Multi-Objective Unit Commitment

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Motivation

- Single-objective formulations (in class & industry) dominate decision-making in the energy sector
    - Unit Commitment, Economic Dispatch
    - *Cost* minimized
- Arrow’s Impossibility Theorem
    - Inherent loss of information in the decision space with single-objective problems
    - Importance of representing competing factors as explicit objectives

Motivation (cont.)

- Increasing importance of environmental objectives in decision making
  - *Reduction in emissions* has tangible, real-world implications
  - As systems push for less environmental impact, necessary to consider sustainability metrics in optimization problems, along with cost

Multi-Objective Optimization

$$\min_{\mathbf{x}\in\Omega} F(\mathbf{x}) =< f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_N(\mathbf{x}) >$$

where $\boldsymbol{x}$ is the vector of decision variables

f_i is the i-th objective function in an N-objective problem

Pareto Dominance

- No single *best* solution in a multi-objective problem
- Rather, a *set of solutions* that captures the trade-offs in the objective space

a solution ***u*** with objective values < u_1 , … , u_N > *dominates* another solution ***v*** iff

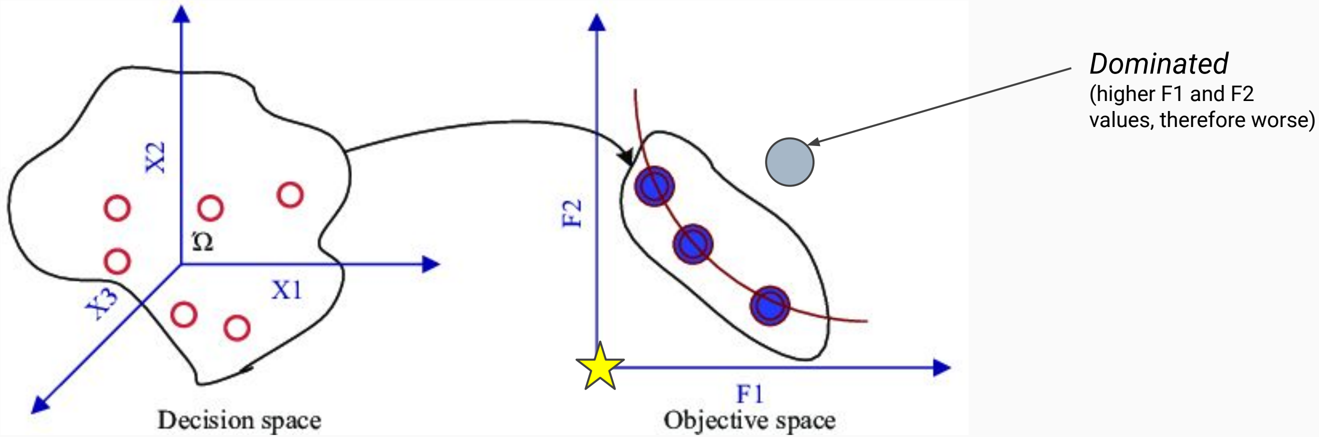
$$\forall i \in \{1, 2, \ldots, N\}, u_i \leq v_i$$

$$\exists j \in \{1, 2, \ldots, N\}, u_j < v_j$$

i.e. ***u*** is better than ***v*** in at least one objective, and the same or better in all others objectives

Pareto Optimal Set

- Set of all solutions that are *not dominated* by any other solution
    - There does not exist a unique solution that is better in every objective



Multi-Objective Optimization Strategies

- Evolutionary Algorithms (MOEAs)
  - Stochastic, population-based search
  - Powerful in non-linear, uncertain problems
- Noninferior Set Estimation (NISE)
  - Extension of single-objective linear programming
  - Optimize by each objective, independently
  - Recursively solve *weighted problems* via the slope of previous solutions
- Linear programs much easier to solve, so I used the NISE method with linear assumptions for my unit-commitment formulation

Bi-Objective Economic Dispatch

- Environmental/Economic Dispatch problem
  - *Minimize* total cost
  - *Minimize* emissions

$$f_1(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} VarCost_g \times GEN_{g,t}$$

$$f_2(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} Emissions_g \times GEN_{g,t}$$

$$\min F(\mathbf{VarCost}, \mathbf{GEN}) = < f_1, f_2 >$$

s.t.

