

A Data-Driven Approach to Comparing Battery Electric Vehicle Architectures

by

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Abstract

The accelerating shift towards sustainable transportation has increased the significance of Battery Electric Vehicles (BEVs) in the automotive sector. This thesis provides a comprehensive exploration of BEV architectures, examining the influence of individual architectural decisions on vehicle performance and market prevalence. Utilizing a data-driven approach, this study utilizes multivariate linear regression and random forest models to analyze a curated dataset of global BEV models from 2022 and 2023, focusing on critical architectural decisions such as battery composition, motor configuration, and thermal management systems. Our research aims to identify potential dominant designs by assessing their impact on performance metrics like range, acceleration, and efficiency. We construct a list of candidate architectural decisions for current market BEVs and discuss the implications and tradeoffs of different decision options, such as battery technologies, motor types, and cooling systems. The analysis then leverages statistical tools to evaluate the correlation between these architectural choices and vehicle performance, emphasizing range as a primary indicator of consumer appeal. Findings from this research indicate significant variance in the adoption of specific BEV architectures, influenced by technological advancements and market dynamics, suggesting that the market has not yet consolidated down to a dominant design. We observed that architectural decisions pertaining to battery capacity, drive type, and number of cells influence range output strongly. We view their frequent representation in the dataset as potential emerging dominant designs.

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To Thalia, Mahmood, Wafaa, Selena, Omar, Will, Simba, and Smores.

I could not have done this without our love and support.

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1 Introduction

1.1 Motivation

Advances in transportation technology, specifically those pertaining to electric vehicles, are challenging how we think about personal and commercial transport (Sperling, Deluci, et al. 2013). Cars are no longer simply a means to get from point A to point B; they now offer specialized utility across different intents and lifestyles. Some cars aim to offer comfort during long commutes, while others offer quick acceleration and sporty handling. There are vehicles of wildly varying cargo space and towing capacity. Contemporary vehicles even provide entertainment functions, such as the ability to be voice controlled, access the internet, display multimedia, and play video games in the cabin (Jameel, 1997).

While functional offerings of modern cars are evolving, so too are their internal mechanical representations. Automobile original equipment manufacturers (OEMs) are experimenting with different propulsion technologies to augment or replace the traditional combustion engine. There are mass market vehicles available today that include alternate fuel cell (such as hydrogen and ethanol) vehicles, combustion and battery plug-in hybrids (PHEVs), and battery-only electric vehicles (BEVs). Recently, BEVs have garnered significant traction and appeal amongst consumers. Their high torque, low center of gravity, convenient day-to-day operations, and advanced driver technology have contributed to that appeal. Governments are also directly incentivizing the adoption of BEVs due to their zero tailpipe emission output.

Rising BEV popularity has driven automobile manufacturers to prioritize electrifying existing models and bringing all-new lines to market. As more and more vehicle manufacturers transition from traditional internal combustion engine (abbreviated ICE) architectures to battery electric vehicle architectures, the question of “Where to Play and How to Win? (Martin, 1997)” draws out the need for a systematic review of vehicle architecture.

Battery Electric Vehicles have seen a resurgence in popularity in later years, partly due to increased regulatory interest. To lawmakers, BEVs offer several desirable properties. BEVs are typically refueled with grid energy, which allows for a smoother transition to renewable energy sources like wind and solar, all while reducing dependence on gas and oil. They also have zero tailpipe emissions, which improves air quality in terms of the concentration of greenhouse gasses like CO₂ (Van Vliet, Oscar, et al. 2011). As a result, legislative bodies globally have created varying incentive programs for BEV purchases, often subsidizing their total cost through direct cash incentives and tax write-offs for new vehicles and new charging infrastructure. Direct government subsidies have rapidly increased the adoption rate of electric vehicles when offered. However, the subsidies are often extremely costly to local and federal governments and cannot be sustained indefinitely (Lu et al., 2020).

Furthermore, consumers are now factoring more subjective value propositions in their vehicle purchasing habits rather than pure cost-to-performance calculi. In a world threatened by human-driven climate change, eco-consumerism has taken a foothold in several key markets. Younger buyers are increasingly choosing products perceived as better for the environment. This shift is mirrored in the automotive sector, where there is a growing preference for battery electric vehicles (BEVs) due to their environmental benefits (Skippon et al., 2016; Lane et al., 2018). E-waste recycling intentions, attitudes, subjective norms, and perceived behavioral control play significant roles in shaping consumer behavior toward sustainable options like BEVs (Bhutto et al., et al. 2022). Millennials, in particular, are motivated by the positive environmental impact of their choices, social norms, and the ease of adopting sustainable behaviors. This trend indicates that the market for BEVs may expand further if societal values continue to evolve toward sustainability (Bhutto et al., et al. 2022).

1.2 General Objectives

The general objective of this thesis is to determine whether there are one or more dominant architectures, also known as dominant designs, within the battery electric vehicle (BEV) sector. A dominant architecture, in the context of industrial innovation, refers to a specific configuration or architecture that becomes standardized across industry due to its superior performance, cost-effectiveness, or alignment with consumer preferences. This design often emerges as the industry standard, influencing subsequent innovations and product development (Abernathy & Utterback, 1978). Dominant designs typically arise from a series of incremental innovations that improve efficiency and effectively meet market demands. Once established, they dictate the strategic directions of companies within the industry, focusing competition primarily on improvements in process efficiency and cost reduction rather than fundamental product changes (Murmann & Frenken, 2006).

As BEVs become more common, manufacturers face the question of how to design each vehicle; is there a dominant design they adhere to? Or is there room for variation in the name of experimentation and competitive advantage? This study aims to identify whether these choices are coalescing around a few standard architectures or if a wide variety of designs will continue to coexist. This investigation is warranted due to the rapid advancements in BEV technology and their growing market presence. With the automotive industry at a potential inflection point, identifying common design patterns or dominant architectures can help streamline production, reduce costs, and influence future technological developments in electric vehicles.

Moreover, the outcome of this research has significant implications for automotive manufacturers, policymakers, and consumers alike. Understanding which BEV architectures are becoming prevalent can aid in decision-making processes related to investment, regulation, and adoption. This thesis, therefore, seeks to clarify the current state of BEV architectural decisions and their potential direction, providing valuable insights into the future landscape of electric vehicle technology.

1.3 Specific Objectives

This thesis aims to decompose and examine current market battery electric vehicle architectures. This will be done by collecting and validating a high-quality dataset on BEVs sold in 2022 and 2023. We will then apply statistical techniques such as frequency analysis, linear regression, and random forest regression to understand the effect of individual architectural decisions on performance to understand the effect that each decision, or regressor, has on the outcome variables we outlined in the general objectives section: range, acceleration performance, and efficiency. We use the results of that analysis to inform a higher-level system design, sort which decisions are most impactful, and, therefore, determine in what order future vehicle developers should tackle BEV design decisions. We provide a broader discussion of patterns observed while analyzing the data within the context of the analysis we conducted and predict the near-term future of the Battery Electric Vehicle. We conclude with a summary of our findings, as well as a discussion of the limitations of our research and suggestions for future research.

1.4 Thesis Outline

Chapter 2 provides an examination of relevant literature in the research area. We reference existing work to establish the foundations of this work and identify the research gap we wish to address. The discussion centers around what dominant designs are, how they shape market dynamics, and examples of industries in which dominant designs change incentives. We also examine literature specific to optimizing architectural decisions in battery-electric vehicles. Chapter 2 concludes by stating the research gap observed.

Chapter 3 dives into the specifics of battery electric vehicle (BEV) architectural decisions. This includes a detailed examination of the critical components, such as battery cathode composition, voltage, pack configurations, and thermal management systems. Individual architectural decisions are explored to determine their impact on vehicle performance and manufacturer preferences. Each section also contains frequency metrics on each architectural decision's representation in a comprehensive dataset of current BEVs on sale in 2023.

Chapter 4 covers the methodological approach to interpreting BEV architecture data. This includes a detailed description of the dataset, evaluation criteria for BEVs, and the formal hypothesis formulation that a dominant design exists in the current market.

Chapter 5 presents findings from the dataset, examining how different architectural decisions influence vehicle performance metrics like range, performance, and efficiency. Relationships between architectural decisions and their combined effects on performance outcomes are statistically analyzed.

Chapter 6 discusses the implications of the findings, discussing how they align with or challenge existing theories and what this means for manufacturers and policymakers within the electric vehicle industry.

Chapter 7 concludes by summarizing the research findings, reiterating the significance of dominant designs in BEV architectures, and suggesting areas for future research. This section also reflects on the study's limitations and the potential generalizability of the results.

2 Literature Review

2.1 Existing Research

The Battery Electric Vehicles (BEVs) market is growing and is expected to do so for the foreseeable future. Models built by Dhakal and Min (2021) utilize data from 2005 to 2018 and apply logistic and Bass diffusion econometric models to analyze the adoption rates and diffusion patterns of BEVs globally. According to their findings, global BEV ownership is predicted to grow significantly, from approximately 5.3 million units in 2019 to nearly 40 million units by 2030. Independent models by Katalevsky and Gareev (2020) agree and predict approximately 46 million units by the end of 2030. These predictions underscore the accelerating pace of BEV adoption, driven by advancements in battery technology, increasing environmental awareness, and supportive government policies worldwide. Such growth suggests a shift towards a more sustainable automotive industry and indicates significant market opportunities for manufacturers, energy suppliers, and new technology entrants. Additionally, the alignment in forecasts from different models reinforces the robustness of these predictions, suggesting that the rise in BEV adoption may even surpass expectations if technological innovations and regulatory frameworks continue to evolve favorably. Strong indicators of an expanding market warrant an exploration of whether or not a dominant design for battery electric vehicle design exists today.

The study of dominant designs dates back to 1978, when William J. Abernathy and James M. Utterback discuss the concept in their article "Patterns of Industrial Innovation," initially published in the *MIT Technology Review*. They discuss the dynamic evolution of innovation within industries, mainly focusing on how companies evolve from flexibility to rigidity as they mature. The authors explore the innovation process through different stages of a company's development—from initial flexibility through intermediate stages of growth to full maturity, where

processes become standardized, and innovation becomes incremental. The study elaborates on how innovation shifts from product-focused in nascent stages to process-oriented as companies scale and the market environment stabilizes. Abernathy and Utterback propose a model that ties a company's stage of development to its innovation strategy, emphasizing the role of incremental innovations in driving efficiency in mature companies. They discuss how mature enterprises often refine existing technologies to improve productivity and reduce costs. This contrasts with the disruptive, radical innovations typical of younger, more flexible companies.

The market trends towards dominant designs through a variety of mechanisms, including technological compromise, where a design satisfies the broadest consumer base; economies of scale, where initial market leadership can lead to a dominant position; and network externalities, where the value of a product increases as more people use it (Murmann & Frenken, 2006). Establishing a dominant design marks the end of the initial turbulent phase of technological development, characterized by a wide array of competing designs and approaches. During this phase, firms and innovators experiment with different configurations to meet diverse market needs and establish a foothold in an emerging market. Murmann and Frenken conclude in their meta-analysis that once a dominant design is established, the nature of innovation within the industry shifts from product-based to process-based. This shift reflects a change in focus from developing new and varied products to refining and optimizing the production process of the accepted design. This often leads to enhanced production efficiency, lower costs, and increased market predictability, leading to economies of scale and solidifying the dominant design's position in the market.

Using the smartphone industry to illustrate market competition and dominant designs, Cecere et al. (2015) investigate whether a dominant design has emerged in the smartphone market, examining product characteristics of all smartphones introduced between 2004 and 2013. However, the findings of this study suggest that while certain features have become more standardized, such as increased adoption of Wi-Fi connectivity and touchscreen interfaces, a dominant design in smartphones has yet to materialize fully. They highlight that substantial product differentiation persists despite some uniformity in hardware specifications,

particularly regarding software and user interface elements. They argue that ongoing differentiation among smartphone manufacturers indicates a competitive landscape where no single design or set of features has yet achieved dominance. Instead, firms continue to innovate in vertical (improvements on existing parameters) and horizontal (introduction of new features) dimensions.

Conversely, Peng and Liang (2016) detail how companies like Apple and HTC navigate the development and growth stages and suggest that the smartphone industry is dominated by a singular design. Initially, multiple companies vied for market dominance with distinct technologies, such as exclusive apps or security features. However, they claim that before the introduction of the iPhone, various firms competed with diverse designs, none of which were dominant. However, post-iPhone, the industry saw a consolidation around touch-based interfaces and other features introduced by Apple, effectively making it the standard that defined the category. The iPhone's influence extended beyond its immediate features—it affected strategic movements within the industry, including patent litigations and partnerships, further cementing its role as a dominant design. Peng and Liang also introduce a supplementary framework to the dominant design paradigm that uses similar capabilities and markets between the focal firm and other players to identify competitors. We did not use their framework, as finding competitors for specific firms is not one of our research objectives. However, we note an opportunity for further research to apply our dataset, methodology, and findings to specific firms.

The use of dominant designs has been prevalent in the academic study of the automotive industry. Ferrigno, Zordan, and Di Minin (2022) focus on the pivotal role of technological experimentation in developing dominant designs within the automotive industry. It specifically examines how Ford's innovative efforts between 1896 and 1906 facilitated the rise of the internal combustion engine (ICE) as the dominant propulsion technology. They attribute Ford's strategic approach, characterized by trials of various design configurations and powertrain technologies, to the modern importance of flexibility and adaptability in automotive development. This exploration period was essential in transitioning from multifarious early prototypes to more standardized designs that effectively supported mass production strategies. The study utilizes an extensive archival database, expert interviews, and historical site visits to trace the evolution of

automotive technology during a formative decade when competing technologies like steam and electric powertrains were also contenders.

More recently, Gorbea et al. (2011) analyzed the current market for dominant designs by examining the automotive industry's shift toward new architectural competitions, mainly focusing on hybrid and electric vehicles. They discuss how these emerging vehicle architectures challenge the century-long dominance of internal combustion engine (ICE) cars. This analysis is grounded in historical context, drawing parallels to earlier periods of intense architectural innovation and competition. The paper elaborates on how the automotive industry, much like its state in the early 1900s, is again experiencing a phase where different vehicle architectures—such as hybrid, plug-in hybrid, and fully electric cars—compete to establish a new dominant design. This competition is driven by various factors, including technological advancements, environmental regulations, and shifts in consumer preferences, particularly toward more sustainable and efficient vehicles.

Gorbea (2011) highlights the strategic implications for automotive manufacturers. They assert that firms that can adeptly navigate these transitions and align their development strategies with the emerging architectural paradigms—particularly those that offer significant environmental and operational benefits—are better positioned to succeed in the evolving market. This strategic alignment involves adapting to new technologies and potentially leading in developing these technologies to gain a competitive edge. The authors anticipate that the current phase of renewed architectural competition will require automakers to adapt and innovate at the component level and more holistically at the architectural level. This shift could disrupt current market leaders who fail to adapt to the changing landscape. To draw these conclusions, Gorbea used an existing performance index to measure and compare the evolution of different vehicle architectures over time using a publicly available dataset from conceptcarz.com (2007). This performance index included in the dataset considers various system variables such as power-to-weight ratio, maximum velocity, fuel efficiency, and cost. By applying this index, they identify key periods of architectural competition and dominance, underscoring how shifts in performance metrics can influence the rise of new dominant designs.

Using an equally weighted performance index is naive, as research in the BEV field indicates that operating cost and range are the most important attributes to consumers. Some metastudies in the field suggest that overall BEV adoption and consumer preferences could be better understood. Wicki et al. (2022) reviewed 94 studies from 2010 to 2019 to understand consumer attitudes and behaviors towards BEVs. Despite the prevalent assumption that key facilitators and obstacles to BEV uptake are well-understood, their findings suggest that existing research often needs more robust evidence on the causal effects of these factors, and results are context-dependent and mixed. They highlighted several concerns about the current research landscape, including the unavailability of data for replication, which compromises the reliability of findings. Additionally, they point out the geographical focus of studies predominantly in North America and Europe, raising questions about the generalizability of the results. Moreover, the methodological approaches in the studies often need to allow for the identification of causal relationships, limiting the understanding of what truly influences BEV adoption.

Lane et al. (2018) suggest that BEV enthusiasts are generally drawn to the vehicle's environmental benefits and technological advancements, emphasizing the importance of sustainability and innovation in their vehicle choices. The vehicle's range mainly influences this preference for a single charge, a critical factor in the decision-making process for potential BEV buyers. However, range anxiety—concern about the sufficiency of the vehicle's range to meet daily needs without frequent recharging—remains a significant deterrent despite most daily travel needs being within the range capabilities of current BEVs. Similarly, Zhang et al. (2016) note that as technological advancements enhance the driving range of BEVs, consumer interest and likelihood to purchase these vehicles increase. This is particularly evident among personal consumers, who prefer BEVs with extended range capabilities that align with their daily use patterns and reduce range anxiety. These works indicate that increasing range positively affects sales, which is why the present study uses range as the primary outcome variable.

Optimizing BEV subsystems is a very active research area. We reference several works in Chapter 3 that inform the construction of architectural decisions and the comparison of tradeoffs per sub-decisions. These studies tend to focus on the optimization and analysis of specific subsystems but do not consider the vehicle

holistically. For instance, Duclos and Hofman (2021) provide an in-depth analysis of battery-electric powertrain design for efficient passenger vehicles to optimize energy consumption and powertrain performance. They recommend utilizing dual-axle (AWD) systems over single-axle (RWD) configurations, which they assert will yield a significant reduction in energy consumption by approximately 12%. They also suggest employing distributed drive systems, or mounting at least one motor on each axle, save about 6.6% in energy over a central (single) motor. Additionally, they conclude that permanent magnet synchronous motors (PMSMs) are favored over asynchronous induction motors (IM), as they are associated with a 3% reduction in energy consumption. They also recommend the adoption of multiple electric motors in single-axle configurations, which offers a slight reduction in energy use.

Ostadi and Kazerani (2014) advocate using metaheuristic optimization algorithms, such as teaching-learning-based optimization (TLBO), to achieve optimal number of cells that balance cost, performance, and range. Pelletier et al. (2020) take a constraint-driven approach to battery pack sizing optimization. By integrating constraints early in the design process, their framework filters out unfeasible configurations, thus streamlining the path to finding the most effective design solutions. Moreover, the framework allows for the customization of objective functions according to specific design goals. This flexibility enhances the designer's ability to tailor the battery pack to particular vehicle needs, significantly reducing the time to market by improving the speed and accuracy of the preliminary design phase.

König et al. (2021) delve into the design and implementation of on-board chargers (OBCs) for high-voltage electric vehicle (EV) powertrains, highlighting the significant role that advancing battery technology and evolving charging infrastructures play in shaping future OBC requirements. According to their analysis, OBC architectures must adapt to higher voltage levels due to advancements in battery capacities and new DC fast charging standards such as the Megawatt Charging System (MCS) and CHAdeMO 3.0. They note that the integration of advanced semiconductor technologies like Silicon Carbide (SiC) and Gallium Nitride (GaN) to manage higher power densities and achieve faster charging speeds will be required by newer generation EVs. They also suggest developing

multifunctional OBC systems that integrate both DC-DC and AC-DC conversions into a single compact system, aiming to reduce costs, improve efficiency, and simplify the vehicle's power electronics architecture. We reference additional literature specific to vehicle components in Chapter 3, where we propose design decisions and decompose them into discrete sub-decisions.

Since the Gorbea study on plugin-hybrid electric vehicles (PHEVs), few studies have been conducted on the overall design of battery-only electric vehicles, likely due to the overall complexity of the subject matter. Park et al. (2022) recently presented a data-driven approach to the conceptual design of battery electric vehicles (BEVs). This approach leverages a proprietary database sourced from market research to establish performance targets and specifications for BEVs at the concept stage. Their dataset includes parameters such as battery capacity, motor output, torque, vehicle mass, and wheelbase from a sample of 37 sedans and 114 SUVs. Their dataset is proprietary and unavailable for further scrutiny, though we did not request a copy from the authors. Park et al. apply multi-linear regression modeling to correlate these parameters, which allows them to predict performance metrics like motor power, torque, and battery capacity based on the vehicle's wheelbase, range, and gross vehicle weight (GVW). This methodology enables the team to define performance targets that align with current electric powertrain technologies and are feasible with mass-produced parts. This research provides a systematic framework for integrating market analysis with system engineering to develop BEVs. However, their work does not provide a comparative analysis of the importance of individual architectural decisions, nor do they provide a connectivity analysis of the interaction of their model inputs to overall performance.

Beyond this analysis, we fail to find a unified high-quality dataset that catalogs current electric vehicles and their architectural decisions for the global market. We also identify a research gap that compares architectures of current market vehicles to determine whether or not a dominant design exists. Moreover, although the literature we refer to in Chapter 3 will discuss the ubiquity of a given sub-decision, we have not found relevant research that analyzes the sensitivity or connectivity of each decision relative to one another.

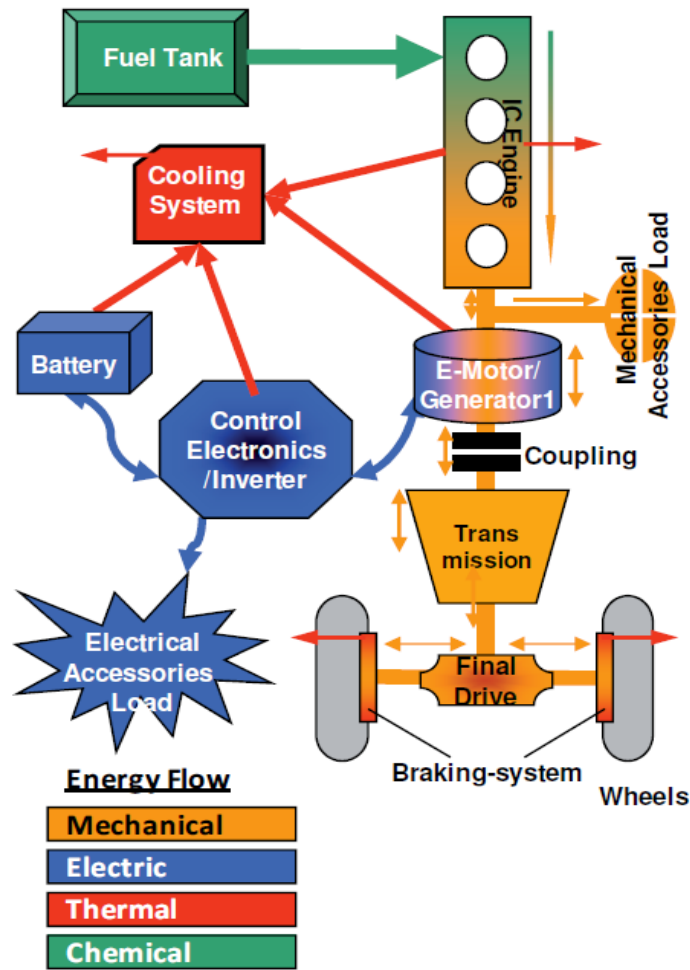
3 Architectural Decisions

3.1 Introduction to Electric Vehicle Architectural Decisions

In this thesis, we evaluate the impact of existing vehicle architectures against each other to answer the research question: “Are all BEVs built on the same architecture, or are there several distinct architectures on the market today?” In order to make such comparisons, we must first decompose and catalog vehicles by their architectural decisions, then analyze the effect of individual architectural decisions on one another, as well as the aggregate effect on crucial outcome metrics, as demonstrated by vehicles on the market today.

