Impact of Managing Electric Vehicle Demand Scheduling on Resource Generation & Average Rates in California

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Introduction

Motivation

California has been a global leader in developing policies to combat climate change. While California has had a long history of setting emissions targets, the latest decision of the California Public Utilities Commission (CPUC) in March 2020 is to reduce the state's yearly electric sector greenhouse gas (GHG) emissions to 25 million metric tons (MMT) by 2035, down nearly 60% compared to the 2020 emissions level [1].

Part of California's plan to curb emissions is electrification. Notably, the California Air Resources Board (CARB) recently approved a rule requiring 100 percent of new car sales in California to be zero-emission vehicles (ZEVs) by 2035 [2]. This ambitious move toward electrification highlights the critical role of electric vehicles (EVs) in decarbonizing transportation, one of the largest contributors to GHG emissions. However, the rapid adoption of EVs brings a new set of challenges to the state's energy infrastructure. The significant increase in electricity demand from EV charging creates pressure on power grid stability and requires careful resource planning.

The California Energy Commission (CEC) has projected that by 2030, electricity consumption from passenger EV charging alone could range from 4.6 GW to 5.5 GW, depending on the time of day, on a typical weekday [3]. This substantial additional load demands innovative solutions to balance supply and demand effectively, especially during periods of peak demand. Without such measures, the grid could face reliability issues, increased operational costs, and missed opportunities for integrating renewable energy.

To manage the new load and maximize EVs as an energy resource, a lot of interest has been directed toward optimizing electric vehicle charging schedules to adjust according to periods of peak demand [4]. California's Pacific Gas & Electric Company (PG&E) has demonstrated how managing EVs as a flexible load increases renewables utilization, minimizes peak loads, and allows for deferred grid upgrades [5].

From an economic perspective, optimized EV charging can also reduce system-wide costs that trickle down to consumer savings [5]. Investigating the impacts of various EV demand scheduling options through modelling becomes critical for policymakers to plan ahead.

Research Question

How do various options for EV demand scheduling affect the following key metrics: total cost, total generation, average rate (total cost/total generation), and amount of non-served energy (NSE)?
General trends about shifts in the generation mix share when flexibility is introduced are also explored.

Methods

This project uses a capacity expansion linear optimization model with flexible demand scheduling. Under all scenarios, the model's objective is to minimize total system costs while meeting demand.

Initially, I ran my model formulations with the additional layer of unit commitment (UC) constraints for improvement of the model's operational detail. While I was able to successfully implement UC on top of my baseline plan for my model, I ultimately opted to ignore UC when running the comprehensive suite of scenarios. This is because including UC leads to slightly longer run times, and I wanted to focus my study on the effects that varying flexible demand constraints had on my test system.

All scenarios considered include California's 2035 mass-based emissions policy constraint of 25 million metric tons of CO2 by 2035.

<u>Scenarios</u>

Detailed examination of various scenarios of managing EV charging demand scheduling on California's grid, including no management:

1) *Baseline Inflexible Demand:* The flexible load availability at each time step is the fraction of total generation at each time-step that is due to EV charging. Since the EV charging fraction is encompassed in generation, no changes from the bare-bones capacity model needed to be implemented for this scenario
2) *Baseline Partially Flexible Demand*: I allow the flexible load availability due to EV charging to be permitted a maximum delay of 5-hours
3) *Added Inflexible Demand:* I experimented with adding 5 GW of annual EV load to the baseline maximum capacity. This directly up-shifts Scenario 1
4) *Added Partially Flexible Demand*: Per timestep, I add the additional EV load to the baseline amount of flexible load availability due to EV charging, allowing this sum to have a 'n'-hour maximum delay option
    a) *Sensitivity Analysis of Adjusting 'n'*: I observed how results change, as I cycle 'n' from 1 through 8
5) *Added Fully Flexible Demand*: As an extension to Scenario 4, I add the additional 5 GW annual EV load to the baseline amount of flexible load availability due to EV charging and allow this sum to have a 12-hour maximum advance and delay option
6) POLICY - *Night Time Charging*: I mandated that all EV load during the night time period (midnight to 6AM) is to all be met within that window. On top of the baseline EV share of usage (which is still at all hours in accordance with the 'Flexible_load_availability' file), I uniformly specify 16.67% (100/6) per "night hour" scaling of the per day 5 GW annual extra share. I imposed the time restriction on top of the most optimal hour amount of maximum delay, based on results from Scenario 4a.
7) POLICY - *Off-Peak Charging*: I mandated that all EV load during the off-peak period (11AM to 5 PM) is to be met within that window. This time period was selected because it corresponds with the "belly" of the duck curve. On top of the baseline EV share of usage (which is still at all hours in accordance with the 'Flexible_load_availability' file), I uniformly specify 16.67% (100/6) per "off-peak hour" scaling of the 5 GW extra share. Again, I imposed the time restriction on top of the most optimal hour amount of maximum delay, based on results from Scenario 4a.

