Investigating policies on increasing the adoption of electric vehicles in Indonesia

Andri D. Setiawan\textsuperscript{a,b,1,*}, Teuku Naraski Zahari\textsuperscript{a,c,1}, Fara Jetira Purba\textsuperscript{a}, Armand O. Moeis\textsuperscript{a}, Akhmad Hidayatno\textsuperscript{a}

\textsuperscript{a} Systems Engineering, Modelling and Simulation Laboratory, Industrial Engineering Department, Universitas Indonesia, Kampus UI Depok, Depok, 16424, Indonesia
\textsuperscript{b} Technology, Innovation & Society, Department of Industrial Engineering & Innovation Sciences, Eindhoven University of Technology, Groene Loper, Atlas 8.409, 5600 MB Eindhoven, The Netherlands
\textsuperscript{c} Energy Economics Research Group, Graduate School of Energy Science, Kyoto University, Yoshida-Hommachi, Sakyo-Ku, Kyoto, 606-8501, Japan

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\textbf{A B S T R A C T}

The transition to electric mobility has been encouraged to curb carbon dioxide (CO\textsubscript{2}) emissions through government policies worldwide. Indonesia is committed to reducing CO\textsubscript{2} emissions, one of which is to increase the adoption of electric vehicles (EVs) despite considerable challenges in infrastructure, technology, cost, and user acceptance. Therefore, since 2019, the government has implemented several fiscal and non-fiscal policies to encourage consumers to purchase EVs. However, the extent to which these policies can effectively increase the long-term adoption of EVs remains a subject of further investigation. Thus, this study aims to investigate the effectiveness of policies for increasing EV adoption in Indonesia by developing a system dynamics model of EV adoption combined with the policy analysis framework. The findings demonstrate that the government should focus on reducing EV taxes that are incurred on consumers. Moreover, additional policies should address the development of EV technology to improve driving range and manufacturing costs, as the results indicate that these factors exert a more significant impact on increasing EV attractiveness. However, the role of financial incentives is more prominent when EV technology advancement is lagging.

\section{1. Introduction}

Global warming has been a central issue in the last few decades, as it imposes multidimensional threats to ecology, environment, economy, and society. As one of the largest emitters of carbon dioxide (CO\textsubscript{2}) in the world (\textit{IEA}, 2020b), Indonesia must reduce its emissions from 1817 metric tonnes of CO\textsubscript{2} equivalent (MtCO\textsubscript{2}e) to below 662 MtCO\textsubscript{2}e in 2030 to maintain global warming under 1.5 \degree C as mandated by the Paris Agreement. As the Indonesian transportation sector is estimated to account for 53\% of the country’s total emissions in 2030, scholars expect the emission from the sector to be reduced by 633.35 MtCO\textsubscript{2}e (\textit{Climate Transparency}, 2020). This projection placed the sector as one of the top priorities for reducing CO\textsubscript{2} emissions. Thus, efforts to increase the usage of electric vehicles (EVs) have been among the most sought-after alternatives in achieving this goal (\textit{OECD}, 2018). Following suit, the Indonesian government has planned to accelerate the adoption of EVs (\textit{GOI}, 2019b).

The transportation sector in Indonesia is dominated by two-wheeled vehicles, especially in urban areas. However, the demand for this type of vehicle would decline due to increasing income per capita (\textit{Jou and Chen}, 2014) and the mass adoption of public transportation (\textit{DEN}, 2019). Conversely, passenger cars and trucks are expected to dominate the road transportation fleet and consume nearly 60\% of 70.3 MTOE total energy demand in the transportation sector in 2030 (\textit{DEN}, 2019). The four-wheeler market in Indonesia has a few selections of EVs that range from hybrid electric vehicles (HEVs) to battery electric vehicles (BEVs). Their sales, however, have been non-significant compared with internal combustion engine vehicles (ICEV). In 2019, the EV market share in Indonesia reached only 0.08\% or around 854 units (\textit{GAIKINDO}, 2019).

Recent studies have shown that environmental concern is growing to be an essential factor in adopting EVs (\textit{Adnan et al.}, 2017; \textit{Chen et al.}, 2014).
The adoption of EVs in Indonesia are lacking. The extent to which these policies can effectively increase the long-term increase the adoption of EVs by issuing a set of policies outlined in Indonesia. The investigation focuses on assessing policy impacts on the attractiveness of EVs when consumers are considering the purchase of a vehicle (Asadi et al., 2021; Sang and Bekhet, 2015; Yu et al., 2018). Moreover, Damayanti et al. (2020) found that users are more concerned about economic benefits in adopting EVs above others. On the other hand, environmental factors were one of their least concerned. This discussion demonstrates that the adoption of EVs generally faces several challenges regarding infrastructure, technology and user acceptance (Asadi et al., 2021; Murugan and Marisamynathan, 2022; Sierzchula, 2014; Tarei et al., 2021; Yu et al., 2018).

Several studies discussed government policies worldwide to promote EV adoption, primarily aimed at consumers. For example, EV adoption policy analysis was done in EV leading markets, including Norway, the Netherlands, and Sweden (WEF, 2019). Studies in Norway found that purchase taxes, BEV technology, toll waivers, and charging station density are the most significant factor in the adoption of BEV (Bjerkan et al., 2016; Deuten et al., 2020; Zhang et al., 2016). A similar result was found in Sweden and Denmark that public charging infrastructure readiness has a positive effect on EV adoption (Egnér and Trosvik, 2018; Haustein et al., 2021). A study in Norway and the Netherlands by Deuten et al. (2020) found that pushing automotive manufacturer to improve emission levels resulted in the most significant share of zero-emission vehicles (ZEV). At the same time, carbon taxes levied on car users gave a minor boost to ZEV adoption. Interestingly, the effectiveness of manufacturer emission standard improvement in driving the adoption of ZEV decreases when paired with the ongoing incentives (Deuten et al., 2020). Some studies are also available in emerging markets like China and India. China, a large automotive market with otherwise low EV penetration, implements an initial purchase subsidy, charging station construction, and exemptions of restrictions imposed to ICEV users (Liu et al., 2021; Wu et al., 2021). It was found that charging station construction and exemption of purchase limitations is an important factor to EV adoption while financial incentives were less significant (Liu et al., 2021). In the case of India, charging infrastructure, battery localisation which reduces EV production cost, and improvement of the vehicle itself as key to EV adoption (Chihikara et al., 2021; Singh et al., 2021).