Architectural decisions are design decisions that directly impact the form-to-function mapping of an architecture. Mutating one or more of these architectural decisions will widen or constrain the viability of other architectural decisions and the final system architecture through cost variability and technical tradeoffs (Crawley, Cameron et al., 2016). In the context of vehicles, one architectural decision might be whether or not the vehicle is front-wheel driven, rear-wheel driven, or all-wheel driven. This decision will have downstream impacts on the architecture, such as whether or not each is independently powered, where to place the motor, and whether or not a driveshaft is required. External and upstream factors may influence the architectural decision, such as whether the car is intended to be used in markets with heavy rain or snowfall. However, the decision to build the car to meet the market's needs is not an architectural decision.

Similarly, architectural decisions are distinct from design decisions, which do not have significant downstream consequences. The choice to offer summer or winter tires at the factory does not materially change other systems or subsystems on the vehicle; thus, it is not an architectural decision. However, providing a heavier suspension system might necessitate larger wheels, qualifying it as an architectural decision (Crawley, Cameron et al., 2016).



Traditional Internal Combustion Engine (ICE) vehicles have several well-studied architectural decisions. Some include the fuel tank, battery, internal combustion engine, transmission, final drive, cooling system, wheels, braking system, inverter, and more (Gorbea, 2011). These systems have significant interplay, as demonstrated in Figure 3.1.1.

While battery-only electric vehicles share most of these systems, there are significant differences in form and function when manifested in a BEV. For example, the inverter in a BEV system is often responsible for converting direct current from the battery into usable power for alternating current motors,

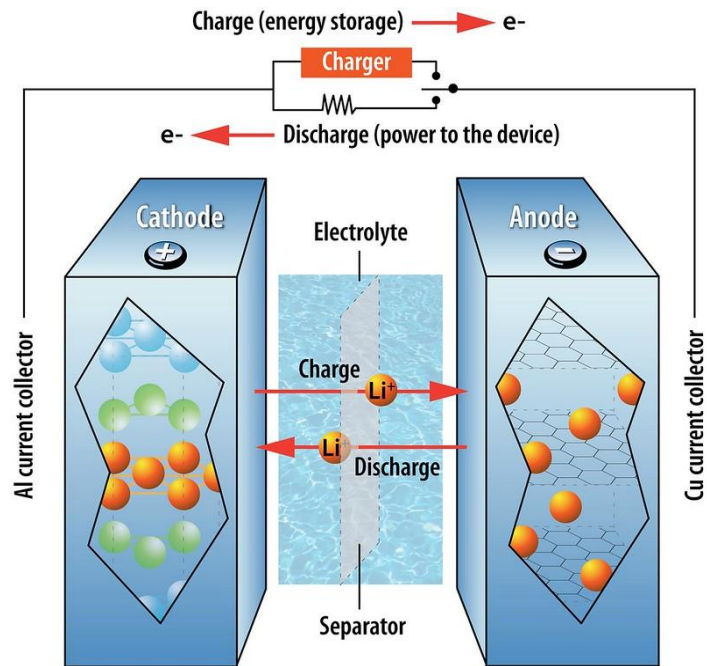
supplying power to primary and secondary electronic systems. This difference in functionality also means the inverter in the battery-only electric vehicle also takes a different form and might affect the decisions in other components.

This thesis identifies the following electric vehicle architectural decisions, summarized in the chart below, which also includes a summary of their function in the system. We provide further explanation and analysis for why we believe the choice represents a significant architectural decision in each architectural decision's subsection below. We conclude this chapter by enumerating other potential architectural decisions of interest that were unrepresented in the subsequent analysis due to data availability constraints.

Architectural Decision	Summary	Section
Battery Cathode Composition	Chemical composition of the main battery pack	3.2
Battery Voltage	Operating voltage of the main battery pack	3.3
Battery Pack Cells in Series	Battery circuitry: how many cells are in series	3.4
Battery Pack Cells in Parallel	Battery circuitry: how many cells are in parallel	3.4
Battery Pack Number of Cells	Battery circuitry: total number of cells	3.4
Charging System	Onboard battery charger: max power	3.5
Thermal Management System	Battery cooling system	3.6
Motor Type	Type of electromagnetic motors	3.7
Motor Quantity	Number of included motors	3.7
Motor Placement	Mounting locations of included motors	3.7
Drive Type	Where the vehicle is driven by the front, rear, or all wheels	3.8
Omitted Decisions	A brief discussion of other potential AD's	3.10

3.2 Battery Cathode Composition

Electric vehicle batteries are a primary technology that makes battery-only electric vehicles possible. Fundamentally, most batteries share the same core architecture in that they include a cathode, which accepts electrons during discharge, an anode, which donates electrons during discharge, and an electrolyte solution that facilitates the transport of the charged particles (Doeff, 2013).



Battery Chemistry Diagram (Argonne National Laboratory)

Anode composition is relatively standard across the automotive industry because anode materials are often constructed of lithium and graphite. Recent advancements in material science are allowing the consideration of nanostructured silicone (Sun et al., 2022). There are few variations of anode compositions; thus, the architectural decision regarding battery chemistry focuses on cathode composition instead. Moreover, virtually all commercially available electric vehicles use lithium-ion in their battery chemistry. While sodium-ion, zinc-ion, and other alternative chemistries are being experimented with the goals of increasing safety and mass reproducibility while decreasing dependence on rare earth metals such as cobalt and lithium (Nayak et al., 2017), they have yet to be fitted in a current or near-future commercial offering.

Nickel Manganese Cobalt (NMC / NCM)

Nickel Manganese Cobalt batteries, commonly abbreviated NMC or NCM, are the most ubiquitously represented cathode composition on the market today. NMC batteries are well-studied and robust, representing some of the highest energy

densities of commercially available batteries. NMC batteries are also relatively inexpensive due to lower costs for raw materials. They are thermally stable during heavy charge and discharge cycles. However, there is still the risk of thermal runaway (Chen et al., 2012), which is when a battery heats up, causing a higher reaction rate, which then causes further temperature increases until catastrophic failure. Lithium and manganese require more environmentally costly mining; battery manufacturers are eager to switch to alternative chemistries.

Nickel Cobalt Aluminium

Nickel Cobalt Aluminum, or NCA batteries, are fairly similar to NMC batteries except that they use aluminum rather than manganese. They boast similar high energy densities (by volume) to NMC batteries and have the added advantage of higher specific energy (battery capacity/weight) and longer lifespan (Zhang et al., 2018). Unfortunately, this chemistry is more prone to thermal runaway at higher temperatures (Ohneseit et al., 2023), thus necessitating increased safety monitoring systems (Miao et al., 2019). Though some analyses opt to bundle NMC and NCA batteries due to their similar energy densities, we have treated them distinctly in the following analysis due to differences in safety considerations, which might impact the overall architecture of the vehicle.

Lithium Iron Phosphate

Lithium iron phosphate (LFP) batteries, sometimes referred to as LiFePO_4 batteries, are the most recently commercialized battery chemistry in battery-only electric vehicles. After Tesla commercialized LFP batteries into the Model 3 in October 2021, LFP batteries quickly gained traction in BEVs. LFP batteries are significantly safer and more reliable than other lithium-ion based batteries due to the addition of phosphates. LFP batteries are incredibly stable during extreme charging and discharging cycles and can operate at high temperatures without significant risk of thermal runaway (Chen et al., 2012). As an added benefit, their chemistry is non-toxic, making LFP batteries easier to dispose of once degraded. Furthermore, LFP batteries are generally more durable than Nickel-based compositions as they can retain their capacity over more charge cycles (Karimov, 2021).

Representation in the Data

The battery compositions represented in the dataset that the following analysis relies on are limited to NMC, NCA, and LFP. Even though newer battery chemistries, such as sodium-ion based batteries, are becoming more robust, no commercially available vehicles utilize other chemistries. The following histogram shows the relative number of vehicles using the respective battery cathode compositions.

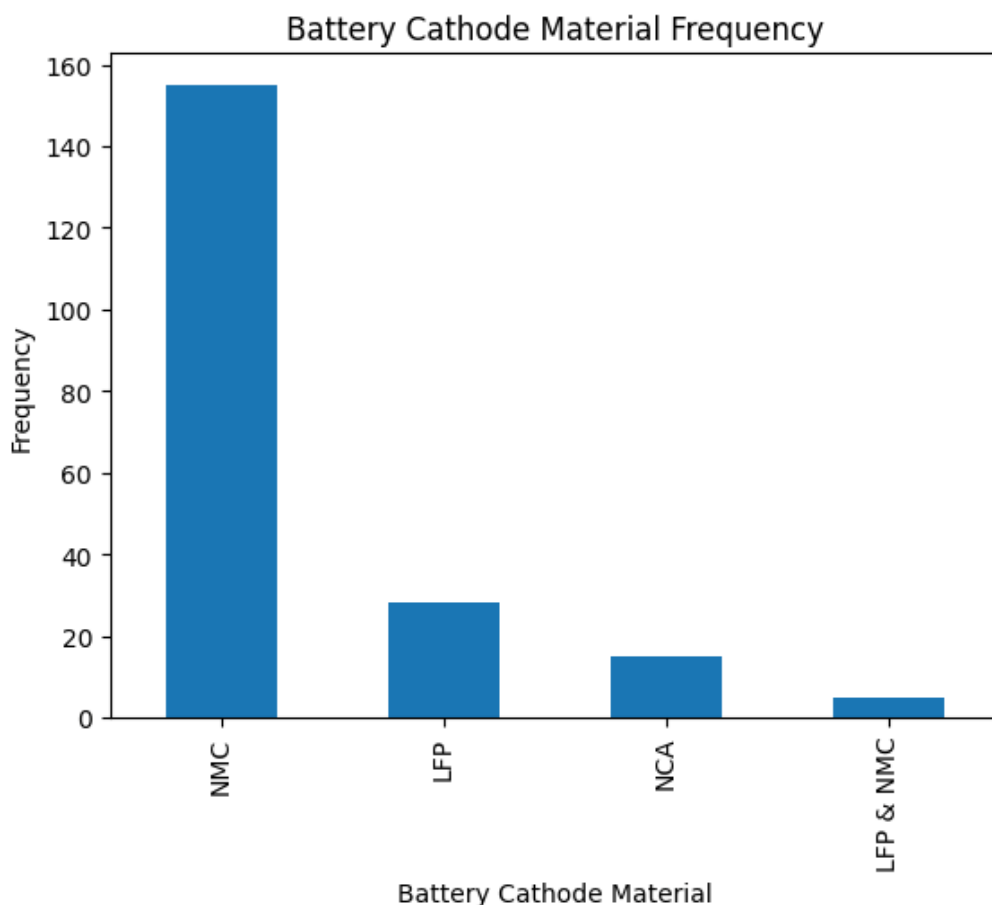


Figure 3.2.1: Battery Cathode Material Frequency Histogram

As shown, the majority of batteries that power BEVs are Nickel-based lithium-ion batteries, with Manganese batteries being the overwhelmingly popular choice. LFP batteries, while representing a smaller current market share, are quickly becoming more utilized due to technological improvements that are improving energy density. Vehicle manufacturers are also considering the longevity of the battery pack when adopting higher voltages, which we discuss in the next section, making LFP chemistry an attractive proposition (Preger et al., 2020).

3.3 Battery Voltage

Selecting the operating voltage for the battery in a battery-only electric vehicle affects various other battery-related decisions and the vehicle's entire design. This architectural decision has two implications for the proposed architecture for each model: deciding between a 400-volt and an 800-volt system and determining the operating voltage for the motor and inverter if an 800-volt system is chosen.

Selecting a 400-volt system has some advantages. First, bringing a 400-volt system to market is less expensive than an 800-volt system due to the cost of materials. 400-volt systems require only half the number of series-connected cells, thus only half the number of cells and battery management voltage-sensing channels. Moreover, ancillary components, such as battery pack contactors, fuses, and cables, must also be rated for at least 900 volts for an 800-volt pack compared with 500 V for a 400-volt battery pack (Aghabali, 2020). Despite the increased cost, vehicle manufacturers have been increasingly adopting 800-volt battery packs, especially as increasing numbers of 800-volt charging infrastructure come online (Graf, 2023). Providing an 800-volt battery pack has several performance advantages over a 400-volt pack.

	Typical range gained per minute of charge (km)	Time to charge for 200 km (minutes)
AC On-board Charging:		
Level 1 (120V, 1.4kW)	0.13	1332
Level 2 (240V, 7.2kW)	0.68	260
DC Off-board Charging:		
Fast Charging (480V, 50kW)	4.70	37
Tesla Supercharger (480V, 140kW)	13.15	13
Ultrafast Charging (800V, 400kW)	37.50	4.7

Figure 3.3.1: Charge time vs Charging Power (kW), source: Aghabali, 2020

The primary benefit of including a higher voltage pack is the reduced charging time through higher power charging at Direct Current Fast Charging stations (DCFC). 800-volt battery architectures allow significantly more current flow through to the battery. Conventional 400-volt batteries have typical charge transfer

rates near 50 kilowatts (kW) but can reach rates of close to 150kW. 800-volt systems, on the other hand, can receive up to 400kW of power, which allows for significantly faster charging from low states of charge with lower temperatures (Rafi et al., 2021). For comparison, a 400-volt electric vehicle charging at 50kW to 150kW would add approximately 47 to 140 miles of range in 10 minutes, respectively. Barring intentional charging curve slowdowns, an 800-volt battery charging at 400kW would receive close to 375 miles of range.

Given an 800-volt system, OEMs can implement a 400-volt or an 800-volt motor. Operating advantages of pairing an 800-volt battery architecture with an 800-volt motor include reductions in weight and increased power output. Moreover, the loss due to inverting the direct current (DC) from the battery to alternating current (AC) is significantly lower when the 800-volt alternator is paired with an 800-volt motor (Aghabali, 2020), which would result in more range, as seen in the provided graph. 800-volt batteries are also able to charge with less thermal overhead. A charging station's power is calculated in kilowatts using the following formula: $Power (kW) = (Volts * Amps) / 1000$. To charge at 140kW, an 800-volt BEV would require 800 volts supplied from the DCFC at 175 amps.

Meanwhile, a 400-volt BEV could only make use of 400 volts and would require a current of 350 amps to retain the same charging rate. This increase in amperage often results in increased battery pack temperatures, which place additional performance requirements on the thermal management system and overall battery management system and may also shorten the total lifespan of the battery itself (Panchal et al., 2016). Currently, the overwhelming majority of vehicles in the dataset are 400-volt architectures, as shown in the histogram below.

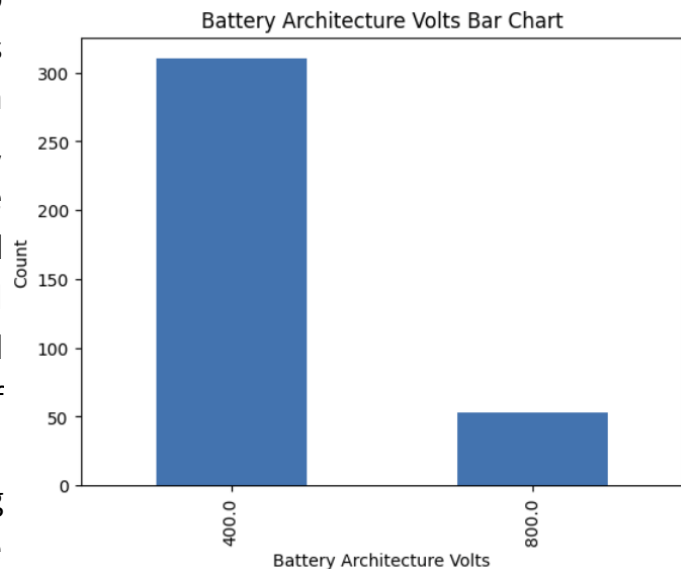


Figure 3.3.2: Frequency of 400 and 800-volt systems

3.4 Battery Pack Configuration

Beyond voltage, architects must also choose the number of cells to be included in the pack and how to arrange them, which is a significantly more complex task than it superficially appears to be. Battery pack sizing is driven by several factors, including vehicle required voltage, weight, target range, and target market. Even so, many concepts have emerged for swappable battery packs, yet none are commercially viable (Barreras et al., 2016).

Batteries can be configured in series or parallel to meet specific power and energy requirements. In a series configuration, the battery cells are connected end-to-end, which increases the total voltage of the pack to the sum of the individual cell voltages while the total capacity (Ah) remains unchanged. This setup is advantageous for applications that require high voltage to operate, such as electric vehicles or power tools, as it allows for more efficient power delivery and performance (Eberhard, 2006). In contrast, a parallel configuration involves connecting the positive terminals of the batteries together and the negative terminals together, resulting in a total capacity that is the sum of the individual cell capacities, while the voltage remains the same as that of a single cell. This arrangement is beneficial for applications needing longer runtime or greater power at a constant voltage, as it enhances the total energy storage (Wh) and allows for a more substantial current draw without overloading individual cells. A simplifying assumption made in the dataset is that individual battery cells are of the same voltage.

Both configurations have their trade-offs: Series configurations can lead to challenges in voltage matching and require complex management systems to ensure all cells are equally charged and discharged, while parallel configurations can increase the overall size and weight of the battery pack and require careful management to prevent imbalances in charge and discharge rates among the cells (Rose, 2020). Thus, the choice between highly series or parallel configurations depends on the application's specific power and energy requirements and weight, space, and battery management complexity considerations.

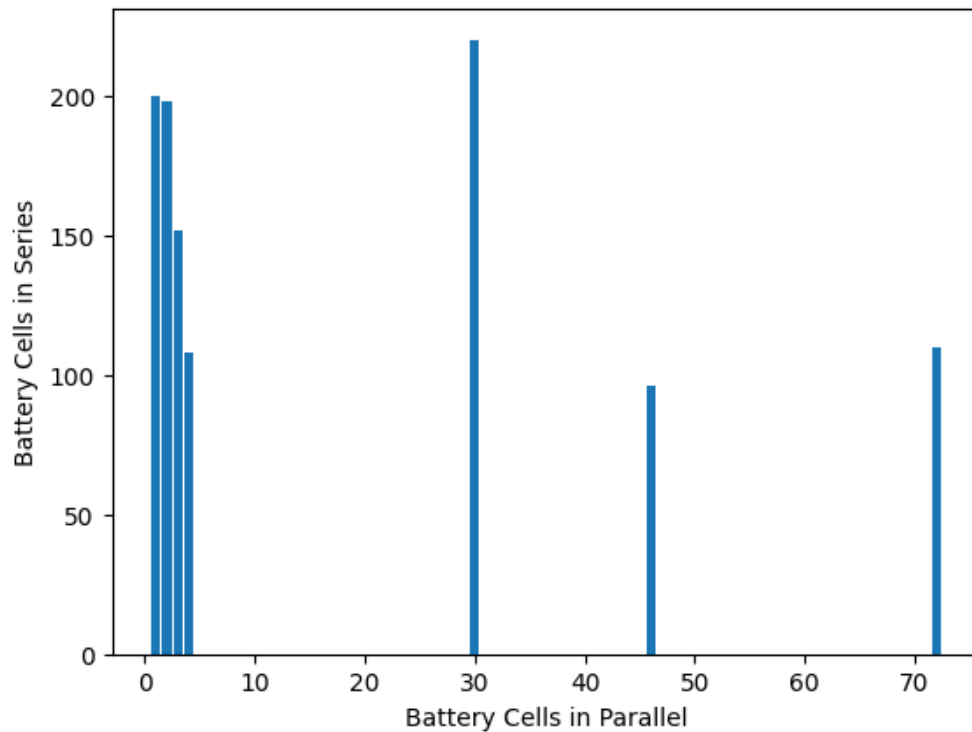


Figure 3.4.1: Battery cell circuitry compared

The dataset indicates a broad range in the number of cells used in battery packs, with values extending from 72 to 7920 cells. The mean value of approximately 524 cells suggests a tendency towards using a moderate number of cells. In comparison, the median value of 288 cells points to a frequent selection of relatively lower cell counts. This variability likely reflects the varying requirements across different EV models, which range from compact urban vehicles to more robust models designed for extended range.

The series configuration of the cells, which directly influences the total voltage output of the battery, shows an average of approximately 117 cells in series, with a standard deviation suggesting considerable variability (ranging from 72 to 220 cells). This aspect of battery design is critical for achieving the required electrical output that dictates vehicle performance. In parallel configurations, the average number of parallel paths per battery pack is approximately 4.29, with a range extending up to 72. This configuration is essential for increasing the total battery capacity and improving reliability by providing redundancy against the failure of individual cells.

3.5 Charging System

An onboard charger (OBC) in a battery electric vehicle (BEV) bridges external AC power sources and the vehicle's DC battery system. The OBC is responsible for converting the alternating current (AC) received from public charging stations or residential power outlets into direct current (DC) suitable for charging the vehicle's battery pack. It regulates the flow of electricity to ensure the charging process is efficient and adheres to local safety standards. The OBC's power rating ranges from 3.3 kW to over 22 kW in some premium models and is critical in determining the speed at which the vehicle can be recharged. The charger's ability to communicate effectively with the charging infrastructure allows it to negotiate the optimal power delivery and continuously monitor the charging process, adjusting the charge rate as needed to enhance efficiency and protect the battery's longevity. Integrated with the vehicle's battery management system (BMS), the OBC manages the battery's charge state and ensures uniform cell balancing within the battery pack, which is crucial for maintaining the battery's health and operational reliability (Pradhan et al., 2023), though we currently do not have the data required to explore differences in cell balancing per OEM.

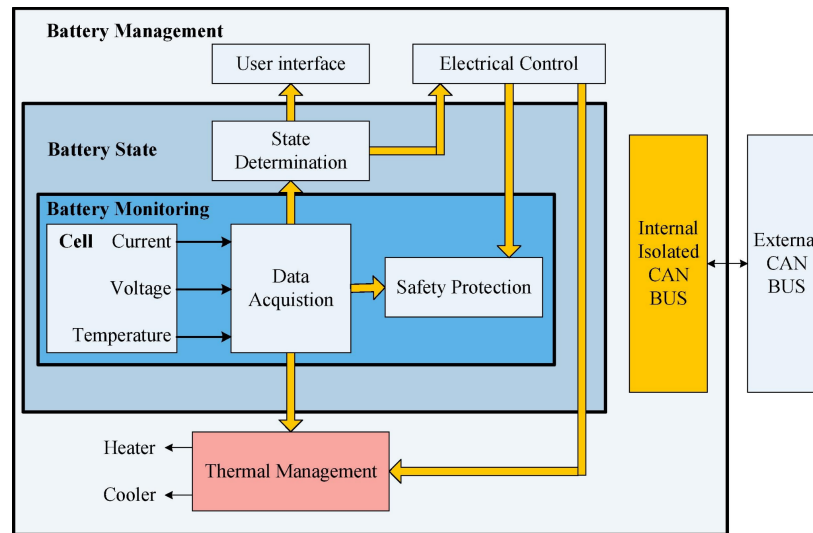
Moreover, the onboard charger is equipped with advanced safety features that prevent potential risks like overcharging, overheating, and electrical faults, thereby safeguarding both the vehicle and its occupants. These features are present on BEVs, and include real-time monitoring of the battery's temperature, voltage, and current during the charging process, with automatic intervention capabilities to halt charging if any abnormalities are detected. The efficiency of the OBC is paramount, as it directly influences the charging speed and the overall energy consumption; higher efficiency means that less energy is wasted as heat, leading to quicker charging times and reduced energy costs. Consequently, the onboard charger in a BEV is not just a component for charging the battery; it is a critical element that ensures the effective, safe, and efficient operation of the vehicle's power system.