$$\sum_g GEN_{g,t} = Demand_t \qquad \forall \quad t \in T$$

$$GEN_{g,t} \leq Pmax_{g,t} \qquad \forall \quad g \in G, t \in T$$

$$GEN_{g,t} \geq Pmin_{g,t} \qquad \forall \quad g \in G, t \in T$$

$$GEN_{g,t+1} - GEN_{g,t} \leq RampUp_g \qquad \forall \quad g \in G, t = 1..T-1$$

$$GEN_{g,t} - GEN_{g,t+1} \leq RampDn_g \qquad \forall \quad g \in G, t = 1..T-1$$

Bi-Objective Economic Dispatch

- Environmental/Economic Dispatch problem
  - *Minimize* total cost
  - *Minimize* emissions
- NISE evaluation converged to singular point
  - Non-competing objectives …
  - Zero marginal cost and zero emissions of renewables

$$f_1(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} VarCost_g \times GEN_{g,t}$$

$$f_2(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} Emissions_g \times GEN_{g,t}$$

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Unit Commitment Problem

- Start-up costs and commitment constraints add complexity
  - Mixed-Integer Programming
  - Now, using all renewables may not be optimal, which introduces competing objectives
- NISE works with MIP, significantly more compute time

Bi-Objective Unit Commitment

$$f_1(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} VarCost_g \times GEN_{g,t} + \sum_{g \in G_{thermal}, t \in T} StartUpCost_g \times START_{g,t}$$

$$f_2(\mathbf{VarCost}, \mathbf{GEN}) = \sum_{g \in G, t \in T} Emissions_g \times GEN_{g,t}$$

$$\min F(\mathbf{VarCost}, \mathbf{GEN}) = < f_1, f_2 >$$

s.t.

$$\sum_g GEN_{g,t} = Demand_t \qquad \forall \quad t \in T$$

$$GEN_{g,t} \leq Pmax_{g,t} \qquad \forall \quad g \notin G_{thermal}, t \in T$$

$$GEN_{g,t} \geq Pmin_{g,t} \qquad \forall \quad g \notin G_{thermal}, t \in T$$

$$GEN_{g,t} \leq Pmax_{g,t} \times COMMIT_{g,t} \qquad \forall \quad g \in G_{thermal}, t \in T$$

$$GEN_{g,t} \geq Pmin_{g,t} \times COMMIT_{g,t} \qquad \forall \quad g \in G_{thermal}, t \in T$$

$$COMMIT_{g,t} \geq \sum_{t' \geq t - MinUp_g}^{t} START_{g,t} \qquad \forall \quad g \in G_{thermal}, t \in T$$

$$1 - COMMIT_{g,t} \geq \sum_{t' \geq t - MinDown_g}^{t} SHUT_{g,t} \qquad \forall \quad g \in G_{thermal}, t \in T$$

$$COMMIT_{g,t+1} - COMMIT_{g,t} = START_{g,t+1} - SHUT_{g,t+1} \qquad \forall \quad G_{thermal} \in G, t = 1..T-1$$

