Fraunhofer
ISI

Agent-based Simulation for Market Diffusion of Passenger Cars and Motorcycles BEV in Greater Jakarta Area

Authors:

Rizqi Ilma Nugroho, Till Gnann, Daniel Speth, Widodo Wahyu Purwanto,
Jessica Hanafi, Sutanto Soehodho

No. S05/2024

Imprint

Agent-based Simulation for Market Diffusion of Passenger Cars and Motorcycles BEV in Greater Jakarta Area

Authors

Rizqi Ilma Nugroho, rizqi.ilma01@ui.ac.id
Chemical Engineering Department, Faculty of Engineering, Universitas Indonesia, Depok, 16424, Indonesia
Sustainable Energy Systems and Policy Research Cluster, Universitas Indonesia, Depok, 16424, Indonesia

Till Gnann, till.gnann@isi.fraunhofer.de
Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139, Karlsruhe

Daniel Speth, daniel.speth@isi.fraunhofer.de
Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Strasse 48, 76139, Karlsruhe

Widodo Wahyu Purwanto, widodo@che.ui.ac.id
Chemical Engineering Department, Faculty of Engineering, Universitas Indonesia, Depok, 16424, Indonesia
Sustainable Energy Systems and Policy Research Cluster, Universitas Indonesia, Depok, 16424, Indonesia

Jessica Hanafi, jessica.hanafi@lifecycleindonesia.com
PT. Life Cycle Indonesia, Jakarta Barat, DKI Jakarta 11620, Indonesia

Sutanto Soehodho, tanto@eng.ui.ac.id
Civil Engineering Department, Faculty of Engineering, Universitas Indonesia, Depok, 16424, Indonesia
Transport Research Group, Civil Engineering, Faculty of Engineering, Universitas Indonesia, Depok, 16424, Indonesia

Picture credits

Cover page: Shutterstock.com/TechSolution

Recommended citation

Nugroho, R. I.; Gnann, T.; Speth, D.; Purwanto, W. W.; Hanafi, J.; Soehodho, S. (2024): Agent-based Simulation for Market Diffusion of Passenger Cars and Motorcycles BEV in Greater Jakarta Area. Depok, Jakarta, Karlsruhe: Universitas Indonesia, Fraunhofer ISI, DKI Jakarta. Working Paper Sustainability and Innovation No. S 05/2024.

Published

April 2024

Digital Object Identifier (DOI)

doi:10.24406/publica-2986

Contact

Fraunhofer Institute for Systems und Innovation Research ISI

Breslauer Strasse 48, 76139 Karlsruhe, Germany
Till Gnann, till.gnann@isi.fraunhofer.de

Notes

Abstract

Battery electric vehicles (BEV) present a promising approach to decarbonizing the transportation sector. This extends beyond electric passenger cars, such as electric motorcycles that hold significant potential in emerging markets with high population density and income disparities. However, providing access to infrastructure remains a challenge in increasing BEV adoption. This research endeavours to determine BEV passenger cars (BEV-PC) and motorcycles (BEV-MC) market diffusion within an emerging market city, focusing on the Greater Jakarta Area, utilizing an Agent-Based Model that considers charging infrastructure availability. Findings indicate that BEV-PC diffusion could attain about 9% of the total vehicle stock by 2030 and almost 75% by 2050 under the Current Policy. Similarly, BEV-MC adoption rates may reach 39% by 2030 and 80% by 2050. Introducing a vehicle purchase subsidy along with full abolishment of fossil fuel subsidies could amplify the diffusion of BEV-PC and BEV-MC to almost triple and double in 2030, respectively.

Contents

1 Introduction

The use of battery electric vehicles (BEV) has a significant potential for reducing greenhouse gas emissions, particularly from the road transport sector, to about half of the total emission produced by conventional internal combustion engine vehicles (ICEV) today in 2030 (IEA, 2020). Despite that, the adoption of BEV globally reached only 1.46% of the total vehicle stock in 2022 (IEA, 2023a). Adopting is even slower in emerging markets (e.g., Indonesia, India, Brazil). Khan et al. (2022) examined that there is a need to improve current policies to raise the uptake of zero-emission vehicles (ZEV), namely BEV and fuel cell electric vehicles (FCEV), in the emerging markets to prevent a doubling of well-to-wheel CO_2 emissions in 2050 compared to 2020 level. In contrast, a widespread diffusion of zero-emission vehicles may reduce CO_2 emissions to half compared to 2020. This implies a need for strategies and proper planning to increase the market diffusion of these vehicles in these regions.

Indonesia, an emerging market country with the largest economy in Southeast Asia (Worldbank, 2022), comprises 38 provinces across five main islands. Nonetheless, the focal point of its economic activities is the Greater Jakarta Area, characterized by the highest per capita Gross Regional Domestic Product (GRDP) and growth compared to other regions (BPS, 2023). The area comprises of the capital city (DKI Jakarta) and its outskirts. Subsequently, the area has 3.5 million passenger cars and 18 million two-wheelers/motorcycles (BPS, 2019). Albeit the high per capita GRDP, the Greater Jakarta experiences significant income inequality (Van Ham et al., 2021), with an average Gini coefficient of around 0.39 from all provinces in the region in 2018. Furthermore, each city/regency in the area exhibits high population densities, ranging from 2,000 to above 15,000 people/km^2 in 2020 (BPS, 2020c, BPS, 2020b, BPS, 2020a). Based on lessons learned from other urban cities with similar demographic conditions (see Table 1), these conditions could raise challenges in increasing BEV adoption, namely access to charging infrastructure and affordability (high vehicle purchase price).

Table 1: BEV Adoption Barriers from Cities Similar to Greater Jakarta Area

Country	City	Population Density (people/km^2)	Gini coefficient	BEV Adoption Barrier	Source
India	Hyderabad	18,480	0.10	Availability of Charging Infrastructure, Recurring cost	Munshi et al. (2022)
China	Beijing	1,330	0.97	Availability of Charging Infrastructure, Vehicle Purchase Price	Ling et al. (2021)
Thailand	Bangkok	3,503	0.35	Vehicle Purchase Price, Availability of Charging Infrastructure	Kongklaew et al. (2021)

Country	City	Population Density (people/km^2)	Gini coefficient	BEV Adoption Barrier	Source
Brazil	Sao Paulo	7,216	0.53	Vehicle Purchase Price, Availability of Charging Infrastructure	Buranelli de Oliveira et al. (2022)
Indonesia	Greater Jakarta Area	4,384	0.39	Availability of Charging Infrastructure, Vehicle purchase price	PwC Indonesia (2023), Deloitte (2022), Gunawan et al. (2022)

Nonetheless, the government of Indonesia has also set targets for BEV rollout. The Ministry of Industry (2022) develops a national production target of 400 thousand in 2025 and 600 thousand in 2030 for passenger car BEV (BEV-PC), 6 million in 2025, and 9 million for electric two and three-wheelers (BEV-2W, BEV-3W) in 2030. Meanwhile, the Ministry of Energy and Mineral Resources (MEMR) targets to deploy around 2.2 million BEV-PC and 13.4 million electric motorcycles (BEV-MC) by 2030 (APPKLI, 2023, IESR, 2023). Efforts to achieve the targets have been outlined in Presidential Regulation 55/2019, which involves fiscal and non-fiscal incentives. In addition, guidance on the mechanisms and incentives for charging infrastructure installation (MEMR, 2023) to support the BEV rollouts has also been deployed.

Researchers have endeavored to investigate the potential market diffusion of BEV through model development, such as Agent-Based Models (ABM) (Shafiei et al., 2012, Noori and Tatari, 2016, Eppstein et al., 2011, Gnann et al., 2015) and System Dynamics (SD) (Setiawan et al., 2022, Pasaoglu et al., 2016, Gómez Vilchez and Jochem, 2020). A recent study demonstrated that the flexibility of ABM can provide a more precise distinction when agents' or individuals' behaviors are included in vehicle purchase decisions, compared to the SD approach (Gnann et al., 2022b). The models built often considered monetary and non-monetary aspects significantly influencing market diffusion. The impact of non-monetary elements, such as charging infrastructure availability (Gunawan et al., 2022, Ruoso and Ribeiro, 2022), are often modeled through a logit model as part of consumer's preference (Noori and Tatari, 2016, Shafiei et al., 2012) or as part of the operational cost (e.g., charging cost) of driving a BEV (Adepetu et al., 2016, Eppstein et al., 2011, Silvia and Krause, 2016). Some studies have also tried incorporating real-world driving behavior into the model and, subsequently, charging infrastructure effect on supporting their daily travel activities (Gnann et al., 2015, Kangur et al., 2017, Plötz et al., 2014). However, studies by (Gnann et al., 2018) and (Kumar and Alok, 2020) identified that many of these investigations focused on developed markets and only focused on the market diffusion of BEV-PC.

Meanwhile, there is a high market potential for BEV-MC in emerging countries. IEA (2023b) reported that the sales of electric two-wheelers, including the BEV-MC, reached 9.2 million in 2022, with China and Vietnam being the major players. ASEAN countries, such as Indonesia, also accounted for the third largest market size of BEV-2W, with about 12 million units (Gupta et al., 2023). Unlike the BEV-PC, some BEV-MC models in the current market can be recharged using a battery-swapping scheme. This scheme allows BEV-MC users to swap the depleted battery with a new one in a battery swapping station, which only takes about a minute to perform (MEMR, 2020). Several studies have explored the potential market diffusion of BEV-MC under scenarios that evaluate different policy options (Saurabh and Majumdar, 2023, Setiawan et al., 2023, Huang et al., 2018). Nonetheless, these studies focus exclusively on the market diffusion of BEV-MC, overlooking the coexistence of passenger cars and gross domestic product (GDP). According to Law et al. (2015), a negative correlation exists between motorcycle per-passenger car ownership and GDP (correspondingly, the GRDP). This implies a gap in understanding how the diffusions interact with the presence of both aspects.

This study aims to determine the potential BEV market diffusion in an emerging market city, such as the Greater Jakarta Area. The work fills previous gaps in the research stream in two folds:

1) Development of an ABM model to comprehensively analyze the market diffusion of BEV that incorporates the interaction between passenger cars and motorcycles, novel underlying agent behavior, determination of willingness to pay more, and agent's hesitancy due to factors such as accessibility to public charging infrastructure and other preferences.
2) Investigating the market diffusion of BEV-PC and BEV-MC, along with their interplay, up to the year 2050 within the context of the Greater Jakarta Area, a densely populated urban city with emerging market dynamics.

The remainder of this paper is outlined as follows. Section 2 will describe the methodology and assumptions for the examination. Section 3 contains results and discussions. Conclusions are drawn and discussed in Section 4.

2 Methods and Data

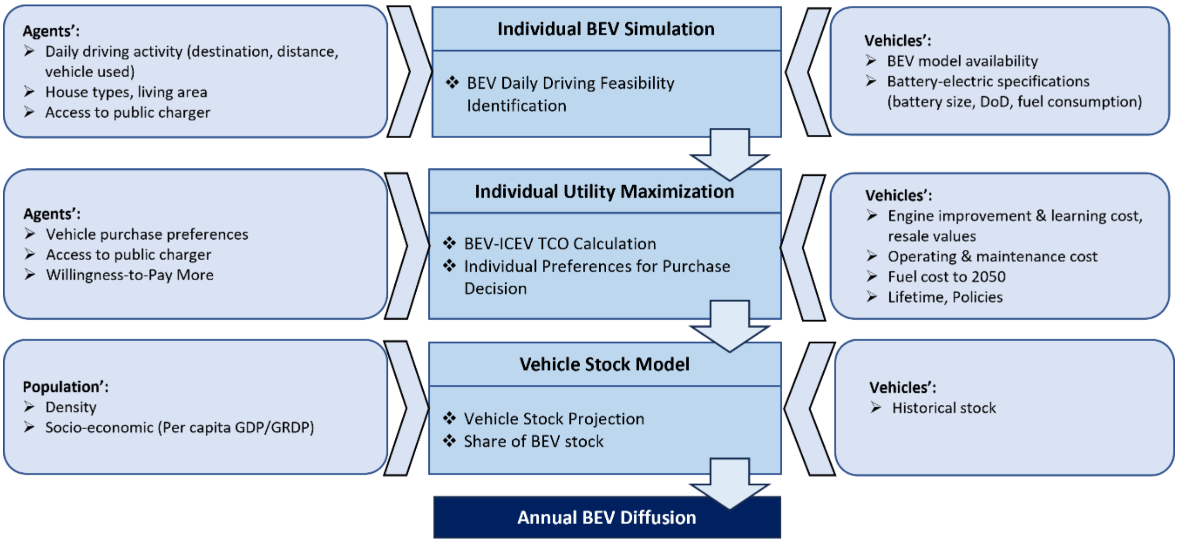
2.1 Market Diffusion Model

The market diffusion model developed for this study is based on the ALternative Automobiles Diffusion and INfrastructure (ALADIN) market diffusion model developed by Plötz et al. (2014). This study uses a modified version of the ALADIN model, as it can simulates the driving data of conventional vehicles using electric vehicles and determines the vehicle technology with the highest utility for individual users, which is later aggregated to market shares and vehicle stock. The model has been utilized to define the market diffusion of BEV in Germany in 2020 (Gnann et al., 2015), 2030 (Gnann et al., 2022b), and 2050 (Gnann et al., 2022a). This section explains the modifications made to the original model to fit with the case study's environment.

In this study, the developed model considers passenger cars with two propulsion and three fuel types (further referred to as propulsion-fuel *s* in this study), namely internal combustion engine vehicles (ICEV) based on gasoline (ICEV-G-PC), based on diesel (ICEV-D-PC), and battery electric vehicles (BEV-PC). Hybrid electric vehicles (HEV) are considered ICEV-G-PC as their primary fuel remains gasoline. Meanwhile, plug-in hybrid vehicles are excluded due to their minimal market share (Gaikindo, 2022) and projected decline in manufacturer interest and policy support (Roberts, 2021, Man, 2023). In terms of motorcycles, this study only considers gasoline-based (ICEV-G-MC) and battery-electric motorcycles (BEV-MC). For public charging infrastructure, passenger cars are assumed to use a 22-kW charger in an electric vehicle charging station (EVCS), considering the minimum requirement of charging stations built in public places (MEMR, 2023). Meanwhile, motorcycles must undergo a battery swapping process in a battery swapping station (BSS) to recharge their vehicles in public.

Generally, the model involves three main steps depicted in Figure 1, in which distinct input data is needed. In this model, an agent is defined as a single driving profile of a person derived from an Activity Daily Travel Survey (ADS) of Jakarta's Greater Area scale in 2018 (JICA, 2018). Further details of the ADS are described in section 2.2.1.

Figure 1: BEV Market Diffusion Model adapted from ALADIN Model (Plötz et al., 2014)



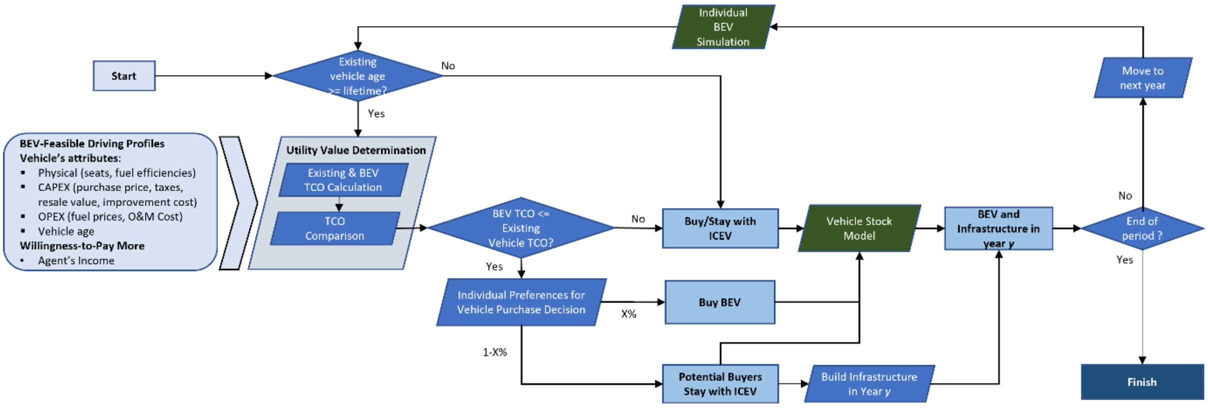
2.1.1 Individual BEV Simulation

Individual BEV simulation is performed for each driving profile by substituting their assigned existing vehicle with their BEV counterparts to identify whether the driving profile can fulfill their daily driving journey with BEV. Hence, an existing vehicle is first assigned to a driving profile. Subsequently, the simulation identifies a potential charging place based on the agent's residential type. Agents with semi-permanent houses and agents living in flats or dormitories must charge their vehicles in an EVCS or BSS in their neighborhood, defined as a Traffic Analysis Zone (TAZ), as they do not have access to home charging. Consequently, charging infrastructure should be available within their TAZ to allow these agents to drive BEV. The availability of EVCS or BSS is estimated based on potential buyers not buying BEV due to the unavailability of infrastructure in previous year, which is further explained in the following section and S.M. 1.3. Meanwhile, further details of this process are explained in S.M. 1.1. Only agents that can fulfill their daily trips will be considered in the next step. This simulation is performed for every period investigated.

2.1.2 Individual Utility Maximization

Should agents capable to accomplish their daily journey with a BEV, these agents then proceed to the Individual Utility Maximization process. The Individual Utility Maximization comprises two main steps: utility value determination and individual preferences for purchase decisions. The overall framework of this process can be found in Figure 2.

Figure 2: Individual Utility Maximization Framework



The process starts with evaluating the vehicle's length of ownership of each agent. Given the absence of vehicle lifetime restriction in Indonesia (Setiawan et al., 2021), the length of ownership is defined as the average time of a vehicle owned by an individual/household before being sold to the used/second-hand vehicle market. This could reach a maximum of ten years for passenger cars (Kurniawan, 2022) and five years for motorcycles (Dash and Bandivadekar, 2021). If this length of ownership reaches its maximum, the utility of every vehicle option is determined. The utility is represented by the total cost of ownership (TCO), with a higher TCO depicting lower utility for the owner. The TCO also considers a willingness to pay more (WTPM) derived from a survey of price expectations for purchasing BEV with 1,000 Indonesian survey participants (Deloitte, 2021) for passenger cars and a Price Sensitivity Index of electric two-wheelers purchased in Indonesia based on the study from Murtiningrum et al. (2022).

