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Modeling Consumer Willingness to Consider Electric Motorcycles in Indonesia: A System Dynamics Approach

Ahmad Rafi Adnanta [1,*], Roni Zakaria Raung [1], Wahyudi Sutopo [1], Ihwan Susila [2]

[1] Department of Industrial Engineering, Faculty of Engineering, Universitas Sebelas Maret, Surakarta, Indonesia
[2] Department of Management, Faculty of Economics and Business, Universitas Muhammadiyah Surakarta, Surakarta, Indonesia

*Corresponding Author: adnantarafi@student.uns.ac.id

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ABSTRACT

Sustainable transport plays a key role in the fight against climate change, particularly in developing countries where reliance on conventional vehicles is high. Motorcycles account for the majority of the fleet of motor vehicles in Indonesia and contribute significantly to emissions. In order to achieve its Paris target of a 29 percent reduction of carbon emissions, the Government is encouraging electric cars with various incentives. This study develops a willingness to consider (WTC) model for electric motorcycles in Indonesia based on the powertrain technology transition market agent model (PTTMAM) and utilizes Vensim software to simulate outcomes. The WTC model is built on the assumption that consumers' willingness to consider electric motorcycles is influenced by factors such as costs, marketing, and exposures. The system dynamics model consists of four modules: the conventional motorcycle, the electric motorcycle, the marketing module, and the willingness to consider module. The simulation results show an increasing trend in consumers' willingness to consider electric motorcycles from 2017-2035, with the WTC value reaching 0.3209 in 2035. While this indicates a positive shift toward greater consumer interest in electric motorcycles, the growth remains modest and slow, reflecting the challenges of widespread adoption. Additionally, this study evaluates three government incentive and subsidy policy scenarios. The scenario results indicate that government subsidies and incentives can increase the consumers' willingness to consider electric motorcycles in Indonesia, thereby increasing their market share. Among the scenarios, the purchase price subsidy is the most effective, as it directly reduces the financial barrier, encouraging more consumers to make the switch to electric motorcycles.

Keywords: technology transition, electric motorcycle, willingness to consider, system dynamics, incentive policy

INTRODUCTION

Global warming has emerged as a central issue in recent decades, posing multidimensional threats to ecology, the environment, the economy, and society [1]. As one of the world's largest carbon dioxide emitters, Indonesia needs to reduce its emissions to below 449 $MtCO_2e$ by 2030 to limit global warming to under 1.5°C [2]. Indonesia is committed to reducing emissions by 29%, as mandated by the Paris Agreement. Research in this field has become increasingly relevant as the government has demonstrated its commitment to encouraging the adoption of electric vehicles (EV), including electric motorcycles (EM), as part of efforts to reduce air pollution and dependence on fossil fuels. This makes Indonesia's transport sector a key focus in the fight against climate change. As of 2023, Indonesia ranks as the third-largest motorcycle user in the world and has long relied on motorcycles as the primary choice for daily transportation [3]. High population density, narrow roads, and well-distributed road networks make motorcycles the most practical option for point-to-point travel in urban areas [4]. Additionally, motorcycles are often favored by low-income households due to their low fuel consumption and small size, which saves time and money while improving access to work opportunities [5]. However, this heavy reliance on conventional motorcycles (CM) has several drawbacks. As of 2022, 125,305,332 motorcycles were registered in Indonesia, accounting for 84.52% of the country's total vehicles [6].

The growing number of CM, with an annual increase of 4.3%, exacerbates air pollution and carbon emissions. To address this, the government issued Presidential Regulation Number 55 of 2019 on the Acceleration of the Battery-Based Electric Motor Vehicle Program for Road Transportation [7]. Additionally, the Ministry of Transportation has established regulations for converting internal combustion engine (ICE) motorcycles into battery-based electric motorcycles through Ministerial Regulation Number 65 of 2020. These regulations aim to reduce the number of ICE motorcycles and further promote the use of electric motorcycles.

Electric motorcycles (EMs) are not yet commonplace in Indonesia, primarily because they represent new technology, which causes many people to hesitate in adopting them [8]. Like any emerging technology, EMs require in-depth studies and evaluations to gain public acceptance and consideration [9]. To better understand consumer behavior, researchers outside of Indonesia, like Wu et al. [10] and Jordan [11] often focuses on purchase intention, which refers to the stage where consumers develop the intent to buy based on a positive attitude toward the product [1]. However, before forming this intention, consumers encounter an earlier stage where they face numerous product options and filter them heuristically into a relevant set, known as the consideration set [12].

The willingness to consider (WTC) a product is the initial stage reflecting the extent to which consumers are familiar with the product, allowing them to include it in their consideration set [13]. WTC captures the cognitive, emotional, and social processes through which consumers gain sufficient information, understanding, and emotional attachment to include the product in their decision-making process [14]. It serves as a tool for consumers to evaluate a product and consider it as a viable choice. In contrast, purchase intention is a more specific and targeted desire to purchase a product after forming a positive attitude toward it. Given the low market penetration of EMs in Indonesia, WTC offers a more suitable framework for assessing consumer behavior. Several studies have successfully used WTC to predict consumer behaviour in similar contexts. For instance, a study by Harrison et al. [15] used WTC to measure consumers' exposure to alternative powertrains in Europe, finding that WTC played a critical role in estimating market share. Similarly, Skippon et al. [16] applied WTC to assess consumer experience in battery electric vehicle (BEV), concluding that direct experience caused an increase in consideration.

While behavioral models provide insight into consumer attitudes, modeling techniques are needed to simulate adoption dynamics over time. Various research has been conducted on electric vehicles (EV) using both markov chains and game theory. The Markov chain assumes a "limited memory" property, meaning that the subsequent event depends solely on the preceding event and the current state. This assumption, however, makes the model overly simplistic and unable to represent complex, time-dependent interactions. Moreover, Markov models cannot be rigorously derived from deterministic and dynamic models [17]. Game theory, however, focuses on scenarios involving a finite number of players and strategies, which might not accurately reflect more complex real-world situations. Furthermore, the assumptions underlying game theory may not align with actual human behavior, making it challenging to test against real-world conditions [18]. Although Markov chains and game theory have broad applicability, they have significant limitations in their flexibility in designing models that account for complex and nonlinear interactions between elements within a system.

To overcome these limitations, simulation-based approaches such as system dynamics (SD) offer a more robust framework. System dynamics (SD), introduced by Jay W. Forrester in the 1950s, is a powerful simulation technique

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that models complex systems through feedback loops, delays, and nonlinear relationships[19]. It has been widely used, including studies like Thies et al. [20], which explored alternative powertrain strategies, and Zahrina et al. [21], which developed a conceptual battery exchange model in Indonesia. Compared to other techniques like discrete event simulation or monte carlo methods, SD excels in analyzing interconnected variables in complex systems. It supports decision-makers in evaluating long-term policy impacts[22]. However, SD models are often limited by their linearity assumptions, which can oversimplify complex interactions within a system [23]. Additionally, the approach is prone to subjectivity and bias in model building, as decisions made by modelers about which variables to include or exclude can influence the results.

To address these challenges, this study incorporates nonlinearity and cross-validates multiple data sources to enhance model robustness. This research employs SD to analyze willingness to consider electric motorcycles in Indonesia, with a model consisting of four modules: the conventional motorcycle module, electric motorcycle module, marketing module, and WTC module. Building on previous research [15], this study adapts the model to the unique conditions in Indonesia, addressing barriers to adoption and identifying strategies to increase public acceptance. The urgency of this research is underscored by Indonesia's ambitious EM adoption targets and current market realities. Transitioning from fuel-powered motorcycles to EM offers potential benefits such as improved air quality, reduced operational costs, and cheaper maintenance [24], [25]. Despite these advantages, EM adoption in Indonesia has been slow. According to Ministerial Regulation Number 28 of 2023, the Ministry of Industry has set a target of 12 million EM units in Indonesia by 2035 [26]. Meanwhile, the Ministry of Energy and Mineral Resources announced a goal of providing 300,000 new and converted EM units in 2023 and 600,000 units in 2024 [27]. However, as of January 2024, the Indonesian Electric Motorcycle Industry Association revealed that the domestic EM population stood at only 74,988 units [28]. This figure falls significantly short of the government's targets, highlighting the low exposure of EMs in Indonesia.

The adoption of EM in Indonesia is hindered by several factors [29]. The limited range and high battery costs, along with insufficient charging infrastructure, make EMs less appealing for long-distance or rural users. The high upfront cost of EMs, even with incentives, also remains a significant barrier for lower-income consumers. Culturally, there is reluctance to shift from CM due to attachment to familiar technology and concerns over battery reliability. The lack of widespread charging infrastructures further limits the practicality of owning an EM, particularly outside urban centers. Additionally, many Indonesians rely on motorcycles for their livelihood, making the initial cost of EMs a tougher investment, especially in areas with low technology literacy and economic constraints. In response to these challenges, this study aims to provide actionable insights into the factors influencing WTC for EMs and assist policymakers in achieving sustainable transportation objectives.

METHODS

This research employs a system dynamics simulation to forecast the willingness to consider (WTC) value for electric motorcycles in Indonesia, utilizing Vensim software. Vensim is a simulation modeling tool for improving the performance of real systems (originally developed as a Pascal extension). It was developed by Ventana Systems Incorporation. Vensim benefits from a vast user community and extensive support, enhancing the ease of troubleshooting and model development [30]. The software is backed by thorough documentation and an active user base, offering assistance through forums, tutorials, and model examples. This ensures that new users can quickly grasp and utilize the software effectively. Vensim also provides a free version (Vensim PLE) with ample features for academic and educational purposes, making it more accessible to students. Vensim holds a dominant position in the market, with a significant proportion of published research relying on this software [31].

The SD model in this research consists of four key modules: the electric motorcycle module, the conventional motorcycle module, the marketing module, and the WTC module. The CM module simulates ownership cost trends by summing up the submodules for life cycle cost, environmental impact cost, and social impact cost. The EM module is generally similar to the CM module, with the addition of factors such as subsidies and battery costs. The marketing module integrates marketing efforts and cost impacts to simulate the effectiveness of marketing strategies. The WTC module simulates the increase or decay of willingness to consider EMs through total social exposure, which is derived from direct exposure, indirect exposure, and marketing effectiveness.

The simulation model used in this study covers the period from 2017 to 2035, as these years incorporate historical data from recent years and provide an adequate timeframe to analyze consumer behavior, capturing both past trends and future projections. To ensure a representative analysis, this study selected both CM and EM product that are similar in type (scooter), front suspension (telescopic fork), wheel size (R14), and overall dimensions. Data for this study are sourced from multiple reputable institutions. Energy costs for CM and EM are calculated using data from Indonesian Petroleum Corporation and Indonesian State Electricity Company, named as Pertamina and PLN, respectively. Meanwhile, gross domestic product (GDP), social cost monetization, and motorcycle ownership statistics are sourced from the Central Bureau of Statistics. Depreciation rates and resale values are based on data from the One-Stop Administration Services Office. Additionally, this study includes data from prior research. We adopted several data from Mitropoulos et al. [34], including the emissions produced and the cost of emissions. Noise costs data of EM and CM are derived from Korzhenevych et al. [32]. Meanwhile, Danielis et al. [33] provided data on external health costs associated with emissions. Finally, we adopted base run and sensitivity data, for marketing and willingness to consider module, from Harrison et al. [15] and Struben & Sterman [14]. The following assumptions were made based on the gathered data:

1. Data from international studies is assumed to be applicable to this model due to its relevance to the subject matter. As comparable data specific to Indonesia is not readily available, international studies often serve as a benchmark or 'rule of thumb' to guide model assumptions. This approach is commonly adopted in similar research across Asia, where market conditions and consumer behaviors may share similarities. Existing Indonesian studies also rely on international data when local data is limited.
2. The variables applied in this research are tailored to the conditions specific to Indonesia.
3. The motorcycle ownership period is set at 6 years based on marketplace surveys and supported by previous studies [34], [35], [36].

Unlike the previous study by Harrison et al. [15], which primarily focused on life cycle costs, this research expands the scope by incorporating not only life cycle costs but also the environmental and social impact costs. Furthermore, this study uniquely emphasizes the role of the government as the sole stakeholder, simplifying the model for more targeted analysis. By focusing on government intervention, the model enables the exploration of various subsidy policies aimed at increasing the willingness to consider (WTC) value. In addition, several variables have been added or adjusted to better reflect the specific conditions in Indonesia. The causal loop diagram is carefully constructed based on these variables, which are considered within the context of the four key modules. A detailed representation of the causal loops in the willingness to consider simulation model can be found in the Appendix.

