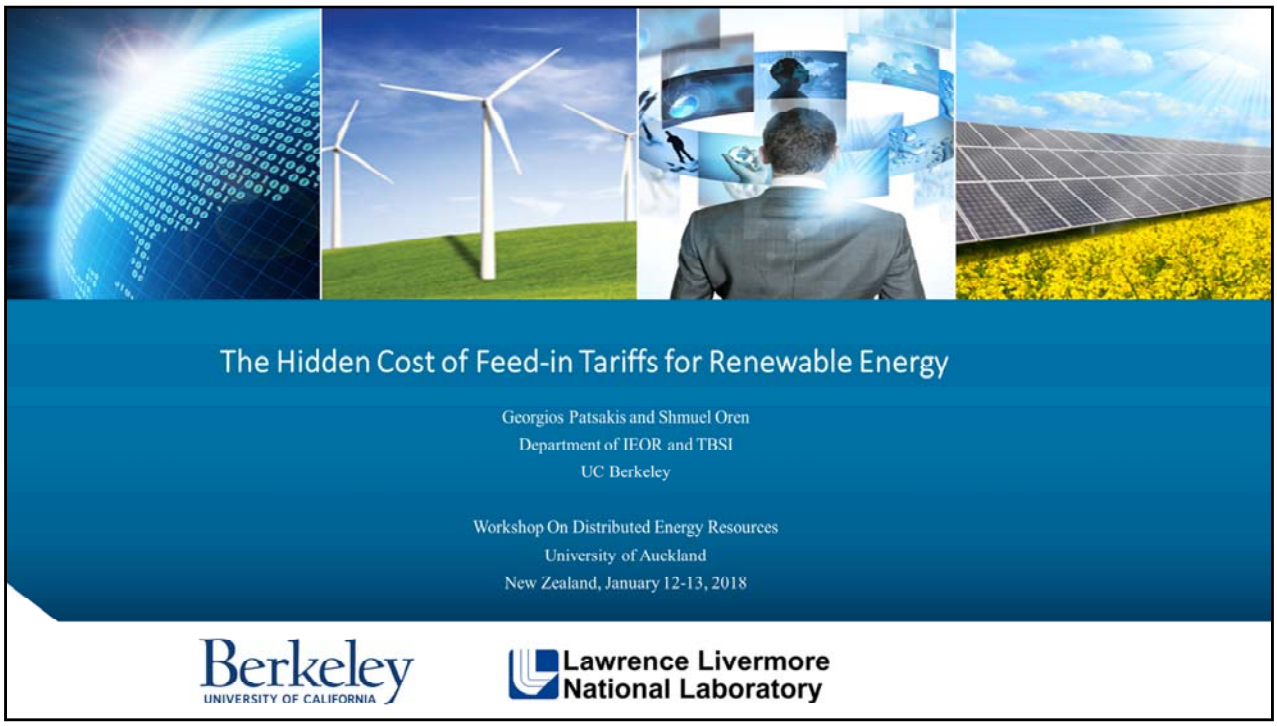

In this work we explored the expected benefit from utilizing the flexibility of wind resources. This work was funded by PSERC. We should also acknowledge the Lawrence Livermore National Laboratory for providing the computational resources to run all our simulations.

Outline

- **Motivation: Wind Reserves**
- Approach
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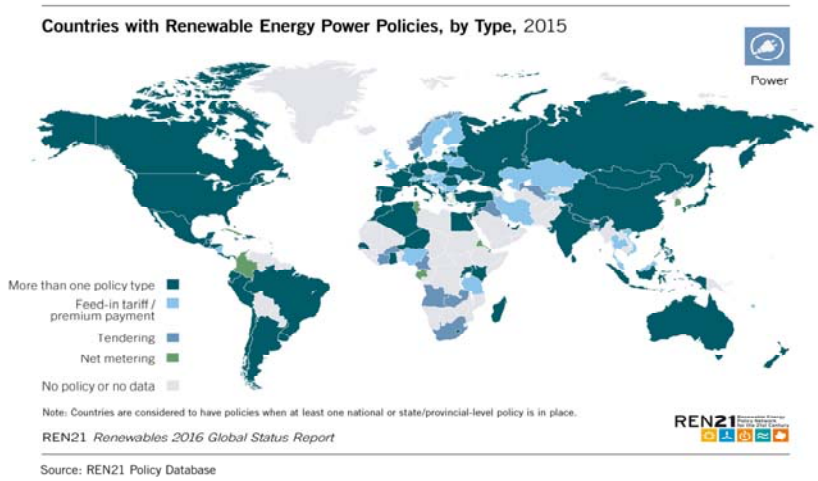
Renewable Energy Policies



