31800

by UMB IJIMEAM

International Journal of Innovation in Mechanical Engineering and Advanced Materials
Vol. 1 (No. 1), 2024, pp. XX-XX
Journal homepage: publikasi.mercubuana.ac.id/index.php/ijimeam
DOI: 10.22441/ijimeam.v6i1.xxx

Correlation Analysis of Capacity, Range, and Charging Time of Electric Vehicle Batteries Using Pearson Formula and MATLAB

Yasa Sanusi [1]*, Sri Pudjiwati [1] and Kontan Tarigan[1]

[1]Mechanical Engineering Masters Study Program, Mechanical Engineering Faculty, Mercu Buana University, West Jakarta 11650 Indonesia
*Corresponding Authors: yasa.sanusi@gmail.com

Abstract

The increasing use of electric vehicles aligns with increasing global awareness regarding climate change and air pollution challenges. Considered a sustainable alternative, electric vehicles produce zero emissions and can reduce carbon and air pollution, mainly when their charging energy is sourced from renewable resources. However, consumers face the challenge of high costs, especially those related to battery components, which are the energy source that drives the system of electric vehicles. In Indonesia, the batteries commonly used in electric vehicles are *Lithium Ferro Phosphate* (LFP) and *Nickel Manganese Cobalt* (NMC), each offering different characteristics and benefits. Based on previous research, the presence of electric vehicles can reduce gas emissions, and from several findings it is known that LFP is suitable for use in everyday vehicles, while NMC is used for vehicles that prioritize performance and long distances. This study aims is evaluate the correlation of these two types of batteries in terms of capacity, range and charging time with Pearson correlation and MATLAB regression analysis simulation methods. The correlation results show a strong and significant relationship between parameters such as battery capacity, driving range, and charging time, with a correlation coefficient value approaching 1 and having a strong correlation. The regression analysis has strong and significant predictions with an R-square value of 0,99. The average energy efficiency for LFP batteries is 7.53 km/kWh, and NMC 6.84 km/kWh, this shows that LFP shows consistent performance regarding energy efficiency compared to NMC. Energy efficiency provides important insights into optimizing the energy use of electric vehicles. Thus, these results can be used for planning and developing more efficient electric vehicle battery systems. The combination of these statistical analyses provides a solid basis for decision making in future electric vehicle research and development.

Article Info:
Received: xx xxx 2025
Revised: xx xxx 2025
Accepted: xx xxx 2025
Available online: xx xxx 2025

Keywords:
Electric Vehicle; Lithium Ferro Phosphate (LFP); Nickel Manganese Cobalt (NMC); Pearson Correlation

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 potential to reduce greenhouse gas emissions, primarily 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 reduce 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] [5][6]. In addition, the Indonesian Government has previously issued a policy on using electric cars, especially EVs based on LFP and NMC batteries, to encourage an electric-based transportation system to overcome carbon emissions through Presidential Regulation Number 55 of 2019 [7]. Carbon emissions are caused by fossil fuel vehicles, and most cars in Indonesia still use fossil fuels. Thus, this

How to cite:

Y. Sanusi, S. Pudjiwati, K. Tarigan, " Correlation Analysis of Capacity, Range, and Charging Time of Electric Vehicle Batteries Using Pearson Formula and MATLAB " *Int. J. Innov. Mech. Eng. Adv. Mater*, vol. 6, no. 1, pp. 1-10, 2025

step is very much in line with global efforts to reduce carbon emissions, one of which is utilizing electric power in vehicles with battery power sources.

Batteries are the most critical component of EVs, significantly affecting their performance, range, and cost [8]. This battery functions as a power source, where the electric current drives the electric generator, ultimately driving the vehicle. Two types of battery materials are commonly used in electric cars in Indonesia: lithium iron phosphate (LFP) and nickel manganese cobalt (NMC). Among the various battery technologies, LFP and NMC batteries are the most used in EVs, each with distinct characteristics and advantages [9]. LFP batteries are known for their long lifespan, thermal stability, and safety. They offer lower energy density but are more cost-effective and have a longer cycle life than other lithium-ion batteries [10]. On the other hand, NMC batteries have a higher energy density and provide longer driving ranges. Still, they are more expensive and have 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, M.K. et al., Long, B. et al., and White, C. et al. have examined the performance characteristics of LFP and NMC batteries also analyzed the thermal behavior of LFP and NMC batteries under various operating conditions, highlighting the importance of thermal management in EV applications. The energy efficiency and degradation rates of LFP and NMC batteries found that LFP batteries offer better longevity but lower energy density [12][13][14]. Then, the research of Guo J. et al., Geisbauer C. et al., and Mishra P.P. et al. concluded that although LFP has a relatively long life, NMC has the advantage of performance and longer range [15][16][17]. According to previous research, the presence of electric vehicles can reduce gas emissions, and from several findings, it is known that LFP is suitable for use in everyday vehicles, while NMC is used for vehicles that prioritize performance and long distances.

Given these considerations, this study aims to evaluate the correlation of these two types of batteries in terms of capacity, range, and charging time with Pearson correlation and MATLAB regression analysis simulation methods and evaluate the efficiency of LFP and NMC batteries in the context of EVs in Indonesia, that is capacity, range, and charging. This research seeks to provide insights into the advantages and disadvantages of each battery type, contributing to informed decision-making for consumers and policymakers in promoting sustainable EV adoption in Indonesia.

