GRID CAPACITY STUDY FOR ELECTRIC VEHICLE CHARGERS

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Abstract. How many electric vehicle (EV) chargers can we fit on a given grid infrastructure? This question depends on many factors: the structure of the grid, what part of the grid is of interest, what kinds of chargers we want to fit, what measures we want to use to fit the chargers, and the load data for the grid. In this paper we come up with an application on top of Awesense's API that can take in live grid data and produce clear and usable answers to this question.

1. Problem Statement

"How many EV chargers can the grid fit?" is a very broad question. Before we can narrow it down, we first need to understand the electrical grid.

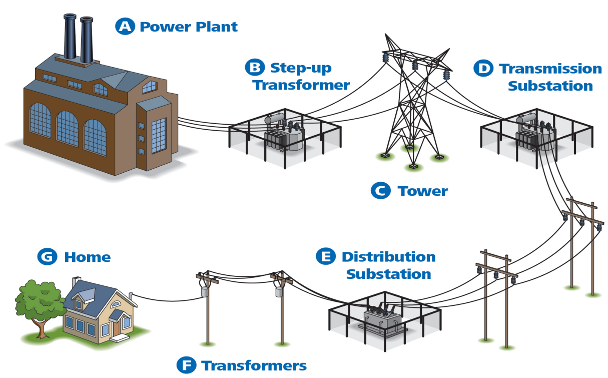

Figure 1. High level power grid structure. Source: [5].

In Figure 1, we see that the grid has a network structure where power flows from power plants through high voltage transmission infrastructure to end up at local distribution substations. Since this infrastructure is designed to transmit vast amounts of power, we exclude them from our analysis.

After the power reaches local substations, it then is transmitted across local power lines to distribution transformers. Distribution transformers step medium voltage current down to low voltage current which is usable for household appliances and

EV chargers. These distribution transformers tend to have much lower capacity limits. Our analysis works with these transformers.

Lastly, power flows from distribution transformers to meters where power usage is measured. The data available to us from Awesense's sandbox was at the meter level, and so our methods need to account for that. Awesense's sandbox contains a synthetic dataset emulating a small portion of Vancouver's power grid.

Given this understanding of the grid and what parts of it we are focusing on, we can clarify our question; design a methodology and implementation that

- uses current load data on meters in the grid, obtained from Awesense's sanndbox database using their SQL interface,
- determines the number of chargers (of one type or multiple types) that fit on a particular distribution transformer or a list of distribution transformers within an allocated power budget,
- account for the variations in load data over time to produce recommendations with different time constraints on the availability of chargers. For example, requiring all chargers be available all the time or requiring all chargers be available during off peak hours while allowing some chargers to be shut down during peak hours.

2. Methodology

Our methodology can be divided into two parts. The first part is data wrangling, which involves pulling electrical grid data from Awesense's sandbox, calculating the *excess load* capacity on each transformer, etc. The second part is basically using these data to come up with an optimized number of electric vehicle chargers under a given transformer.

2.1. Data Wrangling.

The basic structure of the electrical grid we have been working with can be roughly described as the following network (Figure 2), where the left-most transformer is a large transformer with very high *KVA rating* and the

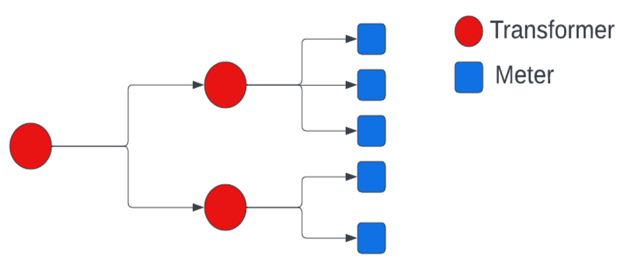

Figure 2. Basic Structure of the Grid

middle ones are the medium or small distribution transformers, connected directly to different meters. As the large transformers have very high *KVA rating*, there is always *excess capacity* on those. So, our study of electric vehicle charger capacity is focused on the distribution transformers.

