Wind Power Systems

1.0 Overview
2.0 Simulation model for wind farm operation
3.0 Research topics

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2. Simulation model of wind farm operations

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3.0 Overview

Challenges in power system operations

Changes in Power system operation and planning

- Fast growth of large-scale distributed renewable energy source
- Deregulated electric power markets
- Responsive demand

New methodologies are required in the following area

1) Complicated power generation scheduling (ED)
2) Correlated uncertainties
3) Energy and environments (Emission, water desalination)
4) Hybrid generation modeling (solar/wind/storage/PHEV, etc)
Economic dispatch (ED)

- Optimization problem to find the optimal allocation of output power among the various generators available to serve the system load.

- Various models have been developed, depending on
  - Cost factors (cost, risk/system security, emissions)
  - Requirements (whether to include reliability requirements, ramping constraints, etc.)
  - Generation source (conventional energy, renewable energy, storage)
  - Uncertainty treatment (deterministic/stochastic optimization)
  - Methodology

- Mostly, non-linear in objective function and constraints
  - Various solution methods: Lagrangian relaxation, direct search method, evolution programming, particle swarm optimization, genetic algorithm, and simulated annealing, etc.

- We will look at a few ED models.
Study 1: ED with wind power \cite{1}

- Considers overestimation/underestimation of wind power generation

\[
\begin{align*}
\min & \quad \sum_{i}^{M} C_i(p_i) + \sum_{i}^{N} C_{w,j}(w_i) + \sum_{i}^{N} C_{p,w,j}(W_{i,av} + w_i) \\
\text{subject to} & \quad \sum_{i}^{M} p_i + \sum_{i}^{N} w_i = L \\
\end{align*}
\]

Objective:
(1) minimizing costs of generation costs from convention and wind-powered generators plus penalty of under- & over-estimation of wind power

Constraints:
(2) & (3): generation range
(4) load balance equation

\( p_{i,\text{min}} \leq p_i \leq p_{i,\text{max}} \) \hspace{2cm} (2)

\( 0 \leq w_i \leq w_{r,i} \) \hspace{2cm} (3)

\( \sum_{i}^{M} p_i + \sum_{i}^{N} w_i = L \) \hspace{2cm} (4)

\( p_i \) power from the \( i \)th conventional generator;

\( w_i \) scheduled wind power from the \( i \)th wind-powered generator;

\( W_{i,av} \) available wind power from the \( i \)th wind-powered generator. This is a random variable, with a value range of \( 0 \leq W_{i,av} \leq w_r \) and probabilities varying with the given pdf. We considered Weibull pdf for wind variation;

\( w_{r,i} \) rated wind power from the \( i \)th wind-powered generator;

\( C_i \) cost function for the \( i \)th conventional generator;

\( C_{w,i} \) cost function for the \( i \)th wind-powered generator. This factor will typically take the form of a payment to the wind farm operator for the wind-generated power actually used;

\( C_{p,w,i} \) penalty cost function for not using all available power from the \( i \)th wind-powered generator;

\( C_{r,w,i} \) required reserve cost function, relating to uncertainty of wind power. This is effectively a penalty associated with the overestimation of the available wind power; system load and losses.

\( L \) system load and losses.
3.1 Economic dispatch

Study 1: ED with wind power \[^{[1]}\]

- Generation cost for conventional generators \( C_i(p_i) = \frac{a_i}{2} p_i^2 + b_i p_i + c_i \)
- Wind power generation cost \( C_{w,i}(w_i) = d_i w_i \)
- Penalty cost for not using wind power
  \[ C_{p,w,i}(W_{i,av} - w_i) = k_{p,i}(W_{i,av} - w_i) = k_{p,i} \int_{w_i}^{w_{r,i}} (w - w_i)f_W(w)dw \]
  where
  - \( k_{p,i} \) penalty cost (underestimation) coefficient for the \( i \)th wind generator;
  - \( f_W(w) \) WECS wind power pdf.
- Reserve requirement cost
  \[ C_{r,w,i}(w_i - W_{i,av}) = k_{r,i}(w_i - W_{i,av}) = k_{r,i} \int_{o}^{w_i} (w_i - w)f_W(w)dw \quad (8) \]
  where \( k_{p,i} \) is the reserve cost (overestimation) coefficient for the \( i \)th wind-powered generator.

