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Correlation Analysis of Battery Capacity, Range, and Charging Time in Electric Vehicles Using Pearson Correlation and MATLAB Regression

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Abstract

The increasing adoption of electric vehicles (EVs) reflects growing global awareness of climate change and air pollution challenges. As a sustainable alternative to conventional internal combustion vehicles, EVs produce zero tailpipe emissions and can significantly reduce carbon emissions—particularly when powered by renewable energy sources. However, one of the primary barriers to widespread EV adoption remains the high cost of battery components, which are essential to vehicle performance and energy storage. In Indonesia, two dominant battery types used in EVs are Lithium Ferro Phosphate (LFP) and Nickel Manganese Cobalt (NMC), each offering distinct advantages. LFP batteries are recognized for their thermal stability and longer life cycles, making them suitable for everyday use, while NMC batteries offer higher energy density and are preferred for performance-focused and long-distance applications. This study aims to evaluate the correlation between battery capacity, driving range, and charging time for LFP and NMC batteries using Pearson correlation and regression analysis through MATLAB simulation. The results indicate a strong and statistically significant correlation among the key parameters, with a Pearson coefficient of 0.576 for battery capacity and range, and an R-square value of 0.99 for the regression model, demonstrating high predictive accuracy. Furthermore, the analysis reveals that LFP batteries have a higher average energy efficiency of 7.53 km/kWh compared to 6.84 km/kWh for NMC batteries, indicating more consistent performance in energy usage. These findings offer valuable insights for optimizing battery selection in EV applications and contribute to strategic planning for the development of more efficient electric vehicle systems. The combination of statistical and simulation-based analysis provides a robust foundation for future research and policy-making in the field of electric mobility.

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1. Introduction

The global shift towards sustainable transportation has led to a significant increase in the adoption of electric vehicles (EVs) [1]. Rising concerns over climate change and air pollution have propelled governments and consumers worldwide to seek alternatives to fossil fuel-powered vehicles [2]. EVs are a viable solution due to their zero tailpipe emissions and their potential to reduce greenhouse gas emissions, especially when powered by renewable energy sources [3]. In Indonesia, the transportation sector is a major contributor to carbon emissions and urban air pollution [4]. The Indonesian government has set ambitious targets to increase EV adoption as part of its commitment to reducing greenhouse gas emissions under the Paris Agreement. Despite these efforts, several challenges hinder the widespread adoption of EVs in Indonesia, particularly the high initial costs associated with battery technology [5], [6]. Additionally, the Indonesian government has issued policies promoting the use of electric vehicles—especially those based on LFP and NMC batteries—through Presidential Regulation Number 55 of 2019 to support the transition toward an electric-based transportation system and to curb carbon emissions [7]. Carbon emissions are largely caused by fossil fuel-powered vehicles, and most cars in Indonesia still rely on fossil fuels. Therefore, this step aligns well with global efforts to reduce carbon emissions, one of which is the use of electric power in battery-powered vehicles.

Batteries are the most critical component of EVs, significantly affecting their performance, range, and cost [8]. These batteries function as the main power source, supplying electric current to the motor, which drives the vehicle. Two types of battery materials are commonly used in electric vehicles in Indonesia: lithium iron phosphate (LFP) and nickel manganese cobalt (NMC). Among the various battery technologies, LFP and NMC are the most widely used, each with distinct characteristics and advantages [9]. LFP batteries are known for their long lifespan, thermal stability, and safety. Although they offer lower energy density, they are more cost-effective and have a longer cycle life than other lithium-ion batteries [10]. In contrast, NMC batteries have higher energy density and provide longer driving ranges, but they are more expensive and pose concerns regarding thermal stability and the ethical sourcing of cobalt [11].

Previous research has explored the performance, efficiency, and longevity of both LFP and NMC batteries in electric vehicles. Studies by Tran et al. (2021), Long et al. (2020), and White et al. (2021) have examined the performance characteristics of LFP and NMC batteries, including their thermal behavior under various operating conditions, highlighting the importance of thermal management in EV applications. These studies found that LFP batteries offer better longevity but lower energy density [12]–[14]. Research conducted by Guo et al. (2021), Geisbauer et al. (2021), and Mishra et al. (2020) concluded that while LFP batteries offer relatively long life, NMC batteries have the advantage in terms of performance and range [15]–[17]. According to previous studies, electric vehicles can reduce gas emissions, and several findings indicate that LFP batteries are suitable for daily-use vehicles, while NMC batteries are preferred for vehicles that prioritize performance and long-distance travel.