Data & Modifications

The input data for this study is the 2035 system projection by the Western Electricity Coordinating Council (WECC). While this test system dataset includes information about geographical regions all throughout the West Coast, I focus on the Northern and Southern California regions (CA_N and CA_S, respectively). Including transmission between the two regions, my formulation effectively treats California like an island.

Before passing in the inputs, I deleted rows in the generation, demand, transmission, and flexible demand files that did not pertain to either California region. In the provided data, all generation resources did not have the "FLEX" flag set to 1, meaning that none had reschedulable demand. My flexible demand implementation is based on the ZERO Lab's GenX model, specifically the file 'flexible_demand.jl'. After reading the corresponding documentation, I decided to change storage and quick start-up resources to be considered flexible. Specifically, batteries, hydroelectric pumped storage, natural gas fired combustion turbines, and peakers for both regions. For the resources that I set to be flexed, I assume 100% energy efficiency for simplicity, meaning that changing the time of demand does not result in an additional generation "tax" when served later/earlier.

Initially, I attempted creating a "FLEX" dummy resource for all of California that had some demand advancement and delay capacity. Under this method, my additional resource would be the only "flexible" one and all other resources would contribute some generation amount to servicing load that gets assigned to the "FLEX" dummy. However, my limited understanding of what additional parameters (represented in the various columns of the generation file) should be populated with for this dummy resource resulted in 0 rescheduled demand across the whole time horizon when I inspected the decision variables related to the flexibility allowance. After unsuccessful experimentation with this method, I decided to change the FLEX flags for specific resources that are already part of the generation mix.

My constant values for carbon emissions constraints and additional GW amount of EV load are informed by the sources mentioned in the motivation section.

Mathematical Formulation

Decision Variables

General Capacity Expansion Decision Variables

Capacity

- $vCAP_g \geq 0$, $\forall g \in G \Leftrightarrow$ Power Capacity (MW)
- $vRET\_CAP_g \geq 0$, $\forall g \in OLD \Leftrightarrow$ Retirement of Power Capacity (MW)
- $vNEW\_CAP_g \geq 0$, $\forall g \in NEW \Leftrightarrow$ New Build Power Capacity (MW)

Storage

- $vE\_CAP_g \geq 0$, $\forall g \in STOR \Leftrightarrow$ Storage Energy Capacity
- $vRET\_E\_CAP_g \geq 0$, $\forall g \in STOR \cap OLD \Leftrightarrow$ Retirement of Storage Energy Capacity (MWh)
- $vNEW\_E\_CAP_g \geq 0$, $\forall g \in STOR \cap NEW \Leftrightarrow$ New Build Storage Energy Capacity (MWh)

Transmission

- $vT\_CAP_l \geq 0$, $\forall l \in L \Leftrightarrow$ Transmission Capacity (MW)
- $vRET\_T\_CAP_l \geq 0$, $\forall l \in L \Leftrightarrow$ Retirement of Transmission Capacity (MW)
- $vNEW\_T\_CAP_l \geq 0$, $\forall l \in L \Leftrightarrow$ New Build Transmission Capacity

Operational Decision Variables

- $vGEN_{t,g} \geq 0$, $\forall t \in T, g \in G \Leftrightarrow$ Power Generation (MW)
- $vCHARGE_{t,g} \geq 0$, $\forall t \in T, g \in STOR \Leftrightarrow$ Power Charging (MW)
- $vSOC_{t,g} \geq 0$, $\forall t \in T, g \in STOR \Leftrightarrow$ Energy Storage SOC (MWh)
- $vNSE_{t,s,z} \geq 0$, $\forall t \in T, s \in S, z \in Z \Leftrightarrow$ NSE By Zone and Segment (MW)
- $vFLOW_{t,l}$, $\forall t \in T, l \in L \Leftrightarrow$ Transmission Line Flow (MW), positive if flowing from source to sink

Flexible Demand Decision Variables

- $vS\_FLEX_{t,g}$, $\forall t \in T, g \in FLEX \Leftrightarrow$ Total advanced (negative) or deferred (positive) demand for flexible resources (MW)
- $vCHARGE\_FLEX_{t,g} \geq 0$, $\forall t \in T, g \in FLEX \Leftrightarrow$ Tracking demand deferred by flex resource g in period t (MW)
- $vF\_CAP_{t,g} \geq 0$, $\forall t \in T, g \in FLEX \Leftrightarrow$ capacity that can be flexed, dependent on total generation at that timestep (scaled down by fractional share of EV usage) (MW)

Objective Function

$$
\begin{aligned}
f : min(&eFixedCostsGeneration \\
&+ eFixedCostsStorage \\
&+ eFixedCostsTransmission \\
&+ eVariableCosts \\
&+ eNSECosts \\
&+ eTotalCVarFlexIn
\end{aligned}
$$

