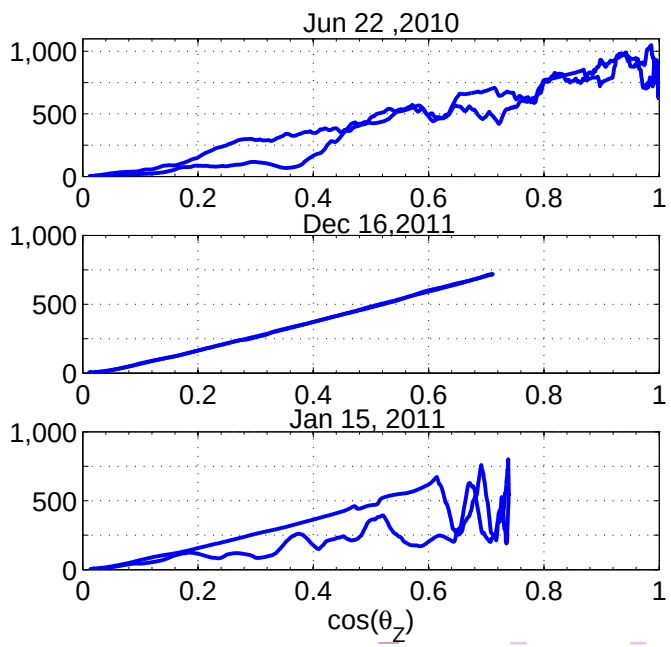
Solar radiation and cosine of zenith angle are highly correlated.



Transform of time index to Cosine of zenith angle

- Since Cosine of zenith angle is a deterministic function of time, we can use it instead of time index.
- This transform change non-linear relationship between irradiation and time of the day to approximately linear relation between irradiation and $\cos\theta_z$.
- This transform remove the seasonal effects related to sun position.
- This transform does not remove the seasonal effects clouds pattern.





Forecasting Model

The k step ahead prediction is given combination of present and past measurements:

$$\hat{x}_{n+k} = (\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + ... + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k)$$

where $\theta_z(n)$ is solar zenith angle at time n and $\alpha_0, \alpha_1, ..., \alpha_m$ are the weight parameters.

Optimization Problem

The optimization problem is

$$\underset{\alpha_0,\alpha_1,\ldots,\alpha_m}{\text{Minimize}} \sum_{i=m}^{M} Loss(\hat{x}_{i+k} - x_{i+k})$$

Where *Loss* is cost function either LinLin or LinEx and M is the total number of samples.

Methods : Suboptimal Solution for LinLin

Adding bias to unbiased forecast: Let our unbiased forecast error be ϵ and cumulative distribution function (CDF) of error be F_ϵ and probability density function of errors be $f(\epsilon)$. If we add bias value β to the unbiased forecast, the cumulative loss with LinLin cost function changes as there is a shift of β resulting in :

$$Loss_{total} = \int_{-\infty}^{+\infty} LinLin(\epsilon + \beta) f(\epsilon) d\epsilon$$

$$= -C_2 \int_{-\infty}^{-\beta} (\epsilon + \beta) f(\epsilon) d\epsilon + C_1 \int_{-\beta}^{+\infty} (\epsilon + \beta) f(\epsilon) d\epsilon$$

To find bias value β which minimizes cumulative loss, we have:

$$\frac{\partial Loss_{total}}{\partial \beta} = -(C_1 + C_2) F_\epsilon(-\beta) + C_1$$

$$\Rightarrow \beta = -F_\epsilon^{-1}\left(\frac{C_1}{C_1 + C_2}\right)$$

Methods : Optimal Solution for LinLin

The LinLin loss function could be expressed by

$$LinLin(\epsilon) = \lambda_1|\epsilon| + \lambda_2\epsilon$$

So we have

$$\min_{\alpha_0,\ldots,\alpha_m} \sum_{n=1}^{M} \{\lambda_1 \Big| (\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k} \Big| + \lambda_2 [(\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k}]\}$$

In order to get rid of absolute value segment, let us introduce new decision variables such that

$$\Big|(\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k}\Big| \leq w_n$$

Methods : Optimal Solution for LinLin

So we have a linear programing problem:

$$\min_{\substack{w_1, w_2, \ldots, w_M \\ \alpha_0, \alpha_1, \ldots, \alpha_m}} \sum_{n=1}^{M} \{\lambda_1 w_n + \lambda_2 [(\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k}]\}$$

subject to $\forall n$

$$w_n \geq 0$$

$$(\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k} \leq w_n$$

$$(\alpha_0 + \frac{\alpha_1 x_n}{\cos\theta_z(n)} + \ldots + \frac{\alpha_m x_{n-m+1}}{\cos\theta_z(n-m+1)}) \cos\theta_z(n+k) - x_{n+k} \geq -w_n$$

Methods : Online Solution for LinLin

Similar to the least mean squares (LMS) algorithm which uses the instantaneous estimate of gradient vector for squared error cost, we use the instantaneous estimate of gradient vector for LinLin cost function.

$$\hat{J} = LinLin(\hat{x}_n - x_n)$$

where $\hat{x}_n$ is computed using forecasting equation . Instantaneous estimate of gradient vector computed by following equations.

$$\nabla\hat{J} = [\frac{\partial\hat{J}}{\partial\alpha_0}, \frac{\partial\hat{J}}{\partial\alpha_1}, ..., \frac{\partial\hat{J}}{\partial\alpha_m}]^T$$

To compute the gradient let define function $g(x)$ using following equation

$$g(x) = \begin{cases} C_1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -C_2 & \text{if } x < 0 \end{cases}$$

Methods : Online Solution for LinLin

The partial derivatives calculated using

$$\frac{\partial \hat{J}}{\partial \alpha_0} = \cos\theta_z(n) g(\hat{x}_n - x_n)$$

In the same way, for $j = 0, 1, 2, ..., m-1$

$$\frac{\partial \hat{J}}{\partial \alpha_{j+1}} = \frac{x_{n-j-k}\cos\theta_z(n)}{\cos\theta_z(n-j-k)} g(\hat{x}_n - x_n)$$

Let $\boldsymbol{\alpha} = [\alpha_0, \alpha_1, ...\alpha_m]^T$. Then $\boldsymbol{\alpha}$ is iteratively updated by following equation.

$$\boldsymbol{\alpha}_{n+1} = \boldsymbol{\alpha}_n - \eta \nabla \hat{J}$$

The total cost up to time $J(n)$ is cumulative sum of instantaneous cost, $\hat{J}$, So

$$J(n) = J(n-1) + \hat{J}(n)$$

Methods : Suboptimal Solution for LinEx

Adding bias to unbiased forecast: Again let our unbiased forecast error be ϵ and probability density function of errors be $f(\epsilon)$. If we add bias value β to the unbiased forecast, the error also add with the β so cumulative loss with LinEx cost function becomes:

$$Loss_{total} = \int_{-\infty}^{+\infty} LinEx(\epsilon + \beta) f(\epsilon) d\epsilon$$

$$= b \int_{-\infty}^{+\infty} (e^{a(\epsilon+\beta)} - a(\epsilon + \beta) - 1) f(\epsilon) d\epsilon$$

To find optimal bias value β which minimizes cumulative loss, we have:

$$\frac{\partial Loss_{total}}{\partial \beta} = abe^{a\beta} \int_{-\infty}^{+\infty} e^{a\epsilon} f(\epsilon) d\epsilon - ab$$

$$\Rightarrow \beta = -\frac{1}{a} \log\left(\int_{-\infty}^{+\infty} e^{a\epsilon} f(\epsilon) d\epsilon \right)$$

Methods : Optimal Solution for LinEx

Since this optimization does not have analytical answer we used gradient descent algorithm. Let $\boldsymbol{\alpha} = [\alpha_0, \alpha_1, ...\alpha_m]^T$ then the $\boldsymbol{\alpha}$ is iteratively updated by following equation.

$$\boldsymbol{\alpha}_{i+1} = \boldsymbol{\alpha}_i - \eta \nabla J$$

where η is step size and ∇J is gradient vector and is computed by following equations

$$\nabla J = [\frac{\partial J}{\partial \alpha_0}, \frac{\partial J}{\partial \alpha_1}, ..., \frac{\partial J}{\partial \alpha_m}]^T$$

$$\frac{\partial J}{\partial \alpha_0} = ab \sum_{n=1}^{M} [\cos\theta_z(n+k)(e^{a(\hat{x}_{n+k} - x_{n+k})} - 1)]$$

similarly for $j = 0, 1, 2, ..., m-1$

$$\frac{\partial J}{\partial \alpha_{j+1}} = ab \sum_{n=1}^{M} [\frac{x_{n-j}\cos\theta_z(n+k)}{\cos\theta_z(n-j)}(e^{a(\hat{x}_{n+k} - x_{n+k})} - 1)]$$

