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From Cell to Pack: Empirical Analysis of the Correlations Between Cell Properties and Battery Pack Characteristics of Electric Vehicles

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Abstract

Lithium-ion batteries are pivotal components in battery electric vehicles, significantly influencing vehicle design and performance. This study investigates the interactions between cell properties and battery pack characteristics through statistical correlation analysis of datasets derived from industry-leading benchmarking platforms. Findings indicate that energy densities are comparable across cell formats at the pack level. While NMC and NCA chemistries outperform LFP in energy density at both cell and pack levels, LFP's favorable cell-to-pack factors mitigate these differences. Analysis of cell properties suggests that increases in cell-level volumetric and gravimetric energy density result in proportionally smaller gains at the pack level due to the growing proportion of required passive components. The impact of cell chemistry and format on the z-dimension of a battery pack is analyzed in order to identify dependencies and influences between nominal cell properties and the geometry of the battery pack. The analysis suggests no significant influence of the used cell chemistry on the vertical dimension of a battery pack. The consideration of cell formats shows a dependency between the battery pack z-dimension and cell geometry, with prismatic cells reaching the highest pack heights and cylindrical cells being observed in packs of smaller vertical dimensions. The study also investigates the emerging sodium-ion battery technology and assesses pack-level energy densities derived from cell-level properties. The insights of this study contribute to the understanding of cell-to-pack relationships, guiding R&D toward improved energy storage solutions for electric vehicles.

Keywords: battery electric vehicles; batteries; energy storage; correlation analysis

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1. Introduction

Given the global energy transition, electrochemical energy storage systems are crucial in future mobility concepts [1]. One of the main drivers for this development is the significant contribution of the transportation sector to climate change. For instance, the transportation sector currently accounts for approximately 22% of total greenhouse gas emissions in Germany [2]. Therefore, reducing environmental impacts in this sector is particularly relevant for achieving climate protection goals [3]. Battery electric vehicles (BEVs) hereby offer a promising mobility alternative. When powered by electricity from renewable sources, they cause lower environmental impact over their lifecycle compared to vehicles with modern internal combustion engines [4].

Battery cells are of significant importance, accounting for approximately 60–80% of the total value creation in battery systems [5]. Cell parameters such as energy density and capacity significantly contribute to the performance and efficiency of the entire battery system and play a crucial role in developing battery pack concepts [6]. However, many interdependencies between battery cell selection and resulting pack characteristics remain insufficiently quantified. Consequently, numerous concepts for battery pack design exist, with no specific approach prevailing [7,8]. A deep understanding of the interactions between battery cell properties and the resulting battery pack characteristics is essential for optimizing the efficiency and practicability of future energy storage systems and advancing the energy transition.

This work is based on and extends a previous publication of ours [9] and aims to fully empirically analyze the fundamental relationships between battery cell properties and battery pack characteristics using a comprehensive database to identify interdependencies. This expanded version contains new, detailed analyses of the influence of cell format and chemistry on the z-dimension of the battery pack and its gravimetric and volumetric energy density. These significant additions, supported by new figures and a more detailed discussion, represent a considerable enhancement of the original work. We strive to contribute to the foundation for optimization strategies for future battery pack designs through a detailed analysis of the interactions between battery cells and packs. Therefore, a systematic literature review was conducted to establish the current state of the art regarding cell-to-pack relationships and to identify research gaps.

Research on the relationships between battery cells and packs is limited. Hettesheimer et al. [7] evaluated the development potential of different lithium iron phosphate (LFP) cell formats using multi-criteria analysis, considering volumetric energy density, cooling requirements, safety, and costs. Their findings indicate that cylindrical and pouch cells exhibit the highest volumetric energy densities at cell and module levels, a trend expected to continue through 2025. However, pack-level analysis was not included in their study. Schöberl et al. [10] provided essential insights into the relationships between cell chemistry and pack performance. While investigating thermal runaway in lithium-ion batteries (LIBs), they analyzed gravimetric and volumetric energy densities at cell and pack levels with the resulting pack factors. Their findings demonstrate that nickel cobalt manganese oxide (NMC) and nickel cobalt aluminum oxide (NCA) battery cells experience significantly higher energy density losses during pack integration than LFP cells. While systems with NMC and NCA cells maintain higher gravimetric energy densities than LFP systems, the volumetric energy density remains comparable across all systems, primarily due to reduced safety requirements for LFP cells in battery packs [10]. These findings highlight the complex interplay between cell chemistry, safety requirements, and overall pack performance. Löbberding et al. [11] examined the differences between gravimetric and volumetric energy density at the cell, module, and pack levels using boxplots and regression analyses to determine cell-to-pack factors. Their study reveals that despite cylindrical cells showing the highest energy density at the cell level, pack-level energy densities remain similar across all three variants. This is attributed to factors including cell volume and system boundary conditions. They suggest that cell chemistry, rather than format, primarily influences pack-level energy density variations, though detailed chemistry analysis was not part of their study scope [11].

While existing research provides data on individual cell and pack characteristics, including cell-to-pack factors for various vehicles and cell types, most analyses are based on limited datasets and focus only on specific aspects of cell-to-pack relationships. A systematic analysis across cell formats, chemistries, and their influence on pack-level characteristics remains unexplored. This work addresses this gap by analyzing cell-to-pack relationships through statistical methods based on a comprehensive empirical dataset of contemporary electric vehicles.

2. Methodology

The methodology is structured as shown in Figure 1. Initially, the structure of the empirical database that forms the analysis's foundation is described. Subsequently, the analysis of nominal and metric battery cell properties and their impact on pack characteristics is presented. Finally, an outlook on sodium-ion battery (SIB) technology's implications for battery pack characteristics is provided within the scope of the study. This study employs box-whisker plots and linear regression analysis to visualize data distributions and reveal correlations between battery cells and packs.

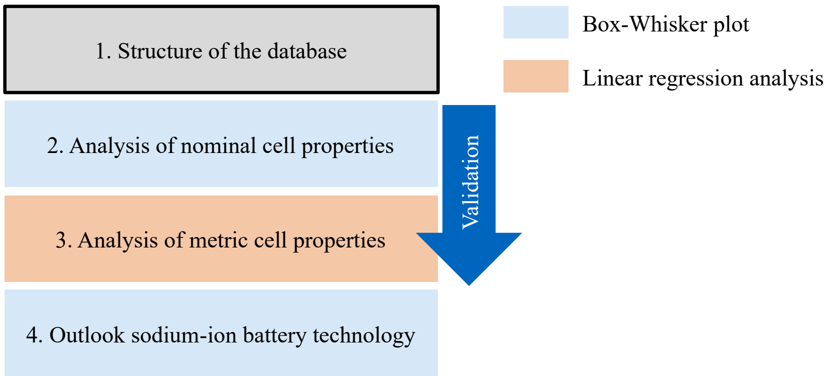


Figure 1. Structure of the methodology.

A comprehensive database of state of the art BEVs is required to perform the study. The database was designed to be sufficiently large to approximate a normal distribution of the investigated battery properties. Data was collected from prominent electric vehicle benchmarking platforms, including the benchmark platform A2MAC1 [12], focusing exclusively on current electric vehicle models to ensure technical comparability of the analysis results and to avoid inconsistencies. The database comprises 145 vehicle models launched between 2020 and 2024, with 17 distinct variables extracted for analysis. Since obtaining all variables for every vehicle in the database was not possible, and analyzing relationships between variables requires the respective cell- and pack-level characteristics, only a subset of the complete dataset can be used for each specific analysis. It is important to note that this data sample is intended to be representative of the state of the art in BEVs recently introduced in global markets, as captured by leading benchmarking platforms, and should not be understood as a comprehensive collection of all BEVs. Nevertheless, the database enables statistical analysis based on a substantial dataset and is therefore suitable for achieving the research objectives of this work.

