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# Essais sur la participation des véhicules électriques sur les marchés de l'énergie : aspects économiques véhicule-à-réseau (V2X) et considérations relatives à la dégradation des batteries

Andrew W. Thompson

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# Essays on Electric Vehicle Participation in Energy Markets: Vehicle-to-Anything (V2X) Energy Service Economics and Battery Degradation Considerations

Thèse de doctorat de l'Université Paris-Saclay  
préparée à l'Université Paris-Sud

Ecole doctorale n°578 Sciences de l'Homme et de la Société (SHS)  
Spécialité de doctorat : Sciences économiques

Thèse présentée et soutenue à Paris, France, le 12 Décembre 2019, par

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# List of Acronyms

**Ah**

Amp-hour

**B2L**

Battery Second Life

**BESS**

Battery Energy Storage System

**BMS**

Battery Management System

**C-rate**

Charge Rate

**CAGR**

Compound Annual Growth Rate

**CAISO**

California Independent System Operator

**CCGT**

Combined Cycle and Gas Turbine

**DER**

Distributed Energy Resource

**DoD**

Depth of Discharge

**DR**

Demand Response

**DSO**

Distribution System Operator

**EC**

Ethylene Carbonate

**ECM**

Equivalent Circuit Model

**EIA**

US Energy Information Administration

**EIS**

Electrochemical Impedance Spectroscopy

**EMC**

Ethel Methyl Carbonate

**EoL**

End of Life

**ERCOT**

Electric Reliability Council of Texas

**EV**

Electric Vehicle

**EVI**

Electric Vehicle Initiative

**EVSE**

Electric Vehicle Supply Equipment

**FCEV**

Fuel Cell Electric Vehicle

**FR**

Frequency Regulation

**G**

Graphite

**HPPC**

Hybrid Pulse Power Characterization

**ICE**

Internal Combustion Engine

**IEA**

International Energy Agency

**LAM**

Loss of Active Material

**LCO**

Lithium Cobalt Oxide

**LCOS**

Levelized Cost of Storage

**LCP**

Lithium Cobalt Phosphate

**LFP**

Lithium Iron Phosphate

**LFSF**

Lithium Iron Fluorosulfate

**Li-O<sub>2</sub>**

Lithium Air

**Li-S**

Lithium Sulfur

**LIB**

Lithium-ion Battery

**LiBF<sub>4</sub>**

Lithium Tetrafluoroborate

**LiPF<sub>6</sub>**

Lithium Hexafluorophosphate

**LLI**

Loss of Lithium Inventory

**LMO**

Lithium Manganese Oxide

**LMO-NMC**

Manganese Oxide/Nickle-Manganese-Cobalt Blend

**LNO**

Lithium Nickel Oxide

**LTO**

Lithium Titanate Oxide

**LTS**

Lithium Titanium Sulfide

**MOBICUS**

Modeling of Batteries Including the Coupling between Calendar and Usage Aging

**MUA**

Multiple-Use Application

**NCA**

Nickel Cobalt Aluminum Oxide

**NMC**

Nickel Cobalt Manganese

**NPV**

Net Present Value

**NREL**

National Renewable Energy Laboratory

**NYISO**

New York Independent System Operator

**OEM**

Original Equipment Manufacturer

**PBR**

Performance Based Regulation

**PEU**

Power Electronics Unit

**PFC**

Power Factor Correction

**PHEV**

Plug-in Hybrid Electric Vehicle

**PJM**

PJM Wholesale Energy Market Operator

**PVT**

Present Value of Throughput

**RA**

Resource Adequacy

**RES**

Renewable Energy Sources

**RPC**

Reactive Power Control

**SEI**

Solid Electrolyte Interface

**SO**

System Operator

**SOC**

State of Charge

**SOH**

State of Health

**SSB**

Solid State Battery

**TCO**

Total Cost of Ownership

**TOU**

Time-of-Use

**TSO**

Transmission System Operator

**V1G**

Mono-directional or Smart Charging

**V2B**

Vehicle-to-Building

**V2C**

Vehicle-to-Community

**V2G**

Vehicle-to-Grid

**V2H**

Vehicle-to-Home

**V2L**

Vehicle-to-Load

**V2V**

Vehicle-to-Vehicle

**V2X**

Vehicle-to-Anything

**VoLL**

Value of Lost Load

**VR**

Voltage Regulation

**WTA**

Willingness-to-Accept

**WTP**

Willingness-to-Pay



## **EV30@30**

The Electric Vehicle Initiative (EVI) shared goal to obtain a 30% EV sales share of all vehicles by 2030 in member nations.

## **Lithium-ion Battery**

A lithium-ion battery or Li-ion battery is a type of rechargeable battery based on the physical principles of reversible ionic intercalation in graphite and cathodic oxides. Lithium-ion technology provides the highest specific power and specific energy over other electro-chemical storage technologies and is the most promising battery storage solution for the near future.

## **System Operator (SO)**

The business unit which ensures technical operation of the electric grid network. Multiple designations can be made such as TSO for the Transmission System Operator, DSO for the Distribution System or even ISO as an Independent System Operator.

## **Value Stream**

A monetization mechanism, energy service product, or cost savings value provided by a V2X resource which can be derived from:

- 1.) The Wholesale Energy Market, through the provision of energy products or use of market mechanisms.
- 2.) Through interaction with Utilities and Network System Operators, by providing value in terms of capital cost deferment and greater efficiency of existing network assets.

- 3.) Or through interaction with Customers, by providing value to Residential, Commercial, or Industrial consumers in terms of cost savings and reliability.

Analogous to revenue stream but allows for a larger definition scope to allow for consideration of enviro-social aspects and to account for energy markets where regulation is not sufficiently modernized to define compensatory structures which reflect the full benefits or range of energy services new technology can provide to the electric grid.

### **Value Stream Framework**

A framework to better express the economic value that V2X technology can offer by identifying the full range of energy services, cost savings measures (see: Value Streams) and designating which V2X topology can provide said value.

### **Vehicle-to-Anything (V2X)**

An umbrella term to explain the use of electric vehicle batteries to derive additional value during times of non-use through dynamic and mono-directional (V1X) or bi-directional (V2X) charging to provide energy services to the electric grid, to reduce energy consumption of buildings and homes, or to provide back-up power to loads.

### **Vehicle-to-Building (V2B)**

Operates much like that of V2H but at larger scale which may employ only a few EVs or aggregate entire fleets to optimize building or site (micro-grid) energy consumption. As V2B is aimed at commercial and industrial buildings, benefits are more pronounced and V2B technology can reach grid-significant capacity through aggregation which opens other avenues that V2H cannot access.

### **Vehicle-to-Grid (V2G)**

The most well-known V2X topology and refers to using EV batteries to interact with and provide value to the electric grid in the form of one or more energy services. While V2G is understood to mean bi-directional charge/discharge capability, V1G entails mono-directional charge control and is also referred to as Smart Charging.

### **Vehicle-to-Home (V2H)**

The next least complex V2X topology which consists of optimizing home energy consumption or using one or several EVs as emergency back-up power for residential homes. V2H will operate with a connection to a central hub/home energy controller,

likely in conjunction with rooftop solar and potentially with small-scale battery storage.

**Vehicle-to-Load (V2L)**

The least complex and smallest scale V2X topology which constitutes any instance of an individual EV battery providing energy to a load. The primary envisioned operation of V2L is in providing emergency back-up energy in the case of an electric grid outage or serving as a source of energy in rural areas with limited grid connections.



# Introduction

The transportation sector accounts for around 25% of global energy-related carbon emissions of which light-duty passenger vehicles account for over half and their impact is expected to grow in the coming years [1, 2]. It is clear, that to achieve the necessary carbon emission reductions agreed upon in the Paris Climate Accords there must be a substantial contribution from the transport sector [3]. Replacement of light-duty vehicles with Electric Vehicles (EVs) and Plug-in Hybrid Electric Vehicles (PHEVs) offers a promising alternative to take advantage of synergies between the Energy and Transport sectors, yet their effectiveness as a solution depends on a decarbonized electric grid and the availability of cost competitive battery technology. While PHEVs and other hybrid vehicle technologies are already well established in the market, key barriers to large scale EV market penetration include battery costs and vehicle range, both areas where recent technology developments provide encouraging signs. Evidence suggests that EVs may reach price parity with Internal Combustion Engine (ICE) vehicles by 2022 [4]. There are several ongoing approaches to these barriers to EV adoption.

The first approach is to lower the cost of battery packs thus lowering the Total Cost of Ownership (TCO) of EVs. This strategy is noted as the “Tesla approach”, which aims to exhaust economies of scale while improving manufacturing techniques and drastically reducing shipping costs by assembling battery packs in-house. The second is to invest in research and development of new battery chemistries and new technology. Research is directed towards the development of longer lasting and safer cells with greater energy density, thus lowering per kWh costs. This includes experimentation with new additives in electrolyte and cathode materials for longer lasting Li-ion cell chemistry [5–9]. New technologies include Lithium Sulfur (Li-S) and Lithium Air (Li-O<sub>2</sub>) battery configurations, the use of solid electrolytes over organic liquid electrolytes for the creation of Solid State Batteries (SSBs), and incorporation of new anode materials such as Silicon and Titanate

[10–15]. The third approach is related to developing more intelligent Battery Management Systems (BMSs) to allow for smaller batteries to satisfy the same mobility demands, thus lowering the TCO of EVs through decreased capacity requirements and the additional cost savings from reduction in vehicle weight [16, 17]. The fourth approach, which is the focus of this dissertation, is to develop new revenue streams to offset the high initial cost of EVs through participation in energy markets and provision of grid services, or through diminishing the energy burden of buildings or homes. Vehicle-to-Grid (V2G), Vehicle-to-Building (V2B), Vehicle-to-Home (V2H), and Vehicle-to-Load (V2L) collectively denoted as Vehicle-to-Anything (V2X) services, aim to derive additional value from the battery asset during times of non-use in the primary objective of mobility.

An important question is to what extent additional use of the vehicle battery will affect battery capacity over its lifetime. Understanding the fundamentals of battery degradation therefore is crucial to estimate the cost of this degradation which impacts the economic viability of V2X. The central claims of this dissertation are 1.) that V2X marginal cost is not zero nor negligible as the economic literature has accepted but is highly dependent on battery degradation cost and that 2.) V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.

Chapter 1 introduces and explains the V2X concept along with an estimation of annual potential value and a discussion of relevant regulatory implications. Chapter 2 focuses on the fundamentals of battery degradation and extracts the important concepts needed for economic considerations of lithium-ion battery assets. Chapter 3 introduces economic approaches to battery degradation cost modeling along with a proposed theory of V2X Marginal Cost. Finally, Chapter 4 contains overall conclusions, a summary of the contributions of this dissertation, and recommendations for future work.

## Part I

# Vehicle-to-Anything (V2X) Energy Services, Value Streams, and Regulatory Policy Implications



# Vehicle-to-Anything (V2X) Energy Services

“ *Either write something worth reading or do something worth writing.* ”

BENJAMIN FRANKLIN

---

## **Abstract.**

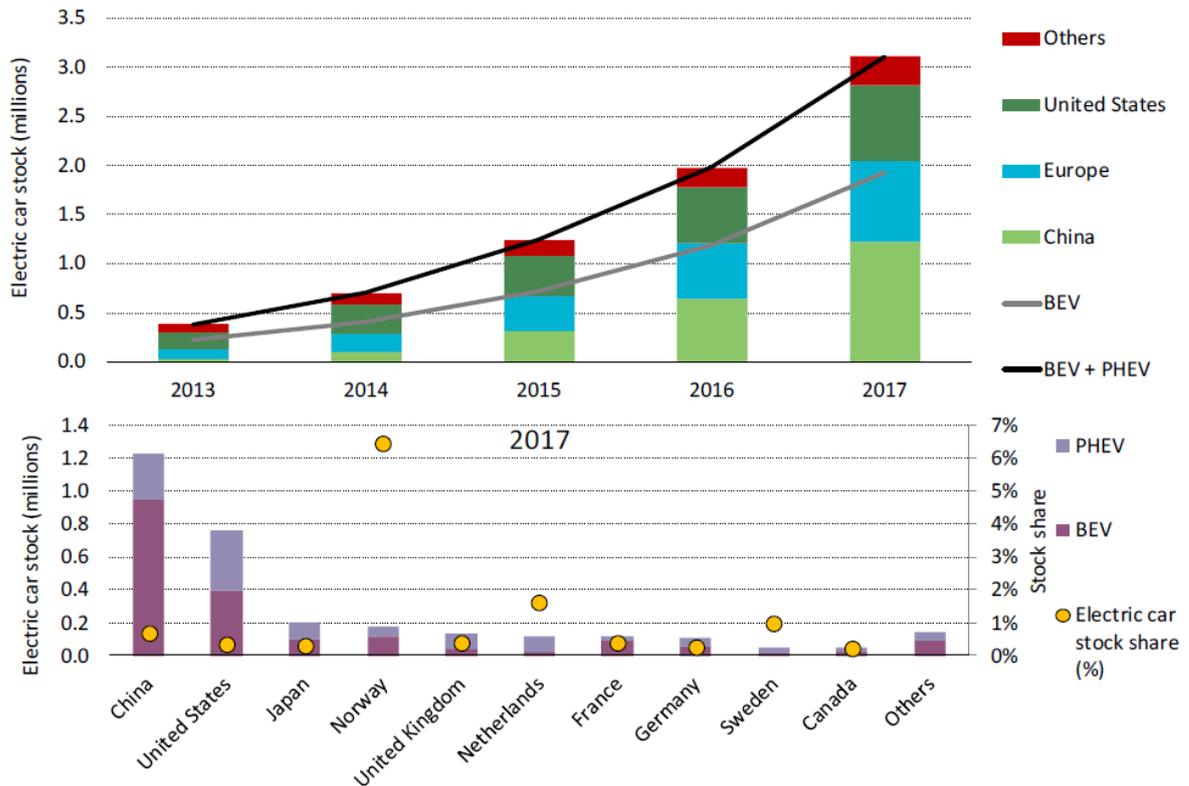
Vehicle-to-Anything (V2X) is an umbrella term to explain the use of electric vehicle batteries to derive additional value during times of non-use. V2X services generate revenue from the battery asset through dynamic mono-directional (V1X) or bi-directional (V2X) charging to provide benefits to the electric grid, to reduce energy consumption of buildings and homes, or to provide back-up power to loads. While relatively unknown and still regarded as a nascent technology, V2X exhibits low capital costs while enabling costs have decreased by 90% since 2014.

In this chapter I present the V2X Value Stream Framework as a means to better communicate and categorize the full economic potential of V2X. A meta-analysis of Value Stream potential gives results contradictory to the literature and indicates that Bill Management, Resource Adequacy, and Network Deferral are more valuable than Energy Arbitrage and Spinning Reserves. I distinguish between Energy and Power Value Streams and show how the latter cause less battery degradation and allow for greater stacking of services. Finally, energy policy recommendations are given to better integrate V2X. While I concur that development is of and by the market, I emphasize that V2X will develop within the constraints of the regulatory environment; therefore regulators have an enabling role to play.

A version of this chapter appears as: Thompson, A.W., Perez, Y., 2019. “Vehicle-to-Anything (V2X) Energy Services, Value Streams, and Regulatory Policy Implications” accepted to Energy Policy.

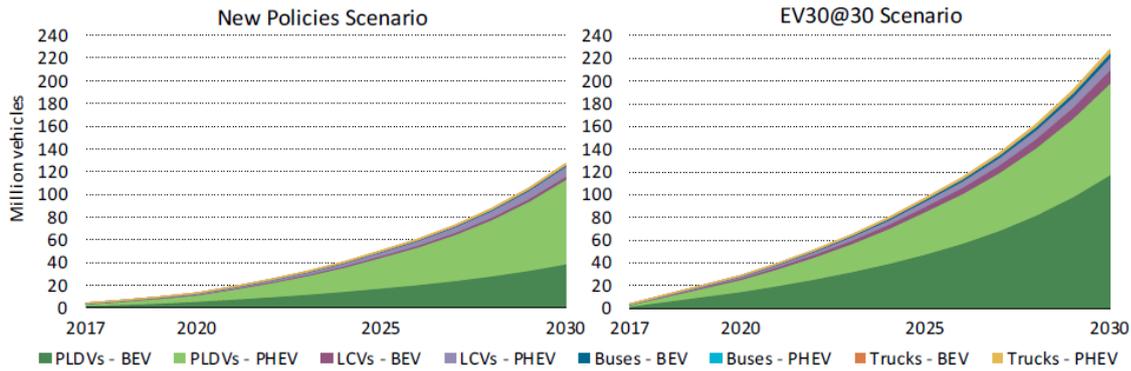
## Introduction

In 2017 the global EV stock surpassed 3 million units, which follows a nearly 60% continuous growth rate since 2015 [Figure 1.1](#). Sustained exponential growth is expected for the near future and will result in an estimated 130 – 220 Million EVs worldwide by 2030 [\[18\]](#). Also in 2017 the Electric Vehicle Initiative (EVI) whose members account for the vast majority of the global EV stock have adopted the EV30@30 campaign which sets a shared goal to obtain a 30% EV sales share of all vehicles by 2030 [Figure 1.2](#) [\[19\]](#).



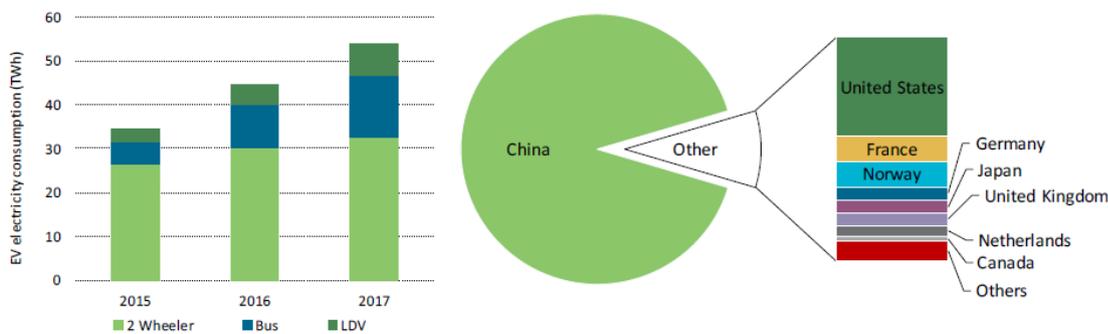
**Figure 1.1:** 2018 IEA Global EV Stock Development and Market Share [\[18\]](#).

Along with growing electric transport will come increased electricity demand. If all light-duty vehicles in the US were suddenly replaced with EVs, they would require about 1,000 TWh of additional electricity per year or an increase of about one-quarter of the



Notes: PLDVs = passenger light duty vehicles; LCVs = light commercial vehicles; BEVs = battery electric vehicles; PHEV = plug-in hybrid electric vehicles.

Figure 1.2: 2018 IEA Global EV Projections [18].



Notes: TWh = terawatt-hours. The pie chart refers to 2017 data. The assumptions are: passenger vehicle consumption 20-27 kWh/100 km, annual mileage 8 500-18 800 km; two-wheelers consumption 3-5 kWh/100 km, annual mileage 5 900-7 500 km; electric urban bus consumption 135-170 kWh/100 km, annual mileage 28 000-47 000 km, (the range indicates the variation across countries). The share of electric driving for PHEVs is assumed to be 36% of the annual mileage. Charging is assumed to have an efficiency of 90%.

Figure 1.3: 2018 IEA Global EV Electricity Demand [18].

current annual US electricity demand [20]. In 2016, the global EV electricity demand was 54 TWh which is approximately the annual energy demand of Greece Figure 1.3. The question of electricity demand driven by EV charging will largely depend on penetration levels. A recent simulation study in New England showed that a 25% EV penetration would cause a 19% increase in peak demand which would require significant investment in new generation, transmission, and distribution capacity [20]. It is clear that unmanaged EV charging is not an economic option in the long-term therefore development of Vehicle-to-Anything (V2X) technology can be a solution to what will become a serious problem in a future with large penetration of EVs.

V2X however is still a developing area and is virtually unheard of amongst the public and within policy spheres. Even among professionals and academics working in the electro-mobility domain V2X remains relatively unknown [21]. This results in research

which only looks at one facet of the V2X concept and usually only considers one revenue stream to draw conclusions about the viability of V2X as a whole without considering the full range of potential value nor the full operational capabilities [see 22, 23]. Additionally the scientific literature is rife with misuse of V2X terminology which conflates meaning, confuses technical audiences and policy-makers alike, and undoubtedly highlights the need for clearer communication.

Therefore this chapter presents a thorough definition of the V2X concept to clarify the literature, introduces the V2X Value Stream Framework to better communicate the full economic potential of V2X, and explains the relevant regulatory policy context. I begin with the **V2X Concept Explained** section where the four main topologies/operating modes are described. I break from previous work in that I highlight lesser researched topologies and present each in the order of increasing scale and complexity. Next the **V2X Value Stream Framework** is introduced and results of a meta-study of economic potential are presented. The V2X concept is further developed with the introduction of the Power vs Energy services distinction. Finally, various energy policy issues are discussed in the **V2X Regulatory Issues** section where I present a methodology to assess energy market adaptability to V2X services and provide final remarks in the **Partial Conclusions: V2X and Policy Implications** section.

## 1.1 V2X Concept Explained

### 1.1.1 V2X Topology

V2X is an umbrella term to explain the use of EV batteries to provide energy services and derive additional value from the battery asset during times of non-use. V2X services aim to generate revenue from the battery asset through dynamic or bi-directional charge control to provide benefits to the electric grid, to reduce/flatten/shift peak energy consumption of buildings and homes, or to provide back-up power to a load. Energy services refer to selling this dynamic charge control in the form of aggregated flexible capacity in Wholesale and Ancillary Services markets to provide much needed flexibility to System Operators (SOs) and other relevant parties for technical operation of the electric grid. V2X topology refers to both the electrical connection involved and the operation mode employed and can be classified as Vehicle-to-Load (V2L), Vehicle-to-Home (V2H), Vehicle-to-Building (V2B), or Vehicle-to-Grid (V2G).

While most research efforts to date have focused on the well-documented and defined Vehicle-to-Grid (V2G) concept, V2X should be understood to represent all topologies of which V2G is one. A few studies have referenced Vehicle-to-Vehicle (V2V) but as this nomenclature is redundant to V2L it has fallen into disuse. Additionally, [24] have identified a Vehicle-to-Community (V2C) topology where aggregated EVs are connected at the distribution grid to serve a residential community, analogous to community storage or community solar. Finally, [25] provide a succinct review of V2X technology which further delves into infrastructure considerations.

When referring to V2X it is implicit that any service would be provided in addition to and apart from the primary purpose of mobility i.e. when the vehicle is parked, which has been proven to be more than 90% of the asset life [26]. The energy capacity of a V2X resource is dependent on a number of factors, namely the EV battery pack capacity and the effective charge rate which is determined by a combination of the Electric Vehicle Supply Equipment (EVSE) and the onboard charger in the vehicle. In the case of an aggregated V2X resource the other key parameter is the number of vehicles needed to provide a given energy capacity with certainty.

#### 1.1.1.1 Energy Capacity

Energy capacity in contemporary battery packs in commercial vehicles range from 16 kWh–100 kWh with gravimetric energy densities ranging from  $89 \text{ Wh kg}^{-1}$  to  $260 \text{ Wh kg}^{-1}$  at the battery cell level [27]. Technological developments aim to increase gravimetric energy densities to  $350 \text{ Wh kg}^{-1}$  in the near future and potentially upwards of  $800 \text{ Wh kg}^{-1}$  for new lithium-air technology, which would result in potential battery packs of up to 230 kWh if pack weights remain the same [28]<sup>1</sup>. However, as EV battery development is focused primarily on vehicle range and energy efficiency and not on total energy capacity, future battery pack capacity will be largely dictated by customer driving needs. Therefore a maximum optimal battery capacity will exist for each consumer driving segment and will result in an upper practical limit on individual V2X capacity, however this limit will only slightly impact the number of vehicles parameter needed for most V2X services.

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<sup>1</sup>Rationale for 230 kWh battery pack: Curb weight is a crucial parameter for EV range, therefore assuming battery pack weight does not change from leading gravimetric energy density technology (2017 Tesla Model 3) from [27]. The calculation is as follows:  $75 \text{ kWh} \div 260 \text{ Wh kg}^{-1} = 288.5 \text{ kg}$  (current leading edge pack weight not including wiring, mounting, or packaging). To find potential future battery pack capacity:  $288.5 \text{ kg} \cdot 800 \text{ Wh kg}^{-1} = 230.8 \text{ kWh} \simeq 230 \text{ kWh}$ .

### 1.1.1.2 Effective Charge Rate

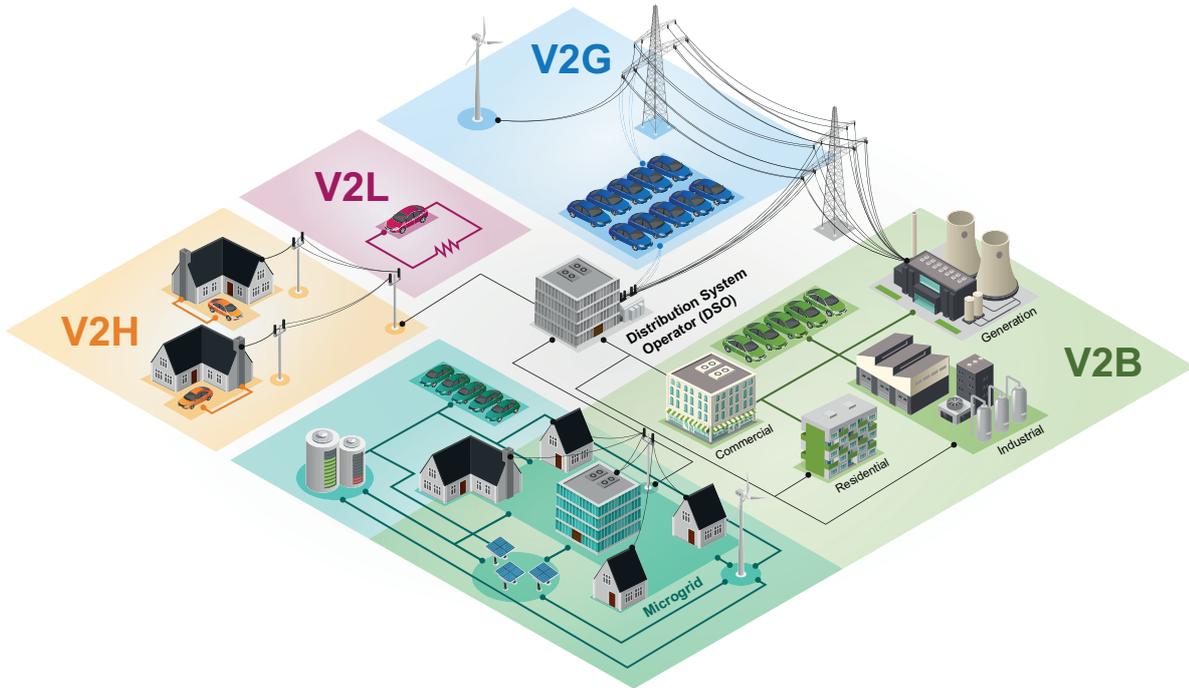
The effective charge rate is determined by the limits of the combination of the Electric Vehicle Supply Equipment which provides electricity to the vehicle, and the onboard charger within the EV which provides electricity to the battery. EVSE have become standardized by charging power where in the U.S. Level 1 = 1.44 kW–3.3 kW on-board single phase AC, Level 2 = 3.3 kW–14.4 kW on-board single or 3-phase AC, and Level 3 = 14.4 kW–240 kW off-board direct DC charging. In Europe standards have developed along similar lines and have designated three charge levels where Normal = 3.7 kW single phase AC, Medium = 3.7 kW–22 kW single or 3-phase AC, and High = greater than 22 kW with an additional two distinctions, one for 3-phase AC and another for DC connections [29].

However the EVSE charge power can be limited by the onboard charger within the EV as is usually the case. The onboard charge power is also known as the acceptance rate which can range from 3.3 kW–19.2 kW in current EVs. For example a vehicle may be connected to a Level 2 EVSE which can provide 7.7 kW of power to the vehicle, however the onboard charger within the vehicle can only charge/discharge the battery pack at a maximum of 6.6 kW, therefore the effective charge rate is limited to 6.6 kW. Conversely the onboard charger may accept up to 19.2 kW but if it is connected the same Level 2 charger, the effective charge rate will be limited by the EVSE to 7.7 kW. Therefore effective charge rate is important to understand when choosing both the vehicle type and EVSE for a V2X resource.

Figure 1.4 is a comprehensive visualization of the V2X concept which highlights each topology, where they operate within the energy system, and the connections with other grid elements. I classify Microgrid operation as a special use-case of the V2B topology as evidenced by the color overlap. In the following sections each topology is presented starting from smallest scale and least complex to largest and most complex.

## 1.1.2 Vehicle-to-Load (V2L)

V2L is the least complex and smallest scale topology and constitutes any instance of an individual EV battery providing energy to a load. The primary envisioned operation of V2L is in providing emergency back-up energy in the case of an electric grid outage or serving as a source of energy in rural areas with limited grid connections. V2L can provide energy to critical equipment in hospitals or research centers, power external electronics, or even operate in recreational non-emergency usages as a generator for camping, construction



**Figure 1.4:** *V2X Topology Explained:*

where  $V2G = \text{Blue}$ ,  $V2B = \text{Green}$ ,  $V2H = \text{Orange}$ , and  $V2L = \text{Red}$ . I classify microgrid operation as a special use-case of the  $V2B$  Topology expressed by the color overlap of green shades. Colored connections indicate interactions within the topology whereas black connections indicate connections/interactions with other grid elements. The Distribution System Operator (DSO) is featured as a central figure due to the unique role of the distribution system in enabling much of  $V2X$  capability.

sites, concerts, parties, and other areas where there are limited grid connections.

While  $V2L$  provides the most easily accessible and recognizable value, it paradoxically has garnered the least amount of academic research which highlights a large opportunity for future work<sup>2</sup>. One of the key areas of inquiry will be the economic valuation of  $V2L$ . Willingness-to-Pay (WTP) and Willingness-to-Accept (WTA) studies are the norm in electric power systems design and energy economics for determining the Value of Lost Load (VoLL). VoLL is a socioeconomic indicator which measures the monetary damage arising from loss of economic activity due to a power outage, or stated differently, a measurement of the maximum electricity price customers are willing to pay to avoid an outage [33, 34].

<sup>2</sup>A recent 2019 scientific publication search of top rated energy journals with keywords “Vehicle to Load  $V2L$ ” yielded a total of 3 publications: Applied Energy [30], IEEE Xplore [31], Journal of Power Sources [32], Energy Policy (0), Energy Economics (0), Renewable Energy (0).

Research on VoLL indicates a heterogeneity of value across segments with the industrial and commercial sectors ranging from a few €/kWh to more than 250€/kWh and a large variation between countries from few €/kWh for EU member states to more than 250€/kWh for the USA and New Zealand. For private users in the residential sector VoLL values range from a few €/kWh up to 45€/kWh [34]. It is clear though that even the lowest estimations of VoLL constitute a significant price gap, and thus value potential, of V2L when compared to the US average residential electricity price of 0.13\$/kWh (0.11€/kWh) with EU member state household electricity prices ranging from 0.10€/kWh to 0.31€/kWh [35, 36].

Recent work which uses more granular socioeconomic data has noted that a higher than average VoLL is exhibited among the fuel poor, early adopters of EVs, and those living in rural locations [37], areas where V2L is a natural fit. V2L technology may develop faster in rural areas or where diesel generators are still heavily relied upon as in Alaska, Hawaii, and other islanded electric grids where even expensive technologies are made competitive due to the high cost of diesel fuel and the associated shipping costs [38, 39]. V2L remains an area of promise for future research as technical barriers are largely absent and development will be focused on application of existing capabilities.

### 1.1.3 Vehicle-to-Home (V2H)

V2H is the next least complex topology and consists of optimizing home energy consumption or using one or several EVs as emergency back-up power for residential homes. V2H will operate with a connection to a central hub/home energy controller, likely in conjunction with rooftop solar and potentially with small-scale battery storage as seen most notably in the Tesla Powerwall and in Nissan’s V2H ecosystems [40, 41]. As an illustration, a single fully charged Tesla Model S with a 100 kWh battery pack even with a very low effective charge rate of 2 kW could provide over 70 hours of electricity consumption for an average residential home in the US and approximately 10 days of electricity for an average home in the European Union<sup>3</sup>, a clear value which explains the existence of several commercial products today.

V2H value derived from energy optimization is largely dependent on locational aspects

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<sup>3</sup>From [42] Annual US average electricity usage = 12,305 kWh, Annual EU average electricity usage = 3600 kWh. US average hourly electricity usage:  $12,305 \text{ kWh} \div 8760 \text{ h} = 1.41 \text{ kW}$ , EU average hourly electricity usage:  $3600 \text{ kWh} \div 8760 \text{ h} = 0.41 \text{ kW}$ . V2H electricity provision from 100 kWh battery pack for US:  $100 \text{ kWh} \div 1.41 \text{ kW} = 70.92 \text{ h}$ . V2H electricity provision for EU:  $100 \text{ kWh} \div 0.41 \text{ kW} = 243.90 \text{ h}$

such as residential tariff structures and electricity prices. Electricity tariffs can be characterized as being either Volumetric (with and without net-metering) or Capacity based. Both structures can either be applied uniformly throughout the 24 hour day or may vary depending on the hour, such as with the Time-of-Use (TOU) or Peak/Off-peak designs [43]. Thus V2H can optimize energy expenditure in two ways: 1.) by flattening the home consumption curve to reduce peak electricity demand thus reducing capacity charges or 2.) by taking advantage of TOU structures along with electricity price and adapting home energy consumption to minimize energy costs. Additionally, there is discussion of developing special EV electricity tariffs which encourage charging in the evening hours when electricity demand is low to reduce wind curtailment and thermal plant shutdowns [44]. In summary, V2H offers a clear value proposition which has already garnered industry support and is the second most commercially developed V2X topology to date.

#### 1.1.4 Vehicle-to-Building (V2B)

V2B operates much like that of V2H but at larger scale which may employ only a few EVs or aggregate entire fleets to optimize building or site (micro-grid) energy consumption. As V2B is aimed at commercial and industrial buildings, benefits are more pronounced and V2B technology can reach grid-significant capacity through aggregation which opens other avenues that V2H cannot access. Industrial and Commercial consumers not only are subject to much higher capacity charges but are also charged for line phase imbalances caused by large inductive loads which increase line power losses and require expensive corrective actions.

These capacity charges, additionally referred to as demand charges, can comprise over half of a monthly commercial/industrial electricity bill yet are induced by only a few brief spikes in building load [25]. US average annual commercial electricity bills range from \$6,671 – \$11,647 (€5.857 – €10.226) and US average annual industrial bills range from \$40,680 – \$491,749 (€35.715 – €431.729) from most recent 2017 data [45]. Therefore a V2B resource that can reduce these peaks by even a few kW can deliver significant cost savings, thus providing a valuable service for a low capacity and time commitment [46].

