Electric Vehicles in Energy Communities:
Investigating the Distribution Grid Hosting Capacity

Albert Ludwig University of Freiburg

Daniil Aktanka

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Abstract

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2 Literature Review

Good intro into EV situation and market: [1]

Really good method, but I can't math: [2]

3 Goal and Method

3.1 Approach

To reiterate, the goal of this thesis was to investigate the distribution grid hosting capacity of electric vehicles and the effect the involvement of energy communities can have on it. Over the span of roughly two months, the method presented in this paper went through countless iterations in terms of functionality as well as network application (down to the last two weeks before deadline). The original testing models were performed on a simple test network with arbitrary values (see fig. 3.1). These tests were done in order to get a feel for the chosen software tools and to better understand their potential real world application and the required scope of work.
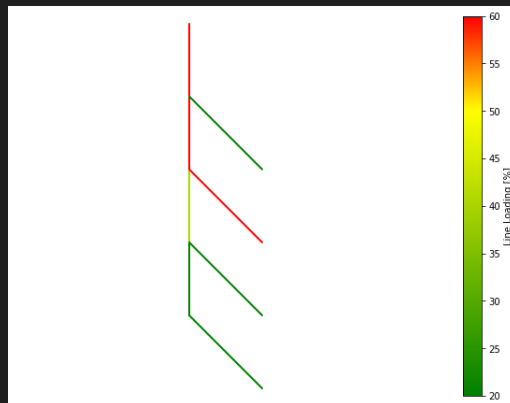

Figure 3.1: An example power flow calculation plot with line loading results. Here, one static generator is active out of four. The example network has generic coordinates instead of geographical, as seen in the rest of the plots in this paper.

Early on, it was decided to incorporate real-world data as a basis of the simulation. Arguably the best (at the time of writing) data platform for this application is Open Power System Data—more specifically, the contributed household data package. It contains measured time series data for various households and businesses relevant for low-voltage power system modeling. In terms of geographical scope, it incorporates data from 11 households in Konstanz, southern Germany, as part of the CoSSMic project for the optimization of energy systems in smart cities. The gathered data is quite expansive, spanning a time range of over 4 years with a resolution of up to 1 minute measurements, even tracking single-device consumption. Cumulative energy measurements accounted for data gaps from communication problems and "all data gaps are either interpolated linearly, or filled with data of prior days" [·], though no further detail is

provided in this regard. Overall, this was the perfect fit for my simulation aimed at a standard European low voltage grid of a residential area.

Using and incorporating the Open Power System Data household dataset proved to be quite a challenge on its own. Details regarding final data analysis are described in section 3.2. Once the data was processed and loaded into the network for further computations, the question became how to formulate and subsequently evaluate simulation scenarios. Hereby, the number of variables to take into account can practically be expanded far beyond the scope of the paper. For instance, an alternative tool considered for the simulation of load data was the LoadProfileGenerator (LPG), which is a highly-customizable tool for modeling residential energy consumption. LPG performs complete behavior simulation of a household residents in order to generate load curves. To that extent, it would have been possible to take said curves and implement them into our network case, while investigating individual households' behaviors across a community of like-minded, cooperative individuals. However, this was deemed far too comprehensive given the time constraints, but also not as potentially insightful.

Additionally, in order to make best use of the historical data, it was decided to perform time series iteration power flows. In a sense, this provides a similar advantage to LPG functionality by mimicking random human behavior over time, only with no unnecessary explanations behind it. The main idea became to sample a random historical load profile per household and to consider when/how an EV charger could optimally function in time. While this may be a relatively simple question to answer for a single household—given the residents' preferences and habits, it's merely a load optimization problem—the main issue lies with multiple parties involved. In turn, those parties are connected on a network in different ways, bringing topology into account. Thus, time and space both dictate the conditions for a given network.

Eventually, the abstract example network got superseded by the benchmark European Low Voltage Test Feeder (from hereon: test feeder) (see fig. 3.2). Three scenarios were chosen for evaluation: critical case, random charging, semi-coordinated charging. The critical case is used for hosting capacity evaluation of our simulation for singular time points, whereas the two other scenarios demonstrate time-dependent charging behavior models. Detailed explanation for this approach is given in section 3.3. From hereon, EV home charging stations will be referred to as static generators in the context of power modeling.
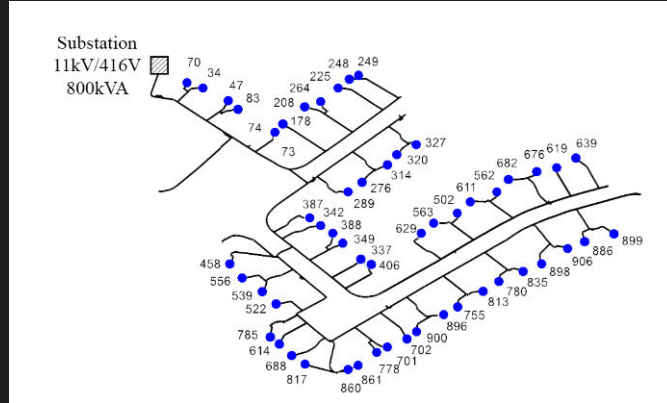

Figure 3.2: European Low Voltage Test Feeder network illustration. The blue dots are the active busses, representing households [4].