Motivation

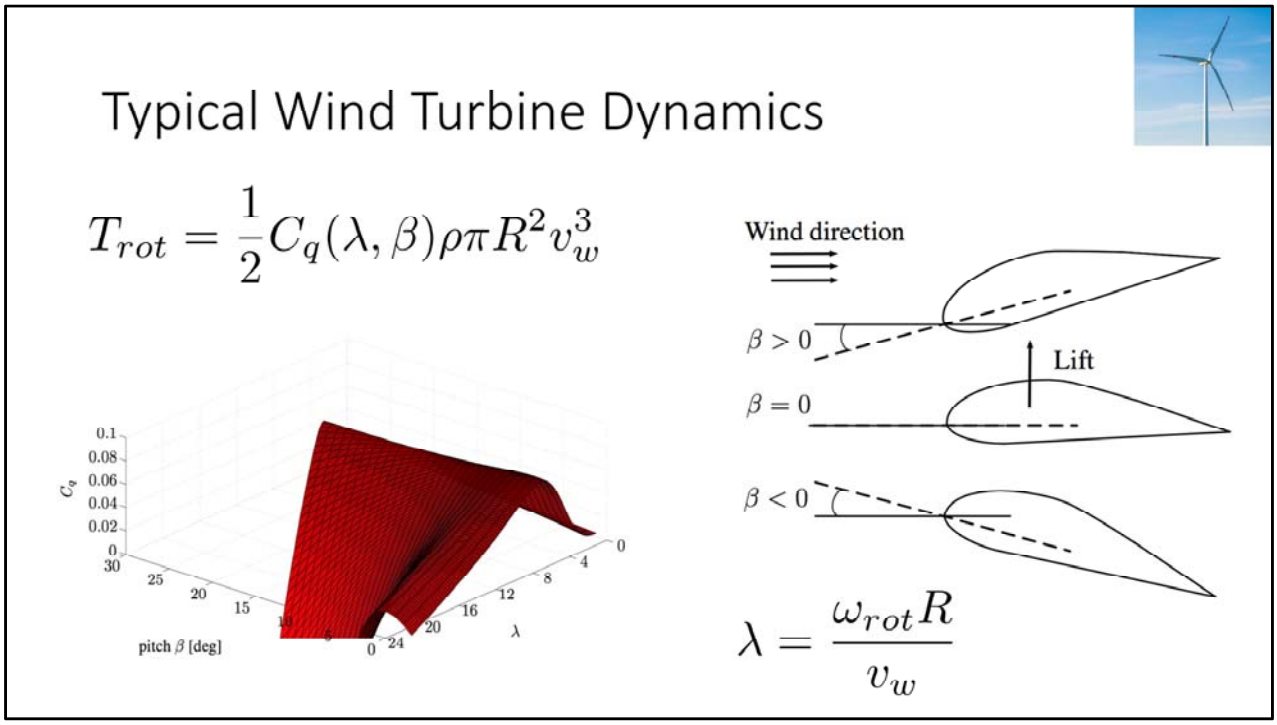
- European directive 2009/28/EC, currently in force, stipulates that:

  "Member States shall ensure that when dispatching electricity generating installations, transmission system operators shall give priority to generating installations using renewable energy sources in so far as the secure operation of the national electricity system permits and based on transparent and non-discriminatory criteria"

- However, current wind turbines have the ability to set active power output at any point between zero and maximum available wind power [1-2]

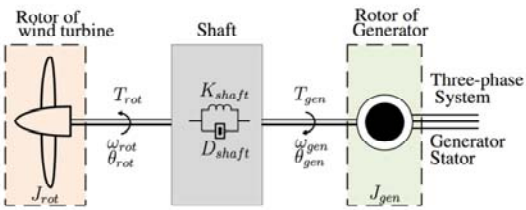
[1] Moutis, Panayiotis, Stavros A. Papathanassiou, and Nikos D. Hatziargyriou. "Improved load-frequency control contribution of variable speed variable pitch wind generators." *Renewable Energy* 48 (2012): 514-523.
[2] Nanou, S. I., Patsakis, G. N. and Papathanassiou S. A. "Assessment of communication-independent grid code compatibility solutions for VSC–HVDC connected offshore wind farms." *Electric Power Systems Research* 121 (2015): 38-51.

Renewable energy, such as wind generation, has been traditionally treated as a must-take resource. That means that, unless operational feasibility issues arise in the power system, all of the wind generation will be integrated into the power system. Prioritizing wind resources against conventional generation, for example, is enforced in Europe by law (European directive). However, many current wind turbines have the ability to control their power output essentially at any point between zero and their maximum power output. What we are interested in is the benefit from mobilizing that flexibility.



The typical modeling for wind turbine torque (which translates to wind power output) is given by this formula. Note that the output depends on
-the wind speed v_w
-the rotor radius R
-the air density rho
-and an efficiency coefficient Cq. This coefficient depends on the pitch angle beta and the tip speed ratio lambda, which depends on the wind speed v_w and the rotational speed omega_rot.
Most of the current wind turbines have what we call “pitch control”. That is, we can control the angle beta and “destroy” the aerodynamics of the wind turbine, through the coefficient Cq. That way, we can reduce the wind power output up to practically zero.

Typical Wind Turbine Dynamics



wind speed -->
mechanical power -->
electrical power

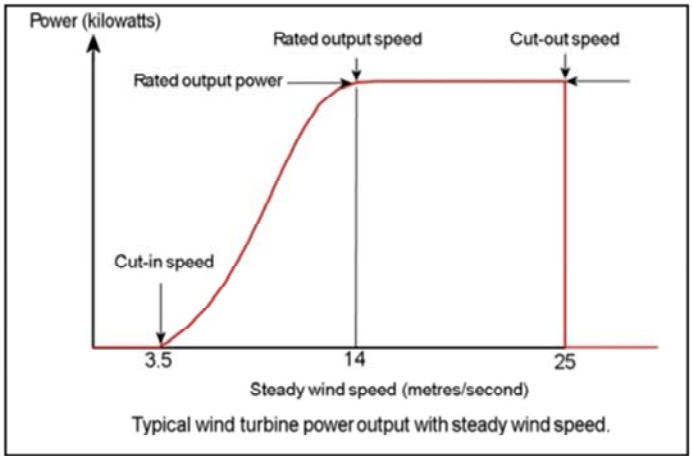


Image from:
http://www.wind-power-program.com/
turbine_characteristics.htm

The plot on the right shows the maximum available wind generation for given wind speeds. This is a typical curve. After a wind speed of 14m/s in this plot, the rated output power of the generator is reached. After that, pitch control is used to destroy the aerodynamics and keep the power within its limits. By controlling the pitch angle, however, we can also reach most of the points within the curve, instead of always trying to maximize the wind turbine output. This is the flexibility that we are examining in this work.

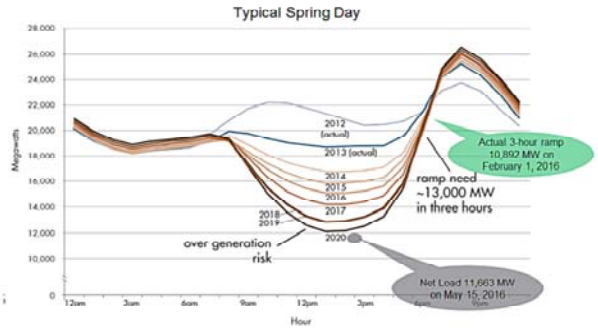
Motivation

- We make the case that wind should not be a must-take resource
- But wind is free (i.e. not penalized in the objective). Why would we spill it?

