Transitioning to Electric Vehicles in the US
– *Communicating System Dynamics Modelling and Systems Thinking*

by
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Abstract

Concerns about growing greenhouse gas emissions from fossil fuels have become increasingly pressing in recent years and reducing energy use and shifting to cleaner fuels have become explicit political goals. The US is lagging behind the global average in transitioning from a fossil fuel-based vehicle fleet to zero emission vehicles. This thesis paper sets out to explore and clarify dynamic interactions that have been holding back adoption of electric vehicles in the US and to identify policies with potential to accelerate adoption in the coming years. Rooted in previous work and existing theories, system dynamics modeling and model simplification steps have been applied to derive new insights into the US passenger vehicle market. The thesis paper aspires to communicate these insights in a way that makes them accessible to a non-SD audience. The thesis findings point to increased familiarity with battery electric vehicle technology and learning curve effects on overall utility of battery electric vehicles, being the main drivers of adoption of battery electric vehicles in the US. The development in familiarity and utility is found to be onset by the global development – i.e. early adopters in other countries where the internal combustion vehicle dominance is less powerful or has been outweighed by successful battery electric vehicle incentives. The thesis model reveals the importance of considering possible influences from other markets for assumed isolated markets that are relatively underdeveloped. Several polices aimed to promote zero emission vehicle adoption, have been deployed in the US over the years, though the US has taken less of a supportive approach than China and several European countries. The thesis paper examines four separate policy categories and finds that Marketing Spending and Vehicle Purchase Subsidies are both feasible policy options, while Infrastructure Incentives have little potential to influence key performance indicators like market share distribution. Taxation of CO_2 emissions from fossil fuel combustion is identified as the most efficient among the policies tested. This policy works to increase the overall relative utility of battery electric vehicles and cancels out some of the strength of the internal combustion vehicle dominance. The thesis paper makes available an interactive learning environment analysis tool that aspires to help users gain understanding of the dynamics at play when transitioning from a vehicle fleet consisting of predominantly internal combustion vehicles to a more diverse vehicle fleet. The analysis tool allows users to experiment with policies that might accelerate the development in battery electric vehicle adoption and explore impacts of adjusting underlying model assumptions, without requiring prior knowledge or skills, nor any subscriptions or software licenses The interactive learning environment enables interaction with model metrics but also aims to communicate structural model insights, which sets it apart from many other available projection tools.

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Chapter 1. Introduction

1.1 Background

Sustainable use of resources has been an explicit political goal since the late 1980s but has not gained much real-world traction until the latest decade. Since the turn of the millennium concerns about greenhouse gas emissions from fossil fuels have become increasingly pressing. In 2015 United Nations defined the global Sustainable Development Goals, which, among other things, are designed to promote a low carbon future and the use of clean energy [1] – emphasizing the need to transition to alternative fuel vehicles. Still, in 2021, less than 1.4 % of the worlds passenger vehicle fleet was electric or plug-in hybrid [2].

In the 2015 paper *Stumbling towards Sustainability*, John Sterman contemplates that:

> The failure of AFV [Alternative Fuel Vehicle] programs to date is commonly attributed to high costs and immature technology. Certainly, the high cost and low functionality of AFVs compared to fossil-ICE [Internal Combustion Engine] limits their market potential today, particularly in nations like the US where gasoline is priced far below the level that would reflect its environmental, climate, health and other externalities. More subtly, the current low functionality and high cost of alternatives, and low gasoline taxes, are endogenous consequences of the dominance of the internal combustion engine and the petroleum industry, transport networks, settlement patterns, technologies, and institutions with which it has coevolved. The dominance of internal combustion suppresses the emergence of alternatives, maintaining the dominance of fossil-ICE. These feedbacks mean that sustained AFV adoption would be difficult even if AFV performance equaled that of fossil-ICE today [3].

Since the publishing of this article, the share of electric or plug-in hybrid vehicles in the US passenger vehicle fleet, has risen from around 0.2 % in 2015 to 0.9 % in 2021. However, despite the positive development, the adoption rate is lagging behind the global average [2]. Still, several polices aimed to promote AFV adoption, have been deployed in the US over the years – both on federal and state level. These include tax credits for AFV purchases, tightening of fuel economy standards, as well as grant and incentive programs to build out infrastructure for charging or refueling, and funding of AFV technology research [4, 5].

1.2 Research Objectives

The aim of this thesis paper is to hypothesize, explore and clarify dynamic interactions that have been holding back adoption of electric vehicles in the US. In addition, considering the relatively weak development in adoption thus far, try and identify policies with potential to accelerate adoption in the coming years.

One approach to investigate these research objectives, is using simulation modeling to explore and analyze structural aspects characterizing the passenger vehicle market in the

US. Simulation modeling has proven useful when trying to develop understanding of systems that are complex in nature, where endogenous interactions and system development over time, might not be intuitive.

Though simulation modeling might be useful for experienced modelers, it is not necessarily easily understood by non-modelers. A third objective is therefore to communicate insights from systems thinking and system dynamic modelling in a way that makes them accessible to a non-SD audience.

1.3 Reference mode

Figures 1 and 2 display projected Battery Electric Vehicle (BEV) market shares and yearly BEV sales in the US, respectively, and represent reference modes for the study.

Figure 1 presents three separate projections of BEV shares of passenger vehicle sales in the US, for the period 2017-2050, as published by Energy Innovation in 2017 [6]:

1. Energy Policy Simulator 2017, 'Business as usual' case (EPS) [7]
2. Energy Information Administration Annual Energy Outlook 2017, 'No Clean Power Plan' case (EIA) [8]
3. Bloomberg New Energy Finance Electric Vehicle Outlook 2017 (BNEF) [9]

Figure 2 presents historical and projected yearly BEV sales in the US, for the period 2010-2030, as published by the US Energy Information Administration in 2022 [2]:

1. Historical data 2010-2022 (EIA HISTORICAL)
2. Stated Policies Scenario (EIA STEPS)
3. Announced Policies Scenario (EIA APS)

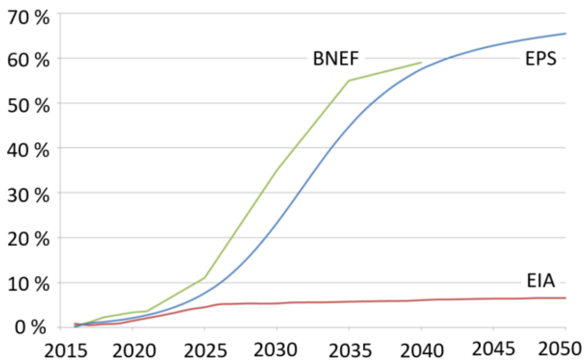

Figure 1 *Three projections of BEV market shares in the US, published in 2017 for the period 2017 - 2050 [6]:*

1. *EPS: Energy Policy Simulator 2017, 'Business as usual ' case [7]*
2. *EIA: Energy Information Administration Annual Energy Outlook 2017, 'No Clean Power Plan' case [8]*
3. *BNEF: Bloomberg New Energy Finance Electric Vehicle Outlook 2017 [9]*

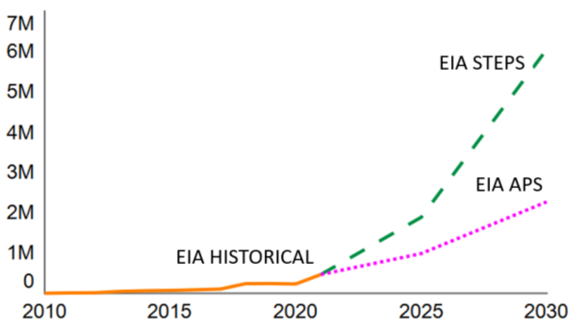

Figure 2 *Historical and projected yearly BEV Sales in the US, published in 2022 for the period 2010 - 2030 [2]:*

1. *Historical data 2010-2022 (EIA HISTORICAL)*
2. *Stated Policies Scenario (EIA STEPS)*
3. *Announced Policies Scenario (EIA APS)*

The projections in figures 1 and 2, provide an indication of the anticipated change in the US passenger vehicle market in the years to come and also of the uncertainty related to forecasting the dynamics of such a complex structure.

1.4 Research Questions

To reach the three objectives described earlier, this study poses the following research questions:

- What are the processes driving adoption of battery electric vehicles in the US?
- Which policies have the potential to accelerate adoption in the coming years?
- How can insights from systems thinking and system dynamic modelling be communicated, to be made accessible to non-SD audiences?

Chapter 2. Methods

2.1 System Dynamics

The methodology used in this thesis is system dynamics modeling. Simulation modeling is well-suited for this study because it allows for interacting with a representation of aggregate real-world processes that make up a complex, dynamic system, which in turn might reveal insights and understanding about how behavior emerges from that system. The system dynamics research strategy adopted to produce this thesis, resembles the Conceptual Virtual Laboratory as defined by Gooyert [10]. The thesis is based heavily on previous work and existing theories, which have been processed, updated, or combined to derive new insights. Model simplification steps have been performed in accordance with the techniques put forward by Saysel and Barlas [11].

2.2 Data and previous work

In the 2020 paper *The Diffusion of Alternative Fuel Vehicles: A Generalised Model and Future Research Agenda*, Keith et al. [12] present a system dynamics model of AFV diffusion in the US, which represents the foundation on which this thesis model is built. Keith et al.'s model considers a market share distribution between ICEVs, BEVs and Plug-in Hybrid Electric Vehicles (PHEVs), and captures important feedbacks governing AFV diffusion, including the turnover of the vehicle fleet, effects of vehicle manufacturer learning and experience, and the coevolution of refueling infrastructure with fuel demand. The developments in market shares are dictated by consumer choice which is modelled as being conditioned by both the utility of the vehicle technology and consumers' willingness to consider purchasing new vehicle technologies; defined as consumer familiarity with the technologies. The consumer utility attributes and their weights were based on existing discrete choice literature published in the period 2000-2005, especially on Brownstone et al.'s *Joint mixed logit models of stated and revealed preferences for alternative fuel vehicles* [13], published in 2000.

This thesis paper presents an alternative, simplified model that better facilitates model exploration by users not as familiar with system dynamics modelling. First, the alternative model presented here, has no arrayed variables and only considers ICEVs and BEVs as PHEVs might be considered a transitory technology [14]. Second, the consumer utility attributes and their weights have been adapted according to a 2020 survey of 10,000 consumers, fleet managers, and industry specialists across eight significant EV markets [15, 16]– the new weights have been normalized to sum to 1 to make them readily comparable. Tables 1 and 2 list the utility attributes and their weights for the Keith et al. model and the alternative thesis model, respectively.

Table 1 Utility attributes and their weights in the Keith et al. model [12].

Utility attribute	*Attribute weight*
Purchase Price	-0.361
Operating Cost	-0.170
Acceleration	-0.149
Top Speed	0.272
Range	0.200
Emissions	-0.673
Fuel Search Cost	-0.170
Scope (maturity of platform)	0.5

Table 2 Adapted and normalized utility attributes and weights according to a 2020 survey of 10,000 consumers, fleet managers, and industry specialists across eight significant EV markets [15, 16].

Utility attribute	*Attribute weight*
Retail Price[1]	-0.285
Operating Cost[1]	-0.095
Model Selection	0.040
Infrastructure Availability	0.110
Charge time / Fueling time	-0.270
Range	0.200

Other modifications done in the thesis model include:

- The assumption that some utility weights will shift with the introduction of Carbon Tax – adding more weight to Operating Cost relative to Retail Price and Charge time /Fueling time.
- The addition of a structure for Model Selection and the assumption that there is a higher ration of luxury models within the BEV segment than the ICEV segment.
- The exclusion of Emissions as a utility attribute and thus the entire sector containing Green House Gas (GHG) metrics.
- Not subjecting drivers of BEVs to Carbon Taxation for GHG emissions generated from electricity production.
- Adding historical gas and electricity prices for the period 2010-2021 and 2010-2022 respectively.
- The assumption that the US BEV market is influenced by the development in the global BEV markets by letting the learning curves take input from historical global vehicle sales rather than solely the domestic.