Methods : Online Solution for LinEx

Instantaneous LinEx cost is given by

$$\hat{J} = LinEx(\hat{x}_n - x_n)$$

where $\hat{x}_n$ is computed using forecasting equation . Instantaneous estimate of gradient vector computed by following equations.

$$\nabla\hat{J} = [\frac{\partial\hat{J}}{\partial\alpha_0}, \frac{\partial\hat{J}}{\partial\alpha_1}, ..., \frac{\partial\hat{J}}{\partial\alpha_m}]^T$$

$$\frac{\partial\hat{J}}{\partial\alpha_0} = ab[\cos\theta_z(n)(e^{a(\hat{x}_n - x_n)} - 1)]$$

similarly for $j = 0, 1, 2, ..., m-1$

$$\frac{\partial\hat{J}}{\partial\alpha_{j+1}} = ab[\frac{x_{n-j-k}\cos\theta_z(n)}{\cos\theta_z(n-j-k)}(e^{a(\hat{x}_n - x_n)} - 1)]$$

The $\boldsymbol{\alpha}$ is iteratively updated by following equation.

$$\boldsymbol{\alpha}_{n+1} = \boldsymbol{\alpha}_n - \eta\nabla\hat{J}$$

Methods : Online Solution for LinEx

- Adding a momentum term to the learning rule could increase the learning rate.
- large momentum results in oscillation in the learning curve.
- A decreasing momentum factor at initial iterations is high and leads to faster learning but in later iterations the momentum factor decreases to zero to avoid over learning.

As a result

$$\gamma_n = \frac{\gamma_0}{(1 + \frac{n}{N})}$$

where N is the number of samples per year.
The learning algorithm with momentum term is implemented using following equations:

$$\boldsymbol{\Delta\alpha}_{n+1} = \gamma_n \boldsymbol{\Delta\alpha}_n - \eta \nabla \hat{J}$$

$$\boldsymbol{\alpha}_{n+1} = \boldsymbol{\alpha}_n + \boldsymbol{\Delta\alpha}_{n+1}$$

Simulation Results-LinLin

- We download the data from http://www.nrel.gov/midc/.
- Nine years records with five minutes resolution, an hour ahead foecast.
- Revenue is avoided cost of reserves by forecasting.
- Maximum possible revenue is average renewable generation times per unit cost of reserves.
- We divide the revenue by maximum possible revenue to get comparable result.
- In batch method one year used for training and next year for testing and averaged the results for nine years or with cross validation eight years is used for training and the other years is used for testing.
- In online method, we use a resampling technique i.e. we use nine yearly datasets seven times then the total 63 yearly datasets are randomly ordered and used as input to the online learning algorithm.

Simulation Results-LinLin

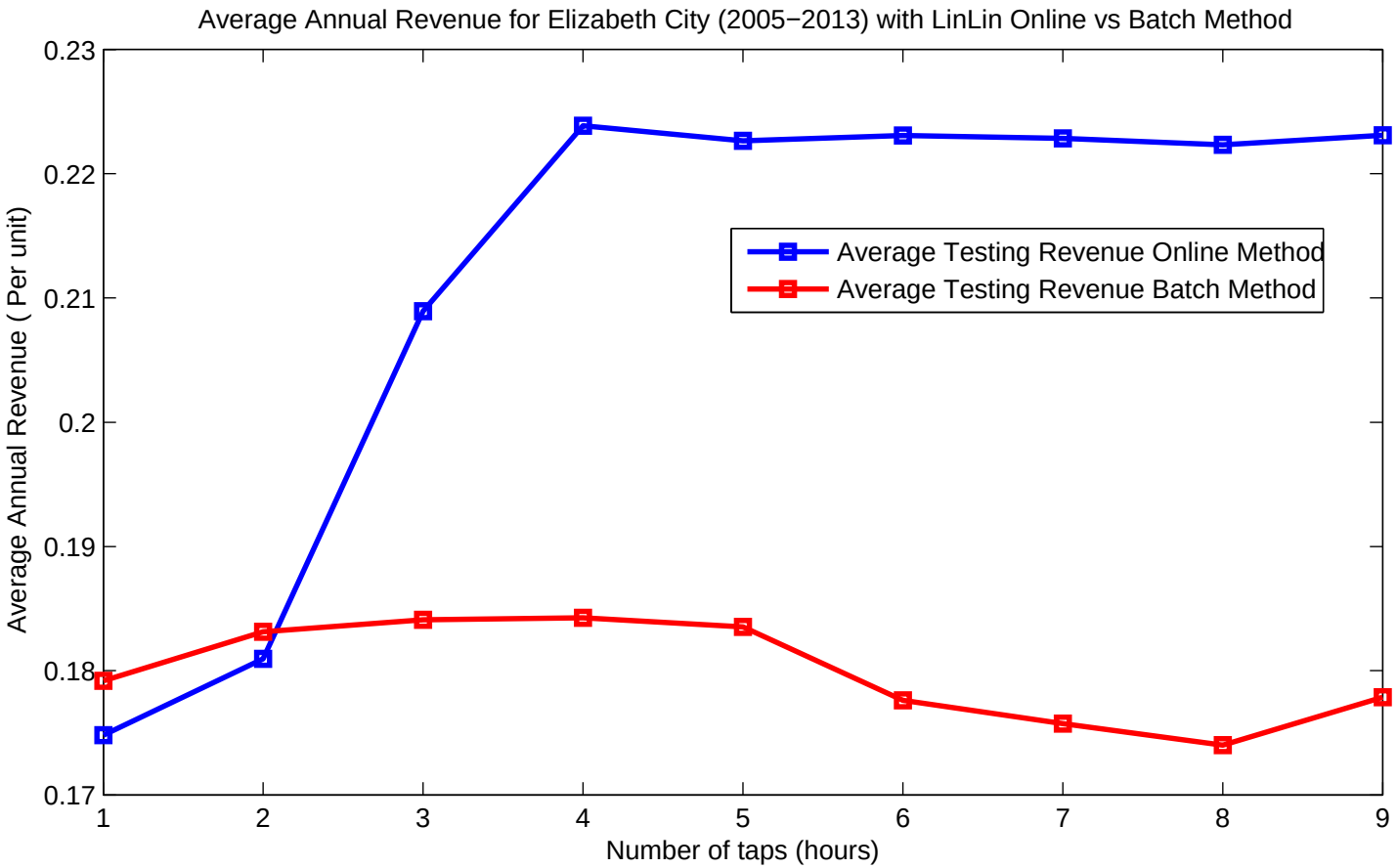


Figure: The per unit revenue of online method for LinLin cost function is more than corresponding batch method. However similar to batch method four taps gives the best performance.