The power usage (load) data is available on the meter level as a time-series. For our purposes, we need the aggregate on the transformer level. So, we pull down live load time-series data on every meter from Awesense's sandbox database using the provided SQL API. We also find all the meters downstream of a given transformer and *aggregate load* from those meters to get the *aggregate load* (L) on that particular transformer. The *excess capacity* (E) on a given transformer is calculated using the following formula:

$$E = r \times p - L,$$

where r is the *KVA rating* and p is the power factor of the given transformer. The *KVA rating* of a transformer can vary depending on its size, e.g. on the sandbox grid (see Figure7), transformer-16 has a *KVA rating* of 5, whereas transformer-92 has a *KVA rating* of 750. The power factor of a transformer is defined as a ratio between real power and apparent power (*KVA rating*). Its value is usually between 0 and 1. For the Awesense sandbox grid, the power factor was given to be 0.98 for all the transformers. Also, we are not allowed to utilize all the *excess capacity* (E) on a transformer, only a *fraction* (f) of it will be allowed to be utilized towards installing electric vehicle chargers. So, the *available capacity* (A) is given by $A = E \times f$.

The *aggregate load*, *excess capacity*, *available capacity* all vary based on time. We have taken this into account and come up with a dynamic solution where transformer ID, date range, fraction of *excess load* allowed, etc. are all user inputs.

2.2. **Fitting Chargers Under a Transformer.** The main goal of this project is to come up with an efficient strategy to fit an optimal number of electric vehicle chargers under a transformer without going over *available capacity* at max usage. There are two cases: namely one charger type and multiple charger types. Each charger has a wattage, *i.e.* the maximum power the charger will draw from the grid when plugged in and utilized fully. By charger type we mean its wattage. For one charger type, we only have chargers with one fixed wattage. For multiple charger types, we can have different number of chargers of different wattage. We will now look into both the cases separately.

(1) **Single Charger Type Model.** If the charger has power draw P and we have total *available capacity* C, then we fit $\lfloor \frac{C}{P} \rfloor$. Note that *available capacity* C will not typically be evenly divisible by charger wattage P, so the floor is required to get an integer number of chargers.
(2) **Multiple Charger Type Model.** When we have multiple charger types, there are multiple different constraints we can consider. We looked at three scenarios:
   - **Use as much available capacity as possible.** In this scenario we want to use as much *available capacity* as possible without going over the power budget. This is an integer programming problem and the brute force solution has exponential run-time in the number of chargers. We

implemented a Maximum Inner Product Search (MIPS) algorithm (see [1]) using the 1-nearest neighbours algorithm. Given a list of chargers with different wattage, we write it as a vector $\mathbf{w}$ and find the vector $\mathbf{n}$ of charger numbers which gives the maximum inner product $\mathbf{w}^T\mathbf{n}$ without going over the power budget. Note that this is not a deterministic algorithm. The MIPS algorithm we used requires random initialization of vectors.

- **Capping the number of chargers.** In practice it may not be feasible to install as many chargers as we want in a grid. Physical locations have limited space, so it is not necessarily feasible to install the full number of chargers that are recommended in the previous scenario. Our algorithm takes this into account in the generation of our random vectors $\mathbf{n}$ by requiring that the sum of the entries in $\mathbf{n}$ is at most the charger cap.
- **Fixed proportions of chargers.** The best possible method in practice is to ask that the chargers appear in roughly fixed proportions. We considered two measures of proportionality. If we have charger types $1, \ldots, n$ then we can assume that the number of chargers of type i accounts for $100c_i\%$ of the total number of chargers or we can assume that the chargers of type i are allocated $100c_i\%$ of the *excess capacity*, where $0 \leq c_i \leq 1$ for all i and $\sum_{i=1}^n c_i = 1$.
  The proportional by number case is handled by creating a virtual charger with power draw $\sum_{i=1}^n c_i P_i$ where P_i is the power draw of charger type i. This virtual charger is then fit to the transformer as in the single charger type case. If n virtual chargers fit on the transformer, then we fit $\lfloor c_i n \rfloor$ chargers of type i. This gives us a distribution of chargers that approximately matches the desired proportions. The requirement that we have integer numbers of chargers makes fitting the proportions exactly unlikely to occur.
  In the proportional by power draw case, we allocate charger type i capacity equal to $c_i C$ where C is the total *available capacity.* We then fit each charger to the smaller capacity number using the single charger type method. This results in a charger distribution where charger type i takes up at most $100c_i\%$ of the total *available capacity.* For large capacities, this will also result in a charger distribution where charger type i uses approximately, but no more than, $100c_i\%$ of the available power.