Power Factor Correction (PFC), Reactive Power Control (RPC), and Voltage Regulation (VR) are all corrective actions employed to improve power quality and thus minimize line losses in power systems. While passive methods such use of capacitor banks are simple but expensive, active methods employ power electronics to dynamically adjust reactive power output. EVs can provide these services by operating their EVSEs with different

goals: by providing reactive power to achieve a reference power factor (PFC), by providing or absorbing reactive power to/from the grid (RPC), or by providing/absorbing reactive power in response to grid conditions to improve node voltage levels (VR) [47]. Research indicates however that Voltage Regulation may be the most impactful service to offer and that EV charging can be effectively operated with minimal influence on the distribution grid [48].

These expanded benefits are not limited to customers alone since, due to the scale, grid operators also reap benefits from reduced industrial/commercial peak loads and improved power factors. Additional considerations such as reduction of carbon emissions, infrastructure capital cost deferral, and reduction of operational costs have been reported by V2B integration [49]. These direct and derivative benefits come at the cost of increased complexity as fully capable V2B services will require connection to building or central energy system controls which may or may not have communication capabilities with the greater electric grid. V2B offers substantial and tangible financial benefits through Industrial and Commercial cost savings and by providing grid-significant capacity resources which can access energy markets as elaborated further in the [V2X Value Stream Framework](#) section.

### 1.1.5 Vehicle-to-Grid (V2G)

V2G is the most well-known V2X topology and refers to using EV batteries to interact with and provide value to the electric grid in the form of one or more energy services [50]. While V2G is understood to mean bi-directional charge/discharge capability, Mono-directional or Smart Charging (V1G) also exists and provides flexibility through dynamic charge control. Both operating modes require sophisticated telecommunication and controls which can receive signals and respond to real-time grid conditions by either varying charge power (V1G) or by varying both charge and discharge power (V2G). V2G presents the largest overall revenue potential with direct access to wholesale energy and ancillary services markets, however it constitutes the most complicated topology due to the need for grid-significant capacity acting in response to real-time grid conditions. V2G services therefore are provided by an Aggregator coordinating a multitude of individual vehicles or by operating a fleet of vehicles.

While V2G approximately doubles the available capacity with a substantially greater revenue potential than a V1G resource, current enabling costs (mono to bi-directional EVSE infrastructure marginal costs) are significant and point to the lack of available

commercial products and technological maturity [51–53]. Cost trends are encouraging however as V2G enabling costs have decreased by a factor of 9.4 or nearly 90% from €44.953 in 2014 to €4.805 in 2018 and will continue to decline as technology develops [51, 54]<sup>4</sup>.

Additionally, an effective charge rate corresponding to Level 2 (6.6 kW) or higher is necessary for V2G services as lower charge rates would require too many vehicles to meet minimum capacity bids in energy markets, the few available V2G EVSE commercial products have settled in the 10 kW–15 kW range. The V2G concept also has attracted significant commercial interest and has spurred a number of start-up companies (NUUVE, EMotorWerks), large investments in hardware and ecosystem development (The Enel Group, Nissan Energy, ChargePoint), and wide participation from automotive OEMs (Renault-Nissan-Mitsubishi Alliance, Groupe PSA, Honda, BMW, Transpower, Volkswagen, Toyota, among others). A recent market report identified at least 50 ongoing V2G research projects that are at the pilot or commercial phase worldwide making V2G the most commercially developed topology [54].

## 1.2 V2X Value Stream Framework

I present economic potential of V2X in terms of Value Streams where value can be derived from the **Wholesale Energy Market**, through use of products or mechanisms; through interaction with **Utilities and Network System Operators (SOs)**, by providing value in terms of capital cost deferment and greater efficiency of existing network assets, or through interaction with **Customers**, by providing value to Residential/Commercial/Industrial consumers in terms of cost savings and reliability.

The term *value* has been deliberately chosen instead of *revenue* to allow for an expanded definition scope since in many instances energy market regulation has either not developed or modernized sufficiently to define adequate compensatory structures which

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<sup>4</sup>2014 numbers from [51] which reported the Princeton Power Systems GTIB-15 V2G EV charger price at \$55,000 compared to the ChargePoint CT4011-GW V1G Charger at \$5,000. Thus V2G enabling costs ( $EC_{2014}$ ) were \$50,000 in 2014. 2018 numbers: Enel X/Magnum Cap V2G 10 1.5 charger price at €5.500 from personal communication compared to Enel X/EMotorWerks JuiceBox Pro 32 V1G charger commercially available for €695 within the EU (Available for \$549 in the USA), thus V2G enabling costs ( $EC_{2018}$ ) were €4.805 in Europe in 2018.

Convert  $EC_{2014}$  to  $USD_{2018}$  with average USD inflation rate of 1.48% = 53,035.20  $USD_{2018}$  Convert  $USD_{2018}$  to  $EUR_{2018}$  using 2018 US/EUR historical average Fx of 0.8476, Therefore  $EC_{2014} = €44.953$   $EUR_{2018}$  and  $EC_{2018} = €4.805$   $EUR_{2018}$

reflect the full benefits new technology can provide. The Value Stream Framework is also intended to eventually include enviro-social aspects such as CO<sub>2</sub> emissions reduction, battery life prolongation, reduction in air pollution/city noise, and wellbeing. In this first iteration I focus primarily on V2X Value Streams which already have identifiable monetization avenues within the energy industry and leave enviro-social aspects for future work. In a future where carbon markets or carbon pricing in energy markets become important, this would likely constitute increased benefits that V2X can offer, however I restrict the Value Stream Framework to current regulatory environments.

Furthermore the Value Stream Framework is presented to categorize the full range of energy services V2X can provide, designate which topology can provide each service, and identify where value is derived while providing some insight to the economic scale of each Value Stream. Finally, the Value Stream Framework is not intended as an affirmation or condemnation of overall economic viability as the feasibility of each V2X topology will depend on a multiplicity of project-specific and locational factors.

## 1.2.1 Value Stream Identification

### 1.2.1.1 Assumptions

V2X energy services are defined by the technical capabilities of lithium ion batteries arranged into packs of differing sizes. As the underlying technology is the same, V2X has similar characteristics as lithium ion Battery Energy Storage Systems (BESS) albeit at reduced scale. Technical operation has been proven to be within System Operator (SO) performance requirements by several pilot projects [55, 56], therefore the first key assumption is that V2X can provide most of the services as BESS.

I develop the V2X Value Stream Framework drawing upon work from Lazard's Levelized Cost of Storage (LCOS) analyses along with US Energy Information Administration (EIA) and national lab reports [57–61]. These approaches have extensively identified potential markets that BESS could access and have developed robust empirical assessments of BESS economics in addition to general Li-ion technological trends. As reiterated in the latest LCOS Version 4.0 [59], key trends include cost declines that have exceeded expectations in addition to improving project economics for most use cases. LCOS 4.0 reports capital costs of Li-ion BESS between 1140 \$/kW to 1814 \$/kW operating in the Wholesale market, with a 5-year capital cost reduction of 28% and a Compound Annual Growth Rate (CAGR) of -8% over the same time period from 2018-2022. This cost range

is also in line with US EIA estimations of 1857\$/kW for new entrant battery storage in 2018 [62].

BESS is cost competitive and indeed already cheaper than other traditional sources of Ancillary Services such as Combined Cycle and Gas Turbine (CCGT) and Coal power plants in select markets [63]. This analysis paired with recent experiences in Australia’s FCAS market, California’s wholesale market (CAISO), and PJM’s frequency regulation service, imply that Li-ion battery storage will continue to capture market share based on price competitiveness alone [64–66]. Therefore the second key assumption is that V2X will primarily compete in the market with lithium-ion BESS and I do not consider other technologies further. Finally, as shown later in the *V2X Regulatory Issues*, many market rules that benefit V2X will also benefit BESS in addition to other capacity-restrained Distributed Energy Resources (DERs). I postulate that V2X and BESS will exhibit competition behavior; competition in the energy market yet cooperation in lobbying energy market regulatory change.

### 1.2.2 V2X Value Streams

Table 1.1 is the V2X Value Stream Framework with explanations of the underlying energy services translated into how they are provided by V2X along with where value is generated within the energy industry. Each Value Stream description expands upon both uni-directional (V1X) and bi-directional (V2X) operation, where X refers to multiple topologies or is replaced by the specific topology referenced (i.e. V2G, V1B). Where no distinction is made indicates that both V1X and V2X operate in the same manner. Additionally Table 1.1 highlights which Value Stream is accessible by each V2X topology, whether the service is provided by an Aggregated or Individual resource, the scale/number of vehicles for each topology, if the service is Power or Energy Based, and designates where each physically operates in the electric grid either In-front-of or Behind-the-Meter (BOM).

**Table 1.1: V2X Value Stream Framework:** Value Streams are presented by sector category (Wholesale, Utilities/SO, Customer) along with definitions and indication of where value is derived in the energy industry. Green indicates Power Value Streams while blue indicates Energy Value Streams (see *Power vs Energy Based Services*). Additionally shows which V2X topology can access each Value Stream, whether the service is provided by an Aggregated or Singular resource, the scale/number of vehicles needed for each topology, and where each operates physically, either In-front-of or Behind-the-Meter (BOM).

Sector	Value Stream	Definition and Value Derivation	Aggregated		Singular		Operation
			V2G	V2B	V2H	V2L	
			(10+)	(1-30)	(1-3)	(1)	
Wholesale	Resource Adequacy	Provides capacity through ability to discharge electricity (V2G) or ability to reduce demand (V1G/V2G) at future peak load hours. Value through RA mechanisms or Capacity Payments.	✓				In-Front-of-the-Meter
	Frequency Regulation	Either fluctuate charge rate (V1G) or charge and discharge (V2G) to follow a 4 second regulation signal. Value through Ancillary Service markets or mechanisms.	✓				
	Demand Response-Wholesale	Reduce charge rate or delay charge (V1G) or in addition to previous, discharge to grid (V2G) in response to grid conditions. Value through wholesale market DR mechanisms.	✓				
	Energy Arbitrage	Buy electricity (charge) during low price hours and sell (discharge) at later high price hours (V2G only). Value through wholesale market in hourly price difference.	✓				
	Spinning Reserves	Maintain electricity balance by immediately discharging to grid (V2G) or by interrupting charge (V1G) in response to grid contingencies. Value through Ancillary Service markets/mechanisms.	✓				
	Load Following	Due to solar peak or wind fluctuation, discharge (V2G) to control system demand ramp rate. Value through Ancillary Services market.	✓				
	Excess RES generation	Charge to absorb excess wind and/or solar generation. Value through reduced RES curtailment.	✓				
	Peak Shaving	Charge at peak hours to reduce demand. Value through wholesale market.	✓				
	Generation Pairing	Paired with RES to control ramp rate of large energy fluctuations or with thermal generator to improve flexibility and allow faster response time. Value through ancillary services markets, bi-lateral contracts, and forgone retro-fit upgrade costs.	✓	✓			
	Reactive Power Support	Adjust Reactive Power output to provide PFC, RPC, or VR (V2X only). Value through Ancillary Services market or through forgone investment to reduce inductive loads.	✓	✓			
Utilities/SO	Network Deferral	Reduce demand (V1X/V2X) or increase supply (V2X) at peak to meet projected load growth in capacity-constrained areas for the purpose of delaying, reducing, or avoiding Trans/Dist. build-out. Value via TSO/DSO direct payments or infrastructure deferral mechanisms.	✓	✓			In-Front-of-the-Meter
	Demand Response-Utility	Reduce charge rate or delay charge (V1X) or in addition to previous, discharge to grid (V2X) in response to grid conditions. Value through utility operated DR mechanisms.	✓	✓	✓		
	Site-located RES firming	Discharge (V2X only) to firm site solar or wind generation capacity to improve RES utilization rates. Value through reduced RES curtailment and/or payments for meeting RES targets.	✓	✓	✓		
Customer	Bill Management	Reduce demand charges and adapt EV battery charge (V1X)/discharge (V2X) depending on tariff or TOU rates to minimize electricity costs. Value through cost savings.		✓	✓		BOM
	Emergency Back-up	Provide emergency energy to buildings in the case of outage (V2X only). Value through costs savings of forgone diesel fuel or through VOLL estimation.		✓	✓		
	Non-Emergency	Mobile source of electricity for recreational activities or rural areas: camping, concerts, construction sites, parties, etc (V2X only). Value through pricing for capability.			✓	✓	

### 1.2.2.1 Power vs Energy Based Services

I introduce a key distinction between Energy and Power (or Capacity) Based Value Streams as these have significant implications for battery degradation costs and greatly impact viability for any energy-constrained resource. As shown in [67], unintelligent prolonged energy throughput (charge and discharge) has pronounced negative effects on Li-ion battery lifetime as will be thoroughly explored in Chapter 2. These lifetime effects are significant to the point that nearly any large energy throughput V2X service will be cost prohibitive if not managed with a thorough understanding of the intricacies of battery degradation.

Conversely, intelligent degradation-cognizant V2X provision has been shown to improve battery lifetime even for large energy throughput, a valuable secondary benefit [68]. In general, V2X Services which result in smaller changes in battery State of Charge (SOC) will have smaller degradation costs than large energy throughput services which induce greater SOC swings. Similarly, V2X services which are able to maintain temperature-dependent optimal SOC set points will also induce less battery degradation. Therefore Power Based Value Streams which either do not contain an energy component or require less energy throughput will be crucial for V2X development.

The first Power Based service is Frequency Regulation (FR) which fundamentally is derived from charge/discharge power flexibility i.e. the ability to vary charge power quickly to follow a grid signal from the System Operator (SO). As the regulation signal is typically designed to result in zero net-energy exchange over the contract period, FR can be provided around an optimal SOC point without inducing large SOC swings. Resource Adequacy (RA) or Capacity Payments are compensatory mechanisms to develop new capacity to maintain safety margins above projected future peak demand. In the case of V2X the ability to alleviate future system peak loads is provided by either interrupting charge (V1G/V2G) thus reducing demand, or by discharging to the grid thus increasing supply (V2G) during peak hours. RA or Capacity payments can be stable, high revenue Value Streams and are remunerated in terms of power (\$/kW per month or per year) as opposed to energy. Similarly, Network Deferral mechanisms develop capacity (or ability to alleviate load at peak hours) in specific capacity-constrained locations in Distribution and Transmission grids to avoid infrastructure investments and build-out.

The remaining Energy Based V2X services must be balanced with their respective degradation costs within the confines of the energy capacity of the aggregated or individual resource. Large energy throughput services such as Non-spinning or Tertiary Reserves are

therefore not considered in the V2X Value Stream Framework due to likely cost prohibitive battery degradation. A preference to capture Power Based Value Streams is important not only for degradation considerations but also since they allow more for stacking of Value Streams.

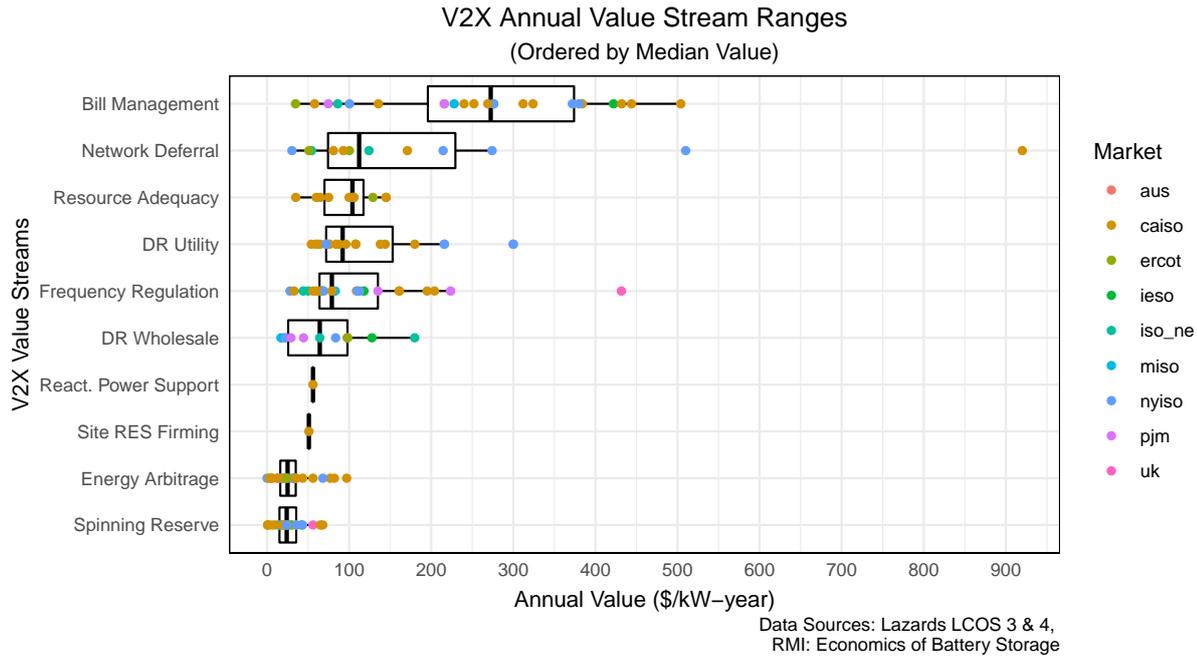
### 1.2.2.2 Stacked Value Streams

Currently BESS assets are capable of providing a variety of simultaneous energy services thus accessing multiple revenue streams however most V2X economic analyses to date have assessed viability based on only one energy service. An important point is that V2X Value Streams will need to be stacked much like current BESS operation. In practical terms this means that a V2X resource can be used to provide simultaneous services throughout the course of the year i.e. X number of hours/yr for FR while providing Resource Adequacy and Demand Response (DR). This is an area where recent regulation from the California Independent System Operator (CAISO) on Multiple Use Applications is illustrative of market development and is explored in the following [V2X Regulatory Issues](#) section.

## 1.2.3 Meta-analysis of V2X Value Stream Potential

[Figure 1.5](#) and [Figure 1.6](#) are data visualizations of a meta-analysis of selected V2X Value Stream annual revenue potential across various wholesale energy markets using data from [[58](#), [59](#), [69](#)] which also incorporate several additional sources to result in a dataset comprised of 15 unique sources. While [Figure 1.5](#) provides a general overview of the Value Streams ranked by revenue potential and includes international markets in Australia, the UK, and Canada, [Figure 1.6](#) only focuses on US wholesale markets as these have been given more investigation in the literature.

The meta-analysis is intended as an indication of Value Stream potential but not of overall economic viability due to complexities arising from locational characteristics, differing market conditions, and regulation. One particular difficulty arises in aligning Value Stream definitions as often different studies consider different product definitions e.g. Capacity products defined as including Demand Response or Bill Management Value Streams as encompassing both TOU management and Demand Charge Reduction in some studies but only TOU management in others. I endeavor to maintain the Value Streams as defined in [Table 1.1](#) to the extent possible and have adapted data from each study accordingly. Although this study was intended to find general valuation trends, several



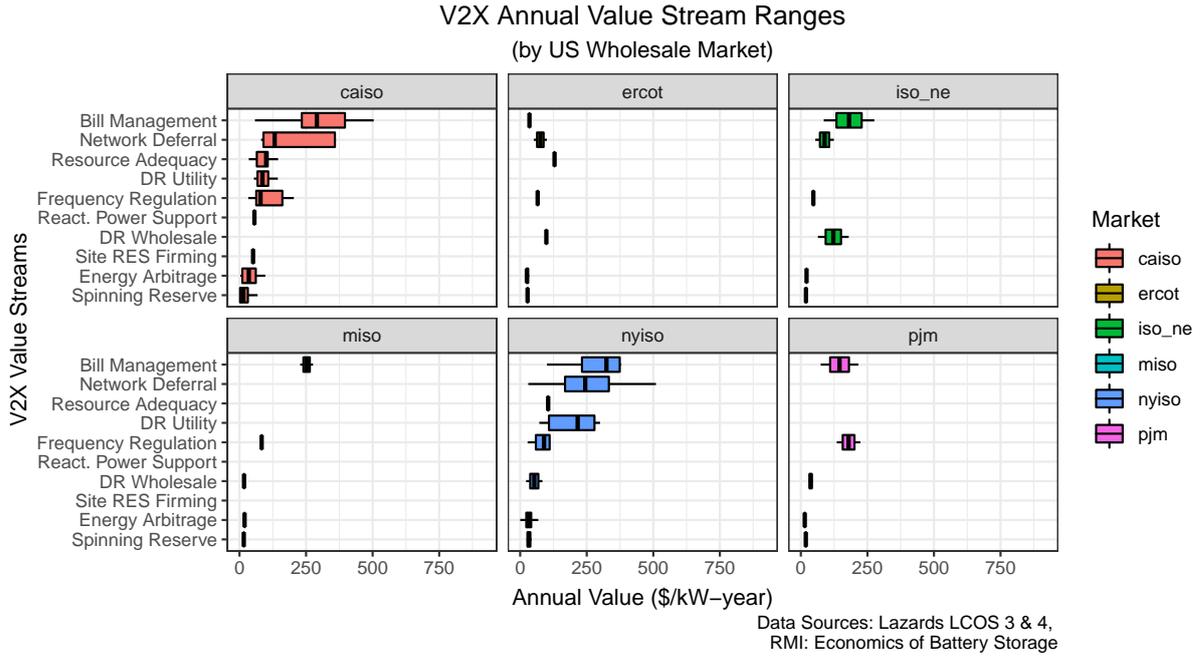
**Figure 1.5:** *V2X Annual Value Stream Meta-Analysis:*

This data visualization shows overall economic potential of key V2X Value Streams in terms of annual revenue (\$/kW-year) which are ordered by median value via boxplots where the individual data points are color-coded by wholesale market to show grouping and outliers. US wholesale markets are considered with the addition of *aus* = AEMO (Australia), *ieso* = IESO (Ontario, Canada), and *uk* = OFGEM (United Kingdom).

interesting conclusions can be drawn.

The first is there are very wide-ranging estimations of market value across Value Streams as evidenced by the spreads in Figure 1.5. For example Network Deferral show estimations ranging from 30 – 920 \$/kW-year while Bill Management ranges from 35 – 504 \$/kW-year. Hence any condemnation of V2X viability based on one Value Stream in one market alone is myopic as the same service or collection of services can be profitable in different markets with more favorable characteristics. Conversely, claims of universal economic viability are also unfounded due to market intricacies such as tariff structure, local and regional energy technology mix, and demand growth, which make drawing conclusions applicable to all markets nearly impossible. Therefore analyses of V2X economic viability must be taken in the context they are performed and may not be transferrable to other markets.

That being said, previously under-investigated Value Streams such as Bill Management, Network Deferral, and Resource Adequacy have higher valuations with surprising consistency across markets as seen in Figure 1.6. Whereas Energy Arbitrage and Spinning



**Figure 1.6:** *V2X Value Stream Meta-Analysis by US Wholesale Market:*

*This data visualization shows economic potential of key V2X Value Streams in terms of annual revenue (\$/kW-year) faceted by US Wholesale market to show similarities in valuation across markets. Here the boxplots are color-coded by market and only show descriptive statistics without individual outliers. It is interesting to note the surprising consistency of median ordered Value Streams across markets with notable exceptions in ERCOT and PJM. This implies an intrinsic economic potential of certain Value Streams over others, most notably seen in Bill Management, Network Deferral, Resource Adequacy, and Frequency Regulation compared to Energy Arbitrage and Spinning Reserves.*

Reserves, which have dominated the V2X literature, are much less lucrative overall. Interesting deviations from the ordered ranking are seen in the Electric Reliability Council of Texas (ERCOT) market with Demand Response via both Utility and Wholesale and in the PJM Wholesale Energy Market Operator (PJM) with Frequency Regulation. The latter is unsurprising due to the introduction of the Reg-D FR signal which has attracted a record amount of battery storage investment in the PJM market.

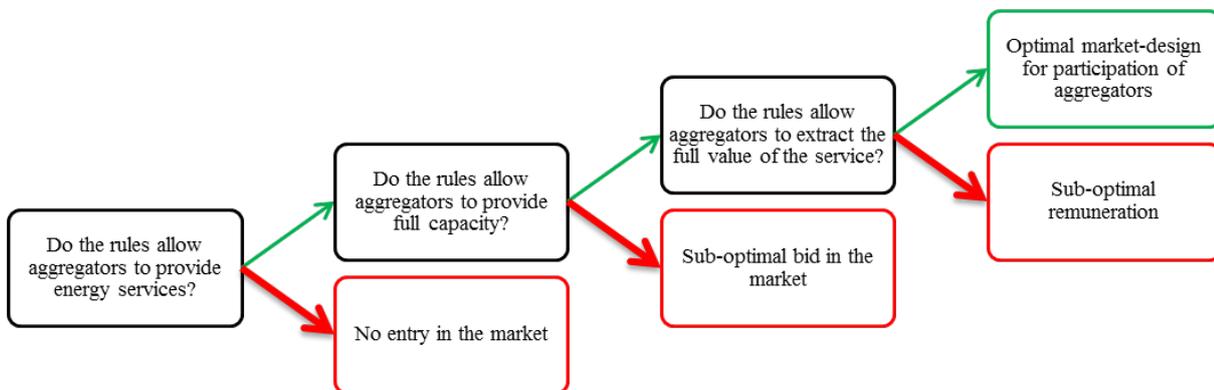
The New York Independent System Operator (NYISO) market remains highly lucrative for Network Deferral with the highest valuation of all the investigated sources. While Network Deferral likely presents a large opportunity for V2X as the second highest ranked Value Stream, I issue a large caveat that it cannot be heavily relied upon for long periods of time. Network Deferral will only generate between 2–3 years of cash flows and not 10-year or greater project life projections which contradicts Lazard’s LCOS and most other valuation studies. This is due to trade-offs between near future and far future demand

projections Transmission System Operators (TSOs) and Distribution System Operators (DSOs) must evaluate. Since large increases in demand will eventually necessitate network capacity increase, build-out will result as the most cost-effective solution. Therefore Transmission/Distribution Deferral alternatives are evaluated annually and will only provide sufficient demand reduction for 2–3 years maximum before build-out would become necessary. Therefore, I present this meta-analysis as a contradiction of most previous work and as an indication of where the potential future of V2X lies.

## 1.3 V2X Regulatory Issues

### 1.3.1 Modular Framework for V2X Aggregator Participation in Energy Markets

In electricity markets, ex-post governance solutions are needed to correct for unforeseen issues or innovations like V2X as there are no perfect market designs and energy service definitions must be updated to incorporate new technology [70]. Current market rules in several wholesale markets have been shown to be insufficient and need to be modified to better accommodate Aggregators offering DERs such as V2X and BESS [71, 72]. V2X Energy Services are wholly dependent on aggregation. Therefore to analyze three forms of entry barriers, I adapt the analytical framework of [73] on market readiness for Aggregator participation in energy markets for the V2X context. This modular framework is summarized in Table 1.2 and is expressed by a decision tree in Figure 1.7. I explain this modular framework as it relates to V2X in the following sections however note that all policy suggestions will additionally benefit BESS and other small-scale DERs.



**Figure 1.7:** *Decision Tree for Modular Regulatory Analysis Framework for V2X Aggregator participation in Energy Markets [73].*

**Table 1.2:** *Modular Analysis Framework for V2X Aggregator Participation in Energy Markets. Adapted from [73]*

Module A: Definition of Aggregation	A1	Technical Discrimination
	A2	Interoperability among DSOs
	A3	Aggregation Methodology
Module B: Definition of Energy Products	B1	Bid Structure
	B2	Power vs Energy Balance
	B3	Distance to Real-time Reservation
	B4	Value Stream Stacking
	B5	Product Symmetry
Module C: Definition of Remuneration	C1	Nature of Payment
	C2	Performance Bonus

### 1.3.2 Module A: Rules Regarding Aggregation

#### 1.3.2.1 Technical Discrimination

Some market rules discriminate against V2X resources through outright bans on aggregation of energy sources, which precludes smaller capacity resources (V2X, DER, and BESS) from participating in wholesale markets *ipso facto*. Rule discrimination can be based on technology type or when the Generation sector in energy systems is envisioned as supply-only resources (e.g. no concept of consumption units). This discrimination can also be based on the voltage level connection to the Transmission grid, by limiting the amount of capacity that can be provided by aggregated resources, or by giving priority to specific non-aggregated market units. Action can be taken regulators relating to this module by removing administrative barriers to entry to allow for aggregation of energy resources.

#### 1.3.2.2 Interoperability among Distribution System Operators (DSO)

As there are a growing number of DSOs in developed energy markets, to ensure that aggregation is possible new entrants must be able to aggregate units across multiple DSOs. This is especially important for V2G aggregating individual vehicles which can move from one DSO to another daily, but is less important for V2G fleets which are typically geographically constrained to sites or microgrids which would be serviced by one DSO.

### 1.3.2.3 Aggregation Methodology

Two methods of aggregation are identified in [71]: telemetric and financial aggregation. Telemetric aggregation allows the Aggregator to combine bids and power flows and to dispatch energy utilizing optimized algorithms which take characteristics of the combined resource into account (capacity limitation and need to maintain optimal SOC set points as examples for V2X). Conversely, financial aggregation only allows for the aggregation of economic bids. Here energy dispatch is controlled solely by the TSO which can lead to over-use and violation of SOC constraints in a V2G or V2B resource. Thus to allow greater participation of V2X, aggregation methodology should be telemetric where economic bids and energy dispatch are controlled by the Aggregator.

## 1.3.3 Module B: Rules Defining Energy Products

### 1.3.3.1 Bid Structure (Size, Increment, Temporal Granularity, Type)

#### 1.3.3.1.a Bid Size

Current wholesale markets vary widely in minimum bid size from 100 kW in PJM to 10 MW and greater in several European markets [74]. This minimum bid size will dictate the number of vehicles necessary to provide an aggregated V2X resource. If the minimum bid is set too high, a V2X resource will be prohibitively complex due to coordination of too many entities and would result in lower revenues per vehicle overall. 100 vehicles with an effective charge rate of between 10 kW–15 kW per vehicle can provide a 1 MW V2G resource, however any minimum bid size higher than this would render a V2X resource unable to access the market due to threshold effects.

#### 1.3.3.1.b Bid Increment and Temporal Granularity

Additionally the minimum bid size increment and the temporal granularity can potentially constitute barriers to market entry. As seen in [75] the authors show the impact of different bid increments and temporal granularity on V2G fleet size assuming a 1 MW minimum bid. Table 1.3 below shows bid structure impact on fleet size to achieve an annual revenue of 50 €/per vehicle which only have access to 3 kW charging at home.

As seen in Table 1.3, a temporal granularity of one week renders a V2G resource unable to participate in the Ancillary Services market whereas a change from a Peak/Off Peak

**Table 1.3:** *Bid Structure Impact on V2G Fleet Size with 3kW Charging only at Home, adapted from [75].*

Bid Increment	Temporal Granularity	Number of Vehicles
1 MW	Week	NA
0.1 MW	Week	NA
1 MW	Peak/Offpeak	1400
0.1 MW	Peak/Offpeak	903
1 MW	4 Hour	400
0.1 MW	4 Hour	50
1 MW	1 Hour	350
0.1 MW	1 Hour	40

to a 4 hour granularity reduces the necessary number of aggregated vehicles by 1,000. Similarly, continuing from a 1 MW to a 0.1 MW minimum bid increment further reduces the fleet size by an additional 350 vehicles such that a fleet of 50 EVs can offer Ancillary Services despite having access at the lowest charge rate (3 kW). Additionally it was shown that fleets with access to higher charge rates (22 kW) could meet 1 MW minimum bids with as little as 17 vehicles if there is a temporal granularity of 4h regardless of the bid increment size.

### 1.3.3.1.c Bid Type: Simple vs Complex

Finally whether bids are simple or complex can impact the optimality of an aggregated V2X resource. Simple bids are effective when system supply and demand are easily aligned and consist of a price-quantity pair given in either hourly or multi-hour blocks for a 24h day. Complex bids are increasingly important in systems with high penetration of Renewable Energy Sources (RES) and flexible demand to allow market players to specify intertemporal dependencies with their bids [76]. An example is taken from Spain which allows for an indication of up to four complex conditions along with bids [77]:

- 1.) Indivisibility: all bids with this condition must be matched in their entirety (to eliminate fractional power dispatch due to inframarginal market clearing).
- 2.) Minimum Income: bids with this condition are only accepted for market clearing if the supplier is guaranteed to recover their designated minimum income.
- 3.) Scheduled Stop Condition: this condition allows bids which are not matched due to the minimum income condition to be treated as simple bids.

- 4.) Production Capacity or Load Gradient: bids can designate a maximum upward or downward difference in energy variation between two consecutive hourly scheduling periods.

In particular the minimum income and load gradient complex conditions are very relevant to V2X to allow Aggregators to better plan fleet scheduling when costs are guaranteed to be met without undue stresses to the V2X resource from energy dispatch required from the SO. Regulators can design market rules to better incorporate V2X, BESS, and DERs by creating minimum bid sizes as low as possible (100 kW) with minimum bid increments as low as possible (100 kW) and temporal granularity of at least 4h (hourly or 15 minute intervals are better) along with complex bids to allow for more optimal aggregated bids.

### 1.3.3.2 Power vs Energy Balance

V2X and BESS would greatly benefit from having energy services better defined by how much energy throughput or power intensity they require. The development of better metrics of service utilization rates and ranking of energy services by energy throughput would allow V2X resources to better manage risk and battery degradation cost trade-offs imposed by Power and Energy Based Value Streams (see Table 1.1). To that end proposals for new energy statistics to be maintained by the SO have been made but have remained largely absent in practice.

The first is the Dispatch-to-Contract ratio  $R_{d-c}$  originally identified by [50] which would measure the quantity of dispatched energy (how much energy was actually called upon) vs the contracted energy amount. In a similar vein I designate the Call Rate  $C_r$  which tracks the frequency of dispatch calls of an energy service over time which is useful for Demand Response and Spinning/other Contingency Reserves. I also designate an FR-Energy-Imbalance statistic  $FR_i$  for Frequency Regulation which measures energy imbalances throughout the year or, stated differently, tracks when net-energy is non-zero over contract periods.

### 1.3.3.3 Distance to Real-time Reservation

This parameter defines how long in advance of delivery the procurement of energy services is made which can be days, weeks, months, or even multi-month periods in advance. Naturally the farther in advance a service is required to be reserved the more conservative V2X Aggregators must be with the amount of capacity they can provide due to the need

to predict behavior of a mobile resource. Long procurement times also negatively impact bidding ability of other intermittent RES (Wind and Solar) which have imperfect long-term forecasting ability. Therefore markets with shorter procurement times (hour ahead or real-time) will allow for more accurate estimation of aggregated capacity and more participation from V2X, DERs, and RES alike.

#### 1.3.3.4 Value Stream Stacking (Multiple-Use Applications)

As with BESS, V2X can operationally offer several simultaneous energy services due to the inherent flexibility of these resources. However nearly all markets, tariffs, and bilateral contract provisions have been designed assuming that resources will only provide one service at a time and therefore do not have adequate language or rules to allow for the paradigm-changing concept of Multiple-Use Applications (MUAs). This is an area where recent developments in California (CAISO) may serve as a guide for other Wholesale markets [78].

Recently adopted rules designate energy services (Value Streams) as either Reliability Services or Non-reliability Services as listed in Table 1.4. Furthermore CAISO has designated three categories of Multiple-Use Applications: 1.) Time Differentiated MUAs, 2.) Capacity Differentiated MUAs, and 3.) Simultaneous MUAs in efforts to introduce necessary regulatory vocabulary along with 11 rules for governing MUAs to allow for revenue from multiple services so long as they are "*specific and measurable*" [78]. Naturally, having Time-Differentiated MUAs are only feasible in markets with sufficiently fine temporal granularity to allow for multi-use throughout the day.