The next section will describe the functionality of custom python classes. For more details, consult the source code on GitHub at: https://github.com/akthonka/EV_energy_comm .

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3.2   Data processing

Given the scope of the project, the idea was to create a system flexible enough for iterative data manipulation and ideally one that would support multiple network types. The project was written entirely in python due to language simplicity as well as availability of advanced modules. Data handling was done using the `pandas` module, whereas the network simulation was performed using the `pandapower` module.

For the sake of clarity, most of the code was split between a python class file and jupyter notebooks. For early testing and code prototyping, jupyter notebooks are sufficient but they quickly lose readability as the code complexity grows. The general methodology was therefore to write core functions in jupyter to then integrate them into an external python class file. The resultant python class file consists of two classes: one for handling data processing and another for operations based on the `pandapower` module. Common input settings (for instance, the time window) are saved as class variables, such that only the most top-level functions are called in jupyter.

3.2.1   DataAction class

The following information describes the code of the python class responsible for core data processing. While the general methodology is applicable to any dataset, these functions are tailored specifically to the household dataset and will be described as such. Additionally, the functions mentioned here target the test feeder network as our simulation case but can be adapted for any network, with several caveats mentioned later. The following paragraphs serve to summarize the operation of one or more functions based on their application.

Data import and segmenting: The raw dataset is imported as a dataframe without additional options. Dropping the rest, we keep only 3 columns: `DE_KN_residential1_grid_import`, `DE_KN_residential2_grid_import` and `utc_timestamp`. Since we will be performing conditional time-based operations, we set the timestamp column as index for ease of use. While it is possible to front-load a lot of data processing functions at this step—such as parsing datetimes—it is not recommended due to unnecessary computation time. A better approach is to segment the data for piece-wise processing and function testing, whereby it would be possible to iterate computations over the entire dataset in the future. Therefore, we split the imported dataframe (of a little over a million data points) into a list of smaller dataframes (each 10000 data points long, with residual last dataframe being a bit smaller). If you are using class variables for storing the dataframe list, don't forget to clear it before each sampling run when performing bulk simulations (see section 3.2.3).

Datetime parsing function: This function converts a segment of the imported data into a specific, time-indexed dataframe. First, we parse datetime index, specifying the format as `"Year-Month-Day Hour:Minute:Second"`, after which we convert from UTC to Berlin time—the local time of the recorded dataset. While it is possible to import data with local time column `cet_cest_timestamp` without the need of conversion, it is not recommended for `pandas 1.4.3` since that will cause errors in datetime operations based on my experience. Second, we take the difference between consecutive rows. This is done in order to obtain minute-wise energy changes, since the household dataset only tracks cumulative energy values. If we use the `pandas.diff()` function, we must also drop the resulting first row, since it's a NaN row.

Night profile functions: This set of functions is fundamental for the simulation, as they are used to create a load profile for a single household. First, we must select a random dataframe segment with either of the two historical load profiles and parse it for datetime. The segment contains data on several days/nights, the dates of which we must identify. Then, for a random date, we must get the starting and ending datetimes for dataframe slicing. Knowing the starting time of our window—in our case, `18:00:00`—we need to create a datetime object for the chosen date, given the starting time. From said datetime (for example, `2015-08-16 18:00:00`) we add one day to the date and update the time with our morning value (getting `2015-08-17 06:00:00`). With these two datetimes, we can now slice the selected dataframe to obtain the required single house overnight load profile. Such datetime manipulations are very commonplace for this simulation.

Create loads and static generators: This function creates the dataframes used for timeseries iteration—from hereon referred to as night dataframes. These hold the inputs for the network values, for both the loads as well as the static generators (sgens). Depending on the timeseries controller, it is important to create the night dataframes in a very specific way: the names and the indices of the network components will dictate the conventions. Unless you are writing your own controller, refer to your documentation for more details.

To create the night dataframes, first get a random night profile. This contains all the necessary time steps in the index, which is what we need; the load values can be set to zero. Then, generate a list of appropriate load names and form a dataframe using the time index. For the case of the test feeder network, the resulting night dataframes are 721 rows × 55 columns (minutes × number of profiles). Repeat for both loads and sgens night dataframes. It is recommended to save these as class variables, since we will be referencing them throughout the entire simulation, as well as for troubleshooting purposes. Finally, we convert our night loads to MW units via a simple conversion factor multiplication.

Random static generators: These functions fill the night sgen dataframe at random times with a select sgen value. It's recommended to first reset the night dataframe by setting all sgen values to zero, otherwise location slicing may not overwrite the value. Getting a random set of starting and ending datetimes follows the same principle as described for night profile functions. It's important to keep track of zero-based indexing when calling random values from range. Additionally, in case of `pandapower`, the sgen sign needs to be set as negative in order to act as a separate static load that is an EV charger.