3. Summary of Implementation

The ultimate goal of our project was to create an application methodology and implementation for determining and reporting the chargers that fit onto the grid. In the GitHub repository [2], the `transformer_functions.py` has all the of the objects and methods described in this section.

3.1. **Setup.** The basic constructs of our implementation are the transformer and charger classes. A charger object simply holds the phase, voltage, and power draw of a charger. The transformer class is the workhorse of our application. A transformer object stores the transformer ID, power factor, grid ID, proportion of *excess capacity* that is available for chargers (between 0 and 1), phase, total capacity in KVA, secondary voltage, a pandas DataFrame containing the transformer's load time series data, and a timestamp indicating when the time series data was last updated. After initializing a transformer object, its `transformer.retrieve_data` method must be called to populate its time series data for the first time.

3.2. **Charger Fitting.** Once a transformer object has been initialized, chargers can be fit onto it. The `transformer.fit_EVC` method takes a single charger object as input and fits that single charger onto the transformer at each timestamp as described in the Single Charger Type Model from section 2.2.

For the multiple charger type models, we have three methods of fitting. To fit multiple charger types with defined proportions of the number of chargers of each type, we use the `transformer.fit_ch_num_proportional` method, which takes a list of pairs (charger, percentage) and fits at each timestamp chargers which roughly match the given proportions.

To fit multiple charger types with defined proportions of the power draw of each type of charger, we use the `transformer.fit_ch_pow_proportional method`. The inputs and outputs of this method are the same as for the `transformer.fit_ch_num_proportional` method, allowing us to use the two methods interchangeably when producing summaries or graphs.

Lastly, we have the optimal power usage case, where we want to use as close to the *available capacity* as possible. Since this is a very computationally intense problem to solve, it is not feasible to solve it at each timestamp. Instead, we have provided a method `transformer.fit_optimal_onetime` which finds distribution of chargers that gives nearly optimal power usage given a fixed capacity. So it works on a single timestamp, instead of providing a charger distribution for each timestamp.

3.3. **Graphing.** First, we have several diagnostic functions to understand the underlying distributions of the loads:

- `transformer.graph_excess_capacity` displays *excess capacity* for the transformer over a given time span. Since *excess capacity* is volatile, we aggregate the data over smaller time intervals, using either the minimum or average *excess capacity* on each interval, to produce a more interpretative graph. This gives us a graph such as in Figure 3.
- `transformer.graph_capacity_hourly` and `transformer.graph_capacity_monthly` produce box-plots indicated the distribution of *excess capacity* by hour of the day and by month respectively. For example, `transformer.graph_capacity_monthly` gives us a graph such as in Figure 4. For example, we can see from this figure that *available capacity* tends to be higher during summer months.

Once we get to fitting chargers onto the transformer, we have two methods.

