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Vehicle to Grid Battery Degradation Impact

A Comprehensive Study of Vehicle to Grid User and Grid Profiles to Model and Understand the Impact on Battery Degradation

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Abstract

Electrification of the mobility sector is necessary to make a lasting impact on emissions from an otherwise entirely dependent fossilized fuel sector. A key component to electrification is ensuring that electric vehicles do not disrupt an already complex energy grid system. This thesis focuses on vehicle to grid (V2G) scenarios in which EVs are used to supplement peak demand periods in the grid while also smartly controlling when the battery is charged up again. This raises the question of, how does the extra charging and discharging affect the battery life? Currently EV manufacturers offer warranties anywhere from 8-10 years when the battery gets to 80% of its original capacity. This metric is compared overall to several usage profile and vehicle to grid (V2G) scenarios to determine the effects on battery degradation with the goal to demonstrate and understand its impact on the battery.

Six weekday usage profiles, with weekend profiles considered, were constructed taking into account driving and charging habits when compared to grid data dictating peak energy demand periods. These profiles were outfitted into an AMESIM model, including a semi-empirical battery ageing model, calibrated to a 71 kWh battery electric vehicle (BEV) using a temperature estimation, charger, a generic nickel manganese cobalt (NMC) battery and driving cycle array. Finally, parameter effects within these profiles, such as power level, state of charge (SOC) limits, and frequency, were hypothesized on and compared in terms of capacity loss.

After running the model for 1 year, the results show that V2G does not significantly add battery degradation versus simply driving and charging on a normal use schedule. There is a 0.35% capacity loss percent difference between the reference no V2G scenario and the heaviest V2G use case, of 2 V2G discharge cycles per day. Over 10 years this would be about 12.5% versus 16.0% capacity loss, still within 20% of the original capacity. These results support the usage of V2G and demonstrate that the battery capacity loss is limited and upon the use of smart SOC management could even be less than non V2G scenarios.

Keywords Vehicle to Grid (V2G), Smart Charging, Bidirectional charging, Usage profile, Battery degradation, Peak demand, Grid management

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Abbreviations

V2G	Vehicle to grid
V2X	Vehicle to everything
EV	Electric vehicle
BEV	Battery electric vehicle
OEM	Original equipment manufacturer
SOC	State of charge
DOD	Depth of discharge
SOH	State of health
EU	European Union
CCS	Combined charging system
CHAdeMO	Charge for moving (type of EV charger)

1 Introduction

Electrification of the mobility and stationary application sectors, especially automobiles and grid side demand, is a major trend to reduce the reliance on fossil fuels to curb the emissions impact on the environment. Emissions from the energy sector make up 39.3% of the global total with transportation making up an additional 17.9% [1]. This is over half of global emissions. Taking advantage of solutions to leverage change in both sectors is highly sought after. Electric vehicles have begun to proliferate the market, with a goal of 60% of new vehicles sold to be electric by 2030 [2]. There will be nearly 350 million EVs by 2030. This means there will be an increase in demand for charging infrastructure as well as grid side support for all this newfound demand. Renewable energies like wind and solar, have become the norm set to make up 5,022 GW by 2026 which is nearly 80% more than the 2020 levels [3]. One main issue still facing these technologies is the ability to store energy effectively. The vehicle batteries do not have as long of a lifetime as customers desire to feel comfortable in their investment since battery replacements make up nearly half the cost of the vehicle and the renewable energies are intermittent, supplying energy during off-peak demand hours. Now, original equipment manufacturers (OEMs) / pure electric vehicle (EV) manufacturers and grid side aggregators / distributors alike see an opportunity to tackle both problems at the same time with vehicle to everything (V2X) capabilities.

This concept is most commonly called vehicle to grid (V2G), which is the ability to bidirectionally charge / discharge the vehicle [4]. Most battery electric vehicles (BEVs) at the moment, outside of a select handful, can only be charged from the grid when they are plugged in. This is helpful for the consumer but not so much for grid flexibility. With the number of EVs expected to rise so quickly, the grid will need to be able to keep up. Driving habits dictate charging times and for most vehicle owners their most consistent habit is commuting to work. This leaves vehicles needing to charge all at the same time which can put an immense load on the grid [5]. However, the peaks will be worse than the load if it can be spread out. This is where smart charging and V2G can come in to play. Smart charging offers the ability to delay charging to off-peak hours and charging up to be ready for a commute instead of relying on higher power levels to charge. Then, V2G allows the vehicle to provide energy to the grid during peak times so that we do not need to run costly, both monetarily and environmentally, peaker coal plants to make up the difference.

Current projects involve certain vehicles, like Nissan Leafs, that offer V2G capability already thanks to their CHAdeMO charging system. The ongoing research is mostly related to the support of the grid but less so on the effects on the EVs themselves [6]. This thesis aims to target specifically the battery degradation side of V2G. OEMs specifically are interested in this aspect because it could potentially put extra stress on the battery cells, with more charge / discharge cycles done per day, decreasing its lifetime. Battery degradation can be broken down into two main consequences, capacity and / or power fade that is influenced by many accelerating factors, such as time, temperature and cycling [7], [8]. A common set of metrics that are compared are the state of charge (SOC), remaining quantity of electricity available in a cell, or depth of discharge (DOD), how much of the battery has been used, in relation to the state of health (SOH), the ratio of the max battery charge to its rated capacity [9]. These metrics are commonly measured in experimental tests of real battery cells but also in models that are calibrated to predict how a battery will behave over time in specific conditions.

This thesis is focused on V2G market / project research combined with the modelling of an EV battery system over a 1 year period in order to understand battery ageing. The 1 year results are then used to understand the impacts on a 10 year warranty period. The modelling is done with an existing simple Siemens AMESIM model, that includes a semi-empirical battery ageing model, that considers calendar and cycle ageing. The V2G research was applied to the construction of usage profiles, taking into account driving cycles, charging instances, and optimal V2G discharging times based on grid peak demand periods. The inclusion of the aforementioned components calibrates the model.

The usage profiles were built to adhere to common driver commuting and charging habits combined with grid side metrics for peak demand, all within the European Union (EU). They can easily be extrapolated to a global scale though since driving commute practices are similar across the globe. The six weekday scenarios are as follows: two baseline ones with no V2G, two with one V2G period of 4 hours in the evening energy peak and two with two 2 hour V2G periods in the morning and evening peak windows. Weekend scenarios were also constructed to be included in the simulation to fit in with the weekday models. There are two stay at home ones, two for quick errands, two for short road trips and one longer road trip that only occurs 5 times a year. Then there are an additional set of parameter changes per scenario with charging frequency, SOC limit and power level differences. Temperature is estimated based on a day / night cycle with seasonal variations. Running the model with these profiles serves to answer the following questions which are explored from an OEM, grid operator and consumer perspective:

1. Does V2G make sense to implement from an EV battery health standpoint over a 10-year warranty period?

2. Which driver usage profile scenario adjusted for charging / discharging frequency, SOC limit, or power level make the biggest impact on battery degradation in terms of capacity loss?

These questions are set to be answered by the validity of the created usage profiles, the accuracy of the model components, and the graphical capacity loss results that are produced from the model. The results can be classified by scenario and parameters to help provide OEMs and battery manufacturers with key insights for future battery technologies and EV optimizations.

2 Vehicle to Grid (V2G) System

The concept of V2G is not new, it was originally thought of as a concept back in 1997 long before EVs were mainstream [10]. This idea was promised as a solution to avoid overloading the grid with large amounts of EVs but also a way for off grid homesteads to remain disconnected from the grid with nothing but solar panels and an electric vehicle. The idea gained traction in 2011 in Japan with the Fukushima nuclear disaster that caused rolling blackouts across the country. People wanted a way to have backup power for their homes plus a way to keep critical services active in emergencies. Nissan then put a lot of focus into adding the capability into their EVs, like the Nissan Leaf. The CHAdeMO charger system was born and most projects to this day involve this type of system. One issue is that CHAdeMO systems are not popular across the EU or the US. The current standard is the central charging system 1 and 2 (CCS1 / CCS2). Taking that into consideration the V2G studies involving CCS are increasing [6].

V2G at the core is a suite of technologies that allow for an EV to bi-directionally receive or provide energy. The main use cases are to shave (lower) peak energy demand windows. Today the standard is just to have vehicles receive charge when connected to electric vehicle supply equipment (EVSE), like chargers and inverters. V2G adds complexity to an otherwise simple system. When a vehicle is plugged in today, the systems onboard can check the SOC and determine how much charge to take on depending on the available power. This is determined by the maximum rate power of the onboard charger of the vehicle but also that of the charging system to be plugged in. The main technologies involved in V2G are the grid itself, charging strategies, and electric vehicles.

2.1 Energy Grid

V2G by definition relates to the use of the vehicles in conjunction with the grid to help balance peak demand. The other added benefit is the use of the system to store excess renewable energies which have been proliferating the market exponentially over the last decade. In order to achieve 100% electrification, renewables will play a significant role, but they are intermittent, occurring during off peak windows. Solar occurs during the middle of the day and wind is even more sporadic depending on weather. At the moment this means that there is underutilized or even wasted energy throughout the day. There are many studies that focus on the shifting of these lulls to lower peak demand. One big focus now is to use the readily available batteries in EVs to store, for example, solar energy during the day and then discharge during the evening peak window. Grid management is key to ensuring that the transition to 100% EVs does not overload the grid. If all the vehicles in the EU were to go EV, there would be 250 million vehicles, with approximately 0.15 kWh per km [11]. With the yearly 12000 km average driving distance there would be an 1800 kWh of charging per year per car [12]. In total to charge all the vehicles for a year would require 450 TWh would be needed. This is 16.2% of the total grid energy generated in the EU, at 2785 TWh [13], so it would technically be feasible to charge all vehicles at once outside of peak demand hours. The main issue it that nearly everyone arrives home at the same time from work and then their EVs are set to charge while lights, ovens, and endless electronic devices are put to use at the same time. This is how the concept of charging strategies could be a solution.

2.2 Charging Strategies

Charging strategies largely come down the users' habits and schedule, plus the availability of charging infrastructure and its power capability. Refueling gasoline / diesel is second nature these days and is quite standard. A driver fills up when they are low or in advance of a large trip. There is rarely any worry about whether or not there will be a place to refuel and the refueling process takes minutes so it does not hinder travel time. These factors are what charging infrastructure is needing to figure out, both in terms of technology but more importantly proliferation speed of the chargers themselves. This is more for public charging infrastructure but eventually V2G could be implemented in these situations as well. The more ideal place for V2G is the work or home, where vehicles will be spending a long time idle. Most consumer electronics are used during peak hours and EVs would be a large load when set to charge so in order to combat this, smart charging and charging levels are necessary.

2.2.1 Smart Charging

Smart charging is a term that is popularly used to describe controlling with a management software when an EV charges or not and at what speed. This system can either delay charging until it is suitable for the grid or provide more or equal energy to certain vehicles in specific locations when there is excess solar [14]. Smart charging allows charging infrastructure to remain as is because even if more vehicles show up to a set of stations the energy can be appropriately distributed [15]. The combination of data connections is what allows smart charging to accomplish these feats [16]. The ability of V2G to both charge and discharge adds variables but with the data management it is still feasible. Therefore, if a company is working on V2G there is also a smart charging component to it. V2G is essentially a smart charging and discharging system.

2.2.2 Charging Levels

There are three common levels of charging, 1, 2, and 3. Level 1 is slow trickle charging coming in at about 1 - 1.8 kW, which is almost unusable for an EV except as back up. Level 2 charging is the current standard for the home, work or public EV charger power level. It is in the 3 - 22 kW range with the trend towards an 11 kW norm. Most installed chargers today are of this level 2 region which goes up to 22 kW. Level 3 charging then is the fast or rapid charging which can be up to 30 - 360 kW [17]. With each level battery degradation increases due to the increased stress applied to the battery over such cycles. When V2G is put into practice then a logic system needs to be applied so that the system knows when to send power to and from the grid. This adds extra complexity, and therefore cost, which is still to be determined where that cost will be accounted for- the vehicle or the charger. The vehicle means it is a consumers cost while in a charger means it could be a cost of the charger company or even the purchaser of said charger. The other challenge is determining what happens to the EV battery during these V2G periods. The additional cycling will cause more degradation but how much and how fast is a raised question. In order to understand this phenomenon, the causes of battery degradation must be analyzed. In addition, the type of EV needs to be taken into consideration, which in turn determines the type of battery in the system.

2.3 Electric Vehicles

Grid infrastructure changes less often than the vehicle market so the change made for the grid needs to match the EVs. From the perspective of OEMs, the focus is to make sure their products are reliable which is why the idea of a battery degrading faster than it should is not desirable. Needing to make space within the vehicle for more capable charging systems could potentially impact design. Other factors that play a part in how V2G can be utilized is accepted power level of the vehicle. Many OEMs are making the business decision whether to include the highest portions of level 3 charging. This is in part because of cost but also for the sake of the vehicles warranty. The most critical and expensive portion of an EV is the powertrain, making up about 51% of the total cost. The powertrain includes the battery packs, inverters and controllers with most of that 51% coming from the battery itself [18]. Due to this fact, consumers maintaining the battery health is of paramount importance. At the same time the OEMs do not want to misjudge how long the battery will last or allow extra strain to be applied to it because that would reflect poorly on the company. The fact that legislation is in place for no new internal combustion engine vehicles (ICE) to be sold by 2035 across the EU [19] and many American states [20] leaves OEMs to change their entire lineups in a short period of time. This makes this research even more important to the future of EV manufacturing and how batteries will be designed. The batteries need to have high energy density in order to be as small as possible to fit into the vehicle while still offering high performance and range. Looking at the characteristics of a battery led to the tracking of the right metrics in order to accurately determine battery degradation from V2G instances.

3 Battery Degradation

The main EV component is the battery and it also determines the performance and range of the EV which are the parts that directly impact the user experience. Then the user experience reflects back on the EV manufacturers first and foremost, not necessarily the battery companies, so it is paramount to get the degradation research right. This way the proper warranty and applications can be offered to customers. Reliability plays big part in the battery degradation research focus.

In order to understand battery degradation, it is important to understand battery assembly. Batteries consist of two electrodes, an anode and cathode, electrolyte, and separator, in addition to a housing mechanism. Using lithium-ion batteries as a reference, the anode is usually graphite that gives the lithium-ions a place to insert when there is a charge. The cathode is an active material consisting of a lithium mix that provides the lithium-ions. The electrolyte is a lithium salt mix that allows for the ease of movement of li-ions [21]. The separator is a plastic material usually made of polyolefin to allow ions to pass but not anything else so that the odds of a short circuit are minimal. Short circuits are a form of instantaneous battery degradation when the anode and cathode touch [22]. This phenomenon is more often than not occurring in a quick period of time like a puncture of the cell. Longer term short circuits can happen thanks to lithium plating that is listed a degradation mechanism in Figure 1. The lithium plating continues to grow off of the edge of the active material until a dendrite is formed. This dendrite can eventually pierce the separator causing a short circuit [23].

The main battery in the EV market currently are the lithium-ion chemistries, either lithium iron phosphate (LFP) or NMC. NMC wins out over other chemistries thanks to higher energy density, power density and charging properties [24]. This thesis study was conducted using a generic NMC lithium-ion cell but battery degradation is a factor irrespective of battery chemistries and applications. Therefore, degradation needs to be considered before any additional usage / charging / discharging strain is put onto a battery.

3.1 Causes

Calendar and cycle ageing are the two main overarching themes of battery degradation. Calendar ageing is simply based on time and can be classified as the lost capacity during storage whereas cycle ageing is due to repeated charging and discharging. The key aspects of battery degradation are related to acceleration factors, degradation mechanisms, degradation modes and the consequences of all those [7]. These can be represented in Figure 1.