Energy community static generators: These functions fill the night sgen dataframe iteratively and cyclically (see section 3.3 for motivation). This method consists of two parts. In the first part, the starting times for sgens are determined. The allowed time values are bound by the time window, and are dependent on the time step (charging time). To compute the list of starting charging times, begin with the evening time value and add the time step iteratively for the number of sgens present. In our case, we have 55 sgens and a time window of 12 hours; for a charging time of 1 hour, that would result in 12 starting charging times. If we only had 7 sgens in the same time conditions, we would have 7 starting charging times, etc. The next part concerns the starting time sgen cycle.

For best practice, set all night sgen values to zero before writing new ones. The following step was done using `cycle()` function from the `itertools` module in python. Beginning with the evening start time (see section 4.3 for caveats), write the sgen charging value for the first generator, for the entire charging duration minus the last minute. The next minute, when the first generator is no longer active, fill the charging time window for the second generator, minus

the last minute. Repeat the process until the last unique starting charging time is reached, after which the next starting charging time will loop back to the beginning of the list. You may need to include a conditional statement for the beginning charging time minute, otherwise the loop will subtract one minute and cause a set of sgen columns to remain unfilled. Similarly, you may need to include a conditional statement for the last minute in the time series index, since that too will remain unfilled otherwise. Repeat this process for all given sgens. The looping time values can be handled with an extra class placeholder-variable for starting times instead of an entire additional look-up table.

3.2.2   NetworkCalculation class

The following information describes the code of the python class generally responsible for functions related to the `pandapower` module. In particular, its main purpose is perform timeseries iteration on a specific network. An additional function to calculate the hosting capacity is also contained here. The NetworkCalculation class is meant to be used directly in conjunction with the DataAction class and contains several direct references to its class name.

Network preparation and controllers: In order to perform the timeseries iteration we first need to prepare our network. In the case of our chosen simulation—test feeder network—this involves some additional steps (see section 3.3). First, create the network, including the loads and sgens. It's recommended to stick to a consistent naming convention for loads and sgens across the network properties and the external night dataframes, in order to avoid unnecessary problems when configuring the controller in the next step.

The controller is a function whose purpose is to update the network values iteratively from a lookup table. The methodology will depend on your software of choice, but in our case we will be using the `pandapower` controllers made specifically for timeseries module. Figure 5.1 in chapter 5 shows a general overview of the built-in module. For our simulation, we will need 2 constant controllers for loads and sgens. Hereby, the correspondent data sources are the night dataframes that were defined in the DataAction class. Lastly, the timeseries iteration needs to be given a defined number of time steps, which in our case will be given by the index length of (either) night dataframe. With this information, the power flow can be computed iteratively based on tabular variable inputs. However, this will yield no useful results on its own, which is why we need to additionally define an output writer.

Time iteration and output: An output writer is a function with a simple job of recording computed information, in an desired format, for each timeseries step. In our case, we will again be using the output writer function supplied with the `pandapower` timeseries module and outputting into an Excel file for the sake of convenience and troubleshooting. However, we aim to continue data processing in `pandas`, so we define another import function for said Excel results file. The imported dataframe can now provide relevant statistics and metrics. For our evaluation, the one of the key computations is the all-time minimum load value across all busses (see section 3.3 for more details).

Hosting capacity evaluation: Hosting capacity was computed iteratively for a network in a single point in time. All pre-loaded network settings (even from the timeseries iteration) stay the same, except for the sgen columns—those need to be set to zero at first. Do not confuse the night sgen dataframe with the network sgen column; for a single point in time, only the network-defined sgens are taken into the calculation.

Iteration was performed over the list of sgen indices using a `for` loop. The list is scrambled prior iteration in order to mimic uncoordinated charging patterns. An additional variable for storing the hosting capacity count is created. For each cycle of the loop, the following metric variables are computed by running a power flow calculation: minimum bus voltage magnitude per unit (vm p.u.) and maximum line loading percent. The next step is conditional. If the metric variables don't exceed preset limits, add an sgen value and increase the hosting capacity count by one. The loop proceeds onto the next cycle and computes the new power flow state of the network. Checking the metric variables again, if (at some point) the preset limits are exceeded, then we need to undo the effects of the last cycle. As such, the hosting capacity count is reduced by one and the last filled sgen is reset to zero. This breaks the loop. The function then computes one final power flow computation to obtain for an output plot and prints the maximum hosting capacity result.

3.2.3 Additional files

In addition to the formally described python class file and jupyter data processing notebooks, several other files were used for the simulation project. They serve as an extension to the already discussed functionality and will therefore not be covered in similar detail but deserve mentioning nonetheless.