As an architectural decision, the onboard charging system limits how fast the car would be able to charge on a level 2 charging station (which operates at

between 15-80 amps today at 200-240v) and DC Fast Charging (DCFS) stations, which top out at 900 volts. The onboard charger decision on a battery electric vehicle primarily depends on whether or not the vehicle will have a large battery or whether or not the vehicle has a high-voltage battery (Nicholas & Hall, 2018). Beyond that, the vehicle's relative cost and market segment may impact which charging system is fitted to the vehicle, as higher-performance vehicles with bigger or higher voltage batteries would derive greater utility from a higher amperage charger than their shorter-ranged counterparts. The dataset represents the charging system in terms of the total level 2 charging power and the maximum DC fast charging rate.

The dataset shows an average AC charging power of approximately 11.04 kW. The standard deviation of 3.65 kW suggests some variability, although most of the values are tightly clustered around the mean, with the 25th, 50th (median), and 75th percentiles aligning at 11 kW. This concentration of values indicates a common standard in AC charging power across different EVs, with the extremities ranging from a minimum of 3.6 kW to a maximum of 22 kW, highlighting a few outliers with significantly lower or higher charging capabilities. Regarding charging speed, the dataset shows an average speed of 49.59 km/h with a standard deviation of 18.46 km/h. This metric, which indicates how many kilometers of range can be added per hour of charging, varies more widely than the AC charging power. The speeds range from a minimum of 18 km/h to a maximum of 120 km/h. The median charging speed is 49 km/h, closely reflecting the mean. Yet, the broader range from the 25th percentile at 40 km/h to the 75th percentile at 55 km/h demonstrates more diversity in charging efficiency across different EVs.

3.6 Battery Thermal Management System



Overview of Battery Management Subsystems (Wu et al., 2019)

Electric vehicle (EV) battery thermal management systems are responsible for maintaining the battery's optimal operating temperatures, which is highly dependent on the cathode composition (Ohneseit et al., 2023). It is often coupled with a number of other components in a Battery Management System (BMS), which is responsible for the longevity and performance of the battery. Each thermal management system has specific applications, advantages, and disadvantages, as discussed below. The choice of thermal management system depends on factors like the vehicle's design, expected performance, cost constraints, and the climatic conditions in which the vehicle will operate. Moreover, there are other thermal management system design choices not represented in the data, including the physical dimensions and layout of the battery pack and thermal gradient limits (Reiter et al., 2019).

Air Cooled Thermal Management

Air cooling in electric vehicles (EVs) uses fans or blowers to circulate air around the battery cells to dissipate heat. This system is straightforward, involving

airflow generation through fans and the design of vents or channels in the battery pack to ensure efficient heat removal. Although air cooling is cost-effective and simpler to maintain than other cooling systems, it has limitations, especially in its cooling capacity and efficiency in high-temperature environments (Sharma & Prabhakar, 2021). The system's effectiveness heavily depends on the ambient temperature and the design of the air circulation paths. While air cooling is less complex and cheaper to implement, it is often inadequate for high-performance EVs in regions with warm climates due to its lower heat dissipation capabilities compared to liquid-based cooling methods (Zhao et al., 2018).

Liquid Cooled Systems

Liquid cooling in electric vehicles (EVs) involves circulating a coolant fluid around the battery cells to absorb and dissipate heat. This solution is more complex than air-cooled alternatives, but they are more efficient (Wu et al., 2019). Liquid cooling utilizes a network of pumps, hoses, and radiators to manage the coolant flow and temperature. The coolant directly contacts the battery cell surfaces or their enclosures, providing superior heat transfer due to liquids' higher heat capacity than air. This allows for closer cell packing and higher performance, especially in demanding situations. However, liquid cooling systems are more expensive to design and maintain, with potential risks such as coolant leakage that can damage the battery. Despite these drawbacks, the system's enhanced cooling efficiency makes it a preferred choice for high-performance EVs and in hotter climates where maintaining optimal battery temperature is crucial for vehicle performance and battery longevity (Wu et al., 2019). Within liquid cooling systems, there are multiple sub-architectures, such as coolant, refrigerant, and immersion cooling. Beyond the type of liquid cooling present, additional design decisions would likely also include the chemistry of the coolant, materials of the heat exchangers, and throughput of the compressor units involved. We were not able to source more specific data for each of the vehicles we analyzed.

Phase Change Materials (PCMs)

Phase Change Materials (PCMs) are battery thermal management systems that moderate temperature fluctuations through latent heat properties during phase transitions between solid and liquid states. Typically, a PCM thermal battery system will start in the solid phase. As the battery heats up, the PCM absorbs the heat and melts. Incorporating PCMs into battery systems involves balancing thermal performance, space utilization, and weight. While PCMs efficiently absorb excess heat and maintain stable temperatures, they often require additional structural support and containment solutions to address potential leakage when in liquid form. This necessitates a careful design approach to integrate PCMs without significantly increasing the weight or compromising the compactness of the battery pack (Liu et al., 2020). Moreover, the selection of PCMs with appropriate melting points and thermal properties must align with the specific thermal requirements of the battery system, ensuring that the PCM activates at the proper temperature range without hindering battery performance. Thus, the use of PCMs in battery thermal management presents a trade-off between enhancing thermal regulation and managing the added complexity, weight, and volume in the battery design (Luo et al., 2022).

Representation in the Dataset

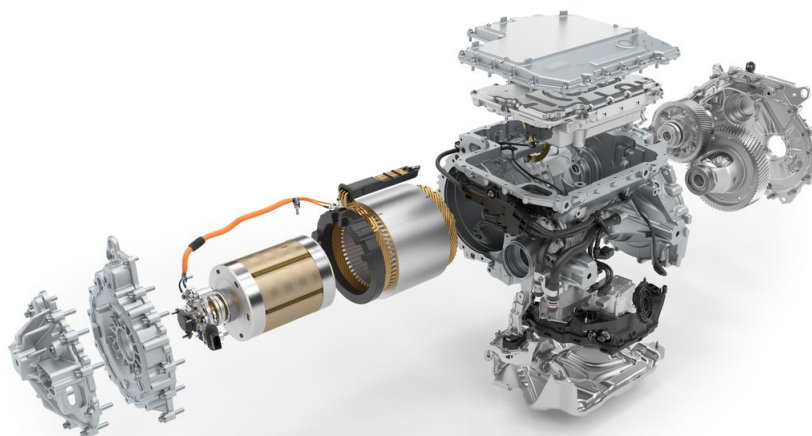
Though several earlier models of electric vehicles used air cooling, such as the first generation Nissan Leaf, all the electric vehicles (EVs) in the dataset now utilize a liquid-cooled thermal management system, indicating a uniform approach to addressing the critical issue of heat management in battery operation. The choice of liquid cooling over alternatives such as air cooling or phase change materials (PCMs) underlines the need for a more efficient and controlled cooling method. Liquid cooling systems circulate a coolant through channels around the battery cells, efficiently removing heat and maintaining optimal temperatures, which is crucial for vehicle safety and battery longevity. This method is generally more effective than air cooling, which is less efficient at heat dissipation and may not adequately manage the higher thermal loads in high-performance EVs or in warmer climates.

3.7 Motor Configuration

3.7.1 Motor Types

Electric vehicle (EV) motors transform electrical energy from the battery into mechanical motion through electromagnetic induction. The process is managed by a controller that modulates the electric current supplied to the motor based on the accelerator input, adjusting the vehicle's speed. Typically employing an AC induction or a permanent magnet DC motor, EVs utilize the principle where an electric current through coils in the motor's stator generates a magnetic field. This field interacts with the rotor, inducing a force that causes it to spin. The rotor's rotation is then mechanically transferred to the vehicle's drivetrain, propelling the wheels.

Additionally, EVs feature regenerative braking systems, where the motor functions as a generator during deceleration, converting kinetic energy into electrical energy to recharge the battery and improve overall energy efficiency. Electric vehicle (EV) motors come in various types, each with its trade-offs. Each motor type presents a balance between efficiency, cost, maintenance, and material availability, making the choice dependent on the specific requirements and constraints of the vehicle design.



Electric Motor Cutaway Diagram (Edmunds, 2022)

DC Motors

DC motors are widely used in electric propulsion due to their optimal torque-speed characteristics and simple speed controls. Despite these advantages, DC motors are bulky, less efficient, less reliable, and require more maintenance because of their mechanical commutators, even though some improvements have been made. However, advancements in robust solid-state power semiconductors have facilitated the adoption of AC induction and synchronous motor drives, which are becoming preferred in traction applications due to their reliability and maintenance-free benefits, especially at higher powers. At lower power levels, DC motors remain a viable option. The introduction of DC chopper power electronics allows for the reengineering of vehicles without altering mechanical components, providing a cost-effective solution due to the simplicity of the power electronics involved (Zeraoulia et al., 2006).

Induction Motor (IM)

Induction motors (IMs) operate through electromagnetic induction, where a rotating magnetic field induces currents in the rotor to generate torque. These motors are robust, cost-effective, and require minimal maintenance, making them popular in electric vehicles (EVs) for their simplicity, reliability, and high-speed capabilities. IMs are especially favored in EV applications where affordability and durability are more critical than achieving maximum efficiency (McGuinness et al., 2015). Zeraoulia et al. (2006) described that Vector control techniques allow IMs to separate torque control from field control, enabling extended operation at constant power beyond the base speed through flux weakening. Despite their advantages, IMs have drawbacks like high losses, low efficiency, and low power factor, which are particularly problematic at high speeds and powers. Additionally, IMs inherently have lower efficiency than permanent magnet (PM) motors due to the absence of rotor winding and rotor copper losses (Zeraoulia et al., 2006).

Synchronous AC Motor

Synchronous AC Motors operate synchronously with the frequency of the AC power source, ensuring constant speed under varying loads. These motors offer high efficiency and precise speed control, making them suitable for electric vehicle applications requiring stable operation. They are commonly used where consistent speed and efficiency are critical. These motor types include several subtypes, including non-excited AC motors, Permanent Magnet Synchronous motors (PMSMs), and reluctance motors. PMSMs are, by far, the most ubiquitously represented of the subtypes. Though PMSMs offer high efficiency and precise control, they may be costlier to manufacture than induction motors (Loukas, 2022). Current Excited Synchronous Motors and Synchronous AC Motors provide superior efficiency and power density but are often more complex and expensive to manufacture.

The motor types represented in the dataset are as follows:

- Permanent Magnet Synchronous Motor (PMSM): 389 occurrences
- Induction Motor (IM): 66 occurrences
- Synchronous Reluctance Motors (SynRM): 14 occurrences

3.7.2 Motor Count and Mounting

Battery Electric Vehicles (BEVs) can differ significantly in their configurations, particularly regarding the number of motors they use and where these motors are mounted. These variations can substantially impact the vehicle's performance, handling, and efficiency. Single-motor BEVs typically have the motor mounted on the front or the rear axle. A front-mounted motor drives the front wheels, which is beneficial for packaging and manufacturing simplicity and often results in better traction when accelerating from a stop, as the weight of the motor is over the driven wheels (Brown & Liu, 2020). Conversely, a rear-mounted motor, driving the rear wheels, can offer better handling and balance, mimicking the driving dynamics traditionally favored in sports cars. The choice between front and rear motor

placement usually hinges on the desired balance of cost, efficiency, and vehicle performance characteristics (Kalcher et al., 2022).

Multi-motor BEVs, on the other hand, include configurations with motors on both axles or even individual motors for each wheel. Dual-motor setups (one on each axle) provide all-wheel drive, enhancing traction in various driving conditions and improving overall vehicle stability and acceleration (Duclos & Hofman, 2021). High-performance electric vehicles often use this configuration to maximize handling and power delivery. Some newer vehicles, such as the Rivian R1S (not included in the data set due to too few vehicles sold), are equipped with a motor for each wheel. Multi-motor configurations allow precise power distribution control, optimize traction, and enable advanced driving dynamics such as torque vectoring. These configurations can be complex and expensive but offer superior performance and handling capabilities.

Most vehicles are equipped with one motor (189 vehicles), followed by those with two motors (133 vehicles). Additionally, fewer vehicles have three motors (5 vehicles), and some vehicles do not have any motors specified (37 vehicles). Regarding specific motor placements, 128 vehicles have motors on both axles, which makes it the most common configuration, followed by motors placed only on the rear axle at 110 vehicles. Front axle placements are present in 79 configurations. There are no quad motor vehicles represented in the dataset.

3.8 Drive Type

Battery-only Electric vehicles (BEVs) have several different configurations in motor placement, each offering distinct benefits and driving characteristics that cater to different types of drivers and environments. Relative to traditional Internal Combustion Engine (ICE) vehicles, motor mounting positions in BEVs are more diverse due to the assumed skateboard platform configuration and the generally more compact motors required for BEV propulsion.

The front axle motor configurations, more commonly found in entry-level BEVs, position the motor(s) at the front of the vehicle, driving the front wheels. This layout leverages the traditional benefits of front-wheel drive, including more efficient use of space within the vehicle and better traction during acceleration, especially in slippery conditions (Frieske et al., 2013). This can make front-driven EVs more practical and safer for everyday commuting in variable weather. However, this setup can sometimes result in torque steer, an effect where the vehicle pulls to one side during acceleration, which might be noticeable during rapid takeoffs or on uneven road surfaces.

Rear axle motor configurations, where the motor drives the rear wheels, are the most ubiquitous BEV configurations and are often favored for performance-oriented vehicles (Frieske et al., 2013). This setup enhances the driving dynamics by improving traction at the rear, which is crucial during rapid acceleration, and by better balancing the vehicle's weight distribution across its chassis. The rear-wheel-drive approach offers a dynamic driving experience favored in sports cars, providing a more engaging ride with superior acceleration and cornering capabilities.

All wheel drive (AWD), where one or more motors power each axle, merges the advantages of front and rear motor configurations. AWD systems enhance vehicle stability and handling and provide safer and more reliable performance across diverse, challenging driving conditions. Vehicles with all-wheel drive adapt well to slippery roads and off-road environments, delivering power and traction where needed. AWD can be achieved with one motor per axle or one per wheel.

Vehicles with more than one motor in either the front or rear can take advantage of torque vectoring, which dynamically adjusts the amount of power sent to each wheel, which can significantly enhance the vehicle's agility and responsiveness during maneuvers, such as sharp turns or while driving on winding roads. Such systems are often represented by higher-cost performance and luxury EVs, where manufacturers aim to maximize control and performance. The dataset has All-Wheel Drive (AWD) as the most prevalent drive type in 152 vehicles. Following that is Front-Wheel Drive, which appears in 135 vehicles. Rear-wheel drive, noted in 77 vehicles, is much less common.

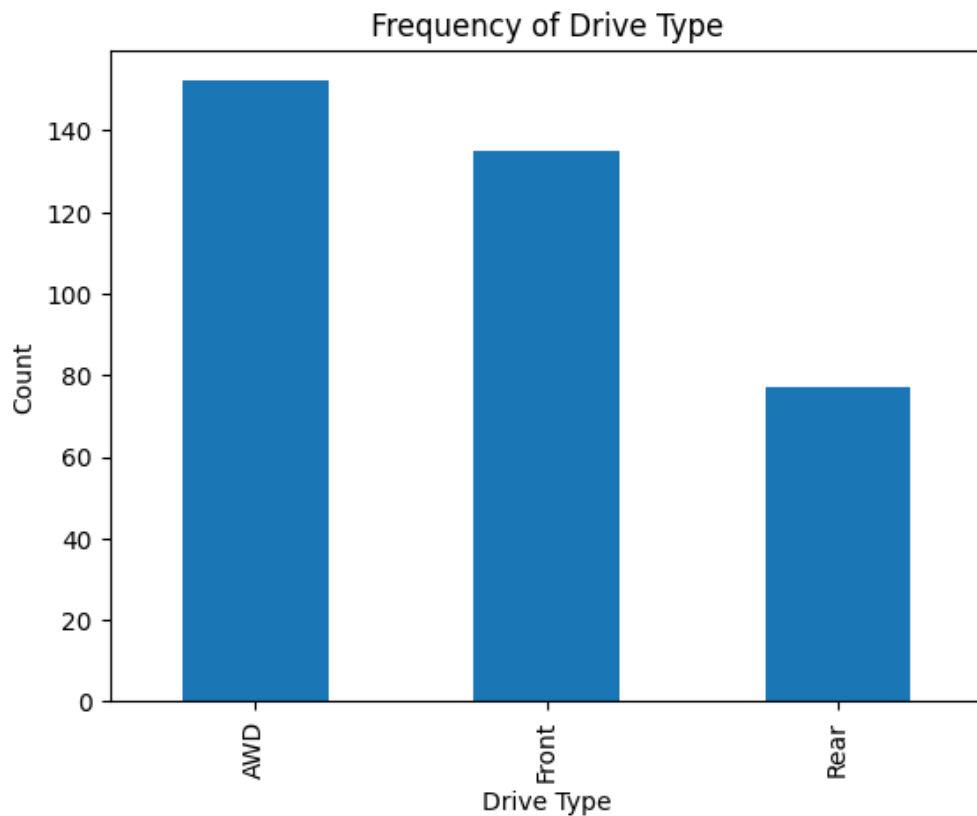


Figure 3.8.1: Frequency of Drive Types

3.9 Architectural Decisions Relationships

Architectural Decisions	units	min	max	categorical options		
Battery Pack Cathode Composition				NMC	LFP	NCA
				NMC & LFP Hybrid		
Battery Pack Voltage	volts	240	800			
Battery Pack Cell Series		72	220			
Battery Pack Cell Parallel		1	72			
Battery Pack Number of Cells		72	7920			
Charging Controller	kWh	3.6	22			
Thermal Management System				air-cooled	liquid-cooled	immersion cooling
Motor Quantity	qty	1	4			
Motor Placement				front axle	rear axle	front and rear axle
				front axle and rear wheels		
Motor Type				Permanent Magnet Synchronous Motor (PMSM)	Induction Motor (IM)	Switched Reluctance Motors (SRM)
				Brushless DC Motors (BLDC)	Synchronous Reluctance Motors (SynRM)	Axial Flux Motors
Drive Type				front wheel drive	rear wheel drive	all-wheel drive

Figure 3.9.1: Morphological Matrix of Architectural Decisions

3.10 Limitations and Excluded Architectural Decisions

In this section, we reflect on several architectural decisions that were not explored in this chapter due to data availability constraints. These omitted decisions could impact the overall architecture and performance of battery electric vehicles (BEVs) and warrant further discussion and exploration in future research. One of the main challenges while constructing the dataset was finding reputable sources for data, especially for technical details on subsystem implementations. Several of the architectural decisions we discuss in this section would be considered by the original equipment manufacturer (OEM) to be proprietary and intellectual property, and thus, specific information available publicly to encode in a dataset is sparse.

The selection of electronic control units (ECUs) and their integration within the vehicle architecture was not covered. ECUs play a critical role in managing and optimizing the performance of electric vehicles by controlling various functions such as motor speed, battery charging, and thermal management. The choice of ECU and its software capabilities could influence the vehicle's efficiency and responsiveness but was outside the scope of our constructed dataset. Different approaches to ECU design, such as the overall count of ECUs, the dispersion of ECUs throughout the vehicle, ECU in-sourcing or out-sourcing, as well as the architecting single responsibility ECUs or general compute ECUs.

Similarly, the role of software in managing vehicle dynamics and battery usage was not deeply analyzed. Modern BEVs rely heavily on sophisticated algorithms for battery management, vehicle power delivery and stability control, and energy optimization. The choice of software strategies and their implementation can drastically affect a vehicle's performance and user experience.

Other omitted decisions due to lack of data include the specifications and performance metrics of power electronics, particularly inverters and converters. These components are crucial for the efficiency of power transfer from the battery to the motor and vice versa. Variations in their design and the materials used can affect the overall power efficiency, cost, and thermal footprint of the vehicle.

4 Methods

4.1 Overview

In this chapter, we introduce the methodology used to explore the research question of whether or not a dominant design exists for the current Battery Electric Vehicle market. Investigating this hypothesis involves a data-driven analysis of BEVs from model years 2022 and 2023 from OEMs that have sold over 100,000 vehicles of any model per annum. We make an exception for Lucid, as they produce consumer vehicles with the highest electric range on the market. We constructed a robust dataset through manual aggregation of data from various credible sources, encoding the architectural decisions we introduced in Chapter 3 along with the primary outcome variable of range and others. The integrity of the data was ensured through statistical cleaning procedures, including the elimination of duplicates, rectification of missing values, and validation of data consistency. This foundation supports Chapter 5's comparative analysis of BEV architectures, providing insights into which design decisions are most likely to be dominant in the current automotive sector.

Finally, the evaluation criteria for determining the existence of a dominant design in BEVs are carefully defined, diverging from traditional metrics used for internal combustion engine vehicles. Instead of adopting existing performance indices, this thesis focuses on metrics that reflect current consumer preferences and market trends, such as vehicle range, acceleration from 0-100 km/h, power output, torque, and energy consumption efficiency. These criteria were chosen to align closely with the factors contributing to commercial success and consumer satisfaction in the BEV market. This approach facilitates a deeper understanding of how specific design elements contribute to the perceived dominance of a particular architecture within the competitive landscape of electric vehicles.

4.2 Hypothesis

The thesis hypothesizes that there exists a dominant design / dominant architecture for the current and near-future market of battery electric vehicles (BEVs) upon which most commercially successful vehicles are based. This hypothesis is grounded in the observation that while the early stages of BEV development have seen a variety of battery technologies, motor types, and vehicle designs, market forces, and technological advancements tend to favor the convergence towards a single, dominant architecture in pursuit of maximizing utility on BEV outcome metrics. Range, efficiency, cost-effectiveness, and consumer appeal constrain the number of viable decision options, which, in turn, further constrain downstream decisions, which potentially sideline other designs. By analyzing both manufacturer and consumer trends in preference, this thesis explores whether or not a dominant design exists today and how a dominant design could influence Battery Electric Vehicles in global markets.

4.3 Approach

This thesis uses a data-driven research approach against globally sold model years 2022 and 2023 vehicles in the dataset to answer the research motivation of whether or not there exists a dominant architecture for battery electric vehicles. In order to compare the architectures of current and near-future electric vehicles, we have built a dataset by collecting and aggregating data on key metrics such as battery capacity, range, charging time, power output, and market adoption rates from various first and third-party sources. First-party data was sourced directly from electric vehicle manufacturers through publicly available technical specifications, press releases, and annual reports, ensuring accuracy and up-to-date information. Third-party data was gathered from industry analyses, automotive research institutions, and market research firms that provide comprehensive insights into consumer trends and industry standards.