Given these considerations, this study aims to evaluate the correlation between these two types of batteries in terms of capacity, range, and charging time using Pearson correlation and MATLAB regression analysis. Furthermore, it seeks to assess the efficiency of LFP and NMC batteries within the context of EV use in Indonesia. The objective is to provide insights into the advantages and limitations of each battery type, contributing to informed decision-making for consumers and policymakers in the promotion of sustainable EV adoption in Indonesia.

2. Methods

This research employs numerical methods using Pearson correlation and MATLAB regression analysis simulations. The approach combines MATLAB-based simulations with mathematical modeling to analyze the correlation between electric vehicle battery characteristics—specifically capacity, range, and charging time. The following presents the methodology and data processing flow used to evaluate the efficiency of LFP and NMC batteries.

Figure 1 illustrates a research methodology that begins with data collection and ends with conclusions. The data collection process involves gathering technical specifications of electric vehicles equipped with LFP and NMC batteries from various manufacturers. This includes battery capacity, driving range, and charging duration. These data serve as the foundation for comparing the characteristics of LFP and NMC batteries in line with the study's objectives.

The collected data were processed numerically using MATLAB to perform descriptive statistics, comparative analysis, and correlation/regression analysis. The correlation between variables is determined using the Pearson correlation coefficient. The Pearson correlation formula is shown below [18]–[21]:

$$r = \sum(x_i - \bar{x})(y_i - \bar{y}) \Big/ \left|\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}\right| \quad (1)$$

The coefficient of determination (R-squared) is calculated using the following formula [20], [22], [23]:

$$R^2 = 1 - \frac{SSR\ (Total\ sum\ of\ regression)}{SST\ (Total\ sum\ of\ square)} \quad \text{or} \quad R^2 = 1 - \frac{\sum(\hat{Y}_i - \bar{Y})^2}{\sum(Y_i - \bar{Y})^2} \quad (2)$$

The correlation between variables is interpreted based on the values of *r* and R^2. An *r* value close to -1 indicates a strong negative correlation, whereas an *r* value near 0 suggests no correlation. Conversely, an *r* value close to 1 indicates a strong positive correlation.

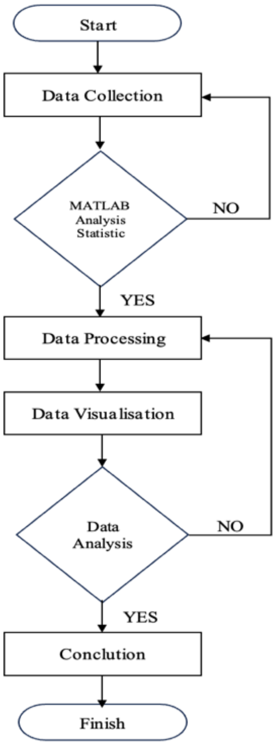


Figure 1. Research methodology

Meanwhile, an R^2 value greater than 0.1 or approaching 1 signifies a strong and significant relationship between the variables. In addition to calculating the Pearson correlation coefficient numerically, the analysis is also conducted using the MATLAB program. A correlation graph is generated between capacity, range, and battery charging time through MATLAB coding using scatterplots and heatmaps based on the collected data.

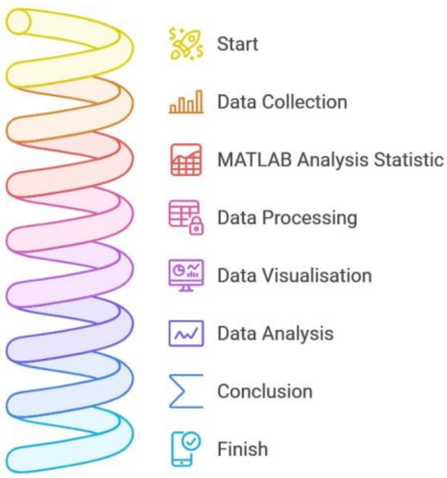


Figure 2. MATLAB process

Figure 2 depicts the data processing workflow using MATLAB. The initial dataset includes information on battery capacity, driving range, and charging time from several electric vehicle manufacturers in Indonesia using LFP and NMC batteries. This data is analyzed in MATLAB through the generation of scatterplots and linear regression heatmaps based on the Pearson correlation formula. These visualizations display the linear regression relationships between capacity, range, and charging time for each battery type. The resulting graphs are then used to conduct regression correlation analysis, which is compared against the minimum threshold values of the Pearson correlation coefficient (*r*) and the coefficient of determination (R^2).