The model is highly complex, comprising multiple submodules and intricate interrelationships between various factors such as willingness to consider, social exposures, marketing effectiveness, and several cost components. Given the model's complexity, understanding the interplay between these factors may require a comprehensive overview of their connections and dynamics. To aid in this understanding, a diagram has been provided to visually represent the key relationships within the model (Figure 1). This diagram illustrates the influence of total cost of ownership and policies on marketing effectiveness, while also highlighting how both direct and indirect exposure contribute to social exposure, ultimately affecting consumers' willingness to consider.

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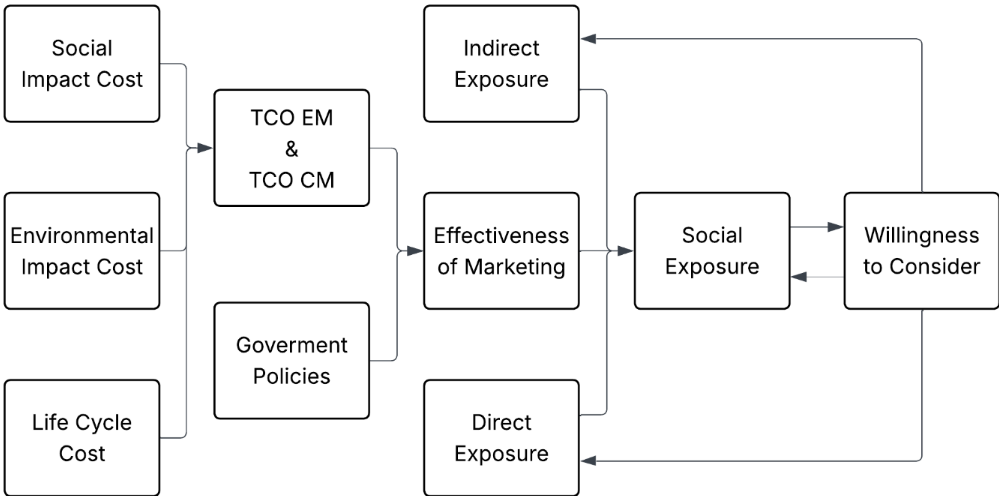

Figure 1. Model Overview

Electric Motorcycle Module

The electric motorcycle (EM) module is designed to simulate the dynamics of the total cost of ownership (TCO) experienced by the owner at the time of purchase. It consists of three submodules: the EM life cycle cost submodule (LCC_{EM}), the EM environmental impact cost submodule (CE_{EM}), and the EM social impact cost submodule (CSI_{EM}). These submodules collectively model the various factors that influence the TCO over time. The following is the formulation for the TCO of electric motorcycles referring to Yuniaristanto et al. [36].

$$\mathrm{TCO_{EM}} = \mathrm{LCC_{EM}} + \mathrm{CE_{EM}} + \mathrm{CSI_{EM}} \tag{1}$$

These components will be discussed in the following submodules.

EM Life Cycle Cost Submodule

The EM life cycle cost submodule is designed to calculate the costs associated with owning and operating an electric motorcycle over its lifetime (Figure 2). These costs are incurred by the vehicle owner during the year of purchase. According to the approaches used by Kong et al. [37], the total purchase cost of an EM (PC_{EM}), its operation cost (OP_{EM}), and the resale value of the EM (RV_{EM}) are key components of the LCC_{EM}. The LCC_{EM} formulation is based on the following equations:

$$\mathrm{LCC_{EM}} = \mathrm{PC_{EM}} + \mathrm{OP_{EM}} - \mathrm{RV_{EM}} \tag{2}$$

$$\mathrm{PC_{EM}} = (\mathrm{PP_{EM}} - \mathrm{PS_{EM}}) + (\mathrm{PTS_{EM}} \times \mathrm{PT_{EM}}) \tag{3}$$

$$\mathrm{OP_{EM}} = (\mathrm{IN_{EM}} + \mathrm{TXY_{EM}} + \mathrm{MN_{EM}} + \mathrm{EC_{EM}}) \times \mathrm{n} + \mathrm{TXF} \tag{4}$$

$$\mathrm{RV_{EM}} = \frac{(1-\mathrm{DR_{EM}})^{n} \times \mathrm{PP_{EM}} + \mathrm{RV_B}}{(1+r)^{n-1}} \tag{5}$$

PC_{EM} is equal to the sum of the purchase price (PP_{EM}) and purchase tax (PT_{EM}). The formula then incorporates subsidies from the government, including the purchase price subsidy (PS_{EM}) and purchase tax subsidy (PTS_{EM}), to provide a comprehensive calculation. OP_{EM} includes several components according to Afraah et al. [34]. The insurance cost (IN_{EM}) represents the annual cost of insuring the vehicle. The yearly tax cost (TXY_{EM}) is the amount of tax paid each year for owning an EM, taking into account the yearly tax subsidy. Maintenance cost (MN_{EM}) refers

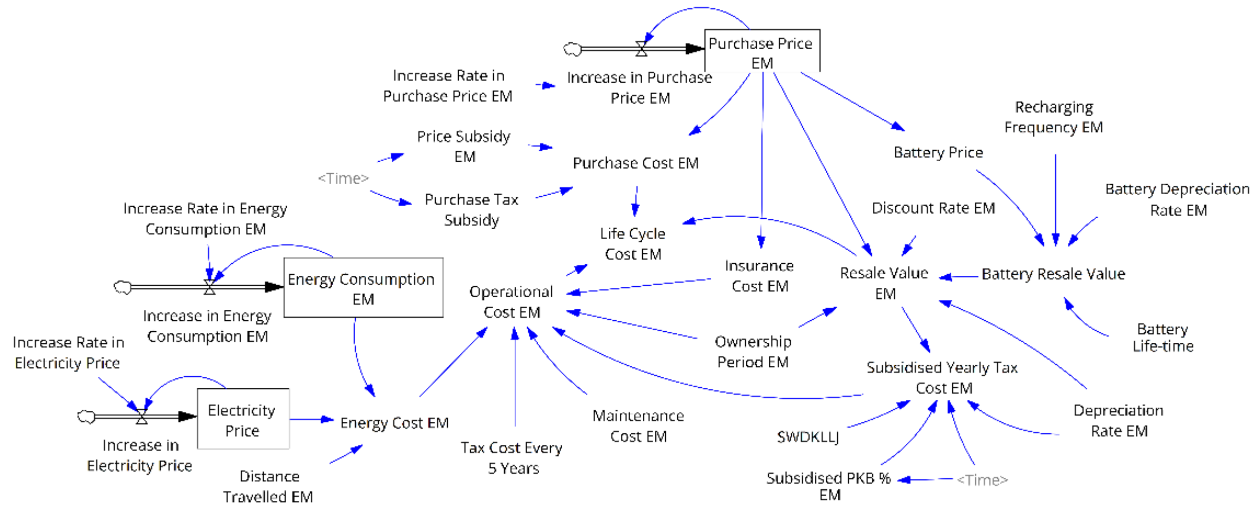

Figure 2. EM Life Cycle Cost Submodule

to the annual expenses of maintaining the EM such as brake pads replacement, v-belt replacement, and oil change. The energy cost (EC_{EM}) is the annual cost of electricity required to power the EM. It is determined by the EM's energy consumption rate, the annual distance travelled (10,000 km on moderate mobility), and the price of electricity. The ownership period (n) is assumed to be six years. The tax cost for every five years (TXF_{EM}) includes the administrative fee for the vehicle registration certificate and the number plate fee. RV_{EM} is calculated based on several factors. The depreciation rate (DR_{EM}) of 7.08% is derived based on the average resale price of motorcycles from Motor Vehicle Administration of Jakarta (named as SAMSAT DKI Jakarta), simulated with the purchase price for that year. The discount rate (r) is the interest rate used to calculate the present value of future costs. Finally, the resale value of the battery (RV_B) reflects the expected value of the battery when reselling the motorcycle.

EM Environmental Impact Cost Submodule

The environmental impact cost (CE_{EM}) submodule is designed to calculate the costs associated with the impact of using an electric motorcycle on the environment (Figure 3). The emissions caused by vehicles are monetized by using external cost due to its contribution to global warming and harmful to the human health. According to the approaches used by Mitropoulos et al. [38], the greenhouse gas external cost of an EM ($CGHG_{EM}$), the noise external cost (CN_{EM}), the air quality external cost (CAQ_{EM}), and n are key components of the CE_{EM}. The CE_{EM} formulation is based on the following equations:

$$\mathrm{CE_{EM}} = (\mathrm{CGHG_{EM}} + \mathrm{CN_{EM}} + \mathrm{CAQ_{EM}}) \times \mathrm{n} \tag{6}$$

$$\mathrm{CGHG_{EM}} = \mathrm{TGHG_{EM}} \times \mathrm{EGHG_{EM}} \times \mathrm{DT_{EM}} \tag{7}$$

$$\mathrm{CN_{EM}} = (\mathrm{CNU_{EM}} + \mathrm{CNS_{EM}}) \times \mathrm{DT_{EM}} \tag{8}$$

$$\mathrm{CAQ_{EM}} = \mathrm{TAQ_{EM}} \times \mathrm{EAQ_{EM}} \tag{9}$$

The $CGHG_{EM}$ represents the external greenhouse gas cost ($TGHG_{EM}$), greenhouse gas emission ($EGHG_{EM}$), and distance travelled (DT_{EM}). Three pollutants accounts for the impact of $EGHG_{EM}$: CH_4 (0.0025 g/km), N_2O (0.0006 g/km), and CO_2 (32.0007 g/km). Mitropoulos et al. [38] have chosen the value of $27 per metric ton carbon (tC) for the monetization of emissions. The CN_{EM} accounts for urban noise cost (CNU_{EM}), suburban noise cost (CNS_{EM}), and DT_{EM}. Noise emissions from traffic are a growing environmental concern due to increased urbanization and traffic

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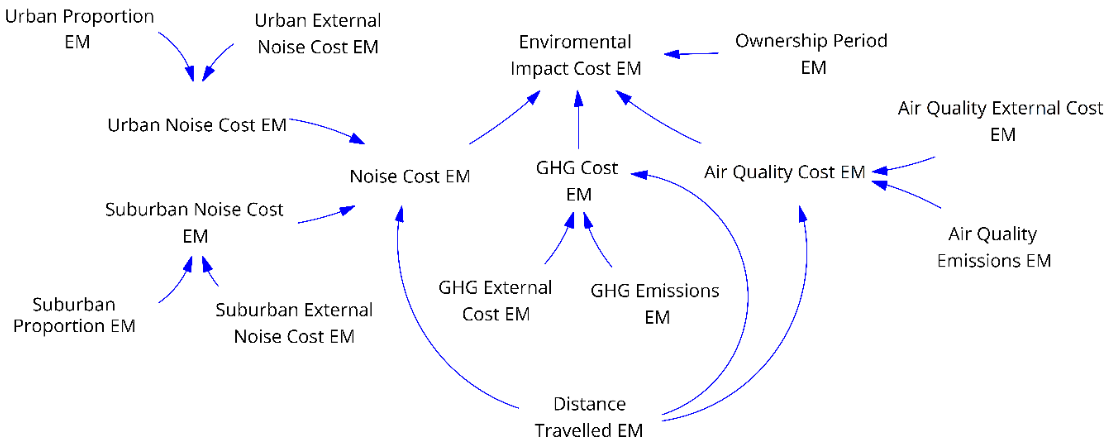

Figure 3. EM Environmental Impact Cost Submodule

volume. This issue not only causes disturbance but also leads to health problems and reduced productivity. In the report for the European Commission, Korzhenevych et al. [32] have chosen the value of €0.005/km for the monetization of urban noise and €0 for suburban noise. With an annual travel distance of 10,000 km, the proportion of urban and suburban trips is assumed to be 53% and 47%, respectively [34]. The CAQ_{EM} is calculated based on the external air quality cost (TAQ_{EM}) and the air quality emissions (EAQ_{EM}). Five pollutants accounts for the impact of CAQ_{EM}: CO (0.02 g/km), NO_X (0.048 g/km), VOC (0.004 g/km), SO_X (0.026 g/km), and PM_{10} (0.017 g/km). Mitropoulos et al. [38] have chosen the value of \$27/tC for the monetization of emissions.