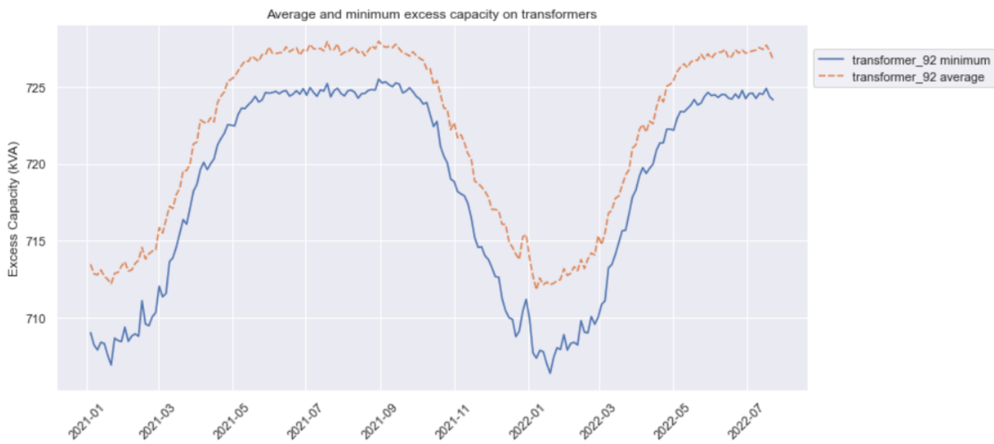

Figure 3. Minimum and average *excess capacity* on transformer 92 from January 1 2021 to July 21 2022

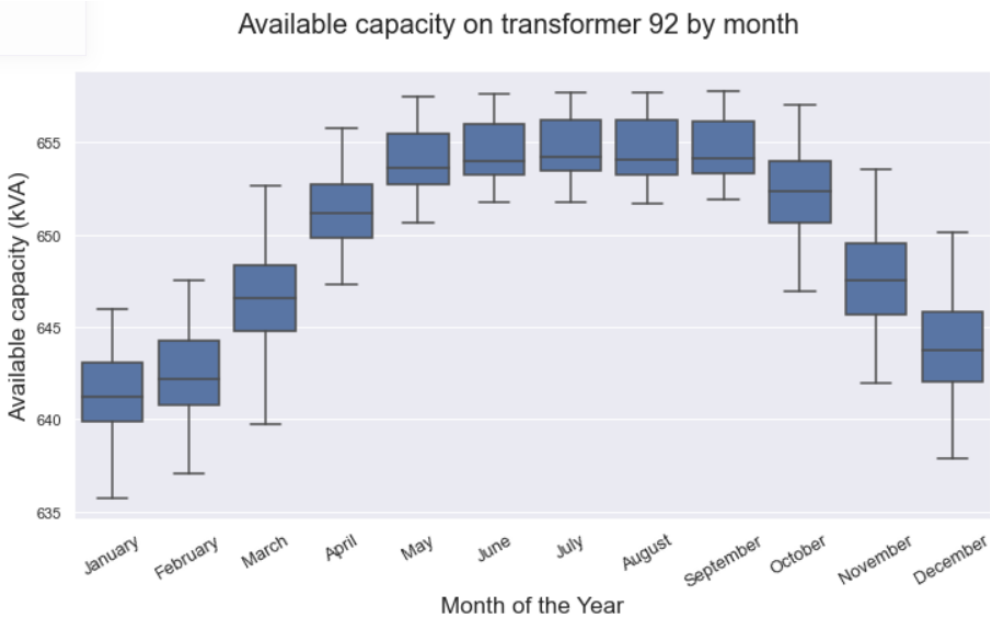

Figure 4. Monthly distributions of *available capacity* on transformer 92 from January 1 2021 to December 31 2021

- `transformer.graph_chargers_on` takes a list of transformers and a single charger and gives an analysis of the chargers that fit on each transformer in the list in four categories:

– The “All time” category reports the number of chargers that fit on a given transformer if we require all chargers to be able to pull their full load simultaneously at any time of day and at any time of year.
– The “Nightly” category reports the number of chargers that fit on a given transformer if we require all chargers to be able to pull their full load simultaneously at night and at any time of year, where night is defined as 10pm to 4am.
– The “All summer” category reports the number of chargers that fit on a given transformer if we require all chargers to be able to pull their full load simultaneously at any time of day during the summer, which is defined as from June to September.
– The “Summer nightly” category reports the number of chargers that fit on a given transformer if we require all chargers to be able to pull their full load simultaneously at night during the summer.