Data cleaning and validation procedures were applied to ensure the dataset's robustness and representativeness. This involved removing duplicates, addressing missing values, and verifying data consistency across different sources, which are cited in the dataset references section of this thesis. The primary challenge in compiling this dataset was collecting and validating data from the public sources we procured, as the dataset collection was largely manual. Once the aggregated dataset was sufficiently completed and validated, summary statistics were generated to ensure the data was sufficiently complete and consistent, providing a reliable basis for comparative analysis. For instance, as we constructed the dataset, we checked each decision's encoding column and metrics to ensure that the dataset was mostly complete ($> 80\%$). We validated that each architectural decision was within expected ranges, such as voltage between 300 - 900 volts.

The dataset also includes metadata such as the year of vehicle release, geographic market, and manufacturer, which allows for a nuanced analysis of trends over time and across different regions. The data upon which the subsequent analysis relies enables a detailed comparison of BEV architectures and offers insights into which architectural decisions are most likely to contribute to the dominance of a particular architecture in the evolving automotive landscape.

4.4 Evaluation Criteria

In order to evaluate whether or not a dominant design exists for Battery Electric Vehicles, we must define criteria upon which to evaluate choices. Similar works for Internal Combustion Engine (ICE) vehicles typically use several outcome metrics to compare the performance of different vehicle designs. One such work, *"Vehicle Architecture and Lifecycle Cost Analysis In a New Age of Architectural Competition"* by Gorbea, reuses an Architectural Performance Index that equally weights power to weight ratio, maximum velocity, fuel economy, and manufacturer's suggested retail price (in United States Dollars). In this writing, we have opted not to use an existing performance index. Instead, we evaluate the efficacy of existing architectures primarily against the maximum range of the

vehicle, as well as other outcome metrics, including 0-100 km acceleration time, power (kW), torque (Nm), and energy consumption efficiency (Wh / km). This assumption simplifies the following analysis and mimics consumer preferences, which leads to commercially successful vehicles (Dimitropoulos et al., 2013).

4.5 Dataset Description

The collected dataset represents 365 vehicle configurations from 51 automakers globally. The vehicle data represented is from 2022 and 2023 only, as this thesis attempts to categorize current vehicle architectures. We do not include vehicles that have been discontinued, nor do we include extremely low-volume vehicles by startups that have not yet achieved mass-market status, as they do not reflect scalable designs at this time. We set the cutoff for OEM inclusion into the dataset at 100k vehicles sold yearly. The dataset described is a comprehensive collection of attributes relating to electric vehicles (EVs), organized into several categories that cover a broad spectrum of specifications essential for analyzing and comparing different EV models. These categories include metadata, battery, charging, physical dimension, energy consumption, motors, and performance. The dataset contains general vehicle information such as manufacturer and specific model name. Specific subsystem metrics, such as battery architecture volts, battery type (e.g., Li-ion, NiMH), and specifics about the battery's cathode material, are also represented. The dataset also delves into the battery's nominal and usable capacities, number of cells, and pack configurations, which are crucial for understanding the vehicle's power storage capabilities.

Moreover, the dataset has several outcome variables that are used in the subsequent analysis to compare architectural efficacy and likeness. All vehicles in the dataset have vehicle range in kilometers, their primary outcome metric, included. Secondary outcome metrics include power consumption (Wh / km), 0-100 km/h performance, total power (kW), charging speed and power, as well as maximum payload (kg). A complete list of dataset columns and their descriptions are available below.

4.6 Dataset Key Columns

Column Name	Description	Values
battery_architecture_volts	Voltage configuration of the battery system.	400.0 - 800.0
battery_cathode_material	Type of material used in the battery's cathode.	NMC, NCA, LFP, LFP & NMC
battery_cathode_material_specific	Specific composition or type of the cathode material.	NMC, NCM622, NCA, NCM811
battery_nominal_voltage	Standard operating voltage of the battery.	240.0 - 800.0
battery_number_of_cells	Total number of individual cells in the battery pack.	72.0 - 7920.0
battery_pack_configuration_parallel	Number of cells connected in parallel within the battery pack.	1.0 - 72.0
battery_pack_configuration_series	Number of cells connected in series within the battery pack.	72.0 - 220.0
charging_charge_power_kW_ac	Maximum power level for charging the battery in kW	3.6 - 22.0
charging_charge_speed_km_h	Speed at which the battery can be charged, in km of range per hour.	18 - 120
dimensions_and_weight_wheelbase_mm	Distance between the front and rear axles.	2322.0 - 3430.0
motor_placement	Location of the motor(s) in the vehicle.	front, both, rear
motor_type_front_1	Type of motor installed at the front of the vehicle.	PMSM, Induction
motor_type_rear_1	Type of motor installed at the rear of the vehicle.	PMSM, AC Induction
motor_type_rear_2	Additional type of motor installed at the rear, if any.	AC Induction, PMSM
motors_qty	Total number of motors in the vehicle.	0 - 3
motors_front_qty	Number of motors installed at the front of the vehicle.	0 - 1
motors_rear_qty	Number of motors installed at the rear of the vehicle.	0 - 2
performance_drive	Drivetrain configuration of the vehicle.	Front, AWD, Rear
performance_electric_range_km	Maximum distance the vehicle can travel per charge.	135 - 685
performance_acceleration_0_100_kmh_seconds	Time it takes to accelerate from 0 to 100 km/h.	2.1 - 19.1
performance_top_speed_kmh	Maximum speed the vehicle can reach.	125 - 320
performance_total_power_kW	Total output power of all motors, measured in kW.	33 - 828
performance_total_power_PS	Total output power of all motors, measured in metric horsepower (PS).	45 - 1126
performance_total_torque_Nm	Total torque output of all motors, measured in Newton meters.	113.0 - 1390.0

5 Analysis

5.1 Overview

In this chapter, we focus on applying the dataset we aggregated to answer our research question of whether or not there exists a dominant battery electric vehicle design on the market. The first sections of this chapter take an individual look into the effect of each design decision, categorized by subsystem, on the outcome variables of this analysis, which are range, 0-100 km/h performance, and efficiency. We then conduct a frequency and regression analysis with the dataset columns that encode the architectural decisions we discussed in the prior chapters to analyze the most impactful architectures on the outcome variables. We conclude the chapter by leveraging the dataset to highlight trends and variances that impact electric vehicle design today.

5.2 Battery Architecture

As stated, this work focuses on range as the primary outcome metric of battery-only electric vehicles. In this section, we examine the relationships of the various architectural decisions on a vehicle's range. Of the vehicles represented in the dataset, 202 models have a total range of less than 400km (approximately 250 miles), whereas only 162 models have a range greater or equal to 400km. Fewer yet have a range greater than or equal to 500km, with only 37 vehicle models. The nominal battery capacity represents how much power a battery can store and is the primary driver of BEV range, as shown in Figure 5.2.1.

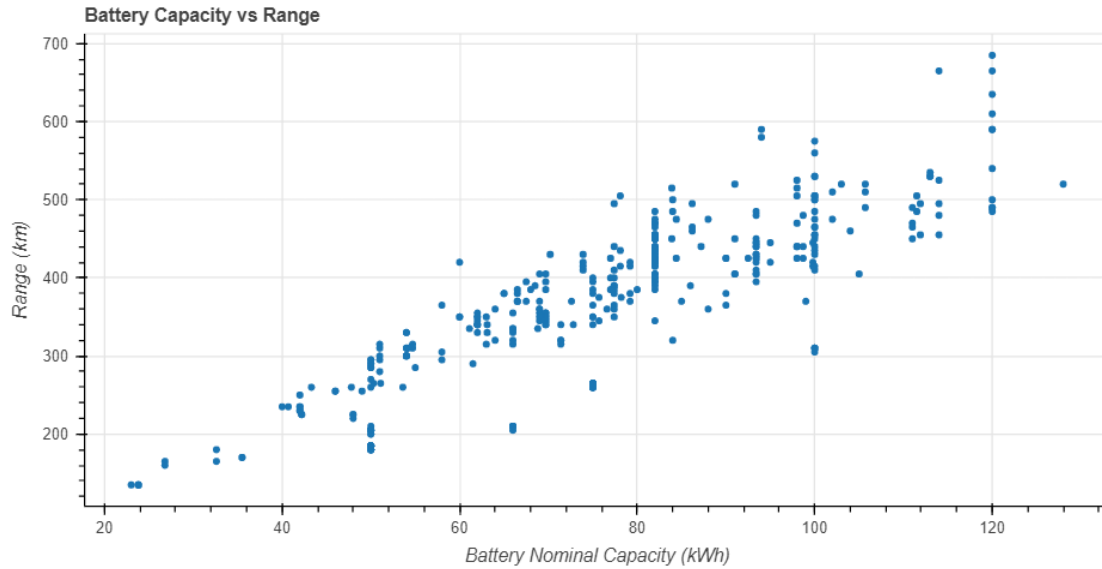


Figure 5.2.1 - Battery Capacity vs Range

A linear relationship ($r^2 = 0.74$, $m = 4.268 \text{ km} / \text{kWh}$) between battery capacity (measured in kilowatt-hours, kWh) and range (in kilometers, km) is evident in the data, albeit with some variability. Naturally, as we plot battery capacity against range, a general upward trend is observed, indicating that vehicles with larger batteries tend to achieve greater distances despite higher battery and overall vehicle weights, as shown in the following graph. This might seem superficially obvious; however, it is important to highlight the variance in range outcomes associated with different battery sizes. This variance tends to increase with battery capacity, as shown discussed in section 5.6, suggesting that while larger batteries are generally linked to longer ranges, other factors such as vehicle weight, aerodynamics, and drive efficiency might play significant roles in determining the exact range. Models with extremely high battery capacities show particularly wide variance, indicating that the simple linear model might not capture all dynamics at play. Thus, while battery capacity is a strong predictor of range, the scatter in the data reflects the influence of these additional factors, underscoring the complexity of electric vehicle design, which we explore this further in section 5.6.

Although the battery capacity is a strong predictor of range, we do not find a similar effect for the discrete number of battery cells on range, as shown in figure 5.2.2. This is consistent with our understanding that the number of cells can be increased or decreased to achieve the desired range target. We observe slight

positive correlation toward the tail end of the graph, indicating that smaller battery cells might be used in higher-range vehicles.

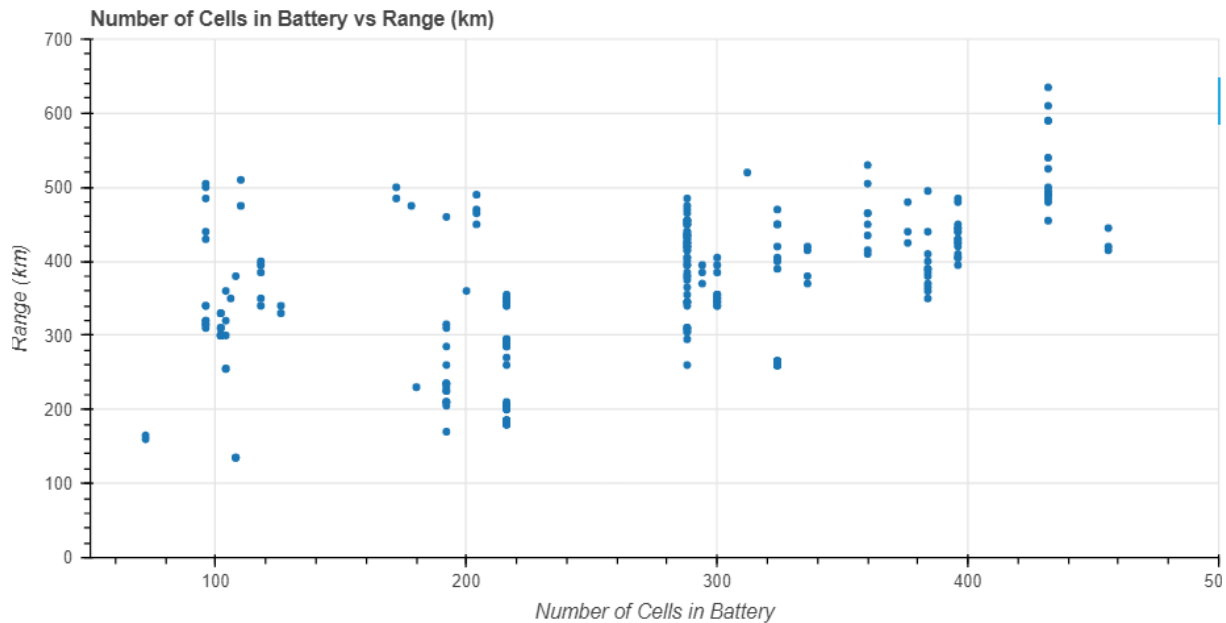


Figure 5.2.2 - Number of Cells vs Range

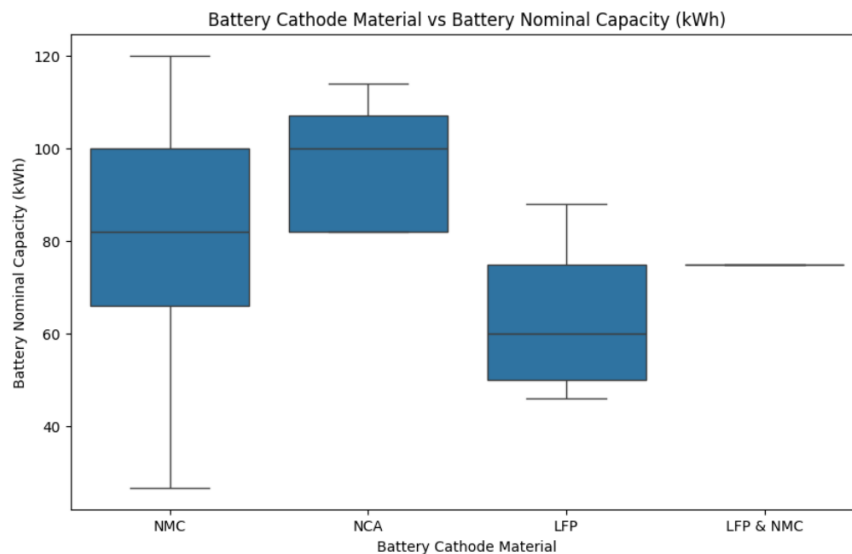


Figure 5.2.3 - Number of Cells vs Range Box and Whisker

There are distinct differences in nominal capacity across the types when comparing the battery cathode materials used in electric vehicles. Lithium Iron

Phosphate (LFP) batteries show the lowest average capacity at 62.23 kWh, with a relatively small range between the minimum and maximum capacities (46 to 88 kWh). This suggests that LFP batteries are fairly consistent in size and may be preferred for applications where a smaller capacity is adequate and consistency is valued over a wide range of options. With a lower standard deviation of 14.35 kWh, the LFP batteries indicate less variability and possibly a more targeted usage scenario, likely in less energy-demanding vehicles or where weight and cost considerations are prioritized over energy density.

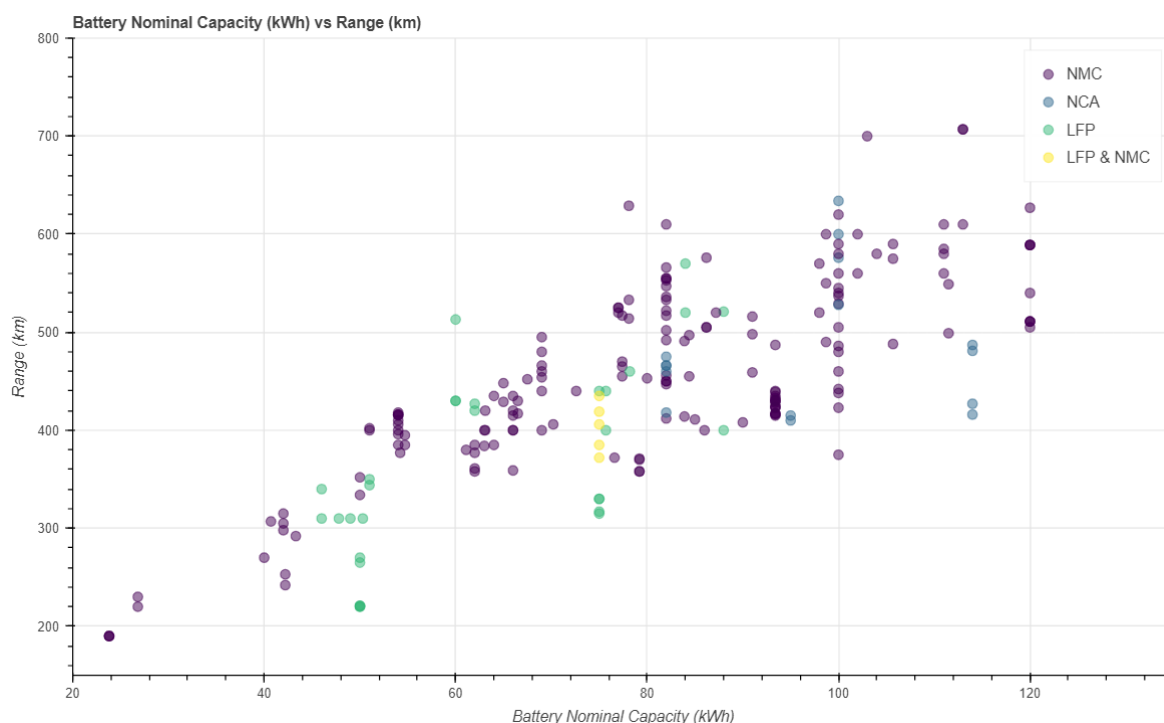


Figure 5.2.4 - Nominal Capacity against Range, colored by Cathode Type

On the other end of the spectrum, Nickel Cobalt Aluminum (NCA) cathode material stands out with the highest average nominal capacity at 97.07 kWh and a median capacity of 100 kWh. The NCA batteries also exhibit a narrow standard deviation of 12.89 kWh, yet they maintain a substantial capacity range from 82 to 114 kWh. This indicates a more focused application in high-capacity scenarios, such as long-range and performance-oriented vehicles, where a larger energy reserve is necessary. The consistency in higher capacities shows that NCA is a preferred choice for applications demanding extended range and performance, albeit with a slightly smaller pool of options compared to NMC.

Nickel Manganese Cobalt (NMC) cathodes demonstrate the most versatility, with a substantial count of 155 batteries and the broadest range of capacities from 26.8 to 120 kWh. The mean capacity for NMC is 82.07 kWh, accompanied by a higher standard deviation of 21.11 kWh, reflecting a broad spectrum of vehicle types and uses, from small city cars to large luxury electric vehicles. The data for batteries combining Lithium Iron Phosphate and Nickel Manganese Cobalt (LFP & NMC) is unique, with all entries at a uniform 75 kWh capacity, which is consistent with a design choice that only a single manufacturer, Nio, uses.

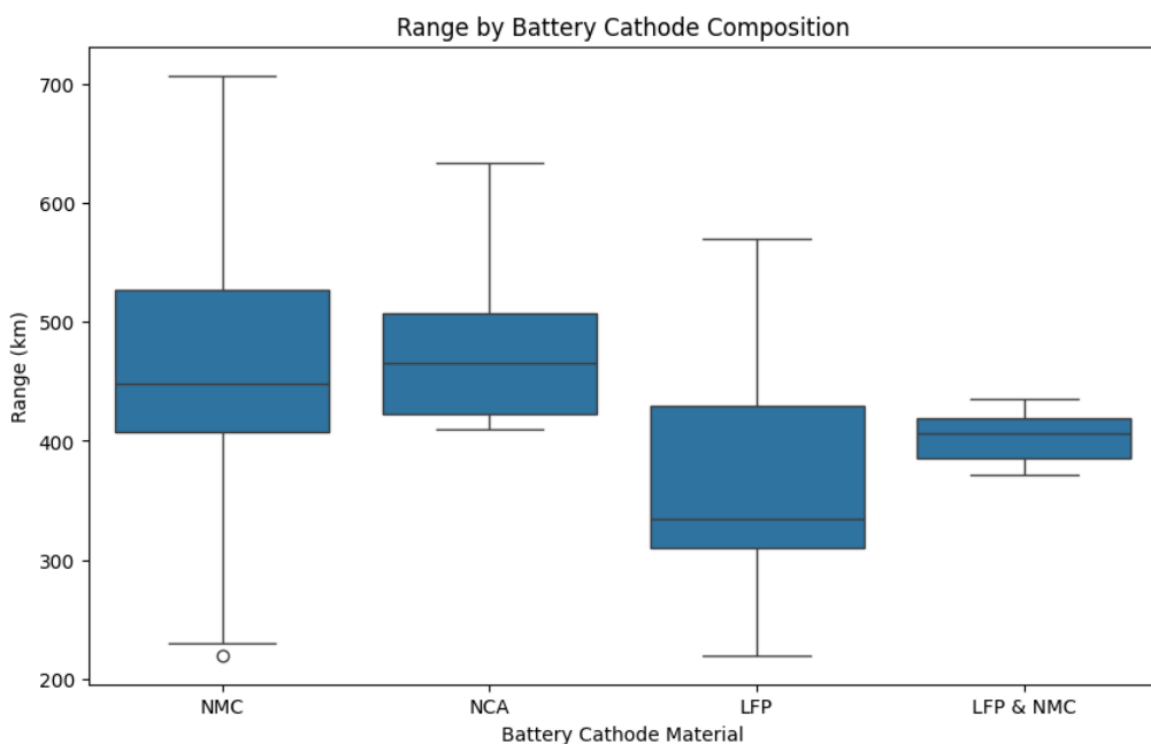


Figure 5.2.5 - Range by Battery Cathode Composition

Lithium Iron Phosphate (LFP) cathode batteries exhibit an average range of 361.21 kilometers, with a standard deviation of 99.31 kilometers, indicating moderate variability within this group. The minimum and maximum ranges for LFP are 220 and 570 kilometers, respectively, which suggests that while some LFP-based vehicles are optimized for shorter, more efficient trips, others are capable of achieving mid-tier range performance. The 50th percentile (median) is at 335 kilometers, leaning towards the lower end of the range spectrum, which may

suggest that LFP cathodes are typically used in vehicles where cost and durability are prioritized over longer distances.

Only one manufacturer utilizes the combination of LFP and Nickel Manganese Cobalt (NMC) cathodes in the dataset, NIO. These hybrid batteries have an average range of 403.4 kilometers, a relatively narrow standard deviation of 25.36 kilometers, and a range spanning from 372 to 435 kilometers. This tight clustering around the mean indicates a consistent performance band, potentially suggesting a design approach that aims to balance the energy density of NMC with the stability and safety of LFP.

Nickel Cobalt Aluminum (NCA) cathode batteries have the highest average range of 483.93 kilometers, reflecting a preference for this chemistry in long-range vehicles. The standard deviation is 70.78 kilometers, with the minimum and maximum range being 410 and 634 kilometers, respectively. The data shows that NCA batteries are employed in vehicles that offer a broad span of capabilities, including those that require extended range for longer journeys, which is underscored by the highest maximum range observed in the dataset.

Nickel Manganese Cobalt (NMC) cathode batteries present a wide average range of 464.38 kilometers with the largest sample size and the highest standard deviation of 90.41 kilometers. The NMC batteries have the broadest range variability, from 220 to 707 kilometers, indicating that this cathode type is used in a diverse set of vehicles, from entry-level to premium long-range electric vehicles. The median range for NMC is 448 kilometers, placing it comfortably in the higher range bracket, suitable for a variety of use cases from daily commutes to long-distance travel.