We make the case that wind not be treated as a must take resource in general, which essentially means that we should actively spill wind energy. However, wind is free. So it is not straightforward that we could have a benefit by spilling it and utilizing costly conventional generation instead. We will initially try to motivate how such a benefit could arise by a few small and intuitive examples.

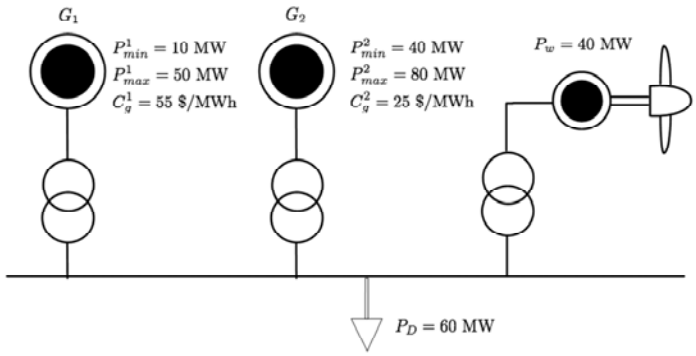
Motivation: Duck Curve

- Oversupply is when all anticipated generation, including renewables, exceeds the real-time demand
- Can lead to overgeneration, which requires manual intervention of the market to maintain reliability
- To reliably manage the green grid, the ISO needs flexible resources with the right operational characteristics in the right location



http://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf

Example 1: Enforcing Min Load



Wind as must-take resource: Need to use G_1

Cost = 20 MW × 55 \$/MWh = 1100 \$/h

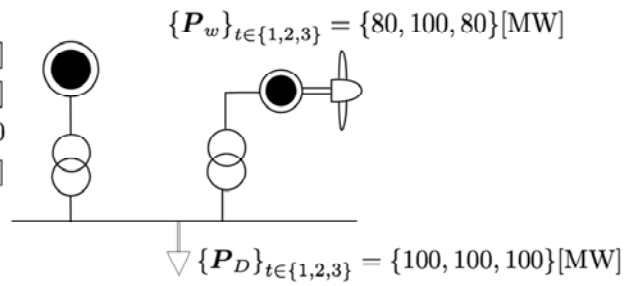
Wind spill allowed: Spill 20 MW of wind and use G_2

Cost = 40 MW × 25 \$/MWh = 1000 \$/h

As a first example, say we have two conventional generators, a cheap one with high technical minimum and an expensive one with a low technical minimum. Say at some point demand is at 60MW and the available wind generation is at 40MW. If wind is treated as a must-take resource, we need to satisfy 60-40=20MW of net demand, therefore due to the technical minimum of the cheap generator, we will have to use the expensive one. If we spill 20MW of the wind generation instead, we can use the cheap generator instead.

Example 2: Startup costs

$P_{min} = 20$ [MW]
$S_g = 4000$ [\$]
$C(P) = 50P + 500$
$C(P)$ [\$/h], P [MW]



Wind as must-take resource: Generator restarts at 3rd time period

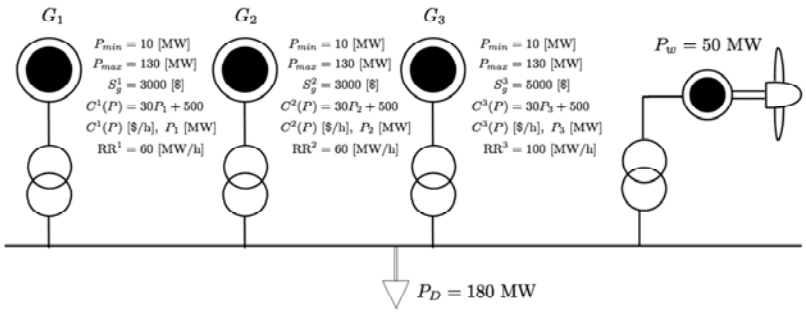
$\text{Cost} = (4000 + 50 \times 20 + 500) + (4000 + 50 \times 20 + 500) = 11000\$$

Wind spill allowed: Spill 20 MW in period 2

$\text{Cost} = (4000 + 50 \times 20 + 500) + (50 \times 20 + 500) + (50 \times 20 + 500) = 8500\$$

As a second example, consider three time periods in this small system, with demand 100MW for all of them. Wind generation for these time periods is 80,100 and 80, which means that the wind can fully cover the demand for time period 2, whereas conventional generation has to be used at time 2. In this case, if no wind is spilled, the generator has to restart at time period 3, which will impose the high startup cost twice. For that purpose, it is preferable to spill 20MW of wind at time 2, to allow the conventional generator to stay online.

Example 3: Ramping Constraints



Wind as must-take resource: must use G_3

$$\text{Cost} = (3000 + 30 \times 100 + 500) + (5000 + 30 \times 30 + 500) = 12900 \ \$$$

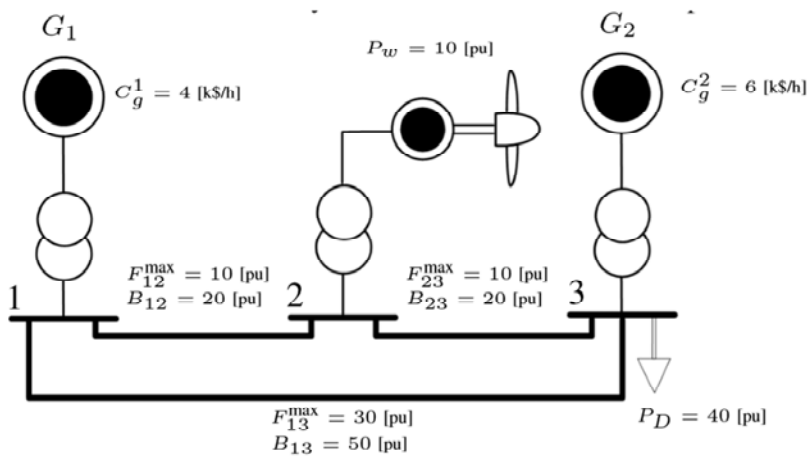
Wind spill allowed: Spill 10 MW and commit G_1 and G_2

$$\text{Cost} = (3000 + 30 \times 70 + 500) + (3000 + 30 \times 70 + 500) = 11200 \ \$$$