[1] The 2020 survey [12, 13] identifies *Price* as one of five attributes that are most important to consumers at 38 %. In the model, *Price* has been divided into the two attributes *Retail Price* at 28.5% and *Operating Cost* at 9,5% that sum to 38 %.

- The assumption that there is full familiarity with ICEV technology for the duration of the simulation period and that it cannot decrease (constant).
- The assumption that the BEV technology Familiarity Exposure is influenced by global development by taking input from the global BEV Fleet rather than solely the domestic.
- The assumption of a delay on the average BEV familiarity.
- The assumption that a fraction of the ICEV manufacturing revenue is made available for BEV marketing.
- The exclusion of fueling station profits is input to infrastructure demand and thus the entire sector containing infrastructure economics.

Model modifications are elaborated on in the Model Overview – Modules and Sectors and the Model Calibration and Assumptions subchapters of the Model Description chapter of this thesis. Table 3 gives an indication of aggregate differences between the thesis model and the Keith et al. model and lists statistics on content type count for the two models. The bulk of the graphical functions included in the thesis model are giving historical data input.

Table 3 Statistics on content type count for the thesis and the Keith et al. models [12].

Content type	*Thesis model Count*	*Keith et al. model Count*
Sectors	9	20
Total Variables	395	1086
Stocks	23	53
Flows	35	99
Converters	337	934
Constants	100	226
Equations	272	807
Graphical Functions	13	1

2.3 Modeling Decisions and Settings

The thesis model has been created in Stella Architect, Version 3.1. A DT of 1/32 and Euler's integration method has been chosen to run the model. The simulation begins January 1st 2010 and runs for 40 years, until 2050. The time horizon is considered sufficiently long to include the start of EV adoption in the US and also to enable exploration of long-term development in BEV adoption. The Keith et al. model is available in Vensim – it is set to a DT of 1/32 and has a time horizon of 30 years. The model file is attached to this thesis and is fully documented according to acknowledged guidelines for system dynamics modeling [17]. The full documentation of the model is provided in Appendix A – Model documentation.

Chapter 3. Model Description

3.1 Model Overview – Causal Loop Diagram

In the model, the utility attributes listed in Table 2, in combination with consumer familiarity, are what dictate consumer choice of vehicle technology. The model hypothesizes that the market share distribution between ICEVs and BEVs is determined by the product of the respective consumer familiarity with the technology and the overall consumer utility of that technology. Thus, the combined effect of familiarity and utility reflects consumer affinity to purchase ICEVs or BEVs and hence dictate the market share distribution.

Figure 3 displays a causal loop diagram (CLD) that summarizes the central structure of the simulation model and illustrates pivotal causal links. The CLD contains central model variables with arrows that illustrate how the variables influence one another to develop feedback loops – it focuses on the feedback loops involving:

I. Familiarity with technology (BEV/ICEV familiarity)
II. Utility of technology selection of car models (BEV/ICEV utility 1)
III. Utility of technology retail price (BEV/ICEV utility 2)
IV. Utility of technology driving range (BEV/ICEV utility 3)
V. Utility of technology charge time / fueling time (BEV/ICEV utility 4)
VI. Utility of technology operating cost (BEV/ICEV utility 5)
VII. Utility of BEV charging / fueling Infrastructure (BEV/ICEV utility 6)

At the center of the CLD are the BEV and ICEV market shares – these variables are influenced by the BEV and ICEV familiarity and utility feedback loops, respectively. These market shares, combined, represent the entire passenger vehicle market, so that if the BEV market share increases, the ICEV market share decreases and vice versa.

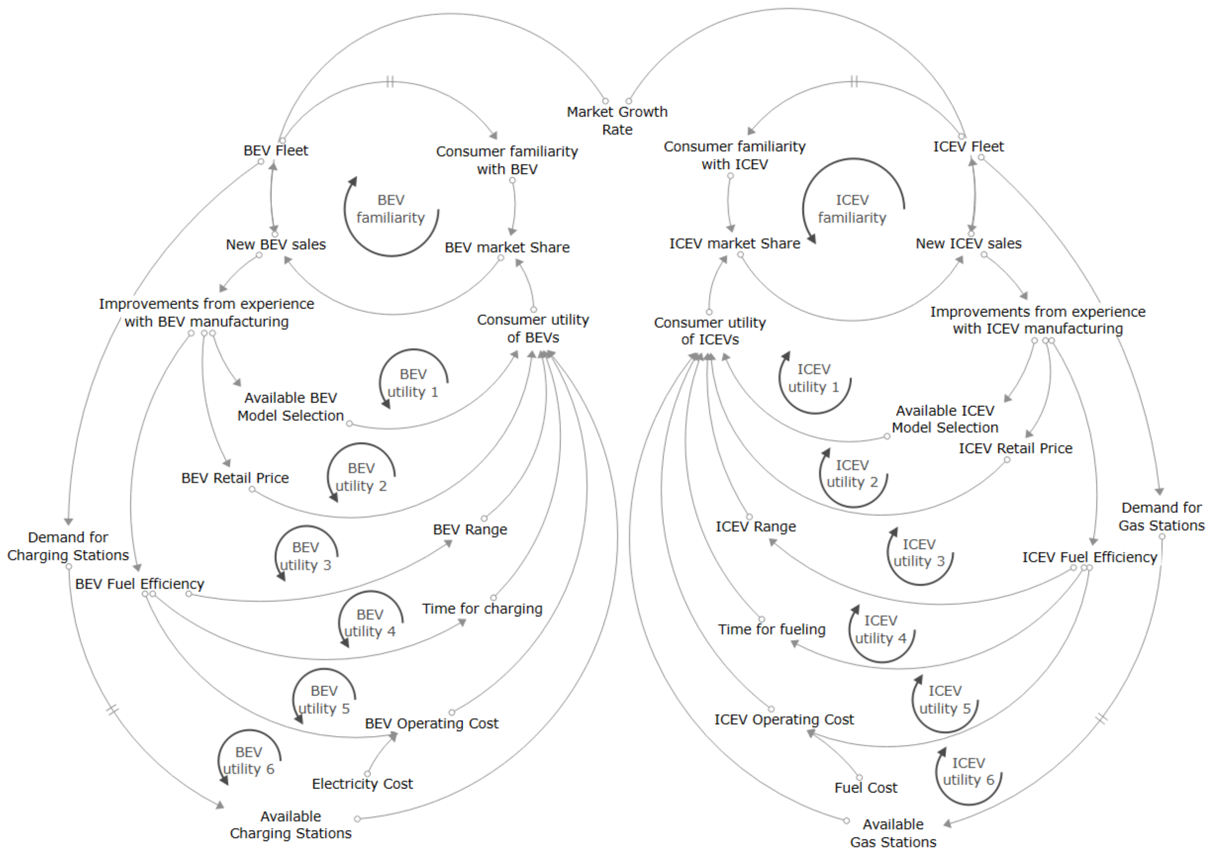

Figure 3 Causal Loop Diagram (CLD).

In the BEV and ICEV **familiarity reinforcing feedback loops**, consumer familiarity is central. The ICEV technology is assumed to have full consumer familiarity, while the BEV technology is assumed to be close to zero in 2010. The BEV market share is determined by the product of the BEV familiarity and BEV utility. The potential BEV market share based on BEV utility, will therefore be restrained as long as BEV technology has not reached full consumer familiarity. So, when BEV familiarity increases, so does the BEV market share which increases new BEV sales and the BEV fleet. This in turn, with some delay, increases consumer familiarity with BEV technology.

In the BEV and ICEV **utility 1 reinforcing feedback loops**, available model selection within respective technology is central. As new BEV sales increase, so do the improvements from experience with BEV manufacturing, which leads to an increase in available model selection after some time. This in turn, increases the positive contribution from BEV model availability utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

In the BEV and ICEV **utility 2 reinforcing feedback loops**, retail price of respective technology is central. As new BEV sales increase, so do the improvements from experience with BEV manufacturing, which leads to a decrease in BEV retail price after some time. This in turn, decreases the negative contribution from BEV retail price utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

In the BEV and ICEV **utility 3 reinforcing feedback loops**, driving range within respective technology is central. As new BEV sales increase, so do the improvements from experience with BEV manufacturing, which leads to an increase in BEV fuel efficiency after some time and an increase in BEV driving range. This in turn, increases the positive contribution from BEV range utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

In the BEV and ICEV **utility 4 reinforcing feedback loops**, charge time and fueling time, respectively, is central. As new BEV sales increase, so do the improvements from experience with BEV manufacturing, which leads to an increase in BEV fuel efficiency after some time and an decrease in BEV charging time. This in turn, decreases the negative contribution from BEV charge time utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

In the BEV and ICEV **utility 5 reinforcing feedback loops**, operating cost of respective technology is central. As new BEV sales increase, so do the improvements from experience with BEV manufacturing, which leads to an increase in BEV fuel efficiency after some time and a decrease in BEV operating cost. This in turn, decreases the negative contribution from BEV operating cost utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

In the BEV and ICEV **utility 6 reinforcing feedback loops**, charging infrastructure and refueling infrastructure, respectively, is central. As the BEV increases according to increases in new BEV sales, so does the demand for charging infrastructure. After some time, this will lead to an increase in available charging infrastructure. This in turn, increases the positive contribution from BEV infrastructure utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

The BEV and ICEV utility variables for each attribute, are continuously compared relative to one another and in sum they give the overall consumer utility for the respective technology. In combination with the respective consumer familiarity, they determine the market share distribution between ICEVs and BEVs.

3.2 Model Overview – Modules and Sectors

The model is arranged into three main modules: Consumer, Vehicles and Fueling, which each contain three sectors. The module subchapters give a description of the main model features in each sector, some of which are elaborated on in the following Model Calibration and Assumptions subchapter.

3.2.1 Consumer module

The sectors in the Consumer module are Projected Market Share, Consumer Familiarity and Consumer Utility.

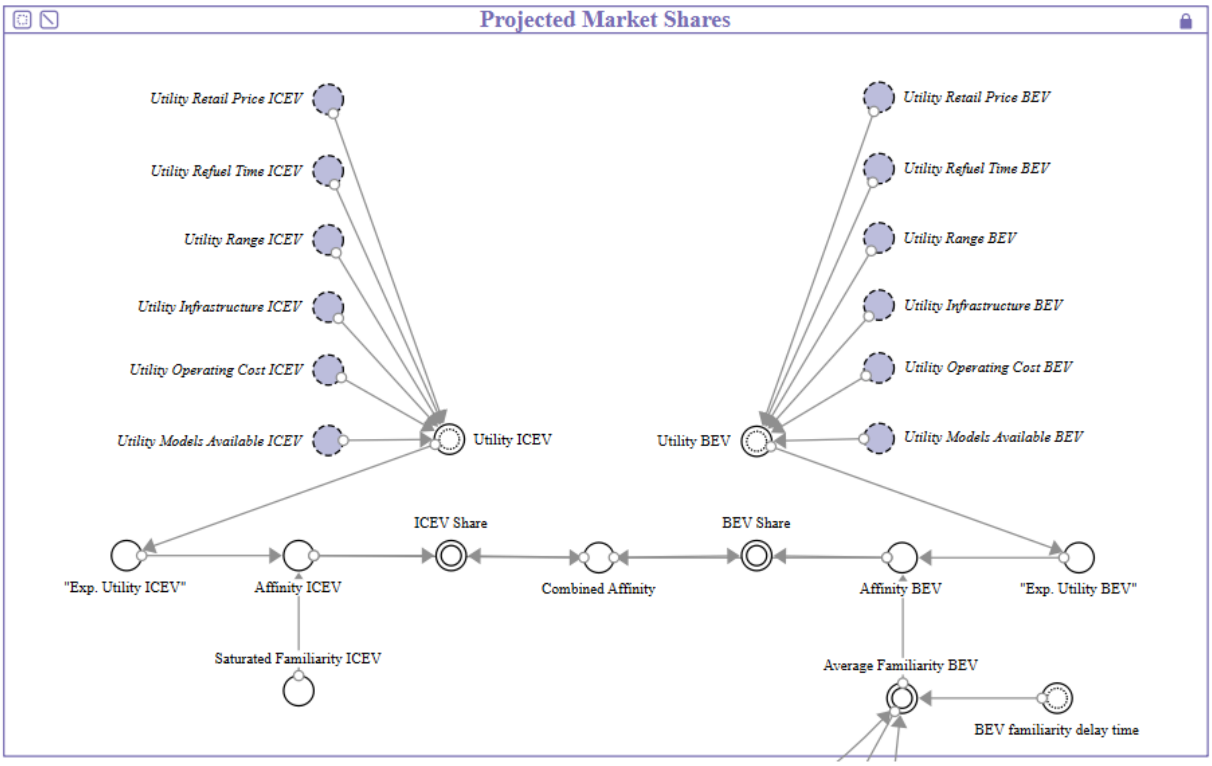

Figure 4 Projected Market Shares sector.

