PROJECTIVE METRICS

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20 September 2023

You can declare different parts as a parentof sections

Part I: Demo Presentation Part

Part II: Demo Presentation Part 2

Part

MOTIVATION

The Problem

Energy Transition

- Shift from fossil fuels to renewables
- Increasing role of wind and solar energy
- Challenges: Variability and storage

The Duck

papera

The Solution

- Balancing generation and demand
- Energy storage as key enabler

Nuclear?

- Too expensive?
- Public opposition?
- Political challenges?

Energy Storage

- Batteries (short-term)
- Hydrogen (long-term)
- Pumped hydro

Challenges in Energy Modeling

- Huge computational costs in high-resolution models
- Need for accurate long-term planning
- Trade-off between accuracy and efficiency

Existing Methods

- Stochastic programming (computationally expensive)
- Robust optimization (conservative approach)
- Rolling horizon techniques

Proposed Approach

- Structure-preserving time series aggregation
- Iterative refinement process
- Heuristic-based selection of time intervals to refine

Mathematical Formulation

- Linear programming model
- Aggregation reduces problem size
- Iterative refinement ensures accuracy

Aggregation Techniques

- Rolling horizon validation
- Selection heuristics (variance-based, failure-based)

Computational Results

- 5-node network simulation
- Comparison of random vs heuristic-based refinement
- Faster convergence with structure-preserving methods

Conclusion

- Time series aggregation reduces computational costs
- Preserves structure and accuracy
- Further work: Adaptive heuristics and dynamic adjustments

Problem description

We consider a two stage stochastic program consisting of a Capacity Expansion Problem (CEP) and an Economic Dispatch (ED) problem:

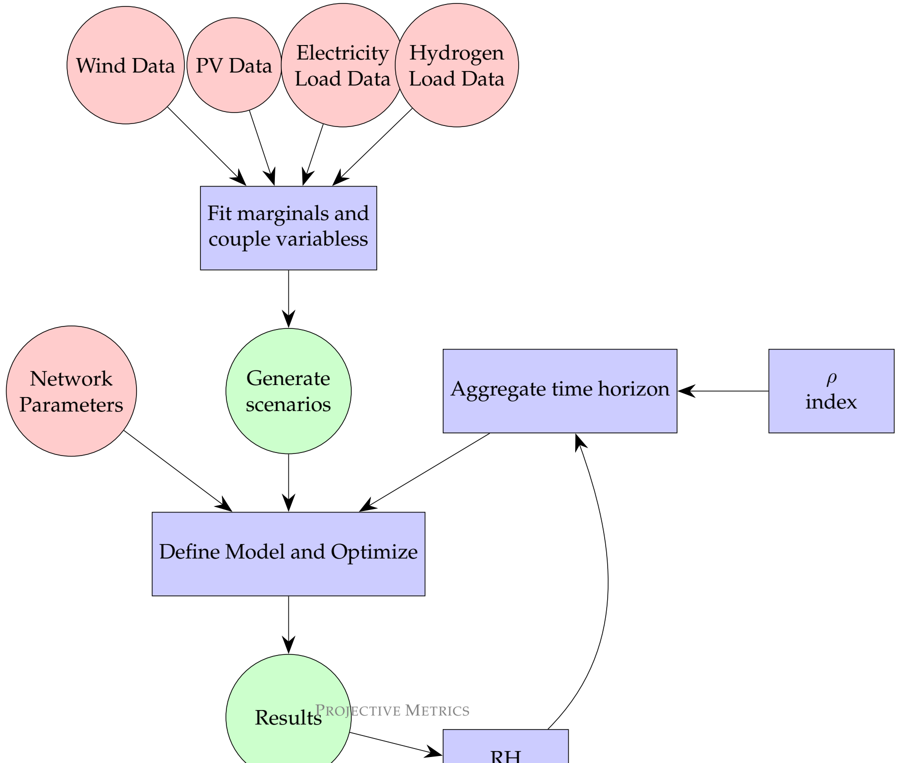
$$\begin{aligned} \min_{x} \quad & c'x + \mathbb{E}_{\omega}\left[\mathcal{V}(x,\omega)\right] \\ s.t. \quad & 0 \leq x \leq x^{max} \end{aligned}$$

- The first stage determines the optimal capacities x for each component of the power grid.
- The second stage solves the Economic Dispatch for a given time horizon in function of the capacities x and the scenario ω, yielding $\mathcal{V}(x,\omega)$ as solution.

