Stochastic processes for renewables: reliability operations and planning

Golbon Zakeri
MIE, UMass–Amherst

Joint work with Geoff Pritchard (UoA),
A. Khojasteh, M.H. Rashidi and H. Sharadga(PEARL)
MIT, CEEPR Workshop Nov 2022

Reliability

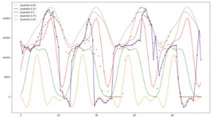
ISO New England defines reliability as:
"Making sure the right amount of electricity is there when it is needed, instantly."
This is particularly difficult as

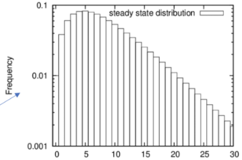
- Demand and supply must match instantaneously.
- We are faced with increasing uncertainty: on the supply side (renewable generation) and on the demand side (electrification, behind the meter solar, etc).
- *Electricity markets* underpin electricity supply and demand, hence we have to pay careful attention to incentives, efficiency and other auction features (cost recovery, revenue adequacy, etc).

Modeller: Planning under uncertainty for electricity systems

- Clearly reliability is a complex problem.
- You can't *operate* what you have not *planned on*.
- To have an efficient and robust *plan* we must have a picture of *operations and this involves uncertainty*.
- The long and short term decisions clearly affect each other.
- How to deal with uncertainty?

Spoiler slide





MDP model

Investment choices

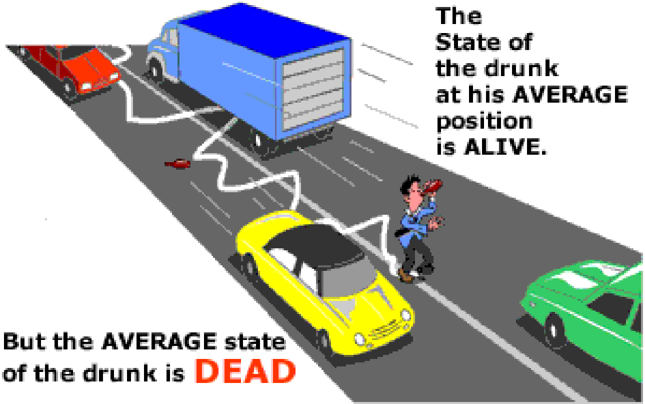
List of allowable actions in each state, e.g. charge battery.

Optimal actions to undertake in each state.

Simple alternatives: Point estimates

- We can dispense with the full range of uncertainty and consider a point representation of the distribution of outcomes and decide based on that.
- The deterministic representation sometimes leads to good decisions, but often does not.
- Even if a point representation does work well, we need to *know* that it works well. So a comparison with a decision that considers uncertainty is required.

