Supplementary Material to

Charging Forward: Unlocking The Acceleration of Electric Vehicles (EVs) Adoption In Indonesia

Theresia Bhekti Putranti[a*] and Aidan Sliwkowski[a]

[a] System Dynamics Group, Department of Geography, University of Bergen P. O. Box 7802, 5020 Bergen, Norway

[*] Correspondence: Theresia.Putranti@student.uib.no

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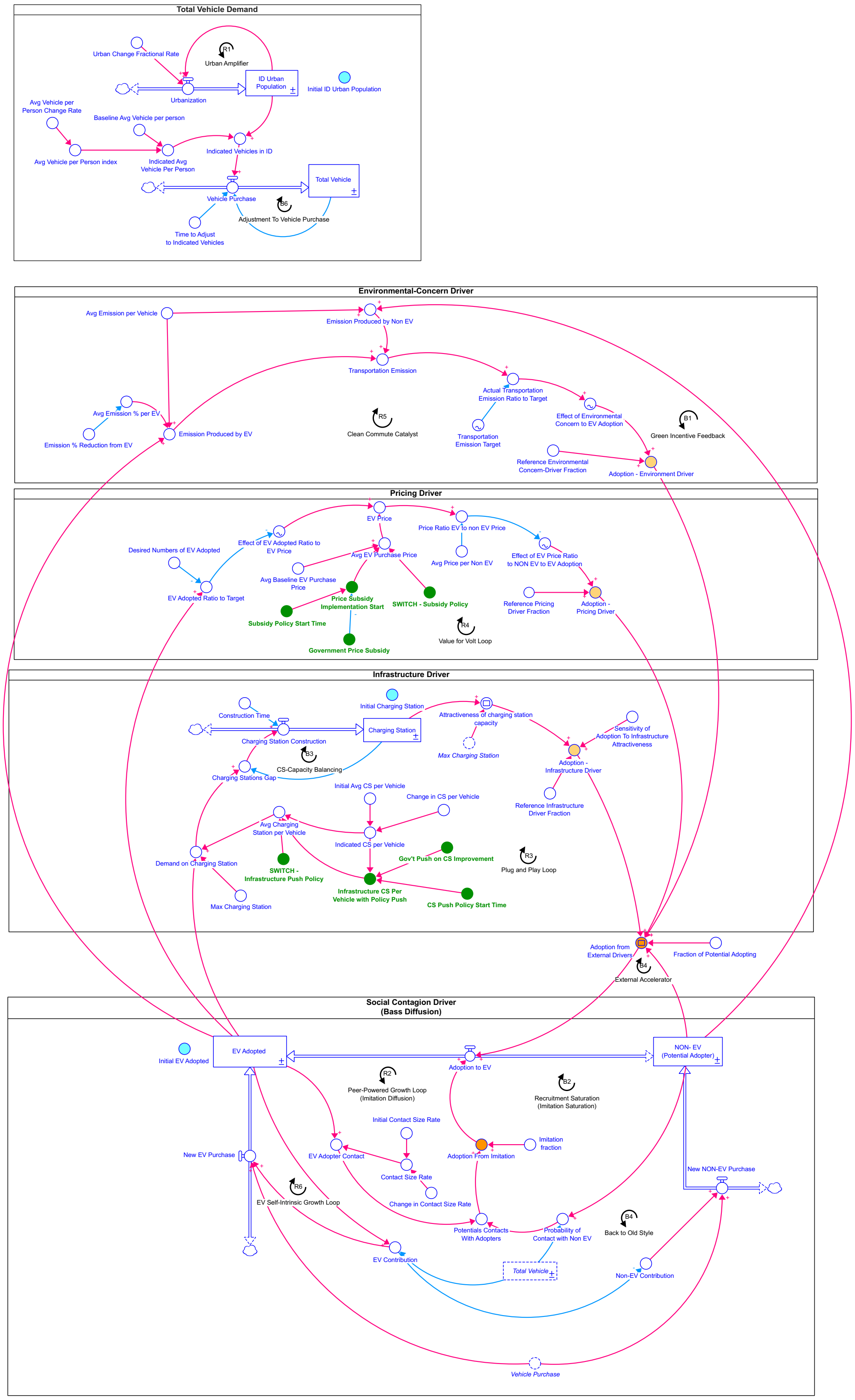
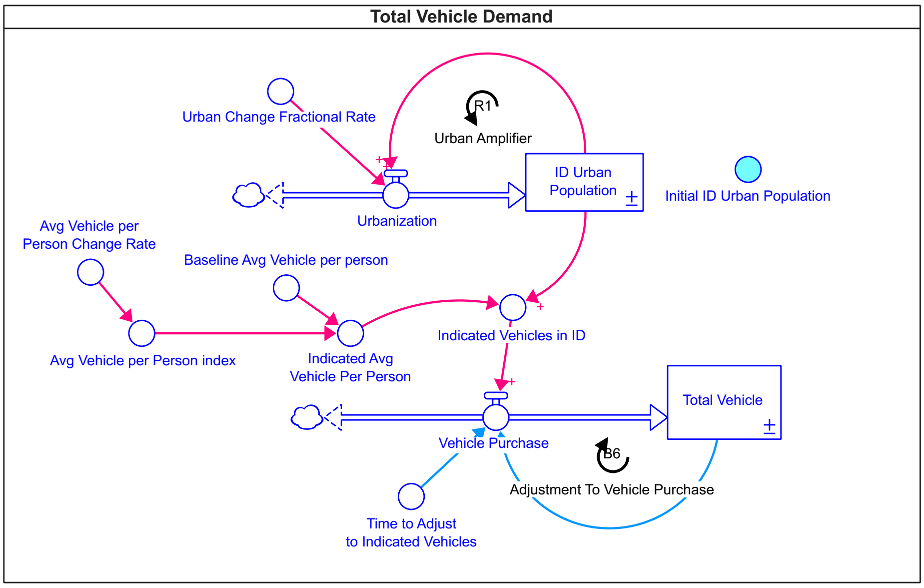


1.2 Sector: Urbanization and Vehicle Demand



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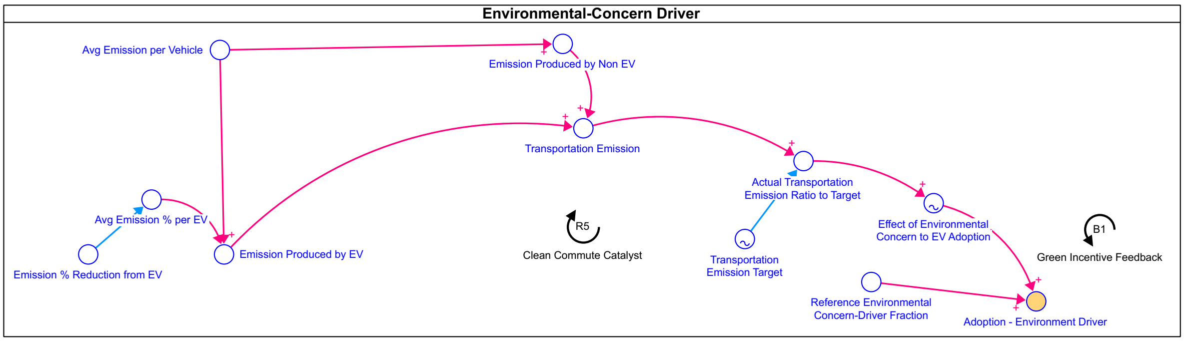

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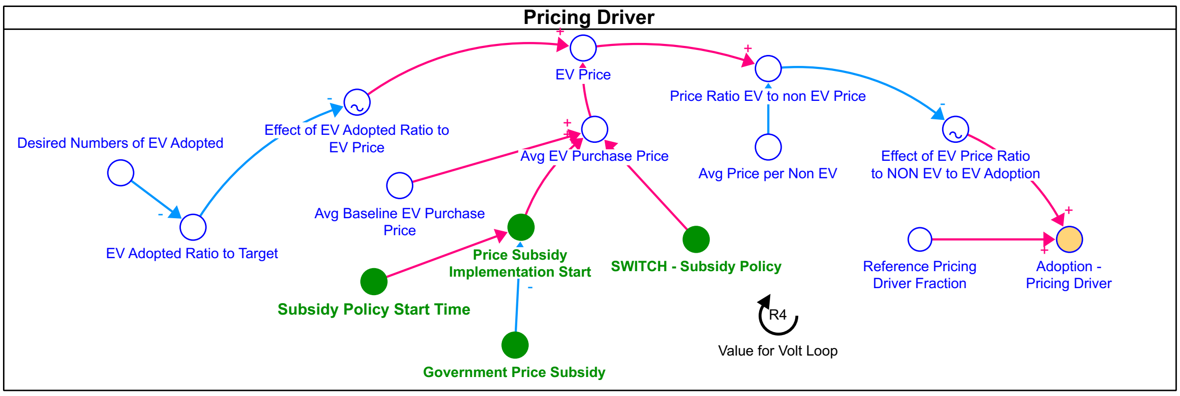