The next stage involves stochastic modelling to capture uncertainties in vehicle purchase decisions. Two influential aspects are considered for each vehicle mode as described as follows:

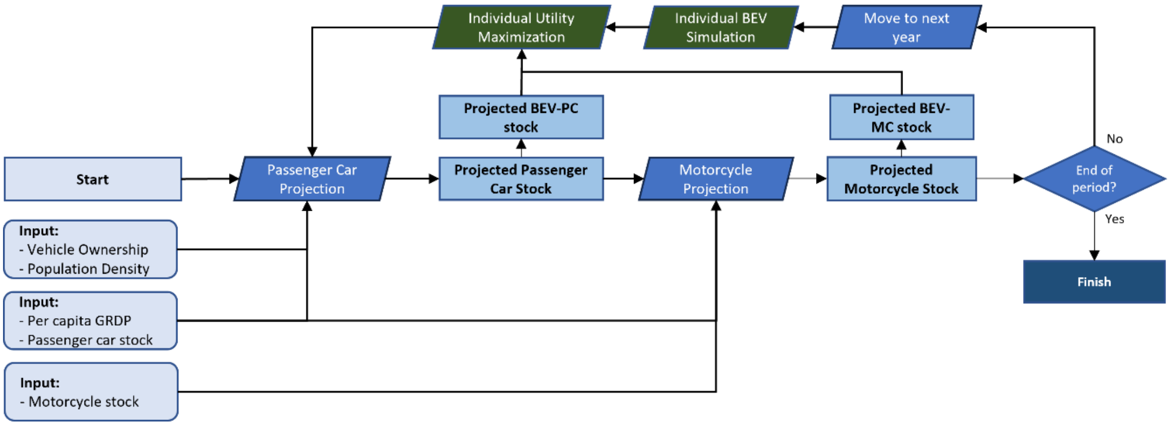
1) Charging infrastructure availability represents the most crucial factor for purchasing BEV in Indonesia (Deloitte, 2022, PwC Indonesia, 2023). In this context, agents evaluate infrastructure sufficiency in their TAZ in the previous year based on the optimal BEV/infrastructure ratio. This aspect applies to both passenger cars and motorcycles. It is assumed that the optimal ratio for passenger cars is 25 BEV-PC/EVCS, which is the average BEV/infrastructure ratio in Europe (Harrison and Thiel, 2017). Meanwhile, the optimal ratio for motorcycles is 180 BEV-MC/BSS, based on current practices from Taiwan's Gogoro battery-swapping motorcycle business (ADB, 2022). Insufficient infrastructure leads to hesitance among some agents, prompting infrastructure development.
2) Vehicle seat similarity factor for BEV-PC and willingness to do home charging for more extended time for BEV-MC. The first is elaborated to reflect Indonesian preferences for large cars that fit more people (Carsome, 2020). Meanwhile, the latter represents reluctance to allocate more resources (e.g., time) to charge BEV-MC at home despite a sufficient daily range (PwC Indonesia, 2023).

Further details of this process are explained in S.M. 1.3.

2.1.3 Vehicle Stock Model

The Vehicle Stock Model calculates the total vehicle stock and the amount of each vehicle category *i* with propulsion *s* in each year *y*. The total vehicle stock projection is performed at the provincial level as the Greater Jakarta Area comprises districts from three different provinces (DKI Jakarta, West Java, and Banten). The overall framework of this process is shown in Figure 3.

Figure 3: Vehicle Stock Projection Process



For passenger cars, the vehicle stock projection is estimated based on the work of Sommer et al. (2007) using Equation (1) - (2).

$$\ln\left(ln\frac{CO^*}{CO_{r,y}}\right) = \ln(-a_r) + b \times GRDP_{r,y} \tag{1}$$

$$PC_{r,y} = \sum_{p\in P} CO_{r,y} \times Pop_{r,y} \tag{2}$$

With $CO_{r,y}$ and CO* denotes car ownership in province *r* in year *y* and car ownership saturation point (passenger cars/1000 inhabitants), respectively. $GRDP_{r,y}$ represents the per capita gross regional domestic product (GRDP) in province *r* and year *y*, and a and b are the regression parameters derived from the correlation of car ownership CO and GRDP from 2010 – 2020. Based on the car ownership $CO_{r,y}$, the number of passenger cars in province *r* in year *y* ($PC_{r,y}$) can then be defined as the car ownership $CO_{r,y}$ multiplied by the (projected) population of province *r* ($Pop_{r,y}$).

Meanwhile, the projected vehicle stock for motorcycles is defined based on the work of Law et al. (2015) using Equation (3) and (4).

$$\ln MPC_{r,y} = a_p + b \times ln\left(GRDP_{p,y}\right) + c \times \ln(GRDP_{p,y})^2 + d \times year_y \tag{3}$$

$$MPC_{r,y} = \frac{MC_{r,y}}{PC_{r,y}} \tag{4}$$

With $MPC_{r,y}$ represent the motorcycle per passenger car ownership in province *r* and year *y*, and $MC_{r,y}$ depicts the number of motorcycles in province *p* and year *y*. Based on the equations, the number of motorcycles is also influenced by the stock of passenger cars. For each vehicle mode, the vehicle stock of each vehicle propulsion in each vehicle group *i* in year *y* can then be derived. Further details are explained in S.M. 1.4.

2.2 Data and Assumptions

This section first describes all data utilized in this study, namely the ADS, technical specifications of vehicles, well-to-wheel emissions, and projection parameters. Subsequently, the assumptions employed in the model are explained. Lastly, scenarios developed for this study are elucidated.

2.2.1 Activity Daily Travel Survey (ADS)

The Activity Daily Travel Survey (ADS) was performed in 2018 by the Japan International Cooperation Agency (JICA) as a part of the Jabodetabek Urban Transportation Policy Integration Phase Two (JUTPI 2) project. It comprises 10,000 driving profiles, including data on living area, occupation, household income, personal income, and vehicle ownership. Among these profiles, a minimum of three working days of driving activity data is available for 5,100 driving profiles. For the remaining, it is assumed that individuals drive daily to their workplace/school. The daily driving data is available as inter-Traffic Analysis Zone (TAZ) information. The distances between the TAZ are measured using the shortest path with the Dijkstra Algorithm (Dijkstra, 1959), considering monetized travel time (valued at US$ 1.10/hour (JICA, 2019)) and toll roads. Specific banned roads are also considered, such as toll roads prohibited for motorcycles in Indonesia.

Considering driving profiles with at least a single passenger car/motorcycle, no personal income data, and insufficient income to afford a vehicle using the installment process, only 1,308 of the total 10,000 driving profiles (about 10% of the total dataset) are considered for the passenger cars and 3,899 driving profiles for the motorcycle (about 38% of the total dataset). The average annual driving distance is 10,220 kilometers for passenger cars and 13,731 for motorcycles. A summary of the socioeconomic data of the driving profiles is presented in S.M. 1.5. These subsamples of the ADS are then used for our further analysis.

2.2.2 Vehicle Data

The vehicle stock is based on registered vehicle data in 2010 and 2018 (JICA, 2019), with adjustments made based on the total vehicles available from national statistics at the provincial level from 2010 – 2020 (BPS, 2019). Due to the absence of vehicle lifetime restriction in Indonesia (Setiawan et al., 2021), the end-of-life of passenger cars and motorcycles are reached at 18 and 12 years, respectively (Mera and Bieker, 2023). Fuel consumption for each vehicle is based on actual driving tests collected from automotive websites in Indonesia (Carmudi, 2023, Otoseken, 2023, KumparanOTO, 2023). The list price of each vehicle was derived from the Ministry of Industry regulation (Permendagri, 2020). Data on existing BEV in Indonesia were gathered from 2020-2022 from Priyantoro and Kurniawan (2022). The specifications of each BEV-PC were mainly derived from EV-Database (2023) and Rasyid (2022), while the BEV-MC was also derived from various automotive websites (Oto.com, 2020, Otomotifo, 2020).

For ICEV, an additional cost of improvement of 0.69% is implemented annually (Wu et al., 2015). For BEV-PC, learning rates of 23% for small vehicles, 29% for medium vehicles, and 24% for large vehicles are applied (Goetzel and Hasanuzzaman, 2022). The learning rate of BEV-MC follows the battery price reduction from Mauler et al. (2021). Annual fuel efficiency improvements for ICEV and BEV are 0.70 % and 1.05%, respectively (Mahalana, 2021). Details on the vehicle data can be seen in S.M. 1.1.

2.2.3 Fuel and Electricity Prices

The gasoline used to fuel ICEV-G is a conventional fossil-based gasoline. In contrast, ICEV-D is powered by a blend of fossil-based diesel and Fatty Acid Methyl Ester (FAME) derived from palm oil (hereafter called biodiesel). In the base year, the fuel should contain 30% of FAME by volume (MEMR, 2015), commonly called B30. Following the recent regulation, the share of FAME is assumed to increase to 35% by volume (B35) in 2023 (DGNREC, 2023) and remain constant thereafter. Historical prices of unsubsidized gasoline (so-called "Pertamax") and unsubsidized biodiesel (so-called "Dexlite") are based on retail prices from the National Oil Company (Pertamina, 2020). The prices of both fuels are primarily influenced by oil prices and associated price margins (e.g.,refining, distribution) (MEMR, 2022). Presuming constant price margins, the fuel price projections align with the price projection of Brent oil (EIA, 2021).

Home-charging electricity prices are defined with household rates varying by province (PLN, 2021). Meanwhile, public charging in the base year costs 17 cents USD 2020/kWh for the 22-kW chargers and 33 cents USD 2020/kWh for battery swapping (PLN, 2022, MEMR, 2023). Notably, battery swapping costs are calculated based on energy usage, reflecting the prevalence of subscription strategies over pay-per-swap approach (Hu et al., 2023, Swap, 2023). The electricity price projections for both cases follow the electricity price projection for Indonesia until 2060 from IEA (2022). The fuel prices are summarized in Table 2.

Table 2: Summary of Fuel Prices (1 USD 2020 = 14,105 Rupiah).

Parameters	Unit	2020	Projected 2030	Projected 2050	Reference
Gasoline price	cent USD 2020/liter	64	83	104	EIA (2021) and Pertamina (2020)
Biodiesel price	cent USD 2020/liter	67	86	107	EIA (2021) and Pertamina (2020)
Home-charging price DKI Jakarta	cent USD 2020/kWh	10	4	3	IEA (2022) and PLN (2021)
Home-charging price West Java (Bogor, Depok, Bekasi)	cent USD 2020/kWh	7	3	2	IEA (2022) and PLN (2021)
Home-charging price Banten (Tangerang, Tangerang Selatan)	cent USD 2020/kWh	7	3	2	IEA (2022) and PLN (2021)
Charging price	cent USD 2020/kWh	17	12	8	IEA (2022), MEMR (2023), and PLN (2022)
Battery swapping price	cent USD 2020/kWh	33	31	22	IEA (2022), MEMR (2023), and PLN (2022)

2.2.4 Emissions Data

The environmental impact of BEV diffusion is investigated by calculating the greenhouse gas (GHG) emissions using a life cycle approach adapted from Mera and Bieker (2023). The approach covers fuel, electricity, and vehicle cycles, considering emissions from production, distribution, and usage. Notably, emissions from supporting infrastructures are excluded. GHG emissions from the electricity cycle align with projections outlined in the IEA's roadmap for Net-Zero Emissions in Indonesia (2022). Additionally, the vehicle cycle includes emissions from raw material extraction, manufacturing, maintenance, and end-of-life recycling. Details on the emission factors can be seen in S.M. 1.6.

2.3 Scenario Development

Greater Jakarta Area is a metropolitan area in Indonesia with the highest population density and, subsequently, the highest number of vehicles (BPS, 2019). The area consists of thirteen cities/regencies located in three different provinces in Indonesia. Following the ADS data, the area is also segregated into 339 TAZs. This study's baseline year is set to 2020, and the model is run annually until 2050. Further details of the socioeconomic conditions of the Greater Jakarta Area and the map of Greater Jakarta Area are presented in Table 13 and Figure 5 in S.M. 1.7.

The study examines two scenarios to analyze the effectiveness of various policy interventions in promoting market diffusion, as seen in Table 3. The Current Policy scenario depicts present regulations and incentives that might influence BEV adoption in Indonesia. Meanwhile, The High Ambition scenario introduces increased support for BEV diffusion, namely the discontinuation of gasoline and biodiesel fuel subsidies, the introduction of vehicle purchase subsidies, and the optimistic annual charging infrastructure rollout.

Table 3: Scenarios Developed in This Study

Scenario	**Gasoline & Biodiesel Subsidy**	**Vehicle Purchase Subsidy**		**Chargers Built (BS_y in Individual Utility Maximization Process)**		**Tax levies**	**Charging price**
	Passenger Cars & Motorcycles	**Passenger Cars**	**Motorcycles**	**Passenger Cars**	**Motorcycles**	**Passenger Cars & Motorcycles**	**Passenger Cars & Motorcycles**
Current Policy (CP)	Gasoline price subsidy: 30%. Diesel price subsidy: 45% (Ichsan et al., 2022, Pertamina, 2020) Subsidy eligibility: Vehicles <= 450 million Rupiah (US$ 31,904) Subsidy remains until 2050		No	2020 - 2025: 30% of 25 BEV-PC/EVCS 2026 - 2050: 90% of 25 BEV-PC/EVCS	2020 - 2025: 10% of 180 BEV-MC/BSS 2026 - 2050: 20% of 180 BEV-MC/BSS	0% for ownership and luxury taxes	30% electricity price reduction on night BEV home charging
High Ambition (HA)	Identical Current Policy Scenario, subsidy gradually decreases and ends in 2030	US$ 5,671 in 2025-2030. Subsidy gradually decreased and ended in 2035 (CNBC, 2023).	US$ 496.28 in 2024-2030. Subsidy gradually decreased and ended in 2035 (Ministry of Industry, 2023).	100% of 25 BEV-PC/EVCS	100% of 180 BEV-MC/BSS	Identical with Current Policy Scenario	Identical with Current Policy Scenario

3 Results and Discussion

3.1 BEV Market Diffusion

This section presents comprehensive analyses of the market diffusion model results, including the feasibility of BEV for daily driving, TCO disparities between different vehicle propulsions in each vehicle size, and the BEV market diffusion under the two scenarios.

3.1.1 Feasibility of BEV for Daily Driving

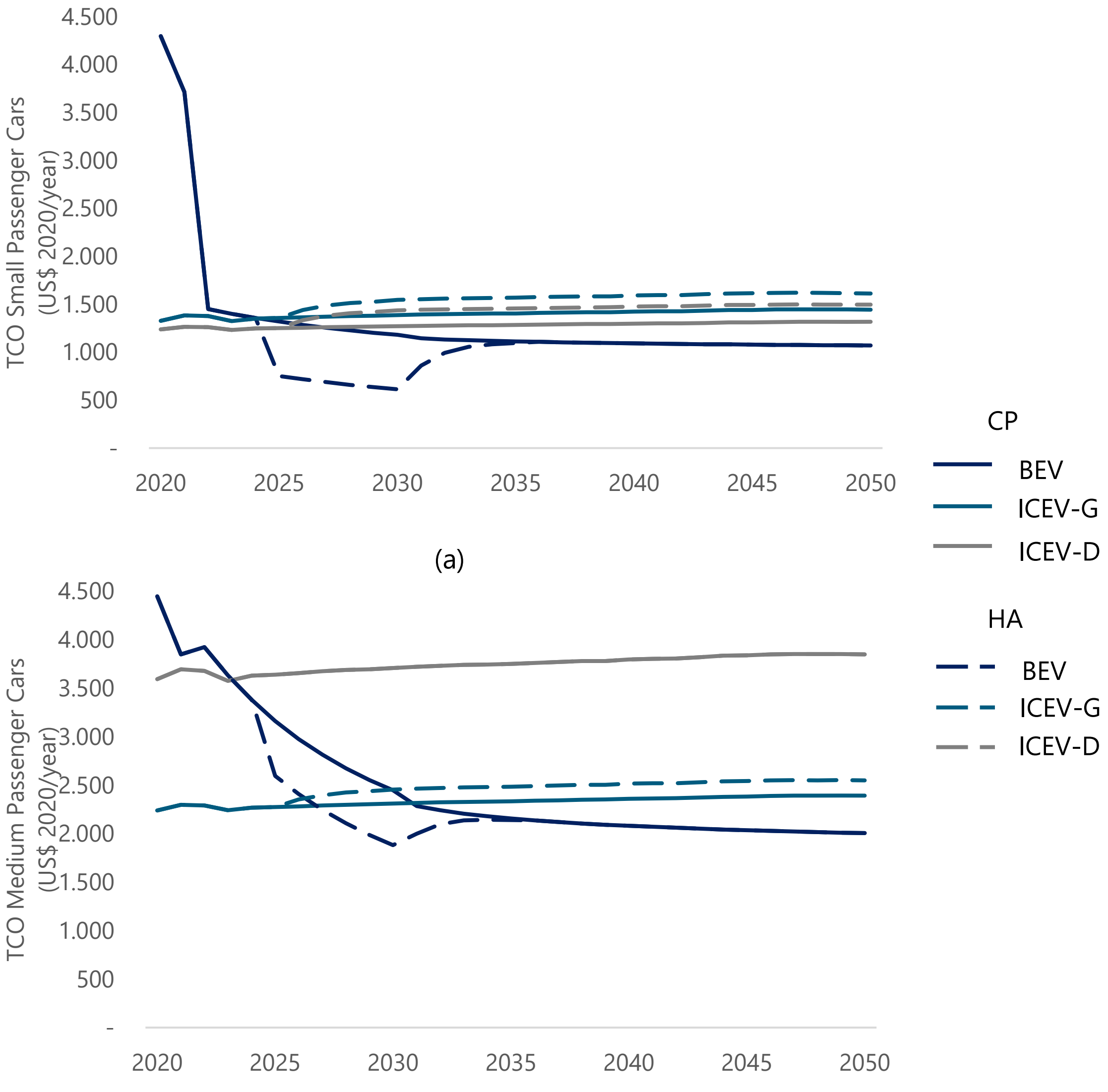
The individual simulation for passenger cars indicates that all agents can fulfill their daily driving journey with a BEV-PC, with the longest daily driving journey of an agent is about 225.45 kilometers. Nonetheless, around 4% of total agents cannot use BEV-PC due to the lack of access to home charging in 2020, and it will decrease to almost zero in 2050 as the installed public infrastructure grows.

For motorcycles, 98.64% of the agents can complete their daily journeys with BEV-MC, with the highest daily driving distance traveled being 346.17 kilometers. Under the Current Policy, 37.55% of agents could not shift to BEV-MC due to the unavailability of infrastructure. The share reduces to about 6% in 2024 and almost zero in 2027. The reduction accelerates in the High Ambition scenario, showing that around 3.69% of agents could not change their vehicles to BEV in the base year and already almost zero in 2026.

