MILP FORMULATION FOR OPTIMAL PLANNING OF ELECTRIC POWER SYSTEMS

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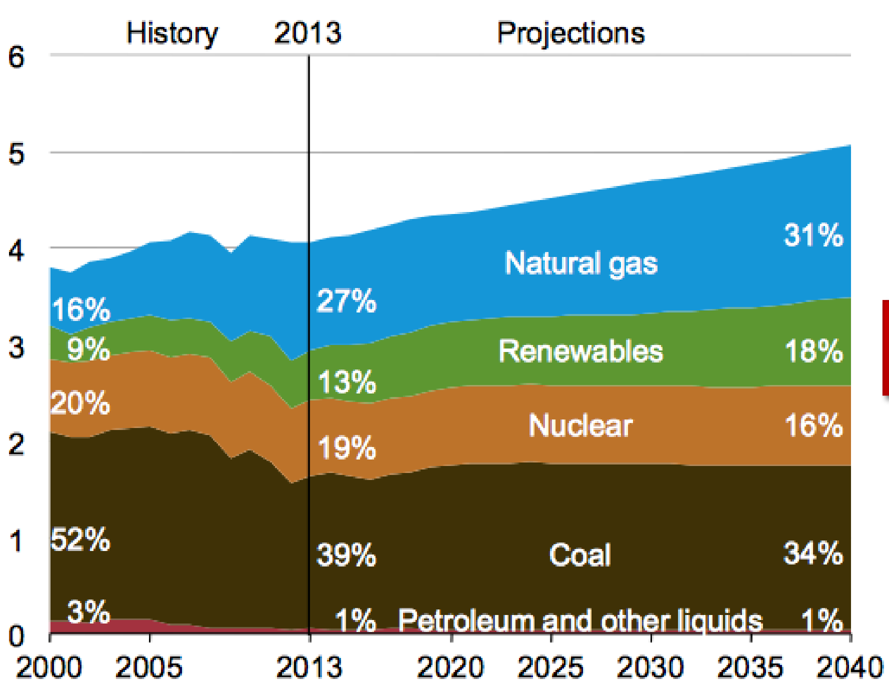
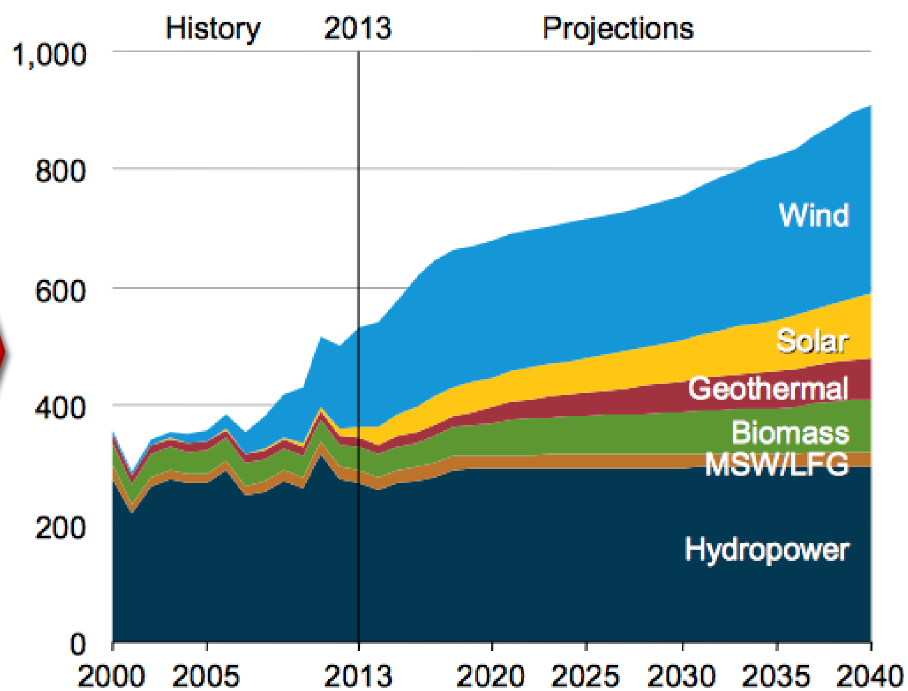
Motivation

Electricity mix gradually shifts to lower-carbon options

Electricity generation by fuel type
(trillion kWh)



Renewable electricity generation by fuel type
(billion kWh)

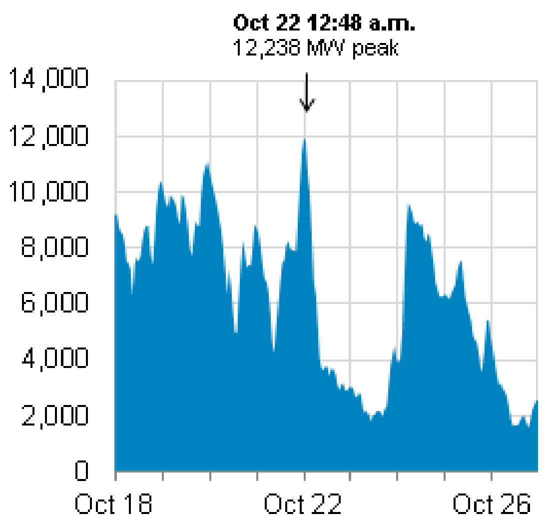


Source: EIA, Annual Energy Outlook 2015 Reference case

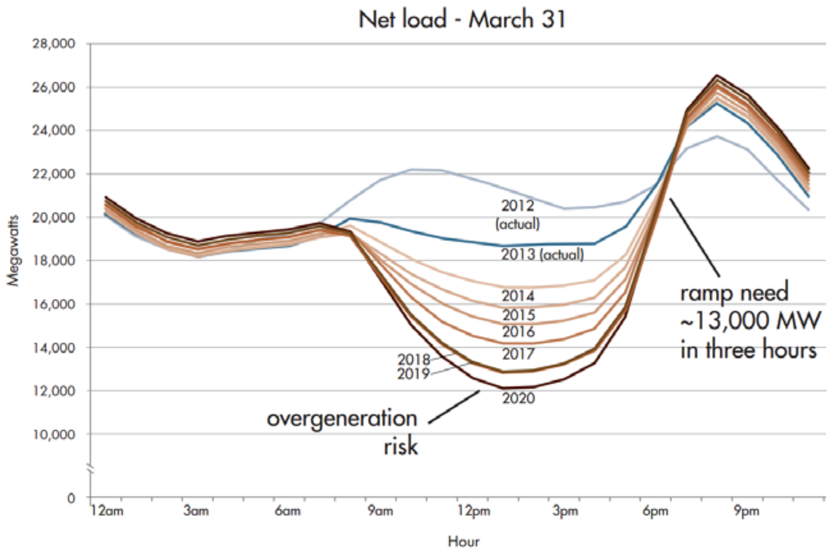
Motivation

High variability in the renewables capacity factor

Hourly generation in the ERCOT(Texas) electric, Sep 18-17, 2015 (MW) grid



CAISO duck curve - Net load in March 31



- Increasing contribution of intermittent renewable power generation in the grid makes it crucial to include **operational details** in the **hourly** and **sub-hourly level** in long term planning models to capture their variability