Simulation Results-LinLin

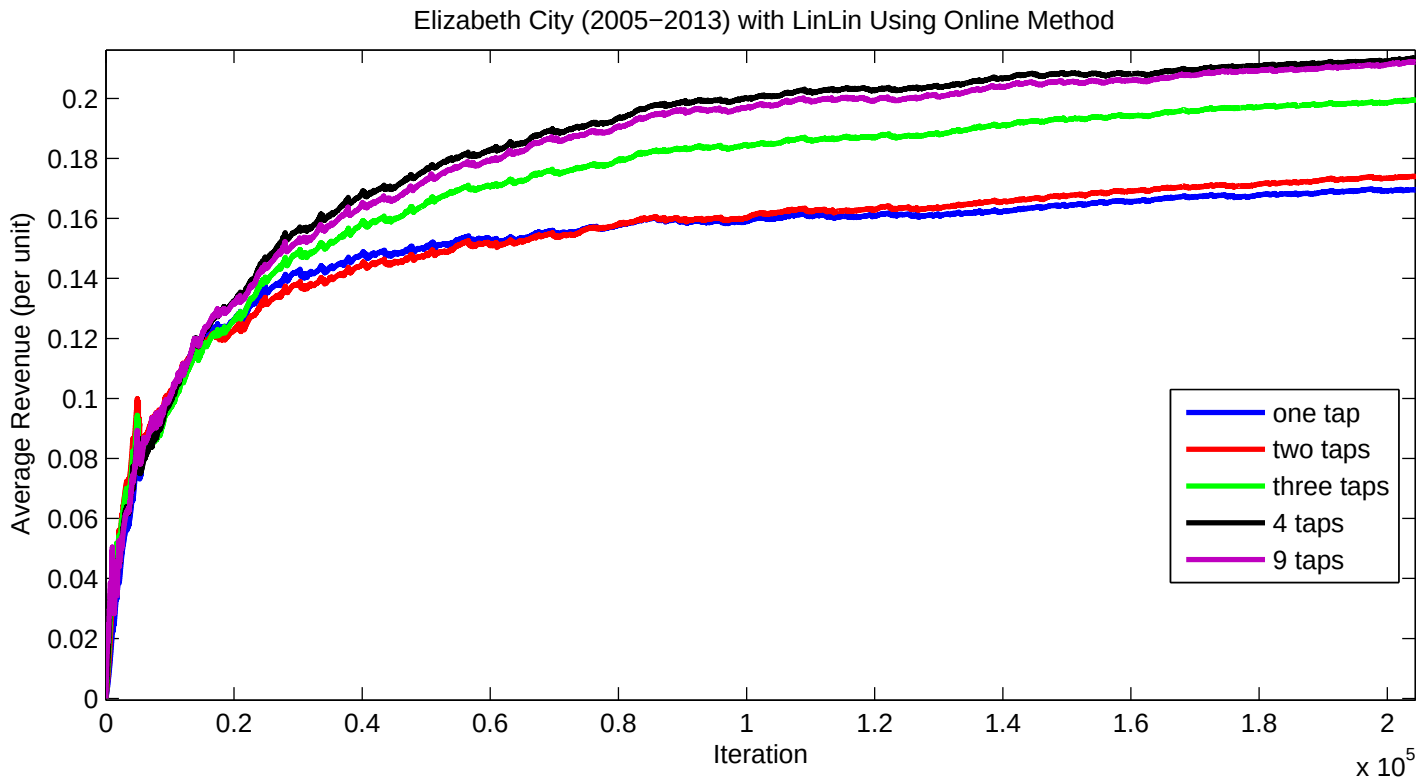


Figure: Comparison of learning curves for methods with different taps under LinLin cost function

Simulation Results-LinEx

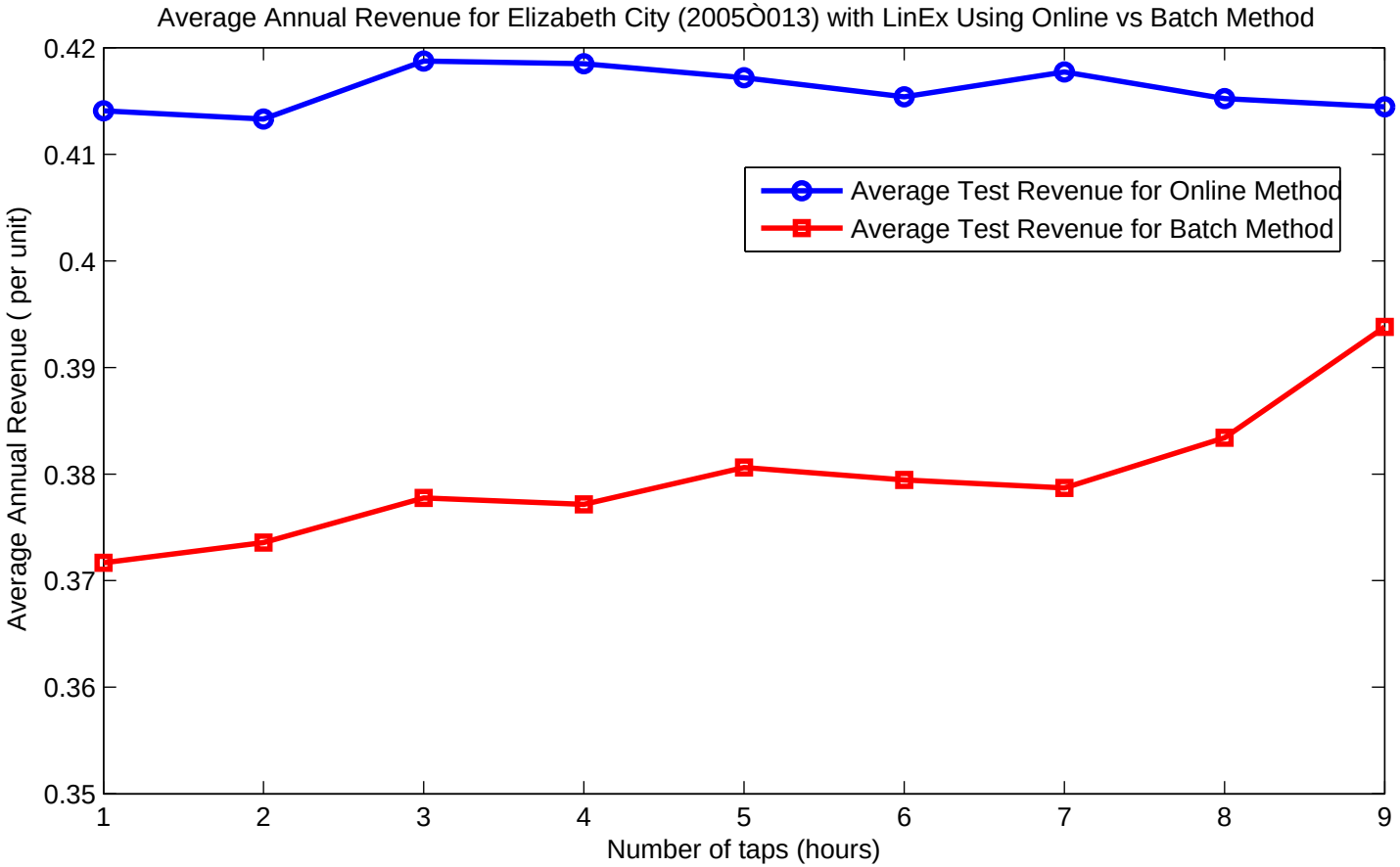


Figure: The per unit revenue of online method for LinEx cost function is more than corresponding batch method. Also, increasing number of taps does not have significant effect.

Simulation Results-LinEx

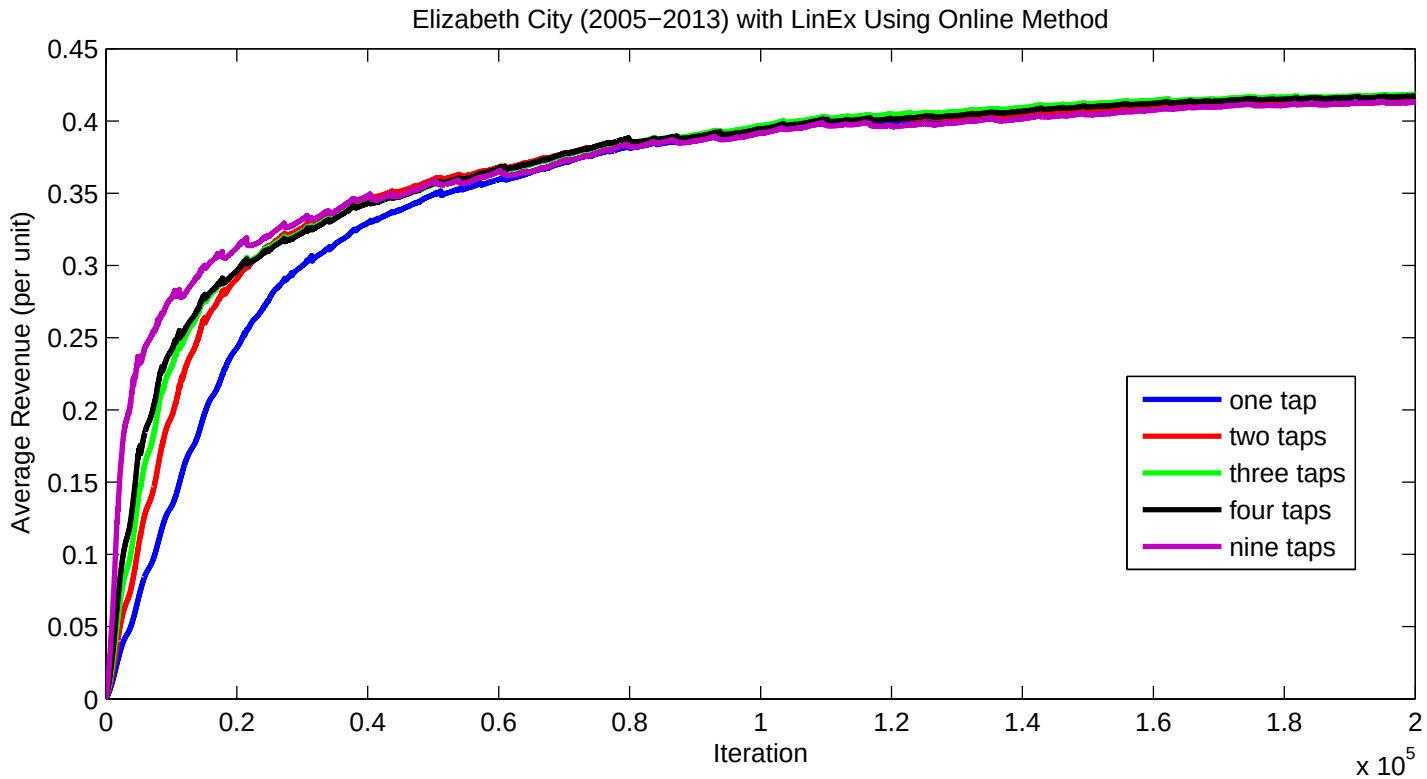


Figure: Under LinEx cost function, the method which has more taps learn faster than others, however, the final performance is similar to others.

