# EENG480/ENGY503 Final Project

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## A. Variable PV Penetration

Historical irradiance data from the NREL National Solar Radiation Database (NSRD) taken from Denver International Airport (DIA) on June 21st, 2022.

| Solar Irradiance (W/m^2) | Beam | Diffuse | Total |
|---|---|---|---|
| 10:00am | 975 | 94 | 1069 |
| 4:00pm | 814 | 84 | 898 |
| 8:00pm | 0 | 0 | 0 |

## B. EV Demand

EV loads are inserted at the tracts that have the highest median income as well as the highest homeownership ratio since this group of people are more likely to own and charge an EV. Therefore, there were ten EV loads connected on tracts 102 and 106 (buses 828, 830, 854, 852, 890, 832, 836, and 840).

## C. Impact of EV and PV on Grid Performance

| Scenario ID | PV Penetration (%) | Time | EV Penetration (%) | Active Power from Distribution (kW) | Reactive Power from Distribution (kvar) | Total Power Losses (kW) | Highest Node Voltage (pu) | Lowest Node Voltage (pu) | No. Of Nodes with Voltage |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 20 % | 10:00am | 20% | 2906.9 | 519.6 | 386.2 | 1.013 | 0.866 | 8 |
| 2 | 20 % | 4:00pm | 20 % | 2973.8 | 525.9 | 401.3 | 1.001 | 0.862 | 11 |
| 3 | 20 % | 8:00pm | 20 % | 3325.2 | 558.7 | 486.1 | 1 | 0.844 | 12 |
| 4 | 50 % | 10:00am | 20 % | 2256.6 | 454.4 | 260.7 | 1.047 | 0.892 | 4 |
| 5 | 50 % | 4:00pm | 20 % | 2440.8 | 475.0 | 291.6 | 1.042 | 0.888 | 4 |
| 6 | 50 % | 8:00pm | 20 % | 3325.2 | 558.7 | 486.1 | 1 | 0.844 | 12 |
| 7 | 20% | 10:00am | 50% | 4435.0 | 887.5 | 799.8 | 1 | 0.760 | 34 |
| 8 | 20 % | 4:00pm | 50 % | 4495.9 | 896.0 | 820.2 | 1 | 0.757 | 34 |
| 9 | 20 % | 8:00pm | 50 % | 4815.3 | 940.1 | 932.0 | 1 | 0.741 | 34 |
| 10 | 50% | 10:00am | 50 % | 3864.6 | 808.7 | 622.5 | 1 | 0.789 | 34 |
| 11 | 50 % | 4:00pm | 50 % | 4016.7 | 829.7 | 667.3 | 1 | 0.781 | 34 |
| 12 | 50 % | 8:00pm | 50 % | 4815.3 | 940.1 | 932.0 | 1 | 0.741 | 34 |
| 13 | 20% | 10:00am | 100 % | 6358.5 | 1588.1 | 1597.5 | 1 | 0.621 | 34 |
| 14 | 20 % | 4:00pm | 100 % | 6411.2 | 1598.5 | 1622.8 | 1 | 0.619 | 34 |
| 15 | 20 % | 8:00pm | 100 % | 6687.8 | 1652.6 | 1759.3 | 1 | 0.601 | 34 |
| 16 | 50% | 10:00am | 100 % | 5864.6 | 1491.5 | 1371.6 | 1 | 0.645 | 34 |
| 17 | 50 % | 4:00pm | 100 % | 5596.3 | 1517.3 | 1429.9 | 1 | 0.639 | 34 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 18 | 50 % | 8:00pm | 100 % | 6687.8 | 1652.7 | 1759.3 | 1 | 0.606 | 34 |

**D. Mitigation**

The worst-case scenario from the results is scenario 15 because it has the highest power losses and the lowest per-unit voltage. One thing to note is that scenario 15 and scenario 18 have nearly identical results, regardless of having different PV penetration levels. Both scenarios are for analysis at 8:00pm, but scenario 15 has 20% PV penetration while scenario 18 has 50%. These scenarios are so similar regardless of PV penetration because the solar irradiance at 8:00pm is zero, in other words, neither scenario is receiving power injection from PVs. However, on a different day of the year there could be nonzero irradiance at 8:00pm, and then scenario 15 would still be the worst-case since PV penetration is only 20% compared to 50% from scenario 18. That being said, the main operational problems with scenario 15 are the low power generation and the high constant loads. High constant loads, due to high EV penetration, cause large voltage drops and subsequently an undervoltage system, as seen by the low per-unit voltage. In addition, the zero irradiance at 8:00pm means there is no PV power injection at the nodes, which makes power losses high due to power being lost in transmission lines from substation to nodes. Below are two proposed solutions and a discussion of their implementation:

<u>Battery Deployment Solution</u>

The issue of high constant loads from EV charging could be addressed through the deployment of large-scale battery storage. While potentially expensive, this solution offers benefits including frequency response, load balancing, and voltage support. The deployment of two batteries into the system during scenario 15 led to an overall increase in all the node voltages. The worst-performing node, 836, saw an increase of >15% in its p.u. voltage. While this was not a perfectly dynamic implementation, and the 836 node voltage was still low, it was as high as the system would allow without encountering a more than 5% overvoltage system.

Additionally, the implementation of batteries reduced power losses in the system by 66% in this scenario. The increase in system efficiency combined with the ancillary benefits make this a good choice, though not necessarily a perfect one given the high cost of deployment, but it will still be cheaper than dealing with the present and future power quality costs. For this model, batteries are just another power injection, but in the real-world batteries would be charged during the night when power demand is low, during power curtailment, or by another distributed energy resource (DER) and then used during peak hours or when needed.

<u>Demand Response Solution</u>

In scenario 15, the high power losses and low node voltages are a direct result of the large EV loads drawing power at the same time. The problem is worse at night when PVs cannot contribute power. One solution is a demand response program that would coordinate EV charging so only a single EV load gets to charge at a time. Incentives would be given to EV owners to charge at a specific time of the day, and assuming an elastic demand response[1], electricity demand at any given time would be significantly reduced.

This solution was modeled by switching on each of the 10 EV loads for one tenth of the total simulation time. See Appendix A1 for more details. This introduces some complexity into the analysis, there is no longer completely static loads throughout the simulation. There is now 10 discrete stages to assess power losses and node voltages at. In Figure A2, depending on which EV load is active, node voltages will still sometimes drop below 0.95 even though their average may now be in the acceptable ±0.05 range. Adjusting the metrics to consider the temporal nature of the loads by looking at the number of nodes with voltage outside ±5% and power losses in a given time window provides:

| **Time Window** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **No. Of Nodes with Voltage outside +-5%** | 9 | 7 | 5 | 9 | 32 | 18 | 19 | 18 | 4 | 4 |
| **Power Losses (kW)** | 229.0 | 235.4 | 243.9 | 357.4 | 513.2 | 566.3 | 518.0 | 552.8 | 282.3 | 302.1 |

In all the time windows, the power losses have been drastically reduced, with a maximum of 566.3 kW in time window 6 (when EV charging at bus 6 is active). While the majority of the low voltage nodes have been raised, there is still up to 32 low node voltages at a given time (window 5, bus 852 with active EV charging), which is a downside but still much less severe than having 10 constant loads connected at once.

Based on the implementation of the two solutions above, the best solution is the EV demand response program due to a larger reduction in power losses for this solution compared to the battery storage solution. Implementing large-scale battery storage results in power losses decreasing by 66% from those in the original worst-case scenario. However, after doing a few calculations, implementing a demand response program reduces power losses from 68% to 87% (from timing window 5 and timing window 1 respectively). Both solutions do an effective job of improving the power losses in the worst case, but objectively, the demand response program does a better job at this and is therefore the best solution based on metrics alone. (Although, realistically, demand response for EV charging would probably be harder to implement as many EV drivers might not be motivated by incentives).

**E. Equity and Justice**

The proposed metric for **distributional justice** is as follows:

Percentage of EV Users Working from Home (EVWH): number of EV users who work from home in an area ($\mathbf{N_h}$) over the total number of EV users in that area ($\mathbf{N_u}$).

[1] In reality, *wealthy* EV owners may respond *inelastically* to electricity price changes. If this is the case, a more stronghanded direct load control program may be necessary.

$$\textbf{EVWH} = \frac{N_h}{N_u} \cdot 100$$

One distributional justice issue with EV demand response is the range of flexibility that people have with their jobs and when they can charge their EV. The demand response solution would incentivize people to charge their EVs at times of high solar irradiance and PV penetration; these times are generally in the middle of the day when many working individuals would be at work. Those who work from home or those who work at night would have an easier time charging at random times of day compared to someone who must be at their physical job the entire day.