EM Social Impact Cost Submodule

The social impact cost submodule is designed to calculate the costs associated with the impact of using an electric motorcycle on the employment and health factors (Figure 4). The monetization of time in this calculation is estimated by multiplying the lost time by the average hourly wage [39]. The average hourly wage in Indonesia was Rp11,434.00 in 2015, with an annual increase of 6.57% [40]. According to the approaches used by Danielis et al. [33], the maintenance losses of an EM (CMR_{EM}), the recharging losses (CR_{EM}), and the emission cost to health impact (CH_{EM}) are key components of the CSI_{EM}. The CSI_{EM} formulation is based on the following equations:

$$\mathrm{CSI_{EM}} = (\mathrm{CMR_{EM}} + \mathrm{CR_{EM}} + \mathrm{CH_{EM}}) \times \mathrm{n} \tag{10}$$

$$\mathrm{CMR_{EM}} = \mathrm{FM_{EM}} \times \mathrm{TM_{EM}} \times \mathrm{CES_{EM}} \tag{11}$$

$$\mathrm{CR_{EM}} = \mathrm{FR_{EM}} \times \mathrm{TR_{EM}} \times \mathrm{CES_{EM}} \tag{12}$$

$$\mathrm{CH_{EM}} = \mathrm{CEH_{EM}} \times \mathrm{DT_{EM}} \tag{13}$$

The CMR_{EM} represents the maintenance frequency (FM_{EM}), the duration per maintenance (TM_{EM}), and the social external cost (CES_{EM}). The frequency of maintenance for EM is estimated to be once per year, with each maintenance session taking 1.5 hours [34]. The CR_{EM} accounts for the recharging frequency (FR_{EM}), the duration per recharge (TR_{EM}), and CES_{EM}. According to Mitropoulos et al. [38], the time loss during nighttime charging can be ignored as it is considered not to interfere with the user's activities. Therefore, charging during the morning, afternoon, and evening, with a value of 25% was derived from Afraah et al. [34]. The frequency of energy charging for electric motorcycles is 156 times per year, with each charging session taking 2 hours. The CH_{EM} is calculated based on the

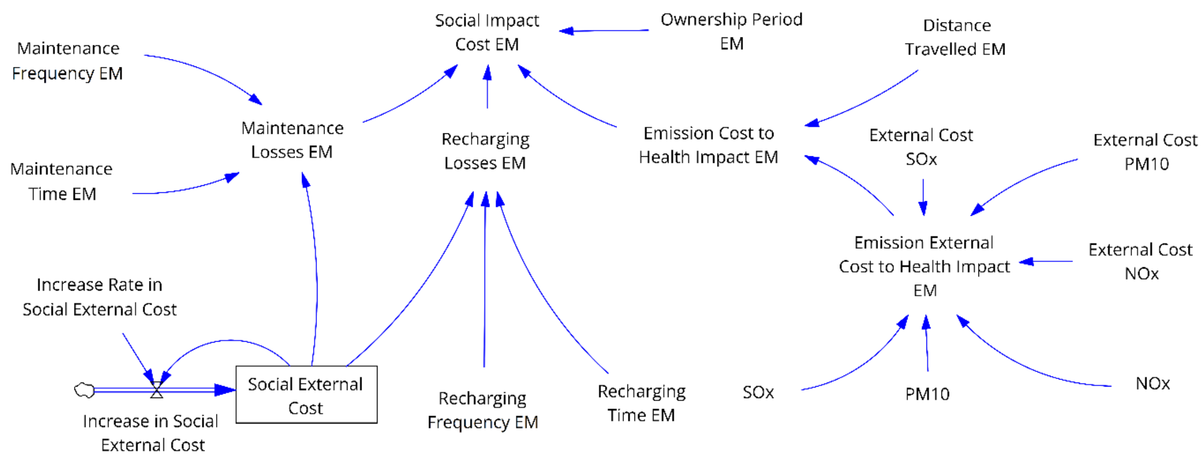

Figure 4. EM Social Impact Cost Submodule

external emission cost to health impact (CEH_{EM}) and DT_{EM}. According to the United States Environmental Protection Agency, the types of emissions that are the main causes of high mortality and morbidity rates are SOx, NOx, and PM10. The increase in emissions for electric motorcycles is assumed to be 0% annually, meaning the emissions remain constant. Each of these emission gases is then multiplied by the external cost based on Krewski et al. [41], with SOx costing \$84,000/ton, NOx at \$6,600/ton, and PM_{10} at \$230,000/ton.

Conventional Motorcycle Module

The conventional motorcycle (CM) module, similar in structure to the EM module, simulates the TCO for CM during the year of purchase. It comprises three submodules: the CM life cycle cost submodule (LCC_{CM}), the CM environmental impact cost submodule (CE_{CM}), and the CM social impact cost submodule (CSI_{CM}). Together, these submodules model the various factors influencing TCO over time. The following is the formulation for the TCO of conventional motorcycles referring to Yuniaristanto et al. [36].

$$\mathrm{TCO_{CM}} = \mathrm{LCC_{CM}} + \mathrm{CE_{CM}} + \mathrm{CSI_{CM}} \tag{14}$$

These components will be elaborated on in the following submodules.

CM Life Cycle Cost Submodule

The CM life cycle cost (LCC_{CM}) submodule shares similarities with the EM life cycle cost submodule, calculating the costs of owning and operating a conventional motorcycle (Figure 5). It incorporates purchase cost of an CM (PC_{CM}), its operation cost (OP_{CM}), and the resale value of the EM (RV_{CM}). Unlike the EM submodule, the government does not provide a purchase price subsidy or purchase tax subsidy for conventional motorcycles. Additionally, conventional motorcycles do not have a battery to resell. The LCC_{CM} formulation is shown in equations 15-18.

$$\mathrm{LCC_{CM}} = \mathrm{PC_{CM}} + \mathrm{OP_{CM}} - \mathrm{RV_{CM}} \tag{15}$$

$$\mathrm{PC_{CM}} = \mathrm{PP_{CM}} \times \mathrm{PT_{CM}} \tag{16}$$

$$\mathrm{OP_{CM}} = (\mathrm{IN_{CM}} + \mathrm{TXY_{CM}} + \mathrm{MN_{CM}} + \mathrm{EC_{CM}}) \times \mathrm{n} + \mathrm{TXF} \tag{17}$$

$$\mathrm{RV_{CM}} = \frac{(1-\mathrm{DR_{CM}})^{n} \times \mathrm{PP_{CM}}}{(1+r)^{n-1}} \tag{18}$$

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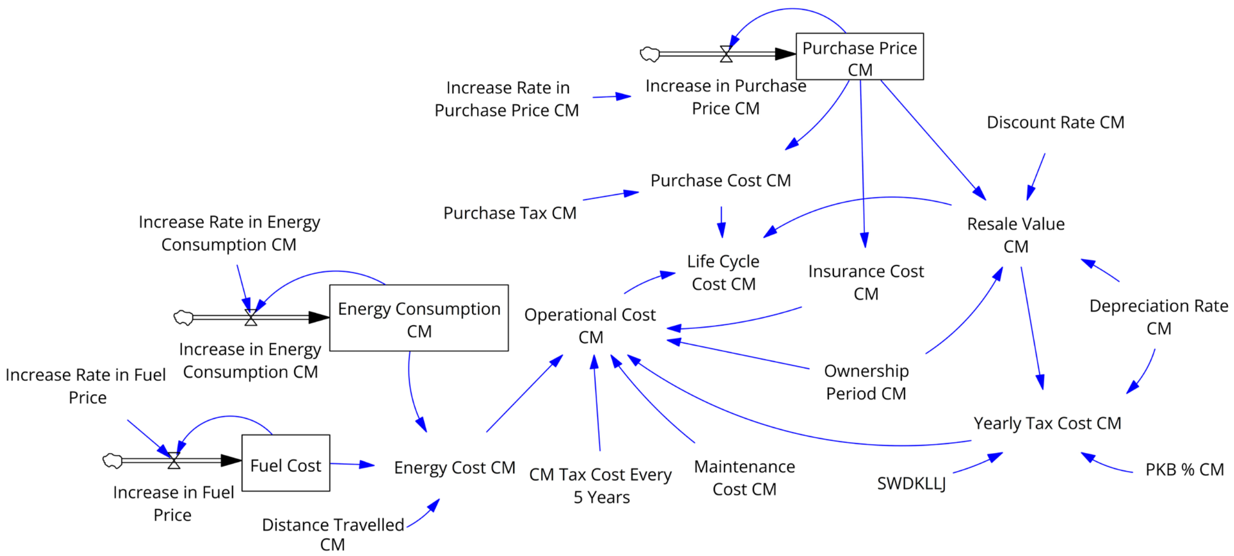

Figure 5. EM Life Cycle Cost Submodule

The PC_{CM} represents the purchase price (PP_{CM}) and purchase tax (PT_{CM}). The OP_{CM} accounts for insurance cost (IN_{CM}), yearly tax cost (TXY_{CM}), maintenance cost (MN_{CM}), the energy cost of the EM (EC_{CM}), the ownership period (n), and the tax cost for every five years (TXF_{CM}). The resale value (RV_{CM}) is calculated based on the depreciation rate (DR_{CM}), the purchase price of the EM (PP_{CM}), the discount rate (r), and period of ownership (n). This breakdown provides a comprehensive view of the financial components influencing the total life cycle cost of a conventional motorcycle.

CM Environmental Impact Cost Submodule

The environmental impact cost (CE_{CM}) submodule (see Figure 6), similar in structure to the CE_{EM} submodule, is designed to calculate the costs associated with the impact of using a conventional motorcycle on the environment. These costs are incurred by the vehicle owner during the year of purchase. The greenhouse gas external cost of an CM ($CGHG_{CM}$), the noise external cost (CN_{CM}), the air quality external cost (CAQ_{CM}), and n are key components of the CE_{CM}. The CE_{CM} formulation is based on the following equations:

$$CE_{CM} = (CGHG_{CM} + CN_{CM} + CAQ_{CM}) \times n \tag{19}$$

$$CGHG_{CM} = TGHG_{CM} \times EGHG_{CM} \times DT_{CM} \tag{20}$$

$$CN_{CM} = (CNU_{CM} + CNU_{CM}) \times DT_{CM} \tag{21}$$

$$CAQ_{CM} = EAQ_{CM} \times TAQ_{CM} \tag{22}$$

The $CGHG_{CM}$ represents the external greenhouse gas cost ($TGHG_{CM}$), greenhouse gas emission ($EGHG_{CM}$), and distance travelled (DT_{CM}). Three pollutants accounts for the impact of $EGHG_{CM}$: CH_4 (0.0354 g/km), N_2O (0.005 g/km), and CO_2 (227.0869 g/km). Mitropoulos et al. [38] have chosen the value of $27 per metric tC for the monetization of emissions. The CN_{CM} accounts for urban noise cost (CNU_{CM}), suburban noise cost (CNS_{CM}), and DT_{CM}. In the report for the European Commission, Korzhenevych et al. [32] have chosen the value of €0.026/km for the monetization of urban noise and €0.002/km for suburban noise. With an annual travel distance of 10,000 km, the proportion of urban and suburban trips is assumed to be 53% and 47%, respectively [34]. The CAQ_{CM} is calculated based on the external air quality cost (TAQ_{CM}) and the air quality emissions (EAQ_{CM}). Five pollutants

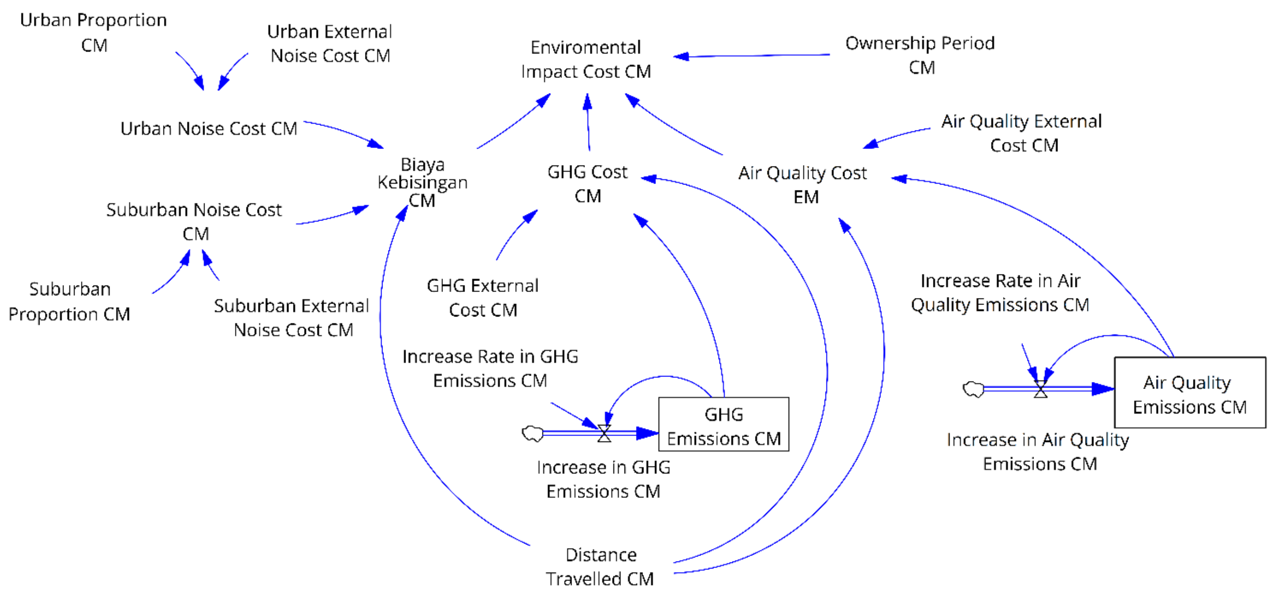

Figure 6. CM Environmental Impact Cost Submodule

accounts for the impact of CAQ_{CM}: CO (20.505 g/km), NO_X (0.741 g/km), VOC (0.016 g/km), SO_X (0.007 g/km), and PM_{10} (0.017 g/km).