The fundamentals of the 11 rules regard the **Connection** and direction of energy service provision, the principle of **Reliability Priority/Exclusivity**, and service **Transparency** which I summarize below:

##### 1.) Connection

- Energy services can be provided to domain in which they are interconnected or a higher level grid domain but not in reverse (Customer connection → All, Distribution connection → Transmission, Transmission connection → Transmission only).
- However resources at all connections points may access the Wholesale market or provide Resource Adequacy provided they are they not limited by their physical location.

**Table 1.4:** *CAISO Multiple-Use Applications: Reliability Services vs Non-Reliability Services [78].*

Domain	Reliability Services	Non-Reliability Services
Customer	None	Bill-Management; Demand charge management; Back-up Power; On-site RES firming; DR program participation
Distribution	Distribution deferral; Voltage support; Reliability (back-tie) services; Resiliency/microgrid/islanding	None
Transmission	Transmission deferral; Inertia*; Primary frequency response*; Voltage support*; Black start	None
Wholesale Market	Frequency regulation; Spinning reserves; Non-spinning reserves; Flexible ramping product	Imbalance Energy
Resource Adequacy	Local capacity; Flexible capacity; System capacity	None

\* Voltage support, inertia, and primary frequency response have traditionally been obtained as inherent characteristics of conventional generators, and are not today procured as distinct services. They are included here as placeholders for services that could be defined and procured in the future by CAISO.

## 2.) Reliability Priority/Exclusivity

- For any bid capacity, priority must be given to reliability services over non-reliability services.
- The same capacity cannot be committed at the same time for multiple reliability services and provision of one reliability service cannot interfere with technical requirements of providing another. The exclusivity principle therefore assumes provision of multiple reliability services are both time and capacity differentiated by definition.

## 3.) Transparency

- Penalties for non-compliance of service provision are clearly communicated in the service definition.
- Resources must declare any other services they are providing apart from the current solicitation.
- Any MUA must be able to be clearly distinguished and measured.

These guidelines have significant implications for V2X and BESS economics and constitute positive advancement toward realizing their full potential while upholding the Principle of Network Access which is a fundamental tenet in most liberalized markets.

#### **1.3.3.5 Product Symmetry**

Product Symmetry relates to Ancillary Services markets and the procurement of Frequency Regulation/Reserves and reserve margins. Two types of regulation/reserve products exist: 1.) upward products – increase of generation or reduction of consumption (i.e. provision of positive reserve) or 2.) downward products – reduction of generation or augmentation of consumption (i.e. provision of negative reserve).

Upward and downward regulation/reserves constitute distinct operations and there is more inherent value in resources which can provide upward regulation/reserves however not all markets differentiate these products. Most markets that do differentiate allow for separate bids for upward and downward provision; while markets that do not only allow for symmetrical bids, meaning the provider must deliver the same amount of downward and upward reserve.

Product symmetry limits new market entrants as explored in [79, 80] which showed that wind energy can economically provide downward reserves through curtailment but not upward reserves due to imperfect forecasting and efficiency losses of sub-maximal production. Similarly, V1G can provide downward reserves with faster reaction times than most other traditional sources; however an obligatory symmetrical offer of upward reserves would preclude it from the market. V2G would likely be limited as well and would have to offer the minimum of available upward reserve or downward reserve throughout the day.

### 1.3.4 Module C: Rules Defining Remuneration

#### 1.3.4.1 Nature of Payment (Regulated vs Market Solution and Mandatory vs Voluntary Service Offer)

Different remuneration schemes exist such as regulated tariffs or market solutions (pay-as-bid and uniform pricing) which are applied to energy service provision that can be on a mandatory or voluntary offer basis. The use of a regulated tariff is typically associated with mandatory service provision and is applied to specific market participants (often large producers). Even if rules allow service provision from new-entrant Aggregators, selection is made by an administrative rule and does not allow Aggregators to compete effectively with incumbent actors. This ultimately leads to market inefficiencies and exercise of market power as energy services are not procured based on their costs.

For market solutions, uniform pricing incentivizes actors to bid at the marginal cost of service which gives efficient pricing signals for the short and long term. Whereas pay-as-bid schemes incentivize actors to bid as high as possible below the expected clearing bid price, which can lead to clearing price elevation and erosion of customer benefits [81]. Voluntary service offers allow Aggregators to bid based on temporal efficiency depending on fleet size and behavior. Therefore, market solutions with uniform pricing bid schemes and voluntary service offers result in more fair and competitive remuneration.

#### 1.3.4.2 Performance Bonus

If a resource offers additional flexibility, a faster response time, or is available a higher percentage of the year, this constitutes added value and should be remunerated as such. However as market rules and service definitions to date have been based on the technical limits of large-scale thermal generation, many wholesale markets have not defined performance bonuses to reflect the value of faster-acting resources. Clearly defined performance metrics and methods for remuneration of resources which meet or exceed them are a fundamental component of Performance Based Regulation (PBR) which has proven to result in greater market efficiencies while unlocking the full potential of new energy technologies.

## 1.4 Partial Conclusions: V2X and Policy Implications

### 1.4.1 V2X Topology

All V2X topologies are developing in tandem with and in spite of the others at varying speeds. Technological maturity and lack of competition remain problems predominately in the enabling hardware and V2X as a whole is still regarded as a nascent technology recently making steps from research labs and demonstration projects into the commercial realm. However V2X exhibits significantly reduced capital costs compared to BESS and bi-directional enabling costs have decreased by 90% since 2014 and will likely continue to decline as V2X develops, see [Vehicle-to-Grid \(V2G\)](#). The lines between each topology can be blurred and confused yet can be easily identified by focusing on the aggregation, connection, or control point and by defining where the operational benefit is derived, see [Figure 1.4](#).

I present the example of a fleet of 100 EVs providing active and reactive power while dynamically responding to grid characteristics but doing so through a building's central energy control hub with the goals of minimizing site inductive loads (Power Factor Correction) and flattening the electricity demand profile. This case would represent a V2B topology despite interaction with the grid as the control/connection point is through the building with operation intended to benefit the building or site. This same fleet can alter active and reactive power output in response to grid conditions which are translated into control signals from an Aggregator. The Aggregator dispatches this fleet with the operational goals of providing Voltage Regulation (VR) to maintain node voltage levels on the distribution grid and to reduce peak loading in specific areas. This second situation constitutes a V2G topology as the fleet operation is for the benefit the grid.

### 1.4.2 V2X Value Stream Framework

I present the V2X Value Stream Framework as a means to categorize the full range of energy services that V2X can provide, designate which topology can provide each service, and identify where value is derived within the Energy Industry, see [Table 1.1](#). The [Meta-analysis of V2X Value Stream Potential](#) expressed in [Figure 1.5](#) and [Figure 1.6](#) shows results that are contradictory to most previous work in that the under-investigated value streams of Bill Management, Resource Adequacy, and Network Deferral have more economic potential compared to the frequently studied Energy Arbitrage and Spinning

Reserves. V2G provision of DSO services are underrepresented globally which seems to stem from lack of DSO service maturity (regulatory policy) rather than limitations of V2G technical ability [54].

Economic viability of V2X must be analyzed and applied only to the market context in which analysis is conducted as results are non-transferrable due to geographic particularities. The differentiation between Energy and Power Based services is important and V2X economic valuations should be based on stacked Value Streams. The results of the [Meta-analysis of V2X Value Stream Potential](#) show that overall the Power Based Value Streams tend to exhibit the highest revenue potential across markets which highlights a clear opportunity for V2X deployment. Hence any universal condemnation or confirmation of V2X viability based on one Value Stream in one market alone is myopic as the same service or collection of services can be profitable in different markets with more favorable characteristics. I present this meta-analysis as an indication of where the potential future of V2X lies.

Another key insight is that most use cases for BESS in the Residential Sector, Microgrids, and additionally some Commercial Sectors, have been deemed to be economically unviable due to prohibitively high capital costs. This may indicate another large opportunity for V2X in these niche markets providing Bill Management, Demand Response, and Reactive Power Support services. Other benefits that V2X affords such as increased Renewable Energy Resource (RES) integration and firming, reduced greenhouse gas emissions, and decreased RES curtailment due to better energy management have significant demonstrable societal value however monetization is largely an artifact of energy policy and regulation.

### 1.4.3 V2X Regulatory Challenges

While I agree with [21] in that V2X technology is a product largely of and by the market, I modify this stance to emphasize that V2X is a product of the market which will develop within the constraints of the regulatory environment. If regulators do not take positive actions in changing rules I predict that industry development of V2X will only be directed toward use-cases where minimum investment and complication is needed. Indications of this limited development which reflects the current market environment are seen in [54] which affirms that Smart Charging (V1G) is sufficient for many energy services and that V2G currently only offers value in specific scenarios where location matters, in areas with surplus solar capacity, and in markets with high peak pricing or demand charges, even

though it allows for longer duration of service provision over V1G.

Insufficient regulatory action will limit the full range of environmental and economic benefits from an electrified Transportation Sector. Transport electrification and integration with the Energy Sector must therefore be implicit goals which can be realized through regulatory policy. In the [V2X Regulatory Issues](#) section I presented a discussion of how regulatory policy can better incorporate V2X which results in three overarching objectives: 1.) to remove administrative barriers to aggregation of energy resources; 2.) to design rules which allow for: (a) greater and more efficient Aggregator access to energy markets and (b) through developing technology-agnostic energy service definitions; and 3.) to design equitable remuneration schemes which give incentives to actors to reveal their costs while ensuring they are compensated for the full value of service they provide.

These policy proposals not only benefit V2X but also Battery Energy Stationary Storage (BESS) and other Distributed Energy Resources (DERs). In conclusion V2X is an innovative development within the energy industry and its effectiveness as one of the suite of solutions to our most pressing energy challenges in the 21<sup>st</sup> Century is not only market driven but driven by regulatory policy.

## Part II

# Lithium-Ion Battery Degradation for V2X Services



## Battery Degradation for V2X Services

“*In the beginner’s mind there are many possibilities,  
but in the expert’s there are few...*”

SHUNRYU SUZUKI

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### **Abstract.**

Electric and Plug-in Hybrid Electric Vehicles are a promising sustainable mobility alternative due to their low emissions impact and the rapidly falling production costs of Li-ion batteries. To lower total vehicle ownership costs, V2X services aim to derive additional value from the battery asset through dynamic or bi-directional charge control to provide benefits to the electric grid or to reduce/flatten/shift peak energy consumption of buildings. In this chapter I outline the relevant electrochemical phenomena which result in unique Lithium-Ion Battery Degradation behavior and explain battery lifetime aging within the context of V2X energy services.

Battery State of Health (SOH) is impacted through reduction of total capacity and/or increase in internal impedance due to various degradation mechanisms which collectively result in Calendar Aging and Cycling Aging behaviors. At moderate temperatures, Calendar Aging is the dominant factor and this understanding paired with the fact that most vehicles are immobile more than 90% of the time, implies that the battery management strategy while at rest will bound lifetime. Evidence suggests that V2X could prolong battery life through integration with optimized management algorithms and that cost effective V2X services may be dependent on battery chemistry. Therefore

economic analyses of battery assets should contain sufficient electrochemical detail to account for chemistry specific degradation behavior.

A version of this chapter appears as: Thompson A.W. 2018, "Economic implications of lithium ion battery degradation for vehicle-to-grid (V2X) services". *Journal of Power Sources*; 396:691–709.

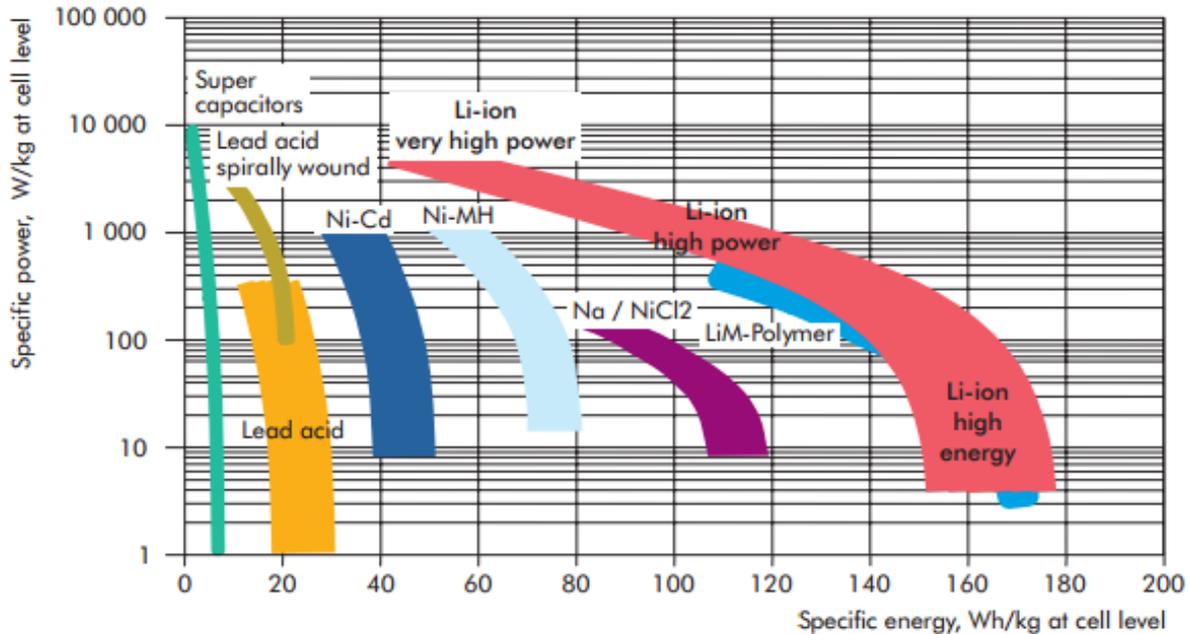
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## Introduction

Replacement of light-duty passenger vehicles with Electric Vehicles (EVs) and Plug-in Hybrid Electric Vehicles (PHEVs) offers a promising measure to combat Climate Change while taking advantage of economic synergies between the Energy and Transport sectors due to their low emissions impact and the rapidly falling production costs of Li-ion batteries. Additional derivative health benefits of lower urban noise and reduction of particulate matter air pollution and smog will become increasingly important as urban population densities continue to rise. 2007 marked the first moment in history where a greater percentage of the world population lived in cities. The Urban population has since continued to increase linearly to 4.13 billion compared to the Rural population which has experienced a relatively flat increase to 3.4 billion in 2017 [82]. However, the effectiveness of EV replacement as a solution depends on a decarbonized electric grid and the availability of cost competitive battery technology.

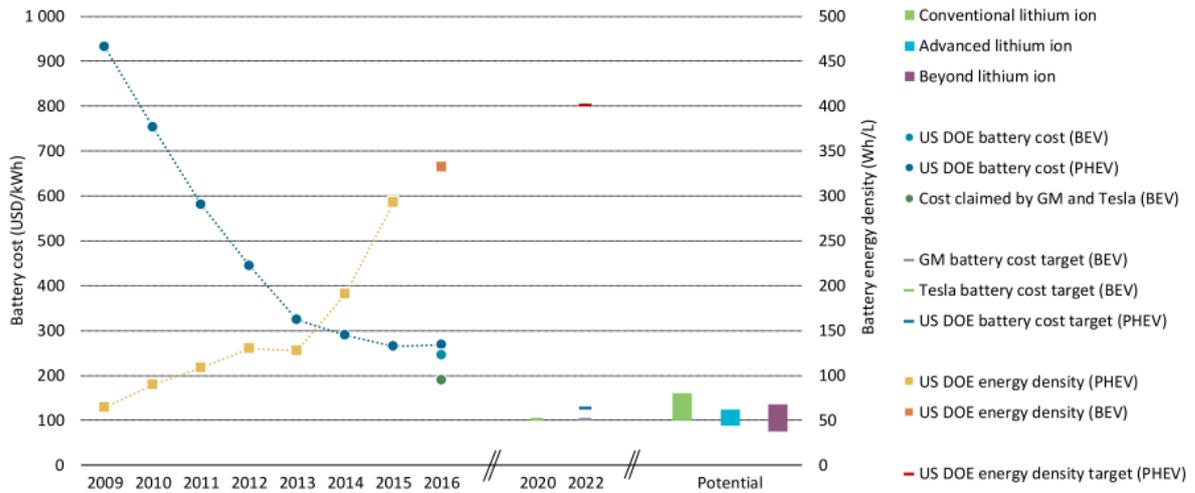
Lithium-ion technology provides the highest specific power and specific energy over other commercial battery types as seen in the Ragone plot in Figure 2.1. Two complementary global trends have been observed in Lithium-ion Battery (LIB) Technology which provide clear signs of the coming EV paradigm: a simultaneous reduction of battery costs paired with an increase in battery energy density. Battery costs have been reduced by a factor of four since 2008 and are set to decrease further [18]. It is a well-communicated notion that a battery pack cost of 100 \$/kW will enable EV price parity with conventional Internal Combustion Engine (ICE) vehicles. According to [83] EV price parity will now be reached in 2022 whereas previous 2017 analysis estimated this point to be in 2026. The improved price parity projection is majorly attributed to drastic battery pack cost reduction which has seen its percentage share of total vehicle cost drop from over half (57%) in 2015 to one third (33%) in 2019 [83]. Industry announcements follow this cost reduction trend where in 2018 Tesla/Panasonic claimed to have achieved a battery cell cost of

111 \$/kW, while LG Chem claimed a cell cost at 148 \$/kW, and Audi claimed a cell cost of 114 \$/kW [84]. At the same time, the energy density of PHEV batteries has increased by almost 400% over the course of seven years from 2009-2015 [1]. Figure 2.2 shows these complementary LIB global trends. Due to these unique characteristics, Lithium-ion technology offers the most promising battery storage solution for the near future.



**Figure 2.1:** Ragone Plot (Specific Power vs Specific Energy) for Commercial Battery Storage Technologies [85].

Chapter 1 introduced the concept of Vehicle-to-Anything (V2X) energy services and their aim to lower Total Cost of Ownership (TCO) of EVs through additional use of the battery asset. In this chapter I explain how V2X services impact battery degradation and conversely, how understanding electrochemical battery degradation greatly influences economic evaluations of V2X. Unlike the standard load demands that EV battery packs which are designed for mobility-only undergo, the resultant load demand from a V2X product is inherently dependent on the underlying energy service it is providing. It is however possible to develop load profiles for individual V2X products depending on the connection topology (Figure 1.4) and the energy service being provided (Table 1.1 in Chapter 1). V2X services can be generalized into Energy Based products and Power Based products. Therefore Energy products such as: performing Vehicle-to-Grid (V2G) Energy Arbitrage (charging/buying energy during times of low energy price and discharging/selling during periods of high energy prices), providing V2G Spinning Reserves (bulk energy discharge, (V2G), or dynamically altering charge rate in response to grid require-



**Figure 2.2:** Observed Li-ion Battery Cost Trends (blue, left axis) and Energy Density Evolution (yellow, right axis) [2]. Note for 2018 that Tesla/Panasonic have claimed a battery cell cost of \$111 per kWh, LG Chem cell cost \$148 per kWh, and Audi cell cost \$114 [84].

ments, Mono-directional or Smart Charging (V1G)), acting as a Demand Response (DR) resource, or serving as emergency back-up power (Vehicle-to-Home (V2H), Vehicle-to-Load (V2L)), will all result in similar load profiles in that a large energy throughput is required which translates to long periods of charging or discharging for a vehicle battery. Power products however (most notably V2G Frequency Regulation (FR)) where fast response time is crucial will result in significantly less energy exchange as the inherent energy service is charge/discharge flexibility. Frequency of use, daily timing, and utilization rates for each service will differ and are further elaborated Chapter 3.

An important question, therefore, is to what extent additional use of the vehicle battery to provide V2X services will affect battery capacity over its lifetime. There have been several studies conducted towards this end, many of which claim these additional effects to be minimal or even negligible while others claim it to be a barrier to V2X [22, 86–88]. Still others claim the additional battery degradation cost will be outweighed by the income which would be generated [89]. While there is disagreement of the viability of V2X as a whole, there is a consensus that services which require a large energy throughput would likely be cost prohibitive as this would cause the greatest capacity degradation [22, 86]. However, to date there has been no published economic study to investigate battery degradation caused by real-world V2X service provision to a sufficiently sophisticated level which takes the interplay of Calendar and Cycling Aging effects and their fundamental drivers of Time, Temperature, State of Charge (SOC), Depth of Discharge (DoD), Charge Rate (C-rate), and Amp-hour (Ah) throughput into account. Truly empirical

lifetime analyses would require time scopes of 10 years or more, which is both impractical and would be rendered obsolete at completion as battery technology is improving rapidly. Due to these challenges, semi-empirical electrochemical models have been developed which aim to model fundamental electrochemical phenomena mathematically while extracting rate relationships from what limited degradation data is available [90–98].

As the intention of this chapter is to explain the *economic* consequences due to battery degradation, semi-empirical electrochemical and combined electrochemical-thermal lifetime models are the main focus while other modeling methods such as equivalent circuit models, reduced order models, statistical methods, fuzzy logic, and other methodologies are not explored as they are mostly used to characterize battery operational behavior and not battery lifetime degradation [99–103]. Furthermore, this chapter does not attempt to incorporate all electrochemical and particle physics theory but instead to extract the most relevant degradation mechanisms needed to predict battery life for economic analyses. This chapter continues with an introduction to **Battery Fundamentals**, followed by an explanation of **Battery Degradation Mechanisms**. Next a discussion of **Battery Degradation Modeling Approaches** and their limitations is presented followed by **Partial Conclusions: Battery Degradation**.

## 2.1 Battery Fundamentals

Lithium Ion batteries are complex electrochemical systems which consist of four primary components: a negative electrode (anode), a positive electrode (cathode), an electrolyte, and a separator. Additionally, copper and aluminum current collectors are located at the positive and negative electrodes respectively. Distinct degradation mechanisms act at each element to contribute to overall life fade and will be explained in more detail in the **Battery Degradation Mechanisms** section.

### 2.1.1 Battery Cells

A battery cell consists of two electrodes (electronic conductors) which produce two half-reactions with the electrolyte (ionic conductor). Reductions occur at the positive electrode which is additionally referred to as the cathode while oxidations occur at the negative electrode which is additionally called the anode [104]. Individual battery cells are packaged together in a combination of string or series configurations to form battery packs which are controlled by a Battery Management System (BMS). The weakest cell in a string can

affect the entire line output since the current which can be extracted from a cell within safe thermal operating conditions is a function of its internal resistance. Additionally, due to manufacturing deviations, weaker cells will charge and discharge more rapidly which can lead to overcharged cells and elevated temperature spots which can compromise the entire pack. Therefore it is crucial that the BMS monitors individual cells and balances the battery pack. Cell balancing refers to the practice of either removing excess charge of cells at risk of overcharge through heat dissipation in internal resistors or through moving charge from higher charged cells to lower charged cells such that all cells are maintained within a defined interval [105]. These two techniques are referred to as passive and active cell balancing respectively.

### 2.1.2 Anode

Anodes are typically graphite-based due to the low cost of material and the wide availability of carbon however graphite alone displays a high reactivity to electrolyte and therefore must be treated. Graphite anodes exhibit a moderate intrinsic specific capacity of  $372 \text{ mA h g}^{-1}$  however current commercial anodes will soon be unable to meet increasing energy density demands from electronic devices, electric vehicles, and energy storage applications [106]. Current graphite-based anode materials are effectively optimized and other anode materials such as metal oxides or alloying materials are either cost prohibitive or suffer reduced robustness. Therefore improvements in battery capacity and lifetime in commercial cells are through development of Silicon/Carbon (Si/C) composite anode materials or through the trend towards new, Nickel-rich cathode materials [12, 107].

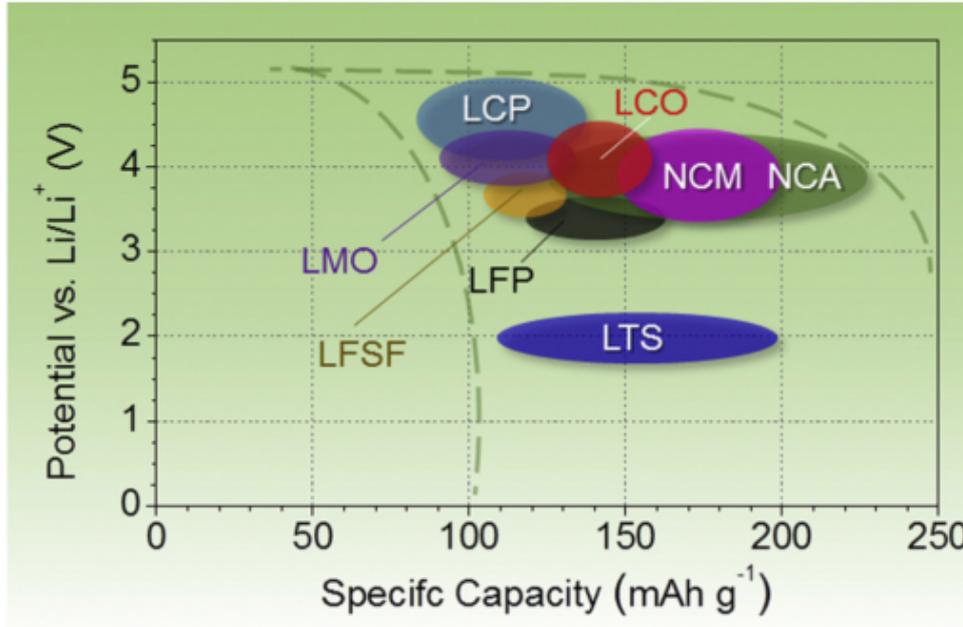
### 2.1.3 Cathode

Cathodes (positive electrode) consist of a complex lithiated compound material which will greatly affect the battery discharge profile, lifetime, and cost [108]. When speaking of Li-Ion battery chemistry, the cathode material is referenced as a graphitic anode is typically assumed. An overview of current commercial batteries, their chemical compounds, a snapshot of the technology characteristics, and current usages is presented in Table 2.1. Figure 2.3 is a visual description of ranges of Cell Potential vs Specific Capacity of the various cathode materials.

Abbreviations used for Table 2.1, Figure 2.3, and to refer to battery chemistry throughout are: Graphite (G), Lithium Titanate Oxide (LTO), Lithium Manganese Oxide (LMO),

**Table 2.1:** *Current Commercial Batteries Characteristics and Usages*

Manufacturer	Chemistry (Anode/Cathode)	Capacity (Ah)	Config.	Voltage (V)	Weight (kg)	Volume (L)	Density (Wh L <sup>-1</sup> )	Specific Energy (Wh kg <sup>-1</sup> )	Used in (OEM & Model)
1 AESC	G/LMO-LNO	32.5	Laminate	3.75	0.79	-	317	157	Nissan Leaf
2 LG Chem	G/NMC-LMO	36	Pouch	3.75	0.86	0.49	275	157	Renault Zoe
3 Li-Tec	G/NMC	52	Pouch	3.65	1.25	0.6	316	152	Daimler Smart
4 Li Energy	G/LMO-NMC	50	Prismatic	3.7	1.7	0.85	218	109	Mitsubishi i-MiEV
5 Samsung	G/NMC-LMO	64	Prismatic	3.7	1.8	0.97	243	132	Fiat 500
6 Lishen Tainjin	G/LFP	16	Prismatic	2.3	0.52	0.23	200	89	Honda Fit
7 Panasonic	G/NCA	3.1	Cylindrical	3.6	0.048	0.018	630	233	Tesla Model S


**Figure 2.3:** *Specific Capacity vs Cell Potential of Intercalation Cathode Materials [109].*

Lithium Nickel Oxide (LNO), Nickel Cobalt Manganese (NMC), Nickel Cobalt Aluminum Oxide (NCA), Lithium Iron Phosphate (LFP), Lithium Cobalt Phosphate (LCP), Lithium Iron Fluorosulfate (LFSF), Lithium Titanium Sulfide (LTS), and LTO (Note that Titante is an anode material).

### 2.1.4 Electrolyte

The electrolyte must serve as an ionic conductor yet provide electronic insulation therefore it must exhibit a low viscosity and a high dielectric constant [110]. The reaction between the anode and electrolyte forms a passivating layer on the negative electrode (anode) surface known as the Solid Electrolyte Interface (SEI). Stability of the lithium battery depends on this reaction product. An SEI layer that is not passivating enough will continue to allow electrolyte molecules to reach the anode surface and will result in

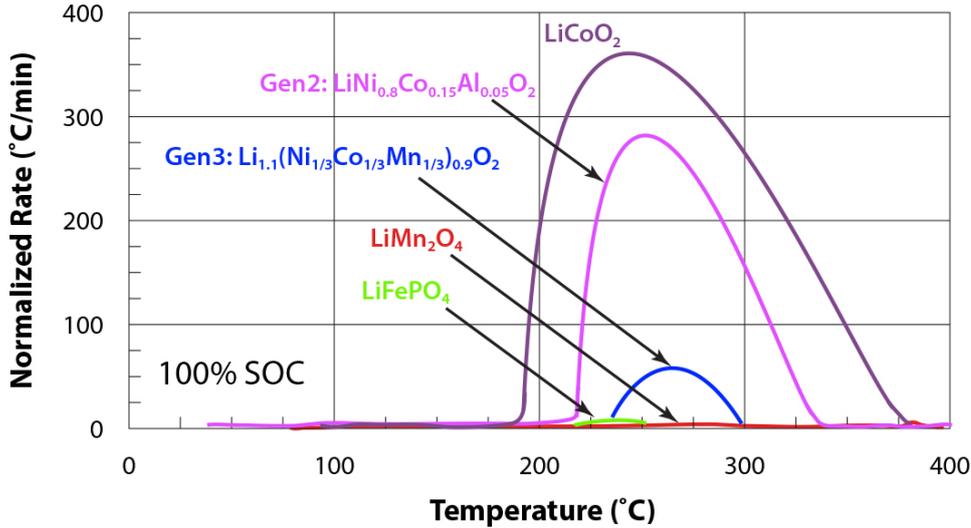
corrosion. An SEI layer that is too thick or insufficiently ionic-conductive can lead to unacceptably large increases in cell internal resistance, which is why only a few organic compounds can be used as solvents for the electrolyte [111]. Thus a key design goal of electrolytes and of film formation additives is to result in a reaction product SEI layer that is ionically conducting, electronically insulating, and mechanically robust [112].

Traditionally Ethylene Carbonate (EC) has been used as electrolyte solvent and was previously thought to be indispensable; however, recent research has proven that EC free electrolyte battery cells perform better at higher voltages [9, 113]. Ethyl Methyl Carbonate (EMC) along with optimized amounts of “enablers”, additives which passivate the graphite electrode and thus enable an EC free cell to operate, has demonstrably improved performance [8].

Thus the electrolyte typically consists of an organic aqueous solvent (typically alkylcarbonates) with a salt compound (typically Lithium Tetrafluoroborate ( $\text{LiBF}_4$ ) or Lithium Hexafluorophosphate ( $\text{LiPF}_6$ )) which have become dominant in the market [112, 114]. Although there is investigation into solid-state electrolytes and ionic liquid electrolytes, the organic aqueous solution is the primary technology used in commercial cells due to its superior ionic conductivity. Much research has been focused on improving the electrolyte performance and safety through either functional additives, enablers, or flame-resistant phosphate compounds and is seen as area which can still be improved in commercial cells [7, 115].

### 2.1.5 Separator

The separator is a thin porous membrane which primarily serves to prevent the anode and cathode from physical contact while maintaining the free flow of ions [116]. For safety of the battery the separator must be able to shut the battery down when overheating occurs, as in the case of a short-circuit, to ensure thermal runaway is avoided [117]. Each battery chemistry has unique thermal runaway characteristics as can be seen in Figure 2.4 with the worst to best ordering as Lithium Cobalt Oxide (LCO), NCA, NMC, LMO, and LFP.



**Figure 2.4:** Thermal Runaway Characteristics of LCO (dark purple) NCA (light purple), NMC (blue), LMO (red), and LFP (green) chemistries [118].

## 2.2 Battery Degradation Mechanisms

### 2.2.1 General Terms

Battery State of Health (SOH) is negatively impacted through a reduction of total capacity and/or an increase in internal impedance. Typically definitions of SOH only focus on a measurement of capacity reduction (Capacity Fade) however internal impedance rise reduces the battery power delivery which is why increasing impedance is additionally referred to as Power Fade. Capacity Fade is caused by the irreversible Loss of Lithium Inventory (LLI) or through Loss of Active Material (LAM), whereas internal impedance rise (Power Fade) is caused by increased kinetic resistance within the system [119–121].

The SOH concept is important to define for when the battery asset reaches its End of Life (EoL). Currently there is no standard definition of EoL however many have taken the view that a 20-30% reduction of Capacity (Q) or a 100% increase from initial internal resistance (R) constitutes EoL [122]. It is important to note that even at EoL, the battery is not fully depleted but still has a significant amount of capacity left (70–80%) which has lead several investigations into Battery Second Life (B2L) products as stationary storage systems or peak voltage provision in high power DC charging systems [123–125]. Furthermore, recent studies have suggested that batteries may continue to satisfy the majority of mobility needs down to 40% percent of remaining capacity [126]. Thus the need for a standardized definition of SOH and EoL along with accurate estimation and

monitoring is clear.

## 2.2.2 Degradation Mechanisms by Cell Component

Various degradation mechanisms act at each cell component to contribute to Capacity Fade and Power Fade, with the growth of the SEI, the passivation layer which forms on the anode, being the most prominent contributor. The SEI layer has been given extensive study due to its central importance not only in life degradation but in proper functioning of the battery. A stable and uniform SEI is required to protect against current collector corrosion at the anode from the highly reactive electrolyte, yet extensive or non-uniform SEI formation can result in dendrite growth, cracking, and a reduction in lithium access to the anode [96, 115]. As an example, during the first full cycle up to 10% of the original battery capacity can be consumed in irreversible SEI formation though this amount has been reduced to 2-3% in recent cells [127]. Lithium plating, current collector corrosion, and mechanical failure are other prominent degradation mechanisms which are further explained in the *Calendar vs Cycling Aging* section. Figure 2.5 is a visual representation of the various aging mechanisms and where they take place in a battery cell.