Expression Breakdown of Objective Function

$$
\begin{aligned}
eFixedCostsGeneration = &\sum_{g \in G} \text{Fixed\_OM\_Cost\_per\_MWyr}[g] \cdot vCAP[g] \\
&+ \sum_{g \in \text{NEW}} \text{Inv\_Cost\_per\_MWyr}[g] \cdot vNEW\_CAP[g]
\end{aligned}
$$

$$
\begin{aligned}
eFixedCostsStorage = &\sum_{g \in STOR} \text{Fixed\_OM\_Cost\_per\_MWhyr}[g] \cdot vE\_CAP[g] \\
&+ \sum_{g \in (\text{STOR} \cap \text{NEW})} \text{Inv\_Cost\_per\_MWyr}[g] \cdot vNEW\_CAP[g]
\end{aligned}
$$

$$
\begin{aligned}
eFixedCostsTransmission = &\sum_{l \in L} \text{Line\_Fixed\_Cost\_per\_MWyr}[l] \cdot vT\_CAP[l] \\
&+ \sum_{l \in L} \text{Line\_Reinforcement\_Cost\_per\_MWyr}[l] \cdot vNEW\_T\_CAP[l]
\end{aligned}
$$

$$
eVariableCosts = \sum_{t \in T, g \in G} \text{sample\_weight}[t] \cdot Var\_Cost[g] \cdot vGEN[t,g]
$$

$$
eNSECosts = \sum_{t \in T, s \in S, z \in Z} \text{sample\_weight}[t] \cdot NSE\_Cost[s] \cdot vNSE[t,s,z]
$$

Cost from Flexed Demand

$$
eTotalCVarFlexIn = \sum_{t \in T} \sum_{g \in FLEX} \text{sample\_weight}[t] \cdot \text{Var\_OM\_Cost\_per\_MWh}[g] \cdot vCHARGE\_FLEX[t,g]
$$

Constraints

Mass-Based CO2 Constraint for California

$$
\begin{aligned}
eEmissionsByZone[z] = &\sum_{t \in T} \sum_{g \in G} \text{CO2\_Rate}[g] \cdot vGEN[t,g] \cdot \text{sample\_weight}[t] \cdot (\text{Zone}[g] == z) \\
&+ \sum_{g \in G} \text{CO2\_Per\_Start}[g] \cdot (\text{Zone}[g] == z)
\end{aligned}
$$

$$
cCO2Emissions\_systemwide: \quad \sum_{z \in Z} eEmissionsByZone[z] \leq 25 \cdot 10^6
$$

Power Balance Constraint - Including Flex Portion

$$
ePowerBalanceDemandFlex[t,z] = \sum_{g \in \text{FLEX} \cap \{g | \text{Zone}[g]=z\}} (vGEN[t,g] + vCHARGE\_FLEX[t,g])
$$

$$
\begin{aligned}
cDemandBalance[t,z]: \quad &\sum_{g \in G \cap \{g | \text{Zone}[g]=z\}} vGEN[t,g] + ePowerBalanceDemandFlex[t,z] \\
&+ \sum_{s \in S} vNSE[t,s,z] - \sum_{g \in \text{STOR} \cap \{g | \text{Zone}[g]=z\}} vCHARGE[t,g] \\
&- \text{demand}[t,z] - \sum_{l \in L} \text{lines}[l,z] \cdot vFLOW[t,l] = 0
\end{aligned}
$$

Capacitated Constraints

$$\begin{aligned}
cMaxPower[t,g]: &\quad vGEN[t,g] \leq \text{variability}[t,g] \cdot vCAP[g], \quad \forall t \in T,\, g \in G \\
cMaxCharge[t,g]: &\quad vCHARGE[t,g] \leq vCAP[g], \quad \forall t \in T,\, g \in \text{STOR} \\
cMaxSOC[t,g]: &\quad vSOC[t,g] \leq vE_CAP[g], \quad \forall t \in T,\, g \in \text{STOR} \\
cMaxNSE[t,s,z]: &\quad vNSE[t,s,z] \leq \text{NSE_Max}[s] \cdot \text{demand}[t,z], \quad \forall t \in T,\, s \in S,\, z \in Z \\
cMaxFlow[t,l]: &\quad vFLOW[t,l] \leq vT_CAP[l], \quad \forall t \in T,\, l \in L \\
cMinFlow[t,l]: &\quad vFLOW[t,l] \geq -vT_CAP[l], \quad \forall t \in T,\, l \in L
\end{aligned}$$