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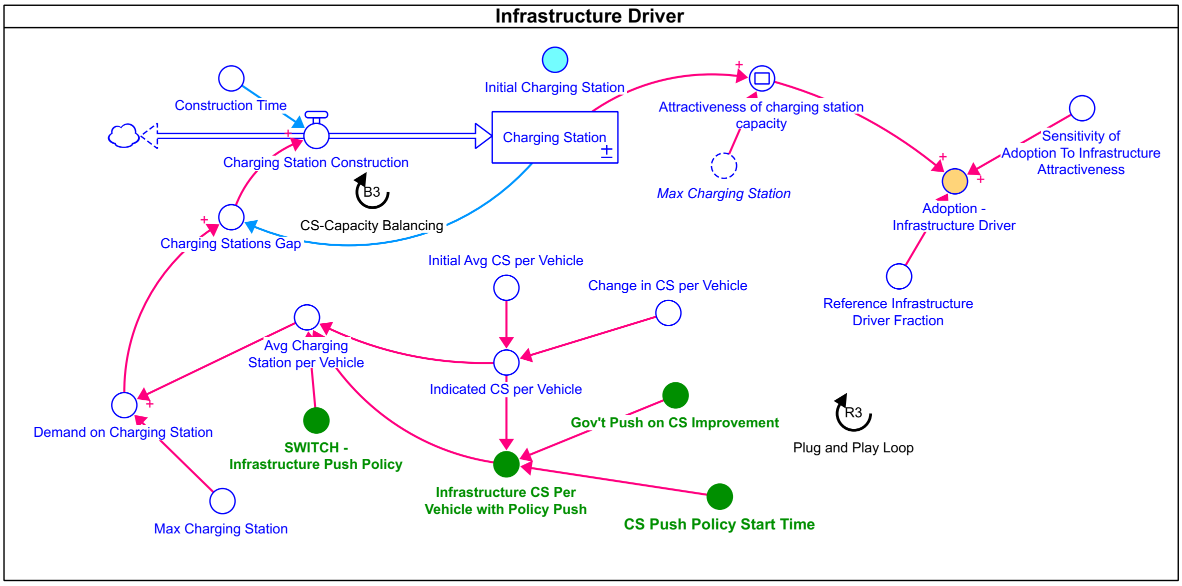

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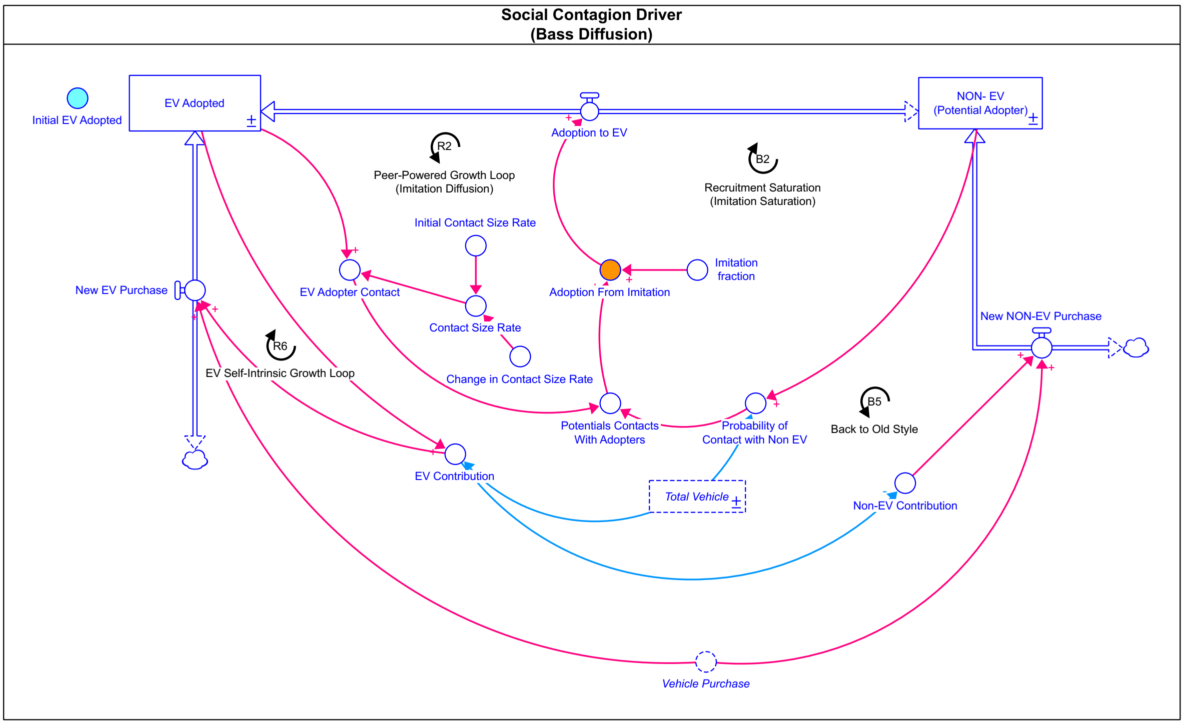


2. Model Documentation

Modelling Software : Stella 3.7.3
Start Time : 2019
End Time : 2040
Integration Method : RK2
DT : 1/16
Time Units : Years

```
STOCK

Charging_Station(t) = Charging_Station(t - dt) + (Charging_Station_Construction) * dt
    INIT Charging_Station = Initial_Charging_Station
    UNITS: Charging Station
```

DOCUMENT: This stock accumulates the number of EV Charging Stations. It increases from Charging Station Constructed. The initial value is determined by Initial Charging Stations, which is set at 40 EVs in 2019.

```
STOCK

EV_Adopted(t) = EV_Adopted(t - dt) + (Adoption_to_EV + New_EV_Purchase) * dt
    INIT EV_Adopted = Initial_EV_Adopted
    UNITS: Vehicle
```

DOCUMENT: This stock represents the total number of electric vehicles (EVs) accumulated in Indonesia, serving as a critical KPI to monitor. It increases through two inflows. First is the Adoption to EV, representing the transition of non-EVs to EVs, and second is EV Purchase, determined by a fixed percentage of the Vehicle Purchase flow, unaffected by external drivers or imitation factors. The initial value of this stock is defined by the Initial EV Adoption, set at 705 EVs.

```
STOCK

ID_Urban_Population(t) = ID_Urban_Population(t - dt) + (Urbanization) * dt
    INIT ID_Urban_Population = Initial_ID_Urban_Population
    UNITS: Person
```

DOCUMENT: This stock represents Indonesia (ID) Urban Population. It changes/ increases from inflow of 'Urbanization'. The initial value is determined by Initial ID Urban Population and set as 150,725,703 as per 2019 data.

```
STOCK

"NON-_EV_(Potential_Adopter)"(t) = "NON-_EV_(Potential_Adopter)"(t - dt) + ("New_NON-EV_Purchase" - Adoption_to_EV) * dt
    INIT "NON-_EV_(Potential_Adopter)" = Total_Vehicle-EV_Adopted
    UNITS: Vehicle
```

DOCUMENT: This stock represents the accumulated number of non-electric vehicles (NON-EVs) in Indonesia, also serving as an indicator of potential electric vehicle (EV) adopters. The stock increases through New NON-EV Purchases, determined by a specific percentage of Vehicle Purchase flow allocated to NON-EVs, and decreases as vehicles transition to EVs through Adoption to EV. The initial value of this stock is calculated as the difference between the Total Vehicles and the number of EVs Adopted.

```
STOCK

Total_Vehicle(t) = Total_Vehicle(t - dt) + (Vehicle_Purchase) * dt
    INIT Total_Vehicle = Indicated_Vehicles_in_ID
    UNITS: Vehicle
```

DOCUMENT: This stock represents the accumulated numbers of total vehicle due to urban mobility. This stock variable changes/ increases from Vehicle Purchase. The initial value is determined by Indicated Vehicles in Indonesia (ID).

FLOW

Adoption_to_EV = Adoption_From_Imitation + Adoption_from_External_Drivers
UNITS: Vehicle/Years

DOCUMENT: This flow represents the annual transition of non-EV adopters into EV adopters. It increases the stock of EV adopters while decreasing the stock of non-EV adopters. The flow consists of two primary components: Adoption from External Driver, influenced by factors such as environmental-concern, infrastructure availability, EV pricing, and Adoption from Imitation, where the behaviors of early adopters inspire others to follow suit.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
This flow aligns with diffusion theory (Bass, 1969), which posits that technology adoption is driven by a combination of external pressures and social contagion, where early adopters play a pivotal role in spreading innovation through networks and peer influence.

FLOW

Charging_Station_Construction = Charging_Stations_Gap/Construction_Time
UNITS: Charging Station/Years

DOCUMENT: This flow represents the number of charging stations (CS) added or built annually. It determines accounts for the rate at which charging infrastructure is developed, considering a delay (construction time) before the stations become operational.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
International Energy Agency (IEA, 2022) highlights that globally, infrastructure expansion often lags EV adoption. As EV sales surge, the demand for charging stations increases, leading to a shortfall (gap) until construction catches up.

FLOW

New_EV_Purchase = Vehicle_Purchase * EV_Contribution
UNITS: Vehicle/Years

DOCUMENT: This flow represents the annual number of EV purchases in urban Indonesia, calculated as a specific percentage of the EV Contribution applied to the total Vehicle Purchases per year in urban areas. It serves as one of the inflows to the EV Stock, capturing the natural demand for new EVs that arises independently of external factors like infrastructure availability, pricing incentives, or environmental concerns, as well as imitation dynamics driven by social influence. A study by Sierzchula et al. (2014) highlights that while infrastructure and pricing are critical factors, some demand for EVs stems from intrinsic preferences, such as a desire for innovation or early adoption tendencies, which are independent of imitation and external conditions.