Simulation Results-LinEx

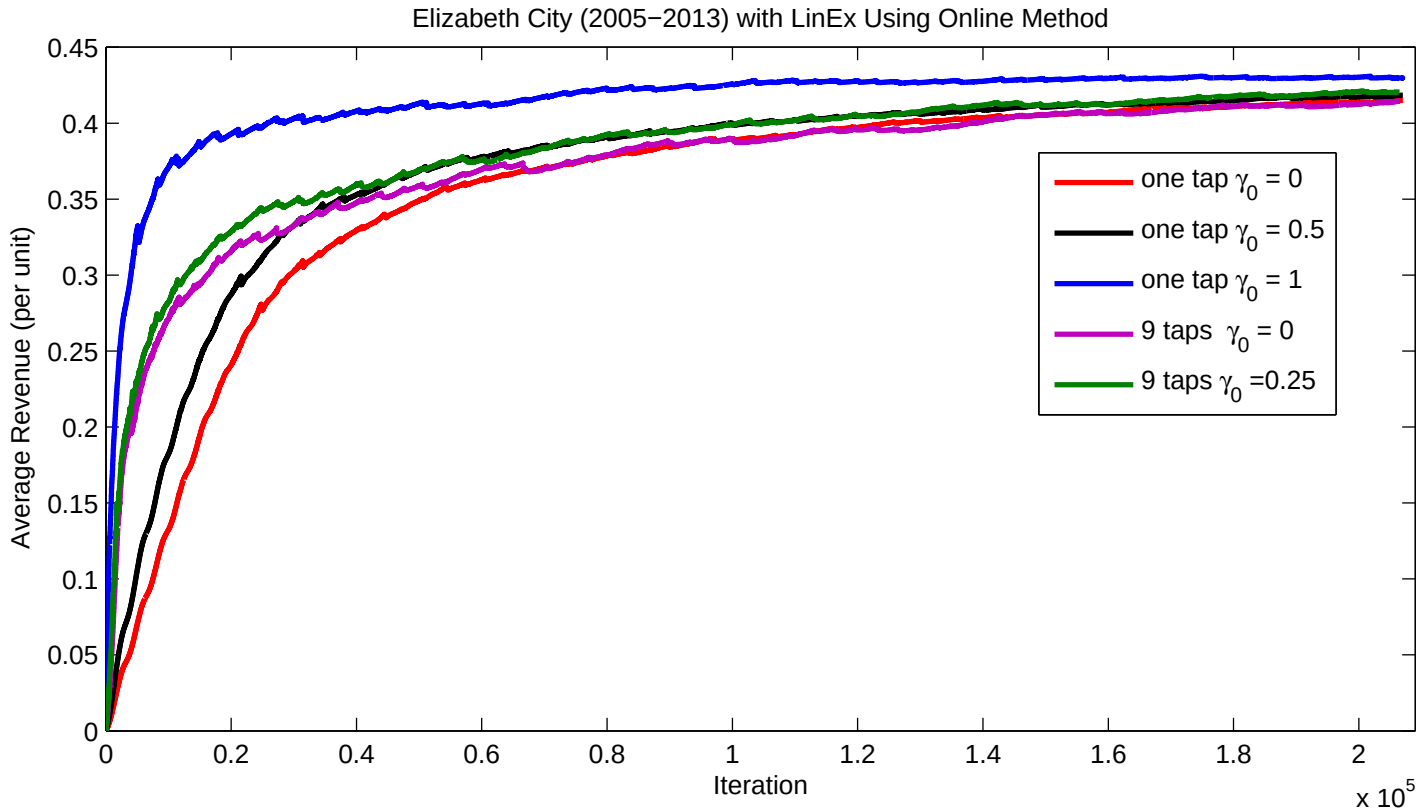


Figure: Using appropriate momentum factor in learning rule increases the learning rate

Conclusion

- Many researchers have studied the solar radiation forecasting using symmetric criteria like root mean square error (RMSE), mean absolute error (MAE) or mean absolute percentage error (MAPE).
- However grid operation do not have equal cost. Load shedding is much more costly than curtailing. Hence we modeled the utility cost using LinLin and LinEx cost functions
- The optimal batch solution given by a linear program for LinLin and by steepest descend algorithms for LinEx.
- The proposed online methods give an improvement over batch solutions due to better tracking ability.
- We find out that direct forecasting under asymmetric cost functions gives substantial more revenue.
- Linex cost gives both more revenue and more reliability since large errors are penalized more with an exponentially weighted cost function.

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Distributed State Estimation

Outline

1. Smart Grid
2. Methodology and Formulation
3. Simulation Results and Discussion
4. Approximation Quality and Connecting to a Detection Problem
5. Conclusions and Further Directions

Introduction

- Smart Grid technology is a promising way to promote energy efficiency which should be able to
  - ✓ meet the future demand growth
  - ✓ ensure the stability and reliability of the Grid
  - ✓ deal with the penetration of distributed local sources
  - ✓ deliver energy to consumers, even if the generation of power changes stochastically
- Centralized estimator is practically infeasible due to complexity
- Distributed state estimation is a prerequisite for smart grid functionality (situational awareness)
  - ✓ Local message passing to do distributed state estimation for linear models

Introduction

At the distribution level:

- Increase in penetration of distributed solar PVs
- Spatial correlations between distributed renewable energy sources such as solar PVs
- We need to take into account the spatial correlations between solar PVs
  - ✓ The central state estimators can incorporate all the spatial correlations
  - ✓ The distributed state estimator uses the graphical representation of the grid
  - ✓ The solar PV spatial correlation add loops to graph
- To get good state estimates we need to decrease the number of loops by a sparse approximation of the spatial correlations

Sparse Approximation

The sparse approximation is done by by eliminating some of the edges of the graph

- The Chow-Liu minimum spanning tree
- The first order Markov chain approximation
- The penalized likelihood methods such as LASSO

Spatial Correlation Between PV Sites

- $\underline{X} \in \mathcal{R}^{p \times 1}$ is the vector of solar irradiation.
- The sample covariance matrix from observed data is

$$\mathbf{S} = \frac{1}{n-1} \sum_{i=1}^{n} (\underline{x}_i - \bar{\underline{x}})(\underline{x}_i - \bar{\underline{x}})^T,$$

  where $\bar{\underline{x}} = \frac{1}{n} \sum_{i=1}^{n} \underline{x}_i$ is the sample mean.
- We don't know the distribution of the vector $\underline{X}$, so, for simplicity, we consider vector $\underline{X}$ to have jointly Gaussian distribution.
- **Goal:** To find the optimal tree structure associated with **S** using Chow-Liu algorithm.

Tree structure is interesting since it decreases lots of loops in the graphical representation of the loopy BP and also increases the accuracy of this algorithm.

Normalizing Data

- *Standard normalization method:* A time interval in a day and the required days of data is selected and then by subtracting mean and dividing by deviation we normalize the data.

- *Zenith angle normalization method:* It is the angle between the perpendicular line to the earth and the line to the sun where at the sunrise and the sunset it is 90 degrees.
- Cosine of the Zenith angle is linearly related to the solar irradiation in sunny days.
- We divide the received irradiation at each time with the cosine of the Zenith angle at that time to make data time decoupled.
- At the end we apply the standard normalization method.