3. Results and Discussion

3.1. Data collection

The data comes from several electric vehicle manufacturers in Indonesia, especially sedans, starting from vehicle models, capacity, range, and charging time of LFP and NMC-type batteries. The following is a table of the data:

Table 1. Lithium Iron Phosphate (LFP) battery data [24]-[27]

Model	Capacity	Range	Charging time
1	76,9 kWh	605 km	30 minutes (DC Fast Charging)
2	50.6 kWh	408 km	30 minutes (DC Fast Charging)
3	61,4 kWh	450 km	30 minutes (DC Fast Charging)
4	51 kWh	350 km	30 minutes (DC Fast Charging)

Table 2. Nickel Manganese Cobalt (NMC) battery data [28]-[31].

Model	Capacity	Range	Charging time
1	72,6 kWh	430 km	18 minutes (DC Fast Charging)
2	77,4 kWh	460 km	18 minutes (DC Fast Charging)
3	62 kWh	560 km	30 minutes (Supercharger)
4	71,4 kWh	460 km	30 minutes (DC Fast Charging)

3.2. Pearson correlation analysis

A. Pearson correlation analysis of capacity and range

The Pearson correlation equation is used to calculate the correlation between battery capacity and range. Based on the data presented:

- Variable X represents battery capacity: X = {76.9, 50.6, 61.4, 51.0, 72.76, 77.4, 62.0, 71,4}
- Variable Y represents range: Y = {605, 408, 450, 350, 430, 460, 560, 460}

From the data, the following values are obtained:

$$\bar{X} = \frac{\sum x}{n} = 65{,}41 \tag{3}$$

$$\bar{Y} = \frac{\sum Y}{n} = 456{,}38 \tag{4}$$

$$\sum (X_i - \bar{X})(Y_i - \bar{Y}) = 6399{,}37 \tag{5}$$

$$\sum (X_i - \bar{X})^2 = 1117{,}93 \tag{6}$$

$$\sum (Y_i - \bar{Y})^2 = 110856{,}25 \tag{7}$$

The Pearson correlation coefficient is calculated as:

$$\boldsymbol{r} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} = \frac{6399{,}37}{\sqrt{1117{,}93 - 110856{,}25}} = 0{,}576$$

This result indicates a positive correlation between battery capacity and range, with a value of 0.576. A positive correlation implies that as battery capacity increases, the vehicle's range also increases. Although the correlation is categorized as moderate, it still signifies a meaningful relationship between the two variables.

This finding is consistent with studies by Y. Han et al. (2021) and H. Wang et al. (2022), which explain that the Pearson coefficient (r) ranges between –1 and 1. An *r* value close to –1 indicates a strong negative correlation, *r* = 0 implies no correlation, and *r* close to 1 indicates a strong positive correlation. According to W. Wu et al. (2024), a Pearson coefficient approaching 1 signifies an ideal correlation. Therefore, based on the calculation and previous studies, the correlation value of 0.576 supports a moderate positive relationship between battery capacity and vehicle range for LFP and NMC batteries.

B. Pearson correlation analysis battery capacity and charging time

The Pearson correlation equation is also used to evaluate the relationship between battery capacity and charging time. The data used are:

- Variable X: Battery capacity = {76.9, 50.6, 61.4, 51.0, 72.76, 77.4, 62.0, 71.4}
- Variable Y: Charging time = {30, 30, 30, 30, 18, 18, 30, 30}

Using the Pearson formula:

$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \tag{8}$$

The computed values are:

$$\bar{X} = \frac{\sum x}{n} = 65{,}41$$

$$\bar{Y} = \frac{\sum Y}{n} = 27$$

$$\sum(X_i - \bar{X})(Y_i - \bar{Y}) = -57{,}68$$

$$\sum(X_i - \bar{X})^2 = 1117{,}93$$

So the slope (regression coefficient) is:

$$b_1 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} = \frac{-57{,}68}{1117{,}93} = -0{,}0516$$

Then, the y-intercept is calculated as:
Regression coefficient value can be determined by calculating the slope of b1:

$$b_0 = \bar{Y} - b_1.\bar{X} = 27 - (-0{,}0516\ x\ 65{,}41) = 30{,}38$$

Substituting into the regression formula:

$$Y = b_0 + b_1.X \tag{9}$$

$$Y = 30{,}38 - 0{,}0516.X$$

Next, the regression performance is evaluated:
Based on X and Y data, we get the values:

$$SSR = \sum(\hat{Y}_i - \bar{Y})^2 = 2{,}14$$

$$SST = \sum(Y_i - \bar{Y})^2 = 216$$

$$R^2 = 1 - \frac{SSR}{SST} = \frac{2{,}14}{216} = 1 - 0{,}010 = 0{,}99$$

The results show a weak negative correlation between battery capacity and charging time, with a slope of –0.0516. This suggests that for every 1 kWh increase in battery capacity, the charging time decreases slightly by approximately 0.0516 minutes. However, the R-squared value of 0.99 indicates that 99% of the variation in charging time is explained by battery capacity, implying a very strong regression relationship. The remaining 1% may be influenced by other factors such as charging technology and efficiency.

