MORFAI JOURNAL Multidiciplinary Output Research For Actual and International Issue
Multidiciplinary Output Research For Actual and International Issue (MORFAI Journal) ISSN (e): 2808-6635
Volumes 6 No. 5 (2026)

LITHIUM ION VS. LEAD ACID STARTER BATTERY OF MOTORCYCLE: TECHNICAL ASSESSMENT AND ECONOMIC FEASIBILITY MODEL

Teguh Juang Sinaga[1], Wahyudi Sutopo[2]*, Roni Zakaria Raung[3], Renny Rochani[4], Rina Wiji Astuti[5]
[1,2,3,4] Department of Industrial Engineering, Universitas Sebelas Maret, Surakarta
[5] PT Batex Energi Mandiri, Surakarta
E-mail: teguhjuangsinagauns@student.uns.ac.id[1], wahyudisutopo@staff.uns.ac.id[2*], ronizakaria@staff.uns.ac.id[3], rennyrochani@staff.uns.ac.id[4], admin@batexindonesia.com[5]

Received : 01 June 2026	Accepted : 19 June 2026
Revised : 05 June 2026	Published : 29 July 2026

Abstract

Exposure to emissions from sealed lead-acid (SLA) starter batteries in internal combustion engine (ICE) motorcycles has been demonstrated to have serious impacts on human health and the environment. This has driven the transition to more environmentally friendly technologies. The objective of this study is to evaluate the technical feasibility, market share estimates, and economic viability of lithium starter batteries in Indonesia. The study employs System Dynamics and Probit analysis for the estimation of market potential and the economic feasibility. The findings indicate that LFP is technically more viable than NMC for replacing SLA in starter batteries applications. Investing in the LFP starter batteries business is economically viable. Price changes result in significant changes in the annual cash flow, IRR, NPV, and payback period. Furthermore, the model's performance has been validated by experts and through statistical testing. Statistical test results showing a McFadden Pseudo R-squared score of 0.3049, indicating that the model's performance is highly reliable. This study contributes to supporting businesses in the LFP starter batteries technology sector in commercializing their products, thereby helping to reduce lead emissions that are harmful to human health and the environment.

Keywords: *Economic Feasibility*; *Probit*; *Starter Battery of Motorcycle*; *System Dynamics*; *Willingness to Buy*.

INTRODUCTION

Lead emissions have become a serious threat in recent decades. Exposure to these emissions has been shown to have adverse effects on human health and ecosystems at both the national and global levels. Recent data indicate that exposure to lead emissions continues to contribute to significant mortality and disease burden worldwide (M. Chen et al., 2025; WHO, 2024). The global economic cost of lead exposure in children exceeded $3.4 trillion in 2021 (M. Chen et al., 2025). The World Health Organization (WHO) estimates that lead exposure caused 1.5 million deaths worldwide in 2021 and resulted in the loss of tens of millions of healthy life-years due to lead exposure. Hundreds of millions of children still have blood lead levels above safe thresholds. These figures highlight the significant impact of lead exposure, particularly in low- and middle-income countries (M. Chen et al., 2025). In Indonesia, it is estimated that more than 8 million children have blood lead levels above 5 micrograms per deciliter (µg/dL). These levels indicate that medical intervention is necessary (UNICEF, 2022).

Motorcycles are the dominant mode of transportation for daily commuting among Indonesians. Indonesia ranks third in the world in terms of motorcycle ownership (Setiawan et al., 2023). Motorcycles dominate Indonesia's national land transport fleet. The number of motorcycles is estimated to be around 139.45 million units (BPS RI, 2025). Motorcycles, particularly those with internal combustion engines (ICE), require a starter batteries. A starter batteries is a device that stores electrical energy and is used in a motorcycle's electrical system, such as the lighting system, starter, and fuel management system. The market leader holds a 78% share of the motorcycle market in Indonesia (Astra International, 2024). Furthermore, Indonesia's leading motorcycle manufacturer uses sealed lead-acid (SLA) batteries as starter batteries for the electrical energy storage systems in the motorcycles it produces (Astra Honda Motor, 2023). The lead content in SLA starter batteries is approximately 43–70% (EastPenn, 2024). SLA battery cells have a relatively short service life of 5 years (Islam et al., 2026). The high lead content in each unit and their relatively short service life have serious implications, particularly in Indonesia, where motorcycles dominate daily transportation. One solution to this problem is the transition from SLA starter batteries to LFP (lithium iron phosphate) and NMC (nickel manganese cobalt) batteries. (Yudhistira et al., 2022). NMC is a kind of lithium battery that uses a cathode made of a mixture of nickel, manganese, and cobalt, and has a higher energy density. This makes NMC superior in providing long-range electrical power. LFP is a kind of lithium battery that uses a $LiFePO_4$ cathode and offers better safety at higher ambient temperatures, a longer cycle life, greater stability, and relatively lower raw material costs (Ayuso et al., 2021; Guven & Ozgur Kayalica, 2023). Lithium starter batteries have been available on the Indonesian battery market since 2016. However, the adoption rate of LFP and NMC-based starter batteries is significantly lower than that of SLA starter batteries.

Recent studies indicate that lithium-ion starter batteries offer performance and cost advantages over their lifecycle. However, no studies have yet projected the size of the potential market share, particularly in Indonesia. Therefore, this study will examine a comparison of the technical aspects of each battery type and evaluate the economic viability of lithium starter batteries in Indonesia. The objective is to provide insights for starter batteries manufacturers to enter the lithium-ion battery technology market.

LITERATURE REVIEW

Willingness to Buy

Willingness to Buy (WTB) indicates a stronger behavioral intention, reflecting a consumer's readiness to make a purchase. WTB captures the intention to make a purchase (Khoiriyah et al., 2018). WTB describes a consumer's intention to purchase a product and is a strong predictor of actual purchasing behavior. Consumers' tendency to buy a product or service is influenced by their evaluations, interests, and trust (Raung et al., 2025).

System Dynamics

System Dynamics is a method for dynamically describing, modeling, simulating, and analyzing complex problems and/or systems in relation to processes, information, organizational constraints, and strategies (Pruyt, 2013). System Dynamics (SD) was first introduced by Jay W. Forrester of the Massachusetts Institute of Technology (MIT) in the mid-1950s. The initial focus was on industrial dynamics, which examined the internal structure of industrial firms and their interactions. Forrester's research expanded to urban dynamics in the 1960s, analyzing the growth and decline of cities. In the early 1970s, Forrester's models were used by the Club of Rome to study global sustainability issues. System dynamics methodology has been widely used in various fields, such as economics, finance, environmental studies, health, information technology, and biology. System dynamics is a methodological approach used to examine problems comprehensively by considering a broad (holistic) perspective. The main concept of system dynamics is an understanding of how all objects within a system interact with one another.

Python Simulation (BPTK-Py)

BPTK-Py is an open-source Python-based library used to model, simulate, and analyze dynamic business systems (Transentis Labs GmbH, 2025). BPTK-Py simplifies the creation of system dynamics and agent-based models, making it highly useful for scenario analysis, forecasting, and data-driven business decision-making. To use this framework, modelers need to build simulation models, either directly in Python (ABM/SD models) or in XMILE (using an XMILE-compatible SD modeling tool, such as Stella from isee systems). Models created in Python are essentially subclasses of the ABM and SD Modeling components, while XMILE models are transpilated into these subclasses by the SD Transpiler component.