2. Methods

This research employs numerical methods with Pearson correlation and MATLAB regression analysis simulation methods. The approach combines MATLAB-based simulations with mathematical modeling to understand the correlation analysis of electric vehicle batteries' capacity, range, and charging time. The following is the methodology or flow in data processing and methodology that can be used in analyzing LFP and NMC battery efficiency using Pearson correlation analysis and MATLAB application:

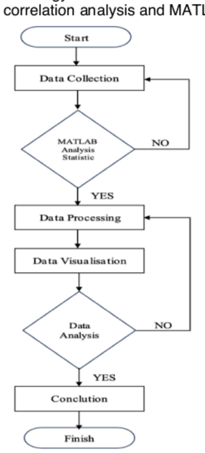


Figure 1. Research Methodology

Figure 1. shows a research methodology that starts from data collection to conclusions. The data collection process includes collecting technical specifications of electric vehicles equipped with LFP and NMC batteries from various manufacturers, including battery capacity, range, and charging duration. This data is the basis for comparing the characteristics of LFP and NMC batteries to the study's objectives. The collected data is processed numerically using the MATLAB program to analyze battery characteristics using descriptive statistics, comparative analysis, and correlation/regression analysis. Then, the data is analyzed by interpreting the processed data numerically using the Pearson formula to measure the relationship between variables. The following is Pearson correlation formula [18][19][20][21]:

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

R-Square value[20][22][23] is:

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

The relationship between these variables is presented based on the r and R-square values; the closer the r value is -1≤ $r \leq 1$, r value is to -1 that variables have a negative correlation or a weak correlation; if the r value is 0 there is no correlation between the variables, and If the r value is close to 1 that variables have a positive correlation or strong correlation, and If the R square value is more significant than 0.1 or close to 1 then the variables have a strong and significant correlation.

In addition to numerically using the Pearson formula, correlation between variables is also carried out by analysis using the MATLAB program. A correlation graph will be obtained between the variables of capacity, range, and battery charging time through coding with a scatterplot and heatmap based on the data collected. The following are the steps for processing data using the MATLAB program:

Figure 2 MATLAB Process

Figure 2 shows the data processing process using MATLAB. The initial data was obtained from capacity, range, and battery charging time data from several electric car manufacturers in Indonesia with LFP and NMC battery types. Then, the data was processed and analyzed using the MATLAB program through scatterplots and linear regression heatmaps using the Pearson formula, which will then be visualized as a linear regression graph between the capacity, range, and charging time variables of each type of battery. A regression correlation analysis can be carried out from the visualization display, which is compared with the minimum correlation (r) and regression (R-square) provisions.

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 Ferro Phosphate [24][25][26][27]

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

Table 2. Nickel Manganese Cobalt [28][29][30][31].

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

3.2 Analysis Pearson Correlation (Numerical Methode)

a. Pearson correlation analysis of capacity and range

Use the Pearson correlation equation to calculate the correlation between battery capacity and range parameters. From the data above it is known:

Variable X is the battery capacity: X = {76.9, 50.6, 61.4, 51.0, 72.76, 77.4, 62.0, 71,4}

Variable Y is the range: Y = {605, 408, 450, 350, 430, 460, 560, 460}

Based on X and Y data, we get the values:

$$\boldsymbol{\bar{X}} = \frac{\sum x}{n} = \mathbf{65,41} \quad (3)$$

$$\boldsymbol{\bar{Y}} = \frac{\sum Y}{n} = \mathbf{456,38} \quad (4)$$

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

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

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

correlation value between battery capacity and range is:

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

Thus, the Pearson correlation efficiency shows a positive relationship between battery capacity and range, proven by calculation to have a positive value of 0.576. A positive value indicates a unidirectional relationship between battery capacity and distance traveled. In other words, the distance a vehicle can travel increases as battery capacity increases. With an R-value of 0.576, this correlation is in the medium range. Although not very strong, this relationship is meaningful enough to show a relationship between the two variables.

In line with the research conducted by Y. Han et al. (2021) and H. Wang et al. (2022) explained the provisions of the Pearson coefficient value (r) between -1 and 1, when the r value approaches -1 then the variables have a weak correlation, the r value is 0 then the variables have no correlation, and when r approaches 1 then the variables have a strong correlation. In the research conducted by W. Wu et al. (2024), if the Pearson correlation coefficient value approaches 1, the variables certainly have an ideal correlation.

According to the results of the Pearson correlation coefficient calculations and previous research, the calculation results are in line with previous research, namely, 0,576, that the correlation between battery capacity and range on LFP and NMC batteries is positive and has a strong correlation (medium correlation).

b. Pearson correlation analysis battery capacity and charging time

Use the Pearson correlation equation to calculate the correlation between battery capacity and charging time parameters. From the data above it is known:

Variable X is the battery capacity: X = {76.9, 50.6, 61.4, 51.0, 72.76, 77.4, 62.0, 71,4}

Variable Y is the charging time: Y = {30, 30, 30, 30, 18, 18, 30, 30}

The following is Pearson correlation formula:

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

Based on X and Y data, we get the values:

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

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

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

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

Correlation value between battery capacity and charging time is:

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

Regression coefficient value can be determined by calculating the slope of b1:

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

Substitute the slope value b1 into the regression formula:

$$\boldsymbol{Y = b_0 + b_1.X} \qquad (9)$$

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

Based on X and Y data, we get the values:

$$\boldsymbol{SSR = \sum(\hat{Y}_i - \bar{Y})^2 = 2,14} \qquad (10)$$

$$\boldsymbol{SST = \sum(Y_i - \bar{Y})^2 = 216} \qquad (11)$$

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

Thus, the Pearson correlation efficiency shows a weak negative correlation coefficient between charging time and battery capacity. This negative correlation implies that increasing battery capacity by 1 kWh typically decreases charging time by 0.0516 minutes, indicating that larger battery capacities are associated with slightly reduced charging times. However, the R-square value showed that 99.0% of the variation in charging time could be explained by battery capacity, and another factor, such as technology and efficiency of charging, may cause 1.0% of the variation. Hence, the relationship between battery capacity and charging time is powerful.

In line with the research conducted by W. Wu et al. (2024), if the R-square value is more significant than 0.8, the variables certainly have substantial and significant predictions in the research of J. Chen et al. (2023) concluded that if the R-square value equals 1, the research variables can be categorized as having ideal regression. Then, the research of X. Zhou et al. (2023) concluded that when the variables have an R-square value greater than 0.1, the regression model can be said to be good.

The regression coefficient calculation results align with previous research. The regression correlation between capacity and charging time on LFP and NMC batteries is 0.99, above the minimum value of 0.8 and approaching 1. Thus, the correlation between these variables is significant, approaching ideal, and good.

c. Pearson correlation analysis of range and charging time

Use the Pearson correlation equation to calculate the correlation between the range (R) parameters and charging time (T). From the data above it is known:

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

Based on R and T data, we get the values:

$$\boldsymbol{r} = \frac{\sum(\boldsymbol{R_i} - \overline{\boldsymbol{R}})(\boldsymbol{T_i} - \overline{\boldsymbol{T}})}{\sqrt{\sum(\boldsymbol{R} - \overline{\boldsymbol{R}})^2 \sum(\boldsymbol{T_i} - \overline{\boldsymbol{T}})^2}} \quad (12)$$

Based on X and Y data, we get the values:

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

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

1) LFP Battery

$$\sum(\boldsymbol{R_i} - \overline{\boldsymbol{R}})(\boldsymbol{T_i} - \overline{\boldsymbol{T}}) = \mathbf{0}$$

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

$$\sum(\boldsymbol{T_i} - \overline{\boldsymbol{T}})^2 = \mathbf{0}$$

2) LNMC Battery

$$\sum(\boldsymbol{R_i} - \overline{\boldsymbol{R}})(\boldsymbol{T_i} - \overline{\boldsymbol{T}}) = \mathbf{780}$$

$$\sum(\boldsymbol{R_i} - \overline{\boldsymbol{R}})^2 = \mathbf{9675}$$

$$\sum(\boldsymbol{T_i} - \overline{\boldsymbol{T}})^2 = \mathbf{144}$$

From the calculations above, we get

1) LFP battery correlation

LFP battery correlation value is $\sum(\boldsymbol{T_i} - \overline{\boldsymbol{T}})^2 = \mathbf{0}$, $r_{LFP} = 0$

2) NMC battery correlation

LFP 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 efficiency shows a Correlation between range and charging time for batteries LFP = 0 (no relationship, because charging time is constant), and for NMC batteries = 0.661 (moderate positive relationship, meaning vehicles with longer charging times tend to have higher range). Thus, the relationship between the distance traveled and the charging time of the LFP battery is not connected because the charging time remains constant. In contrast, NMC batteries show a moderate positive correlation between these two factors, indicating that longer charging times are generally associated with greater distances traveled. This examination highlights the influence of battery type on the interaction between charging time and distance.

In line with the research conducted by Y. Han et al. (2021) and H. Wang et al. (2022) explained the provisions of the Pearson coefficient value (r) between -1 and 1, when the r value approaches -1 then the variables have a weak correlation, the r value is 0 then the variables have no correlation, and when r approaches 1 then the variables have a strong correlation. In the research conducted by W. Wu et al. (2024), if the Pearson correlation coefficient value approaches 1, the variables certainly have an ideal correlation.

The results of the Pearson correlation coefficient calculation and previous research align, namely that the correlation between range and charging time on LFP batteries has no correlation with r = 0. The correlation between range and charging time on NMC batteries is positive and strongly correlated (Moderate correlation) with r = 0,661.

d. Battery efficiency

From the data above it is known:

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

To get battery efficiency, we can use energy efficiency formula, that is:

$$E_i = \frac{R_i}{C_i} \quad (13)$$

$$\bar{E} = \frac{\sum E_i}{n} \quad (14)$$

1) LFP battery

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

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

Battery efficiency value is:

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

2) NMC battery

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

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

Battery efficiency value is:

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

Vehicles with LFP batteries have a higher average energy efficiency of 7.53 km/kwh than NMC of 6.83 km/kWh. This shows that LFP shows consistent performance regarding energy efficiency compared to NMC, but the energy efficiency variation is minor, indicating more consistent performance. While LFP battery technology appears to prioritize stability in charging duration, NMC batteries show a stronger relationship between charging time and range performance. Furthermore, LFP batteries show less efficiency variation than NMC batteries, indicating that they provide more reliable performance. In contrast, NMC batteries experience a wider range of energy efficiencies, implying that their performance may be more significantly affected by additional factors.