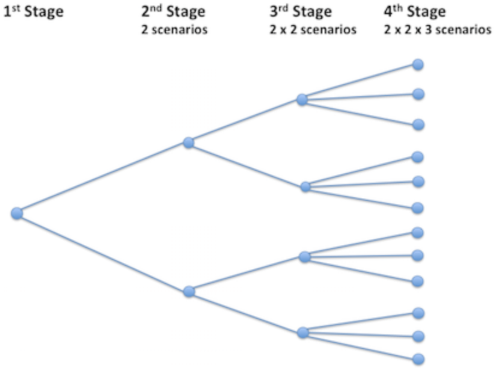
Flaw of averages



Incorporating uncertainty

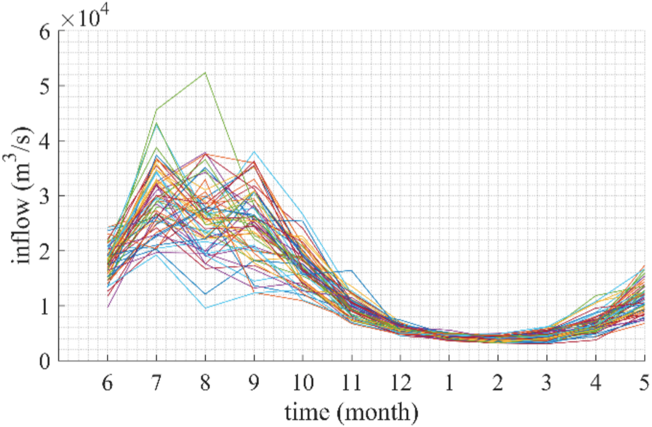
- My early background is in hydro/thermal scheduling.
- In that context, the aim was to balance the use of hydro and various thermal resources to be cost efficient, being faced with a distribution of inflows, over the course of a year.
- To be more concrete, "How much water to release each week in a yearly time horizon".
- So make the decisions for the weeks (in a year, in each scenario), then operate (respecting the given decision) during the week.

Small representation of a MSSP



Scenario tree for a stochastic model with four stages

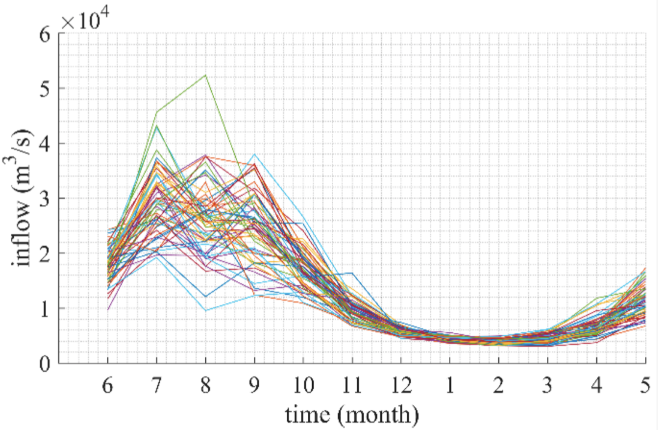
The real sequences



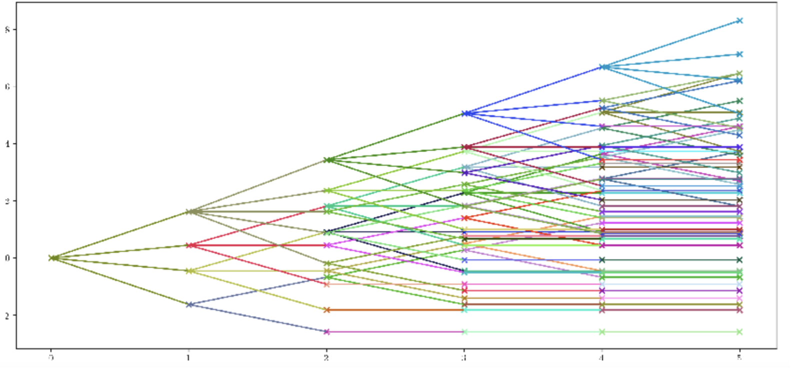
Stochstic processes for MSSP

- MSSPs are typically large and take a long time to run.
- The hydro-thermal problem for instance would have 52 stages!
- The scenario trees input into them are more than just a bunch of sample paths.
- To make a fit for purpose scenario tree, scenario reduction techniques, bundling, approximation and heuristics are applied (see e.g. Heitsch and Romisch 2008).
- MSSP solution algorithms tend to rely on stagewise independence or Markov models.

The real sequences



Turn into something tidy though very large



Back up and firming investment for renewables

- Similar to hydro-thermal scheduling this is a problem of decision making under uncertainty.
- There are more decisions here regarding what "infrastructure" we have, and how to operate this efficiently under uncertainty.
- A very precise model would allow for investment decisions at the start of the time horizon (or at regular intervals during the time horizon, in different scenarios), and within those epochs operate the system.
- The system would be faced with uncertainty on different scales, e.g. hourly, weekly, seasonally, etc.
- So to cast the problem as a MSSP becomes prohibitive.