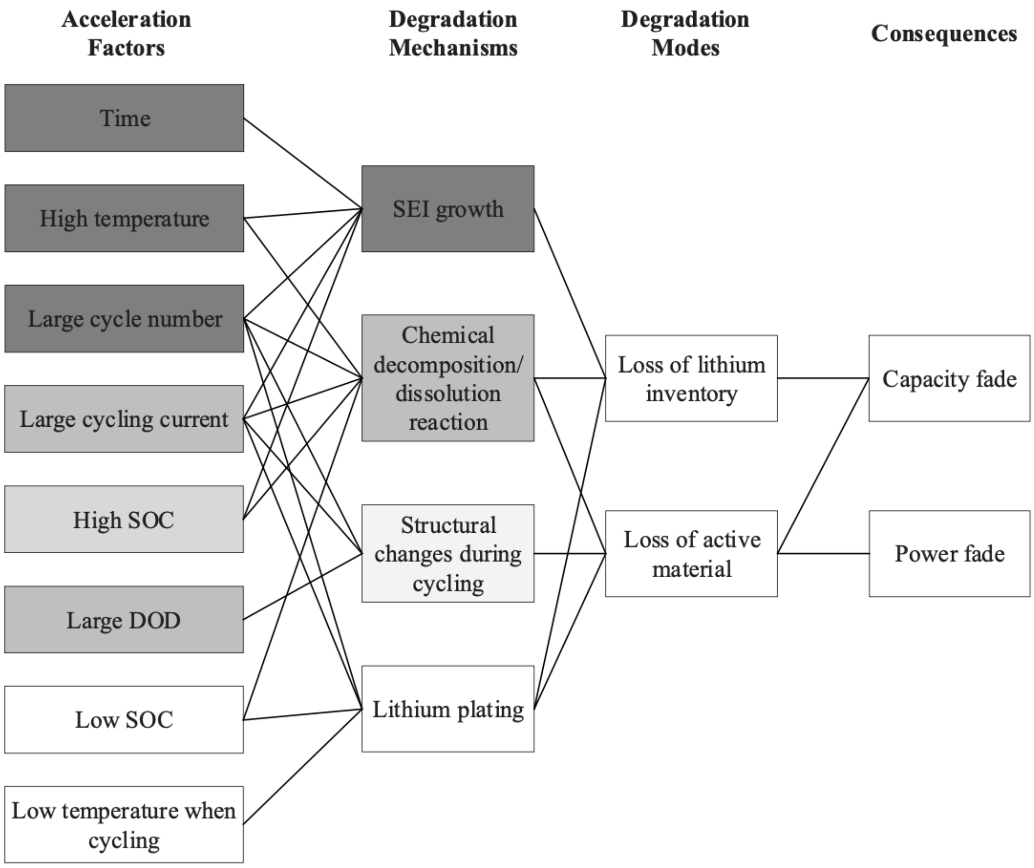


Figure 1: Battery degradation components [7]

Starting from the consequences and working backwards there are two consequences, power fade and capacity fade. Power fade is the loss of power output available and capacity fade is the loss of capacity compared to the original battery levels. These then are the metrics which can be measured easiest to determine battery degradation. In terms of this thesis the main focus output for comparison is only capacity fade. Different models can output different metrics and capacity fade is the straightforward result from the semi-empirical model, this will be discussed in further detail in section 3.3 below.

As shown in Figure 1, the consequences come from the degradation modes which are loss of lithium inventory and loss of active material. Both impact capacity fade so it is a bit more accurate of a metric than power fade which is only influenced by the loss of active material. Active material is located in the cathode as the lithium portion and it accounts for the number of lithium-ions available for intercalation [25]. As the active material shrinks there is less space for the lithium-ions to go to. The loss of lithium inventory happens over time as more and more lithium-ions become stuck in the graphite anode layers, like a leak draining a basin of water. This lowers the capacity further since less and less of the ions are moving during charge and discharge [26].

The degradation mechanisms are what perpetrate the degradation modes. Solid electrolyte interphase (SEI) growth, chemical decomposition / dissolution reaction, and lithium plating impact the loss of lithium. Then the addition of structural changes during cycling and subtraction of SEI growth work to enact the loss of active material. The SEI layer is an important factor that initially helps cell performance, without it there is a harder time for the lithium-ions to intercalate in between the graphite sheets of the anode. It forms on the edge of the anode as some of the electrolyte solidifies during formation of cells at slow current rates (C-rates) [27]. The issue with the SEI layer is that it continues to grow as the cell ages, eventually making it harder for ions to cross, which in turn creates a loss of lithium inventory and capacity fade.

The acceleration factors are plenty and are the main focus of this thesis because they create the mechanisms and modes which eventually lead to the consequential mechanisms that can be tracked from outside of a cell, via tests or by a model. Time is a constant accelerator of the SEI layer. All the factors from temperature and cycling effect the degradation of the battery the most. High temperature causes the electrolyte to break down between the electrodes leaving the SEI to form quicker as well. Low temperatures during cycling cause lithium plating. A cycle of a battery is one charge and discharge so large cycling numbers put the system into stress more often [28]. Large cycling currents leave the system during cycles at a higher stress, since there is an optimal current level that is best for the battery. During quicker charging sessions, this is increased. Keeping the battery at a high or low SOC for extended periods of time can cause expedited chemical decomposition. Instances of large DOD also leave structural changes [29]. Each of these factors that occur with regular use, especially with driving use cases and charging strategies, can be varied in order to achieve different levels of consequences. The tests and models used in these types of studies and how they are applied in the V2G context is continued in the following two sections, 3.2 and 3.3.

3.2 Standards / Tests

Due to the prevalence of battery degradation each and every cell must be checked for compliance with the standards. These standards set the baselines for each chemistry type. What starts with testing at lab scale becomes very important when batteries hit Gigafactory scale for mass production. Battery cells are everywhere but especially at the large cell count present in EVs safety becomes a big concern in hand with degradation. Most testing of cells comes in the form of cycling them over and over again to understand cycling ageing. Companies will run formation cycles, test those, then run cycle and impedance tests within a cycler. The comparisons between time, temperature, various C-rates and charge / discharge cycles become how the cells are verified for performance. Usually, capacity is plotted against voltage to show the batteries difference at different C-rates for discharge / charging [30]. Then for calendar ageing it becomes easier to enter the details of the cell into a model because then the results will come out much quicker. The model used in this thesis could do 10 years' worth of simulating in about 4 hours. The simplest way to measure battery degradation is to use capacity or power fade. Other common ways are remaining useful life (RUL) or to combine capacity and power fade into degradation cost [31]. Since the AMESIM semi-empirical model does not take into account power fade the study will focus on capacity fade as the main metric. This is essentially a measure of state of health (SOH) because it is current capacity compared to the initial capacity.

3.3 Models

There are several categories of models for the use of battery degradation which all provide a different accuracy, complexity level, and data dependency. Due to this the models are all best used for specific applications. The categories can be broken down into theoretical models, empirical models, and semi-empirical models, each of which have their own subcategories as detailed by Figure 2.

Models		Indicators	Degradation Origins Captured	Accuracy	Complexity of Model Implementation	Data Dependency	Suitable Applications
Theoretical models		Capacity loss; Resistance increase	Calendar ageing; Cycle ageing	High	High	Low	Mechanism analysis
Empirical models	Arrhenius-based models	Capacity loss; Resistance increase	Calendar ageing; Cycle ageing	Low	Low	Medium	System planning and operation analysis; On-board estimation
	Cycle counting models	RUL	Cycle ageing	Low	Low	Medium	
	Ah/Wh-throughput models	RUL	Cycle ageing	Low	Low	Medium	
	Other regression models	Capacity loss; Resistance increase	Calendar ageing; Cycle ageing	Low	Low	Medium	
	ANN-based models	SOH	Calendar ageing; Cycle ageing	Medium	Low	High	
Semi-empirical models		Capacity loss; Resistance increase	Calendar ageing; Cycle ageing	Medium	Medium	Medium	System planning and operation analysis

Figure 2: Battery degradation model comparison [7]

3.3.1 Theoretical Models

First, the theoretical models can output both capacity loss and power fade. The focus is on the use of equations reflecting the electrochemical and physical principles that impact battery lifetime and even performance [32]. Specific battery design features, like porosity or electrode thickness, are adjusted to understand their effects on degradation. Due to the inclusion of these features the model's accuracy is highly dependent on the availability of this information. The models also tend to focus more on main degradation mechanisms, like SEI growth, than some of the others so they are best for mechanism analysis.

3.3.2 Empirical Models

Empirical models rely more on large datasets and equivalent circuits than equations like theoretical models. There are also many types, so the types of degradation metrics are not necessarily both calendar and cycle ageing. The types are Arrhenius-based, cycle counting, Ah / Wh throughput, regression and artificial neural network (ANN) based models.

The most common battery degradation model is the Arrhenius-based model. They can also be classified as semi-empirical since they combine parameter estimation with physical equations. This model using the Arrhenius equation takes into account stress factors, at the most basic level just temperature, and how they factor into the ageing rate [33].

Cycle counting models focus on the number of cycles until a battery is considered at end of life. This is generally agreed upon in the industry for mobility applications as 80% of its initial capacity, 1500-2000 cycles, or in the 161000 – 322000 km range [34], [35]. Where this value starts to change is when the DOD is adjusted within those cycles so that is the main factor in cycle counting models.

Ah / Wh throughput models are more interested in the capacity fade due to how extreme charging / discharging events are. Typically, only charging throughput is looked at but V2G scenarios could easily be incorporated. The battery can only withstand a certain level of throughput for both Ah, current charge, or Wh, energy, and therefore it is tested until it fails [36].

Regression models are just an analysis of specific stress factors using regression methods, such as polynomial or linear. The expressions for the type of data are chosen and then there is a fit done to them to represent the battery degradation [37].

Lastly, the ANN based models sift through a lot of input and output data to make comparisons which is a form of guided or unguided training of the model. Accurate datasets are necessary as they determine the accuracy of the model but also of the ANN system itself. The other empirical models are based on equations so the parameters can easily be changed to incorporate various battery chemistries but with the ANN this would require entirely new data sets and training [38].

Overall, empirical models are better for system planning and operation analysis than theoretical models but also useful for faster calculations needed for on-board estimations. The on-board estimations help with calibrating battery management systems, these keep track of SOC and SOH for the user but also to keep the battery healthy for longer. The issue with empirical models is that many of them have low accuracy due to a low level of complexity in the incorporated data.

3.3.3 Semi-Empirical Models

Semi-empirical models offer the best of both theoretical and empirical models by taking into account mathematical theories and also datasets from experiments. The higher level of accuracy compared to empirical models is a generally longer computational time. This is the reason that these models cannot be used for battery management systems as they are too slow but also, they tend to be offline. Common factors included are discharge rate, temperature and cycle numbers [39]. The semi-empirical model offers higher accuracy but also enough complexity to have the factors most associated with V2G included. Therefore, the semi-empirical model is the most appropriate for the sake of this thesis centered on the charging / discharging heavy scenario of V2G.

4 Research Methodology

In order to create a proper comparative picture of the effects of V2G, first usage profiles needed to be created. These profiles would demonstrate what a typical EV and its battery would go through on a daily / weekly / yearly basis. The profiles can be split into weekday scenarios and weekend scenarios. This distinction is important because during the week schedules are pretty routine for commuters heading to work and back home. The weekend can be much more varied involving even instances of rapid charging. The usage profiles once constructed gave the semi-empirical model the direction to output the battery degradation metrics, taking into account both calendar and cycling aging, in terms of capacity fade.

4.1 Usage Profiles

The goal of the usage profiles was to create as close to real life scenarios based on a combination of research into prior studies, interviewing EV drivers and the balancing act between keeping the vehicle always charged and keeping the battery healthy. The main assumptions, some researched and the others created from the research, were as follows:

1. Most drivers would follow battery health recommendations set forth by the car manufacturer (SOC max/min of 90/10% or 80/20%) [40]
2. Weekly driving consists primarily of commuting to and from work
3. The battery size of the vehicle is 71 kWh of useable energy (right at the current average for EV battery size ~65 kWh [41])
4. The grid would only need V2G during peak periods [42]
5. Users' vehicles are available for V2G for 95% of a normal work day

4.1.1 Weekday Scenarios

The weekday scenario was the main focus because this takes up majority of the year. Five out of 7 days in the week are dedicated to regular commuting patterns. The average EU commuter drives for an average of 30 minutes to work in the morning with a subsequent 30 minute drive back home in the evening [43]. Analyzing data from the EU showed that most work schedules are from 09:00 – 17:00 [44]. Therefore, a commute period was established from 08:00 – 08:30 and from 17:00 – 17:30 each weekday.

Taking into account a generic NMC battery vehicle with 71 kWh of useable energy a 30 minute and 23 km distance worldwide harmonized light-duty test procedure (WLTP) was run in a more complex thermal EV model. This includes some low, medium, high and extra high-speed phases of driving, simulating a bit of city and highway driving within the commute. This will be explained in further detail in section 4.2 describing the AMESIM semi-empirical model and the components that make it up.

The weekday scenario can be further broken down by when an EV user decides to charge, when their vehicle is available for V2G and when the grid could potentially require V2G. EV users can be broken into a couple categories for how they like to charge, overnight plug in only, always keeping the vehicle topped up, just charging when absolutely necessary or a combination of the them [45]. These charging habits play a big part into when the vehicle is available for V2G.

Considering a normal work week as described above vehicles are available for up to 95% of the day. This is due to the nature of commuting 1 hour of total time to work and back, leaving the rest of the day as potential V2G periods [46].

$$24\ hrs\ in\ day - 1\ hr\ commute = \frac{23\ hrs}{24\ hrs} * 100 \approx 95\% \tag{1}$$

Most EV owners today are homeowners with a place to charge at their home but as the numbers increase there will be more of a shift to charging at fast chargers or work with all of the people living in apartments. For the sake of this thesis, it is assumed that drivers have access to bi-directional chargers at both home and work. This gives the ability to demonstrate V2G at a maximum capability in an effort to prove that the battery degradation is of a reasonable amount.

The nature of the grid means that even with EVs available 95% of the time during the work week they cannot be utilized that entire time. The optimal V2G windows become the morning and evening peak periods which allows for slower charging at all other times of the day. Research was conducted to discern the optimal time for V2G utilization. Figure 3 was created showcasing the results of 9 studies [47]-[55]:

Figure 3: V2G peak demand article comparison [47]-[55]

Taking all these factors into account the following weekday scenarios were created:

1. No V2G with only overnight charging
2. No V2G with overnight & solar charging
3. One V2G evening period with only overnight charging
4. One V2G evening period with overnight & solar charging
5. Two V2G periods with only overnight charging
6. Two V2G periods with overnight & solar charging

Scenario 1, Figure 4, and 2, Figure 5, are used as the baseline to set the stage for the V2G comparison. Considering the grid fluctuations from solar energy, the importance to utilize charging during the day allows for a deeper depth of discharge (DOD) from the battery to the grid. The comparison helps to paint a picture of the benefits of combining V2G with smart charging.