Total Capacity Constraints

$$\begin{aligned}
cCapOld[g]: &\quad vCAP[g] = \text{Existing_Cap_MW}[g] - vRET_CAP[g], \quad \forall g \in \text{OLD} \\
cCapNew[g]: &\quad vCAP[g] = vNEW_CAP[g], \quad \forall g \in \text{NEW} \\
cCapEnergyOld[g]: &\quad vE_CAP[g] = \text{Existing_Cap_MWh}[g] - vRET_E_CAP[g], \quad \forall g \in \text{STOR} \cap \text{OLD} \\
cCapEnergyNew[g]: &\quad vE_CAP[g] = vNEW_E_CAP[g], \quad \forall g \in \text{STOR} \cap \text{NEW} \\
cTransCap[l]: &\quad vT_CAP[l] = \text{Line_Max_Flow_MW}[l] - vRET_T_CAP[l] + vNEW_T_CAP[l], \quad \forall l \in L
\end{aligned}$$

Time Coupling Constraints

DEFINE TIME-RELEVANT SETS

$$\begin{aligned}
\text{STARTS} &= \{1, \text{hours_per_period}, \ldots, \lfloor \max(T)/\text{hours_per_period} \rfloor \cdot \text{hours_per_period}\} \\
\text{INTERIORS} &= T \setminus \text{STARTS}
\end{aligned}$$

$$\begin{aligned}
cRampUp[t,g]: &\quad vGEN[t,g] - vGEN[t-1,g] \leq \text{Ramp_Up_Percentage}[g] \cdot vCAP[g], \\
&\quad \forall t \in \text{INTERIORS},\, g \in G \\
cRampUpWrap[t,g]: &\quad vGEN[t,g] - vGEN[t + \text{hours_per_period} - 1, g] \leq \text{Ramp_Up_Percentage}[g] \\
&\quad \cdot vCAP[g], \quad \forall t \in \text{STARTS},\, g \in G \\
cRampDown[t,g]: &\quad vGEN[t-1,g] - vGEN[t,g] \leq \text{Ramp_Dn_Percentage}[g] \cdot vCAP[g], \\
&\quad \forall t \in \text{INTERIORS},\, g \in G \\
cRampDownWrap[t,g]: &\quad vGEN[t + \text{hours_per_period} - 1, g] - vGEN[t,g] \leq \text{Ramp_Dn_Percentage}[g] \\
&\quad \cdot vCAP[g], \quad \forall t \in \text{STARTS},\, g \in G \\
cSOC[t,g]: &\quad vSOC[t,g] = vSOC[t-1,g] + \text{Eff_Up}[g] \cdot vCHARGE[t,g] - \frac{vGEN[t,g]}{\text{Eff_Down}[g]}, \\
&\quad \forall t \in \text{INTERIORS},\, g \in \text{STOR} \\
cSOCWrap[t,g]: &\quad vSOC[t,g] = vSOC[t + \text{hours_per_period} - 1, g] + \text{Eff_Up}[g] \cdot vCHARGE[t,g] \\
&\quad - \frac{vGEN[t,g]}{\text{Eff_Down}[g]}, \quad \forall t \in \text{STARTS},\, g \in \text{STOR}
\end{aligned}$$

Demand Delay/Advance Formulation

Ensure Flexible Demand is Restricted to Specific Hours

Let FLEX_Z = FLEX $\cap \{g \mid \text{Zone}[g] = z\}$. Then, for $t \in T, g \in$ FLEX_Z:

$$vF\_CAP[t,g] \leq \text{flex\_percentage}[t,z] \cdot (\text{demand}[t, \text{Original\_Load\_MW}[z]] + \text{demand}[t, \text{Added\_EV\_Load}[z]])$$

State of Charge Balance and Rate Constraints

This section uses utility functions specified in the Appendix.

For $z \in Z$ and $g \in$ FLEX_Z:

$$\begin{aligned} vS\_FLEX[t,g] &= vS\_FLEX[\text{hoursbefore}(\text{hours\_per\_period}, t, 1), g] \\ &\quad - \text{Flexible\_Demand\_Energy\_Eff}[g] \cdot vGEN[t,g] \\ &\quad + vCHARGE\_FLEX[t,g] \\ vCHARGE\_FLEX[t,g] &\leq vF\_CAP[t,g] \\ \text{Flexible\_Demand\_Energy\_Eff}[g] \cdot vGEN[t,g] &\leq vF\_CAP[t,g] \end{aligned}$$

Delay and Advance Constraints

Define max_flex_demand_delay $= n$ and max_flex_demand_advance $= m$ according to scenario needs.

For $g \in$ FLEX_Z:
Delay constraints for when max_flex_demand_delay > 0:

$$\sum_{e \in \text{hoursafter}(\text{hours\_per\_period}, t, 1:\text{max\_flex\_demand\_delay})} vGEN[e,g] \geq vS\_FLEX[t,g], \quad \forall t \in T$$

Advance constraints for when max_flex_demand_advance > 0:

$$\sum_{e \in \text{hoursafter}(\text{hours\_per\_period}, t, 1:\text{max\_flex\_demand\_advance})} vCHARGE\_FLEX[e,g] \geq -vS\_FLEX[t,g], \quad \forall t \in T$$

Detailed code on how inputs were modified and slight constraints for each scenario are clearly labeled as notebooks in the attached zip file. The LaTeX write-up is for the baseline model that investigation of all scenarios is built upon.