According to the results of efficient batteries and previous research, electric vehicles can reduce gas emissions. Several findings indicate that LFP suits everyday vehicles, while NMC is used for cars that prioritize performance and long distances.

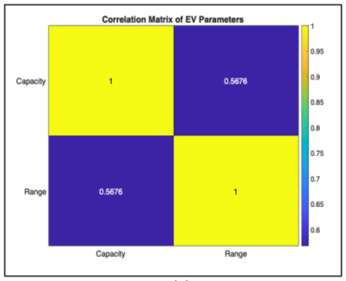
3.3 Analysis MATLAB

a. MATLAB Program

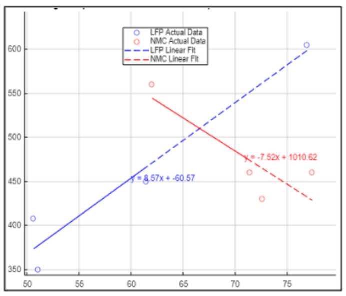
Based on tables 1 and 2 regarding data on capacity, range and charging time for LFP and NMC batteries, regression correlation can be obtained through programming in MATLAB. The following is the MATLAB code:

```
%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



(a)



(b)

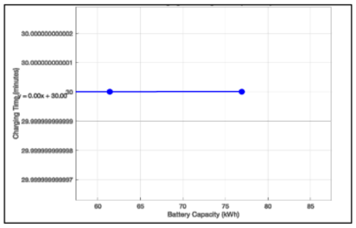
Figure 3 Correlation Regression analysis of capacity and range

In general, Figure 3 shows that an increase in battery capacity usually goes hand in hand with an increase in the range of an electric vehicle. However, this correlation is not completely strong, indicating that other elements, such as energy efficiency, vehicle condition, and driving habits, also play an essential role in determining range. Nevertheless, the correlation values show that battery capacity remains the main factor to consider when seeking to improve the range performance of electric vehicles. The increase in battery capacity corresponds to the increased distance that an electric vehicle can cover. This phenomenon applies to both types of batteries, where the increased capacity facilitates more excellent energy storage, thus enhancing the driving range. Regression analysis shows that a linear model can effectively represent the relationship between battery capacity and driving range, which states that increased battery capacity significantly increases driving range.

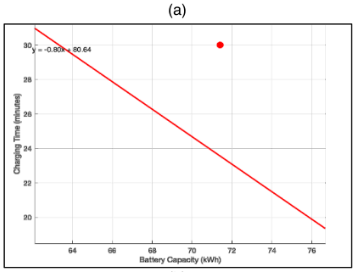
Figure 3. (a) shows a correlation matrix between the two main parameters of electric vehicles, namely battery capacity and driving range. The dominant yellow

color in the diagonal cells indicates a strong positive correlation between the two variables. The correlation coefficient value of 0.5676 strengthens these findings, indicating that the greater the battery capacity, the longer the electric vehicle can travel. Then, figure 3. (b) visually shows the relationship between battery capacity and cruising range through a scatter plot and regression line. The regression lines for both battery types (LFP and NMC) show a similar trend to the correlation matrix results, namely a positive relationship between capacity and range. The LFP cell regression line has a flatter slope, indicating increasing capacity. The increase in the range of LFP batteries is smaller than that of NMC batteries. Although the NMC battery regression line has a steeper slope, indicating that increasing NMC battery capacity can increase driving range more significantly, it can be said that the relationship between battery capacity and driving range is more complex for NMC batteries compared to LFP batteries. However, there is a relatively negative trend in the NMC curve, indicating that there are other factors to consider when designing electric vehicles using NMC batteries.

c. Correlation analysis of capacity and charging time



(a)



(b)

Figure 4 Correlation Regression analysis of capacity and charger time
(a) LFP, (b) MNC

Figure 4. shows that increasing battery capacity does not significantly impact charging duration; therefore, it is essential to consider additional elements, such as fast charging technology, to improve the charging time efficiency of electric vehicles. Furthermore, this analysis verifies that factors beyond battery capacity play a more significant role in determining charging time. Charging duration is also affected by battery capacity. Batteries with larger capacities generally require extended charging times, depending on the charging level. The horizontal regression line in Figure 4. (a) shows no significant correlation between LFP battery capacity and charging time. This means that changes in battery capacity will not affect the time it takes for the battery to be fully charged. The LFP battery charging system can be optimized so that charging time remains relatively constant regardless of battery capacity. Figure 4. (b) shows a downward-sloping regression line, meaning a negative correlation exists between

NMC battery capacity and charging time. The larger the NMC battery capacity, the shorter it takes to charge fully. This may be because a ternary battery with a larger capacity may have a higher charging efficiency and can be charged more quickly. Fast charging technology in ternary batteries may be more effective if the capacity is more significant, and larger-capacity batteries tend to have shorter charging times.

d. Correlation analysis of range and charging time

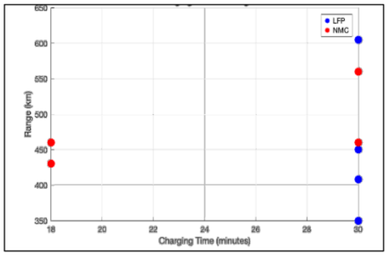


Figure 5 Correlation Regression analysis of range and charger time