In a similar manner, the Indonesian government has taken steps to increase the adoption of EVs by issuing a set of policies outlined in Presidential Regulation 55/2019, including fiscal and non-fiscal policies as part of its commitment to reducing greenhouse gas emissions by 29% by 2030 (GOI, 2019b). In this regard, Damayanti et al. (2020) conducted a preliminary study by developing a model that captures complex relationships between the elements accompanying government policies. These relationships play roles in increasing EV adoption in Indonesia. However, previous studies provided only a conceptual model without an empirical investigation for Indonesia. Thus, studies that assessed the extent to which these policies can effectively increase the long-term adoption of EVs in Indonesia are lacking.

This study aims to fill this research gap by investigating the effectiveness of government policies to increase the adoption of EVs in Indonesia. The investigation focuses on assessing policy impacts on the attractiveness of EVs and on the preference of consumers when purchasing vehicles. Consumer acceptance of innovation is a complex and dynamic process that is dependent on several elements (Ulli-Beer et al., 2010). As EV adoption reflects these characteristics, the study proposes a system dynamics model (Forrester, 1994) to elucidate the complex and dynamic relationships between the government policies, the influencing factors, and other elements that play a central role in adopting EVs in Indonesia. Further, policy analysis (Walker, 2000) is carried out to assist policymakers in assessing and selecting the most appropriate alternatives by clarifying the problem, describing alternative solutions and presenting the consequences for each alternative solution. The critical indicator measured for evaluating policy effectiveness under different scenarios is EV market volume (number of EV sold).

The remainder of this paper is structured as follows. Section 2 presents a literature review on the barriers to EV adoption and the policies to promote them. Section 3 provides the methodology used, whereas Sections 4 and 5 present the results and provide a discussion, respectively. Finally, Section 6 concludes.

2. Literature review

2.1. Opportunities and barriers for EV adoption in Indonesia

With the surging importance of reducing CO₂ emissions, the transportation sector must shift away from fossil fuels. Electrifying fleets could be one of the solutions (Egbue and Long, 2012; Rezvani et al., 2015). Currently, several types of EVs are available globally, including BEVs, HEVs, plug-in hybrid (PHEVs), extended-range (E-BEVs) and fuel cell electric vehicles (FCEVs) (Li et al., 2017). Only BEVs and FCEVs completely disuse fossil fuels directly, whereas other types continue to use fossil fuels. However, cases exist where alternative fuels, such as ethanol, can replace fossil fuels in hybrid vehicles (Costa et al., 2017; He et al., 2020; Toyota, 2018). However, the automotive market in Indonesia offers only HEVs, PHEVs and BEVs, whereas alternative fuels for internal combustion engines (ICEs) are unavailable. BEV is frequently promoted as the cleanest alternative out of the three models due to its fully electric nature.

Compared to ICEVs, BEVs pose several advantages, such as higher energy efficiency and the possibility of using energy from renewable sources, which may reduce dependence on fossil fuels (Egbue and Long, 2012; Fiori et al., 2016; Hacker et al., 2009; Li et al., 2017; Sang and Bekhet, 2015). Using BEV can also reduce local air pollution, such as photochemical ozone formation and particulate matter, adversely affecting the human respiratory system (Pero et al., 2018). However, the ability of BEVs in reducing CO₂, particularly BEVs, remains inconclusive. Several scholars have reported that BEVs emit low amounts of CO₂ to the atmosphere and reduce global warming potential (Falcão et al., 2017; Hawkins et al., 2013). In contrast, several studies showed that BEVs life cycle CO₂ (LCCO₂) could exceed that of ICEVs depending on the grid CO₂ emission factor (Bickert et al., 2015; Loref et al., 2013; Oxley et al., 2012; Zhao et al., 2016; Zheng and Peng, 2021). The fact that BEVs would heavily depend on the electricity grid during their operations, one should investigate the LCCO₂ of BEV when examining the impact of BEV on CO₂ emissions. The Indonesian grid CO₂ emission factor is still relatively high at 0.813 kgCO₂/kWh (Takahashi and Louhisuo, 2020) due to 86% of electricity being from fossil fuel power plants, particularly coal-fired power plants (DEN, 2019). To mitigate this, the Indonesian government has planned to increase the share of renewables up to 23% of total electricity generated in 2025 (GOI, 2017) and will start to phase-down coal-fired power plants in the same year (PLN, 2021). In terms of electricity availability, electrification across the nation has reached 99.4% in 2021 (ESDM, 2021).

From the consumer’s point of view, BEVs also offer several benefits. A study in China found that the operational costs of BEVs are up to 50% lower than those for ICEVs after comparing oil prices, electricity tariffs, and energy efficiency between BEV and ICEV (She et al., 2017). Indeed, the operational cost benefits would need to be reviewed when incentives and tax exemptions for EVs are lifted (Ouyang et al., 2021). However, EV’s initial purchase cost is high (Egbue and Long, 2012; Rezvani et al., 2015; Ouyang et al., 2021; Liu et al., 2021; Hawkins et al., 2013). In contrast, several studies showed that BEVs emit low amounts of CO₂ to the atmosphere and reduce global warming potential (Falcão et al., 2017; Hawkins et al., 2013). As EV adoption reflects these characteristics, the study proposes a system dynamics model (Forrester, 1994) to elucidate the complex and dynamic relationships between the government policies, the influencing factors, and other elements that play a central role in adopting EVs in Indonesia. Further, policy analysis (Walker, 2000) is carried out to assist policymakers in assessing and selecting the most appropriate alternatives by clarifying the problem, describing alternative solutions and presenting the consequences for each alternative solution. The critical indicator measured for evaluating policy effectiveness under different scenarios is EV market volume (number of EV sold).

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In Indonesia, this cost is more than twice as high as comparable ICEVs. Moreover, the maintenance costs are lower, albeit marginal, due to the lesser components used in its drivetrain (Christian and Marciano, 2020; Krause et al., 2013). However, battery replacement cost is high after the battery has degraded to 70–80% of its initial capacity (Haram et al., 2021). It makes the battery replacement an important cost factor.

The demand for commuting increases as the economy grows, especially in large cities across Indonesia. Most commuters in Jakarta, Indonesia’s capital and centre of economy, travel up to 60 km (km) daily or more than 400 km during the weekdays (BPS, 2019). One major barrier to adopting BEVs in terms of quality is its limited driving range and the rarity of charging stations (Liu et al., 2021; Shafiei et al., 2012). To date, one of the most affordable BEVs in Indonesia could only go up to 305 km on a fully charged battery (Hyundai, 2021). In contrast, its ICEV counterpart offers up to 450 km driving range in a full tank (GoE, 2020). This disadvantage is exacerbated by the fact that refuelling stations outnumber the charging stations that are publicly available (BP-HMigas, 2019; ESDM, 2020). Furthermore, a BEV would require almost an hour to be fully charged, whereas most ICEVs would only require less than 5 min to fill up their tank (Stone, 2021). The charging time can be greatly reduced to half the time if using fast charging (power output ≤50 kW) and one-sixth of the time if using ultra-fast charging (power output ≤150 kW) (ESDM, 2020).