Bulk simulation: Due to the random nature of the simulated load profiles selected from historical data, the results are prone to some degree of deviation. In particular, the network bus voltage minimum and maximum values in time are affected. While such deviations may not have a direct impact on the analysis of the hosting capacity evaluation, the two other scenarios—random charging time and energy community charging pattern—are more severely affected. Given the fact that our aim is to make a comparison between the random and the community scenarios, the simulation needed to be performed multiple times in order to obtain a reliable average and a convincing statement. For this purpose, a python file was created to perform bulk simulations. It follows through the same general steps described above with the inclusion of saving the vm p.u. minima (our limiting factor) to an external file per simulation per scenario. The loops are performed for 3 scenarios: random and community, as well as control, which does not include any active sgens. The results are loaded in and processed in jupyter and can be found in section 4.2.

Average minima and maxima times: As supplementary part of the analysis, the time extrema for the entire dataset were calculated. The goal was to compute the time point of highest and lowest network bus loads. The computation was performed in jupyter and follows the same data parsing principles described earlier with the addition of a running average. This is required in order to analyze the general trend and not the outlying points; for this purpose, a rolling average of 10 minutes was found to give the best results. While this computation does not directly affect the core simulation, it does justify the chosen time window as well as the starting point of the energy community algorithm. See section 4.3 for how these two points can be used to improve the proposed model.

3.3 Network application

This section builds upon the fundamental operating principles of the two classes introduced in section 3.2. It aims to explain the usage of the python class file in order to obtain the three scenarios for the test feeder. First, consider the following assumptions.

The network used in the simulation is an altered version of the standard test feeder. The original network itself is 3-phase, which would require a different power flow model—in case of `pandapower`, that would be handled by `pandapower.pf.runpp_3ph.runpp_3ph()`. However, given the right circumstances, it is possible to treat a 3-phase network as single-phase; namely, if we assume that all network loads are balanced. This assumption is plausible and corresponds to most real-world households, to the extent that some power modeling software don't even include a separate 3-phase computation option for this reason. With this assumption, all loads and sgens were defined and handled as single-phase in our simulation. The network was furthermore scaled down from 3-phase by dividing all the bus voltages by $\sqrt{3}$ to arrive at its single-phase equivalent.

The night-time bracket was chosen as `18:00:00-06:00:00` and serves as the allowed time frame for EV charging during the night. This night time is based around the common Western world business day hours, such as the standard office hours of 9 a.m. to 5 p.m. in USA; the time bracket is adjusted to account for often earlier starting hours in Europe. Hereby the EVs are assumed to be used for transportation to and from work, where charging is assumed to not be available. The chosen hours are commonly referred to as night time hours in this paper and code, even if the phrasing is applied somewhat generously.

One of the key factors of the simulation was the chosen sgen value. This corresponds to the charging rate of EVs, measured in kW. In terms of voltage levels—and by extension, the EV charging speed—AC charging is commonly separated into three levels. "The Levels 1 and 2 charging facilities can be installed in a private location while setting up of Level 3 charging facilities, involving separate wiring and transformer, requires permission from utility providers and are usually built in public charging stations" [1]. For this reason, level 2 charging was chosen. Most home charging stations that support level 2 charging usually provide an output of around 7 kW. The most common figure on the market as of this writing seems to be 7.7 kW, which was is why it was chosen as the sgen value.

With these assumptions and adjustments to the test feeder, the following 3 case scenarios were identified and analyzed.

3.3.1 Critical case scenario

This case scenario aims to address the hosting capacity of our test feeder given the most unfavorable circumstances. The evaluation process outline was as follows:

1. Load and prepare dataset

2. Create loads and sgens night dataframes

3. Load and prepare test feeder network

4. Define output writer and run the timeseries

5. Import the voltage magnitude timeseries results

6. Evaluate the all-time minimum and maximum load time points

7. Load the network configuration for those time points

8. Calculate hosting capacity at both critical time points

Hereby, at step 8, the sgens are placed in a random network locations for two points (minutes) in time. Timeseries iteration in step 4 is used to locate those points in time, but it does not compute over any sgen values. The hosting capacity is expected to be under 100 % for this scenario.

3.3.2 Random time scenario

This case scenario aims to represent completely uncoordinated charging patterns over the night time window period. It's used as a comparison for the energy community scenario. The evaluation process is similar to the critical case scenario:

1. Load and prepare dataset

2. Create loads and sgens night dataframes

3. Place sgens at random locations in the network

4. Load and prepare test feeder network

5. Define output writer and run the timeseries

6. Import the voltage magnitude timeseries results

7. Evaluate the all-time minimum load time point

Opt: Load network configuration for all-time minimum vm p.u. time point

The main difference from the critical case scenario is that we load sgens in our network before we run the timeseries iteration. Since the sgens charging times are spread across the night window, all sgens can be active at one point or another. This only becomes problematic should a relatively large number of sgens happen to be charging at once. At the same time, the household load profiles may offset a potential network overload if the charging convergence happens late a night when the loads are lowest—since most people are asleep and little to no household appliances are running.