CM Social Impact Cost Submodule

The social impact cost submodule is designed to calculate the costs associated with the impact of using a conventional motorcycle on the employment and health factors. These costs are incurred by the vehicle owner during the year of purchase. The maintenance losses of an EM (CMR_{CM}), the refueling losses (CR_{CM}), and the emission cost to health impact (CH_{CM}) are key components of the CSI_{CM}. The CSI_{CM} formulation is based on the following equations:

$$CSI_{CM} = (CMR_{CM} + CR_{CM} + CH_{CM}) \times n \tag{23}$$

$$CMR_{CM} = FM_{CM} \times TM_{CM} \times CES_{CM} \tag{24}$$

$$CR_{CM} = FR_{CM} \times TR_{CM} \times CES_{CM} \tag{25}$$

$$CH_{CM} = CEH_{CM} \times DT_{CM} \tag{26}$$

As shown in Figure 7, the CMR_{CM} represents the maintenance frequency (FM_{CM}), the duration per maintenance (TM_{CM}), and the social external cost (CES_{CM}). The frequency of maintenance for EM is estimated to be twice per year, with each maintenance session taking 2 hours [34]. The CR_{CM} accounts for the refueling frequency (FR_{CM}), the duration per refuels (TR_{CM}), and CES_{CM}. According to Mitropoulos et al. [38], the time loss during nighttime refueling can be ignored as it is considered not to interfere with the user's activities. Therefore, refueling during the morning, afternoon, and evening, with a value of 25% was derived from Afraah et al. [34]. The frequency of refueling for conventional motorcycles is 104 times per year, with each charging session taking 8.9 minutes or 0.148 hours. The CH_{CM} is calculated based on the external emission cost to health impact (CEH_{CM}) and DT_{CM}. According to the United States Environmental Protection Agency, the types of emissions that are the main causes of high mortality and morbidity rates are SOx, NOx, and PM10. The increase in emissions for electric motorcycles is assumed to be

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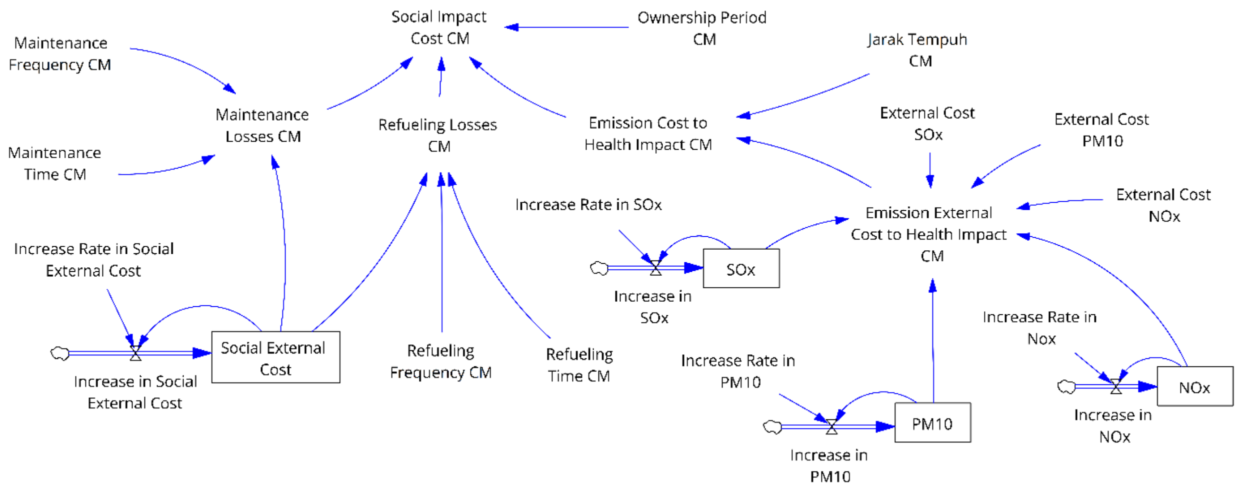

Figure 7. CM Social Impact Cost Submodule

6% annually [42]. Each of these emission gases is then multiplied by the external cost based on Krewski et al. [41], with SOx costing \$84,000/ton, NOx at \$6,600/ton, and PM_{10} at \$230,000/ton.

Marketing Module

The marketing module is designed to calculate the value associated with the impact of the stakeholder policies on the effectiveness of marketing (EOM_{EM}). This module is crucial as it connects the CM and EM modules to the WTC module. It provides valuable insights into how costs and efforts in marketing influence the exposure of EM. The base marketing response (BRM) value of 0.025 was chosen by Struben & Sterman [14] and is directly applied in this research. Combining the BRM with the marketing effect (MEE_{EM}) and the cost impact (CI_{EM}), the EOM_{EM} value is obtained. The formulation can be seen in equation 27.

$$\mathrm{EOM_{EM}} = \mathrm{BMR} \times \mathrm{MEE_{EM}} \times \mathrm{CI_{EM}} \tag{27}$$

These components will be elaborated on in the following submodules.

Marketing Effort Submodule

Marketing effort (MEO_{EM}), as depicted in Figure 8, is a measure of the intensity of marketing a vehicle measured on a zero (no marketing) to one (saturation) scale. In this research, two types of marketing effort are considered: the marketing effort for the initial launch (MEL_{EM}) and the marketing effort resulting from subsidies (MES_{EM}). MEL_{EM} reflects the promotional activities and campaigns conducted during the vehicle's initial introduction to the market, aimed at creating brand awareness and attracting early adopters. On the other hand, MES_{EM} captures the marketing intensity driven by subsidies, which can be used to further incentivize purchases or enhance the vehicle's attractiveness to a wider group of potential buyers. The MEO_{EM} formulation is based on the following equations:

$$\mathrm{MEO_{EM}} = \mathrm{IF\ THEN\ ELSE\ (MEL_{EM}} > 0, \mathrm{MEL_{EM}}, \mathrm{MES_{EM})} \tag{28}$$

$$\mathrm{MES_{EM}} = \mathrm{BMM} \times (\mathrm{TS_{EM}} \div \mathrm{BSM})^{\mathrm{SM}} \tag{29}$$

MEL_{EM} is valued at 1 for 5 years starting from the year before EM becomes commercially available and valued at 0 for the following years. The base marketing modifier for subsidy (BMM), base subsidy for marketing (BSM), and

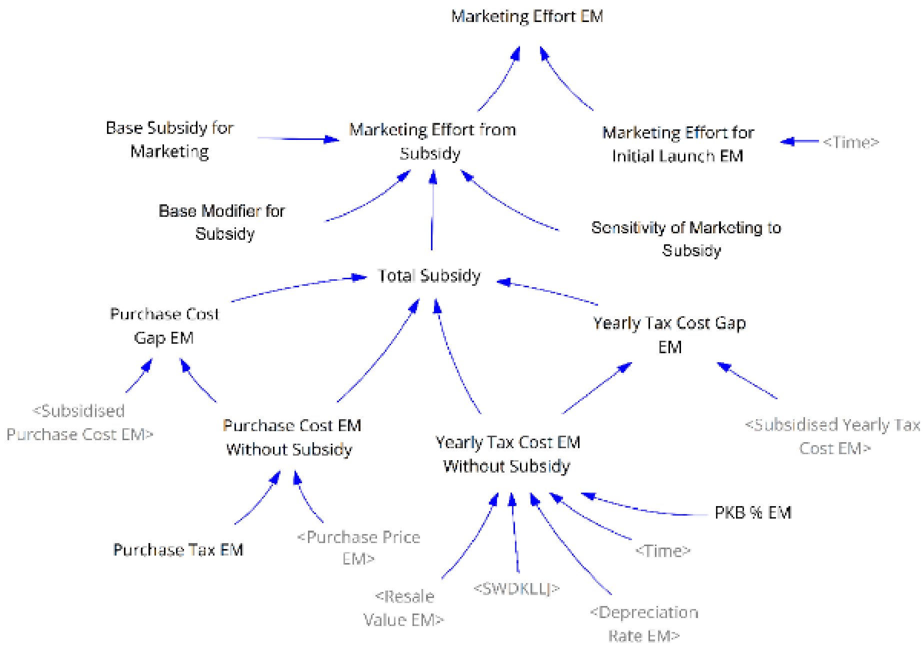

Figure 8. Marketing Effort Submodule

sensitivity of marketing to subsidy (SM) values in MEO_{EM} are exogenous inputs based on the findings of Harrison et al. [15]. Several government incentives have been introduced to support the adoption of EMs. In 2021, the introduced a regulation providing incentives for EMs, offering an annual tax reduction of 10% of the tax base [43]. In 2023, the government expanded these incentives by implementing annual tax exemptions. That same year, the Ministry of Industry introduced a regulation offering a price discount of IDR 7,000,000 for the purchase of a single electric two-wheeled vehicle [44]. Additionally, the government enacted a regulation reducing the purchase tax from 11% to 1%. These three subsidies together contribute to the total subsidy (TS_{EM}).

Cost Impact Submodule

The cost impact (CI_{EM}) in a given country plays a significant role in shaping the growth of WTC as it serves as a modifier of EOM_{EM}. When vehicles are substantially more expensive than the typical market prices within that country, only a smaller proportion of the population can realistically afford or consider purchasing them. This cost differential creates a barrier, limiting the broader exposure of higher-priced vehicles.The CI_{EM} formulations refers to Harrison et al. [15], which can be seen in equations 30-32.

$$\mathrm{CI_{EM}} = \frac{\mathrm{PTCO_{EM}} - \mathrm{CD_{MIN}}}{\mathrm{CD_{MAX}} - \mathrm{CD_{MIN}}} \tag{30}$$

$$\mathrm{CD_{MAX}} = 1 + (\mathrm{RCD_{MAX}} \times GDPCR^{SA}) \tag{31}$$

$$\mathrm{CD_{MIN}} = 1 + (\mathrm{RCD_{MIN}} \times GDPCR^{SA}) \tag{32}$$

The reference value for maximum cost differential (RCD_{MAX}) and minimum cost differential (RCD_{MIN}) are obtained from the previous study [14], which explains the limit before users start omitting the vehicle from their options. The next step is to find $GDPCR_{EM}$ by comparing the current gross domestic product (GDP) per capita of Indonesia with Asia's average GDP per capita. Differences between the two are translated into higher or lower tolerance of price differentials through an exogenous sensitivity of affordability (SA). By combining all those variables, the maximum

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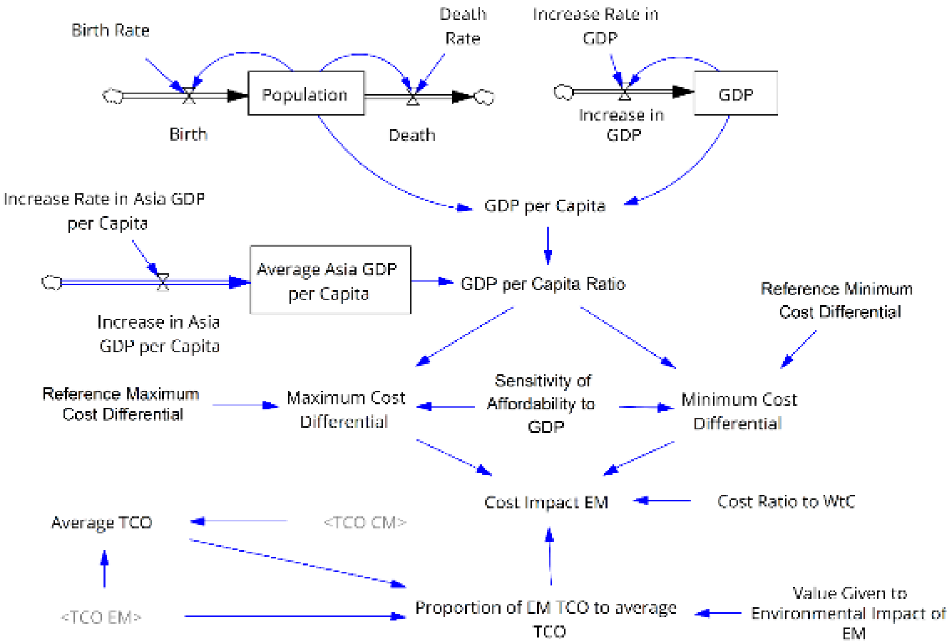

Figure 9. Cost Impact Submodule

differential (CD_{MAX}) and minimum differential (CD_{MIN}) are obtained. $PTCO_{EM}$ represents the ratio of EM TCO to the average TCO of motorcycles. Equation 32 essentially normalizes the $PTCO_{EM}$ by the range of the cost differentials, helping to assess the relative cost against the maximum and minimum tolerances for price differences. This provides a scaled measure of how the $PTCO_{EM}$ compares to the price tolerance limits set by the cost differentials.