2.2. Policy for increasing electric vehicle adoption

Several researchers agree that government interventions, whether fiscal or non-fiscal, are an essential stimulus for the adoption of EVs: the interventions implemented by the government may alleviate the barriers to EV adoption and may increase EV attractiveness over ICEVs as long as they are not cost-competitive with ICE (Bjerkan et al., 2016; Langbroek et al., 2016; Yu et al., 2018). Fiscal policies, such as purchase tax and value-added tax (VAT) exemptions, have enabled EVs to gain a large market share in Norway (Bjerkan et al., 2016). Using multiple linear regression analysis, Sierzchula (2014) found that financial incentives, charging infrastructure, and production facilities’ local presence are strong and significant predictors of EV adoption in 30 countries. Kester et al. (2018) use qualitative analysis to demonstrate that the provision of tax incentives is favoured over subsidies in the Nordic Region. A study in China illustrates that charging discounts and infrastructure construction subsidies are essential policies, whereas the purchase subsidy policy exerted no significant effect (Qiu et al., 2019).

In 2019, HEVs were the only EV options available in the Indonesian market, contributing only 0.08% of all new vehicle sales (GAIKINDO, 2020). In the same year, the Indonesian government provided a policy package to encourage EV adoption, particularly that of BEVs. These policies include purchase tax exemption, exemption or reduction of annual tax, exemption or reduction of registration tax, electricity price incentives, parking fee incentives, toll tariff incentives and ICEV purchase restriction (GOI, 2019b). The government set a 15% luxury tax for EVs, whereas a minimum of 20% is charged for ICEVs according to the energy efficiency level of the vehicle (GOI, 2019a). In addition, local governments hold power to implement EV policies. For example, in Jakarta, EVs are exempted from vehicle registration tax (GOJ, 2020), whereas ICEVs are charged 12.5% of their base price (GOJ, 2019). To control the ownership costs of EVs, the government also determined the charging rate for charging stations (ESDM, 2016) and provided further incentives through a state-owned electricity company (PLN). PLN provides discounts on two occasions; the first was approximately 21% for charging in stations (Mulyana, 2020), while the second was 30% for charging in houses (CNN, 2021). PLN also sets out to build more than 7000 charging stations in 2030 to accommodate the government’s EV goal (PLN, 2020b). Ultimately, these policies are intended to realise the government’s 2030 target, where 25% of all vehicles are Low Carbon Emission Vehicles (LCEVs), including EVs (Kemenperin, 2020). Implementing the aforementioned policies has shown positive results for EV sales (total sales of EV), jumping to 0.36% of all vehicles sales in 2021 (GAIKINDO, 2022).

3. Methodology

The study employed a combination of the system dynamics approach (Forrester, 1994; Sterman, 2000) and policy analysis framework (Walker, 2000) to analyse EV adoption mechanisms and investigate the effectiveness of policy instruments. The system dynamics approach has been prominently used to address the complexity and transition dynamics (Salim et al., 2021; Selvakumar and Ahlgren, 2017, 2020). Moreover, its integration with the policy analysis framework has been used to investigate the robustness of a specific policy mix for the adoption of technologies (Castrejon-Campos et al., 2020; Hidayatno et al., 2020; Shibayama et al., 2020).

The adoption of new technologies, such as alternative energy and EVs, are commonly described using the Bass diffusion model (Brdulak et al., 2021; Park et al., 2011; Ulli-Beer et al., 2010; van der Kam et al., 2018). The model captures the growth behaviour of a new product’s initial purchases and sales forecast (Bass, 1969). Yu et al. (2018) employed a system dynamics model that incorporates the diffusion model to evaluate the effectiveness of policies in the adoption of EVs in China. A study in Morocco also used the same approach to predict the EV market (Ayyadi and Maaroufi, 2018). Further, a recent study by Lopez-Arboleda and Cardenas (2021) also used system dynamics to analyse the synergy between EV market dynamics and sustainability in Colombia.

This study is initiated with problem analysis, which includes actor analysis and defining the system boundary. Actor analysis aims to identify the involved or affected stakeholders and how they define the problem in the adoption process (Walker, 2000), while defining the system boundary is to delineate the elements that are inside and outside the system. It is then followed by model conceptualisation that identifies and captures the variables within the EV adoption system and the interactions between them (in this case, the Bass diffusion model is used to describe the process of EV adoption). Based on the actor analysis, model conceptualisation translates the problem owner’s objectives into the system’s output of interests or indicators. It also analyses the problem owner’s policy interventions to achieve the goal and external factors that influence the problem owner’s objectives. In this regard, model conceptualisation translates the problem owner’s objectives and policy interventions into output and policy variables in the model, respectively. The next step is model development where the conceptual model is translated into a quantitative system dynamics model or stock-flow diagram (SFD). The quantitative model is then used to test and evaluate the policy interventions or alternatives under plausible scenarios.

3.1. Problem analysis

3.1.1. Actor analysis

The adoption of EV is a complex socio-technical development process involving various actors. Identifying who are involved and affected by the action of problem owner (i.e. the government) is an essential step in analysing problem (Walker, 2000). An actor analysis defines stakeholders’ perceptions, objectives, interests regarding the problem, and their position in a system. Actors can be classified into three types, namely, (1) parties affected by the problem and solutions to be implemented, (2) parties involved formally in policy intervention and (3) parties involved in solution implementation. Table 1 presents the actor analysis regarding EV adoption.

The initiator of EV implementation in Indonesia is the central government with the involvement of several ministries, such as the Ministry of Finance, the Ministry of Industry, the Ministry of Environment and Forestry, the Ministry of Energy and Mineral Resources, and local governments. Adopting EVs is an alternative for reducing CO₂ emissions in Indonesia (PLN, 2020c). Thus, the goal of the Indonesian government is...
to increase EV adoption and reduce the CO$_2$ emissions of the transportation sector.

The second actor is ICEV users, who are the target of the Indonesian government. However, they currently lack the urgency to shift to EVs because they perceive EVs as more expensive and less reliable than ICEVs. Conversely, ICEVs are perceived superior to EVs in affordability and driving range. The latter issue is amplified because charging stations for EVs remain limited.

The concerns of ICEV users can be addressed by the third and fourth actors, namely, automotive companies and charging station providers. Unlike most of the top selling ICEVs in Indonesia, EVs are still imported by automotive companies and are subject to 50% import tax (Remenkeu, 2017). EV production can be localised to increase its affordability. However, the high uncertainty of EV future demand and unclear regulation influences their decision to manufacture EVs locally which is a large investment. Anxiety about the driving range of EVs can be resolved by increasing the number of charging stations, a power that lies on charging station providers. Nonetheless, ICEV users are also concerned by the limited number of EV users.