Results

As expected, the results of my experiment show that allowing EV charging demand to be rescheduled helps reduce costs by approximately a 25% margin and reduces the amount of NSE by approximately a 40% margin. This test system focused specifically on California supports the well-researched conclusion that introducing load shifting creates net benefit, from a cost and reliability perspective, as mentioned in this study's motivation.

Comparing Scenario 1 and Scenario 2, the total demand over the time horizon stayed constant, but a maximum 5 hour delay for EV load was incorporated in Scenario 2. The reduction in value across all four metrics offer the strongest signal of deferred demand benefits.

Comparing Scenario 1 and Scenario 3 where I add 5 GW of load without introducing flexibility, I expected total cost to increase, total generation to remain about the same, average rate to increase, and total NSE to increase. So, the result of decreased absolute generation and decreased NSE was surprising. A possible explanation for this result is that the way I added the 5 GW of load is by considering a given time-step's load proportional to the system's entire load over the full time horizon and scaling the 5 GW additional annual load with that fraction. Since temporal considerations likely play a larger role in this study than thus far examined, the results may have been different if the 5 GW were distributed differently.

Scenario 4 and Scenario 5 are also fairly parallel and worth examination. I had expected that enabling the system full flexibility, both in terms of advancing and delaying demand, would lead to lower rates. By a marginal amount, my results back this prediction. However, it is surprising that the amount of NSE with a fully flexible system is markedly higher. This result may be due to the way my model's objective is formulated, where cost reduction is prioritized over minimizing NSE. The increased liberty of the model might allow for too much demand to shift to periods of low generation availability.

Lastly, the two policies should be considered in conjunction with each other, since their design is a shift between a six-hour window during night-time and a six-hour window during day-time that corresponds to the "belly" of the duck curve. As expected, charging at night compared to off-peak hours results in higher total cost and average rate. These results suggest that charging during off-peak hours may reduce unnecessary dispatch. However, there is surprisingly less NSE when implementing the off-peak charging policy, possibly because the set of flexible resources do not include renewables, and the system can serve demand well with the generators most responsible for meeting loads.

Scenario Number	Scenario Title	Total Cost (millions of $)	Total Generation (GWh)	Average Rate ($/MWh)	Total NSE (MWh)
1	Baseline Inflexible Demand	3707.49015	346,404.39	10.703	9077.60804
2	Baseline Partially Flexible Demand	2272.12611	278,671.20	8.153	5048.26768
3	Added Inflexible Demand	3707.89433	346,195.70	10.710	9074.36645
4	Added Partially Flexible Demand	2272.40271	278,479.14	8.160	5048.33017
5	Added Fully Flexible Demand	2278.9988	279,348.12	8.158	5508.60435
6	POLICY - Night Time Charging	2274.44814	278,010.77	8.181	4888.06869
7	POLICY - Off-Peak Charging	2273.15975	278,274.36	8.169	5048.26768