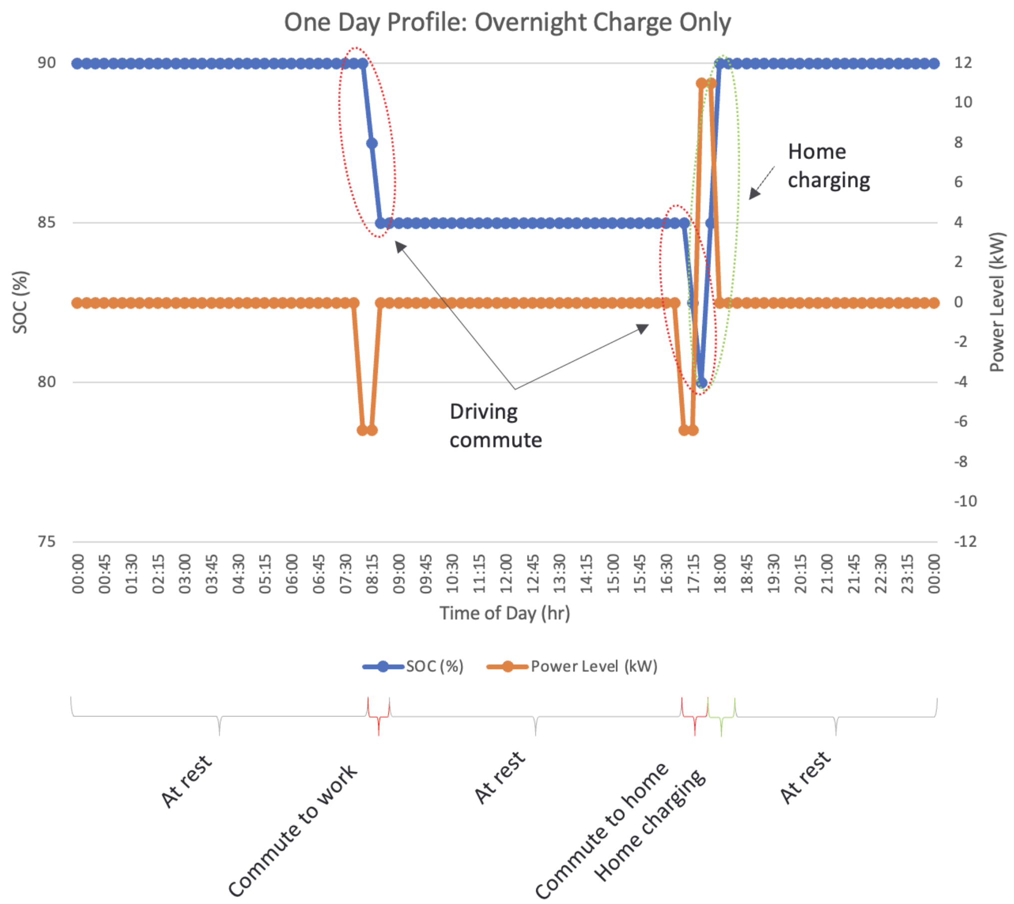


Figure 4: Scenario 1 daily custom-built profile

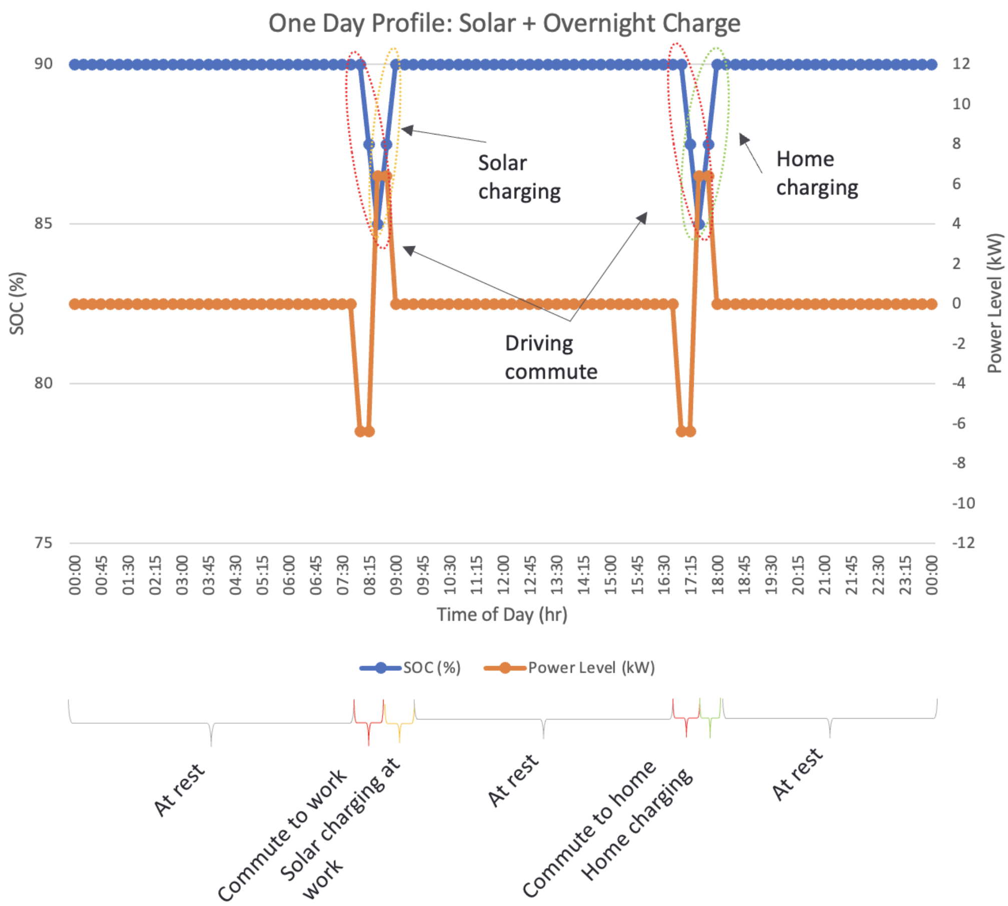


Figure 5: Scenario 2 daily custom-built profile

Scenarios 3, Figure 6, and 4, Figure 7, are then addressing the largest energy peak demand of the day in the evening, between 18:00 – 22:00. This four hour period is especially crucial because of the habit for many EV drivers to simply come home and plug in their vehicles. This way the vehicles are still plugged in but they can support the grid before slowly being recharged overnight when they are required again.

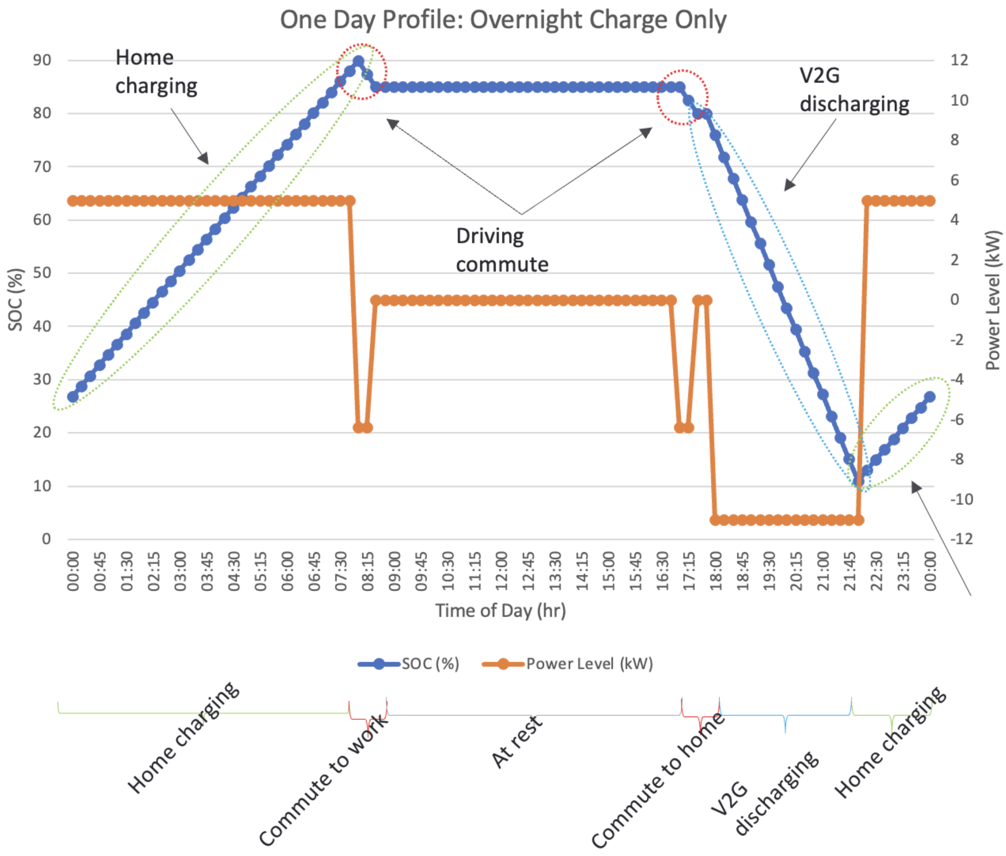


Figure 6: Scenario 3 daily custom-built profile

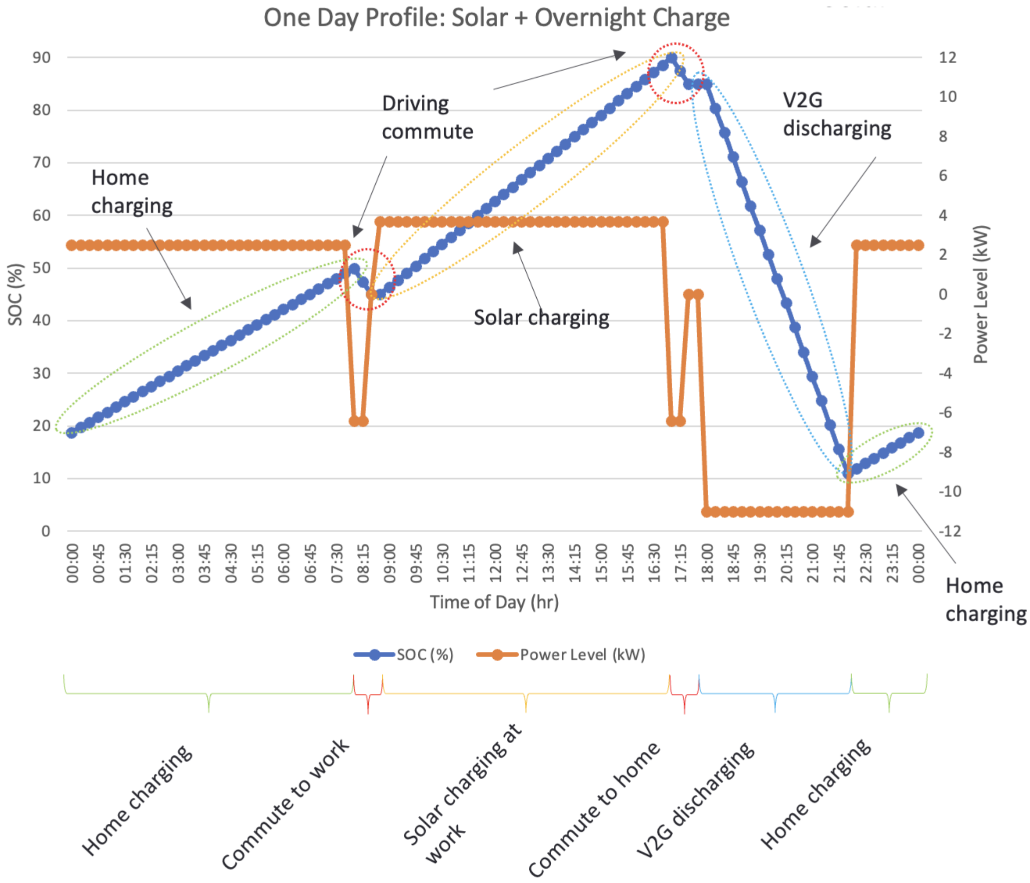


Figure 7: Scenario 4 daily custom-built profile

Lastly, scenarios 5, Figure 8, and 6, Figure 9, offer two V2G periods both morning (06:00 – 08:00) and evening (20:00 – 22:00) to completely cover the peak periods while still providing the user with the ability to use their vehicle. A key component of this system will require a manual override for users in order to ensure the necessary amount of charge if they so require it outside of normal scheduling.

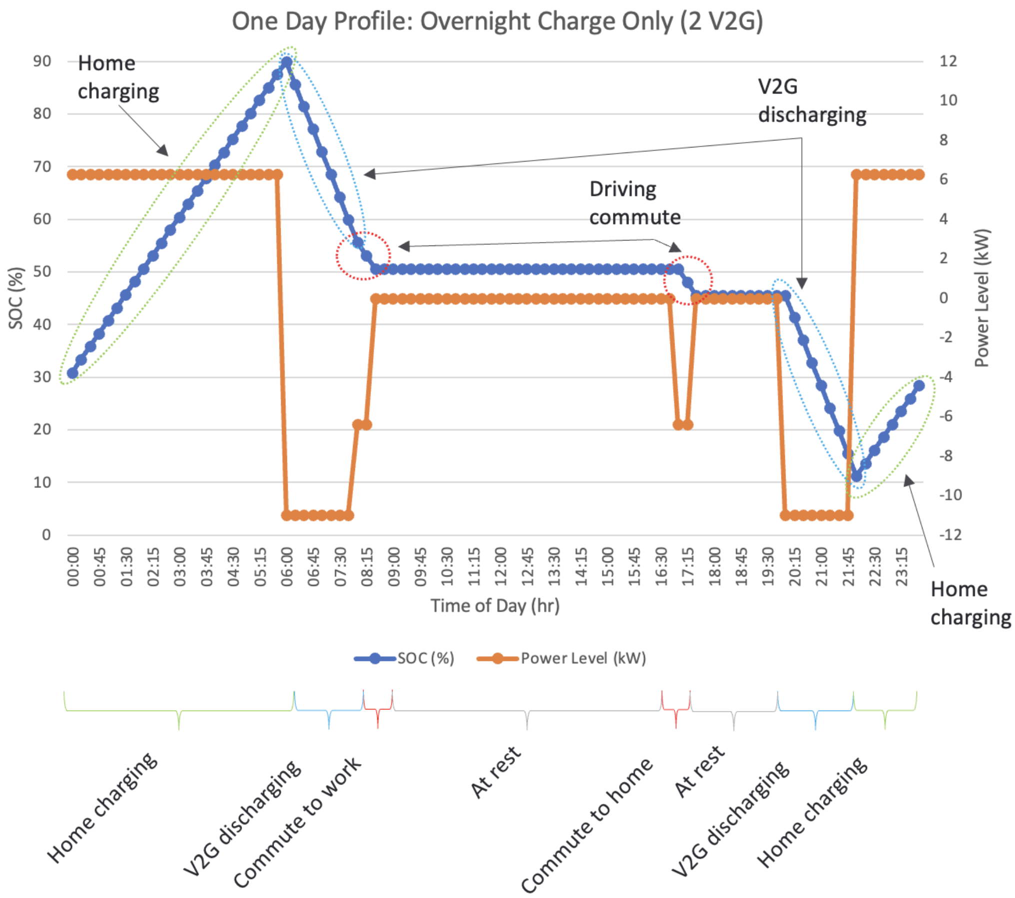


Figure 8: Scenario 5 daily custom-built profile

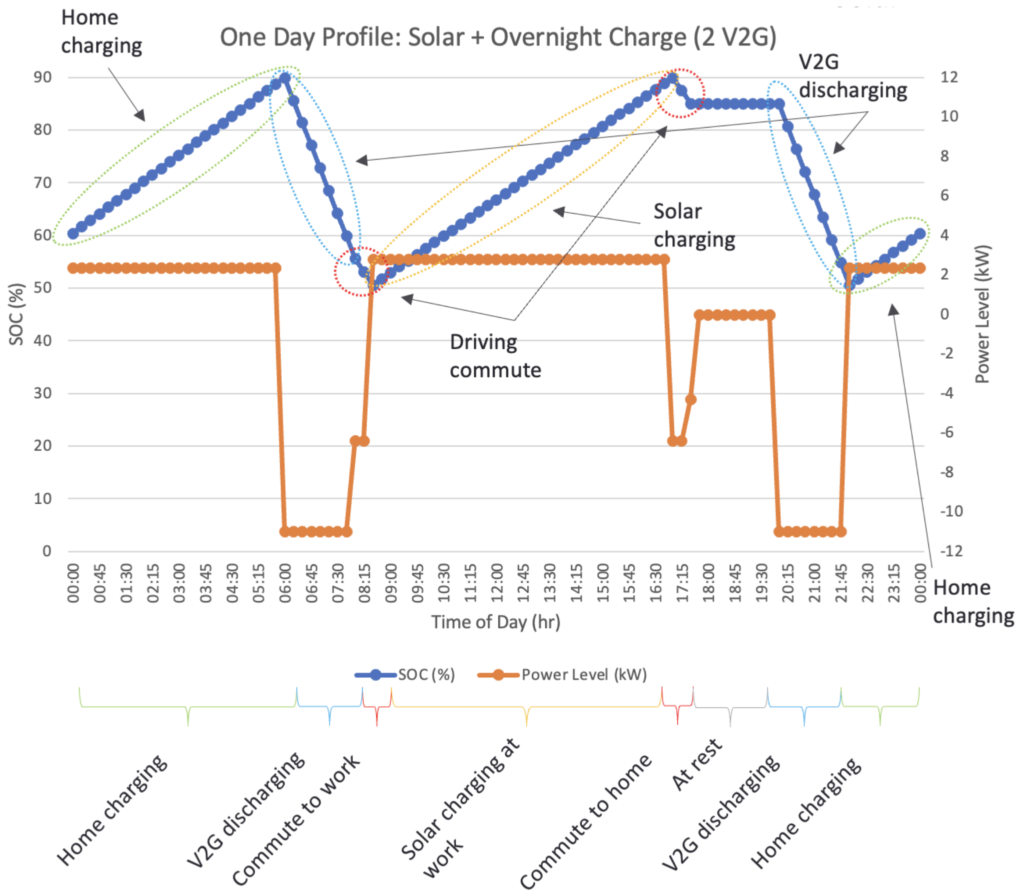


Figure 9: Scenario 6 daily custom-built profile

The weekday is quite regimented in terms of schedule and this helps keep the battery healthy for longer. The weekdays are the biggest percentage of the week, so they have more impact on the battery in theory. However, if driving habits are analyzed then longer weekend trip behaviors could possibly have an impact on this percentage makeup.

4.1.2 Weekend Scenarios

The weekend can be a complex scenario to quantify because users do a multitude of different tasks, from road trips to errands to absolutely nothing. The assumptions here were based more on leisure trip statistics for the EU. Majority of EU residents travelled anywhere between 300-1000 km in a year for leisure [56]. Therefore, the weekend scenarios were split into two sections, more standard weekends and then longer road trips that occur 5 times a year to reach near to those distances. The weekend scenarios can be thought of more as parameters, adjusting the weekly scenarios, since they will be chosen one at a time to function alongside each weekly scenario. The weekend scenarios are as follows:

1. Staying at home without V2G
2. Staying at home with V2G
3. Errands without V2G
4. Errands with V2G
5. Short road trip without V2G (1x rapid charging)
6. Short road trip with V2G (1x rapid charging)
7. Long road trip without V2G (2x rapid charging)

In reference to the staying home weekend scenarios, 1 and 2 give the ability for V2G to step in for two 4 hour windows because there is no need a for a commute to work. Weekend scenarios 3 and 4 offer a similar situation to the work week but allow for shorter slow charging windows in between driving from errand to errand. There is a driving cycle of 30 minutes 3 times in the day with 3 two hour charging sessions, followed by a normal longer overnight charge. Retail stores are interested in having V2G capabilities in their parking lots in order to incentivize employees to have their vehicles charge but also bring down the store's energy costs [57]. Weekend scenarios 5 and 6 factor in longer driving periods, 2 two hour sessions, and the addition of rapid charging (level 3 charging), one time per day while on the road. Finally, the longer road trip, 3 three hour driving sessions, was curated to include two instances of rapid charging with no possibility for V2G. There is a recharge overnight though in all cases. The long road trip will also be considered as happening in a weekend but the model has the potential to elaborate further and make this kind of trip last for a week or more. The weekend scenarios were created with the intent to interweave them with the weekday scenarios. The original 6 scenarios with no parameters (to be discussed in section 4.2.5) changed will use the 5x a year road trip as standard and the stay at home on the weekends option as well. This way, a 1 year simulation of the model is as close to real life as possible. The integration of these scenarios into the model is crucial for meaningful results. The model and this process are detailed below.