3.3.3 Energy community scenario

This case scenario aims to propose the concept of semi-coordinated charging, whose main idea is that of simplicity with minimum requirements. As mentioned in chapter 2, there is no shortage of highly optimized models proposed. Both centralized charging management algorithms and decentralized/distributed charging mechanisms should undoubtedly serve as the goal of EV technology and its future implementation. That being said, these models remain mostly conceptual in nature, owing to their intricacy of operation as well as high upfront resource demands.

Indeed, while there have been tremendous advancements made in making individual grid elements and devices smarter, there's yet to exist a truly unified system at scale. The internet of things (IoT) offers a glimpse into a fully synchronized smart-device architecture but this concept does not transfer to vehicles as readily, due to their mobile nature and dependence on existing infrastructure. Arguably the minimum precondition for large-scale smart EV charging mechanisms is the existence of installed smart meters in residential homes. The spread of smart meter technology has proven to be highly incentivised by progressive energy tariffs and some success has been found in countries across Europe, such as Spain adopting a Real-Time-Pricing

(RTP) tariff in 2015. Unfortunately, many countries are still lagging behind the practically-feasible due to their complex governmental policies—Germany in particular has been struggling with residential smart meter roll out, despite its ambitious push towards embracing renewables. Needless to say, there still remain plenty of obstacles in the way of widespread, advanced EV charging systems.

With these considerations in mind, this paper proposes the most simplistic way to improve grid stability through altered charging patterns. This method in fact does not rely on the existence of smart meters or intelligent controllers and can therefore be implemented in any local network (section) in a form of a rudimentary energy community. In the scope of this paper, the concept of energy community is also simplified to its most basic premise—coordinated energy use. As such, the method can be viewed as the first stepping-stone in transition towards smart grid EV charging.

Theoretical considerations

Consider the following theoretical network depicted in fig. 3.3, not dissimilar from the original test case network.
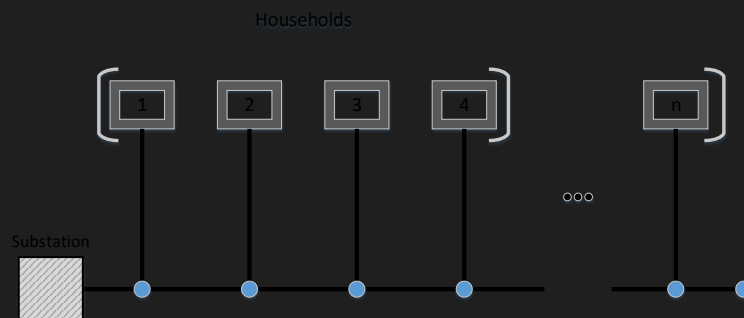

Figure 3.3: A theoretical network scenario for linearly placed single-line households. The energy community aims to include every new household member.

The linear topology of the theoretical network is reminiscent of the test feeder. Known as radial operation, this is the most widespread design in both MV and LV networks. Hereby, the North American system differs from the European in transformer placement and is not discussed further, as the application of the developed model is aimed at the European LV grid, although the results can in some extent be transferable. Furthermore, spot networks (commonly found in business and industry districts) as well as grid networks (typical for downtowns of large cities) are omitted in this theoretical scenario.

The theoretical radial network demonstrates a relatively straightforward load pattern. Every consecutively added household down the line from the substation increases the overall network load; the last household n acquires the network minimum in voltage magnitude in case of constant household load profiles. The goal is then to avoid the critical case scenario of network overload, which is most likely to happen at, or close to, the n'th household bus. Given these spacial considerations, we must also distribute the sgen loads temporally so as to minimize the network load. This amounts to two conditions. First, avoid multiple sgens charging at the same time as much as possible—this is the deciding factor between the two conditions. The best case scenario (generally) is an even distribution of sgens in time. Second, should there be a in crossover

charging times, the beginning of the network line should be prioritized, since its local voltage magnitudes will be (albeit slightly) lower than those at the end of the transmission line. The crossover of charging times is guaranteed to occur for a sufficiently large n and depends on charging time, which we assume is constant across all households. Next, consider the concept of coordination.

Coordination of energy use, in the context of our energy communities, begins with communication between multiple parties. In the most primitive sense, this can be as simple as an agreement between two neighbors to not charge their EVs at the same time of day. Assuming they both come home from work around the same time and want to immediately plug in their EVs to charge, one neighbor can agree to start charging after the other one is done. This alone will have an obvious beneficial effect on grid stability but would still imply most households charging around peak grid hours in the evening. The more coordinating pairs, the better. Eventually, we can extend this idea to the entire neighborhood, thus forming an energy community. The community decides to agree on dedicated charging times for individual households based on the philosophy described above.

Referring back to fig. 3.3, the energy community decides to allocate charging times iteratively, starting from the household closest to the substation. The first household will take the charging time closest to peak grid hours in the evening, the second will take the next available time slot after the first and so on. Once all the available charging time slots per night have been filled, the time slots will cycle.