FLOW

"New_NON-EV_Purchase" = Vehicle_Purchase * "Non-EV_Contribution"
UNITS: Vehicle/Years

DOCUMENT: This flow represents the annual number of NON-EV Purchases in urban Indonesia. It is calculated as a specific percentage of the NON-EV Contribution applied to the total number of Vehicle Purchases per year in urban areas. This flow serves as inflow to NON-EV stock, capturing the demand for new NON-EVs within the overall vehicle purchase demand in urban regions.

FLOW

Urbanization = ID_Urban_Population * Urban_Change_Fractional_Rate
UNITS: Person/Years

DOCUMENT: This flow determines number of people added to Urban Population every year. It is calculated by multiplying the Urban Population and Urban Change Fractional Rate.

EMPIRICAL SUPPORT FOR ANALYTICAL EQUATION:

Larger urban populations create agglomeration economies and opportunities. This, in turn, draws more people into cities seeking economic benefits (Glaeser et al.,1992).

FLOW

Vehicle_Purchase=(Indicated_Vehicles_in_ID-Total_Vehicle)/ Time_to_Adjust_to_Indicated_Vehicles
UNITS: Vehicle/Years

DOCUMENT: This flow determines the number of vehicles purchased every year, which will add the total vehicle. The equation in this flow captures the information delay by adjusting the indicated vehicle to actual total vehicle (stock) using time to adjust.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION
Urban growth is closely linked to vehicle demand, as cities provide more employment opportunities and require personal mobility solutions, especially where public transportation systems are underdeveloped (Barter, 1999).

Actual_Transportation_Emission_Ratio_to_Target = Transportation_Emission / Transportation_Emission_Target
UNITS: Dimensionless

DOCUMENT: This ratio compares the transportation emission to the desired/target level, referring to government's intention. The higher the actual transportation emission, the higher the ratio, indicating that the emission level is getting farther than the desired level.

"Adoption_-_Environment_Driver" = "Reference_Environmental_Concern-Driver_Fraction"*Effect_of_Environmental_Concern_to_EV_Adoption
UNITS: Dimensionless

DOCUMENT: This variable represents the fraction of EV adoption driven by environmental concerns, particularly the impact of transportation emissions on pollution. As environmental awareness grows, especially regarding the consequences of emissions, the adoption driven by this factor increases proportionally. This relationship shows how heightened environmental concern leads to greater motivation for EV adoption, as individuals respond to emissions exceeding acceptable or target levels.

EMPIRICAL SUPPORT:
According to Bass diffusion models and studies on environmentally significant behavior (Rogers, 2003; Ajzen, 1991), highlighted that perceived environmental benefits, combined with social and normative influences, significantly affect early adoption rates.

"Adoption_-_Infrastructure_Driver" = Attractiveness_of_charging_station_capacity*Sensitivity_of_Adoption_To_Infrastructure_Attractiveness*
Reference_Infrastructure_Driver_Fraction
UNITS: Dimensionless

DOCUMENT: This variable captures how the perceived adequacy of charging infrastructure interacts with other factors to drive the adoption of electric vehicles.

EMPIRICAL SUPPORT:
In Europe, studies such as those by Axsen et al. (2016) and European Commission (2021) show that consumers are significantly more likely to adopt EVs when charging infrastructure is perceived as sufficient. In Indonesia, Ministry of Energy and Mineral Resources (2023) observed that EV adoption rates remain slow despite government incentives, due to consumers' concerns over the availability of charging stations.

"Adoption_-_Pricing_Driver" = Reference_Pricing_Driver_Fraction*Effect_of_EV_Price_Ratio_to_NON_EV_to_EV_Adoption
UNITS: dmnl

DOCUMENT: This variable represents the total fraction of EV adoption driven by price.As the effect of EV price ratio on EV adoption increases (due to lower/ closer EV price compared to NON EV), the fraction of EV adoption attributable to this driver grows proportionally. In emerging markets like Indonesia, where EVs are still relatively expensive compared to traditional vehicles, the price disparity significantly limits adoption (AC Ventures & AEML, 2023; IEA, 2021).

Adoption_from_External_Drivers = SMTH1(("NON-_EV_(Potential_Adopter)"*"Adoption_-_Pricing_Driver"*"Adoption_-_Environment_Driver"*"Adoption_-_Infrastructure_Driver")*Fraction_of_Potential_Adopting, 2)

{DELAY CONVERTER}
UNITS: Vehicle/Years

DOCUMENT: This variable calculates the annual EV adoption influenced by external factors, including environmental concerns, infrastructure availability, and pricing. The equation also incorporates a smoothing function to account for time delays between awareness of external factors and actual adoption. These delays reflect real-world processes such as saving for a purchase or researching EV options (Sterman, 2000).

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
Research shows that infrastructure development is a key enabler for EV adoption in emerging markets (Coffman et al., 2017), while pollution concerns (Lonan et al., 2020) and financial incentives like subsidies or tax breaks also play significant roles (Muehlegger, 2011). However, not all individuals affected by these external drivers will adopt EVs due to personal preferences. Hence, The equation calculates the multiplication of all external adoption driver with NON-EV Adopted and fraction of potential adopting.

Adoption_From_Imitation = Potentials_Contacts_With_Adopters*Imitation_fraction
UNITS: Vehicle/Years

DOCUMENT: This variable calculates the annual EV adoption influenced by imitation or social contagion. Research shows that the presence of adopters within a community can amplify adoption likelihood due to peer effects, trust in early adopters' experiences, and increased awareness (Brownstone & Train, 1999) and social network effects accounted for a substantial portion of EV adoption, emphasizing the importance of contact between adopters and non-adopters in driving diffusion (Zhang et al., 2018).

Attractiveness_of_charging_station_capacity = SMTH1(Charging_Station/Max_Charging_Station, 1.5)

{DELAY CONVERTER}
UNITS: Dimensionless

DOCUMENT: This variable represents the relative availability of charging stations compared to the maximum target set by the Indonesian government for 2040. This ratio evaluates the adequacy of current infrastructure in meeting future goals, while also serving as a attractiveness of adoption due to infrastructure accessibility. The equation used incorporates a smoothing function to account for gradual perception or attractiveness changes in infrastructure availability over time.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
Research by Li et al. (2017) highlights a time delay in consumers' perception of infrastructure improvements. While charging infrastructure increases, it takes 1–2 years for adoption rates to reflect these changes due to behavioral inertia and lagging awareness.

Avg_Baseline_EV_Purchase_Price = 35000000
UNITS: IDR/vehicle

DOCUMENT: This parameter represents the average price of an electric vehicle (EV) in Indonesia. The value of IDR 35 million is used in this variable as a moderate estimate for the average EV price in Indonesia.

EMPIRICAL SUPPORT FOR ASSUMPTION:
Given that motorcycles comprise approximately 80% of all vehicles in the country (Statistics Indonesia), and these vehicles generally range in price between IDR 30 million to IDR 45 million, this aligns with the findings from the AC Ventures and AEML 2023 report on Indonesia’s EV outlook.

Avg_Charging_Station_per_Vehicle = Infrastructure_CS_Per_Vehicle_with_Policy_Push*"SWITCH_-_Infrastructure_Push_Policy" + Indicated_CS_per_Vehicle*(1-"SWITCH_-_Infrastructure_Push_Policy")
UNITS: Charging Station/Vehicle

DOCUMENT: This variable represents the average Charging Station (CS) per vehicle, but it is also impacted by average baseline CS per Vehicle and a government intervention policy switch. These additional variables are used for policy testing.

Avg_Emission_%_per_EV = 1-Emission_%_Reduction_from_EV
UNITS: Dimensionless

DOCUMENT: This variable represents the emission percentage per EV. A study by the ASEAN Centre for Energy revealed that EVs reduce CO_2 emissions by about 20-30% compared to ICE vehicles. However, EVs still produce significant amounts of NOx and N2O emissions due to the high dependency on fossil fuels in Indonesia's electricity generation mix (Veza et al., 2023)

PARAMETER

Avg_Emission_per_Vehicle = 0.97
UNITS: C02 Ton/Vehicle/year

DOCUMENT: This parameter represents the average annual CO2 emissions per vehicle. This model uses 0.97 tons of CO2 per vehicle annually.

EMPIRICAL SUPPORT FOR ASSUMPTION:
According to data from Statistics Indonesia (BPS, 2023) and Worldometer (2024), the average emissions for vehicles (99% of which are non-EVs) from 2019-2023 was around 0.98 tons of CO2 per vehicle per year. Further, with averagely CO2 emission factor of 2.31 kg CO2 per liter of gasoline and an average mileage of 12,000 km/year, it results in approximately 0.9 tons of CO2 annually (EPA, 2022).

Avg_EV_Purchase_Price = Avg_Baseline_EV_Purchase_Price*Price_Subsidy_Implementation_Start*"SWITCH_-_Subsidy_Policy" + Avg_Baseline_EV_Purchase_Price*(1-"SWITCH_-_Subsidy_Policy")
UNITS: IDR/vehicle

DOCUMENT: This variable represents the average purchase price of an electric vehicle (EV) in the model, incorporating the effect of a government price subsidy policy, using a dynamic policy switch.

EMPIRICAL SUPPORT FOR VARIABLE CONCEPT: Studies consistently show that EV adoption is highly price sensitive. According to Hardman et al. (2017), purchase subsidies directly reduce upfront costs, making EVs more affordable and leading to higher adoption rates. Countries like Norway, where subsidies and incentives are substantial, have achieved EV market penetration exceeding 80% in recent years.

PARAMETER

Avg_Price_per_Non_EV = 15000000
UNITS: IDR/vehicle

DOCUMENT: This parameter represents the average price of an NON-EV in Indonesia. The value of IDR 15 million is used in this variable as a moderate estimate for the average NON-EV price in Indonesia.