To conduct the statistical analysis based on the compiled dataset, relevant cell properties are systematically compared and combined with pack characteristics. Figure 2 illustrates these properties and characteristics and categorizes them into nominal and metric variables. The nominal variables comprise cell format and cell chemistry. In contrast, the metric variables include the cell energy densities and properties such as the battery cell's mass, volume, and energy content.

Figure 2 also shows the battery pack characteristics as metric variables. These include energy densities, cell-to-pack factors, and metrics addressing passive components. The cell-to-pack factor is a key metric used throughout this study to quantify the packaging efficiency of the battery system [13]. It is defined for both gravimetric and volumetric properties. The gravimetric cell-to-pack factor is the ratio of the total mass of all cells to the total mass of the battery pack. The volumetric cell-to-pack factor is correspondingly defined as the ratio of the total volume of all cells to the total volume of the battery pack. The passive components' mass fractions directly influence energy densities and pack factors, making them essential for interpreting differences in these metrics. While an analysis of passive components' volume fractions would be valuable for identifying volumetric effects, this was not feasible due to missing volume data in the current database. All analyses conducted within this study are derived from cell properties and pack characteristics combinations for nominal and metric variables. Since this work focuses on the influence of battery cell properties on pack characteristics, cell properties are consistently handled as independent variables. In contrast, pack properties are shown as dependent variables.

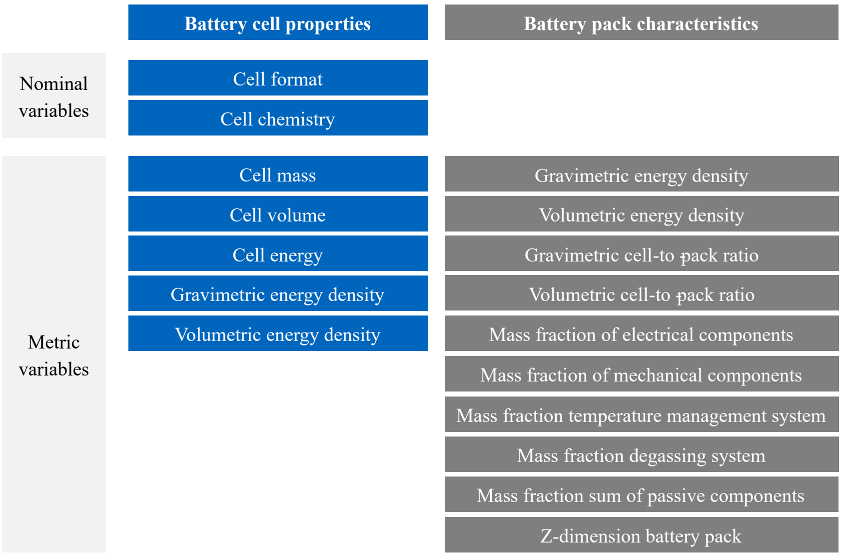


Figure 2. Classification of the analyzed battery cell properties and battery pack characteristics.

The effects of nominal cell properties on battery pack characteristics are analyzed using box-whisker plots. These plots provide statistical representations of the pack energy densities, pack factors, and mass fractions for different cell formats and chemistries. The resulting box-whisker plots reveal the comparative strengths and weaknesses of various cell formats and chemistries. The evaluation is conducted visually and through statistical measures in the box plots. The interpretation focuses on relative comparisons between cell formats and chemistries, explicitly examining the datasets' medians, quartiles, whiskers, and ranges.

The influence of metric cell properties on battery pack characteristics is investigated using linear regression analyses. This analysis focuses on identifying the direction and strength of relationships to determine correlations relevant to the study's research objectives. Key statistical measures include the Pearson correlation coefficient r and sample size n. According to Völkl and Korb [14], r quantifies the strength and direction of linear relationships between variables. The coefficient is normalized for sample size and units of measurement, resulting in values bounded between -1 and $+1$. Values near ± 1 indicate strong correlations, while values approaching 0 suggest weak or no linear correlation. Correlations are classified as strong ($|r| \geq 0.7$), moderate ($0.5 \leq |r| < 0.7$), or weak ($|r| < 0.5$) [15]. A positive coefficient indicates variables increasing together, while a negative coefficient implies an inverse relationship.

The evaluation of correlations is based on both the correlation coefficient classification and statistical completeness. Visual assessment of diagrams and data points is essential, as r alone may be misleading for non-linear relationships. While correlations are evaluated against threshold values for r and n, the assessment is not bound to rigid criteria. Despite small sample sizes, this approach prevents the categorical exclusion of relationships with good correlation properties. Such flexibility in evaluation is significant, given the uneven distribution of cell properties in the database. Each result is individually assessed for significance, considering both n and r. Combining box plots and linear regression analyses yields 108 analysis plots, necessitating a structured evaluation approach.

The validation is based on data from [10,11,16]. This data includes gravimetric and volumetric energy densities at the pack level in relation to their respective cells, as well as corresponding cell-to-pack factors. This information is used to validate the value ranges and trends identified in both nominal and metric analyses. Care is taken to ensure that validation vehicles are not already included in the database to avoid circular references and subsequent false validation of results.

It is crucial that throughout the analysis, the distinction between module-to-pack (MtP) and cell-to-pack (CtP) [17] battery pack architectures is used as an important explanatory variable for interpreting the observed trends, as this design decision fundamentally influences the properties at the pack level.

Estimation of SIB pack characteristics is based on the analysis results and literature values, starting with cell-level properties of SIBs derived from an extensive literature review. Both current and long-term expectations for gravimetric and volumetric energy density are derived alongside long-term expected values for the considered LIBs. Pack characteristics for SIBs are then calculated using appropriate pack factors. Building on this, a prediction of energy density ranges for current and long-term expected SIB packs is conducted, including a comparison to the considered LIB packs.

3. Results

The following section presents the statistical analysis results based on the empirical database. The results are organized into three sections. The first section examines the effects of nominal cell properties on battery pack characteristics. Subsequently, the metric relationships between battery cells and packs are analyzed. The final section derives insights for SIB packs from these findings. Given the extensive number of analyses, only the most relevant findings from each section are discussed and interpreted. All results not presented in this paper are available upon request.

3.1. Results of the Nominal Analysis

The analysis of nominal variables focuses explicitly on the gravimetric and volumetric battery pack energy densities and corresponding cell-to-pack factors, as these metrics provide the highest information content and are supported by the most extensive available dataset. Figure 3 illustrates the nominal analysis examining the cell format's influence on volumetric battery pack energy density and cell-to-pack factor.

Regarding volumetric energy density, battery packs with cylindrical cells range from 150–280 Wh/L, pouch cells from 110–305 Wh/L, and prismatic cells from 140–290 Wh/L. The corresponding median values are located near the center of these ranges. While pouch cells can achieve the highest volumetric energy densities at the pack level, they exhibit lower average values than cylindrical and prismatic cells.