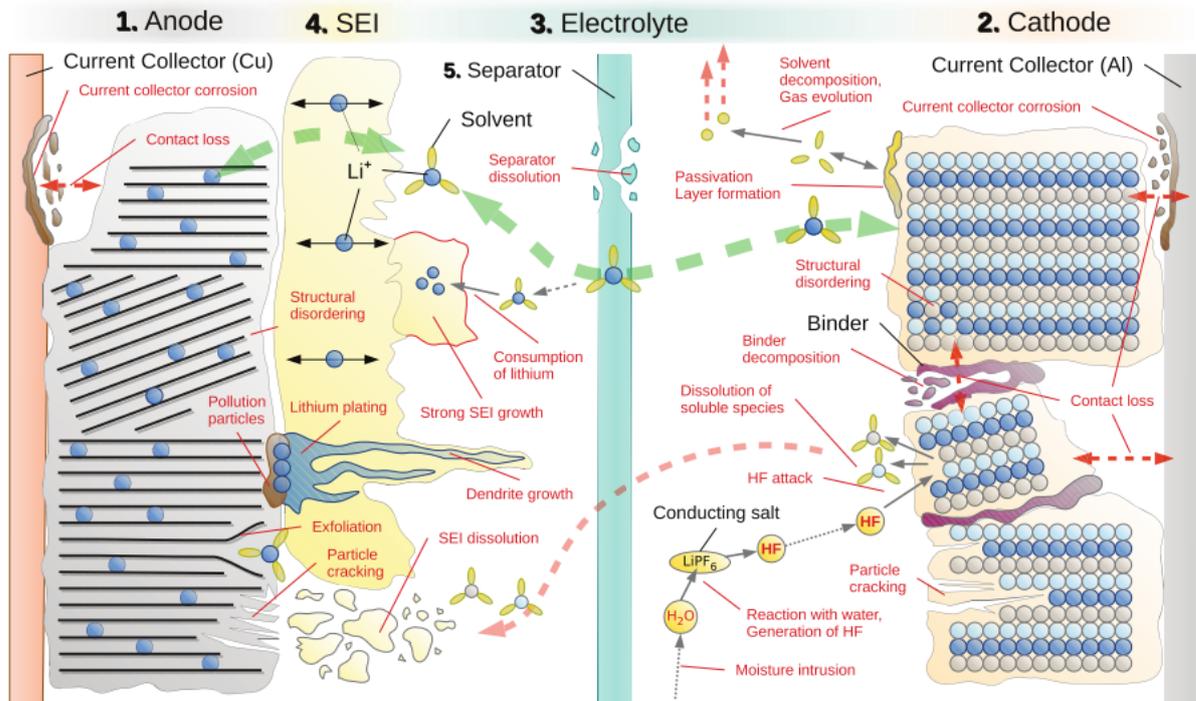


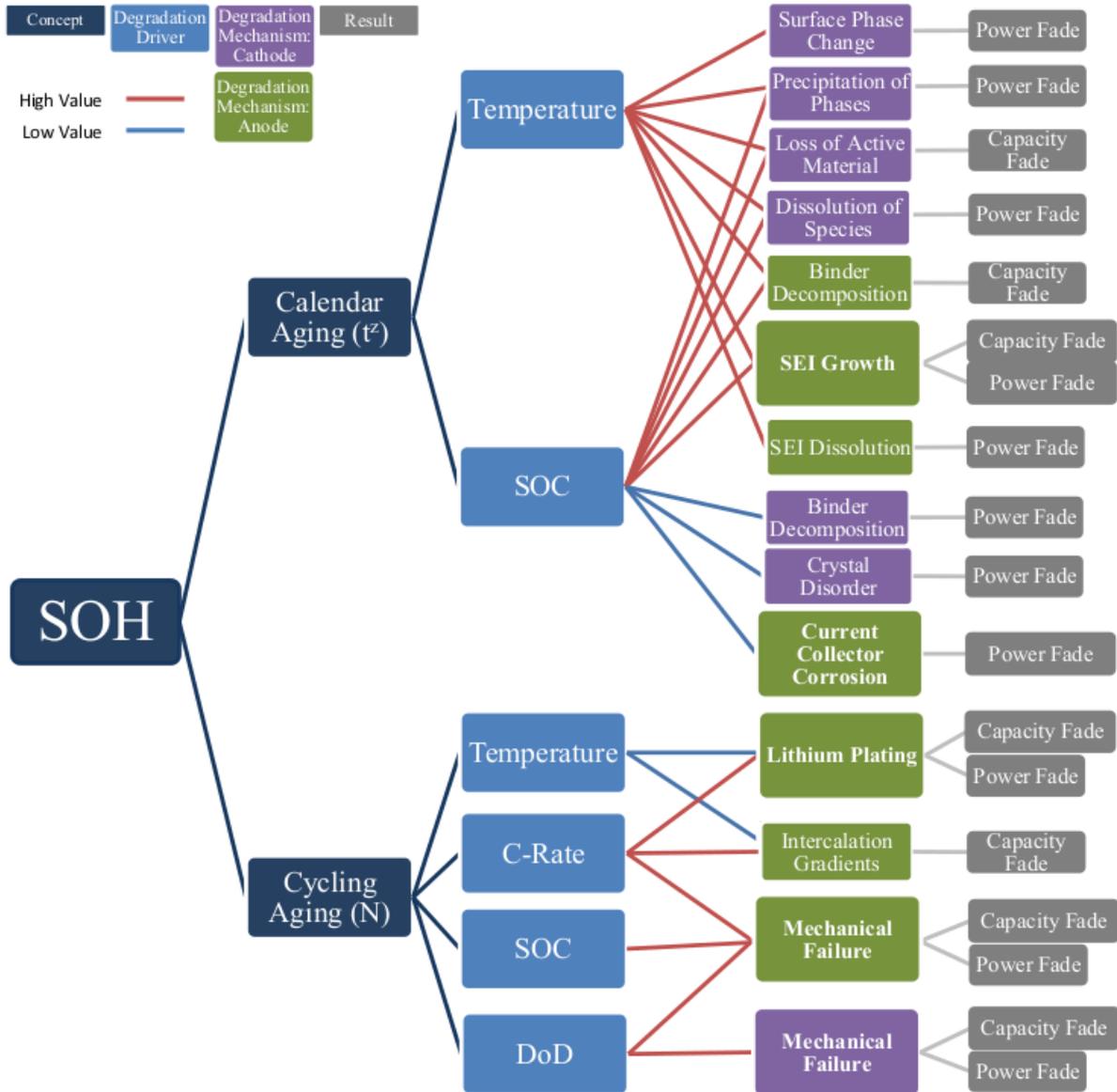
Figure 2.5: *Lithium Ion Battery Aging Mechanisms and Battery Cell Structure* [119].

### 2.2.3 Calendar vs Cycling Aging

These electrochemical degradation mechanisms collectively result in two aging behaviors known as Calendar Aging and Cycling Aging which are exacerbated by degradation drivers (or stress factors). Calendar Aging is the degradation experienced when the battery is at rest and is dependent on Temperature and SOC. Temperature and SOC are coupled through an Arrhenius relationship which has been empirically proven to adequately model SEI layer growth which is diffusion limited [128]. This results in Calendar Aging showing an underlying dependency on time ( $t^z$ ) where  $z$  tends to be  $1/2$ , thus a square-root of time dependency [129–131]. Cycling Aging is the degradation resulting from battery usage and is dependent on the Temperature, SOC, charge current (C-rate), and Depth of Discharge ( $DoD$  or  $\Delta SOC$ ). C-rate is a representation of charge current normalized to battery capacity such that a current expressed as 1C would charge a given battery in 1 hour. Similarly a current expressed as 2C would charge a battery in 30 minutes while a C/2 current would charge the battery in 2 hours. While previously the underlying dependency of Cycling Aging was expressed as cycle number ( $N$ ), recent research has shown that total Ah throughput, the total amount of amps extracted from the battery, is true underlying dependency of Cycling Aging [68, 95, 132].

Figure 2.6 is a visual summary which shows conceptual and causal links between the Degradation Concepts (SOH, Calendar and Cycling Aging), Degradation Drivers (Temperature, SOC, C-rate, DoD), and various Degradation Mechanisms [119, 121, 131, 133]. For example, the large size of the SEI Layer Growth box in Figure 2.6 indicates that it is a prominent Degradation Mechanism while the green color of the box indicates that it acts at the anode. Figure 2.6 also shows that SEI Growth is caused by high Temperatures and high SOCs while at rest (Calendar Aging), and results in a large amount of both Capacity Fade and Power Fade. Lithium Plating is another prominent Degradation Mechanism which acts at the anode, is caused by low Temperatures and high C-rates while cycling, and primarily results in a large amount of Capacity Fade with a lesser secondary result of Power Fade [119, 121]. Mechanical Failure can occur at both the Anode and Cathode and is the result of volumetric changes during cycling which can lead to cracking of the SEI layer, lithium exfoliation, isolation of active electrode material, and contact loss at each current collector. Overcharge (Overpotential) and Overdischarge are also prominent degradation mechanisms which can cause gas evolution, particle cracking, and lithium plating [119, 121]. Additionally, Current Collector Corrosion occurs at the anode and is caused by long periods of rest at low SOCs which results in a large contribution to Power Fade [119, 121, 131, 133]. Apart from structural or manufacturing defects

however, Overcharge and Overdischarge conditions will not be encountered in batteries which are properly protected by a BMS therefore are omitted here as V2X services will only operate batteries within manufacturer specified limitations. While Current Collector Corrosion can be avoided as well through manufacturer prescribed lower SOC limits, it is included in this visualization. What follows is a more in-depth discussion of the fundamental degradation drivers and their contribution to life degradation summarized in Figure 2.6.



**Figure 2.6:** Battery Degradation Flowchart:

Shows conceptual and causal links between the Degradation Concepts (SOH, Calendar and Cycling Aging), Degradation Drivers (Temperature, SOC, C-rate, DoD), and various Degradation Mechanisms which could be controlled through active management of charging or V2X strategy.

### 2.2.3.1 Temperature

While most manufacturers designate a large operating temperature margin from  $-30^{\circ}\text{C}$  to  $55^{\circ}\text{C}$ , the optimal operating temperature window is much smaller and pronounced life fade can be experienced at the extremes. High temperatures accelerate aging side reactions and SEI layer growth within a battery cell (Calendar Aging). Conversely, low cell temperatures cause lithium plating to occur on the anode while charging the battery (Cycling Aging). Therefore an optimal operating temperature which minimizes degradation from both Calendar Aging and Cycling Aging can be found, however it is chemistry specific. Figure 2.7 provides a generalized visualization Temperature convexity.

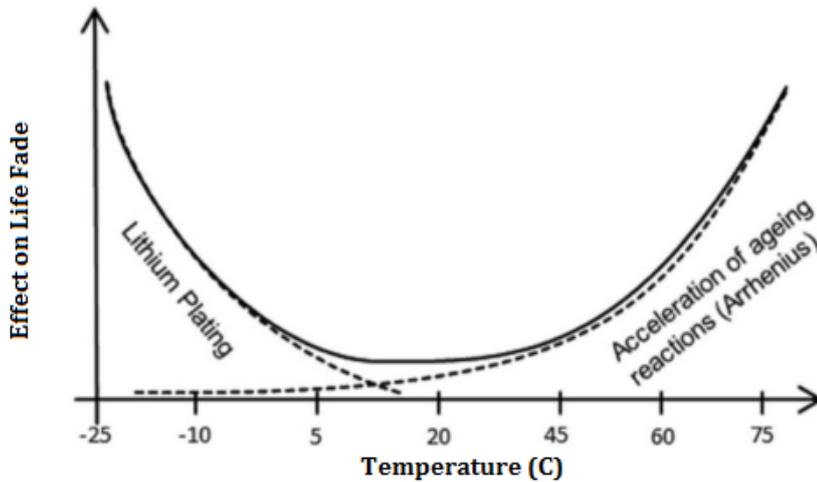


Figure 2.7: Generalized Thermal Convexity Effects [107]

As temperature is the most prominent environmental cause of battery degradation, proper thermal management is crucial. Additionally cell temperature affects battery power output at extreme points such that high powered charging or discharging at very high or low temperatures would generate a diminished response. Figure 2.8 outlines a generalized thermal control strategy where it is clear that temperature should be maintained at an optimal point for both power output and Capacity Fade considerations.

### 2.2.3.2 State-of-Charge (SOC)

High SOC causes higher Li-ion concentration at the surface of the anode and results in a higher rate of aging side reactions [129]. Additionally, high SOC cycling causes morphological changes such as binder and electrolyte decomposition within the cell. From this

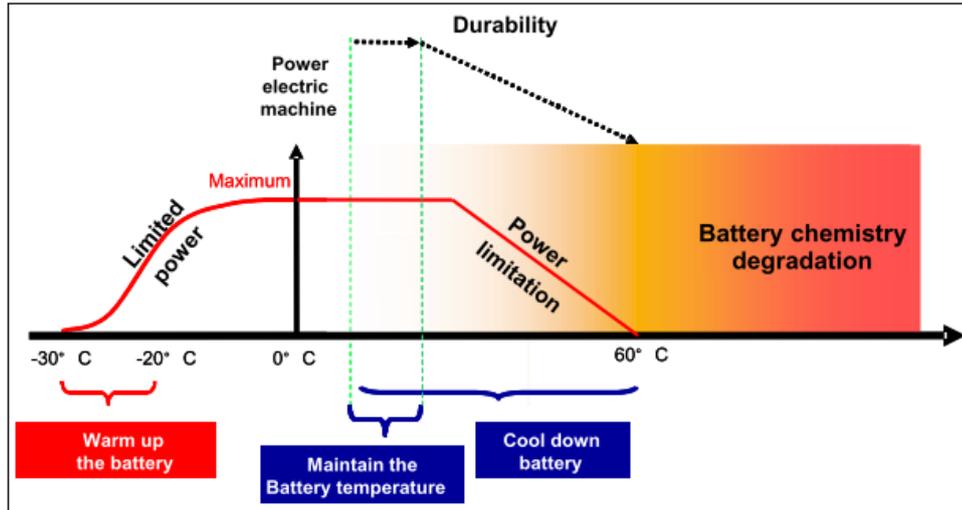
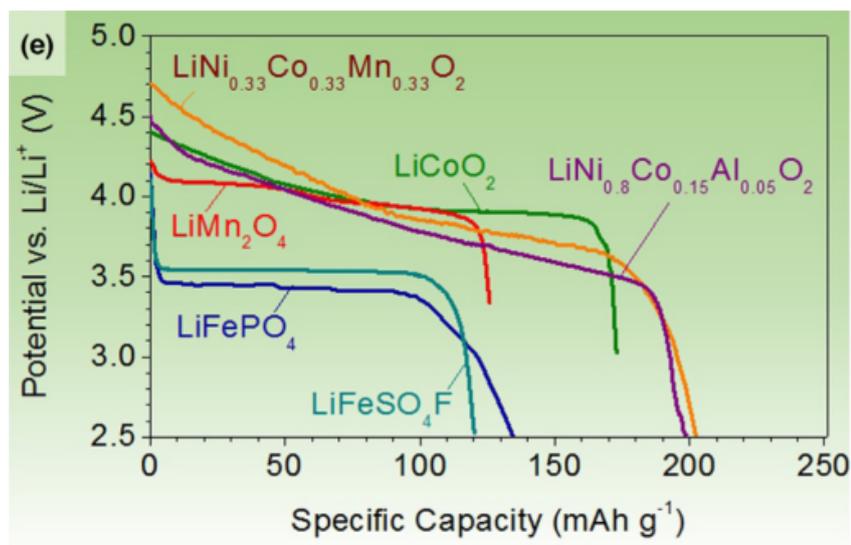


Figure 2.8: Generalized Thermal Management Strategy [93].

understanding it is clear that cycling from a lower average SOC will cause less degradation than cycling at a higher average SOC. This is important when considering Depth of Discharge, since a 20% DoD will be different if it is cycled from SOC 80 – SOC 100 than it would if cycled from SOC 20 – SOC 40. Due to its importance in battery life estimation, tracking and accurately estimating SOC is crucial.

State of Charge is a metric similar to the fuel gauge in a traditional ICE vehicle and is often presented as a percentage. It reflects the amount of energy which can be extracted from the usable capacity in a battery, however it is difficult to calculate with precision thus it is normally referred to as an estimation. As seen in Figure 2.9, the voltage discharge profile of a LIB cell is highly dependent on the cathode material used. It can be seen from the flat discharge profile of most Li-ion chemistries that relying on voltage alone as a SOC indicator is very difficult without high resolution and high fidelity measurement capabilities, particularly for LFP.

Due to these challenges, coulomb counting (current integration) is most accurate method of SOC estimation but it is computationally expensive as it requires a constant monitoring of voltage and current which is impractical for memory-constrained BMS. Thus other methods have been employed to allow embedded Battery Management Systems to provide accurate measurements in real or close to real time [134]. An accurate SOC estimation is not only important for both range estimation and control methods, but also for proper management and logging of SOH.

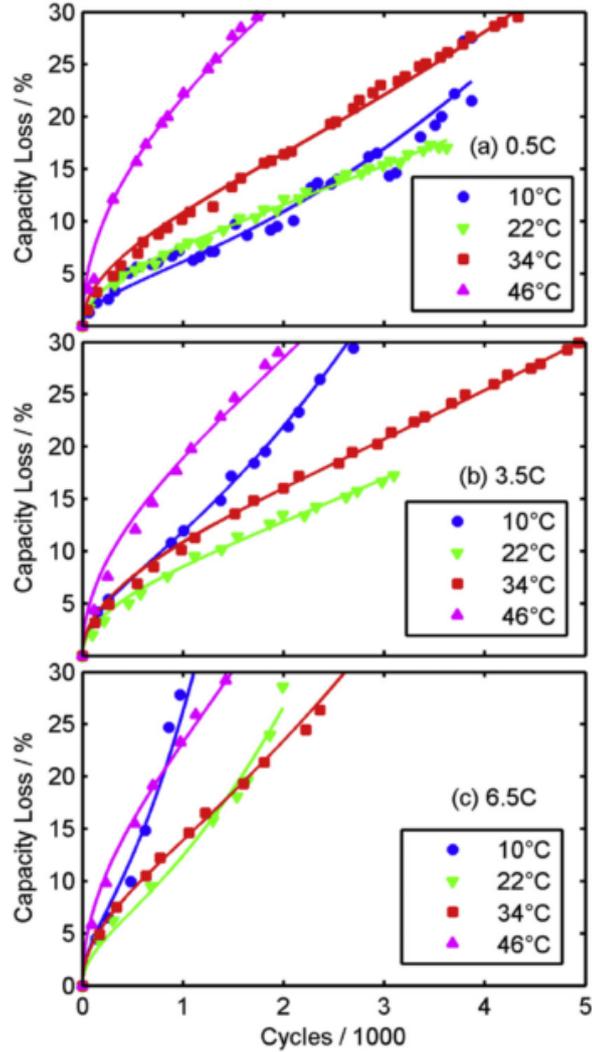


**Figure 2.9:** *Lithium Ion Battery Discharge Profiles by Chemistry [109].*

### 2.2.3.3 Charge Rate (C-rate)

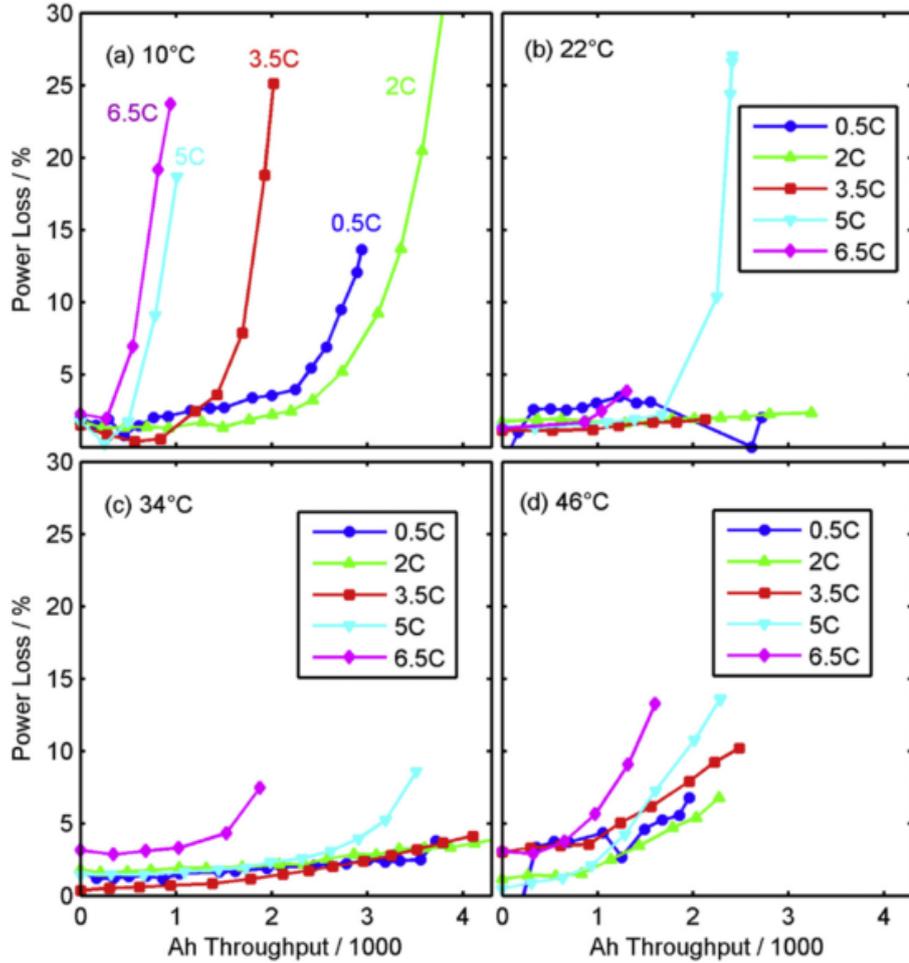
As previously mentioned, battery charge rates are expressed as the C-rate (current) which is normalized to the battery capacity. Some notations use C-rate for charge current and E-rate for discharge current as they are rarely the same due to varying molecular kinetics at charge and discharge [135]. High currents contribute to an increased SEI layer growth at the anode which, by definition of current being non-zero, results in Cycling Aging. This both decreases the actively available lithium (LAM, Capacity Fade) and increases resistive behavior (Power Fade). Furthermore high C-rates, especially at low temperatures, can cause mechanical fracture due to particle cracking of the SEI which can form dendrites or introduce soluble species into the electrolyte. Figure 2.10 shows the C-rate effect on Capacity Fade. Due to the convex Temperature effect (Figure 2.7), high C-rates when combined with low temperatures cause the most amount of Capacity Fade followed by high C-rates combined with high temperatures which can mostly clearly seen in Panel C (C-rate = 6.5C, in the blue (10 °C) and purple (46 °C trends)). Additionally, Figure 2.11 shows the C-rate effect on Power Fade which also exhibits convex temperature dependence with the most Power Fade experienced at low temperatures paired with high C-rates, followed by high temperatures paired with high C-rates. Moderate C-rates (0.5C – 2C) exhibit less comparative Power Fade regardless of temperature. One interesting observations to note is that the 2C rate exhibits less power fade than the 0.5C indicating that the optimal cycling current from the perspective of cell life prolongation may not always be low.

Additionally, high currents generate more ohmic heating which in turn increases bat-



**Figure 2.10:** *C-rate Effect on Capacity Fade at  $T = 10^\circ\text{C}$ ,  $22^\circ\text{C}$ ,  $34^\circ\text{C}$ ,  $46^\circ\text{C}$ . The panels each correspond to a single C-rate ( $0.5C$ ,  $3.5C$ ,  $6.5C$ , respectively). DoD is 50% for all data points [98].*

tery temperature and contributes to the resultant temperature effects. The amount of ohmic heating will also depend on the cell internal impedance, thus Power Fade is connected to Capacity Fade through the thermal secondary effects of C-rate. Figure 2.12 and Figure 2.13 demonstrate the C-rate effect on cell temperature for both charging and discharging scenarios. Finally, C-rate is known to affect charge efficiency with lower C-rates being more efficient following a non-linear trend as can be seen in Figure 2.14.



**Figure 2.11:** *C-rate Effect on Power Fade [98]*

There is an apparent anomaly in the aging data shown in Panel B for the 22°C temperature profile which is unexplained in [98]. At moderate cell temperatures it would not be expected that a 5C current (cyan) would cause more Power Fade than a 6.5C current (purple), however looking closer at the 6.5C current data in Panel B it seems the cycle life test was prematurely terminated or data was not collected beyond 1.2 Ah throughput/1000 in contrast to all other cycle tests. Through extrapolation, if this test was continued or if data was still collected the 6.5C trend would likely exhibit a greater Power Fade rate than the 5C current data at 22°C. This early termination could be explained by premature cell failure due to manufacturing defects.

#### 2.2.3.4 Depth of Discharge (DOD)

The DoD is defined as the SOC swing ( $\Delta SOC$ ) a battery undergoes during charging and discharging and should therefore only be used in a cycling context. The DoD has been used as a proxy for Cycling Aging by both industry and academia, however due to SOC effects, a discharge from SOC 100 to SOC 80 will not have the same life degradation effect as from SOC 40 to SOC 20 although they both would constitute a DoD of 20%.

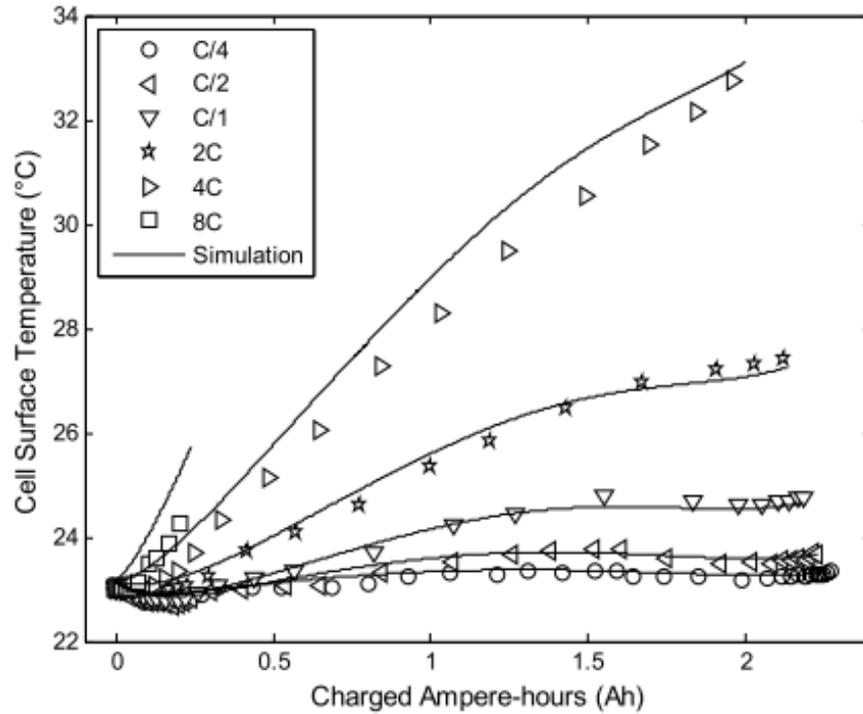


Figure 2.12: *C-rate Effect on Cell Temperature (Charge)* [129].

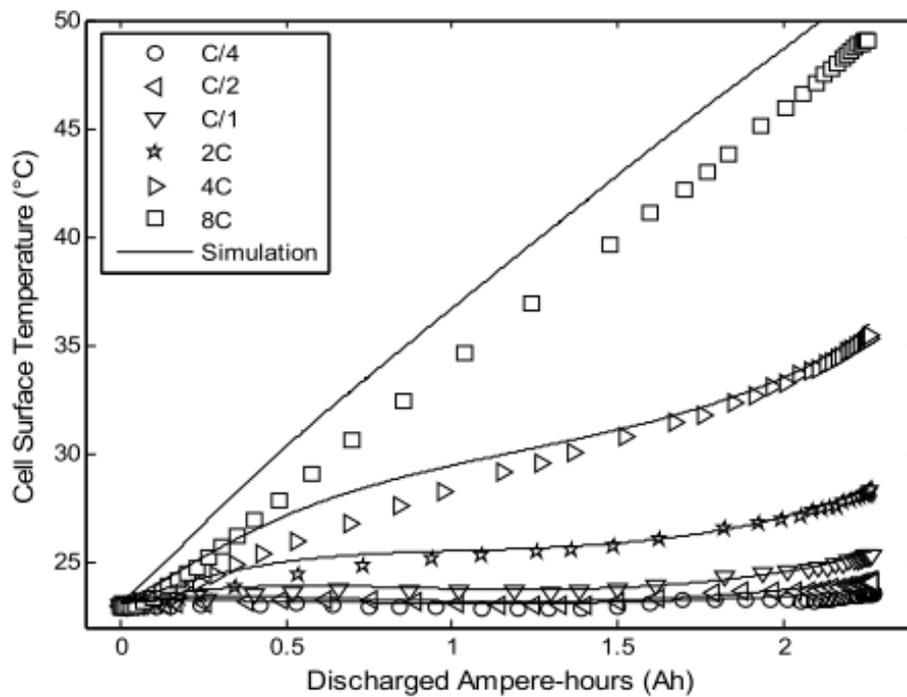
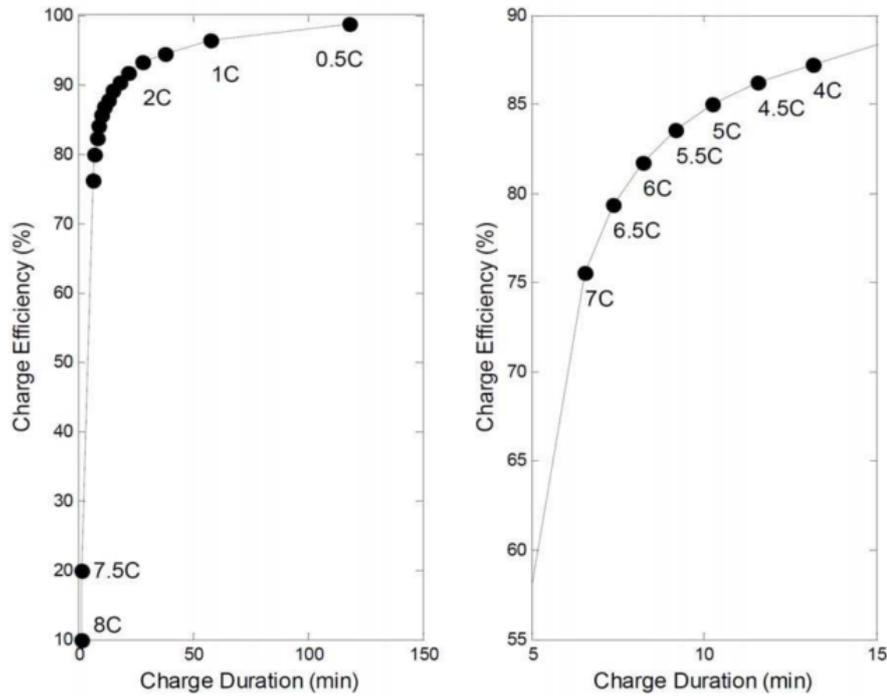


Figure 2.13: *C-rate Effect on Cell Temperature (Discharge)* [129].

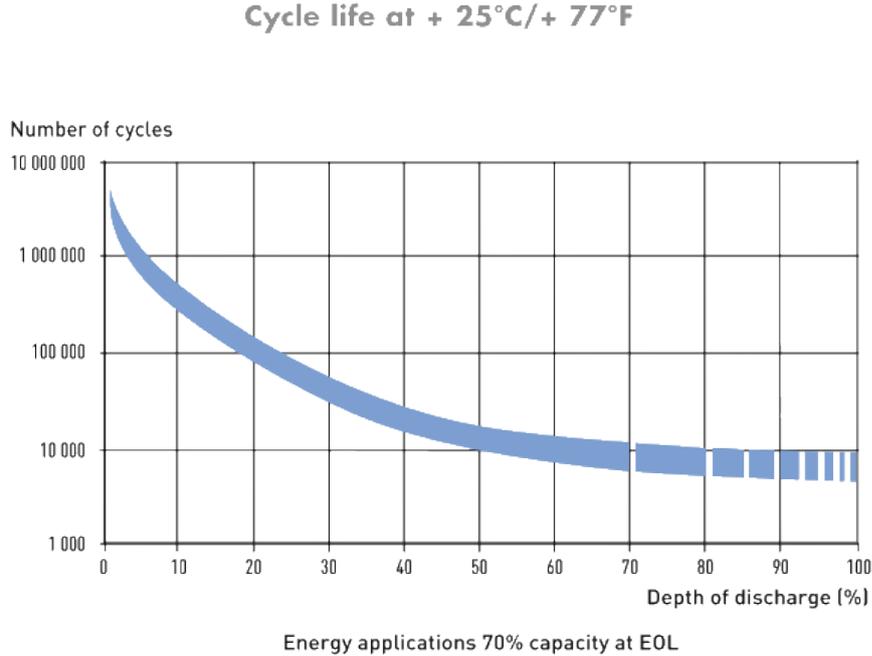
Furthermore, cycles which pass into high ( $>95\%$ ) SOC regions will have the greatest detrimental effect. As such, when given DoD data it is important to clearly define the



**Figure 2.14:** *C-rate Effect on Charge Efficiency (magnified view in right panel) [129]*

cycle profile used, a point which is rarely provided in cycle life tests. In general however, a clear relationship exists that a greater DoD leads to increased Capacity Fade and results in a fewer number of lifetime cycles which can be performed. Higher DoD cycling results in greater mechanical stresses applied to the cell due to volumetric changes which cause SEI layer cracking, lithium exfoliation, isolation of active electrode material, and contact loss at each current collector. Cell Cycle Life typically exhibits a non-linear dependence on DoD as seen in Figure 2.15.

Based on Figure 2.15, a DoD of 10% would permit over 100,000 cycles while a DoD of 50% or more would only permit 10,000 cycles, an order of magnitude difference [136]. However, since the definition of the cycle profile is unclear, the total Amp-hour (Ah) throughput is a more transparent metric as it allows for comparisons of cycling on the similar basis of cumulative charge rather than the number of unknown cycle profiles. In Figure 2.16, the Capacity Fade effect of various DoD cycles normalized by the Ah throughput metric is shown. As the total amount of extractable energy from a battery will vary over time depending on the operating parameters: Temperature, C-rate, and cycle profile, clear definition of cycling and aging protocols is crucial for battery lifetime studies.

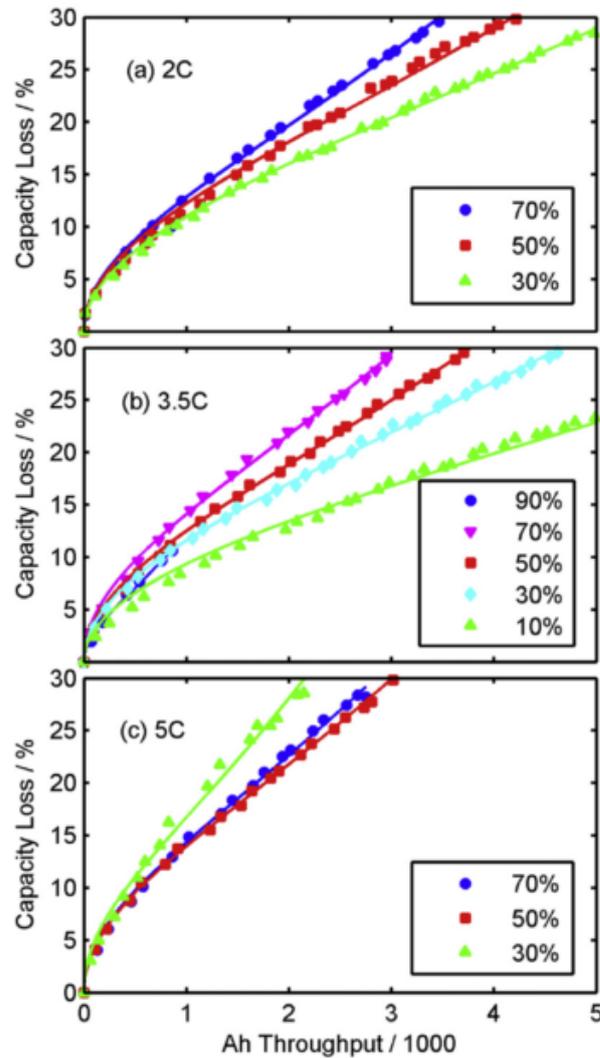


**Figure 2.15:** *Cycle Life vs Depth of Discharge (DoD) from Saft Datasheet [136]*

## 2.2.4 Combined Aging Visualization

As previously mentioned, the total Amp-hour (Ah) throughput refers to the total cumulative *charge* (amps) passed through a battery over the course of its lifetime. Ah throughput implies both the number of amps extracted (discharged) from and injected (charged) into the battery, and therefore only has a positive notation. Ah throughput is distinct from Watt-hour (Wh) throughput which is a measurement of the cumulative *energy* (watts) passed through the battery. Although both are measurements of battery capacity, Wh is impacted by the operating voltage of the battery, whereas Ah is not. An analogy for battery charging can be thought of as pumping water into a balloon. Ah capacity is the total volume of water the balloon holds which will be essentially be the same regardless if measuring the water put in or taken out at a given moment in time (near 100% efficiency). Whereas Wh capacity is the measure of work it takes to pump the full volume of water into the balloon (charge) or the work resulting from letting the balloon force the water out (discharge), which can be different (less than 100% efficiency).<sup>1</sup> Over time the balloon's volume (Capacity) will shrink due to environmental factors from sitting (Calendar Aging) and due to use (Cycling Aging). Therefore Ah capacity and Ah throughput are metrics which are unaffected by battery voltage rises due to internal resistance increase (Power

<sup>1</sup>Credit is due to [137] for the original balloon analogy which I have further developed here.