In this third example we introduce reserves for N-1 security. In the first case, where all of the 50MW of wind are integrated, we essentially need to satisfy a load of 180-50=130MW. we would like to do that with G1 and G3 that have lower startup cost. However, assume we let G1 produce 70 and G2 60. If G1 fails we are helpless, because of the ramping rate of G2 (which is 60). Even in the case where we let both produce 65, again if one fails the other one can not fully cover the failure. So we must use G3, in combination with one of G1 or G2.

Now if we keep reserve 10MW from the wind, we can use G1 and G3 both producing 70. If G1 goes out, we get 60 from G2 and 10 from the wind reserve, which is fast due to the high ramping rate of wind controls, so we are good. And it is cheaper

Example 4: Congestion



Wind as must-take resource: $130000/h
Wind spill allowed: $128000/h

As a fourth and final example, consider this small power system. For the purposes of this example, we will use dc analysis. In the case where the 10pu of wind power are treated as a must-take resource, in the optimum they all pass through branch 2-3 to satisfy the load of bus 3, binding the phase angle difference between buses 2 and 3 as well. That means the flow of branch 2-3 is at its capacity, so the flow on the line 1-2 must be zero, leading to a total cost of $130000/h by utilizing both the expensive and the local generator. If we instead dispatch wind at 8pu, we can satisfy the load without using the expensive generator at all, by generating 32pu with G_1 and the remaining 8pu through wind, leading to a lower total cost of $128000/h.

Motivation

- All the previous are favorable wind scenarios that could lead to positive wind reserves. Of course, they need to be evaluated against all the non favorable ones.
- A stochastic unit commitment formulation is used to approach the problem.
- All the uncertainties can be explicitly taken into account through scenarios.

As in the slide text

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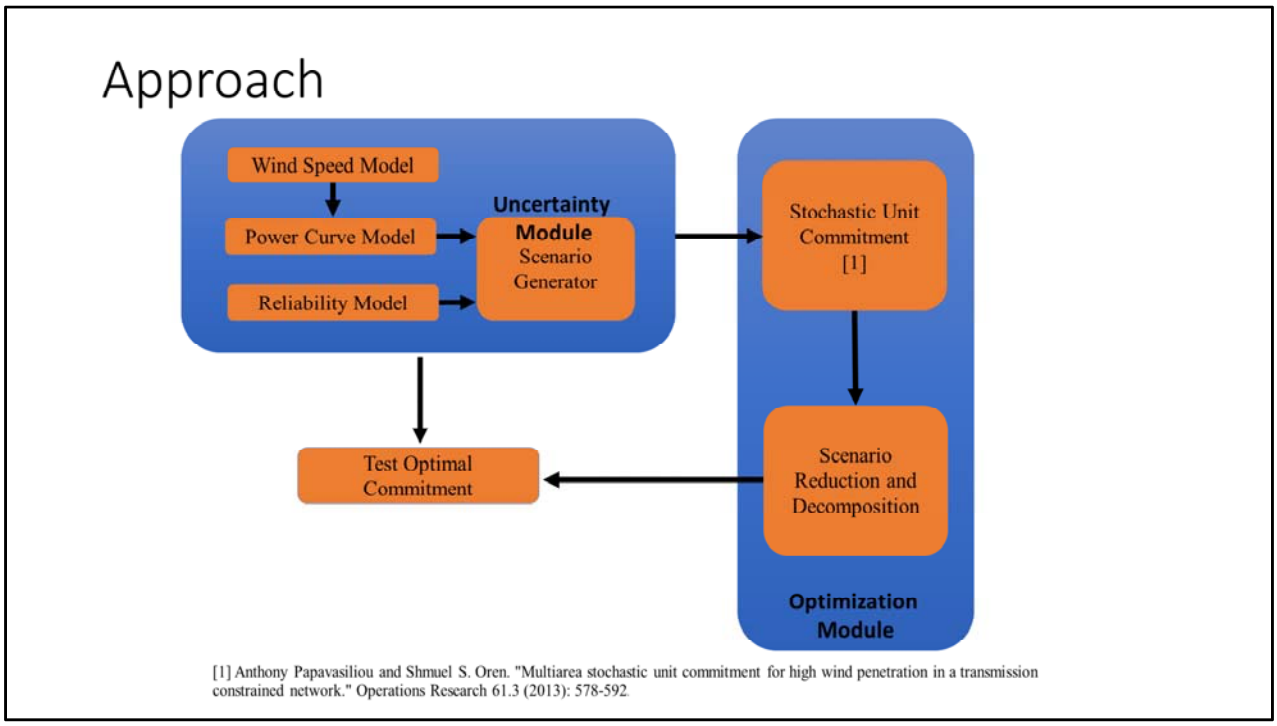

The developed model comprises of two basic components, the Uncertainty Module and the the Optimization Module. The Uncertainty Module tries to capture the underlying uncertainty of the system, which in our case is assumed to come from wind generation and line or generator faults. The module is trained based on a data set and then used to generate scenarios whenever these are necessary. The Optimization Module, on the other hand, takes as input a set of scenarios and solves or heuristically approximates the solution of a stochastic unit commitment problem, providing in its output a commitment schedule of the slow generators for the next day. The Optimization Module can be treated as a black box that a system operator uses to make the day ahead scheduling based on a set of available scenarios. Based on these modules, the testing process is the following: initially, the Uncertainty Module generates a set of scenarios. These scenarios are treated as the uncertainty information the system operator utilizes to make the scheduling decision. Based on this information, the Optimization Module makes one scheduling decision for each of two cases: the one in which wind is a must-take resource, and the one that it is not. In the final step, we wish to evaluate the difference between the costs associated with each case. To that end, we generate a new set of scenarios from the Uncertainty Module, representing possible actual

realizations of the uncertainty the next day, and compare the expected costs of each of the two cases (Test Optimal Commitment Block).

