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BEE 4880

Final Report

Multi-Objective Unit Commitment

1. Introduction

Unit commitment is an important optimization problem in managing power systems generation. Traditionally, the generation and commitment of energy resources are determined to minimize cost in a short-term time period. In many sectors, growing environmental concerns have shifted focus from economic to sustainability goals, and stakeholders hold a wide array of interests. In response, multi-objective optimization has become a popular tool in modeling and decision making; the added dimensionality to the objective space provides valuable information on the fundamental system trade-offs that would otherwise be lost in the one objective case (Woodruff et al., 2013). Here, we propose a multi-objective unit commitment problem formulation that analyzes the principal economic/environmental trade-offs in power generation systems.

A multi-objective optimization problem is defined by

$$\min_{\mathbf{x}\in\Omega} F(\mathbf{x}) =< f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_N(\mathbf{x}) > \qquad (1)$$

where $\boldsymbol{x}$ is the decision variable vector, $\boldsymbol{\Omega}$ is the decision space, and each f_i is an individual objective. A few key differences between multi- and single-objective optimization arise, namely the notion of *multiple* optimal solutions (Deb, 2014). Rather than a single solution to the optimization problem (e.g. the cost minimizing point for the Unit Commitment problem), multi-objective problems yield a set of *Pareto optimal solutions*, determined by the trade-offs between objectives (Hadka and Reed, 2013). To compare solutions, we say solution $\boldsymbol{u}$ *dominates* solution $\boldsymbol{v}$ in a N-objective problem if

$$\begin{aligned} &\forall i \in \{1, 2, \ldots, N\}, u_i \leq v_i \\ &\exists j \in \{1, 2, \ldots, N\}, u_j < v_j \end{aligned} \qquad (2)$$

i.e. ***u*** and ***v*** are distinct, and ***u*** has lower (minimized) objective values. Dominance of solutions yields a Pareto front, which is defined as the set of solutions that are *not dominated* by any other solution (Deb, 2014). In Figure 1, the decision space (left) is mapped to a Pareto front (right), in which no solution is "better" than another in all objectives. Here, an ideal solution would be located at the origin (minimized *F1* and *F2* objectives). The goal of a multi-objective problem is to find the Pareto front to better understand the trade-offs between objectives.

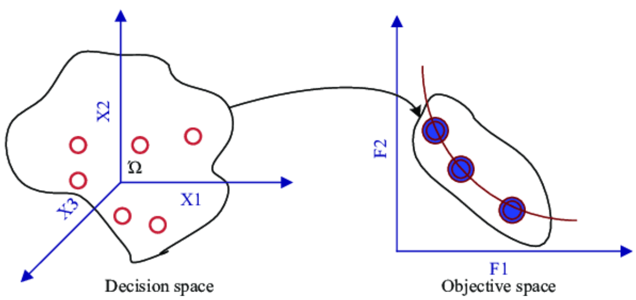

Figure 1: Illustration of a Pareto front mapping. (Lui et al., 2016)

To solve multi-objective optimization problems, various strategies exist, including Multi-Objective Evolutionary Algorithms (MOEAs) and various linear programming techniques. MOEAs use stochastic, population-based search to efficiently explore the decision space (Deb, 2014). They are massively parallelizable (Hadka and Reed, 2015) and powerful in real-world problems with nonlinearity and uncertainty (Quinn et al., 2017). For linear and mixed-integer multi-objective programs, Noninferior Set Estimation (NISE) is a popular strategy (Przybylski et al., 2010) The NISE algorithm first solves the optimization problem for each objective, independently. Recursively, it then solves weighted optimization problems via the slopes between the previous two solutions, until a certain error threshold is met (Cohon, 1979). For this project, I used the NISE method, since the unit-commitment problem follows linearity assumptions, and MOEAs take much longer to solve than linear programs.

2. Problem Formulation

The growing importance of environmental impact in decisions naturally lends to the formulation of objectives that capture this impact. In the case of power systems, the most significant environmental impact is the emission of greenhouse gasses by nonrenewable, fuel-based resources (Davis, 2010). Reduction in greenhouse gas emissions is critical in the slowing of climate change, and stakeholders are placing increasing value on clean energy generation (State of California). Thus, I chose to introduce an emissions objective, to be minimized, in my problem formulation.