The structure in the **Projected Market Shares sector (figure 4)**, is analogous to the structure in the Keith et al. model. The sector takes input from the Consumer Utility sector – here the BEV and ICEV utility variables for each attribute, are summed to give the overall consumer BEV and ICEV utility. The BEV and ICEV utility are processed with the multinominal logic function, a standard function in consumer choice theory, and multiplied by the BEV and ICEV familiarity to give the BEV and ICEV affinity, respectively. The average BEV familiarity is determined based on input from the Consumer Familiarity sector and has a value between 0, which represents no consumer familiarity, and 1, which represents full consumer familiarity. The consumer familiarity with ICEV technology is assumed to be full and is set constant at 1. The BEV and ICEV affinity ratio to the combined BEV and ICEV affinity, give the respective market shares.

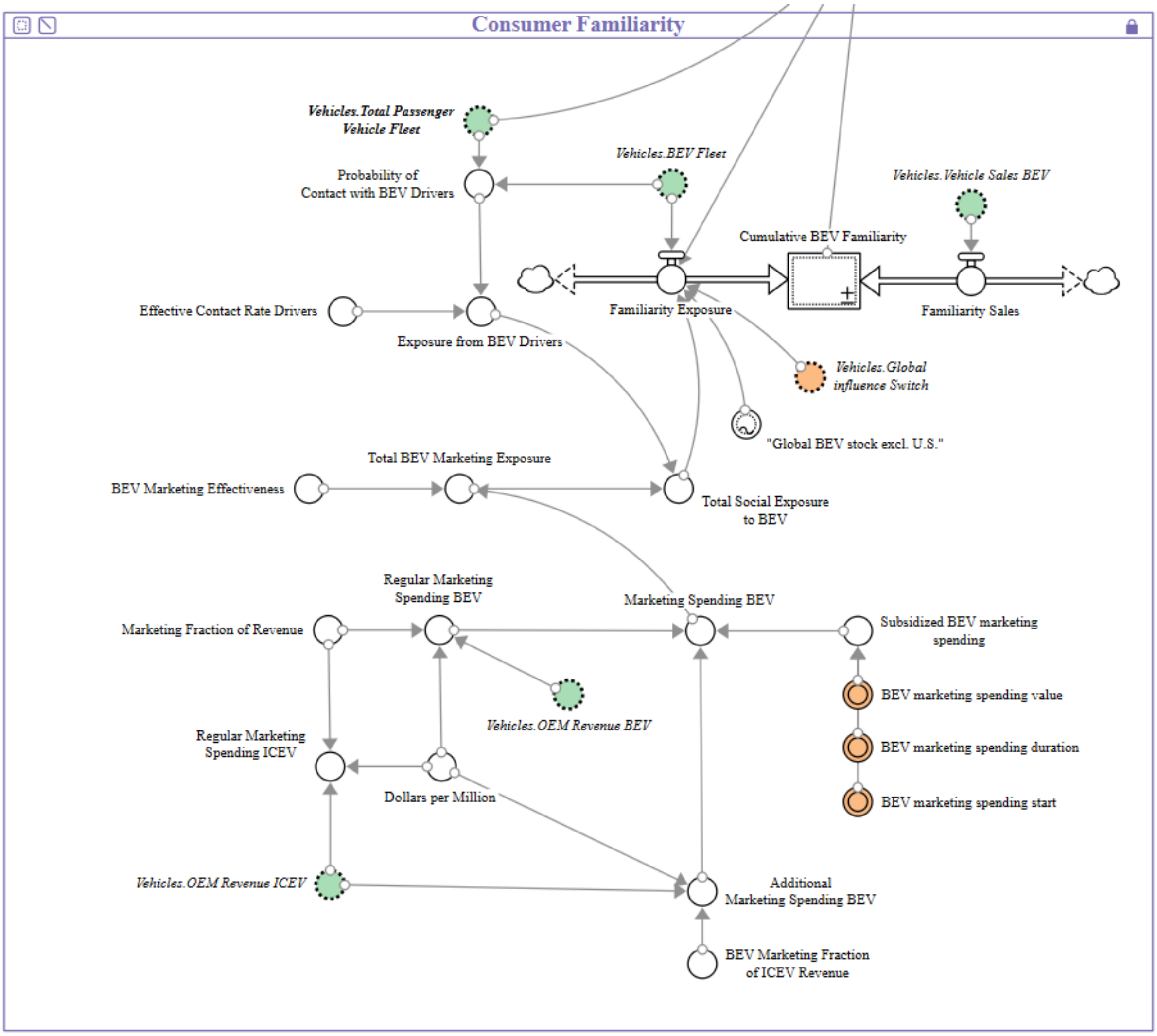

Figure 5 Consumer Familiarity sector.

The **Consumer Familiarity sector (figure 5)** takes input from the Vehicles module's Fleet Turnover sector and Vehicle Price and Revenue sectors – here, the input to the average BEV familiarity is determined. While the ICEV technology is assumed to have full consumer familiarity, the familiarity with BEV technology is assumed to be close to zero in 2010. The average BEV familiarity is determined as the ratio between the cumulative

BEV familiarity and the total passenger vehicle fleet and is delayed by the BEV familiarity delay time of 4 years, which differs from the Keith et al. model that does not include a delay variable.

The cumulative BEV familiarity is measured in 'vehicles' and increases with, among other input, the sales of new BEVs. It also increases with the product of the inverse BEV familiarity, Total Social Exposure to BEV technology and the global BEV Fleet – a switch enables replacement the global BEV Fleet, which is the model default, with the US BEV Fleet. The assumption that the US market is influenced by the global market is an assumption not shared with the Keith et al. model. The Keith et al. model also contains a cumulative familiarity variable – it increases or decreases with Familiarity Sales ij, Familiarity Forgetting ij, Familiarity Increase ij and Familiarity Discards ij and thus differs from the thesis model.

Total Social Exposure to BEV technology comprises two elements: the Total BEV Marketing Exposure and the Exposure from BEV Drivers. The Exposure from BEV Drivers is determined by the Probability of Contact with BEV Drivers and the Effective Contact Rate Drivers and represents a negligible contribution to Total Social Exposure to BEV.

The Total BEV Marketing Exposure is the product of BEV Marketing Effectiveness and Marketing Spending BEV – it represents the major contributor to Total Social Exposure to BEV and also to Cumulative BEV familiarity per se. The Marketing Spending BEV is determined by the Regular Marketing Spending BEV and the Additional Marketing Spending BEV. The Regular Marketing Spending BEV is set to 4 % of the OEM (Original equipment manufacturer) revenue from BEV manufacturing and is the same for the ICEV technology – in the Keith et al. model it is set to 5 %. The Additional Marketing Spending BEV is set to 1 % of the OEM revenue from ICEV manufacturing and is an assumption that as most OEMs manufacture both BEV and ICEV technology, they might distribute parts of the marketing funds between the two technologies – the Keith et al. model has no such assumption.

The BEV Marketing Effectiveness represents the effectiveness of advertising activities in reducing the gap to full familiarity with BEVs per million dollars spent – it is assumed to be higher in the thesis model compared to the Keith et al. model and is set to 4e-03 and 1.5e-05, respectively.

The **Consumer Utility sector (figure 12)** takes input from several sectors which forms the foundations for determining the six BEV and six ICEV utility attributes: Retail Price, Charge Time, Range, Infrastructure Availability, Operating Cost and Model Selection. The utility attributes are multiplied by the associated utility weights of which some are assumed to be impacted by Carbon Tax if it is introduced – the utility weights are therefore represented as graphical functions which are presented in figures 6-11. The six utility weights sum to absolute 1 for any value of Carbon Tax. The utility attributes, the utility weights in a no Carbon Tax scenario (default) and the utility weights in a Carbon Tax scenario, are listed in Table 4. The assumption that utility weights shift with the introduction of Carbon Tax is not shared with the Keith et al. model and is elaborated on in the Model Calibration and Assumptions chapter.

Table 4 Utility attributes, utility weights in no Carbon Tax scenario (default) and max utility weights in Carbon Tax scenario. If Carbon Tax is introduced, the default utility weights (Carbon Tax $0 per tonne CO2 equivalent) will increase linearly to max utility weights (Carbon Tax $500 per tonne CO2 equivalent).

Utility attribute	***Attribute weight (no Carbon Tax)***	***Weight Change with Carbon Tax***	***Max. Attribute weight (Carbon Tax)***
Retail Price	-0.285	Linear Decrease	-0.049
Operating Cost	-0.095	Linear Increase	-0.555
Model Selection	0.040	No Change	0.040
Infrastructure Availability	0.110	No Change	0.110
Charge time / Fueling time	-0.270	Linear Decrease	-0.046
Range	0.200	No Change	0.200

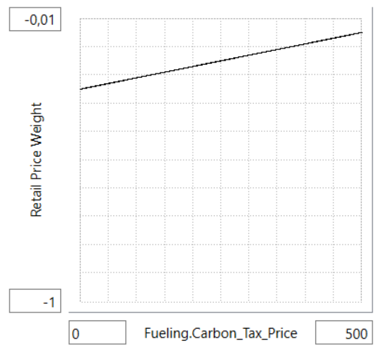

Figure 6 Retail Price Weight.

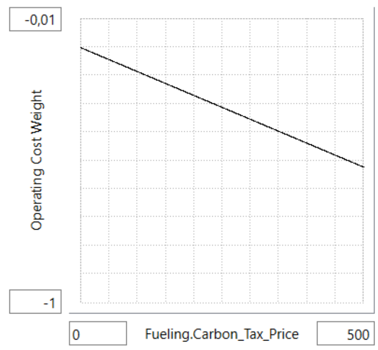

Figure 7 Operating Cost Weight.

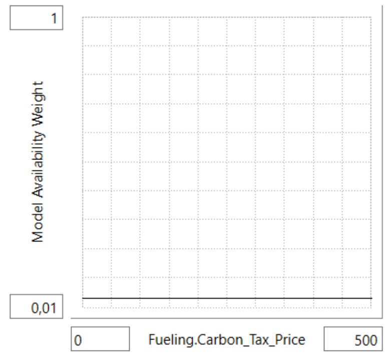

Figure 8 Model Availability Weight.

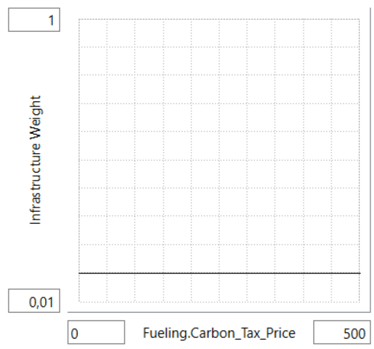

Figure 9 Infrastructure Availability Weight.

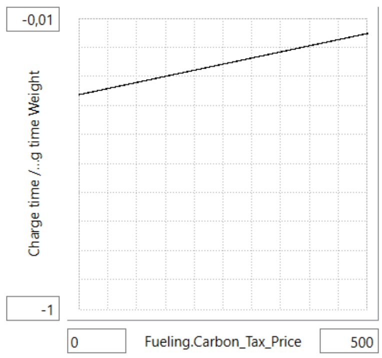

Figure 10 Charge time / Fueling time Weight.