3.1.2 Total Cost of Ownership Disparities

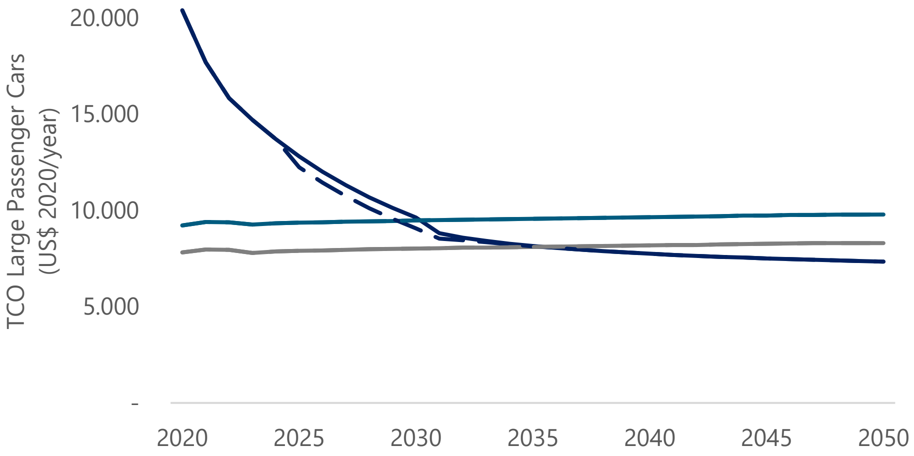
Analyses of the disparities in the average total cost of ownership (TCO) between each vehicle propulsion in both scenarios are presented in this subsection. It is important to note that the TCO discussed in this subsection are excluded from the WTPM. Overall, the average TCO for each vehicle is presented in Figure 4.

Figure 4: **Average Total Cost of Ownership for (a) small passenger cars, (b) medium passenger cars, (c) large passenger cars, and (d) motorcycles in Current Policy (CP) and High Ambition (HA) scenarios**

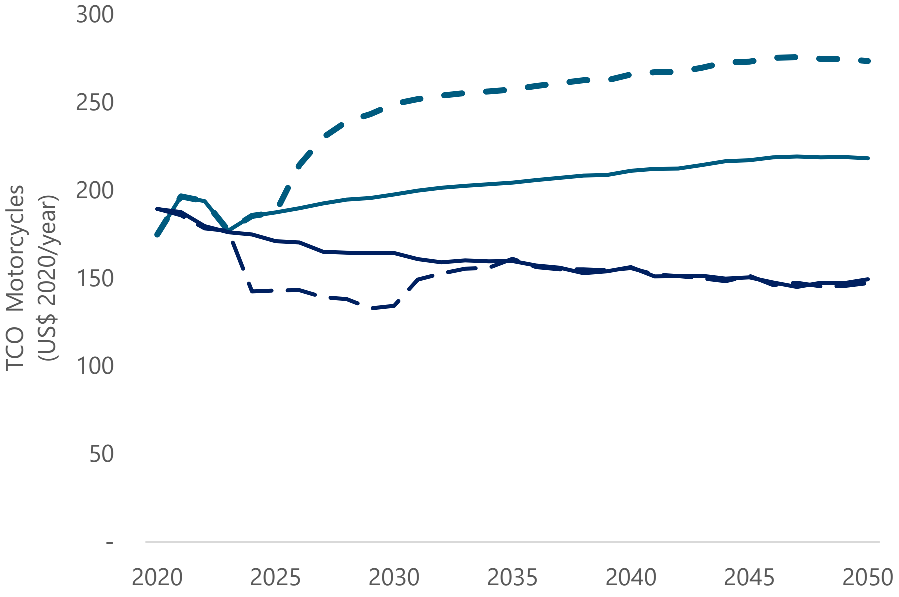


(a)

(b)



(c)



(d)

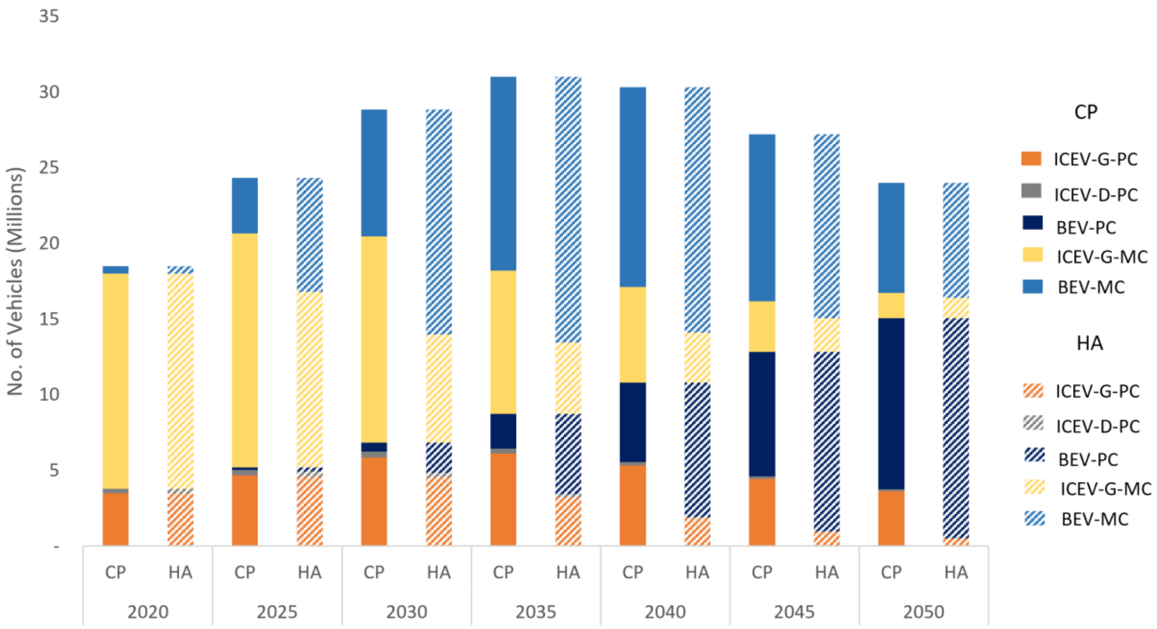
The average TCO of conventional vehicles in the Current Policy scenario is relatively constant for passenger cars throughout the study period. This indicates that the annual improvement cost does not significantly affect the overall TCO. In the other scenario, the phase-out of fuel subsidies started in 2025 results in a slight increase in the TCO of ICEVs. Notably, ICEV-D-PC demonstrates lower average TCO than the ICEV-G-PC in small and large vehicle categories, while higher TCO is observed in the medium-sized category. The limited availability of ICEV-D-PC in this group leads to higher purchase prices and, consequently, the prohibition of using subsidized diesel fuel. Meanwhile, the average TCO of BEV-PC in both scenarios experiences a substantial drop in the small vehicle category and a slight increase in the medium category in 2022, primarily attributable to the introduction of small BEV-PC and Completely Knocked Down (CKD)-produced BEV-PC in the market. Aligning with the previous analysis, the earliest price parity is reached in 2024 by BEV-PC and ICEV-D-PC in the medium-size category in both scenarios. However, introducing a vehicle purchase subsidy significantly accelerates the price parity of BEV-PC and ICEV-G-PC within the same vehicle size, creating a six-year gap between the scenarios. In the small-size category, the price parity between BEV-PC and ICEV-G-PC is reached in 2025 in both scenarios, while BEV-PC and ICEV-D PC parity occur two years earlier in the High Ambition scenario. Price parity in the large vehicles category is projected after 2030 in both scenarios due to the relatively high purchase price of BEV.

In the motorcycle category, the cost parity between BEV-MC and ICEV-G-MC is achieved in 2021, prior to the intervention of High Ambition scenario policies. Subsequent introduction of vehicle purchase subsidies could lower the TCO of BEV-MC to below US$150, creating 23% price gap compared to the ICEV counterparts as opposed to a 5% gap in the Current Policy scenario. In addition, the abatement of fossil fuels subsidies significantly impact the ICEV-G-MC, increasing the TCO by up to 26% compared to the Current Policy. Applying a complete policy interventions in the High Ambition scenario could create an almost 50% TCO gap between the technologies.

3.1.3 BEV Market Diffusion under Different Scenarios

The BEV market diffusion under the two built scenarios is presented in Figure 5.

Figure 5. Market Diffusion in Current Policy (CP) and High Ambition (HA) Scenario



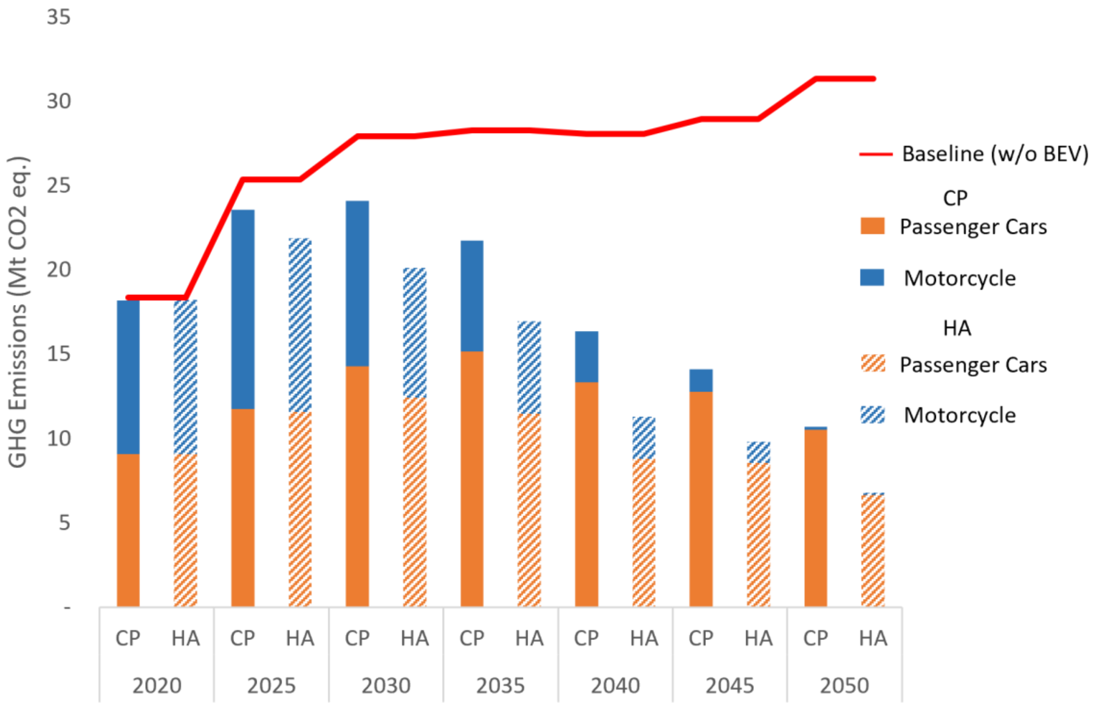
Overall, the total number of passenger cars and motorcycles experience a growth trajectory, rising from 18.5 million in the base year to approximately 31 million in 2035 and declining afterward to around 24 million in 2050. This trend occurs due to the decrease of motorcycle per passenger car ownership as GRDP increases, implying a potential transition of motorcycle owners to passenger cars as their purchasing power improves. Specifically, the number of motorcycles peaks at 22.2 million vehicles in 2035 before diminishing to 8.9 million in 2050. Meanwhile, the number of passenger cars is seen to increase to almost fourfold in 2050.

Results under the Current Policy scenario show a significant increase in BEV-PC starting in 2030, amounting to about 11% of total passenger cars. The share substantially escalates after 2030, reaching above 47% in 2040 and approximately 75% of total passenger cars in 2050. Compared to IEA's estimation for net-zero emissions in Indonesia in the Announced Pledges Scenario (IEA, 2022), the model produces a slightly higher diffusion rate in 2030 (8% in IEA's study) but lower in 2050 (below 90% in 2050). Meanwhile, the growth of BEV-MC experiences the opposite. Before 2030, the number of BEV-MC surges by nearly 40% and continues to advance to over 67% in 2040. Subsequently, the pace of growth gradually moderates, reaching 80% of total motorcycles by 2050.

In the High Ambition scenario, the high deployment of charging infrastructure for BEV-PC leads to a 37% increase in diffusion compared to the Current Policy scenario. Subsequently, introducing the vehicle purchase subsidy for BEV-PC boosts the adoption by 55%. In addition, decreasing the conventional fuel subsidies by half escalates the gap to around 84% and above 2.5 times when the subsidies are abolished entirely. Phasing out the vehicle purchase subsidy diminishes the gap by 30%. By the final year, there's a 27% gap between the scenarios, translating to a BEV diffusion rate of above 95%. For BEV-MC, setting the ratio of BEV-MC/BSS to 180 increases the diffusion by about 54%, while initiating a vehicle purchase subsidy could raise the diffusion by 92% compared to the Current Policy scenario. The impact of fossil fuel abatement exhibits a less pronounced effect than the BEV-PC case. In this context, achieving complete fossil fuel abatement only increases the diffusion to about 10% from the level of BEV-MC purchase subsidy introduced.

Analysis of the potential life cycle GHG emissions reduction as a result of BEV diffusion is presented in Figure 6.

Figure 6: **Life Cycle GHG Emissions without BEV (Baseline w/o BEV) compared to Current Policy (CP) and High Ambition (HA) scenarios**

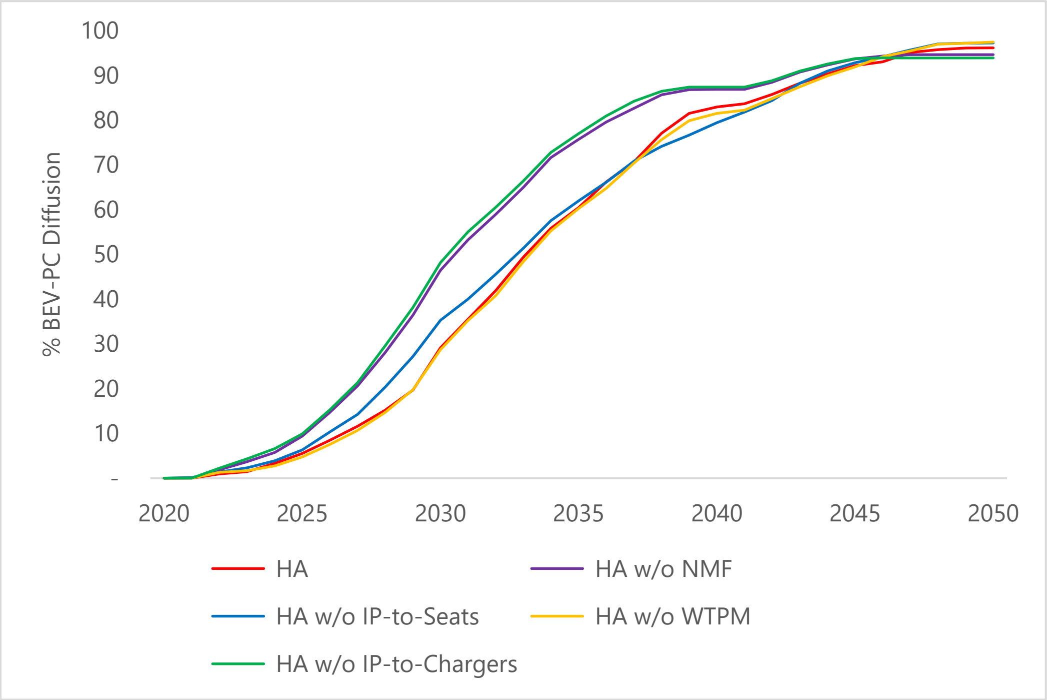


In the base year, the total GHG emissions from the two vehicle modes reached 18.3 million tons of CO_2 equivalent, of which 51% were produced by motorcycles. Considering the average annual driving distance of both vehicle modes, the average GHG emissions intensity in the base year for every vehicle is 0.23 and 0.05 kg CO_2 eq./km for passenger cars and motorcycles, respectively. A study from Mera and Bieker (2023) reveals comparable emissions intensity values for ICEV passenger cars. Meanwhile, there are 20% higher GHG emissions in motorcycles than in scenarios where BEV-MC has already been introduced. These discrepancies can likely be attributed to the differences between the average annual daily driving distances used in the study. Another IEA (2022) study shows that around 35 Mt CO_2 eq. and 33 Mt CO_2 eq. are currently emitted from 11 million passenger cars and almost 50 million motorcycles in Indonesia. Correspondingly, these figures lead to approximately 30% and 40% higher for passenger cars and motorcycles than this study's results.

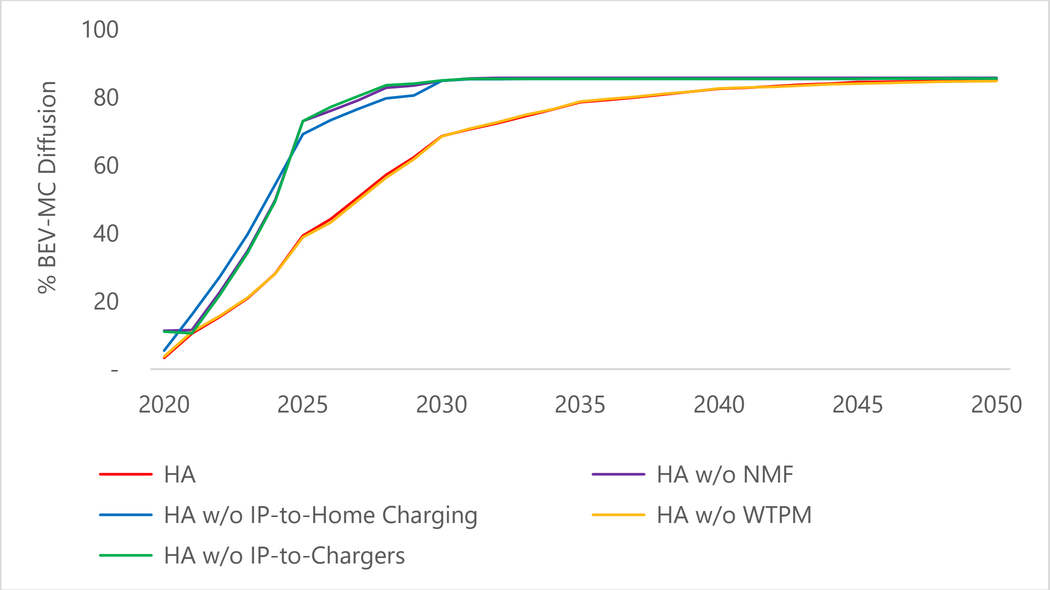
Without BEV, GHG emissions will constantly increase to 70% in 2050. Meanwhile, the diffusion of BEV in the Current Policy scenario could reduce these emissions by 3.83 Mt CO_2 eq. in 2030. The reduction goes to 6.52 Mt CO_2 eq. by 2035 and 20.69 Mt CO_2 eq. by 2050. In the High Ambition scenario, the GHG emissions reduction escalates to about 7.81 Mt CO_2 eq. in 2030, 11.31 Mt CO_2 eq. in 2035, and 24.58 Mt CO_2 eq. in 2050. A similar trend is also found in the IEA's roadmap for net-zero emissions in Indonesia, in which the GHG emissions start to decrease in 2030 (IEA, 2022). Nonetheless, the reductions are highly dependent on the emissions produced from the electricity cycle.