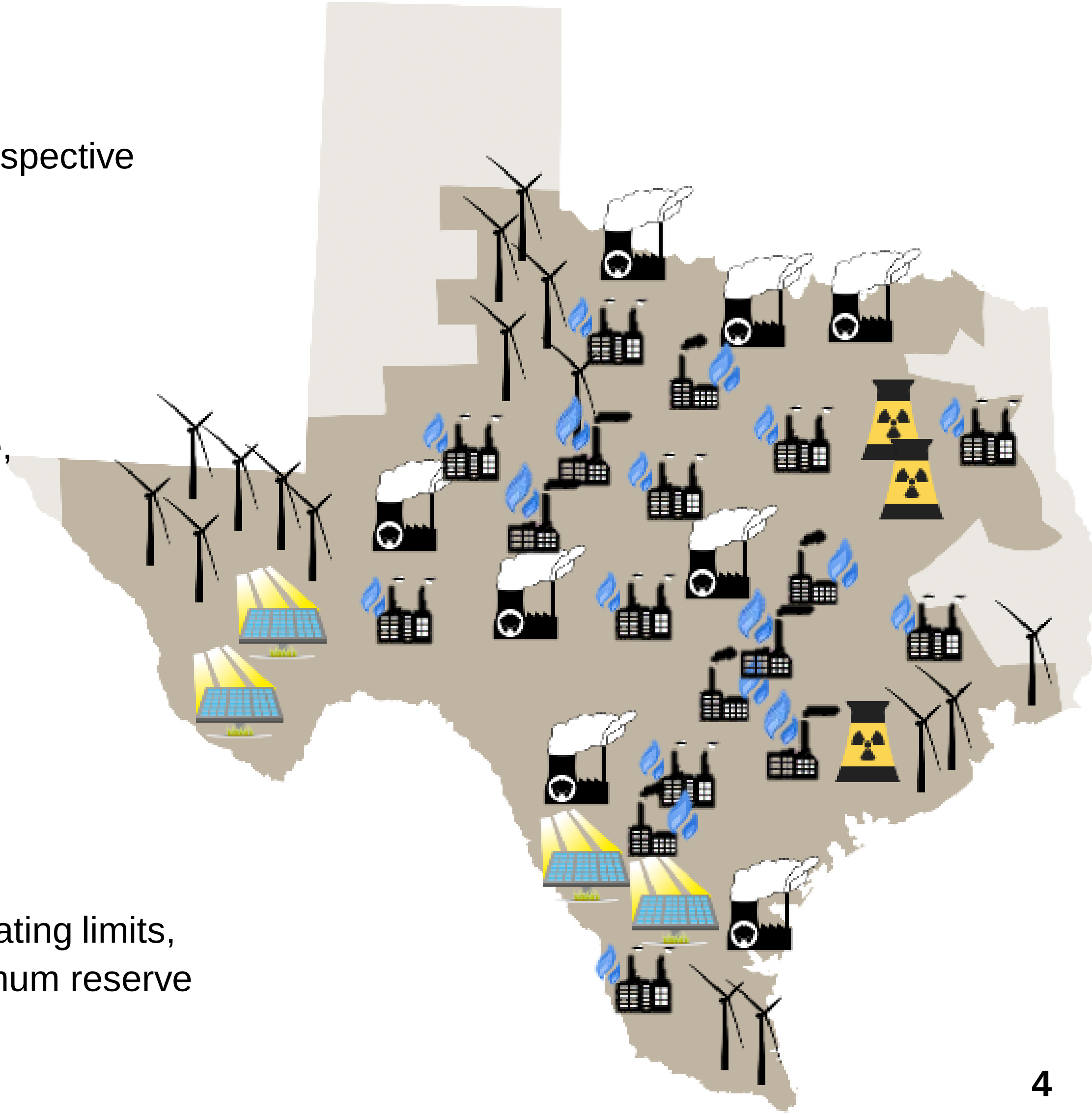
Source: • U.S. Energy Information Administration, based on the Electric Reliability Council of Texas (ERCOT)
• California ISO (CAISO)

Problem Statement

Given:

A set of **existing generators** with the respective

- generation technology*
  - nuclear: steam turbine
  - coal: steam turbine
  - natural gas:
    steam turbine,
    gas-fired combustion turbine,
    and combined cycle
  - solar: photo-voltaic
  - wind turbines
- location
- nameplate capacity
- age and expected lifetime
- CO_2 emission
- operating costs
- operating data
  - if thermal: ramping rates, operating limits, spinning and quick-start maximum reserve
  - If renewable: capacity factor