Chow-Liu MST for Gaussian distributions

- $\mathcal{T}$ denote the set of all positive definite covariance matrices that has a tree structured graphical representation.
- $f(\underline{X}) \triangleq \mathcal{N}(\underline{0}, \mathbf{S})$
- $\widetilde{\mathbf{S}} \in \mathcal{T}$ be an approximation of the sample covariance matrix and $g(\underline{X}) \triangleq \mathcal{N}(\underline{0}, \widetilde{\mathbf{S}})$.
- The Chow-Liu algorithm minimizes the KL divergence between $f(\underline{X})$ and $g(\underline{X})$:

$$\mathcal{D}(f(\underline{X})||g(\underline{X})) = \frac{1}{2}\Big(\text{tr}(\mathbf{S}\widetilde{\mathbf{S}}^{-1}) - \log\det(\mathbf{S}\widetilde{\mathbf{S}}^{-1}) - p\Big).$$

Normalizing the KL divergence

- The KL divergence between the distribution and its optimal tree approximation varies for graphs with different number of nodes.
- To compare tree approximations of graphs with different number of nodes, we normalize the minimum KL divergence by the number of removed edges (l_e) in the tree structured graph

$$l_e = \frac{(p-1)(p-2)}{2}$$

- In other words, it is the penalty that one pays for removing one edge when doing the tree modeling.

Fields Definition (NREL solar data)

1) Oahu solar measurement grid sites (Kaleloa, Hawaii):

- Data from 19 sensors (17 sensors at horizontal position and 2 sensors tilted toward the west)
- We extracted data of a year from April 1, 2010 to March 31, 2011.
- Data was segmented to times between 9:00 AM to 5:00 PM.
- Data is normalized using the standard normalization and the zenith angle normalization with time intervals of 1 minute, 5 minutes and 10 minutes.

Fields Definition (NREL solar data)

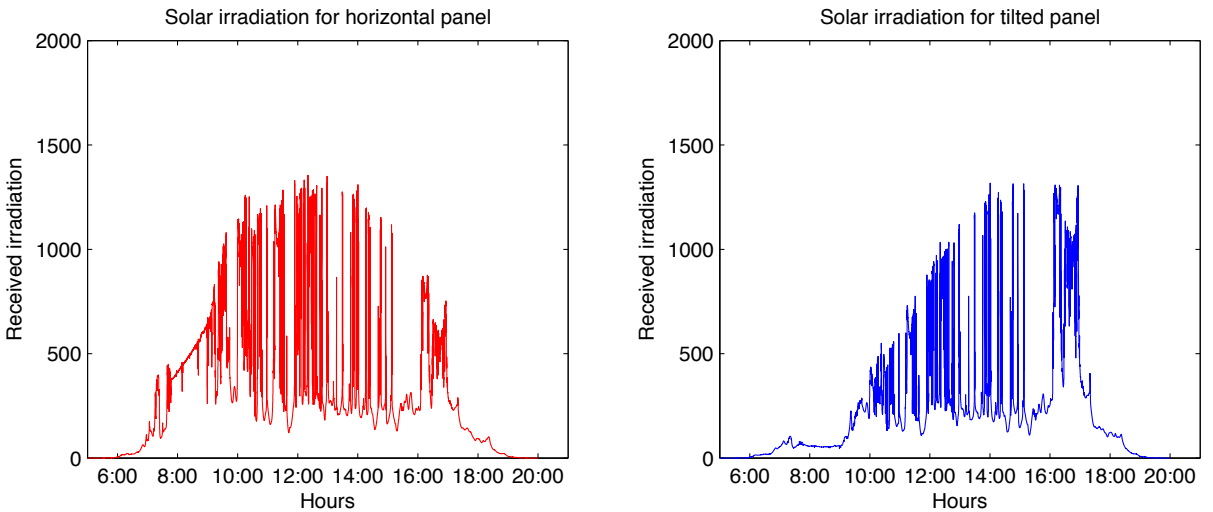


Figure: **Left:** Solar received irradiation for a panel with horizontal angle. **Right:** Solar received irradiation at the same position for a panel with angle 45 degrees tilted toward the west.

Fields Definition (NREL solar data)

2) Colorado sites (Denver, Colorado):

- 6 sites near city of Denver, Colorado.
- Two sites are fairly close to each other (the distance between them is around 400 meters) while the distance between any other pair of sites is between 22Km and 92Km.
- Data of year 2013 was extracted and segmented to times between 8:00 AM to 4:00 PM.
- Data is normalized using the standard normalization and the zenith angle normalization with time intervals of 1 minute, 5 minutes and 10 minutes.

Simulation

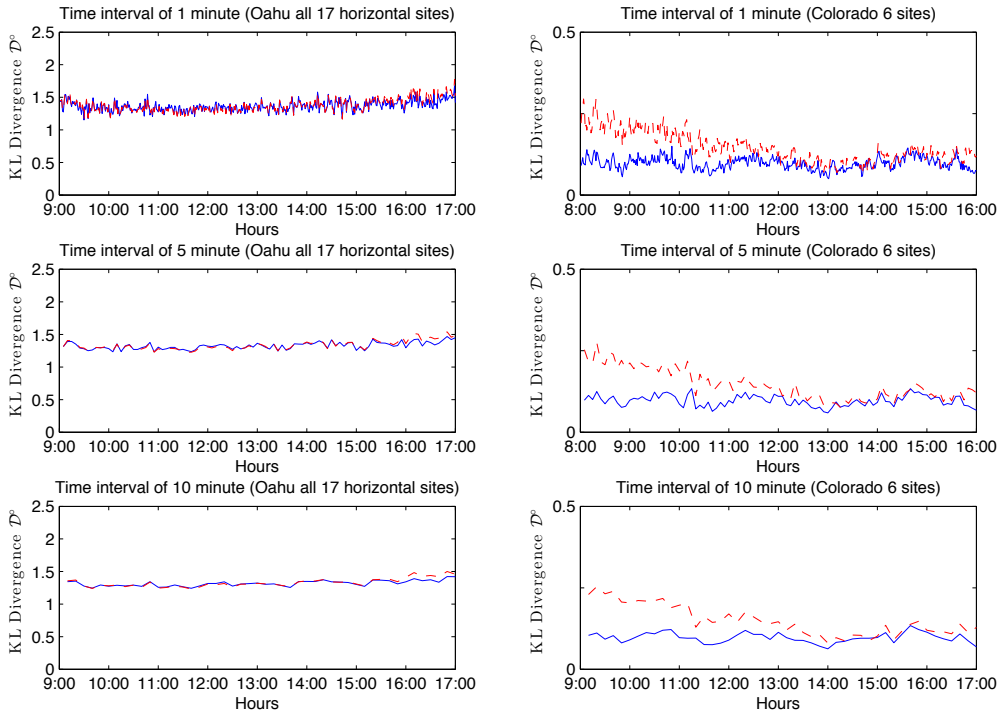


Figure: The minimum KL divergence distance comparison between all the 17 horizontal Oahu measurement grid and the 6 Colorado sites for windowing time interval 1 minute, 5 minutes and 10 minutes (Solid lines show the Zenith angle normalization while dashed lines indicate the standard normalization method.)