A detailed examination of the analyzed vehicles within the database reveals that cylindrical and pouch cells predominantly employ a MtP architecture. This architectural choice necessitates additional components, such as module housings and module contacts, leading to unutilized volume at the pack level. The modules' thermal management and volumetric efficiency vary significantly between cell formats. Due to geometric constraints, cylindrical cells inherently result in the highest dead volume within modules. Meanwhile, pouch cells achieve better volumetric utilization within modules than cylindrical cells.

However, unlike hard-case cells with integrated structural stability, they often require increased module wall thickness as well as additional components within the modules to meet the additional mechanical requirements. In contrast, prismatic cells with a LFP chemistry in the database predominantly utilize CtP designs, where cells are directly integrated into the battery pack rather than MtP architectures. This approach vastly reduces the overall number and size of passive components while maximizing packing efficiency. Consequently, prismatic cells show the best performance regarding the volumetric pack factor, while pouch and cylindrical cells yield lower packaging efficiencies. Prismatic cells' superior volumetric cell-to-pack factor can also be traced to their ability to be better stacked within the given battery pack space. This relationship does not result in better volumetric energy density at the pack level because prismatic cells generally have lower volumetric energy densities at the cell level due to the significant structural void spaces inherent to this cell type.

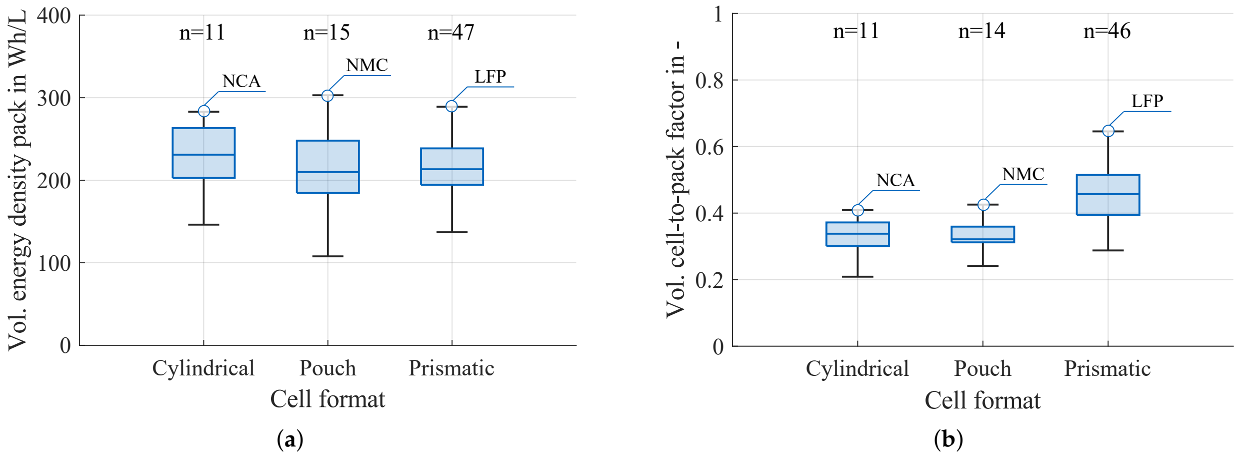


Figure 3. Nominal analysis of cell formats on: (**a**) pack volumetric energy density and (**b**) volumetric cell-to-pack factor. The chemistry of the cells with the highest values is indicated.

Figure 4 illustrates the nominal analysis examining the influence of cell chemistry on gravimetric energy density and cell-to-pack factor. For the gravimetric energy density, battery packs with LFP cells range from 125–145 Wh/kg, NCA cells from 150–174 Wh/kg, and NMC cells from 140–180 Wh/kg. While the median values for LFP and NMC cells are located near the center of their ranges, the median for NCA cells lies directly below the upper whisker and, thus, above the medians of LFP and NMC cells. Consequently, NCA cells achieve the highest gravimetric energy density at the pack level, followed by NMC and LFP cells. Compared to the volumetric energy densities in Figure 3, the variations between cell chemistries are less pronounced, with only NMC cells exhibiting larger spreads.

Among the chemistries examined, NMC shows the highest variation in the gravimetric cell-to-pack factor, while LFP cells demonstrate significantly higher cell-to-pack factors compared to both NCA and NMC. Unlike NMC and NCA cells predominantly used in MtP concepts, many vehicles with LFP cells utilize CtP concepts, significantly reducing the mass proportion of passive components and increasing the gravimetric cell-to-pack factor. LFP vehicles are almost exclusively purpose-built BEVs, enabling optimal storage architectures dominated by flat storage designs. In contrast, NMC and NCA cell vehicles include purpose-built and conversion BEVs, often resulting in complex storage geometries that necessitate additional passive components, leading to increased weight and reduced cell-to-pack factors.

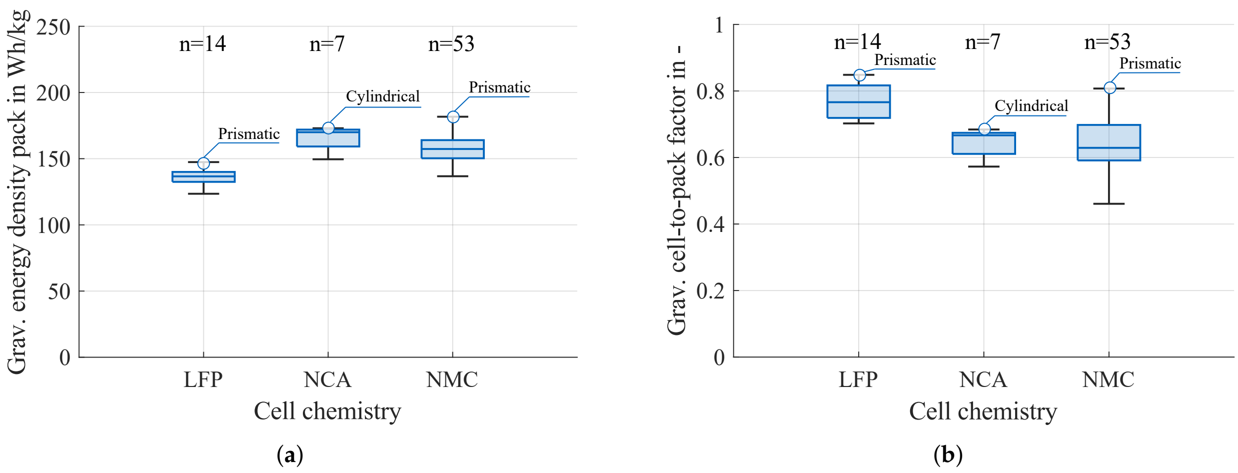
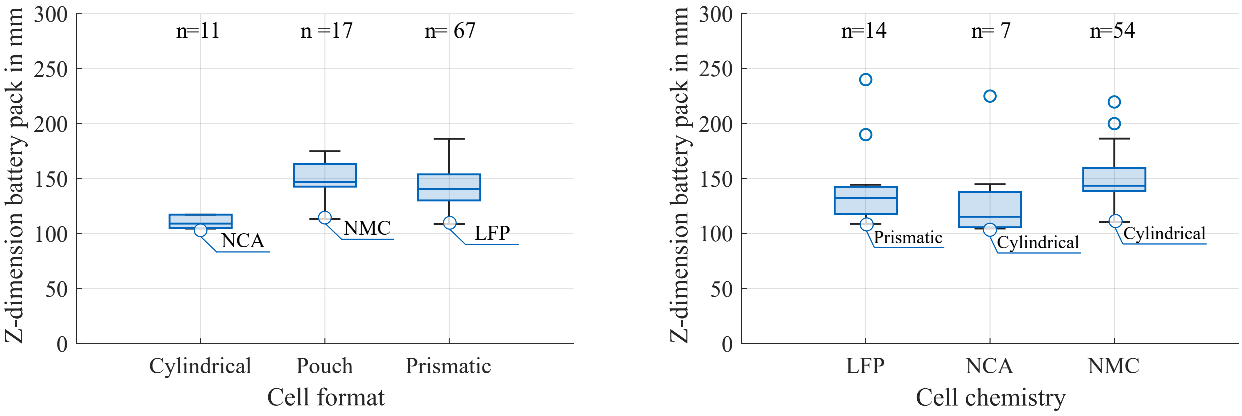


Figure 4. Nominal analysis of cell chemistries on: (**a**) pack gravimetric energy density and (**b**) gravimetric cell-to-pack factor. The format of the cells with the highest values is indicated.