Figure 5. shows a graph comparing the distance an electric vehicle travels versus the time it takes to charge the battery. The results show significant differences between lithium iron phosphate batteries and ternary batteries. LFP batteries do not show a clear correlation between driving distance and charging time, meaning charging time tends to be consistent regardless of driving distance. On the other hand, ternary batteries show a positive correlation; that is, the longer the distance traveled, the longer it takes to charge. This indicates that vehicles with longer distances have larger batteries and require longer charging times. These findings are essential for selecting electric vehicle battery types and planning charging infrastructure. Vehicles showing higher range may require long charging periods; However, with increased charging rates (as observed in NMC), users can reduce the time allocated for charging. Analysis reveals that, although NMC offers a more excellent range, its accelerated charging duration makes it more practical for everyday use, especially when time efficiency is essential. However, the charging efficiency may differ between LFP and NMC. In the empirical analysis, the NMC demonstrated a superior charging rate (20.86 km/min) compared to the LFP (15.11 km/min), implying that although the NMC potentially has a larger capacity, the charging duration may be more efficient than the LFP.

3.4 Correlation Analysis of Coefficient Pearson and MATLAB Operation

From the results of the Pearson correlation coefficient and regression calculations, as well as scatterplots and heatmaps in MATLAB operations, it can be said that the numerical computation of the Pearson correlation coefficient shows that the correlation between the capacity and range of LFP and NMC batteries has a reasonably strong correlation, which is reinforced by the scatterplot and heatmap visualization in MATLAB has a correlation value of 0.567, although in NMC batteries the correlation between capacity and range is inversely proportional, the greater the capacity, the smaller the range, it is suspected that other factors influence this such as technology and vehicle weight.

Correlation between capacity and charging time in numerical calculations can be seen in both LFP and NMC batteries, which have a significant positive regression value, approaching ideal and well above 0.8. However, the results of MATLAB visualization in graphs, although having significant regression in LFP batteries, tend not to correlate. This happens because, in general, all LFP battery capacities have the same charging time, which is 30 minutes. Unlike NMC batteries, this battery has an inverse correlation; the greater the capacity, the faster the charging time; this is because this NMC battery has good fast charging features and capabilities and better technology than LFP batteries.

Then, when viewed from the correlation between range and charging time, numerically, the LFP battery has a constant charging time, so there is no correlation between these variables. Meanwhile, the NMC battery, range, and charging time variables strongly correlate with a 0.661 (moderate correlation) value. This is also reinforced by the visualization of MATLAB operations, which show that the LFP battery also has a weak correlation with a constant charging time, while for the NMC battery, the greater the charging time, the longer or further the range traveled by the vehicle.

4. Conclusions

Electric vehicles with LFP batteries are more suitable for daily use where cost and long life are a priority, while NMC batteries are more suitable for high performance and long distances. Then, the correlation results show a strong and significant relationship between parameters such as battery capacity, range, and charging time. Regression analysis provides a numerical model that can predict the relationship between variables with good accuracy. From the results of the analysis, it can be concluded that 1) Correlation efficiency shows a positive relationship between battery capacity and distance travelled; this is proven by calculation with Pearson formula, and MATLAB has the same and positive value of 0.576. 2) The relationship between battery capacity and charging time is very weak; correlation efficiency shows that an increase in battery capacity of 1 kWh will indicate that an increase in battery capacity will reduce the charging time by 0.0516 minutes. 3) Correlation efficiency shows a Correlation between range and charging time for batteries. LFP has no relationship (charging time is constant), and NMC batteries have a positive relationship, meaning vehicles with longer charging times tend to have a higher range. 4) The average energy efficiency for LFP batteries is 7.53 km/kWh, and NMC is 6.84 km/kWh; this shows that LFP shows consistent performance regarding energy efficiency compared to NMC. Energy efficiency provides important insights into optimizing the energy use of electric vehicles. Electric vehicles can reduce gas emissions, and from several findings, it is known that LFP is suitable for use in everyday vehicles, while NMC is used for vehicles that prioritize performance and long distances. Thus, these results can be used to plan and develop more efficient electric vehicle battery systems. The combination of these statistical analyses provides a solid basis for decision-making in future electric vehicle research and development.

References

[1] International Energy Agency (IEA), “Global EV Outlook 2021,” *Global EV Outlook 2021*, p. 101, 2021, [Online]. Available: https://iea.blob.core.windows.net/assets/ed5f4484-f556-4110-8c5c-4ede8bcba637/GlobalEVOutlook2021.pdf

[2] T. Gül, A. F. Pales, and E. Connelly, “Global EV Outlook 2024 Moving towards increased affordability,” *Electric Vehicles Intitiative* , p. 79, 2024, [Online]. Available: www.iea.org

[3] F. Alanazi, “Electric Vehicles: Benefits Challenges and Potential Solutions,” *Journal of Applied Scienc*, vol. 13, pp. 1–23, 2023.

[4] AC Ventures, “Indonesia’s Electric Vehicle Outlook - Supercharging Tomorrow’s Mobility,” *AC Ventures*, no. July, 2023, [Online]. Available: https://acv.vc/wp-content/uploads/2023/07/Report-Indonesias-Electric-Vehicle-Outlook-Supercharging-Tomorrows-Mobility_NEW.pdf