Willingness to Consider Module

The willingness to consider module is designed to calculate the value associated with consumers' willingness to consider electric motorcycle (WTC_{EM}) in Indonesia. Vehicle users learn about a particular platform through three social exposure channels: the effectiveness of marketing, direct exposure, and indirect exposure from users and non-users of that vehicle type. According to the approaches used by Struben & Sterman [20] and Harrison et al. [15], the increase in WTC_{EM} ($IWTC_{EM}$) and the decrease in WTC_{EM} ($DWTC_{EM}$) are key components of the WTC_{EM}. The WTC_{EM} formulation is based on the following equations:

$$\mathrm{WTC_{EM(t)}} = \mathrm{WTC_{EM(t=0)}} + \int_{t=0}^{t} (\mathrm{IWTC}_{EM} - \mathrm{DWTC}_{EM})\,\mathrm{dt} \tag{33}$$

$$\mathrm{IWTC_{EM(t)}} = \mathrm{ITSE_{EM}} \times \mathrm{WTC}_{EM(t-1)} \tag{34}$$

$$\mathrm{ITSE_{EM(t)}} = \mathrm{DE_{EM}} + \mathrm{IE_{EM}} + \mathrm{EOM_{EM}} \tag{35}$$

$$\mathrm{DE_{EM(t)}} = \mathrm{FEC_{DE}} \times \mathrm{WTC_{EM}} \times \mathrm{PTOW_{EM}} \times \mathrm{CI_{EM}} \tag{36}$$

$$\mathrm{IE_{EM(t)}} = \mathrm{FEC_{IE}} \times \mathrm{WTC_{EM}} \times \mathrm{PTOW_{CM}} \times \mathrm{CI_{EM}} \tag{37}$$

$$\mathrm{IE_{EM(t)}} = \mathrm{FEC_{IE}} \times \mathrm{WTC_{EM}} \times \mathrm{PTOW_{CM}} \times \mathrm{CI_{EM}} \tag{38}$$

$$\mathrm{AFD_{EM(t)}} = \mathrm{BD} \times \frac{\exp[-4\times \mathrm{SDR}(\mathrm{ITSE_{EM}} - \mathrm{SER})]}{1+exp[-4\times \mathrm{SDR}(\mathrm{ITSE_{EM}} - \mathrm{SER})]} \tag{39}$$

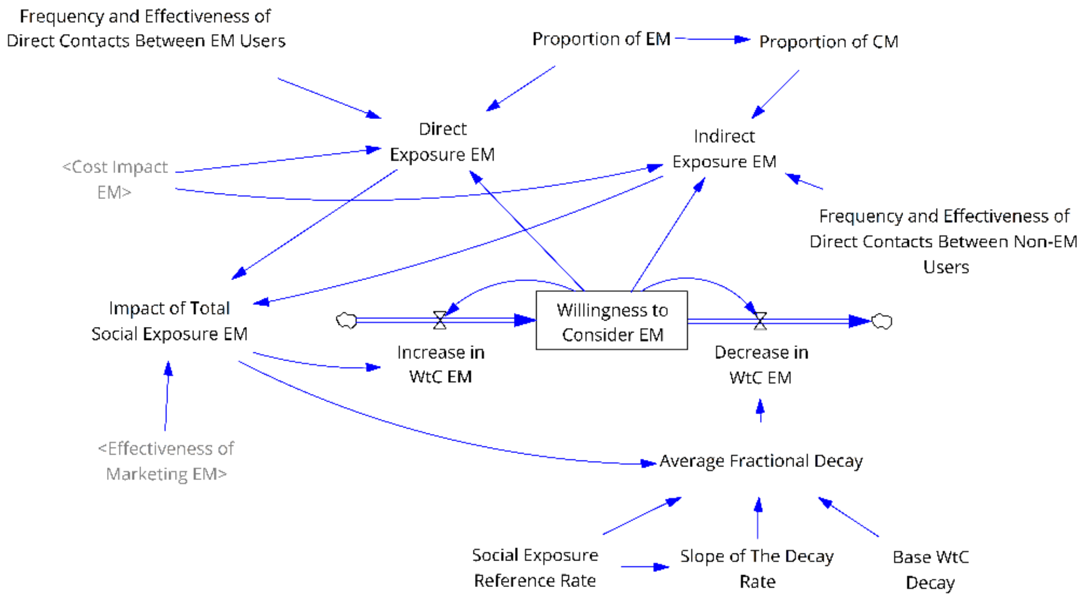

Figure 10. Willingness to Consider Module

$$SDR_{EM(t)} = \frac{1}{(2 \times SER)} \tag{40}$$

Consumers' willingness to consider a particular type of vehicle increases through the impact of total social exposure ($ITSE_{EM}$). Vehicle users learn about a particular platform through three social exposure channels: the effectiveness of marketing (EOM_{EM}), direct exposure (DE_{EM}), and indirect exposure (IE_{EM}) from users and non-users of that vehicle type. Direct exposure refers to the word-of-mouth influence about EM from interactions between EM and CM users. DE_{EM} is determined by multiplying the frequency and effectiveness of contact between EM users and non-users (FEC_{EM}), the willingness to consider EM, the proportion of EM ownership ($PTOW_{EM}$), and the cost impact of EM. The frequency and effectiveness of contact between EM users and non-users is valued at 25% [14]. Meanwhile, Indirect exposure (IE_{EM}) refers to the word-of-mouth influence about EM through interactions with others who have knowledge of the vehicle type. In other words, IE_{EM} is the word-of-mouth influence about EM from contact between CM users to other CM users. Indirect exposure is determined by the frequency and effectiveness of contact between non-users of EM (FEC_{CM}), WTC EM, the proportion of CM ownership ($PTOW_{CM}$), and the cost impact. The frequency and effectiveness of contact between non-users of EM is assumed to be weaker than direct interaction, valued at 15% [14].

$PTOW_{EM}$ measures the proportion of the number of EM to the total motorcycle population. This proportion is obtained by dividing the number of EM by the total number of motorcycles, then multiplying by 100% to get the result in percentage form. To forecast the number of electric motorcycles and the total motorcycle population, the autoregressive integrated moving average (ARIMA) method is applied. ARIMA (2,4,1) is used to forecast the number of electric motorcycles, while ARIMA (1,1,1) is used to forecast the total motorcycle population, as it produces the lowest percentage error. Historical data from 2015 to 2023 is used to forecast the future growth of both electric motorcycles and total motorcycle population.

Consumers' willingness to consider a particular type of vehicle can also decrease through an average fractional decay (AFD_{EM}). Effort and attention are required to stay updated with the development of new vehicle models and features. Therefore, the willingness to consider the platform will diminish if it is not renewed through marketing or social

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exposure. When exposure is infrequent, WTC decreases rapidly. On the other hand, greater exposure will reduce the rate of decay. Struben & Sterman [14] captures these characteristics by using a logistic function, which can be seen in equation 39. The base WTC decay (BD) represents the initial rate of decay and sets the starting point for how quickly WTC would decline if no external influences were at play. The WTC decay rate slope (SDR) is a key factor that controls how steep the decay curve is. A higher slope will make WTC decay faster with smaller increases in social exposure, meaning WTC will drop more quickly as exposure decreases. A smaller slope, on the other hand, results in a more gradual decay. As social exposure increases, the likelihood of people considering electric motorcycles also rises. SER is the reference rate of social exposure at which WTC decays at half the normal rate. SER value of 0.05 implies that inflection point for forgetting is at 10% of adoption. The formula includes an exponential function to account for how changes in exposure levels either slow down or accelerate the decay of WTC.

RESULTS AND DISCUSSION

Model Verification and Validation

The verification of the simulation program was conducted through writing, debugging, and checking the logical relationships between variables, as well as ensuring unit consistency within the model. The bottom-up approach is used to verify each module designed into a causal loop diagram. The model was run using Vensim software, and the results showed that the model ran smoothly without any warnings such as "model has errors and cannot be simulated." This indicates that the relationships between the variables in the model, along with the units assigned to each variable, were consistent. Therefore, it can be concluded that the developed model is a consistent model.

After verifying that the model is consistent, the next step was to validate it by involving a group of experts to assess whether the model accurately reflects the intended concept. These experts were professors or lecturers who have studied and published in the same field or on similar models. Their evaluation aimed to confirm the model's relevance, accuracy, and applicability. The validation process involved direct evaluation, during which the experts reviewed the model's assumptions, parameters, and results. After their comprehensive review, it was confirmed that the model designed in this study is valid.

The statistical test used to validate the output of the simulation model in this study was the Mean Absolute Percentage Error (MAPE) test. The model is considered valid if the deviation between the simulation output and the actual system output is statistically acceptable. The MAPE calculation follows the formula by Montaño Moreno et al. [45]. The MAPE values can be classified into several categories according to their prediction accuracy. A MAPE value under 10% is considered excellent, as it indicates a very small deviation between the predicted and actual values, reflecting a high level of accuracy in the model's forecasts. Such a low MAPE is typically associated with models that make precise predictions, which is crucial for reliable decision-making in real-world applications. A MAPE between 10% and 20% is considered good, indicating that the model's prediction is reasonably close to the actual values. If the MAPE falls between 20% and 50%, the prediction accuracy is considered fair, though there may be room for improvement in the model. However, if the MAPE exceeds 50%, the prediction accuracy is considered poor, and the model is deemed less reliable. The validity test was performed on the response variables, which represent the system's performance or output variables. Based on this, and the availability of data, the variables selected for validation were population and GDP calculated over 2015-2023 period. Table 1 displays the validity results for the population variable, with a MAPE value is 0.30%, or the model is deemed to be valid because the MAPE value is <10%. Simultaneously, the second validation was carried out on the GDP, yielding a MAPE value of 2.49% that is deemed to be valid.

Table 1. Validity Test

No.	Year	Population		MAPE	GDP (In Billions IDR)		MAPE
		Existing	Simulation		Existing	Simulation	
1	2015	255,587,900	255,588,000	0.00004%	11,526,332.00	11,526,300.00	0.0003%
2	2016	258,496,500	258,476,000	0.00793%	12,401,728.00	12,427,700.00	0.2094%
3	2017	261,355,500	261,397,000	0.01588%	13,589,825.00	13,399,500.00	1.4005%
4	2018	264,161,600	264,351,000	0.07170%	14,838,756.00	14,447,300.00	2.6381%
5	2019	266,911,900	267,338,000	0.15964%	15,832,657.00	15,577,100.00	1.6141%
6	2020	269,576,540	270,359,000	0.29026%	15,443,353.00	16,795,300.00	8.7542%
7	2021	272,248,500	273,414,000	0.42810%	16,976,751.00	18,108,600.00	6.6671%
8	2022	272,679,150	276,503,000	1.40233%	19,588,089.00	19,524,700.00	0.3236%
9	2023	278,696,190	279,628,000	0.33435%	20,892,376.00	21,051,600.00	0.7621%
MAPE				**0.30%**			**2.49%**

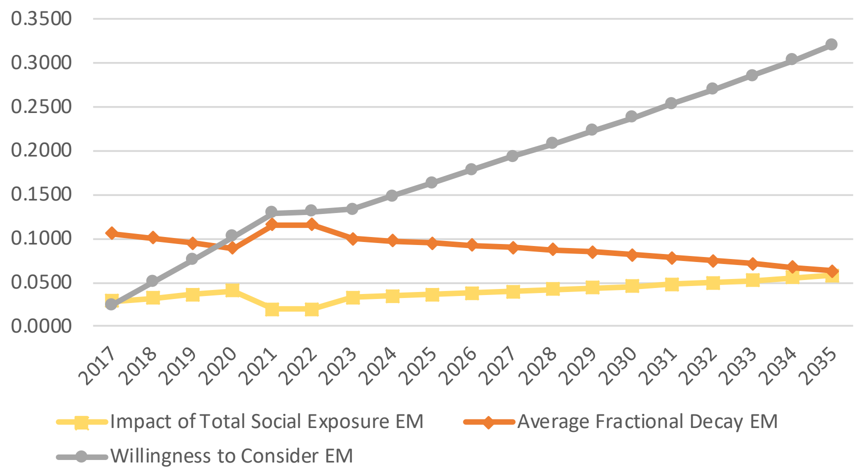

Figure 11. Willingness to Consider Value of Baseline Simulation

Simulation Result

Figure 11 illustrates the changes in two main variables related to willingness to consider (WTC) for electric motorcycles over the period from 2017 to 2035. These two variables are the impact of total social exposure (ITSE) and the average fractional decay (AFD). This graph helps visualize how social exposure and the rate of decay affect user willingness over time. The impact of total social exposure is a variable that increases WTC, derived from the sum of the effectiveness of marketing (EOM), direct exposure (DE), and indirect exposure (IE) of electric motorcycles (EM). At the start of the simulation, the value of ITSE is 0.0286 and increases until 2020. This increase is due to the growing number of EM, which raises the values of DE and IE. Another contributing factor is the EOM, which is valued at 1 due to significant marketing efforts during the first five years, as discussed in the previous section. Once this five-year period ends in 2021, ITSE experiences a significant decline from 0.0403 to 0.0194. However, marketing efforts in the form of vehicle tax incentives boost ITSE again to 0.0581 by 2035.