Further observation was performed on the effects of non-monetary factors on BEV diffusion, such as the WTPM and individual preferences for vehicle purchase decisions. The observation comprises systematic deactivation of each parameter and, subsequently, excluding all parameters from the model. The analysis is performed in the High Ambition scenario to reflect the highest diffusion possible when a parameter is changed. Figure 7 illustrates the outcome of the assessment.

Figure 7: **Effects of the exclusion of non-monetary factors to the BEV-PC diffusion (a) and BEV-MC diffusion (b)**



(a)



(b)

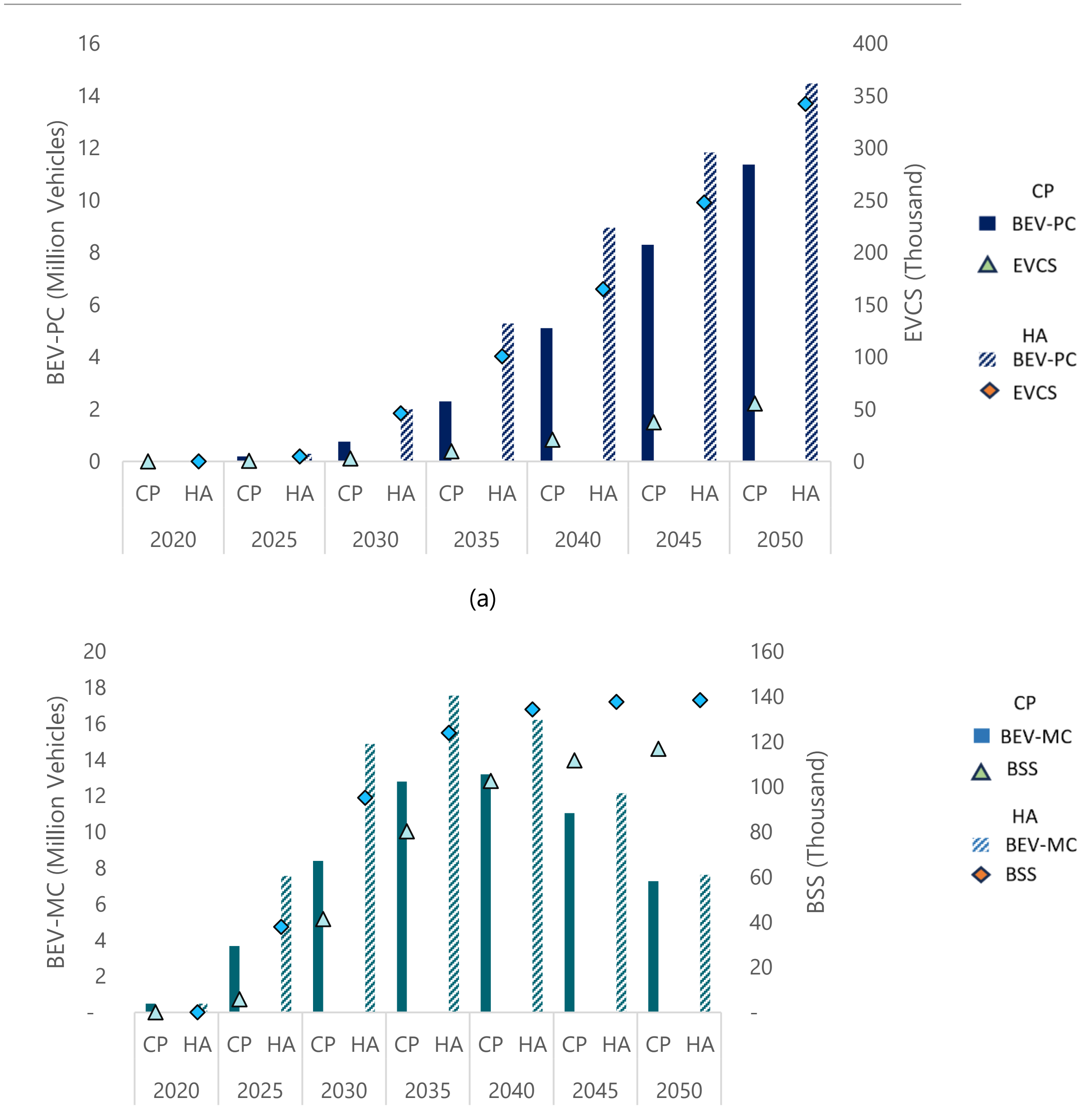
Overall, the deactivation of each parameter shows a considerable effect prior to the year 2040. This is reasonable as most parameters are designed to stimulate BEV adoption in the early years. As influencing factors become more accessible, such as widespread infrastructure rollouts and extensive vehicle options for every user, the effects start to wear off. For both vehicle modes, excluding the WTPM effect

(HA w/o WTPM line in the Figure) from the model slightly decreases the diffusion, which can be translated to the higher effectiveness of the increased WTPM in innovators, early adopters, and majority group compared to the reduced WTPM in the laggards group.

In contrast, the deactivation of individual preferences leads to an increase in diffusion. For BEV-PC, excluding the individual preferences for vehicle seat similarity (HA w/o IP-Seats line) resulted in only a 3% BEV diffusion increase. However, a significant increase in the diffusion, amounting to around 13%, is observed when the individual preferences related to EVCS availability are excluded. A similar trend is also found when eliminating all non-monetary factor parameters, indicating the substantial effect of the availability of public charging infrastructure in this study. In the case of BEV-MC, deactivating the individual preferences effect from the model yields a notable increase in diffusion, particularly about 20% higher. Negligible variances are observed among the deactivation of each individual preference parameter. Unlike the BEV-PC, excluding all influencing non-monetary factors indicates similar results compared to deactivating individual preferences.

As charging infrastructure plays a significant role in the diffusion, further analysis is also performed on the number of charging infrastructures that should be built in each scenario. The results of the analysis are shown in Figure 8.

Figure 8: **BEV diffusion and number of charging infrastructure in Current Policy (CP) and High Ambition (HA) scenarios for BEV-PC (a) and BEV-MC (b)**



(a)

(b)

Figure 8 (a) illustrates the demand for EVCS to support BEV-PC within different scenarios. It can be seen that almost 500 EVCS are required to accommodate 163 thousand BEV-PC in the Current Policy scenario, resulting in an average ratio of 330 BEV-PC/EVCS for the Greater Jakarta Area. The ratio declines to 208 BEV-PC/EVCS in 2030 and 203 BEV-PC/EVCS in 2050. Conversely, the high ambition scenario achieves an average 52 BEV-PC/EVCS ratio by 2025. Subsequently, there is a slight increase in

2030 to 60 BEV-PC/EVCS, possibly attributed to the more aggressive policy supports. Nonetheless, the ratio gradually decreases to 45 BEV-PC/EVCS by 2050. Further analysis of the EVCS distribution shows concentration in a single area initially, and shift towards more even distribution from 2030 to 2050. EVCS installed is highly concentrated in a single area in 2025 and will slowly begin to be evenly distributed from 2030 until 2050. In 2025, the lowest BEV-PC/EVCS ratio in a city/regency level stands at 0.86 in both scenarios. Conversely, the highest ratio is 410 BEV-PC/EVCS in the Current Policy scenario and 31 BEV-PC/EVCS in the High Ambition scenario. The large disparities decrease throughout the year, narrowing the gaps to only 40% in the Current Policy scenario and 17% in the high-ambition scenario by 2050. The distribution of EVCS, exemplified by the High Ambition scenario, throughout the Greater Jakarta Area can be seen in S.M. 2.2. Comparing both scenarios, it is observed that while BEV-PC experiences a threefold increase in the High Ambition scenario, reaching the optimal 25 BEV/EVCS ratio in a city/regency level requires a rise of built EVCS to about elevenfold compared to the other scenario.

Figure 8 (b) illustrates the projected installation of BSS to support BEV-MC under different scenarios. In the Current Policy scenario by 2025, around 5.7 thousand BSS are required to support 3.6 million BEV-MC, equivalent to approximately 638 BEV-MC/BSS. However, the ratio declines to 202 BEV-MC/BSS in 2030 and further decreases to 62 BEV-MC/BSS by 2050. The alternative scenario also exhibits a similar trend but with a lower ratio, indicating the high ambition of deploying the BSS. In 2025, the ratio of BEV-MC/BSS has already reached 200 and continues to decrease to 156 BEV-MC/BSS in 2030 and 55 BEV-MC/BSS in 2050. The findings shows slightly different ratios in the final year due to the declining motorcycle population and the dominance of BEV-MC in the market. Analysis of BSS distribution across the Greater Jakarta Area shows similar trend to that EVCS, exhibiting substantial disparities that gradually diminish overtime. The distribution of the BSS, taking an example of the High Ambition scenario, can be seen in S.M. 2.3. It’s worth noting that the model does not account for the abolishment of EVCS and BSS throughout the study period.

3.2 Policy Implications

This study exemplifies the market diffusion of BEV in emerging markets and cities with high population density and income inequality, such as the Greater Jakarta Area. Regarding BEV-PC, the findings show that vehicle purchase price and fuel price majorly affect diffusion from an economic perspective. The initiation of vehicle purchase subsidies in this study is evident to increase the diffusion, as in other emerging market cities with similar conditions, such as Beijing (Li et al., 2022, Zhuge et al., 2019). However, it is notable that the allocation of subsidies should not be uniform across all vehicle categories but relatively proportional to the vehicle's purchase price. In addition, introducing affordable small BEV-PCs to the market significantly impacts diffusion. Hence, it is imperative to explore other policy options to promote the adoption of such vehicles, such as import tax exemptions and incentives for local BEV-PC development. Furthermore, changes in fuel prices are observed to impact the diffusion rates substantially. The finding is consistent with research performed by Munshi et al. (2022), which underscores that recurring costs, such as operational and maintenance expenses, are primary considerations for BEV-PC adopters in Hyderabad, India. Similar trends are also evident for BEV-MC, with wider diffusion rate gaps observed upon introducing vehicle purchase subsidies. Given the relatively less variability in the prices of motorcycles, it can be concluded that the subsidies introduced, amounting to around 40% of the total vehicle price, have already significantly impacted the BEV diffusion.

Encouraging policies should also be introduced to increase the availability of charging infrastructure, which plays a significant role in the diffusion of both BEV-PC and BEV-MC. These include providing subsidies for infrastructure construction, operational costs, and/or charging tariff subsidies (Hall and Lutsey, 2020, IEA, 2023c). A study from Chen et al. (2023) suggested that for cities in China, some of which have socioeconomic profiles similar to those of the Greater Jakarta Area, providing operational costs such as electricity discounts is the most effective way to promote infrastructure deployment.

Using the market diffusion model, the effectiveness of the current policies on BEV diffusion in achieving the BEV rollout target set by the MEMR (APPKLI, 2023) is also evaluated. The target was adjusted from the national level to the Greater Jakarta Area case based on the ratio of projected vehicle stocks. The model shows that the Current Policy scenario yields 40% higher values in the BEV-PC stock in 2030, possibly due to the large number of vehicle stocks each agent represents. For BEV-MC, the model projects nearly ten times more vehicles in the Current Policy scenario prior to 2025, primarily attributed to the achievement of price parity before the specified year. However, it is noteworthy that the government plan demonstrates a rising projection for BEV-MC from 2027 – 2030, surpassing the estimated figures in the Current Policy scenario by approximately 43%. Nevertheless, the numbers still fall 13% below the projected BEV-MC under the High Ambition scenario. This indicates potential unaccounted factors influencing early diffusion, such as vehicle compatibility and battery-related issues. Despite the effectiveness of current policy, the distribution of public charging infrastructure should be evenly distributed to achieve the targets. In addition, aligning BEV production and rollout targets between ministries is essential for a coherent deployment roadmap and ensuring clear direction for stakeholders.

3.3 Model Limitations

The developed market diffusion model covers several limitations. First, the model does not consider the competition of BEV with other alternative vehicles in the market, such as fuel cell hydrogen vehicles. Second, the driving profiles used in this study only correspond to about 0.03% for each vehicle mode out of the total vehicle stock in the base year. Subsequently, based on the model validation (see S.M. 2.1), this may lead to overestimations in BEV stock changes as an agent can represent thousands of vehicles and the represented driving behavior in the Greater Jakarta Area. Subsequently, the driving profile data were obtained in 2018 and may not accurately reflect present driving behaviors, particularly potential changes due to the COVID-19 pandemic. Furthermore, as BEV are still a niche market in Indonesia, limited data on potential consumers intentions, BEV users’ driving, and charging behavior exists, which could create discrepancies in depicting the actual condition.

4 Conclusion

This study explores the diffusion of battery electric vehicles passenger cars (BEV-PC) and battery electric vehicles motorcycles (BEV-MC) utilizing an Agent-based model that integrates real-world driving behavior data, monetary aspects, individual preferences, and correlated passenger car and motorcycle stock projections. The model determines potential BEV-diffusion in a densely populated, high income disparities emerging market city, such as the Greater Jakarta Area, that spans from 2025 to 2050. Scenarios that reflect the Current Policy (Current Policy Scenario) and a more ambitious effort (High Ambition Scenario) in BEV deployment are employed.

The diffusion of BEV-PC under the Current Policy scenario could reach about 9% and 75% of the total vehicle stock in 2030 and 2050, respectively. Meanwhile, the diffusion of BEV-MC could achieve 39% in 2030 and 80% in 2050. Charging infrastructure availability emerges as the most influential non-monetary factor in driving the diffusion of BEV. High deployment and even distribution of charging infrastructure across the Greater Jakarta Area could potentially achieve the MEMR target of BEV deployment within the existing policies framework. In contrast, results from the market diffusion simulation under the High Ambition scenario show that implementing a vehicle purchase subsidy could substantially increase the BEV-PC diffusion to above 50% and BEV-MC by double. Furthermore, the diffusion of BEV-PC is projected to nearly triple when the purchase subsidy incentive, coupled with the complete abolishment of fossil fuel subsidies, is introduced.

Overall, this study highlights the effectiveness of the developed ABM model to represent potential BEV diffusion in emerging market city, which offer beneficial insights for enhancing BEV-PC and BEV-MC diffusion in similar cities worldwide. Nevertheless, future research should explore additional factors to better depict the conditions, such as real-world charging behaviors in the area and other non-monetary factors for BEV-MC.

Data Availability

The Activity Daily Survey (ADS) data is collected from government and private institutions. The availability of the data is restricted, and it was licensed to be used in this study. Other data is as stated in the published article.

Acknowledgements

The authors are grateful to Direktorat Riset dan Pengembangan Universitas Indonesia (DRPM UI) for supporting this work financially under the Hibah Publikasi Terindeks Internasional (PUTI) Q1, Contract Number: NKB-1157/UN2.RST/HKP.05.00/2022. We would also like to acknowledge the Japan International Cooperation Agency (JICA) and the Coordinating Ministry for Economic Affairs of the Republic of Indonesia for providing ADS and other data used in this study. Till Gnann and Daniel Speth thank the Fraunhofer Gesellschaft for their financial support in KAMO - High Performance Center/Profilregion.

5 List of figures

6 List of tables

7 References

ADB. 2022. Electric Motorcycle Charging Infrastructure Road Map for Indonesia. *In:* BANK, A. D. (ed.). Manila, Philippines: Asian Development Bank.

Adepetu, A., Keshav, S. & Arya, V., 2016. An agent-based electric vehicle ecosystem model: San Francisco case study. *Transport Policy,* 46**,** 109-122.

APPKLI. 2023. Dukungan Badan Usaha Dalam Investasi Charging Station. *Acara: Sosialisasi Tarif dan Biaya Layanan untuk percepatan pengembangan Charging Station*. Jakarta: Association of Indonesian Electric Vehicle Chargers Entrepreneurs.

BPS. 2019. Statistik Transportasi Darat 2019. *In:* TRANSPORTASI, S. S. (ed.). Badan Pusat Statistik.

BPS. 2020a. Kepadatan Penduduk Menurut Kabupaten/Kota (jiwa/km), 2020-2022. *In:* PROVINCE, S. I. W. J. (ed.). Statistics Indonesia West Java Province.

BPS. 2020b. Kepadatan Penduduk Menurut Kabupaten/Kota di Provinsi Banten (Jiwa/Km2), 2020-2022. *In:* PROVINCE, S. I. B. (ed.). Statistics Indonesia Banten Province.

BPS. 2020c. Penduduk, Laju Pertumbuhan Penduduk, Distribusi Persentase Penduduk Kepadatan Penduduk, Rasio Jenis Kelamin Penduduk Menurut Provinsi/Kabupaten/Kota 2019-2021. *In:* STATISTIK, B. P. (ed.). Badan Pusat Statistik.

BPS. 2023. Gross Regional Domestic Product of Provinces in Indonesia by Industry. BPS Statistics Indonesia.

Buranelli de Oliveira, M., Moretti Ribeiro da Silva, H., Jugend, D., De Camargo Fiorini, P. & Paro, C. E., 2022. Factors influencing the intention to use electric cars in Brazil. *Transportation Research Part A: Policy and Practice,* 155**,** 418-433.

Carmudi, I., 2023. *Carmudi Mobil* [Online]. Available: https://www.carmudi.co.id/journal/category/cars/ [Accessed 2023].

Carsome. 2020. Car Purchase Preference Survey 2020. Indonesia: Carsome.

CNBC. 2023. Harga Mobil Listrik Mulai Naik, Jokowi Subsidi Rp 80 Juta! *CNBC Indonesia*, 28 January 2023.

Dash, N. & Bandivadekar, A., 2021. Cost comparison of battery swapping, point charging, and ICE two-wheelers in India. *Working Paper*.

Deloitte. 2021. Supercharging Electric Mobility in Southeast Asia. *In:* DELOITTE (ed.) *Full Speed Ahead.* Deloitte.