[5] E. Yuliandari and L. N. Violie, “Electric Vehicle Policy Based on Juridical Foundation to Realize Environmental Resilience in Indonesia,” *Proceedings of the International Conference For Democracy and National Resilience (ICDNR 2021)*, vol. 620, no. x, pp. 37–44, 2022, doi: 10.2991/assehr.k.211221.007.

[6] McKinsey Center for Future Mobility, “Making Electric Vehicles Profitable,” *McKinsey & Company*, no. March, 2019, [Online]. Available: https://www.mckinsey.com/~/media/McKinsey/Industries/Automotive and Assembly/Our Insights/Making electric vehicles profitable/Making-electric-vehicles-profitable.pdf

[7] M. Aziz, Y. Marcellino, I. A. Rizki, S. A. Ikhwanuddin, and J. W. Simatupang, “Studi Analisis Perkembangan Teknologi dan Dukungan Pemerintah Indonesia Terkait Mobil Listrik,” *TESLA: Jurnal Teknik Elektro*, vol. 22, no. 1, p. 45, 2020.

[8] M. A. Pradhana, “Pengisi Daya Baterai Lifepo4 Sebagai Sumber Energi Pada Sepeda Listrik,” *Transient: Jurnal Ilmiah Teknik Elektro*, vol. 11, no. 2, pp. 70–74, 2022, doi: 10.14710/transient.v11i2.70-74.

[9] R. O’Malley, L. Liu, and C. Depcik, “Comparative study of various cathodes for lithium ion batteries using an enhanced Peukert capacity model,” *J Power Sources*, vol. 396, no. February, pp. 621–631, 2018, doi: 10.1016/j.jpowsour.2018.06.066.

[10] S. Ohneseit *et al.*, “Thermal and Mechanical Safety Assessment of Type 21700 Lithium-Ion Batteries with NMC, NCA and LFP Cathodes–Investigation of Cell Abuse by Means of Accelerating Rate Calorimetry (ARC),” *Batteries*, vol. 9, no. 5, 2023, doi: 10.3390/batteries9050237.

[11] L. V. Thomas, O. Schmidt, A. Gambhir, S. Few, and I. Staffell, “Comparative life cycle assessment of lithium-ion battery chemistries for residential storage,” *J Energy Storage*, vol. 28, no. June, 2020, doi: 10.1016/j.est.2020.101230.

[12] M. K. Tran, A. Dacosta, A. Mevawalla, S. Panchal, and M. Fowler, “Comparative study of equivalent circuit models performance in four common lithium-ion batteries: LFP, NMC, LMO, NCA,” *Batteries*, vol. 7, no. 3, Sep. 2021, doi: 10.3390/batteries7030051.

[13] B. Long, X. Gao, P. Li, and Z. Liu, “Multi-Parameter Optimization Method for Remaining Useful Life Prediction of Lithium-Ion Batteries,” *IEEE Access*, vol. 8, pp. 142557–142570, 2020, doi: 10.1109/ACCESS.2020.3011625.

[14] C. White, B. Thompson, and L. G. Swan, “Comparative performance study of electric vehicle batteries repurposed for electricity grid energy arbitrage,” *Appl Energy*, vol. 288, no. February, p. 116637, 2021, doi: 10.1016/j.apenergy.2021.116637.

[15] J. Guo, Y. Li, K. Pedersen, and D. I. Stroe, “Lithium-ion battery operation, degradation, and aging mechanism in electric vehicles: An overview,” *Energies (Basel)*, vol. 14, no. 17, 2021, doi: 10.3390/en14175220.

[16] C. Geisbauer, K. Wöhrl, D. Koch, G. Wilhelm, G. Schneider, and H. G. Schweiger, “Comparative study on the calendar aging behavior of six different lithium-ion cell chemistries in terms of parameter variation,” *Energies (Basel)*, vol. 14, no. 11, 2021, doi: 10.3390/en14113358.

[17] P. P. Mishra *et al.*, “Analysis of degradation in residential battery energy storage systems for rate-based use-cases,” *Appl Energy*, vol. 264, no. November 2019, p. 114632, 2020, doi: 10.1016/j.apenergy.2020.114632.

[18] Pearson Education Ltd., *Pearson Edexcel Level 3 Advanced Subsidiary and Advanced GCE in Statistics Statistical formulae and tables*. 2017.

[19] H. Wang, J. Li, X. Liu, J. Rao, Y. Fan, and X. Tan, “Online state of health estimation for lithium-ion batteries based on a dual self-attention multivariate time series prediction network,” *Energy Reports*, vol. 8, pp. 8953–8964, Nov. 2022, doi: 10.1016/j.egyr.2022.07.017.

[20] W. Wu, Z. Chen, W. Liu, and E. Pan, “Correlation based-graph neural network for health prognosis of non-fully charged and discharged lithium-ion batteries,” 2024. [Online]. Available: https://ssrn.com/abstract=4932318

[21] Y. Han, H. Yuan, J. Li, J. Du, Y. Hu, and X. Huang, “Study on Influencing Factors of Consistency in Manufacturing Process of Vehicle Lithium-Ion Battery Based on Correlation Coefficient and Multivariate Linear Regression Model,” *Adv Theory Simul*, vol. 4, no. 8, Aug. 2021, doi: 10.1002/adts.202100070.

[22] J. Chen, D. Chen, X. Han, Z. Li, W. Zhang, and C. S. Lai, “State-of-Health Estimation of Lithium-Ion Battery Based on Constant Voltage Charging Duration,” *Batteries*, vol. 9, no. 12, Dec. 2023, doi: 10.3390/batteries9120565.

[23] X. Zhou, X. Han, Y. Wang, L. Lu, and M. Ouyang, “A Data-Driven LiFePO4 Battery Capacity Estimation Method Based on Cloud Charging Data from Electric Vehicles,” *Batteries*, vol. 9, no. 3, Mar. 2023, doi: 10.3390/batteries9030181.

[24] BYD, “BYD Han,” BYD Website. Accessed: Nov. 14, 2024. [Online]. Available: https:/www.byd.com/en/vehicles/han/specs

[25] Wuling, “Wuling Cloud Ev.” Accessed: Nov. 14, 2024. [Online]. Available: https://wuling.id/id/cloud-ev

[26] Chery International, “Chery Omoda 5.” Accessed: Nov. 14, 2024. [Online]. Available: https://www.cheryinternational.com/omoda5

[27] MG Motors, “MG 4.” Accessed: Nov. 14, 2024. [Online]. Available: https://www.mgmotors.id/mgmodels/mg4ev

[28] Hyundai, "Hyundai Ioniq 5." Accessed: Nov. 14, 2024. [Online]. Available: https://www.hyundai.com/world-wide/en/eco/ioniq5/specs

[29] KIA, "KIA Ev 7." Accessed: Nov. 14, 2024. [Online]. Available: https://www.kia.com/uk/new-cars/7-seat-family-electric-cars/

[30] Tesla, "Tesla Model 3." Accessed: Nov. 14, 2024. [Online]. Available: https://www.tesla.com/model3

[31] Toyota, "Toyota bz4x." Accessed: Nov. 14, 2024. [Online]. Available: https://www.toyota.com/bz4x/

APPENDIX