On the other hand, the average fractional decay (AFD) is a variable that decreases WTC. Several studies on consumer behavior regarding electric vehicle adoption in Indonesia, such as those by Yuniaristanto et al. [36], Sulistyono et al.

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[35], and Setiawan et al. [46], do not account for the decaying effect over time. This omission overlooks the important dynamic that as consumers are exposed to information, their willingness to adopt new technologies, such as electric motorcycles, can diminish or stabilize after an initial period of heightened interest. In contrast, researches like Harrison et al. [15], and Yu et al. [47] have suggested incorporating the decaying effect into models of consumer behavior. They argue that the decaying effect is crucial for accurately simulating the long-term adoption of technologies, as it captures the reality that initial enthusiasm tends to wane without continued exposures or new incentives.

AFD is calculated from the baseline decay, the reference social exposure level, and the slope of the decay rate. At the beginning of the simulation, when total social exposure is still low, the decay rate for WTC is very high. As exposures such as marketing, direct exposure, and indirect exposure become less frequent, WTC decreases rapidly. The average fractional decay is derived from the logistic function developed by Struben & Sterman [14]. As social exposure approaches the reference level, the rate of WTC decay starts to slow down. This aligns with the midpoint of the logistic function, where the rate of change becomes slower because people begin to get accustomed to the information exposure. In the graph, this is reflected as a more stable decrease in the orange line after some time, where the fractional decay slows down, but not as quickly as before. As exposure increases and people are frequently exposed, the logistic function reaches its saturation point, where the WTC decay almost stops or becomes very slow. Once saturation is reached, additional exposure does not have a significant effect on further reducing WTC.

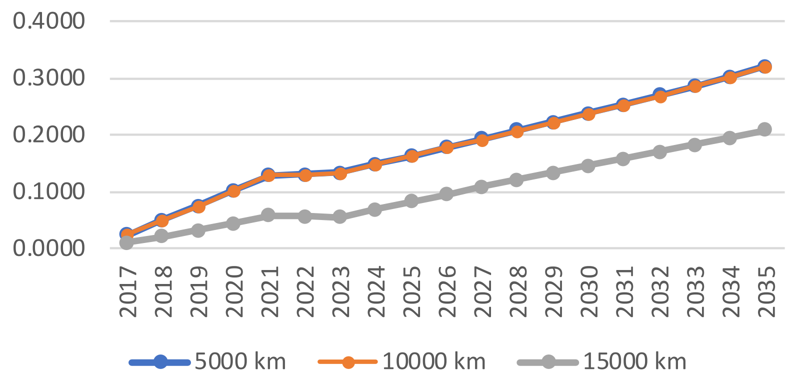

Figure 12. Sensitivity of Willingness to Consider Value to EM Travel Distance

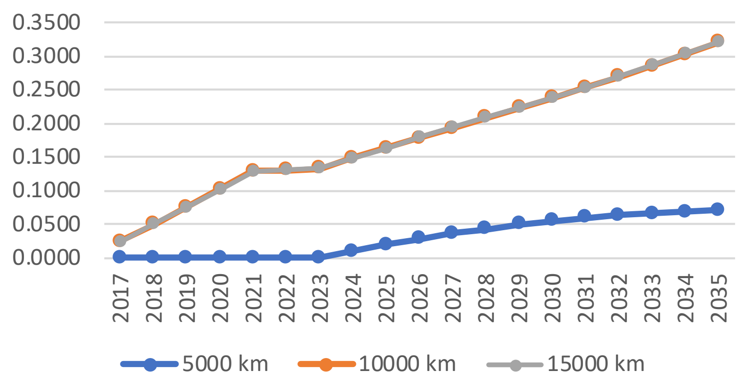

Figure 13. Sensitivity of Willingness to Consider Value to CM Travel Distance

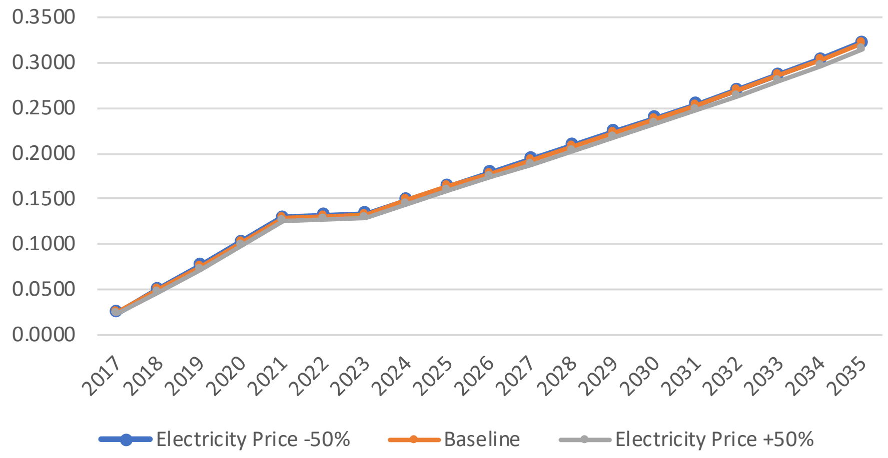

Figure 14. Sensitivity of Willingness to Consider Value to Electricity Price

Sensitivity Analysis

Sensitivity analysis is used to examine how changes in parameter values influence system behavior [48] Two parameters (travel distance and electricity price) were chosen to assess their impact on the willingness to consider (WTC) electric motorcycle (EM). The result of the two sensitivity analyses is presented in Figure 12, Figure 13, and Figure 14.

The annual travel distances used in this sensitivity analysis were 5,000 km, 10,000 km (baseline), and 15,000 km. Based on Figure 13, it can be seen that the change in annual travel distance affects the WTC value for EM. When the annual travel distance for EM is changed to 5,000 km, the WTC value for EM increases by 0.28% compared to the 10,000 km annual travel distance in 2035. On the other hand, Figure 14 shows when the annual travel distance for CM is changed to 5,000 km, the WTC for EM decreases by 78%. When the annual travel distance for EM is increased to 15,000 km, the WTC for EM decreases by 35% compared to the baseline of 10,000 km in 2035. However, when the annual travel distance for CM is increased to 15,000 km, the WTC for EM increases by 0.28%. This indicates a significant decrease in the WTC for EM caused by an increase in the annual travel distance of EM or a decrease in the annual travel distance of CM.

The significant decrease in the WTC for EM as travel distance increases can be attributed to higher operational costs, such as charging and maintenance. As the travel distance increases, the need for more frequent charging and maintenance escalates, which in turn raises the overall operational costs for the user. Additionally, longer travel distances lead to higher external costs such as environmental and social impacts, which can be monetized according to Danielis et al. [33]. All of these factors contribute to a higher TCO of EM which reduces the willingness to consider EM.

Scenarios Analysis

This section explains the policy scenarios based on the results of the simulation using system dynamics. The policy scenarios developed in this study are designed by considering variables that can be adjusted through government policies to increase the willingness to consider (WTC) electric motorcycles (EM) in Indonesia. The policy scenarios to be explored in this study include purchase price subsidies, purchase tax subsidies, and the yearly vehicle tax subsidies.

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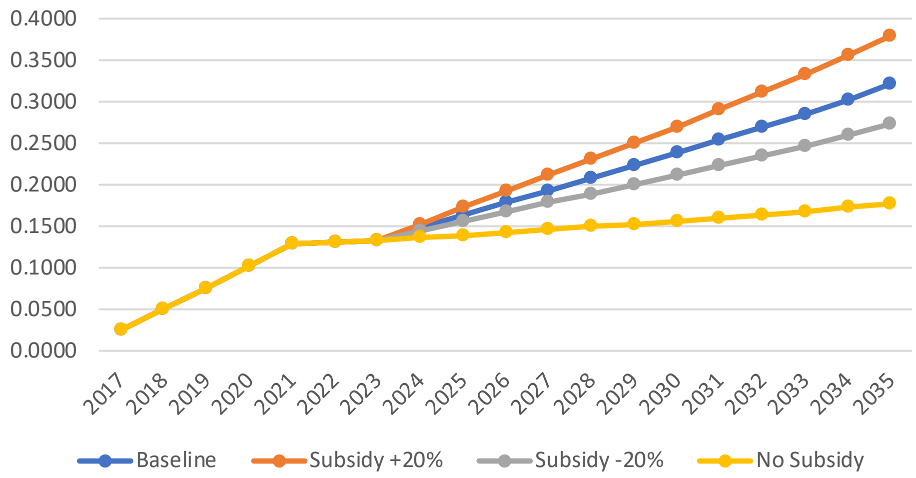

Figure 15. Willingness to Consider Value in Purchase Price Subsidy Scenario

Scenario 1: Purchase Price Subsidy

The purchase price subsidy scenario is used to assess the impact of this scenario on the WTC EM. This scenario is based on the research by [15], which used the purchase price subsidy variable as a method to increase the WTC for vehicle transition in Europe. Other studies, such as [35], have also used the purchase price subsidy as one of their scenarios. This scenario will use three parameters: increasing the subsidy by 20%, reducing the subsidy by 20%, and eliminating the subsidy altogether. The 20% increase reflects a realistic scenario where the government seeks to boost electric vehicle adoption without major fiscal changes, while the 20% decrease models a potential policy rollback or budget cuts due to fiscal pressures or shifting priorities. China has also implemented purchase price incentives to support EV adoption, offering a similar approach to government subsidies. It is important to note that the baseline purchase price subsidy is Rp 0.00 at the start of the simulation period until 2022, and Rp 7,000,000.00 from 2023 until the end of the simulation period. Figure 15 illustrates the impact of the purchase price subsidy scenario on WTC EM. When the purchase price subsidy is increased by 20%, the WTC EM value increases significantly, reaching 0.38 by 2035, an 18% increase from the baseline WTC EM. When the purchase price subsidy is reduced by 20%, it leads to a decrease in WTC EM to 0.27, a 15% decline from the baseline in 2035. When the purchase price subsidy is eliminated, it results in a significant drop in WTC EM, reaching 0.1775, a 45% reduction from the baseline in 2035. Based on these results, offering a purchase price subsidy can significantly increase the willingness to consider electric motorcycles.