Test feeder application

In the case of the test feeder, the allocated sgen charging times and cycles can be seen in table 3.1. On average we can expect $55 \, \text{sgens}/12 \, \text{hours} \approx 4.583$ sgens per given hour in the night frame, which correlates with our results.

start time	end time	sgens active
18:00:00	18:59:00	5
19:00:00	19:59:00	5
20:00:00	20:59:00	5
21:00:00	21:59:00	5
22:00:00	22:59:00	5
23:00:00	23:59:00	5
00:00:00	00:59:00	5
01:00:00	01:59:00	4
02:00:00	02:59:00	4
03:00:00	03:59:00	4
04:00:00	04:59:00	4
05:00:00	05:59:00	4

Table 3.1: Energy community charging times for test feeder network.

For spacial allocation, the sequence of predefined sgen locations in `pandapower` test feeder network was used. Additionally, line loading is generally expected to be around 1% per household line and was shown not to be the limiting factor for hosting capacity calculation.

4 Results and Discussion

The simulation results can be divided into two groups: hosting capacity and random vs energy community scenarios comparison.
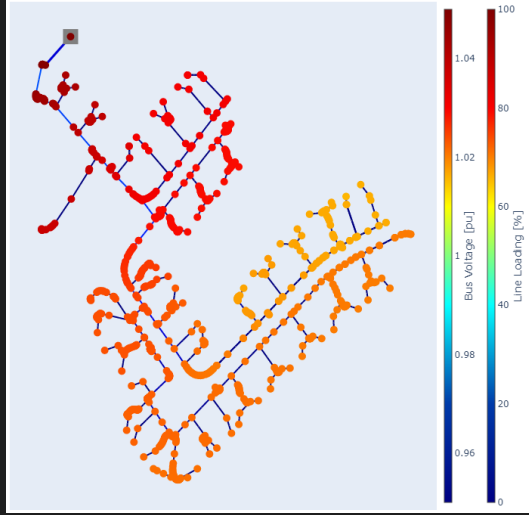
4.1 Hosting capacity

Hosting capacity calculations began by computing the time series with no sgens active. The network bus load example results can be seen in table 4.1. As expected, the the voltage magnitude per unit drops with each bus load—hereby the extrema are sometimes shared across multiple busses (even at higher significant figure counts). The time points for voltage magnitude extremes are unique however, which leads to two cases: minimum bus vm p.u and maximum bus vm p.u.

	bus_0	bus_1	bus_2	...	bus_904	bus_905	bus_906
count	721.000	721.000	721.000	...	721.000	721.000	721.000
mean	1.050	1.050	1.049	...	1.031	1.031	1.031
std	0.000	0.000	0.000	...	0.006	0.006	0.006
min	1.050	1.049	1.049	...	1.014	1.014	1.014
25%	1.050	1.050	1.049	...	1.027	1.027	1.027
50%	1.050	1.050	1.050	...	1.033	1.033	1.033
75%	1.050	1.050	1.050	...	1.036	1.036	1.036
max	1.050	1.050	1.050	...	1.041	1.041	1.041

Table 4.1: Example simulation timeseries results. The first bus's vm p.u. is at the upper acceptable bracket limit (both minima and maxima), whereby the last bus's vm p.u. minima is close to the middle of the bracket, which is optimal. This indicates that historical network loads are well suited for this network.