This finding is in line with research by Wu et al. (2024), which states that an R-squared value greater than 0.8 indicates a strong and reliable model [20]. Similarly, Chen et al. (2023) noted that an R-squared value of 1 denotes a perfect regression fit [22], while Zhou et al. (2023) stated that an R-squared value above 0.1 qualifies a regression model as good [23]. Therefore, with an R-squared value of 0.99, the regression correlation between battery capacity and charging time is considered highly significant and close to ideal.

C. Pearson correlation analysis of range and charging time

The Pearson correlation equation is used to calculate the correlation between range (R) and charging time (T). Based on the available data:

- R_{LFP} : LFP battery range, [605, 408, 450, 350]
- T_{LFP} : LFP battery charging time, [30, 30, 30, 30]
- R_{NMC} : NMC battery range, [430, 460, 560, 460]
- T_{NMC} : NMC battery charging time, [18, 18, 30, 30]

The Pearson correlation formula is:

$$r = \frac{\sum(R_i - \bar{R})(T_i - \bar{T})}{\sqrt{\sum(R - \bar{R})^2 \sum(T_i - \bar{T})^2}} \tag{10}$$

For LFP batteries, the calculations yield:

$$\bar{R}_{LFPC} = \frac{\sum R}{n} = 453{,}25 \qquad \bar{T}_{LFP} = \frac{\sum T}{n} = 30$$

$$\bar{R}_{NMC} = \frac{\sum R}{n} = 477{,}5 \qquad \bar{T}_{NMC} = \frac{\sum T}{n} = 24$$

For LFP batteries, the calculations yield:

$$\sum(R_i - \bar{R})(T_i - \bar{T}) = 0$$

$$\sum(R_i - \bar{R})^2 = 35.764{,}25$$

$$\sum(T_i - \bar{T})^2 = 0$$

For NMC batteries, the calculations yield:

$$\sum(R_i - \bar{R})(T_i - \bar{T}) = 780$$

$$\sum(R_i - \bar{R})^2 = 9675$$

$$\sum(T_i - \bar{T})^2 = 144$$

From the calculations above, we get LFP battery correlation value is $\sum(T_i - \bar{T})^2 = 0$, $r_{LFP} = 0$, and NMC battery correlation value is $r = \frac{\sum(R_i - \bar{R})(T_i - \bar{T})}{\sqrt{\sum(R - \bar{R})^2 \sum(T_i - \bar{T})^2}} = \frac{780}{\sqrt{9675.144}} = 0{,}661.$

The Pearson correlation analysis shows no relationship between range and charging time for LFP batteries due to the constant charging time (r = 0). However, for NMC batteries, the correlation value of 0.661 indicates a moderate positive relationship, meaning vehicles with longer charging times tend to have a higher range. This result emphasizes that LFP batteries, with their stable charging duration, do not show variation in range with charging time. In contrast, NMC batteries demonstrate a clearer relationship between these two factors, suggesting that higher range performance may come at the cost of longer charging durations.

These findings align with those of Y. Han et al. (2021) and H. Wang et al. (2022), who explained that Pearson correlation coefficients range from –1 to 1, with values close to –1 indicating a strong negative correlation, values near 0 indicating no correlation, and values close to 1 indicating a strong positive correlation. W. Wu et al. (2024) similarly noted that correlation values near 1 signify an ideal correlation. Therefore, the calculated Pearson coefficients confirm that LFP batteries have no correlation between range and charging time (r = 0), while NMC batteries exhibit a meaningful, moderate correlation (r = 0.661).

D. Battery efficiency

Based on the available data:

- C_{LFP} : LFP capacity, [76.9, 50.6, 61.4, 51.0]
- R_{LFP} : LFP battery range, [605, 408, 450, 350]
- C_{NMC} : NMC battery capacity, [72.6, 77.4, 62.0, 71.4]
- R_{NMC} : NMC battery range, [430, 460, 560, 460]

The energy efficiency of batteries is calculated using the formula:

$$E_i = \frac{R_i}{C_i} \tag{11}$$

$$\bar{E} = \frac{\sum E_i}{n} \tag{12}$$

where E_i is the energy efficiency in km/kWh, R_i is the range, and C_i is the battery capacity.
LFP battery calculations:

$$E_1 = \frac{R_1}{C_1} = \frac{605}{76.9} = 7.87 \qquad E_3 = \frac{R_3}{C_3} = \frac{450}{61.4} = 7.33$$

$$E_2 = \frac{R_2}{C_2} = \frac{408}{50.6} = 8{,}06 \qquad E_4 = \frac{R_4}{C_4} = \frac{350}{6.86} = 6.86$$