The unit commitment problem is a constrained form of economic dispatch, the short-term decision making for optimal power generation given a local demand that minimizes cost. Economic dispatch introduces important aspects of utility planning: generation must meet demand, individual generators have capacity limits, and certain power sources have ramping constraints (Davidson and Jenkins, 2020). My first attempt at bi-objective, economic/environmental optimization was solving the economic dispatch problem. Formally, given a set *G* of generators, a time period *T*, determine $GEN_{g,t}$ based on the following multi-objective formulation:

$$\begin{aligned}
&f_1(\mathbf{VarCost}, \mathbf{GEN}) = \textstyle\sum_{g \in G, t \in T} VarCost_g \times GEN_{g,t} \\
&f_2(\mathbf{VarCost}, \mathbf{GEN}) = \textstyle\sum_{g \in G, t \in T} Emissions_g \times GEN_{g,t} \\
&\min F(\mathbf{VarCost}, \mathbf{GEN}) = < f_1, f_2 > \\
&\text{s.t.} \\
&\quad \sum_g GEN_{g,t} = Demand_t \qquad \forall \quad t \in T \\
&\quad GEN_{g,t} \leq Pmax_{g,t} \qquad \forall \quad g \in G, t \in T \\
&\quad GEN_{g,t} \geq Pmin_{g,t} \qquad \forall \quad g \in G, t \in T \\
&\quad GEN_{g,t+1} - GEN_{g,t} \leq RampUp_g \qquad \forall \quad g \in G, t = 1..T-1 \\
&\quad GEN_{g,t} - GEN_{g,t+1} \leq RampDn_g \qquad \forall \quad g \in G, t = 1..T-1
\end{aligned} \tag{3}$$

where $VarCost_g$ is the variable (short-term) cost of generator *g*, $Emissions_g$ is the tons CO_2 emitted per MWH for generator *g*. Here, we are minimizing the vector of objectives $<f_1, f_2>$, where f_1 is the (standard) cost objective and f_2 is the emissions objective, calculated as the sum over all generators and time periods of generation times emissions. The relaxed nature of the economic dispatch problem does not offer any trade-offs between objectives; the lowest cost solution will always use the most renewable sources, since these renewables have zero variable cost. Thus, a more realistic, complex problem is necessary to give functionality to the economic/environmental objectives – hence the unit commitment problem.

The key simplification of the economic dispatch problem is the absence of start-up costs and constraints, which are a bottleneck factor in real engineered systems (Davidson and Jenkins, 2020). Large thermal plants, due to sheer magnitude and material properties, cannot simply be turned on/off as in the economic dispatch problem; there are costs and constraints associated with such rapid behavior. Thus, resources must be "committed" during each time step (i.e. planned ahead), and minimum up/down times must be incurred on certain generators. This more realistic problem framing allows for flexibility and tradeoffs, since the cheapest solution may not always use the most renewables. Formally, we define the multi-objective unit commitment as follows, building off (3)

$$
\begin{aligned}
&f_1(\mathbf{VarCost}, \mathbf{GEN}) = \textstyle\sum_{g \in G, t \in T} VarCost_g \times GEN_{g,t} + \sum_{g \in G_{thermal}, t \in T} StartUpCost_g \times START_{g,t} \\
&f_2(\mathbf{VarCost}, \mathbf{GEN}) = \textstyle\sum_{g \in G, t \in T} Emissions_g \times GEN_{g,t} \\
&\min F(\mathbf{VarCost}, \mathbf{GEN}) = < f_1, f_2 > \\
&\text{s.t.} \\
&\quad \sum_g GEN_{g,t} = Demand_t && \forall \quad t \in T \\
&\quad GEN_{g,t} \le Pmax_{g,t} && \forall \quad g \notin G_{thermal}, t \in T \\
&\quad GEN_{g,t} \ge Pmin_{g,t} && \forall \quad g \notin G_{thermal}, t \in T \\
&\quad GEN_{g,t} \le Pmax_{g,t} \times COMMIT_{g,t} && \forall \quad g \in G_{thermal}, t \in T \\
&\quad GEN_{g,t} \ge Pmin_{g,t} \times COMMIT_{g,t} && \forall \quad g \in G_{thermal}, t \in T \\
&\quad COMMIT_{g,t} \ge \sum_{t' \ge t - MinUp_g}^{t} START_{g,t} && \forall \quad g \in G_{thermal}, t \in T \\
&\quad 1 - COMMIT_{g,t} \ge \sum_{t' \ge t - MinDown_g}^{t} SHUT_{g,t} && \forall \quad g \in G_{thermal}, t \in T \\
&\quad COMMIT_{g,t+1} - COMMIT_{g,t} = \\
&\quad\quad START_{g,t+1} - SHUT_{g,t+1} && \forall \quad G_{thermal} \in G, t = 1..T-1
\end{aligned}
\tag{4}
$$

where $StartUpCost_g$ is the start-up cost associated with generator g, and $COMMIT_{g,t}$, $START_{g,t}$, and $SHUT_{g,t}$ are binary decision variables representing generator g commitment (scheduling), starting up, and shutting down, respectively at time t.