5.3 Charging Controller

The battery electric vehicles represented in the dataset are all capable of level 2 charging, which is defined as charging current greater than 120 volts but fewer or equal to 240 volts, and have varying direct charging speeds. The dataset contains several columns that encode BEV charging data. One of which is maximum power, measured in kilowatts (kW), which encodes the maximum power a vehicle can draw from an AC (alternating current) source. This metric represents how effectively a vehicle can utilize standard charging facilities, which are commonly available at home or public stations. The higher the kW rating, the faster an EV can charge using AC power, reducing the overall downtime required to recharge the battery. Similarly, we can look at the distance regained per hour charged for insight into the rate at which the vehicle's battery can gain energy from an AC charging source, expressed in kilometers of range gained per hour (km/h). This figure directly affects how quickly the battery can be charged from an empty state to full capacity, impacting daily usability, especially for users who may need to recharge quickly between trips during the day. Though they represent similar metrics and are collinear, they are not entirely aligned.

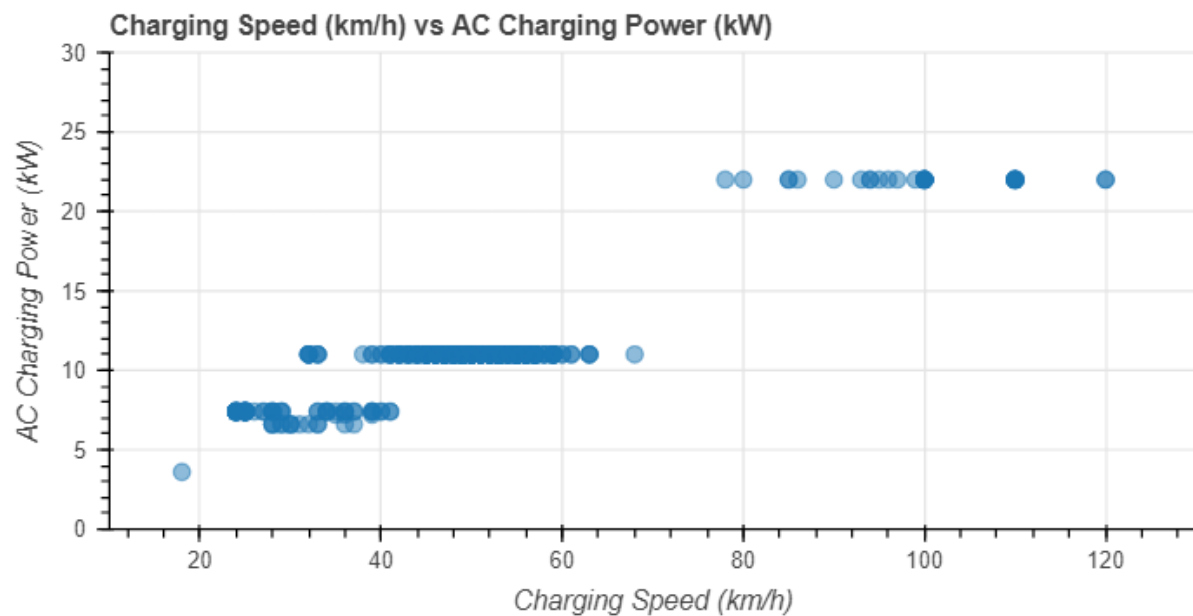


Figure 5.3.1: A comparison of charging speeds at given Charging Powers

The observation that vehicles with the same AC charging power exhibit different charging speeds raises interesting points about the complexity of electric vehicle charging dynamics. Although one might expect that vehicles with identical charging power capacities would charge at similar rates, several factors can lead to variations in charging speed. Different battery materials and constructions can affect how efficiently a battery can accept and store incoming power. For instance, some batteries might be more capable of handling higher power inputs without degrading, while others might need to moderate the charge rate to maintain battery health and longevity. Figure 5.3.2, shown below, broadly indicates that LFP batteries, with the exception of the Tesla Model 3 (11 kW charger, but charges at 68 km/h), regain range at a slower rate even though their onboard chargers are capable of faster charging.

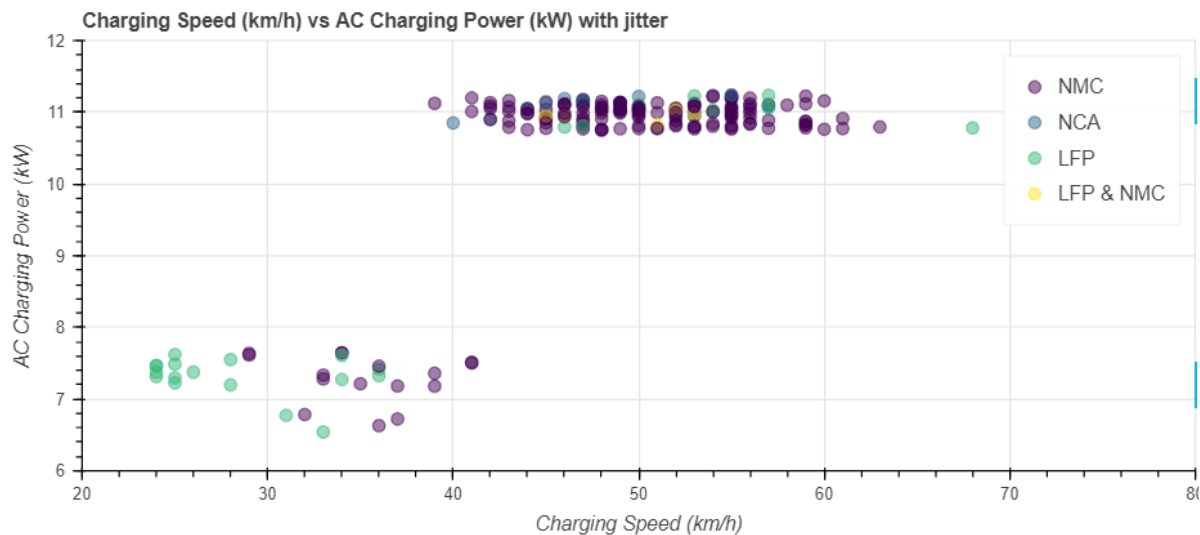


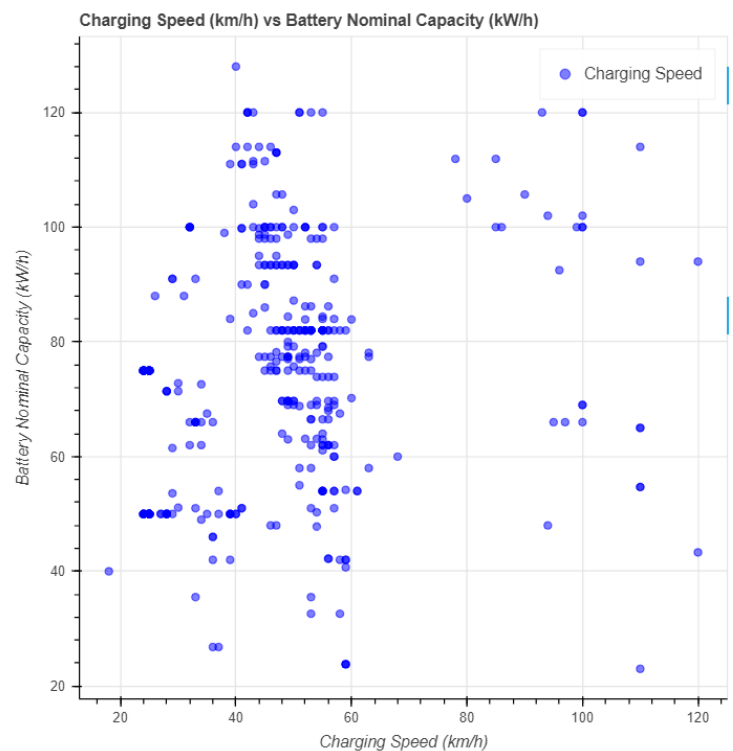
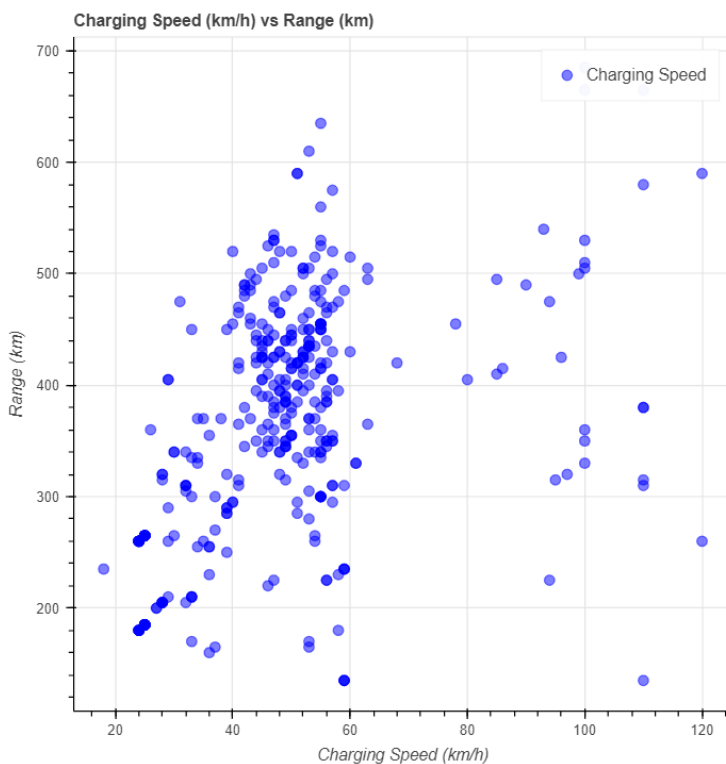
Figure 5.3.2: A closer look at charging powers vs speed, categorized by battery cathode.

The 22kW chargers are omitted due to the fact that all of the vehicles have an NMC cathode type. Jitter was added to the Y axis to show variation in charging power.

We believe this difference can be attributed to the battery management system (BMS) charging characteristics as tuned by the manufacturer, but we do not have the data to test this hypothesis. The BMS regulates the charge rate to optimize battery health, efficiency, and safety. In vehicles with the same AC charging power, a more sophisticated BMS can use the available power more effectively, translating

to faster charging speeds. Additionally, OEM perceptions of environmental factors such as temperature can affect charging speed. Batteries often charge more efficiently at certain temperatures, and built-in thermal management systems might reduce charging power under less-than-ideal conditions to prevent overheating or excessive cooling of the battery.

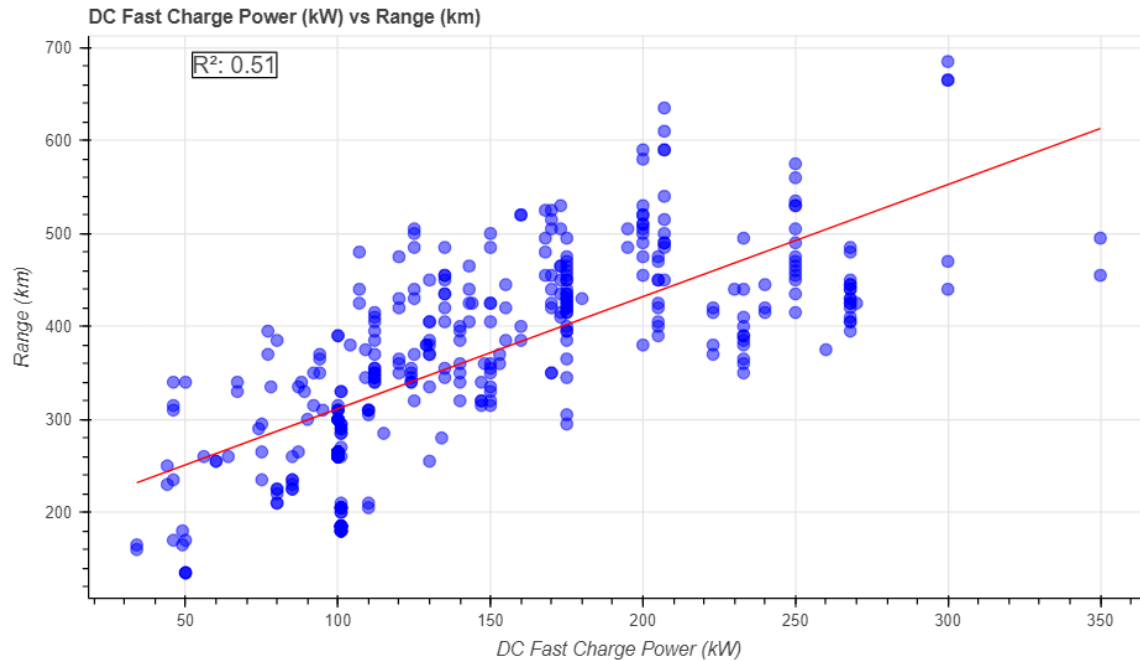
The average AC Charging Power across the vehicles is 11.04 kW, with a standard deviation of 3.65 kW. The values range from a low of 3.6 kW to a high of 22 kW. This indicates that while there is standardization around an 11 kW median for AC charging, variability exists that could influence compatibility with home and public charging stations. Charging Speed, measured in kilometers per hour, averages 49.59 km/h with a standard deviation of 18.46 km/h. This metric, spanning from 18 km/h to 120 km/h, shows how quickly the battery can gain energy, directly tied to the practical downtime the vehicle spends at a charging station.



Figures 5.3.4 and 5.3.5: Charging speed compared to Nominal Capacity

Comparing the charging speed against a BEV's battery capacity, no significant trends are observed. The scatter plot shown in Figure 5.3.3 contains a large number of data points spread primarily across the middle of the range for both axes, with a notable cluster around nominal capacities of 50 to 100 and charging speeds of 40 to 80. There are some outliers, particularly at higher capacities and speeds. Based on this visualization, there does not appear to be a clear linear relationship between battery capacity and charging speed; the distribution of points is somewhat scattered without a discernible pattern or trend. When plotted directly against range, there are several outliers, particularly at higher charging speeds and ranges. Figure 5.3.4 suggests that there might be a moderate relationship where a higher charging speed correlates with a longer range, but the correlation does not seem particularly strong as the data points are quite spread out and do not form a clear linear pattern.

Direct charging, or charging that bypasses the vehicle's onboard charger to intake as much power as allowed from a DC Fast Charger (DCFS), is represented in maximum power in kilowatts (kW) by the `charging_fastcharge_power_max_kW_dc` column. DC fast charging is crucial for significantly reducing charging time, particularly beneficial during long-distance travel, where time spent charging is a critical factor. Vehicles with a higher kW capacity for DC charging can replenish their battery levels much faster, enhancing travel efficiency and convenience. `charging_fastcharge_speed_km_h` indicates the amount of range (in kilometers per hour) that an EV can add during one hour of fast charging. This column is particularly valuable for assessing an EV's capability for long trips, as it reflects how quickly the vehicle can "refuel" and get back on the road. A higher value here means less time waiting during travel breaks and more time moving, which is a key consideration for potential EV buyers looking at vehicle performance over long distances.



Figures 5.3.6: DC Fast Charging Power vs Range

DC Fast Charging Power also shows some variation, with an average of 150.13 kW and a standard deviation of 62.53 kW. This range is quite broad, from 34 kW to 350 kW, highlighting a diverse set of capabilities that cater to different user needs and scenarios, such as quick top-ups during long trips. Fast Charging Speed, measured in km/h, has an average value of 552 km/h and varies significantly, demonstrated by a standard deviation of 234 km/h. It ranges from 170 km/h to a rapid 1290 km/h. This statistic is particularly important for assessing how practical an EV is for long-distance travel, reflecting how quickly a vehicle can be "refueled" and back on the road. Overall, these statistics underline the diversity in EV charging technology, with faster charging capabilities strongly linked to higher-end models that have the highest top speeds, power, and fastest 0-100 km/h accelerations (correlation of 0.80, 0.75, and -0.66, respectively). Moreover, we see some correlation with battery architecture decisions. Higher battery voltages are correlated with increased DCFS charging power (0.62), as higher voltage allows for double the power at the same amperage. Battery pack cells series in parallel is also positively correlated (0.65), however, this is expected as batteries with parallel configurations can safely be charged faster (Aghabali, 2020), as discussed in Chapter 3.

5.4 Electric Motor Configuration

This section examines the relationship between the number of motors and the electric range. Vehicles with a single motor, which represent the bulk of the dataset, serve as a benchmark for understanding how manufacturers balance cost, efficiency, and performance. These vehicles are typically priced lower and emphasize practicality over performance. The median range for these vehicles is 385 km, with a mean of approximately 376 km, reflecting a broad distribution of performance outcomes likely influenced by various vehicle design factors beyond the number of motors. The presence of a substantial standard deviation of 105 km in the electric range further suggests significant variability and highlights that other technical specifications impact vehicle range.

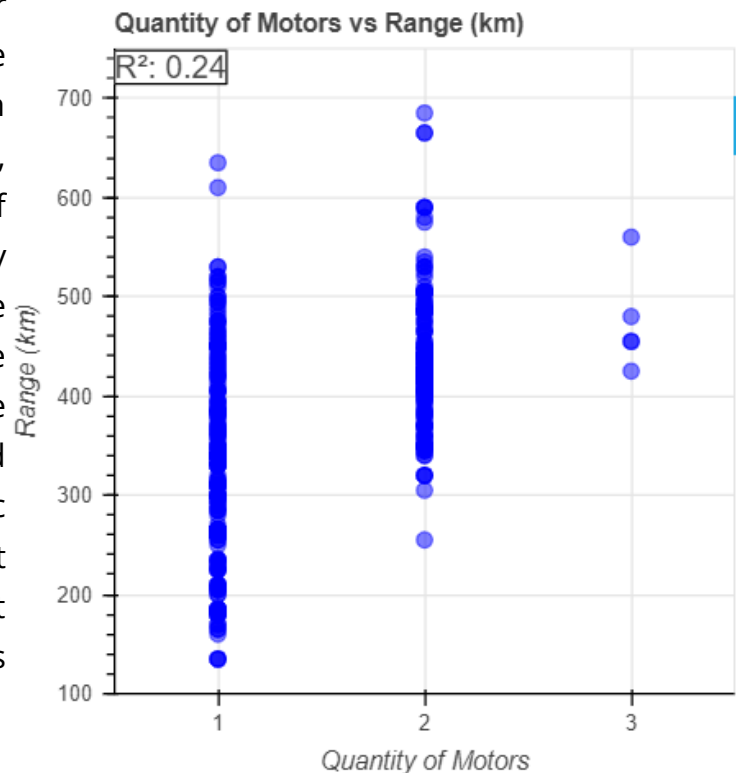


Figure 5.4.1: Range broadly increases as motor count rises

Considering vehicles with two or more motors, we observe that these typically target higher performance and all-wheel-drive capabilities, appealing to a segment of consumers looking for enhanced driving dynamics or better handling under different weather conditions. The average for two motor BEVs is approximately 435 kilometers, with a standard deviation of 72 kilometers. The minimum range in this category is considerably higher than that of single motor vehicles at 255 kilometers, and the maximum extends up to 685 kilometers. Although data for triple motor vehicles is limited (only five observations), they exhibit the highest average range of about 475 kilometers. The spread of range values is relatively small, with a standard deviation of about 51 kilometers, and

ranges from a minimum of 425 kilometers to a maximum of 560 kilometers. However, the increase in motor count does not necessarily correlate with a proportionate increase in electric range. For instance, the vehicles in the dataset with two motors show a range often similar to single-motor models, suggesting that the additional motor is primarily enhancing performance rather than extending range, as shown in Figure 5.4.2. This pattern indicates that while additional motors can improve torque and acceleration, they also increase the vehicle's energy requirements, which can offset the potential range benefits unless accompanied by larger or more efficient batteries.

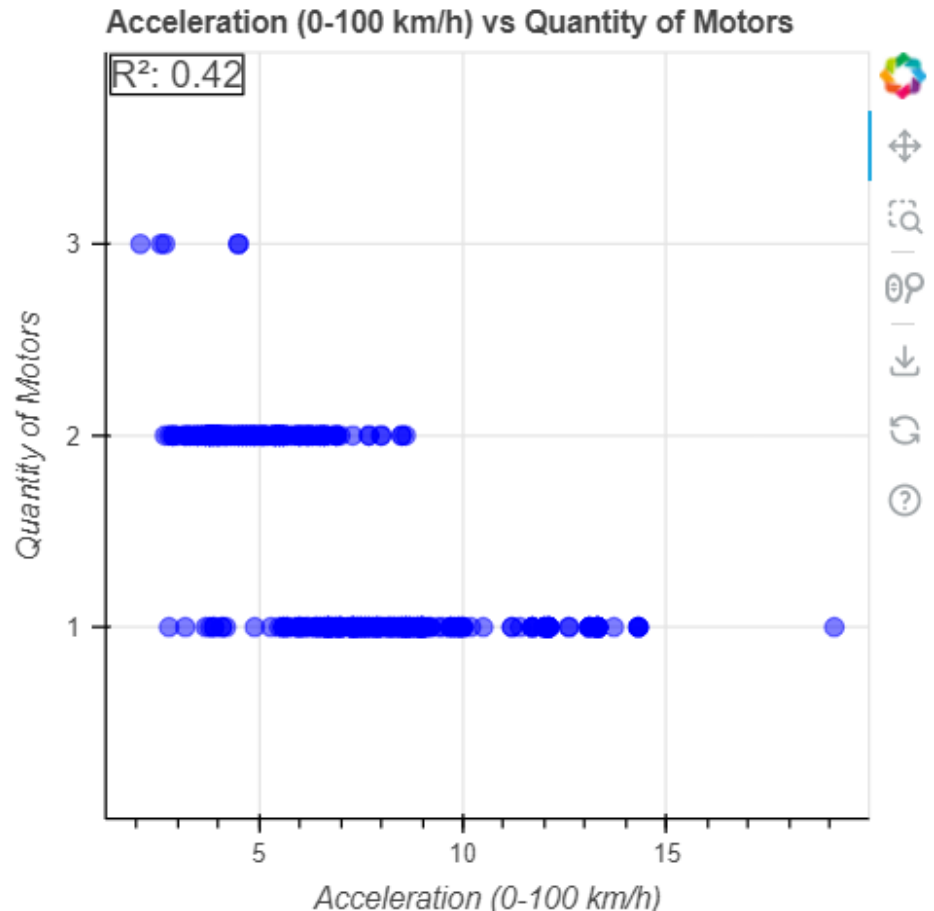


Figure 5.4.2: Acceleration performance increases with motor count

To understand how motor placement affects the electric range, we can look at more descriptive statistics for each placement category, which include the median, minimum, and maximum of the electric ranges, as shown in Figure 5.4.3, as well as the standard deviation. Front motor configurations, which are typically seen in more compact or budget-friendly electric vehicles, had an average range of about 310 kilometers with a broader standard deviation of 95.4 kilometers. This variability might be attributed to the diverse designs and purposes of these vehicles, ranging from budget-friendly models to more compact city cars. This type of placement generally offers the simplest and most cost-effective engineering solution, which may be why it is prevalent in lower-range models.