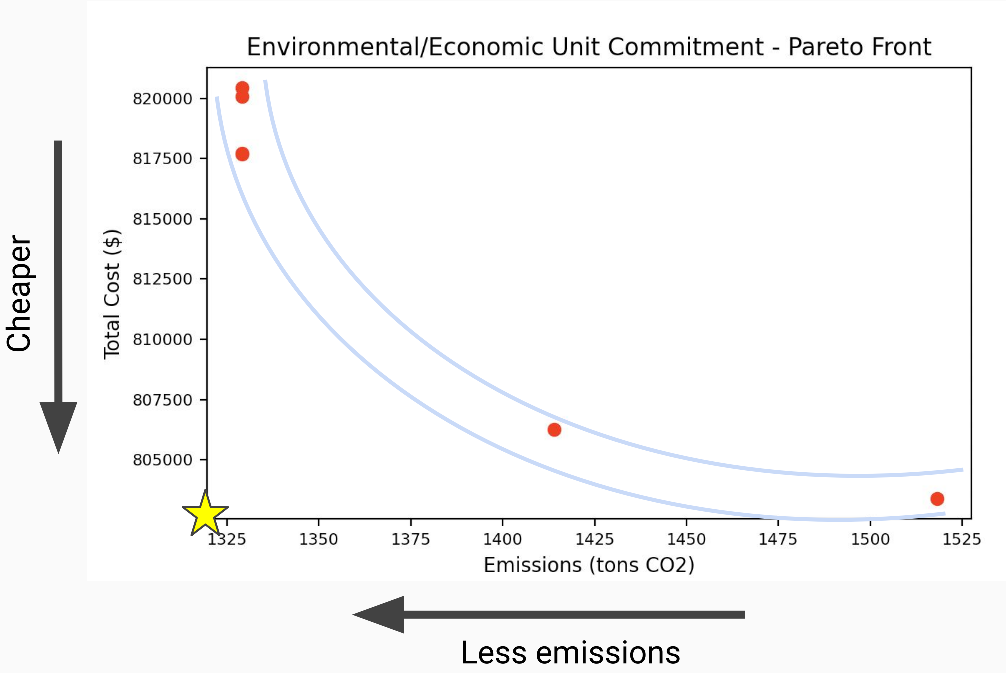
Data

- San Diego Gas and Electric *(SDG&E)*
  - 33 generators
  - 2020 estimated demand
  - Similar to assignment 2&3 in class
- PowerGenome
  - https://github.com/PowerGenome/PowerGenome

Model Methods

- *vOptGeneric.jl*
  - Package for multiobjective linear optimization
  - Implements NISE (referred to as *dichotomy* method)
  - Straightforward extension to JuMP optimization framework, with *@addobjective*
- GLPK solver
- 24 hour decision period

Results - Pareto Front



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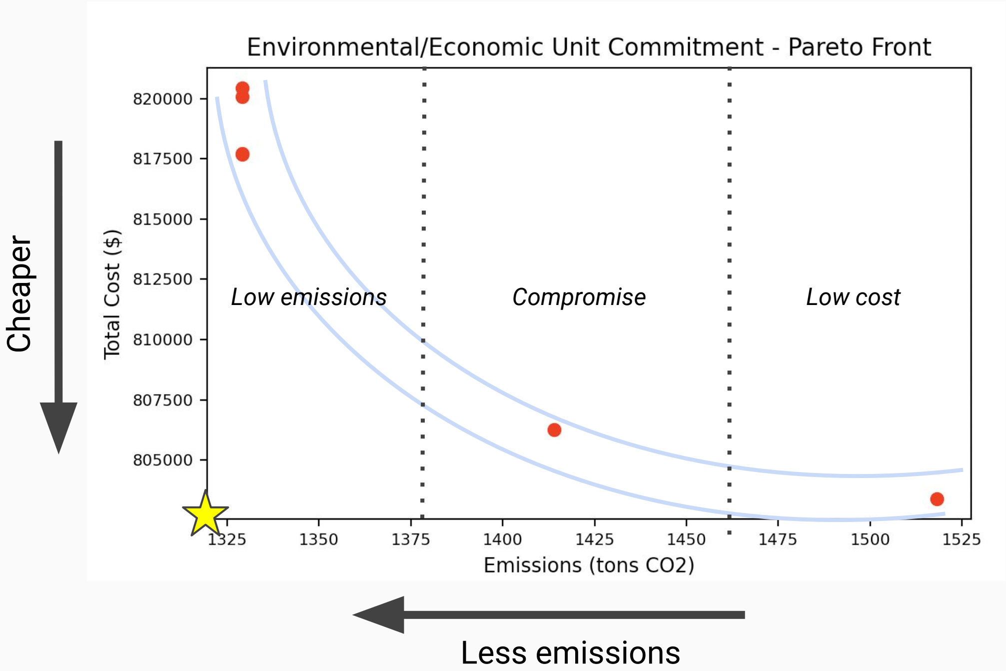
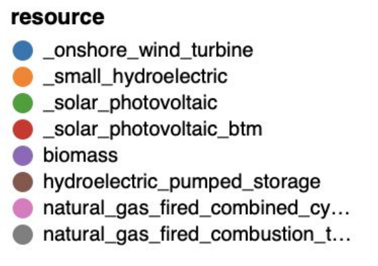
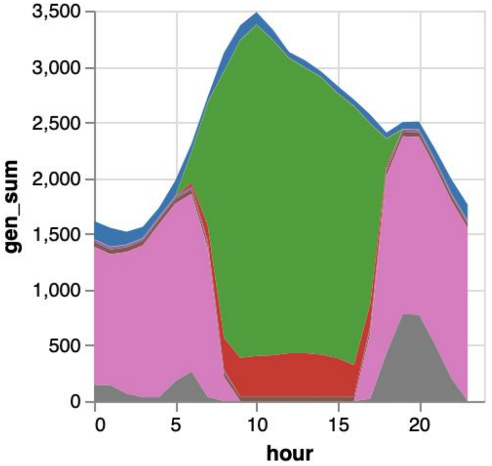