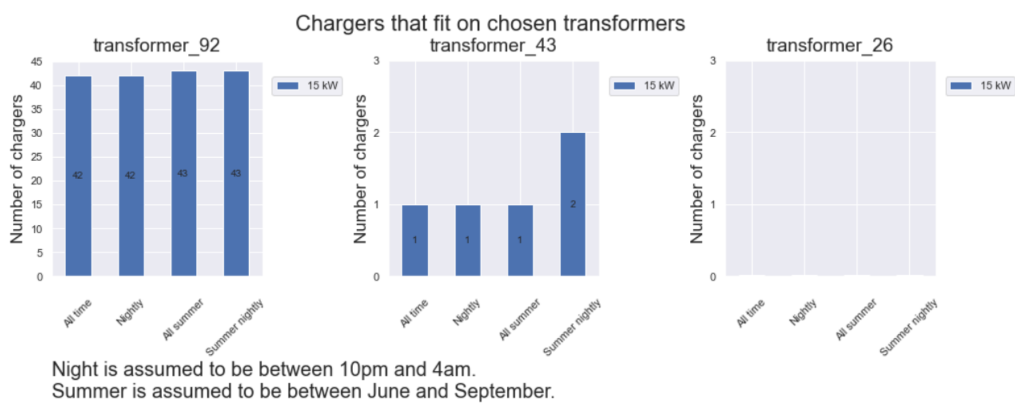

Figure 5. 15kW chargers that fit on transformers 92, 43, and 26

For example, fitting a 15kW charger to transformers 92, 43, and 26 produces a graph as in Figure 5.

- `transformer.graph_power_scenarios` function takes in a list of chargers and a graphing mode, indicating which multi-charger type method to fit the chargers with, and produces a graph giving the number of each type of charger used and the power drawn by each type of charger. For example, in Figure 6, we fit 7kW, 20kW, and 110kW chargers onto transformer 92 with the stipulation that approximately 20% of the chargers should be 7kW, 50% should be 20kW, and 30% should be 110kW.

4. Case Study - Parking Lot

Using the data on Awesense’s Energy Data Model sandbox, we can use our application to investigate installing chargers in a specific area.

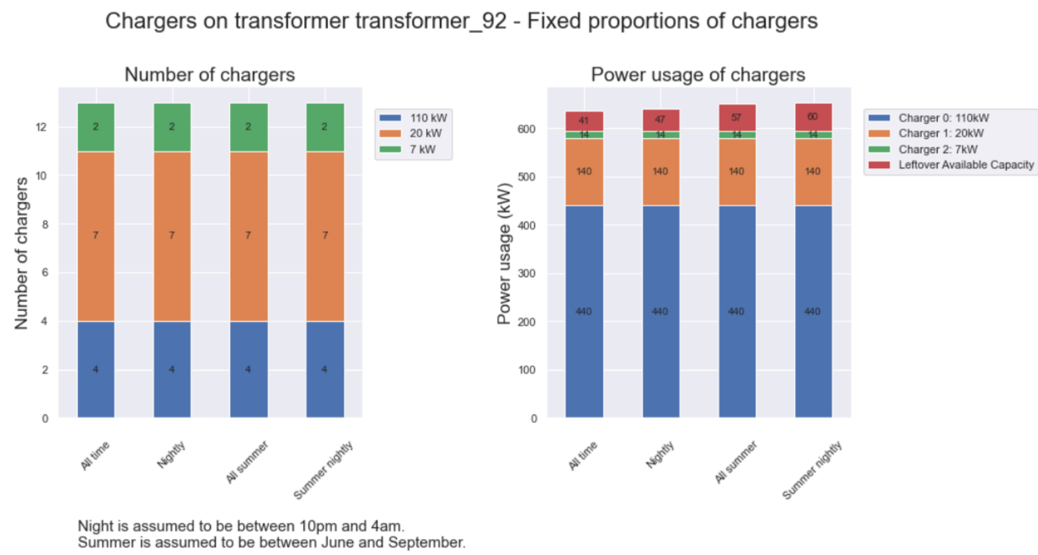

FIGURE 6. Number of 7kW, 20kW, and 110kW chargers that fit on transformer 92 with given proportions