Probit Analysis

The Probit model is a type of binary response model (K.-P. Lin, 2001). Linear models have a fundamental limitation because a straight line fitted to the data can produce illogical probability predictions, i.e., values less than 0 or greater than 1. To address this limitation, the Probit model uses a nonlinear probability curve shaped like the letter "S." Mathematically, this elegant "S" curve is based on the standard cumulative normal distribution function. The use of this function acts as a natural constraint, ensuring that the estimated probability will always fall within the range of 0 to 1 (Gujarati. Damodar. N, 2004). Thus, the Probit model is capable of providing more consistent and statistically sound predictions for modeling discrete choices. The general form of the Probit model can be written as shown in Eq. (1) (Greene, 2012).

$$P(Y = 1|X) = \Phi(\beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k) \quad (1)$$

Future Research Directions

Previous studies have extensively analyzed the technical performance, economic impact, and environmental impact of starter batteries made from NMC, LFP, and SLA materials (Cetegen et al., 2025; Evro et al., 2024). However, these studies are still limited in their specific discussion of motorcycle starter batteries. Previous studies have also extensively discussed life cycle assessment comparisons (Hasselwander et al., 2023; Sutopo et al., 2018). However, existing studies have been limited in their comprehensive comparison of the total cost of ownership of NMC, LFP, and SLA battery types. Total Cost of Ownership (TCO) is defined as the sum of all costs incurred over the asset's lifecycle, including the initial purchase price, energy operating costs, maintenance and repair costs, financing costs, depreciation, and final disposal or recycling costs (Bauer et al., 2025). These studies are also dominated by deterministic analyses and offer only limited discussion of more comprehensive simulation modeling approaches for representing systems. System Dynamics (SD) is a modeling and simulation method for understanding how complex systems change over time (Transentis Labs GmbH, 2025).

Studies examining consumer attitudes toward starter batteries remain limited (Agnew & Dargusch, 2017; Osawa, 2025). Previous studies have primarily focused on consumer attitudes toward EV batteries (Hidayah et al., 2025; Sutopo & Kadir, 2018) and other applications (Sutopo et al., 2016). Given this gap, this study will assess willingness to buy (WTB) for starter batteries based on total cost of ownership (TCO) levels that fall within consumers' cost tolerance range, ensuring that consumers remain willing to buy such starter batteries. WTB captures the intention to make a purchase (Khoiriyah et al., 2018).

Based on the scientific gaps discussed in previous studies, this study aims to assess the technical feasibility of LFP and NMC as replacements for SLA in starter batteries applications and to design an economic feasibility model capable of predicting the market demand potential for LFP and NMC starter batteries based on the ratio of annual TCO to average costs, using a combined approach of System Dynamics and Probit analysis. The designed model is also capable of analyzing economic feasibility using a techno-economic approach. The model is fully developed using Python and connected to a cloud database, enabling real-time analysis of changes in parameters or future simulation data. The use of Python enables the integration of System Dynamics frameworks and Probit analysis, which cannot be integrated using commercial software (Filippo et al., 2025).

METHOD

This study was conducted in collaboration with PT. Batex Energi Mandiri. Its primary objective is to accurately measure the potential market demand, Internal Rate of Return (IRR), Net Present Value (NPV), and Payback Period (PP) of starter batteries. The methodology employed includes the configuration of starter batteries technical specifications, data collection procedures, and a computational framework for performance evaluation and optimization. Unlike previous studies, which mostly relied on deterministic analysis, this study offers a simulation model that is conceptually robust and performs well in practical applications. It provides a more representative estimate of market demand potential and an economic feasibility analysis that meets established standards. The model was designed using a hybrid approach combining System Dynamics and Probit analysis and was tailored to the preferences of the Indonesian population. The workflow diagram for this study is shown in Figure 1, and the model framework is shown in Figure 2.

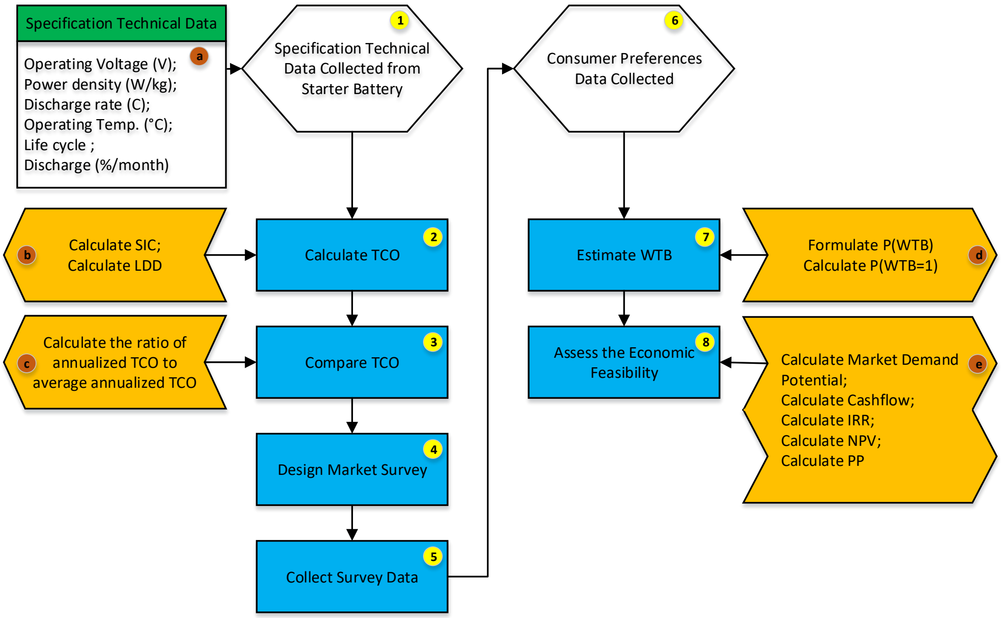


Figure 1. Methodological workflow adopted for comparing technical specifications, estimating WTB starter batteries, and economic feasibility.

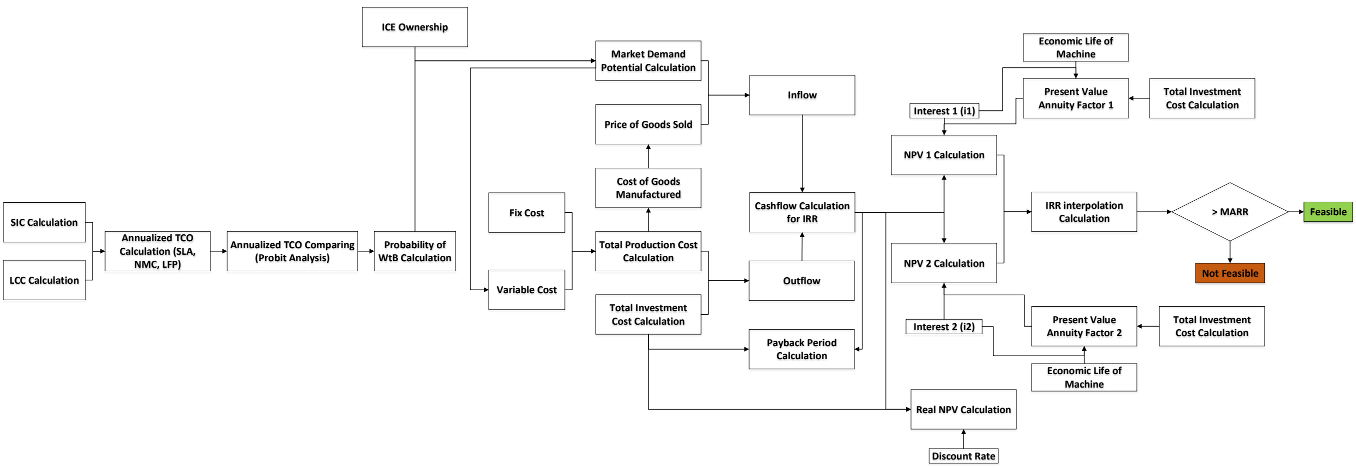


Figure 2. Model Overview.

Simulation of Total Cost Ownership

The TCO of starter batteries in this study is the sum of social impact costs (SIC_{SB}) and life cycle costs (LCC_{SB}). TCO for starter batteries in this study is the sum of social impact costs and life cycle costs.

$$TCO_{SB} = SIC_{SB} + LCC_{SB} \tag{2}$$

The social impact cost (SIC_{SB}) is designed to assess the financial losses incurred due to the use of starter batteries. These costs include lost wages from time spent recharging (RLC_{SB}), maintenance costs (MLC_{SB}), and costs associated with health issues caused by soil contamination from starter batteries.

$$SIC_{SB} = RLC_{SB} + MLC_{SB} + HC_{SB} \tag{3}$$

The health impacts of emissions (HC_{SB}) are assessed based on the total emissions of hazardous chemicals from starter batteries released into the environment, which have significant adverse effects on human health and the ecosystem.