A state-owned electricity company, PLN, is the sole off-taker and distributor of electricity in Indonesia (Setyawan, 2013). Thus, the large-scale adoption of EVs will increase the load on the electricity grid. Moreover, they are responsible for most electricity generations, which continue to use fossil fuels (Burke et al., 2019). They also have the power to switch to clean energy sources, such as geothermal, solar and wind.

### 3.1.2 Defining system boundary

System boundary is a delineation of a system that explains what is included and not included in the system. This study discusses EV adoption, focusing on EV attractiveness and consumer preference of vehicles in Indonesia. The model is simulated from 2020 to 2035. This time duration is based on the Ministry of Industry National Industry Development Master Plan, which emphasises the importance of EV volume as the primary driver of their objectives (Kemenperin, 2015). This research limits its scope to adopting BEVs as the major EV encouraged by the government. We use the four-wheeler market size to estimate the number of EV potential adopters which includes both first-time four-wheeler buyers and returning four-wheeler buyers. The vehicle technology option for the potential adopters is limited to pure ICEVs only. Hence, the study did not consider other alternative vehicle technologies, such as HEVs, PHEVs or bio-fuel vehicles. This study assumes that adding charging stations is solely based on the number of EVs adopted.

### 3.2 Model conceptualisation

Fig. 1 describes the conceptual model for this research using the system diagram adapted from Damayanti et al. (2020). The system diagram includes problem owner and his goal, output of interests or indicators, system inputs, policy interventions, stakeholders and a causal loop diagram (CLD) that illustrates the dynamics of the EV adoption process. We use the Bass diffusion model to explain the dynamics of the adoption process especially related to the following causal relationship between variables. The adoption process explains the transition from ICEVs to EVs, highlighting the factors of consumer preference and how policy interventions can promote the shift. Two causality loops exist within the process: the social influence loop and the infrastructure loop.

Following actor analysis, the output of interests or indicators are (1) EV volume (sales from EVs), (2) the number of charging stations and (3) reduction of CO$_2$ emissions. These indicators are in line with the objective and interest of problem owner as seen in Table 1. Inputs to the systems are categorised as those influenced and not influenced by the problem owner. The external variables cannot be controlled or are barely influenced by the problem owner. Meanwhile, policy variables are input variables that can be controlled, reflecting the problem owner’s policy interventions. The effect of policy interventions is observed through the behaviour and output of the simulated model.

The CLD in the system diagram with two loops explains the modelled EV adoption process based on the Bass diffusion model. The Bass diffusion model is commonly used as a reference model in developing a dynamic system model related to the adoption model, including the diffusion of innovation (Rogers, 2010). It shows that a temporal adoption of products or diffusion of innovation is also characterised by S-shaped diffusion curves (Bass, 1969). The social influence loop explains the role of word-of-mouth (WOM) in the EV adoption process. It is driven by EV volume and the effectiveness of the influence of WOM. EV adoption will also be influenced by its promotion activities and benefits.

Furthermore, the benefit of the EV is gauged through its economic benefits and vehicle quality, which influences its attractiveness and, ultimately, its chance for adoption. The infrastructure loop explains the relationship between EV volume and the number of charging stations.
An increase in EV volume will increase the demand for charging stations. With the investment from investors, state electricity companies and private companies will further develop and increase the number of charging stations. This notion indicates that the number of charging stations is increasing. An increase in the number of charging stations will improve the infrastructure readiness level of EV implementation, which will eliminate the anxiety of potential adopters about the limited driving range and reluctance to adopt EVs.

3.3. Model development

The SFD was developed with the help of Powersim Studio software based on the CLD (Fig. 2). The SFD consists of three modules: EV adoption, EV attractiveness, and EV emission reduction. Each module contains graphical symbols of the variables (see Appendix A for a brief legend). Appendixes B, C and D provide the details of the formulas of the EV adoption, attractiveness and emission reduction modules, respectively.

3.3.1. EV adoption module

Fig. 3 presents the EV adoption module, which determines the factors and the relationships among them, influencing the decision of potential adopters of EVs to shift from ICEVs to EVs. EVs’ annual sales are driven by the willingness to adopt and EV attractiveness. Moreover, willingness to adopt is driven by the promotion influence and social influence loop, which is based on the Bass diffusion theory in terms of the effect of WOM.
EV attractiveness denotes the reaction and factors that influence EV attractiveness, which, in turn, drives EV purchase. The new adoption of EV at year $t$ is formulated as follows:

$$\frac{dX}{dt} = S = N \times W \times A$$

(1)

where $X$ is the cumulative number of EVs; $S$ represents EV annual sales; $N$ points to the number of potential adopters; $W$ stands for the willingness to adopt; and $A$ denotes EV attractiveness. $W$ is further derived as follows:

$$W = \alpha + a_p \frac{S}{N}$$

(2)

where $a_p$ pertains to the effectiveness of promotional activities; $a_p$ refers to the effectiveness of WOM; $S/N$ is the market share of EV. In contrast to Struben and Sterman (2008) and Yu et al. (2018), the current study assumes that EV promotion and WOM effectiveness are constant. In addition, all potential adopters are considered aware of EVs.

Struben and Sterman (2008) suggest that EV promotion and WOM effectiveness are 0.01 and 0.25, respectively. However, the latest study on EV diffusion in European countries suggests that promotion effectiveness is between 0.000015 and 0.0008073, whereas WOM effectiveness is between 0.387 and 0.686 (Brdulak et al., 2021). Other studies suggest that promotion effectiveness reaches between 0.0016 (Cordill, 2012) and 0.025 (Becker et al., 2009), whereas WOM effectiveness lies between 0.0905 (Steffens, 2003) and 1.45 (Cordill, 2012). Another study uses data on EV sales in Germany and determined promotion and WOM effectiveness to be 0.0019 and 1.2513, respectively (Massiani and Gohs, 2015). However, these studies were primarily conducted in European countries that have established EV penetration in contrast to Indonesia. A study in Korea on the penetration of the relatively-new hydrogen fuel cell vehicle (HFCV) reached promotion and WOM effectiveness at 0.0037 and 0.3454, respectively (Park et al., 2011). The last study is considered more suitable for the current research because it forecasts the sales of HFCV, which displays a market situation similar to EVs in Indonesia. As the number of EVs increases, the number of potential adopters that shifts to EVs would accelerate due to the increasing number of EV adopters over time that could influence potential adopters.