At the pack level, NMC and NCA cells achieve higher gravimetric energy densities due to their superior energy density at the cell level. However, these differences are substantially reduced compared to cell-level ratios, as LFP cells show distinct advantages in pack integration. They achieve notably better pack factors since the mass proportions of electrical and mechanical components in the battery pack are significantly lower than in packs with NMC or NCA cells. The spreads in the gravimetric cell-to-pack factor are more pronounced, which can be attributed to the various cell integration approaches in the pack. Additionally, the pack integration efficiency is significantly better in the gravimetric case compared to the volumetric case shown in Figure 3.

Additionally, within the nominal analysis, an investigation of the relationship between battery pack z-dimension, cell format, and cell chemistry was conducted. This investigation is motivated by the significant influence of the height of battery packs on the design of electric vehicles. The height of the battery pack restricts the vehicle's package, plays a key role in the design of the passenger compartment, and has a direct impact on the overall height of the vehicle, affecting characteristics such as the center of gravity and aerodynamics [18,19]. In order to further analyze the mentioned correlations and to ensure the comparability of the battery packs, the vertical dimensions were determined based on their unique topology. Many of the vehicles considered in this study use battery packs with a complex geometry consisting of intrusions serving as a foot-garage or extruded areas meant to house additional battery modules or passive components. In order to overcome the challenges related to the topological differences between packs, the investigated heights were defined at points without any in- or extrusions. In effect, every battery pack was, from this point on, considered a flat storage high-voltage battery, ensuring the comparability of the data points.

Figure 5 uses box plots to depict the height ranges for battery packs with respect to the used cell formats (a) and chemistries (b). The investigated battery packs show in (a) a range of 105–117 mm height for packs using cylindrical cells, with the median lying close to the lower bound. For pouch cells, the battery packs' heights range from 113–175 mm, with the median close to the middle of the range. Finally, a greater range of height values can be determined for battery packs using prismatic cells, with the values starting at 109 mm and ending at 190 mm, with a median in the lower half of the range.



(**a**) (**b**)

Figure 5. Nominal analysis of the battery pack z-dimension based on (**a**) cell format and (**b**) cell chemistry. The chemistry or format of the cells with the lowest values is indicated.

The presented box plots reveal that the investigated heights in battery packs that use cylindrical cells are significantly smaller than in packs using pouch or prismatic cells. A closer examination of the data shows that those battery packs primarily use the MtP concept and deploy cells of smaller heights, compared to CtP architectures, which predominantly use prismatic cells in this data. The apparent linkage between cell and pack heights and the fact that vertical stacking of the modules is not observed in the considered vehicles with cylindrical cells further explains the results.

Prismatic cells show the biggest range of values for battery pack heights. They also show the highest number of data points in the considered data and are applied in different vehicles across segments, explaining the high range in pack height values. Furthermore, the data show the deployment of prismatic cells in both MtP and the CtP concepts. The main prerogative of the CtP approach is to maximize cell-to-pack factors, increasing the packing efficiency [17,20]. The lack of modules in CtP approaches further amplifies the influence of the cells' vertical dimension on the pack's height. At this point, the linkage between cell height and pack height can be seen once more, with the data showing increased pack heights when larger (vertically speaking) cells are being used (in both MtP and CtP architectures). Nevertheless, the median height values for pack heights in battery packs using prismatic cells appear in the lower half of the range. This is caused by the number of applications using smaller-sized cells, which can be explained by the high variability in cell sizes and vehicle dimensions across the considered battery packs with prismatic cells.

When investigating pouch cells, the first important observation is the location of the median. Pouch cells show similar median values to prismatic cells. The reason for this can be traced to the cell design itself, which shows many similarities with prismatic cells except for the lack of a metal casing [21]. The absence of a hard case necessitates the use of the MtP architecture, in which the modules must fulfill additional requirements to ensure the mechanical stability of the cells [22]. The issues regarding pouch cells' mechanical stability and their dependency on additional components within the battery pack could act as a restriction on the cell dimensions. This may explain the battery pack's lower maximum heights. Furthermore, a detailed data analysis revealed that vertical stacking of cells is only used in one of the vehicles examined. All others show a horizontal stacking approach, meaning the long edges of the pouch cells point upwards (in z-direction). Therefore, a linkage between cell dimensions and pack heights can be identified, similar to both cylindrical and prismatic cells.

The investigation of the relation between cell chemistry and battery pack height shown in Figure 5b results in LFP cells achieving a height range of 109–240 mm with a median at about 140 mm. NCA cells range from 105–225 mm, with a median at 115 mm, and NMC cells from 110–220 mm, with a median at about 145 mm.

While investigating the results of the shown box-whisker plots, it appears that for all considered chemistries, the values of height ranges are similar, except for the slightly higher range of heights for LFP cells. A detailed data review revealed that the depicted values for LFP cells belong exclusively to vehicles using prismatic cells and are mainly applied in CtP designs. When considering the top value, the data analysis shows that it belongs to a vehicle using prismartic cells in a CtP architecture with an additional row of cells stacked on top in the form of an MtP approach, while still retaining the topology of a flat battery pack. The mentioned vehicle's characteristics and the exclusive use of LFP in prismatic formats instantly explain the box-whisker plot.

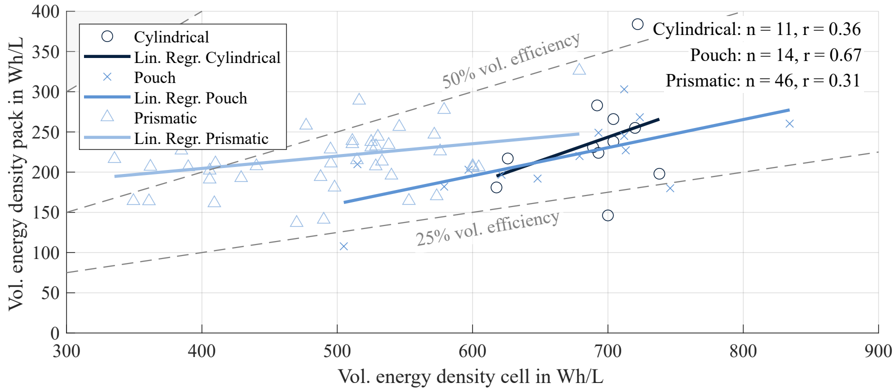
The similarity in height ranges can be observed with the consideration of outliers in the depicted box-whisker plot. The presence and location of those outliers concludes that no explicit dependency between cell chemistry and pack z-dimension can be seen, in contrast to the consideration of cell formats. Therefore, the considered data does not suggest any restrictions on pack heights due to the choice of cell chemistry.