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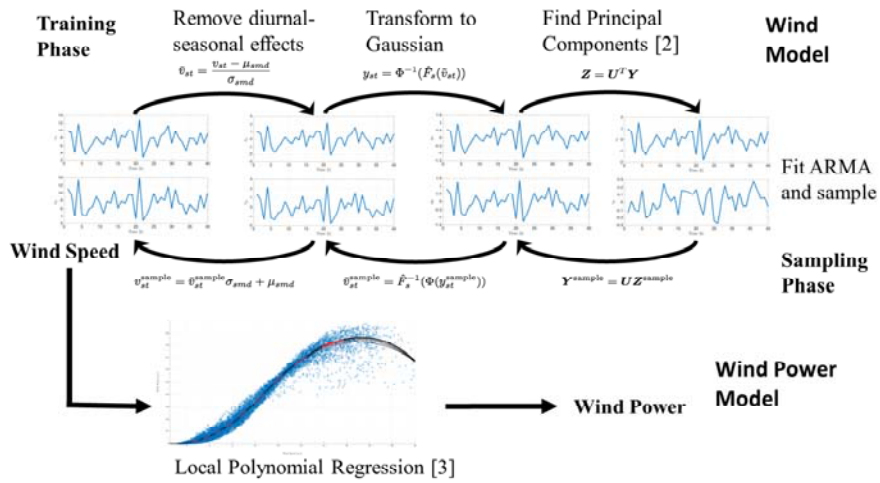
Wind and Wind Power Model



[2] Duong D. Le, George Gross and Alberto Berizzi. "Probabilistic Modeling of Multisite Wind Farm Production for Scenario-Based Applications." IEEE Transactions on Sustainable Energy 6.3 (2015): 748-758.

[3] Cleveland, William S. "Robust locally weighted regression and smoothing scatterplots." *Journal of the American statistical association* 74.368 (1979): 829-836.

The procedure we utilize to model wind generation is depicted in this slide. The wind model is trained based on wind speed measurements in a few locations. We use a standardized procedure that tries to extract a stationary Gaussian process from the data, by first removing diurnal and seasonal effects and then utilizing a transformation based on the empirical cdf of the data. The special correlations are taken into account via a principal component analysis decomposition scheme, as in [2]. An Arma model is then fit to the data and used for sampling, and the reverse transformations gives us wind speed sample time series. A wind power model that takes wind speed as input and outputs a corresponding available power output is also trained and used to transform the sample wind speeds to available wind generation.

Wind Speed Model: why PCA?

Let v,w be two random variables with covariance matrix:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_v^2 & r_{vw} \\ r_{vw} & \sigma_w^2 \end{bmatrix}$$

By taking the diagonalization of $\boldsymbol{\Sigma}$:

$$\boldsymbol{\Sigma} = \boldsymbol{U}\boldsymbol{\Lambda}\boldsymbol{U}^T = \begin{bmatrix} \boldsymbol{U}_1 & \boldsymbol{U}_2 \end{bmatrix} \boldsymbol{\Lambda} \begin{bmatrix} \boldsymbol{U}_1^T \\ \boldsymbol{U}_2^T \end{bmatrix}$$

the variables:

$$\begin{bmatrix} \hat{v} \\ \hat{w} \end{bmatrix} = \boldsymbol{U}^T \begin{bmatrix} v \\ w \end{bmatrix}$$

are uncorrelated:

$$r_{\hat{v}\hat{w}} = \mathrm{cov}(\hat{v}, \hat{w}) = \mathrm{cov}(\boldsymbol{U}_1^T \begin{bmatrix} v \\ w \end{bmatrix}, \begin{bmatrix} v & w \end{bmatrix} \boldsymbol{U}_2) = \boldsymbol{U}_1^T \Sigma \boldsymbol{U}_2 = 0$$

[2] Duong D. Le, George Gross and Alberto Berizzi. "Probabilistic Modeling of Multisite Wind Farm Production for Scenario-Based Applications." IEEE Transactions on Sustainable Energy 6.3 (2015): 748-758.

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Stochastic Unit Commitment

minimize $\sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$

$u_{gst} \in \{0,1\}$: commitment, $v_{gst} \in \{0,1\}$: startup,
p_{gst}: production of generator g in scenario s, period t

Constraints:

Introduce a partition of the generators: $G_{slow} \cup G_{fast} = G$.

First Stage Variables: $\boldsymbol{x} = (\boldsymbol{w}, \boldsymbol{z}) \in \boldsymbol{X} \subset B^{|G_{slow}|} \times B^{|G_{slow}|}$

Second Stage Variables: $\boldsymbol{y}_s = (\boldsymbol{u}_s, \boldsymbol{v}_s, \boldsymbol{p}_s) \in \boldsymbol{Y}^s$

Non-Anticipativaty Constraints: $\boldsymbol{w}_g = \boldsymbol{u}_{gs}$, $\boldsymbol{z}_g = \boldsymbol{v}_{gs}$, $\forall g \in G_{slow}$, $\forall s \in S$

Constraints include: Linearized Power Flow Equations, Line Flow Limits, Minimum and Maximum Generator Capacity Limits, Generator Ramping Constraints, Minimum Up-Down Time Constraints, Scenario Generator/Line Faults

[1] Anthony Papavasiliou and Shmuel S. Oren. "Multiarea stochastic unit commitment for high wind penetration in a transmission constrained network." *Operations Research* 61.3 (2013): 578-592.

The problem of interest is the stochastic unit commitment. The Unit Commitment problem is a widely studied mixed integer program that determines the set of generators, among all the available ones, that will be committed to satisfy the load during the following day. The two stage Stochastic Unit Commitment problem formulates the same decision in the presence of uncertainty (renewable generation, faults, load), captured by a finite set of possible realizations (scenarios).