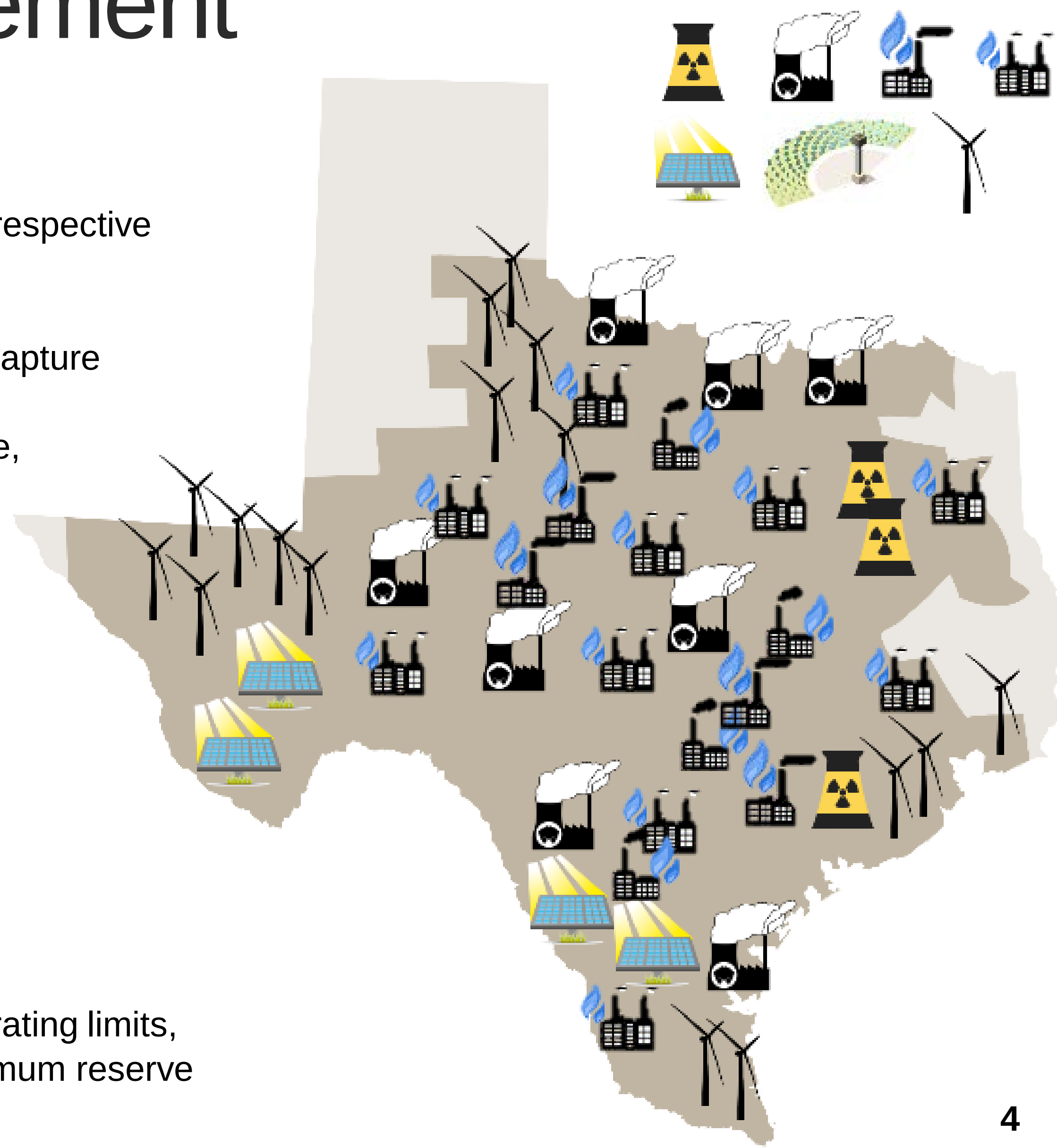
* Assume no hydropower

Problem Statement

Given:

A set of **potential generators** with the respective

- generation technology
  - nuclear: steam turbine
  - coal: IGCC w/ or w/o carbon capture
  - natural gas:
    gas-fired combustion turbine,
    combined cycle w/
    or w/o carbon capture
  - solar:
    photo-voltaic
    concentrated solar panel
  - wind turbines
- nameplate capacity
- expected lifetime
- CO_2 emission
- investment cost
- operating costs
- operating data
  - if thermal: ramping rates, operating limits, spinning and quick-start maximum reserve
  - If renewable: capacity factor



Problem Statement

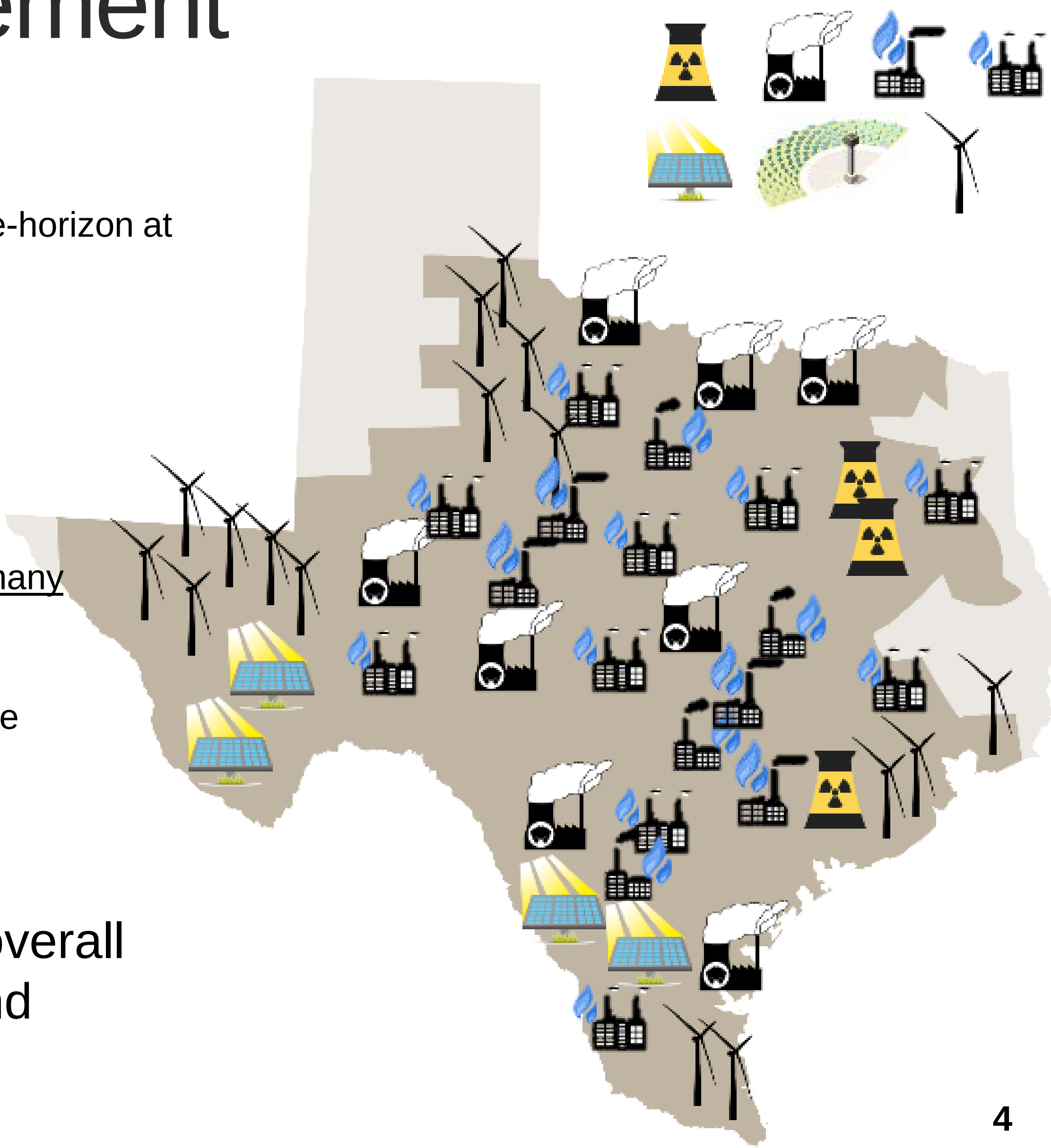
Given:

- Projected load demand over the time-horizon at each location
- Distance between locations
- Transmission loss per mile

Find:

- <u>When</u>, <u>where</u>, <u>which type</u> and <u>how many</u> generators to invest
- When to retire the generators
- Whether or not to extend their lifetime
- Power flow between locations
- Detailed operating schedule

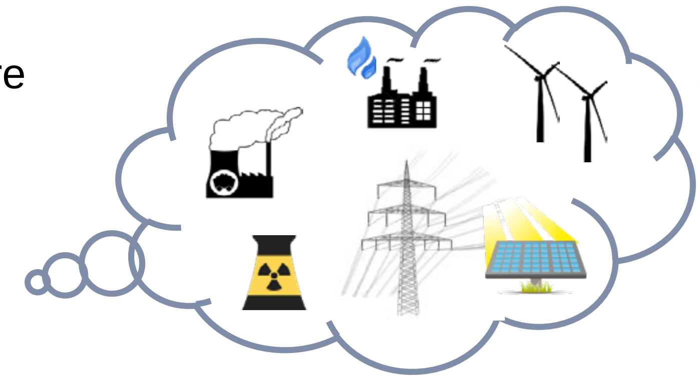
in order to minimize the overall operating, investment, and environmental costs



Modeling Challenges

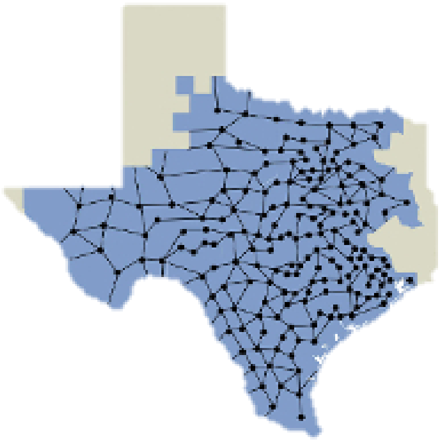
Hourly time resolution

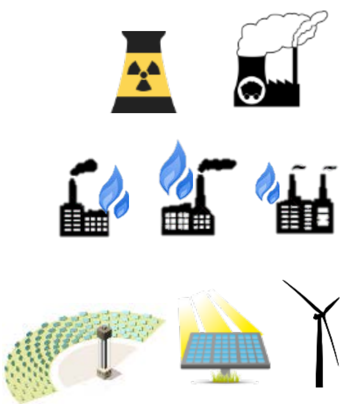
Long term investment plans



- **Temporal** multi-scale aspect of the problem:
  - For a 30 year horizon, there are **262,800** hourly sub-periods of time

- **Spatial** multi-scale aspect of the problem
  - Large number of potential locations
  - Large number of generators (hundreds or thousands depending on the area of scope)