Scenario 2: Purchase Tax Subsidy

The purchase tax subsidy scenario is used to evaluate the impact of this scenario on the WTC EM. This scenario is based on the research by Yuniaristanto et al. [36]. The scenario will use three parameters: 0%, 5%, and 11% purchase tax rates. The 0% tax rate represents a full tax exemption to maximize electric vehicle adoption, similar to tax exemptions already implemented in Norway and China. The 5% tax rate offers a moderate reduction, balancing incentives with fiscal stability. The 11% tax rate reflects the normal rate in Indonesia without any subsidy, serving as a control to assess the impact of tax relief. It is important to note that the baseline purchase tax subsidy is 11% at the start of the simulation period until 2022, and 1% from 2023 until the end of the simulation period. Figure 16 shows

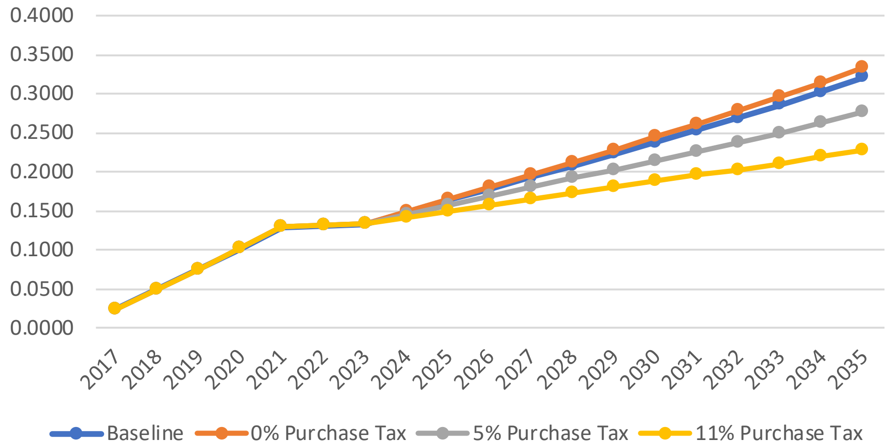

Figure 16. Willingness to Consider Value in Purchase Tax Scenario

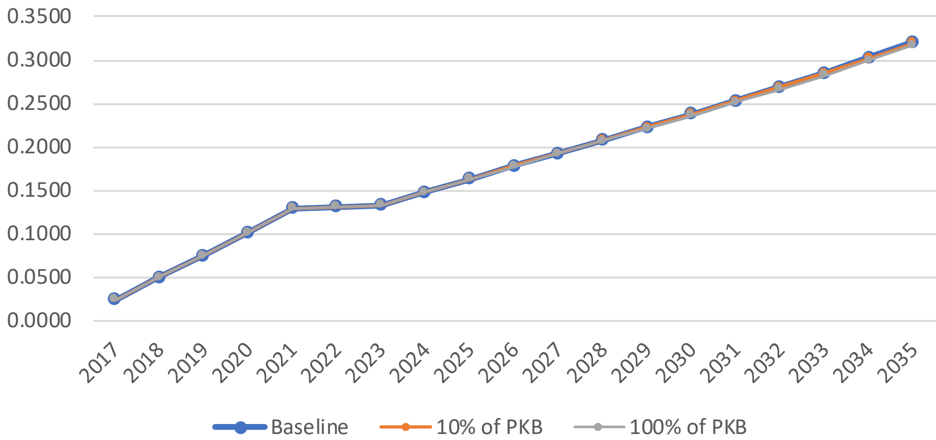

Figure 17. Willingness to Consider Value in Yearly Tax Scenario

the effect of the purchase tax subsidy scenario on WTC EM. When there is no purchase tax, the WTC EM value increases to 0.3336 by 2035, representing a 4% increase from the baseline WTC EM. When the purchase tax is set to 5%, it causes a decrease in WTC EM, dropping to 0.2764, a 14% reduction from the baseline in 2035. When the purchase tax is set to 11%, it results in a significant drop in WTC EM, reaching 0.2281, a 29% decline from the baseline in 2035. Based on these results, offering a purchase tax subsidy can increase the willingness to consider electric motorcycles.

Scenario 3: Motor Vehicle Tax Subsidy

The motor vehicle tax or PKB subsidy scenario is used to examine how this scenario influences the WTC EM. This scenario is based on the research by Yuniaristanto et al.[36]. The scenario will use two parameters: a 10% motor vehicle tax and a 100% motor vehicle tax from the base PKB rate. The 10% tax reflects Indonesia's past policy, offering moderate relief to encourage EV adoption without significant revenue loss, while the 100% tax represents the normal rate, showing the impact of no subsidy. Countries like the Netherlands and Italy have also implemented motor vehicle tax incentives for EVs, ranging from full exemptions to gradual reductions. It is important to note that the baseline motor vehicle tax subsidy is 100% of the base PKB rate at the start of the simulation period until 2020, 10% from 2021 to 2022, and 0% from 2023 until the end of the simulation period. The following are the simulation results showing the impact of the motor vehicle tax subsidy scenario on WTC EM. Figure 18 shows the impact of the motor

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vehicle tax subsidy scenario on WTC EM. When the motor vehicle tax is reduced to 10% of the base PKB rate, the WTC EM value decreases to 0.3204 by 2035, representing a 0.15% reduction from the baseline WTC EM. When the motor vehicle tax is set to 100% of the base PKB rate, it results in a further decrease in WTC EM, reaching 0.3173, a 1.11% decline from the baseline in 2035. Based on these results, providing a motor vehicle tax subsidy still increases the willingness to consider electric motorcycles, although not as much as the previously discussed subsidy policies.

CONCLUSION

This study developed a system dynamics model to assess the willingness to consider (WTC) electric motorcycles (EMs) in Indonesia. The model integrates four key modules—conventional and electric motorcycle modules, a marketing module, and a WTC module—capturing factors such as life cycle cost, social exposure, and marketing incentives. Simulation results indicate a consistent upward trend in consumer willingness to consider electric motorcycles over time, reflecting growing awareness, acceptance, and potential market readiness in Indonesia. Among the policy scenarios tested, providing purchase price subsidies emerged as the most effective strategy to boost WTC. This highlights the importance of financial incentives in reducing the upfront cost barrier and encouraging EM adoption. To support this transition, the government is advised to maintain and enhance existing subsidies through purchase discounts and tax reductions. These measures can help reduce consumer financial burdens and accelerate the shift toward sustainable transportation. Targeted financial incentives have proven to be a decisive factor in shaping consumer attitudes toward EMs and represent a strategic policy tool for achieving Indonesia's emission reduction and sustainability goals. Future research should expand the WTC model by incorporating additional factors such as virtual exposure and the influence of public electric vehicle charging stations. These additions would enhance the model's ability to capture real-world dynamics affecting consumer consideration. Furthermore, integrating a choice model could improve the simulation of consumer decision-making by accounting for trade-offs between attributes such as environmental impact, performance, reliability, comfort, and popularity. This would allow for more accurate predictions of market behavior and provide deeper insights into the drivers of consumer preferences.

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DECLARATION OF AI TOOL USAGE

During the preparation of this manuscript, the authors used ChatGPT (GPT-4, OpenAI) solely to improve the academic tone and clarity of selected paragraphs. All AI-generated outputs were critically reviewed and thoroughly edited by the authors to ensure factual accuracy, clarity of expression, and compliance with academic standards. The authors take full responsibility for the integrity and content of this manuscript.

CONFLICT OF INTEREST

The authors declare that they have no competing interests related to the research presented in this article.

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References

[1] C. R. Setiawan and V. Briliana, "Entertainment, Informativeness, Credibility, Attitudes terhadap Purchase Intention pada Subscriber Channel Youtube," *Jurnal Bisnis dan Akuntansi*, vol. 23, no. 1, pp. 111–120, Feb. 2021, doi: 10.34208/jba.v23i1.820.

[2] Climate Transparency, "Climate Transparency Report: Comparing G20 Climate Action," 2022. Accessed: Aug. 05, 2024. [Online]. Available: https://www.climate-transparency.org/wp-content/uploads/2022/10/CT2022-Indonesia-Web.pdf.

[3] The Thaiger and Pew Research Center, "Share of households owning a motorcycle in Asia as 2023, by country," *Statista*, [Online]. Available: https://www.statista.com/statistics/1373225/asia-household-share-owning-a-motorcycle-by-country.

[4] E. Guerra, "Electric Vehicles, Air pollution, and The Motorcycle City: A Stated Preference Survey of Consumers' Willingness to Adopt Electric Motorcycles in Solo, Indonesia," *Transp. Res. D Transp. Environ.*, vol. 68, pp. 52–64, Mar. 2019, doi: 10.1016/j.trd.2017.07.027.

[5] B. Chiu, "Transforming the Asian Motorcycle City? Evaluating the Travel and Urban Development Effects of the Mass Rapid Transit in Taipei, Taiwan," Ph.D. dissertation, 2023. [Online]. Available: https://repository.upenn.edu/handle/20.500.14332/59034

[6] Central Bureau of Statistics, "Development of the Number of Motor Vehicles by Type (Unit)," [Online]. Available: https://www.bps.go.id/id/statistics-table/2/NTcjMg==/perkembangan-jumlah-kendaraan-bermotor-menurut-jenis--unit-.html.

[7] E. Guerra, "Electric Vehicles, Air pollution, and The Motorcycle City: A Stated Preference Survey of Consumers' Willingness to Adopt Electric Motorcycles in Solo, Indonesia," *Transp. Res. D Transp. Environ.*, vol. 68, pp. 52–64, Mar. 2019, doi: 10.1016/j.trd.2017.07.027.

[8] S. Baharsyah, Z. Ramdhan, and Y. Sudaryat, "Perancangan Storyboard untuk Memperkenalkan Sepeda Motor Listrik (Molis) kepada Masyarakat Kota Bandung Melalui Animasi Hybrid (2D & 3D)," *e-Proceeding of Art & Design*, vol. 10, no. 6, p. 10975, 2023.

[9] U. Wahyuningsih, V. A. Desiawan, and L. Rasyidi, "Pengembangan Desain Produk Sepeda Motor Listrik Menggunakan Metode Pengintegrasian Kano Model dalam Quality Function Deployment (QFD)," *KILAT*, vol. 12, no. 1, pp. 49–63, May 2023, doi: 10.33322/kilat.v12i1.1893.

[10] J.-H. Wu, C.-W. Wu, C.-T. Lee, and H.-J. Lee, "Green purchase intentions: An exploratory study of the Taiwanese electric motorcycle market," *J. Bus. Res.*, vol. 68, no. 4, pp. 829–833, Apr. 2015, doi: 10.1016/j.jbusres.2014.11.036.

[11] S. Jordan, "Carrot or Stick? How Policy Type Influences Consumer Intention to Purchase Electric Vehicles," *Transportation Research Procedia*, vol. 70, pp. 13–19, 2023, doi: 10.1016/j.trpro.2023.10.003.

[12] J. R. Hauser and B. Wernerfelt, "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, vol. 16, no. 4, pp. 393–408, Mar. 1990, doi: 10.1086/209225.

[13] D. R. Keith, J. D. Sterman, and J. Struben, "Supply constraints and waitlists in new product diffusion," *Syst. Dyn. Rev.*, vol. 33, no. 3–4, pp. 254–279, Jul. 2017, doi: 10.1002/sdr.1588.

[14] J. Struben and J. D. Sterman, "Transition challenges for alternative fuel vehicle and transportation systems," *Environ. Plann. B Plann. Des.*, vol. 35, no. 6, pp. 1070–1097, 2008, doi: 10.1068/b33022t.

[15] G. Harrison, C. Thiel, and L. Jones, "Powertrain Technology Transition Market Agent Model (PTTMAM)," *Publications Office*, 2016, doi: 10.2790/719385.

[16] S. M. Skippon, N. Kinnear, L. Lloyd, and J. Stannard, "How experience of use influences mass-market drivers' willingness to consider a battery electric vehicle: A randomised controlled trial," *Transp. Res. Part A Policy Pract.*, vol. 92, pp. 26–42, Oct. 2016, doi: 10.1016/j.tra.2016.06.034.

[17] T. Delsole, "A Fundamental Limitation of Markov Models," *J. Atmos. Sci.*, vol. 57, no. 13, pp. 2158–2168, 2000, doi: https://doi.org/10.1175/1520-0469(2000)057%3C2158:AFLOMM%3E2.0.CO;2.

[18] L. H. Siregar, "Game Theory dan Keunggulan dalam Bersaing Perspektif Konvensional dan Syariah," *Jurnal Bisnis Net*, vol. 2, no. 3, pp. 55–60, 2019, doi: https://doi.org/10.46576/bn.v2i3.425.

[19] J. Sterman, *Business dynamics: systems thinking and modeling for a complex world*, Irwin/McGraw-Hill, 2000.

[20] C. Thies, K. Kieckhäfer, and T. S. Spengler, "Market introduction strategies for alternative powertrains in long-range passenger cars under competition," *Transp. Res. D Transp. Environ.*, vol. 45, pp. 4–27, 2016, doi: 10.1016/j.trd.2015.05.002.

[21] N. Zahrina, A. Hidayatno, and A. D. Setiawan, "Model Conceptualization of Battery Swapping Industry Development Using System Dynamics," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Jun. 2020, pp. 129–134, doi: 10.1145/3400934.3400959.

[22] G. Heijkoop and S. Cunningham, "Using System Dynamics for Modeling Benefit Realization in the Adoption of New Business Software," in *System Dynamics Society: Proceedings of the 25th International Conference*, System Dynamics Society, 2007, pp. 1–31.

[23] E. Eidin et al., "Thinking in Terms of Change over Time: Opportunities and Challenges of Using System Dynamics Models," *J. Sci. Educ. Technol.*, vol. 33, no. 1, pp. 1–28, Feb. 2024, doi: 10.1007/s10956-023-10047-y.

[24] W. Sutopo, R. W. Astuti, A. Purwanto, and M. Nizam, *Proceedings of the 2013 Joint International Conference on Rural Information & Communication Technology and Electric-Vehicle Technology (rICT & ICEV-T)*, 26-28 Nov. 2013, Bandung, Bali, Indonesia, IEEE, 2013.

[25] C. R. Cherry, J. X. Weinert, and Y. Xinmiao, "Comparative Environmental Impacts of Electric Bikes in China," *Transp. Res. D Transp. Environ.*, vol. 14, no. 5, pp. 281–290, 2009, doi: 10.1016/j.trd.2008.11.003.