Deloitte. 2022. 2022 Global Automotive Consumer Study: Southeast Asia Perspectives. *In:* DELOITTE (ed.). Deloitte.

DGNREC. 2023. Pedoman Implementasi Pencampuran Bahan Bakar Nabati Jenis Biodiesel ke Dalam Bahan Bakar Minyak Jenis Minyak Solar sebesar 35% (B35). *In:* CONSERVATION, D. G. O. N. R. E. A. (ed.).

Dijkstra, E. W., 1959. A note on two problems in connexion with graphs. *Numerische Mathematik,* 1**,** 269-271.

EIA. 2021. Annual Energy Outlook 2021, with Projections to 2050. Washington DC: U.S. Energy Information Administration (EIA).

Eppstein, M. J., Grover, D. K., Marshall, J. S. & Rizzo, D. M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. *Energy Policy,* 39**,** 3789-3802.

EV-Database, E. V. D., 2023. *Current and Upcoming Electric Vehicles* [Online]. Available: https://ev-database.org/ [Accessed 2023].

Gaikindo. 2022. *Indonesian Automobile Industry Data* [Online]. Available: https://www.gaikindo.or.id/indonesian-automobile-industry-data/ [Accessed 2022].

Gnann, T., Plötz, P., Kühn, A. & Wietschel, M., 2015. Modelling market diffusion of electric vehicles with real world driving data–German market and policy options. *Transportation Research Part A: Policy and Practice,* 77**,** 95-112.

Gnann, T., Speth, D., Krail, M., Wietschel, M. & Oberle, S., 2022a. Pathways to carbon-free transport in Germany until 2050. *World Electric Vehicle Journal,* 13**,** 136.

Gnann, T., Speth, D., Seddig, K., Stich, M., Schade, W. & Vilchez, J. G., 2022b. How to integrate real-world user behavior into models of the market diffusion of alternative fuels in passenger cars-An in-depth comparison of three models for Germany. *Renewable and Sustainable Energy Reviews,* 158**,** 112103.

Gnann, T., Stephens, T. S., Lin, Z., Plötz, P., Liu, C. & Brokate, J., 2018. What drives the market for plug-in electric vehicles? - A review of international PEV market diffusion models. *Renewable and Sustainable Energy Reviews,* 93**,** 158-164.

Goetzel, N. & Hasanuzzaman, M., 2022. An empirical analysis of electric vehicle cost trends: A case study in Germany. *Research in Transportation Business & Management,* 43**,** 100825.

Gómez Vilchez, J. J. & Jochem, P., 2020. Powertrain technologies and their impact on greenhouse gas emissions in key car markets. *Transportation Research Part D: Transport and Environment,* 80**,** 102214.

Gunawan, I., Redi, A. A. N. P., Santosa, A. A., Maghfiroh, M. F. N., Pandyaswargo, A. H. & Kurniawan, A. C., 2022. Determinants of customer intentions to use electric vehicle in Indonesia: An integrated model analysis. *Sustainability,* 14**,** 1972.

Gupta, R., Hertzke, P., Vivek, L. & Vig, G., 2023. The real global EV buzz comes on two wheels. McKinsey & Company.

Hall, D. & Lutsey, N., 2020. Charging infrastructure in cities: Metrics for evaluating future needs. *Europe,* 6**,** 8,000,000.

Harrison, G. & Thiel, C., 2017. An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe. *Technological Forecasting and Social Change,* 114**,** 165-178.

Hu, X., Yang, Z., Sun, J. & Zhang, Y., 2023. Optimal pricing strategy for electric vehicle battery swapping: Pay-per-swap or subscription? *Transportation Research Part E: Logistics and Transportation Review,* 171**,** 103030.

Huang, S. K., Kuo, L. & Chou, K.-L., 2018. The impacts of government policies on green utilization diffusion and social benefits–A case study of electric motorcycles in Taiwan. *Energy Policy,* 119**,** 473-486.

Ichsan, M., Lockwood, M. & Ramadhani, M., 2022. National oil companies and fossil fuel subsidy regimes in transition: The case of Indonesia. *The Extractive Industries and Society,* 11**,** 101104.

IEA. 2020. Global EV Outlook. *Entering the decade of electric drive?* France: IEA.

IEA. 2022. An Energy Sector Roadmap to Net Zero Emissions in Indonesia. *In:* AGENCY, I. E. (ed.) *International Energy Agency Special Report.*

IEA. 2023a. *Global EV Data Explorer* [Online]. Available: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer [Accessed 24th September 2023].

IEA. 2023b. Global EV Outlook 2023. International Energy Agency.

IEA. 2023c. *Global EV Policy Explorer* [Online]. Available: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer [Accessed 24th September 2023].

IESR. 2023. Indonesia Energy Transition Outlook 2023: Tracking Progress of Energy Transition in Indonesia: Pursuing Energy Security in the Time of Transition. Jakarta: Institute of Essential Services Reform.

JICA. 2018. Activity-Travel Diary Survey (Paper and Smartphone-based).

JICA. 2019. JABODETABEK Urban Transportation Policy Integration Project Phase 2 in the Republic of Indonesia. JICA.

Kangur, A., Jager, W., Verbrugge, R. & Bockarjova, M., 2017. An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology,* 52**,** 166-182.

Khan, T., Yang, Z., Kohli, S. & Miller, J., 2022. A critical review of ZEV deployment in emerging markets. *The International Council on Clean Transportation*.

Kongklaew, C., Phoungthong, K., Prabpayak, C., Chowdhury, M. S., Khan, I., Yuangyai, N., Yuangyai, C. & Techato, K., 2021. Barriers to Electric Vehicle Adoption in Thailand. *Sustainability,* 13**,** 12839.

Kumar, R. R. & Alok, K., 2020. Adoption of electric vehicle: A literature review and prospects for sustainability. *Journal of Cleaner Production,* 253**,** 119911.

KumparanOTO. 2023. *Informasi komunitas dan apa saja tentang dunia otomotif* [Online]. Available: https://kumparan.com/kumparanoto [Accessed 2023].

Kurniawan. 2022. *The Right Time for Selling Used Cars* [Online]. Jakarta: SuperProf. Available: https://www.superprof.co.id/blog/kapan-harus-menjual-mobil/ [Accessed 2022].

Law, T. H., Hamid, H. & Goh, C. N., 2015. The motorcycle to passenger car ownership ratio and economic growth: A cross-country analysis. *Journal of Transport Geography,* 46**,** 122-128.

Li, J., Nian, V. & Jiao, J., 2022. Diffusion and benefits evaluation of electric vehicles under policy interventions based on a multiagent system dynamics model. *Applied Energy,* 309**,** 118430.

Ling, Z., Cherry, C. R. & Wen, Y., 2021. Determining the Factors That Influence Electric Vehicle Adoption: A Stated Preference Survey Study in Beijing, China. *Sustainability,* 13**,** 11719.

Mahalana, A. Y., Zifei. 2021. Overview of Vehicle Fuel Efficiency and Electrification Policies in Indonesia. *In:* ICCT (ed.) *Briefing.* The International Council on Clean Transportation.

Man, H., 2023. *Subaru to stop PHEV development* [Online]. Australia: whichcar.com.au. Available: https://www.whichcar.com.au/news/subaru-to-stop-phev-development [Accessed 22/03/2024 2024].

Mauler, L., Duffner, F., Zeier, W. G. & Leker, J., 2021. Battery cost forecasting: a review of methods and results with an outlook to 2050. *Energy & Environmental Science,* 14**,** 4712-4739.

MEMR. 2015. Perubahan Ketiga atas Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 32 Tahun 2008 tentang Penyediaan, Pemanfaatan dan Tata Niaga Bahan Bakar Nabati (Biofuel) sebagai Bahan Bakar Lain. *In:* INDONESIA, M. O. E. A. M. R. R. (ed.). Ministry of Energy and Mineral Resources Republic of Indonesia.

MEMR. 2020. PERMEN NO. 13 TAHUN 2020 TENTANG PENYEDIAAN INFRASTRUKTUR PENGISIAN LISTRIK UNTUK KENDARAAN BERMOTOR LISTRIK BERBASIS BATERAI.

MEMR. 2022. Perubahan Atas Keputusan Menteri Energi Dan Sumber Daya Mineral Nomor 62.K/12/Mem/2020 Tentang Formula Harga Dasar Dalam Perhitungan Harga Jual Eceran Jenis Bahan Bakar Minyak Umum Jenis Bensin Dan Minyak Solar Yang Disalurkan Melalui Stasiun Pengisian Bahan Bakar Umum Dan/Atau Stasiun Pengisian Bahan Bakar Nelayan. Ministry of Energy and Mineral Resources Republic of Indonesia.

MEMR. 2023. Provision of Electricity Charging Infrastructure For Battery Based Electric Motorized Vehicles. Indonesia: Ministry of Energy and Mineral Resources Republic of Indonesia.

Mera, Z. & Bieker, G., 2023. Comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars and two-wheelers in Indonesia. International Council on Clean Transportation. https://theicct. org ….

Ministry of Industry. 2022. Updated Specifications, Roadmap Development, and Domestic Component Calculation Guidelines for Domestic Battery Electric Motor Vehicles. *In:* INDONESIA, M. O. I. R. O. (ed.). Jakarta.

Ministry of Industry. 2023. PEDOMAN PEMBERIAN BANTUAN PEMERINTAH UNTUK PEMBELIAN KENDARAAN BERMOTOR LISTRIK BERBASIS BATERAI RODA DUA. Indonesia: Ministry of Industry Republic Indonesia.

Munshi, T., Dhar, S. & Painuly, J., 2022. Understanding barriers to electric vehicle adoption for personal mobility: A case study of middle income in-service residents in Hyderabad city, India. *Energy Policy,* 167**,** 112956.

Murtiningrum, A. D., Darmawan, A. & Wong, H., 2022. The adoption of electric motorcycles: A survey of public perception in Indonesia. *Journal of cleaner production,* 379**,** 134737.

Noori, M. & Tatari, O., 2016. Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. *Energy,* 96**,** 215-230.

Oto.com. 2020. *Gesits Electric* [Online]. Indonesia. Available: https://www.oto.com/motor-baru/gesits/electric [Accessed 2023].

Otomotifo. 2020. *10 Motor Listrik Terbaik Di Indonesia Terbaru 2024* [Online]. DKI Jakarta. Available: https://www.otomotifo.com/motor-listrik-terbaik-di-indonesia/ [Accessed 2023].

Otoseken. 2023. *Otoseken Mobil* [Online]. Available: https://otoseken.gridoto.com/mobil [Accessed 2023].

Pasaoglu, G., Harrison, G., Jones, L., Hill, A., Beaudet, A. & Thiel, C., 2016. A system dynamics based market agent model simulating future powertrain technology transition: Scenarios in the EU light duty vehicle road transport sector. *Technological Forecasting and Social Change,* 104**,** 133-146.

Permendagri. 2020. Penghitungan Dasar Pengenaan Pajak Kendaraan Bermotor dan Bea Balik Nama Kendaraan Bermotor Tahun 2020. *In:* KEMENDAGRI (ed.). Jakarta.

Pertamina, P., 2020. *Daftar Harga BBK Tmt* [Online]. Available: https://www.pertamina.com/id/news-room/announcement [Accessed 2023].

PLN. 2021. National Electricity Statistics 2020 (Statistik PLN 2020). Jakarta: PT. PLN (Persero).

PLN. 2022. Realisasi & Rencana Pengembangan Infrastuktur Pendukung Kendaraan Listrik di Jawa dan Nasional. Jakarta: PT PLN Persero.

Plötz, P., Gnann, T. & Wietschel, M., 2014. Modelling market diffusion of electric vehicles with real world driving data — Part I: Model structure and validation. *Ecological Economics,* 107**,** 411-421.

Priyantoro, D. D. & Kurniawan, A., 2022. *Berencana Beli Mobil Listrik, Cek Daftar Harganya per September 2022* [Online]. Kompas.com. Available: https://otomotif.kompas.com/read/2022/09/07/110200815/berencana-beli-mobil-listrik-cek-daftar-harganya-per-september-2022 [Accessed 2023].

PwC Indonesia. 2023. Indonesia Electric Vehicle Consumer Survey 2023. *In:* INDONESIA, P. (ed.). Indonesia: PwC Indonesia.

Rasyid, H., 2022. *Mau Mobil Listrik Murah? Harga Mobil Baru Wuling Air ev per November 2022 Masih Stabil Mulai Rp 230 Jutaan* [Online]. GridOto.com. Available: https://www.gridoto.com/read/223589260/mau-mobil-listrik-murah-harga-mobil-baru-wuling-air-ev-per-november-2022-masih-stabil-mulai-rp-230-jutaan [Accessed 2023].

Roberts, G., 2021. *Updated: Mitsubishi will stop selling new cars in the autumn* [Online]. United Kingdom: Fleetnews.co.uk. Available: https://www.fleetnews.co.uk/news/manufacturer-news/2020/09/01/mitsubishi-gives-vehicle-stock-outlook-after-fleet-guarantee [Accessed 22/03/2024 2024].

Ruoso, A. C. & Ribeiro, J. L. D., 2022. An assessment of barriers and solutions for the deployment of electric vehicles in the Brazilian market. *Transport Policy,* 127**,** 218-229.

Saurabh, K. & Majumdar, R., 2023. Sub-segment-based approach for assessing growth and energy transition trajectories of Indian two-wheelers. *Journal of Cleaner Production,* 430**,** 139559.

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.

Setiawan, A. D., Zahari, T. N., Purba, F. J., Moeis, A. O. & Hidayatno, A., 2022. Investigating policies on increasing the adoption of electric vehicles in Indonesia. *Journal of Cleaner Production,* 380**,** 135097.

Setiawan, I. C., Indarto & Deendarlianto. 2021. Quantitative analysis of automobile sector in Indonesian automotive roadmap for achieving national oil and CO2 emission reduction targets by 2030. *Energy Policy,* 150**,** 112135.

Shafiei, E., Thorkelsson, H., Ásgeirsson, E. I., Davidsdottir, B., Raberto, M. & Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. *Technological Forecasting and Social Change,* 79**,** 1638-1653.

Silvia, C. & Krause, R. M., 2016. Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. *Energy policy,* 96**,** 105-118.

Sommer, M., Dargay, J. & Gately, D., 2007. Vehicle Ownership and Income Growth, Worldwide: 1960-2030. *The Energy Journal,* 28**,** 143-170.

Swap. 2023. *Teknologi Tukar Baterai Swap* [Online]. Indonesia: Swap Energi Indonesia. Available: https://www.swap.id/produk?lang=id [Accessed 22/03/2024 2024].

Van Ham, M., Tammaru, T., Ubarevičienė, R. & Janssen, H., 2021. *Urban socio-economic segregation and income inequality: A global perspective*, Springer Nature.

Worldbank, T., 2022. *The World Bank in Indonesia* [Online]. Available: https://www.worldbank.org/en/country/indonesia/overview [Accessed 24 September 2023].

Wu, G., Inderbitzin, A. & Bening, C., 2015. Total cost of ownership of electric vehicles compared to conventional vehicles: A probabilistic analysis and projection across market segments. *Energy Policy,* 80**,** 196-214.

Zhuge, C., Wei, B., Dong, C., Shao, C. & Shan, Y., 2019. Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. *Journal of Cleaner Production,* 221**,** 710-737.

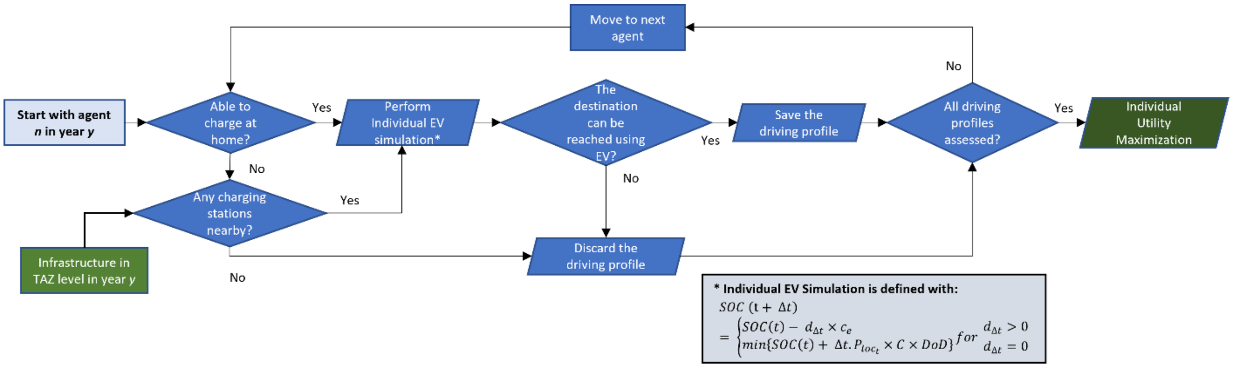
A.1 Supplementary Materials

A.1.1 Data and Detailed Description of Market Diffusion Models

A.1.1.1 Details on the Individual BEV Simulation Process

The overall framework of the process is defined in Figure 9. The individual BEV simulation is performed using Equation (5).

Figure 9: Individual BEV Simulation Framework



$$SOC_a\,(\mathrm{t}+\Delta t) = \begin{cases} SOC_a(t) - d_a(\Delta t) \times f_{i,s} \\ min\{SOC_a(t) + \Delta t.Stop_{a,loc_t} \times BCap_{i,s} \times DoD\} \end{cases} for \begin{matrix} d_{\Delta t} > 0 \\ d_{\Delta t} = 0 \end{matrix} \qquad \textbf{(5)}$$

Where $SOC_a(t)$ is the state of charge of the vehicle at time (t), $d_{\mathrm{a}}(\Delta t)$ is the distance traveled between time t and $t+\Delta t$, and $f_{i,s}$ is the energy consumption of vehicle i with propulsion s. $Stop_{a,loc_t}$ represents the charging power of the charger at a location where agent a stops at time t ($Stop_{a,loc_t}$ = 0 if no charger available), $BCap_{i,s}$ is the battery capacity of each vehicle i, and DoD is the battery's discharge depth.

While the ADS provides vehicle ownership information, the data does not include a specific vehicle type (such as vehicle make or vehicle model) that each driving profile owns. Hence, a process is performed to assign available vehicles from the stock in the baseline year to each driving profile before the Individual BEV Simulation.