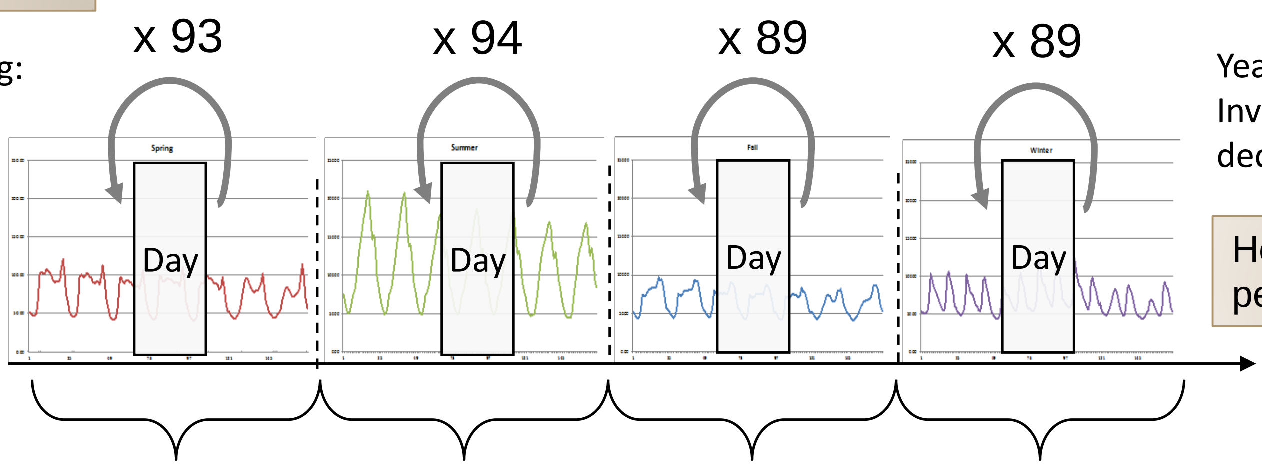
Modeling Strategies

Time scale approach

2,880 subperiods vs. **262,800** for full model

Time period: $t \in T$

Year 1, spring: Investment decisions



Year 2, spring: Investment decisions

Hourly Sub-period: $s \in S$

Season: $ss \in SS$

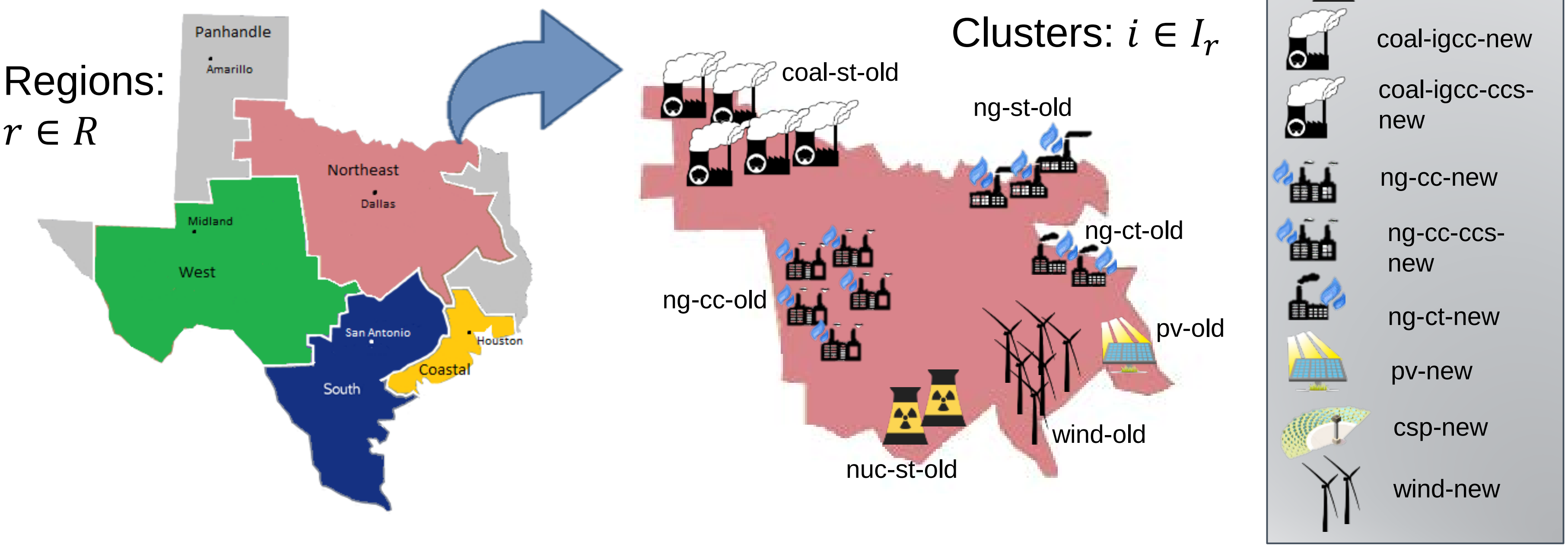
Spring Summer Fall Winter

- Horizon: **30 years**, each year has **4 periods** (spring, summer, fall, winter)
- Each period is represented by **one representative day on an hourly basis**
  Varying inputs: **load demand data, capacity factor of renewable generators**
- Each representative day is repeated in a **cyclic** manner (~3 months reduced to **1 day**)

Mitra, S., Pinto, J. M., & Grossmann, I. E. (2014). *Optimal multi-scale capacity planning for power-intensive continuous process under time-sensitive electricity prices and demand uncertainty*

Modeling Strategies

Region and cluster representation



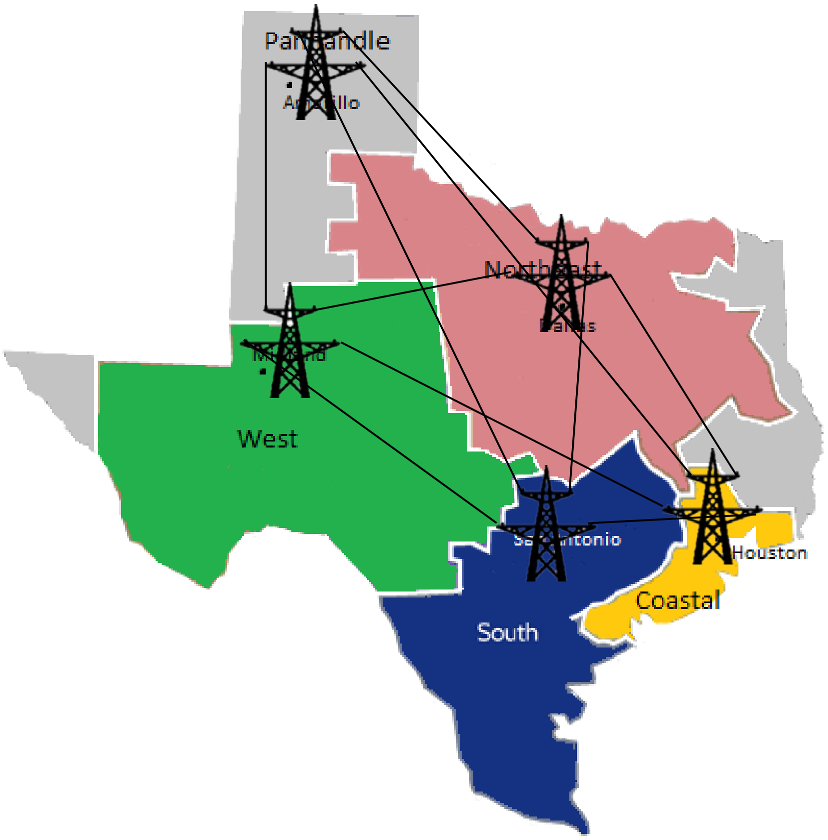
- Area of scope divided into regions *r* (similar climate and load demand).
- Potential location for generators are the midpoint of each region *r*.
- Instead of representing each generator separately, aggregate same generation technology and status (existing or potential) in **clusters *i*** in each region *r.*
- Decision of building/retiring and starting up/shutting down a generator switched from binary to **integer variables**

Palmintier, B., & Webster, M. (2014). *Heterogeneous unit clustering for efficient operational flexibility modeling*

Modeling Strategies

Transmission: “truck-route” representation

- Flow in each line is determined by the energy balance between each region *r*.
- This approximation ignores *Kirchhoff’s Circuit Law*, which dictates that the power will flow along the path of least impedance.
- Transmission capacity constraints are not binding for the considered case.
- The transmission losses are characterized by a factor of 1%/100 miles (not endogenously calculated)



Short, W. et al (2011). *Regional Energy Deployment System (ReEDS)*

MILP Model

Continuous variables:
- Power output at sub-period *s*
- Curtailment generation slack at *s*
- Power flow between regions at *s*
- Deficit from RES quota at *t*
- Spinning reserve at *s*
- Quick-start reserve at *s*

Discrete variables:
- # of generators installed at period *t*
- # of generators built at *t*
- # of generators retired at *t*
- # of generators with life extended at *t*
- # generators ON at sub-period *s*
- # generators starting up at *s*
- # generators shutting down at *s*

Operating constraints:

- **Energy balance:** ensures that the sum of instantaneous power generated at region *r* plus the net power flow being sent to this region equal the load demand plus a slack for curtailment.
- **Capacity factor:** limits the generation of renewable generators to be less than or equal to a given fraction of the capacity in each hour.
- **Unit minimum and maximum output constraint:** implies that each thermal unit is either OFF and outputting zero power, or ON and running within operating limits.
- **Unit commitment constraint:** computes the startup and shutdown of thermal generators.
- **Ramping limits:** captures the limitation on how fast thermal units can adjust their output power

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- # generators shutting down at *s*

Operating constraints:

- **Total operating reserve:** dictates that the total spinning reserve plus quick-start reserve must exceed a specific percentage of the load at each subperiod.
- **Total spinning reserves:** specifies that the total spinning reserve has to make up at least to a specific percentage of the load in a reserve sharing region at each subperiod.
- **Maximum spinning reserve constraint:** specifies the maximum fraction of capacity of each generator cluster that can contribute to spinning reserves.
- **Maximum quick-start reserve constraint:** specifies the maximum fraction of the capacity of each generator cluster that can contribute to quick-start reserves, and imposes that quick-start reserves can only be provided by the generators that are OFF, i.e., not active.

MILP Model

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- Power output at sub-period *s*
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Discrete variables:
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- # generators ON at sub-period *s*
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- # generators shutting down at *s*

Investment constraints:

- **Planning reserve requirement:** ensures that operating capacity is greater than or equal the annual peak load plus a predefined reserve margin.
- **Minimum annual RES energy contribution requirement:** the RES quota target (imposed by environmental treaties) must be satisfied.
- **Maximum yearly installation:** Limits the yearly installation per generation type to an upper bound.