The results reveal that the cell geometry influences the battery packs' z-dimension. Therefore, a dependency between cell format and pack height can be identified. However, when considering the cell chemistry, the dependencies appear less significant, with further data analysis revealing underlying geometric dependencies, which in turn point to the mentioned interdependence between cell format and battery pack height.

3.2. Results of the Metric Analysis

Figure 6 depicts the impact of changes in cell-level volumetric energy density on pack-level volumetric energy density and cell-to-pack factor according to the cell formats. Analysis reveals that increasing cell-level energy density leads to higher volumetric energy density at the pack level across all cell formats, with battery packs using cylindrical cells showing the most pronounced response to cell-level energy density changes.

Pouch cells demonstrate the most substantial interdependencies with a moderate correlation coefficient of 0.67, while cylindrical and prismatic cells show only weak correlations. The volumetric cell-to-pack factor decreases for prismatic cells with a moderate correlation coefficient of -0.56. In contrast, no clear correlation can be established for cylindrical and pouch cells due to significant data scatter and weak correlations. Prismatic cells exhibit the lowest volumetric energy densities at the cell level, while pouch cells achieve the highest volumetric energy density at both cell and pack levels. Notably, prismatic cells demonstrate superior volumetric cell-to-pack factors compared to pouch and cylindrical cells, primarily due to their rectangular hard-case housing that minimizes unused space in the battery pack. When analyzing vehicles by energy density, prismatic cells with lower energy density are predominantly used in CtP concepts, while higher energy density cells tend toward MtP architectures. In contrast, cylindrical and pouch cells are particularly used in modular designs and typically employ higher energy density cathode materials like NMC and NCA. The observed decline in pack factors for prismatic cells can be attributed to increased proportions of passive components, particularly the additional mechanical structures required to ensure safety in the usage of high energy density cells. Furthermore, the relationship may not be strictly linear. Potential threshold effects of passive components could lead to nonlinear relationships. Investigating these complex dynamics would be valuable for future research with larger datasets.



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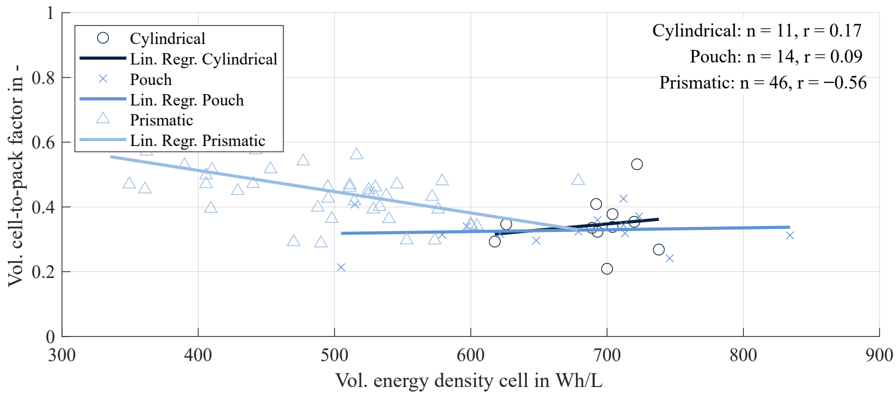


(**b**)

Figure 6. Impact of cell volumetric energy density on pack characteristics for different cell formats: (**a**) pack volumetric energy density and (**b**) volumetric cell-to-pack factor.

Figure 7 illustrates the relationship between the grav. energy density of cells and battery packs concerning the used cell format and the dependency of the energy density on cell level and the grav. cell-to-pack factor.

The correlations in (a) show a positive dependency between both investigated properties. However, a strong correlation can only be observed for pouch cells. In contrast, both prismatic and cylindrical cells show a moderate correlation between the energy densities of the cell and pack. Nevertheless, a general tendency for all cell formats can be observed: when a cell's gravimetric energy density increases, the pack's energy density increases simultaneously.

The correlation coefficient of pouch cells and the relatively steep angle of the regression line may be caused by the cells' lack of a hard case. The increase in the cells' grav. energy density appears to impact the energy density on the pack level more directly than in the case of cells with metal housings. However, using pouch cells necessitates deploying the MtP architecture, as the module must implement measures to ensure mechanical stability and stop thermal propagation [22]. This explains why pouch cells display a lower overall grav. energy density at the pack level, compared to other formats.

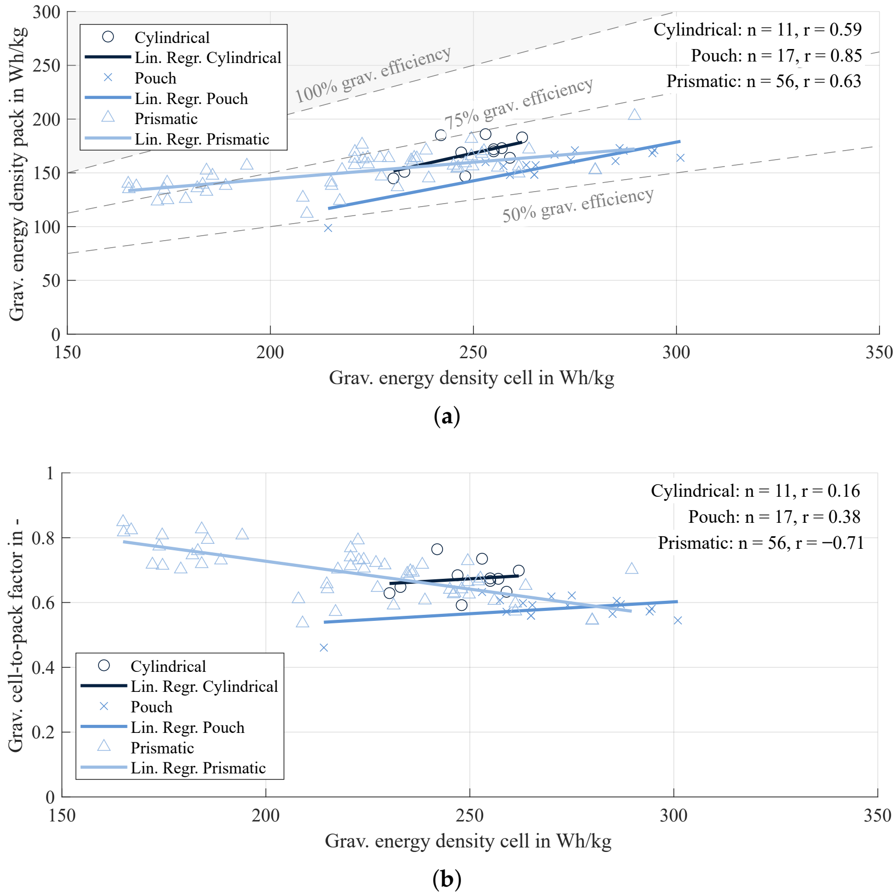


Figure 7. Impact of cell gravimetric energy density on pack characteristics for different cell formats: (**a**) pack gravimetric energy density and (**b**) gravimetric cell-to-pack factor.