\[ \Rightarrow \] Numerically solve the optimization problem with two conventional and two wind generators using MATLAB optimization toolbox.
Study 2: ED with wind power [2]

- Considers security factor when wind power is integrated to power grid

- X-axis: wind penetration level
- Y-axis: system security level

Two objective functions
- Minimize system risk level: \( R(\mu) = \frac{1}{\mu} \)
- Minimize operational cost: \( \text{TOC}(P_G, \mu) = \text{FC}(P_G) + \text{WC}(P_G, \mu) \)

Fuel cost for conventional generators
\[
\text{FC}(P_G) = \sum_{i=1}^{M} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + d_i \sin[e_i(P_{Gi}^{\text{min}} - P_{Gi})]
\]

Running cost of wind power
\[
\text{WC}(P_G, \mu) = C_w \left( W_{av} - (P_D + P_L - \sum_{i=1}^{M} P_{Gi}) \right)
\]

\[ \mu \times \Delta \text{WC} + \text{WC}_{\text{max}} \]

Not-used wind power

Operation (or, integrating cost at the current security factor \( \mu \))
\[
\Delta \text{WC} = \text{WC}_{\text{max}} - \text{WC}_{\text{min}}.
\]
Study 2: ED with wind power \cite{2}

- **Methods:** Multi-Objective Particle swamp Optimization (MOPSO)

- **Particle swamp Optimization**
  - Population-based stochastic optimization technique, inspired by the movement pattern in a bird flock or fish school.
  - Individuals (i.e., particles) move around in a multidimensional search space to approach the optima.
  - Each particle adjusts its position based on its own experience (pbest) as well as the experience (gbest) of other particles by utilizing the best position encountered by itself and others. It combines both local and global search methods.

\begin{align*}
  v_{id}^{(t+1)} &= \chi \left( w \cdot v_{id}^{(t)} + c_1 \cdot \text{rand()} \cdot (pbest_{id} - x_{id}^{(t)}) \\
  &\quad + c_2 \cdot \text{Rand()} \cdot (gbest_{d} - x_{id}^{(t)}) \right), \quad (4.1)
\end{align*}

\begin{align*}
  x_{id}^{(t+1)} &= x_{id}^{(t)} + v_{id}^{(t+1)}, \quad i = 1, 2, \ldots, N, \\
  d &= 1, 2, \ldots, M + 1. \quad (4.2)
\end{align*}

Velocity: adjusts the direction (and amount) of each particle based on its best value (pbest) and the best value (gbest) of all particles.

Adjusts the value of each particle.
Study 2: ED with wind power \cite{2}

To tackle “Multi-Objective” Optimization, use pareto-front method

For \( m \) objectives to be minimized, the Pareto optimal solutions are recorded based on Pareto dominance, which states that a decision vector \( a \) dominates another \( b \) if and only if

\[
\forall i \in \{1 \ldots m\}; \quad f_i(a) \leq f_i(b) \quad \text{and} \quad \exists i \in \{1 \ldots m\}; \quad f_i(a) < f_i(b).
\]

The set of all Pareto optimal solutions (non-dominated outcome vectors) is called the Pareto front. Each particle in the swarm is attracted by one of the Pareto optimal solution, and search for a better Pareto front iteratively.
Study 2: ED with wind power \(^2\)

- Example: IEEE 30-bus test system with six conventional generators

![Diagram showing IEEE 30-bus test system with six conventional generators](image)

![Graph showing Pareto fronts obtained based on different membership functions](image)

Fig. 6. Pareto fronts obtained based on different membership functions.
Consider risk factors using stochastic dominance concept
- Multiple criteria → single scalarizing achievement function as expressing utility to be Maximized
- Achievement function enforces reaching the reservation levels prior to further improving of criteria. (reservation levels: soft lower bounds on the maximized criteria)
- When all these lower bounds are satisfied, then the optimization process attempts to reach the aspiration levels