The network graphs for hosting capacity time extremes calculation are shown in fig. 4.1. Visually, we can see a big difference in color profiles for cases with different starting time points. Figure 4.1a shows significant line stress in the bottom two branches of the network (seen in yellow), as opposed to fig. 4.1c where the entire network is stabilized, implying less deviation between bus loads. Hereby we expect a greater hosting capacity for the maximum bus voltage time point case due to its color profile homogeneity (shown in red) and a bigger maximum range of vm p.u., which would allow to accommodate more sgens at the lower branches. As far as filled sgen hosting capacity graphs are concerned, there's little visual difference between fig. 4.1b and fig. 4.1d at this scale. For more insight, consider numerical data in table 4.2 and table 4.3.
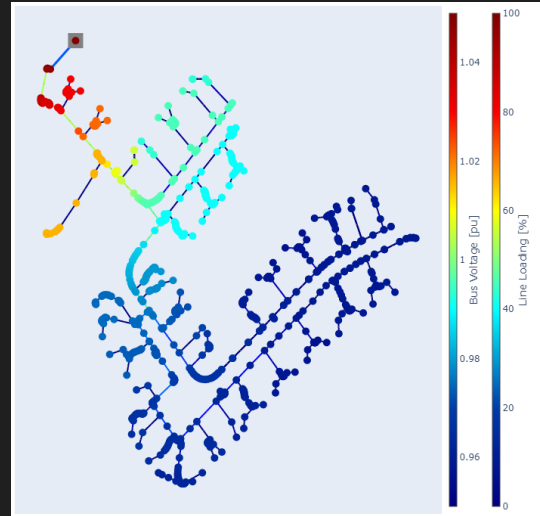
(a) No sgens at min bus voltage
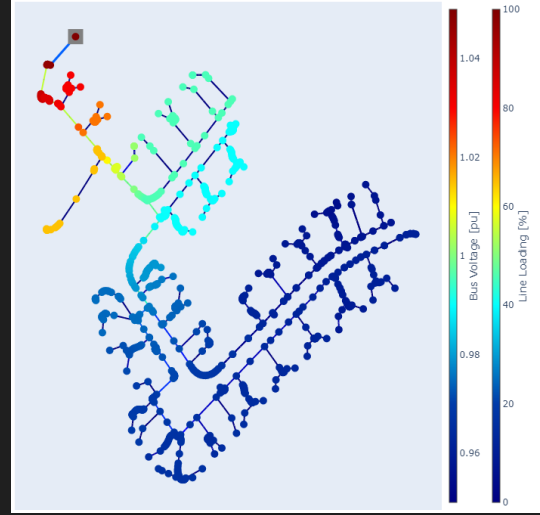
(b) Filled sgens at min bus voltage
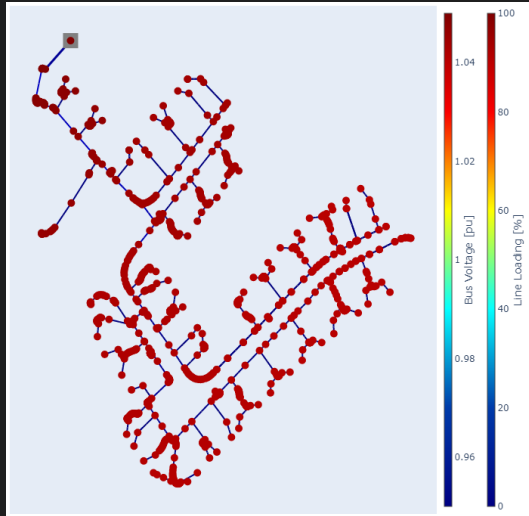
(c) No sgens at max bus voltage

(d) Filled sgens at max bus voltage

Figure 4.1: Comparison between hosting capacity during minimum (subfigures (a) and (b)) and maximum (subfigures (c) and (d)) load time cases with and without sgens.

The details of time point cases for each network are shown in table 4.2. We can see a significant difference in minimum vm p.u. values between the "Min bus empty" and "Max bus empty" cases. This is a numerical indication of a greater hosting capacity potential for the maximum time point case. For the columns "Min bus full" and "Max bus full", we observe no significant difference between the two min values—this indicates that the maximum hosting capacity has been reached in both cases at a vm p.u. lower bracket.

	Min bus empty	Min bus full	Max bus empty	Max bus full
count	907.000	907.000	907.000	907.000
mean	1.020	0.980	1.042	0.976
std	0.009	0.022	0.002	0.021
min	1.005	0.953	1.039	0.950
25%	1.014	0.963	1.040	0.963
50%	1.018	0.975	1.041	0.970
75%	1.025	0.994	1.043	0.987
max	1.050	1.050	1.050	1.050

Table 4.2: Hosting capacity voltage magnitudes in detail.

The key results of the hosting capacity simulations are summarized in table 4.3.

	Minimum bus voltage	Maximum bus voltage
number of sgens	6	12
total capacity [%]	10.9	21.8

Table 4.3: Hosting capacity results.

The scenario results show a rather low hosting capacity for both time point cases. As expected, the best case of maximum bus voltage has a significantly better hosting capacity—about double that of the worst case of minimum bus voltage. In a way, this is alarming because the probability of a network overload is definitely not negligible: it only takes $\approx 10\,\%$ of all households to charge their EVs during peak hours to cause a potential brownout/blackout. Furthermore, this time point is the most probable charging time point for any given individual under our assumptions of European work hours; without the presence of smart meters, a person is most likely to park their EV and set it to charge immediately. Considering the habitual nature of human actions, a network overload is only a matter of time in this case.

That being said, the issue can be easily avoided with relatively little intervention. Undoubtedly, all EV chargers do (and if not, will soon) include a time setting option, which is very easy to implement. Hereby, an EV owner only needs to enable and setup the charging hour parameter once, which is a matter of seconds. At the same time, one cannot deny that not everyone will bother to do so, nor that any potential software/firmware updates will reset the setting. As such, one is able to compensate for technological shortcomings (i.e. lack of smart EV charging) with conscious human intervention (i.e. manually setting the EV to charge outside of peak hours) and vice versa.