The generating units available to the system operator are divided into slow and fast, based on how long prior to operation a commitment decision for that unit has to be made. The output of the SUC problem is the commitment of slow generating units into the grid. The challenge is that the commitment decision for slow units has to be made a day before operation, when the underlying uncertainty is still unknown, i.e. the commitment decisions (binary variables) for these units have to be the same across all scenarios (first stage variables). On the other hand, the other variables of the problem, such as the commitment of fast generating units and the generation levels, are allowed to vary depending on which scenario of nature was realized (the decision for them is made with knowledge of the uncertainty), hence the value that they are assigned can be different for every scenario (second stage variables).

around 20000 variables per scenario, and constraints in the same order per scenario.. around 6000 binaries.
Say 1000000 for that reduced system

Decomposition Algorithm [4]

$\min \{\sum_{i=1}^{N} \pi_i f_i(x) : x \in X\}$

The Algorithm

Step 1: for $i = 1..N$ solve:

$\min\{f_i(x) : x \in X \setminus W\}$

Let z_i be the optimal value and x_i be the optimal solution

easy because fixed scenario

Step 2: Clearly a lower bound is:

$\text{LB}=\sum_{i=1}^{N} \pi_i z_i$

Step 3: for $i = 1..N$ compute:

$\text{UB}_i = \sum_{j=1}^{N} \pi_j f_j(x_i)$

easy because fixed first stage

Step 4: for $i = 1..N$ add a cut:

$W = W \cup \{x_i\}$

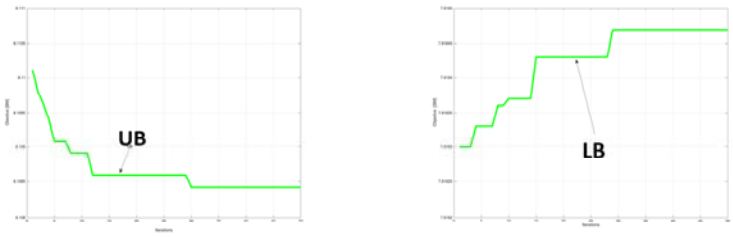
guarantees optimality

Step 5: If UB > LB, go to Step 1.

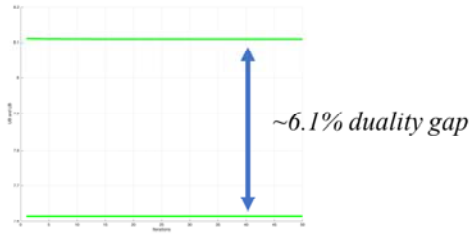
[4] Ahmed, Shabbir. "A scenario decomposition algorithm for 0–1 stochastic programs." *Operations Research Letters* 41.6 (2013): 565-569.

For a set of scenarios S={1,2,..N}, a stochastic program with first stage variables has the form:
Min{sum pi * fi(x)}, where fi(x) is a function that evaluates the cost of scenario i for first stage variables fixed at x (i.e. fi(x) solves an optimization problem with respect to the second stage variables).
The SUC is a large scale MIP, so decomposition methods are usually employed to handle it. The algorithm that was used to solve the problem, based on a paper by Shabbir Ahmed, has two phases: a LB phase and an UB phase. In the LB phase a problem is solved for each scenario and candidate first stage solutions are identified. The rest as in slide.

A first take



If we put them together:



*The plots are for 5 scenarios, low wind integration, where all binary decisions are first stage variables (no fast generators)

Here is the behavior for a small test case of 5 scenarios in the case where the Lagrangian penalties are not used and we only utilize NoGoodCuts. The UB is going down and the LB up, however the duality gap does not close fast enough.

Scenario Decomposition adapted [4]

- LB phase: solve every scenario in isolation
- UB phase: test the points
- Run LB Phase until LB does not improve much
- Run UB Phase
- Typically 2-3 iterations

Lower Bounding and Lagrangian Update Phase

Solve scenario subproblems:

for $s \in S$ **do**

$\quad x_s^t \in \operatorname{argmin}_{x \in X \setminus W} \{ f_s(x) + x^T w_s^{t-1} \}$

end for

Update Lower Bound:

$\mathrm{LB} \leftarrow \sum_{s \in S} \pi_s f_s(x_s^t)$

Update objective weights:

for $s \in S$ **do**

$\quad \hat{x}^t \leftarrow \sum_{s \in S} \pi_s x_s^t$

$\quad w_s^t \leftarrow w_s^{t-1} + \rho \left(x_s^t - \hat{x}^t \right)$

end for

Upper Bounding and Cut Phase

Evaluate scenario solutions for Upper Bounds:

for $s \in S$ **do**

$\quad \mathrm{UB}_s \leftarrow \sum_{i \in S} \pi_j f_i(x_s^t)$

end for

Update Upper Bound:

$\mathrm{UB} \leftarrow \min\{\mathrm{UB}, \{\mathrm{UB}_s\}_{s \in S}\}$

Exclude points tested:

for $s \in S$ **do**

$\quad W \leftarrow W \cup \{x_s^t\}$

end for

until $\mathrm{UB} \leq \mathrm{LB}$

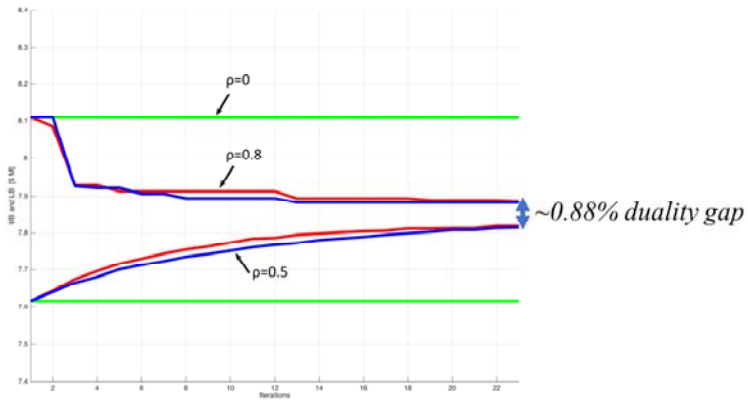
[4] Ahmed, Shabbir. "A scenario decomposition algorithm for 0–1 stochastic programs." *Operations Research Letters* 41.6 (2013): 565-569.