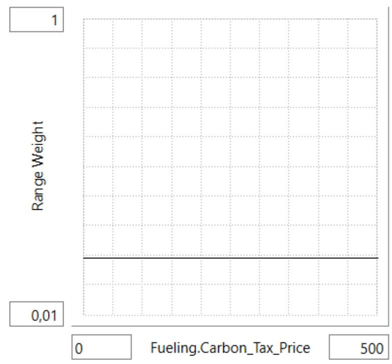

Figure 11 Range Weight.

The Retail Price utility calculation structure is analogous to the structure in the Keith et al. model, though the weight differs as well as the normalization step. It takes input from the Vehicles module's Vehicle Price and Revenue sector. The Retail Price utility weight is assumed to be 28.5 % which impacts the overall utility negatively. If Carbon Tax is introduced, the weight is assumed to be reduced linearly to 4.9 % when Carbon tax reaches $ 500 per tonne CO_2 equivalents (CO_2e).

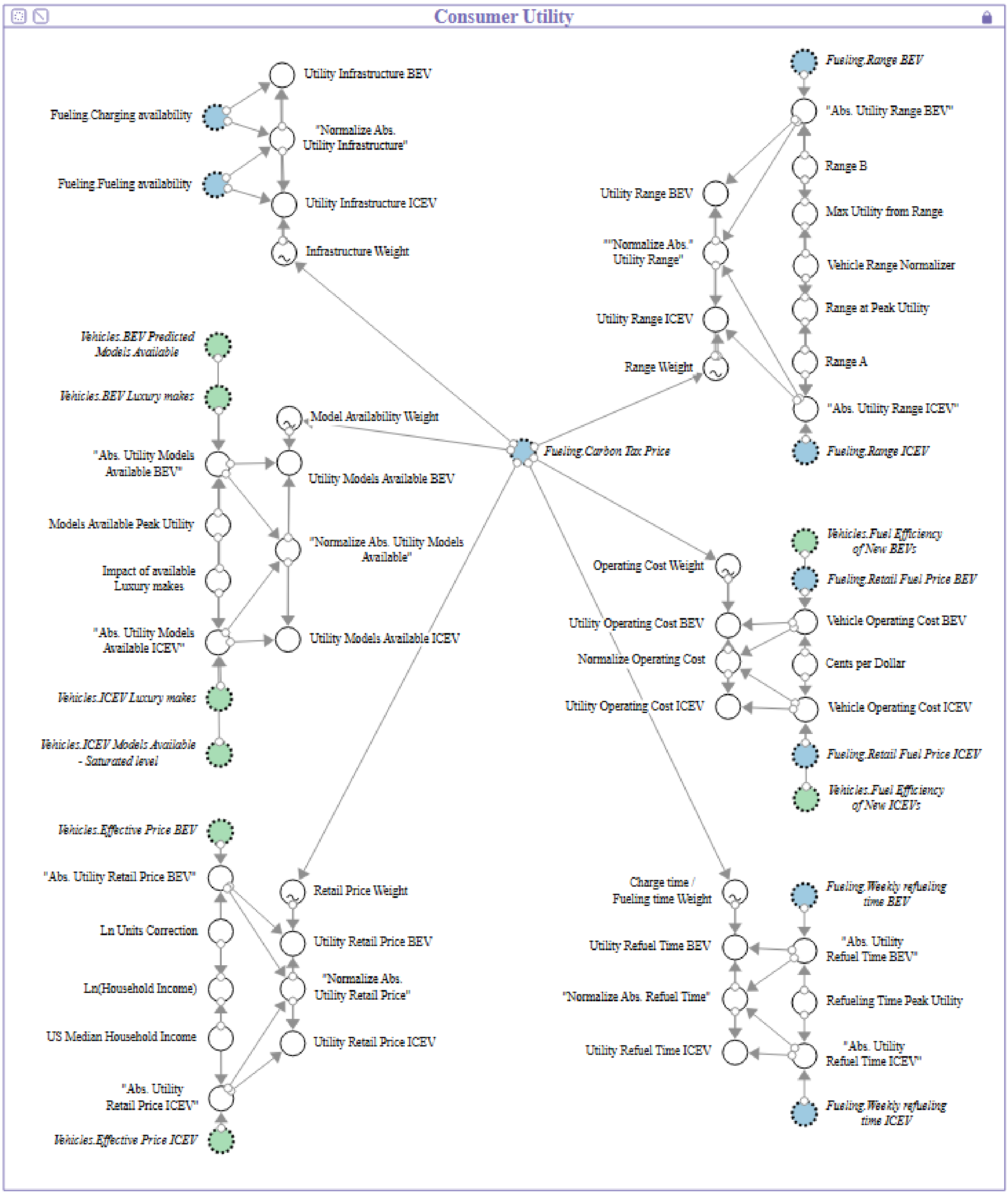

Figure 12 Consumer Utility sector.

The Charge Time utility calculation structure does not have a corresponding structure in the Keith et al. model. It takes input from the Fueling module's Fueling metrics sector. The Charge Time utility weight is assumed to be 27% which impacts the overall utility negatively. If Carbon Tax is introduced, the weight is assumed to be reduced linearly to 4.6 % when Carbon tax reaches $ 500 per tonne CO_2e.

The Range utility calculation structure is analogous to the structure in the Keith et al. model, though the normalization step differs – the weight is set to 0.2 in both models. The input is taken from the Fueling module's Fueling metrics sector. As mentioned, the Range utility weight is assumed to be 20 % which impacts the overall utility positively. If Carbon Tax is introduced, the weight is assumed to be unaffected.

The Infrastructure Availability utility calculation structure does not have a corresponding structure in the Keith et al. model. The input is taken from the Fueling module's Fueling infrastructure sector. The Infrastructure utility weight is assumed to be 11 % which impacts the overall utility positively. If Carbon Tax is introduced, the weight is assumed to be unaffected.

The Operating Cost utility calculation structure is analogous to the structure in the Keith et al. model, though the weight differs as well as the normalization step. It takes input from the Vehicles module's OEM Learning Curve Effects sector and the Fueling module's Fuel Prices sector. The Operating Cost utility weight is assumed to be 9.5 % which impacts the overall utility negatively. If Carbon Tax is introduced, the weight is assumed to be increased linearly to 55.5 % when Carbon tax reaches $ 500 per tonne CO_2e.

The Model Selection utility calculation structure does not have a corresponding structure in the Keith et al. model. The input is taken from the Vehicles module's OEM Learning Curve Effects sector. The Model Selection utility weight is assumed to be 4 % which impacts the overall utility positively. If Carbon Tax is introduced, the weight is assumed to be unaffected.

3.2.2 Vehicles module

The sectors in the Vehicles module are OEM Learning Curve Effects, Fleet Turnover and Vehicle Price and Revenue.

The structure in the **OEM Learning Curve Effects sector (figure 13)**, is similar to the structure in the Keith et al. model – however an important difference is the assumption of global influence in the thesis model. A switch enables replacement the global BEV and ICEV Sales, which is the default, with solely domestic sales.

At the center of this structure are the learning curve rates for BEV and ICEV manufacturing. The learning curve rates indicate fractional decrease in principal variable, for example Base Vehicle Cost, with every doubling of experience. The learning curve rates have been set to 15 % [18] for both BEV and ICEV manufacturing in the thesis model, though it could be argued that the BEV learning curve might be higher than that of ICEV [19]. In the Keith et al. model, the learning curve rates have been set to 5 %.

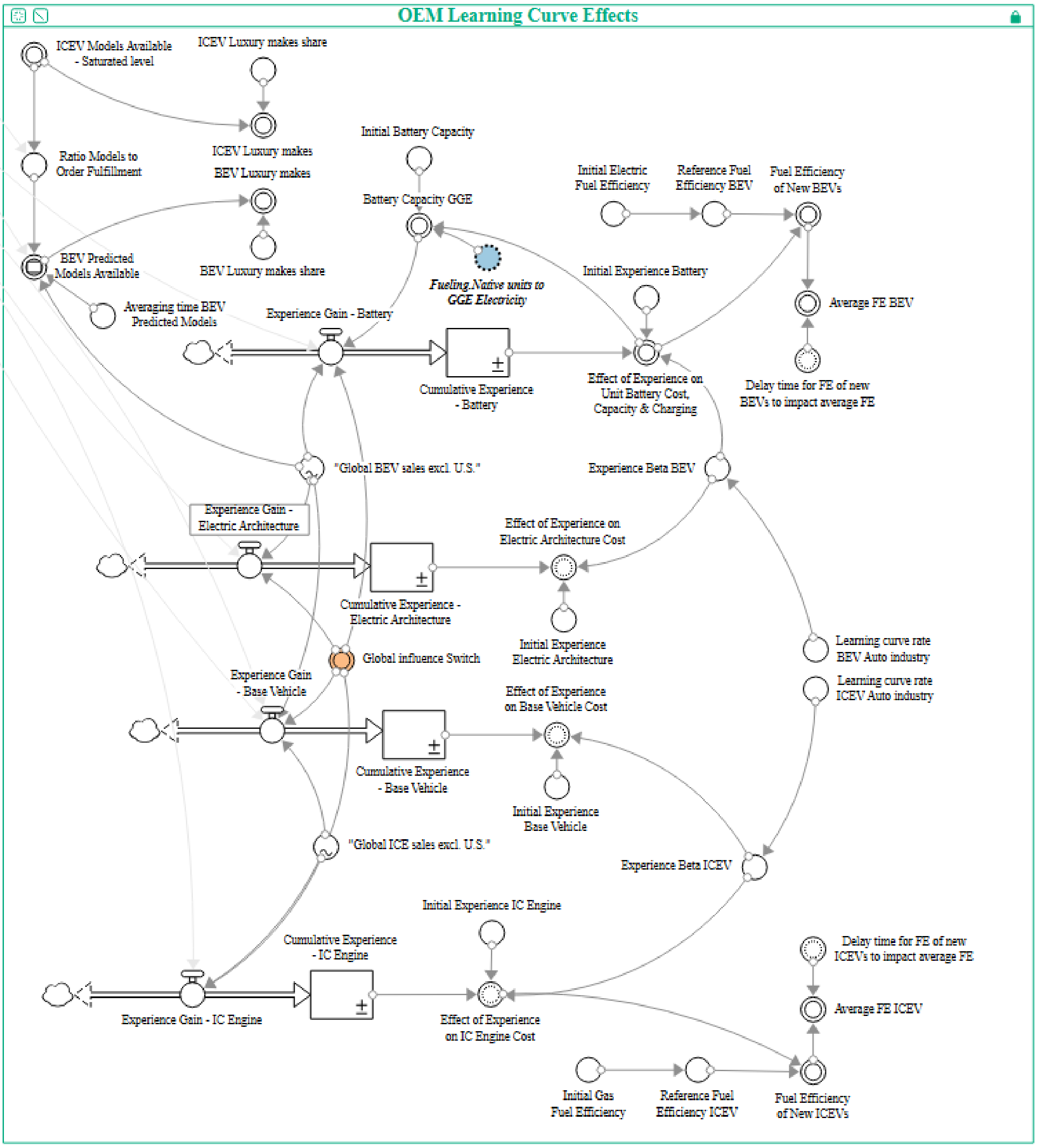

Figure 13 OEM Learning Curve Effects sector.

The structure in the **Fleet Turnover sector (figure 14)**, is analogous to the structure in the Keith et al. model. The sector takes input from the Projected Market Shares sector and the variables BEV share and ICEV share to determine the distribution of new vehicle sales between ICEV and BEV technology. In addition, Market Growth Rate and Vehicle discards are used as input to determine new vehicle sales. The sector contains eight stocks that represent BEVs and ICEVs aged 0-4 years, 5-8 years, 9-12 years and 13+ years. There are also two stocks that represent the cumulative order fulfillment of BEVs and ICEVs.