With this discussion we arrive at the transitional phase of semi-smart charging and the comparison between uncoordinated and semi-coordinated scenarios.
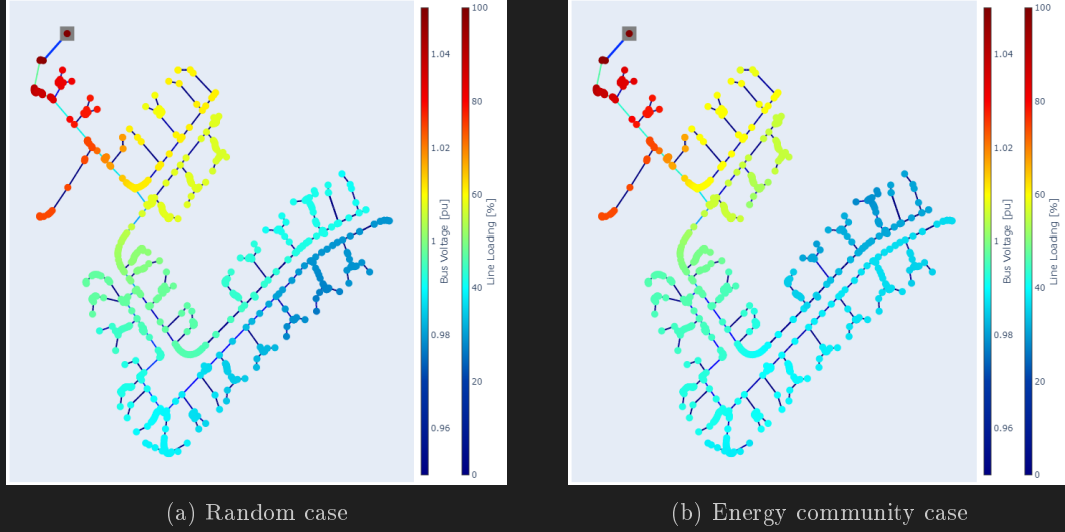
4.2 Random vs energy community comparison

(a) Random case   (b) Energy community case

Figure 4.2: Graphical comparison between random and energy community scenarios.

Scenario	Random	Community	Control
simulations count	10	10	10
avg min voltage mag [p.u.]	0.949	0.974	1.010
bracket deviation [%]	100.8	75.9	39.5

Table 4.4: Comparison between random and energy community scenarios.

Load bracket is defined as the acceptable range of bus voltage magnitude per unit. Following common network guidelines, it's taken as the open interval $(0.95, 1.05)$. Load bracket deviation percent is defined as:

$$\text{Deviation [\%]} = \frac{\text{upper bracket} - \text{average voltage}}{\text{upper bracket} - \text{lower bracket}} \times 100 \qquad (4.1)$$

Community is approximately 24.9% more effective than random case.

4.3 Suggested improvements

4.3.1 Assumptions

Charging time window of 1hr: how much driving is typically done? Time in traffic? Car energy efficiency?
Batteries will improve - hard to predict
Price considerations, cheaper chargers may be more popular
Not all grids will be able to support three-phase Level 3 charging

4.3.2 Method

The energy community spatio-temporal algorithm is in no way optimal and is an extreme over-simplification of the problem. Its main purpose is to serve as a starting point when there is none, and to serve as a demonstration for what said minimum effort can achieve in the context of grid stability.

Spacial: relies on correct ordering of busses for iteration and does not account for significant deviation or branching from linear topology

Temporal: Most sgens should be shifted towards night time for lowest loads. Code computed it as 20:26:30 but that doesn't make sense, need to examine larger trends.

4.3.3 Code

splitting function could waste less data (first day, last two days in list)
energy comm func could start the cycle at peak time (requires nested conditional for loop for both times and community function)
the matrix is exactly singular—jacobian could not be solved: no clue

5 Conclusion

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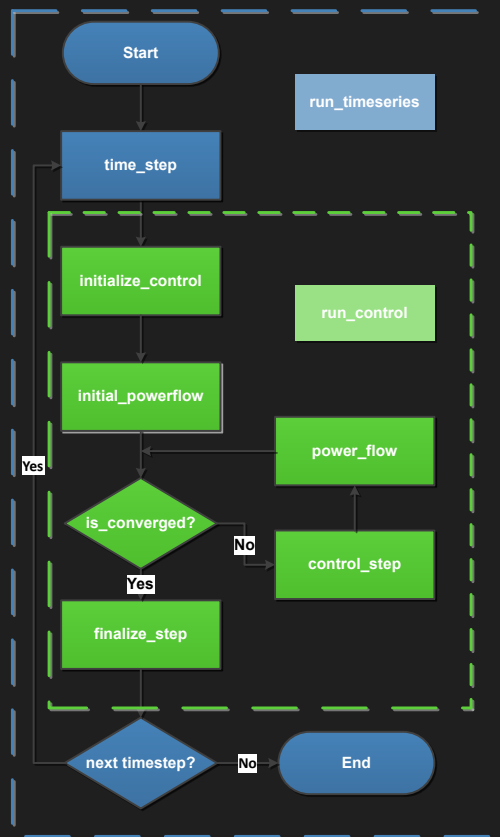
Appendix

Figure 5.1: The diagram shows the time series loop of the time series module. The basic functionality is compute the power flow for each time step using the given values—such as sgens or loads. Step-wise convergence will depend on several factors, such as the network parameters (i.e. load magnitudes) as well as the algorithm used for solving the power flow problem. For more module details, see the `pandapower` [wiki](#).