3. Methods

The formulation in (4) was implemented in the Julia programming language. The model input data is taken from San Diego Gas and Electric *(SDG&E)*, with 33 local generators (including behind-the-meter solar), demand data from 2020, and variable solar forecasting. The data was collected using the *PowerGenome* open-source platform. To solve the bi-objective mixed-integer program, a fork of the package *vOptGeneric.jl* was utilized. This package builds off of the *JuMP* optimization framework and implements the noninferior set estimation algorithm for multi-objective linear programs. The GLPK mixed-integer solver was used to solve the individual program instances of the NISE algorithm. The system was optimized for a 24-hour period of a typical Southern California spring day.

4. Results

Figure 2 shows the discovered Pareto front of the model. The yellow star represents an optimal solution, and the axis arrows point in the optimal direction for each objective. Note two important features: the general shape of the solution set and the distinct gaps between solutions. The shape is similar to Figure 1, which is indicative of strong trade-offs between objectives; as emissions lower, cost increase sharply, and vice versa. This figure breaks the Pareto front into three regions: low emissions, low cost, and compromise. The non-uniformity of the solution set is not a coincidence, but rather a direct result of the binary nature of the unit commitment problem.

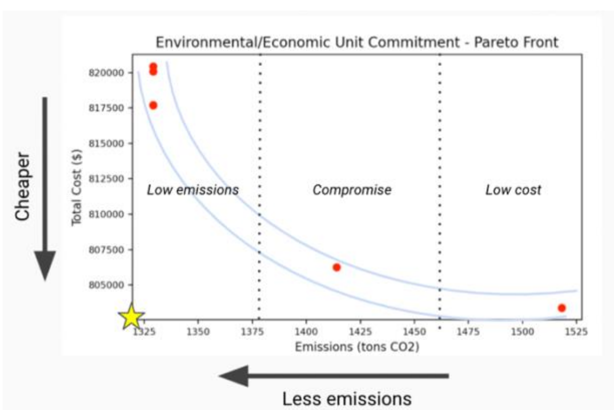

Figure 2: Pareto front for multi-objective unit commitment.

Three solutions, one from each Pareto region, are analyzed for their generation and commitment decisions. Figure 3 shows the generation of each resource for the entire 24-hour time period. As emissions increase (from left to right), a smaller portion of the demand is met with renewable sources (mainly PV solar, shown in green), and the difference in demand is generated by natural gas fired combustion plants, which have higher emissions. To reason about price, we focus on the *StartUpCost*$_g$ term, which dominates during peak solar hours. In the low-cost solution, we see the most nonrenewable generation during peak sunlight; this seems counterintuitive, since these fuels are associated with a higher variable cost. However, by committing more natural gas in the afternoon, the system incurs a smaller start-up cost associated with restarting the generators for nighttime, when no solar is available. Thus, we see a fundamental trade-off between emissions and cost driven by the start-up costs of thermal plants.

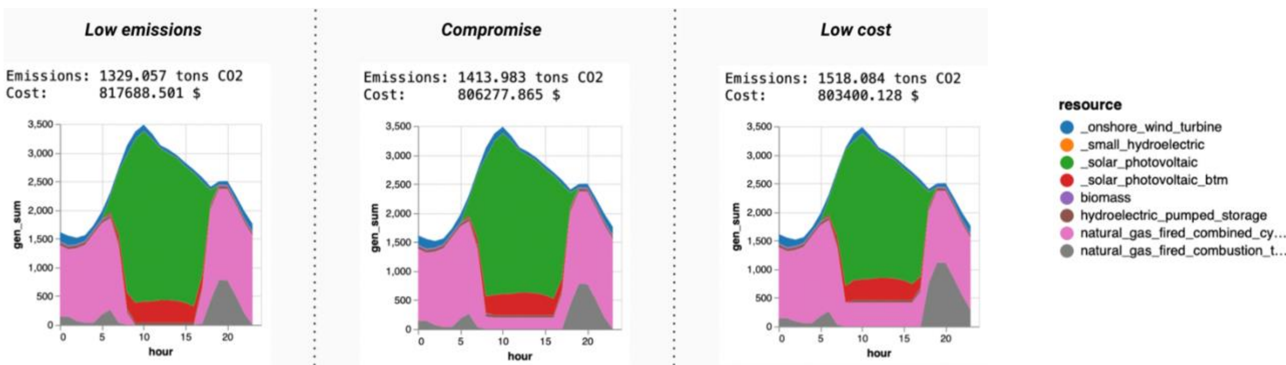

Figure 3: Resource generation for each solution region.