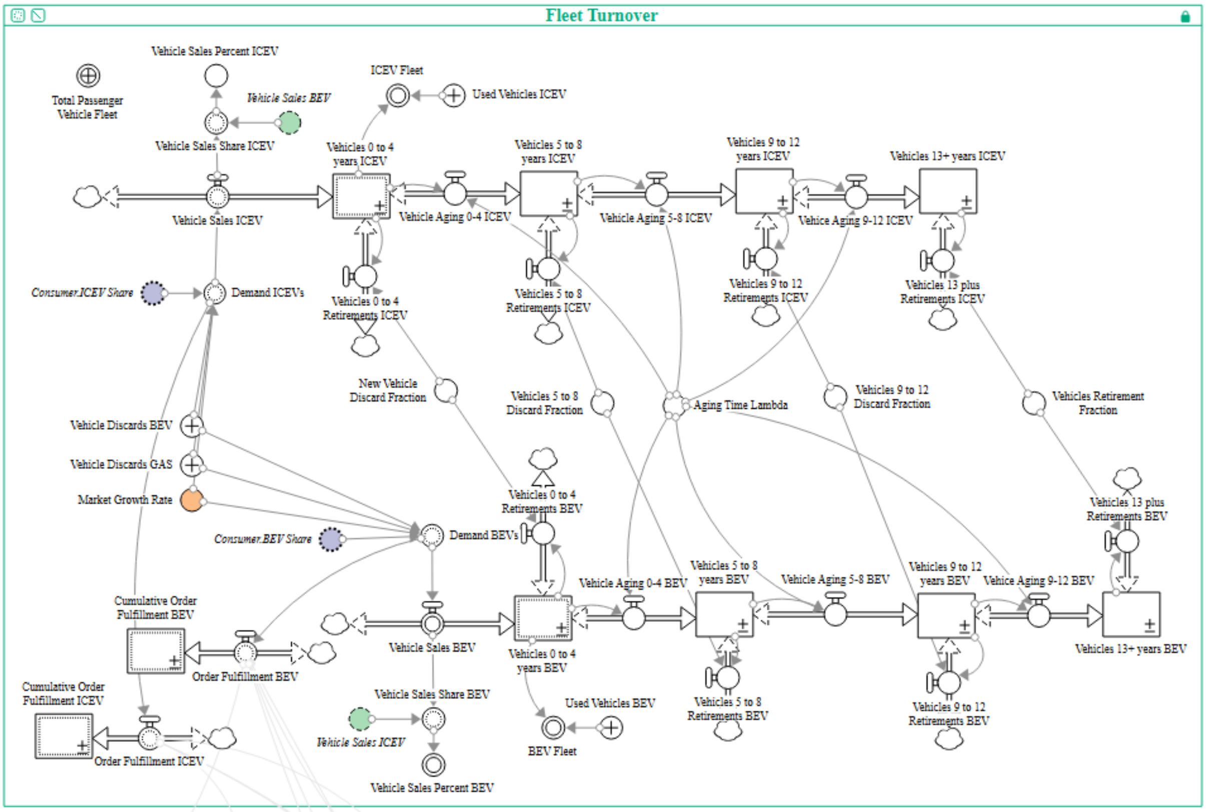

Figure 14 Fleet Turnover sector.

The structure in the **Vehicle Price and Revenue sector (figure 15)**, is analogous to the structure in the Keith et al. model. It takes input from the OEM Learning Curve Effects sector to determine the BEV and ICEV retail prices and OEM revenue. There are several vehicle price subsidy polices in this sector – most of these policies are turned off as the default setting. The exception is the 2010 Tax Credit subsidy that was effective from 2010 [20].

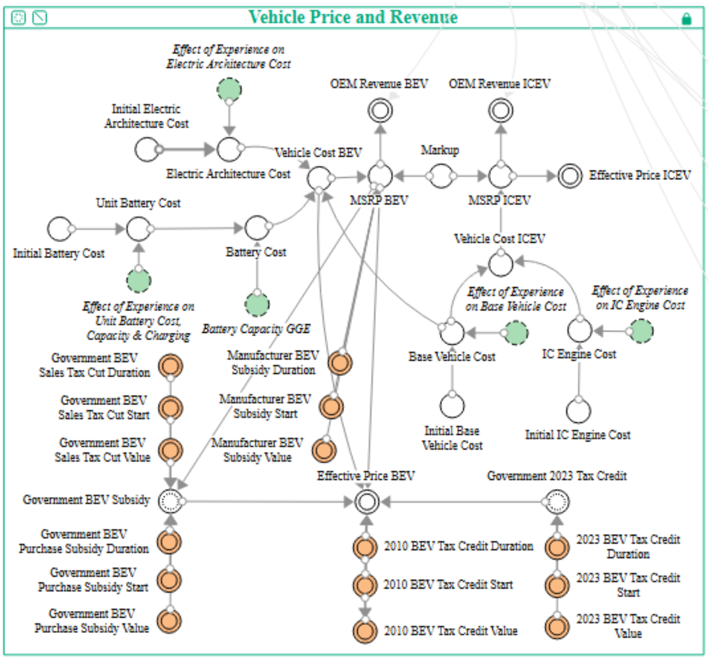

Figure 15 Vehicle Price and Revenue sector.

3.2.3 Fueling module

The sectors in the Fueling module are Fueling Infrastructure, Fuel Prices and Fueling Metrics.

The **Fueling Infrastructure sector (figure 16)** contains the structures that represent the available BEV charging infrastructure and ICEV fueling infrastructure, and also infrastructure in construction. There is also a structure that estimates Fueling and Charging availability based on Density of stations and Fuel buffer. The sector provides input to the Infrastructure Utility BEV and ICEV variables in the Consumer Utility Sector and contains six stocks; BEV and ICEV Available Infrastructure, BEV and ICEV Infrastructure in Construction and BEV and ICEV Fuel Buffer. In the Keith et al. model Infrastructure is divided into five separate sectors; Availability, Demand, Economics, Buffer and Fuel Search Cost, containing seven stocks in total. One of the main differences in the thesis model is that it does not include station profits as an input to infrastructure demand.

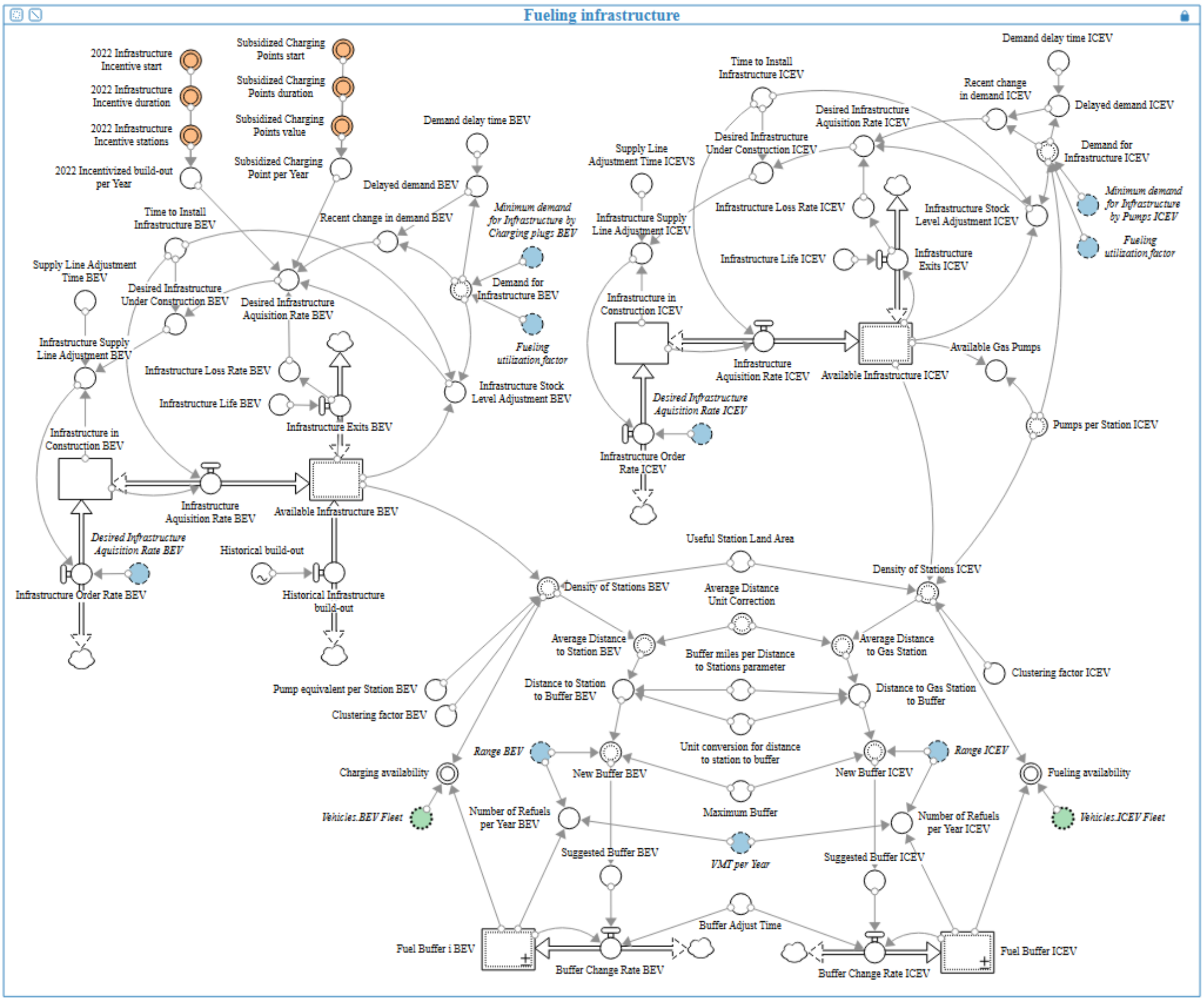

Figure 16 Fueling Infrastructure sector.

In both models, for both BEV and ICEV technology, the input to Desired Infrastructure Acquisition Rate is the sum of Infrastructure Loss Rate and Infrastructure Stock Level Adjustment. However, in the thesis model, this sum is multiplied by a variable representing Recent change in demand which is assumed to impact infrastructure investments and thus the acquisition rate, though investments are not explicitly modeled in either model. In both models, the definition of Infrastructure Stock Level Adjustment is the difference between Available Infrastructure and Demand for Infrastructure or Desired Infrastructure, over the Time to Install Infrastructure. However, the determination of Demand for Infrastructure in the thesis model and Desired Infrastructure in the Keith et al. model, differ.

In the Keith et al. model Desired Infrastructure, is defined as Available Infrastructure multiplied by the Combined effect. Combined effect is a dimensionless variable derived from Ratio of Projected Utilization and Target Utilization, Ratio of Recent Profit Margin to Target Profitability, TF Effect of Profit on Desired Infrastructure, which is a graphical function describing the effect of profitability on desired infrastructure as a function of profit and Sensitivity Effect Alpha, which represents the sensitivity of the effect of utilization on desired infrastructure.

In the thesis model Demand for Infrastructure, is defined as the Minimum Demand for Infrastructure, with units 'Stations', divided by the Utilization factor, which is the fraction of time any pump or plug is in actual service and has been set to 15 % [21]. The Minimum Demand for Infrastructure is defined as the ratio between Fleet Refuels Required per Year and Refueling Capacity per Year.

In the **Fuel Prices sector (figure 17)**, the exogenous gasoline and electricity prices are given. Historical prices are used in the period 2010-2021 and 2010-2022 for gasoline and electricity respectively. After this, the price development is dictated by a growth rate, set to 1 % per year.