Achievement function

\[
a(q) = \min_{1 \leq i \leq m} \left\{ a_i(q_i, q_i^a, q_i^r) \right\} + \varepsilon \sum_{i=1}^{m} a_i(q_i, q_i^a, q_i^r)
\]

Partial achievement function
Outcome (ith risk decision variable)
Reservation level
Aspiration level

3.1 Economic dispatch

[18] Market clearing prices are stochastic. Consider mean revenues and other risk factors
Study 3: ED with emission factor [5], [6], [14]

(may not have wind generations)

- Combined Economic and Emission Dispatch [5]
  - Include the emission factor (CO2, SO2, Nox) in objective function

\[
\hat{\phi}_T = w_1 F_T(P) + w_2 h E_T(P)
\]

 Fuel cost (Quadratic & sine function)

\[
h = \frac{F_T(P_{i\text{max}})}{P_{i\text{max}}} \div \frac{E_T(P_{i\text{max}})}{P_{i\text{max}}}
\]

Total emissions (Quadratic and exponential function)

- Multi objective problem [6]:
  - Consider two objectives separately
  - Use genetic algorithm with pareto-optimal.

< Convergence of cost and emission objective functions >

Fig. 5. Pareto-optimal front of the proposed approach in a single run, Case 1.
Study 4: Applying stochastic programming [7]

- Stochastic Programming (SP)
  - Basically generalizations of deterministic mathematical programs in which uncontrollable data are not known with certainty
  - Note: The "certainty" assumption in linear programming (LP) is violated!
  - Stochastic linear programming (SLP) deals with linear programs with random data (course focus)
  - Stochastic mixed-integer programming (SMIP) deals with mixed integer programs with random data
Study 4: Applying stochastic programming [7]

- A general two-stage SLP with recourse model can be written as follows:

\[
\begin{align*}
\text{Min} & \quad c^T x + E\bar{\omega} [f(x, \bar{\omega})] \\
\text{s.t.} & \quad Ax \geq b, \\
& \quad x \geq 0,
\end{align*}
\]

where for any realization \( \omega \) of \( \bar{\omega} \) we have

\[
\begin{align*}
\text{Min} & \quad q(\omega)^T y \\
\text{s.t.} & \quad W(\omega)y \geq r(\omega) - T(\omega)x, \\
& \quad y \geq 0,
\end{align*}
\]
Study 4: Applying stochastic programming [8]

- **Spot market** (a day-ahead auction) in Spanish and Nordic system
  - Power suppliers submit their hourly bids, and the market operator performs the clearing algorithm in order to select the accepted and rejected bids.
  - To build these bids, wind producers need to forecast their production from 00:00 to 24:00 of the following day, 14–38 h in advance → 30%–50% prediction error
  - There is also uncertainty about market prices

- **Intra-day balancing markets** covering the remaining hours of the trading day
  - To sell or to buy the positive or negative differences between the expected real production and the last cleared schedule.
  - In the Spanish case, there are six intra-day balancing markets
  - The bids must be submitted approximately 4 h in advance: → 15%–25% prediction error

- The final error between the last energy schedule and real production of the wind producer is penalized.
Study 4: Applying stochastic programming [8]

- Use pumped-storage facility (pump-turbine)
  - The composed of an upper reservoir and a lower reservoir.
  - A pump-turbine consumes/stores energy in off-peak hours (Move water from a lower reservoir to upper reservoir)
  - Water is released from the upper reservoir to the lower one, injecting its production to the network.