Results - Generation



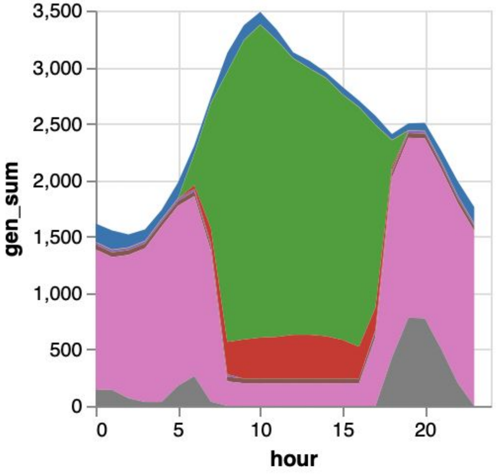
Low emissions

```
Emissions: 1329.057 tons CO2
Cost:      817688.501 $
```



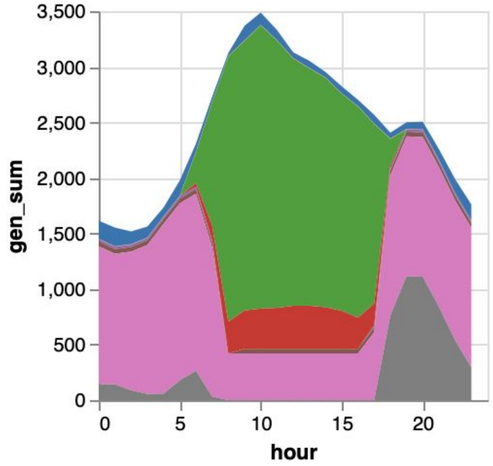
Compromise

```
Emissions: 1413.983 tons CO2
Cost:      806277.865 $
```

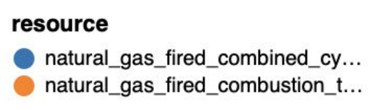


Low cost

```
Emissions: 1518.084 tons CO2
Cost:      803400.128 $
```



Results - Commitment



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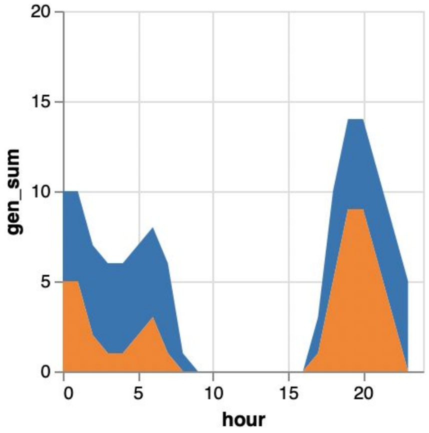

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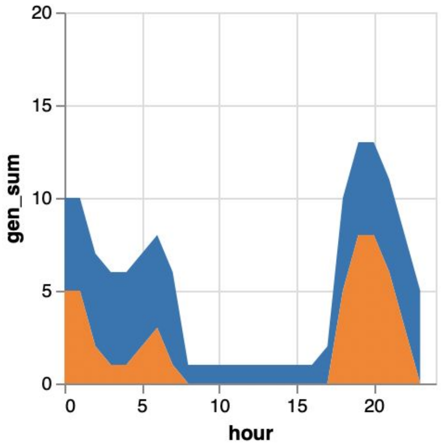