[26] Ministry of Industry, "Regulation of the Minister of Industry Number 28 of 2023," [Online]. Available: https://www.regulasip.id/themes/default/resources/js/pdfjs/web/viewer.html?file=/eBooks/2024/January/65a73682dea93/Peraturan%20Menteri%20Perindustrian%20Nomor%2028%20Tahun%202023.pdf.

[27] Ministry of Energy and Mineral Resources, "ESDM Targetkan Ada 300 Ribu Motor Listrik di 2023 dan 600 Ribu di 2024," Accessed: Aug. 06, 2024. [Online]. Available: https://www.cnnindonesia.com/ekonomi/20230223102956-85-916799/esdm-targetkan-ada-300-ribu-motor-listrik-di-2023-dan-600-ribu-di-2024.

[28] Aismoli, "Populasi Motor Listrik di Indonesia Nyaris 75 Ribu Unit," Accessed: Dec. 03, 2024. [Online]. Available: https://www.cnnindonesia.com/otomotif/20240126131720-603-1054724/populasi-motor-listrik-di-indonesia-nyaris-75-ribu-unit.

[29] V. T. P. Sidabutar, "Study on Electric Vehicle Development in Indonesia: Prospects and Constraints," *Journal of Economic Paradigm*, vol. 15, no. 1, pp. 21–38, May 2020, doi: 10.22437/paradigma.v15i1.9217.

[30] J. M. Garcia, *System Dynamics Modelling with Vensim*, 2019.

[31] V. Bureš, "Comparative Analysis of System Dynamics Software Packages," *Int. Rev. Modelling Simul. (IREMOS)*, vol. 8, no. 2, p. 245, Apr. 2015, doi: 10.15866/iremos.v8i2.5401.

[32] A. Korzhenevych et al., "Update of the Handbook on External Costs of Transport Final Report for the European Commission: DG MOVE," London, Jan. 2014. Accessed: Aug. 11, 2024. [Online]. Available: https://transport.ec.europa.eu/system/files/2016-09/2014-handbook-external-costs-transport.pdf.

[33] R. Danielis, M. Scorrano, M. Giansoldati, and S. Alessandrini, "The Economic Case for Electric Vehicles in Public Sector Fleets: An Italian Case Study," *World Electric Vehicle Journal*, vol. 11, no. 1, p. 22, Mar. 2020, doi: 10.3390/wevj11010022.

[34] S. M. Afraah, Y. Yuniaristanto, W. Sutopo, and M. Hisjam, "Comparing Total Cost of Ownership of Electric and Conventional Motorcycles in Indonesia," *Jurnal Teknik Industri*, vol. 22, no. 2, pp. 196–210, Aug. 2021, doi: 10.22219/JTIUMM.Vol22.No2.196-210.

[35] D. S. Sulistyono, Y. Yuniaristanto, W. Sutopo, and M. Hisjam, "Proposing Electric Motorcycle Adoption-Diffusion Model in Indonesia: A System Dynamics Approach," *Jurnal Optimasi Sistem Industri*, vol. 20, no. 2, pp. 83–92, Nov. 2021, doi: 10.25077/josi.v20.n2.p83-92.2021.

[36] Yuniaristanto, W. Sutopo, M. Hisjam, and H. Wicaksono, "Estimating The Market Share of Electric Motorcycles: A System Dynamics Approach with The Policy Mix and Sustainable Life cycle costs," *Energy Policy*, vol. 195, p. 114345, Dec. 2024, doi: 10.1016/j.enpol.2024.114345.

[37] D. Kong, Q. Xia, Y. Xue, and X. Zhao, "Effects of multi policies on electric vehicle diffusion under subsidy policy abolishment in China: A multi-actor perspective," *Appl. Energy*, vol. 266, p. 114887, May 2020, doi: 10.1016/j.apenergy.2020.114887.

[38] L. K. Mitropoulos, P. D. Prevedouros, and P. Kopelias, "Total cost of ownership and externalities of conventional, hybrid and electric vehicle," *Transportation Research Procedia*, vol. 24, pp. 267–274, 2017, doi: 10.1016/j.trpro.2017.05.117.

[39] L. Galaï-Dol, A. De Bernardinis, A. Nassiopoulos, A. Peny, and F. Bourquin, "On the Use of Train Braking Energy Regarding the Electrical Consumption Optimization in Railway Station," *Transportation Research Procedia*, vol. 14, pp. 655–664, 2016, doi: 10.1016/j.trpro.2016.05.321.

[40] Central Bureau of Statistics, "Upah Rata - Rata Per Jam Pekerja Menurut Provinsi (Rupiah/Jam), 2015-2017," [Online]. Available: https://www.bps.go.id/id/statistics-table/2/MTE3MiMy/upah-rata---rata-per-jam-pekerja-menurut-provinsi.html.

[41] D. Krewski et al., "Extended Follow-Up and Spatial Analysis of the American Cancer Society Study Linking Particulate Air Pollution and Mortality," 2009. [Online]. Available: https://www.researchgate.net/publication/26690365.

[42] A. Hassani and V. Hosseini, "An Assessment of Gasoline Motorcycle Emissions Performance and Understanding Their Contribution to Tehran Air Pollution," *Transp. Res. D Transp. Environ.*, vol. 47, pp. 1–12, Aug. 2016, doi: 10.1016/j.trd.2016.05.003.

[43] Ministry of Home Affairs, "Peraturan Menteri Dalam Negeri Nomor 1 Tahun 2021 tentang Penghitungan Dasar Pengenaan Pajak Kendaraan Bermotor dan Bea Balik Nama Kendaraan Bermotor Tahun 2021," [Online]. Available: https://peraturan.bpk.go.id/Details/163288/permendagri-no-1-tahun-2021.

[44] Ministry of Industry, "Regulation of the Minister of Industry Number 28 of 2023 concerning Amendments to Regulation of the Minister of Industry Number 6 of 2022 concerning Specifications, Development Roadmaps, and Provisions for Calculating the Value of Domestic Component Levels for Battery-Based Electric Motor Vehicles (Battery Electric Vehicles)," Accessed: Aug. 05, 2024. [Online]. Available: https://infoperaturan.id/peraturan-menteri-perindustrian-nomor-28-tahun-2023/.

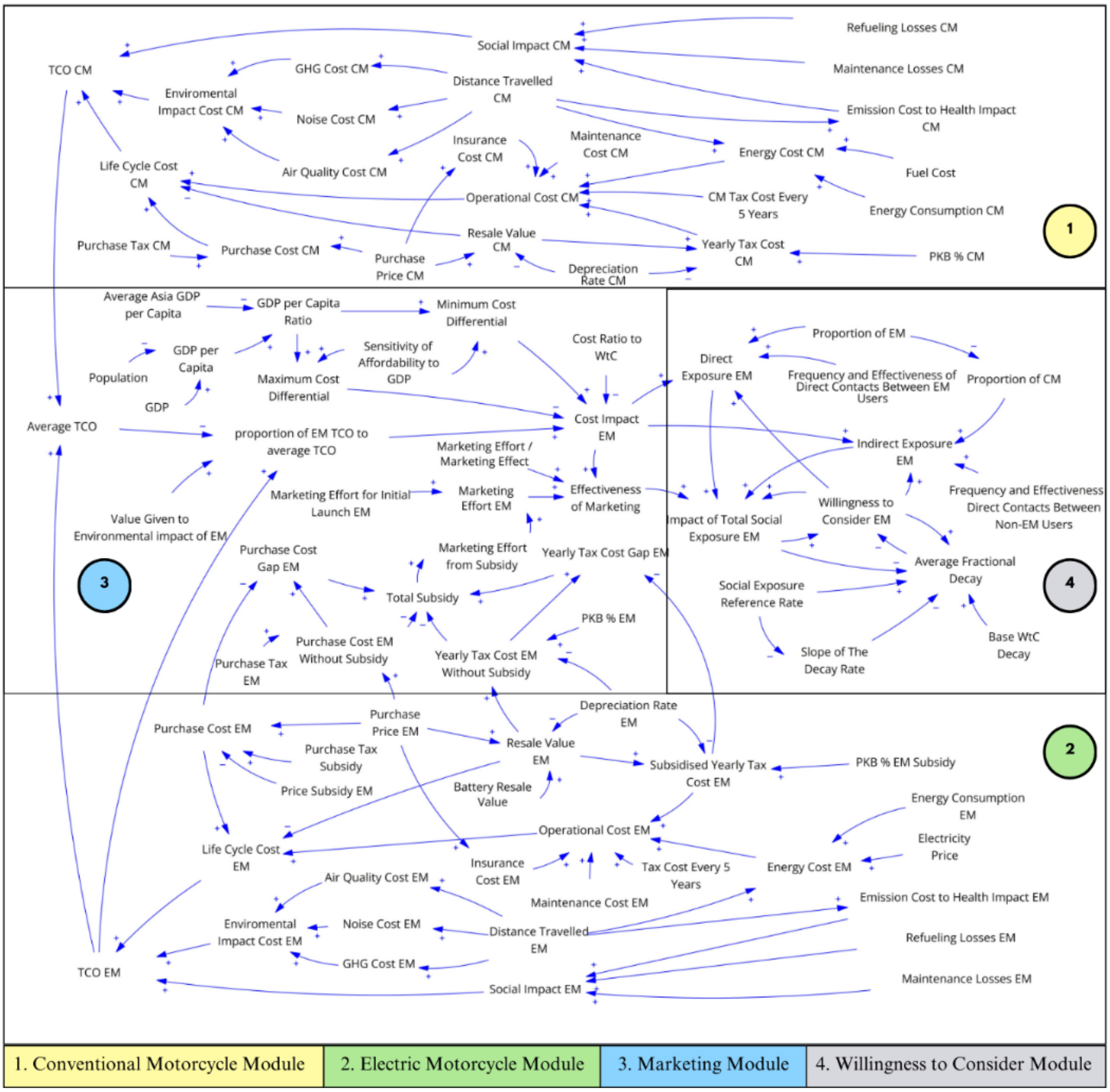
[45] J. J. Montaño Moreno, A. Palmer Pol, A. Sesé Abad, and B. Cajal Blasco, "El índice R-MAPE como medida resistente del ajuste en la previsioń n," *Psicothema*, vol. 25, no. 4, pp. 500–506, 2013, doi: 10.7334/psicothema2013.23.

[46] A. D. Setiawan, T. N. Zahari, F. J. Purba, A. O. Moeis, and A. Hidayatno, "Investigating policies on increasing the adoption of electric vehicles in Indonesia," *J. Clean Prod.*, vol. 380, p. 135097, Dec. 2022, doi: 10.1016/j.jclepro.2022.135097.

[47] J. Yu, P. Yang, K. Zhang, F. Wang, and L. Miao, "Evaluating the Effect of Policies and the Development of Charging Infrastructure on Electric Vehicle Diffusion in China," *Sustainability*, vol. 10, no. 10, p. 3394, Sep. 2018, doi: 10.3390/su10103394.

[48] J. H. M. Langbroek, J. P. Franklin, and Y. O. Susilo, "The Effect of Policy Incentives on Electric Vehicle Adoption," *Energy Policy*, vol. 94, pp. 94–103, Jul. 2016, doi: 10.1016/j.enpol.2016.03.050.

Appendix: The Causal Loops Diagram of The WTC Simulation Model.



AUTHORS BIOGRAPHY

Ahmad Rafi Adnanta is an undergraduate student in Industrial Engineering Department, Faculty of Engineering, Universitas Sebelas Maret. His research interests are supply chain management, operations research, and simulation modeling. This paper marks his first academic publication. Email: adnantarafi@student.uns.ac.id

Roni Zakaria Raung is a doctoral student and a lecturer in Industrial Engineering Department, Faculty of Engineering, Universitas Sebelas Maret. He earned his Bachelor and Master Degree in Industrial Engineering from Institut Teknologi Bandung. His research interests are business management, strategic management and organizational behavior. Email: ronizakaria@staff.uns.ac.id

Wahyudi Sutopo is a lecturer and researcher in Industrial Engineering Department, Faculty of Engineering, Universitas Sebelas Maret. He obtained his Bachelor's degree in Industrial Engineering from Institut Teknologi

Bandung. He completed his Master's degree in Management Science at Universitas Indonesia. He also earned a Doctoral degree in Industrial Engineering and Management from Institut Teknologi Bandung. His research interests are engineering economy & cost analysis, supply chain, and technology commercialization. Email: wahyudisutopo@staff.uns.ac.id

Ihwan Susila is a Professor in Management at the Faculty of Economics and Business, Universitas Muhammadiyah Surakarta. He obtained his Bachelor's degree in Economics from the Faculty of Economics, Universitas Muhammadiyah Surakarta and obtained his Master of Science degree from the Faculty of Economics and Business, Universitas Gadjah Mada. He earned his Ph.D. from the University of Hull, United Kingdom. His research interests are consumer behavior, marketing strategy, political marketing, and strategic management. Email: ihwan.susila@ums.ac.id

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