Life Cycle Cost (LCC_{SB}) is designed to calculate the total costs incurred by a starter batteries user in operating the battery over its lifetime ($AEYK_{SB}$). The costs in this case are the purchase price (P_{SB}) of the starter batteries and operating costs (OC_{SB}). These costs are incurred by the user during the year of purchase.

$$LCC_{SB} = \frac{P_{SB}}{AEYK_{SB}} + OC_{SB} - RV_{SB} \quad (4)$$

$$P_{SB}(t) = P_{SB}(t_0) + \int_{t_0}^{t} PI_{SB}(\tau) d \quad (5)$$

$$OC_{SB} = EC_{SB} + MC_{SB} \quad (6)$$

The TCO calculated in this study is the annual equivalent value of TCO, taking into account the time value of money, such that the future resale value is converted into a uniform annual cash flow (Shoeibi et al., 2021; Yazici & Kose, 2024). The resale value is also influenced by the depreciation rate and the discount rate.

$$RV_{SB} = \frac{(1 - DR_{SB})^{AEYK_{SB}} \times P_{SB} \times RDR_{SB}}{(1 + RDR_{SB})^{AEYK_{SB}} - 1} \quad (7)$$

WTB Estimation

This study estimates the probability of WTB ($P(WtB)$) based on the annual TCO ratio relative to the average. The equation used to estimate WTB based on the TCO ratio can be written as shown in Eq. (8).

$$P(WtB = 1 \mid RTCO) = \Phi(\beta_0 + \beta_1 \times RTCO) \quad (8)$$

The survey design was developed to assess the probability that respondents would purchase a starter batteries at a specific annual TCO ratio. Respondents will select the minimum annual TCO ratio at which they would still be willing to purchase the starter batteries. The survey design used in this study is an adaptation of the survey design developed by Frimpong et al. (2019) (Frimpong et al., 2019) which also employs Probit analysis. The survey design used in this study is shown in Figure 3.

Based on the technical specifications of SLA, LFP, and NMC, what type of starter battery do you recommend using?

- ☐ SLA
- ☐ NMC
- ☐ LFP

If you want to buy a battery starter for yout motorcycle, what would be the minimum TCO ratio for that battery compared to the average TCO for all battery types that would make you want to buy it? (Check one option)

- ☐ 2 times more costly
- ☐ 1.75 times more costly
- ☐ 1.5 times more costly
- ☐ 1.25 times more costly
- ☐ Equal
- ☐ 1.25 times more savings
- ☐ 1.5 times more savings
- ☐ 1.75 times more savings
- ☐ 2 times more savings

Figure 3. Survey Design.

Motorcycle users learn about starter batteries through two variables that influence social exposure, direct exposure (E_{Direct}) and indirect exposure ($E_{Indirect}$).

$$E_{Direct} = P_{WTB} \times O_{SB} \times C_{UN} \times WTB_{SB} \tag{9}$$
$$E_{Indirect} = P_{WTB} \times (1 - O_{SB}) \times C_{NN} \times WTB_{SB} \tag{10}$$
$$E_{Total} = E_{Direct} + E_{Indirect} \tag{11}$$
$$\frac{dWTB_{SB}}{dt} = E_{Total} \times max(1.0 - WTB_{SB}, 0.0) \tag{12}$$
$$WTB_{SB}(t) = \int_0^t \left(\frac{dWTB_{SB}}{dt}\right) dt + WTB_{Initial} \tag{13}$$

Direct exposure (E_{Direct}) refers to word-of-mouth influence regarding starter batteries through interactions between starter batteries users and non-users. Direct exposure is determined by multiplying the frequency and impact of contact activities between users and non-users (C_{UN}), WTB starter batteries (WTB_{SB}), ownership proportion (O_{SB}), and the probability of WTB (P_{WTB}). Meanwhile, indirect exposure ($E_{Indirect}$) refers to word-of-mouth influence regarding LFP starter batteries through interactions with others who have knowledge of this type of starter batteries. In other words, indirect exposure is word-of-mouth influence regarding LFP starter batteries resulting from contact between non-users of LFP starter batteries and other non-users of LFP starter batteries. Indirect exposure is determined by the frequency and impact of contact activities among non-users (C_{NN}), WTB starter batteries (WTB_{SB}), ownership proportion (O_{SB}), and the probability of WTB (P_{WTB}).

$$O_{SB}(t) = \int_0^t \left(\frac{dO_{SB}}{dt}\right) dt + O_{Initial} \tag{14}$$

WTB will be used to estimate market demand potential by multiplying WTB by the proportion of ICE motorcycles owned (IMO). The market demand potential (MDP_{SB}) equation can be written as shown in Eq.(15).

$$MDP_{SB} = WTB_{SB} \times IMO \tag{15}$$

Simulation of Techno-Economic

An economic feasibility analysis aims to develop a financial model for the business based on the payback period expected from the business development. This analysis uses the Internal Rate of Return (IRR), Net Present Value (NPV), and Payback Period (PP) as indicators to determine the feasibility of the decision. The Internal Rate of Return (IRR) is the rate of return on an investment (Das, 2024; De Santis et al., 2025). An IRR is considered acceptable when it is equal to or exceeds the Minimum Acceptable Rate of Return ($MARR$). The calculation of the MARR for the IRR can be written as shown in Eq. (16).

$$MARR = (1 + RDR + RR) \times (1 + IR) - 1 \tag{16}$$

The formula for calculating IRR can be written as shown in Eq. (17) (Adriani et al., 2024; Sari et al., 2025)::

$$IRR_{SB} = i_1 + \left(\frac{NPV1_{SB}}{NPV1_{SB} - NPV2_{SB}}\right) \times (i_2 - i_1) \tag{17}$$

In this study, the IRR (IRR_{SB}) uses both positive ($NPV1_{SB}$) and negative NPV ($NPV2_{SB}$) values to obtain more accurate estimates by selecting scenarios with lower (i_1) and higher (i_2) discount rates (Blank & Tarquin, 2018).

NPV (NPV_{SB}) is a financial analysis method used to measure the rate of return on an investment ("Financial Planning Competency Handbook," 2015). NPV (NPV_{SB}) represents the present value of future cash flows (ACF_{SB}) (De Santis et al., 2025). Specifically, NPV (NPV_{SB}) is an analytical method that calculates the present value of net cash inflows (Adriani et al., 2024). A project is profitable if the NPV is greater than 0 (Sari et al., 2025). This indicates that the present value can cover all total investment costs (TIC) incurred based on the applicable discount rate (RDR). Here is the formula for calculating the NPV. The formula for calculating the NPV can be written as shown in Eq. (18).

$$NPV_{SB} = \left(\sum_{n=1}^{ML} \frac{ACF_{SB}}{(1 + RDR)^n} \right) - TIC \quad (18)$$

The techno-economic analysis also evaluates the payback period (PP). The assessment of the payback period aims to analyze the time required for an economic project to reach the break-even point (W. M. Lin et al., 2015; Liu et al., 2022). An investment becomes more viable if its payback period is shorter, and the project is considered viable if its payback period is shorter than the desired payback period payback period (PP).

$$PP_{SB} = \frac{TIC}{ACF_{SB}} \quad (19)$$

RESULTS AND DISCUSSION

Technical Comparison

Ensuring that the starter batteries remains within the minimum/maximum voltage range is essential for preventing damage, extending the battery's lifespan, and minimizing safety risks (Haghverdi et al., 2025). In particular, lithium-ion (Li-Ion) starter batteries must be used within a specific voltage range (Goksu et al., 2020). The starter batteries is equipped with a voltage regulator to maintain an output between 12 and 14.5 V (Zau et al., 2022). Based on these ranges, the battery cell array in a starter batteries application must fall within a safe operating voltage range. NMC has an operating range of 2.5 V to 4.2 V per cell, while LFP has an operating range of 2.8 V to 3.8 V per cell (Hammou et al., 2026), and the SLA has an operating range of 1.81 V to 2.35 V (Ribič et al., 2019).