4.2 Battery Ageing Model

The chosen model for conducting the V2G battery degradation analysis is an AMESIM model, with a semi-empirical model battery ageing model within it. This type of model has better accuracy, complexity and data dependency than most other types of models. The complexity of including a charging / discharging strategy, WLTP driving cycle, temperature estimation, and various scenario parameters help calibrate the high voltage (HV) battery semi-empirical model results. At medium accuracy, the semi-empirical model was an appropriate choice for the battery degradation analysis. Then the original model has space for enough adjustments for operation analysis and system planning of V2G. Taking advantage of the already existing AMESIM model helped to have a framework in place to build from. This allowed for consistency and prevented breaking the model during simulations. The purpose of the existing model was to take a look at charging / discharging strategies, so the natural progression was to add research-based assumptions into the mix for the next level of smart charging / discharging. Figure 10 shows the original demo model and Figure 11 shows the edited model for this research.

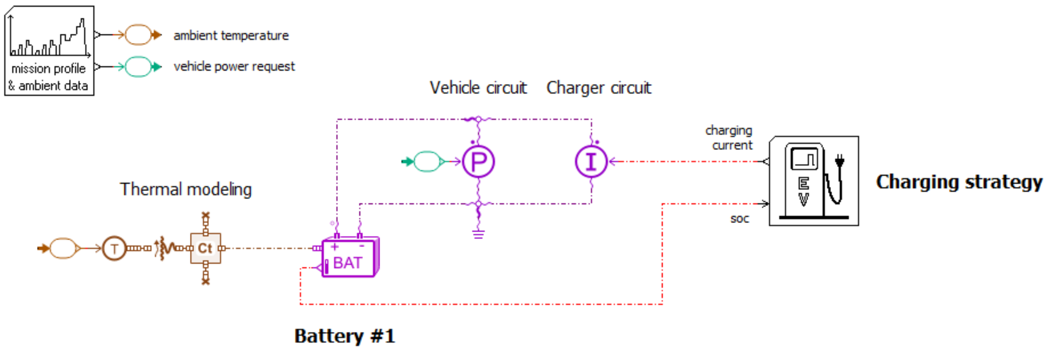


Figure 10: Siemens AMESIM charging strategy demo model

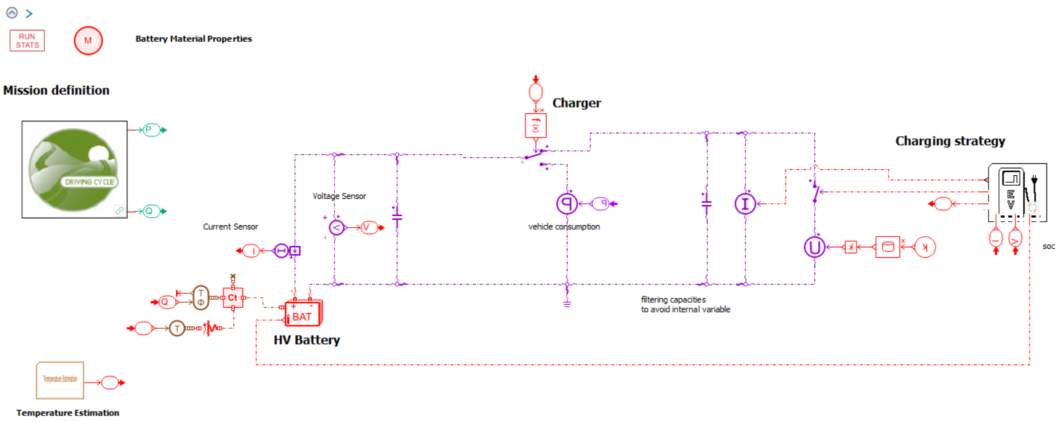


Figure 11: Custom V2G semi-empirical model

The adjustments made were building more scenarios, adding a specific driving cycle, and filtering the days to differentiate between weekday and weekend scenarios. This added complexity, but more importantly, accuracy to the model because based on assumptions of EV user behavior and seasonal temperature it matches the real world over 1 year. In future versions of this model, longer driving cycles, different battery chemistries and additional parameters for the scenarios could be considered.

4.2.1 Charging / Discharging Strategy

The charging and discharging strategy portion of the model for weekdays and weekends are shown in Figure 12 and Figure 13 respectively. The first adjustments made were to the strategies built into the model. The aforementioned weekday and weekend scenarios were created into signals starting at their desired time.

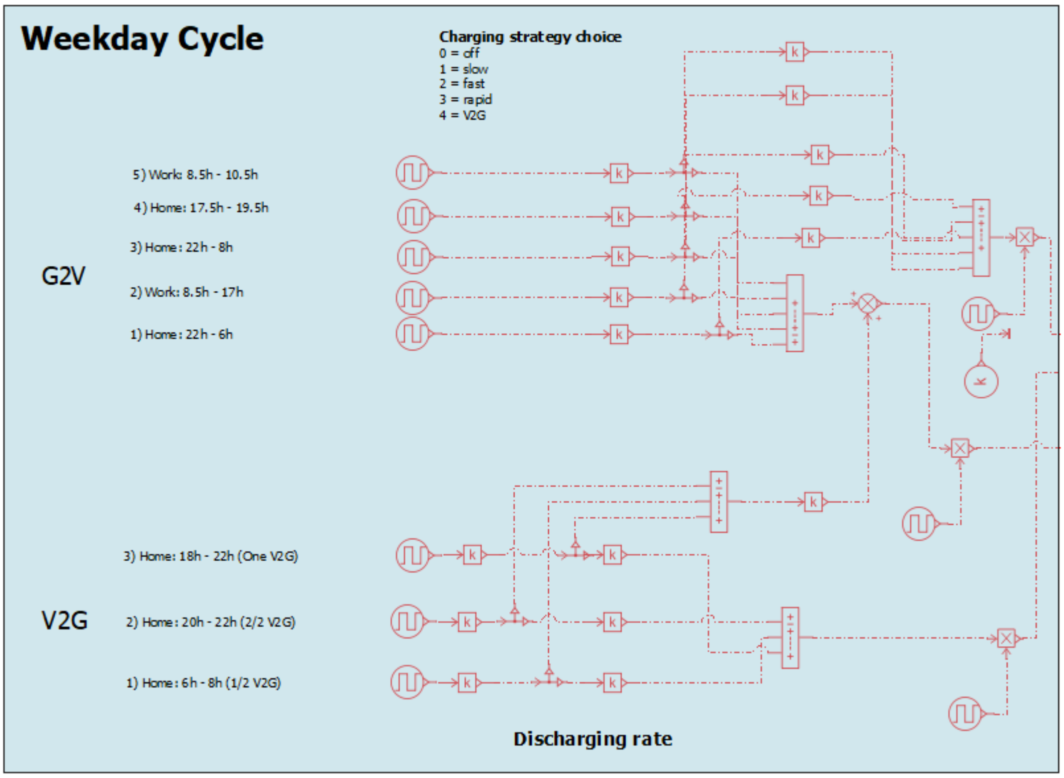


Figure 12: Weekday charging / discharging strategies

In Figure 12, next to the G2V and V2G headings are signal symbols which dictate start time in hours from 0, the pulse ratio, a way to set the length of the charging / discharging signal, and frequency, how often it occurs within a period of time. In most cases the frequency is set to once per day. Following away from the signal is a strategy determiner. This indicates if the system should be off, slow, fast, rapid charge, or discharge via V2G (1, 2, 3, 4 in the system respectively). The next junction is a summing function allowing the turned-on signals to reach the state chart. Right before completion there is a location where the signals are hit with a pulse ratio that allows the signal through 5 out of 7 days of the week, mimicking a work week.

The weekend scenarios are demonstrated in Figure 13. Similarly, these were entered into the model in the exact manner as the weekday scenarios. The only differences were the rapid charging scenarios as these required the value 3 instead of a 1 in order to trigger the new charging speed. Otherwise, the application flows through the same chain of signal, type of charging / discharging speed and the summation functions. Being a weekend scenario, the final signal allows it to go through only after the 120th hour of the week and through to the end of 48 hours. The weekend signals took a long time to get right as at first the various weekend charges / discharges were occurring at the same time crashing the simulation. There were also instances when the weekend scenarios picked up from the SOC level before the weekend and overcharge because the system thought that was the new minimum. Changes were made to the signals to start and stop at the correct time. The statechart (discussed below) needed to be adjusted in order to keep the same original SOC minimum and maximum. Lastly, the weekend scenarios required longer driving cycles of 2 and 3 hours. Therefore, the 30 minute WLTP needed to be repeated 4 times for 2 hours and 6 times for 3 hours. The higher rapid charging use cases could cause the degradation to be worse so it is important to incorporate those scenarios.

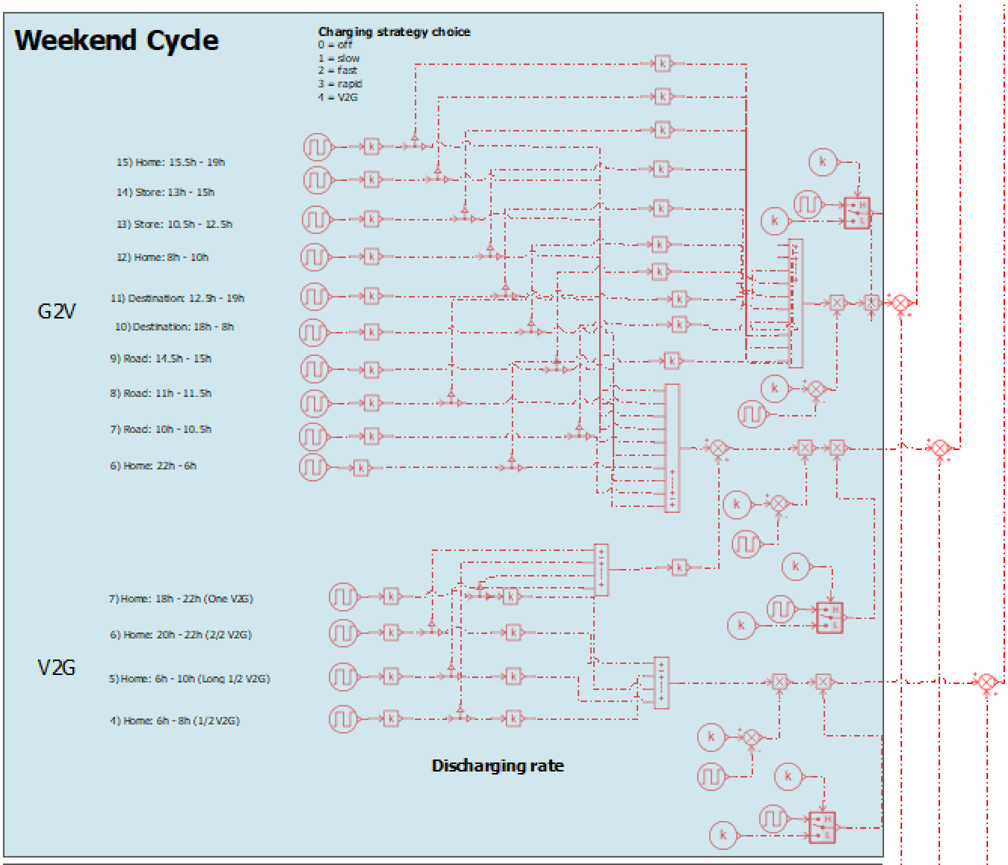


Figure 13: Weekend charging / discharging strategies

Included in the charging / discharging strategies portion of the model is a statechart, the outside of which is demonstrated in Figure 14. It is one of the most important sections as without it there is no way for the system to recognize when a new action occurs. The demo could only do slow, fast, and rapid charging but it did not include a way for the statechart to differentiate between those and V2G rates. The statechart was changed to form increased logic for the model, the inside is detailed in Figure 15.

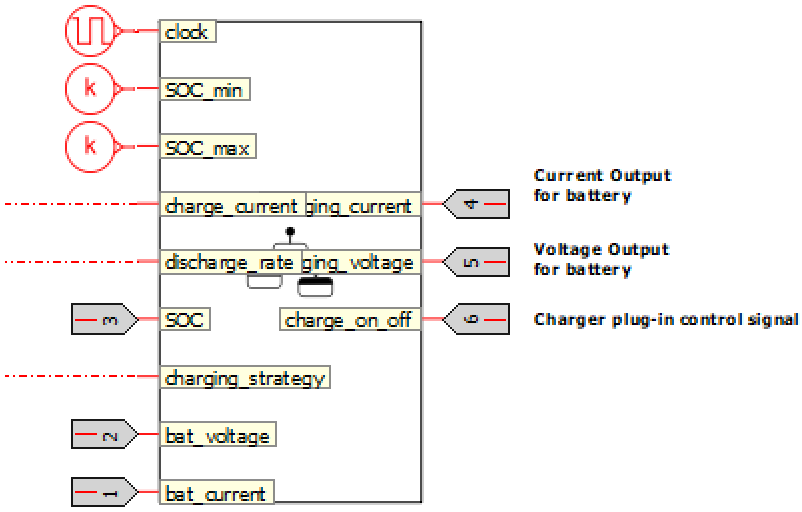


Figure 14: Statechart representation in the model

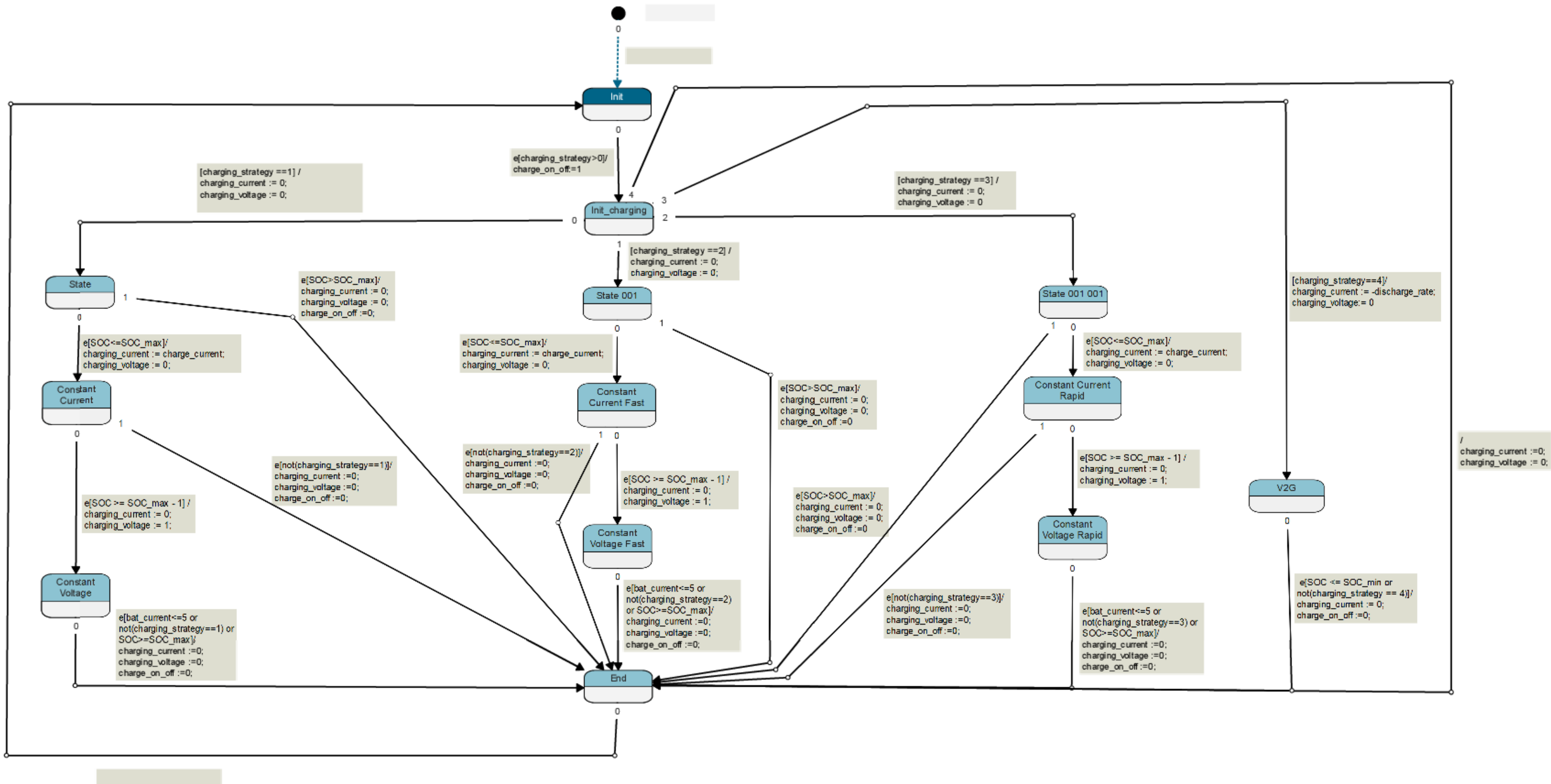
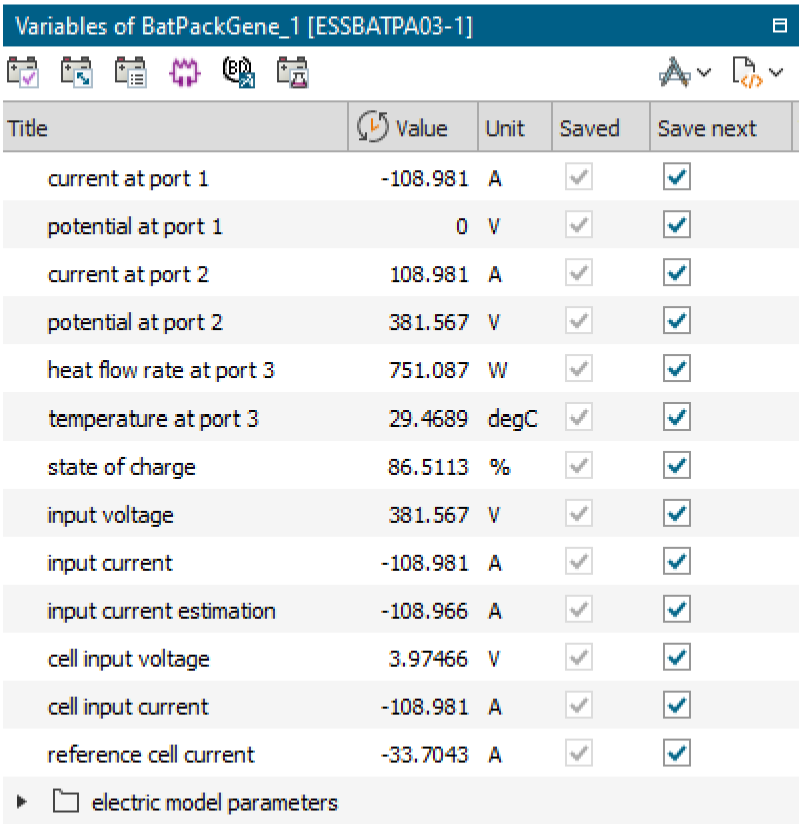