- Applying SP

Wind energy production, market price

Decide the generation amount from wind and hydro turbines

Operate pumped-storage facility to meet the committed amount for each scenario (420 scenarios)
### Study 4: Applying stochastic programming \[^8\]

#### Master variable: bidding amount

\[
\max \sum_{s \in S} \rho_s \cdot \sum_{h \in H} \left[ \pi_{sh} \cdot \left( g^u_{sh} + g^p_{sh} - d^p_{sh} \right) - c^{su} \cdot y_{sh} - c^{sd} \cdot z_{sh} - \omega \cdot \pi_{sh} \cdot \left| g^w_{sh} + g^p_{sh} - d^p_{sh} - x^\text{wp}_{h} \right| \right]
\]

\[
\text{s.t.}
\begin{align*}
0 \leq g^w_{sh} & \leq W_{sh}, \quad \forall s \in S, \forall h \in H \\
v^u_{sh} &= v^u_{sh-1} + \eta \cdot d^p_{sh} - g^p_{sh}, \quad \forall s \in S, \forall h \in H \\
v^l_{sh} &= v^l_{sh-1} + g^p_{sh} - \eta \cdot d^p_{sh}, \quad \forall s \in S, \forall h \in H \\
v^u_{sh} &\leq v^u_{sh} \leq \bar{v}^u, \quad \forall s \in S, \forall h \in H \\
v^l_{sh} &\leq v^l_{sh} \leq \bar{v}^l, \quad \forall s \in S, \forall h \in H \\
v^u_{sh} &= v^f_{h}, \quad \forall s \in S, h = 24 \\
v^l_{sh} &= v^f_{h}, \quad \forall s \in S, h = 24 \\
u_{sh+1} &= u_{sh} + y_{sh} - z_{sh}, \quad \forall s \in S, \forall h \in H \\
d^p \cdot u_{sh} &\leq d^p_{sh} \leq d^p \cdot u_{sh}, \quad \forall s \in S, \forall h \in H \\
0 &\leq g^p_{sh} \leq t_{sh} \cdot \bar{g}^p \cdot N, \quad \forall s \in S, \forall h \in H \\
t_{sh} &\leq 1 - \frac{1}{N} \cdot u_{sh}, \quad \forall s \in S, \forall h \in H \\
-d^p \cdot N &\leq x^\text{wp}_{h} \leq (\bar{g}^w + \bar{g}^p) \cdot N, \quad \forall h \in H \\
u_{sh}, y_{sh}, z_{sh} &\in \{0, 1, \ldots, N\} \\
t_{sh} &\in \{0, 1\}.
\end{align*}
\]

- Mixed integer stochastic programming

\(s:\) scenario (price, wind), \(h:\) hour \((1, \ldots, 24)\)

- \(v^u_{sh}\): Energy stored in the upper reservoir in scenario \(s\) at the end of period \(h\) [MWh].
- \(v^l_{sh}\): Energy stored in the lower reservoir in scenario \(s\) at the end of period \(h\) [MWh].
- \(d^p_{sh}\): Discharge power output of the pumped-storage plant in scenario \(s\) in period \(h\) [MW].
- \(\bar{d}^p_{sh}\): Pumping power input of the pumped-storage plant in scenario \(s\) in period \(h\) [MW].
- \(g^w_{sh}\): Power output of the wind farm in scenario \(s\) in period \(h\) [MW].
- \(x^\text{wp}_{h}\): Joint energy bid to the day-ahead market by the wind farm and the pumped-storage plant in period \(h\) [MWh].
- \(t_{sh}\): Binary variable that indicates whether the pumped-storage plant can work or not as a hydro-turbine, in scenario \(s\) in period \(h\) \(\{0, 1\}\).
- \(u_{sh}\): Integer variable that indicates the number of units that are running in the pumping mode in scenario \(s\) in period \(h\) \(\{0, 1, \ldots, N\}\).
- \(y_{sh}, z_{sh}\): Integer variables that indicate the number of units that are start-up and shut-down in the pumping mode in scenario \(s\) in period \(h\) \(\{0, 1, \ldots, N\}\).
Study 4: Applying stochastic programming

\[ \pi_{sh} \] Expected market price in scenario \( s \) in period \( h \) [Euro/MWh].

\[ W_{sh} \] Wind generation forecast in scenario \( s \) in period \( h \) [MW].