Simulation

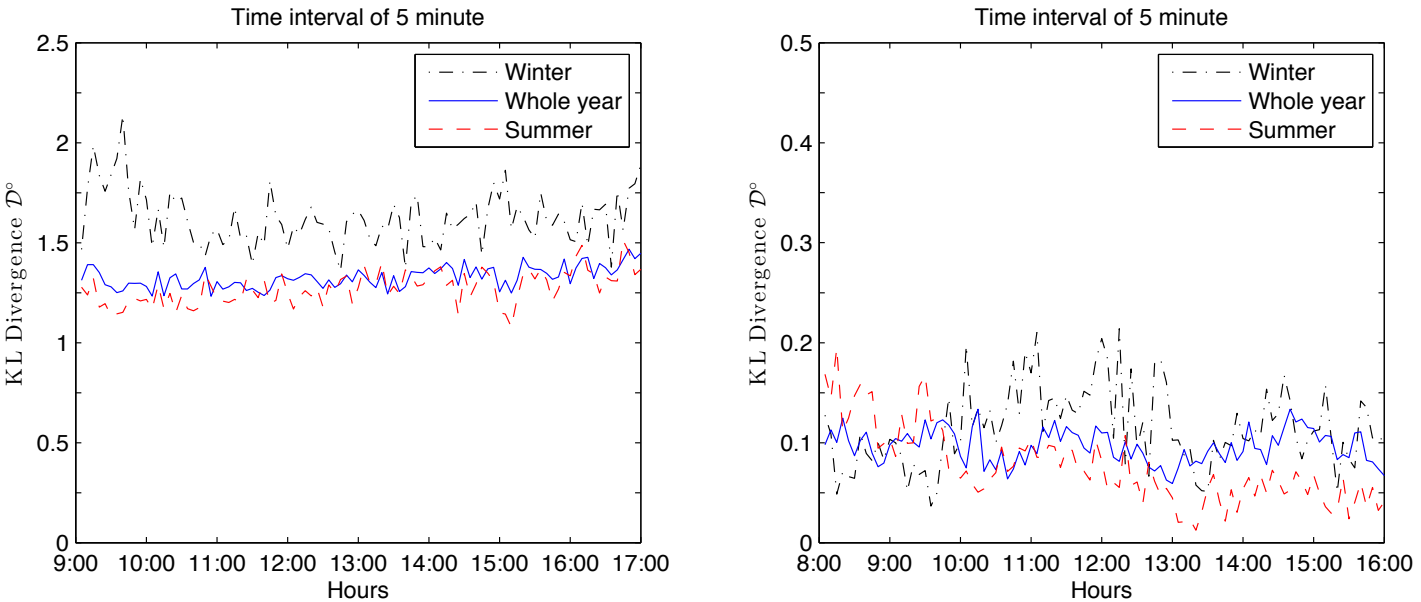


Figure: The minimum KL divergence distance comparison between seasonal data (average over summer, winter and whole year) for all the 17 horizontal Oahu measurement grid (left) and the 6 Colorado sites (right) with windowing time interval of 5 minutes

Simulation

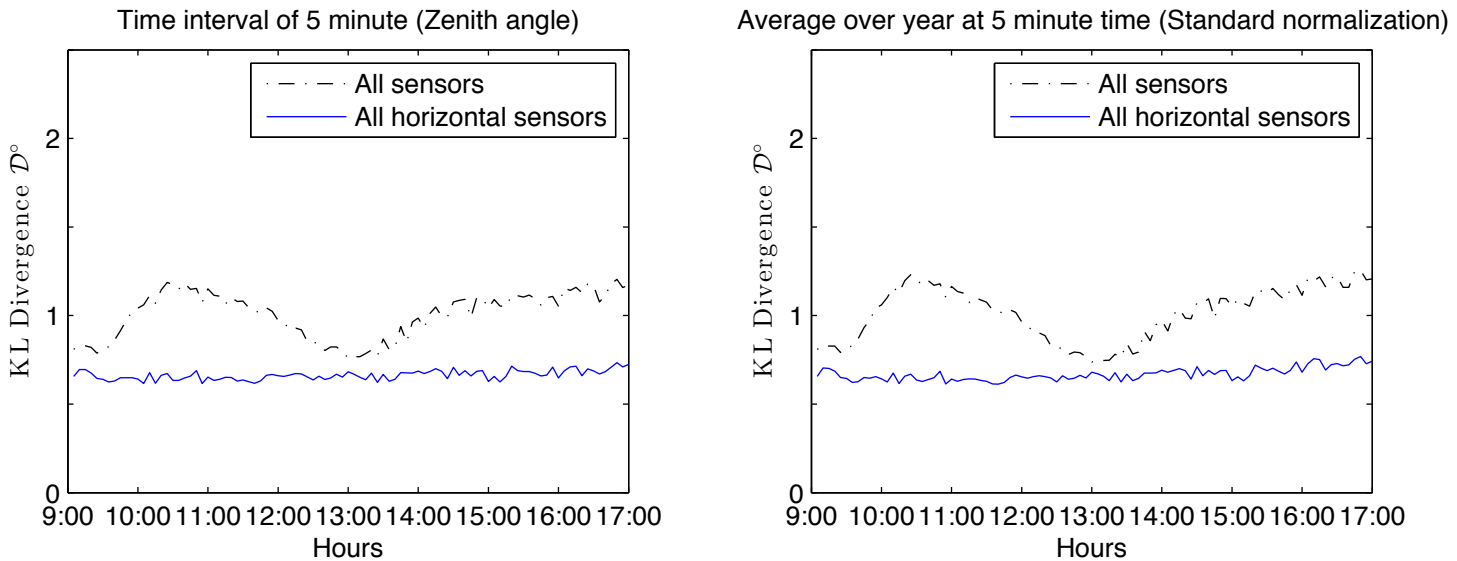


Figure: The minimum KL divergence distance by taking into account all the sensors for Oahu sites

Simulation

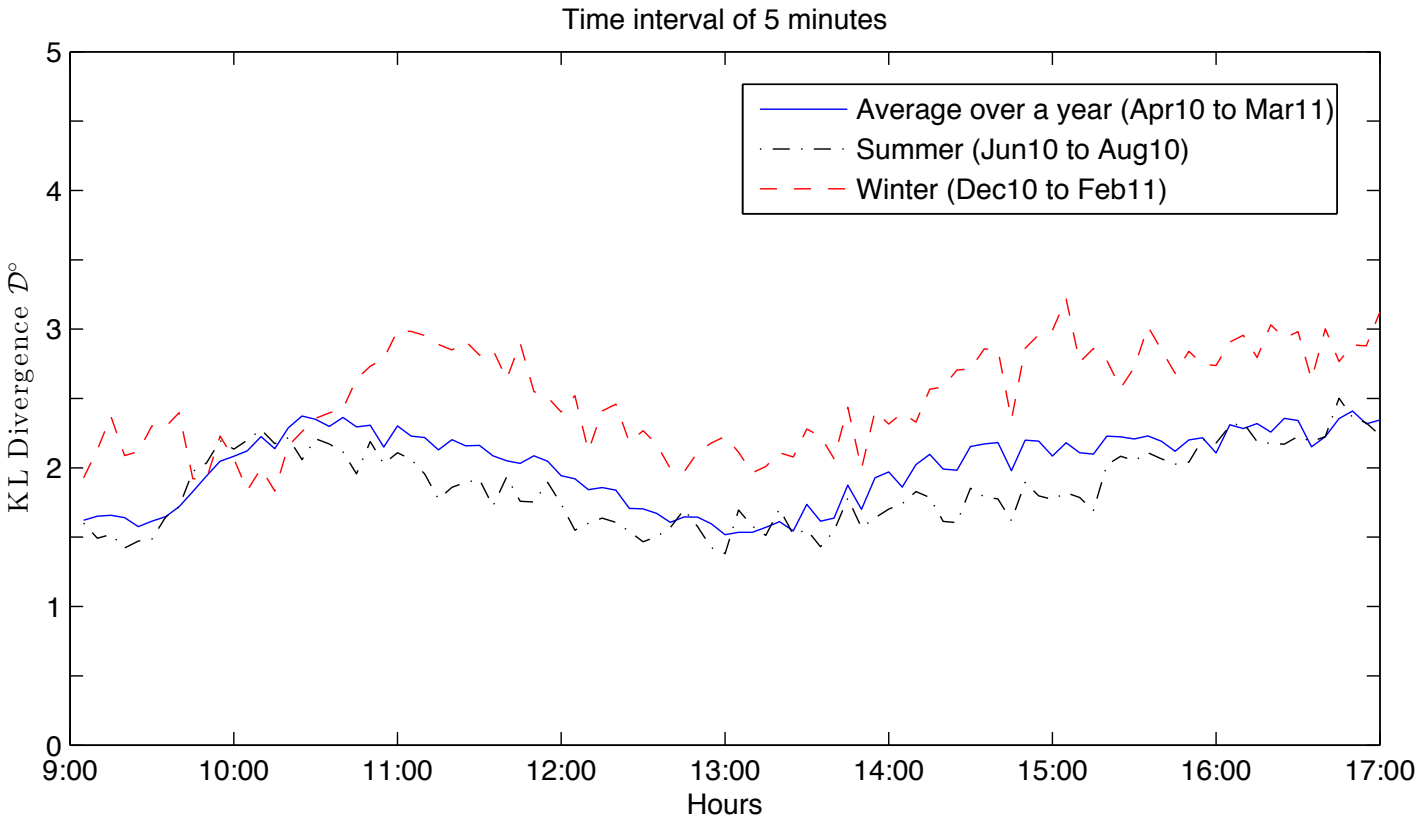


Figure: The minimum KL divergence distance by taking into account all the sensors for Oahu sites (average over summer, winter and whole year)