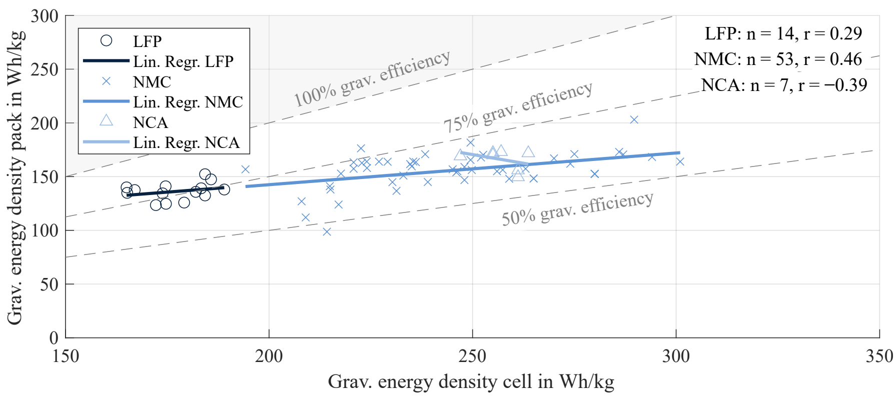
When considering the results for prismatic cells, the angle of the regression line is notably smaller than that of the other two cell designs, depicting a slower growing trend between the considered energy densities. The reason for this may lie in the cell chemistry. The LFP cells considered in this study are primarily prismatic cells. LFP cells show lower gravimetric cell energy density and, therefore, can be seen on the left end of the regression line. However, the same cells are often used in CtP battery packs, which reduces the number of passive components and increases the packs' energy density relative to MtP approaches. Therefore, compensation of the lower energy content of LFP due to the CtP architecture can be observed [17,20]. An opposite effect can be seen on the other side of the regression line. NMC and NCA cells show higher grav. energy density than LFP, but in this data, they are mainly used in MtP battery packs. The cells' high energy density is negatively affected by the pack's design, as well as the increasing need for safety measures, which leads to a reduced energy density on the pack level compared to a CtP approach. Both these effects can contribute to a slower-growing trend depicted by the regression line. The described dependencies can be further confirmed by looking at the lines for prismatic and cylindrical cells. Both formats utilize mainly NCA and NMC, two chemistries with similar thermal properties [23]. The lines for cylindrical and pouch cells are parallel and represent battery packs using mainly MtP designs and with similar safety requirements due to the used chemistries.

The mentioned dependencies can also be observed in (b), where the diagram depicts the relationship between the grav. energy density on the cell level and the grav. cell-to-pack factor, considering different cell formats. The regression analysis results show a positive but weak correlation for cylindrical and pouch cells, with correlation coefficients $r = 0.16$

for cylindrical and $r = 0.38$ for pouch cells. Prismatic cells show a strong and negative correlation with a correlation coefficient $r = -0.71$. The opposite direction of the regression line for prismatic cells compared to the other formats can again be explained by the different approaches in designing the pack architecture and the chosen cell chemistry. Similarly to the previous figure, on the left side of the regression line for prismatic cells, LFP cells are positioned. Due to the high number of CtP applications, the data leads to high grav. cell-to-pack factors. On the other end, NMC or NCA cells are positioned, which are mainly deployed in packs using MtP designs and need additional safety measures, leading to lower grav. cell-to-pack factors. This leads to the depicted trend, showing that for prismatic cells, an increase in grav. energy density results in a decrease in grav. cell-to-pack factors.

The data for both cylindrical and pouch cells mainly consists of NCA and NMC cells, which are typically applied in MtP battery packs. Due to mostly the same architectural approaches and similar properties of both chemistries, nearly parallel regression lines, and the positive, however weak, correlation between energy density and grav. cell-to-pack factor can be observed [23].

Figure 8 illustrates the impact of changes in cell-level gravimetric energy density on pack-level gravimetric energy density and the gravimetric cell-to-pack factor for the investigated cell chemistries. Notable differences in cell-level energy densities are evident among the three cell chemistries compared. NMC cells show the broadest spectrum of cell energy density, including the highest cell and pack gravimetric energy densities. In contrast, LFP cells exhibit the lowest energy density values on the cell and pack levels. NCA cells rank in the upper mid-range for gravimetric energy density at the cell level and in the upper range at the pack level.



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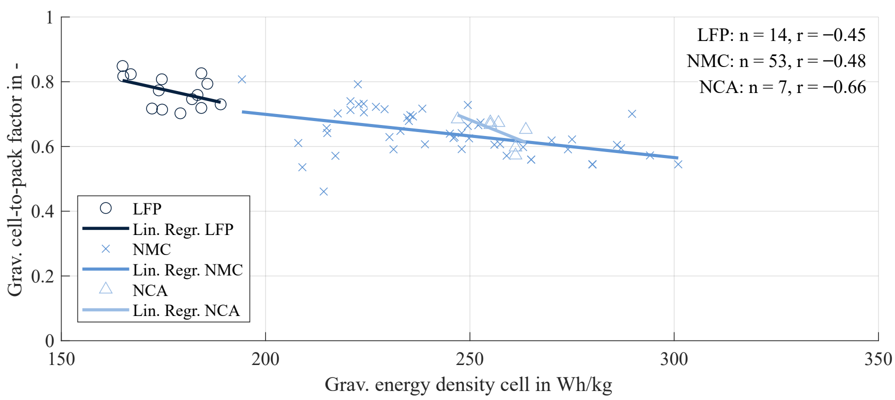

(**b**)

Figure 8. Impact of cell gravimetric energy density on pack characteristics for different cell chemistries: (**a**) pack gravimetric energy density and (**b**) gravimetric cell-to-pack factor.

Due to the scattering of values, the correlation coefficients for all cell chemistries are below 0.5, indicating weak correlations. The correlations are more pronounced for cell-to-pack factors, with LFP and NMC showing correlation coefficients just above −0.50, while NCA exhibits a moderate correlation coefficient of −0.66. Linear regression analysis reveals that an increase in cell-level gravimetric energy density leads to higher pack-level energy density, with one notable exception considering NCA cells, which negatively correlate with pack-level gravimetric energy density. This anomaly may be attributed to the limited statistical significance due to the small sample size of NCA cells. Despite the general increase in pack-level energy density, cell-to-pack factors decrease with increasing energy density across all cell chemistries. LFP demonstrates the best cell-to-pack factors among all cell chemistries, primarily due to the prevalent use of CtP approaches, as discussed in the previous section. In contrast, NCA and NMC show similar, lower cell-to-pack factors, which can be attributed to their predominant use in MtP architectures with higher energy-density cells. The decline in cell-to-pack factors for all cell chemistries can be attributed to the growing proportion of passive components required as cell-level energy density increases.

Figure 9 shows the regression analysis results for different cell chemistries between vol. energy density of cells and the vol. energy density on the pack level, as well as its influence on the vol. cell-to-pack factor. In subfigure (a), all analyzed battery packs show a positive correlation between the energy densities of the cell and the pack, however, with different intensities. The highest Pearson correlation coefficient and therefore the strongest correlation can be observed for NCA cells. LFP cells are slightly below the margin for a moderate correlation and therefore achieve, alongside NMC cells, only a weak correlation. Further analysis of the figures reveals that LFP cells achieve the highest vol. efficiency, whereas both NMC and NCA lie below 50 %, with some NMC data points even showing an efficiency below 25 %. A detailed data review reveals the dominating number of LFP cell applications in CtP battery pack architectures. This and the fact that all considered LFP battery packs use prismatic cells explain the high vol. efficiency values for LFP-based battery packs. In the considered data, NMC and NCA are predominantly used in MtP approaches, which explains their lower vol. efficiencies compared to LFP. Furthermore, as mentioned, the LFP cells considered in this study are mainly prismatic, whereas NMC cells are also deployed in cylindrical and pouch formats. In the analysed data, NCA cells use cylindrical and prismatic formats. The geometry of cylindrical cells leads to reduced package efficiency [24]. In addition, pouch cells require a more robust module design to ensure the cells' mechanical stability and an increased amount of passive components [22]. The dominant use of MtP approaches, the differences in cell formats, and additional passive components cause the decreased vol. efficiency of NMC and NCA relative to LFP cells.