3.3.2. EV attractiveness module

The EV attractiveness module contains the infrastructure loop, which represents the influence of charging stations on the new sales of EVs. Thus, EV attractiveness can be viewed as the probability to purchase EVs; hence, its value will be between 0 and 1. Purchase probability is the sum of the multiplication between each factor’s relative importance and benefit. Relative importance is obtained from the survey data. Moreover, the benefit is calculated as the difference between EVs and ICEVs per attribute divided by the attribute value of EVs or ICEVs. This calculation will yield benefit values ranging from −1 to 1. The utility value is then normalised to ensure that probability lies between 0 and 1 (Yu et al., 2018). This model considers four factors: economic benefit, charging time benefit, driving range, and infrastructure (charging station) readiness. The economic benefit of EV is derived from purchase, ownership and maintenance costs. Lastly, EV attractiveness is defined as follows:

$$A = \beta_E u_E + \beta_C u_C + \beta_R u_R + \beta_I u_I$$

(3)

where $\beta_E, \beta_C, \beta_R$ and $\beta_I$ denotes the relative importance of the economic, charging time, driving range benefit and infrastructure readiness. Moreover, $u_E, u_C, u_R$, and $u_I$ represent the economic benefit, charging time benefit, driving range benefit and infrastructure readiness, which are derived as follows:

$$u_E = \frac{P_{EV} - P_{ICEV}}{\max(P_{EV}, P_{ICEV})} + \frac{O_{EV} - O_{ICEV}}{\max(O_{EV}, O_{ICEV})} + \frac{M_{EV} - M_{ICEV}}{\max(M_{EV}, M_{ICEV})} + 0.5$$

(4)

$$u_C = \frac{C_{EV} - C_{ICEV}}{\max(C_{EV}, C_{ICEV})}$$

(5)

$$u_R = \frac{R_{EV} - R_{ICEV}}{\max(R_{EV}, R_{ICEV})}$$

(6)

$$u_I = \frac{I_{EV} - I_{ICEV}}{\max(I_{EV}, I_{ICEV})}$$

(7)

where $u_E, u_C, u_R, u_I \in [0, 1]$. $P_{EV}$ and $P_{ICEV}$ are the purchase costs; $O_{EV}$ and $O_{ICEV}$ pertain to the ownership costs; $M_{EV}$ and $M_{ICEV}$ are the maintenance costs of; $C_{EV}$ and $C_{ICEV}$ stand for the charging/refuelling time; $R_{EV}$ and $R_{ICEV}$ represent driving ranges; and $I_{EV}$ and $I_{ICEV}$ refer to the number of charging/refuelling stations for EVs and ICEVs.

For concreteness, this research compares the economic benefits, charging time and driving range of the Toyota Avanza Low-MPV and Hyundai Kona EV Compact-SUV. Although their body types and market segments differ, they are the best-selling ICEVs and EVs in Indonesia (GAIKINDO, 2020). The rationale for this selection is that an EV should have a close price range to an ICEV to enable widespread acceptance from the public. The base price of each vehicle is obtained based on the 2020 Off-The-Road price. For simplicity, the base price for ICEV is assumed to be constant. However, EV prices are assumed to decline according to Wright’s law unit cost curve due to a learning rate of 6%–9% cost reduction for each doubling of cumulative production (Nykvist and Nilsson, 2015). The base prices are then subjected to an array of taxes to yield the final price for end-consumers (GOI, 2009a, 2009b, 2019a; GOI, 2015, 2019). The maintenance cost follows the estimates for the published maintenance cost of each vehicle. The ownership cost of each vehicle comprises annual tax and the cost of energy consumption.
(gasoline for ICEV, electricity for EV). The annual tax is calculated by multiplying each vehicle’s annual tax rate and base price. Moreover, the energy consumption cost is a product of annual driving range, vehicle efficiency, energy distribution, refuelling efficiency and energy price. The formulas for calculating ownership costs are as follows:

\[ O_{\text{ICEV}} = (\eta_{\text{ICEV}} \times f_{\text{ICEV}} \times r) + T_{\text{ICEV}} \]  
(8)

\[ O_{\text{EV}} = (\eta_{\text{EV}} \times \eta_{\text{td}} \times \eta_{\text{c}} \times f_{\text{EV}} \times r) + T_{\text{EV}} \]  
(9)

where \( r \) represents the annual driving range; \( \eta_{\text{ICEV}}, f_{\text{ICEV}} \) and \( T_{\text{ICEV}} \) are fuel efficiency, fuel price and annual tax of ICEVs, respectively, whereas \( \eta_{\text{EV}}, \eta_{\text{td}}, \eta_{\text{c}} \) and \( f_{\text{EV}} \) are energy efficiency, electricity transmission and distribution efficiency, charging efficiency, electricity price and annual tax of EVs, respectively. The annual driving range is estimated using the average travel distance from all Indonesian provinces obtained from Pratama and Tokai (2018). \( \eta_{\text{ICEV}} \) is estimated according to the fuel efficiency of light-duty vehicles in South-East Asian countries (ASEAN, 2019). \( \eta_{\text{EV}}, \eta_{\text{td}} \) and \( \eta_{\text{c}} \) were adapted from Desreveaux et al. (2020), ESDM (2018) and Apostolaki-Iosifidou et al. (2017), respectively. Meanwhile, \( f_{\text{ICEV}} \) and \( f_{\text{EV}} \) were adapted from the authors in (Pertamina, 2020) and (ESDM, 2016), respectively.

The charging attractiveness of an EV will be relative to the time required to refuel an ICEV. Presumably, refuelling an ICEV lasts for 5 min regardless of the time spent waiting in line. The charging time of an EV is determined by its battery capacity, charging loss and power rate of the charging station. Thus, this study assumes that EV users will use a fast-charging outlet with 50 kW (kW) power output. With a battery capacity of 39.2 kW per hour (kWh) and a charging loss of 12.38% (Apostolaki-Iosifidou et al., 2017), the time to fully charge EVs maybe 53 min. Thus, we assume that an improvement will occur to charging time with a 3.97% compound annual growth rate (CAGR) (Stone, 2021).

In terms of charging attractiveness, the attractiveness of the EV driving range is illustrated by comparing it to its ICEV counterpart. The ICEV driving range is simply obtained from the average fuel efficiency (ASEAN, 2019) and fuel tank capacity of the ICEV. The initial driving range of EVs is obtained from an official vehicle specification (Hyundai, 2021). The driving range is assumed to improve by approximately 6.7% CAGR, which is calculated from the average range of globally available EV models between the 2015 and 2035 linear forecasts, which uses data from 2015 to 2020 (IEA, 2021).