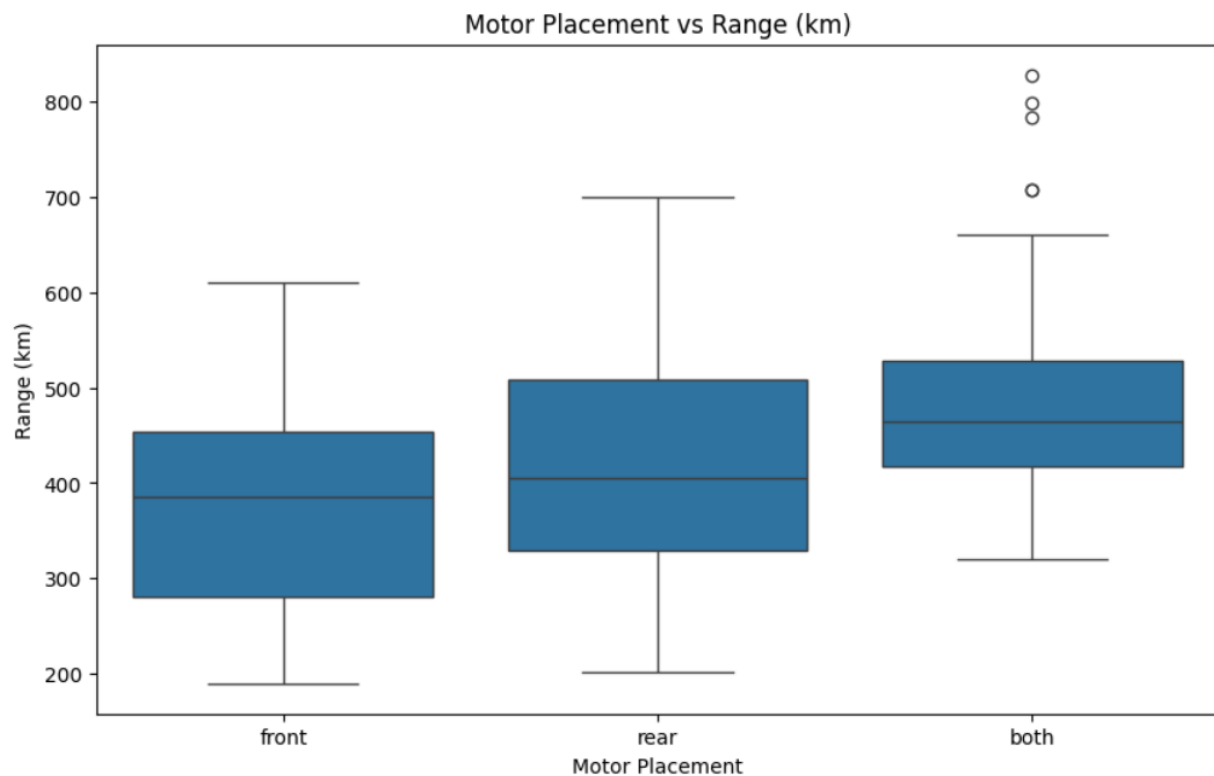


Figure 5.4.3: Motor placement vs Range (km)

Rear-mounted motor vehicles boast a slightly higher range, averaging about 352 kilometers. The data includes a mix of performance-oriented and luxury models, which favor rear placement for better driving dynamics. When broken down by single and dual motor rear placements, the single on-axle motors have an average of approximately 346 km. In contrast, vehicles with a motor on each rear

wheel show higher average ranges of 481 kilometers. Vehicles with two rear motors are often equipped with much larger batteries. However, the configuration might offer traction and energy efficiency advantages, particularly at higher speeds, which are crucial for achieving better long-distance capabilities.

Vehicles with both front and rear motors boast the highest average range at approximately 436 kilometers, with a relatively consistent performance (standard deviation of 70.9 km). This configuration is often employed in premium or performance models that require balanced power distribution for optimal performance and traction, contributing to more efficient energy usage under various driving conditions. This suggests a balanced distribution of power and efficiency, which is ideal for premium models designed for extended range and superior handling.

This analysis reveals significant insights into how the motor type of electric vehicles influences their electric range. Vehicles equipped with Synchronous Motors, particularly when configured both at the front and rear, exhibit the highest average electric range, reaching approximately 510 kilometers. Similarly, Synchronous Reluctance Motors (SynRM), especially when combined with other types like Permanent Magnet Synchronous Motors (PMSM), also demonstrate strong performance, with maximum ranges around 505 kilometers. These configurations suggest that certain synchronous motor types are highly efficient for extending vehicle range.

On the other hand, Induction Motors (IMs) show varied results depending on their combination with other motor types. Alone, IMs typically support an average range of around 380 kilometers, but this significantly increases when combined with PMSM, indicating the benefits of hybrid motor configurations for range enhancement. Permanent Magnet Synchronous Motors (PMSM) are versatile and commonly used in various combinations, yielding a wide spectrum of range outcomes—from as low as 326 kilometers when used alone to much higher when paired with other motor technologies.

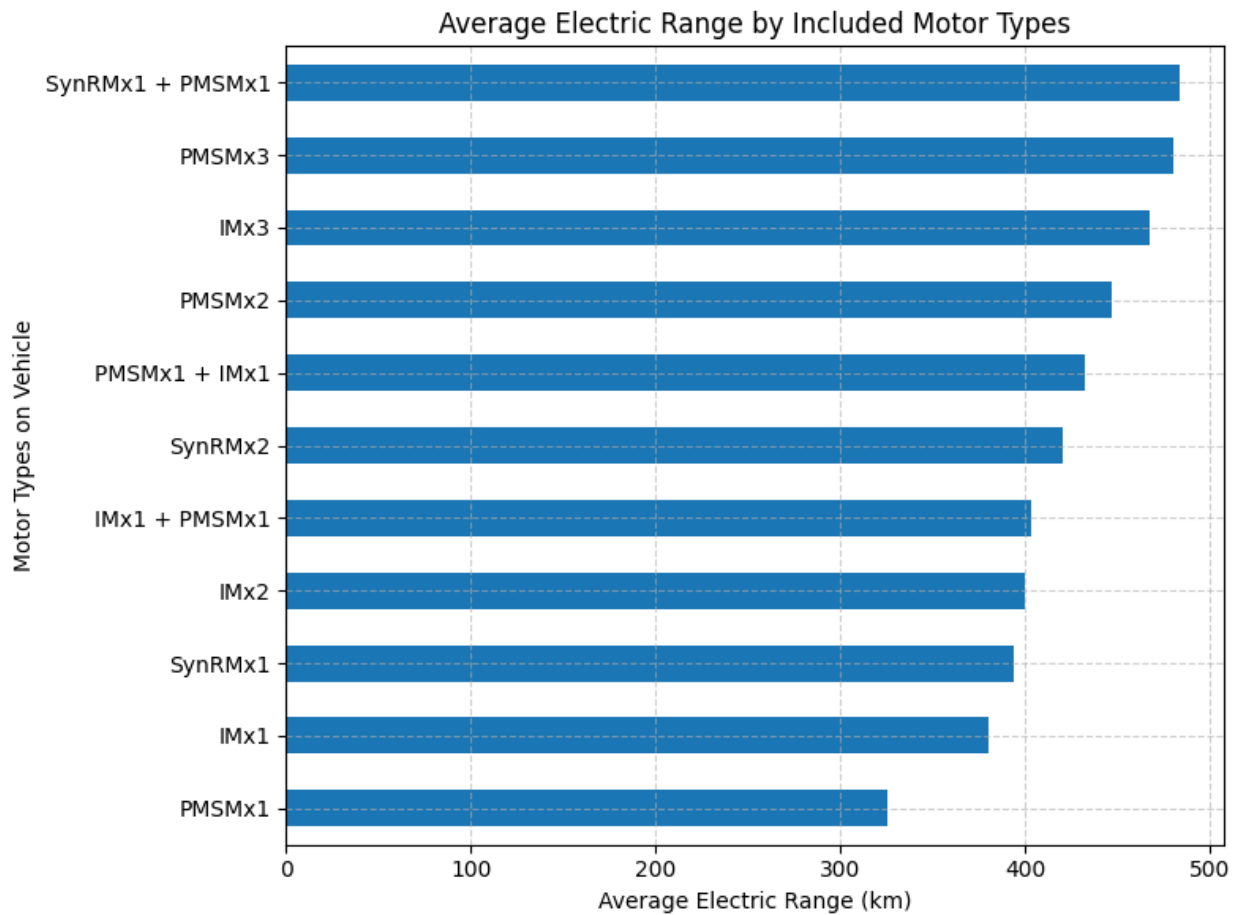


Figure 5.4.4: Motor types vs Range (km)

When comparing the effect of the different types of specific motors on range, we see an increase in range based on the type of motor(s) applied. However, we do not believe these vehicle range differences are significantly attributed to the motor type. By far, the most common configuration (293 / 365) of motor types includes at least one Permanent Magnet Synchronous Motor (PMSM). Of the vehicles that only have one PMSM motor, they are overwhelmingly lower-budget vehicles with a lower range. Similarly, vehicles with more than one motor tend to be performance variants and often have larger batteries. Figure 5.4.5, shown below, illustrates the fact that most vehicles with two or more motors also have greater battery capacities than their one-motor counterparts. A notable insight is that, unlike Internal Combustion Engine (ICE) vehicles, there do not appear to be BEVs with transaxles that enable independently driven (4x4) powertrains.

5.5 Drive Type

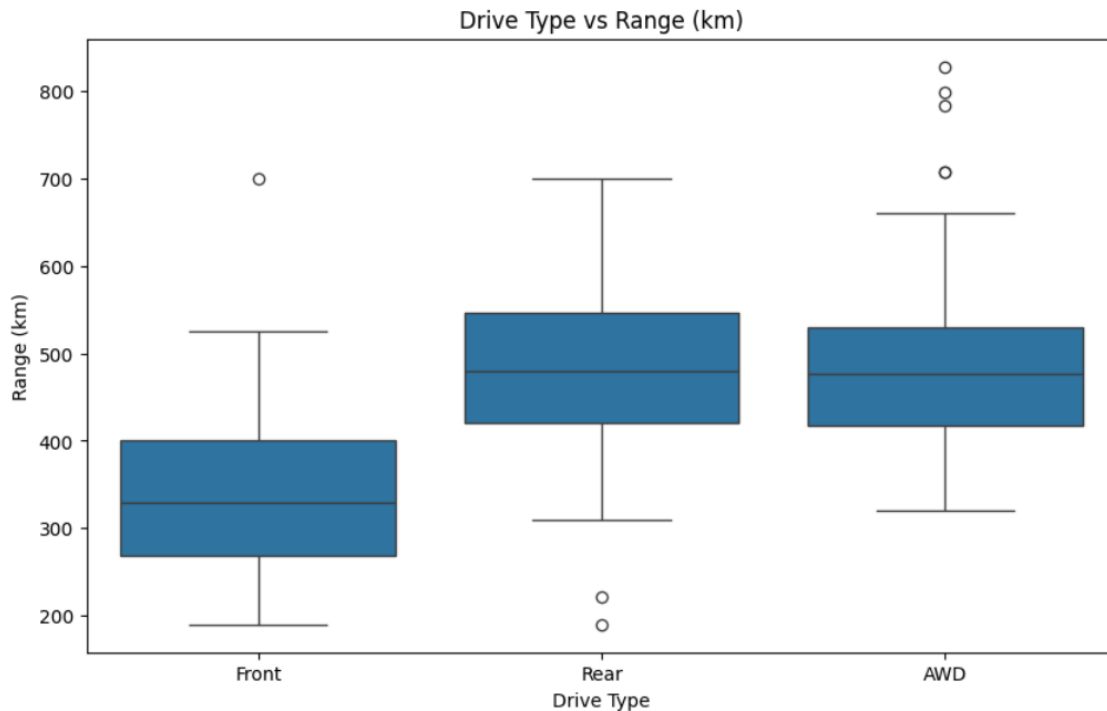


Figure 5.5.1: Drive Type vs Range (km)

The relationship between drive type and electric range in electric vehicles (EVs) exhibits differences based on the type of drive system that is similar to motor placement. All-wheel drive (AWD) and rear-wheel drive (RWD) vehicles generally exhibit superior electric range compared to their front-wheel drive (FWD) counterparts. Specifically, AWD vehicles lead with an average electric range of approximately 436 km, closely followed by RWD vehicles at about 411 km. In contrast, FWD vehicles average around 275 km, indicating a notable disparity in range performance. This variance can be attributed to the increased capacity of more premium EV models that accommodate larger battery capacities and more advanced powertrain technologies. Meanwhile, FWD vehicles, which frequently target efficiency and cost-effectiveness, incorporate smaller batteries and simpler powertrains, influencing their reduced range. As discussed in Chapter 3, we did not find sufficient publicly available data on motor sizing specifications beyond total output that would allow us to explore efficiencies at a more granular level.

5.6 Variance in OEMs

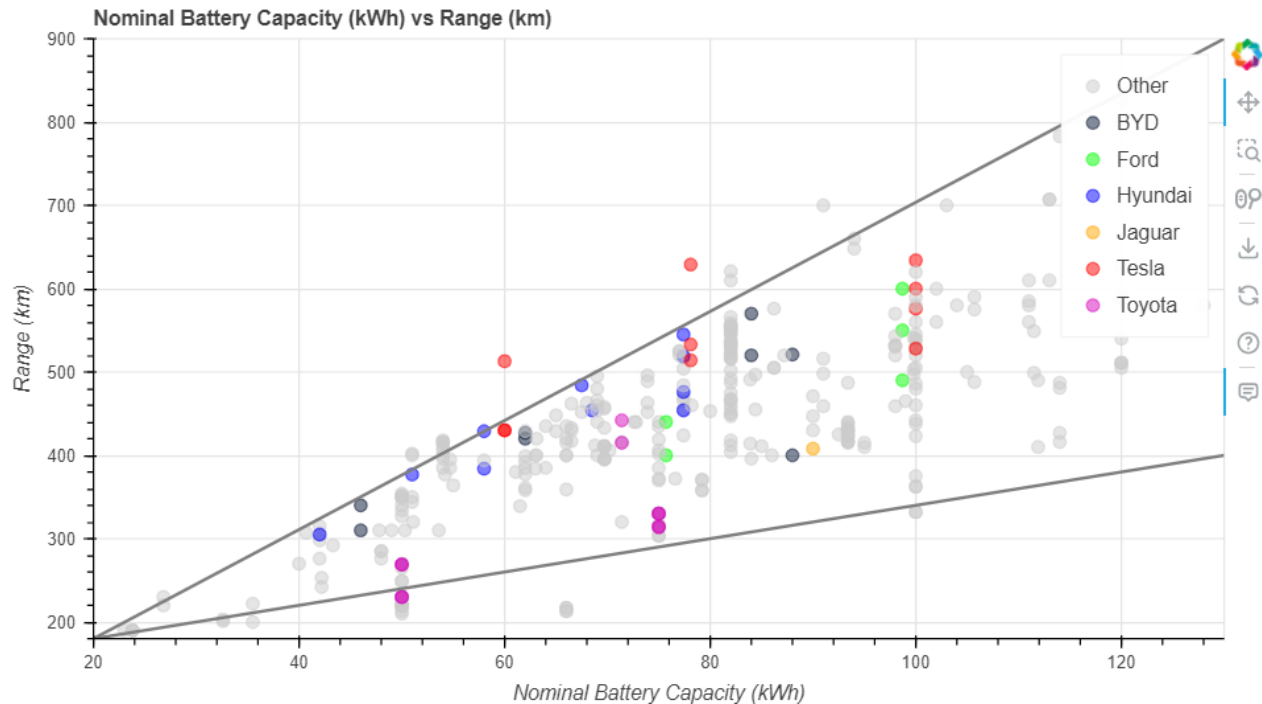


Figure 5.6.1: Range prediction error by 20kWh bins

We briefly discussed in Chapter 5.2 that we generally expect electric ranges to increase as battery capacities increase. However, we also observed growing variance between the highest and lowest-range vehicles in each battery band. This is evident in Figure 5.6.2, as it shows the Root Mean Square Error (RMSE) of electric range predictions across various battery capacity bins, each spanning 20 kWh. The RMSE values represent the discrepancy between predicted and actual electric vehicle ranges, indicating the prediction model's accuracy within specific battery capacity intervals. As battery capacity increases from 20 kWh to 140 kWh, so too does the bin's RMSE,

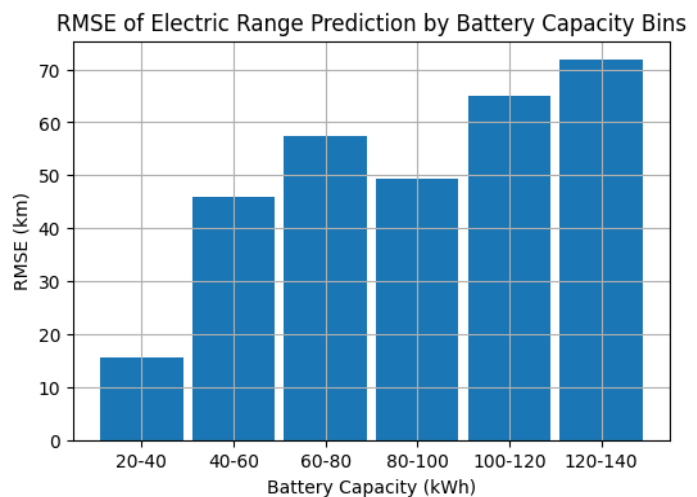


Figure 5.6.1: Range prediction error by 20kWh bins

suggesting that manufacturers might observe challenges scaling high-range vehicles linearly.

Given this insight, we regress battery capacity onto electric range and reiterate a strong linear relationship ($r^2 = 0.74$, $m = 4.268 \text{ km} / \text{kWh}$) as we did in section 5.2. We used this linear regression to predict the hypothetical range of each vehicle given its battery capacity, then calculated the aggregate average deviation for each manufacturer and plotted it in a descending vertical bar chart in Figure 5.6.3 below, colored by deviation magnitude.

The top performer is Lucid; this is expected, though we note them as somewhat of an outlier, as their Lucid Air model (all variants) is highly optimized specifically for range at the expense of affordability. Tesla, Skoda (Volkswagon Motor Group), and Hyundai are able to get the most range out of the large EV OEMs near +50 km of range. This would indicate that their in-house expertise in building EVs gives them a competitive edge over their counterparts. Interestingly, although Hyundai models express higher ranges than expected for their given battery capacities, Kia and Genesis, both of which are subsidiaries of the Hyundai Motor Group, are almost exactly on the mean across their vehicles. This might indicate differential strategies per brand. Hyundai models might focus on building BEV technical expertise, whereas Kia models might be tailored towards mass market and affordability and Genesis models are built to provide more luxury features over raw EV performance metrics.

Several luxury brands are among the worst-performing OEMs by this metric. Rolls-Royce, Mercedes, Lexus, Lotus, Jaguar, and Toyota, Hongqi all performed worse than average. This observation gives plausibility to the deviation we observed for Genesis, but further investigation with additional data is required to concretely make that claim. Toyota, the world's largest vehicle OEM by volume, is the second worst-performing manufacturer at extracting range from similarly sized batteries. On average, their vehicles have 61 km of range less than expected. Their latest entry into BEVs, the 2024 bZ4X, only achieves 340km of range with a 71.4 kWh battery pack. For comparison, the Hyundai Kona achieves 390km of range with a 68 kWh pack. We assert that this difference is due to Toyota's late entry into and overall resistance to BEVs, but we recognize that more research is warranted.

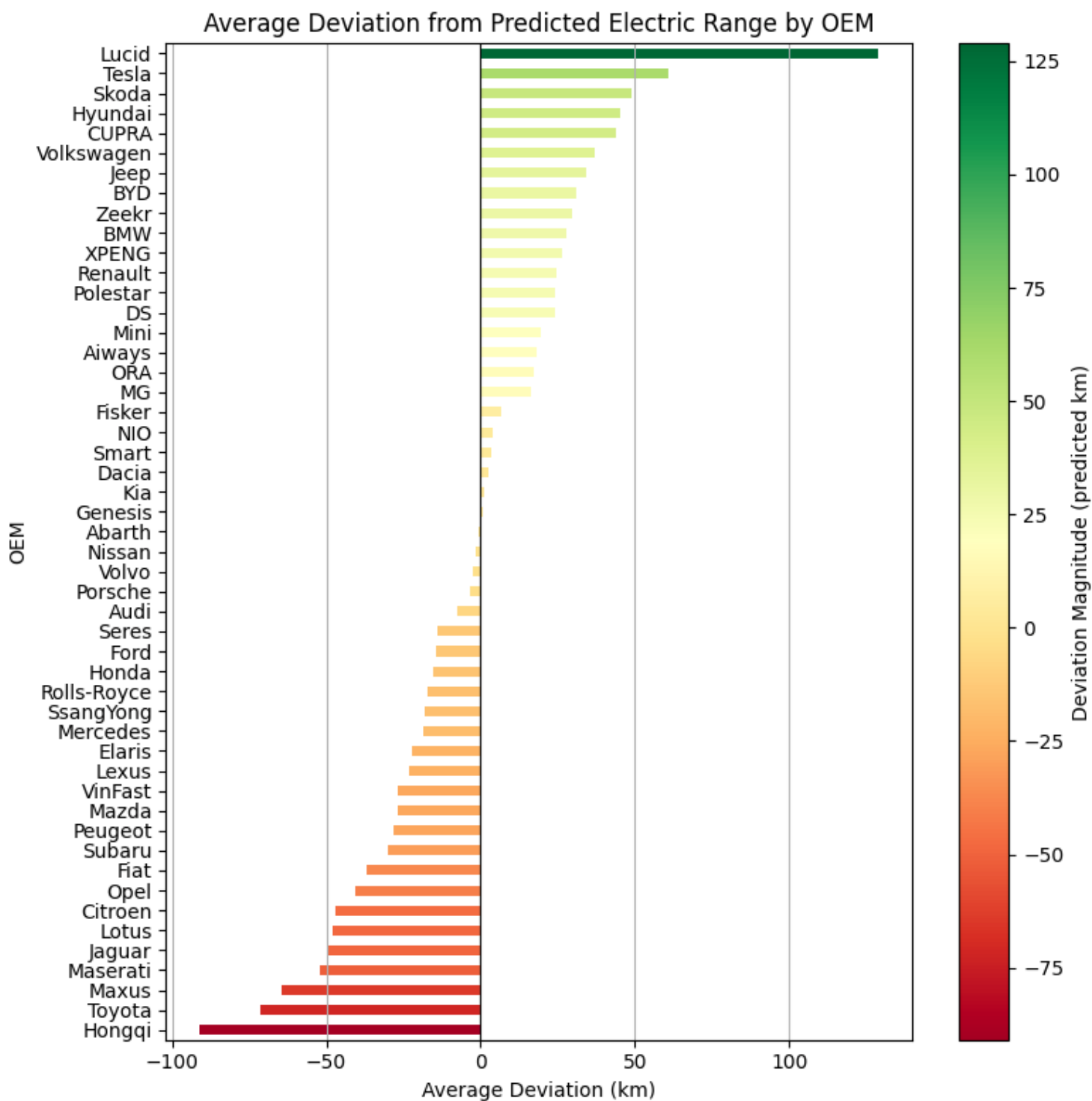


Figure 5.6.3: Average vehicle model deviation from the battery capacity mean

5.7 Frequent Architectures

In an attempt to understand which decisions are most frequent in current electric vehicles, we have conducted a frequency analysis based on modal architectures. We chose mode rather than the mean, as the choices represented in the morphological matrix presented in Section 3.9 are discrete. When considering the 365 vehicles represented, we used the encoded columns to calculate the mode of each decision in the dataset independently from one another. The result is represented in the following table, shown in Figure 5.7.1:

Decisions	Mode
Battery Cathode Material	NMC
Battery Nominal Voltage	400
Battery Number Of Cells	288
Battery Pack Configuration Parallel	2
Battery Pack Configuration Series	108
Charging Charge Power kW	11
Motor Placement	Both axles
Primary Front Motor Type	PMSM
Primary Rear Motor Type	PMSM
Secondary Rear Motor Type	None
Motors Qty	2
Motors Front Qty	1
Motors Rear Qty	1
Performance Drive	AWD

Figure 5.7.1: Most frequently represented decisions.