\[ N \] Number of identical pumped-storage units associated in the same pond.

\[ \omega \] Penalty factor over the market price for energy imbalances [p.u.].

\[ \rho_s \] Probability of scenario \( s \) [p.u.].

\[ \eta \] Efficiency of the pump-turbine cycle [p.u.].

\[ \bar{g}^p, \bar{d}^p \] Generation power limit for each pumped-storage unit [MW].

\[ \bar{g}^w \] Pumping power limits for each pumped-storage unit [MW].

\[ \bar{u}^u, \bar{u}^u \] Maximum installed power of the wind farm [MW].

\[ \bar{u}^u, \bar{u}^u \] Capacity limits of the upper reservoir [MWh].

\[ \bar{u}^l, \bar{u}^l \] Capacity limits of the lower reservoir [MWh].

\[ u^o_u, u^f_u \] Initial and final levels in the upper reservoir [MWh].

\[ u^o_l, u^f_l \] Initial and final levels in the lower reservoir [MWh].

\[ c^{su}, c^{sd} \] Start-up and shut-down costs of pumping units [Euro].
Study 4: Applying stochastic programming [8]

- Compare two cases
  - Uncoordinated operation (UO): wind farm and the pumped storage unit are operated independently
  - Joint operation (JO)
- Example
  - 30-MW wind farm and a 10-MW pumped-storage plant (two pumps)
  - 420 scenarios (20 prices predictions * 21 wind predictions over 24 hours)
  - implemented in GAMS, using CPLEX 10.0

**Expected Profits for Each Configuration**

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Mean value [Eur]</th>
<th>Std. deviation [Eur]</th>
</tr>
</thead>
<tbody>
<tr>
<td>UO Wind farm</td>
<td>16301</td>
<td>2570</td>
</tr>
<tr>
<td>Pumped-storage</td>
<td>193</td>
<td>64</td>
</tr>
<tr>
<td>Sum</td>
<td>16494</td>
<td>2577</td>
</tr>
<tr>
<td>JO</td>
<td>16912</td>
<td>2614</td>
</tr>
</tbody>
</table>

**Penalties for Imbalance**

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Penalties [Eur]</th>
</tr>
</thead>
<tbody>
<tr>
<td>UO</td>
<td>1653</td>
</tr>
<tr>
<td>JO</td>
<td>1066</td>
</tr>
</tbody>
</table>

Fig. 5. Obtained optimal hourly bids.
Study 4: Applying stochastic programming [8]

< Lower reservoir operation through the day for each scenario (JO) >

< Pumping-storage operation in scenario #26 >
Study 4: Applying stochastic programming [8]

- Difficulties in SP
  - how to generate scenarios and assign probability
  - how to deal with continuous variable (wind generation)
    - Sampling? What if the realized wind speed is not belong to the sampled scenario set?
3.1 Economic dispatch

Study 5: ED with wind and storage [3], [4]

- Optimal wind–battery coordination [3]: Develop optimal operating schedule for a battery storage system to minimize cost and maximize wind energy utilization.
  - Consider up-spinning reserve (reserve capacity for shortage of power generation)
  - Consider down-spinning reserve (reserve capacity for surplus power production)
  - Use evolutionary iteration particle swarm optimization

- Evaluating value of energy storage for managing wind power fluctuations in terms of [4]
  - System operation efficiency
  - Wind power absorption level
  - Fuel cost savings
  - CO2 emissions reduction
  - Reduction of spinning reserve
Other studies in IE/OR society


- Unit commitment for one week for a company with diverse generation units
- Consider one-day ahead spot market and intra-adjustment market
- Multi-stage stochastic IP
- Uncertainty: possible spot market outcomes for each day (weekly scenario tree)
- Scenarios depend on the company's price decision in bidding


- Use Stochastic programming


- Formulate the problem as a multistage stochastic problem
- Propose a solution procedure that integrates forward-moving Monte Carlo simulation with backward-moving dynamic programming.