Fig 1: Consolidated key metrics across all scenarios

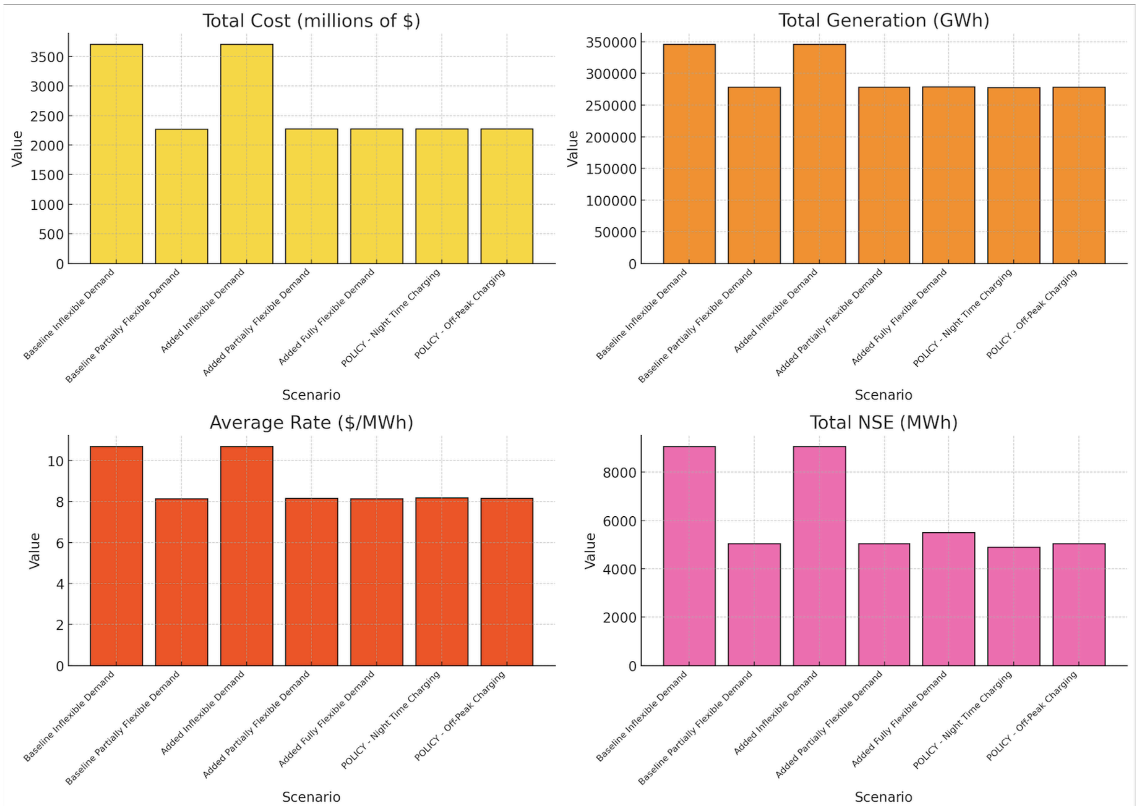

Fig 2: Graphical representation of key metrics across all scenarios

Scenario 4a) Max Delay Allowance Sensitivity Analysis

In Scenario 4, I additionally explore the impact of varying over a range of maximum flex delay hour allowances on the system with added EV load. I expected to see a negative slope in the average electricity rate as flex demand delay allowance increases. However, aside from 4 as the outlier, the values from hours 1 through 3 are generally higher than hours 5 to 8 (Fig. 3). Since I was running my formulation in a loop, I am unsure what physical explanation there may be for such a result, which leads me to question the correctness of my model from an implementation standpoint.

That said, the result of total cost and total NSE being completely uniform across all hour modulations was expected. This is because flexible demand shifting redistributes demand over time but does not alter the total load over the analyzed period.

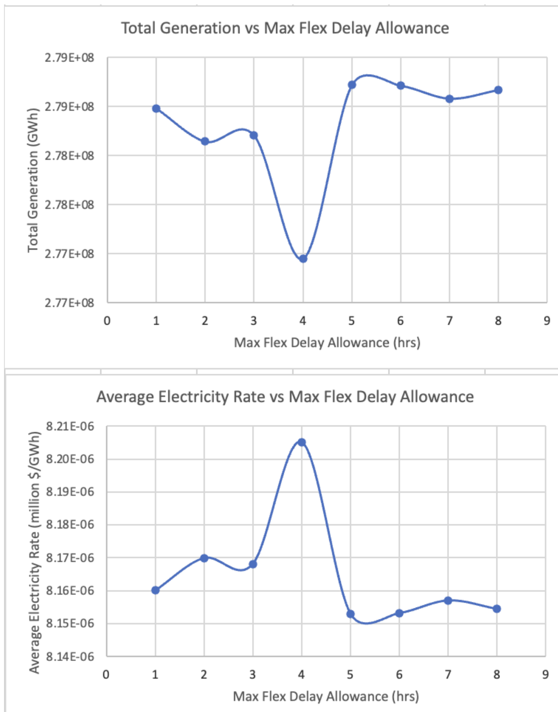

Fig 3: Impact of varying maximum flexible demand delay on total generation and average rate (graphical)

MAX_FLEX_DEMAND_DELAY	total_cost	total_generation	total_nse	average_rate
1	2272.40271	2.78E+08	5048.330172	8.16E-06
2	2272.40271	2.78E+08	5048.330172	8.17E-06
3	2272.40271	2.78E+08	5048.330172	8.17E-06
4	2272.40271	2.77E+08	5048.330172	8.21E-06
5	2272.40271	2.79E+08	5048.330172	8.15E-06
6	2272.40271	2.79E+08	5048.330172	8.15E-06
7	2272.40271	2.79E+08	5048.330172	8.16E-06
8	2272.40271	2.79E+08	5048.330172	8.15E-06

Fig 4: Impact of varying maximum flexible demand delay on key metrics (tabular)

<u>Shift in Generation Mix With Rescheduling</u>

When introducing flexible demand, the resources that are tagged with the “FLEX” take on a lot more of the generation share. Specifically, the system sees increases in percentage of generation from battery, hydro pumped storage, natural gas fired combustion turbine, and peaker resources. The system also notes a reduction in solar PV, both utility scale and otherwise.

This is likely because the flexible demand rescheduling allows the system to better align energy consumption with the availability of dispatchable resources, particularly during periods when renewable generation (such as solar PV) is limited. By shifting demand to later hours or more constrained periods, the model naturally relies on resources that can provide on-demand generation. Conversely, solar PV generation, which is time-dependent and cannot easily adapt to shifted demand, sees a reduction in its percentage share. These results suggest that there needs to be more management in terms of what percentage of the total flexible resources’ generation can be used to meet demand so that they are not considered so low-cost and readily available that renewable resources are left underutilized.