Figure 15: Charging / discharging strategies statechart (inside)

The statechart flows as follows. The incoming signal at the top is a certain value between 0 – 4 to tell the model which path to go down. The statechart also includes cut off points for when the battery switches from constant current to constant voltage when charging. This is important in order to protect the battery from overheating with constant current as it gets closer to being charged and then protecting it from overcharging with constant voltage [58]. This value changes as the battery ages which is a flaw of this model that it just remains constant. For the sake of this study, it was changed to be very low since there is only one scenario where the battery is pushed up to 100% SOC. The battery details themselves like the SOC upper and lower limit are controlled in the battery parameters themselves but are represented within the statechart to tell it when to stop charging / discharging. The limit is set as SOC_max – 1 or SOC_min – 1. There is also a chance for the model to exit charging before the switch from constant current to constant voltage. This was designed as a failsafe due to several simulations overcharging if the same numbered signal was repeated one after another.

4.2.2 HV Battery

The HV battery component is the semi-empirical model factoring in equations that describe battery ageing phenomena and also theoretical components that in this case are the usage profiles. It is important as it allows for the specification of the battery by how many cells there are, how many are in parallel / series, the capacity size, the initial SOC, and the upper / lower SOC limits. Based on the kWh sizing of the energy, the type of battery chemistry can be hypothesized. In this study, the battery is a generic NMC cell as mentioned before, and it is 71 kWh in size. In order to visualize the results, like in Figure 16, the final capacity loss is kept track of in the HV battery subsection. This subsection takes into account the temperature from the driving cycle and the ambient temperature estimation but also the information from the charger. The charger controls if the system is experiencing driving or if one of the V2G actions are happening.



Variables of BatPackGene_1 [ESSBATPA03-1]

Title	Value	Unit	Saved	Save next
current at port 1	-108.981	A	✓	✓
potential at port 1	0	V	✓	✓
current at port 2	108.981	A	✓	✓
potential at port 2	381.567	V	✓	✓
heat flow rate at port 3	751.087	W	✓	✓
temperature at port 3	29.4689	degC	✓	✓
state of charge	86.5113	%	✓	✓
input voltage	381.567	V	✓	✓
input current	-108.981	A	✓	✓
input current estimation	-108.966	A	✓	✓
cell input voltage	3.97466	V	✓	✓
cell input current	-108.981	A	✓	✓
reference cell current	-33.7043	A	✓	✓
electric model parameters				

Figure 16: HV battery / semi-empirical model variables

A helpful feature of the semi-empirical model is the ability to watch battery functions in real time as the simulation runs. The SOC monitor allows for the matching the scenarios to their base assumptions and can highlight potential issues. Take for example Scenario 6, there are supposed to be two V2G periods followed by charging but in early runs of the simulation only one of the charging periods occurred. This caused the simulation to crash because suddenly there was two V2G sessions back-to-back without any recharging causing a negative SOC which is impossible. The next iteration of the model could utilize this space, as shown in Figure 17, to change the features of the battery chemistry, pack size and arrangement.

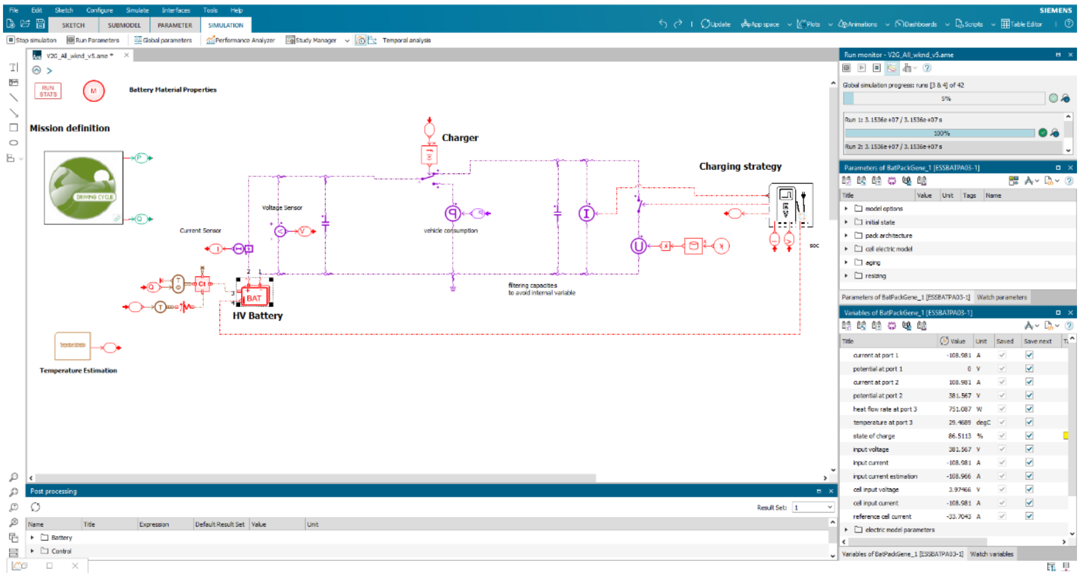


Figure 17: Full model interface & HV battery parameters list

4.2.3 Driving Cycle

The original model also included a driving cycle but here the focus was on the V2G and less on the driving cycle so not a very specific one was used. The cycle just needed to be 30 minutes long for scalability purposes and include a bit of city and highway driving. The WLTP data, in Figure 18, shows the duration, distance, stops, accelerations and overall speed per phase.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
Phase	Total elapsed time	WLTC class 3, version 5, vehicle speed	WLTC class 3, version 5, acceleration	WLTC class 3, version 5, acceleration		duration	stop duration	distance	p_stop	v_max	v_ave without stops	v_ave with stops	a_min	a_max
Phase	s	km/h	m/s²	km/h/s		s	s	m		km/h	km/h	km/h	m/s²	m/s²
Low	0	0.0	0.00	0.00	low	589	156	3095	26.5%	56.5	25.7	18.9	-1.47	1.47
Low	1	0.0	0.00	0.00	medium	433	48	4756	11.1%	76.6	44.5	39.5	-1.49	1.57
Low	2	0.0	0.00	0.00	high	455	31	7158	6.8%	97.4	60.8	56.6	-1.49	1.58
Low	3	0.0	0.00	0.00	extra high	323	7	8254	2.2%	131.3	94.0	92.0	-1.21	1.03
Low	4	0.0	0.00	0.00		**1800**	**242**	**23262**						
Low	5	0.0	0.00	0.00										
Low	6	0.0	0.00	0.00										
Low	7	0.0	0.00	0.00										
Low	8	0.0	0.00	0.00										
Low	9	0.0	0.00	0.00										
Low	10	0.0	0.00	0.00										
Low	11	0.0	0.03	0.10										
Low	12	0.2	0.24	0.85										
Low	13	1.7	0.72	2.60										
Low	14	5.4	1.14	4.10										
Low	15	9.9	1.07	3.85										
Low	16	13.1	0.97	3.50										
Low	17	16.9	1.19	4.30										
Low	18	21.7	1.26	4.55										
Low	19	26.0	0.81	2.90										
Low	20	27.5	0.29	1.05										
Low	21	28.1	0.11	0.40										
Low	22	28.3	0.10	0.35										
Low	23	28.8	0.11	0.40										

Figure 18: WLTP of 30 minute drive cycle

The power data can be derived from those parameters as shown in Figure 19. The 30 minute WLTP cycle was ran in a more detailed thermal model to output battery temperature data during driving. The heat flow data from the thermal model system, Figure 20, then becomes inputs for the new model. Within the model the heat flow data goes to the HV battery and the power data goes to the vehicle consumption circuit to tell the system when there is a driving cycle occurring instead of a period of rest, charging or discharging.

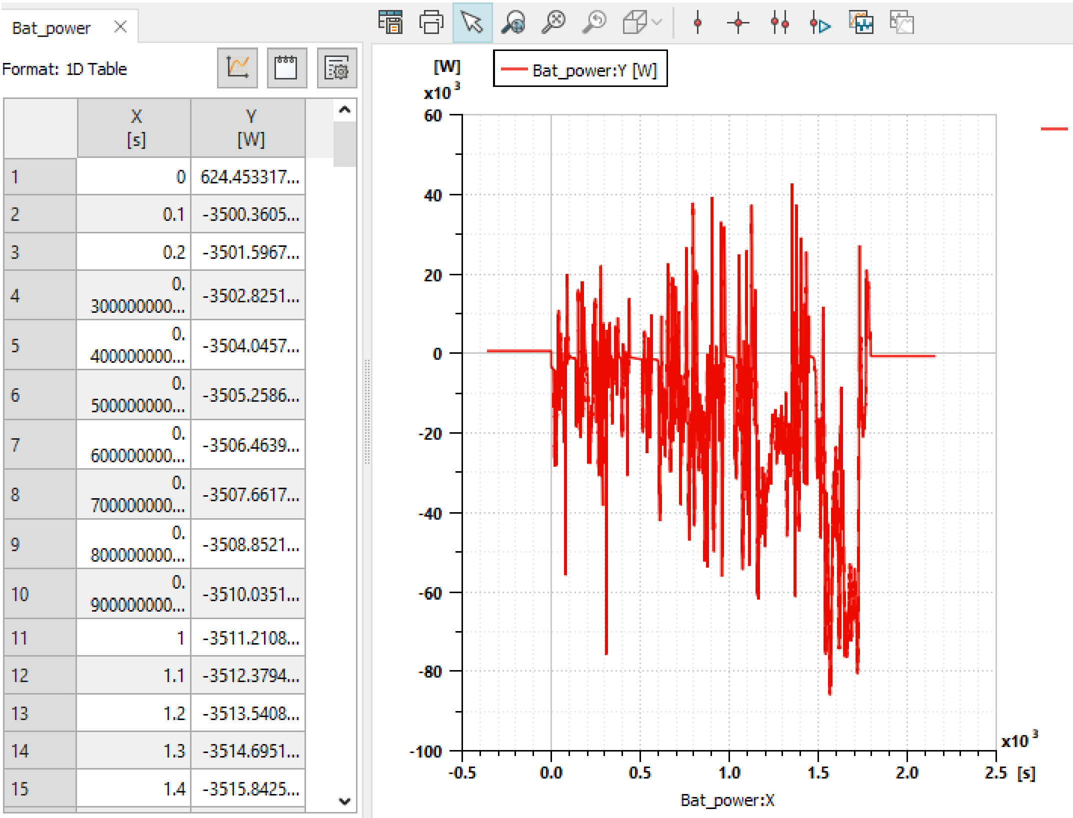


Figure 19: HV battery power data

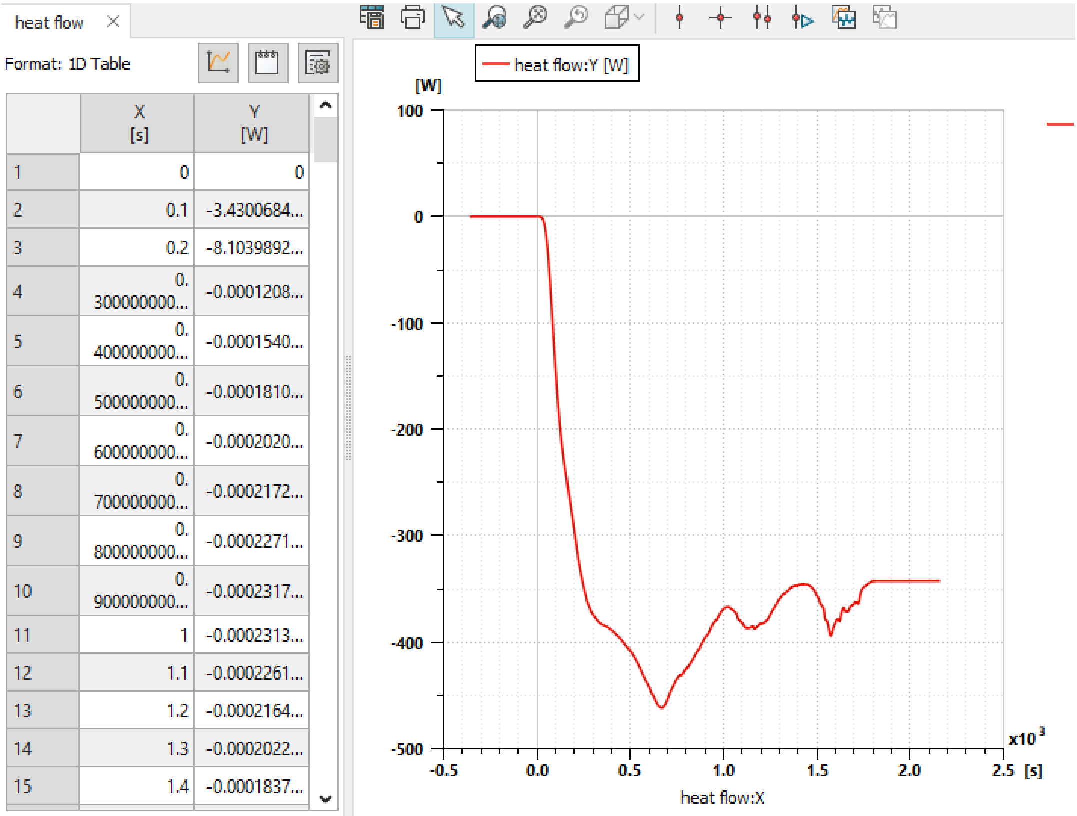


Figure 20: HV battery heat data

The driving cycles themselves are split into sections within the model for weekday, weekends and longer road trips. This way each of their signals can be filtered by when they are supposed to occur in the week / year. The weekly driving cycle of two 30 minute commutes, one to work and one back home, occurs each day outside of the weekends. This is represented in Figure 21. The weekend cycles are limited to the two days of the week that the other signal is suppressed for, as shown in Figure 22. The complexity of the longer road trips is that they occur 5 times a year but in reality, would occur during the week most likely as part of a vacation. Due to the simplicity of the model and a time constraint, the long road trips will also be confined to the weekend. They will include a lot more driving, 9 hrs, in that short period as opposed to driving less per day, 4 hrs, and stopping more often, as represented in Figure 23. A future version of the model could include a feature for week long road trips, or even other driving occurrences, like higher speed highway driving.