- Use Dynamic Programming

3.2 Correlation analysis

Correlation study: Overview

- In the case of negative correlation among wind farms → smoothing effect in power output fluctuation
- In the case of positive correlation → unstable security level, transmission line congestions
- Negative correlation with load → storage/spinning reserve requirement

- Correlation analysis is not fully explored in the studies.
- Most studies are empirical studies, or simulation studies, based on data
  - Descriptive studies
  - Impact of correlation to wind energy integration to power grid in terms of reliability (mostly, Monte-carlo simulation method)

- Few analytical studies
  - to evaluate correlation level among wind farms
3.2 Correlation analysis

[1] Descriptive study \([10]\]

- Study of correlation in power outputs between two wind farms 200 km apart in Midwest, U.S.
  - High correlation during longer time frames (hours, days) are
  - Low correlation during short time frames (sec, min) due to random fluctuation of wind speeds each site

Fig. 2  Daily outputs of Lake Benton II and Storm Lake

Fig. 3  Weekly output power example

- Modeling variability in the output from six South Australian wind farms
- Use data at the half-hourly time interval
- Apply a measure to determine overall correlation of wind farms, called correlative cohesion

Procedure

- R: correlation matrix
- Measure the diversity of the eigenvalues $\lambda_i$ of $R$ as

$$C(X^n) = 1 - \frac{1}{\ln(1/n)} \sum_{i=1}^{n} \left( \frac{\lambda_i}{n} \right) \ln \left( \frac{\lambda_i}{n} \right)$$

- If off-diagonal elements of $R$ have the same value $r$,

$$C_n(r) = \frac{(1+(n-1)r)\ln(1+(n-1)r)+(n-1)(1-r)\ln(1-r)}{n \ln n}$$

- If $r=0$, $C(X^n) = 0$. If $r=1$, $C(X^n) = 1$

- Correlative coherence is defined as $r$, obtained by Newton’s method

$$r = C_n^{-1}(C(X^n))$$

For illustration purpose, the authors developed data sets in which some or all of the farms were highly correlated, determine the resulting $r$ values for various combinations.

Table 1. $r$ values for different correlated combinations of six wind farms.

<table>
<thead>
<tr>
<th>Correlation configuration</th>
<th>$r$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>6</td>
<td>.95</td>
</tr>
<tr>
<td>5,1</td>
<td>.830041</td>
</tr>
<tr>
<td>4, 2</td>
<td>.765551</td>
</tr>
<tr>
<td>4, 1, 1</td>
<td>.684299</td>
</tr>
<tr>
<td>3, 3</td>
<td>.74424</td>
</tr>
<tr>
<td>3, 2, 1</td>
<td>.620647</td>
</tr>
<tr>
<td>3, 1, 1, 1</td>
<td>.515792</td>
</tr>
<tr>
<td>2, 2, 2</td>
<td>.57879</td>
</tr>
<tr>
<td>2, 2, 1, 1</td>
<td>.465469</td>
</tr>
<tr>
<td>2, 1, 1, 1, 1</td>
<td>.321067</td>
</tr>
<tr>
<td>1, 1, 1, 1, 1</td>
<td>.049996</td>
</tr>
</tbody>
</table>

(example)

3,1,1,1 means 3 highly correlated farms, and 3 uncorrelated (from the first 3 farms, and each other) farms.
[2] Evaluating correlation level\textsuperscript{[11]}

- For six wind farms, actual $r$ value is $r=0.209662 \rightarrow$ is it correlated???
- Null distribution of $r$
  - Step 1. Generate a sequence of outputs of each wind farm independently 20 times
  - Step 2. Build R matrix and get $r$ value
  - Repeat Step 1 & 2 many times (5000 times) to get a null distribution of $r$

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4.png}
\caption{Histogram of 5000 $r$ values calculated from the manufactured data}
\end{figure}