Average LFP battery efficiency:

$$\bar{E} = \frac{\sum E_i}{n} = \frac{7.87 + 8.06 + 7.33 + 6.86}{4} = 7.53\ km/Kwh$$

NMC battery calculations:

$$E_1 = \frac{R_1}{C_1} = \frac{430}{72.6} = 5.92 \qquad E_3 = \frac{R_3}{C_3} = \frac{560}{62.0} = 9.03$$

$$E_2 = \frac{R_2}{C_2} = \frac{460}{77.4} = 5{,}94 \qquad E_4 = \frac{R_4}{C_4} = \frac{460}{71.4} = 6.44$$

Average NMC battery efficiency:

$$\bar{E} = \frac{\sum E_i}{n} = \frac{5.92 + 5.94 + 9.03 + 6.44}{4} = 6.83\ km/Kwh$$

The results show that vehicles equipped with LFP batteries have a higher average energy efficiency (7.53 km/kWh) compared to NMC batteries (6.83 km/kWh). This indicates that LFP batteries deliver more consistent performance in terms of energy usage. Moreover, the variation in energy efficiency among LFP batteries is smaller than that of NMC batteries, suggesting that LFP technology offers more reliable and predictable performance.

While LFP batteries tend to provide stable charging durations and consistent efficiency, NMC batteries display a stronger correlation between charging time and range, implying that their performance may vary more due to other influencing factors such as temperature sensitivity, energy density, and fast-charging compatibility.

These results support previous research indicating that electric vehicles can significantly reduce greenhouse gas emissions. Furthermore, the findings reinforce that LFP batteries are well-suited for everyday vehicles that prioritize reliability and efficiency, whereas NMC batteries are more appropriate for vehicles that emphasize performance and extended range.

3.3. MATLAB analysis

A. MATLAB program

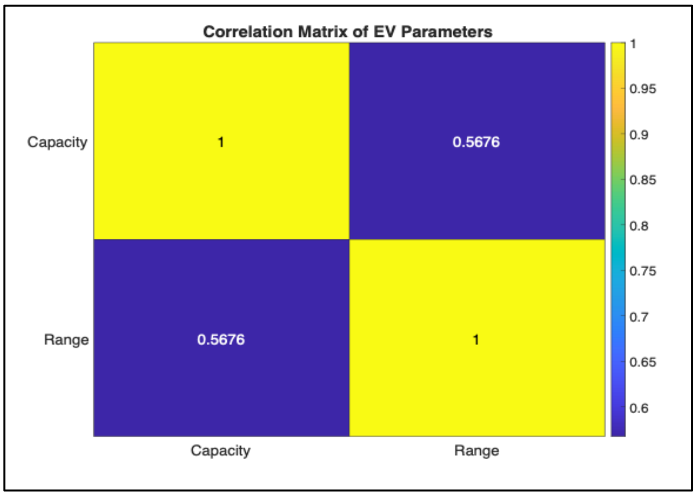
Based on Tables 1 and 2, which present data on the capacity, range, and charging time for LFP and NMC batteries, regression correlation analysis can be performed using MATLAB programming. The following is the MATLAB code used in this study:

```
%Comparation battery capacity with range,
% FP dan NMC battery data:
lfp_battery_capacity = [76.9, 50.6, 61.4, 51.0]; % kWh
lfp_range = [605, 408, 450, 350]; % km
nmc_battery_capacity = [72.6, 77.4, 62.0, 71.4]; % kWh
nmc_range = [430, 460, 560, 460]; % km

% Regresi linier LFP
p_lfp = polyfit(lfp_battery_capacity, lfp_range, 1);
fit_lfp = polyval(p_lfp, lfp_battery_capacity);

% Regresi linier NMC
p_nmc = polyfit(nmc_battery_capacity, nmc_range, 1);
fit_nmc = polyval(p_nmc, nmc_battery_capacity);
```