Logical constraints:

Define the number of generators that are:
- operational,
- built,
- retired,
- have their life extended

at each time period t.

MILP Model

Continuous variables:
- Power output at sub-period *s*
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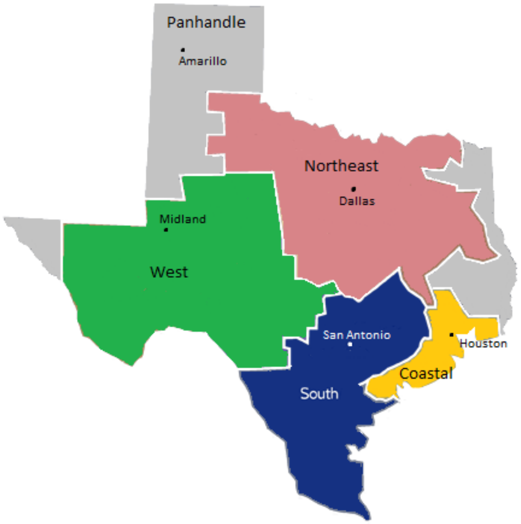
Objective function:

Minimization of the discounted total cost over the planning horizon comprising:

- Variable operating cost
- Fixed operating cost
- Startup costs
- Cost of investments in new generators
- Cost to extend the life of generators that achieved their expected lifetime
- Fuel consumption
- Carbon tax for CO_2 emission
- Penalty for not meeting the minimum renewable annual energy production requirement

Case Study: ERCOT (Texas)

- **30 year** time horizon
- Data from **ERCOT database**
- Cost information from NREL (Annual Technology Baseline (ATB) Spreadsheet
- All costs in **2015 USD**
- Regions:
  - Northeast (midpoint: Dallas)
  - West (midpoint : Glasscock County)
  - Coastal (midpoint: Houston)
  - South (midpoint : San Antonio)
  - Panhandle (midpoint : Amarillo)
- Fuel price data from EIA Annual Energy Outlook 2015 - Reference case
- No imposed carbon tax
- No RES quota requirement



MILP Model

Discrete variables: 413,644

Continuous variables: 682,947

Equations: 1,370,051

Solver: CPLEX

optcr: 1%

CPU Time: 6.4 hours

Objective value: $183.4 billion

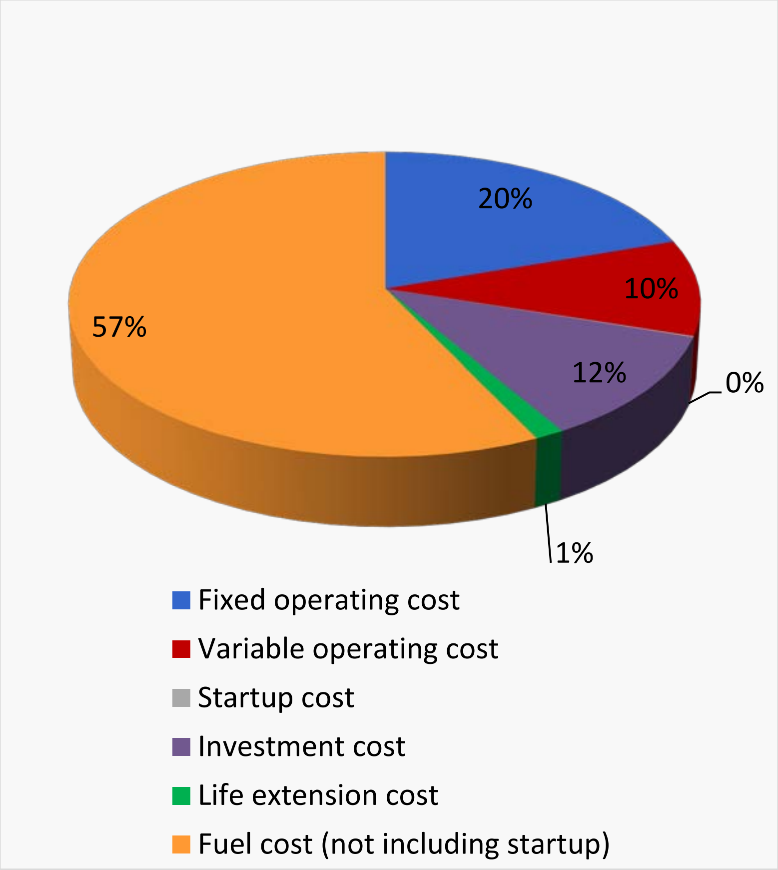
Optimality gap: 1%

Case Study: ERCOT (Texas)

Summary of Results:

Cost Breakdown

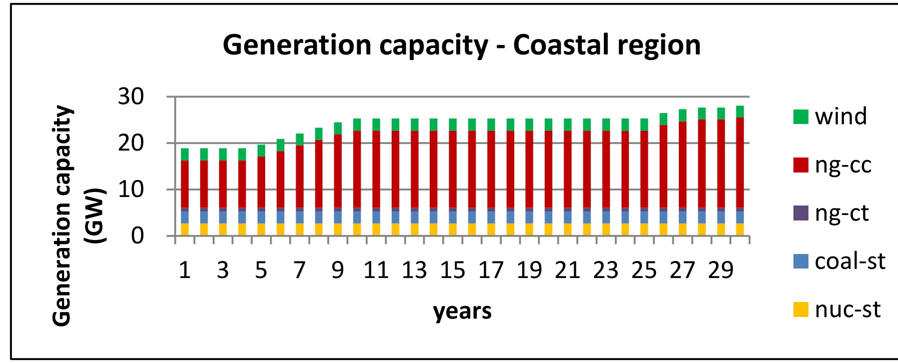
	Cost breakdown (billion $)
Fixed operating cost	36.3
Variable operating cost	18.7
Startup cost	0.2
Investment cost	20.1
Life extension cost	2.5
Fuel cost (not including startup)	104.8
Total Cost	183.4