$r=0.209662 \rightarrow$ Six wind farms are correlated
3.2 Correlation analysis

[3] Clustering in Monte Carlo Simulation (MCS)\textsuperscript{[12],[13]}

- MCS is often used to evaluate generation adequacy, reliability, transfer capability
- So, Many random variables (r.v.) are simulated.
- When r.v.’s are highly correlated (similar types of loads, renewable generation in small areas), clustering of these r.v’s may
  - accelerate the convergence speed
  - reduce variance
  - provide additional information.
Estimating avoided emissions by wind generation

- Several studies quantify the emission reduction by wind generations using ED
  - Compare two cases: with / without wind generation
  - Then, quantify the emission reduction from the reduced generated power from convention power plants

- One study using correlation analysis
  - Not very accurate model, but gives insights

\[ d = f(h) \]: For \( h \) hours, load is greater than, or equal to \( d \)
- Nuclear– always run for base load
- When load is less than \( d_1 \), run Hydro.
- When load is between \( d_1 \) and \( d_2 \) (\( h_3 - h_2 \) hours/year), operate Nuclear plus coal generators
- When load is between \( d_2 \) and \( d_3 \) (\( h_2 - h_1 \) hours/year), operate Nuclear plus gas turbines
- When load is over \( d_3 \) (\( h_1 \) hours/year), operate Nuclear plus oil/mix generators

- Fix the load curve for one week
- Get the wind power generation curve for each week a year
- Compute the hourly reduced emissions by wind power each week on a hourly basis
- Compute the correlation between the reduced emission and wind power generation for each week

- Fit the correlation factor vs. emission reduction

Fig. 13. Average displaced emissions by wind versus the correlation factor.
(Use fixed loads for June 15-21 week)

Fig. 14. Lowest, average, and highest linear fits found.
[2] Using renewable systems for desalination system\textsuperscript{[15]}

- Use Markov decision process (or, stochastic dynamic programming) to find optimal policy in operation of desalination modules powered by solar PV array and storage system.
- Consider stochastic power production from solar PV array.

Optimal policy
- July 8 am-4pm: $[0 1 0 1 1 1 1 1 1 1 2 1 0 1 0 1 1 1]$
- Jan 6 am- 6pm: $[1 1 1 1 2 1 1 2 1 2 2 2 1 1 1 1 2 1]$
So, the key challenge (in EE society) is
   • to reliably balance electrical generation and load over time
   • with a large portion of energy coming from a variable, non-dispatchable, renewable power source

Dr. Singh’s advise
   • Relationship between spinning reserve and wind turbine operation
   • How to combine renewable energy sources?
     • Wind power vs. load: negative correlation (x)
     • Wind power vs. solar power: negative correlation (o)
   • Plug-in hybrid electrical vehicle (PHEV) and wind energy
   • There is a special project to improve forecast accuracy (not very good topic for my research at this time).
   • A faculty candidate (EE) from Carnegie Mellon presents the study related to ED which incorporates Risk Issue
   • NREL provides data from real wind farm site
Research opportunities as Industrial engineers

1. ED: many non-linear, non-convex, large-scale constrained optimization problem
   • Can we apply advanced sampling-based optimization for complicated ED problems?

2. Stochastic dynamic programming (or, MDP) and multi-stage stochastic programming problem
   • In multi-stage SP, can we incorporate the ideas of sampling-based optimization and Bender’s decomposition?
   • Stochastic dual dynamic programming??

3. Multiple criteria decision making in capacity sizing and/or generation scheduling
   • In EE literature, Pareto front or weighted sum are used.
   • But, there are advanced studies using stochastic dominance concept in IE/OR society

4. Correlation study
   • Develop the relation between correlation level and reserve (spinning, standing/storage reserve) capacity with high penetration level of non-dispatchable renewable energy sources
   • Correlation analysis with solar and wind power
   • Can we apply advanced statistical methods?
Reference


[7] From Dr.Ntaimo’s lecture note (INEN 698, large scale stochastic optimization)


[9] Jung-Uk Lim and John N. Jiang , Bibliography review on applications of correlation analysis in power system operation and planning, EUROPEAN TRANSACTIONS ON ELECTRICAL POWER


Reference


  • Market clearing prices are stochastic. Consider mean revenues and other risk factors