EMPIRICAL SUPPORT FOR ASSUMPTION:
Given that motorcycles comprise approximately 80% of all vehicles in the country (Statistics Indonesia), and these vehicles generally range in price between IDR 10 million to IDR 25 million (AC Ventures & AEML, 2023).

PARAMETER

Avg_Vehicle_per_Person_Change_Rate = 0.025
UNITS: Dimensionless/year

DOCUMENT: This parameter represents how vehicle per person changes over time. The value accommodates the increasing change rate with +0.025 per year.

EMPIRICAL SUPPORT FOR ASSUMPTION:
According to historical and forecast data of urban population and total vehicle (Statistics Indonesia & Worldometers), number of vehicles will be growing faster than the growth of urban population. Average vehicle/person in 2019-2023 was 0.9 and average vehicle/person in 2024-2030 will be 1.6.

Avg_Vehicle_per_Person_index = EXP((Avg_Vehicle_per_Person_Change_Rate)*(TIME-STARTTIME))
UNITS: Dimensionless

DOCUMENT: This variable represents an exponential growth model, where the average number of vehicles per person changes over time. The exponential function indicates that the growth of vehicle ownership follows a compounding pattern. This means that as time progresses, the rate of growth builds on itself with 0.02 annual rate of change in the number of vehicles per person. TIME-STARTTIME in the equation calculates the time elapsed since the starting point of the model. It allows the formula to project growth dynamically from the start of the analysis.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION
This is aligned with the theory that says as economies develop, motorization rates increase disproportionately to population growth (Schafer & Victor, 2000).

PAREMETER

Baseline_Avg_Vehicle_per_person = 0.9
UNITS: Vehicle/Person

DOCUMENT: This parameter indicates the number of vehicle, in average, per person. This parameter is calculated by dividing Total Vehicle over Urban Population, which are sourced from Statistics Indonesia (BPS) and Worldometers. Considering historical average vehicle/person in 2019-2023 is 0.9, this parameter uses the same value.

PAREMETER

Change_in_Contact_Size_Rate = 0.750804433
UNITS: Dimensionless

DOCUMENT: This parameter represent the change in contact size rate. While in the early simulation years (which is also the beginning of EV acceleration program), the contact size is 10.3, substantial efforts to promote EVs, including government-led campaigns and events, mass advertising and promotional events have largely ceased, leading to contact size reduced by to only 1/4 of it. Consequently, EV awareness now grows organically, driven by interpersonal influence rather than broad media outreach

EMPIRICAL SUPPORT FOR ASSUMPTION:
This behavior is supported by the fact that from 2022 onward, public communication efforts have waned, with the government shifting their focus more on finding investor for infrastructure development and regulatory adjustments rather than extensive public promotions (Modern Diplomacy, 2024; AEI, 2024).

PAREMETER

Change_in_CS_per_Vehicle = 0.42
UNITS: Dimensionless

DOCUMENT: This parameter represents the change in Charging Station per EV. While in the early simulation years (which is also the beginning of EV acceleration program), government tries to cover 4-5% EVs for each of charging station. However, from 2022 to 2040, the average expected ratio is only around 0.007 charging stations per EV. Target-based trends suggest slightly lower ratios, with an average of 0.007 from 2022 to 2040 and 0.011 overall for 2019-2040. These trends align with government targets and the practical challenges of infrastructure development, such as the need for consistent policy support, budget allocation, and stakeholder participation. (AC Ventures and IDN Financial).
This parameter uses value of 0.42 post calibration.

Charging_Stations_Gap = Demand_on_Charging_Station-Charging_Station
UNITS: Charging Station

DOCUMENT: This variable calculates the gap between the demand for charging stations and the actual charging station. This gap represents the demand to be fulfilled with the charging station construction.

PARAMETER

Construction_Time = 1.5
UNITS: year

DOCUMENT: This parameter represents the time to construct charging station. This parameter assumes 1.5 years of construction due to investor finding, planning, designing, and construction itself.

EMPIRICAL SUPPORT FOR PARAMETER:
Large-scale charging networks or public infrastructure projects that involve multiple stations across a wide area may also need extensive planning and coordination, further extending the construction period (Kampshoff et al., McKinsey, 2022). The process can also be slowed down by regulatory requirements and the need to coordinate with local utilities and government agencies. In Indonesia, PLN (state utility) reported that constructing a public charging station (SPKLU) can take 4–15 months, depending on location and infrastructure readiness (Jakarta Post, 2022).

Contact_Size_Rate = Initial_Contact_Size_Rate*(1-STEP(Change_in_Contact_Size_Rate, 2023))
UNITS: Dimensionless/year

DOCUMENT: This variable represents the final annual number of potential EV adopters encounter existing adopters, and it changes in certain time. The equation indicates that the contact size rate is decreasing over time, represented by the factor (1−STEP), which means the rate reduces after 2023.

POLICY

CS_Push_Policy_Start_Time = 2029
UNITS: Dimensionless

DOCUMENT: This parameter represent the year when the policy starts to be implemented. The infrastructure acceleration policy is assumed to start in 2029, allowing the government to build collaboration with investor, set up the location and infrastructure materials, and finishing construction process until it is ready to used.

Demand_on_Charging_Station = MIN(EV_Adopted * Avg_Charging_Station_per_Vehicle, Max_Charging_Station)
UNITS: Charging Station

DOCUMENT: This variable represents the demand for charging stations, calculated by multiplying the number of charging stations required per EV by the number of EVs adopted. As the adoption of EVs increases, so does the demand for charging stations. However, the maximum demand is capped at 441,000 charging stations.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
According to the Indonesian Ministry of Energy and Mineral Resources (2022), this target aligns with the country's broader goal of supporting EV adoption while acknowledging the practical constraints of infrastructure expansion. Furthermore, research by Hossain et al. (2023) emphasizes the importance of infrastructure readiness in accelerating EV adoption, highlighting that charging station development must be aligned with the rate of EV adoption to avoid infrastructure bottlenecks.

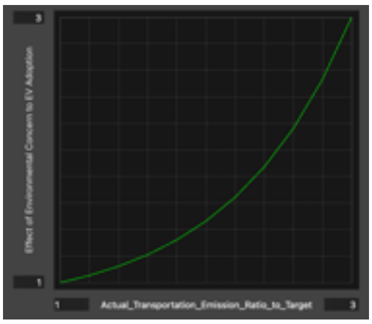
PARAMETER

Desired_Numbers_of_EV_Adopted = 106000000
UNITS: Vehicle

DOCUMENT: This parameter represents the desired number of electric vehicles (EVs) to be adopted by 2040 (end simulation).

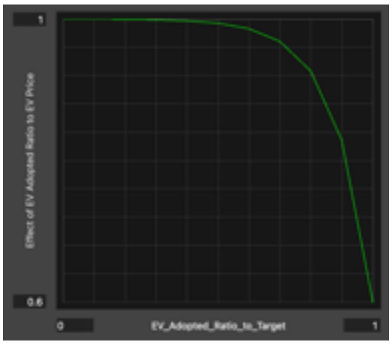
EMPIRICAL SUPPORT FOR ASSUMPTION:
The value reflects the government intention to have 2.2Mn EVs by 2025 (Ministry of Industry's plan as reported in the AC Ventures & AEML Report, 2023) and 15Mn EVs by 2030 (Coordinating Ministry for Maritime Affairs and Investment, reported by AntaraNews, 2024). To estimate the 2040 value, a moderate 23% growth rate is applied (vs CAGR 2025-2030 at 47%). This approach assumes a more sustainable trajectory for scaling EV adoption. The resulting calculated value for Desired Numbers of EV Adopted is approximately 106,000,000 EVs.

Effect_of_Environmental_Concern_to_EV_Adoption = GRAPH(Actual_Transportation_Emission_Ratio_to_Target)
Points: (1.000, 1.000), (1.200, 1.054), (1.400, 1.123), (1.600, 1.210), (1.800, 1.322), (2.000, 1.463), (2.200, 1.643), (2.400, 1.871), (2.600, 2.161), (2.800, 2.531), (3.000, 3.000)
UNITS: Dimensionless



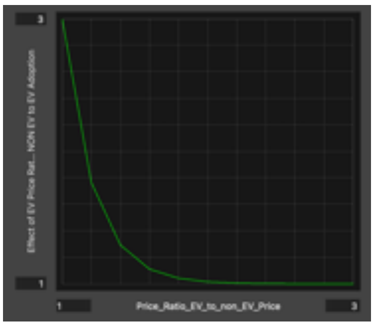
DOCUMENT: Effect of Environmental Concern on EV Adoption represents a graphical relationship where higher transportation emissions ratio to target trigger greater EV adoption due to pollution concerns. As emissions exceed desired level, the perceived urgency for environmentally friendly solutions, such as EVs, increases (Lonan et al., 2020).
The graphical function displays a positively sloped curve with increasing-increasingly behavior. When the ratio of actual emissions to target emissions is less than or equal to 1, the effect on EV adoption remains at a value of 1, making the effect of emission to EV adoption equals to the Reference Environmental Concern-Driver Fraction. However, as the ratio significantly exceeds 1, in current emission projection could be 3x of desired level, the adoption effect intensifies, potentially reaching up to 3 times the baseline Reference Fraction.