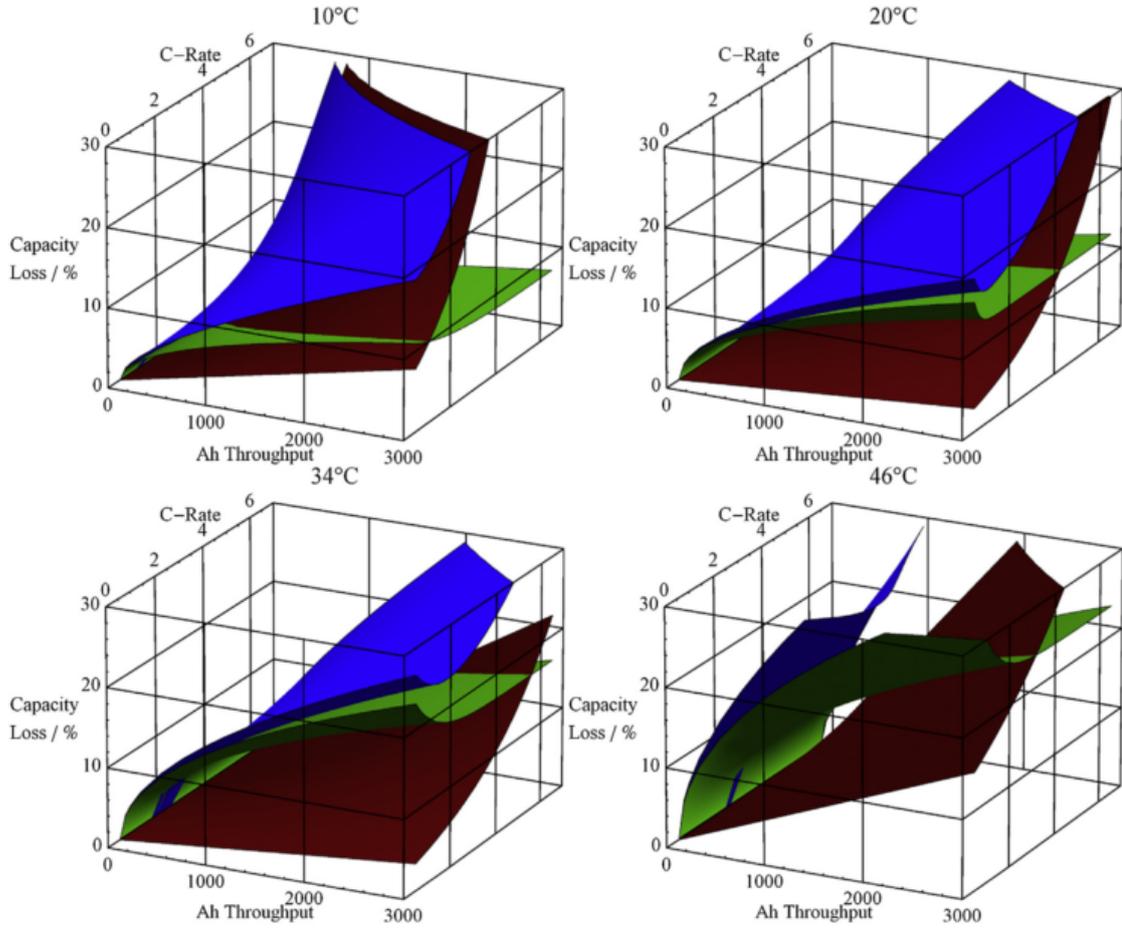


**Figure 2.16:** Depth of Discharge (DoD) Effect on Capacity Fade compared by Ah throughput [98]

Fade) and thus give more accurate measurements of Capacity Fade over time.

Ah throughput is useful to compare the degradation impact of different usage profiles with various DoDs due to previously mentioned SOC effects. By changing the X axis from cycle number to Ah throughput the true degradation effects of various cycle and usage profiles can be compared on the same basis of cumulative charge. Figure 2.17 is a concise visualization of Capacity Fade which differentiates between the impact from both Calendar and Cycling Aging. It is important to note that for most operating conditions, Calendar Aging is the dominant aging behavior with the exception of high C-rates paired with low Temperatures where Cycling Aging becomes dominant.

While high temperatures trigger more Calendar Aging (chemical degradation) through increased SEI layer growth, low temperatures and high charge rates induce more Cycling

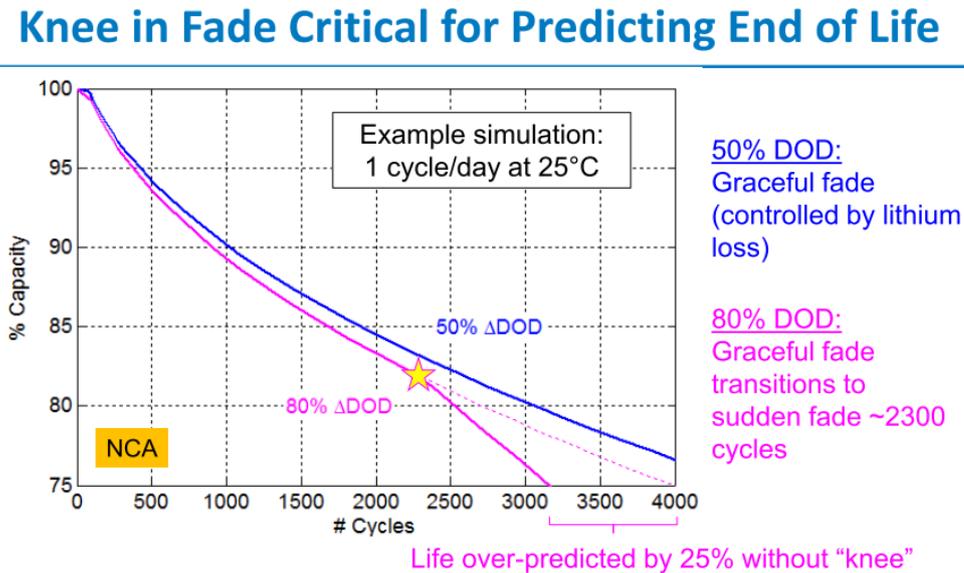


**Figure 2.17:** Visualization of Combined Calendar and Cycling Aging:

Results from semi-empirical electrochemical lifetime model developed for LMO-NMC chemistry from [98]. Presents Capacity Fade as a function of C-rate and Ah throughput for four experimental temperatures: 10°C, 20°C, 34°C, 46°C. Where Blue = total capacity loss (Capacity Fade), Green = capacity loss due to Calendar Aging, and Red = capacity loss due to Cycling Aging. It is important to note that for most operating conditions, Calendar Aging is the dominant aging behavior with the exception of high C-rates paired with low Temperatures where Cycling Aging becomes dominant.

Aging (mechanical degradation) through increased lithium plating. Additionally, high DoD cycling induces more mechanical failure especially if performed at high SOC and high C-rates. To minimize Calendar Aging while the battery is at rest, maintain a low SOC and a low Temperature. To minimize Cycling Aging while the battery is in use, maintain a moderate Temperature, a low/moderate C-rate, and a low DoD centered around an optimal SOC point. Preliminary evidence suggests this optimal cycling point to be around SOC 50% as this is known to minimize joule heating yet more research is necessary [68, 138].

As temperature is the most prominent environmental cause of battery degradation, proper thermal management is crucial and can even mitigate C-rate effects up to 2C [120]. Additionally cell temperature affects battery power output at extreme points such that high powered charging or discharging at very high or low temperatures would generate a diminished response. At all temperatures (except for very low,  $T < 10^\circ\text{C}$ ) while operating in the pre-knee region, Calendar Aging is the dominant lifetime reducing factor. After the knee region, Cycling Aging becomes dominant due to a change in mechanism where capacity loss begins to be governed by graphite site loss (a mechanical process) rather than lithium loss (a chemical process) as can be seen in Figure 2.18 [139].



**Figure 2.18:** *Knee Region Visualization for NCA Chemistry [139].*

However an intelligent management strategy could prolong the knee region point until after the vehicle battery EoL. Understanding the fundamentals of battery degradation paired with the fact that most electric vehicles are immobile more than 90% of the time, implies that Calendar Aging is the dominant reduction factor for the majority if not all of an EV asset lifetime. This is counter intuitive and leads to the conclusion that how a battery is managed while it is at rest will be the determining factor in lifetime performance. Stated differently, how an EV battery is managed at rest is more important than how it is used.

The effects of each degradation driver form non-linear interdependencies which highlight the complexity of lithium ion aging behavior and results in the relationship between Calendar and Cycling Aging as visualized in Figure 2.17. However the visualized relationships have been developed for an Manganese Oxide/Nickle-Manganese-Cobalt Blend (LMO-NMC) chemistry cell type and cannot be generalized to other chemistries. While

the dependency on the degradation drivers outlined in [Figure 2.6](#) will remain the same, the sensitivities to these drivers will vary greatly across battery chemistries and even between battery manufacturers of the same cell chemistry due to proprietary additives and different design choices as explored in the following [Chemistry Dependency](#) section.

### 2.2.5 Chemistry Dependency

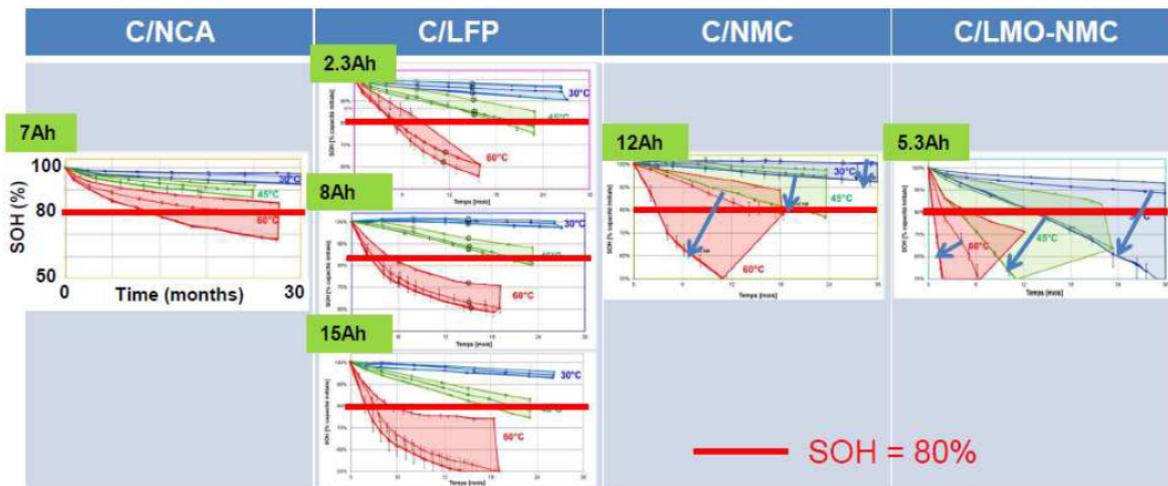
When referring to Li-Ion battery chemistry, the cathode material is referenced as most commercial cells use a graphitic anode (Carbon). Due to long chemical names, batteries are referenced in short hand in the form of anode material/cathode material, however due the prevalence of Carbon (C) as an anode material, it is often omitted. An example battery cell with a Carbon anode/Nickle-Cobalt-Aluminum cathode would be written as C/NCA, or NCA. Along with NCA, the most common chemistries used in commercial cells are Iron Phosphate (LFP) Nickle-Manganese-Cobalt (NMC), and Manganese Oxide/Nickle-Manganese-Cobalt blend (LMO-NMC). Consequently, each battery technology will exhibit varying sensitivities to degradation drivers due to differences in the cathode materials, electrolyte additives, and other nano-coatings.

[Figure 2.19](#), is a composite result of several Calendar Aging studies with various battery chemistry cells and manufacturers. A matrix of 9 storage conditions including 3 temperatures (30 °C, 45 °C, and 60 °C) and 3 SOCs (30%, 65%, and 100%) were applied to a batch of cells with unique chemistries (NCA, LFP, NMC, LMO-NMC) which were disconnected and kept in storage over a period of 2.5 years [[140](#)]. All cells of the same chemistry were from the same manufacturer with the exception of the Carbon anode/Iron Phosphate cathode batteries (C/LFP), which were compared across three different manufacturers. SOH was defined only in terms of Capacity Fade and the End of Life (EoL) criterion was defined as when cell capacity fell below 80% of original capacity.

The Blue (30 °C), Green (45 °C), and Red (60 °C) spreads provide a visualization of the aging effect of Temperature across various chemistries. Within each spread, the effect of storage SOC can be seen as well, with the highest point in each temperature spread equal to SOC 30, the middle point = SOC 65 and the lowest point = SOC 100. Temperature sensitivity is manifested through the trend and shape of each spread, while SOC sensitivity can be seen in the width of each spread. As clearly shown in [Figure 2.19](#), there are pronounced differences in aging rates, aging profiles (how batteries lose capacity), and sensitivity to Temperature and SOC across battery chemistries.

However looking at Calendar Aging performance alone results in an incomplete pic-

- Comparison between the different Li-ion technologies tested at a glance



Common behavior for a same chemistry

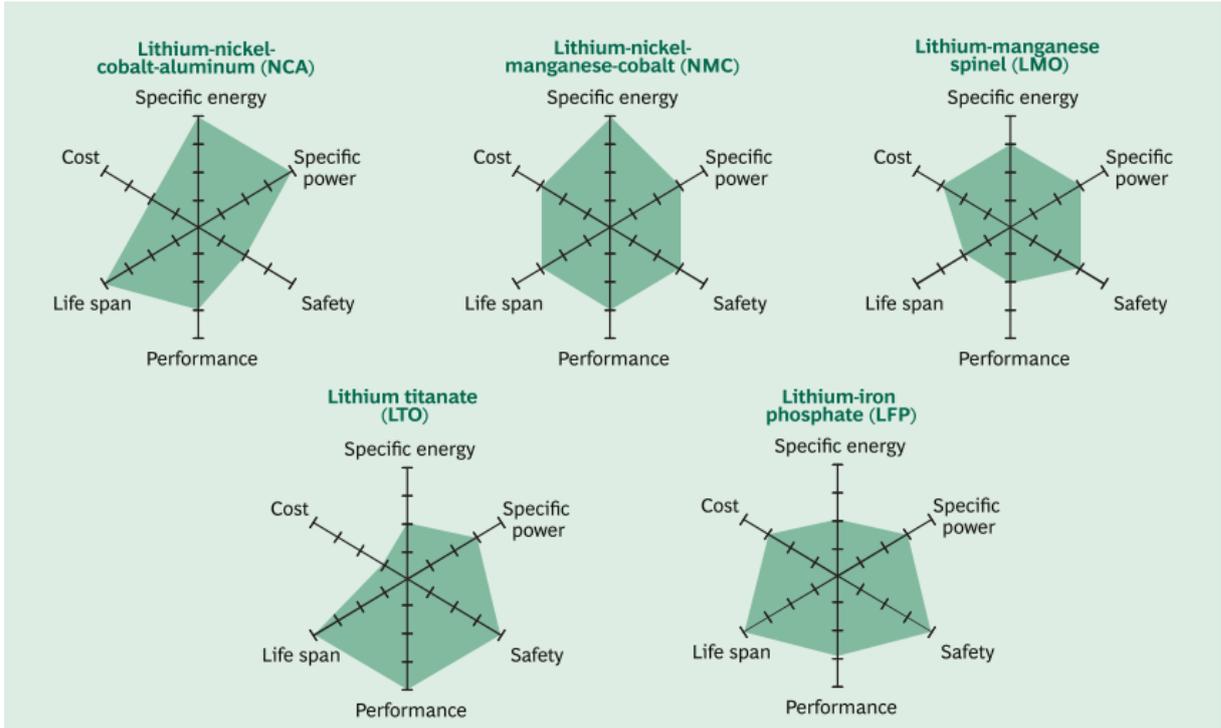
Calendar Ageing mostly affected by Temperature and State of Charge

**Figure 2.19:** Chemistry Effect on Calendar Aging for SOC= 30 (high), 65 (mid), 100 (low) and  $T= 30^{\circ}\text{C}$  (blue),  $45^{\circ}\text{C}$  (green), and  $60^{\circ}\text{C}$  (red) for various cell chemistries and battery manufacturers [93].

ture. When referring again to Figure 2.3, Table 2.1, and Figure 2.4, each chemistry has additional unique Cycling Aging Profiles, cell capacity to potential ratios, and safety characteristics. Thus choosing the “best” battery chemistry results in a trade-off which will largely depend on the system application. A visual representation of this trade-off for current commercial battery technologies can be found in Figure 2.20 below.

### 2.2.5.1 NCA

We can see from Figure 2.19 and Figure 2.20 that Nickle Cobalt Aluminum (NCA) is the superior commercial technology in terms of Calendar Life as it exhibits the least sensitivity to both Temperature (seen in a close grouping of the Temperature spreads) and SOC (seen through the narrow width of each spread) and results in the least amount of Capacity Fade overall. Furthermore it can be concluded that for NCA the effect of Temperature is greater than the effect of SOC as there is no crossover between temperature spreads. Expressed differently, a higher storage temperature will always cause more capacity reduction than a lower temperature regardless of the storage SOC. To cause the least degradation, high temperatures should be avoided first with preference to lower SOC as a low secondary importance. Additionally NCA exhibits the highest Specific Capacity vs Cell Potential ratio (Figure 2.3); however this all comes at the increased risk of thermal runaway and



**Figure 2.20:** *Battery Chemistry Snapshots:*

*The farther the colored shape extends along a given axis, the better the performance along that dimension (i.e. NCA is more expensive than NMC) [141]*

high cost. Consequently NCA requires the most investment to be operated safely in vehicles.

### 2.2.5.2 LFP

LFP generally exhibits a high Temperature sensitivity as seen in the large gaps between spreads in Figure 2.19 but a low SOC sensitivity as seen in the narrow widths of the spreads. The effect of Temperature is again greater than the effect of SOC and a non-linear degradation rate (aging profile) is seen which is especially pronounced at high Temperatures. Interestingly, the study presented in Figure 2.19 found that the same battery chemistry exhibited similar aging profiles regardless of the manufacturer, with the exception of the 15 Ah manufacturer cell which was more prone to degradation at storage SOC's greater than 30%. To cause the least degradation, high temperatures should be avoided first with a low storage SOC as a medium secondary importance. While the safety aspect is greatly improved as LFP is the least prone to thermal runaway, this comes at the cost of Specific Capacity vs Cell Potential and a reduced Specific Energy.

### 2.2.5.3 NMC

NMC exhibits a high Temperature sensitivity and a variable SOC sensitivity which is still greater than NCA or LFP at low temperatures and dramatically increases as temperature rises. Due to this variable SOC sensitivity, there is some crossover between Temperature spreads which results a more complex relationship. While Temperature is still the more dominant effect, due to increased SOC sensitivity low storage SOCs can compensate for the increased aging effect of higher temperature.

This can especially be seen when comparing the Red and Green crossover in [Figure 2.19](#), it can be concluded that a cell stored at 60°C and SOC 30 would result in less degradation than a cell stored at a lower storage temperature of 45°C but at a higher SOC of 100. Similarly, from the Green/Blue crossover, a cell stored at 45°C and SOC 30 would result in less degradation than a cell stored at 30°C and SOC 100. To cause the least degradation for NMC, high Temperatures should be avoided and low SOCss preferred with increasing importance as temperature increases. NMC has the second highest Specific Capacity vs Cell Potential ratio and often overlaps NCA. The thermal runaway characteristics are also the second worst however are drastically reduced from NCA.

### 2.2.5.4 LMO-NMC

Meanwhile the Manganese Oxide + Nickle Manganese Cobalt (LMO-NMC) blend exhibits a very high sensitivity to both SOC and Temperature which has the poorest Calendar Life performance resulting in the most Capacity Fade overall. Similarly to the pure NMC, there is significant crossover due to high SOC sensitivity which results in several scenarios where low SOC can compensate for higher temperature. Furthermore LMO-NMC exhibits an almost linear degradation (aging profile) across all storage conditions. To cause the least degradation, high temperatures and high SOCs should be avoided at all times. Pure LMO has the second best thermal runaway characteristics, therefore a blend with NMC is done in attempts to improve safety (from LMO) while increasing Cell Potential vs Specific Capacity (from NMC).

## 2.3 Battery Degradation Modeling Approaches

This section consists of an overview of three semi-empirical lifetime models, so named due to their extrapolations of battery behavior based on experimental data, which have

influenced many other models and research efforts. Each follows a similar process which consists of hypothesizing fundamental degradation equations, generating rate laws and other coefficients, and fitting the original hypothesis to experimental data to generate the general model. In all models the degradation effect from Calendar Aging and Cycling Aging is assumed to be additive. Further references to each will be known as the National Renewable Energy Laboratory (NREL) model [95], the Wang Model [98], and the Modeling of Batteries Including the Coupling between Calendar and Usage Aging (MOBICUS) Model [92].

### 2.3.1 NREL Model

#### 2.3.1.1 Model Equations and Approach

The NREL Model was originally based upon an NCA chemistry dataset presented in [6, 142, 143] which was later updated to incorporate an LFP chemistry [94–96, 125, 139, 144, 145]. Figure 2.21 shows the NCA datasets to populate the original NREL model.

	Test	Source	Temperature	End-of-Chg. or Storage Voltage	Depth-of- Discharge	Cycles/day
Fitted Data	Resistance Growth	Broussely (Saft), 2007	20,40,60°C	3.6,4.1V	Storage	0
		Hall (Boeing), 2006	20°C	3.9,4.0,4.1V	20,40,60,80%	1,4
	Capacity Fade	Smart (NASA), 2009	10,23,40,55°C	3.6V	Storage	0
		Broussely (Saft), 2001	20°C	3.6,4.1V	Storage	0
		Hall (Boeing), 2006	20°C	3.9,4.0,4.1V	20,40,60,80%	1,4
Validation Cases	HEV combined cycling + calendar	Belt (Idaho Nat. Lab.), 2008	30,45,53°C	3.6V	1.5%	95,290,500
	PHEV accelerated cycling	Gaillac (S. Calif. Edison), 2009	25°C	4.0V	75%	4

**Figure 2.21:** *NREL Model Population Datasets for NCA Chemistry [146].*

The model assumes fundamental degradation behavior is similar for all lithium ion technologies but is tuned by degradation coefficients which are chemistry dependent. The primary model outputs are battery capacity ( $Q$ ) and internal impedance ( $R$ ) and both Calendar Aging and Cycling Aging are incorporated. The equation for internal resistance is:

$$R = a_0 + a_1 t^{1/2} + a_2 N \quad (2.1)$$

The equation for cell capacity is the minimum of the capacity loss attributed to the loss of active material lithium ( $Q_{li}$ ) vs the loss of active sites ( $Q_{sites}$ ) in the electrolyte of the cell:

$$Q = \min(Q_{li}, Q_{sites}) \quad (2.2)$$

Where:

$$Q_{li} = b_0 + b_1 t^z + \dots \quad (2.3)$$

$$Q_{sites} = c_0 + c_1 N + \dots \quad (2.4)$$

The coefficients are rate constants for the time effect on Resistance ( $a_1$ ), the cycle number effect on Resistance ( $a_2$ ), the time effect on Lithium Loss ( $b_1$ ), and the cycle number effect on Site Loss ( $c_1$ ). The ellipses signify the fact that the final model is hypothesized and chosen from empirical fits based upon statistics, thus new terms could be introduced into the model equation depending on the aging data. Indeed [139] implied an existence of a cycle number dependency of lithium loss ( $Q_{li}$ ) term to be denoted as  $b_2 N$ , however this term does not exist in any know published representation of the NREL model and therefore has been omitted here. While  $z$  is understood to normally be  $1/2$  due to the well-known  $\sqrt{t}$  dependency of active lithium loss due to the SEI layer growth, the model nomenclature was generalized to allow for empirical fits which do not exhibit this dependency.

The model coefficients are developed from generalized rate constant equations which assumes an Arrhenius dependence on Temperature ( $\Theta_T$ ), a Tafel dependence on Open Circuit Voltage ( $\Theta_{V_{oc}}$ , which is related to SOC), and a Wöhler dependence on changes in Depth of Discharge ( $\Theta_{\Delta DOD}$ )

$$\Theta_T = \exp \left[ \frac{-E}{R_{ug}} \left( \frac{1}{T(t)} - \frac{1}{T_{ref}} \right) \right] \quad (2.5)$$

$$\Theta_{V_{oc}} = \exp \left[ \frac{\alpha F}{R_{ug}} \left( \frac{V_{oc}(t)}{T(t)} - \frac{V_{ref}}{T_{ref}} \right) \right] \quad (2.6)$$

$$\Theta_{\Delta D_oD} = \left( \frac{\Delta D_oD}{\Delta D_oD_{ref}} \right)^\beta \quad (2.7)$$

Furthermore the effect of all rate constant equations is assumed to be multiplicative.

$$\Theta = \Theta_{ref} \prod \Theta_k. \quad (2.8)$$

Note that  $E$ ,  $\alpha$ ,  $\beta$ , and  $\Theta_{ref}$  are fitting parameters and is where the chemistry specific behavior is captured while  $R_{ug}$  is the universal gas constant and  $F$  is the Faraday constant. The reference parameters are chosen to normalize aging to standard conditions and are defined as follows:  $T_{ref} = 298.15$  K,  $V_{ref} = 3.6$  V, and  $\Delta DOD_{ref} = 1$ . In short, the NREL model predicts incremental aging over an assumed standard aging profile [146]. This approach was chosen due to the reality that Calendar Aging (i.e. the effect of time) cannot be separated from Cycling Aging effects.

### 2.3.1.2 Knee Region Modeling

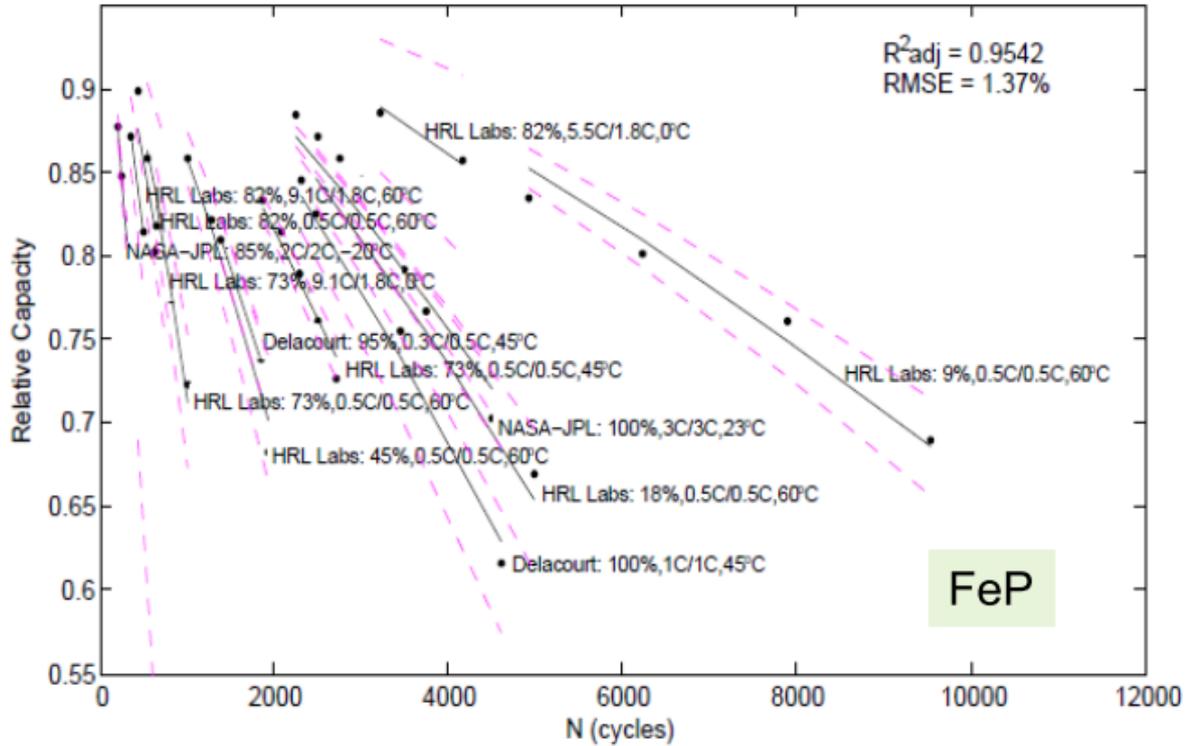
A discrepancy between model prediction and aging data was found in mid-to-high DoD cycling data, therefore later the  $c_1$  rate constant for Equation 2.4 was updated to better account for the “knee region” (see Figure 2.18) where capacity loss is governed by the graphite site loss (mechanical process) rather than lithium loss (predominately chemical process) [139]. Calculations based on model extrapolation indicated that battery life would be over-predicted by up to 25% if the knee region was not accounted for.

The hypothesized cause of the knee region was attributed to mechanical stress effects due to a combination of 1.) accelerated polymer failure at high temperatures, 2.) bulk intercalation strain, 3.) bulk thermal strain, and 4.) intercalation gradient strain accelerated by low temperature [139]. Therefore  $c_1$  was updated to account for these effects as follows<sup>2</sup>:

$$c_1 = c_{1,ref} \left\{ \exp \left( \frac{-E_a^{binder}}{R} \left( \frac{1}{T} - \frac{1}{T_{ref}} \right) \right) [m_1 DOD + m_2 \Delta T] + m_3 \exp \left( \frac{-E_a^{intercal}}{R} \left( \frac{1}{T} - \frac{1}{T_{ref}} \right) \right) \left( \frac{C_{rate}}{C_{rate,ref}} \right) \left( \sqrt{\frac{t_{pulse}}{t_{pulse,ref}}} \right) \right\}. \quad (2.9)$$

<sup>2</sup>Note in [139] the coefficient appears as  $c_2$  however there is no clear indication of why chronological order was not followed.

It was later shown that bulk intercalation strains had the strongest correlation to capacity fade at the knee region. The updated model with the new  $c1$  parameter was then applied to an LFP aging meta-dataset and was shown to be able to adequately predict 13 aging conditions with temperatures ranging from 0°C–60°C as seen in Figure 2.22 [139].



**Figure 2.22:** NREL Model Fit (Solid Black Lines) with Updated Knee Region Parameter ( $C1$ ) Compared to LFP Meta-Dataset (Points) [139].

### 2.3.2 Wang Model

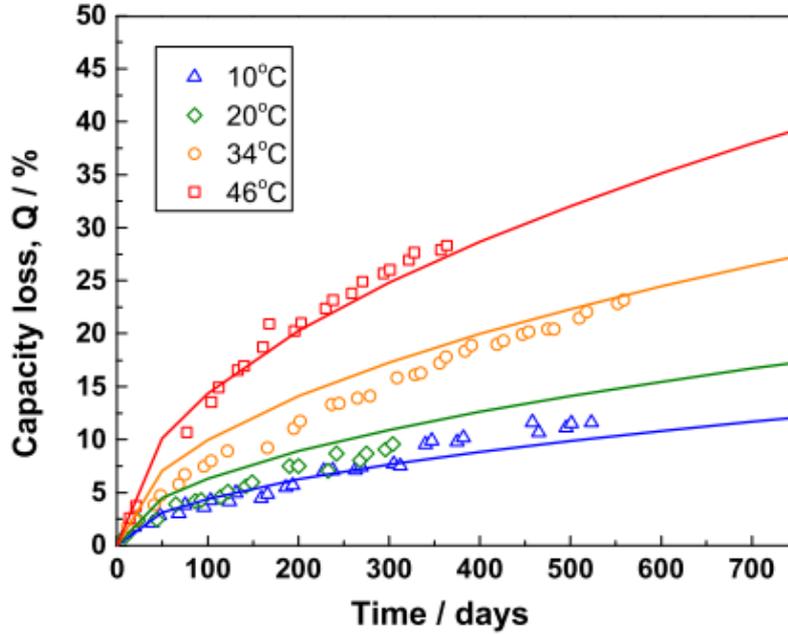
The Wang model was based upon accelerated life testing of a large test matrix of battery conditions of the 1.5 Ah 18650 LMO-NMC Sanyo technology which drew upon previous work which modeled cycle life of LFP cells [97, 98]. This study also provided a thorough description of both the test conditions and the measurement techniques employed to characterize the batteries. Cells were characterized by four techniques: capacity characterization (with well-defined charge/discharge profiles), relaxation tests, Electrochemical Impedance Spectroscopy (EIS), and Hybrid Pulse Power Characterization (HPPC). Additionally, this study conducted a voltage differential analysis to examine the source of capacity loss and concluded that lithium (material) loss was the limiting factor thus the active site loss was not modeled.

The Calendar Life loss model was developed from fitting model parameters to a fundamental capacity loss equation which assumed an Arrhenius dependence on Temperature.

$$Q_{loss,\%} = A \cdot \exp\left(\frac{-E_a}{RT}\right) t^{1/2} \quad (2.10)$$

Where  $A$  is the pre-exponential factor,  $E_a$  is the activation energy in  $\text{J mol}^{-1}$ ,  $R$  is the gas constant, and  $T$  is the absolute temperature in Kelvin. As the test matrix did not include stored cells, the low rate ( $C/2$ ) and shallow DoD (10%) cycling data set was taken as approximate storage conditions and the model parameters were fitted to result in the Calendar Life loss model. The result of the model fit is expressed in Equation 2.11 and can be seen in Figure 2.23.

$$Q_{loss,\%} = 14876 \cdot \exp\left(\frac{-24.5 \text{ kJ}}{RT}\right) \text{days}^{1/2} \quad (2.11)$$



**Figure 2.23:** Simulations of Calendar Aging prediction model (line) are compared with experimental data (markers) for all four temperatures (10, 20, 34, and 46 °C) for LMO-NMC chemistry cell [98].