A lithium starter batteries consists of several lithium battery cells connected in series. To meet the voltage standard of 12 V to 14.5 V, each NMC battery cell must have a voltage within the range of 4 V to 4.83 V in a series configuration of three NMC battery cells. This voltage exceeds the maximum operating voltage limit of each NMC battery cell. If using 4 series circuits, each NMC battery cell must have a voltage in the range of 3 V to 3.63 V. This voltage does not exceed the minimum and maximum operating voltage limits of each NMC battery cell, but the starter batteries will never be fully charged each time it is recharged.

Unlike a starter batteries designed with LFP battery cells, when using four cells in series, each LFP battery cell must have a voltage within the range of 3 V to 3.63 V. This voltage is within the operational voltage range of each LFP battery cell, which is 2.8 V to 3.8 V. Furthermore, SLA starter batteries that are commonly used in 6-cell series configurations have a voltage range of 2 V to 2.42 V. This voltage falls within the operational voltage range of each SLA battery cell, which is 1.81 V to 2.35 V. This indicates that LFP is a more suitable replacement for SLA in starter batteries applications than NMC. In addition to voltage, Table 1 provide information on the technical comparison parameters of LFP and SLA, and indicate whether LFP are suitable replacements for SLA as starter batteries based on those parameters.

Table 1. Technical Comparison SLA and LFP (Islam et al., 2026).

Parameter	Lead-Acid (SLA)	Li-ion (LFP)	Status	Notes (Why it is a Substitute)
Power density (W/kg)	180–400	200–1200	Substitute	LFP batteries can deliver a higher peak power output than SLA batteries, making them better suited for meeting the high energy demands required to start an engine.
Discharge rate (C)	0.2	1–5	Substitute	A discharge rate of 1–5 C causes the starter batteries to drain quickly without damaging the cells.
Operating Temperature (°C)	-20–60	-20–65	Substitute	LFP has better resistance to higher ambient temperatures than SLA, making it more heat-resistant.
Life cycle (80% DoD)	300–500	2000–5000	Substitute	LFP batteries have a longer service life than SLA batteries.
Self-Discharge (%/month)	3–20	1–3	Substitute	The self-discharge rate of LFP batteries is lower than that of SLA batteries.

The use of a battery management system (BMS) cannot reduce or increase the voltage of the charging source for the starter batteries (H. C. Chen et al., 2021). The BMS only disconnects the voltage source if it is overvoltage or undervoltage (Ferg et al., 2019; Schweiger & Löchel, 2016). Based on a comparison of the technical specifications of NMC, LFP, and SLA, LFP is more suitable for use in a series configuration in motorcycle *starter batteries*.

Simulation Result of Total Cost Ownership

The results of TCO SLA, LFP, and NMC for the period 2016–2030 are shown in Figure 4.

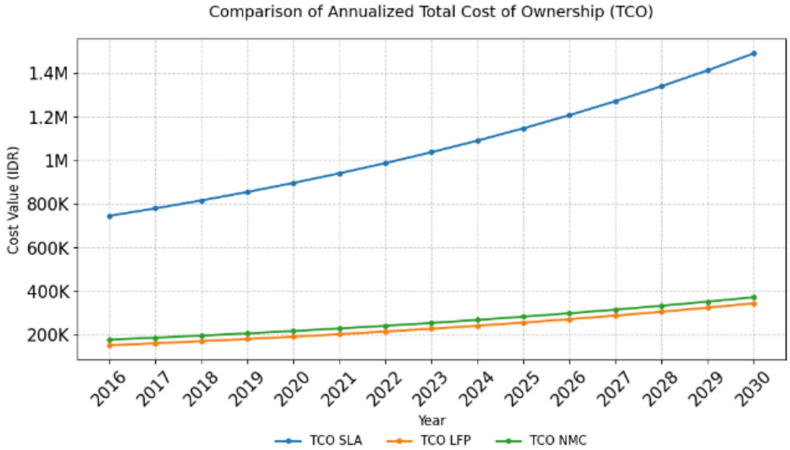


Figure 4. Comparison of Annualized Total Cost of Ownership (TCO) 2016-2030

WTB Estimation Result and Market Demand Potential

The estimated WTB probability for the LFP is determined by the ratio of the LFP annual TCO to the average NMC, LFP, and SLA. The WTB of LFP starter batteries results from the Probit analysis are shown in Figure 5.

Figure 5. Willingness to buy LFP 2016-2030.

After obtaining the WTB value, the next step is to calculate the market demand potential. The results of the market demand potential simulation are shown in Figure 6.

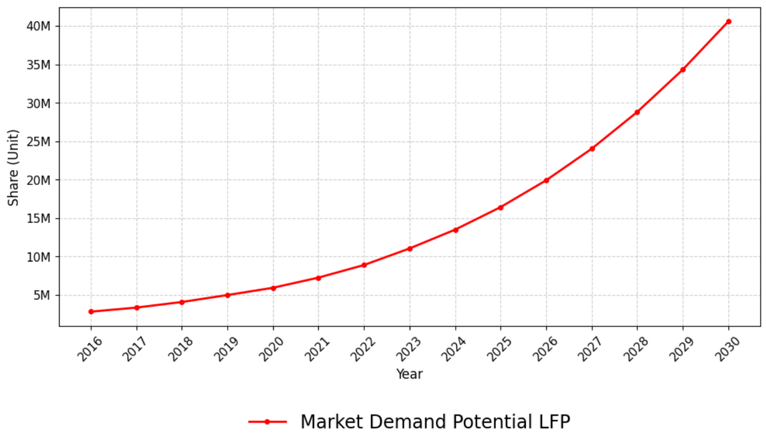


Figure 6. Market Demand Potential 2016-2030.

Simulation Result of Techno-Economic

The discount rates used for interpolation were 188% for Discount Rate 1 and 490% for Discount Rate 2. In this study, the MARR refers to an economic interest rate of 10.5% with an inflation rate of 2.79%, as set by Bank Indonesia (Sutopo et al., 2018), and a risk rate assumption of 5%. The following is the MARR calculation for the IRR:

MARR = (1+10.5%+5%)×(1+2.79%)-1 = 18.72%

Thus, based on the NPV1 and NPV2 alternatives, the IRR simulation results are shown in Figure 7.

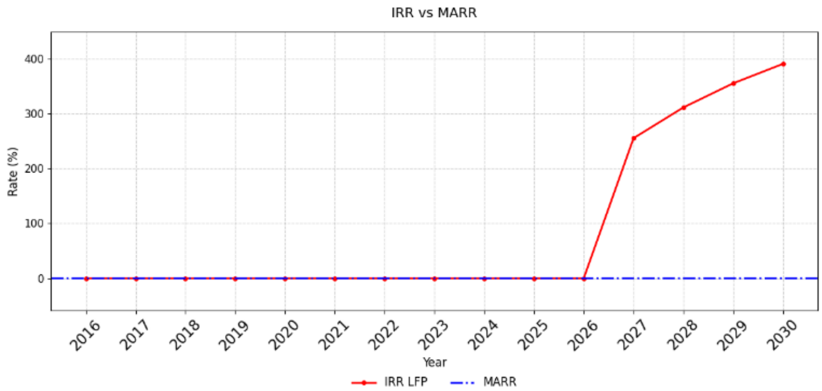


Figure 7. IRR LFP 2016-2030.

The IRR shows an upward trend from 2027 to 2030. This indicates that investing in the starter batteries business is becoming increasingly viable and yielding greater returns. The high IRR values—ranging from 2.55 to 3.90 times the return on investment—are driven by substantial annual cash flow and a very short payback period during that timeframe, which significantly boosts the IRR. (Dao et al., 2025; Naeimi et al., 2026). This makes it feasible for large-scale projects with a broad target market and a shorter payback period (Ziesemer, 2024). However, from 2016 to 2026, the IRR is 0. The model returns a value of 0 if the NPV will never be positive. This indicates that the investment during that period is not yet viable. The NPV calculation serves to show the present value of cash flows in the current period, derived from the valuation of cash flows in future periods. The results of the NPV simulation are shown in Figure 8.