Effect_of_EV_Adopted_Ratio_to_EV_Price = GRAPH(EV_Adopted_Ratio_to_Target)
Points: (0.000, 1.0000), (0.100, 0.9999), (0.200, 0.9996), (0.300, 0.9990), (0.400, 0.9976), (0.500, 0.9943), (0.600, 0.9865), (0.700, 0.9685), (0.800, 0.9264), (0.900, 0.8284), (1.000, 0.6000)
UNITS: Dimensionless



DOCUMENT: Effect of EV Adopted Ratio to EV Price represents a graphical function that illustrates the relationship between numbers of EV Adopted and EV prices. As the number of EVs adopted increases, the EV Adopted Ratio to Target rises, this results in decreased EV Prices due to production efficiencies and market dynamics. Increased adoption drives innovation, efficiency, and competition, lowering prices over time (Rogers, 2003). Historical trends in the adoption of technologies like solar panels and smartphones confirm this pattern.
Therefore, it creates negative slope with decreasing-increasingly behavior. When the ratio of EV Adopted to Desired level is minimum or lower than 0.3, the EV price will not change. As the more EV adopted, the more efficient is the production and more competitive due to increasing demand, hence the price is gradually declining until lower bound at 60% of initial price. The lower bound of 60% (0.6) reflects a minimum price ratio accounting for current and foreseeable production economics. These insights are consistent with the constraints imposed by technological, material, and competitive market factors.

Effect_of_EV_Price_Ratio_to_NON_EV_to_EV_Adoption = GRAPH(Price_Ratio_EV_to_non_EV_Price)
Points: (1.000, 3.000), (1.200, 1.766), (1.400, 1.294), (1.600, 1.112), (1.800, 1.043), (2.000, 1.016), (2.200, 1.006), (2.400, 1.002), (2.600, 1.001), (2.800, 1.000), (3.000, 1.000) {GF EXTRAPOLATED}
UNITS: Dimensionless



DOCUMENT: Effect of EV Price Ratio to EV adoption is a graphical function that illustrates the relationship between the price competitiveness of EVs compared to non-EVs and their impact on adoption rates. As the price of EVs becomes more competitive (i.e., the price ratio decreases), the adoption fraction driven by pricing incentives increases. This results in a negative slope with decreasing-decreasingly behavior. In this graphical function, when the EV price ratio is 2 or higher (in this case EV price is more than twice than NON-EV), the impact on adoption is set at 1x the reference pricing driver fraction. However, as the price ratio decreases (i.e., EVs Price become more comparable to non-EVs), the impact on adoption fraction grows, potentially up to 3x the reference fraction.

PARAMETER

Emission_%_Reduction_from_EV = 0.3
UNITS: Dimensionless

DOCUMENT: This parameter represents the percentage of emission reduction produced by each electric vehicle. In this parameter, a moderate reduction value of 30% is used, reflecting typical emission savings due to the lower carbon footprint of EVs relative to conventional vehicles.

EMPIRICAL SUPPORT FOR ASSUMPTION:
Although comprehensive studies on the exact emission reduction per EV are limited, regional studies provide useful estimates. For example, in China and India, emission reductions from EVs range from 19-45%, depending on the fossil fuel dependency of the electricity grid (International Council on Clean Transportation, 2021).

Emission_Produced_by_EV = Avg_Emission_per_Vehicle * EV_Adopted * Avg_Emission_%_per_EV
UNITS: C02 Ton/Years

DOCUMENT: This variable quantifies the transportation emissions generated by the total number of electric vehicles (EVs) on the road. It reflects the positive impact that switching from conventional internal combustion engine (ICE) vehicles to EVs reduces overall transportation emission.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
Analysis by the International Energy Agency (IEA) emphasizes that transitioning to renewable energy sources in Indonesia's grid can significantly enhance the emissions reduction potential of EVs. While EVs currently offer a modest reduction in lifecycle emissions, broader decarbonization of the power sector is crucial to realizing their full environmental benefits.

Emission_Produced_by_Non_EV = "NON-_EV_(Potential_Adopter)" * Avg_Emission_per_Vehicle
UNITS: C02 Ton/Years

DOCUMENT: This variable calculates the emission produced by NON-EV every year, by multiplying numbers of NON-EV and average emission per vehicle. Despite constant average annual emission per vehicle, increasing numbers of NON-EV will increase the transportation emission.

EV_Adopted_Ratio_to_Target = EV_Adopted/Desired_Numbers_of_EV_Adopted
UNITS: Dimensionless

DOCUMENT: This variable calculates the ratio of actual EV adoption compared to the intended or desired level of adoption set by government targets. The ratio increases as the number of EVs adopted approaches or exceeds the target and decreases if the actual adoption falls short of the desired target.

EV_Adopter_Contact = EV_Adopted * Contact_Size_Rate
UNITS: Vehicle/Years

DOCUMENT: This variable represents the interaction or exposure of potential adopters (non-EVs) to existing EV adopters. It is calculated as the product of EV Adopted (the number of adopted EVs) and the Contact Size Rate (the rate at which adopters interact with potential adopters within their social networks).

EMPIRICAL SUPPORT:
A study by Zhang et al. (2018) emphasized that in urban areas, the presence of early adopters creates a network effect, where potential adopters are more likely to adopt an EV after interacting with those who already own one.

EV_Contribution = EV_Adopted/Total_Vehicle
UNITS: Dimensionless

DOCUMENT: This variable represents the proportion of EVs within the total vehicle stock, calculated as the ratio of EV Stock to Total Vehicle Stock. It provides a key measure of EV penetration in the market, reflecting the transition from traditional vehicles to electric alternatives. Initially, the EV Contribution starts near 0, as the number of EVs is minimal compared to the vast number of NON-EVs. However, as EV adoption grows over the years, this variable steadily increases, indicating a growing share of EVs in the total vehicle population. This dynamic highlight the market shift toward electrification and the increasing prominence of EVs as a sustainable transportation option.

EV_Price = Effect_of_EV_Adopted_Ratio_to_EV_Price * Avg_EV_Purchase_Price

UNITS: IDR/vehicle

DOCUMENT: This variable represents the price level of electric vehicles, which is influenced by the average market price of EVs and the dynamic effect of the number of EVs adopted ratio to its target.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
A study by Nykvist & Sprei (2015) demonstrates that as the market for EVs expands, costs decrease, particularly due to manufacturing efficiencies and technological advancements. Research by Breetz et al. (2018) highlights that the lower EV prices through economies of scale and increased competition is a critical factor in driving adoption.

PARAMETER

Fraction_of_Potential_Adopting = 0.6
UNITS: Dimensionless/year

DOCUMENT: This parameter represents the proportion of potential adopters influenced by external drivers who decide to adopt electric vehicles (EVs). This parameter is set at 0.6, indicating that 60% of individuals aware of these external drivers act on adopting EVs.

EMPIRICAL SUPPORT FOR ASSUMPTION:
Indonesia's Electric Vehicle Outlook from AC Venture (2023) found that 63% of respondents are aware of EV and a study by Rezvani et al. (2015) in Renewable and Sustainable Energy Reviews highlights that while awareness and positive attitudes toward EVs are high, the actual adoption rate tends to be influenced by practical barriers such as cost and infrastructure, resulting in partial conversion of intent into action.

POLICY

Gov't_Push_on_CS_Improvement = 1 OR 2
UNITS: Dimensionless

DOCUMENT: This parameter represents the government's effort to accelerate the development of electric vehicle (EV) charging station (CS) infrastructure beyond the "business-as-usual" (BAU) rate of construction. It serves as a simplified mechanism to model the scale of government intervention in expanding charging infrastructure, which is a critical enabler for EV adoption.

POLICY IMPLEMENTATION THROUGH VARIABLE VALUES:
When value = 1, the rate of CS construction is doubled relative to the BAU rate, indicating moderate government intervention.
When value = 2, the rate of CS construction is tripled relative to the BAU rate, indicating a more aggressive government push.

POLICY

Government_Price_Subsidy = 0.15 OR 0.4 OR 0.6
UNITS: Dimensionless

DOCUMENT: This parameter represents the financial incentive provided by the government to reduce the effective purchase price of electric vehicles (EVs).In this model, the Government Price Subsidy parameter serves as a simplified representation of these policy mechanisms. By reducing the effective EV price, it enhances the Pricing Driver, which directly influences consumer adoption decisions.

POLICY IMPLEMENTATION THROUGH VARIABLE VALUES:
1. Maintain the existing policy, reducing prices through EV tax removal (15% price reduction).
2. Moderate Scenario: Tax removal combined with a 25% price subsidy (40% price reduction).
3. Optimistic Scenario: Tax removal combined with a 45% price subsidy (60% price reduction).

PARAMETER

Imitation_fraction = 0.108
UNITS: dimensionless

DOCUMENT: This parameter captures the imitation effect, a key aspect of the diffusion of innovations theory (Rogers, 1962), representing the influence of social dynamics on individuals' decision-making. It quantifies the likelihood that non-adopters of a product (like EVs) will adopt based on observing others who have already done. Setting the imitation fraction to 0.108 implies that 10.8% of potential non-adopters that are contacted by existing adopters are influenced in given time.

EMPIRICAL STUDY FOR ASSUMPTION:
Zhang et al. in their study of Social network effects on EV adoption: Insights from China (Renewable and Sustainable Energy Reviews, 2018, pg.94) highlighted that imitation effect contributed to 10–12% of the adoption rate in their China EV diffusion model for urban areas. A paper of Electric Vehicle Diffusion in the Indonesian Automobile Market: A System Dynamics Modelling (Lonan, et al., 2020) found that the imitation fraction in their study is at the range of 0.23 to 0.7.