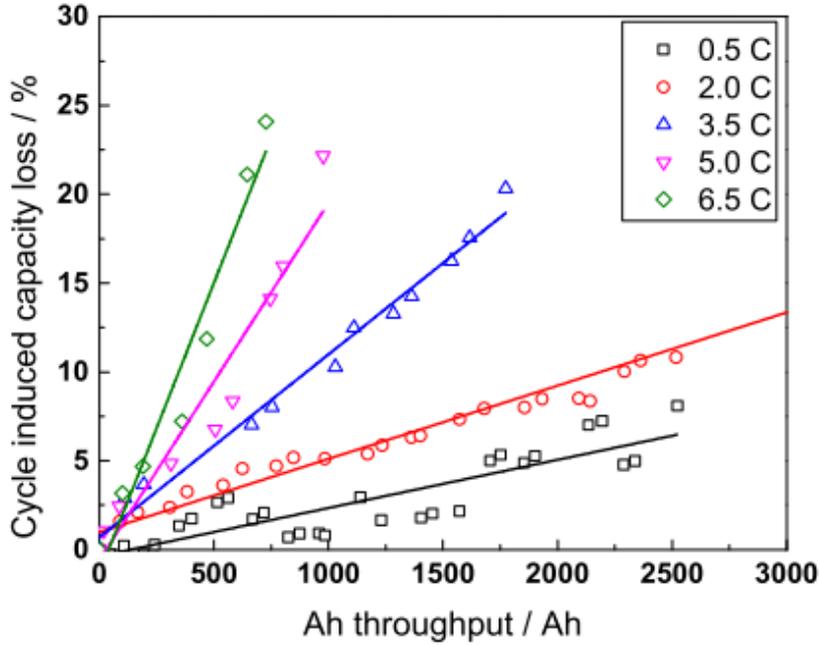
The degradation due to cycling was calculated by subtracting the Calendar Life loss model from the total loss measured from the data. The fundamental cycle loss equation was hypothesized from the rate effect of the C-rate and is of the functional form:

**Table 2.2:** Wang Cycle Life Model

Temperature Dependent Equations	
10 °C	$0.0021 \exp(0.4278 \cdot C\text{-rate}) \cdot A_{\text{throughput}}$
20 °C	$0.0008 \exp(0.3903 \cdot C\text{-rate}) \cdot A_{\text{throughput}}$
34 °C	$0.0010 \exp(0.3107 \cdot C\text{-rate}) \cdot A_{\text{throughput}}$
46 °C	$0.0045 \exp(0.1826 \cdot C\text{-rate}) \cdot A_{\text{throughput}}$

$$Q_{\text{loss},\%} = B_1 \cdot \exp(B_2 \cdot C\text{-rate}) \cdot A_{\text{throughput}} \quad (2.12)$$

Where  $B_1$  is the pre-exponential fitting factor and  $B_2$  is an exponential fitting factor. Data from the 50% DoD cycling conditions were fitted to Equation 2.12 to result in the Cycle Life Model which results in unique values for  $B_1$  and  $B_2$  at each experimental temperature as seen in Table 2.2. The Cycle Life model fit to experimental data can be seen in Figure 2.24.

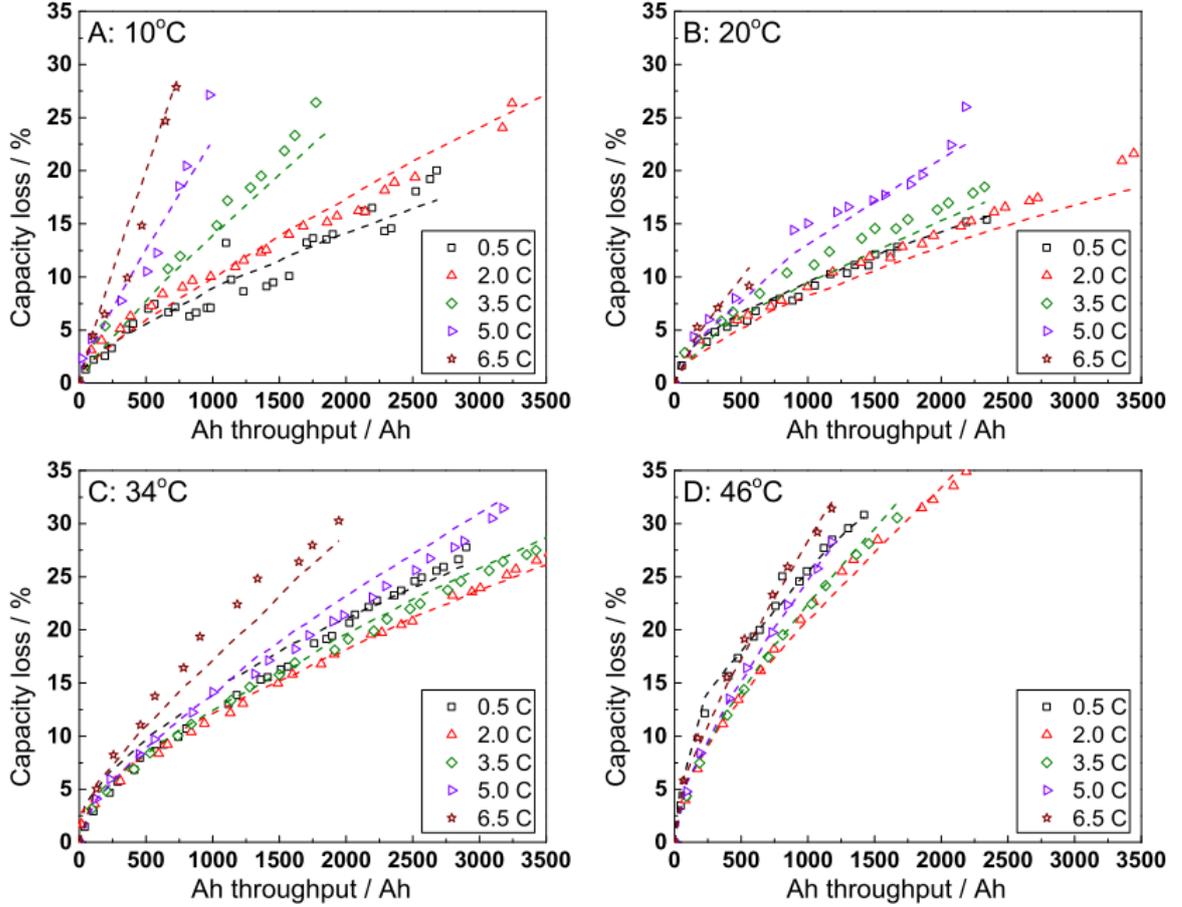


**Figure 2.24:** Cycle life loss is plotted as a function of Ah-throughput at 10 °C for 5 different charge rates:  $C/2$ ,  $2C$ ,  $3.5C$ ,  $5C$ , and  $6.5C$  rate. Linear fits (lines) were achieved, indicating the capacity loss follows linear trend with Ah throughput or time for the LMO-NMC chemistry [98].

Finally a generalized equation to take all temperatures and rates into account was found by an empirical fitting of  $B_1$  and  $B_2$  factors of the cycle life loss model. Thus the overall Lifetime Model is represented by Equation 2.13 while Figure 2.25 is the complete

Lifetime model fit compared to experimental data.

$$Q_{loss,\%} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] \cdot Ah_{throughput} + f \cdot t^{1/2} \cdot \exp\left(\frac{-E_a}{RT}\right) \quad (2.13)$$



**Figure 2.25:** Simulations of combined Calendar Aging and Cycling Aging prediction model (line) are compared with experimental data (markers) for four temperatures (10, 20, 34, and 46 °C), five C-rates (C/2, 2C, 3.5C, 5C, and 6.5C) and at 50% DOD for LMO-NMC chemistry [98].

It can be seen that at lower temperatures (10 °C) life degradation exhibits a linear relationship as Cycling Aging is the dominant mechanism, while at high temperatures (46 °C) a more exponential relationship is seen due to Calendar Aging dominance. Understanding of the interrelation of C-rates, Temperatures, and Ah throughput lead to a concise visualization of Calendar vs Cycling Aging effects which was shown previously in Figure 2.17.

### 2.3.3 MOBICUS Model

The MOBICUS Model is still in development and has been the product of ongoing research projects since 2007 [91–93, 140, 147, 148]. Currently the MOBICUS project is expanding the model for more usage profiles and coupling the effects of previously developed aging models. The Cycling Aging model was the product of the SIMSTOCK project from 2007-2011 which investigated 3 Li-ion technologies while the Calendar Aging model was a product of the SIMCAL project from 2009-2012 which investigated 6 different Li-ion technologies. A summary of the technologies investigated in each project is presented in Table 2.3.

**Table 2.3:** *SIMSTOCK and SIMCAL Battery Technologies Investigated*

	NCA	LMO-NMC	NMC	LFP
SIMSTOCK	Saft 7 Ah	LG Chem 5.3 Ah	–	LiFeBatt 8 Ah
SIMCAL	Saft 7 Ah	LG Chem 5.3 Ah	Kokam 12 Ah	LiFeBatt 8 Ah LiFeBatt 15 Ah A123 2.3 Ah

While databases of the aging characteristics of the previous battery chemistries were built throughout the SIMSTOCK and SIMCAL projects, only a few chemistries have been further developed into models which have been published in the literature. While the MOBICUS project seems to claim integration of all available chemistry datasets into the latest model iteration, it is not clear how each dataset is taken into account as there have been no comprehensive published articles to date. Thus the Calendar Aging and Cycling Aging model representations will be described in their limited capacities available in the literature along with the latest understanding of the final MOBICUS model.

#### 2.3.3.1 SIMSTOCK Cycling Aging Model

The SIMSTOCK project representation of Cycling Aging is found in [92] for an LMO-NMC blend battery chemistry and was initially formulated as a polynomial expression of the form:

$$F(Y) = y_0 + y_1 \cdot X_1 + y_2 \cdot X_2 + y_3 \cdot X_3 + y_4 \cdot X_4 \quad (2.14)$$

Where  $X_1$  = current (A),  $X_2$  = Temperature ( $^{\circ}$ C),  $X_3$  = Ah throughput (A s), and

$X_4 = \Delta SOC$  (%) and the variable  $Y$  represented the total aging, considered as cumulative ampere-hours. The paper references the NREL model but notes that aging parameters are considered static throughout the life of the battery cell which is a limitation as the rates at which degradation parameters affect the overall life fade will change as the battery ages. Therefore to capture changes in degradation rate losses, the Cycling Aging model was adapted to calculate the differential capacity loss and was formulated as follows:

$$a_j = a_0 + a_1 \cdot X_1 + a_2 \cdot X_2 + a_3 \cdot X_3 + a_4 \cdot X_4 \quad (2.15)$$

The model was then fitted to the results of the testing conditions which cycled the four parameters ( $X_1 - X_4$ ) through all possible binary permutations (0,1) where 0 was the minimum condition and 1 was the maximum condition, resulting in eleven total tests. As this model is in derivative form  $\left(\frac{dQ}{d(\sqrt{t})}\right)$  it attempts to predict the instantaneous rate at which capacity declines during each battery test condition, then integrates each individual slope over time to result in the full capacity degradation. The paper derived three conclusions from the LMO-NMC Calendar Aging model: that the predominate aging effect was temperature, the effect of Ah throughput was greater than the effect of current, and that without stress, the coefficient  $a_0$  is positive and indicated that the battery would regain some capacity at low temperatures.

### 2.3.3.2 SIMCAL Calendar Aging Model

The SIMCAL Calendar Aging model is presented in [91] for an LFP battery chemistry which was subjected to six storage conditions for a total of 14 tests. Batteries were stored at SOC: 30, 65, and 100 while being subjected to temperatures of 30 °C, 45 °C, 60 °C, and a thermal cycling test which varied temperature from 30 °C to 45 °C. This model was also initially formulated as a derivative equation as follows:

$$\frac{dQ_{loss}}{dt} = k(T, SOC) \cdot \left(1 + \frac{Q_{loss}(t)}{C_{nom}}\right)^{-\alpha(T)} \quad (2.16)$$

Where:

- $\frac{dQ_{loss}}{dt}$  is the fractional capacity loss at time  $t$ .
- $k(T, SOC)$  is the kinetic dependence of capacity fade evolution dependent on Temperature and SOC during storage.

- $\left(1 + \frac{Q_{loss}(t)}{C_{nom}}\right)^{-\alpha(T)}$  with  $\alpha(T) > 0$  is related to the diffusion limitation of solvent molecules inside the SEI layer which tends to decrease the capacity fade rate and is temperature dependent.

In order to express the total capacity loss as a function of time, the incremental representation seen in Equation 2.16 was integrated by setting  $\alpha = 1$  at  $t = 0$  for  $Q_{loss} = 0$  and resulted in:

$$Q_{loss}(t) + \frac{1}{2} \cdot \frac{Q_{loss}(t)^2}{C_{nom}} = k(T, SOC) \cdot t \quad (2.17)$$

Later it was noted that this representation did not fit the aging dataset well. Therefore the model was further generalized to allow for model tuning to aging data that did not follow an Arrhenius  $t^{(1/2)}$  evolution. This was accomplished by integrating Equation 2.17 and assuming that  $T$  and  $SOC$  remain constant to result in:

$$t = \frac{C_{nom}}{(\alpha + 1) \cdot k(T, SOC)} \cdot \left\{ \left(1 + \frac{Q_{loss}}{C_{nom}}\right)^{\alpha+1} - 1 \right\} \quad (2.18)$$

Additionally the kinetic dependence of capacity fade ( $k(T, SOC)$ ) was further expressed as follows:

$$k(T, SOC) = A(T) \cdot SOC + B(T) \quad (2.19)$$

$$A(T) = k_a \cdot \exp \left\{ \frac{-Ea_A}{R} \cdot \left( \frac{1}{T} - \frac{1}{T_{ref}} \right) \right\} \quad (2.20)$$

$$B(T) = k_b \cdot \exp \left\{ \frac{-Ea_B}{R} \cdot \left( \frac{1}{T} - \frac{1}{T_{ref}} \right) \right\} \quad (2.21)$$

Where  $R$  is the ideal gas constant,  $T$  is represented in Kelvin,  $SOC$  represented as a percentage, and the reference Temperature ( $T_{ref}$ ) was set at 298 K. The model parameters  $\alpha$  and  $k$  were estimated through non-linear regression techniques to fit the baseline model to the aging data.

Storage temperature was shown to have a stronger effect on battery life than storage SOC and that higher storage values of temperature and SOC impacted battery life more than lower values if the trend continues. The effect of temperature and SOC was most

apparent in the 65 °C case which exhibited a  $t^{(1/2)}$  dependency and a clear delineation of each SOC condition; however, at lower temperatures life fade exhibited a more linear degradation.

### 2.3.3.3 MOBICUS Representation

What is known of the MOBICUS model representation can be found in [93] and seems to be an extension of the NREL representation. While the NREL model is referenced, it seems that the most current version of Equation 2.3 was not incorporated and thus a  $t^{(1/2)}$  dependency is assumed. The MOBICUS representation hypothesizes that since overall life degradation tends to be dominated by Calendar Aging effects, and that cycle frequency additionally influences the effect seen from those cycles, all degradation must therefore be time dependent. Thus, the MOBICUS model updates Equation 2.4 to become:

$$Q_{sites} = c_0 + c_1 t \quad (2.22)$$

It was claimed that with the MOBICUS representation, the knee region can be predicted with more accuracy, but it is unclear as to whether the updated NREL model parameter  $c_1$  (active site loss model seen in Equation 2.9) was taken into account. While the MOBICUS representation claims better fit to data so that Cycling Aging is not overestimated, there is no attempt to specify how this knee region develops or to what mechanism it is attributed to as in the NREL model. While may be possible to speculate the functional forms of the MOBICUS model from the SIMSTOCK and SIMCAL model outlines, there are no known published sources to confirm.

## 2.4 Limitations of Semi-Empirical Battery Models

Semi-empirical battery models allow for extrapolation of future conditions which would be time and cost prohibitive to find empirically, however this entails they are inherently dependent on the aging data which is used to generate degradation rate laws. This limitation is manifested in several ways which are enumerated below.

### 2.4.1 Time Resolution

The time resolution of the battery model is a limiting factor. As most models are based on average hourly values for temperature and minute-based values for SOC and other parameters, they cannot capture the effects of high frequency cycling or small deviations in Temperature. Additionally, effects of high charge rates other than average hourly increases in temperature are not captured. This is important to note when attempting to evaluate degradation of fast grid services such as Frequency Regulation which operates at the seconds' time interval.

### 2.4.2 Data Limitation

As noted in [146] current models do not capture effects of accelerating degradation mechanisms which could occur after 30% Capacity Fade. As rate relationships can only be assumed to hold true and are bounded by the underlying time period of the aging data, effects of degradation beyond 10 years cannot be predicted with certainty. Non-accelerated storage aging data is costly to generate due to experimental and time requirements and it is unclear if low impact cycling could approximate storage conditions. The effects of extreme temperatures are not captured as none of the previous studies have investigated Temperatures above 50°C and below 0°C. From stress testing research it is clear though there would be pronounced degradation and potentially catastrophic cell failure at extreme temperatures. Finally cell degradation effects are known to be non-transferrable to pack level degradation as additional degradation beyond what could be explained by scaled effects exists [120]. This is likely due temperature non-uniformities within the battery pack which are not adequately captured by BMS temperature sensors, and results that cell-level characterized aging data does not adequately explain pack aging.

### 2.4.3 Cycling Definition and Frequency

The cycling frequency and cycling definition are known to drastically affect life degradation such that, any model which is based on accelerated cycling data alone could over predict battery life [96, 143]. Various definitions of what constitutes a cycle exist depending on the application; such as when current passes through zero or another chosen point, the point where charge power slope changes, or the point where charge power returns to a previous value.

Currently there is no widely accepted standardization of battery test cycles; therefore it is crucial that battery cycles are well defined in aging studies. Cycle definitions should include charge rate, temperature (both ambient and effective cycle temperature), a well-documented charge profile, clear definition of what a cycle constitutes, and acknowledgment of rest times between cycles or between measurements. Clear definition of battery measurement and characterization techniques (EIS, charge/discharge, HPPC, etc.) should also be provided. Recent progress in battery test standardization been made in the US and China however more work is needed [149, 150].

#### 2.4.4 Chemistry Specificity

Current models can only postulate degradation laws based on the chemistry of the underlying aging data. Each battery chemistry exhibits different sensitivities to degradation drivers, especially the effects of Temperature and SOC. Therefore it is important when employing semi-empirical models in economic cost evaluations to note the battery chemistry used and to understand that results are non-transferrable to other battery technologies. Furthermore some chemistries may be more prone than others to the Knee Region where capacity quickly drops due to increased mechanical degradation. This Knee Region is potentially avoidable or deferrable if battery usage conditions are constrained.

### 2.5 Partial Conclusions: Battery Degradation

Li-ion batteries are complicated electrochemical systems with non-linear interdependencies which exhibit two complementary aging behaviors known as Calendar Aging and Cycling Aging. Calendar Aging is dependent on the degradation drivers of Temperature and State of Charge (SOC) which are coupled through an Arrhenius relationship which results in an underlying dependency on time ( $t^z$ ) where  $z$  tends to be 1/2. Cycling Aging is the degradation resulting from battery usage and is dependent on the drivers of Temperature, SOC, charge current (C-rate), and Depth of Discharge (DoD or  $\Delta$ SOC) as shown in Figure 2.6. Cycling Aging results in an underlying dependency on total extracted energy (Ah throughput) rather than cycle number ( $N$ ) as previously thought. Furthermore, each battery chemistry will exhibit varying sensitivities to these degradation drivers thus it is imperative that aging data is characterized by its underlying chemistry. Each of these degradation drivers influences fundamental mechanical and chemical degradation mechanisms (see Figure 2.5) to impact battery State of Health (SOH). SOH is reduced

through either a decrease in total battery capacity (Capacity Fade) or an increase in internal impedance (Power Fade).

Capacity Fade is caused by the irreversible Loss of Lithium Inventory (LLI) or through Loss of Active Material (LAM) and active intercalation sites, while internal impedance rise (Power Fade) is associated with increased kinetic resistance within the system. Both life fade metrics are predominately attributed to an increased Solid Electrolyte Interface (SEI) layer growth. While high temperatures trigger more Calendar Aging (chemical degradation), low temperatures and high C-rates induce more Cycling Aging (mechanical degradation). To minimize Calendar Aging while the battery is at rest, maintain a low SOC and a low Temperature. To minimize Cycling Aging while the battery is in use, maintain a moderate Temperature, a low/moderate C-rate, and a low DoD centered around an optimal SOC point, which may be around SOC 50% as this point is known to produce the least joule heating, however more research into this phenomena is warranted.

At all temperatures (except for very low,  $T < 10^{\circ}\text{C}$ ) while operating in the pre-knee region, Calendar Aging is the dominant lifetime reducing factor. After the knee region, Cycling Aging becomes dominant due to a change in mechanism where capacity loss begins to be governed by graphite site loss (a mechanical process) rather than active lithium loss (predominately chemical process). However an intelligent battery management strategy could prolong the knee region point until after the vehicle EoL. This understanding paired with the fact that most vehicles are immobile more than 90% of the time[26, 151], implies that Calendar Aging is the dominant reduction factor therefore the battery management strategy while at rest will bound lifetime.

Truly empirical LIB lifetime analyses would require time scopes of 10 years or more, which is both impractical and would be rendered obsolete at completion as battery technology is improving rapidly. Due to these challenges, semi-empirical lifetime models have been developed which aim to represent fundamental electrochemical phenomena mathematically while extracting rate relationships from what limited degradation data is available. Semi-empirical models are preferred over other methods for economic analyses as they allow for extrapolation beyond experimental aging conditions while being based on electrochemical phenomena. The three primary semi-empirical models explored in this chapter are known as the NREL Model [146], the Wang Model [98], and the MOBICUS Model [93, 132] which have influenced or have been incorporated into several other models and research efforts as will be explored in Chapter 3.

While the NREL Model seems to be the most well developed, it is limited to two

chemistries and is based on population data primarily from geosynchronous orbit satellite life qualification tests. The Wang Model is also well developed which provides additional insights into which degradation mechanisms bound capacity loss and provides for a clear visualization of the Calendar vs Cycling Aging effects as seen in Figure 2.17. However the Wang Model is limited to the LMO-NMC chemistry and does not employ actual storage data as it assumed low C-rate, low DoD rate cycling data would be comparable. The MOBICUS project has access to the most robust aging data set from the greatest variety of battery chemistries; however the overall modeling approach to couple Calendar and Cycling Aging is not clear as there are no known published works. Therefore model dependencies must be inferred from previously published models developed out of the SIMSTOCK and SIMCAL research projects.

While semi-empirical battery models are the best tools for predictive analyses due to the cost prohibitive elements of empirical full life-cycle testing, they are inherently limited by their source data. This limitation is manifested in several ways:

- 1.) Time resolution: current models do not take micro cycling into account and calculate temperature degradation from average impact normally at an hourly time-frame. Therefore they cannot be used to estimate Frequency Regulation or other high frequency charge/discharge service costs.
- 2.) Data Limitation: it is difficult to predict beyond 10 years and below 30% Capacity Fade as no empirical dataset has been generated, lack of data at extreme temperatures. Additionally cell-to-pack translations of aging data are known to produce biased results. This is due to cell-to-cell variations within the battery pack which produce temperature non-uniformities and thus non-uniform aging.
- 3.) Lack of test cycle standardization: testing cycle definitions should include charge rate, temperature (both ambient and effective cycle temperature), a well-documented charge profile, clear definition of what a cycle constitutes, and acknowledgment of rest times between cycles or between measurements. Clear definition of battery measurement and characterization techniques (EIS, charge/discharge, HPPC, etc.) should also be provided.
- 4.) Chemistry limitation: different Li-ion chemistries have drastically different aging profiles, thus the need to expand current models to additional chemistries is clear.

Failure to properly account for battery degradation costs results in skewed capital projections and requires costly oversized capacity margins for Battery Energy Storage

System (BESS) and misconstrues the value proposal of new V2X services. Lack of sufficiently sophisticated economic degradation cost estimations will ultimately inhibit V2X technology if early adopters experience untenable battery lifetime reduction due to service provision. Therefore economic analyses of LIB assets whether they are employed via V2X or for BESS use cases should contain sufficient electrochemical detail to account for chemistry specific degradation behavior to produce results based on physical reality.



## Part III

# V2X Economics



## Vehicle-to-Anything (V2X) Economics

“*It is impossible for a man to learn what he thinks he already knows.*”

EPICETETUS

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### **Abstract.**

Calendar Aging tends to be the dominant aging factor for Li-ion batteries in vehicular applications which implies that the Temperature and SOC at which a battery is at rest over time will have a more significant impact than any other consideration. This reduces down to the fact that battery degradation cost is fundamentally *time-dependent*, however economic cost calculations to date have mostly focused on cycle number as the determining factor of lifetime. To be economically viable, V2X services must generate greater revenue than the costs incurred; however, without a clear understanding of marginal costs, economic bids to the energy market will be misinformed.

Herein, I propose a V2X Marginal Cost Theory which is based on two main principles: 1.) there is an efficiency cost associated not only with V2X but any charge operation, and 2.) the true V2X degradation cost takes opportunity cost into account, that is, only considers degradation beyond what would have been experienced by operating the vehicle normally. This results in a more nuanced understanding of marginal costs as the resultant battery lifetime impact from V2X can be either be considered a cost, a benefit, or zero. I conclude that V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.

This chapter constitutes a working paper: Thompson A.W. 2019, "A Theory of Vehicle-to-Anything (V2X) Energy Services Marginal Cost including Battery Degradation."

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## Introduction

As explained in [Chapter 2](#), Calendar Aging tends to be the dominant aging factor for Lithium-ion Batteries in vehicular applications which implies that the Temperature and SOC at which a battery is at rest over time will have a more significant impact than any other consideration. This reduces down to the fact that battery degradation cost is fundamentally *time-dependent*. Additionally the total Ah throughput and how this current is extracted from the battery will further degrade battery State-of-Health (SOH). Since battery operational conditions will determine lifetime, all degradation drivers should be accounted for in economic analyses, however degradation cost evaluations have only recently come to integrate sophisticated battery lifetime models.

Economic profitability of V2X requires that the cost of service provision be outweighed by the revenue it generates. While revenue calculation is relatively straightforward, without a clear understanding of how a usage profile impacts battery life, V2X marginal costs cannot be properly accounted for to inform bids to the energy market. Thus the focus of this chapter is on economic valuations of battery degradation costs. First I summarize previous efforts at accounting for battery degradation costs and show how semi-empirical battery lifetime models can inform economic cost estimations. Next I comment on two prevailing theories of V2X Marginal Cost and show how they are inadequate as they result from what I call "The Iron Balloon Fallacy" understanding of battery degradation. I use the understanding of electro-chemical battery degradation developed throughout the previous chapters to develop a Marginal Cost Theory for V2X and present mathematical formulations which better account for the relevant cost components. Finally, I conclude with three generalized strategies of how V2X can be combined with optimized charging algorithms to potentially prolong battery life.

## 3.1 Economic Modeling of Battery Degradation

### 3.1.1 First Approximations of Battery Degradation Costs

The first V2X (specifically V2G) cost evaluation can be found in the seminal works in [50, 152], which developed the fundamental equations of battery asset costs. While cost estimations for capital, purchased energy, and labor are well defined, battery degradation cost ( $c_d$ ) is based on a Cycle Life only understanding of the battery which incorporates DoD but no other degradation drivers as can be seen in Equation 3.1.

$$c_d = \frac{c_{bat}}{L_{ET}} \quad , \quad L_{ET} = L_c E_s DoD \quad (3.1)$$

Where  $c_d$  is the battery degradation cost (\$/kWh),  $c_{bat}$  is the battery capital cost including labor for replacement (\$), and  $L_{ET}$  is the lifetime energy throughput of the battery (kWh).  $L_c$  is the cycle lifetime number (N),  $E_s$  the total energy storage of the battery (kWh), and  $DoD$  is the depth-of-discharge (% , dimensionless) at which  $L_c$  was determined. This formulation assumes that the extractable energy of the battery does not change over time for each cycle and that battery lifetime is defined as the number of cycles at a certain DoD.

Net Present Value (NPV) is a widely accepted metric for economic valuation of assets which takes the *Time Value of Money* into account. Similarly, as Calendar Aging is the most important factor in battery asset fade, it follows that battery degradation costs must be also time dependent. A first attempt to include time into battery degradation costs is found in [124] which defined a Present Value of Throughput (PVT) metric in attempts to account for the time dependency of battery energy as seen in Equation 3.2.

$$PVT = \sum_{i=1}^n \frac{(1 + 0.025)^{i-0.5}}{(1 + 0.1)^{i-0.5}} x_i \quad (3.2)$$

Where  $i$  = years,  $n$  = battery life in years,  $x_i$  = annual battery energy throughput in kWh. PVT accounts for the present value of both the capacity and cycle life of the battery assuming a discount rate of 10% per year and that the value of a kWh of energy storage increases at a rate of 2.5% per year [124]. While this formulation does include some notion of time, calculation of  $x_i$  would still require an understanding of both battery usage and degradation due to that usage. Furthermore the assumption that the value of battery energy increases over time is not accurate as that value is intrinsically an artifact

of battery operation. Thus battery degradation costs are best informed by lifetime models which already incorporate all (or most) of the degradation drivers.

## 3.1.2 Model-based Battery Degradation Costs

### 3.1.2.1 V2X Optimized Charging Algorithm

The first known incorporation of a battery lifetime model to estimate degradation costs is found in [153] which develops an algorithm to optimize EV or PHEV charging based on both electricity and degradation costs. This work employs a simplified version of the NREL Model to allow for reduced calculation time and is particularly interesting as it demonstrates an understanding for and incorporates nearly all degradation drivers for cost estimation. The results of the optimized charging power profile and strategy was dependent on the exogenous signal of electricity price with fixed inputs for ambient temperature ( $T$ ), battery energy capacity ( $Q$ ), initial SOC ( $SOC_0$ ), plug-in time ( $t_0$ ), and target time for full charge ( $t_{max}$ ), where a full charge was defined to be 90% SOC. Only charge power was optimized as actual charge voltage and current was assumed to be controlled separately by the battery charger.

As seen in Figure 3.1 a characteristic "stepped" power profile results as the optimal least cost charging strategy when given a constant electricity price and fixed inputs for ambient temperature ( $T = 25^\circ\text{C}$ ), and thermal resistance ( $R_{th} = 0.002^\circ\text{C W}^{-1}$ ) when including degradation. The tendency to charge later is due to Calendar Aging considerations which discourages spending time at high SOC. The spreading of charge over time, hence the stepped power profile, is due Cycling Aging considerations which discourages high power (high current) charging to minimize temperature rise.

Later the effect of a variable electricity price and V2G power exportation was explored in vehicles with good thermal control ( $R_{th} = 0.0004^\circ\text{C W}^{-1}$ ). In this example vehicles exported power immediately to lower resting SOC's even if this required a higher powered step charge later Figure 3.2, which again implies that minimization of Calendar Aging effects outweigh subsequent increases in Cycling Aging effects. In all instances the optimized charge profile was found to outperform other charge strategies and resulted in prolonging battery life between 4% - 50% over other strategies. This leads to the conclusion that if temperature can be adequately controlled, bulk power V2X exportation can be beneficial to minimize battery degradation costs even before including the primary additional value of revenue generation.

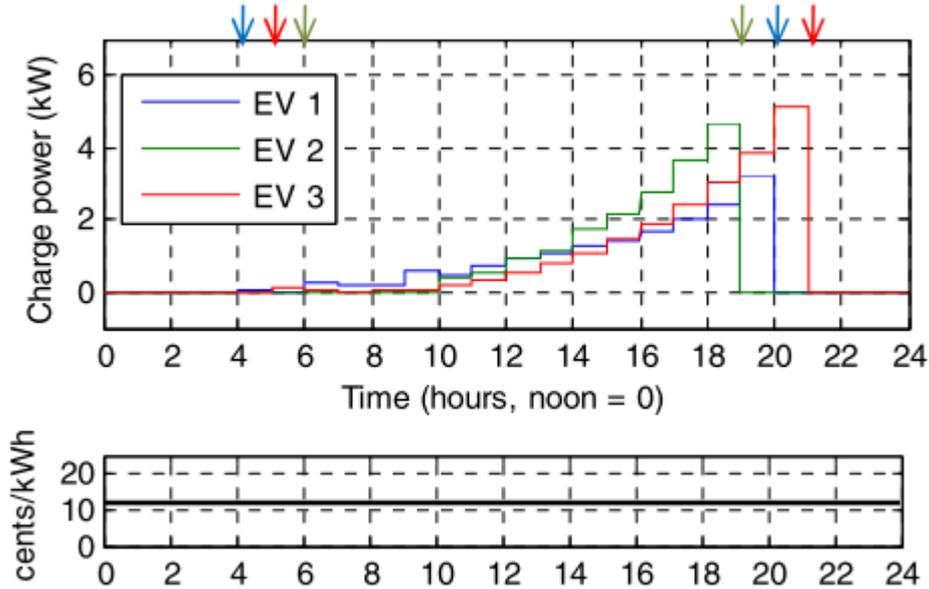


Fig. 6. Optimized charging of 3 EVs with constant cost of energy

**Figure 3.1:** *Degradation Optimized Charging Power Profile (upper panel) for three EVs at a fixed electricity price (lower panel). EV1 (blue) begins at SOC 35, EV2 (green) begins at SOC 30, and EV3 (red) begins at SOC 20 where the related colored arrows signify the user-specified plug-in and unplug time. Electricity price is constant at \$0.12/kWh [153].*

### 3.1.2.2 V2X Service Cost Study

While previously shown that bulk energy transfer can be beneficial in certain circumstances, typically extended periods in this operational mode is highly detrimental to battery lifetime [22, 154]. Therefore grid services which require extended bulk energy transfer constitute the highest cost V2X service however several other services exist. In [53] the previously explained Wang battery model in Chapter 2 was paired with a lumped thermal model from [155] and the V2G-SIM software platform [126, 156] to quantify battery degradation costs associated with driving only vs driving paired with a range of V2G services. The degradation effects of providing Peak Load Shaving (Demand Response from Table 1.1), Frequency Regulation, and Net Load Shaping (Bill Management, Table 1.1) services were quantified by assuming each vehicle repeated the same itinerary for 10 years which consisted of daily driving and service provision profiles. Only capacity reduction was studied as internal impedance rise was omitted. All battery degradation costs were calculated assuming a replacement battery cost of \$6,000.00 and an EoL of 30% reduction of initial capacity.