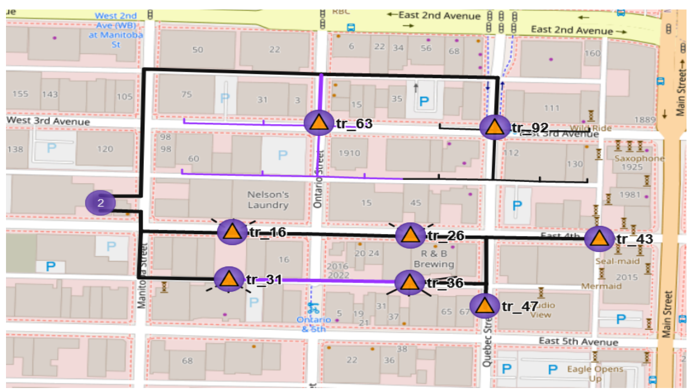

FIGURE 7. Visual of transformer and distribution lines in Awesense's sandbox grid

Suppose the owner of the parking lot between transformers 26, 43, and 92 wishes to install chargers on that lot. How many chargers could they install and on which transformers should they be installed?

Charger characteristics are user input. For this example, we first consider installing chargers with 15kW constant draw.We note from the grid that transformers 26, 43, and 92 are the only transformers that can be connected to loads in the parking lot due to geospatial concerns. The percentage of capacity we are allowed to use on each of these transformers is also user input. In this example, we allow 50% of transformer 26's and transformer 42's *excess capacity* to be allocated for chargers, as well as 90% of transformer 92's *excess capacity*.

From figure 5, we immediately see that transformer 26 is totally unavailable for chargers and that transformer 43 can fit one or two, depending on the client's availability criteria. Transformer 92 can fit a large number of chargers.

If the client only wants to install 15kW chargers, rather than a mix of different chargers with different power draws, then we have an immediate answer. They can install up to 42 or 43 chargers, and they should be installed on transformer 92. They can install an additional one or two chargers on transformer 43. Since these would need to be metered separately, the client may wish to consider the cost efficacy of installing a meter for just one or two chargers.

Since transformer 92 has significantly more capacity than either of transformers 26 or 43, we will focus on it for now. Next, we will consider installing a mix of charger types with different power draws.

Suppose now the client wants to install a mix of 7kW, 20kW, and 110kW chargers on transformer 92 and their only stipulation is that they want to use as much of their *available capacity* as possible at night without any consideration for time of year. In that case, we can generate Figure 4. From this figure, we can see that installing 16 7kW chargers, 4 20kW chargers, and 4 110kW chargers is the best fit for the client's specifications.

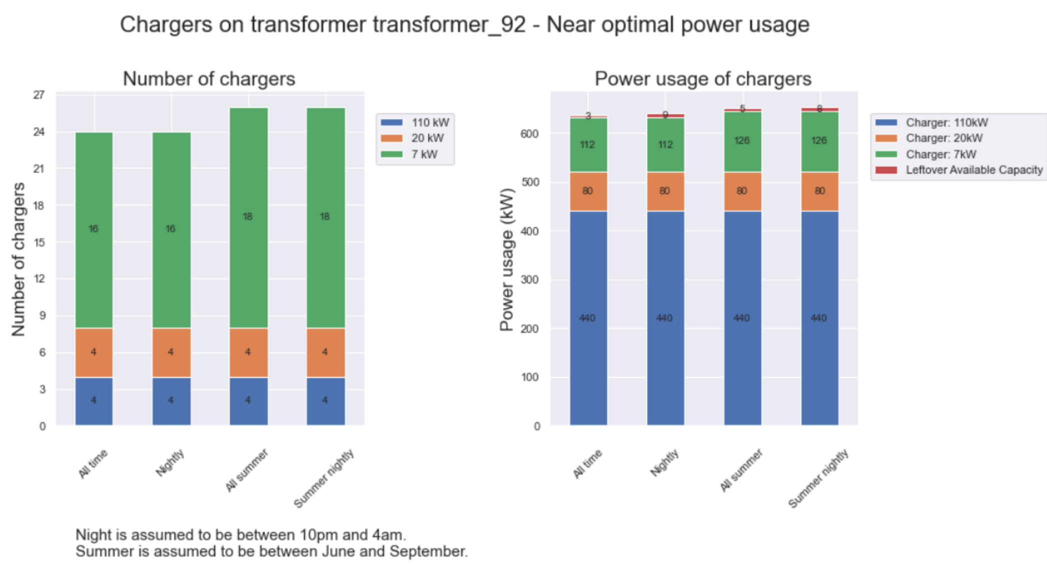

FIGURE 8. Number of 7kW, 20kW, and 110kW chargers that fit on transformer 92 using all *available capacity*