Indicated_Avg_Vehicle_Per_Person = Baseline_Avg_Vehicle_per_person * Avg_Vehicle_per_Person_index
UNITS: Vehicle/Person

DOCUMENT: The variable calculates the indicated average number of vehicles per person at any given point of time by considering two factors: (a) Baseline Average Vehicle per Person, which is is the initial or starting value of the average vehicle ownership per person, based on observed historical data, and (b) Avg Vehicle per Person Index, which is an adjustment factor representing how the average vehicle ownership is expected to change over time due to influencing factors such as economic growth, urbanization, or societal trends.

Indicated_CS_per_Vehicle = Initial_Avg_CS_per_Vehicle*(1-STEP(Change_in_CS_per_Vehicle, 2023))
UNITS: Charging Station/Vehicle

DOCUMENT: This parameter represents the average number of charging stations (CS) available per electric vehicle (EV) in the system, adjusted to account for a potential shift in infrastructure growth starting in a specific year (e.g., 2023). It captures the dynamic relationship between EV adoption growth and the scaling of charging infrastructure to maintain an adequate charging station-to-vehicle ratio. The STEP function is used to represent a change (reduction) in the CS per vehicle ratio starting in a specific year (e.g., 2023). This reflects the anticipated decrease in CS availability per vehicle as EV adoption accelerates unless infrastructure growth keeps pace.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
By March 2022, the number of charging stations had increased to 267 across 195 locations, reflecting significant progress in infrastructure development (Indonesia Investment Coordinating Board, 2024). As of April 2023, Indonesia had approximately 842 charging stations, achieving only about 47% of the annual target. This indicates a slowdown in infrastructure development relative to earlier years. The existing charging stations are predominantly located in regions like Bali and Java, including West Java and DKI Jakarta provinces, suggesting uneven distribution and potential accessibility issues for EV users in other parts of the country (www.un-page.org).

Indicated_Vehicles_in_ID = ID_Urban_Population*Indicated_Avg_Vehicle_Per_Person
UNITS: Vehicle

DOCUMENT: This variable represents the indicated number of total vehicle in Indonesia by multiplying the indicated average vehicle per person and the Urban Population. Higher population brings the indication of higher numbers of vehicles.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION:
Kenworthy and Laube (2001) suggest that urban population growth fosters vehicle ownership as people seek improved mobility options in expanding cities.

Infrastructure_CS_Per_Vehicle_with_Policy_Push = Indicated_CS_per_Vehicle*(1+STEP(Gov't_Push_on_CS_Improvement, CS_Push_Policy_Start_Time))
UNITS: Charging Station/Vehicle

DOCUMENT:
This variable simplifies the representation of government policies aimed at boosting charging infrastructure development to support EV adoption. It represents the effective availability of charging stations per electric vehicle (EV) under the influence of a government policy push. It adjusts the indicated charging stations per vehicle by incorporating the government's intervention to accelerate charging station (CS) development. The STEP function models the timing of the government's policy intervention.

PARAMETER

Initial_Avg_CS_per_Vehicle = 0.0244
UNITS: Charging Station/Vehicle

DOCUMENT: This parameter reflects the average number of charging stations per EV in Indonesia, derived from sources such as Statistics Indonesia and Worldometers. From historical data, government initiatives aimed to install more charging stations, resulting in a ratio where each station served 4% of EVs in 2019-2020. This reflects the heavy push in infrastructure development during the initial years of adoption. However, projections indicate a decreasing trend in the ratio over time (AC Ventures and IDN Financial). The value of 0.244 is the average charging station per vehicle in 2019-2023.

PARAMETER

Initial_Charging_Station = 40
UNITS: Charging Station

DOCUMENT: This parameter determines the initial number of charging stations in 2019 (start time), which is set at 40 charging stations (Akker & Ascendis, 2022).

PARAMETER

Initial_Contact_Size_Rate = 10.3489
UNITS: Dimensionless/year

DOCUMENT: This parameter represents the annual number of potential EV adopters encounter existing adopters, which influences the likelihood of adoption. This parameter is set to 10.3489 post calibration-optimization, assuming higher contact size rate in the early years of simulation.

EMPIRICAL SUPPORT FOR PARAMETER:
The Indonesian government actively promoted EV adoption through initiatives like trial electric buses and e-fleet taxis (2020–2021), heavy communication campaigns at national and international events such as the B20/G20 Summits (2021–2022), and directives from the Ministry of State-Owned Enterprises encouraging EV use in government operations (2022–2023) (AC Ventures and AEML, July 2023). However, starting 2023, the communication of EV started to dwindle.
In emerging markets like Indonesia and other Southeast Asian countries, the adoption of new technologies, including EVs, is strongly influenced by peer networks, especially when infrastructure is limited, or price sensitivity is high. Studies have found that in these regions, EV adoption is often driven by word-of-mouth and the visibility of early adopters.

PARAMETER

Initial_EV_Adopted = 705
UNITS: Vehicle

DOCUMENT: This parameter determines the initial number of EV Adopted in 2019 (start time), which is set at 705 vehicles (Maximize Vehicle Market, 2023). Government has set the target of EV Adopted of 15Mn by 2030 (or closing to 8% penetration) and 106Mn vehicles by 2040 (or closing to one-third of the vehicle population).

PARAMETER

Initial_ID_Urban_Population = 150725703
UNITS: Person

DOCUMENT: This parameter defines the Urban population in 2019, sourced from Statistics Indonesia (BPS), and is set as 150,725,703.

PARAMETER

Max_Charging_Station = 441000
UNITS: Charging Station

DOCUMENT: This parameter represents the desired number or charging station that government aim to have in Indonesia by 2040. The value refers to government's target on numbers of charging station in 2030 which is 32,000 (Nair, 2024) and extrapolated to 2040 to be 441,000 charging station. This maximum charging station serves as limitation of infrastructure due to limitation in resources, investor, or funding.

"Non-EV_Contribution" = 1-EV_Contribution
UNITS: Dimensionless

DOCUMENT: This variable represents the proportion of NON-EVs in the total vehicle stock, calculated as the ratio of NON-EV Stock to Total Vehicle Stock. It serves as a critical indicator of the dominance of traditional vehicles in the market and plays a significant role in determining the probability of interactions between NON-EV users and EV adopters. Initially, the NON-EV Contribution starts close to 1, reflecting the overwhelming prevalence of NON-EVs due to the limited number of EVs in the early stages of adoption. However, as EV adoption grows over time and the NON-EV stock diminishes, this variable steadily decreases, signaling the transition toward a more EV-dominant market.

Potentials_Contacts_With_Adopters = Probability_of_Contact_with_Non_EV * EV_Adopter_Contact
UNITS: Vehicle/Years

DOCUMENT: This variable represents the potential number of NON-EV vehicles (which also defines the number of NON-EV users) that could come into contact with EV adopters. It serves as a dynamic mechanism for modeling the spread of EV adoption, capturing the interaction between NON-EV users and EV adopters.

EMPIRICAL SUPPORT FOR ANALYTIC EQUATION
The variable is grounded in the principles of the Bass Diffusion Model, which explains how innovations spread through imitation process, where exposure to adopters increases the likelihood of non-users transitioning to EVs.
Zhang et al. (2018, Social network effects on EV adoption: Insights from China) found that social network effects accounted for a substantial portion of EV adoption, emphasizing the importance of contact between adopters and non-adopters in driving diffusion.

Price_Ratio_EV_to_non_EV_Price = EV_Price / Avg_Price_per_Non_EV
UNITS: Dimensionless

DOCUMENT: This variable calculates the ratio of the EV price to the average market price of non-EV vehicles. The ratio will to be higher when the price of EVs exceeds that of non-EVs, which is often the case in many markets, particularly in the early stages of EV adoption such as Indonesia.

Price_Subsidy_Implementation_Start = 1-STEP(Government_Price_Subsidy, Subsidy_Policy_Start_Time)
UNITS: Dimensionless

DOCUMENT: This formulation indicates a stepwise % EV price after incorporating government subsidy at a specific time. Before the Subsidy_Policy_Start_Time, the price subsidy value remains at zero (no policy in place). At the Subsidy_Policy_Start_Time, the subsidy immediately steps up to the value defined by Government_Price_Subsidy. This approach simplifies the modeling of a policy intervention, assuming the subsidy is implemented fully and abruptly at a specific point in time.

Probability_of_Contact_with_Non_EV = "NON-_EV_(Potential_Adopter)" / Total_Vehicle
UNITS: Dimensionless

DOCUMENT: This variable represents the probability of encountering or interacting with a NON-EV within a given year. It is calculated by dividing the NON-EV Stock by the Total Vehicle Stock, which serves as the overall 'population'. Initially, when only a few EVs have been adopted, the likelihood of encountering a NON-EV is high. However, as EV adoption increases and the number of NON-EVs decreases, the probability of contact with a NON-EV becomes progressively lower.

PARAMETER

"Reference_Environmental_Concern-Driver_Fraction" = 0.1
UNITS: Dimensionless

DOCUMENT: This parameter represents the baseline fraction at which transportation emissions influence individuals to adopt EVs. It reflects the "normal" level of environmental concern. The parameter value is 0.1.