The results in (b) show a weak and negative correlation for LFP cells with a correlation coefficient of $r = -0.05$ between the cells' vol. energy density and the vol. cell-to-pack factor. A stronger correlation can be observed for both NCA and NMC, with a moderate correlation coefficient for NMC. When looking at all depicted LFP datapoints and the result of the regression analysis, no clear trend between the vol. cell-to-pack factor and the vol. energy density on the cell level can be identified. However, LFP shows significantly higher efficiencies than NMC and NCA due to the high number of battery packs with the CtP approach. A different behavior can be observed for NMC cells, where an increased vol. energy density leads to decreased vol. cell-to-pack factors. NMC cells, due to their increased energy density, compared to LFP, require additional passive components to ensure propagation stop measures and an efficient and robust thermal management [10]. The primary use of NMC cells in MtP concepts further amplifies this effect. NCA shows a slightly different behavior than NMC, which, in the case of the results considered, could be explained by the smaller number of data points available for NCA cells and should not necessarily be further analysed.

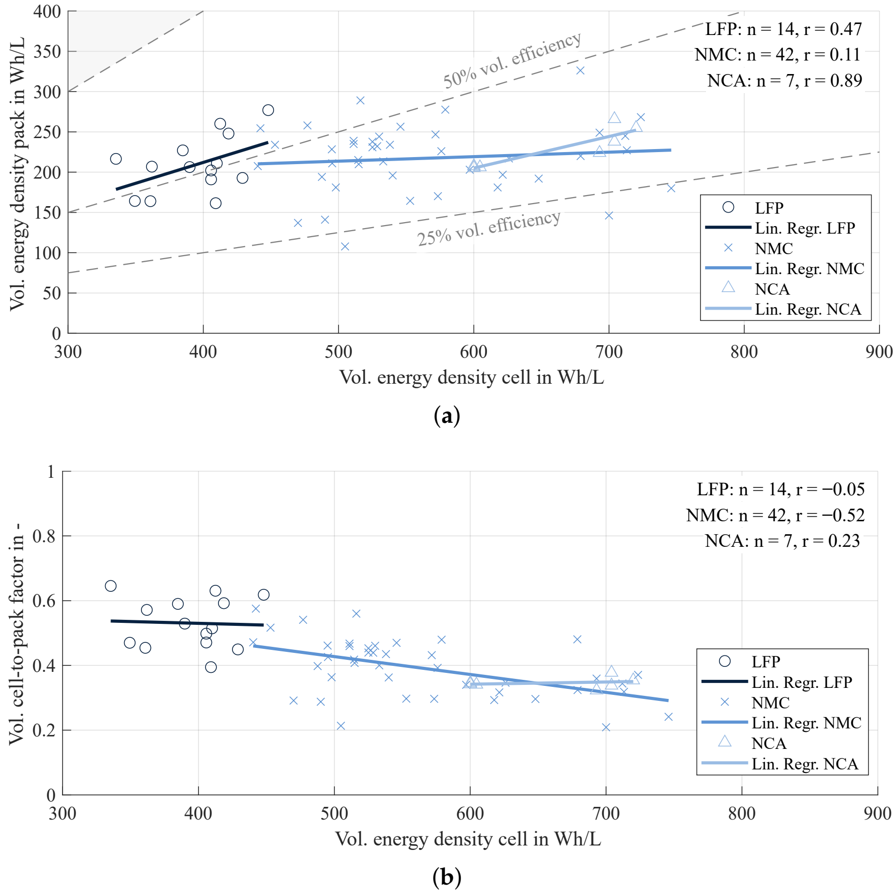

Figure 9. Impact of cell volumetric energy density on pack characteristics for different cell chemistries: (**a**) pack volumetric energy density and (**b**) volumetric cell-to-pack factor.

3.3. Outlook Sodium-Ion Battery Technology

Based on the interdependencies between the battery cells and packs of LIBs presented thus far, the following section aims to provide an outlook on current and future developments of the gravimetric and volumetric energy density of LIBs and SIBs at the battery pack level. This requires determining a cell-to-pack factor for SIBs, which can be used to estimate pack-level characteristics from cell-level properties. It is important to note in advance that BEVs with SIBs have not yet been commercially introduced, so no direct data is available at the pack level. The following analysis is therefore based on an estimate of pack-level characteristics derived from cell-level characteristics reported in the literature. The reliability of these forecasts depends directly on the validity of the cell-to-pack factors applied, which in turn are estimated based on similarities with LFP technology, as explained below. Table 1 presents the current gravimetric and volumetric energy densities of LFP, NMC, and NCA cells and their corresponding cell-to-pack factors. Additionally, gravimetric and volumetric energy densities for SIBs were derived from a comprehensive literature review. Long-term projections for cell-level energy densities are also presented to assess future implications for all cell chemistries.

Table 1. Current and long-term expected cell energy densities and cell-to-pack factors for LIBs and SIBs.

	Unit		LFP	NMC	NCA	SIB
Grav. cell energy density	Wh/kg	Current:	165–190	195–300	250–265	140–160 [25–31]
		Expected:	200–250 [25]	300–400 [25]	300–400 [25]	180–220 [25,27–29,31–34]
Vol. cell energy density	Wh/L	Current:	340–450	440–750	600–720	290–350 [25,28,35]
		Expected:	500–550 [25]	750–1000 [25]	750–1000 [36]	380–500 [25,28,34]
Grav. cell-to-pack factor	-		0.77	0.63	0.67	0.77 [1]
Vol. cell-to-pack factor	-		0.52	0.40	0.34	0.52 [1]

[1] Theoretically estimated based on Mei et al. [37], Kim [38] and Rudola et al. [39].

The comparison of LIBs and SIBs regarding pack properties can be based on either cell formats or cell chemistries. Since SIBs utilize the same cell formats as LIBs and primarily differ in chemical composition, the comparison in this study focuses solely on cell chemistries [40]. The gravimetric and volumetric cell-to-pack factors for SIBs can only be estimated theoretically based on the literature. These estimations are based on Mei et al. [37], Kim [38] and Rudola et al. [39], demonstrating that SIBs exhibit thermal stability characteristics similar to LFP cells, suggesting that SIBs can employ a battery pack design with a cell-to-pack ratio comparable to an LFP system — consequently, the same cell-to-pack factors as LFP were applied for SIBs.

Figure 10 compares current pack-level energy densities between LIBs and SIBs, along with future projections. The results indicate that energy densities of battery packs with SIBs are situated at the lower boundary of LIB pack energy densities, given the assumption of similar pack factors. Considering expected cell-level developments, the analysis reveals that SIB packs can achieve energy density levels comparable to current lower and mid-range LIB packs, reaching up to 150 Wh/kg and 200 Wh/L.