A metric that could be used to measure this distributional justice issue is to measure the number of EV users that work from home in an area and divide by the total number of EV users in that area or tract. This would give a percentage of how flexible EV users are in different areas, and therefore how likely they are to participate in the program. This is important because it is unfair if some users are unable to participate in the program or receive the incentive due to limits with their job, meaning the benefits of this program are not equally distributed among all users. To improve the energy justice of this solution, the demand response could be adjusted to not only incentivize charging during high solar irradiance, but also incentivize charging later at night, say between 10:00pm and 5:00am. This way those who work all day could still have the opportunity to participate and reap the benefits of the program, but at the same time our solution wouldn't necessarily be ineffective by doing this as there is already less power loss and pressure on the grid in the middle of the night.

The proposed metric/solution for **recognition justice** is the following:

Social Sensibility to Power Consumption (S2PC): A quantity to measure social sensibility per household in user groups or regions consuming power.

$$\textbf{S2PC} = \frac{E + C}{100} \cdot H$$

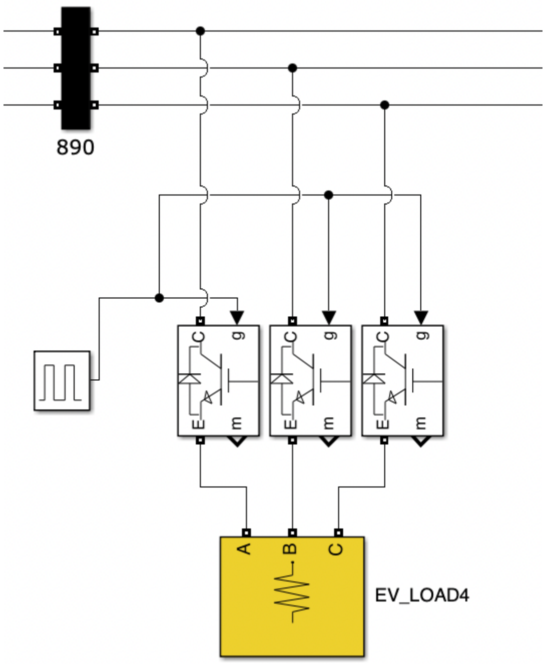
where **E** is the population percentage of people above 65 years old, **C** is the population percentage of people under 4 years old, and **H** is the region/tract household average size

This metric shows that the higher the result of this formula, the higher the sensibility these regions or user groups from this tract have to power usage. In other words, this is trying to show how important power is for these people because of their living status. For example, if there is a power shortage in a region, the S2PC number assigned to this tract shows how severe this outage is to the people living in this region regardless of income or home ownership. This energy justice metric will help our battery storage solution from part D. Specifically, it will show utilities some strategic location points of where to add battery storage or another source of power, having in mind not just the technical issues such as undervoltage, but also social sensibility of different regions due to potential power shortages. However, some of highest population of sensible user groups (**E** and **C**) are on tracts 102 and 106, which is where the EV loads were added. Thus, if EV or any other large loads increase in these sensible regions it will help utilities prioritize these regions for future power developments (battery storage, demand response, etc.) due to technical and social vulnerability issues.