Figure 5.6.1 shows the most common independent architecture. It is primarily centered around a battery setup with a nominal voltage of 400 volts, which is typical for modern EVs aiming to balance efficiency with high energy

capacity. This architecture's battery uses Nickel Manganese Cobalt (NMC) as the cathode material is a popular choice due to its high energy density and relatively good thermal stability, which aligns with the industry's push towards extending range without compromising safety. The battery's configuration comprises 288 cells arranged in a combination of 2 parallel and 108 series connections. Note that these decisions don't exactly agree based on the fact that the modal analysis treats them independently. The use of a 400-volt system is particularly significant as it strikes a balance between charging speed and infrastructure compatibility. The most common onboard level 2 charging system is an 11 kW AC charger that allows for a moderate charging speed of 55 km per hour, making it feasible for both home and semi-public charging stations. On the motor front, the dataset highlights the use of dual Permanent Magnet Synchronous Motors (PMSMs), located both at the front and rear, indicative of an all-wheel-drive (AWD) setup.

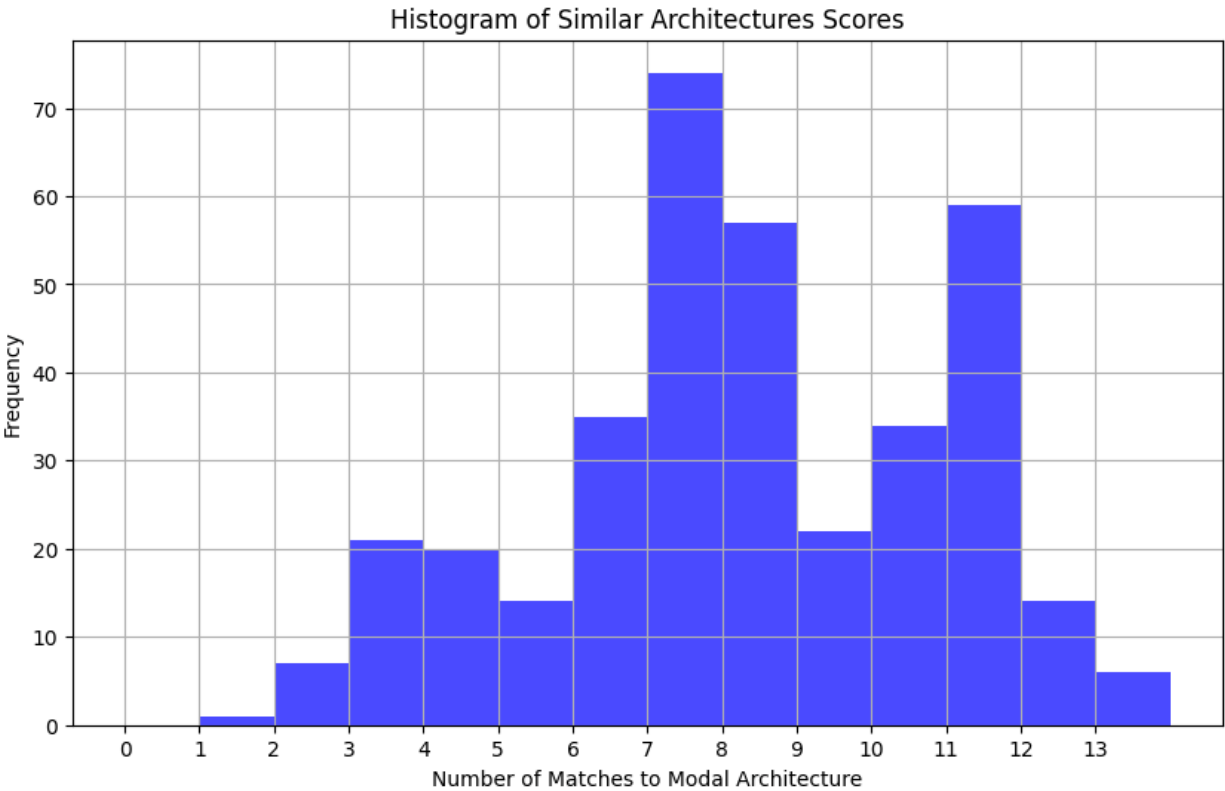


Figure 5.7.2: Distribution of vehicles with modal architectures

OEM	Model	Similarity
Mercedes	EQS 580 4MATIC	13
Mercedes	EQS 500 4MATIC	13
Polestar	2 Long Range Dual Motor	13
Mercedes	EQS SUV 580 4MATIC	13
Mercedes	EQS SUV 500 4MATIC	13
Volvo	XC40 Recharge Twin Motor	13
Polestar	3 Long Range Performance	12
BMW	i5 M60 xDrive Sedan	12
Tesla	Model S Dual Motor	12
Audi	Q8 e-tron Sportback 55 quattro	12
Mercedes	EQS AMG 53 4MATIC+	12
Audi	Q8 e-tron 55 quattro	12
Volvo	EX90 Twin Motor	12
Tesla	Model X Dual Motor	12
Polestar	3 Long Range Dual motor	12
Volvo	EX90 Twin Motor Performance	12
Audi	Q4 e-tron 55 quattro	12
Audi	Q4 e-tron 50 quattro	12
Audi	Q4 e-tron 45 quattro	12
Jaguar	I-Pace EV400	12
Porsche	Taycan 4S Plus Sport Turismo	11
Porsche	Taycan 4S Plus	11
Porsche	Taycan 4S Sport Turismo	11
Porsche	Taycan 4S Cross Turismo	11
Porsche	Taycan GTS Sport Turismo	11

OEM	Model	Similarity
Smart	#1 Brabus	3
Opel	Astra Sports Tourer Electric	3
Nissan	Ariya 87kWh	3
NIO	EL7 75 kWh	3
NIO	EL6 75 kWh	3
Renault	Megane E-Tech EV40 130hp	3
Renault	Megane E-Tech EV60 220hp	3
Mercedes	EQB 250+	3
Peugeot	e-3008 98 kWh Long Range	3
Skoda	Enyaq 85	3
Smart	#1 Pulse	3
Mercedes	eVito Tourer Long 90 kWh	3
Mercedes	EQV 300 Long	3
Toyota	PROACE Verso L 75 kWh	3
VinFast	VF 8 Eco Extended Range	3
Genesis	GV60 Premium	3
Honda	e Advance	3
Smart	#3	2
Rolls-Royce	Spectre	2
XPENG	G9 RWD Long Range	2
Renault	Kangoo E-Tech Electric	2
Mercedes	EQE 300	2
Opel	Corsa Electric 51 kWh	2
Smart	#1	2
Renault	Twingo Electric	1

Figure 5.7.3: Tables with the most (left) and least (right) common architectures. The higher the similarity score, the more modal architectural decisions are included.

Using the modal architecture, we ranked vehicles with the most and least number of modal architectural decisions present. In the table below (Figure 5.7.2), we see that the cars most aligned with the modal architecture are from leading automakers such as Volvo, Mercedes, Tesla, BMW, Polestar, and Ford and exhibit

several commonalities that reflect current trends and consumer preferences in the EV market. Predominantly, these vehicles feature all-wheel-drive (AWD) capabilities, facilitated either by dual motors or sophisticated drivetrain technologies. Most of these vehicles utilize high-performance components, such as large batteries, multiple motors, and higher voltage batteries with luxury features, indicating a target for the premium segment of the EV market. Models like the Tesla Model S Plaid and Mercedes EQS 580 4MATIC are designed to deliver greater speed and acceleration by using high-performance battery technology that offers substantial range and efficiency. In terms of battery and charging technology, these models are often equipped with high-voltage systems to support faster charging and longer range, aligning with the industry's push toward reducing electric range anxiety. The focus on expanding battery capacity and optimizing energy consumption reflects an industry-wide effort to make EVs more appealing and practical for a broader range of consumers, further driving the transition from traditional combustion engines to electric mobility solutions.

Vehicles that are the most divergent seem to differ for a variety of reasons. First, there are a number of vehicles that are considered niche, such as the Rolls Royce Specter, which is an ultra-luxury vehicle, and the Mercedes eVito Tourer Long, which is a 9-seater utility van. A significant number of the other vehicles in the least common architectures list have much shorter wheelbases than the common architectures. Vehicles like the Smart #1 (all variants) and #3 and Honda e Advance are extremely compact, which would explain differences in dimensions such as battery construction, number of motors, and motor placement. Notably, most of the vehicles on the least represented architecture list do not have a large market share, indicating that these vehicles are still nascent in design. Deviating from the modal architecture, however, does not directly imply negative performance. We interpret the architectures represented by the vehicles that deviate from the norm as an indicator that the BEV market is innovating and is not yet clearly dominated.

5.8 Main Effects of Architectural Decisions

In the previous sections, we have examined the relationship of one to two architectural decisions to the primary outcome variable, electric range, individually. However, one of the research objectives of this work is to quantify and rank each decision's sensitivity, i.e. how much changing a decision impacts the key metric, to range. Thus far, our research implies that battery capacity is the most impactful architectural decision for both range and acceleration performance. If this is the case, we are led to believe that there might be covariate effects in the dataset, in that higher ranges and better acceleration performance come in cars that have larger batteries, which also tend to be more expensive. To understand this, we created a visualization for each architectural sub-decision, shown in Figure 5.8.1 below, which graphs the relationship between individual decisions and the primary metric, range, independently. In the correlation matrix, though all decisions have some degree of sensitivity, their direct correlation with range is weak at best.

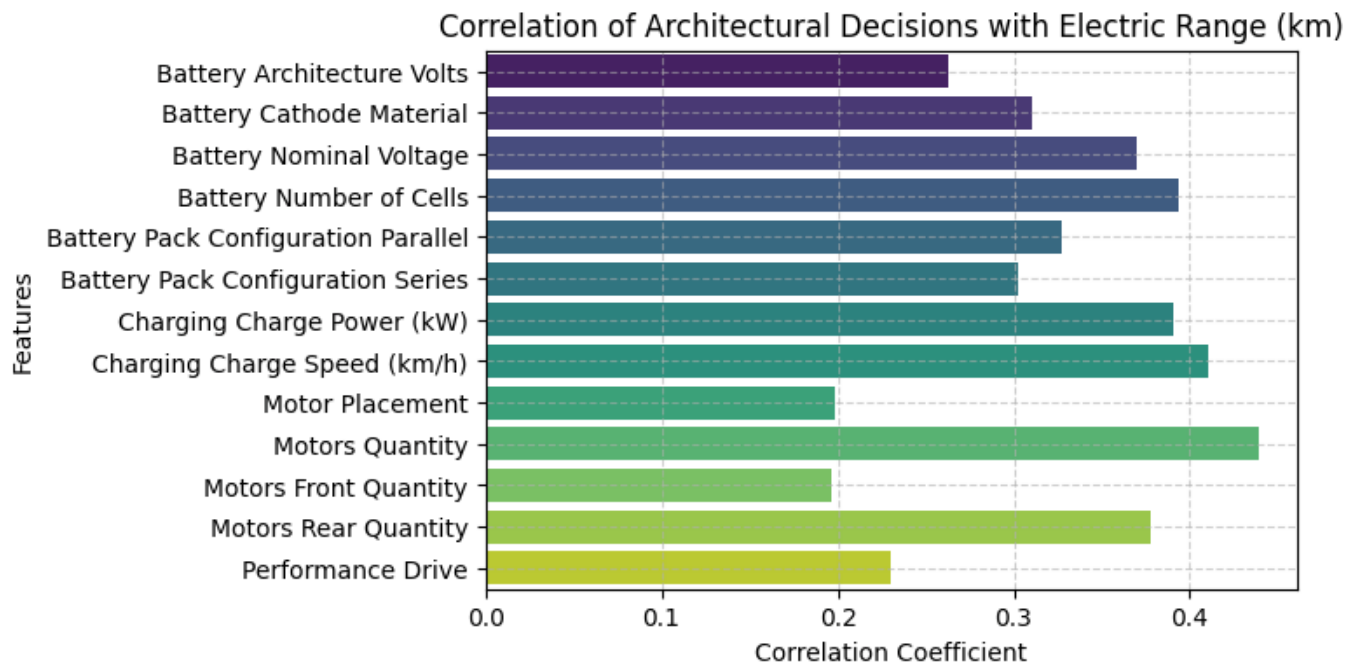


Figure 5.8.1: Correlation map of individual features against Range (km)

In order to understand the sensitivity of each architectural decision relative to others, we conducted and visualized a multivariate regression analysis in which a line is fitted based on the minimization of the Root Mean Square Error (RMSE). In this analysis, the x-axis represents the coefficient values associated with each feature, quantifying each decision's sensitivity, or how much the EV's range is expected to increase or decrease with a one-unit change, assuming other variables remain constant. In the linear regression model, the drive type (FWD, RWD, AWD) decision is the most impactful, which indicates that range is highly sensitive to which drive type is selected and where motors will be placed by proxy, as those decisions are highly connected (coupled). We also see effects on range by the choice of battery cathode material, although its impact is relatively milder compared to the adverse effects from the motor configuration. The model does not weigh the battery choices heavily relative to motor and drive choices; however, this is likely due to covariation, in that the battery capacity already captures the main effect on range, and battery number of cells, series, and parallel are connected decisions made after total battery sizing.

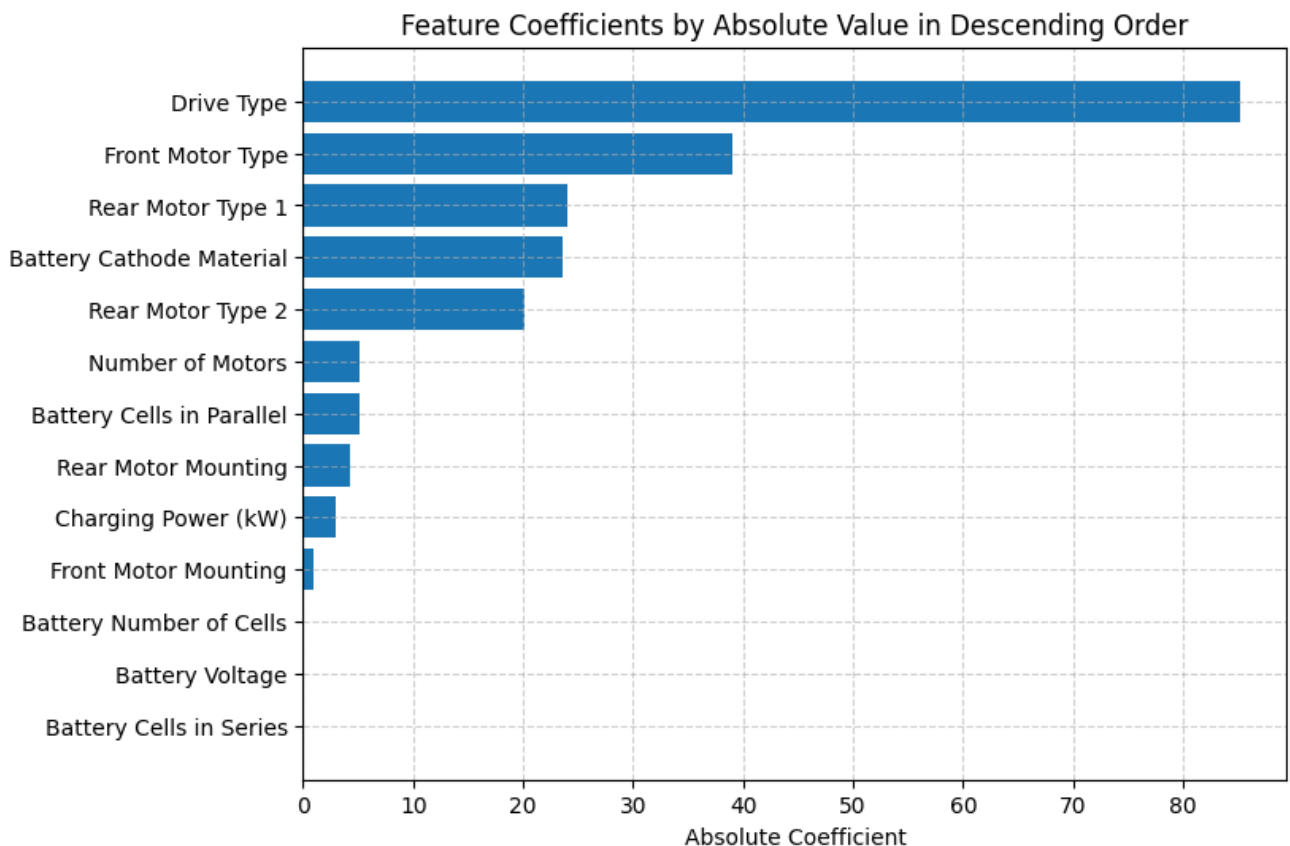


Figure 5.8.2: Main Effect Coefficients of Trained Linear Model

In order to account for the covariance we observed, as well as to capture a more accurate sensitivity weight from the data, we also trained a random forest model. Random Forest is a non-parametric, ensemble learning method that operates by constructing multiple decision trees during training time and outputting the average prediction of the individual trees. This model helps us account for outliers and can model complex non-linear (polynomial, logarithmic, etc) relationships, making it more flexible than linear regression. Shown in Figure 5.7.3 below is a weighted ranking of the features in the random forest regression. We see that the single most impactful decision once again is the drive type, as front-wheel drive heavily weighs the model and is mutually exclusive with rear wheel and all-wheel drive. The models differ significantly on the sensitivity of other decisions to range, as the random forest model weighs the charging speed and battery configuration decisions much more heavily than the cathode composition.

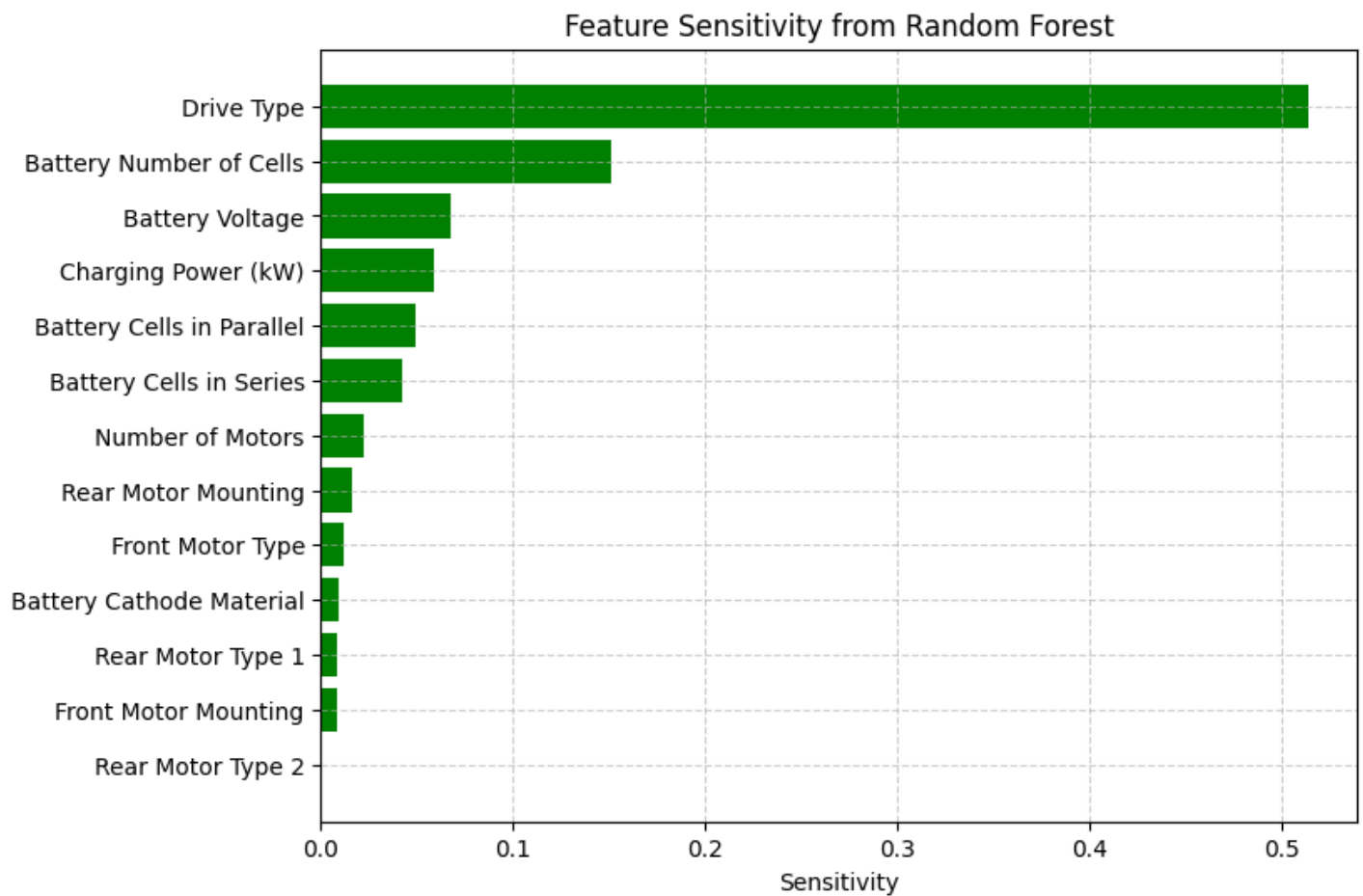


Figure 5.8.3: Weighted ranking of features in random forest model

Both the linear regression and random forest models heavily weigh the front wheel drive as the most predictive feature for range, which is to say that vehicles that are front-wheel driven strongly tend to have lower ranges than their rear-wheel or all-wheel driven counterparts. As mentioned, the models disagree, on the weight attributed to the number of battery cells in an architecture, battery voltage, wheelbase length, and charging speed, as well as others. Comparing the predictive performances of both models, we observe that the random forest model has a lower error (RMSE) and significantly less variance than the linear regression model, which is visualized in Figure 5.8.4. Given the covariance we alluded to at the beginning of this section, as well as the better performance of the random forest, we have ranked the sensitivity of each of the architectural decisions we discussed in previous chapters based solely on the results of the random forest model.

