Stochastic Modeling of Multi-Area Wind Production

PMAPS 2012, Constantinople, Turkey

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June 11th, 2012

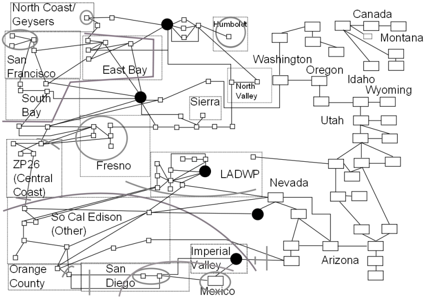
Outline

Stochastic Unit Commitment

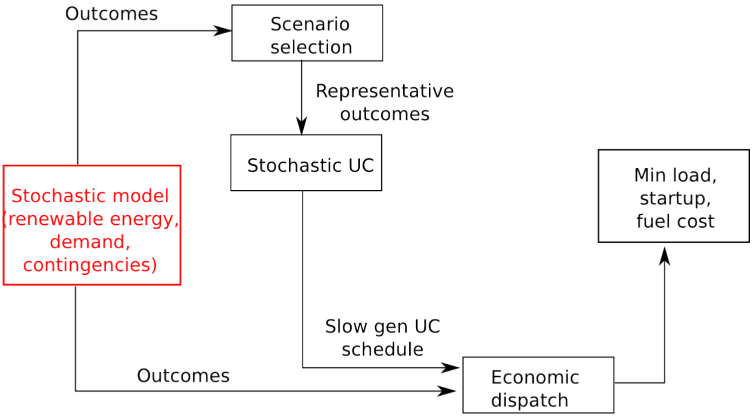
- Stochastic unit commitment has become a useful tool for assessing the impact of large-scale renewable energy integration on power system operations:
  - (Wang, Shahidehpour et al., 2008), (Bouffard, Galiana, 2008).
  - (Ruiz, Philbrick et al., 2009), (Tuohy, Meibom et al., 2009), (Morales, Conejo et al., 2009).
  - (Constantinescu, Zavala et al., 2011), (Papavasiliou, Oren et al, 2011).
- Ability to quantify:
  - Renewable energy utilization
  - Cost of unit commitment and economic dispatch
  - Capital investment in generation capacity

The Need for Multi-Area Wind Production Models

- Two sources of uncertainty:
  - Continuous disturbances: load/renewable forecast errors
  - Discrete disturbances: generator/line failures
- Transmission constraints affect operating costs, reserve requirements. Where wind power is produced matters.



Integration of Wind Models in Unit Commitment



Previous Work

- (Brown, Katz et al., 1984): Model wind speed, use exponential transformation of data set to fit autoregressive model, capture hourly patterns of wind speed.
- (Torres, Garcia et al., 2005): Same approach as Brown, using autoregressive moving average model.
- (Morales, Minguez et al., 2010): Noise vector drives a vector autoregressive process. Authors assume a diagonal matrix of autoregressive coefficients (spatial correlations captured by noise vector).

Autoregressive Model

- Mathematical model:

$$Y_{k,t+1} = \sum_{j=0}^{p} \phi_{kj} Y_{k,t-j} + \omega_{kt},$$

  where $\Phi = (\phi_{kj})$ is the matrix of autoregressive parameters and $(\omega_{kt}), k \in \{1, \cdots, K\}$, are iid, multivariate Gaussian random variables with mean 0 and covariance matrix Σ
- No diagonal terms assumed in autoregressive parameter matrix
- Spatial correlations are captured by noise vector ω_{kt}

Calibration

1. Remove systematic seasonal and diurnal effects:

$$y_{kt}^{S} = \frac{y_{kt} - \hat{\mu}_{kmt}}{\hat{\sigma}_{kmt}}.$$

2. Transform data to obtain a Gaussian stationary distribution:

$$y_{kt}^{GS} = N^{-1}(\hat{F}_k(y_{kt}^{S})).$$

3. Estimate the autoregressive parameters $\hat{\phi}_{kj}$ and covariance matrix $\hat{\Sigma}$ using Yule-Walker equations.

Calibration Details

- Important to work with wind speed model if possible
- Data fit:
  - (Brown, Katz et al, 1984) and (Torres, Garcia et al.) use Weibull distribution, (Papavasiliou, Oren et al., 2011) use inverse Gaussian distribution to fit wind speed data
  - (Callaway, 2010) uses non-parametric distribution
  - In current study we use non-parametric distribution since each area has different distribution
- Shorter epochs increase accuracy of fit but require estimation of more parameters $\hat{\mu}_{kmt}, \hat{\sigma}_{kmt}$

Simulation

- Generate autoregressive noise of order p:

$$Y_{k,t+1}^{GS} = \sum_{j=0}^{p} \hat{\phi}_{kj} Y_{k,t-j}^{GS} + \omega_{kt}$$

- Transform to non-Gaussian distribution:

$$Y_{kt}^{S} = \hat{F}_k^{-1}(N(Y_{kt}^{GS}))$$

- Add seasonal and hourly mean and variance:

$$Y_{kt} = \hat{\sigma}_{kmt} Y_{kt}^{S} + \hat{\mu}_{kmt}$$

- Simulate power using approximate power curve:

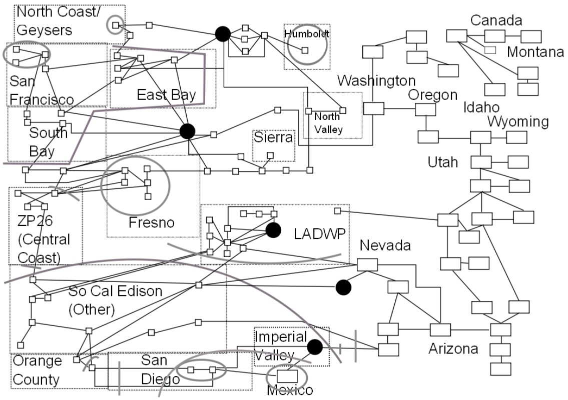
$$P_{kt} = \hat{P}_k(Y_{kt})$$

Wind Model Data Source

- 2 wind integration cases: moderate (7.1% energy integration, 2012), deep (14% energy integration, 2020)
- California ISO interconnection queue lists locations of planned wind power installations
- NREL Western Wind and Solar Interconnection Study archives wind speed - wind power for Western US

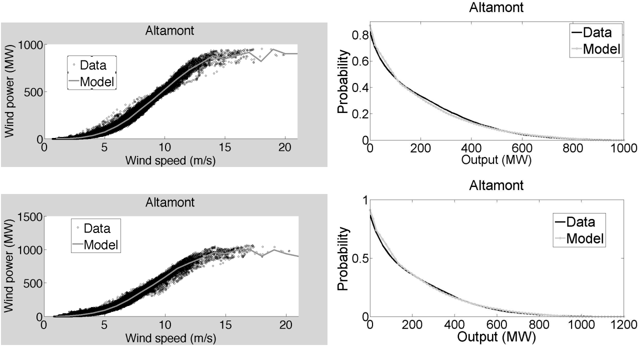
County	Existing	Moderate	Deep
Altamont	954	954	1,086
Clark	-	-	1,500
Imperial	-	-	2,075
Solano	348	848	1,149
Tehachapi	1,346	4,886	8,333
Total	2,766	6,688	14,143

WECC Model


North Coast/
Geysers
Humboldt
Canada
Montana
San
Francisco
East Bay
Washington
Oregon
Idaho
Wyoming
North
Valley
South
Bay
Sierra
Utah
Fresno
ZP26
(Central
Coast)
LADWP
Nevada
So Cal Edison
(Other)
Imperial
Valley
Arizona
Orange
County
San
Diego
Mexico

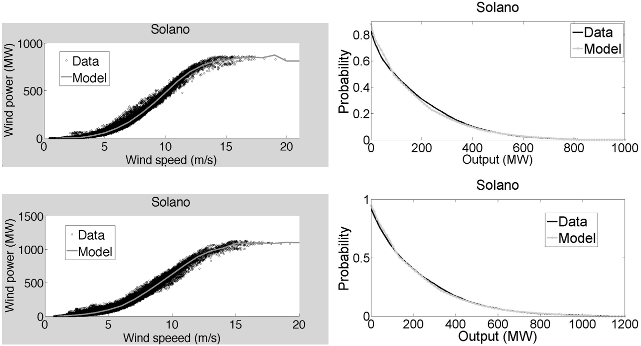
Altamont County

Power curves (left) and complementary cdf of wind output (right) for moderate (up) and deep (down) integration study



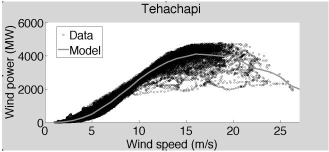
Solano County

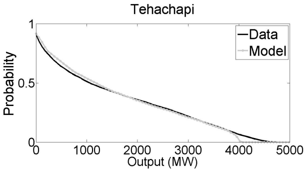
Power curves (left) and complementary cdf of wind output (right) for moderate (up) and deep (down) integration study

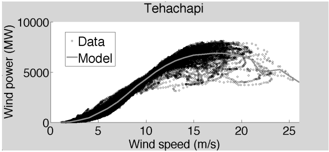


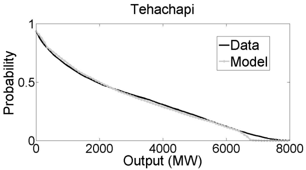
Tehachapi County

Power curves (left) and complementary cdf of wind output (right) for moderate (up) and deep (down) integration study



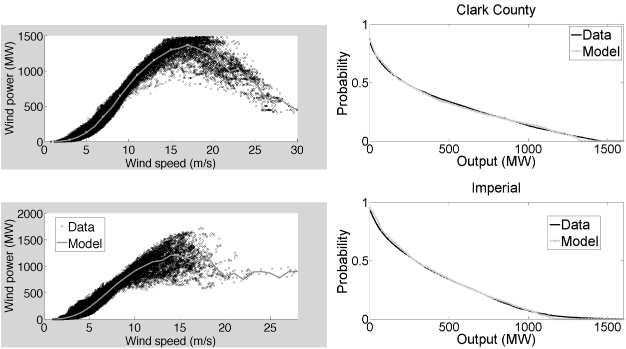






Clark County and Imperial Valley

Power curves (left) and complementary cdf (right) for Clark County (up) and Imperial Valley (down) for deep integration



Remarks

- Slight deviation of cdf for deep integration study in high power output levels of Tehachapi and Solano area
- Approximate power curve cannot capture scatter diagram accurately due to wide geographical dispersion of wind sites
- Remedy is to increase number of wind sites at the cost of increasing number of estimated parameters in correlation matrix Σ
- Acceptable approximation in unit commitment studies since low-power output outcomes are represented accurately

Conclusions and Perspectives

- Conclusions
  - **Multi-area wind power production model** that captures nonlinearities of power conversion, systematic seasonal and diurnal effects, non-Gaussian distribution of original data set, spatial correlations and inter-temporal dependencies
  - **Tradeoff** between accuracy of correlation matrix estimation and accuracy of approximate power curves
- Perspectives
  - **Solar power production modeling**
  - **Check fit of model to 2004, 2005 NREL data**

Thank you

Questions?

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http://www3.decf.berkeley.edu/∼tonypap/publications.html