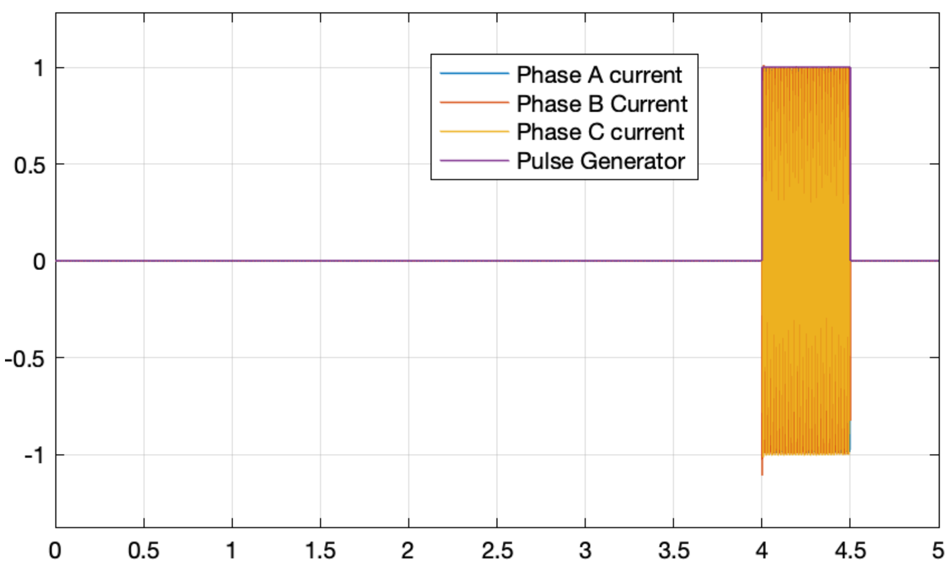
Social metrics are challenging to create, since there are many variables that have to be taken into account. For instance, this metric does not care about household income or home ownership percentages, which would be great when analyzing power outages due to the sensibility of these people to people no matter how much they earned. On the contrary, this metric might not help when people need to evacuate for weather or other extreme events. When there is an evacuation order, household income and home ownership will play a big role in the decision making of some of these people. Therefore, some recommendations to this metric would be to integrate household income and home ownership ratios somewhere in the equation to have more accurate results for sensibility of these user groups to different events. Also, this equation can be split into two different ones; one that just includes the elderly people (**E**) and another that just includes the children under the age of 4 (**C**) so utilities know the specific ratio of people they are working with.

**Appendix**

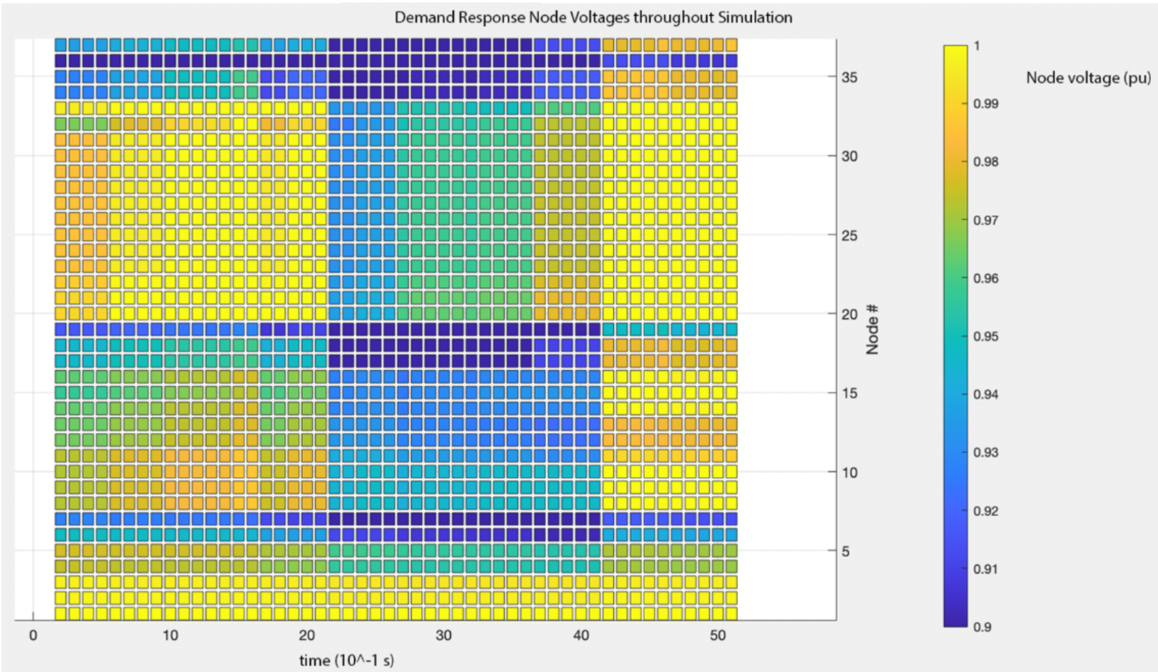
A1. Staged EV Charging Modeling




To coordinate EV charging, each EV load (a 3-phase load pictured here, although some are single phase), is put behind a switch (or a set of switches). The switches are turned on for 1/10th of the total simulation time—which is 0.5s for a 5s simulation—using a pulse generator that controls the set of switches, resulting in current through one specific EV load as shown in the plot below.



A2. Staged EV Charging Analysis




| **Time Window** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Bus where EV charging is active** | 862 | 838 | 856 | 890 | 852 | 854 | 830 | 828 | 840 | 836 |