**Literature:**

*Papers for you to skim this week:*

Simoes, S. *et al.* Impact of different levels of geographical disaggregation of wind and PV electricity generation in large energy system models: A case study for Austria. *Renew. Energy* **105**, 183–198 (2017).

Liu, L. *et al.* Optimizing wind/solar combinations at finer scales to mitigate renewable energy variability in China. *Renew. Sustain. Energy Rev.* **132**, 110151 (2020).

Killinger, S., Lassahn, D., Guthke, P., Bright, J. M. & Wille-Haussmann, B. Sensitivity analysis of PV power simulations for different temporal resolutions and spatial aggregation levels. *2018 IEEE 7th World Conf. Photovolt. Energy Conversion, WCPEC 2018 - A Jt. Conf. 45th IEEE PVSC, 28th PVSEC 34th EU PVSEC* 2730–2735 (2018) doi:10.1109/PVSC.2018.8547649.

*Papers for later weeks:*

Bright, J. M., Babacan, O., Kleissl, J., Taylor, P. G. & Crook, R. A synthetic, spatially decorrelating solar irradiance generator and application to a LV grid model with high PV penetration. *Sol. Energy* **147**, 83–98 (2017).

Widén, J., Shepero, M. & Munkhammar, J. On the properties of aggregate clear-sky index distributions and an improved model for spatially correlated instantaneous solar irradiance. (2017) doi:10.1016/j.solener.2017.08.033.

Jang, H. S., Bae, K. Y., Park, H. S. & Sung, D. K. Effect of aggregation for multi-site photovoltaic (PV) farms. *2015 IEEE Int. Conf. Smart Grid Commun. SmartGridComm 2015* 623–628 (2016) doi:10.1109/SmartGridComm.2015.7436370.

Gutiérrez, C., Gaertner, M. Á., Perpiñán, O., Gallardo, C. & Sánchez, E. A multi-step scheme for spatial analysis of solar and photovoltaic production variability and complementarity. (2017) doi:10.1016/j.solener.2017.09.037.

\*\*note: use Sci-hub to access papers if MIT does not have a journal subscription

**Description of our study:**

On the highest level, we want to explore the challenges of decarbonizing the power sector. You will be focusing on renewable resources and their impact on the grid’s stability.

I want to create one variable renewable energy (VRE) “reliability score” vector which will reflect the amount of electricity that we are confident can be supplied by some VRE generator (solar, wind, or run-of-river (RoR) hydro). We will generate this vector by looking at the historical VRE power output trends over the past few years. In XX location, over the past years, how often have the sun been shining on XX date at XX time? How often has the wind been blowing or river been flowing? How likely is it that NO VRE is generating power? We can talk more about this concept in future conversation because I am not sure that I am articulating myself well. In general, we want to describe the RELIABILITY of VREs.

I will also generate decarbonization strategies with my capacity expansion model (CEM). We will run the same decarbonization target for a series of years to see how robust our decarbonization strategies are. Do we install the same generator and energy storage capacities each year? With these results, we can create a decarbonization “reliability score”. Then we can track the correlation between VRE reliability and decarbonization reliability. What I hope to show is that your VRE reliability directly dictates your decarbonization reliability. Because XX region has a low VRE reliability, it also has a low decarbonization reliability. A good VRE reliability target is XX.

Legend:

Stuff you will be focusing on (but I will help with).

Stuff that I will be focusing on (but you will help with).

**Getting set up with PAIRS:**

*YouTube tutorial:*

<https://www.youtube.com/watch?v=HNkQ6ely3gw&list=PL0VD16H1q5IO3sP-i667TVyn4OsSP6kPc>

*Documentation:*

https://pairs.res.ibm.com/tutorial/

*GUI:*

[https://ibmpairs.mybluemix.net](https://ibmpairs.mybluemix.net/)

username: [amfarnsw@mit.edu](mailto:amfarnsw@mit.edu)

password: MOTH313dona

*Data explorer:*

<https://ibmpairs.mybluemix.net/data-explorer>

*Relevant data:*

<https://ibm.ent.box.com/folder/139172050663>

access via: “Not a part of IBM”

username: [amfarnsw@mit.edu](mailto:amfarnsw@mit.edu)

password: MOTH313dona

*Review my most recent PAIRS slide decks:*

IBM\_PAIRS\_update.pptx

IBM\_PAIRS\_update\_2.pptx

*Spend some time going through my IBM\_PAIRS folder. It is not well organized, so I have included the important files in the order that they should be run. Each script is in “New\_data\_format < level\_1” folder:*