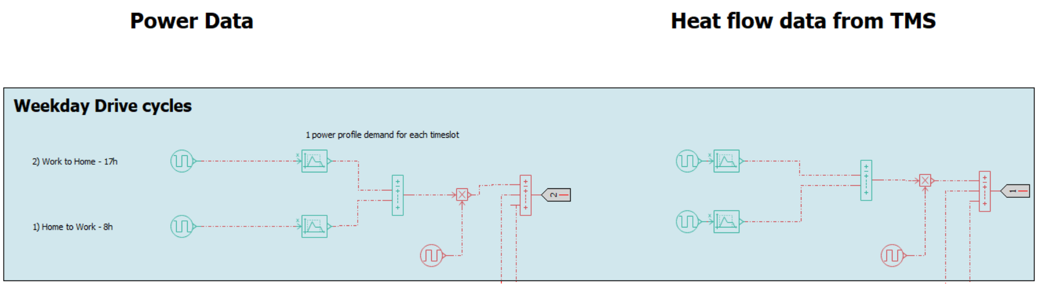


Figure 21: Weekday drive cycle power and heat flow data

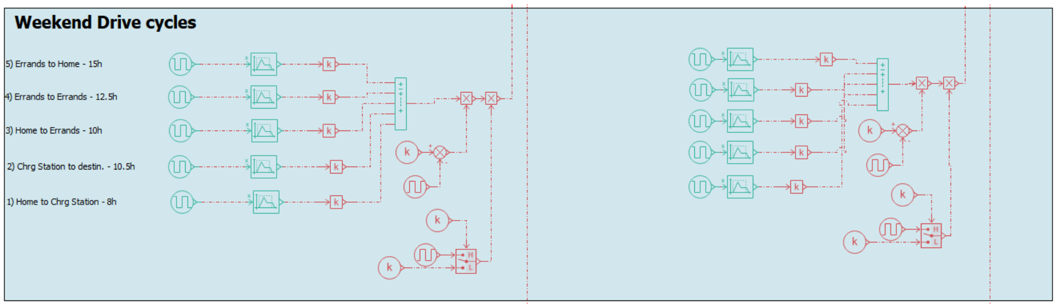


Figure 22: Weekend drive cycle power and heat flow data

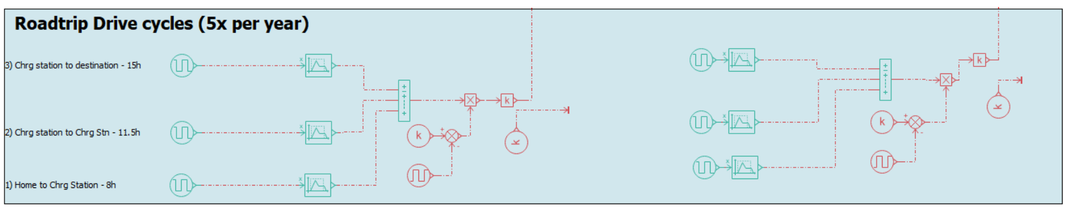


Figure 23: Road trip drive cycle power and heat flow data

4.2.4 Temperature Estimation

The AMESIM demo model initially included a temperature estimator throughout the year. This was not included in the initial version of the battery ageing template that was constructed and instead a set ambient temperature was used. This proved appropriate for short time span simulations, where the temperature could become a changeable parameter. The results here were according to literature, the higher the temperature the more degradation, which did not provide any additional depth to the study. The metric also proved inaccurate for full year to year length simulations due to day and night cycles, plus seasonal changes. Therefore, the previous temperature estimation tool, Figure 24, was utilized to make for more realistic scenarios. Figure 25 shows the estimator has a profile of average European day and night temperatures, alternating through them. While also taking into account a seasonal variation from a separate oscillating signal.

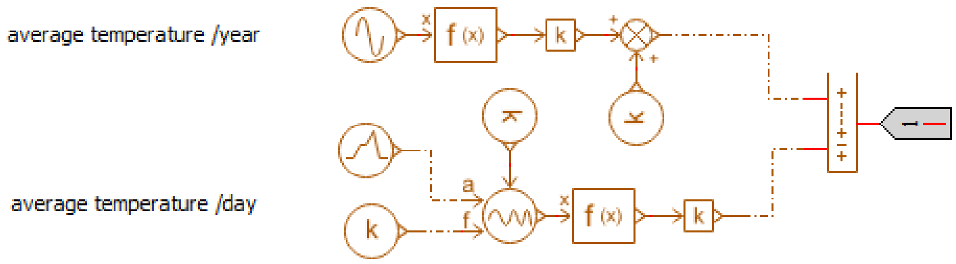


Figure 24: Temperature estimator

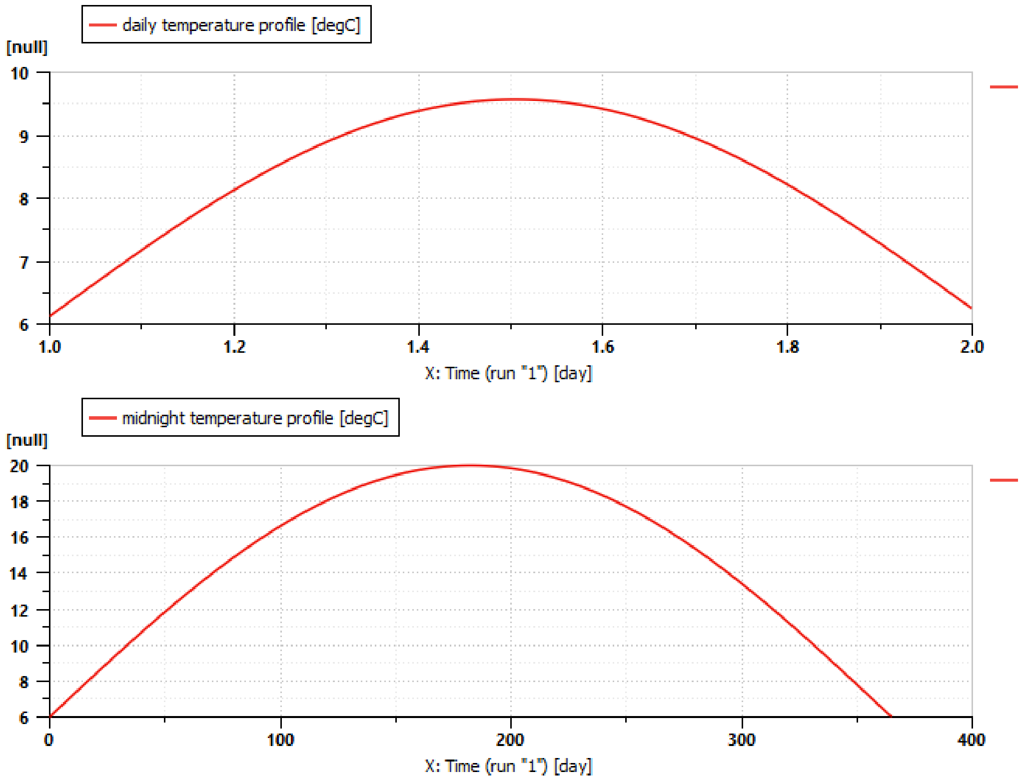


Figure 25: Temperature day and night cycle plus seasonal fluctuation

4.2.5 Scenario Parameters

Siemens AMESIM allows for the changing of any global parameters, as demonstrated in Figure 26. Then when it is time to run the simulation changes can be made to the global parameters through a study manager. The study manager is shown in Figure 27 as allowing for multiple sets to be run simultaneously. This saves a lot of time as the model does not need to be recreated for each scenario. Instead, what can be changed are the parameters for each scenario specifically.

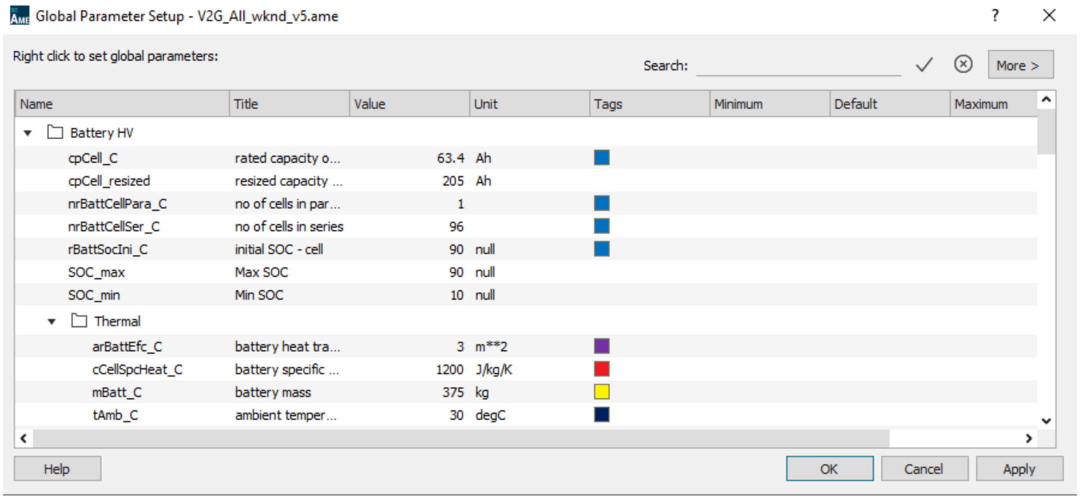


Figure 26: Global parameters list

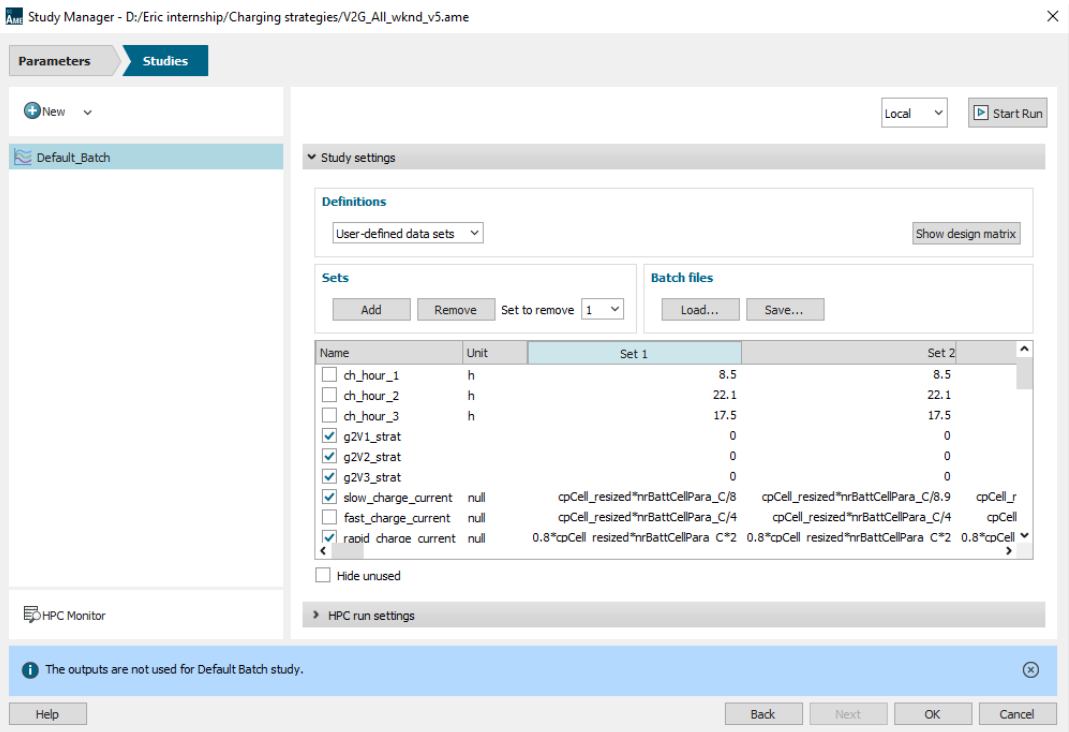


Figure 27: Study manager list of adjusted parameters

In the case of Scenario 1, where there is no V2G and only charging during the night, the V2G portions are set to 0 while the driving cycle and evening charging session still occurs. The chosen parameters to be adjusted were power level (11 vs 22 kW discharge rate), charging frequency (every 24 vs 48 hours for only the baseline scenarios), SOC upper and lower limits (100/0 vs 90/10 vs 80/20), cycles per day (1x vs 2x V2G, 1x vs 2x charge), and driving profiles (weekday vs weekend). The time was kept constant to a window of 1 year for the sake of run time. Ten years would have been optimal in order to match current warranty standards and car ownership habits. The time constraint of the thesis combined with 42 sets divvied up between the 6 main weekday scenarios has left only time to assume each year would be the same. The estimate of 10 times 1 year of degradation should be appropriate because even though EV battery degradation is more nonlinear than linear, 10 years is not long enough for there to be a drastic drop off. Usually there is an initial drop in capacity, followed by a slow in ageing, until closer to end of life when there is another larger drop in capacity and SOH [59]. End of life is quantified as when the battery is at 80% capacity so as long as the results are within that threshold, they will be a good representation. Between the 42 sets an overview comparison of the capacity loss results per scenario can still be created. In the future this model can be ran for the full 10 years to achieve potentially more accurate results but also to do a comparison which could be interesting. The results are broken down in detail in the following section.

5 Results

The main results of this study are all in terms of capacity loss. Initially when testing the model, SOC was used in order to match the usage profiles created with assumptions to that of the model output. This way it could be determined if both the assumptions were correct and that the model was working properly. Figure 28 compared to Figure 5 and Figure 9 is one such detail to ensure that the model was functioning appropriately. The SOC levels match outside of the driving cycle which in the model takes closer to 10% SOC. In the initial calculations based on total kWh of the battery versus the time to work, 30 minutes, it was expected to take only 5% of the SOC. The power levels also change significantly during the first driving cycle at 08:00. These differences are because the road load was not adjusted for the theoretical vehicle used. It provides different acceleration times within the drive cycle causing more SOC loss and power level jumps. The assumptions were correct in the shapes of the profile.

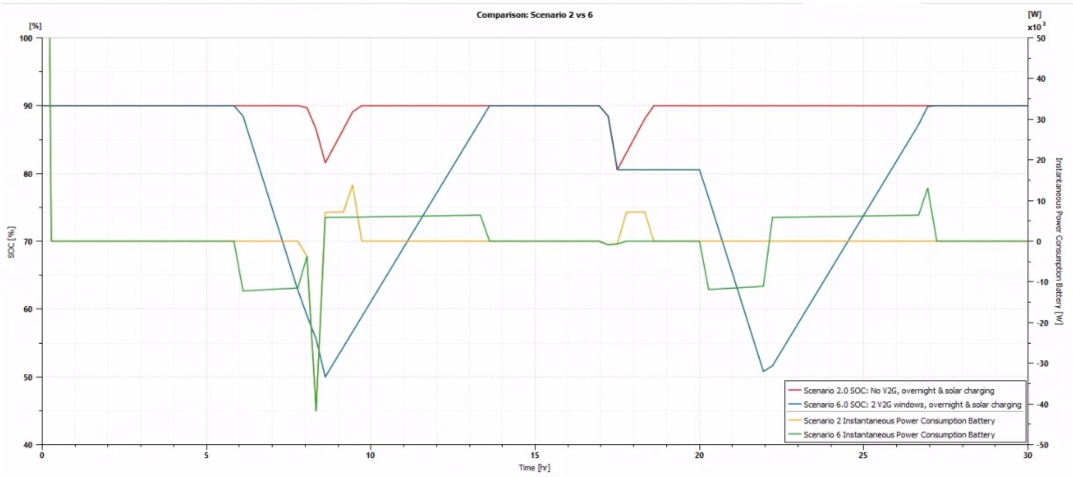


Figure 28: Scenario 2 vs 6 SOC & power comparison

The compared results can be broken down as follows. Each weekday scenario 1-6 is used as a reference for parameter changes within that specific scenario. The overall baseline is non V2G compared to V2G which is essentially Scenarios 1 and 2 versus Scenarios 3, 4, 5 and 6, ranging from lowest cycles and energy throughput to most. First, the main 6 scenarios will simply be compared to one another. Then afterwards their variations will be compared within their original scenario. Followed by a comparison of the variations from each of the 6 main scenarios. Each scenarios' default includes SOC max of 90%, SOC min of 10%, an 11 kW power discharge level, 24 hr signal frequency, overnight charging and the long road trip 5 times per year with otherwise no driving on the weekends. Then as mentioned in section 4.2.5, the parameters that are changed are SOC max / min limits, charging frequency, discharge power level and weekend scenarios. The charging frequency is only changed for the non V2G scenarios (1 & 2) while the discharge power level is only changed for the V2G scenarios (3, 4, 5, & 6). The following table provides clarity on the specific comparison adjustments:

Table 1: Scenarios arranged by changes

Scenario	Set	Description	Change
1.0	1	No V2G	N/A
1.1	13		SOC max 80% & 20% min
1.2	47		48 hr charge
1.3	49		Weekend errands
1.4	50		SOC max 100% & 0% min
1.5	51		No long road trip (no rapid charge)
1.6	52		Short road trip (1x rapid charge)
2.0	2	No V2G, solar charge	N/A
2.1	18		SOC max 80% & 20% min
2.2	48		48 hr charge
2.3	53		Weekend errands
2.4	54		SOC max 100% & 0% min
2.5	55		No long road trip (no rapid charge)
2.6	56		Short road trip (1x rapid charge)
3.0	3	One V2G	N/A
3.1	23		SOC max 80% & 20% min
3.2	28		22 kW power level
3.3	57		Weekend errands
3.4	58		SOC max 100% & 0% min
3.5	59		No long road trip (no rapid charge)
3.6	60		Short road trip (1x rapid charge)
4.0	4	One V2G, solar charge	N/A
4.1	29		SOC max 80% & 20% min
4.2	34		22 kW power level
4.3	61		Weekend errands
4.4	62		SOC max 100% & 0% min
4.5	63		No long road trip (no rapid charge)
4.6	64		Short road trip (1x rapid charge)
5.0	5	Two V2G	N/A
5.1	35		SOC max 80% & 20% min
5.2	40		22 kW power level
5.3	65		Weekend errands
5.4	66		SOC max 100% & 0% min
5.5	67		No long road trip (no rapid charge)
5.6	68		Short road trip (1x rapid charge)
6.0	6	Two V2G, solar charge	N/A
6.1	7		SOC max 80% & 20% min
6.2	12		22 kW power level
6.3	69		Weekend errands

6.4	70		SOC max 100% & 0% min
6.5	71		No long road trip (no rapid charge)
6.6	72		Short road trip (1x rapid charge)

The main 6 scenarios compared to each other bases the capacity loss purely on V2G happening not at all, once, or twice in 24 hours. The assumption here based on previous studies in the field is that the higher V2G scenarios will have a higher capacity loss percentage than the non V2G scenarios. Figure 29 and Figure 30 show this not to be entirely the case.