EMPIRICAL SUPPORT FOR ASSUMPTION:
Based on empirical reference of EV study in Indonesia, there is 6% of respondents strongly prefer EVs due to style, autonomous features, and low emissions, demonstrating advanced EV knowledge on positive impact to environment

(Novizayanti et al., 2021). Meanwhile, a study in China found that pollution smog correlates with EV purchase intention at a factor of 0.25 (Lin & Wu, 2018)

PARAMETER

Reference_Infrastructure_Driver_Fraction = 0.282251
UNITS: Dimensionless

DOCUMENT: This parameter represents the baseline influence of charging infrastructure availability on EV adoption decisions, capturing the "normal" level of motivation driven by infrastructure. The parameter is set at 0.282251, reflecting a median value between 0.085-0.5 and post calibration-optimization

EMPIRICAL SUPPORT FOR ASSUMPTION:
Empirical evidence supports this value: Lazuardy et al. (2024) in Electric Vehicle Diffusion in the Indonesian Automobile Market: A System Dynamics Modelling uses a pessimistic scenario with a Charging Infrastructure Capacity Strategy rate of 0.5. Similarly, Lin et al. (2018), in their study on EV adoption in Chinese first-tier cities, report a correlation coefficient of 0.085 between charging station availability and purchase intention.

PARAMETER

Reference_Pricing_Driver_Fraction = 0.291173
UNITS: Dimensionless

DOCUMENT: This parameter quantifies the baseline/reference influence of EV price on adoption decisions, representing the "normal" level of pricing motivation. This parameter uses value of 0.291173 post calibration-optimization

EMPIRICAL SUPPORT FOR ASSUMPTION:
This is supported by empirical findings such as Novizayanti et al. (2021), which indicate that 34% of respondents in Indonesia prioritize vehicle price and range when choosing an EV. Additionally, Lin & Wu (2018) found that in China, price acceptability correlates with EV purchase intention at a factor of 0.29. Other studies, like Zaino et al. (2024), estimate that price factors (upfront costs, incentives, and perceived long-term savings) contribute 30-50% to the adoption decision. These findings underscore the significant role that price plays in influencing consumer behavior toward EV adoption.

PARAMETER

Sensitivity_of_Adoption_To_Infrastructure_Attractiveness = 1.00154
UNITS: Dimensionless

DOCUMENT: This parameter represents how sensitive the adoption rate is to improvements in charging infrastructure. It quantifies the responsiveness of consumers' EV adoption decisions to changes in the availability and perceived accessibility of charging stations. Assigning a sensitivity value of 1.00154 (post calibration-optimization) suggests that charging availability significantly enhances consumer confidence to the Reference Infrastructure Driver Fraction, accelerating adoption rates.

EMPIRICAL SUPPORT FOR ASSUMPTION:
A study by Lazuardy et al. (2024) emphasizes "range anxiety" as a major deterrent, reflecting consumers' hesitation to adopt EVs due to the insufficient availability of charging stations.

POLICY

Subsidy_Policy_Start_Time = 2026
UNITS: Dimensionless

DOCUMENT: This parameter represent the year when the policy starts to be implemented. The price subsidy is assumed to start in 2026 fiscal year.

POLICY

"SWITCH_-_Infrastructure_Push_Policy" = 0
UNITS: Dimensionless

DOCUMENT: This variable serves as switch on/off to activate the policy. 1 is when the policy activated, 0 is when policy deactivated.

POLICY

"SWITCH_-_Subsidy_Policy" = 0
UNITS: Dimensionless

DOCUMENT: This variable serves as switch on/off to activate the policy. 1 is when the policy activated, 0 is when policy deactivated.

PARAMETER

Time_to_Adjust_to_Indicated_Vehicles = 1
UNITS: year

DOCUMENT: This parameter represents the time to adjust the indicated number of vehicles in Indonesia with the actual number of vehicles. The value is 1, meaning the adjustment time takes in 1 year.

Transportation_Emission = Emission_Produced_by_Non_EV+Emission_Produced_by_EV
UNITS: C02 Ton/Years

DOCUMENT: This variable calculates the total emission from both NON-EV and EV. Transportation Emission variable is one of key indicators of the model to be monitored as emission concern is one of the backgrounds for this study. Emission (CO_2 Ton per year) is defined as a rate of release into the atmosphere. Since it is modeled as a function of other variables (emission level from number of vehicles), making it a dynamic variable rather than a stock.

Transportation_Emission_Target = GRAPH(TIME)
Points: (2019.00, 126419170.0), (2020.00, 130807700.0), (2021.00, 143291550.0), (2022.00, 148733641.0), (2023.00, 143291660.0), (2024.00, 138048793.0), (2025.00, 132997757.0), (2026.00, 128131532.0), (2027.00, 123443356.0), (2028.00, 118926715.0), (2029.00, 114575332.0), (2030.00, 110383161.0), (2031.00, 110000046.0), (2032.00, 109618261.0), (2033.00, 109237800.0), (2034.00, 108858661.0), (2035.00, 108480837.0), (2036.00, 108104325.0), (2037.00, 107729119.0), (2038.00, 107355216.0), (2039.00, 106982610.0), (2040.00, 106611298.0)
UNITS: C02 Ton/Years

DOCUMENT: This variables represents the desired level of emissions set by the government. This target is modeled as a table function projecting GHG reductions in line with Indonesia's broader climate goals.

EMPIRICAL SUPPORT:
According to Indonesia's climate action plan, the overall greenhouse gas (GHG) emissions target is 1,244 million tons CO_2 by 2030 and 892 million tons CO_2 by 2040 (The Ministry of Environment and Forestry, 2023). While specific targets for transportation emissions are not explicitly outlined, the transportation target is estimated based on its historical contribution to national GHG emissions, as sourced from Worldometer and related reports.

PARAMETER

Urban_Change_Fractional_Rate = 0.02
UNITS: Dimensionless/year
DOCUMENT: This parameter represents the rate at which Indonesia (ID) Urban population change every year. The rate has considered population net change rate factors which are birth, death, and migration within Indonesia Urban.

EMPIRICAL SUPPORT FOR ASSUMPTION:
The value of 0.02 is determined by considering historical Indonesia Urban Population growth in 2019-2023 (Statistic Indonesia - BPS), which is 2.2% annually, and projected Indonesia Urban Population growth in 2023-2040 (Worldometer), which is 1.6% annually.

3. Model Sensitivity

Local Sensitivity Test

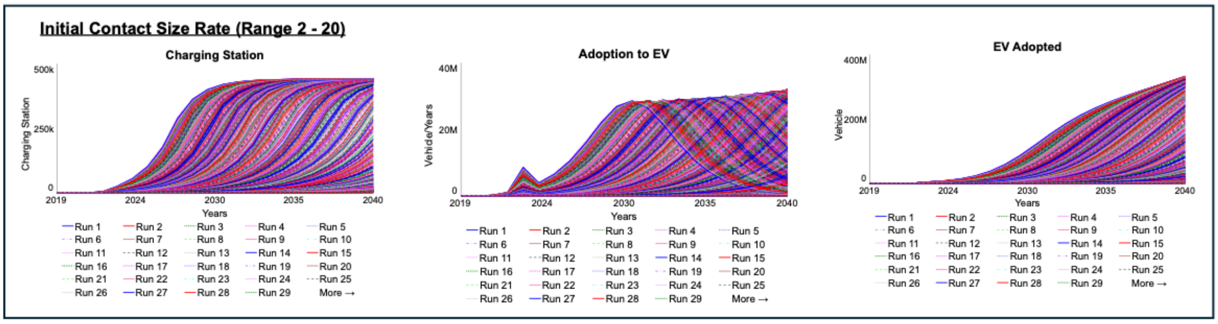
Local sensitivity test was conducted for the uncertain parameters on baseline scenario. The Sobol Sequence sampling method was employed, with uniform distribution random. The 1,000 runs ensured thorough, reliable confidence intervals. The result is summarized in the following table.

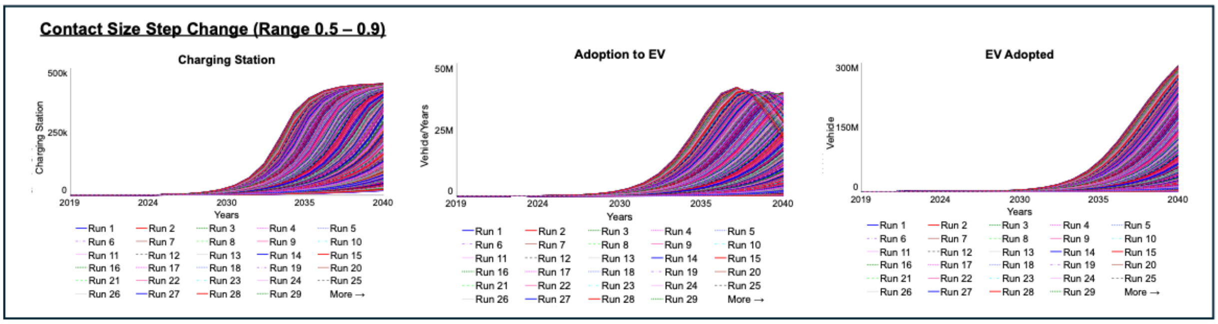
PARAMETERS					
Sector	**Variable**	**MIN**	**BASELINE**	**MAX**	**Sensitivity**
Total Vehicle Projection	Urban Change Fractional Rate	0.0125	0.02	0.05	Numerically Sensitive
	Avg Vehicle per Person Change Rate	0.018	0.025	0.05	Numerically Sensitive
	Baseline Avg Vehicle per person	0.5	0.9	1.5	Numerically Sensitive
Environmental Concern Driver	Avg Emission per Vehicle	0.5	0.97	1.5	Numerically Sensitive
	Reference Environmental Concern-Driver Fraction	0.005	0.1	1	Numerically Sensitive
Pricing Driver	Avg Baseline EV Purchase Price	15,000,000	35,000,000	60,000,000	Numerically Sensitive
	Avg Price per Non EV	10,000,000	15,000,000	30,000,000	Numerically Sensitive
	Reference Pricing Driver Fraction	0.1	0.291173	1	Numerically Sensitive
Infrastructure Driver	Initial Avg CS per Vehicle	0.01	0.0244	0.06	Behaviourally Sensitive
	Change in CS per Vehicle	0	0.42	0.75	Numerically Sensitive
	Construction Time	0.5	1.5	2.5	Numerically Sensitive
	Sensitivity of Adoption To Infrastructure Attractiveness	0.1	1.00154	2	Numerically Sensitive
	Reference Infrastructure Driver Fraction	0.1	0.282251	1	Numerically Sensitive
	Fraction of Potential Adopting	0.05	0.6	0.99	Numerically Sensitive
Social Contagion Driver	Imitation fraction	0.01	0.108	0.5	Behaviourally Sensitive
	Initial Contact Size Rate	2	10.3489	20	Behaviourally Sensitive
	Change in Contact Size Rate	0.5	0.750804433	0.9	Behaviourally Sensitive