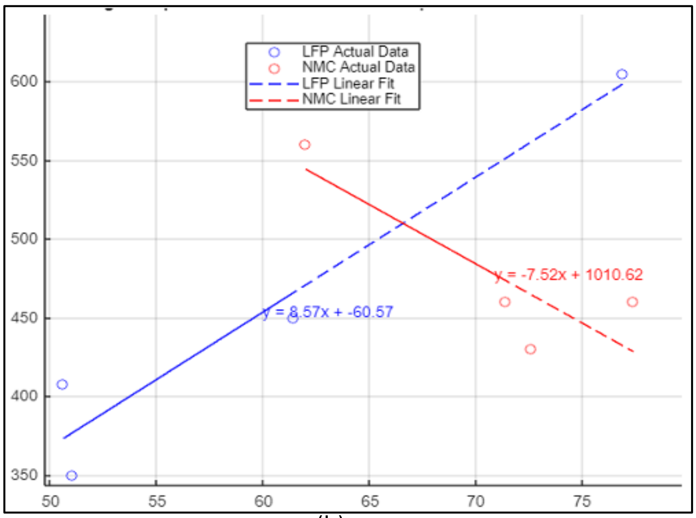
```
% Plot regresi value
figure;
hold on;
scatter(lfp_battery_capacity, lfp_range, 'bo', 'DisplayName', 'LFP Actual Data');
scatter(nmc_battery_capacity, nmc_range, 'ro', 'DisplayName', 'NMC Actual Data');
plot(lfp_battery_capacity, fit_lfp, 'b--', 'DisplayName', 'LFP Linear Fit');
plot(nmc_battery_capacity, fit_nmc, 'r--', 'DisplayName', 'NMC Linear Fit');
% Regresi linier graph
text(mean(lfp_battery_capacity), mean(fit_lfp), sprintf('y = %.2fx + %.2f', p_lfp(1), p_lfp(2)),
'Color', 'blue', 'FontSize', 10);
text(mean(nmc_battery_capacity), mean(fit_nmc), sprintf('y = %.2fx + %.2f', p_nmc(1),
p_nmc(2)), 'Color', 'red', 'FontSize', 10);
xlabel('Battery Capacity (kWh)');
ylabel('Range (km)');
title('Capacity Battery and Range correlation according battery tipe');
legend('show');
grid on;
hold off;
```

B. Regression correlation analysis of capacity and range

In general, Figure 3 shows that an increase in battery capacity typically corresponds to an increase in the driving range of an electric vehicle.



(a)



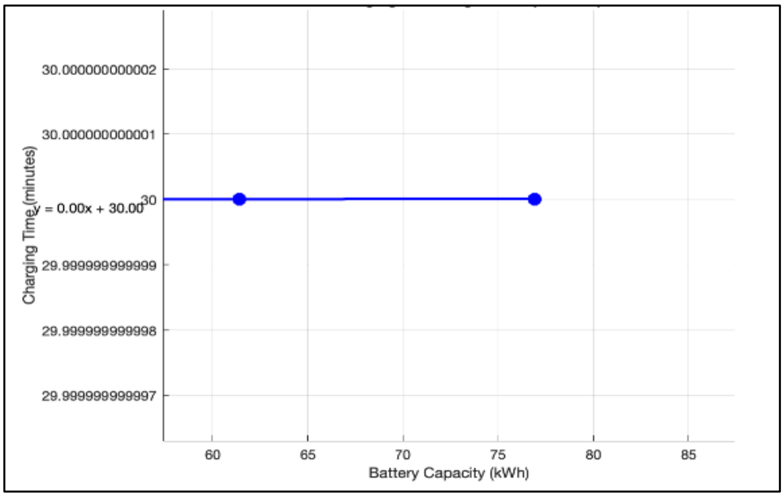
(b)

Figure 3. Correlation regression analysis of capacity and range: (a) Correlation matrix, (b) Correlation regression

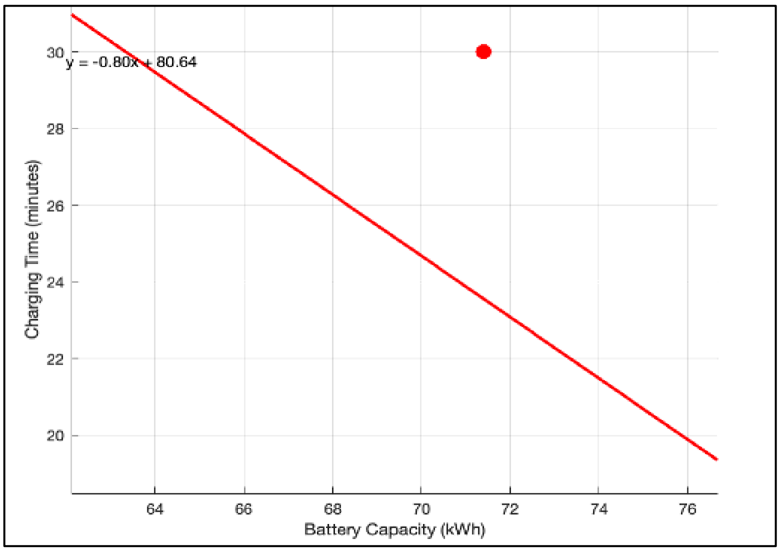
However, this correlation is not perfectly strong, indicating that other factors—such as energy efficiency, vehicle condition, and driving behavior—also play significant roles in determining range. Despite this, the correlation values confirm that battery capacity remains a key factor when aiming to improve electric vehicle range performance. An increase in battery capacity allows for greater energy storage, thereby enhancing the overall driving range. The regression analysis further suggests that a linear model can effectively represent this relationship, where an increase in battery capacity leads to a notable increase in driving range.