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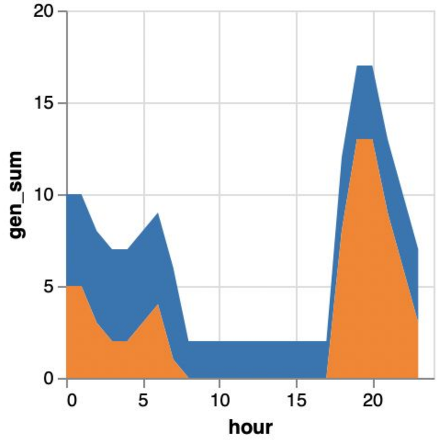

Results - Commitment

resource
- natural_gas_fired_combined_cy...
- natural_gas_fired_combustion_t...

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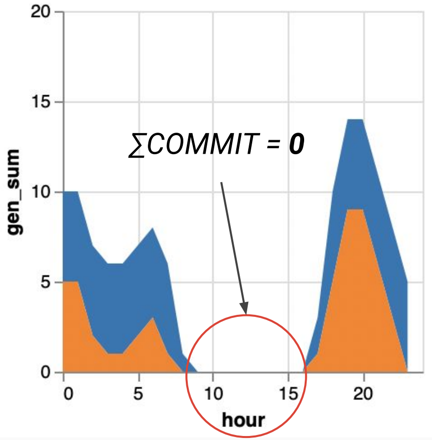

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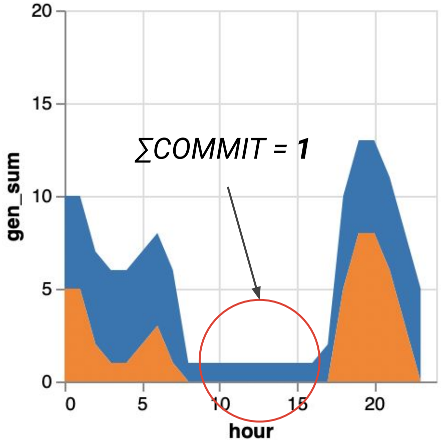

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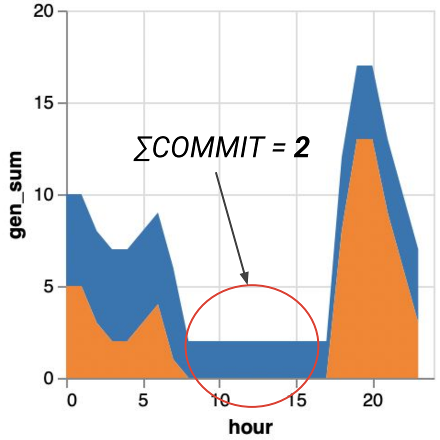
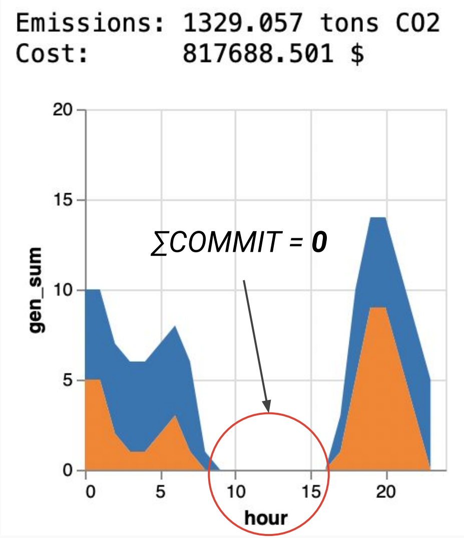


Since COMMIT variables are binary, we see distinct classes of optimal solutions, rather than a continuous Pareto Front.