The vehicle assignment process starts with classifying the passenger cars stock data into groups based on vehicle sizes (small, medium, large), propulsions and fuels (ICEV-Gasoline, HEV-Gasoline, ICEV-Diesel, and BEV-Electricity), and vehicle seats (4-5, 7-9 seats). A total of fourteen groups are then identified. Each vehicle group is then denoted with the following notations: vehicle size/vehicle propulsion/vehicle seaters (e.g., S/G/5 stands for small ICEV-Gasoline vehicles with five seaters). Subsequently, vehicle specifications (e.g., fuel efficiency and vehicle list price) for each group are determined based on the average specifications of vehicles belonging to each group. Meanwhile, motorcycles are treated as a singular group, encompassing scooters that dominate the Indonesian market, constituting over 90% of the total motorcycle stock (Aimi, 2022).

A similar treatment is also applied to the BEV data. However, as the list price of some BEVs is unknown, an estimated on-the-road price for each BEV group is used. Table 4 and Table 5 present the existing vehicles and BEVs available in the Greater Jakarta Area, respectively.

Table 4: Existing vehicles in the Greater Jakarta Area

Vehicle Size	Propulsion	Seater	Vehicle Group	Top maker (model)	Average Fuel Consumption (Km/L Eq.)	Number of Vehicles in Base Year	Average List Price (US$ 2020)
Small	BEV	4-5	S/B/5	Hyundai (Ioniq Hatchback)	57.80	10	34,172.28
Small	ICEV-Gasoline	4-5	S/G/5	Honda (Brio RS)	18.24	444,077	11,017.37
Small	ICEV-Diesel	7+	S/D/7	Chevrolet (Spin)	13.33	1,752	10,388.75
Small	ICEV-Gasoline	7+	S/G/7	Toyota (Calya)	14.72	658,245	8,190.94
Medium	ICEV-Diesel	4-5	M/D/5	Renault (Duster)	17.86	405	15,632.75
Medium	BEV	4-5	M/B/5	Hyundai (Ioniq Sedan)	56.24	46	32,571.13
Medium	ICEV-Gasoline	4-5	M/G/5	Toyota (Camry)	14.50	53,032	38,651.31
Medium	HEV	4-5	M/H/5	Toyota (Corolla Cross Hybrid)	19.55	668	28,772.00
Medium	ICEV-Diesel	7+	M/D/7	Toyota (Kijang Innova D)	12.77	272,359	20,850.53
Medium	ICEV-Gasoline	7+	M/G/7	Toyota (Avanza)	14.30	2,294,169	15,485.86
Large	ICEV-Diesel	4-5	L/D/5	BMW (520d)	17.74	503	77,427.35
Large	ICEV-Gasoline	4-5	L/G/5	Jeep (Wrangler Rubicon)	9.32	5,295	117,985.50
Large	ICEV-Diesel	7+	L/D/7	Hyundai (H-1)	10.52	7,442	30,627.06
Large	ICEV-Gasoline	7+	L/G/7	Toyota (Alphard 2.5)	11.17	53,583	37,061.16
Motorcycles	ICEV-Gasoline	2	MC	Honda Beat	60	15,617,636	879.56

Table 5: BEV available in the Greater Jakarta Area

Vehicle Size	Seats	Vehicle Makers	Vehicle Models	Vehicle Available in Year	Average Battery Capacity (kWh)	Average Usable Battery Capacity (kWh)	Average Range (km)	Average Fuel Consumption (km/kWh)	(Estimated) On-the-Road Price in Indonesia (US$ 2020)
Small	4-5	Hyundai	Hyundai Ioniq Hatchback	2020	38.30	34.32	311.00	9.06	51,258.42
Small	4-5	Mini	Mini Electric	2022	32.60	29.21	203.00	6.95	74,441.69
Small	4-5	Wuling, DFSK	Wuling Air EV 250, Wuling Air EV 300, DFSK Mini EV	2022	22.25	19.94	275.00	13.79	19,461.18
Medium	4-5	Hyundai	Hyundai Ioniq Sedan	2020	38.30	34.32	311.00	9.06	51,258.42
Medium	4-5	Tesla	Tesla Model 3	2020	54.00	48.39	313.00	6.47	106,345.27
Medium	4-5	Hyundai, Nissan, Toyota, KIA	Hyundai Kona EV, Nissan Leaf	2020	38.75	34.73	305.50	8.80	52,605.46
Medium	4-5	Hyundai	Hyundai Ioniq 5	2022	60.00	53.77	384.00	7.14	60,900.39
Large	4-5	Tesla, BMW, Mustang, Lexus	Tesla Model S, BMW i4, BMW iX, Mustang Mach-E, Lexus UX-300E	2020	78.65	73.33	469.50	6.40	283,587.38
Large	7-9	Tesla	Tesla Model X	2020	100.00	95.00	576.00	6.06	174,796.17

Vehicle Size	Seats	Vehicle Makers	Vehicle Models	Vehicle Available in Year	Average Battery Capacity (kWh)	Average Usable Battery Capacity (kWh)	Average Range (km)	Average Fuel Consumption (km/kWh)	(Estimated) On-the-Road Price in Indonesia (US$ 2020)
Motorcycles	2	Gesits, Viar, Volta, Niu, United, Alva	Gesits G1, Viar New Q1, Volta 401, Niu NQI, United T1800, Alva One	2020	2.34 (single battery)	2.10 (single battery)	60.83	29.03	1604.5

Based on the vehicle stock data derived from annual vehicle sales from 2010-2020, the age of vehicles in each existing vehicle group can then be determined. Vehicles sold in 2020 (base year) are considered zero-aged vehicles, while those taken in 2010 will have an age of 10.

Next, the purchase price of each vehicle group i and propulsion s is determined based on the on-the-road vehicle price with a five-year installment purchase scheme, which is commonly applied in Indonesia. The on-the-road vehicle price for each vehicle size group i and propulsion s ($OTR_{i,s}$) is calculated using Equation (6), which is a function of the list price ($BP_{i,s}$) and taxes (except progressive motorized vehicle tax that will be implemented later). Further explanation regarding the taxes is explained in Section A.1.2.

$$OTR_{i,s} = BP_{i,s} + Taxes \qquad \textbf{(6)}$$

Subsequently, the purchase price is annuitized using Equation (7). The first term in the equation shows a down payment that must be paid in advance, while the second term represents the five-year installment process. The down payment of a vehicle is set to 30% of the on-the-road vehicle price, following the regulation of the Bank of Indonesia (2018). The remaining 70% is then paid with a five-year installment scheme with an interest rate (IR) of 5.65%) annually (Finance, 2022; Lestari, 2023).

$$VPP_{i,s} = \left(\frac{OTR_{i,s} \times 30\%}{5}\right) + \left(\frac{OTR_{i,s} \times 70\%}{5}\right) * IR \qquad \textbf{(7)}$$

The affordability of each driving profile to own a specific type of vehicle is defined based on its household income for immediate family members and personal income for non-immediate family members. Subsequently, affordability also considers the 28/36 Rule (Kagan, 2023), which states that vehicle spending should be less than 35% of the total household income. Complying with the rule, the vehicle purchase price ($VPP_{i,s}$) is adjusted monthly and increased by 65%. After that, income and the adjusted vehicle purchase price are classified into four categories based on certain thresholds: low, mid, high, and very high income. The minimum/maximum thresholds of each income category can be seen in Table 6. The result of this categorizing process is presented in Table 7.

Table 6: **Income categories and its thresholds**

Income Category	Income (ID Rupiah)	Income (US$ 2020)
Low	<= 10,000,000	<= 708.97
Mid	10,000,001 - 20,000,000	708.98 – 1,417.94
High	20,000,001 - 40,000,000	1,417.95 – 2,835.87
Very High	> 40,000,000	> 2,835.87

Table 7: Vehicle purchase price, minimum monthly income for purchasing a vehicle.

Vehicle Group	Top maker (model)	Vehicle Purchase Price (US$ 2020)	Monthly Loan (US$ 2020/month)	Minimum Income to afford vehicle (US$2020/month)	Income Category
S/B/5	Hyundai Ioniq Hatchback	52,889.90	881.50	2,518.57	High
S/G/5	Honda Brio RS	18,830.82	313.85	896.71	Mid
S/D/7	Chevrolet Spin	18,398.04	306.63	876.10	Mid
S/G/7	Toyota Calya	14,505.80	241.76	690.75	Low
M/D/5	Renault Duster	24,402.08	406.70	1,162.00	Mid
M/B/5	Hyundai Ioniq Sedan	49,635.14	827.25	2,363.58	High
M/G/5	Toyota Camry	68,449.85	1,140.83	3,259.52	Very High
M/H/5	Toyota Corolla Cross Hybrid	43,845.65	730.76	2,087.89	High
M/D/7	Toyota Kijang Innova D	36,925.42	615.42	1,758.35	High
M/G/7	Toyota Avanza	27,424.82	457.08	1,305.94	Mid
L/D/5	BMW 520d	132,338.32	2,205.64	6,301.82	Very High
L/G/5	Jeep Wrangler (Rubicon)	216,234.69	3,603.91	10,296.89	Very High
L/D/7	Hyundai H-1	69,372.57	1,156.21	3,303.46	Very High
L/G/7	Toyota Alphard 2.5	83,946.29	1,399.10	3,997.44	Very High
MC	Honda Beat	1,215.45	33.76	96.46	Very low

Each driving profile is assigned to a vehicle group with a specific age in the same or lower income category. Lastly, each vehicle with a specific age is randomly assigned to a driving profile within the same or lower category. For passenger cars, the result of the vehicle assignment process is depicted in Figure 10. Vehicle group S/G/7 is assigned to almost 600 driving profiles. This corresponds linearly to the distribution of vehicles in the existing stock, with vehicle group S/G/7 having the highest share. Consequently, a single driving profile owning the corresponding vehicle accounted for 1,101 vehicles in the base year. Meanwhile, a single driving profile in motorcycles represents 3,235 vehicles in the base year.

Regarding vehicle age, Figure 10 also shows that most existing vehicles are below five years old, accounting for about 66.44%. About 13.23% of the total existing vehicles are two years old. For motorcycles, Figure 11 illustrates the age distribution of motorcycles in the dataset.

Figure 10: **Vehicle groups for passenger cars are assigned to driving profiles, segregated by vehicle age**

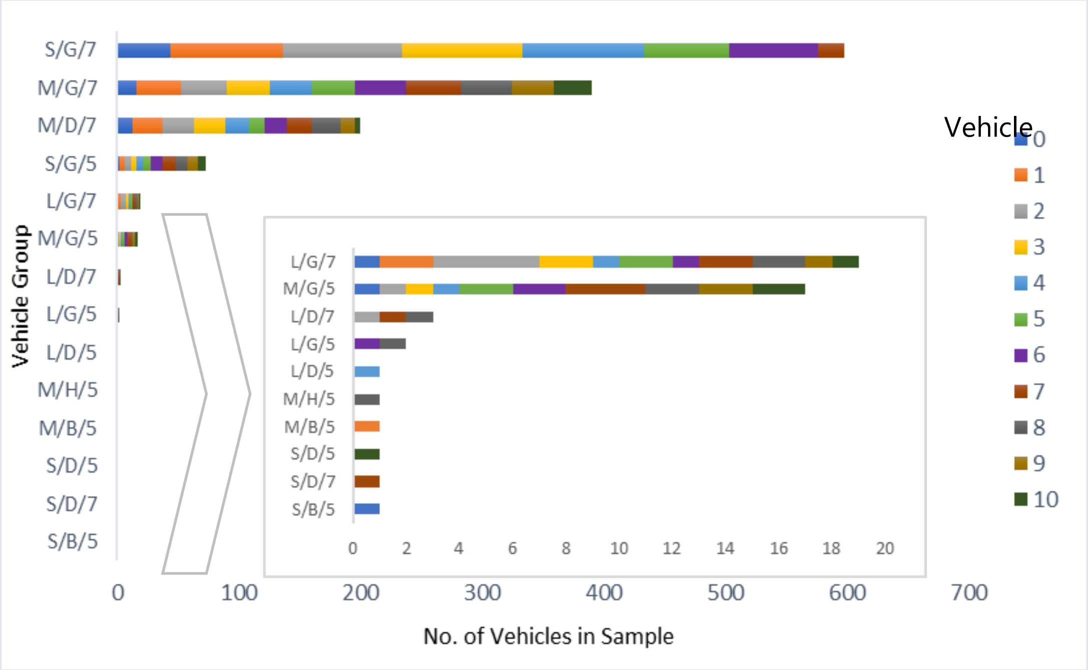
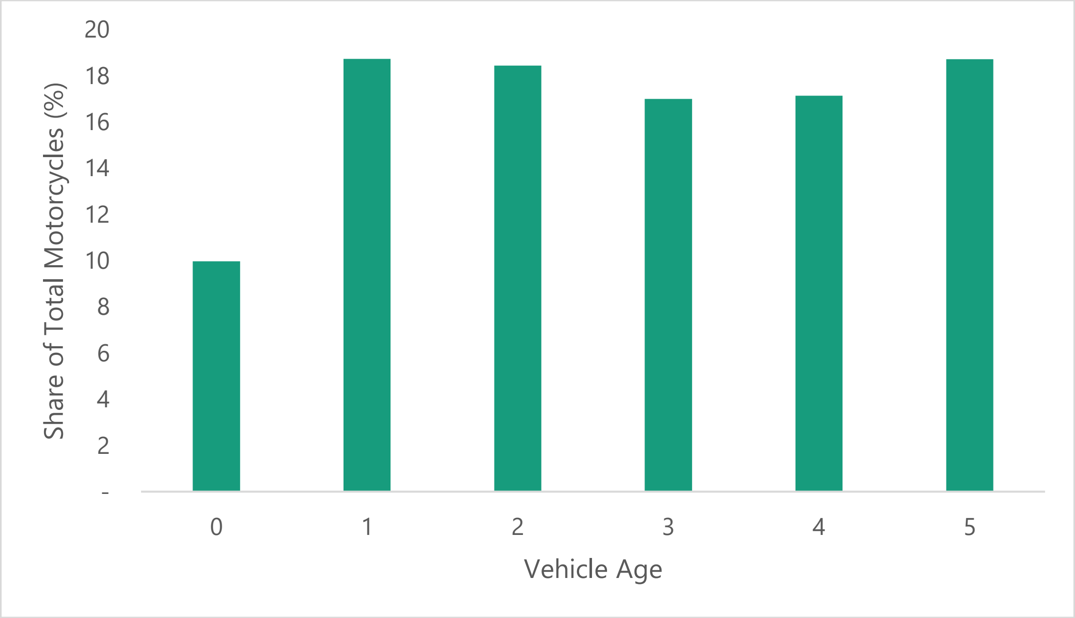


Figure 11: **Vehicle age distribution for motorcycles**



Small-sized BEVs are introduced in 2022 in the Indonesian passenger cars market, such as Wuling Air EV and DFSK mini-EV. These models are then utilized to supplant the 2020 BEV counterparts for existing small-sized vehicles in 2022. Additionally, the arrival of the Hyundai Ioniq 5, the first Completely Knocked Down (CKD) production of BEV in Indonesia, resulted in the replacement of BEV counterparts for some vehicle groups. The replacement was performed as the Hyundai Ioniq 5 complies more closely with the industry regulations and can be more attractive for future Indonesian automotive markets. It is also worth noting that until recently, the Tesla Model X has been the only BEV in the market with a seven-seater. As a result, only 71.43% of the vehicle groups have a similar number of vehicle seats to their BEV counterparts.

A.1.2 Vehicle Purchase Taxes

In Indonesia, vehicle purchasing is subject to various taxes, namely luxury tax, value-added tax (VAT), transfer tax, and road insurance. Luxury tax is regulated by Government Regulation No.74/2021. The tax amount is based on the average CO_2 produced per kilometer vehicle traveled, commonly derived from fuel consumption. The VAT for each vehicle equals 10% of the vehicle list price, as regulated in Act 42/2009. The vehicle transfer tax can be defined as the tax that is given every time the vehicle changes its ownership, e.g., when people buy the vehicle for the first time or when the vehicle is sold to another person/entity and is based on the Ministry of Home Affairs (MoHA) regulation No.8/2020. The transfer tax varies between regions in Indonesia. For The Greater Jakarta Area, the transfer tax is 12.5%. Road insurance is an annual tax regulated by Act No.33/1964 that covers accidents that might occur, amounting to IDR 143,000 (US$ 10). Apart from taxes, additional costs must be paid to the car dealer for on-the-road vehicle purchases, mainly in Indonesia. While the maximum share of this cost is 20% of a vehicle's list price (GridOto, 2017), this study assumed this cost is about 10%.

Additionally, a progressive motorized vehicle tax $PTax_{i,a}$ is also applied to each customer depending on the number of vehicles owned in each household. The first vehicle is subject to 2% of the list price. The tax then increases by 0.5% for the following vehicle owned with a maximum cap of 10% (equal to the 17th vehicle owned). As this tax is subjected explicitly to every agent, the tax is embedded in the calculation of Individual Utility Maximization (see SM A.1.3).

A.1.3 Details on Individual Utility Maximization

The utility value of each vehicle technology is determined using Equation (8). The Equation explains that the utility of vehicle i with propulsion s for agent a at time t ($u_{i,s,a}(t)$) is the sum of total cost of ownership ($TCO_{i,s,a}\ (t)$) plus a percentage of agent's willingness-to-pay-more (WTPM) than the total cost of ownership $WTPM_{i,s,a}(t)$.

$$\boldsymbol{u_{i,s,a}(t)} = \sum_{\boldsymbol{s}} \left(\boldsymbol{TCO_{i,s,a}(t)} + \left(\boldsymbol{WTPM_{i,s,a}(t)} \times \boldsymbol{TCO_{i,s,a}(t)}\right)\right) \qquad \textbf{(8)}$$

Firstly, this subsection explains each component used to define the utility value $u_{i,s,a}(t)$. Equation (9) describes the calculation of the total cost of ownership ($TCO_{i,s,a}(\mathrm{t})$), which is the sum of annuitized capital expenditure ($CAPEX_{i,s,a}(t)$) and operational expenditures ($OPEX_{i,s,a}(t)$). Subsequently, the annuitized capital expenditure of vehicles $CAPEX_{i,s,a}(t)$ is calculated using Equation (10) - (11).

$$TCO_{i,s,a}(\mathrm{t}) = CAPEX_{i,s,a}(t) + OPEX_{i,s,a}(t) \qquad \textbf{(9)}$$

$$\begin{aligned} CAPEX_{i,s,a}(t) = {} & \left(18\% \times VPP_{i,s,a} \times Imp_{i,s,a}\ (t)\right) + \left(82\% \times VPP_{i,s,a}\right) + HUp_{i,s,a} \\ & + PTax_{i,s,a} - RS_{i,s} \end{aligned} \qquad \textbf{(10)}$$

$$Imp_{i,s,a}(t) = \begin{cases} (1+EC)^{t-t_0} & i \in ICEV \\ (\frac{CP_{BEV}(t)}{CP_{BEV}(t_0)})^{b} - 1 & i \in BEV \end{cases} \tag{11}$$

$$OPEX_{a,s}(t) = OM_{a,s}(t) + FC_{a,s}(t) \tag{12}$$

$$FC_{i,s,a}(t) = \left(VKT_a(t) \times f_{i,s}(t-1) \times FE_s \times FP_{i,s}(t)\right) \tag{13}$$

The first term in Equation (10) determines the capital expenditures (CAPEX), composed of the annuitized vehicle purchase price $VPP_{i,s,a}$, motorized vehicle tax $PTax_{i,a}$, and home power upgrade cost HUp_a, and the benefit of vehicle's resale value $RS_{i,s}$. The vehicle resale values are defined based on the annual depreciation rate of each vehicle group. For ICEVs, the depreciation rates are defined from a web-scrapping process on Indonesia's secondhand automotive websites. Based on the process, the annual depreciation rate for ICEVs ranges from 4.94% to 15.34%, depending on the vehicle group, with an average of 7.50% annually. Meanwhile, the annual depreciation rate for BEV is derived from Schloter (2022), which is about 13.90%. Considering the future improvement of engines in ICEVs and the learning factor of batteries in BEVs, the cost of the improvements $Imp_{i,s,a}\ (t)$ is considered for each vehicle propulsion type. This improvement only affects the cost for engine-related components, amounting to about 18% of the $VPP_{i,s,a}$ (Goetzel and Hasanuzzaman, 2022). As depicted in Equation (11), an additional annual improvement cost is implemented for ICEV. In contrast, for BEV, the cost of improvement takes the form of a reduction cost following the learning curve of electrical components in the vehicle.