While the previous figure explains the trade-offs and Pareto front shape, it does not reason about the distinct regions of solutions. For that, we focus on the $COMMIT_{g,t}$ decision variables of the natural gas plants. Due to the engineering constraints of thermal plants, the generated power is either zero (plant is shut down, *COMMIT=0*) or full capacity (plant is on, *COMMIT=1*). Figure 4 highlights the sum of generator commitments during peak solar hours.

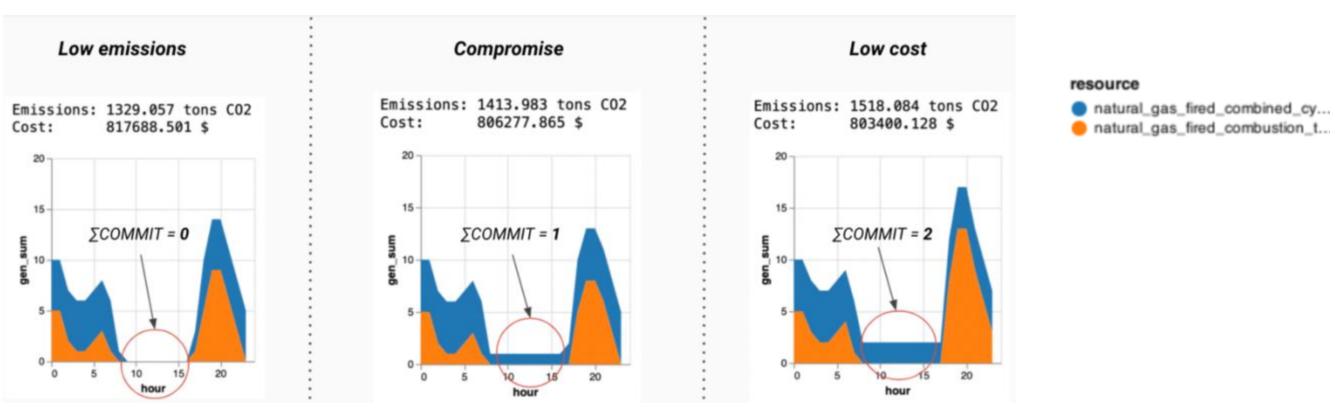

Figure 4: Thermal resource commitment for each solution region.

These results are consistent with the flat natural-gas sections of Figure 3 and highlight the binary nature of the unit commitment problem. It is not possible to commit between 0 and 1 thermal plants in the afternoon, so no solutions will exist with emissions and cost objectives between the “low emissions” and “compromise” regions. The same logic can be applied for the gap between committing 1 and 2 thermal plants at this time. This explains the distinct regions of solutions in the Pareto front.

5. Conclusion

The multi-objective unit commitment problem gives valuable insight to the fundamental trade-offs in energy production and optimization. Including real engineered constraints creates underlying conflicts between more sustainable energy generation and cost-effective dispatch. Start-up costs drive this economic/environmental trade-off, and binary commitment statuses create a discontinuous solution set.

Optimizing for multiple objectives gives exponentially more insight into the problem, based on the considerations of various stakeholders. For example, if a government entity that had stake in the unit commitment decision placed significant value on environmental impact, optimizing cost only would not discover a compromising solution, nor would it generate the insight into the trade-offs between stakeholders’ goals that could further inform infrastructure investments in the future. By limiting a problem to a single objective, decision makers are forgoing valuable information about the problem space that could better inform future choices.

As environmental concerns continue to grow, the importance of framing decision problems with sustainability objectives will become increasingly necessary. In the case of energy generation and dispatch, the rapid expansion of renewable energy infrastructure will introduce new problems, and the most sustainable solutions often may not be the most cost-effective, at least in the short term. Analyzing the complex relationships between economic efficiency and environmental impact will be a crucial part of decision making in the future.

6. Discussion

Future work may include adding a reliability objective into the problem formulation. Due to computational complexity and resources, I was unable to generate an efficient representation of reliability, which could be calculated as the percentage of states of the world in which a solution meets demand. This reliability objective is prevalent in the literature surrounding decision making under deep uncertainty (Marchau et al., 2019). Monte Carlo sampling over generated solar forecasts would add the notion of *robustness* into the unit commitment problem space, another key factor in solution quality for uncertain systems (Quinn et al., 2017). Additionally, adding transmission constraints and networks to make the system more realistic would likely add new discoveries about the trade-offs between objectives.

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Software

Julia: https://jump.dev

PowerGenome: https://github.com/PowerGenome/PowerGenome

vOptGeneric.jl: https://github.com/andrewdircks/vOptGeneric.jl

JuMP: https://jump.dev

GLPK: *https://www.gnu.org/software/glpk/*

Code

All the source code for this project can be found here: https://github.com/andrewdircks/multi_uc