Figure 3(a) displays a correlation matrix between two key parameters: battery capacity and driving range. The dominant yellow hue along the diagonal axis indicates a strong positive correlation between these variables. The calculated correlation coefficient value of 0.5676 further supports this observation, reinforcing the finding that vehicles with higher battery capacity tend to achieve longer ranges. Figure 3(b) provides a visual representation of this relationship through a scatter plot and regression lines for both battery types. Both LFP and NMC battery regression lines follow a positive trend, consistent with the matrix analysis.

However, the slope of the regression line for LFP batteries is flatter, indicating that increases in LFP battery capacity led to relatively modest gains in range. In contrast, the steeper slope observed in the NMC battery regression line implies that range increases more significantly with greater battery capacity in NMC systems. This suggests that the relationship between capacity and range is more sensitive and potentially more complex in NMC batteries compared to LFP batteries.



(a)



(b)

Figure 4. Correlation regression analysis of capacity and charger time; (a) LFP, (b) NMC

Moreover, the slight negative deviation observed in the NMC regression curve may indicate the influence of additional variables such as battery technology, vehicle mass, or energy management strategies, which should be considered in the design of NMC-equipped electric vehicles.

C. Correlation analysis of capacity and charging time

Figure 4 shows that increasing battery capacity does not significantly impact charging duration. Therefore, it is important to consider additional factors, such as fast-charging technology, to improve the efficiency of electric vehicle (EV) charging times. This analysis confirms that factors beyond battery capacity play a more substantial role in determining charging duration. Although charging time is influenced by capacity, batteries with larger capacities generally require longer charging times—depending on the charging level.

In Figure 4(a), the horizontal regression line indicates that there is no significant correlation between LFP battery capacity and charging time. This implies that changes in LFP battery capacity do not affect how long it takes to fully charge the battery. The LFP battery system appears to be optimized so that charging time remains relatively constant, regardless of capacity. On the other hand, Figure 4(b) displays a downward-sloping regression line for NMC batteries, indicating a negative correlation between battery capacity and charging time. This means that as the NMC battery capacity increases, the time required for full charging decreases. This may be attributed to the fact that larger-capacity ternary (NMC) batteries often support higher charging efficiency and benefit from more advanced fast-charging technologies. As such, NMC batteries with higher capacities tend to charge faster, making them more suitable for applications that demand quick turnaround times.

D. Correlation analysis of range and charging time

Figure 5 presents a comparison between the driving range of electric vehicles and the time required to charge their batteries. The results reveal distinct differences between lithium iron phosphate (LFP) and ternary (NMC) batteries. LFP batteries do not exhibit a clear correlation between driving distance and charging time, indicating that charging durations remain consistent regardless of how far the vehicle can travel on a full charge. Conversely, NMC batteries show a positive correlation—the longer the distance traveled, the longer it takes to charge. This implies that vehicles designed for longer ranges are equipped with larger batteries, which naturally require more time to recharge.

These findings are crucial for selecting the appropriate battery type and for designing EV charging infrastructure. Vehicles with longer driving ranges may require extended charging times. However, with the availability of faster charging rates—particularly in NMC batteries—users can reduce the time spent charging, even for long-range vehicles. The analysis also indicates that while NMC batteries provide greater driving range, their rapid charging capability makes them more practical for daily use, especially where time efficiency is a priority.

Moreover, the charging efficiency between LFP and NMC batteries differs. Empirical analysis reveals that NMC batteries offer a superior charging rate of 20.86 km/min, compared to 15.11 km/min for LFP batteries. This suggests that, despite potentially larger capacities, NMC batteries achieve faster overall charging times, making them a more efficient choice for high-performance or long-distance electric vehicles.