Offshore wind power data: A first cut

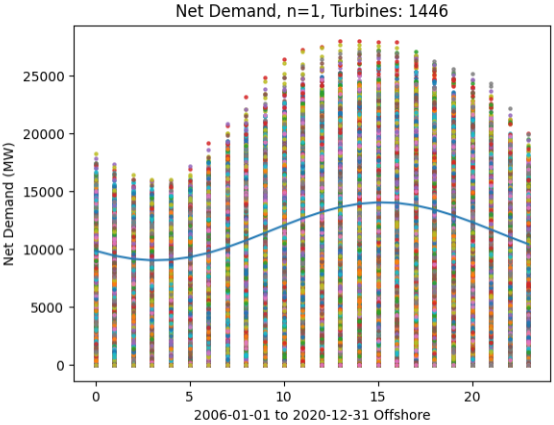
- Consider the Offshore wind in mix 2025-2030.
- The proportion of generation from offshore wind is based on ISO-NE's report on New England System Outlook 2022.
- Take into account wind speed data (data from NOAA).
- Power curve adjusted for the IEA 15 MW turbine.

Reference Turbine

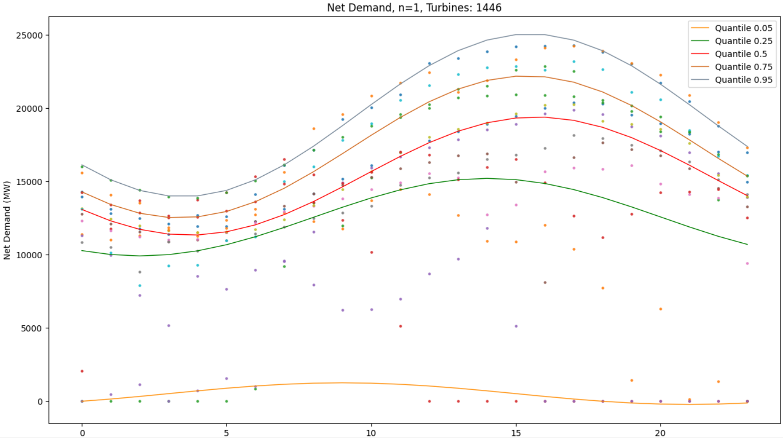
Stochastic processes for demand and renewables

- We have hourly demand data and now we have hourly wind generation data.
- Consider capturing residual demand (demand - wind power) by regression model.
- There are likely to be diurnal and seasonal patterns.
- A suitable form of regression is Fourier regression that uses periodic (trigonometric) functions to capture such patterns.

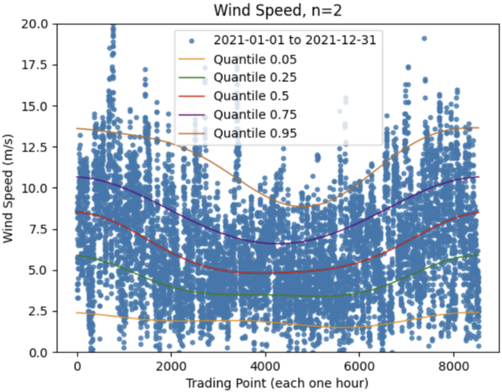
Fourier regression fitted to residual demand



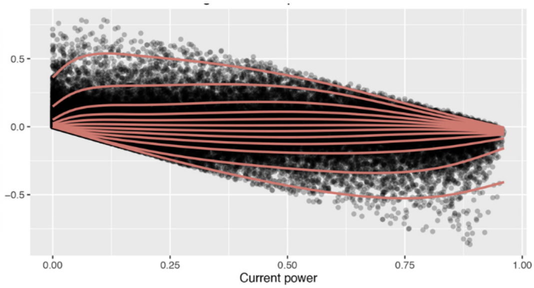
Capturing volatility around the trend



Seasonal Quantile Fourier regressions for wind generation



Persistance Future distribution depends on the present

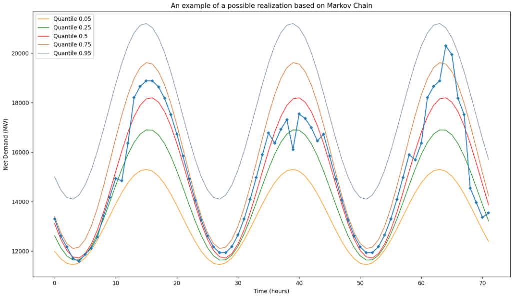


Given the current speed of wind, what is the wind speed distribution in the next period?