Low emissions



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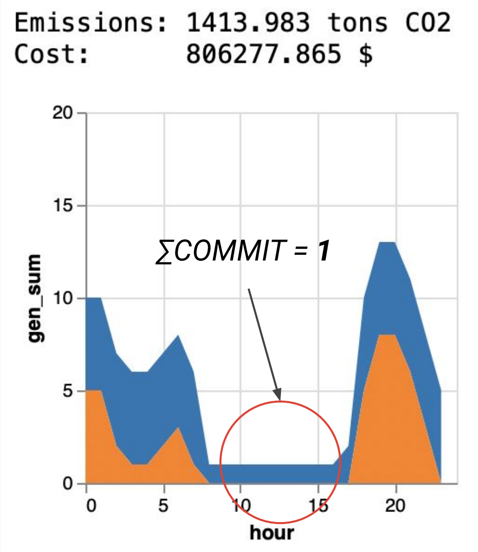

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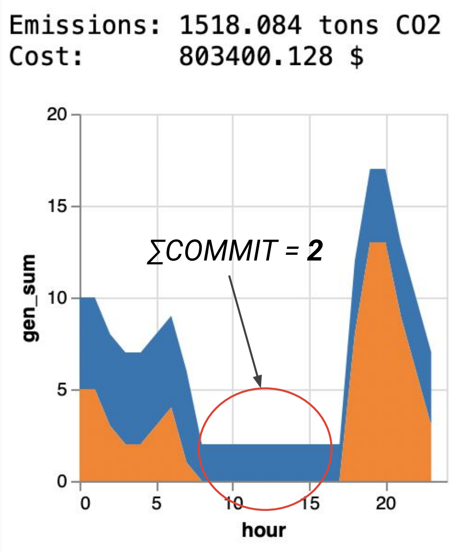
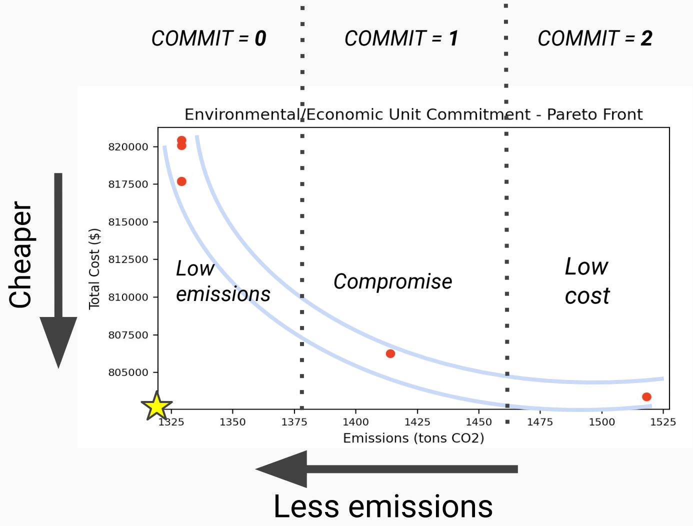


Analysis - Solution Classes

Since COMMIT variables are binary, we see distinct classes of optimal solutions, rather than a continuous Pareto Front.



Trade-Offs

Start-up costs drive the environmental-economic tradeoff in the Unit-Commitment problem.

- In the *"sustainable"* solution, we commit nothing during peak solar availability, lowering emissions but incurring a large start-up cost in hour 15
- In the *"cheap"* solution, we commit two natural gas generators during peak solar availability, which increases emissions and increases cost in the short term, but limits the start-up cost

Conclusion

- Binary nature of Unit-Commitment introduces solution classes
  - Each represents a unique cost-emissions tradeoff
  - Start-up cost drives these competing objectives
- Optimizing multiple objectives gives more insight into the problem space
  - If a stakeholder in the Unit-Commitment decision process (e.g. the EPA) placed importance on environmental impact, optimizing cost only would prevent a compromising solution

References

Woodruff, Matthew J., et al. “Many Objective Visual Analytics: Rethinking the Design of Complex Engineered Systems.” *Structural and Multidisciplinary Optimization*, vol. 48, no. 1, 2013, pp. 201–219., doi:10.1007/s00158-013-0891-z.

Przybylski, Anthony, et al. “A Recursive Algorithm for Finding All Nondominated Extreme Points in the Outcome Set of a Multiobjective Integer Programme.” *INFORMS Journal on Computing*, vol. 22, no. 3, 2010, pp. 371–386., doi:10.1287/ijoc.1090.0342.

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