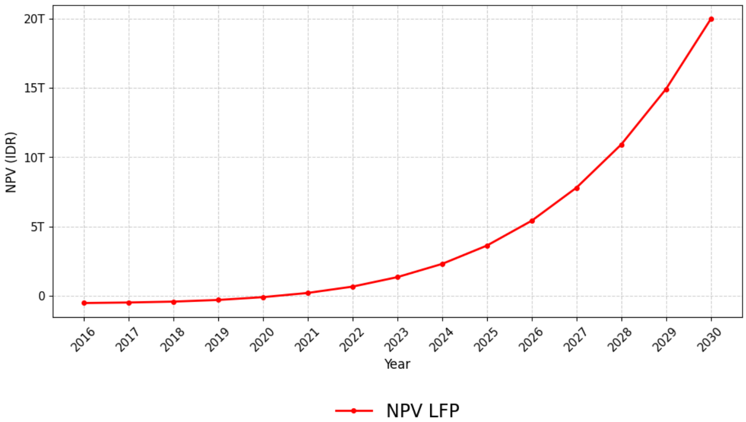


Figure 8. Real NPV LFP 2016-2030.

The NPV values for 2016–2020 indicate that the investment had not yet earned a return based on the cash flow projections for upcoming periods. The NPV began to show a positive trend starting in 2021. This indicates that the investment has become viable, as it has begun to generate a return based on the cash flow projections for upcoming periods. Furthermore, to further analyze the feasibility of commercializing LFP starter batteries, the payback period (PP) method is used to determine how long it will take to recoup the investment. Each alternative assumption regarding market share with different numbers of users will affect the time required for capital recovery. The payback period (PP) calculation results are shown in Figure 9.

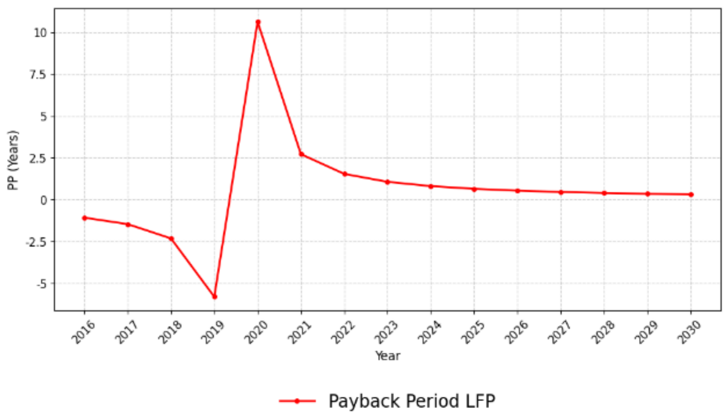


Figure 9. Payback Period LFP 2016-2030.

The negative payback period values for 2016–2019 indicate that the capital invested will never be returned from investment returns. The payback period began to show the possibility of capital recovery starting in 2020, but this timeframe is considered very long because the total costs incurred are still significantly greater than the cash flow. The payback period (PP) trend begins to show a downward trend in 2021–2030. This aligns with the results of the previous NPV simulation, which showed that NPV increased significantly starting in 2021, thereby shortening the estimated payback period.

Model Verification and Validation

The survey obtained a total of 450 respondents. This sample size is representative of the population, with a margin of error of 4.62%. Upon confirming that the sample size is sufficient to represent the population, the data will be analyzed using the designed model (Lodhi et al., 2022). Verification of the System Dynamics simulation code was conducted through code debugging and examination of logical causal relationships between variables, as well as ensuring that the units of measurement used were standard and consistent. A bottom-up approach was used to verify each designed module. The model was run using Python programming, and the results showed that the model ran smoothly without warnings such as “an error was found in the model and it cannot be simulated.” This indicates that the relationships between variables in the model, along with the units of measurement assigned to each variable, are consistent. Therefore, it can be concluded that the developed model is a consistent model. After ensuring that the model is consistent, the next step is to validate it by involving several experts to assess whether it accurately reflects the intended concept. The experts involved are a professor, two doctors, and an entrepreneur who have conducted studies and published works in the same field or on similar models. Their evaluation aims to confirm the model's relevance, accuracy, and applicability. The validation process involves a direct evaluation, in which the experts review the model's assumptions, parameters, and results. Following their comprehensive review, it was confirmed that the model designed in this study is valid.

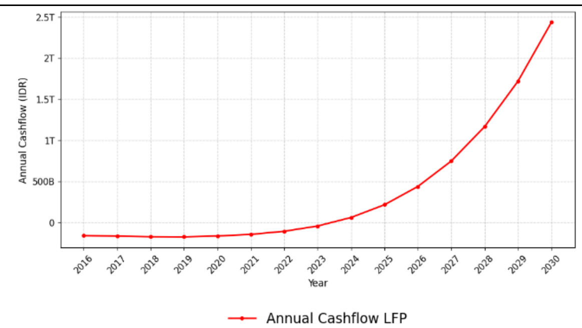
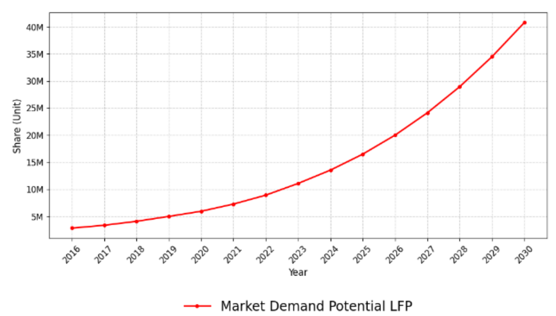
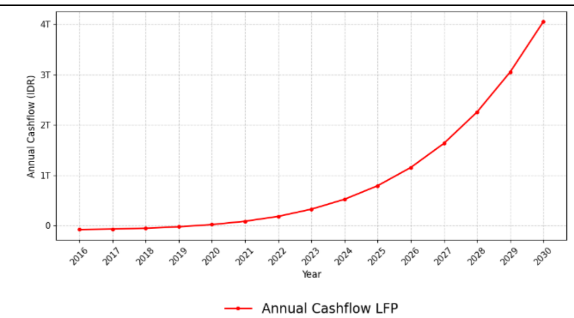
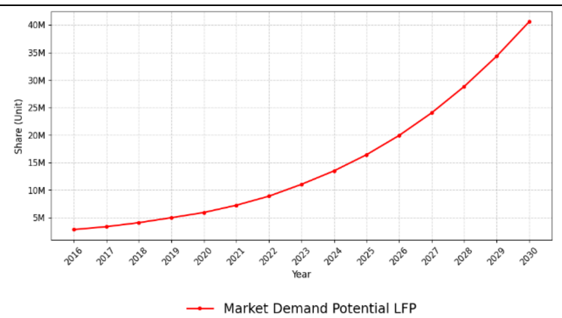
The statistical tests used to validate the Probit model's output in this study include the McFadden coefficient and pseudo-R^2 to assess goodness-of-fit, the Likelihood Ratio (LLR) p-value to assess the overall significance of the model, and the block bootstrapping method with 1.000 iterations to test the reliability of the supply curve and the confidence intervals of the Willingness to buy (WTB) thresholds. Additionally, validation was conducted through a robustness check by comparing the sample-based thresholds with those generated by the Probit model to ensure model consistency. The Probit model developed in this study demonstrates a very strong model fit, with a McFadden pseudo R-squared score of 0.3049. According to methodological standards, a pseudo-R^2 value in the range of 0.2 to 0.4 is classified as having a "very good" fit (Galick et al., 2025). The overall significance of the model is confirmed by an LLR p-value of 0.000, indicating that the TCO variable is statistically significant in explaining the probability of WTB.

Sensitivity Analysis

The sensitivity analysis in this study aims to examine the impact of changes in the price of LFP starter batteries Market Demand Potential, IRR, NPV, and Payback Period.

a. Parameter: Starter batteries LFP Price

This study assesses the impact of price changes on Market Demand Potential, IRR, NPV, and Payback Period in a sensitivity analysis by reducing the price by 10% and increasing the price by 10%. The results of the sensitivity analysis are presented in Figure 10.