GRAPHICAL FUNCTIONS					
Graphical Functions	**Variable**	**MIN**	**BASE**	**MAX**	**Sensitivity**
Effect of Environmental Concern to EV Adoption	Exponent Effect of Environmental Concern to EV Adoption	1	2.39	3.58	Minor Numerical Sensitive
Effect of Environmental Concern to EV Adoption - Multivariate Sensitivity					Numerical Sensitive
Effect of EV Adopted Ratio to EV Price	Exponent Effect of EV Adopted Ratio to EV Price	-0.615	-0.41	-0.205	Not Sensitive
Effect of EV Adopted Ratio to EV Price - Multivariate Sensitivity					Numerical Sensitive
Effect of EV Price Ratio to NON EV to EV Adoption	Exponent Effect of EV Price Ratio to NON EV to EV Adoption	-14.5	-9.75	-4.5	Not Sensitive
Effect of EV Price Ratio to NON EV to EV Adoption - Multivariate Sensitivity					Numerical Sensitive

The following analysis is purpose to clarify and explain the sensitivity of the key and uncertain parameters in the model.

Initial Contact Size Rate and Contact Size Step Change

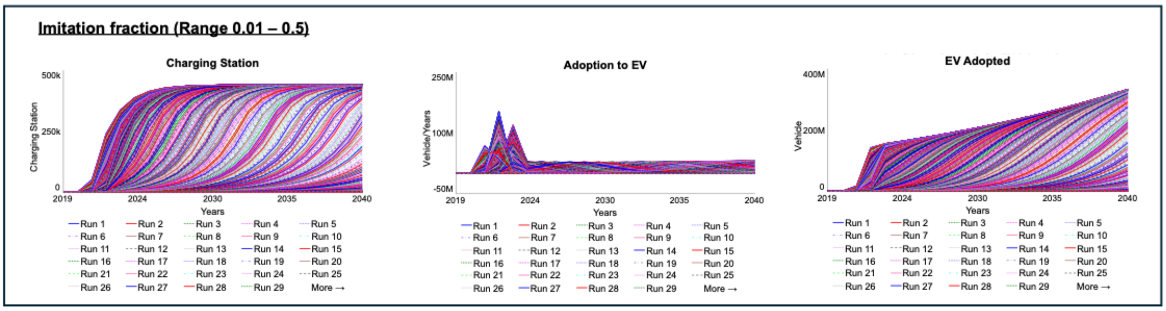




The model's KPIs are behavior sensitive to the changes in these two parameters, particularly due to the influence of Peer-Powered Growth loop (R2) – which is also the one of the dominant loops in the system. This loop emphasizes the role of peer influence in accelerating the adoption of electric vehicles (EVs). Behavioral shift will occur when the contact size increase or decrease.

In this model, it becomes more pronounced after 2023. It aligns with the analysis that indicating government-led initiatives to promote and advertise EVs ceased after 2022/2023, hence awareness growth slowed, and individuals relied more heavily on information from their immediate, smaller social circle. Therefore, this sensitivity analysis becomes a leverage point when exploring the policy.

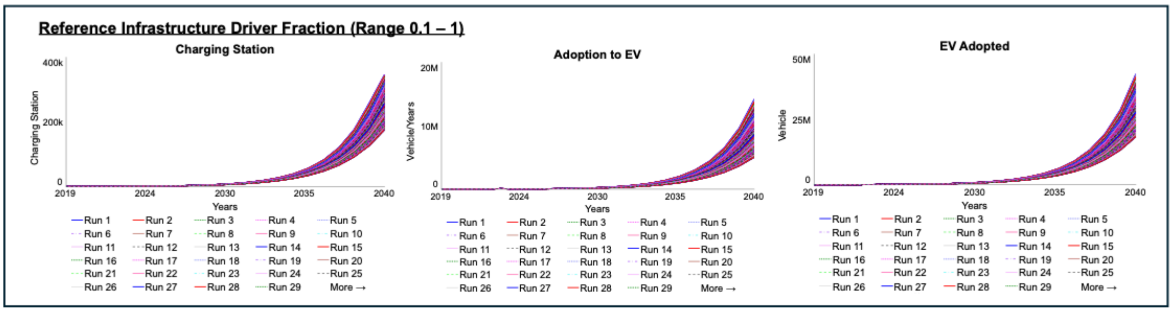
Imitation Fraction



Similarly, the model is behaviorally sensitive to the change in this Imitation Fraction. This parameter is closely linked to Peer-Powered Growth loop (R2) and Recruitment Saturation (B2), both of which directly influence EV adoption through imitation.

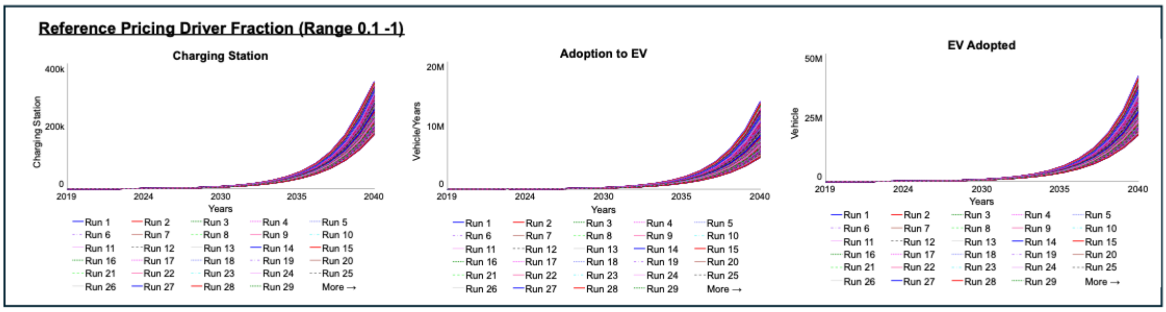
The model itself is a simplification of Bass Diffusion model, where the imitation fraction is represented by a single parameter capturing societal norm and interaction. In reality, imitation fraction can be influenced by various factors, including word of mouth, targeted advertising, and compatibility of the advertisement content with the potential adopters. In the future project, imitation fraction is highly suggested to be detailed as explicit as possible to capture different factors that driving social contagion.

Reference Infrastructure Driver Fraction



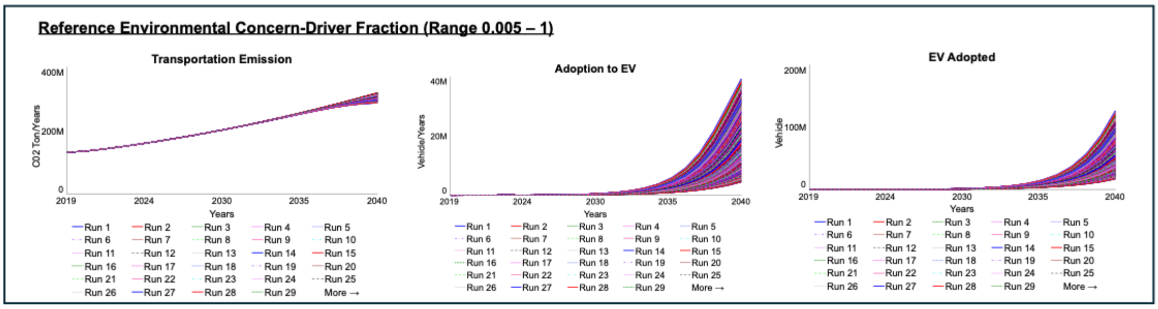
The model simulation demonstrates numerical sensitivity to this parameter, but the number differences are considerable, particularly after 2035. However, the model does not exhibit behavioral change, which is aligned with the expectation. This parameter drives the adoption of EV through Plug and Play (R3) reinforcing loop.

Reference Pricing Driver Fraction



Similar to Reference Infrastructure Driver Fraction, the model simulation also demonstrates the numerical sensitivity to the parameter of Reference Pricing Driver Fraction. However, the model does not exhibit behavioral change, which is aligned with the intention. This parameter drives the adoption of EV through Value for Volt (R4) reinforcing loop.

Reference Environmental-Concern Driver Fraction



The model is also numerically sensitive to Reference Environmental-Concern Driver Fraction with considerable number difference, particularly in KPI's Adoption to EV and EV Adopted. The behavior doesn't change, which is as per expected, since this parameter drives the reinforcing behavior of Clean Commute Catalyst loop (R5).