With the increasing number of EVs, utilities are assumed to increase the number of charging stations. Ideally, one charging station should be available for every 25 units of EV (Harrison and Thiel, 2017). However, the ratio of charging stations varies from 1:5 to more than 1:40 (Hall and Lutsey, 2017). Alternatively, the number of refuelling stations for ICEV is expected to increase by 100 stations per year as projected by the Ministry of Energy and Mineral Resources of Indonesia. Fig. 4 presents the complete module for EV attractiveness.

3.3.3. EV emission reduction module

The last module (Fig. 5) explores the impact of EV adoption on the environment. CO\(_2\) emission would increase with the increasing demand for transportation. However, commuters have the option to choose cleaner alternatives, one of which by using EVs as studied in this research. Thus, what is measured in this study is the avoided CO\(_2\) emission from using EVs. The factor considered is the well-to-tank (WTT) CO\(_2\) emission of EV instead of the entire life cycle of CO\(_2\) (LCCO\(_2\)) reduction. The WTT CO\(_2\) of ICEV is calculated as fuel consumption multiplied by the average CO\(_2\) emission rate of the ICEVs. Although EVs lack tailpipe emissions, they require electrical energy for the battery. Hence, its WTT CO\(_2\) emission is dependent on the emission factor of the Indonesian electricity grid. The WTT CO\(_2\) emissions for EVs are calculated as the total consumption of electric energy multiplied by

Fig. 5. Stock-flow diagram module of avoided CO\(_2\) emissions from using EV.
the emission factor of the current electricity grid. Finally, the avoided CO₂ emission is calculated as the difference between WTT CO₂ emissions of the ICEVs and EVs multiplied by the number of EV units adopted. The ICEV CO₂ emission is calculated by multiplying its average fuel consumption and CO₂ emission factor, which is assumed to be 3172.31 g CO₂ (gCO₂) per 1 kg of fuel and the specific gravity of gasoline is 0.715 kg per litre (kg/litre) (IPCC, 1998). EV electricity consumption is multiplied by the electricity grid CO₂ emission factor of 0.813 as reported in (Takahashi and Louhisuo, 2020) to calculate its CO₂ emission. We assume the grid CO₂ emission factor as a constant to evaluate the base effect of EV avoided CO₂ emission.

The developed model was then tested for validity using several standard tests in the system dynamics approach. The test checks for dimensional consistency on whether the units of all variables are consistent and correspond to reality. This process was conducted with the help of Powersim Studio by examining any errors that may appear in the links between variables. The test found no errors. Next, the study conducted the structural assessment test, which investigates the compatibility of the model’s behaviour with its structure. This test was inherently conducted with the integration error test, which uses different time steps, such as 30 and 60 days, to simulate the model. Fig. 6 presents the result of the integration error test, which indicates no significant behavioural differences between the results after simulating the model under different time steps. These testing results conclude the robustness of the model.

3.4. Scenario development

The Indonesian government is enforcing EV tax reductions to reduce purchase and annual tax costs and promote the adoption of EVs. They also added electricity price incentives to reduce charging costs through the PLN. Two scenarios were developed to investigate the effectiveness of these policies under future uncertainties regarding the advancement in EV technology and the willingness of private parties to build charging stations. The scenarios are described as follows.

1. Full Collaboration

Automotive manufacturers accelerate breakthroughs in EV technology simultaneously by improving the learning effect on EV price and significantly increasing driving range. The learning effect on price will increase to 9% (Nykvist and Nilsson, 2015), whereas the driving range is assumed to improve annually by 9.8% (Compounded Annual Growth Rate, CAGR) based on the 2015–2020 data (IEA, 2021).

Alternatively, private charging station providers are determined to develop the EV ecosystem to achieve the ideal charging station ratio to EVs of 1:25 (Harrison and Thiel, 2017). These factors work together to create a situation that supports EV adoption, leading to high rates of EV adoption.

2. Technology Plateau

No breakthroughs have occurred in EV battery technology, which will force current lithium-ion batteries to reach their theoretical energy density limit by 2035. With its current energy density of 250 Watts hour per kilogram (Wh/kg) and theoretical limitation of 350 Wh/kg, the annual improvement rate is expected to be approximately 2.3% CAGR (Ding et al., 2019). Furthermore, innovation in EV production technology is limited, which yields a low learning rate of 6% (Nykvist and Nilsson, 2015; Weiss et al., 2019). With the seemingly unattractive prospects of EV, private parties are reluctant to build charging stations, which leaves the building of charging stations in the hands of the government. Learning from refuelling stations in Indonesia, the government owns approximately 28% of the total available refuelling stations through Pertamina, its oil state-owned company (Pertamina, 2021). Therefore, this scenario assumes that the charging stations to EV ratio are 1:45 (Hall and Lutsey, 2017).

4. Results

The model was first simulated without EV tax reduction and charging price incentive as a baseline to evaluate the effectiveness of the policies. Tax incentive policies and charging price incentives were separately simulated and combined. Two alternatives for charging price incentives were considered. The first is reducing the charging price at charging stations by 11% to the level of residential electricity tariff (PLN, 2020a) and approximately 21% following the latest incentives at the charging station to date (Mulyana, 2020). The simulation was repeated for all scenarios, including business as usual (BaU).

Fig. 7 presents the simulation under the BaU scenario, which displays a 31% CAGR of EV volume without policies and accumulates to 37,898 EV units by the beginning of 2035. The growth rate increases to 32.1% with the introduction of tax reduction policies, which yields a 13.41% increase in the number of EVs at the end of the simulation. The final EV volume is further increased by up to 2.13% with the introduction of charging price incentives. Behaviours related to the avoided CO₂ emission and the number of charging stations follow those of EV volume. This finding aligns with our model formulation that sets the avoided CO₂ emission and the number of charging proportionally to EV volume. By 2035, 915 and 1060 charging stations would be available at the end of the simulation with and without all policies, respectively. The cumulative CO₂ reduction by 2030 is 274 MtCO₂e without policies, which increases to 318 MtCO₂e with the enforcement of all policies.

The results in Fig. 7 indicate that charging price incentives cannot optimise the promotion of EV adoption. The cost for the utility is substantial compared with the marginal increase in EVs. Alternatively, tax reduction reduces EV purchase and annual tax costs and dramatically increases the number of adopted EVs.

Comparing the results of a specific policy across scenarios (Fig. 8), the results indicate that technology advancement contributes more significantly to the adoption of EV compared with tax reduction and other policies that aim to reduce the cost of EV. Fig. 8(a) demonstrates that the number of EVs at the end of the Full Collaboration scenario even without policies is more significant than that under the BaU scenario with all policies in place. This finding can be explained by the higher EV attractiveness under the Full Collaboration scenario than EV attractiveness under the BaU scenario, as illustrated in Fig. 8(b). The gap is primarily due to the major influence of vehicle quality, mainly driving range, on EV attractiveness. Tax reduction and charging price policies substantially boost the ownership-cost benefit and indicate a slight
increase in the purchase-cost benefit. Nevertheless, these factors are less significant than the factors of vehicle quality. Fig. 9 provides comparisons between attractiveness factors.