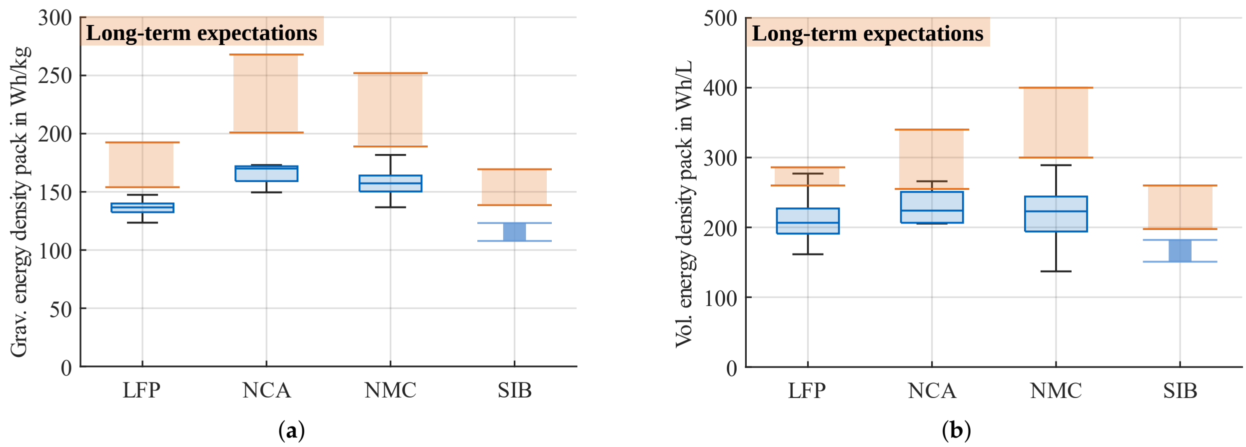

Figure 10. Comparison of the current energy densities at pack level of LIBs and SIBs and long-term expectations. (**a**) Gravimetric energy density at the pack level. (**b**) Volumetric energy density at the pack level.

4. Discussion and Outlook

This study investigates the interactions between cell properties and battery pack characteristics through statistical analysis of empirical datasets derived from industry-leading benchmarking platforms. This comprehensive analysis contributes to the ongoing discourse on battery design optimization and offers a robust methodology for evaluating cell-to-pack relationships. By addressing critical trade-offs in energy density, pack factors, and passive component integration, the study provides a valuable resource for researchers in energy storage systems.

The database's large number of cells and packs provides a good starting point for a comprehensive statistical analysis of the interactions between battery cell properties and pack characteristics and enables detailed component analyses. A limitation of the database is its incompleteness. The presence of missing values in the database reduces the number of properties and characteristics that can be used for the analysis. This applies particularly to detailed component analyses, where the limited database restricts a complete interpretation of the results.

The two main nominal properties of battery cells, the cell format and the cell chemistry, were examined for their effects on various battery pack characteristics using box-whisker plots. The focus of the evaluation is on the comparison of statistical parameters such as medians, quartiles, and value ranges. This method is well-suited for the analysis as it provides a quick and intuitive overview of the statistical properties of the respective data sets. However, interpreting results based on small amounts of data is more difficult. This is because statistical measures can be influenced by a small amount of data and therefore distorted.

The influence of metric cell properties on the characteristics of the battery pack is analyzed as part of the study using linear regression. Linear regression analysis is well-suited for identifying correlations, as it is based on a simple calculation logic. It enables a statement about the strength and direction of a correlation. One advantage of the method is that it can also be used for smaller data sets, although this requires individual consideration of the respective data set. A disadvantage of linear regression is that it assumes a linear relationship between the variables. Although linear regression analysis is suitable for identifying first-order correlations, it does not capture potential nonlinear relationships. Future work should employ more advanced analytical methods to investigate these complex interactions more deeply.

SIBs are considered a promising alternative to LIBs in automotive applications. So far, however, data for SIBs is almost exclusively available at the cell level and not at the pack level. Based on the knowledge gained in this work on LIB packs, value ranges for their properties at the pack level are derived from the known cell properties of SIBs. These are then compared with LIBs, and the future development expectations of both technologies are presented. This approach allows an initial realistic estimation of SIB packs' energy densities and packing factors. In the future, more in-depth studies on using SIBs in vehicle battery packs could further refine this analysis.

The following key findings on the interactions between the properties of the cell and the characteristics of the battery pack can be concluded from this study:

- Analysis of nominal cell characteristics suggests that volumetric energy densities at the pack level exhibit comparable values across all cell formats. The results indicate that this comparable behavior of cell formats is attributed to pack factors being higher for prismatic cells than cylindrical and pouch cells. Regarding cell chemistries, NMC and NCA cells show higher gravimetric energy densities than LFP cells at both cell and pack levels. However, these differences at the pack level are reduced due to the advantageous pack factors of LFP cells. The analysis of battery pack z-dimensions suggests no significant influence of the used cell chemistry on the vertical dimensions of a battery pack; however, it shows the linkage between pack height and cell format. The highest z-dimension values are observed in packs using prismatic cells, whereas cylindrical cells are used in battery packs of smaller heights.
- Analysis of metric cell characteristics indicate that increases in volumetric and gravimetric cell-level energy density lead to proportionally smaller increases in corresponding pack-level energy density. This effect is particularly pronounced in prismatic cells, where the volumetric cell-to-pack factor significantly decreases with increasing

volumetric cell energy density. A similar trend is observed in the progression of the gravimetric cell-to-pack factor for NMC and LFP cells. These correlations can be attributed to the growing proportion of passive components required as cell-level energy density increases. Furthermore, cells with lower energy density are predominantly implemented in CtP architectures, with the database showing this approach is primarily represented by vehicles using prismatic LFP cells. This architectural choice results in superior cell-to-pack factors for this specific cell format and chemistry combination in gravimetric and volumetric terms.

- The outlook for SIBs shows that, due to the lack of pack factors for SIBs, these can only be estimated based on pack factors of LFP cells. This approach is justified by the similar thermal characteristics exhibited by sodium-ion and LFP cells. Results indicate that SIBs position themselves at the lower boundary of LIB energy densities at both cell and pack levels. As both technologies are expected to advance, similar relative performance levels are projected for the long term.

A key limitation of this study is the dataset size for specific subgroups. While the overall database of 145 vehicles is extensive, the sample sizes for vehicles with cylindrical and pouch cells are relatively small. This is an inherent challenge in this area of research due to the proprietary nature of BEV data. Therefore, while our results provide valuable and insightful trends, they should not be interpreted as universal principles for the entire industry. The statistical significance for these subgroups is limited, and the results should be considered a preliminary analysis that requires further validation as more data becomes publicly available. Another limitation of this study is the lack of detailed volume fractions for individual passive components. While this does not affect the validity of our main volumetric analyses, it does prevent a more detailed investigation of the specific contributions of these subsystems.

Expanding the database with additional data points is recommended for future research to increase data coverage, alongside enhanced analytical methods for identifying non-linear relationships. Developing a specialized neural network is proposed as one approach for analyzing these non-linear correlations. Additionally, as commercial SIBs become available on the market, the analysis should be extended to include SIB data to verify or adjust their positioning within the current findings. Furthermore, future work on SIBs should include sensitivity scenarios for the cell-to-pack factor assumption to better understand the range of potential outcomes at the pack level under different integration scenarios. All results of this paper are available upon request.

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Abbreviations

The following abbreviations are used in this manuscript:

BEV	Battery electric vehicle
NMC	Nickel cobalt manganese oxide
NCA	nickel cobalt aluminum oxide
LFP	lithium iron phosphate
SIB	Sodium-ion battery
LIB	Lithium-ion battery
MtP	Module-to-pack
CtP	Cell-to-pack

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