Time series aggregation method

Give various examples of what has been used

Workflow


Wind Data
PV Data
Electricity Load Data
Hydrogen Load Data
Fit marginals and couple variabless
Network Parameters
Generate scenarios
Aggregate time horizon
ρ index
Define Model and Optimize
Results
RH

Model - Variables

- The grid is modelled as an undirected graph $(\mathcal{N}, \mathcal{E} = \mathcal{E}_P \cup \mathcal{E}_H)$.
- CEP variables include:
  - for each node $n \in \mathcal{N}$, number of generators $(ns_n,\ nw_n)$ and capacities for hydrogen management $(nh_n,\ mhte_n,\ meth_n)$;
  - for each edge $l \in \mathcal{E}$, capacity expansion for electricity and hydrogen transmission.

- ED variables include, for each scenario j and time-step t:
  - for each node $n \in \mathcal{N}$, stored hydrogen $(H_{j,t,n})$ and hydrogen-electricity conversion $(HtE_{j,t,n},\ EtH_{j,t,n})$;
  - for each edge $l \in \mathcal{E}$, electricity and hydrogen transmission.

Model - Objective function

$$
\begin{aligned}
\min \quad & \sum_{n\in\mathcal{N}} (\mathrm{cs}_n \cdot \mathrm{ns}_n + && \mathrm{cw}_n \cdot \mathrm{nw}_n + \mathrm{ch}_n \cdot \mathrm{nh}_n) + \\
+ \quad & \sum_{n\in\mathcal{N}} (\mathrm{cmhte}_n \cdot \mathrm{m} && \mathrm{hte}_n + \mathrm{cmeth}_n \cdot \mathrm{meth}_n) + \\
+ \quad & \sum_{l\in\mathcal{E}_P} (\mathrm{cNTC}_l \cdot \mathrm{ad} && \mathrm{dNTC}_l) + \sum_{l\in\mathcal{E}_H} (\mathrm{cMH}_l \cdot \mathrm{addMH}_l) + \\
+ \quad & \frac{1}{d} \sum_{j=1}^{d} \sum_{t=1}^{T} \left(\sum_{n\in\mathcal{N}} (\right. && \mathrm{chte}_n \cdot \mathrm{HtE}_{j,t,n} + \mathrm{ceth}_n \cdot \mathrm{EtH}_{j,t,n}) + \\
& && \left. + \sum_{l\in\mathcal{E}_H} (\mathrm{cH\_edge}_l \cdot \mathrm{H\_edge}_{j,t,l}) \right)
\end{aligned}
$$

Model - Constraints

For all nodes $n \in \mathcal{N}$, time steps $t \in \{1...T\}$ and scenarios $j \in J$:

Electricity Balance:

$$
\begin{aligned}
&\mathrm{ns}_n \cdot \mathrm{ES}_{j,t,n} + \mathrm{nw}_n \cdot \mathrm{EW}_{j,t,n} - \mathrm{EL}_{j,t,n} + \\
&+ 0.033 \cdot \mathit{fhte}_n \cdot \mathrm{HtE}_{j,t,n} - \mathrm{EtH}_{j,t,n} \; + \\
&+ \sum_{l \in Out(n)} \mathrm{P\_edge}_{j,t,l} + \sum_{l \in In(n)} \mathrm{P\_edge}_{j,t,l} \geq 0;
\end{aligned}
\tag{1}
$$

Hydrogen Storage:

$$
\begin{aligned}
\mathrm{H}_{j,t+1,n} = {} & \mathrm{H}_{j,t,n} - \mathrm{HL}_{j,t,n} + \\
& + 30 \cdot \mathit{feth}_n \cdot \mathrm{EtH}_{j,t,n} - \mathrm{HtE}_{j,t,n} \; + \\
& - \sum_{l \in Out(n)} \mathrm{H\_edge}_{j,t,l} + \sum_{l \in In(n)} \mathrm{H\_edge}_{j,t,l}
\end{aligned}
\tag{2}
$$