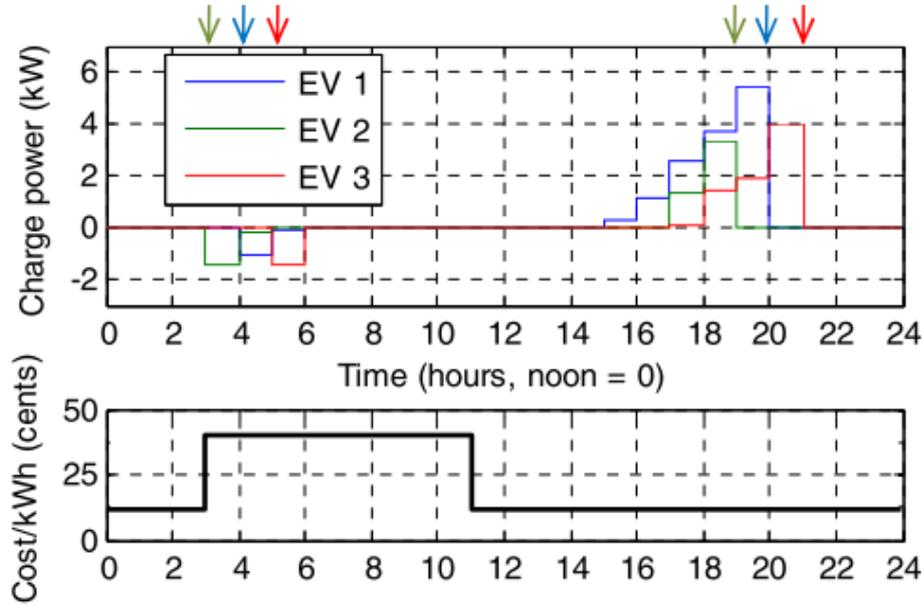


Fig. 9. Optimized charging of 3 EVs showing V2G operation

**Figure 3.2:** *Degradation Optimized Charging Power Profile with V2G (upper panel) for three EVs at a variable electricity price (lower panel). EV1 (blue) begins at SOC 50, EV2 (green) begins at SOC 80, and EV3 (red) begins at SOC 70 where the related colored arrows signify the user-specified plug-in and unplug time. Electricity price varies between \$0.12/kWh and \$0.40/kWh [153].*

### 3.1.2.2.a Peak Load Shaving

When Peak Load Shaving was assumed to be provided every day for 10 years, the resultant additional capacity reduction ranged from 2.79% – 9.69% over the 31.41% reduction from the base/uncontrolled charging scenario, highlighting the detrimental effect of extensive bulk power transfer (Energy Based Services). However providing Peak Load Shaving every day is unrealistic and is likely only to be called during times of emergency, approximately 20 times per year [157]. Therefore V2G emergency Peak Load Shaving was calculated for the 20 hottest days of the year and was found to increase capacity losses by 0.38% with an L1 charger and 0.82% with an L2 charger over the base/uncontrolled charging case. The battery degradation cost from the 2-h emergency V2G Peak Load Shaving service was calculated to be \$0.38 using an L1 charger at home and \$0.82 using an L2 charger at home.

### 3.1.2.2.b Frequency Regulation

It was assumed that vehicles could adequately follow a Frequency Regulation signal from 19:00-21:00 every day based on results from [56]. The regulation signal was based on the PJM Wholesale Energy Market Operator (PJM) market Reg-D signal which is a fast-response signal designed to have zero net energy over each 15 minute contract period. The Frequency Regulation service resulted in an average additional 3.62% capacity loss with an L1 charger and an additional 11.15% loss with L2 charging over the base case. The battery degradation cost from the 2-hour Frequency Regulation was \$0.20 using L1 charging and \$0.46 using L2 charging.

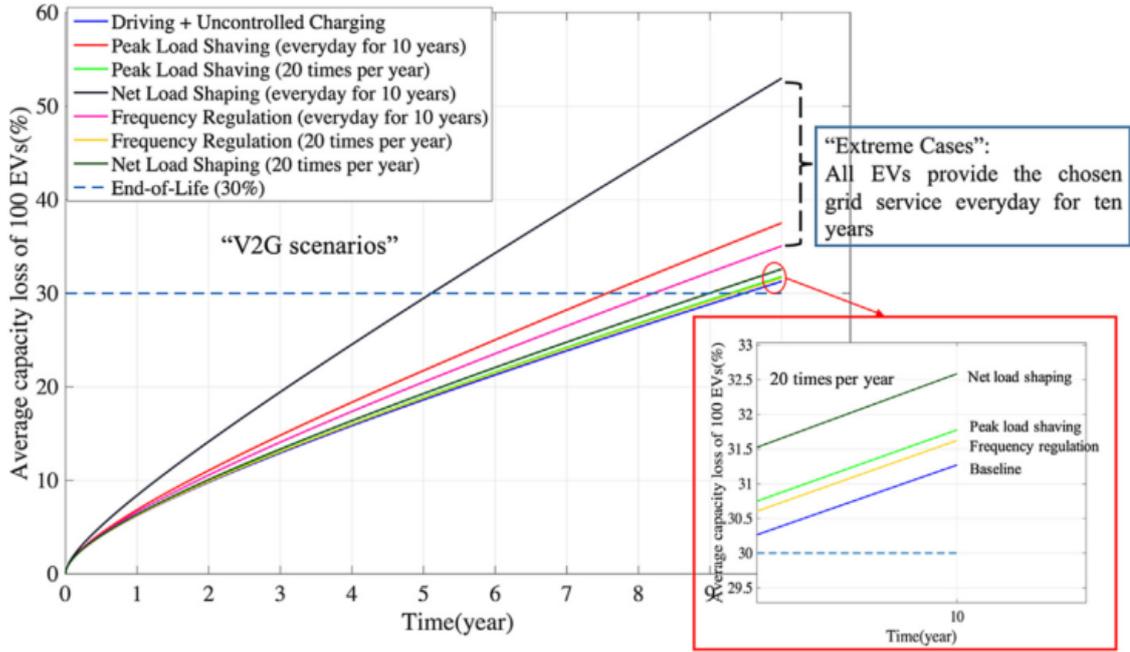
### 3.1.2.2.c Net Load Shaping

Net Load Shaping consists of flattening the shape of the system load profile i.e. filling in valleys while reducing the peak. While V1G was found to help reduce the system peak, V2G could both flatten the peak and shift consumption to off peak hours. The increased load shifting potential of V2G does come at an increased cost however as it would require deeper cycles and more bulk energy transfer than V1G. Therefore V2G Net Load Shaping service resulted in an additional 1.18% capacity loss with L1 charging and 2.60% with L2 charging over the base case. The battery degradation cost from the load shaping service was calculated for 20 days per year as \$1.18 using L1 charging and \$2.60 using L2 charging at home.

Overall it was concluded that V2G services could be dispatched in ways that result in very little additional cost to EV owners but extended bulk energy transfer services if provided daily would likely be cost prohibitive. The results of all three grid services is summarized in Figure 3.3 which compares both the extreme cases where service is provided every day and the more realistic 2-hr service provision scenarios for each V2G service.

### 3.1.2.3 V2X Battery Chemistry Impact Study

In [159] a semi-empirical model which incorporated both Calendar and Cycling Aging was used to assess the impact of V2G and the charging strategy on battery lifetime. This model attempted to capture chemistry effects as well and was verified using the same aging data used in [97] for an A123s 2.3Ah LFP cell and from the MOBICUS project for a Saft VLGP 7Ah NCA cell. The model assumed Calendar Aging was dominated



**Figure 3.3:** *V2G Service Capacity Fade Impact*

Average capacity losses of 100 EVs by performing different V2G services over ten years. In the extreme cases where all EVs provide the selected grid service every day, ten-year capacity losses from peak load shaving, frequency regulation and net load shaping increase by 3.62%, 5.6% and 22.6% compared to the base case, respectively. In the more realistic cases, EVs provide V2G services for 20 times per year with ten year capacity losses of 0.38%, 0.21% and 1.18% over the base case, respectively [158].

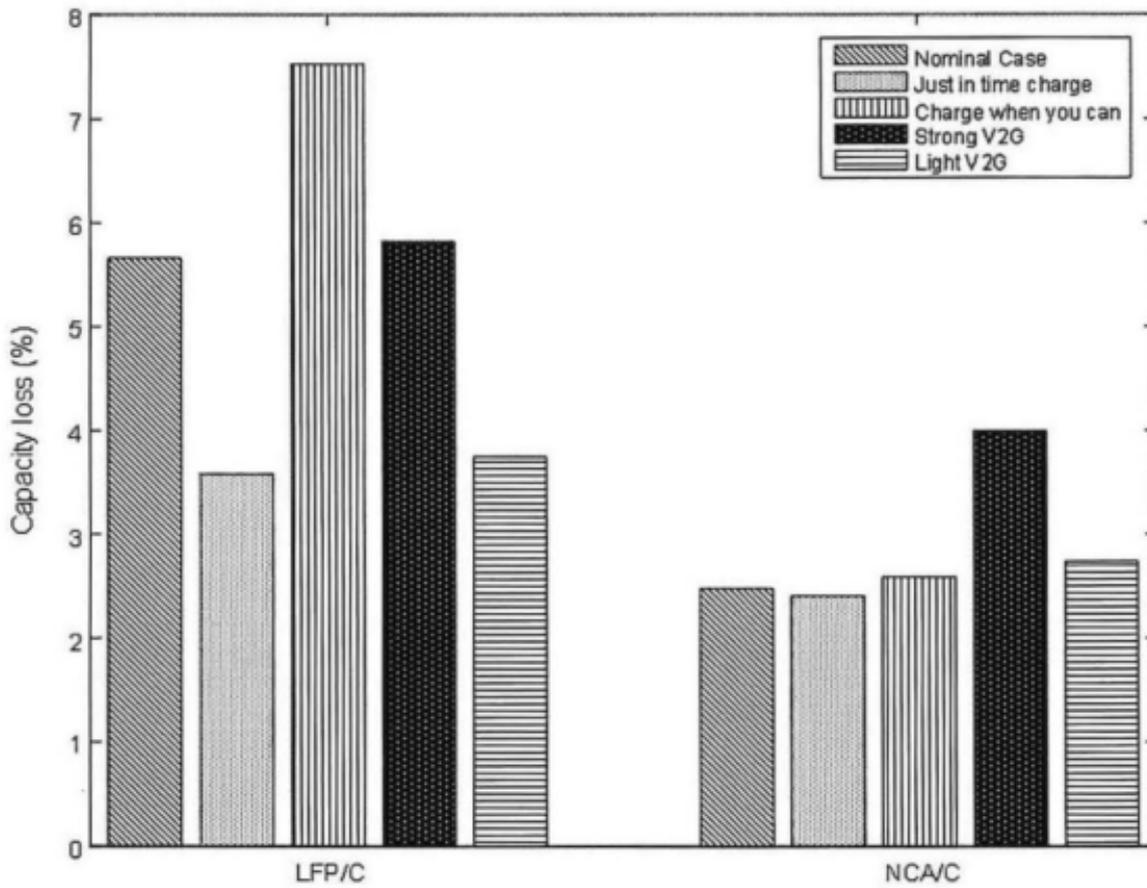
by Temperature and SOC while the Cycling Aging was dominated by Temperature and C-rate thus the other degradation mechanisms were omitted. The degradation model was simplified such that one form of aging could take place at a time, assuming that Calendar Aging was already taken into account when Cycling Aging occurred. The battery life effect of different charging strategies characterized through cycling profiles referred to as: Just In Time, Charge When You Can, Strong V2G, and Light V2G, which were compared to the Nominal Strategy of charging upon plug-in.

The Nominal case consisted of a medium DoD cycle profile with a relatively high average SOC and long periods of rest at high SOC. The Just In Time strategy consisted of medium DoD cycling with low average SOC and long periods of rest at low SOC. The Charge When You Can strategy consisted of very low DoD cycling, a high average SOC over time, and long periods at high SOC. The Strong V2G scenario consisted of several high DoD cycles, a medium average SOC, and long periods at low SOC. Finally the Light V2G consisted of high DoD cycling, a medium average SOC, and long periods at low

SOC. These trends are summarized in Table 3.1.

**Table 3.1:** *General Characteristics of Various Charging Strategies*

	DoD Cycling	Average SOC	Rest SOC
Nominal	Mid	High	High
Just in time	Mid	Low	Low
Charge when you can	Low	High	High
Strong V2G	High (x3)	Mid	Low
Light V2G	High	Mid	Low



**Figure 3.4:** *Comparison of Capacity Loss due to various charging and V2G profiles for LFP and NCA Battery Chemistries [159].*

The capacity loss results of each charging strategy are summarized Figure 3.4 for both chemistries. The most notable result is how different the two technologies are affected by the charging strategy and that NCA exhibits superior capacity retention over LFP for every strategy. Overall the Just In Time strategy is the best as it simultaneously mitigates

Calendar Aging by having long periods of storage at low SOC and does not require large DoD cycling which mitigates Cycling Aging compared to the other strategies. For LFP the Just In Time strategy results in a 3.5% capacity reduction compared the Nominal of 5.6% while for NCA the strategy benefit is less significant with 2.2% capacity reduction compared with the Nominal of 2.3%.

When looking closer at LFP, the Just In Time and Light V2G strategies cause the least degradation and actually decrease the life loss when compared to the Nominal case. However the Strong V2G case, which would require large amounts of battery throughput, is only slightly worse than the Nominal strategy. These two observations lend to the conclusion that incorporation of some level of V2G can be beneficial to battery life regardless, but that significant levels of V2G usage should be evaluated against the revenue benefit. For LFP the additional life loss of the Strong V2G strategy is only 0.02% over the Nominal and would likely be outweighed by revenue.

When looking at NCA the situation changes however as the Charge When You Can strategy exhibits less life loss than the Light V2G. Referring again to [Figure 2.19](#) this does not seem surprising as the NCA Calendar Aging effect has a low sensitivity to SOC, therefore periods stored at high SOC would only have a slightly more negative impact compared with storage at low SOC on life fade. However for NCA the Strong V2G (4%) is worse than the Nominal (2.6%) and all others. This result would imply that the Calendar Aging mitigating effect of a low storage SOC is outweighed by the large DoD and subsequent increased Cycling Aging. This is an interesting result as it conflicts with [\[153\]](#) which also based on an NCA chemistry and concluded that the DoD effect on capacity loss was very small compared to the Temperature and SOC effects. One possible explanation is that the three large DoD swings raises the average battery temperature much higher than normal which would induce more capacity degradation. Why this effect would be more prominent for NCA and not seen in the LFP results is not clear however as LFP is known to be more Temperature sensitive.

While the Just In Time strategy resulted in the least Capacity Fade there was little difference compared to the Light V2G scenario in both chemistries. This study indicates that certain chemistries are better suited to certain usage profiles; therefore the cost effectiveness of V2X products may be chemistry dependent. This hypothesis may be evidenced by the different chemistry employed by Tesla for their vehicle (NCA) vs storage batteries (NMC).

### 3.1.2.4 V2X for Battery Life Prolongation

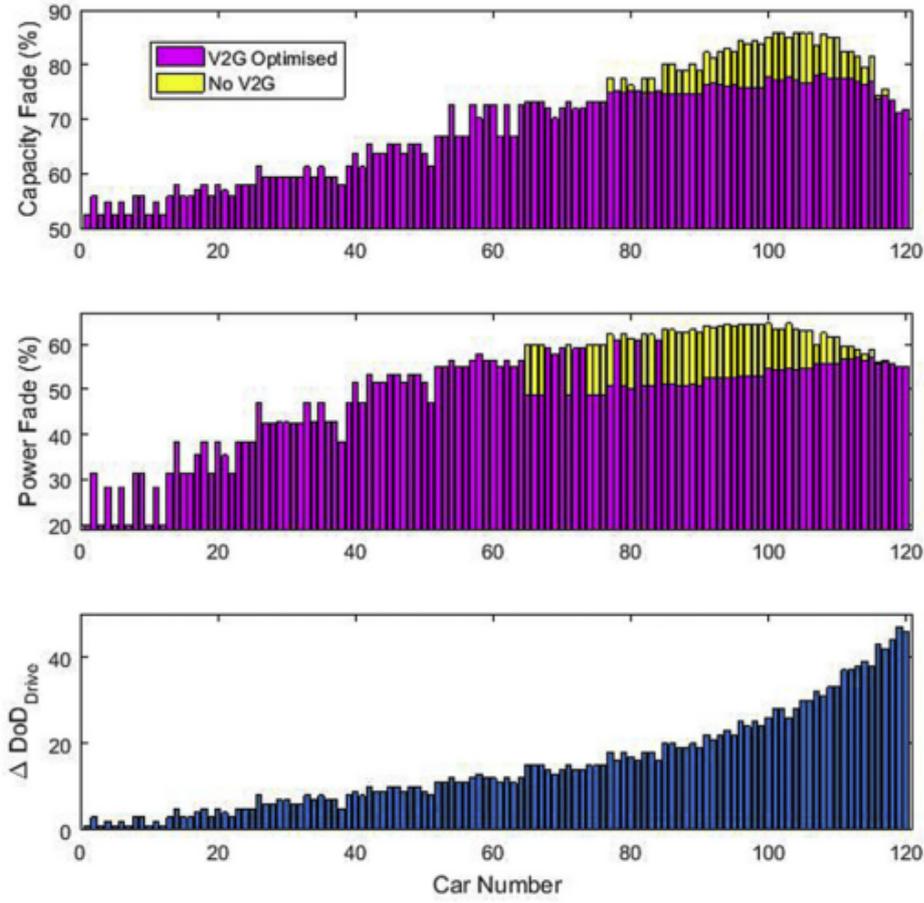
The first known paper to outright claim the positive life effect of V2X services can be found in [68]. While here an Equivalent Circuit Model (ECM) was employed, it was fitted with battery aging data effectively making it a semi-empirical ECM as each parameter varies over time and in response to degradation drivers. Capacity Fade and Power Fade were both investigated and SOH was defined such that EoL would be encountered if either end condition was met for Capacity Fade (80% remaining initial capacity) or Power Fade (100% increase in initial internal resistance). The model was populated with a robust aging dataset of 3 Ah NCA 18650 cylindrical cells from an unnamed manufacturer. Fifty long-term aging tests with a well-defined experimental protocol were conducted under a wide range of operational conditions spanning  $0^\circ\text{C} < T < 45^\circ\text{C}$ ,  $15\% < \text{SOC} < 95\%$ ,  $0\% < \text{DoD} < 80\%$ . Additionally each test condition was conducted on three separate cells to ensure robustness. Instead of using a phenomenological model, this work opted to instead fit a generalized model without hypothesizing rate constants with a fractional polynomial of the form:

$$Y = Y_0 + \alpha X^\beta \quad (3.3)$$

Where  $Y$  was either Capacity or Resistance,  $Y_0$  was the corresponding value determined from the initial characterization test,  $X$  was either time or Ah throughput ( $K$ ) and  $\alpha$  and  $\beta$  were fitting parameters found through linear interpolation.

In contrast to previous studies, this work proposed a Vehicle-to-Building (V2B) topology where EVs would discharge into a larger BESS, pumped storage, or compressed air system intermediary which could be used for either energy arbitrage or for flattening/shifting peak consumption of the commercial building to off-peak hours. V2B discharge was managed with the primary goal to minimize battery degradation through an iterative algorithm which compared the expected degradation cost at an initial resting  $\text{SOC}_i$  to the expected degradation cost of a lower  $\text{SOC}_{i+1}$  (Calendar Aging Mitigation) where  $\Delta\text{SOC}$  was discharged to the storage intermediary. If  $\text{SOC}_{i+1}$  was found to be beneficial, the algorithm next compared whether the life gains from resting at  $\text{SOC}_{i+1}$  would outweigh the Cycling Aging induced to discharge  $\Delta\text{SOC}$  and if all conditions were true, the algorithm would discharge to  $\text{SOC}_{i+1}$ , update it as the new  $\text{SOC}_i$ , and continue in increments of 1%  $\Delta\text{SOC}$  until the optimal resting SOC was reached.

This study only used V2B to minimize battery degradation cost and did not optimize



**Figure 3.5:** *V2B Optimized Charging Battery Life Impact Capacity Fade (Upper Panel), Power Fade (Middle Panel), and driving behavior by DoD impact (Bottom Panel) from 120 simulated driving cycles. The battery life impact from the normal (Charge on plugin) charging strategy is shown in yellow whereas the V2B optimized charging life impact is shown in purple. For certain driving profiles, incorporation of V2B reduced both the Capacity Fade and Power Fade life impact [68].*

financial gains vs battery degradation cost. While this V2B topology would result in a bulk energy transfer product, results indicated that both Capacity Fade and Power Fade could be reduced in certain circumstances. If a vehicle arrived with an initial SOC between 79 – 62%, discharging an additional 8 – 40% through V2B could reduce Capacity Fade by 6% and Power Fade by 3% over the first three months, Figure 3.5. While the V2B optimized algorithm was employed with an opportunistic charge strategy (analogous to Charge When You Can in [159]), the authors noted that incorporating a Just-in-Time strategy would likely deliver more pronounced life gains.

Next the V2B algorithm was investigated in a case study which tracked actual driving patterns of 349 EV, PHEV, and Fuel Cell Electric Vehicle (FCEV) owners and calculated

the available V2B energy when integrated with an actual energy usage profile of a commercial building. It was found that vehicles could provide 2.8 MWh of energy weekly which would equate to a 145.6 MWh annual energy arbitrage potential. Additionally, Capacity Fade was reduced up to 9.1% and Power Fade by up to 12.1% for vehicle owners which translated to an annual savings of \$555.00 for a single EV owner when assuming a replacement battery cost at 200 \$/kWh.

### 3.1.3 The Iron Balloon Fallacy

Revisiting the balloon analogy from [Chapter 2](#), equating battery lifetime exclusively to cycle number assumes that the balloon capacity never reduces in size over time, such that the same amount of water is able to be pumped into and out of the balloon *ad infinitum* until one day suddenly the balloon pops (EoL). I call this representation of battery degradation costs "The Iron Balloon Fallacy" as it treats battery capacity as if it were a balloon made of iron whose capacity cannot change over time and is not impacted by operating conditions.

From the previous chapters several degradation cost principles can be extracted:

- 1.) Degradation Drivers: Electro-chemical degradation drivers should be accounted for in cost estimations: Temperature, SOC, DoD, and C-rate which are dependent on time and Ah throughput.
- 2.) Time Dependence: Time is the single most important degradation consideration. Degradation cost therefore is fundamentally time-dependent.
- 3.) Calendar Aging Dominance: Operation/charging strategies to mitigate Calendar Aging can compensate for subsequent increased Cycling Aging impact.
- 4.) Chemistry Dependence: Each chemistry technology exhibits different sensitivity to degradation drivers and will experience different aging during operation, therefore results are non-transferrable to other chemistry technologies.
- 5.) End of Life Definition: EoL calculations should be defined in both Capacity Fade and Power Fade (internal resistance) metrics. EoL = 80% of initial Capacity ( $Q$ ) and/or 100% increase in initial internal resistance ( $R$ ) are good references.
- 6.) High impact cycling: not only is the DoD important but due to SOC effects, the nominal SOC point at which cycling is performed and the SOC region that the cycle

penetrates into are also highly impactful. The same 20% DoD cycle from SOC 100–80 will have a drastically increased degradation impact than the same 20% DoD from SOC 70–50. Additionally, cycles which penetrate into the high region (SOC 90 and greater) will have a drastically greater aging impact.

## 3.2 V2X Economic Theory

In this section I define V2X variable costs and propose a Marginal Cost Theory for V2X in which I claim that V2X marginal cost is not zero as accepted in the economic literature, but is in fact highly dependent on battery degradation cost.

### 3.2.1 Literature Marginal Cost

Currently, two prevailing theories of V2X marginal cost exist: 1.) Since the EV or PHEV asset has already been purchased for the intended purpose of mobility, any additional secondary use of the asset for V2X would be "free" if the vehicle asset life is less than the battery life. And 2.) since the operating current experienced when providing V2X is significantly less than the current induced from driving (especially aggressive stop and go driving), V2X does not noticeably impact asset lifetime compared to driving and is therefore zero marginal cost. Both theories stem from a lack of understanding the intricacies of electro-chemical degradation, especially the phenomena of Calendar Aging dominance.

The first V2X marginal cost theory cannot yet be fully disproven empirically since even the oldest commercial EV battery packs with reliable and available aging data are less than 10 years old; however, automotive Original Equipment Manufacturers (OEMs) legal stances on battery degradation are telling. All current OEM battery capacity warranties are highly conservative and are rated 10% to 20% below experimental estimations of battery EoL to only guarantee between 60–70% remaining capacity for a maximum period of 8 years (Tesla) with most only covering 5 years (Nissan, Chevrolet) [160]. Most notably, battery technology leader Tesla had not guaranteed capacity until 2017 with the Model 3 production version and still does not cover battery capacity for the Model S and X vehicles. Additionally all OEM battery capacity warranties contain a mileage limit which have settled between 100,000 – 120,000 miles (approx. 161,000 – 193,000 kms) such that whichever limit (calendar or mileage) is reached first will determine the end of warranty period. These warranties are products of OEMs risk assessment and is reflective

of manufacturer confidence of battery asset life. With the current average age of light duty vehicles between 10–15 years and all trends pointing to this average age increasing over time, it can be said with near certainty that the battery pack will not outlast the vehicle [161, 162].

The second marginal cost theory clearly results from the Iron Balloon Fallacy since current only impacts Cycling Aging and, as has been shown extensively throughout this dissertation, Calendar Aging is the limiting lifetime factor for EVs. This equates to Temperature and SOC coupled and dependent on time being the most important degradation considerations. Cycle life only estimations of asset life rely on standardized cycling aging data to determine the total energy throughput a given battery cell is rated for, however lifetime energy throughput cannot be universally guaranteed and is path-dependent (i.e how the battery is operated over time will drastically change the extractable energy throughput). Furthermore, battery manufacturer lifetime estimations based on cycle life measured by remaining energy capacity are only valid for the controlled temperature and cycling regime these cells are subjected to during testing which disregards that a.) lifetime is the lesser of Calendar and Cycling Aging and b.) that End of Life should be defined by both capacity and internal resistance metrics. Basing V2X economic analyses on lifetime energy throughput taken from standardized cycling aging estimations is a flawed methodology and produces erroneous results as it does not consider impact from actual battery operation. Thus it is crucial that degradation costs be informed by semi-empirical battery lifetime models which account for and can capture usage impacts from the degradation drivers.

### 3.2.2 Proposed V2X Marginal Cost Theory

To begin, a fitting analogy can be found by drawing upon well-developed marginal cost theory for thermal generation in power systems. Total costs ( $TC$ ) consist of a fixed cost ( $FC$ ) and variable cost component dependent on generation output ( $VC(q)$ ) Equation 3.4. In the short run, variable costs are comprised mostly of the fuel cost as variable Operation and Maintenance costs are comparatively small and typically are treated as negligible for thermal plants. The Marginal Cost ( $MC$ ) that results consists of an efficiency metric expressed as the Heat Rate ( $HR$ ) in mmBTU/MWh, and a unit cost for fuel ( $F$ ) in €/MWh Equation 3.5 (see Chapter 2 of [163]).

$$TC(q) = FC + VC(q) \tag{3.4}$$

$$MC_{thermal} = HR \cdot F \quad (3.5)$$

Along similar lines, since a V2X resource comprises of EVs paired with Electric Vehicle Supply Equipment (EVSE) which interact with either buildings or the electric grid, there will be a round trip electric efficiency associated with the total delivery system from the battery to the final load. "Fuel" of a V2X resource would be the electricity used to charge the EV batteries and the price of electricity will typically vary over a 24 hour day depending on the electricity tariff structure. However there is an added element which must be considered as any additional kWh of electricity provided will impact the battery asset life, this is the battery degradation cost. Therefore the fundamental equation for V2X marginal cost is seen in Equation 3.6 where  $\eta$  is the round trip efficiency (%) which is dependent on the charge current ( $i$ ) and the battery State-of-Charge (SOC),  $E$  is the electricity price in (€/MWh) which is dependent on time ( $t$ ) and  $D$  is the battery degradation cost in (€/MWh) which I have shown is dependent on the degradation drivers: time, Temperature, State-of-Charge, charge current, Depth of Discharge, and Ah throughput. I will elaborate on the fundamental equation elements in the following sections.

$$MC_{V2X} = \eta_{(SOC,i)} \cdot E_{(t)} + D_{(t,T,SOC,i,DoD,Ah)} \quad (3.6)$$

### 3.2.2.1 Costs due to efficiency losses, $\eta_{(SOC,i)}$

The round-trip electrical efficiency of a V2X resource will be impacted by the individual efficiencies of all energy elements which comprise the electricity delivery system. These will naturally change depending on the V2X topology employed as the energy losses when electrically coupled with a home or building can be different than when coupled to the distribution grid directly (see Chapter 1 for V2X topologies). In the seminal work of [164], a study of round-trip electrical efficiency of a fleet of 10 EVs acting as a V2G resource was conducted and measured from the site components (grid connection/meter point to EVSE) down to the EV components (on-board charger or Power Electronics Unit (PEU) to the battery).

The complete V2G electrical system consisted of a LFP battery chemistry pack with an on-board PEU in a proprietary EV and an Aggregator energy dispatch module which was connected to the building via a single phase EVSE, a 100 A breaker panel (protection circuit), and an intermediate transformer which stepped the 480 V building voltage down

**Table 3.2:** *V2X Round-trip Efficiency Losses as a function of SOC and AC Current [164].*

		SOC			
		20%	40%	60%	80%
AC Current	10 A	24.49	20.30	26.89	19.08
	30 A	18.33	16.15	18.41	15.77
	50 A	18.96	18.36	17.83	17.40
	70 A	22.08	22.45	22.19	20.07

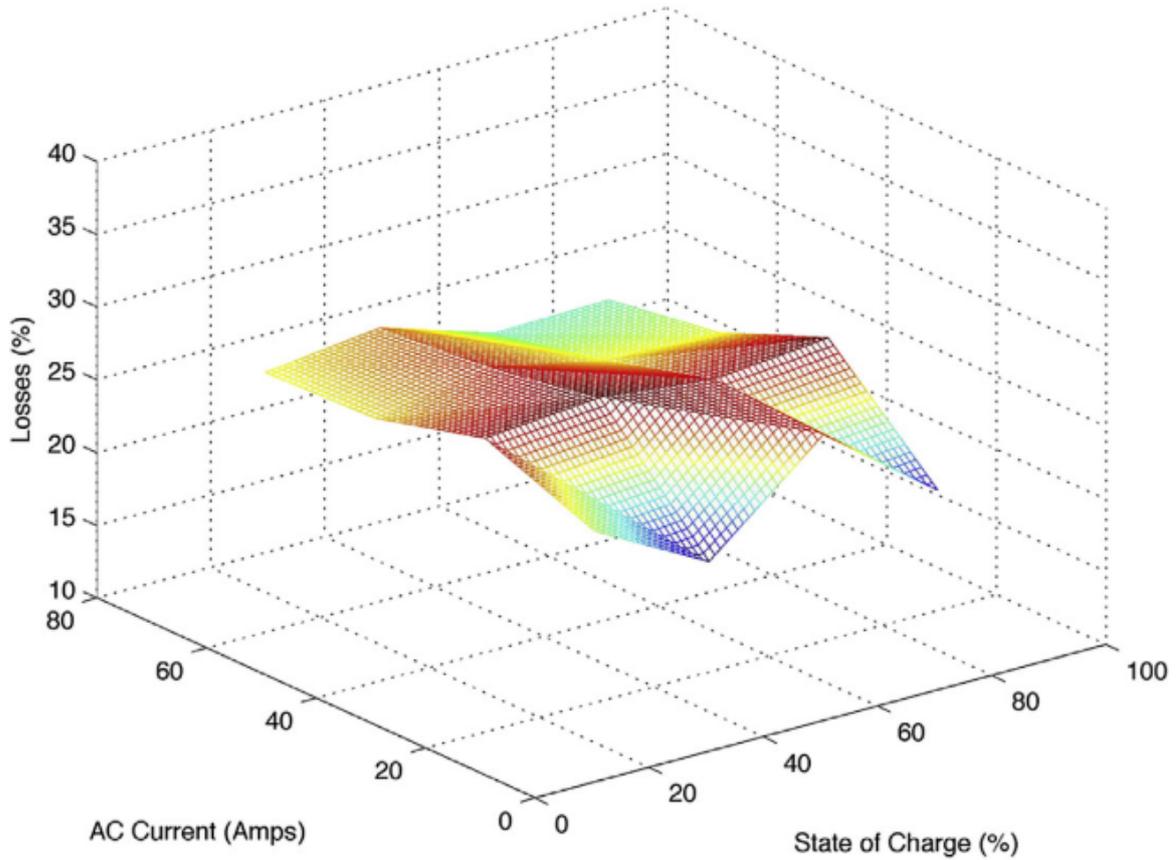
**Table 3.3:** *EV Battery only Round-trip Efficiency Losses as a function of SOC and AC Current [164].*

		SOC			
		20%	40%	60%	80%
AC Current	10 A	1.37	1.15	1.28	1.34
	30 A	2.74	3.26	2.50	2.65
	50 A	5.04	4.39	4.33	3.85
	70 A	6.39	7.87	6.27	5.27

to the 240 V distribution panel. The Voltage at the EVSE was 240 V (supplied from the distribution panel) and the maximum current on the AC line was limited by the vehicle to make the maximum effective charge rate of 75 A translating into a maximum power flow 18 kW for either charging or discharging.

What was determined is that charge efficiency is fundamentally dependent on the EV SOC and AC charge current as seen in Table 3.2, this relationship was expanded through linear interpolation to result in the 3-D dependency map seen in Figure 3.6. We see that both low and high AC charge currents cause greater efficiency losses than more moderate currents, which is a counter-intuitive assessment at first glance. One would think that lower charge rates are less impactful however this is not true because the losses generated by the onboard charger (PEU) are much greater than the other components and have greater efficiency at higher currents.

This is an important finding as typically EV charge efficiency is assumed at a baseline or average at the engineering design phase but is never considered during charge operation and certainly not for V2X economic evaluations. This operation-dependent charge efficiency allowed for design of a V2G fleet charging algorithm that simultaneously ensured that enough aggregated capacity was available to provide a Frequency Regulation service (see Chapter 1) and that the fleet of vehicles were charged in a way that minimized system



**Figure 3.6:** Charge Efficiency Dependency Map ( $1 - \eta_{(SOC,i)}$ )

Round-trip charge efficiency losses ( $y$ -axis) are shown for the variables of AC current ( $x$ -axis) and EV State-of-Charge ( $z$ -axis) with a color gradient where red = worse/high losses and blue = better/lower losses [164].

efficiency losses. This efficiency-cognizant V2G Aggregator charging algorithm was found via simulation to reduce efficiency losses by 8.5% which translated into a cost savings of \$10.6/day assuming a uniform electricity cost of 0.129\$/kWh and 24 h period provision of service.

It is noted as this was a novel approach based on a proprietary on-board charger (PEU) and a non-production EV with out-dated battery technology. Actual implementations will vary depending on the efficiencies of the particular EV, EVSE, and building elements in any given V2X system. Therefore it is clear that additional work in characterizing V2X system efficiency losses is needed; however, understanding that charge efficiency is impacted by operation is significant.

Optimal operation for the efficiency of the onboard charger may sub-optimal for the battery where efficiency losses increase with both charge current and SOC as seen in

**Table 3.3.** While this approach is useful and would allow for potentially significant cost savings over time, without considering the impact of high charge rates on battery life a V2X cost evaluation based on efficiency losses alone would be incomplete, choosing to minimize efficiency losses at the expense of increasing degradation costs. Thus the need to account for all costs arising from battery operation is clear.

### 3.2.2.2 Battery Degradation Cost, $D_{(t,T,SOC,i,DoD,Ah)}$

The cost of battery degradation ( $D$ ) is determined by the End of Life (EoL) condition and the replacement cost, as it is assumed that a user will incur the full replacement cost of the battery asset at EoL. Degradation refers to the incremental lifetime capacity that is consumed by a given operation profile compared to the total usable asset life. Said differently, the degradation from use is prorated to the remaining usable capacity which depends on the EoL definition. If the EoL criteria is defined as being met when the asset has 80% remaining capacity, the usable capacity life is 20% thus degradation cost will refer to incremental consumption of this usable 20% capacity; if EoL is defined at 70% remaining capacity, the usable capacity is 30%. Therefore the cost of battery degradation is:

$$D = C_{bat} * \frac{(L_{V2X} - L_{nominal})}{L_{lifetime}} \quad (3.7)$$

Where,

$$L_{lifetime} = 1 - EoL \quad (3.8)$$

#### 3.2.2.2.a Capacity Cost, $C_{bat}$

The cost of battery capacity ( $C_{bat}$ ) is determined by the full cost of the battery asset replacement which depends on: the pack size ( $Q$ ) in kWh, the replacement battery cost ( $C_{kWh}$ ) in \$/kWh, and labor costs which can be expressed as a base hourly rate ( $C_{hr}$ ) in \$/h multiplied by the number of hours ( $N$ ) needed for replacement, as seen in [Equation 3.9](#).

$$C_{bat} = C_{kWh} * Q + C_{hr} * N \quad (3.9)$$

The reason that replacement costs are used in lieu of initial pack price is that V2X is a secondary use of an already purchased asset for mobility, therefore the true cost that V2X can incur is that of pre-mature replacement of the battery.