[5] Ryan, Kevin, Deepak Rajan, and Shabbir Ahmed. "Scenario decomposition for 0-1 stochastic programs: Improvements and asynchronous implementation." *Available at Optimization-Online http://www. optimization-online. org/DB_FILE/2015/11/5201. pdf* (2015).

Each scenario has a penalty in the objective that penalizes the deviation from other scenarios, so that hopefully the solutions we get from isolated scenarios can perform well for all other senarios.

In practice, the LB phase is executed multiple times at the beginning of the algorithm. This essentially leads to a projected subgradient descent method. Following that, the UB phase is executed one time, and the whole process is repeated 2-3 times.

The penalized performance



*The plots are for 5 scenarios, low wind integration, where all binary decisions are first stage variables (no fast generators)

Here is the behavior for different values of the parameter rho of the altorithm for the same example.

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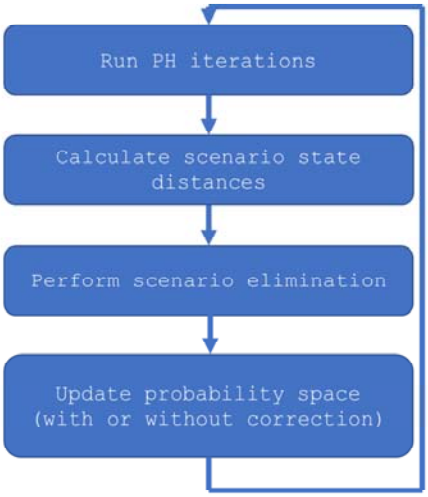
Heuristic Scenario Reduction PH

- Motivation: reduce the number of scenarios by eliminating similar scenarios.
- Intuition: evaluate similarity of scenarios based on their impact on the system state.
- Integrate reduction in the Progressive Hedging (PH) execution.



A heuristic scenario reduction technique was also used in conjunction with PH. The goal is to make the problem more tractable by eliminating scenarios that are similar to others. To evaluate similarity of scenarios, we evaluate how different the impacts of scenarios are upon the power system. In the context of PH, at every iteration we solve a problem for every scenario. We use the states (flows) of the system for every scenario to calculate distances between scenarios and then eliminate scenarios that are close. That way we gradually decrease the number of scenarios at every iteration, while simultaneously execute Progressive Hedging.

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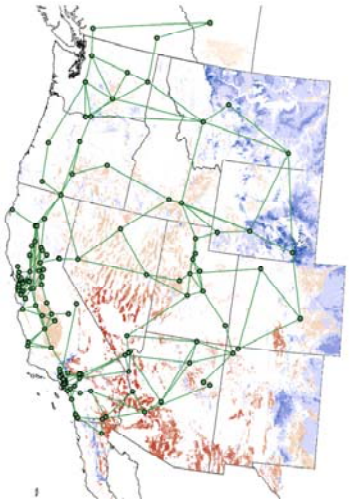
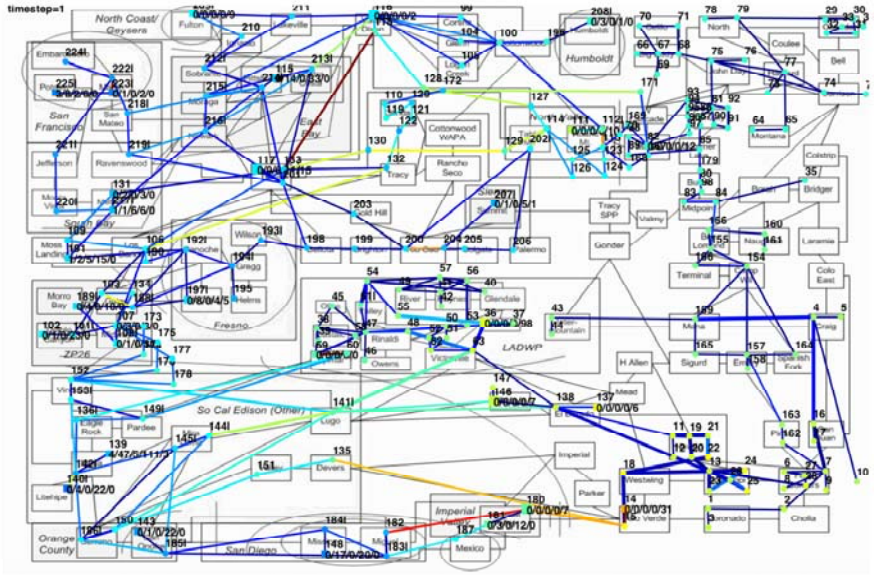
WECC System

- 225 buses, 371 lines and 130 conventional generators
- Average load 28056MW, with a minimum of 21438MW and a maximum of 32300MW
- The capacity of thermal generation is 31281MW and the total generating capacity, not including wind resources, is 51402MW.
- Three integration cases:
  - Low (13% wind energy penetration)
  - Medium (19% wind energy penetration)
  - High (33% wind energy penetration)