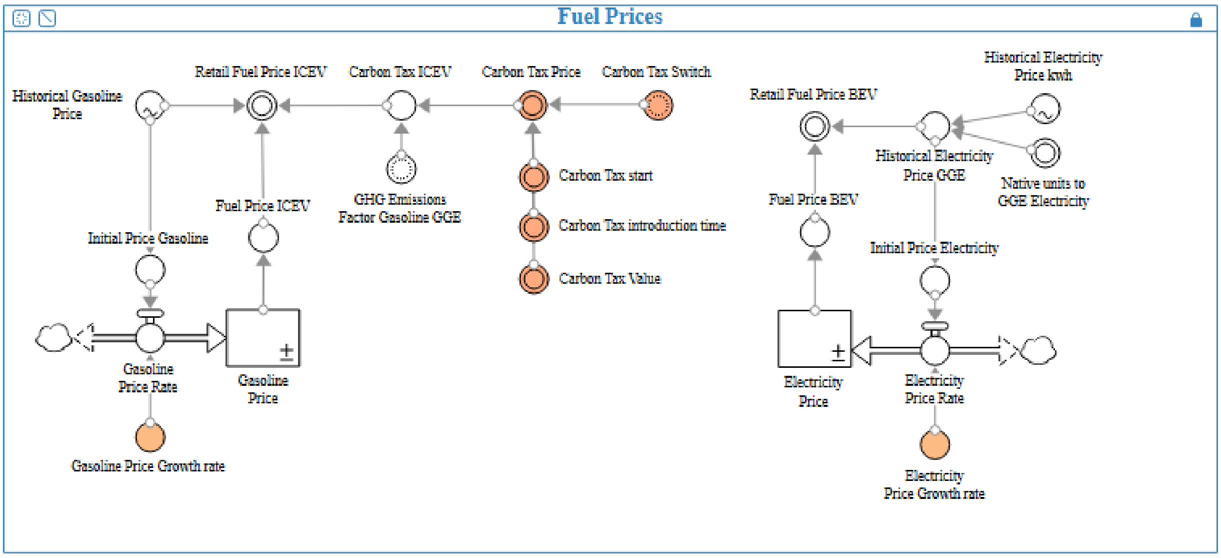

Figure 17 Fuel Prices sector.

The sector contains the Carbon Tax structure that will impact gasoline price, but not electricity price if introduced. Not including Green House Gas (GHG) emissions from electricity production differs from the Keith et al. model. Because a large portion of US electricity is produced from coal, the US electricity grid has a GHG factor which is relatively high, 0.00069 tonnes CO_2e per kWh or 0.023 tonnes CO_2e per Gallon Gasoline Equivalent (GGE) [22]. The GHG Emissions Factor for gasoline is around 0.008887 tonnes CO_2e per GGE [22].

In the **Fueling Metrics sector (figure 18)**, important metrics involving charging and refueling are determined. The sector takes input from the Fleet Turnover and OEM Learning Curve Effects sectors in the Vehicles module and provides input to the Utility Range and the Utility Refuel Time BEV and ICEV variables in the Consumer Utility Sector.

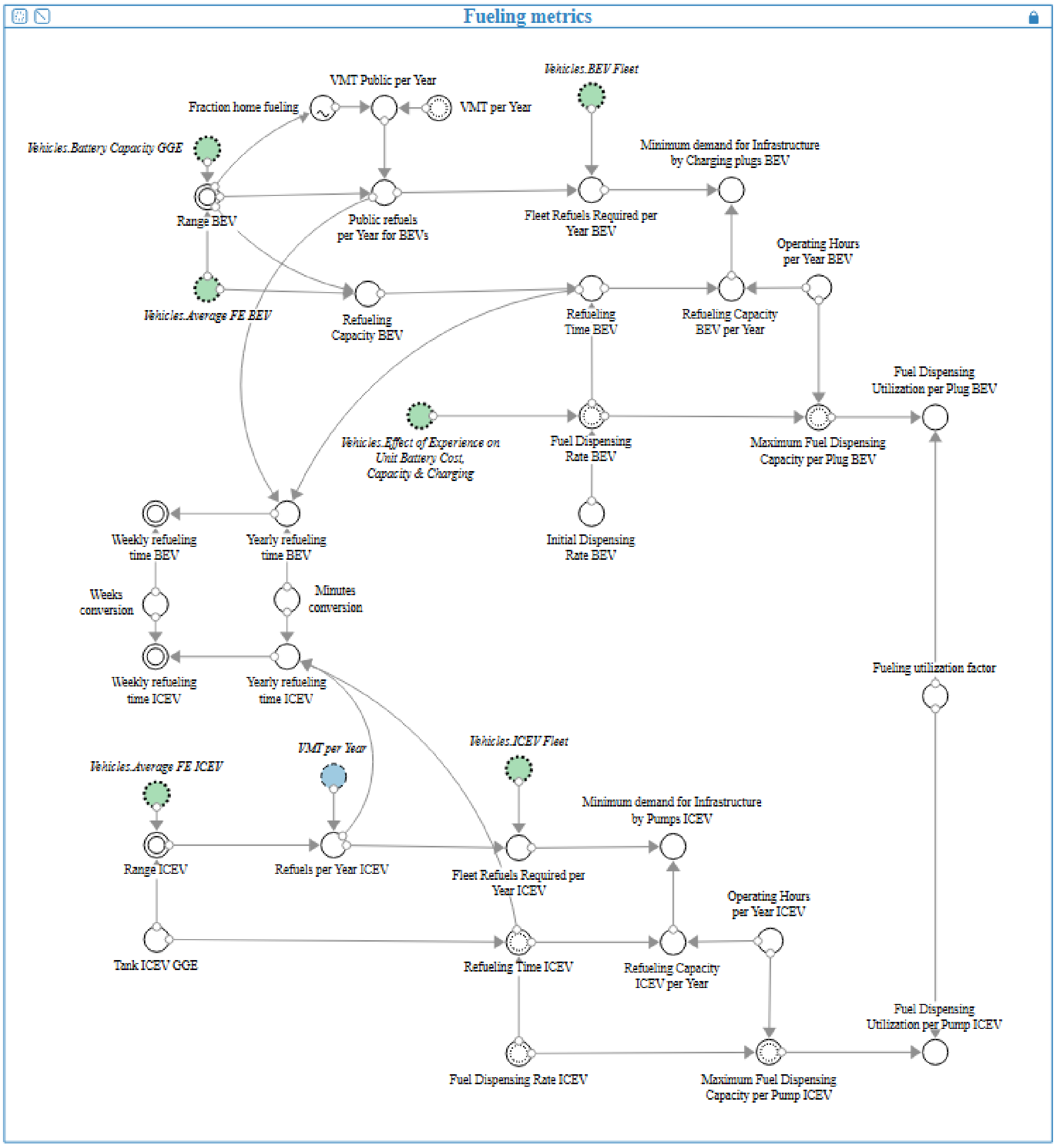

Figure 18 Fueling Metrics sector.

The fraction of home fueling is represented by a graphical function and presented in figure 19. The graphical function shows that the fraction of home fueling will increase with range of battery electric vehicles. As long as the range is low, the need for and use of remote charging will be relatively high.

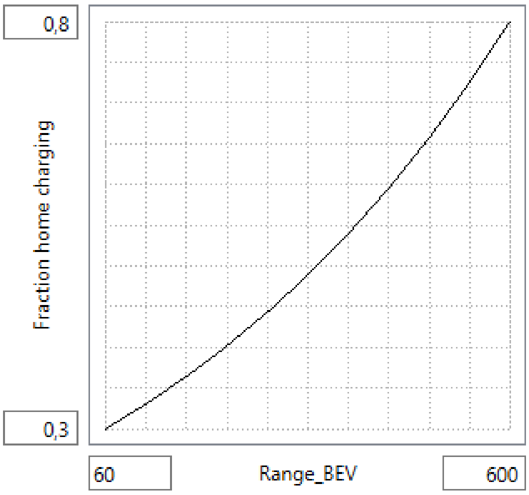

Figure 19 Fraction home charging.

3.3 Model Calibration and Assumptions

Most of the parameter values used in the model have been adopted from the Keith et al. model, though some parameter values have been updated or altered according to values retrieved from other sources. An overview of model parameters and parameter value sources can be found in tables 5-12 in the Model Analysis – Sensitivity Analysis chapter of this paper. A small selection of variables has been calibrated manually to fit data – this is elaborated on in the Model Analysis – Behavior Reproduction and Validation chapter.

A central assumption in the thesis model is that the US market is influenced by the global market, which is an assumption not shared with the Keith et al. model. This assumption has substantial ramifications on the OEM Learning Curve Effects, namely that the BEV sales and expanding BEV fleets outside the US provide the BEV industry as a whole with experience that lead to improvements, also in the US. In addition, it means the exposure to BEV technology in the US is not solely impacted by the size of the US BEV fleet, but also by the growing BEV fleets outside the US.

Another key assumption in the thesis model, is that a selection of utility weights are impacted and will change with the introduction of Carbon Tax – an assumption that is not shared with the Keith et al. model. The Carbon Tax is derived from the CO_2e emissions associated with gasoline combustion which is added to the gasoline price in the range $0 to $500 per tonne CO_2e. No Carbon Tax is added to the electricity price, though GHG emissions from current US electricity sources are higher than emissions from gasoline combustion, at 0.023 and 0.008887 tonnes CO_2e per GGE respectively [22]. The structure for Carbon Tax in the Keith et al. model applies to both gasoline and electricity and thus reduces the negative impact of Operating Cost of ICEVs relative to BEVs. The assumption to exclude electricity price from the taxation, instead increases the negative impact of Operating Cost of ICEVs relative to BEVs. This assumption makes sense as the US energy mix might change and shift from coal to renewables – a shift that could be accelerated by placing the tax with the purchaser of the fossil fuel, where it is combusted, rather than with the purchaser of electricity generated from its combustion.

With the increased Operating Cost caused by Carbon Tax, follows the assumption that the importance of this utility attribute relative to the two other utility attributes that impact overall utility negatively, Retail Price and Charge Time, is increased. The utility attributes that impact utility positively, Range, Infrastructure Availability and Model Selection, are not influenced by Carbon Tax.

Other important assumptions in the thesis model are that consumer familiarity with ICEV technology is full (set to 1) for the duration of the simulation period and that there is hardly any consumer familiarity with BEV technology (close to 0) at the start of the simulation period. As familiarity with BEV technology might cumulate over time, it has the potential to increase and reach full familiarity at 1, but not to decline. For the time horizon of the study this assumption is arguably valid, though it would not be for any given time horizon, especially for a very long time horizon. In the arrayed Keith et al. model, familiarity with both technologies has potential to vary in the 0 to 1 range and familiarity values will immediately impact sales shares via the associated technology affinities. In the thesis model, it is assumed that changes in BEV familiarity will be subject to a delay time of 4 years – that there is a period where newfound familiarity with BEV technology is consolidated in consumers before influencing their purchasing decisions.

Another assumption that differs from the Keith et al. model, is that the thesis model does not include station profits as input to infrastructure demand and excludes a structure for station profits altogether. It is assumed that demand will follow the development in the vehicle fleets.

Chapter 4. Model Analysis

4.1 Model Behavior

The reference modes from figures 1 and 2 are presented again in figures 20 and 21 below, which also include the Base Case run of the thesis model. Comparing the reference mode projections to the modelled Base Case run, they generally exhibit similar behavior – the exception is the EIA 'No Clean Power Plan' case in figure 20 that is much more pessimistic and does not display the growth seen in the other projections. In figure 20, the modelled Base Case is somewhat pessimistic compared to the EPS and BNEF cases, though the behavior is similar with rapid growth in BEV sales share in the period around 2025-2035, followed by a period of stabilization. The modelled Base Case stabilizes in excess of 50 % by 2050, while the EPS and EIA cases stabilize around 65 % and below 10 % respectively – the BNEF case stabilizes around 60 % by 2040. In figure 21, the modelled Base Case is pessimistic relative to the EIA STEPS case and optimistic relative to the EIA APS case, in the period until 2030.