5. IMPACT

5.1. **Climate change.** The climate change is increasing at an exponential rate and happens to be one of the major problem nowadays if not the greatest threat of global health in the 21-st century. In fact, it's a large contributor to extreme weather events, ocean acidification, global warming, rising sea levels, etc. Moreover, each of the last three decades has been successively warmer at the earth's surface than any preceding decade since 1850 (see Figure 9 for more details).

One of the main cause of climate change is greenhouse gas emission in which transportation is the highest- emitting sector which accounts for 15% to 20%. Enormous effort have been taken to reduce the carbon emission around the world. A study showed that 67% of voters in 2019 federal election wanting climate change policies to be implemented, and 78% aiming for a large scale investment in clean energy. Large scale electric vehicles adoption will significantly reduce the CO_2 emissions from transportation sector.

5.2. **Economic trends towards green infrastructure.** EV adoption is accelerating and growing fast. The shift toward EV is not only seen from individual persons but also from big companies and countries. The number of EVs is expected to raise by 30% in 2040, in some countries like Europe, China and US are expected to have more than 60% of EV share of all sale by 2040 (see Figure 10).

6. Conclusion

With the rapid growth and demand of EV, the nationwide charging grid infrastructures becomes a challenging problem. Which brings the question question how many EVCs can be installed at the given transformer without overloading it. Indeed, If the grids can't support more EVCs, then that transition becomes impossible. So it is essential to know how we can accommodate more and more EVCs on our current grids. Our project was one piece towards having grid infrastructure that meets with the increasing EV demand.

We have successfully solved the problem with an efficient strategy to fit an optimal number of electric vehicle chargers under a transformer without going over *available capacity* at max usage supported by a number of visualizations. Indeed, we provided optimal answers for different scenarios without overloading the grid which takes into account

- one single charger type.
- multiple charger type.
- multiple charger type with defined proportions of the power draw.
- optimal power usage, *i.e.* uses as much as possible.

As stated earlier our results are dynamic and user friendly and can be adapted to any data from different grids across the country.

Building a smooth functioning charging infrastructure in the existing power grid has some challenges that need to be taken into account. For example:

- Cost of charging infrastructure.
- Risk of overloading the grid.
- Smart and flexible charging system (charging time).
- Battery shortage.