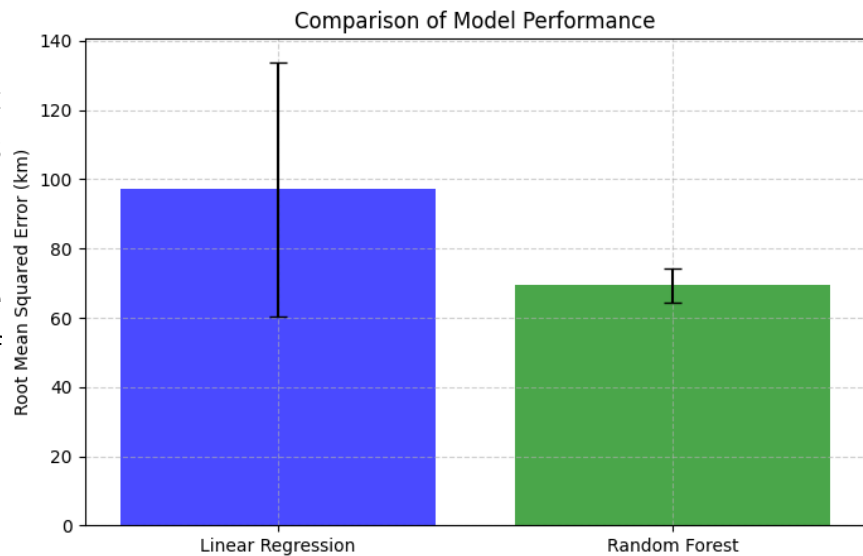


Figure 5.8.4: RMSE of each sensitivity model

The analysis of feature importance from the random forest model clearly indicates that certain architectural decisions play pivotal roles in determining the electric range of vehicles. We find that the single most impactful decision is the overall battery capacity, which we've discussed throughout this chapter. This is expected, as OEMs must first consider the general sizing of a battery based on the market niche they hope to fill with a proposed vehicle. Based on the result of our model, we rank drive type as the next sensitive decision, as this decision significantly impacts the overall range and constrains other decisions downstream, such as the number of motors and motor placement, which our analysis indicates are design decisions rather than architectural decisions. We find that other battery decisions, such as the choice of cathode material, number of cells, cells in series, cells in parallel, and voltage, are also design decisions that are to be made after the battery capacity is sized. This analysis is consistent with the decisions OEMs have

made, which are reflected in the data. In order to visualize the relationship between each decision's sensitivity, as provided by the model, and connectivity, which is a notional mapping of the decision's coupling, we provide Figure 5.8.5.

	Battery Pack Number of Cells	Battery Pack Cathode Composition	Battery Pack Voltage	Battery Pack Cell Series	Battery Pack Cell Parallel	Charging Power	Motor Placement Front	Motor Placement Rear	Number of Motors	Motor Type	Drive Type		Average
Battery Pack Number of Cells		2	2	3	3	3	1	1	1	1	1		1.8
Battery Pack Cathode Composition	2		2	2	2	3	1	1	1	1	1		1.6
Battery Pack Voltage	2	3		3	3	2	1	1	1	1	1		1.8
Battery Pack Cell Series	3	2	2		3	2	1	1	1	1	1		1.7
Battery Pack Cell Parallel	3	2	2	2		3	1	1	1	1	1		1.7
Charging Power	3	3	3	2	3		1	1	1	1	1		1.9
Motor Placement Front	1	1	1	1	1	1		1	3	3	3		1.6
Motor Placement Rear	1	1	1	1	1	1	1		3	3	3		1.6
Number of Motors	1	1	1	1	1	1	3	3		2	2		1.6
Motor Type	1	1	1	1	1	1	1	1	2		1		1.1
Drive Type	1	1	1	1	1	1	1	1	2	1			1.1
Average	1.8	1.7	1.6	1.7	1.9	1.8	1.2	1.2	1.6	1.5	1.5		

Figure 5.8.5: Connectivity Design Structure Matrix for each architectural and design decision

We constructed the design structure matrix (DSM) diagram shown in Figure 5.8.5 by interviewing experts involved in battery electric vehicle design. We recognize this mapping as notional; follow-up research should be conducted to build a formal model of connectivity between decisions. As shown in Figure 5.8.5, though the drive type decision is highly sensitive, it is not very connected. Charging power, on the other hand, is extremely connected but is not a sensitive decision.

This can be reasoned by stating that selecting a drive type can be done independently from most other decisions, including all decisions that pertain to the battery system. However, changing the charging power after the fact will likely necessitate changes to the battery voltage and structure (cells in parallel / series), which will force other upstream changes. This relationship can be visualized in Figure 5.8.6, where we show the decisions in quadrants representing their connectivity and sensitivity relationship. Note that the total battery capacity is not graphed due to its high colinearity (fitting vehicles with largely almost always increases range), but we assert that it is highly sensitive and strongly connected.

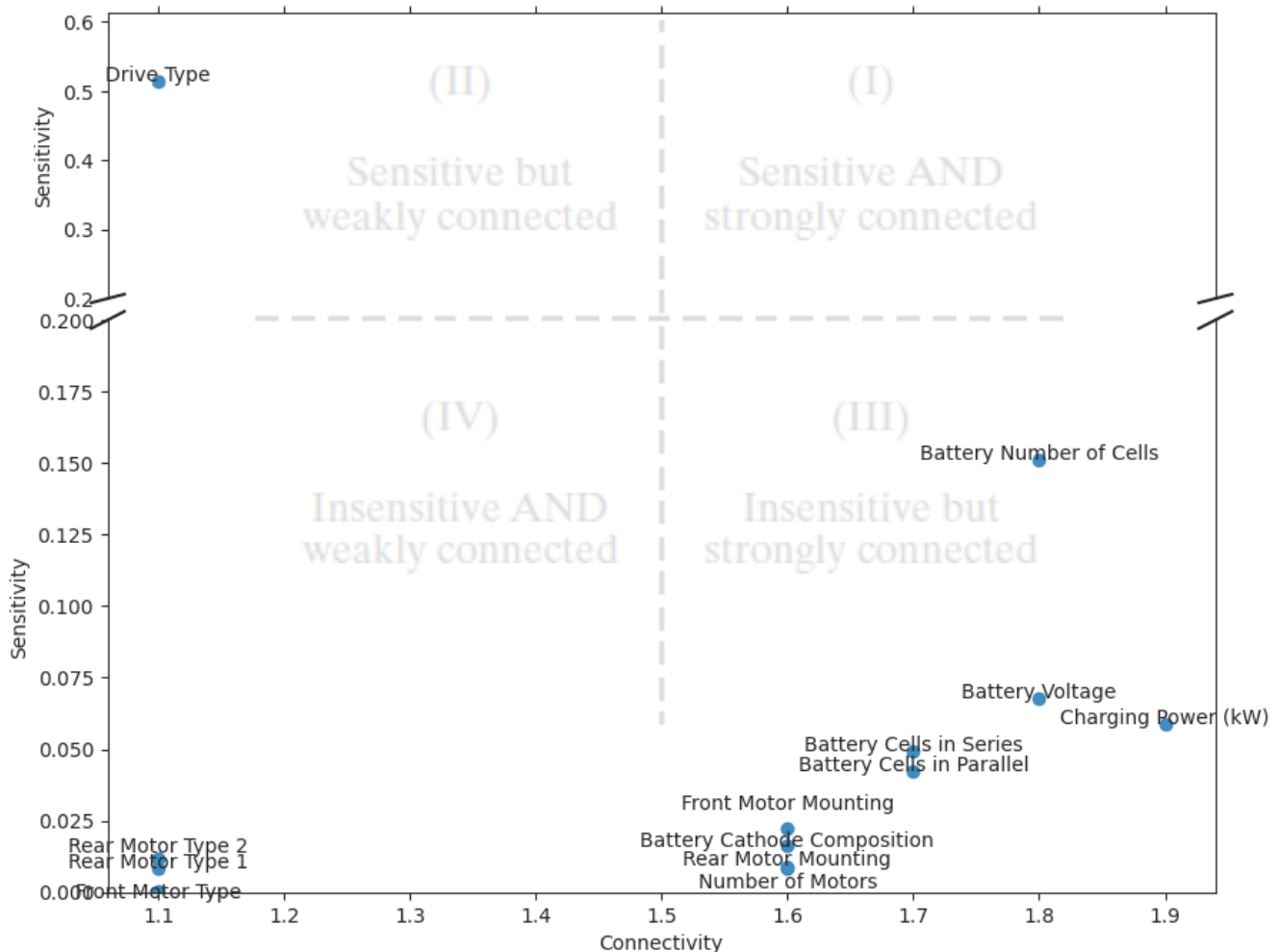


Figure 5.8.6: Connectivity vs Sensitivity, as dictated by the random forest model

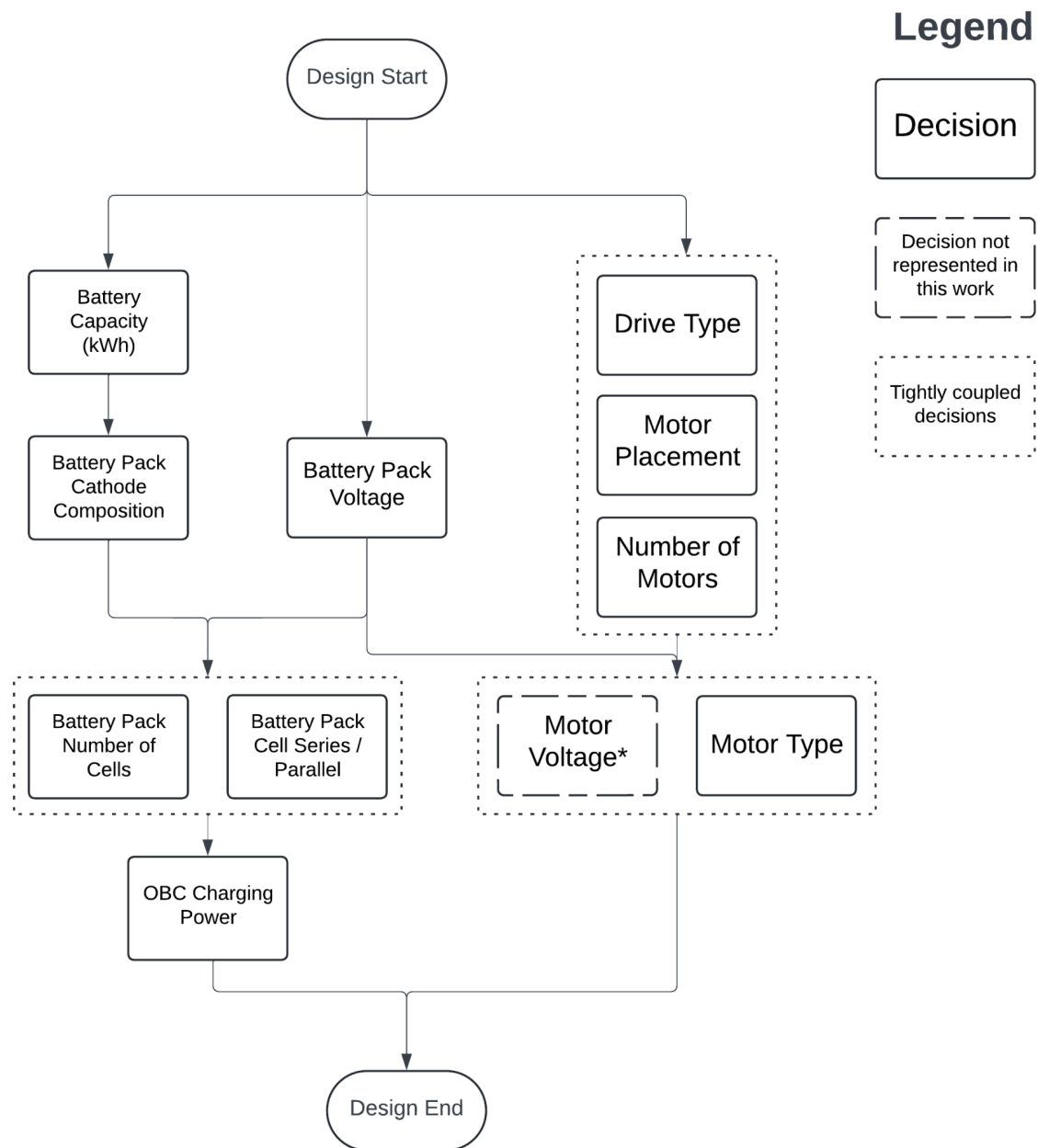
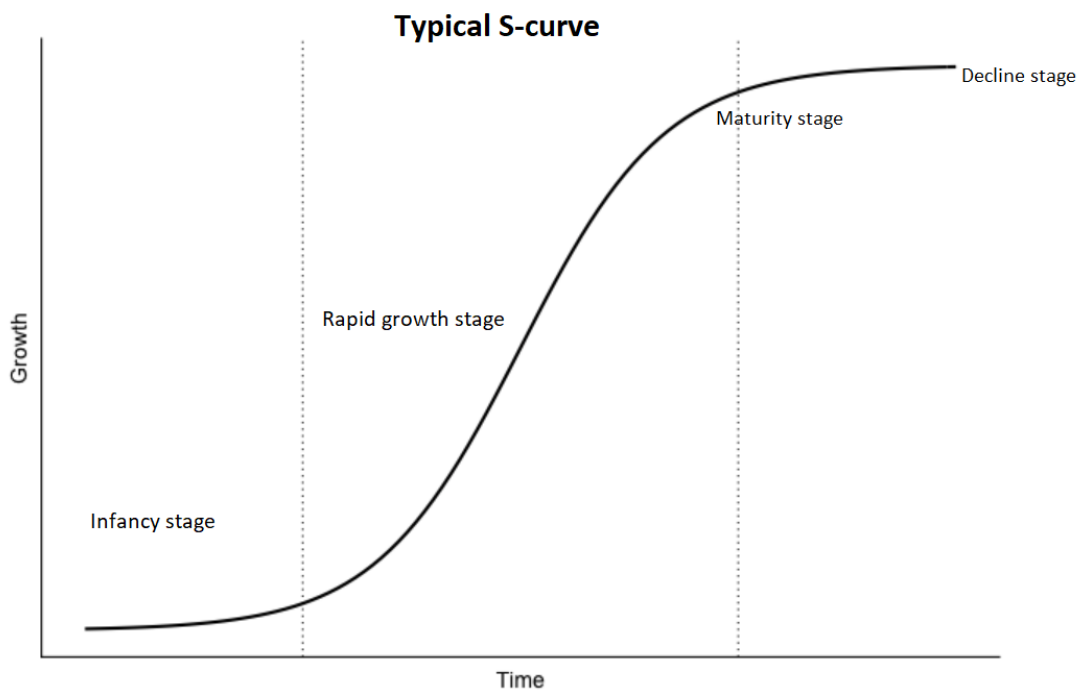


Figure 5.8.7: Connectivity for each architectural and design decision

To conclude our analysis, we present a notional diagram of architectural and design decision ordering that can be used to reason about BEV architecture planning. The parallel tracks indicate that decisions pertaining to the battery sizing and drive type can be done concurrently and without significant coupling. We notate strongly coupled decisions within a dashed border, as illustrated by the battery sizing decision being tightly coupled to the cathode composition as well as the operating voltage.

6 Discussion

6.1 BEVs on the S-Curve of Innovation



The S-curve of innovation, first introduced by Foster (1986) and then popularized by Christensen (1992), is a graphical representation (shown above) that depicts the life cycle of a new technology or product in the market. It is characterized by three distinct phases: introduction, growth, and maturity. In the introduction phase, the technology is newly developed and released into the market. This stage often sees slow growth as the product is initially adopted by a limited number of early adopters who are willing to experiment with new and untested technologies. These early adopters play a critical role, as their feedback can guide further development and refinement.

As the technology enters the growth phase, it begins to gain acceptance among a wider audience. This acceleration in adoption can be attributed to increased awareness and proven reliability of the technology, which reduces the

perceived risk for more conservative adopters. During this phase, the rate of adoption typically increases significantly, leading to rapid market expansion. The technology's features and benefits become more widely recognized, driving demand and encouraging competitive improvements and innovations.

The maturity phase marks the peak of the technology's market penetration. At this point, the majority of potential customers have adopted the technology, and the rate of new adoption begins to slow down. The market becomes saturated, and the focus of innovation shifts towards incremental improvements and differentiation from competitors. This phase is often characterized by fierce competition among established players, price reductions, and efforts to increase efficiency and maximize the value proposition to consumers. Eventually, the technology may enter a decline phase, which is sometimes considered an extension of the S curve. This occurs when a new, superior technology emerges, rendering the older technology obsolete, or when the market dynamics change significantly. Companies that wish to remain competitive must anticipate or react to these changes by innovating or adapting to newer technologies.

Battery Electric Vehicles (BEVs) have been navigating the S-curve of innovation since the late 1980s, evolving from niche prototypes to increasingly mainstream transportation options. Initially, BEVs entered the market in the introduction phase, where they were seen as novel but impractical solutions due to high costs, limited range, and sparse charging infrastructure. Early models like the GM EV1 and the original Tesla Roadster catered to a small segment of environmentally conscious consumers and technology enthusiasts who were less deterred by these limitations and more motivated by the novelty and environmental benefits of emission-free driving.

BEVs have experienced significant advancements in technology and increasing consumer acceptance over the last decade, which would indicate that they have experienced or are currently experiencing their growth phase. This surge is fueled by improvements in battery technology, which have dramatically increased the range of these vehicles and decreased their charging times. Simultaneously, the cost of batteries has dropped, making BEVs more affordable. Governments around the world have also played a crucial role by implementing policies that encourage BEV adoption through incentives like tax breaks, grants, and exemptions from

certain fees. Moreover, the expansion of charging infrastructure has addressed one of the most significant barriers to adoption, further accelerating growth. Companies like Tesla and Volkswagen, although in the latter's case somewhat unwillingly, have built extensive charging networks that lead to a broader acceptance and excitement around BEVs.

Currently, we believe that BEVs are moving towards the upper end of the growth phase and approaching the early stages of maturity in some markets. This is evidenced by Figure 5.7.2, in which current vehicles represent modal choices in architecture in a near-normal distribution, with a larger right tail. We believe that if BEVs were still in the growth phase, we would see less uniform conformity to any given modal decision. The number of available models has expanded across nearly all vehicle segments, from economy cars to luxury SUVs, indicating widespread industry investment. Consumer demand continues to grow as awareness of the environmental impacts of fossil fuels increases and as BEVs become integrated into corporate and governmental fleets. However, challenges such as raw material sourcing for batteries, the environmental impact of battery disposal, and the need for more renewable energy sources to power these vehicles loom large. These challenges must be addressed to ensure that BEVs can transition fully into the maturity phase and become the dominant form of personal and commercial transportation, aligning with global sustainability goals.

Moreover, we have yet to see the impact of new emergent functions of Battery Electric Vehicles. A minority of the vehicles in the dataset we built supported bi-directional charging, in which the vehicle can send power from its battery pack to a home or to the electrical grid. Doing so can help in emergency power loss situations locally and can also flatten load curves for electrical grids by supplying energy during peak hours while charging in off-peak hours. Strategically, the advent of bidirectional charging can propel BEVs toward the maturity phase faster by establishing them as essential components of smart grid and smart home technologies. As utilities and consumers alike recognize the benefits of integrated energy management, the demand for BEVs equipped might grow faster than their unidirectional charging counterparts.

6.2 Future of EV Marketplace

Though we believe that the Battery Electric Vehicle (BEV) market is rapidly maturing, we still see innovations that suggest the market isn't completely dominated. Companies are still experimenting, to some extent, with deviations from the architectural choices we enumerated in previous sections. For instance, Rivian is building commercially available vehicles with four motors, one on each wheel. Though Rivian did not meet the minimum sales threshold to be included in the dataset, we expect them to in the near future.

Other technologies, such as advanced driver-assistance systems (ADAS) and enhanced entertainment and connectivity features, are continuously evolving and pushing the boundaries of what BEVs can offer beyond simple transportation. These advancements not only improve the functionality and appeal of BEVs but also open up new niches within the automotive market, keeping the sector competitive. The transition from electric vehicles featuring driver assistance systems to full autonomy represents a significant technological leap within the automotive industry. Current advanced driver-assistance systems (ADAS), such as adaptive cruise control, lane-keeping assistance, and automatic braking, are foundational steps toward fully autonomous driving. These systems utilize a combination of sensors, cameras, and artificial intelligence to perform driving tasks, enhancing safety and convenience in current market vehicles. Though some of these technologies are available in Internal Combustion Engine (ICE) models, they are significantly more prevalent in BEVs.

Moreover, companies attempting to implement fully automated driving, such as Waymo, Zoox, and Tesla, exclusively use Battery Electric Vehicles as test mules. As ADAS technologies become more sophisticated, fully autonomous EVs shift from pipe dreams to reality. This potential future might shift the driving experience by removing the human from the driving process altogether. If humans are removed from behind the wheel, the current vehicle paradigm and the weights we place on the subsequent architectural decisions will likely change drastically, especially if the private ownership model of Battery Electric Vehicles is challenged.

7 Conclusion

Throughout this thesis, we explored the complexities of battery electric vehicle (BEV) architectures to determine if there is a dominant design that is emerging within the market. We first examined existing research to set the foundation for the design landscape of electric vehicles. In our literature review, we highlighted that a research gap exists for holistic evaluations of battery electric vehicle architectures. We further referenced existing research to inform the construction of our architectural decision list, as well as the tradeoffs of their sub-decisions. One of our main research contributions was the construction of a comprehensive BEV dataset for mass-sold current market Battery Electric Vehicles (BEVs). We then applied statistical techniques to analyze which of the architectural decisions we enumerated impacted electric range most significantly and combined it with the coupling analysis to provide heuristics for BEV architecture planning.

There are opportunities to expand this work. We recognize that collecting high-quality and reliable data was a challenge and that new vehicles are being introduced at a rapid rate globally. Our results are specific to the current market for battery-only electric vehicles. We expect the results to deviate as time passes between replication attempts. However, we do believe that our methodology can be reused in the future to inquire whether or not a dominant design for battery electric vehicles emerges at a future time. We also believe that the methodology can be expanded to include architectural decisions and data for hybrid electric vehicles. It would be interesting to see if the sensitivity we computed for each decision still holds in the presence of an internal combustion engine, though the primary outcome metric, electric range, might not be as desirable in PHEV contexts.

Moreover, as data becomes available for specific vehicle subsystems, we would like to explore how the data affects the construction of and reasoning about architectural decisions. Future studies might find that the list we based our analysis on is no longer a representative set of the major decisions that automakers face when constructing a battery electric vehicle, especially if the current driving paradigm of humans behind the wheel changes.

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Appendix

A1 List of Acronyms

BEV: Battery (only) Electric Vehicle

BoL: Beginning of Life

DSM: Design Structure Matrix

ECU: Electronic Control Unit

EoL: End of Life

ICE: Internal Combustion Engine

LFP: Lithium Iron Phosphate

LIB: Lithium Ion Battery

LMO: Lithium Manganese Oxide

NCA: Lithium Nickel Cobalt oxide

NMC: Nickel Manganese Cobalt oxide

OBC: On-Board (vehicle) Charger

OEM: Original Equipment Manufacturer

PHEV: Plugin Hybrid Electric Vehicle

SOC: State of Charge

SUV: Sports Utility Vehicle

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