Simulation

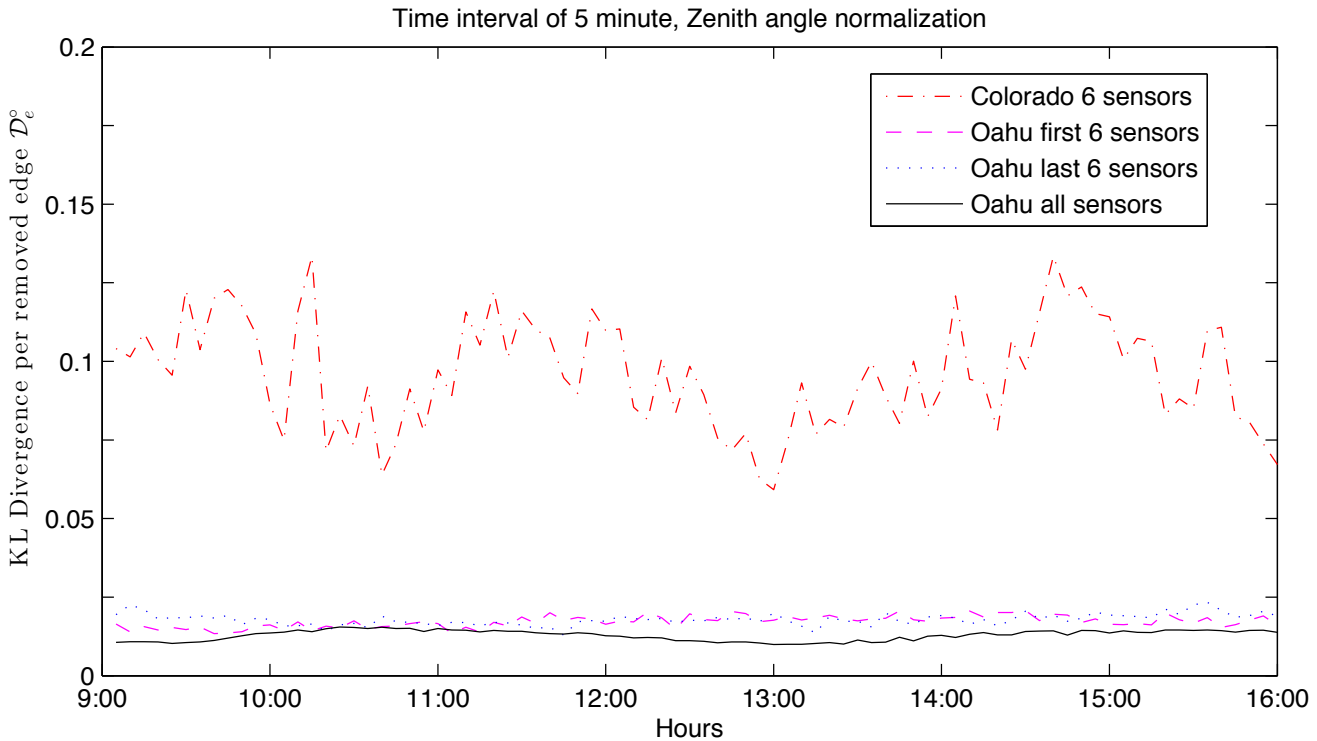


Figure: The normalized minimum KL divergence distance per removed edge for four scenarios: 1) all the 6 Colorado sensors, 2) the first 6 Oahu sensors (201-206 sensors), 3) the last 6 Oahu sensors (212-217 sensors) and 4) all the 19 Oahu sensors.

Distribution of Trees for Oahu data

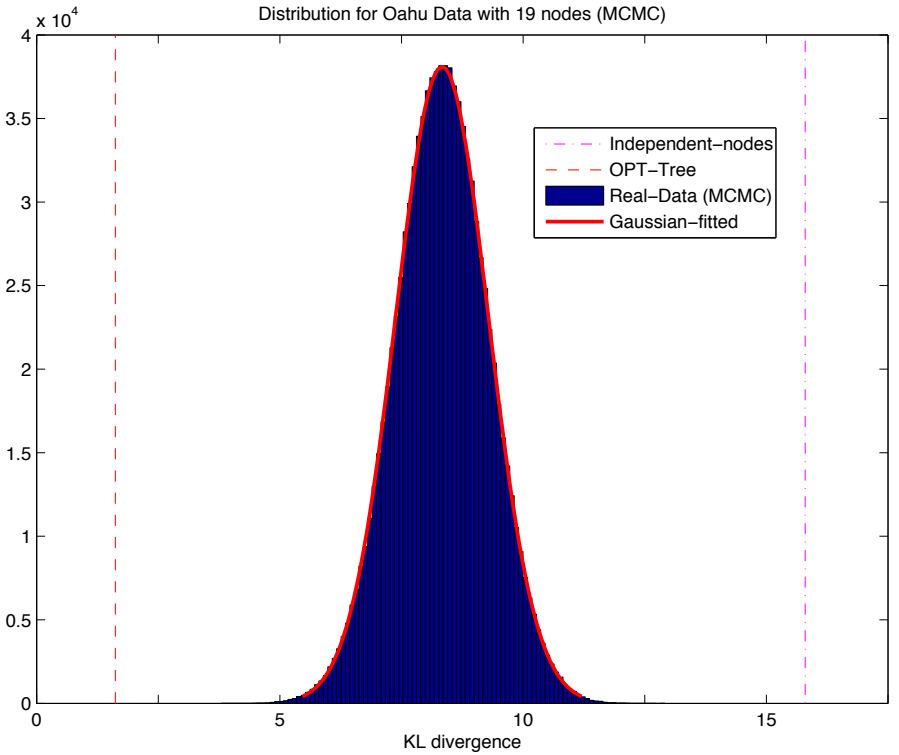


Figure: Comparison of of the optimal tree approximation, the uncorrelated approximation and the histogram of other trees obtains by Markov chain Monte Carlo (MCMC) method.

Distribution of Trees for Colorado data

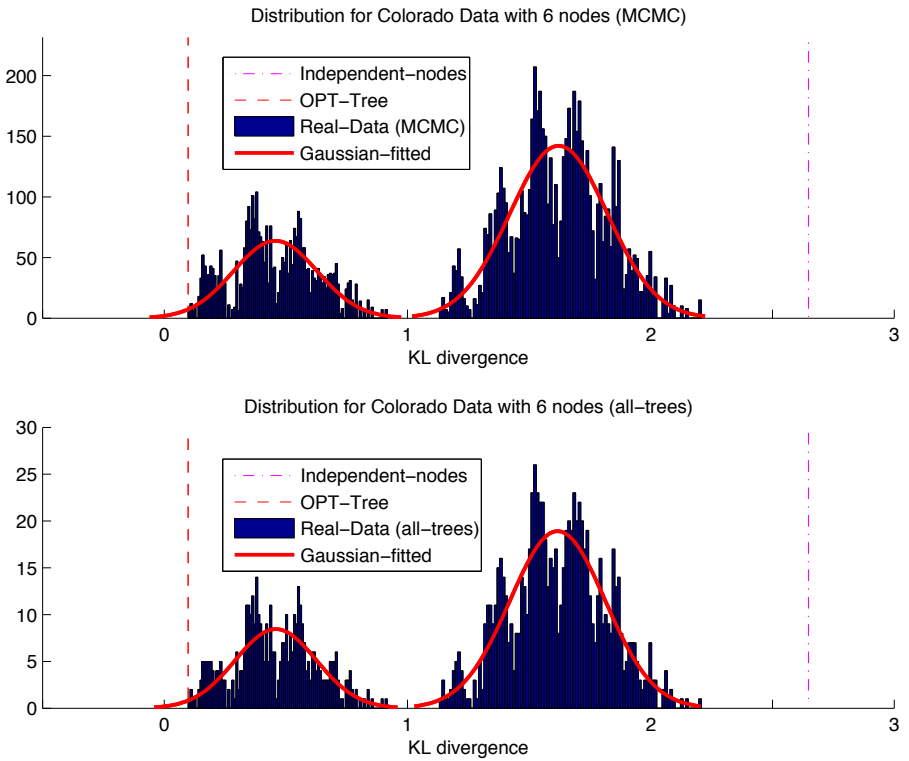


Figure: Comparison of of the optimal tree approximation, the uncorrelated approximation and the histogram of other trees. **Above:** Histogram of trees obtains by Markov chain Monte Carlo (MCMC) method **Below:** Histogram of all trees (6^4).

Remarks

- The distribution of KL divergence distance for different tree approximations for Oahu data is approximately Gaussian.

- The distribution of KL divergence distance for different tree approximations for Colorado data is more like a mixture of two distributions.
- Two sites are very close to each other. If these two sites are connected in tree approximation we are in left cluster of distribution, otherwise tree is in right cluster of distribution.