Equation (12) defines the operational expenditure as the sum of annual operation and maintenance cost $OM_{a,s}(t)$ and annual fuel cost of vehicle i with propulsion s for agent a $FC_{i,s,a}(t)$. The annual fuel cost for each vehicle is defined with Equation (13), which is a function of the annual vehicle kilometer traveled by each agent, vehicle fuel consumption in the previous year $f_{i,s,a}(t-1)$, annual fuel efficiency improvement for each vehicle propulsion s, and the fuel price used by each vehicle i with propulsion s in the given year t. As public chargers will be mainly utilized to substitute for the unavailability of home chargers, it is assumed that drivers who need to charge their vehicle in a public charger will utilize a slow charger. Consequently, the price for slow charging is applicable for these drivers. Further details about annual fuel efficiency improvement and other improvement costs are presented in Table 8, while the fuel prices are presented in Table 9.

Table 8: **Annual fuel efficiency improvements, home power upgrade cost, annual depreciation of vehicles, annual cost of improvements, learning rates, and operation and maintenance cost.**

Vehicle Propulsion	Annual fuel efficiency improvement (%)	Home power upgrade cost	Annual vehicle's value depreciation (%)	Annual cost of improvement	Learning rates	Operation and maintenance cost
ICEV	0.7	0	7.50	0.70% of 18% VPP	0	11% of VPP
Small BEV	1.05	$60.26	13.90	0	23%	6% of VPP
Medium BEV	1.05	$60.26	13.90	0	29%	6% of VPP
Large BEV	1.05	$60.26	13.90	0	24%	6% of VPP

Table 9: **Fuel Prices**

Parameters	Unit	2020	2030	2050	Reference
Gasoline price	cent USD 2020/liter	64	83	104	EIA (2021) and Pertamina (2020)
Biodiesel price	cent USD 2020/liter	67	86	107	EIA (2021) and Pertamina (2020)
Home-charging price DKI Jakarta	cent USD 2020/kWh	10	4	3	IEA (2022) and PLN (2021)
Home-charging price West Java (Bogor, Depok, Bekasi)	cent USD 2020/kWh	7	3	2	IEA (2022) and PLN (2021)
Home-charging price Banten (Tangerang, Tangerang Selatan)	cent USD 2020/kWh	7	3	2	IEA (2022) and PLN (2021)
Slow charging price	cent USD 2020/kWh	17	12	8	IEA (2022), MEMR (2023), and PLN (2022)
Battery Swapping Price	cent USD 2020/kWh	33	31	22	IEA (2022), MEMR (2023), and PLN (2022)

The WTPM for purchasing BEV-PC as an emerging vehicle technology is elaborated in the model based on a survey of price expectations for purchasing BEVs with a sample of 1000 Indonesian population (Deloitte, 2021). The survey categorized willingness to purchase BEV into four groups based on qualitative price categories: premium price, above average price, average price, and lower than average price. The survey's results resembled Roger's Diffusion of Innovation (Rogers, 2010). Specific percentage allocations were assigned to each category to quantitatively represent these qualitative price segments.

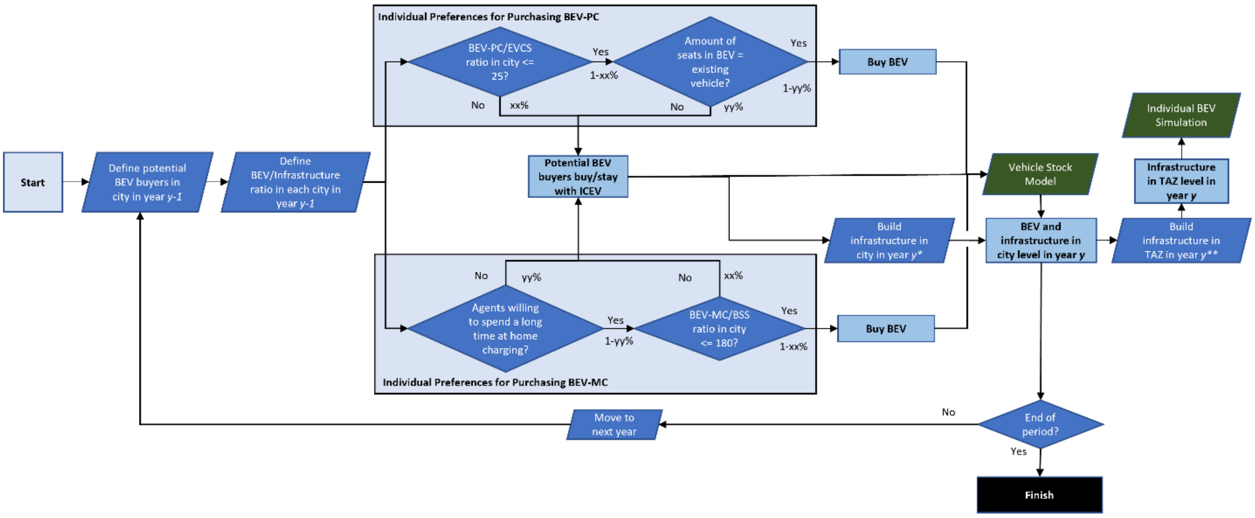
Meanwhile, WTPM for motorcycles is derived from a study by Murtiningrum et al. (2022) based on a Price Sensitivity Meter. Here, the "non-expensive" curve is used as the basis for the WTPM. Subsequently, each group was associated with a driving profile linked to household income levels, as higher-income individuals in Indonesia were more likely to purchase a BEV (Febransyah, 2021). A summary of the WTPM classification can be seen in Table 10.

Table 10: Classification of Willingness-to-Pay More (own estimation based on Deloitte (2021) and Murtiningrum et al. (2022))

Survey Results' Category	Roger's Adoption Category	Agent's Income Category	Passenger Cars		Motorcycles	
			Share of Population	Willingness-to-Pay More	Share of Population	Willingness-to-Pay More
Willing to pay for premium price	Innovators	Very high	3.00%	20.00%	3%	79.92%
Willing to pay more than the average price	Early Adopters	High	13.00%	10.00%	10%	49.93%
Willing to pay for the average price	Majority	Medium	61.00%	1.00%	57%	1.96%
Willing to pay for less than the average price	Laggards	Low	23.00%	-10.00%	30%	-28.03%

The next step, individual preferences for vehicle purchase decisions, follows the Framework shown in Figure 12.

Figure 12: Individual Preferences for Vehicle Purchase Decision Framework



The process starts with defining potential buyers and the ratio of BEV/infrastructure in each city in the previous year. Here, potential buyers are defined as agents that have lower BEV TCO compared to the ICEV. However, these potential buyers are subject to certain hesitancy factors regarding BEV adoption, which are influenced by their individual preferences. For passenger cars, potential buyers consider the availability of EVCS in their TAZ and vehicle seat similarity. Meanwhile, potential BEV-MC owners assess their willingness to do charging at home and accessibility to do battery swapping in their area. The hesitancy factors are represented by probability function, with the probabilities outlined in Table 11. Should these potential buyers decide to stay with ICEV, then a certain number of EVCS or BSS will be built in their TAZ in the particular year to reduce their hesitancy. The number of infrastructures available in year *y* is defined using Equations (14) and (15).

$$CI_{j,y}^{r} = CI_{j,y-1}^{r} + BS_y \times \frac{(\sum_{a \in A} PB_{a,\mathrm{j},\mathrm{y}-1} \times RV_{a,\mathrm{j},\mathrm{y}-1})}{CI_{opt}} \qquad \textbf{(14)}$$

$$CI_{z,y}^{r,j} = CI_{z,y-1}^{r,j} + \frac{BEV_{z,y}^{r,j}}{\sum_{z \epsilon Z_j^r} BEV_{z,y}^{r,j}} \times (CI_{j,y}^{r} - CI_{j,y-1}^{r}) \qquad \textbf{(15)}$$

Where $CI_{j,y}^{p}$ represents the number of charging infrastructure in city/regency *j* within province *r* in year *y* and $CI_{j,y-1}^{p}$ is the number of charging infrastructure available in city/regency *j* within province *p* in previous year. $PB_{a,\mathrm{j},y}$ depicts the number of agents *a* that become a potential buyer in city/regency *j* in year *y*, $RV_{a,y}$ is the amount of projected stock vehicle represented by a single agent *a* in city/regency *j* in year *y*, and CI_{opt} is the optimal BEV/infrastructure ratio. A potential buyer is defined as an agent with a TCO of BEV that is already lower than that of its CEV counterparts. However, the agent did not buy the BEV due to hesitancy or unavailability of charging infrastructure the previous year. BS_y is defined as a parameter to limit the built infrastructure in year *y*. For example, should BS_y is equal to 30%, then only 30% of the optimal amount of infrastructure is built in the corresponding year. Equation (1) is used to determine the number of EVCS/BSS in TAZ level $CI_{z,\mathrm{y}}$, in which the share of BEV available in TAZ *z* ($BEV_{z,y}^{r,j}$) over the total BEV available in all TAZ within a city/regency (Z_j^r) is multiplied with the total number of charging infrastructure available in the corresponding year ($CI_{j,y}^{r}$). Parameters used for this model are defined in Table 11.

Table 11: Individual Preferences for Vehicle Purchase Decision Parameters

Aspect	Amount	Source
Optimal BEV/EVCS ratio		
BEV-PC/EVCS ratio	25:1	Based on the average BEV-PC/EVCS in Europe (Harrison and Thiel, 2017)
BEV-MC/BSS ratio	180:1	Based on Gogoro's practice in Taiwan (ADB, 2022)
Hesitancy due to infrastructure unavailability (xx%)		
BEV-PC	40%	(Deloitte, 2021)
BEV-MC	53%	(PwC Indonesia, 2023)
Hesitancy due to other individual preferences (yy%)		
Seat similarity (for BEV-PC)	50%	(Carsome, 2020)
Willingness to spend a long-time home charging (for BEV-MC)	33%	(PwC Indonesia, 2023)

A.1.4 Details on Vehicle Stock Model

Based on the total vehicle stock projection, the number of vehicle stock in each vehicle group i in year y ($p_{i,y}$) can then be defined using Equation (16). Subsequently, the amount of each vehicle propulsion technology s in group i and year y ($m_{i,s,y}$) is defined based on the proportion of agent in each vehicle group i using propulsion s in year y ($l_{i,s,y}$) multiplied by $p_{i,y}$, as shown in Equation (17).

$$\boldsymbol{p_{i,y}} = \frac{\boldsymbol{p_{i,y-1}}}{\boldsymbol{P_{y-1}}} \times \boldsymbol{P_y} \tag{16}$$

$$\boldsymbol{m_{i,s,y}} = \frac{\boldsymbol{l_{i,s,y}}}{\sum_{s \in S} \boldsymbol{l_{i,s,y}}} \times \boldsymbol{p_{i,y}} \tag{17}$$

In projecting the vehicle stock, the car ownership saturation point is 470 cars derived (ASEAN, 2019). The GRDP data is derived from historical GRDP from national statistics (BPS, 2020c, BPS, 2020a, BPS, 2020b), while the projection follows the national Gross Domestic Product (GDP) projection from the IEA (2022). The projected population of each district for 2020-2045 is derived from (BPS and UNFPA, 2018) and is extrapolated from 2045 to 2050.

A.1.5 Details on Driving Profiles

Summary of the socioeconomic of the driving profiles are presented in Table 12.

Table 12: Summary of the Socioeconomic of Driving Profiles

Category	Criteria	Share of total passenger cars driving profiles (%)	Share of total motorcycle driving profiles (%)
Vehicle Ownership	>1	21.80	53.00
	1	78.20	47.00
Income category	>= high	18.81	2.41
	< high	81.19	97.59
Daily driving distance	>50km	22.40	25.52
	<=50km	77.60	74.48
Household size	>5	5.58	3.78
	<=5	94.42	96.22
House type	Non-permanent	4.66	4.78
	Permanent	95.34	95.22

A.1.6 Details on Emissions

Data on the fuel cycle and vehicle cycle greenhouse gas (GHG) emissions are mainly derived from a study of life-cycle GHG emissions for various vehicles in Indonesia (Mera and Bieker, 2023). However, the study did not cover the B30 fuel emissions. The B30 emissions are then estimated based on the lower heating value (LHV) and the GHG emissions of fossil-based diesel and 100% FAME fuel, presuming the blending ratio of 70% fossil-based diesel and 30% FAME. Emissions from FAME production includes plant cultivation and biofuel production while excluding direct land use change (DLUC) emissions. The use of biofuels in vehicles is assumed to be zero as it produces biogenic emissions. The values of these fuel cycle GHG emissions are estimated from the same study and assumed to remain constant until 2050. On the other hand, GHG emissions of the electricity cycle in the base year are derived from Nugroho et al. (2022), covering emissions from electricity generation, transmission, and distribution. Subsequently, the use of electricity in BEV produces zero emissions.

Each vehicle group is represented by the top model sold for the vehicle cycle. The vehicle production and maintenance emissions are based on Mera and Bieker (2023). Vehicles with no data available are assumed to have similar production and maintenance emissions as vehicles of a similar size. For BEV, additional GHG emissions from battery production are included and are derived from the same report from 2020 - 2030. Concerning a high probability of high local battery production in Indonesia (Ministry of Industry, 2022), it is assumed that the emissions from battery production follow the trend of GHG emissions of electricity generation. Details on the fuel and electricity cycle are presented in Table 13. Meanwhile, Table 14 and Table 15 exhibit the GHG emissions from the vehicle cycle for ICEV and BEV, respectively.

Table 13: Well-to-tank (WTT), Tank-to-Wheel (TTW), and total Fuel Cycle Emissions

Fuel/Electricity	Lower Heating Value (LHV, MJ/L)	Well-to-Tank GHG emissions (g CO2 eq./MJ)	Tank-to-Wheel GHG emissions (g CO2 eq./MJ)	Fuel Cycle GHG emissions (g CO2 eq./MJ)	Source
Gasoline	32.10	19.90	73.40	93.30	Mera and Bieker (2023)
Fossil-based Diesel	33.10	21.90	73.20	95.10	Mera and Bieker (2023)
FAME	33.10	44.50	-	44.50	Mera and Bieker (2023)
B30	35.06	28.30	52.79	81.09	Estimated from LHV and GHG emissions from Fossil-based diesel and FAME Mera and Bieker (2023)
B35	34.90	29.41	48.90	78.31	Mera and Bieker (2023)
B40	34.80	30.49	45.30	75.79	Mera and Bieker (2023)
Electricity - 2020	-	293.47	0	293.47	Nugroho et al. (2022)

Fuel/Electricity	Lower Heating Value (LHV, MJ/L)	Well-to-Tank GHG emissions (g CO2 eq./MJ)	Tank-to-Wheel GHG emissions (g CO2 eq./MJ)	Fuel Cycle GHG emissions (g CO2 eq./MJ)	Source
Electricity - 2030	-	220.64	0	220.64	Nugroho et al. (2022) and IEA (2022)
Electricity - 2050	-	13.89	0	13.89	Nugroho et al. (2022) and IEA (2022)

Table 14: **ICEV Vehicle Cycle Emissions (Mera and Bieker, 2023)**

Vehicle Group	Vehicle Segment	Top model sold	Vehicle production emissions over the lifetime (kg CO2 eq.)	Vehicle maintenance emissions (g CO2 eq. /km)
S/G/5	Small	Honda Brio RS	4,700.00	3.60
S/D/7	Small	Chevrolet Spin	4,700.00	3.60
S/G/7	Small	Toyota Calya	4,700.00	3.60
M/D/5	Medium	Renault Duster	7,100.00	3.60
M/G/5	Medium	Toyota Camry	7,500.00	3.60
M/H/5	Medium	Toyota Corolla Cross Hybrid	7,500.00	3.60
M/D/7	Medium	Toyota Kijang Innova D	9,800.00	3.60
M/G/7	Medium	Toyota Avanza	6,600.00	3.60
L/D/5	Large	BMW 520d	10,400.00	3.60
L/G/5	Large	Jeep Wrangler (Rubicon)	9,800.00	3.60
L/D/7	Large	Hyundai H-1	10,400.00	3.60
L/G/7	Large	Toyota Alphard 2.5	9,800.00	3.60
MC	Motorcycle	Honda Beat	3,600.00	1.90

Table 15: **BEV Vehicle Cycle Emissions (Mera and Bieker, 2023)**

BEV Model	Average Battery Capacity (kWh)	Vehicle production emissions over the lifetime (kg CO2 eq.)	Battery production emissions over the lifetime (kg CO2 eq.)	Vehicle maintenance emissions (g CO2 eq. /km)	Remarks
Hyundai Ioniq Hatchback	38.3	7200	2144.8	3.6	Assume similar to the Hyundai Kona
Wuling Air EV 250, Wuling Air EV 300, DFSK Mini EV	22.25	3600	1246	3.5	
Hyundai Ioniq 5	60	7200	3360	3.6	Assume similar to the Hyundai Kona
Hyundai Ioniq Sedan, Hyundai Kona EV, Nissan Leaf, KIA Niro	38.75	7200	2170	3.6	Assume similar to the Hyundai Kona
Tesla Model 3	40	7200	2240	3.6	Assume similar to the BYD e6
Lexus UX 300e, Tesla Model S, BMW i4, BMW iX, Mustang Mach-E	74.65	7800	4180.4	3.7	Assume similar to the BYD e6
Tesla Model X	95	7800	5320	3.7	Assume similar to the BYD e6
Gesits G1, Viar New Q1, Volta 401, Niu NQI, United T1800, Alva One	2.34 (single battery)	4,800	1000	0.001	