<table>
<tr><th>Annual Cashflow LFP</th><th>Market Demand Potential LFP</th><th>Scenario</th></tr>
<tr><td>
</td><td>
</td><td>A</td></tr>
<tr><td>
</td><td>
</td><td>B</td></tr>
</table>

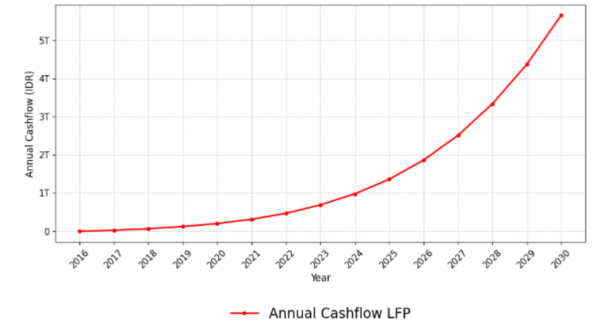
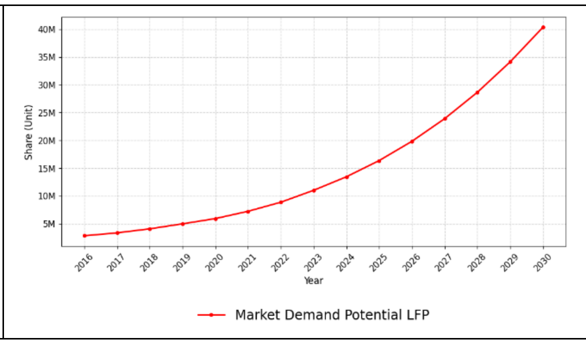
		C

Figure 10. Sensitivity of Annual Cashflow and Market Demand Potential Toward Starter batteries LFP Price: : (A) 10% Lower; (B) Base; (C) 10% higher.

Price reductions of 10% set by the company result in a 39.89% decrease in annual cash flow by 2030. Price increases of 10% result in a 39.43% increase in annual cash flow by 2030. Neither price reductions nor increases of 10% significantly affect potential market demand. This indicates that demand is insensitive to price changes. Lowering prices, coupled with demand that is insensitive to price changes, will result in smaller cash inflows. Cash inflows that are smaller than cash outflows cause annual cash flow to decrease further in each investment period. Conversely, raising prices, coupled with demand that is insensitive to price changes, will result in larger cash inflows. Cash inflows that are larger than cash outflows cause annual cash flow to increase further in each investment period.

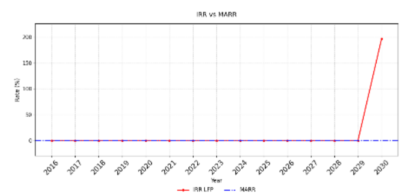
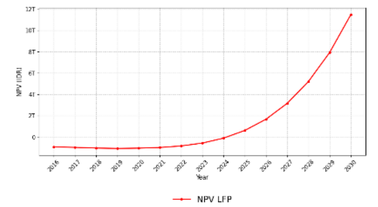
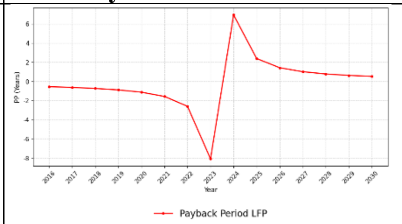
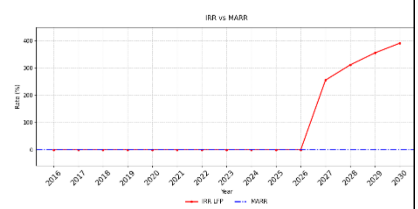
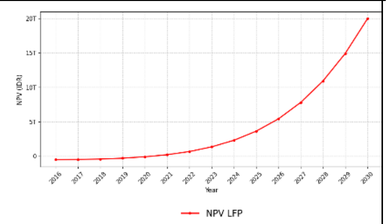
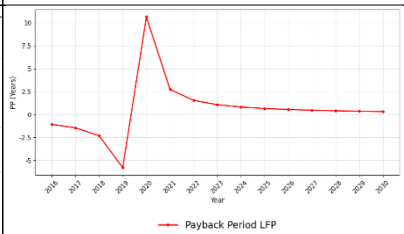
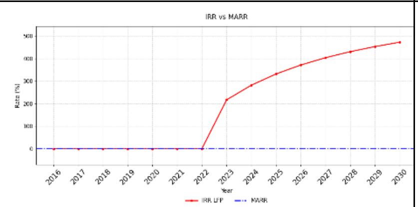
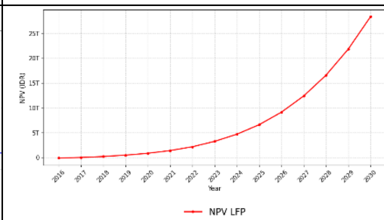
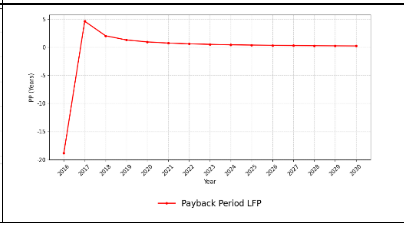
IRR LFP	NPV LFP	Payback Period LFP	Scenario
			A
			B
			C

Figure 11. Sensitivity of IRR, NPV, and Payback Period Toward Starter batteries LFP Price: : (A) 10% Lower; (B) Base; (C) 10% higher.

Sensitivity analysis shows that price changes affect the IRR, NPV, and payback period. Price reduction of 10% results in a 49.62% lower IRR in 2030. Price increases of 10% result in a 21.15% higher IRR in 2030. Lower prices coupled with demand that is insensitive to price changes result in cash inflows for each investment period showing a downward trend, causing the rate of return on capital or investment to decrease. Higher prices coupled with demand that is insensitive to price changes result in cash inflows for each investment period showing an upward trend, causing the rate of return on capital or investment to increase. Price reduction of 10% results in a 42.45% decrease in NPV by 2030. Price increase of 10% results in a 41.97% increase in NPV by 2030. Decreases and increases in price of 10% have a significant impact on NPV because they affect annual cash flow. Lower prices combined with demand that is insensitive to price changes result in incoming cash flows for each investment period showing a downward trend, causing the present net profit—measured by the valuation of future cash flows—to decrease further. Higher prices coupled with demand that is insensitive to price changes result in incoming cash flows for each investment period showing an upward trend, thereby increasing the present net profit as measured by the valuation of future cash flows.

Price reduction of 10% results in an estimated payback period that is 67.29% longer if the investment begins in 2030. Price increase of 10% results in an estimated payback period that is 28.69% shorter if the investment begins in 2030. Price reduction of 10% has a significant impact on the payback period because it affects annual cash flow. Lower prices coupled with demand that is insensitive to price changes result in cash inflows during each investment period showing a downward trend, making it impossible or taking longer to recover the capital or investment used. Higher prices coupled with demand that is insensitive to price changes result in cash inflows during each investment period showing an upward trend, making it possible to recover the capital or investment used more quickly (Karl E. Case et al., 2012).

CONCLUSION

Based on a review of the technical specifications of SLA, LFP, and NMC, it is evident that NMC is not suitable for starter batteries applications when considering the voltage of both 3-cell and 4-cell series configurations. LFP is a more suitable replacement for SLA in starter batteries applications. LFP demonstrates superior power density, discharge rate, operating temperature, cycle life, and self-discharge compared to SLA. The results of the economic feasibility model simulation for LFP starter batteries show that the NPV has been increasing steadily since 2021. This has led to a significant decrease in the payback period since 2021. However, although the project has been viable since 2021, the IRR value only shows a positive trend starting in 2027. This indicates that the 2021–2026 period is still in the market share expansion phase, where cash inflows begin to cover investments but have not yet reached an optimal point. The significant surge in the IRR in 2027 signifies the achievement of economies of scale, where production efficiency and sales volume reach their peak, resulting in a very high annual rate of return. Thus, investment in the LFP starter batteries industry is not only economically viable but also offers more promising profitability in the long term starting in 2027.