```
% Statistical Analysis of Electric Vehicles (LFP vs NMC)
%% Input Data
% LFP Vehicles Data
lfp_models = {'BYD Han', 'Wuling Cloud EV', 'Chery Omoda 5', 'MG 4 EV'};
lfp_capacity = [76.9, 50.6, 61.4, 51.0];              % kWh
lfp_range = [605, 408, 450, 350];                     % km
lfp_charging = [30, 30, 30, 30];                      % minutes

% NMC Vehicles Data
nmc_models = {'Hyundai Ioniq 5', 'KIA EV 7', 'Tesla Model 3', 'Toyota bZ4x'};
nmc_capacity = [72.6, 77.4, 62.0, 71.4];              % kWh
nmc_range = [430, 460, 560, 460];                      % km
nmc_charging = [18, 18, 30, 30];                      % minutes

%% 1. Correlation Analysis
% Combine data for correlation analysis
all_capacity = [lfp_capacity nmc_capacity];
all_range = [lfp_range nmc_range];

% Calculate correlation matrix
corr_matrix = corr([all_capacity' all_range']);

% Visualize correlation matrix
figure('Position', [100, 100, 800, 600]);
heatmap({'Capacity', 'Range'}, ...
        {'Capacity', 'Range'}, ...
        corr_matrix, 'Colormap', jet);
title('Correlation Matrix of EV Parameters');

%% 2. Regression Analysis
% Figure for capacity vs range regression
figure('Position', [100, 100, 1200, 400]);

% LFP Regression
subplot(1,2,1);
mdl_lfp = fitlm(lfp_capacity, lfp_range);
scatter(lfp_capacity, lfp_range, 100, 'filled', 'b');
hold on;
x_lfp = linspace(min(lfp_capacity), max(lfp_capacity), 100);
y_lfp = mdl_lfp.Coefficients.Estimate(1) + mdl_lfp.Coefficients.Estimate(2) * x_lfp;
plot(x_lfp, y_lfp, 'b-', 'LineWidth', 2);
xlabel('Battery Capacity (kWh)');
ylabel('Range (km)');
title(['LFP Regression (R² = ' num2str(mdl_lfp.Rsquared.Ordinary, '%.3f') ')']);
grid on;
```

```
text(min(lfp_capacity), max(lfp_range), ...
    sprintf('y = %.2fx + %.2f', mdl_lfp.Coefficients.Estimate(2), ...
    mdl_lfp.Coefficients.Estimate(1)), ...
    'VerticalAlignment', 'top');

% NMC Regression
subplot(1,2,2);
mdl_nmc = fitlm(nmc_capacity, nmc_range);
scatter(nmc_capacity, nmc_range, 100, 'filled', 'r');
hold on;
x_nmc = linspace(min(nmc_capacity), max(nmc_capacity), 100);
y_nmc = mdl_nmc.Coefficients.Estimate(1) + mdl_nmc.Coefficients.Estimate(2) * x_nmc;
plot(x_nmc, y_nmc, 'r-', 'LineWidth', 2);
xlabel('Battery Capacity (kWh)');
ylabel('Range (km)');
title(['NMC Regression (R² = ' num2str(mdl_nmc.Rsquared.Ordinary, '%.3f') ')']);
grid on;
text(min(nmc_capacity), max(nmc_range), ...
    sprintf('y = %.2fx + %.2f', mdl_nmc.Coefficients.Estimate(2), ...
    mdl_nmc.Coefficients.Estimate(1)), ...
    'VerticalAlignment', 'top');