ID	Resource	FLEX	Zone	Total_MW	Start_MW	Change_in_I	Percent_MV	GWh	Percent_GWh		Total_MW	Start_MW	Change_in_MW	Percent_MV	GWh	Percent_GWh
1	CA_N_batteries_1	1	1	2653.8	2653.8	0	3.6757251	3962.951515	1.223390896		2653.8	2653.8	0	3.6757251	13624.958	4.206119835
2	CA_N_biomass_1	0	1	0	236.2	-236.2	0	0	0		0	236.2	-236.2	0	0	0
3	CA_N_conventional_hydroelectric_1	0	1	0	7519.1	-7519.1	0	0	0		0	7519.1	-7519.1	0	0	0
4	CA_N_geothermal_1	0	1	0	987.4	-987.4	0	0	0		0	987.4	-987.4	0	0	0
5	CA_N_hydroelectric_pumped_storage_1	1	1	373.4562	2276.9	-1903.444	0.5172667	834.452665	0.257601384		1543.9146	2276.9	-732.9854455	2.138445	6878.4336	2.123420638
6	CA_N_natural_gas_fired_combined_cycle_1	0	1	7928.7953	11409.7	-3480.905	10.982015	5348.340568	1.651070203		1795.0186	11409.7	-9614.681389	2.4862442	647.27699	0.199818941
7	CA_N_natural_gas_fired_combustion_turbine_	1	1	0	4732.2	-4732.2	0	0	0		285.23	4732.2	-4446.97	0.3950663	316.91179	0.09783289
8	CA_N_natural_gas_steam_turbine_1	0	1	0	2.9	-2.9	0	0	0		0	2.9	-2.9	0	0	0
9	CA_N_onshore_wind_turbine_1	0	1	0	1473.5	-1473.5	0	0	0		0	1473.5	-1473.5	0	0	0
10	CA_N_other_peaker_1	1	1	0	786	-786	0	0	0		28.228422	786	-757.7715783	0.0390986	78.674172	0.024287268
11	CA_N_small_hydroelectric_1	0	1	227.3	227.3	0	0.3148287	754.4087	0.232891251		227.3	227.3	0	0.3148287	1203.3262	0.371475228
12	CA_N_solar_photovoltaic_1	0	1	6333.4	6333.4	0	8.7722652	9297.982856	2.870352447		0	6333.4	-6333.4	0	0	0
13	CA_S_batteries_1	1	2	7147.7239	9806.2	-2658.476	9.9001689	14123.81202	4.360119717		9806.2	9806.2	0	13.582371	36886.586	11.3871474
14	CA_S_biomass_1	0	2	0	181.4	-181.4	0	0	0		0	181.4	-181.4	0	0	0
15	CA_S_conventional_hydroelectric_1	0	2	0	1346.4	-1346.4	0	0	0		0	1346.4	-1346.4	0	0	0
16	CA_S_conventional_steam_coal_1	0	2	0	57	-57	0	0	0		0	57	-57	0	0	0
17	CA_S_geothermal_1	0	2	0	1093	-1093	0	0	0		0	1093	-1093	0	0	0
18	CA_S_hydroelectric_pumped_storage_1	1	2	0	1665	-1665	0	0	0		1665	1665	0	2.3061581	6061.0062	1.87107507
19	CA_S_natural_gas_fired_combined_cycle_1	0	2	6572.4205	10043	-3470.58	9.1033276	1048.623531	0.323717431		2122.4885	10043	-7920.511484	2.9398162	133.92852	0.041344672
20	CA_S_natural_gas_fired_combustion_turbine_	1	2	709.63553	6952.2	-6242.564	0.9829019	9.599408868	0.002963405		483.94545	6952.2	-6468.254551	0.6703031	224.3864	0.069269654
21	CA_S_natural_gas_steam_turbine_1	0	2	0	2942	-2942	0	0	0		0	2942	-2942	0	0	0
22	CA_S_onshore_wind_turbine_1	0	2	0	4793.4	-4793.4	0	0	0		0	4793.4	-4793.4	0	0	0
23	CA_S_other_peaker_1	1	2	0	115.1	-115.1	0	0	0		23.669109	115.1	-91.43089133	0.0327836	53.148547	0.016407329
24	CA_S_small_hydroelectric_1	0	2	120.3	120.3	0	0.1666251	193.4424	0.059717024		120.3	120.3	0	0.1666251	503.0946	0.155308828
25	CA_S_solar_photovoltaic_1	0	2	15583.1	15583.1	0	21.583839	17022.42457	5.25494172		0	15583.1	-15583.1	0	0	0
38	CA_N_utilitypv_class1_moderate_2	0	1	10305.113	0	10305.113	14.273405	89741.51572	27.70383461		7262.6577	0	7262.657711	10.059361	63122.719	19.48642569
62	CA_S_utilitypv_class1_moderate_1	0	2	24925.267	0	24925.267	34.523487	204066.8348	62.99686155		17209.088	0	17209.08829	23.835963	148936.75	45.97781708
						SCENARIO 1 ^							SCENARIO 2 ^			

Fig 5: Impact of rescheduling on generation mix (Scenario 1 & 2 comparison of non-zero rows)

Discussion

The results from this study is a start at answering the research question and provide evidence that supports known claims about benefits from shifting demand. The results across the key cumulative metrics selected of total cost, total generation, average rate, and total NSE are good indicators on what aspects about EV load scheduling merit further investigation.