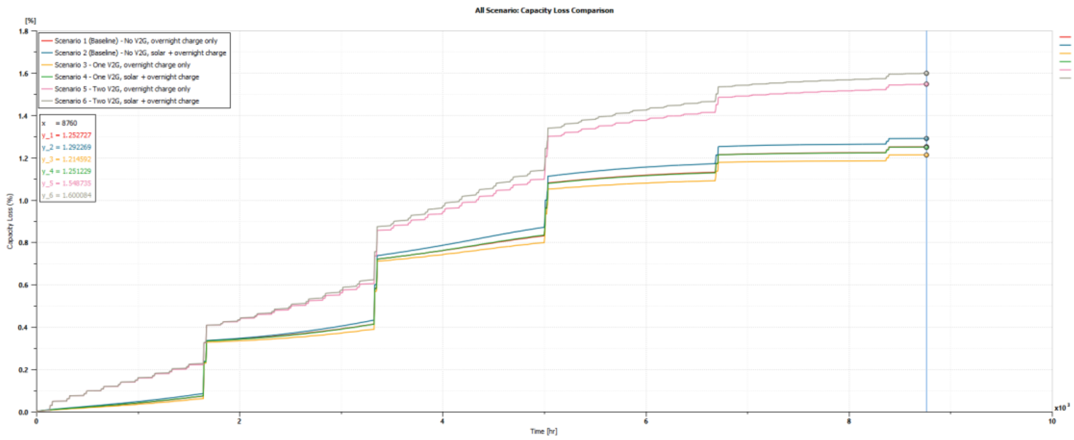


Figure 29: Main scenarios capacity loss comparison

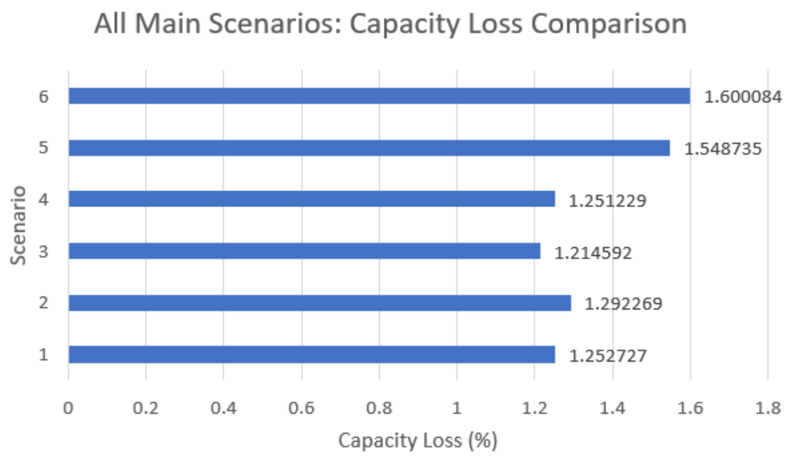


Figure 30: Bar graph main scenarios capacity loss comparison

Scenarios 3 and 4, with one V2G period, are both lower than both baseline non V2G scenarios of 1 and 2. This bodes well for the idea that mitigated V2G combined with smart charging can result in keeping the battery in more ideal SOC states. The baseline scenarios are of a user who plugs in their vehicle as soon as they get the chance. This causes the vehicle to stay between 80-90% SOC which, as mentioned in section 3.1, high SOC for prolonged periods of time can cause degradation. The lowest scenario is scenario 3, coming in at 1.214952% capacity loss over 1 year. Therefore, over 10 years the degradation would be ~ 12.15% still well under the 20% capacity loss that equals a spent EV battery. In order to reach the end of life criteria the EV battery would need to experience ~ 6.46 more similar years. This would give the EV an expected lifetime of over 16.5 years, longer than the average ICE counterpart at 12 years of lifetime [60]. The other thing about EVs is that they require less maintenance since there are less components to fail. Vehicles in the EU right now are on average 11.8 years old and that has gone up over the last few years as people are waiting to purchase EVs [61]. The perks of a vehicle lasting longer saves drivers money and reliability is always a focus. The worry about V2G causing extra degradation is warranted because the highest usage scenario, scenario 6, is up at 1.600084% capacity loss. This is only ~0.35% higher than the lowest scenario, scenario 3, but it results in 4 years of functionality of that EV left versus the ~6.5 of the one V2G scenario. Overall Scenario 6 still demonstrates a 14 year lifespan of the EV battery which is better than the current average vehicle.

A feature of Figure 29 that is distinctly visible is the jump up in degradation for the 5x a year longer road trips. The 3 three hour driving cycles mixed with two rapid charging instances adds at its largest a ~0.32% capacity loss increase, nearly an ~82.1% increase in just one weekend. A large cycling current is known to cause more degradation and this is a clear example of this. The V2G aspects themselves are much less impactful on the overall capacity loss, even if there is an increase in the power level. Demonstrated in Figure 31, of the four scenarios run with 22 kW discharge power versus the original 11 kW, only one successfully ran in its entirety.

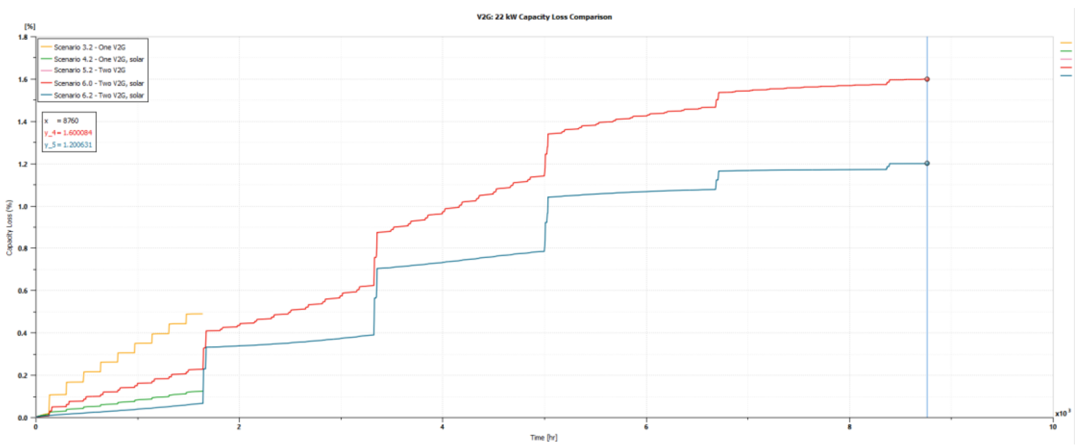


Figure 31: V2G scenarios 11 kW vs 22 kW power discharge level

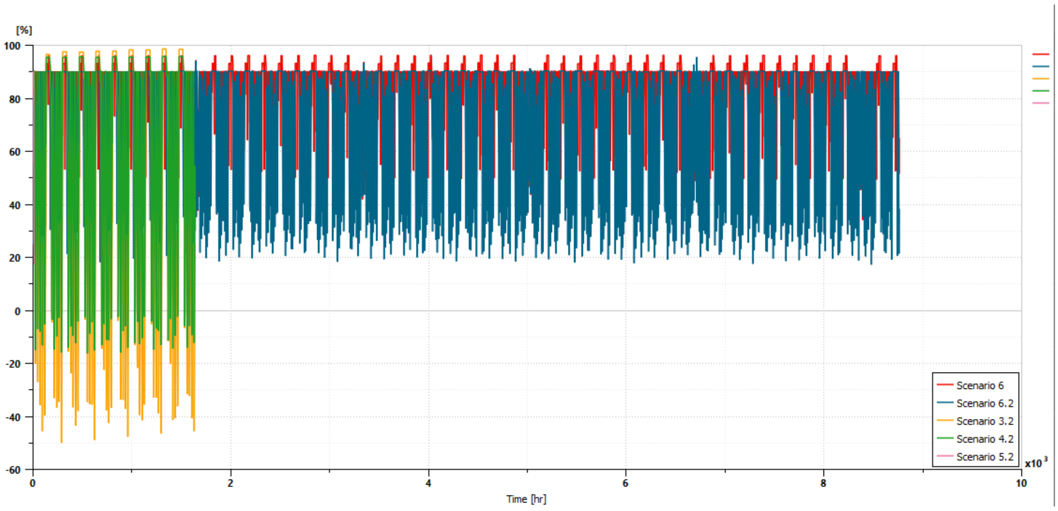


Figure 32: Power level comparison SOC impact on simulation failure

Figure 32 shows that the run failures can be attributed to a deep DOD, bringing the SOC into the negatives. This in turn broke the statecharts reasoning and halted the simulation. Scenario 6 still managed to run because it has more charging scenarios than any other scenario allowing it the chance to recharge before another large 22 kW V2G period occurred. Figure 33 even shows that the 22 kW scenario had less degradation than the baseline scenario 6. This shows a key point for the success of maintaining a batteries health while implementing V2G, that there needs to be enough instances throughout the day of adequate charging. The EV and EVSE market is heading towards a 22 kW power level which can be feasible if there is matching charging to go with it. For the sake of this model only a 22 kW discharge power was considered, due to time constraints, which made the difference.

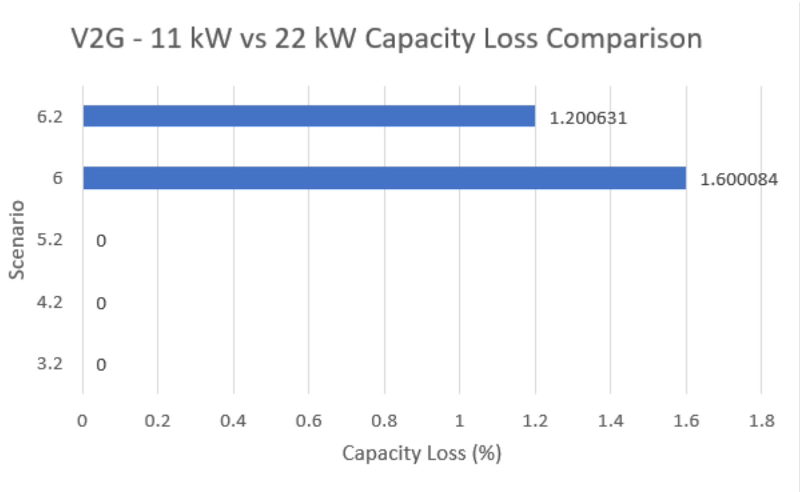


Figure 33: V2G scenarios 11 kW vs 22 kW comparison graph

The main scenarios are all a plug in the vehicle whenever possible type situation for the user but there are people who tend to only plug in when necessary. In order to see how much this makes an impact on non V2G scenarios and in an effort bring them lower than the one time V2G scenarios in capacity loss. The parameter of charging frequency is explored in Figure 34.

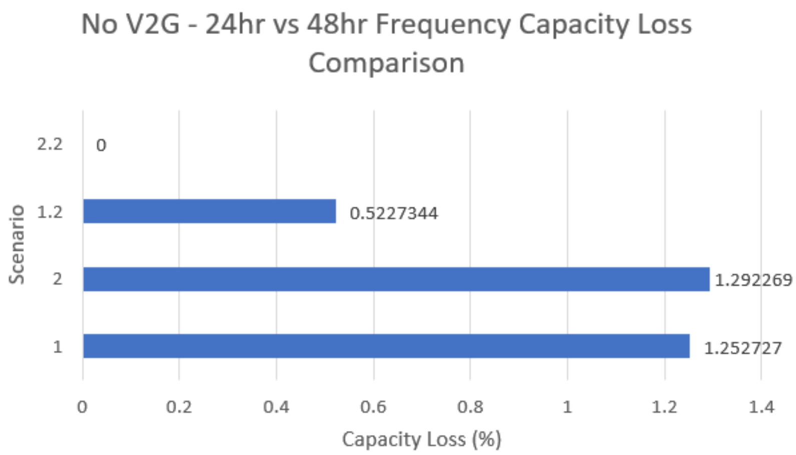


Figure 34: No V2G charge frequency 24 vs 48 hour comparison graph

Only scenario 1 ran using this parameter change because scenario 2 had a large DOD during the start of long road trip weekend having started at a lower SOC. This is a fault of the inputs into the model as it should have been a parameter of every 48 hours with a charge session before the weekend. A driver would know that they are going on a trip and override their smart charging routine in order to have a "full" charge for the road trip. The next iteration of this study can include such logic behaviors in the statechart in order to fix this scenario. The baseline scenario is more than halved in terms of capacity loss with the decrease in charging frequency. This falls into the category of allowing the battery to sit at a lower SOC rather than just staying between 80-90%. Most drivers are paranoid about how much range they are going to need so allowing smart charging and V2G to dictate these values will take some adjustment but it means longer term battery health.

The next comparison is between the SOC limit changes. First, the 80% max and 20% minimum simulation, as shown in Figure 35. Then Figure 36 shows that scenarios 5 and 6 achieved their lowest capacity loss percentage of any simulation. For the rest of the scenarios, it was the second lowest. Most EV manufacturers make claims to their customers that to keep an EV battery healthy on of the best methods is to keep it between 80% and 20% SOC. This proves to be true regardless of the V2G amount with scenario 6 achieving less than a percent in one year, ~0.9% loss. This is nearly a ~44% decrease in the total capacity loss percentage over the year compared to the main scenario.

Holding to these SOC limits could allow V2G to be used more often. The grid might not need it for major peak shaving windows but a more vehicle to building scale could be thought of to reduce reliance on the grid throughout the day.