The performance of the System Dynamics model and the Probit analysis demonstrates high validity and reliability. This has been verified by experts, and statistical tests indicate that the model has a McFadden Pseudo R-squared score of 0.3049, indicating that the model provides excellent estimation results. A sensitivity analysis of LFP starter batteries prices was conducted to assess changes in annual cash flow, market demand potential, IRR, NPV, and payback period. The higher cash inflows will increase annual cash flow, increase the return on capital or investment, increase current net profit, and shorten the payback period. However, price changes do not significantly affect market demand potential. This indicates that consumers are not price-sensitive because LFP batteries offer a cost advantage over their lifetime compared to SLA starter batteries, so the total cost over the lifetime of an LFP starter batteries remains lower than that of an SLA starter batteries. This is the reason that consumers are not sensitive to product prices at the initial purchase.

The recommended business strategy for the company is to focus on increasing its market share, thereby generating a more profitable cash flow. In addition, the company must improve cost efficiency to set more competitive prices. This study acknowledges that some assumptions regarding the data used remain due to data limitations in the relevant systems. Future studies are expected to utilize more real-world data to provide better analytical results. This study also has not yet considered the impact of marketing on WTB. Incorporating the impact of marketing in future studies could provide a more comprehensive and representative understanding of market dynamics.

ACKNOWLEDGEMENTS AND/OR FUNDING RESOURCES

This research was funded by the Ministry of Education, Culture, Research, and Technology for the 2026 fiscal year through a research grant under the Master's to Doctoral Scholarship Program for Outstanding Undergraduates (PMDSU), pursuant to Research Assignment Agreement No. 320/C3/DT.05.00/PL-PMDSU/2026.

REFERENCES

Adriani, D., Yazid, M., Riswani, Damayanthy, D., Choi, E., & Yang, H. (2024). Livelihood Alternatives in Restored Peatland Areas in South Sumatra Province, Indonesia. *Land*, *13*(5). https://doi.org/10.3390/land13050643

Agnew, S., & Dargusch, P. (2017). Consumer preferences for household-level battery energy storage. In *Renewable and Sustainable Energy Reviews* (Vol. 75, pp. 609–617). Elsevier Ltd. https://doi.org/10.1016/j.rser.2016.11.030

Astra Honda Motor. (2023, May 30). *Apa itu Baterai MF (Maintenance Free) ?*

Astra International. (2024). *Full Year Financial Statements*. https://www.londonstockexchange.com/news-article/JAR/pt-astra-2023-full-year-financial-statements/16351119

Ayuso, P., Beltran, H., Segarra-Tamarit, J., & Pérez, E. (2021). Optimized profitability of LFP and NMC Li-ion batteries in residential PV applications. *Mathematics and Computers in Simulation*, *183*, 97–115. https://doi.org/10.1016/j.matcom.2020.02.011

Bauer, J., Letmathe, P., & Woeste, R. (2025). Total cost of ownership for battery electric vehicles: The role of energy prices. *Applied Energy*, *389*. https://doi.org/10.1016/j.apenergy.2025.125764

Blank, L. T., & Tarquin, A. J. (2018). *Engineering Economy*. McGraw-Hill Education. https://books.google.co.id/books?id=VbFijwEACAAJ

BPS RI. (2025, December 8). *Perkembangan Jumlah Kendaraan Bermotor Menurut Jenis (Unit), 2024*. https://www.bps.go.id/assets/statistics-table/2/NTcjMg%3D%3D/perkembangan-jumlah-kendaraan-bermotor-menurut-jenis--unit-.html

Cetegen, S. A., Gundersen, T., & Barton, P. I. (2025). Evaluating economic feasibility of lithium-ion battery energy storage systems in future US electricity markets. *Energy*, *337*. https://doi.org/10.1016/j.energy.2025.138469

Chen, H. C., Li, S. S., Wu, S. L., & Lee, C. Y. (2021). Design of a modular battery management system for electric motorcycle. *Energies*, *14*(12). https://doi.org/10.3390/en14123532

Chen, M., Gazze, L., DiTraglia, F. J., Das, R., Nriagu, J., Erel, Y., Boyle, E. A., Taylor, C. M., & Weiss, D. (2025). Environmental lead risk in the 21st century. In *Communications Earth and Environment* (Vol. 6, Number 1). Nature Publishing Group. https://doi.org/10.1038/s43247-025-02735-x

Dao, C. N., Tabil, L. G., Mupondwa, E., Dumonceaux, T., Li, X., & Dalai, A. K. (2025). Technoeconomic analysis of an integrated camelina straw-based pellet and ethanol production system. *RSC Sustainability*, *3*(3), 1564–1583. https://doi.org/10.1039/d4su00769g

Das, S. (2024). Enabling role of policies to make public charging infrastructure development viable in an Indian city: A modelling-based analysis. *Transport Economics and Management*, *2*, 286–301. https://doi.org/10.1016/j.team.2024.09.005

De Santis, D., Giagnorio, M., & Matteucci, G. (2025). Investments in local public transport: A systematic literature review on evaluation methods with a focus on the role of uncertainty. In *Transport Economics and Management* (Vol. 3, pp. 441–459). Elsevier B.V. https://doi.org/10.1016/j.team.2025.11.002

EastPenn. (2024). *Safety Data Sheet*. https://www.eastpennmanufacturing.com/wp-content/uploads/Wet-Batteries.pdf

Evro, S., Ajumobi, A., Mayon, D., & Tomomewo, O. S. (2024). Navigating battery choices: A comparative study of lithium iron phosphate and nickel manganese cobalt battery technologies. *Future Batteries*, *4*, 100007. https://doi.org/10.1016/j.fub.2024.100007

Ferg, E. E., Schuldt, F., & Schmidt, J. (2019). The challenges of a Li-ion starter lighting and ignition battery: A review from cradle to grave. In *Journal of Power Sources* (Vol. 423, pp. 380–403). Elsevier B.V. https://doi.org/10.1016/j.jpowsour.2019.03.063

Filippo, O., Zenezini, G., & Viero, P. (2025). *OpenCLD: A Python-Native Library for Hybrid System Dynamics and*.

Financial Planning Competency Handbook (John Wiley & Sons, Tran.). (2015). In *Financial Planning Competency Handbook*. https://doi.org/https://doi.org/10.1002/9781119642497.ch11

Frimpong, E., Kruse, J., Howard, G., Davidson, R., Trainor, J., & Nozick, L. (2019). Measuring Heterogeneous Price Effects for Home Acquisition Programs in At-Risk Regions. *Southern Economic Journal*, *85*(4), 1108–1131. https://doi.org/10.1002/soej.12341

Galick, D. S., Eyono, J. N. M., Rivas, M. R., Phiri, W. P., Guerra, C. A., & García, G. A. (2025). Indoor residual spraying household visits as a platform for engaging pregnant women in malaria prevention on Bioko Island, Equatorial Guinea. *BMC Pregnancy and Childbirth*, *25*(1). https://doi.org/10.1186/s12884-025-08257-w

Goksu, O. F., Arabul, A. Y., & Vural, R. A. (2020). Low voltage battery management system with internal adaptive charger and fuzzy logic controller. *Energies*, *13*(9). https://doi.org/10.3390/en13092221

Greene, W. H. . (2012). *Econometric Analysis: Seventh Edition*. Prentice Hall.

Gujarati. Damodar. N. (2004). *Basic Econometrics: Fourth Edition*. The McGraw−Hill Companies.