The fact that this study does not analyze system metrics to look for trends according to time step is a limitation of research design. However, the process of implementing the existing system also has several limitations that are worth discussion. First is the selection of which generators are flexible resources and that their energy efficiency of rescheduled demand is 100%. This is likely unrealistic from the real-world and artificially inflates the effects of rescheduling EV load. As mentioned earlier, another research decision for this study’s scope was to not consider unit commitment constraints and reserve requirements that would have improved operational detail but are not critical to this specific investigative question. From a research process standpoint, the timing of this study also resulted in a lack of peer review about formulations and approach. If I were able to discuss implementation and experimental design with other peers and mentors more throughout the process, I would likely be more confident about the conceptual correctness/relevance of the model, and subsequent modifications, I implemented.

In terms of future work, the most critical next step will be introducing more granular ways to analyze the temporal dimensions of each scenario/policy. Specifically, looking into the flexible-demand decision variables at each time step will generate insights on daily patterns. Additionally, exploring whether rescheduled demand decreases renewable curtailment, especially during the middle of the day would be worthwhile. Such study would form the groundwork for considering the amount of savings that may be generated on both the system and consumer side, which would justify exploring financial incentive structures for consumers to reschedule their EV charging. Additionally, this study included the 5 GW EV load add-on as a fixed value, so to do much longer term planning, it would be worthwhile to see how the aggregated key metrics vary (linear, quadratic, etc.) when that amount functions as an independent variable.

Appendix

Sets

- G = all resources
- T = all time steps
- Z = all zones
- S = all demand segments
- L = all transmission lines
- $STOR \subseteq G$ = all storage resources
- $VRE \subseteq G$ = all variable renewable resources
- $FLEX \subseteq G$ = all flexible resources
- $OLD \subseteq G$ = all existing resources
- $NEW \subseteq G$ = all new build resources

Utility Functions for Flexing Demand

Function: `hoursbefore` (Vector)

$$\text{hoursbefore}(p, t, b : \text{UnitRange}) \to \text{Vector}$$
$$\text{period} = \left\lfloor \frac{t-1}{p} \right\rfloor$$
$$\text{return} = \text{period} \cdot p + \text{mod1}(t - b, p)$$

Function: `hoursbefore` (Integer)

$$\text{hoursbefore}(p, t, b : \text{Int}) \to \text{Int}$$
$$\text{period} = \left\lfloor \frac{t-1}{p} \right\rfloor$$
$$\text{return} = \text{period} \cdot p + \text{mod1}(t - b, p)$$

Function: `hoursafter`

$$\text{hoursafter}(p, t, a : \text{UnitRange}) \to \text{Vector}$$
$$\text{period} = \left\lfloor \frac{t-1}{p} \right\rfloor$$
$$\text{return} = \text{period} \cdot p + \text{mod1}(t + a, p)$$

Function: `is_in_time_window`

$$\text{is\_in\_time\_window}(t, s, e) \to \text{Bool}$$
$$\text{hour\_of\_day} = t \mod 24$$
$$\text{return} = s \leq \text{hour\_of\_day} < e$$

Parameters

$$\begin{aligned}
\text{CO2_Rate}[g] &: \text{CO}_2 \text{ emission rate of generator } g \text{ (tons/MWh)} \\
\text{CO2_Per_Start}[g] &: \text{CO}_2 \text{ emissions per start-up of generator } g \text{ (tons)} \\
\text{Max_Cap_MW}[g] &: \text{Maximum capacity of generator } g \text{ (MW)} \\
\text{Line_Max_Reinforcement_MW}[l] &: \text{Maximum transmission capacity reinforcement for line } l \text{ (MW)} \\
\text{Demand}[t, z] &: \text{Demand in zone } z \text{ at time } t \text{ (MW)} \\
\text{Sample_Weight}[t] &: \text{Weight of sample period } t \text{ (hours)} \\
\text{Hours_Per_Period} &: \text{Number of hours in each sample period} \\
\text{NSE_Max}[s] &: \text{Maximum allowable non-served energy in segment } s \text{ as a fraction of demand} \\
\text{Flex_Percentage}[t, z] &: \text{Percentage of flexible load available in zone } z \text{ at time } t
\end{aligned}$$

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References

Subject Matter

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Codebases

Lab1_code.jl
Lab1.jl
GenX.jl (GitHub)