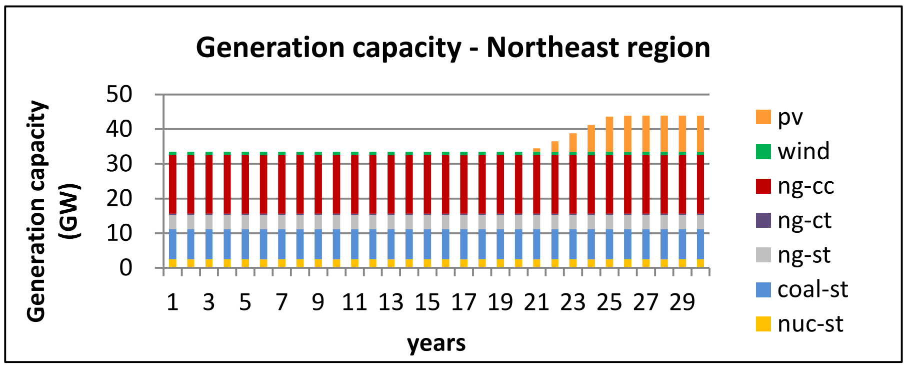


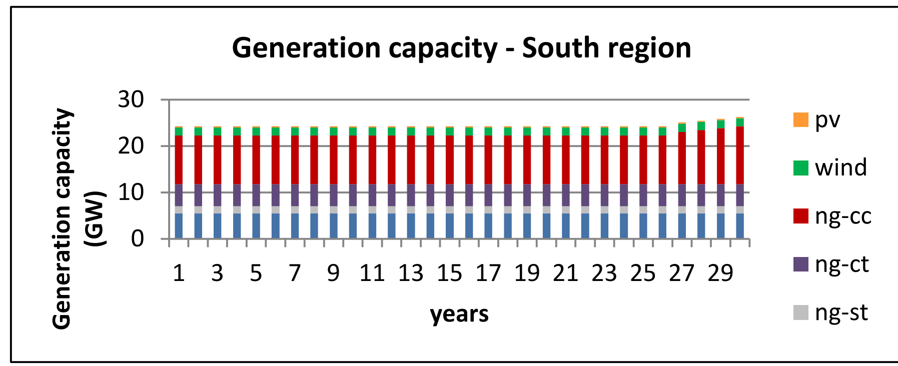
Case study: ERCOT (Texas)

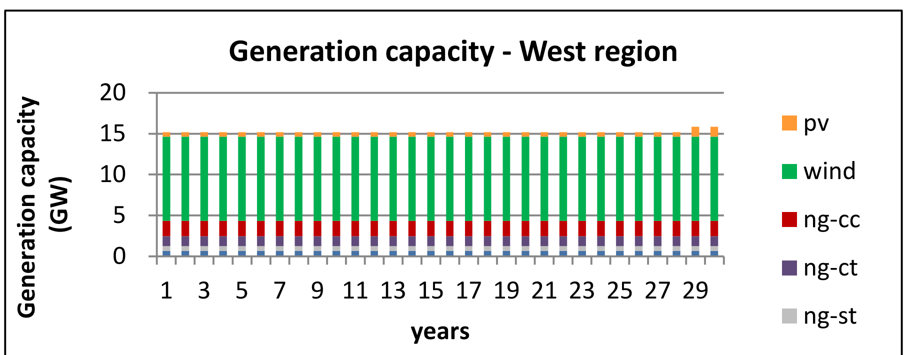
Summary of Results

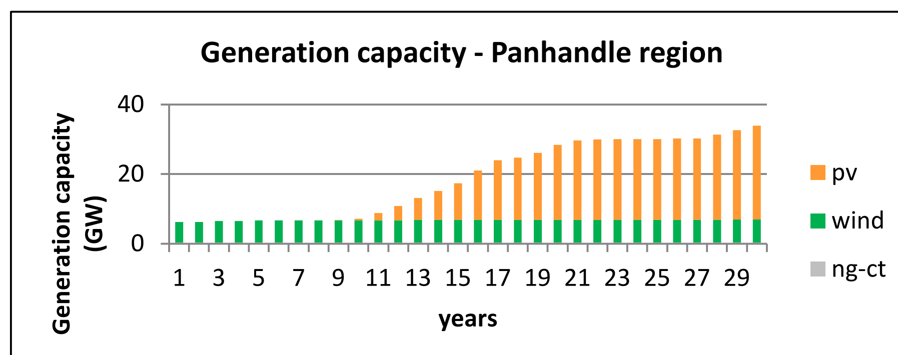
- **Generation Capacity**







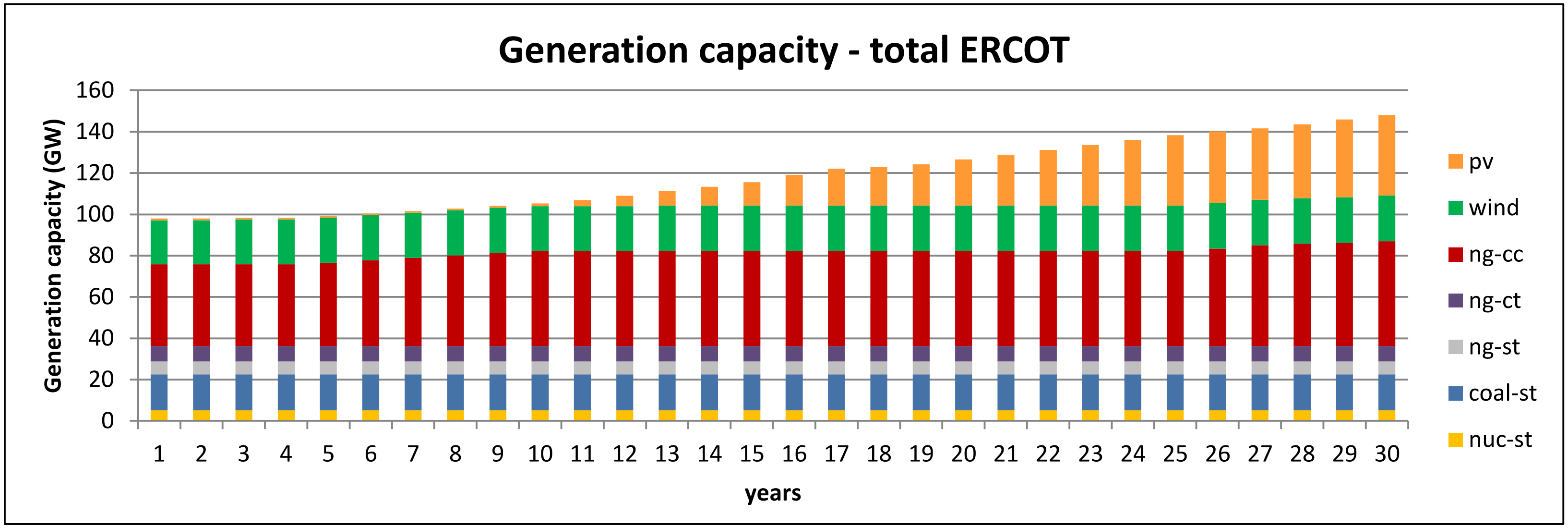




Case study: ERCOT (Texas)