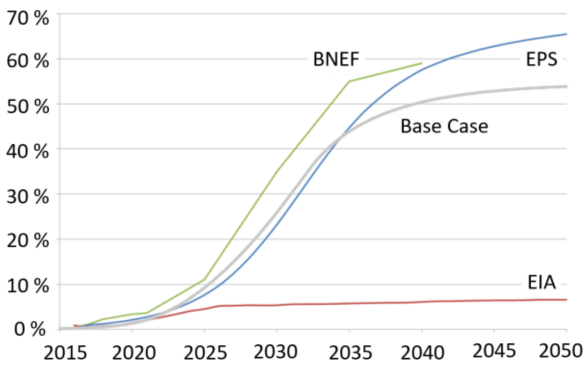

Figure 20 Three projections of BEV market shares in the US, published in 2017 for the period 2017 - 2050 [6] and Base Case run of the thesis model:

1. *EPS: Energy Policy Simulator 2017, 'Business as usual ' case [7]*
2. *EIA: Energy Information Administration Annual Energy Outlook 2017, 'No Clean Power Plan' case [8]*
3. BNEF: Bloomberg New Energy Finance Electric Vehicle Outlook 2017 [9]
4. *Base Case run of the thesis model*

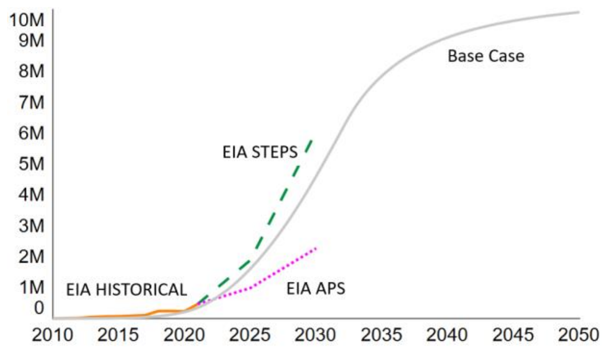

Figure 21 Historical and projected yearly BEV Sales in the US, published in 2022 for the period 2010 - 2030 [2] and Base Case run of the thesis model:

1. *Historical data 2010-2022 (EIA HISTORICAL)*
2. *Stated Policies Scenario (EIA STEPS)*
3. *Announced Policies Scenario (EIA APS)*
4. *Base Case run of the thesis model*

As displayed in figure 22, the modelled base case projects that the development in US BEV adoption starts becoming significant around 2020, that the increase in rate of BEV adoption is at its steepest around 2030 and that the development has started flatting out by 2035 and enters a stable phase from 2045. The modelled base case projects that the BEV share of new car sales in the US will reach and surpass 50 % around 2040 and reach around 52 % in 2050. A major contributor to the onset of BEV adoption in the US, is the increase in BEV familiarity that starts picking up around 2020, as can be seen in figure 23. The development in BEV familiarity follows an S-shaped growth curve that reaches its steepest growth in the early 2030 and surpasses halfway to full familiarity around 2030.

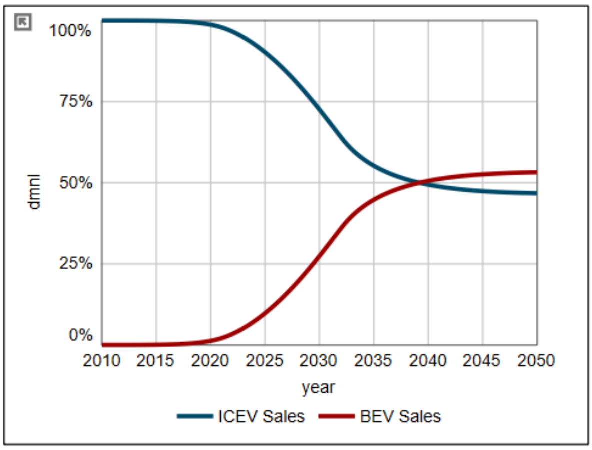

Figure 22 Modelled sales shares of new ICEVs (blue) and BEVs (red) (axis in percent).

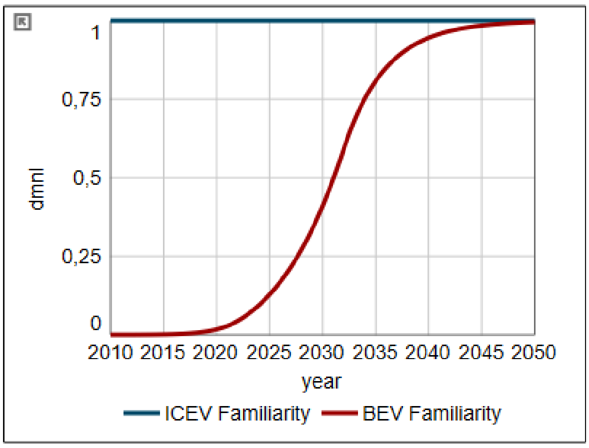

Figure 23 Familiarity with ICEV (blue) and BEV (red) technology (axis in fraction).

As long as BEV technology has not reached full consumer familiarity, it will constrain the full potential increase in BEV market share in spite of improvements on overall BEV utility relative to ICEV utility. The BEV familiarity feedback loop is reinforcing – when BEV familiarity increases, so does the BEV market share, which increases new BEV sales and the BEV fleet. This in turn, increases consumer familiarity with BEV technology.

Figures 24 and 25 display a counterfactual scenario for developments in technology familiarity and vehicle fleets respectively, for an expanded time horizon until 2100, when the global influence is disregarded. The development in BEV familiarity is influenced by the exposure to BEV technology in the US, which, the thesis model hypothesizes, is not solely influenced by the size of the US BEV fleet, but also by the growing BEV fleets in the global markets. Excluding the influence from global markets means the onset of BEV familiarity development will occur much later.

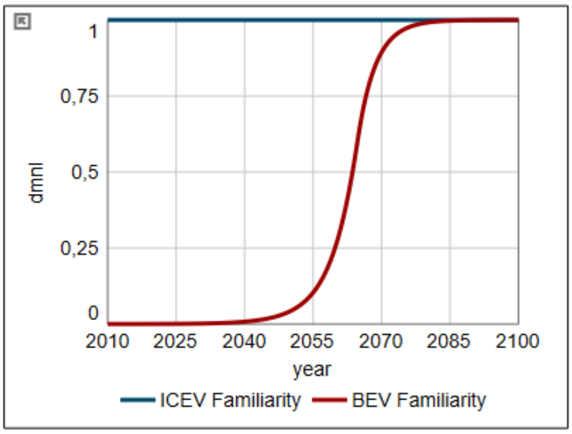

Figure 24 Modelled development of the ICEV (blue) and BEV (red) familiarity in the US when isolated from influence by global markets in the period 2010-2100.

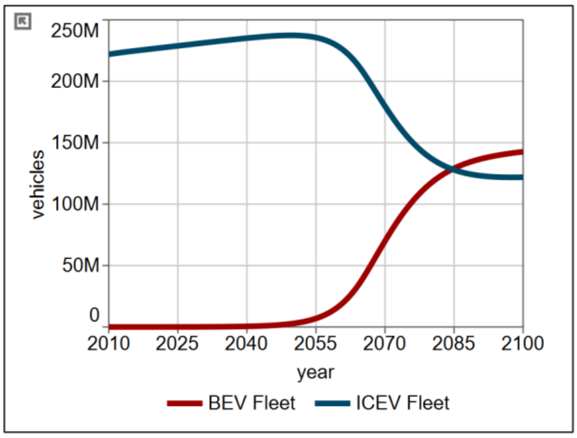

Figure 25 Modelled development of the ICEV (blue) and BEV (red) fleets in the US when isolated from influence by global markets in the period 2010-2100.

Excluding the influence from global markets also means the OEM Learning Curve Effects are based on solely US vehicle sales rather than vehicle sales across global markets as a whole, thus delaying the development in all BEV utility attributes, except Available Infrastructure, which further delay BEV familiarity development. In the model, a switch enables replacement of the global BEV and ICEV Sales and Fleets, which are included as default setting, with solely US domestic sales and fleets. As can be seen in figures 16 and 17, the development in BEV familiarity and adoption will exhibit the same behavior when global influence is switched off, though the development will be delayed around 30-35 years when considering the US market and industry in isolation.

The default model setting includes the influence by global markets. In the modelled base case, the Utility Operating Cost, displayed in figure 26, is the only utility attribute where BEV technology outperforms ICEV technology for the duration of the simulation period and thus contribute positively to the overall relative utility of BEVs. The feedback loop involving BEV Operating Cost is reinforcing and following the positive development in

BEV adoption and the improvements in fuel efficiency with cumulative experience, from the middle of the simulation period, the gap between BEV and ICEV Utility Operating Cost exhibit a slight and steady increase.

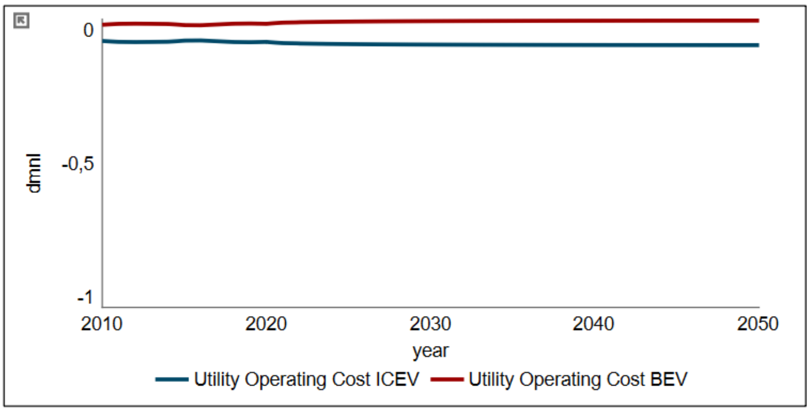

Figure 26 *Utility of Operating Cost of ICEVs (blue) and BEVs (red) technology (axis is dimensionless).*

For the Utility Range attribute, displayed in figure 27, ICEV ranges are relatively longer than BEV ranges in the beginning of the simulation period and thus contribute negatively to the overall relative utility of BEVs. The feedback loop involving BEV Range is reinforcing and as more and more new BEVs are sold, more and more experience with BEV manufacturing is gained, which leads to an increase in BEV fuel efficiency after some time an increase in BEV driving range. Improvements with experience are also taking place with the ICEV technology, however, the learning curve indicates a 15 % improvement with every doubling of experience, which is occurring much more frequently for the BEV technology. In the simulation period, the first doubling in BEV technology experience happens during the fourth year and then doubles again within two years later. For ICEV technology on the other hand, the first doubling happens during the twelfth year and does not happen again until 2048. Model simulations show that in 2010, the average driving range of BEVs and ICEVs were around 54 and 280 miles or 87 and 450 km, respectively. In 2050, ranges have increased to around 573 and 372 miles or 922 and 599 km, for BEVs and ICEVs respectively. The average BEV range surpasses the average ICEV range sometime in the mid-2030s, which means the Utility Range attribute contributes positively to the overall relative utility of BEVs from that point, though not by much.

The improvement in average BEV range, impact the average weekly time a driver would need to charge their BEV, which reduces the negative contribution from BEV Utility Refuel Time relative to ICEV technology. Figure 28 shows that the difference between ICEV and BEV Utility Refuel Time become quite small from the mid-2030s, though the negative contribution from BEV Utility Refuel Time, remain higher than the negative contribution from ICEV Utility Refuel Time for the duration of the simulation period.

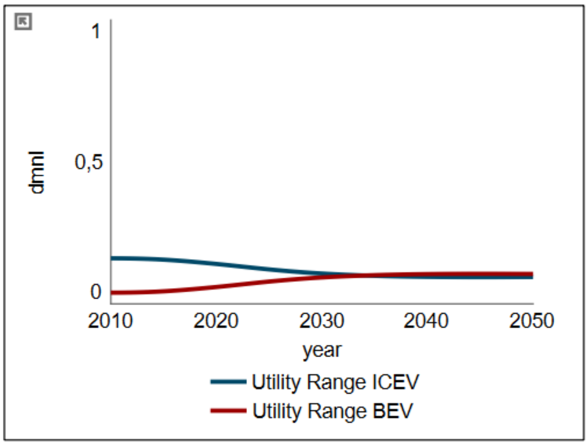

Figure 27 Utility of driving Range of ICEVs (blue) and BEVs (red) (axis is dimensionless).