%% 3. Battery Capacity vs Charging Time
% Scatter plot for LFP and NMC
figure('Position', [100, 100, 1200, 400]);

% LFP Analysis
subplot(1,2,1);
mdl_lfp_charging = fitlm(lfp_capacity, lfp_charging);
scatter(lfp_capacity, lfp_charging, 100, 'filled', 'b');
hold on;
x_lfp_charging = linspace(min(lfp_capacity), max(lfp_capacity), 100);
y_lfp_charging = mdl_lfp_charging.Coefficients.Estimate(1) + mdl_lfp_charging.Coefficients.Estimate(2) * x_lfp_charging;
plot(x_lfp_charging, y_lfp_charging, 'b-', 'LineWidth', 2);
xlabel('Battery Capacity (kWh)');
ylabel('Charging Time (minutes)');
title(['LFP Charging Time Regression (R² = ' num2str(mdl_lfp_charging.Rsquared.Ordinary, '%.3f') ')']);
grid on;
text(min(lfp_capacity), max(lfp_charging), ...
    sprintf('y = %.2fx + %.2f', mdl_lfp_charging.Coefficients.Estimate(2), ...
    mdl_lfp_charging.Coefficients.Estimate(1)), ...
    'VerticalAlignment', 'top');

% NMC Analysis
subplot(1,2,2);
mdl_nmc_charging = fitlm(nmc_capacity, nmc_charging);
scatter(nmc_capacity, nmc_charging, 100, 'filled', 'r');
hold on;
x_nmc_charging = linspace(min(nmc_capacity), max(nmc_capacity), 100);
y_nmc_charging = mdl_nmc_charging.Coefficients.Estimate(1) + mdl_nmc_charging.Coefficients.Estimate(2) * x_nmc_charging;
plot(x_nmc_charging, y_nmc_charging, 'r-', 'LineWidth', 2);
xlabel('Battery Capacity (kWh)');
ylabel('Charging Time (minutes)');
title(['NMC Charging Time Regression (R² = ' num2str(mdl_nmc_charging.Rsquared.Ordinary, '%.3f') ')']);
grid on;
text(min(nmc_capacity), max(nmc_charging), ...
    sprintf('y = %.2fx + %.2f', mdl_nmc_charging.Coefficients.Estimate(2), ...
    mdl_nmc_charging.Coefficients.Estimate(1)), ...
    'VerticalAlignment', 'top');

%% Statistical Tests and Metrics
fprintf('\nStatistical Analysis Results:\n');

% Correlation Analysis Summary
fprintf('\n1. Correlation Analysis:');
fprintf('\nCapacity-Range Correlation: %.3f', corr_matrix(1,2));
```

```
% Regression Analysis Summary
fprintf('\n\n2. Regression Analysis:');
fprintf('\nLFP Range-Capacity Model:');
fprintf('\n    R-squared: %.3f', mdl_lfp.Rsquared.Ordinary);
fprintf('\n    p-value: %.4f', mdl_lfp.Coefficients.pValue(2));
fprintf('\nNMC Range-Capacity Model:');
fprintf('\n    R-squared: %.3f', mdl_nmc.Rsquared.Ordinary);
fprintf('\n    p-value: %.4f', mdl_nmc.Coefficients.pValue(2));

% Performance Metrics Summary
fprintf('\n\n3. Performance Metrics:');
fprintf('\nEnergy Efficiency (km/kWh):');
fprintf('\nRange (km):');
fprintf('\n    LFP Mean: %.2f, Std: %.2f', mean(lfp_range), std(lfp_range));
fprintf('\n    NMC Mean: %.2f, Std: %.2f', mean(nmc_range), std(nmc_range));

% Statistical Analysis Summary
fprintf('\n4. Battery Capacity vs Charging Time Analysis:');
fprintf('\nLFP Regression Model:');
fprintf('\n    R-squared: %.3f', mdl_lfp_charging.Rsquared.Ordinary);
fprintf('\n    p-value: %.4f', mdl_lfp_charging.Coefficients.pValue(2));
fprintf('\nNMC Regression Model:');
fprintf('\n    R-squared: %.3f', mdl_nmc_charging.Rsquared.Ordinary);
fprintf('\n    p-value: %.4f', mdl_nmc_charging.Coefficients.pValue(2));
```

31800

ORIGINALITY REPORT

6%	4%	3%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to United International University Student Paper	3%
2	Submitted to Aristotle University of Thessaloniki Student Paper	<1%
3	jetbis.al-makkipublisher.com Internet Source	<1%
4	www.math.oregonstate.edu Internet Source	<1%
5	Untari Novia Wisesty, Tjokorda Agung Budi Wirayuda, Febryanti Sthevanie, Rita Rismala. "Analysis of Data and Feature Processing on Stroke Prediction using Wide Range Machine Learning Model", Jurnal Online Informatika, 2024 Publication	<1%
6	ebuah.uah.es Internet Source	<1%
7	www.mechanicaljournals.com Internet Source	<1%
8	www.atlantis-press.com Internet Source	<1%

Exclude quotes	On	Exclude matches	< 17 words
Exclude bibliography	On		