Current price quotes for commercial pack replacement excluding labor costs for the Nissan LEAF are \$6200 for the 24 kWh pack, \$7600 for the 30 kWh, and \$7800 for the 40 kWh which results in a replacement cost ( $C_{kWh}$ ) of 258 \$/kWh, 253 \$/kWh, and 195 \$/kWh respectively [165]. Initial quotes from individual LEAF owners have indicated a labor cost of \$1500 over the replacement cost, which would result in a base rate ( $C_{hr}$ ) of 500 \$/h assuming a three hour replacement time. Meanwhile Tesla has indicated Model 3 replacement costs will be between from \$5000 – \$7000 for the three pack options of 50 kWh, 62 kWh, and 75 kWh, which would result in a replacement cost of between 93.33 \$/kWh to 100 \$/kWh. However it should be noted this was in reference to only replacing the modules and not the entire cost of replacing the pack which would be significantly higher. It is reasonable to assume that full pack replacement cost would be at least as high the cost of new battery packs which have been reported as 190 \$/kWh [166]. However, cross-referencing with real price quotes of complete replacement costs including labor which are \$15,000 for Model 3 packs and \$20,000 for older Model S packs, make a 190 \$/kWh replacement price point for the 75 kWh model unlikely (only \$750 attributable to labor cost) but is plausible for the 50 kWh pack as it would result in \$5500 due to labor costs. Assuming a uniform \$5500 labor cost and a baseline replacement cost of 190 \$/kWh for the 50 kWh pack, the remaining replacement costs come to 158 \$/kWh for the 62 kWh pack and 126 \$/kWh for the 75 kWh. In summary, the assumption of full replacement costs including labor ( $C_{bat}$ ) taken here is \$7700 – \$9300 for the Nissan LEAF, \$15k for the Tesla Model 3 and \$20k for the Tesla Model S <sup>1</sup>.

### 3.2.2.2.b Capacity Loss, $L_{V2X}$ and $L_{nominal}$

$L_{V2X}$  and  $L_{nominal}$  are the capacity loss (degradation) incurred by either a V2X operation or the nominal operation (driving) that is being compared. This formulation is important to highlight since the true degradation cost of a V2X service is the difference between the degradation caused by the service compared to the nominal degradation that the vehicle would have experienced had it not been operated for V2X i.e. the additional degradation above nominal caused by V2X operation. The nominal degradation will depend on the

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<sup>1</sup>All real price quotes for full replacement costs including labor for Nissan have come from the mynissanleaf.com forums whereas all price quotes for Tesla have come from the teslamotorsclub.com forums, therefore this data is provided with a caveat of potential misinformation or bias.

driving behavior and charge strategy that is being compared and multiple charge strategies can be compared on the basis of cost by replacing  $L_{V2X}$  with any given operation profile. This formulation is key as it takes opportunity cost into account, is cognizant of the fact that all battery operation (or lack thereof) results in degradation, and allows for comparisons of different charge strategies as well.

The capacity degradation in both cases ( $L_{V2X}$ ,  $L_{nominal}$ ) are determined by a semi-empirical battery degradation model specific for the chemistry technology that a given EV uses. Taking the case of an NMC chemistry,  $L_x$  can be estimated by the generalized form of Wang model from [Chapter 2](#) where "x" is replaced by either *v2x* or *nominal*.

$$L_{x,NMC} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] \cdot Ah_{throughput} + f \cdot t^{1/2} \cdot \exp\left(\frac{-E_a}{RT}\right) \quad (3.10)$$

With model parameters seen in [Table 3.4](#). It should be noted that this formulation is indicative of *cumulative capacity loss* which can be tracked as Ah throughput increases.

**Table 3.4:** Wang Model Parameters [\[98\]](#)

Coefficient values and units			
a	8.61E-6 [1/Ah-K <sup>2</sup> ]	$I_{rate}$	C-rate
b	-5.13E-3 [1/Ah-K]	t	Days
c	7.63E-1 [1/Ah]	$E_a$	24.5 [kJ mol <sup>-1</sup> ]
d	-6.7E-3 [1/K-(C-rate)]	R	8.314 [J mol <sup>-1</sup> K <sup>-1</sup> ]
e	2.35 [1/C-rate]	T	K
f	14,876 [1/day <sup>0.5</sup> ]		

### 3.3 Partial Conclusions: V2X Marginal Cost

#### 3.3.1 Battery Degradation Cost

Since Calendar Aging tends to be the dominating life degradation effect in vehicular applications, this reduces to Time being the most important component of degradation; thus economic degradation cost calculations should be time dependent. Battery Temperature

is also highly impactful followed by SOC and the total Ah throughput, however cost calculations to date have mostly focused on cycle number as the determining factor of lifetime. For Cycling Aging there is consensus that the amount of energy which is extracted (Ah throughput) from the battery will be more significant than number of cycles however, the manner of how the energy is extracted (i.e. at what temperature and what C-rate) will still be important. Charging strategies for vehicular applications should therefore be first designed to mitigate Calendar Aging, but ideally should be able to balance both Calendar and Cycling Aging effects.

The best battery management strategy for minimizing degradation impact is based on three principles with decreasing order of importance: 1.) Minimize Temperature rise, 2.) Minimize time spent at high SOC, and 3.) Minimize average charge power (C-rate). Therefore relatively simple designs such as delayed or “Just-In-Time” charge strategies will always outperform the typical charge when plug-in, regardless of battery chemistry. Furthermore, V2X services may in fact prolong battery life rather than shorten it by contributing to the three principles if incorporated with sufficiently sophisticated battery models. Even bulk energy transfer V2X products with their high Ah throughput can be beneficial when incorporated with a holistic battery management strategy.

Furthermore, the value of V2X products may in fact be chemistry dependent as some chemistries are more suited than others to specific usage profiles. While there still have been no sophisticated studies to look at the degradation effects of fast charging and discharging as would be employed in a Frequency Regulation product, the key conclusion is that integration of V2X services with controlled charging regimes could in fact prolong battery life while delivering tangible energy and cost savings to both EV owners and building managers.

### 3.3.2 Marginal Cost Theory

Based on this understanding of battery degradation, I have proposed a V2X Marginal Cost Theory which is based on two main principles: 1.) there is an efficiency cost associated not only with V2X but *any* charge operation, and 2.) the true V2X degradation cost takes opportunity cost into account, that is, only considers degradation beyond what would have been experienced by operating the vehicle normally. This results in a more comprehensive understanding of V2X marginal cost that is better aligned with classical economic theory in that only the costs resulting from provision of an additional kWh are considered.

This formulation would allow the impact of charge time and power to be balanced with their resultant impact on system efficiency and battery degradation while accounting for the cost of electricity throughout the day. This results in a more nuanced understanding of marginal costs as the resultant battery lifetime impact from V2X can be either be considered:

- 1.) a cost (when the operation profile from a V2X service negatively impacts/reduces battery lifetime compared to the nominal operation),
- 2.) a benefit (when the operation profile from a V2X service positively impacts/increases lifetime compared to the nominal operation), or
- 3.) zero (where the V2X service results in no additional impact on lifetime beyond the life impact which would be experienced from normal use).

To highlight the idea of opportunity cost, I present the typical case of EV overnight charging which employs a charge on plug-in strategy. This entails that upon plug in the EV charges at the maximum charge power rate allowable using a CC/CV (Constant Current/Constant Voltage) protocol to reach full charge in the shortest time possible. In the absence of a SOC limiter, after charge the EV will sit at full SOC until the next morning when it is used again. We see two costs which arise from this operation which are not taken into account. One is that charging at maximum power regardless of system state (EV SOC, ambient temperature, component efficiencies) results in greater losses and requires additional purchased electricity. A charge protocol more aligned with system-optimal operational efficiency can lower losses and reduce energy cost as shown in [164]. Second, is the life impact which results from a max power charge and, because of Calendar Aging dominance, the greater negative impact of sitting for long periods of time at 100% SOC. The true cost of V2X is the lifetime impact that alternate operation induces beyond the baseline charging strategy, which is often inefficient.

I envision that V2X services can be cost-effectively incorporated with vehicle battery management strategies to result in equal to or less degradation impact than the typical usage by employing the following generalized charging regimes.

V2X Frequency Regulation:

- Upon plugin for long period, decrease SOC to lowest level such that the charging rate required to reach the SOC needed for the next trip would not significantly increase battery temperature.

- Perform Frequency Regulation around this nominal SOC value (if temperature rise can be sufficiently contained).
- Step charge back up to required SOC level for mobility needs at last possible moment. Timing for this step charge should calculate the trade-off between market participation duration and battery temperature rise due to increased charge rate.

V2X Bulk Energy Service:

- Upon plugin for long period, decrease SOC to lowest level such that the charging rate required to reach the SOC needed for the next trip would not significantly increase battery temperature while using discharge for bulk power V2X service simultaneously.
- Sit until last possible moment
- Step charge back up to required SOC for mobility needs at last possible moment.

Degradation-cognizant charging without V2X:

- Upon plugin for long period, decrease SOC to lowest level such that the charging rate required to reach the SOC needed for the next trip would not significantly increase battery temperature.
- Sit until last possible moment.
- Step charge back up to required SOC for mobility needs at last possible moment.

Most all discussion of EV/grid integration whether for aggregated "smart charging" (V1X) or V2X, has revolved around the assumption of operating the asset for the benefit of the grid or building. There is rarely ever consideration of EV owner benefits beyond a financial transaction nor are there methods for taking their true costs into account. Even current "smart" charge control methods which take the variable electricity tariff into account to minimize energy costs, fail to consider the much larger costs of charge efficiency and battery degradation. To encourage consumer buy-in to the V2X concept, the EV owner benefit should be considered in developing charging algorithms, or at the very least, V2X must be able to objectively show that service provision will not negatively impact the battery compared to only mobility.

Therefore having a clear concept of V2X Marginal Cost which can properly account for and balance all true costs: the cost of electricity, the system-efficiency costs, and

battery degradation, will allow for development of optimal charge strategies. With a battery asset that can value \$20,000, optimal operation which can result in even a 5% relative annual increase in lifetime would be worth \$1000/yr, an order of magnitude greater than the estimated annual revenue that V2X services could generate (Chapter 1). This comparison gives rise to my final conclusion, that V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.



## Part IV

# Conclusions, Contributions, and Future Work



# Conclusions, Contributions, and Future Work

## 4.1 Conclusions

### 4.1.1 V2X Energy Services

Vehicle-to-Anything (V2X) is an umbrella term to explain the use of EV batteries to provide energy services and derive additional value from the battery asset during times of non-use. V2X services aim to generate revenue from the battery asset through dynamic or bi-directional charge control to provide benefits to the electric grid, to reduce/flatten/shift peak energy consumption of buildings and homes, or to provide back-up power to a load. Energy services refer to selling this dynamic charge control in the form of aggregated flexible capacity in Wholesale and Ancillary Services markets to provide much needed flexibility to System Operators (SOs) and other relevant parties for technical operation of the electric grid. V2X topology refers to both the electrical connection involved and the operation mode employed and can be classified as Vehicle-to-Load (V2L), Vehicle-to-Home (V2H), Vehicle-to-Building (V2B), or Vehicle-to-Grid (V2G).

All V2X topologies are developing in tandem with and in spite of the others at varying speeds. Technological maturity and lack of competition remain problems predominately in the enabling hardware and V2X as a whole is still regarded as a nascent technology recently making steps from research labs and demonstration projects into the commercial realm. However, V2X exhibits significantly reduced capital costs compared to BESS and bi-directional enabling costs have decreased by 90% since 2014 and will likely continue to decline as V2X develops.

I have developed the V2X Value Stream Framework as a means to categorize the full range of energy services that V2X can provide, designate which topology can provide each service, and identify where value is derived within the Energy Industry (see Table 1.1). The Meta-analysis of V2X Value Stream Potential expressed in Figure 1.5 and Figure 1.6 shows results that are contradictory to most previous work in that the under-investigated value streams of Bill Management, Resource Adequacy, and Network Deferral have more economic potential compared to the frequently studied Energy Arbitrage and Spinning Reserves. Economic viability of V2X must be analyzed and applied only to the market context in which analysis is conducted as results are non-transferrable due to geographic particularities. The differentiation between Energy and Power Based services is important and V2X economic valuations should be based on stacked Value Streams. Hence any universal condemnation or confirmation of V2X viability based on one Value Stream in one market alone is myopic as the same service or collection of services can be profitable in different markets with more favorable characteristics.

I have presented several regulatory policy proposals to better incorporate V2X which result in three overarching objectives:

- 1.) to remove administrative barriers to aggregation of energy resources.
- 2.) to design rules which allow for:
  - (a) greater and more efficient Aggregator access to energy markets, and
  - (b) technology-agnostic energy service definitions.
- 3.) to design equitable remuneration schemes which give incentives to actors to reveal their costs while ensuring they are compensated for the full value of service they provide.

These policy proposals not only benefit V2X but also Battery Energy Stationary Storage (BESS) and other Distributed Energy Resources (DERs). In conclusion V2X is an innovative development within the energy industry and its effectiveness as one of the suite of solutions to our most pressing energy challenges in the 21<sup>st</sup> Century is not only market driven but driven by regulatory policy.

## 4.1.2 Battery Degradation

Li-ion batteries are complicated electrochemical systems with non-linear interdependencies. Battery SOH is impacted through reduction of total capacity and/or increase in

internal impedance due to various degradation mechanisms which collectively result in Calendar Aging and Cycling Aging behaviors. This understanding paired with the fact that most vehicles are immobile more than 90% of the time, implies that Calendar Aging is the dominant reduction factor therefore the battery management strategy while at rest will bound lifetime.

Truly empirical LIB lifetime analyses would require time scopes of 10 years or more, which is both impractical and would be rendered obsolete at completion as battery technology is improving rapidly. Due to these challenges, semi-empirical lifetime models have been developed which aim to represent fundamental electrochemical phenomena mathematically while extracting rate relationships from what limited degradation data is available. Semi-empirical models are preferred over other methods for economic analyses as they allow for extrapolation beyond experimental aging conditions while being based on electrochemical phenomena.

Preliminary evidence based on these semi-empirical models suggests that V2X could prolong battery life through integration with optimized management algorithms and that cost effective V2X services may be dependent on battery chemistry. Failure to properly account for battery degradation costs results in skewed capital projections and requires costly oversized capacity margins for BESS and misconstrues the value proposal of new V2X services. Lack of sufficiently sophisticated economic degradation cost estimations will ultimately inhibit V2X if early adopters experience untenable battery lifetime reduction due to service provision. Therefore economic analyses of LIB assets should contain sufficient electrochemical detail to account for chemistry-specific degradation behavior to produce results based on physical reality.

### 4.1.3 V2X Economics

Since Calendar Aging tends to be the dominating life degradation effect in vehicular applications, this reduces to Time being the most important component of degradation. Therefore economic degradation cost is fundamentally *time-dependent*. The best battery management strategy for minimizing degradation impact is based on three principles with decreasing order of importance: 1.) Minimize Temperature rise, 2.) Minimize time spent at high SOC, and 3.) Minimize average charge power (C-rate). Therefore relatively simple designs such as delayed or “Just-In-Time” charge strategies will always outperform the typical charge when plug-in, regardless of battery chemistry. Furthermore, the value of V2X products may in fact be chemistry dependent as some chemistries are more suited

than others to specific usage profiles.

I have proposed a V2X Marginal Cost Theory which is based on two main principles: 1.) there is an efficiency cost associated not only with V2X but any charge operation, and 2.) the true V2X degradation cost takes opportunity cost into account, that is, only considers degradation beyond what would have been experienced by operating the vehicle normally. This formulation would allow the impact of charge time and power to be balanced with their resultant impact on system efficiency and battery degradation while accounting for the cost of electricity throughout the day. This results in a more nuanced understanding of marginal costs as the resultant battery lifetime impact from V2X can be either be considered:

- 1.) a cost (when the operation profile from a V2X service negatively impacts/reduces battery lifetime compared to the nominal operation),
- 2.) a benefit (when the operation profile from a V2X service positively impacts/increases lifetime compared to the nominal operation), or
- 3.) zero (where the V2X service results in no additional impact on lifetime beyond the life impact which would be experienced from normal use).

Therefore having a clear concept of V2X Marginal Cost which can properly account for and balance all true costs: the cost of electricity, the system-efficiency costs, and battery degradation, will allow for development of optimal charge strategies and will properly inform energy market bids.

In EV battery assets which can value \$20,000, optimal operation which can result in even a 5% relative annual increase in lifetime would be worth \$1000/yr, an order of magnitude greater than the highest estimated annual revenue that V2X services could generate. This comparison gives rise to my final conclusion, that V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.

## 4.2 Contributions

While the idea of using EV battery packs for benefit of the electric grid has been present since the late 1990's, the expansion of the original V2G idea into the additional use-cases

of V2X has gradually developed, most notably in the past 10 years. My contributions to an already thriving technical research community thus are not foundational, but branching, to better involve the Energy Economics field and perspective. I highlight three core contributions of this dissertation, one of which is explanatory, one which is technical, and the final which is theoretical.

First, I have provided a thorough definition of the V2X concept along with common terminology explaining and describing the various V2X topologies. In an academic literature which suffers from lack of clarity on the topic, rife with misuse of basic terms, this contribution is non-trivial and will allow for more concise communication of research efforts going forward. I have built upon this definition to create the V2X Value Stream Framework to better communicate the full economic potential of V2X and to emphasize the multifarious services that can be offered, where they participate in the energy market, and how this operation looks when provided by V2X. The V2X concept is presented visually in [Figure 1.4](#) and the Value Streams are summarized in [Table 1.1](#). I have conducted a [Meta-analysis of V2X Value Stream Potential](#) expressed in [Figure 1.5](#) and [Figure 1.6](#), which constitutes the first estimation of annual value for the full range of energy services that V2X can provide. This study has shown that previously under-investigated value streams may be more profitable and I present it as an indication of where the future of V2X may lie. I have concluded with a novel discussion of relevant regulatory issues and how they impact the ability of V2X to participate efficiently in energy markets.

The second contribution, technical in nature, has been realized through bridging electro-chemical degradation theory and lifetime modeling to economic evaluations of cost. This bridging effort has been conducted by extracting the most important degradation mechanisms from electro-chemical theory, explaining and communicating their relevance for economic modeling, and identifying key metrics needed for estimations of battery asset End-of-Life (EoL). This knowledge has been formulated into a novel representation and is summarized in [Figure 2.6](#). This understanding of battery degradation gives rise to the explanation of Calendar vs Cycling Aging behaviors, how time/temperature/and SOC are coupled, that Cycling Aging is not wholly dependent on cycle number but rather on Ah throughput, and most importantly, the persistence of Calendar Aging dominance. This results in a non-intuitive conclusion that how an EV battery is managed at rest will outweigh the effects from driving and any other consideration. From these insights, I postulate that degradation cost is fundamentally time-dependent and argue that semi-empirical battery lifetime models are the best methodology for determining economic impact of battery degradation. Finally I put forth the novel claim that V2X service

cost-effectiveness may be chemistry/technology dependent due to empirical evidence of differing sensitivities to degradation drivers across tested battery chemistries.

The third core contribution is theoretical in that I have developed a Marginal Cost Theory for V2X which aligns with already well-developed Power Systems/Energy Economics Theory. This theory is based on empirical testing, which has concluded that EV charge efficiency is operation-dependent, and thorough knowledge of the intricacies of battery degradation developed throughout this dissertation. I make the strong claim that the marginal cost of V2X services is not zero nor is it negligible as the academic literature has accepted, but is highly dependent on battery degradation cost. Furthermore, this proposed theory considers opportunity cost in that the proper attribution of cost is reserved only for the degradation which could have been avoided without V2X operation, or stated differently, degradation cost is the lifetime impact that V2X operation causes beyond the nominal use-case (driving). When looking at EV charging through a degradation perspective, it is clear that the typical use-case of driving and charging upon plug-in causes many inefficiencies such that the battery degradation impact from V2X can be considered a cost, a benefit, or zero. This is a novel concept and results in a more nuanced understanding of marginal cost which I have represented via a mathematical formulation which can properly account for and balance all true costs: the cost of electricity, the system-efficiency costs, and the battery degradation cost. I have outlined novel strategies of how V2X could be incorporated with charging protocols to result in minimal life impact or perhaps even life prolongation compared to the typical use-case. Therefore, the final and central contribution of this dissertation is that V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.

### 4.3 Future Work

These contributions may be significant due to the insight and novel concepts generated, yet they truly constitute a branch; a beginning for further research. There are several areas for future work which can be immediately identified to bring the ideas and results presented herein to practical significance; however, I will discuss two overarching research efforts. One can directed toward how to develop the mathematical formulation of V2X marginal and battery degradation costs into functional models which can be used to inform and control EV charging for a V2X resource. Whereas the other can be directed

towards better economic analyses of V2X viability through more in-depth market studies and better understanding of V2X fixed costs to inform business plans.

### 4.3.1 Battery Degradation Cost Modeling

The main question in this research area will be how to account for the time-dependence of battery degradation. The approach explored here is through incorporating semi-empirical lifetime models which prorate capacity by the cost for replacement. However this approach is only valid for ex-ante analyses as often these semi-empirical lifetime models are defined on the basis of cumulative Ah throughput, meaning that the lifetime energy and an estimation of the lifetime operating conditions a vehicle will experience would need to be known beforehand to compare the degradation impact of different use profiles.

What is needed for charge algorithms or V2X controls, which often must operate on the seconds timescale, would be models which can accurately represent the incremental degradation impact of minuscule changes in operating conditions. This also rouses engineering questions of mathematical formulation and whether non-linear models can be made fast enough with the limited computing power available in on-board vehicle computers or aggregator control units to allow for a time-step optimized control strategy which can respond to real-time operation. The few available degradation optimized charging strategies have relied on simplified versions of lifetime models which approximate the true lifetime impact of incremental changes, however the question of the validity of these approaches remains unanswered. Also in relation to models is the question of how to account for differences in battery chemistry/technology to develop a general modeling methodology, or if this is even possible.

Another key question will be to better understand if high frequency energy throughput has the same impact on battery life as normal bulk energy throughput, i.e. if how the energy is extracted impacts the State-of-Health differently. This is most relevant to frequency regulation which often results in a net-energy zero balanced signal. It is unclear if the absolute value of the energy which is charged and discharged over-time in a frequency regulation signal has the same degradation impact as a battery which discharges the same amount of energy in long charge and discharge cycles. This line of inquiry highlights a need for more degradation data and experiments.

Additionally, future R&D may result that cost of battery capacity becomes significantly less expensive due to advanced manufacturing techniques and increased energy densities. In this case, the economic value in prolonging battery life/reducing degra-

dation will become less relevant and overbuild may be found as a more cost-effective alternative. Similarly, it may result that the magnitude of the cost of battery degradation far outweighs the related efficiency costs, therefore optimization approaches could be simplified by only accounting for battery degradation. The latter point is a question of V2X Marginal Cost and leads to more questions of economic viability.

### 4.3.2 V2X Economic Viability

The first readily identified research line is to develop more acute economic estimations of the V2X Value Streams identified in this work based on actual market data and conditions. Instead of relying on generalized estimations of annual revenue potential like the [Meta-analysis of V2X Value Stream Potential](#) provided here, business cases would need to be developed using actual hourly market prices/data, as opposed to average prices, and a thorough understanding the bidding strategies actors play in these markets. The generalized estimation of annual value gives some notion of which Value Streams are likely to generate the most revenue and should be explored further but these should be investigated individually. The goal should be directed towards estimating the annual value that V2X could be expected to capture in the presence of other players/competitors for multiple energy services while keeping in mind the unique profitability of different market environments. The same Value Stream in one market can be highly profitable in one yet unviable in another due primarily to differences in regulation and market structure.

Of particular interest will be in the interaction between V2X and Li-ion BESS. Here, I have postulated they will exhibit a cooperation behavior, competition in the market, yet cooperation in lobbying energy regulatory change; however, it remains to be seen if their operation in the market will be complementary due to niche products each can offer more efficiency or whether they will be directly competitive for the same energy services. The question will hinge on whether the lower capital costs and relative ease of developing a V2X resource can compensate for the limited capacity and lack of scalability compared to BESS. Clearer understanding of potential revenues of each Value Stream will determine if there is a place in the market for V2X in the presence of BESS and other DERs which are also becoming cheaper. The niche Value Streams of Bill Management, Demand Response, and Reactive Power Support particularly in the Residential but also in the Commercial/Industrial sectors and Microgrids, may play a more important role in future V2X development as they have currently been deemed unviable for BESS due to preclusive capital costs. It is clear from the initiation of several pilot projects that

energy utilities have identified significant value to invest so heavily in charge control of EVs. Whether to position themselves as Aggregators in efforts to expand their business activities or to develop capabilities to hedge against the physical stresses that increased demand driven by an electrified transport will create, utilities see an opportunity with V2X.

Finally, this work has only commented directly on variable costs, specifically Marginal Cost, as this directly informs bid price in the energy market; however, full economic viability analyses must incorporate fixed costs as well. Two fixed costs have already been identified and mentioned briefly, that of installation cost and the bi-directional EVSE enabling cost. Installation cost refers to the hardware/software and labor necessary to install EVSE which have advanced charge control (V1X) capabilities. Whereas, enabling cost refers to the additional cost necessary to move from V1X (smart charging) capability to fully functional bi-directional V2X. Enabling cost is inferred by the price difference between commercially available V1X EVSE and V2X EVSE which I have shown has already decreased by 90% since 2014.

Full economic lifetime analyses of V2X must include these capital costs along with estimated cash inflows. One approach could be to use inflows inferred from the [Meta-analysis of V2X Value Stream Potential](#), treating annual cash-flow as a random variable over the range of annual potential value and performing a Monte Carlo or bootstrapping analysis. A more accurate method would be to develop annual estimated cash-flows based on actual hourly price data for each Value Stream in a specific market along with an estimation on future price development. As I have emphasized, due to the large spread in potential value identified across wholesale markets, results from one market context are non-transferrable. A different approach could be made on a cost perspective. By first estimating the resultant cost impacts of a given usage profile corresponding to the Value Stream product (e.g. a frequency regulation signal followed for a number of hours annually) a minimum annual market price to cover these costs could be determined, which could then be compared to estimations of future market prices to determine viability. Or yet even a third, two-pronged, approach which assumes both cash-flows and fixed costs to calculate the minimum allowable degradation cost to remain profitable over the economic lifetime. In conclusion there remain many interesting questions that this work raises which presents ample opportunity for future research efforts.



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## Résumé en Français

Vehicle-to-Anything (V2X) est un terme générique qui explique l'utilisation de batteries de véhicules électriques pour obtenir une valeur supplémentaire lors de périodes de non-utilisation. Les services V2X génèrent des revenus de la batterie grâce à la charge dynamique monodirectionnelle (V1X) ou bidirectionnelle (V2X) afin de fournir des avantages au réseau électrique, de réduire la consommation énergétique des bâtiments et des maisons ou de fournir une alimentation de secours aux charges. Une méta-analyse du potentiel économique donne des résultats contradictoires avec la littérature et indique que la gestion de la consommation électrique, l'adéquation des ressources et le report de l'investissement dans le réseau ont plus de valeur que d'arbitrage sur les marchés d'énergie et réserve secondaire. Bien que je convienne que le développement soit pour et par le marché, je souligne que V2X se développera dans les limites du contexte réglementaire; les régulateurs ont donc un rôle de catalyseur à jouer.

Une question importante est de savoir dans quelle mesure une utilisation supplémentaire de la batterie du véhicule affectera la capacité de la batterie au cours de sa durée de vie. Il est donc essentiel de comprendre les subtilités de la dégradation de la batterie pour estimer les coûts. Les batteries Li-ion sont des systèmes électrochimiques compliqués qui présentent deux phénomènes de dégradation simultanés, le vieillissement calendaire et le vieillissement cyclique. Dans les applications véhiculaires, le vieillissement calendaire a tendance à être l'effet dominant de dégradation de la durée de vie. Ce qui réduit que le temps c'est l'élément le plus important de la dégradation; par conséquent, le coût de la dégradation dépend fondamentalement du temps.

Une affirmation centrale de cette thèse est que le coût marginal de V2X n'est ni nul ni négligeable comme l'a accepté la littérature économique, mais dépend fortement de la dégradation de la batterie. Nous proposons ici une théorie des coûts marginaux V2X

qui repose sur deux principes: 1.) il existe un coût d'efficacité associé au chargement de la batterie, et 2.) le véritable coût de dégradation de V2X prend en compte le coût d'opportunité, c'est-à-dire, la dégradation au-delà de ce qu'aurait été l'utilisation normale du véhicule.

Avoir un concept clair du coût marginal de V2X, permet de comptabiliser et d'équilibrer correctement tous les coûts réels: coût de l'électricité, coûts d'efficacité du système et dégradation de la batterie. Cela permettra d'élaborer des stratégies de charge optimales et d'informer correctement les offres du marché de l'énergie. Il en résulte une compréhension plus nuancée des coûts marginaux. L'impact de la batterie V2X sur la vie de la batterie pourrait être considéré comme un coût, un bénéfice ou nul. Je conclus que le V2X peut offrir une valeur économique supérieure à celle précédemment entendue et que cette valeur supplémentaire sera réalisée grâce à l'amélioration simultanée de l'efficacité de la charge et de la réduction de la dégradation de la batterie EV.

**Titre :** Essais sur la participation des véhicules électriques sur les marchés de l'énergie: aspects économiques véhicule-à-réseau (V2X) et considérations relatives à la dégradation des batteries

**Mots clés :** Véhicule à tout (V2X); Économie de l'énergie; Services auxiliaires; Analyses de faisabilité économique; Marchés de l'électricité; Véhicule vers réseau (V2G)

**Résumé :** Vehicle-to-Anything (V2X) est un terme générique qui explique l'utilisation de batteries de véhicules électriques pour obtenir une valeur supplémentaire lors de périodes de non-utilisation. Les services V2X génèrent des revenus de la batterie grâce à la charge dynamique monodirectionnelle (V1X) ou bidirectionnelle (V2X) afin de fournir des avantages au réseau électrique, de réduire la consommation énergétique des bâtiments et des maisons ou de fournir une alimentation de secours aux charges. Une méta-analyse du potentiel économique donne des résultats contradictoires avec la littérature et indique que la gestion de la consommation électrique, l'adéquation des ressources et le report de l'investissement dans le réseau ont plus de valeur que d'arbitrage sur les marchés d'énergie et réserve secondaire. Bien que je convienne que le développement soit pour et par le marché, je souligne que V2X se développera dans les limites du contexte réglementaire; les régulateurs ont donc un rôle de catalyseur à jouer. Une question importante est de savoir dans quelle mesure une utilisation supplémentaire de la batterie du véhicule affectera la capacité de la batterie au cours de sa durée de vie. Il est donc essentiel de comprendre les subtilités de la dégradation de la batterie pour estimer les coûts. Les batteries Li-ion sont des systèmes électrochimiques compliqués qui présentent deux phénomènes de dégradation simultanés, le vieillissement calendaire et le vieillissement cyclique. Dans les applications véhiculaires, le vieillissement du calendrier a

tendance à être l'effet dominant de dégradation de la durée de vie, ce qui réduit le temps, élément le plus important de la dégradation; par conséquent, le coût de la dégradation dépend fondamentalement du temps. Une affirmation centrale de cette thèse est que le coût marginal de V2X n'est ni nul ni négligeable comme l'a accepté la littérature économique, mais dépend fortement de la dégradation de la batterie. Nous proposons ici une théorie des coûts marginaux V2X qui repose sur deux principes: 1.) il existe un coût d'efficacité associé au chargement de la batterie, et 2.) le véritable coût de dégradation de V2X prend en compte le coût d'opportunité, c'est-à-dire, la dégradation au-delà de ce qu'aurait été l'utilisation normale du véhicule. Avoir un concept clair du coût marginal de V2X, permet de comptabiliser et d'équilibrer correctement tous les coûts réels: coût de l'électricité, coûts d'efficacité du système et dégradation de la batterie. Cela permettra d'élaborer des stratégies de charge optimales et d'informer correctement les offres du marché de l'énergie. Il en résulte une compréhension plus nuancée des coûts marginaux. L'impact de la batterie V2X sur la vie de la batterie pourrait être considéré comme un coût, un bénéfice ou nul. Je conclus que le V2X peut offrir une valeur économique supérieure à celle précédemment entendue et que cette valeur supplémentaire sera réalisée grâce à l'amélioration simultanée de l'efficacité de la charge et de la réduction de la dégradation de la batterie pour véhicules électriques.

**Titre :** Essays on Electric Vehicle Participation in Energy Markets: Vehicle-to-Anything (V2X) Energy Service Economics and Battery Degradation Considerations

**Keywords :** Vehicle-to-Anything (V2X); Energy Economics; Ancillary Services; Economic Feasibility Analyses; Electricity Markets; Vehicle-to-Grid (V2G)

**Abstract :** Vehicle-to-Anything (V2X) is an umbrella term to explain the use of electric vehicle batteries to derive additional value during times of non-use. V2X services generate revenue from the battery asset through dynamic mono-directional (V1X) or bi-directional (V2X) charging to provide benefits to the electric grid, to reduce energy consumption of buildings and homes, or to provide back-up power to loads. A meta-analysis of economic potential gives results contradictory to the literature and indicates that Bill Management, Resource Adequacy, and Network Deferral are more valuable than Energy Arbitrage and Spinning Reserves. While I concur that development is of and by the market, I emphasize that V2X will develop within the constraints of the regulatory environment; therefore regulators have an enabling role to play. An important question is to what extent additional use of the vehicle battery will affect battery capacity over its lifetime, therefore understanding the intricacies of battery degradation is crucial to estimate costs. Li-ion batteries are complicated electrochemical systems which exhibit two concurrent degradation phenomena, Calendar Aging and Cycling Aging. In vehicular applications, Calendar Aging tends to be the dominating life degradation effect, which reduces to time being the most impor-

tant component of degradation; therefore degradation cost is fundamentally time-dependent. A central claim of this dissertation is that V2X Marginal Cost is not zero nor negligible as the economic literature has accepted but is highly dependent on battery degradation. Herein, a V2X Marginal Cost Theory is proposed which is based on two main principles: 1.) there is an efficiency cost associated with charge operation, and 2.) the true V2X degradation cost takes opportunity cost into account, that is, only considers degradation beyond what would have been experienced by operating the vehicle normally. Having a clear concept of V2X Marginal Cost which can properly account for and balance all true costs: the cost of electricity, the system-efficiency costs, and battery degradation, will allow for development of optimal charge strategies and will properly inform energy market bids. This results in a more nuanced understanding of marginal costs as the resultant battery lifetime impact from V2X can be either be considered a cost, a benefit, or zero. I conclude that V2X may offer greater economic value than previously understood and that this additional value will be realized through the simultaneous improvement in charge efficiency and reduction of EV battery degradation.