The dominance of the factors of vehicle quality in influencing EV adoption does not indicate that the financial incentives fail to provide benefits. The importance of financial incentives is accentuated when technology development is lacking. Under the BaU scenario, the number of EVs with the enforcement of all policies was greater by 15.81% compared with the scenario where no policies were implemented. The difference decreased slightly to 15.14% under the Full Collaboration scenario in the presence of the rapid development of technology. Conversely, the tax reduction and charging price incentive policies can boost EV volume by 17.37% under the Technology Plateau scenario.

Finally, even with the enforcement of all policies, the CO$_2$ emission only reduced 374 MtCO$_2$eq and could not meet the 2030 target of 633.35 MtCO$_2$eq. This finding is primarily due to the high emission factor of electricity generation. Fig. 10 illustrates how the marginal change in the grid CO$_2$ emission factor may result in a counterproductive result. Hence, a shift to a clean energy mix for electricity generation is required to reap the full benefits of EVs to reduce CO$_2$ emissions.

5. Discussion

The current study extended the previous research of Damayanti et al. (2020) by developing a system dynamics model to investigate the effectiveness of the policies imposed by the Indonesian government to promote EV adoption. The tax reduction policies boosted EV adoption, while charging price incentives failed to benefit the adoption substantially. However, the improvement in the factors of EV quality demonstrated to exert more impact than any fiscal policies considered in this study. Our key finding concurs with previous studies that show improvement in vehicle quality as the determinant in increasing EV adoption in countries like the Netherlands and Norway (Deuten et al., 2020), and India (Chhikara et al., 2021; Singh et al., 2021). Indeed, when technology advancement is lacking, financial incentives may aid with the adoption of EVs, which agrees with results obtained by a previous study (Deuten et al., 2020). As an additional finding, our model shows that investing in an EV would not be break-even in 15 years. This due to the fact that the initial purchase cost gap is so large between EV and ICEV. Under the Full Collaboration scenario where the condition is most favourable for EV adoption, the cumulative EV cost savings was only IDR 26 million compared to more than IDR 450 million initial purchase cost gap. However, EV cost savings increases dramatically when annual driving range becomes larger. For instance, our model shows that if the annual driving range is doubled, EV cost savings would increase three times.

The combination of system dynamics and policy analysis framework has enabled the holistic and systematic analysis of EV adoption in Indonesia. This study contributed to the literature on energy-related cases that use a similar approach (i.e. Eker and van Daalen, 2015;
Hidayatno et al., 2020). CLD enabled the researchers to thoroughly examine the dynamic complexity of EV adoption by capturing its underlying structure and critical variables. Meanwhile, the simulation of the SFD model enabled the researchers to assess the effectiveness of the implementation of EV tax reduction and charging price incentives by evaluating changes in EV volume under different scenarios. This study also enriched the literature on understanding EV market dynamics (i.e. Harrison and Thiel, 2017; Lopez-Arboleda and Cardenas, 2021).

In Indonesia, EV adoption remains in its early stage. Thus, further studies on this topic are required. The current study assumes that EV users only influence potential EV adopters. Future research should also consider the contact between them and non-EV users, which may influence the effectiveness of EV promotion. This study pays attention to the economic benefits and infrastructure readiness as the factors in adopting EVs. Future studies could add psychological considerations such as attitudes, subjective norms, technology affinity, environmental concerns, or symbolic value as in line with Chu et al. (2019) and Skippon and Garwood (2011). Evaluating promotion effectiveness should also consider the decaying effect, as suggested by Yu et al. (2018) and Struben and Sterman (2008). When calculating the declining cost of EV, further research should consider the change in EV volume at the global level to provide an increasingly accurate estimation of the learning rate of EV price.

Moreover, future studies should consider potential adopters to opt for other eco-friendly alternative vehicles, such as HEVs and PHEVs. They may also investigate changes in behaviour, such as selecting more efficient ICEVs or using public transportation. The behaviour of the commuter should also be addressed to reduce energy consumption for transportation sustainably. Aside from improving the current mode of transport or shifting towards cleaner ones, the changes might avoid the need to travel altogether (Creutzig et al., 2015; Dia, 2019; Wilson et al., 2020). In this study, we used a constant grid CO₂ emission factor. Future studies can add a dynamic electricity grid emission factor which may give an interaction between energy policies and EV policies. Future research can also compare EVs’ CO₂ emission life cycles and ICEVs to provide a comprehensive avoided CO₂ emission from the adoption of EVs. This study also has yet observed the effect of charging station quantity to EV adoption rate since it was modelled simply as the ratio to EV volume. Finally, although this study is limited to EV adoption in Indonesia, the findings can remain relevant to other countries with similar characteristics, especially the lessons learned.

6. Conclusion and recommendation

This paper highlighted several contributions to the research on EV adoption by demonstrating that purchase tax and annual tax reductions are two policies that can effectively boost consumer preference for EV, which may result in increased EV adoption in Indonesia. However, vehicle quality was a more dominant factor in attracting potential EV
adopters. Moreover, EV adoption can avoid higher levels of CO₂ emissions over time significantly given that the electricity grid CO₂ emission factor is kept below 0.82. Based on the results, this paper presents the following recommendations regarding the policies on EV adoption:

1. The government should provide the automotive industry and related industries with incentives to accelerate EV innovation and manufacturing. Incentives such as tax holiday, tax allowance, and super tax deduction can be used as alternatives to attract more investors to invest in EV industry development. Further, such incentives are expected to grow the EV industry and reduce its production costs.

2. The government should maintain tax reduction policies to reduce EVs’ purchase and ownership costs until EVs can sufficiently penetrate the market. Alternatively, the government should consider excluding or limiting the charging price incentives as they provide only marginal benefits at a high cost to the utility.

3. This study suggests increasing the adoption of renewable energy into the energy mix to reduce the emission factor of electricity generation. As the findings indicate, the grid CO₂ emission factor should not exceed 0.82. PLN, as the current sole purchaser and distributor of electricity, could purchase more renewable energy sourced electricity from electricity producers.

4. Instead of imposing policies separately, the government could enact a more unified policy package. Reducing fuel subsidies accompanied by carbon tax at the same time could be an alternative to disincentivize the use of ICEV. However, it should also be accompanied by EV infrastructure and market readiness.