Guven, D., & Ozgur Kayalica, M. (2023). Life-cycle assessment and life-cycle cost assessment of lithium-ion batteries for passenger ferry. *Transportation Research Part D: Transport and Environment*, *115*. https://doi.org/10.1016/j.trd.2022.103586

Haghverdi, K., Danilov, D. L., Mulder, G., Couto, L. D., Guo, F., & Eichel, R. A. (2025). Review of the Safe

Operating Area (SOA) for Batteries: Evolving concepts and structured frameworks. In *Journal of Power Sources* (Vol. 652). Elsevier B.V. https://doi.org/10.1016/j.jpowsour.2025.237483

Hammou, A., Petrone, R., Diallo, D., Delpha, C., & Gualous, H. (2026). State of Health Evaluation of Lithium-Ion Batteries Using the Statistical Properties of the Voltage. *Entropy*, *28*(2). https://doi.org/10.3390/e28020221

Hasselwander, S., Meyer, M., & Österle, I. (2023). Techno-Economic Analysis of Different Battery Cell Chemistries for the Passenger Vehicle Market. *Batteries*, *9*(7). https://doi.org/10.3390/batteries9070379

Hidayah, F. N., Hisjam, M., Ma'aram, A., & Sutopo, W. (2025). Comparison of customer preferences in Malaysia and Indonesia to evaluate the need of charging infrastructure and dual battery electric motorcycle as an effort to increase the adoption rate of electric motorcycles. *Case Studies on Transport Policy*, *20*. https://doi.org/10.1016/j.cstp.2025.101446

Islam, Md. I., Mahbubul, I. M., Jadin, M. S., Mansur, A. Al, & Alharbi, T. (2026). Lead-acid and lithium-ion batteries for electric mobility applications: A comparative review of performance, economics, industry trends, and future outlook. *Journal of Energy Storage*, *155*, 121187. https://doi.org/10.1016/j.est.2026.121187

Karl E. Case, Ray C. Fair, & Sharon M. Oster. (2012). *Principles of Economics*.

Khoiriyah, S., Juan, M., & Toro, S. (2018). ATTITUDE TOWARD GREEN PRODUCT, WILLINGNESS TO PAY AND INTENTION TO PURCHASE. In *International Journal of Business and Society* (Vol. 19, Number 4).

Lin, K.-P. (2001). *GAUSS Programming for Econometricians and Financial Analysts*. ETEXT Publishing.

Lin, W. M., Chang, K. C., & Chung, K. M. (2015). Payback period for residential solar water heaters in Taiwan. In *Renewable and Sustainable Energy Reviews* (Vol. 41, pp. 901–906). Elsevier Ltd. https://doi.org/10.1016/j.rser.2014.09.005

Liu, B., Chen, Y., Yang, H., Peng, B., & Luo, K. (2022). Optimal service life analysis of shared bicycles under 'three-year mandatory scrapping' policy. *Sustainable Production and Consumption*, *30*, 518–526. https://doi.org/10.1016/j.spc.2021.12.029

Lodhi, R. H., Rana, I. A., & Waheed, A. (2022). Gendered mode choice preferences and characteristics for educational trips in Abbottabad, Pakistan: An empirical investigation. *Case Studies on Transport Policy*, *10*(4), 2102–2110. https://doi.org/10.1016/j.cstp.2022.09.010

Naeimi, M., Samiei Moghaddam, M., Azarfar, A., Vahedi, M., & Koochaksaraei, J. S. (2026). Investigating the impact of electric vehicles on increasing the reliability of the distribution system using the enhanced gray wolf evolutionary algorithm model. *Scientific Reports*, *16*(1). https://doi.org/10.1038/s41598-026-46206-5

Osawa, J. (2025). Consumer preferences for second-life electric vehicle batteries across multiple applications. *Cleaner and Responsible Consumption*, *19*. https://doi.org/10.1016/j.clrc.2025.100337

Pruyt, E. (2013). *Small System Dynamics Models for Big Issues: Triple Jump towards Real-World Dynamic Complexity*.

Raung, R. Z., Sutopo, W., Hisjam, M., & Hartono, D. (2025). Scenario analysis of subsidy policies on electric motorcycle market in Indonesia using system dynamics simulation. *Transportation Research Interdisciplinary Perspectives*, *32*, 101487. https://doi.org/https://doi.org/10.1016/j.trip.2025.101487

Ribič, J., Pihler, J., Maruša, R., Kokalj, F., & Kitak, P. (2019). Lead-acid battery sizing for a DC auxiliary system in a substation by the optimization method. *Energies*, *12*(22). https://doi.org/10.3390/en12224400

Sari, M., Setyawati, F., Berawi, M. A., & Miraj, P. (2025). Logistic Aerocity: Optimizing financial feasibility through public-private partnerships. *Transportation Research Interdisciplinary Perspectives*, *34*. https://doi.org/10.1016/j.trip.2025.101675

Schweiger, H.-G., & Löchel, J. (2016, May 10). *2 V lithium ion starter batteries*.

Setiawan, A. D., Zahari, T. N., Anderson, K., Moeis, A. O., & Hidayatno, A. (2023). Examining the effectiveness of policies for developing battery swapping service industry. *Energy Reports*, *9*, 4682–4700. https://doi.org/10.1016/j.egyr.2023.03.121

Shenzhen Li-ion Battery Bodyguard Technology Co., L. (2019). *Motorcycle Start BMS 3s/4s 30A LiFePO4 PCM*. https://lws-pcm.en.made-in-china.com/product/aNWQGAglYjhe/China-Motorcycle-Start-BMS-3s-4s-30A-LiFePO4-PCM.html?

Shoeibi, S., Rahbar, N., Abedini Esfahlani, A., & Kargarsharifabad, H. (2021). A comprehensive review of Enviro-Exergo-economic analysis of solar stills. In *Renewable and Sustainable Energy Reviews* (Vol. 149). Elsevier Ltd. https://doi.org/10.1016/j.rser.2021.111404

Sutopo, W., & Kadir, E. A. (2018). Designing Framework for Standardization Case Study: Lithium-Ion Battery Module in Electric Vehicle Application. *International Journal of Electrical and Computer Engineering*, *8*(1), 220–226. https://doi.org/10.11591/IJECE.V8I1.PP220-226

Sutopo, W., Kurniyati, I., & Zakaria, R. (2018). Markov Chain and Techno-Economic Analysis to Identify the Commercial Potential of New Technology: A Case Study of Motorcycle in Surakarta, Indonesia. *Technologies*, *6*(3). https://doi.org/10.3390/technologies6030073

Sutopo, W., Nizam, M., Purwanto, A., Atikah, N., & Putri, A. S. (2016). A cost estimation application for determining feasibility assessment of Li-Ion battery in mini plant scale. *International Journal on Electrical Engineering and Informatics*, *8*(1), 189–199. https://doi.org/10.15676/ijeei.2016.8.1.13

Transentis Labs GmbH. (2025). *BPTK-Py: System dynamics and agent-based modeling in Python*. Transentis Labs. https://bptk.transentis.com

UNICEF. (2022). *Ringkasan Kebijakan: Mengurangi Keracunan Timbal pada Anak-Anak di Indonesia*. https://www.unicef.org/indonesia/media/15311/file/Ringkasan%20Kebijakan%20-%20Mengurangi%20Keracunan%20Timbal%20pada%20Anak-anak%20di%20Indonesia.pdf

WHO. (2024, September 27). *Lead poisoning*. https://www.who.int/news-room/fact-sheets/detail/lead-poisoning-and-health

Yazici, M., & Kose, R. (2024). Comparative and comprehensive experimental analysis: Performance variation of a novel hybrid dryer. *Applied Thermal Engineering*, *240*. https://doi.org/10.1016/j.applthermaleng.2023.122226

Yudhistira, R., Khatiwada, D., & Sanchez, F. (2022). A comparative life cycle assessment of lithium-ion and lead-acid batteries for grid energy storage. *Journal of Cleaner Production*, *358*. https://doi.org/10.1016/j.jclepro.2022.131999

Zau, A. T. P., Lencwe, M. J., Chowdhury, S. P. D., & Olwal, T. O. (2022). A Battery Management Strategy in a Lead-Acid and Lithium-Ion Hybrid Battery Energy Storage System for Conventional Transport Vehicles. *Energies*, *15*(7). https://doi.org/10.3390/en15072577

Ziesemer, T. H. W. (2024). Internal rates of return for public R&D from VECM estimates for 17 OECD Countries. *Economic Change and Restructuring*, *57*(5). https://doi.org/10.1007/s10644-024-09740-8