Inputting PAIRS N wind and PAIRS W wind and outputting the vector value: combing\_wind\_values\_into\_one\_vector

Inputting PAIRS weather data and outputting solar CF vectors: solar\_calculations\_try2.py OR solar\_calculations.py

Inputting PAIRS weather data and outputting wind CF vectors: wind\_calculations\_try2.py OR wind\_calculations.py

Calculate economics, and emissions intensities on solar power output values: solar\_power\_output\_to\_TEA.py, and solar\_power\_output\_to\_LCA.py

Calculate economics, and emissions intensities on wind power output values: wind\_power\_output\_to\_TEA.py, and wind\_power\_output\_to\_LCA.py

Producing interesting graphs for solar, and wind: graphing\_solar\_results.py, graphing\_wind\_results.py, and graphing\_city\_results.py

*Later you MIGHT need to set up a SuperCloud account. We will see….*

**For you to build/do:**

You have two project pipelines that you can work on simultaneously. I will outline the steps for each and you can work simultaneously.

*Pipeline A: Import PAIRS weather data and export VRE power output curves. (HARDER)*

1. Look at my equations that I have used in the past.
   1. For wind:
      1. Look at IBM\_PAIRS\_update.pptx, slide 3-4.
      2. Look at suggested steps in IBM\_PAIRS\_update\_2.pptx, slide 12.
      3. Briefly glance at operations in script IBM\_PAIRS < New\_data\_format < solar\_calculations\_try2.py and operations in script IBM\_PAIRS < New\_data\_format < solar\_calculations.py
   2. For solar
      1. Look at IBM\_PAIRS\_update.pptx, slide 5, 12.
      2. Look at descriptions included in IBM\_PAIRS\_update\_2.pptx slides 4-6.
      3. Briefly glance at operations in script IBM\_PAIRS < New\_data\_format < wind\_calculations\_try2.py and operations in script IBM\_PAIRS < New\_data\_format < wind\_calculations.py
2. Ultimately, we need to find the error in our calculations. I have reached out to another person doing this type of work, so I will get back to you once we have the equations that she uses. Once we do, you will need to write a script similar to the ones you looked at in 1.a.iii. and 1.b.iii.
3. Put the correct equations into a word document with the appropriate sources for a future paper.

Note: CF = hourly power output/rated power capacity OR how well is the generator performing in comparison to its max output level?

*Pipeline B: Convert VRE capacity factor (CF) curves to reliability curves. (EASIER)*

1. We need to figure out the best way to calculate our “reliability factor”
   1. At each hour, at each location, we will need a reliability factor.
   2. I am thinking that we do something like: CF = mean – 2\* standard deviation == μ - 2σ, which would mean that we have a 98% confidence that power output will be at or above this value (based on a normal distribution curve)
   3. You can brainstorm and see if you come up with a better way to describe reliability than what I suggested in 1.b. I am always open to ideas and suggestions 😊
2. Compiling all relevant reliability factors which might add to the story that we are telling. I want this data at a lot of levels of granularity and different aggregation schemes because we never know which numbers might be interesting or really stand out at us.
   1. For each VRE type that you are modeling (only PV and wind for now because RoR presents a unique set of challenges), I want you to have reliability vectors for every hour, for every location. For example, if we are modeling the USA in a 25 by 50 matrix, you would have two (one for wind and one for PV) three-dimensional 25 x 50 x 8760 matrices (because there are 8760 hours in a year).
   2. Condense the matrices in 2.a. to be 25 x 50 to show how reliability varies regionally for each VRE. You can do this in a way similar to what is described in 1.b. Graph this. It’ll be interesting.
   3. Add the 25 x 50 x 8760 CF profiles of wind and solar together. Then condense in the way described in 2.b. Graph this. It will show how complimentary wind and solar are.
   4. Ununiformly combine geographical scope to have 1 CF vector (8760 long) for each region of my CEM. I have 9 regions, so you should have 9 solar vectors and 9 wind vectors. You can combine by just averaging (I think…) Make one graph with all 9 wind vectors, and one graph with all 9 solar vectors.
   5. Average the wind and solar vectors from 2.d. and graph. This is probably the most important graph.
   6. Condense down to one reliability value for each region. Do this via the technique described in 1.b. Make a bar graph comparing the reliability of each region. This is the other most important graph.

Note: 25 x 50 is a random dimension that I chose which is significantly less granular than what we will actually be using.

Note: you can make this code with dummy data, so that you aren’t bottlenecked by Pipeline A.