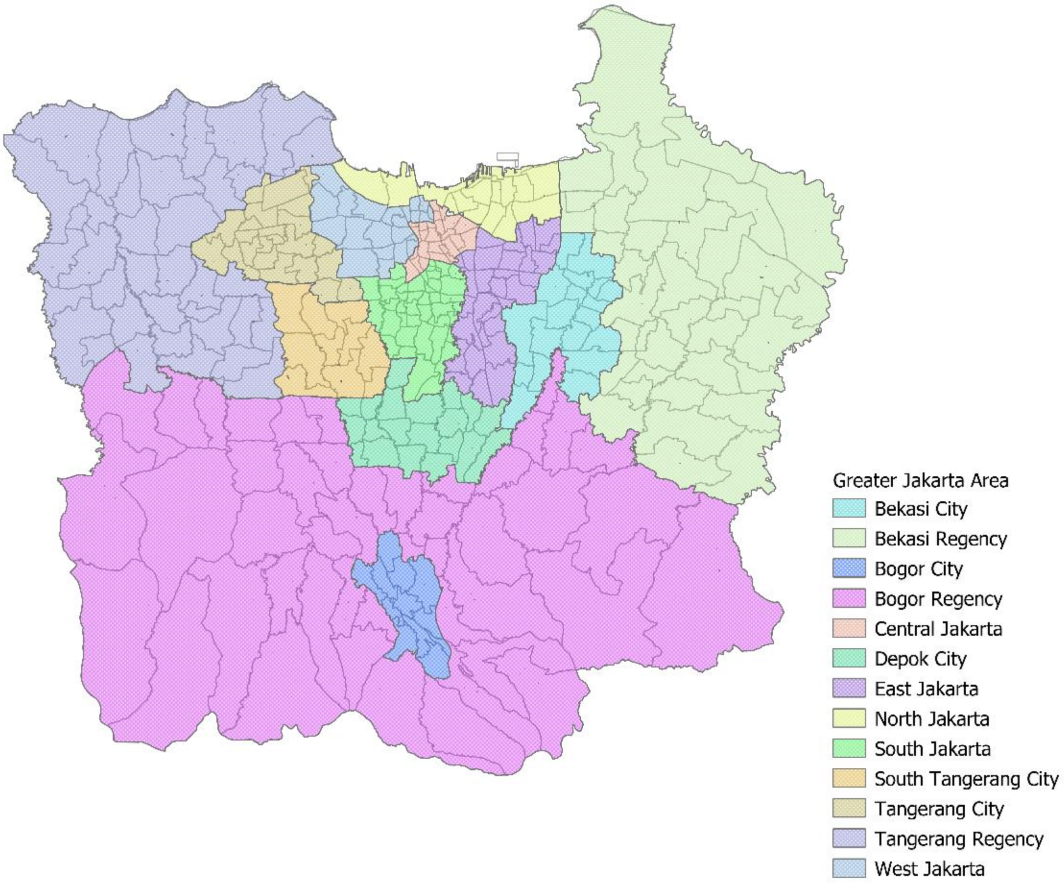
A.1.7 Details on Greater Jakarta Area

The details for the socio-economic profile of Greater Jakarta Area are shown in Table 16. Meanwhile, Figure 13 shows the map of thirteen cities/regencies along with its TAZ of the Greater Jakarta Area.

Table 16: Details of the Socioeconomic Profile of Greater Jakarta Area

Province	Population Density (People/km2)			GRDP (thousand USD 2020/capita)			Figure 13	Total TAZ
	2020	2030	2050	2020	2030	2050		
DKI Jakarta	15,968	16,786	17,152	12.02	19.59	54.56	South Jakarta	65
							East Jakarta	66
							Central Jakarta	44
							West Jakarta	56
							North Jakarta	34
West Java	3,480	3,843	4,360	2.44	3.56	7.93	Depok City	63
							Bogor City	68
							Bogor Regency	438
							Bekasi City	56
							Bekasi Regency	189
Banten	6,079	6,880	8,115	2.27	3.33	7.55	Tangerang City	105
							South Tangerang City	54
							Tangerang Regency	276

Figure 13: Map of Greater Jakarta Area



A.2 Details on the Result of the Study

A.2.1 Model Validation

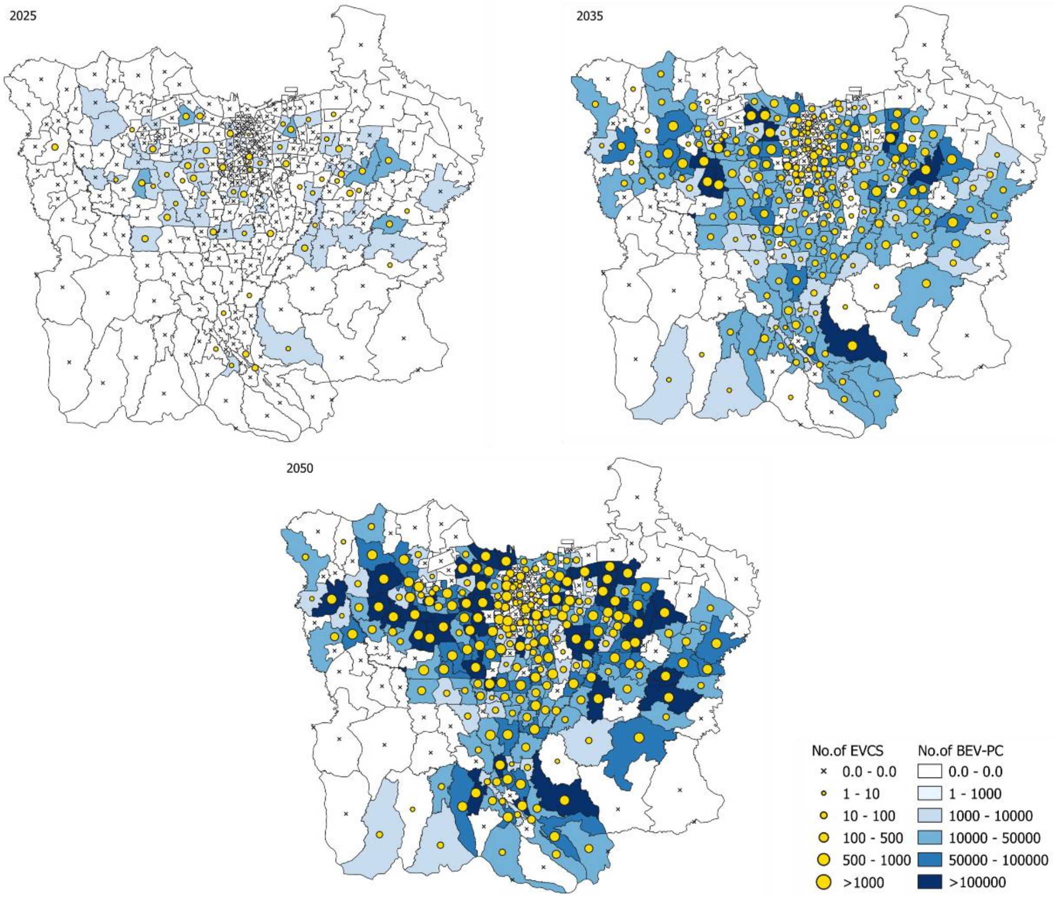
Model validation was carried out by comparing the model's output in the Current Policy scenario and the actual data in 2022. The actual data for both vehicles are derived from the total vehicle sales data at the national level (Gaikindo, 2022, Foundry and Deloitte, 2023). The data is adjusted to the Greater Jakarta Area context based on the existing national and vehicle stock data ratio in the Greater Jakarta Area.

The validation process demonstrates that the model's output reaches almost four times higher BEV-PC in the vehicle stock than the actual data. However, only four agents purchased BEV-PC in the corresponding year. It was observed that an agent purchases a BEV-PC represents an increase of up to 3,000 BEV in the vehicle stock in 2022. Kangur et al. (2017) highlighted that validating BEV diffusion is challenging when a low volume of BEV diffusion is present in the actual data, and a small sample of agents is utilized. Their investigation, which employed an agent-based model consisting of 1,795 distinct driving profiles to simulate the market diffusion of electric cars in the Netherlands, also found similar phenomena. Notably, their model generated outcomes that were nearly fourfold greater than the empirical data.

Concurrently, this study exhibits 57 times more BEV-MC than the vehicle stock data. Subsequent analysis shows that the TCO for BEV-MC and its ICEV counterpart converged in 2021, consistent with the current analysis (Gupta et al., 2023). This suggests the potential omission of non-monetary factors by the model in depicting the current situation.

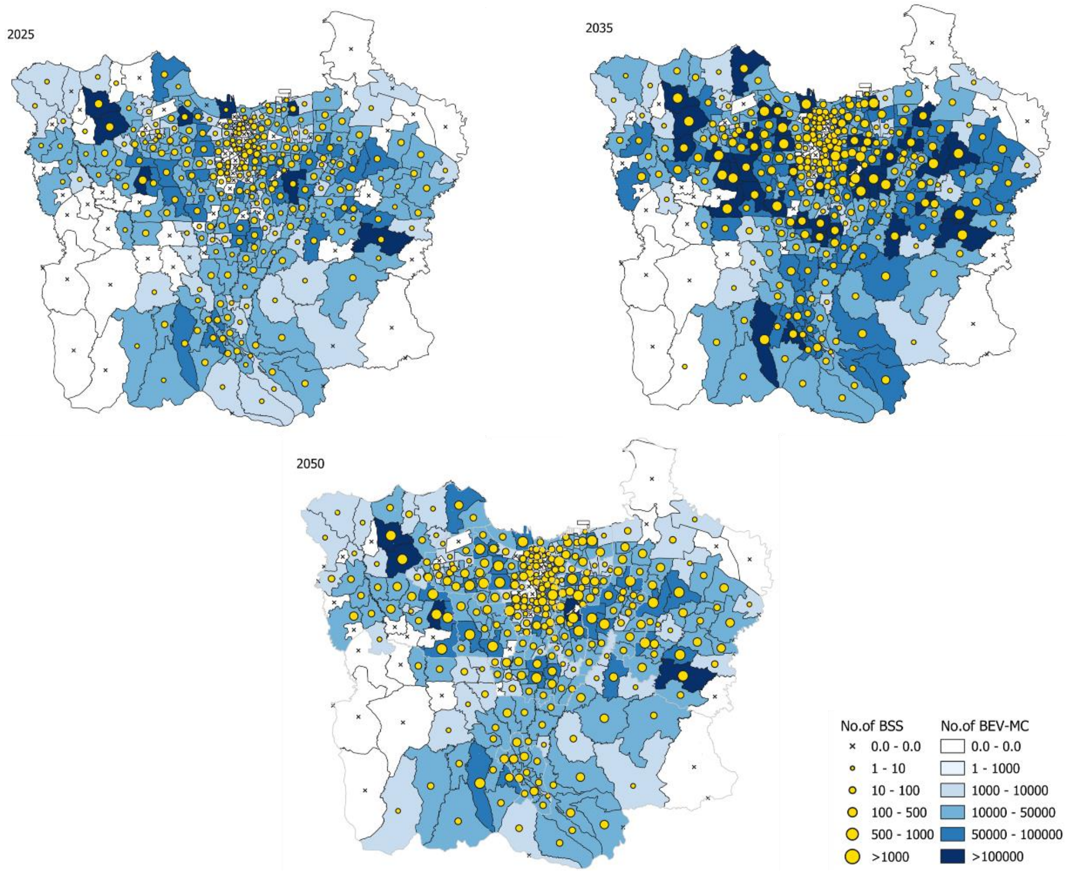
A.2.2 Details on Distribution of EVCS and BEV-PC in the Greater Jakarta Area

Figure 14: Distribution of EVCS and BEV-PC in the Greater Jakarta Area



A.2.3 Details on Distribution of BSS and BEV-MC in the Greater Jakarta Area

Figure 15: Distribution of BSS and BEV-MC in the Greater Jakarta Area



A.3 References in Annex

ADB. 2022. Electric Motorcycle Charging Infrastructure Road Map for Indonesia. *In:* BANK, A. D. (ed.). Manila, Philippines: Asian Development Bank.

Aimi. 2022. *Statistic Distribution* [Online]. DKI Jakarta. Available: https://www.aisi.or.id/statistic/ [Accessed 01/07/2023 2023].

ASEAN. 2019. ASEAN Fuel Economy Roadmap for the Transport Sector 2018-2025: with Focus on Light-Duty Vehicles. *In:* ASEAN (ed.) *ASEAN Fuel Economy Roadmap.* Jakarta.

Bank of Indonesia. 2018. RASIO LOAN TO VALUE UNTUK KREDIT PROPERTI, RASIO FINANCING TO VALUE UNTUK PEMBIAYAAN PROPERTI, DAN UANG MUKA UNTUK KREDIT ATAU PEMBIAYAAN KENDARAAN BERMOTOR. *In:* INDONESIA, B. (ed.). DKI Jakarta: Bank of Indonesia.

BPS. 2020a. *PDRB Atas Dasar Harga Konstan Menurut Kabupaten/Kota Wilayah Banten* [Online]. Available: https://banten.bps.go.id/site/resultTab [Accessed 24 Mei 2020].

BPS. 2020b. *PDRB Atas Dasar Harga Konstan Menurut Kabupaten/Kota Wilayah DKI Jakarta* [Online]. Available: https://jakarta.bps.go.id/indicator/52/59/1/pdrb-atas-dasar-harga-konstan-2010-menurut-lapangan-usaha.html [Accessed 24 Mei 2020].

BPS. 2020c. *PDRB Atas Dasar Harga Konstan Menurut Kabupaten/Kota Wilayah Jawa Barat* [Online]. Available: https://jabar.bps.go.id/site/resultTab [Accessed 24 Mei 2020].

BPS & UNFPA. 2018. Proyeksi Penduduk Indonesia 2015 -2045. Jakarta: Badan Pusat Statistik.

Carsome. 2020. Car Purchase Preference Survey 2020. Indonesia: Carsome.

Deloitte. 2021. Supercharging Electric Mobility in Southeast Asia. *In:* DELOITTE (ed.) *Full Speed Ahead.* Deloitte.

EIA. 2021. Annual Energy Outlook 2021, with Projections to 2050. Washington DC: U.S. Energy Information Administration (EIA).

Febransyah, A., 2021. Predicting purchase intention towards battery electric vehicles: A case of indonesian market. *World Electric Vehicle Journal,* 12**,** 240.

Foundry & Deloitte. 2023. An electric revolution: The rise of Indonesia's e-motorcycle. *In:* INDONESIA, D. (ed.). Indonesia: Deloitte Indonesia.

Gaikindo. 2022. *Indonesian Automobile Industry Data* [Online]. Available: https://www.gaikindo.or.id/indonesian-automobile-industry-data/ [Accessed 2022].

Goetzel, N. & Hasanuzzaman, M., 2022. An empirical analysis of electric vehicle cost trends: A case study in Germany. *Research in Transportation Business & Management,* 43**,** 100825.

GridOto. 2017. *Harga NJKB Xpander Ultimate Hanya Rp 153 juta? Begini Perhitungannya* [Online]. Available: https://www.gridoto.com/read/221004856/harga-njkb-xpander-ultimate-hanya-rp-153-juta-begini-perhitungannya [Accessed].

Gupta, R., Hertzke, P., Vivek, L. & Vig, G., 2023. The real global EV buzz comes on two wheels. McKinsey & Company.

Harrison, G. & Thiel, C., 2017. An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe. *Technological Forecasting and Social Change,* 114**,** 165-178.

IEA. 2022. An Energy Sector Roadmap to Net Zero Emissions in Indonesia. *In:* AGENCY, I. E. (ed.) *International Energy Agency Special Report.*

Kagan, J., 2023. *28/36 Rule: What It Is, How to Use It, Example* [Online]. Investopedia. Available: https://www.investopedia.com/terms/t/twenty-eight-thirty-six-rule.asp [Accessed 12/07 2023].

Kangur, A., Jager, W., Verbrugge, R. & Bockarjova, M., 2017. An agent-based model for diffusion of electric vehicles. *Journal of Environmental Psychology,* 52**,** 166-182.

MEMR. 2023. Provision of Electricity Charging Infrastructure For Battery Based Electric Motorized Vehicles. Indonesia: Ministry of Energy and Mineral Resources Republic of Indonesia.

Mera, Z. & Bieker, G., 2023. Comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars and two-wheelers in Indonesia. International Council on Clean Transportation. https://theicct. org ....

Ministry of Industry. 2022. Updated Specifications, Roadmap Development, and Domestic Component Calculation Guidelines for Domestic Battery Electric Motor Vehicles. *In:* INDONESIA, M. O. I. R. O. (ed.). Jakarta.

Murtiningrum, A. D., Darmawan, A. & Wong, H., 2022. The adoption of electric motorcycles: A survey of public perception in Indonesia. *Journal of cleaner production,* 379**,** 134737.

Nugroho, R., Hanafi, J., Shobatake, K., Chun, Y.-Y., Tahara, K. & Purwanto, W. W., 2022. Life cycle inventories and life cycle assessment for an electricity grid network: case study of the Jamali grid, Indonesia. *The International Journal of Life Cycle Assessment,* 27**,** 1081-1091.

Pertamina, P., 2020. *Daftar Harga BBK Tmt* [Online]. Available: https://www.pertamina.com/id/news-room/announcement [Accessed 2023].

PLN. 2021. National Electricity Statistics 2020 (Statistik PLN 2020). Jakarta: PT. PLN (Persero).

PLN. 2022. Realisasi & Rencana Pengembangan Infrastuktur Pendukung Kendaraan Listrik di Jawa dan Nasional. Jakarta: PT PLN Persero.

PwC Indonesia. 2023. Indonesia Electric Vehicle Consumer Survey 2023. *In:* INDONESIA, P. (ed.). Indonesia: PwC Indonesia.

Rogers, E. M., 2010. *Diffusion of innovations*, Simon and Schuster.

Schloter, L., 2022. Empirical analysis of the depreciation of electric vehicles compared to gasoline vehicles. *Transport Policy,* 126**,** 268-279.