Detection Problem Formulation

Look at the problem as a detection problem:

- $\mathcal{H}_{\mathcal{F}}$: The fully-connected graph hypothesis with sample covariance matrix $\mathbf{S}$
- $\mathcal{H}_{\mathcal{T}}$: The tree-structured graph hypothesis with sample covariance matrix $\widetilde{\mathbf{S}}$
- The sufficient test statistic based on the log likelihood ratio test (LLRT) is:

$$l(\underline{y}) = \log \frac{f_{\underline{Y}}(\underline{y}|\mathcal{H}_{\mathcal{F}})}{f_{\underline{Y}}(\underline{y}|\mathcal{H}_{\mathcal{T}})}.$$

- For the Gaussian set up, $l(\underline{y}) = c - \frac{1}{2}\underline{y}^T\mathbf{K}\underline{y}$ where $c = -\frac{1}{2}\log\left(|\mathbf{S}\widetilde{\mathbf{S}}^{-1}|\right)$ is a constant and $\mathbf{K} = (\mathbf{S}^{-1} - \widetilde{\mathbf{S}}^{-1})$ is an indefinite matrix.
- $l(\underline{y})$ has generalized Chi-squared distribution under both hypotheses.

ROC for different trees

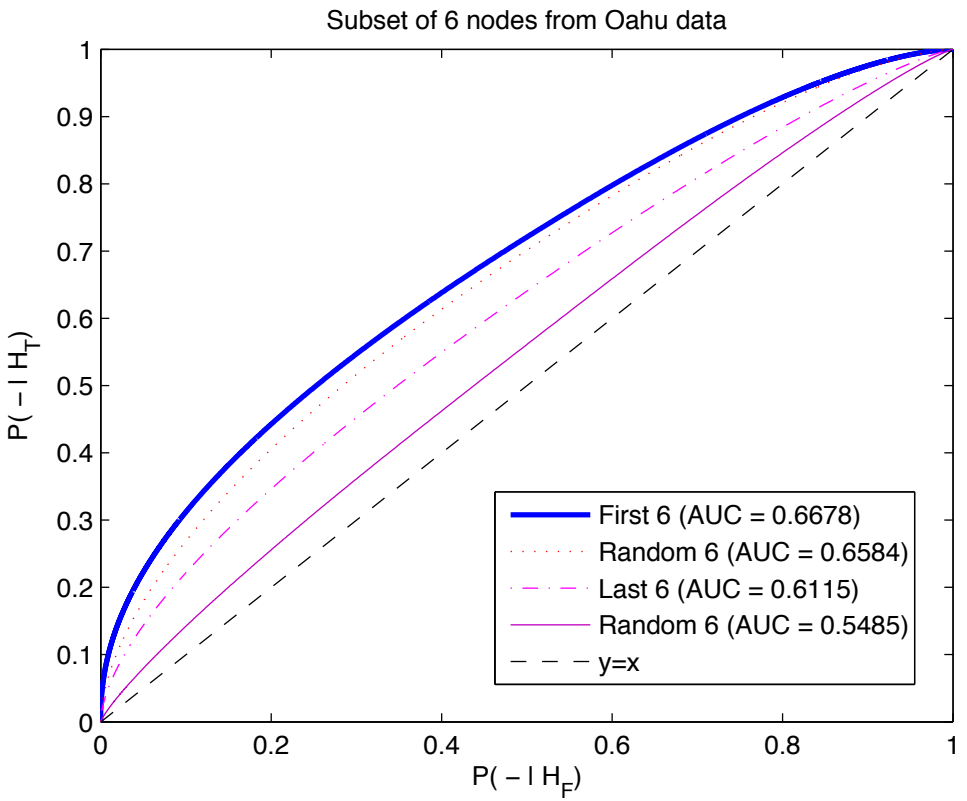


Figure: ROC curve and corresponding area under the curve (AUC) for different subsets of 6 nodes of the Oahu data

Example of better tree performance

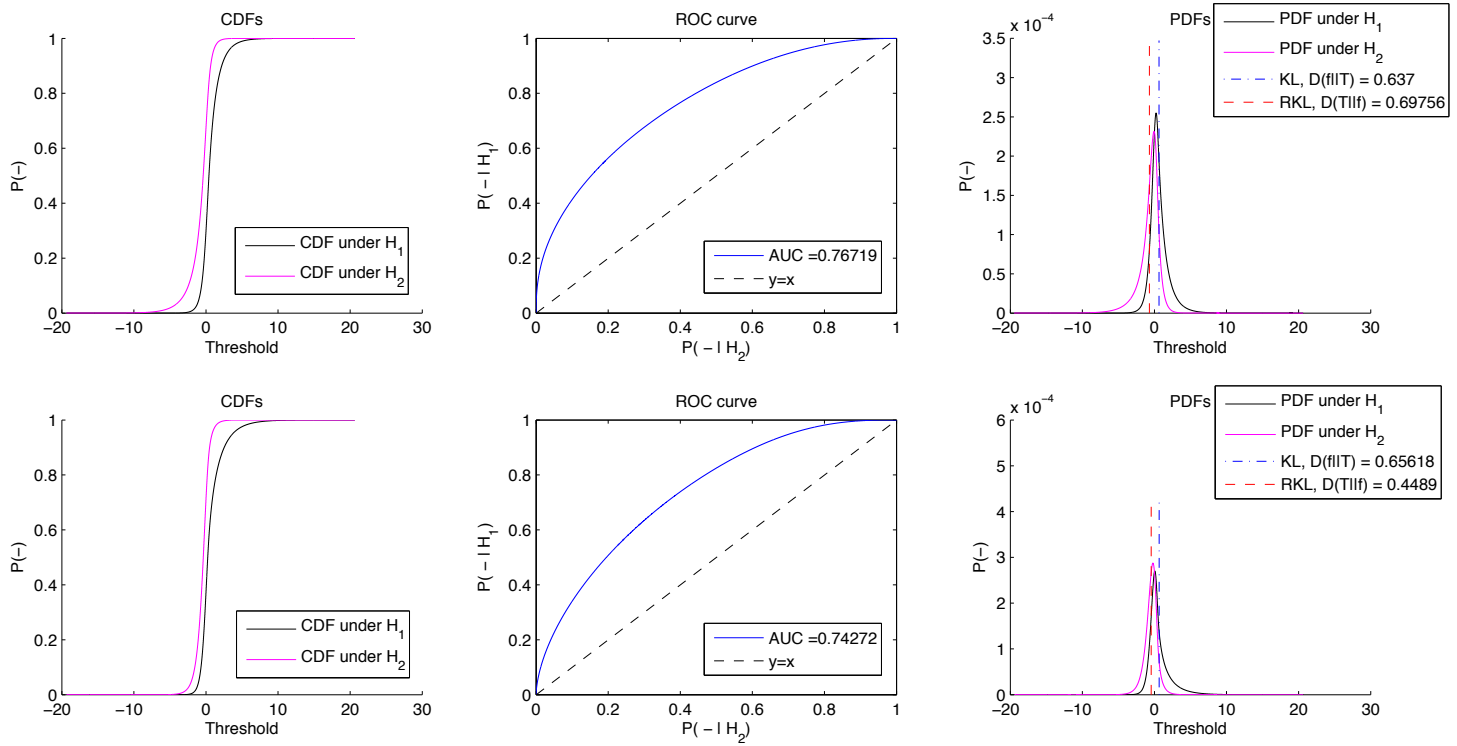


Figure: An example of tree approximation that outperform the optimal Chow-Liu tree in the sense of the AUC

Conclusions

- We modeled the spatial correlations among the distributed PV solar sites using the minimum spanning tree approximation method.
- The KL divergence used as the measure of closeness between the original and the model distribution.
- The data normalized using the Zenith angle normalization method (time decoupled)
- Simulation results presented for two major sites
- We conclude that the position of solar PV cells and their angles effect the tree approximated model and the accuracy cost that the tree approximation algorithm pays.

Further Directions

- Establishing more connections between normalized KL divergence and AUC.
- Looking at other information measures such as reverse KL divergence and Jeffery divergence. Establishing more connections between information measures and detection problem.
- Establishing connections between information measures and error cost functions such as mean squared error and regret functions.
- Using good approximations to perform distributed estimation for the power grid. Comparing quality of solutions and examining tradeoffs between performance and complexity.

Summary

- Discussed Hawaii energy landscape and education program
- Discussed research in solar PV using signal processing methods
  - Solar forecasting using asymmetric cost functions
  - Modeling distributed solar PV sources using distributed estimation

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Mahalo!!

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