Markov transition matrix

n	0	1	2	3	4	5
0	0.85	0.1	0.03	0.01	0	0
1	0.08	0.74	0.14	0.03	0.01	0
2	0.03	0.18	0.54	0.21	0.04	0.01
3	0.01	0.04	0.2	0.52	0.22	0.01
4	0	0.01	0.03	0.16	0.69	0.12
5	0	0	0	0.01	0.06	0.93

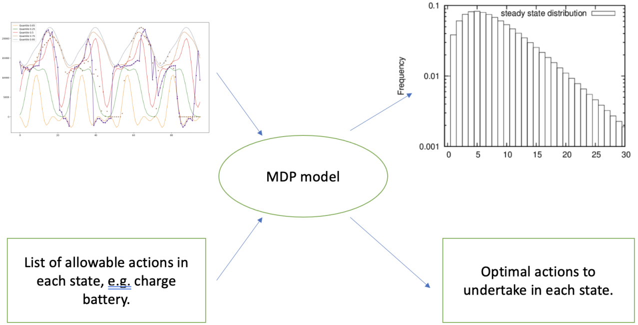
Sample path illustration



Markov decision processes

- Equipped with a Markov process for net demand we can (nearly) optimize the short term operations.
- Model what *actions* can be undertaken in each *state* and its *cost*. E.g. during an off peak period with net demand in state *low, a battery can be charged*.
- Add in the transition probability of moving from one state to another given an executed action.
- This can all be put into a (linear programming) model resulting in actions that produce a steady state distribution of the system operations with minimum expected cost.

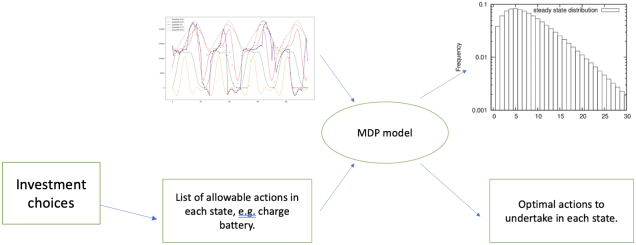
MDP Model


steady state distribution
Frequency
0.1
0.01
0.001
0
5
10
15
20
25
30
MDP model
List of allowable actions in each state, e.g. charge battery.
Optimal actions to undertake in each state.

Investment decisions over operations

- This model can be embedded within a higher level planning model that determines investment (e.g. battery size).
- Increased investment allows for more possible actions, of course at a cost.

Investment over MDP Model



Some results

Ramping cap in MW	Total Lost Demand	Total cost of Lost Demand	Variable cost of production	Total amortized cost of establishing CCGTs	Total Costs
12000	15821	47463000	198450	4080000	51741450
16500	182	546000	276645	5610000	6432645
				Total Saving	45308805
				Total Saving each day	1132720.125

Expand to an array of investment options

- Rather than just CCGT ramping generation to firm wind models should consider many more options.
- Short, medium and long term storage, each with their costs.
- Demand response, again over different time intervals.
- Transmission options.
- Other forms of generation, e.g. geothermal.
- Energy efficiency.
- As an aside, a model like this can be used to guide the value of an option, e.g. a contract to curtail demand for a few days in a row.

Capturing Risk

- We have leverage to change the objective of the MDP model to capture risk (and not just expectation).
- To this end, we have developed optimization models with coherent risk measures (in particular CVaR).
- This can be illustrated on small examples, but for real world data it is still in progress.
- As an aside, a model like this can be used to guide the value of an option, e.g. a contract to curtail demand for a few days in a row.

Take aways

- Decision making under uncertainty model.
- Capable of approximating uncertainty in such a way that is not too compromising.
- Results in manageable (linear programming) models for decision making.
- Can be validated through simulation.

Questions??