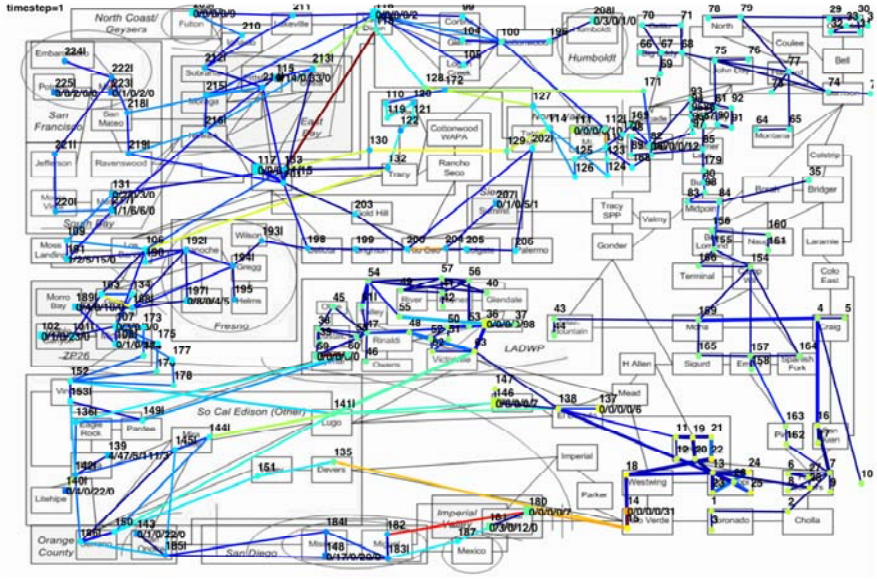
For the SUC formulation, we consider a reduced model of the Western Electricity Coordinating Council (WECC) system with 225 buses, 371 lines and 130 conventional generators. A typical winter weekday is simulated for three different integration cases: high, medium and low. High integration corresponds to 33% wind energy penetration, the medium integration corresponds to 19 % penetration and the low integration to 13 %. The average load is 28056MW, with a minimum of 21438MW and a maximum of 32300MW. The capacity of thermal generation is 31281MW and the total generating capacity, not including wind resources, is 51402MW. The cost of load shedding is assumed 5000$/MW-h.

WECC System


timestep=1
North Coast/ Geysers
Humboldt
San Francisco
East Bay
Fresno
ZP26
So Cal Edison (Other)
LADWP
Orange County
San Diego
Imperial
Mexico

Computational Data

- The simulations were parallelized in 10 nodes of the Cab cluster at LLNL.
- 160 scenarios used (for test set & for training set)



Time Simulation t=1..24

This is a time simulation for one scenario and 24 hourly time instances, in a way that congestion in the system is shown. Wind generation is depicted with squares, whereas circles indicate other types of generation.

Some results (value)

Wind Integration Level	Training Set Total Cost [$M]		Test Set Total Cost [$M]	
	Must Take	Wind Spill	Must Take	Wind Spill
Low	8.28	8.25	8.23	8.23
Medium	7.02	6.97	6.98	6.95
High	12.82	6.10	16.09	6.11

Here are some out of sample-testing results for the SUC. The problem was solved with a 2%optimality guarantee in each case. The costs include a load shed cost of 5000$/MW-h. In the next slide, the results without load shedding will be shown.

Some results (value)

Wind Integration Level	Cost without load shed [$M]		Wind Penetration [%]	
	Must Take	Wind Spill	Must Take	Wind Spill
Low	8.23	8.23	13.2	13.0
Medium	6.98	6.95	19.8	18.9
High	7.27	6.11	26.3	23.4

In this slide the results without the cost of load shedding are shown for the test set. Note that there is no significant difference between the two cases; must take and wind spill, for the low and medium integration scenarios. However, for the high integration case, there is a significant difference; we get more than 15% better objective by allowing wind to be spilled.

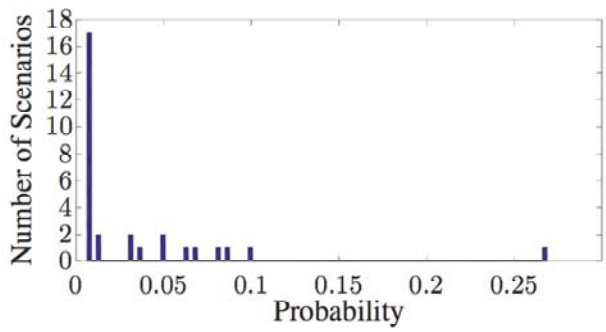
Some results (scenario reduction)

Objective Cost	Training Set	Test Set
Full Set (160 scenarios)	6.965	6.947
10 scenarios, 5 steps	6.988	6.965
30 scenarios, 5 steps	6.970	6.955
10 scenarios, 10 steps	6.995	6.968
30 scenarios, 10 steps	6.964	6.950

Objective Cost	Training Set	Test Set
Full Set (160 scenarios)	8.253	8.229
10 scenarios, 5 steps	8.266	8.235
30 scenarios, 5 steps	8.252	8.219
10 scenarios, 10 steps	8.259	8.235
30 scenarios, 10 steps	8.254	8.223

These are some results for the decomposition&reduction algorithm. The initial set of 160 scenarios is reduced to a smaller set of 10 or 30 scenarios after 5 or 10 steps (iterations) of PH. After that, the cost is reported and compared with the full set solution we found using the pure decomposition algorithm. Note that, for the 2% accuracy that the problem was solved, the decomposition algorithm performs quite well.

Some results (scenario reduction)



This is an interesting observation from the groups formed after the reduction takes place. The plot shows the probabilities of each one of the remaining clusters. Note that a few scenarios ("base scenarios") seem to have high probabilities, whereas most of the other clusters are "extreme cases" that stay with their initial small probability in the set of scenarios.

What next?

- Theoretical guarantees for the heuristic
- How small can we make the final gap using cuts?

As a future direction, we wish to develop, if possible, a theoretical guarantee for the heuristic, since it seems to perform quite well in practice. Also, the nature of this work did not require a very high precision in the SUC simulations. However, the construction of the algorithm is ideal to help calculate better guarantees, since the algorithm by construction is guaranteed to eventually converge to the optimal solution and is not bound by the possible duality gap between the primal and dual (as a typical projected subgradient method would be).

It is still in question whether we actually need very small gaps for the SUC problem. Certainly, for the type of work presented here, we recognize that the lack of precision of the wind model would probably make it futile or at least unimformative to try and solve the SUC with a higher precision than what we used. However, if the solution of the SUC is to be used as an actual tool with economic implications, a standardized procedure with high precision could be more motivated, since the commitment of small conventional generation units could be very different in similar solutions.

Thank you