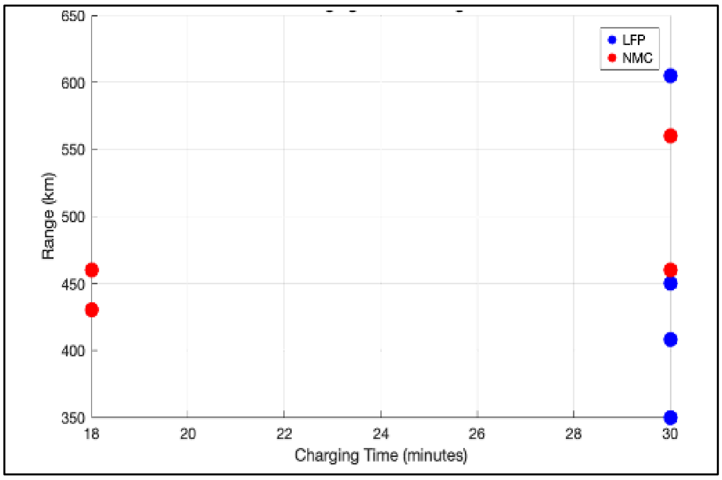


Figure 5. Correlation regression analysis of range and charger time

3.4. Correlation analysis of Pearson coefficient and MATLAB operations

Based on the results of the Pearson correlation coefficient, regression analysis, scatterplots, and heatmaps generated through MATLAB, it can be concluded that there is a reasonably strong correlation between battery capacity and driving range for both LFP and NMC batteries. This is evidenced by the correlation value of 0.567, as well as the visual representation in MATLAB. However, for NMC batteries, an inverse trend is observed—greater capacity is sometimes associated with a shorter range. This suggests the influence of additional factors such as battery technology, vehicle design, and weight.

The correlation between capacity and charging time also shows a strong positive regression value for both battery types in numerical calculations, with coefficients well above 0.8, indicating a high degree of predictability. Despite this, MATLAB visualizations reveal inconsistencies—particularly with LFP batteries, where all capacity values correspond to the same charging duration (30 minutes). As a result, no real variation is present, making correlation in the graph appear weak or nonexistent. In contrast, NMC batteries demonstrate an inverse correlation, where increased capacity corresponds with shorter charging times. This supports the conclusion that NMC batteries benefit from faster charging technologies and improved efficiency compared to LFP batteries.

When analyzing the correlation between driving range and charging time, LFP batteries again show no correlation due to their consistent charging time. Meanwhile, NMC batteries display a moderate correlation with a Pearson coefficient of 0.661. This suggests that in NMC-equipped vehicles, longer charging times are generally associated with longer driving ranges. MATLAB visualizations reinforce these findings, showing that while LFP batteries have weak or negligible correlation due to uniform charging times, NMC batteries clearly exhibit a trend: as charging time increases, so does the distance the vehicle can travel.

4. Conclusions

This study concludes that the selection of battery type significantly influences the performance characteristics of electric vehicles (EVs), particularly in terms of driving range, charging time, and energy efficiency. Lithium Iron Phosphate (LFP) batteries are more suitable for daily use, where cost-effectiveness, safety, and long cycle life are key priorities. In contrast, Nickel Manganese Cobalt (NMC) batteries are better suited for applications that demand high performance and longer driving distances. The correlation and regression analyses revealed a strong and statistically significant relationship between key parameters, including battery capacity, range, and charging time. The Pearson correlation coefficient and MATLAB-based regression models consistently demonstrated these relationships. First, a positive correlation was found between battery capacity and driving range, with a coefficient of 0.576, indicating that higher battery capacity enables longer travel distances. Second, the relationship between battery capacity and charging time was found to be very weak and slightly negative, with a correlation coefficient of –0.0516. This implies that increasing battery capacity can slightly reduce charging duration, particularly in NMC batteries with fast-charging capability. The correlation between range and charging time varied depending on the battery type. For LFP batteries, no correlation was observed due to the constant charging duration across different capacities and ranges. However, NMC batteries exhibited a moderate positive correlation, indicating that vehicles capable of longer ranges generally require more time to charge, likely due to the presence of larger batteries. In terms of energy efficiency, LFP batteries performed better, with an average of 7.53 km/kWh compared to 6.84 km/kWh for NMC batteries. This highlights LFP's consistent performance in optimizing energy use, making it highly suitable for energy-conscious applications. In summary, the results of this study confirm that electric vehicles, regardless of battery type, offer considerable potential for reducing greenhouse gas emissions. However, selecting the appropriate battery type should be aligned with the intended usage of the vehicle. LFP batteries are ideal for urban commuting and daily driving due to their reliability and energy efficiency, while NMC batteries are better suited for long-distance or performance-intensive applications. The use of statistical analysis methods, including Pearson correlation and MATLAB regression modeling, has proven effective in quantifying these relationships and provides a valuable foundation for future research and development in electric vehicle battery systems.

Supplementary Documentation

More detailed MATLAB coding has been provided in the Supplementary Document. To access the Supplementary Document, please visit the article homepage.

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