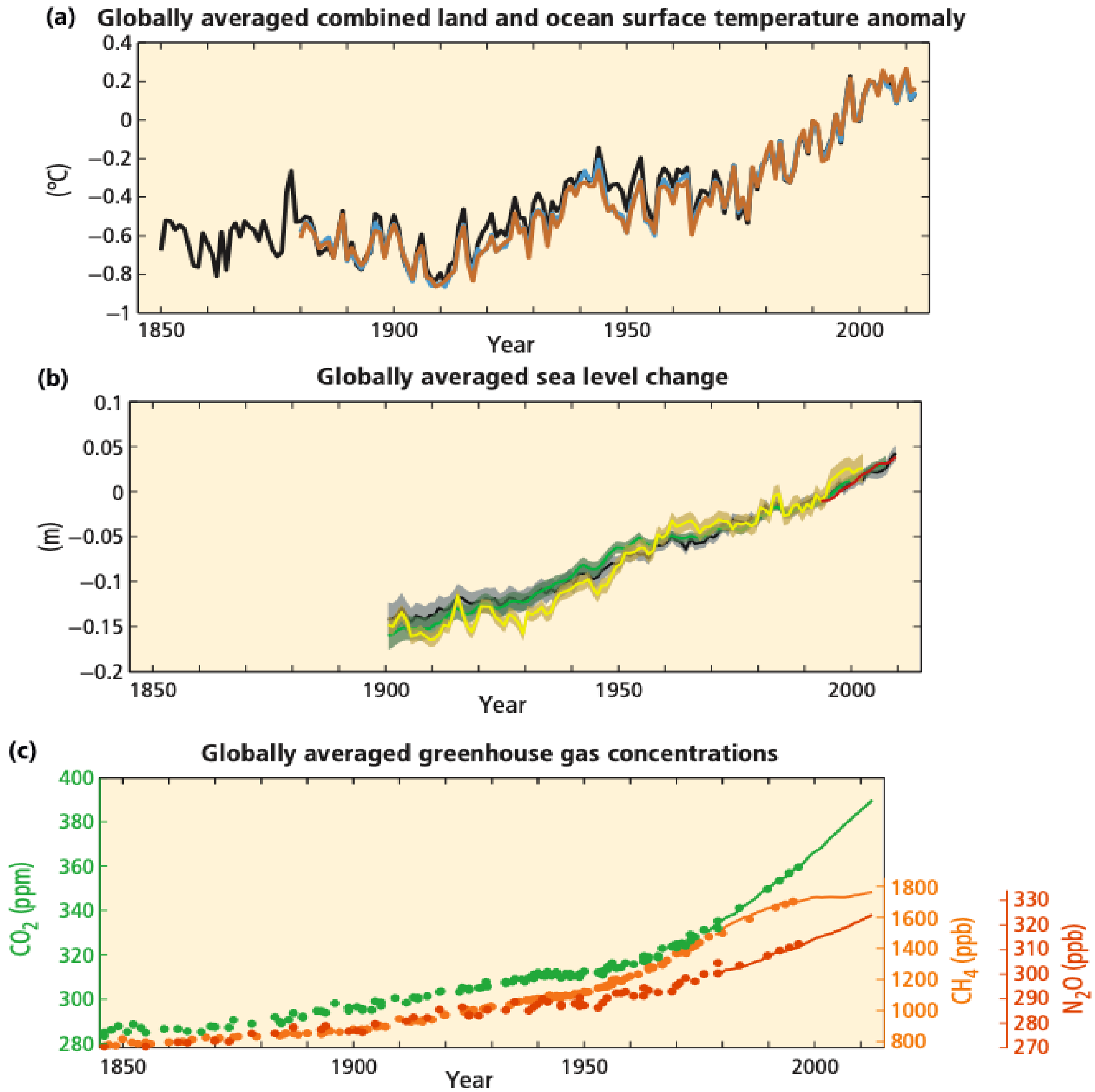

FIGURE 9. (Source [4]): (a) Annually and globally averaged combined land and ocean surface temperature. Colours indicate different data sets. (b) Annually and globally averaged sea level change relative to the average over the period 1986 to 2005 in the longest-running dataset. Colours indicate different data sets. All datasets are aligned to have the same value in 1993, the first year of satellite altimetry data (red). Where assessed, uncertainties are indicated by coloured shading. (c) Atmospheric concentrations of the greenhouse gases carbon dioxide (CO2, green), methane (CH4, orange) and nitrous oxide (N2O, red) determined from ice core data (dots) and from direct atmospheric measurements (lines).

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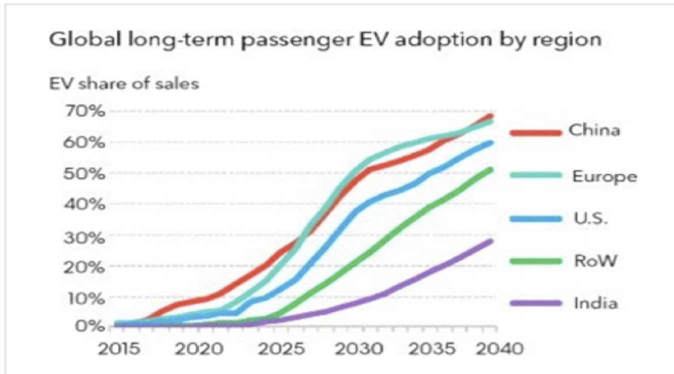

FIGURE 10. (Source [6]): Global long-term passenger EV adoption by region

to the quality of this paper. The authors would also like to express their profound gratitude to PIMS for the opportunity to participate in the Math to Power Industry workshop.

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