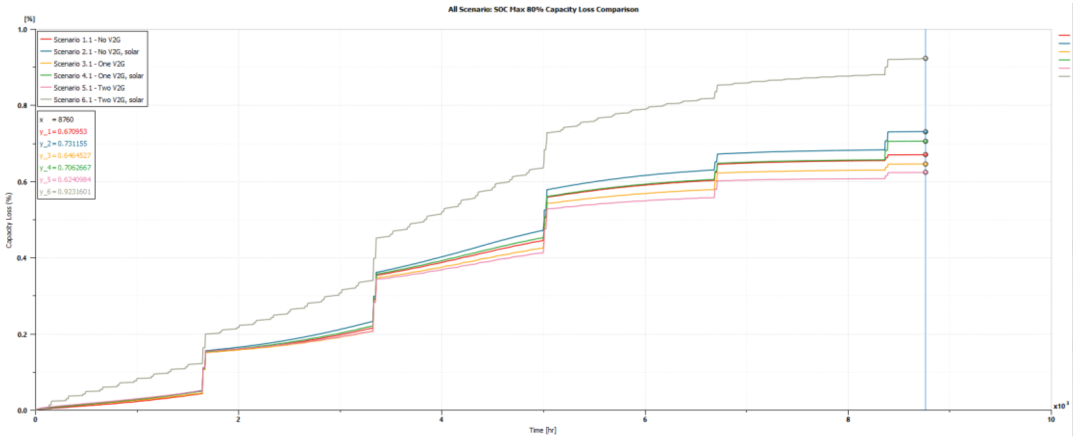


Figure 35: All scenario 80 max SOC capacity loss comparison

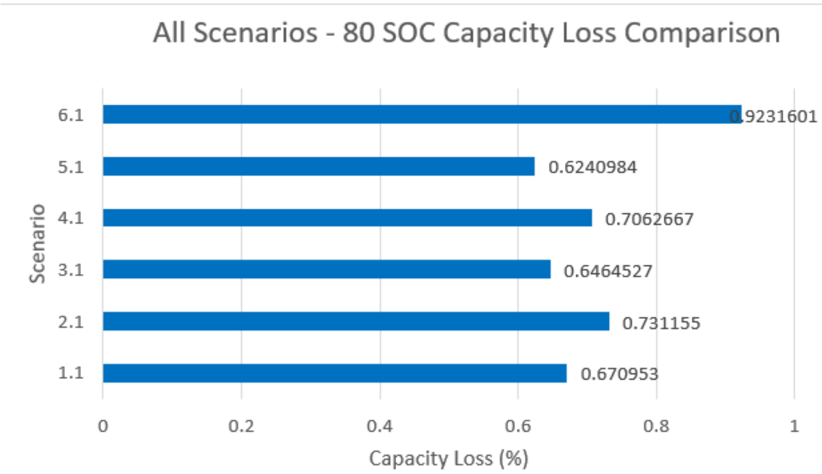


Figure 36: All scenario 80 max SOC capacity loss graph

On the other side of the SOC parameter change is the 100% SOC max and 0% minimum. These are considered for the reason of consumers wanting more range and occasionally charging up their battery fully. Discharging a battery completely is not good for its long-term health at all so much so that the model has protections for the cell stopping it a bit before zero SOC. The low SOC combined with the DOD is large enough to warrant the worst capacity loss results of any of the scenarios. This follows the literature that keeping a battery healthy is to keep it in a comfort zone for temperature, c-rate, SOC and number of rapid cycles. Comparing the best overall parameter change, or the success of V2G versus the worst, between Figure 36 and Figure 37 shows that it causes capacity loss to more than double. Not only that but scenarios 5 and 6 are the first and only instances of capacity loss breaching the 20% loss end of life criteria. This happening in 10 years is lower than the usual promised EV lifespan but is still in the range of when drivers tend to buy new cars so it is not a disaster. It is worth noting that all vehicles will never go through 10 years of 100% to 0% SOC cycles. This is because batteries used in EVs come with protections set by the OEMs and / or battery manufacturers that keeps part of the battery's upper and lower SOC safe from use. Essentially a logic system, similar to the statechart, that stops the vehicle from ever being completely discharged. These limits may not even be listed anywhere with the consumer thinking they are charging up to 100% but it really is not. Either way a lot of battery degradation comes down to user control over what they do with their vehicle and so allowing smart charging and V2G to make the right battery health decisions based on logic can make a big difference in how long EVs and the batteries that make them up will last.

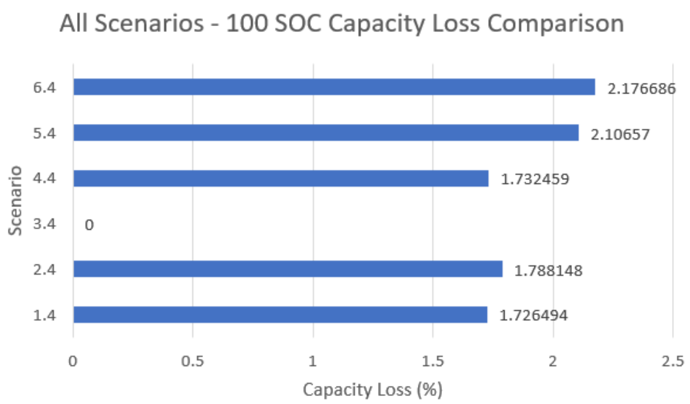


Figure 37: All scenario 100 max SOC capacity loss graph

There is a trend of the first four scenarios being quite close to each other regardless of the parameter changes and this shows that maintaining a high SOC is about equal to one V2G period per day. The addition of the V2G discharge only really adds that extra half of the cycle (discharge) because the charging cycle stays the same, regardless of solar charging or not. This holds true for the three weekend related parameter adjustments. First, the weekend errands in Figure 38, then the short road trips in Figure 39 and Figure 40, and lastly the no long trip in Figure 41.

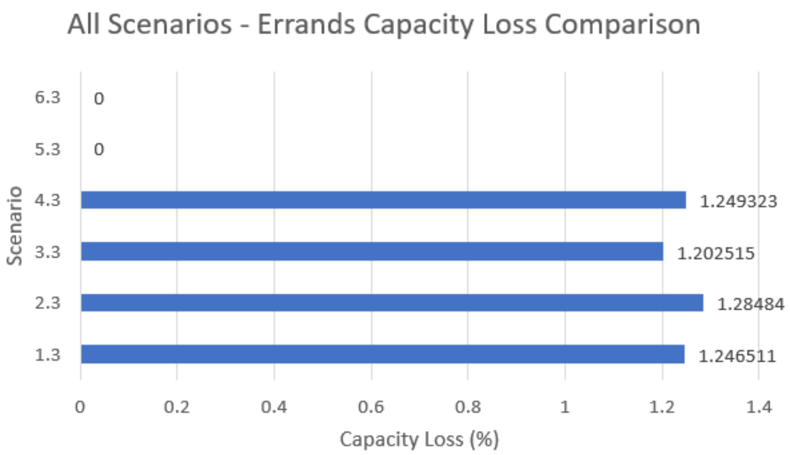


Figure 38: All scenario weekend errands capacity loss graph

The errands weekend scenario nearly matches the values from the main reference scenario, Figure 30, for each of the four scenarios (1, 2, 3, 4) that completed their simulations. There is a mere 0.01% difference between each of them. This shows that if the weekends are rest periods or there are small errand runs with charging at the stores, both with or without V2G, the capacity loss changes a negligible amount. Therefore, it is well within reason to also run V2G on the weekends as part of a user's vehicle usage profile. A good test for future studies could be to completely maximize V2G discharge cycles throughout the day irrespective of the grid need, just to see the capacity loss at both extremes. This study was kept more in line with reality and assumptions based on research in order to find the real-world scenarios that V2G makes an impact on.

The one parameter change that all six scenarios crashed in simulation is the short road trips weekend scenario. This is unusual that all the scenarios have crashed but it fits with the theme that the statechart is not operating as it should. Figure 39 shows that all the scenarios stop in nearly the identical spot of a bit past 120-130 hours. This lines up with when a regular weekend cycle is supposed to occur, in the case of this overall scenario the stay at home version with V2G or not depending on the specific scenario number.

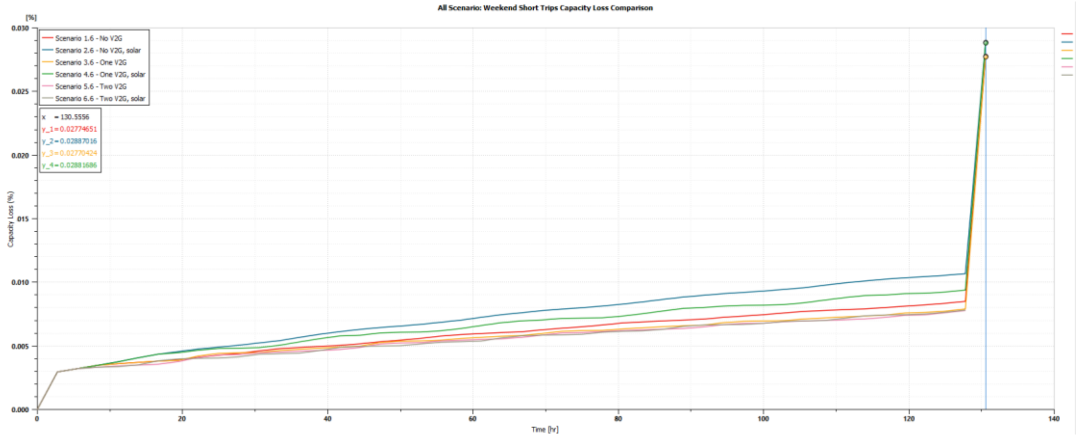


Figure 39: All scenario short road trips capacity loss comparison

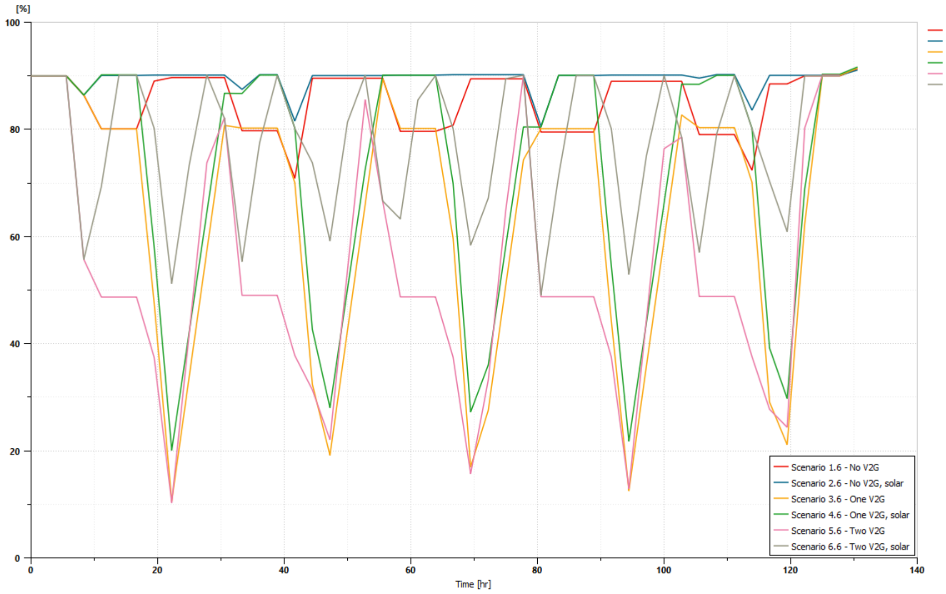


Figure 40: Short road trips simulation failure check via SOC

By checking the SOC in Figure 40, the easiest way to see what went wrong with the scenario, it shows that the SOC was able to go above the max of 90% right before the simulation crashed. This means that the weekend scenario did not trigger rest properly and instead continued to charge. For future updates to the model the statechart logic needs to be verified. It was working perfect for most scenarios outside of one so then a change was made to incorporate variables instead of events and that might have caused the issue.

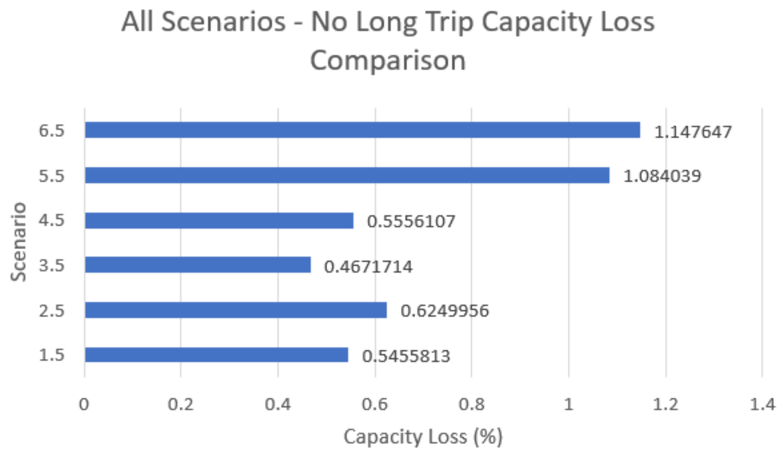


Figure 41: All scenario no long trip capacity loss graph

The long trip adjustment to the scenarios was a good addition to alleviate concerns over longer driving sessions combined with fast charging in addition to V2G. Verification of how much the impact the parameter has is based on Figure 41 compared to the main scenario in Figure 30. This is the lowest capacity loss out of any scenario for weekday scenarios 1, 2, 3 and 4. Scenarios 1, 2 and 4 are nearly half of their main scenario counterparts, while scenario 4 is almost 3 times less. The takeaway here is that once again V2G is making less of an impact than regular driving habits that users would do regardless of attempting to keep their battery healthy. For battery and EV manufacturers this is promising because it makes the application of V2G make sense from a battery degradation point of view. The other factors like the wear and tear on other components related to charging or the cost of the components themselves is a different story but purely from a degradation point of view the marginal additions to capacity loss, or even the lower capacity loss scenarios, point to V2G being successful. The perks and benefits are all there from the grid peak shaving side, the electrification environmental side, the emergencies side and the ease-of-use side for the drivers.

6 Conclusions

The continued push towards 100% electrification is only gaining momentum so any solutions that can help mitigate the need for new infrastructure will be extremely beneficial. V2G could be part of this solution allowing the private users to use their EVs to benefit more than themselves. V2G offers a unique solution to the intermittency of renewables and also encourages the continued turnover of ICE vehicles to EVs which are key to clean up the energy industry. The continued concern over EV batteries, in terms of safety, performance and range leave V2G a hot topic. The idea of stressing out a battery further than necessary is unwanted by both users and OEMs. This thesis has explored the concept of V2G, its benefits and potential detriments, all the while seeking to explore battery degradation. The key component to V2G becoming implemented is less the technology, as that is already in existence, and more the degradation impact. For it to proliferate the market, both between charging infrastructure and on board EVs, the concerns need to be quelled or at the very least better understood.

The results of the AMESIM model are noteworthy in the fact that they demonstrate V2G scenarios as only being marginally more impactful on the battery in a handful of scenarios but also better with one V2G session per day. The two baseline scenarios are actually worse to begin with because they are always keeping the battery at a high SOC, between a 10% range of the upper SOC limit. This is a real-life scenario though as many people plug in right when they get home from work and the smart charging option to delay charging or slow it down has not been quick to spread just yet. When changing the baseline scenarios to charging every 48 hours instead of every 24 then the capacity loss is right in line with the higher V2G scenarios. The aspect of V2G that could revolutionize how people charge is the ability to plug in and forget. The battery management system of the vehicle, the smart charging infrastructure and the ability to V2G will keep the vehicle optimally charged and discharged to maximize the battery lifetime. The failed simulations due to the statechart were not ideal but the overall results still were able to offer valuable insight. Future iterations of the study can put a focus into adjusting the statechart for the current scenarios but also add in deeper complexity. For example, in this model there is only a minimal smart charging system implemented based on calculations from assumed usage profiles so this could be further optimized and then the results should become more in favor of V2G.

This study was done with a semi-empirical model but if it were to be redone with theoretical model to include power fade / loss then the results could be even more accurate and conclusive. The testing of this in the real world will also need to be conducted to see what sort of other factors might need to be considered. For example, factors like number of EVs in a specific location, power levels changes for charging instead of only for discharging, or even taking into account other charging components like power converters. All of the components related to charging would need to be analyzed for their potential degradation as well. Going from a vehicle and its components resting for 95% of the day to suddenly being utilized for V2G and extra charge cycles at up to 83% of the day. That is a major increase on the systems and components. The battery has shown the ability to handle to increase but some of the other components need to be studied. If they do not last with the increase in utilization then it will mean more repairs or more costly longer lasting components, all which could increase the cost of EVs and charging infrastructure immensely. A main adjustment that would tailor this study for more EVs would be the inclusion of a battery chemistry comparison. At the moment it is only a wholistic comparison more of scenarios than of specific battery types. This study would need to continue to follow the market trends as LFP batteries are becoming more popular in EVs already. Tesla, MG and BYD have already begun to use LFP cells in some of their vehicles even at the technical lower energy density but at a lower cost with a longer life cycle [62]. NMC will continue to live alongside LFP and may even remain the higher used option, but it is good to be able to adapt the model for different use cases. This way regardless of the vehicle in a line-up that is tested it will suffice. This change will continue as costs factor heavily into the purchase decisions for EVs right now, more so than the range or performance anxieties of more premium customers.

The V2G concept that has been on the minds of scientists longer than EVs have been in the center stage. Now the current market dictates EV warranties at around 10-12 years which match that of ICE vehicles. The time to change a battery in an electric vehicle is at 80% capacity and the goal of this study was to ensure that V2G could still stay within the industry average warranty window for EVs. The scenarios all stayed well within 20% capacity loss in 10 years outside of the two V2G sessions per day during the SOC 100% max and 0% min simulation. That was the only time that the numbers were even close. It is also not a scenario that EV owners will do often, or even at all. Partially because they are told not to but also because EV manufacturers and OEMS place protection limits on their batteries as well. Based on this study the detriments of V2G on battery degradation are not as bad as they have been made out to be. V2G can even keep a battery healthier than if it was just kept charged as often as possible so it is a win-win-win situation. This is very promising for the industry and should help allow for V2G to become a normal part of EV user, grid side operators and OEMs practices.

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A. Appendix for Figures

Table of Figures:

B. Appendix for Tables

C. Appendix for Equations