Model - Constraints

Variables of the inner ED problem are bound by the respective capacities to be determined in the CEP.
For all time steps $t \in \{1...T\}$, scenarios $j \in J$ and nodes $n \in \mathcal{N}$:

$$\begin{aligned} \text{Storage Capacity Limit:} \quad & \mathrm{H}_{j,t,n} \leq \mathrm{nh}_n; && (3)\\ \text{EtH Conversion Limit:} \quad & \mathrm{EtH}_{j,t,n} \leq \mathrm{meth}_n; && (4)\\ \text{HtE Conversion Limit:} \quad & \mathrm{HtE}_{j,t,n} \leq \mathrm{mhte}_n. && (5) \end{aligned}$$

For all time steps $t \in \{1...T\}$, scenarios $j \in J$ and edges $l \in \mathcal{E}_P$ and $l \in \mathcal{E}_H$ respectively:

$$\begin{aligned} \text{Net Transfer Capacity:} \quad & \mathrm{P\_edge}^{\pm}_{j,t,l} \leq \mathrm{NTC}_l + \mathrm{addNTC}_l; && (6)\\ H_2 \text{ Transfer Capacity:} \quad & \mathrm{H\_edge}^{\pm}_{j,t,l} \leq \mathrm{MH}_l + \mathrm{addMH}_l. && (7) \end{aligned}$$

Validation through Rolling Horizon

Consider a solution $\mathbf{x}_{CEP}$ to the Capacity Expansion Problem solved over train scenarios J_{train} and a test scenario $\hat{j}$.

Rolling Horizon algorithm:

1. **Initialization:** Set $H^{test}_{0,n} = \max_{j \in J_{train}} H_{j,0,n}$.
2. **Daily Iteration:** For each day in the time horizon:
   - Optimize the inner Economic Dispatch problem for the given day. If the problem is infeasible, terminate the process.
   - Update the hydrogen storage levels: $H^{day+1}_{0,n} = H^{day}_{24,n}$.

Credit: Glomb et al. 2022

Validation through Rolling Horizon

Definition 4.1

We consider $\mathbf{x}_{CEP}$ to be ***RH-feasible*** *over scenario $\hat{\jmath}$ if the Rolling Horizon optimization algorithm terminates at the end of the year and $H_{\hat{\jmath},T,n} \geq H_{\hat{\jmath},0,n}$ for all nodes $n \in \mathcal{N}$.*

Note: the solution $\mathcal{V}_{RH}(\mathbf{x}_{CEP}, \hat{\jmath})$ to the inner ED problem given by the RH is not necessarily optimal, and conversely, solutions $\mathbf{x}_{CEP}$ that are feasible for the perfect foresight ED aren't necessarily RH-feasible.

To incentivize better hydrogen storage management in the RH, we define positive variables $loss_{t,n}$ for each time step t and node n, with positive cost, and add the contraints:

$$loss_{t,n} \geq \frac{1}{d}\left(\sum_{j \in J_{train}} H_{j,t,n}\right) - H^{test}_{t,n} \tag{8}$$

Time Aggregation

Consider a time aggregation $\{I_0, ..., I_n\} \subseteq \mathcal{P}(\{1, ..., 8760\})$. For all time dependent variables for the inner ED problem, define the aggregated variables as follows:

$$EtH_{j,I,n} = \sum_{i \in I} EtH_{j,i,e}, \qquad HtE_{j,I,e} = \sum_{i \in I} HtE_{j,i,e}.$$

Similarly for $\Delta H_{j,I,e}$, $P\_edge^{\pm}_{j,I,e}$ and $H\_edge^{\pm}_{j,I,e}$, separately on the two directions. Define the aggregated scenario parameters as:

$$ES_{j,I,n} := \sum_{i \in I} ES_{j,i,n}, \quad EW_{j,I,n} := \sum_{i \in I} EW_{j,i,n}$$

and similarly for $HL_{j,I,n}$ and $HR_{j,I,n}$.

Proposition

The linear problem defined through the above is a relaxation of the unaggregated problem.

Time Aggregation

Algorithm: iterations on time aggregations

1. Set up the model environment with enough variables for the iterations to come. Impose the constraints relative to an initial time partition, and solve.
2. Select a day using a given *selection method*.
3. Add the constraints relative to each hour of the selected day. Solve the model using a warm start.
4. Repeat step 2 and 3 until a given *halting condition* is met.

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