Credit authorship contribution statement

Andri D. Setiawan: Conceptualisation, Formal analysis, Methodology, Software, Supervision, Validation, Writing – review & editing, Teuku Naraski Zahari: Conceptualisation, Formal analysis, Methodology, Software, Supervision, Validation, Writing – review & editing, Fara Jetira Purba: Data curation, Formal analysis, Software, Writing – original draft, Armand O. Moeis: Data curation, Supervision, Akhmad Hidayatno: Conceptualisation, Methodology, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data has been included in the appendix.

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Appendix A. (Variable Symbols in the Stock-Flow Diagram)

Appendix B. (Formula for the EV Adoption Module)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Formula/Value (variable value “0” indicates an initial value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contact Effectiveness</td>
<td>1/yr</td>
<td>0.3454</td>
</tr>
<tr>
<td>EV Potential adopters</td>
<td>units</td>
<td>ICEV_initial_annual_sales</td>
</tr>
<tr>
<td>EV Volume</td>
<td>units</td>
<td>EV_initial_volume</td>
</tr>
<tr>
<td>EV_annual_sales</td>
<td>units/yr</td>
<td>‘EV Potential adopters’ ‘EV_willingness_toadopt’ ‘EV_attractiveness</td>
</tr>
<tr>
<td>EV_initial_volume</td>
<td>units</td>
<td>0</td>
</tr>
<tr>
<td>EV_willingness_to adopts</td>
<td>yr⁻¹</td>
<td>(‘Promotion effectiveness’ + ‘Influence from WOM’)</td>
</tr>
<tr>
<td>ICEV Growth rate</td>
<td>units/yr</td>
<td>‘EV Potential adopters’ ‘ICEV_market_growth’</td>
</tr>
<tr>
<td>ICEV_initial_annual_sales</td>
<td>units</td>
<td>946,537</td>
</tr>
<tr>
<td>ICEV_market_growth</td>
<td>1/yr</td>
<td>0.05</td>
</tr>
<tr>
<td>Influence from WOM</td>
<td>yr⁻¹</td>
<td>‘Contact Effectiveness’ ‘market share’</td>
</tr>
<tr>
<td>market share</td>
<td></td>
<td>‘EV Volume’ ‘(EV Potential adopters’ ‘EV Volume’)</td>
</tr>
<tr>
<td>Promotion effectiveness</td>
<td>1/yr</td>
<td>0.0037</td>
</tr>
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</table>

Appendix C. (Formula for the EV Attractiveness Module)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Formula/Value (variable value “0” indicates an initial value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avoided CO2 Emissions</td>
<td>kgCO2</td>
<td>0</td>
</tr>
<tr>
<td>Avoided CO2 Emissions rate</td>
<td>kgCO2/yr</td>
<td>(ICEV_co2_emission EV_CO2_emission) EV_annual_sales * 1 &lt; yr &gt;&gt;</td>
</tr>
<tr>
<td>EV_CO2_emission</td>
<td>kgCO2/yr</td>
<td>EV_electricity_consumption Grid_co2_emission_factor</td>
</tr>
<tr>
<td>(yr^units)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(continued on next page)
continued on next page
Table A.D. (Formula for the EV CO2 Emission Reduction Module)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Formula/Value (variable value “0” indicates an initial value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO2 Emission reduction</td>
<td>kgCO2</td>
<td>0</td>
</tr>
<tr>
<td>CO2 Emission rate reduction</td>
<td>kgCO2/yr</td>
<td>(ICEV_co2_emission-ICEV_co2_emission)<em>EV_annual_sales</em>1&lt;&lt;yr&gt;</td>
</tr>
<tr>
<td>EV CO2emission</td>
<td>kgCO2/(yr*units)</td>
<td>EV_electricity_consumption*grid_co2_emission_factor</td>
</tr>
<tr>
<td>grid co2_emission_factor</td>
<td>kgCO2/KWh</td>
<td>0.813</td>
</tr>
<tr>
<td>ICEV co2_emission</td>
<td>kgCO2/(yr*units)</td>
<td>ICEV_fuel_consumption*ICEV_co2_emission_factor</td>
</tr>
<tr>
<td>ICEV co2_emission_factor</td>
<td>kgCO2/litre</td>
<td>3.17231<em>0.715</em>1/kgCO2/litre</td>
</tr>
</tbody>
</table>

Appendix D. (Formula for the EV CO2 Emission Reduction Module)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Formula/Value (variable value “0” indicates an initial value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICEV base_price</td>
<td>IDR/units</td>
<td>163,000,000</td>
</tr>
<tr>
<td>ICEV_BBN-KB</td>
<td>%</td>
<td>12.5</td>
</tr>
<tr>
<td>ICEV DPP</td>
<td></td>
<td>1.05</td>
</tr>
<tr>
<td>ICEV fuel_capacity</td>
<td>litre</td>
<td>40</td>
</tr>
<tr>
<td>ICEV fuel_consumption</td>
<td>litre/yr/units</td>
<td>1.05<em>annual_driving_range</em>ICEV_fuel_efficiency</td>
</tr>
<tr>
<td>ICEV fuel_efficiency</td>
<td>litre/Km</td>
<td>0.073</td>
</tr>
<tr>
<td>ICEV maint_cost</td>
<td>IDR/yr</td>
<td>1,450,618</td>
</tr>
<tr>
<td>ICEV ownership_cost</td>
<td>IDR/yr/units</td>
<td>ICEV_annual_tax=(ICEV_fuel_consumption*(‘Fuel Price’ ‘Fuel subsidies’)+ICEV_base_price*ICEV_BBN-KB)</td>
</tr>
<tr>
<td>ICEV refueling_time</td>
<td>min</td>
<td>5</td>
</tr>
<tr>
<td>Infrastructure readiness</td>
<td></td>
<td>((charging_station_ideal_number-fuel_station_ideal_number)/MAX (charging_station_ideal_number, fuel_station_ideal_number))/2 + 0.5</td>
</tr>
<tr>
<td>Init_charge_time</td>
<td>min</td>
<td>(EV_battery_capacity*(1 + EV_charging_loss))/charging_station_power_rate</td>
</tr>
<tr>
<td>Initial driving range</td>
<td>Km</td>
<td>305</td>
</tr>
<tr>
<td>Initial number of charging station</td>
<td>station</td>
<td>52</td>
</tr>
<tr>
<td>learning rate</td>
<td>yr^-1</td>
<td>((('EV Volume' 'EV_annual_sales<em>1&lt;&lt;yr&gt;')/'EV Volume')</em>(LOG (EV_price_learning_effect)/(LOG (2)))</td>
</tr>
<tr>
<td>refuel_station_ideal_number</td>
<td>station</td>
<td>26,667</td>
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References