Summary of Results

- **Generation Capacity**

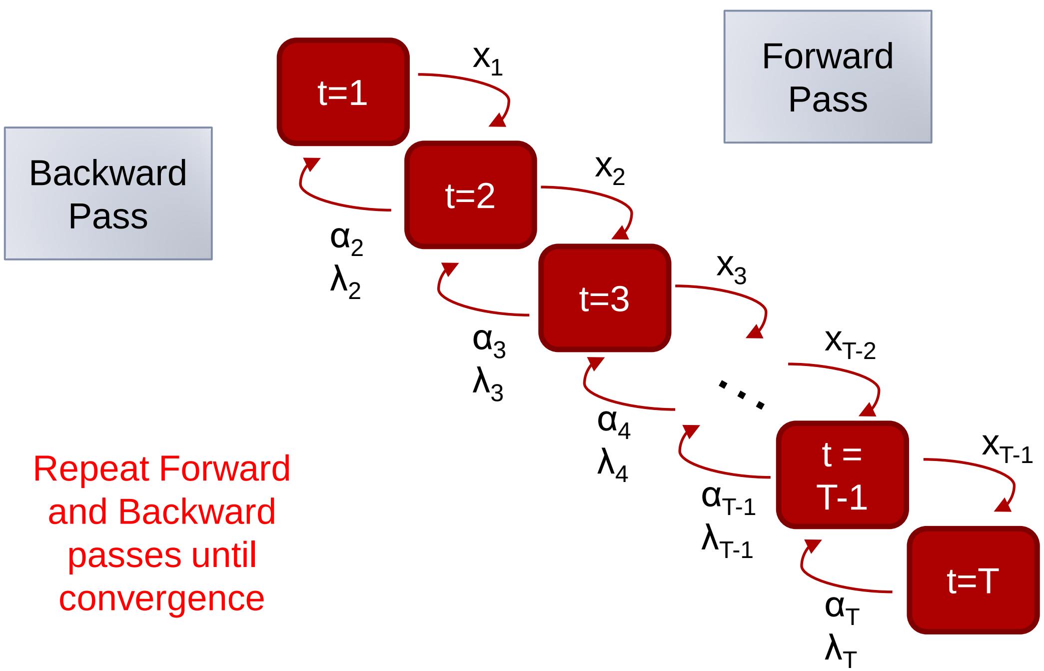


- 47-fold increase in **photo-voltaic** capacity
- 4% increase in **wind** capacity
- 28% increase in **natural gas combined-cycle** capacity

Decomposition Scheme

Nested Benders-like Decomposition for Mixed-Integer Programming

Combination of Nested Benders and Lagrangean Relaxation



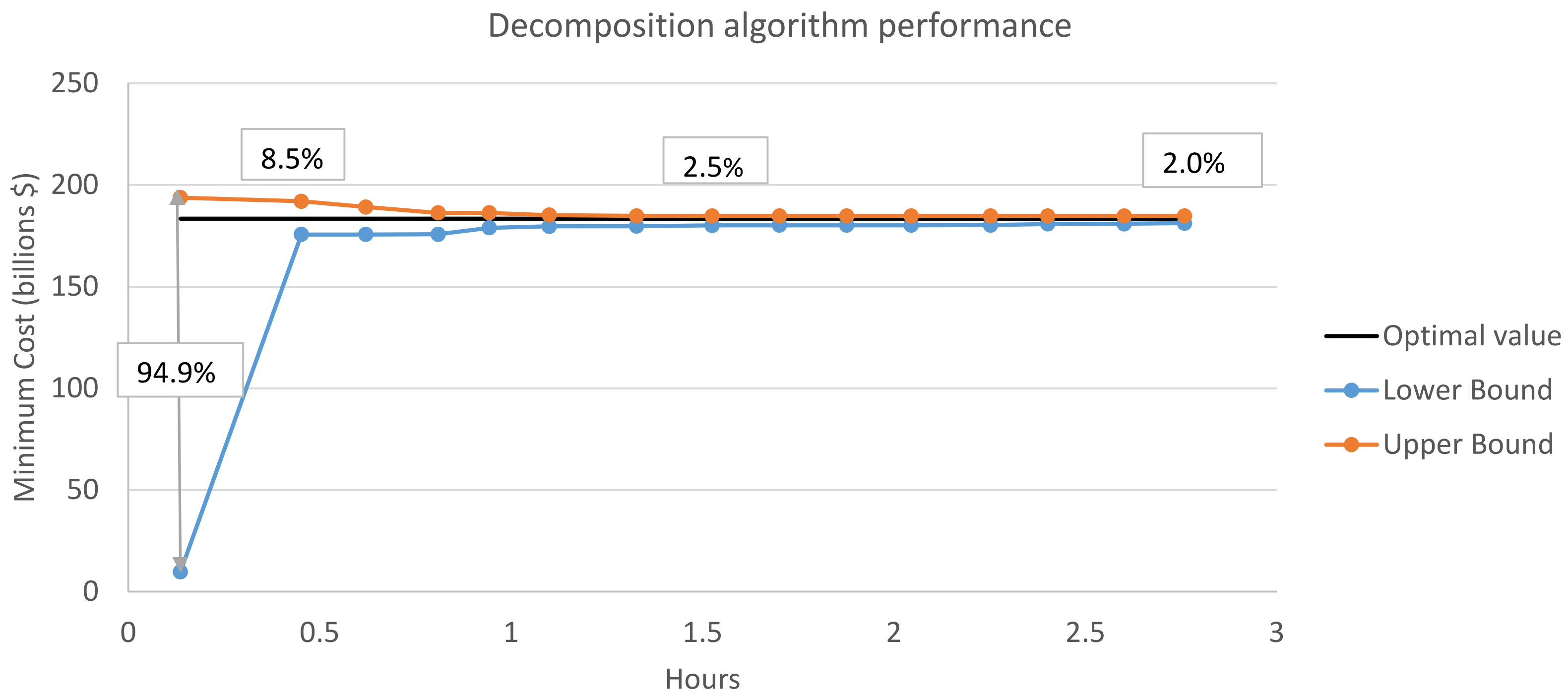
- In the **backwards pass** it solves a **Lagrangean relaxation** of the subproblem and each time period *t* to get the cuts from next time period *t+1*. The multipliers for the cut are calculated from the Lagrangean problem and updated using **subgradient method**.

- This framework can be very useful in the future when we extend the model to **stochastic.**

- Sun & Ahmed, *Nested Decomposition of Multistage Stochastic Integer Programs with Binary State Variables,* May 2016

Decomposition Scheme

Preliminary results – ERCOT case study



Conclusions

- Time scale, region and clustering approaches reduce considerably the size of the MILP, making it possible to solve large instances.
- For ERCOT region, future growth in generation capacity will be met by a portfolio of different generation technologies
- Decomposition algorithm has great potential to speed up the solution and allow a more refined representation of time.

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