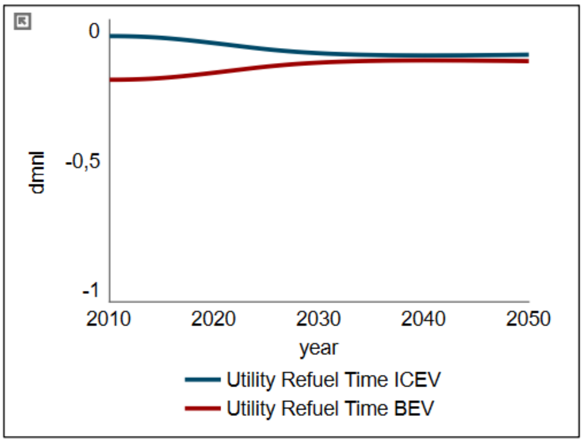

Figure 28 Utility of Refuel Time for ICEVs (blue) and BEVs (red) (axis is dimensionless).

Figures 29 and 30 display the development in vehicle Utility Retail Price. In 2010, a government Tax Credit incentive to promote BEVs was introduced [23]. This incentive is included in the model as default and its effects can be seen in figure 29, while in figure 30 the Tax Credit regime has been excluded.

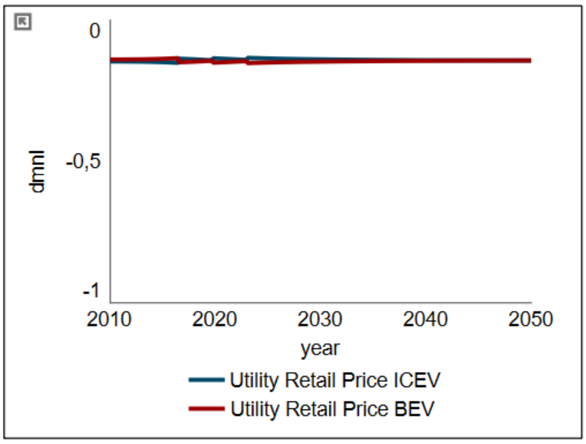

Figure 29 Utility of Retail Price of ICEVs (blue) and BEVs (red) as influenced by 2010 tax credit initiative (axis is dimensionless).

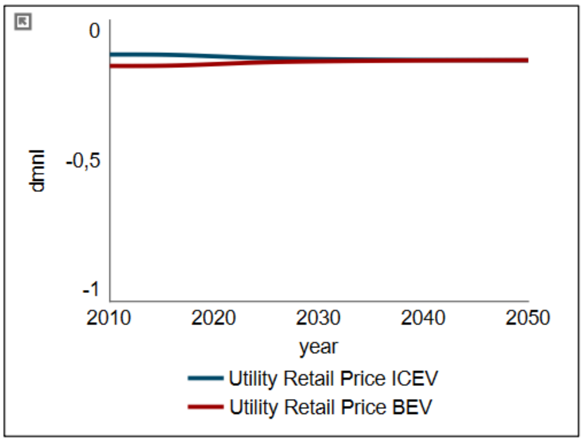

Figure 30 Utility of Retail Price of ICEVs (blue) and BEVs (red) without influence by 2010 tax credit initiative (axis is dimensionless).

The tax credit was effective from 2010 and ranged from $2,500 to $7,500 for each vehicle based on battery capacity and vehicle weight. The tax credit was available until a manufacturer had sold 200,000 BEVs, at which point the credit began to phase out over time for vehicles sold by that company. The credit would halve for the six months following the sale of the 200,000th vehicle, and then halve again for the next six months, and finally disappears entirely[23]. In the model, this tax credit is defined as a reduction in all BEV retail prices of $7,500 from 2010 through 2015, then a reduction of $3,750 from 2015 through 2019 and then a reduction of $1,875 from 2019 through 2022. The Tax Credit is now being phased out and has been replaced by provisions the Inflation Reduction Act of 2022 [24], which has not been included in the model as default but as a policy and is elaborated on in the Policy design and tests chapter.

The utility of vehicle retail prices remains quite similar for BEV and ICEV technology for the duration of the simulation period. Model simulations show that in 2010, the average retail price of BEVs and ICEVs were around $26,400 and $19,800. However, the 2010 tax credit incentive causes the BEV Utility Retail Price to be relatively better than ICEV technology until 2015, after this ICEV Utility Retail Price outperforms BEV technology until 2048 when BEV Utility Retail Price drops slightly below the price for ICEV technology. The feedback loop involving BEV Retail Price is reinforcing and following the positive development in BEV adoption and improvements with cumulative experience, the gap between ICEV and BEV Utility Retail Price is steadily decreasing.

For the Utility Model Selection attribute, displayed in figure 31, ICEV model selection is relatively better than for BEVs in the beginning of the simulation period and thus contribute negatively to the overall relative utility of BEVs. The feedback loop involving BEV Model Selection is reinforcing and as more and more new BEVs are sold, more and more experience with BEV manufacturing is gained, which leads to an increase in BEV Model Selection after some time. This in turn, increases the positive contribution from BEV model selection utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

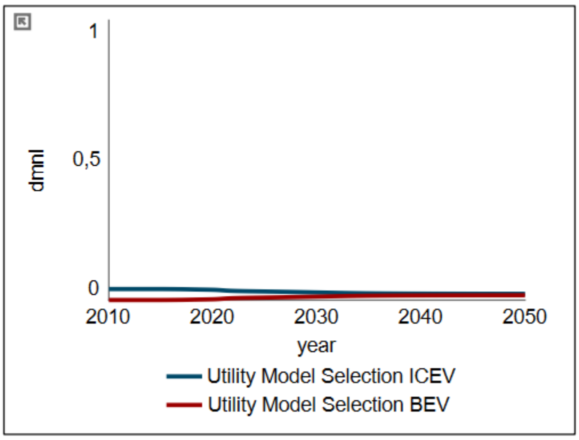

Figure 31 *Utility of Model Selection of ICEVs (blue) and BEVs (red) (axis is dimensionless).*

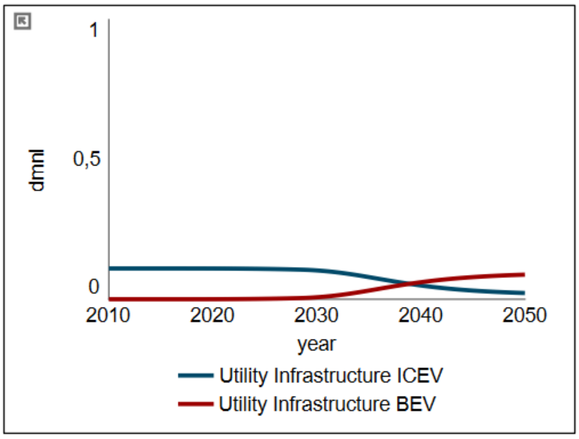

Figure 32 *Utility of refueling Infrastructure for ICEVs (blue) and BEVs (red) (axis is dimensionless).*

The difference between Utility Model Selection for ICEV and BEV technologies is quite stable, with ICEV selection outperforming BEV selection in the 2010s, then it is on the decline in the 2020s and from the 2030s there is no significant difference in model selection.

For the Utility of refueling Infrastructure attribute, displayed in figure 32, ICEV Infrastructure is relatively better than for BEVs from the beginning of the simulation period and thus contribute negatively to the overall relative utility of BEVs. The feedback loop involving BEV Utility of refueling Infrastructure is reinforcing and as an increasing number of BEVs are on the road, the demand for charging infrastructure increases. After some time, this will lead to an increase in available charging infrastructure. This in turn, increases the positive contribution from BEV infrastructure utility to total consumer utility of BEV technology and leads to an increase in BEV market share and new BEV sales.

4.2 Validation testing

The model has been subjected to several tests in order to strengthen its credibility and verify its validity. The tests have been performed in accordance with acknowledged guidelines for system dynamics modeling [17] and the results are presented in this chapter.

4.2.1 Structural Verification

The structure of the thesis model is supported by literature and builds heavily on the work done by Keith et al. [12], presented in the paper *The Diffusion of Alternative Fuel Vehicles: A Generalised Model and Future Research Agenda*. While the thesis model has simplified the Keith et al. model, and certainly oversimplifies the real-world processes of the US passenger car vehicle market, the processes that are included have sufficient theoretical backing in literature to provide confidence that the structure sufficiently represents the real-world system for the purposes of this thesis.

4.2.2 Parameter Verification

All of the model parameters have real-world counterparts and have been given values supported by data. A few variables, adopted from the original Keith et al. model, are re-representations of economic theory or unit correction variables. An overview of parameter assumptions along with source references and sensitivity testing of each parameter, is presented in tables 4-8 in the Model Analysis – Sensitivity Analysis chapter of this paper. In Appendix A – Model documentation, the full documentation is presented.

4.2.3 Dimensional Consistency Testing

The units of this thesis model are dimensionally consistent, and no warnings of unit errors or equation inconsistencies are given from the software.

4.2.4 Integration Error Testing

The model is set up using Euler integration and is not sensitive to choice of integration method. When tested using Cycle time, Runge-Kutta 2 and Runge-Kutta 4, the model does not exhibit changes in behavior. Different DT values have also been tested – the DT used in the model is 1/32 years. In the tests, a DT of 1/16 years or 1/64 years do not impact behavior.

4.2.5 Direct Extreme-Condition Testing

For the purposes of the thesis model, the responses to extreme values are adequate. Figure 33 displays the development in BEV Sales in the Base Case Scenario compared to when gas price has been set to $0 – the response might be surprising as one might expect that BEV sales would never pick up as long as gas is free and the operation cost of ICEVs is negligible. Figure 34 displays the response in Utility of Operating Cost, where there is no negative contribution to overall ICEV utility from the ICEV Utility Operating Cost for the duration of the simulation period. However, due to the structure of weighted attributes, the Utility Operating Cost attribute will never contribute more than 9.5 % in a scenario without Carbon Tax.

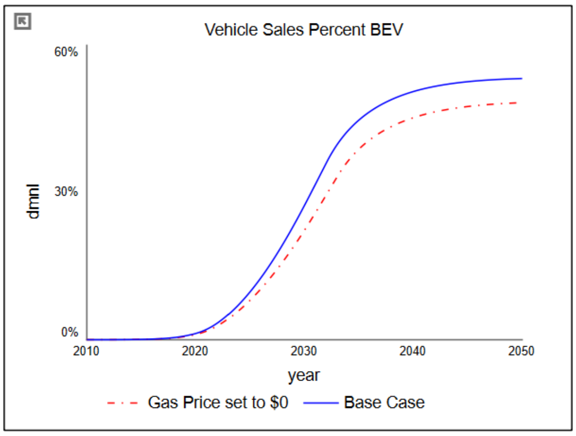

Figure 33 BEV Sales Base Case (blue) and when gas price is set to $0 (red) (axis in percent).

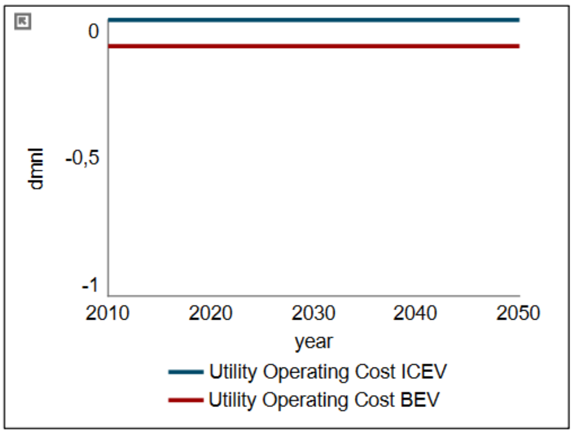

Figure 34 Utility of Operating Cost for ICEVs (blue) and BEVs (red) when gas price is set to $0 (axis is dimensionless).

4.2.6 Sensitivity testing

The sensitivity of key parameters has been considered by running tests using Sobol Sequence sampling over 250 runs within a range of ± 25 % from the parameter value used in the model. The results of the sensitivity analysis are presented in tables 5-12. The tables are arranged by sectors, starting with the sectors from the Consumer module, then the Vehicles module and lastly the Fueling module.

There are seven graphical functions in the model – six of which are the weights in the Consumer Utility Sector presented in Table 6. The six weight parameters remain constant whenever Carbon Tax is set to zero – these parameters have been tested based on their constant values when there is no Carbon Tax. The other graphical function, presented in Table 10, has been tested by multiplying the function with ± 25 %.

Table 5 Results from sensitivity testing of selected variables in the **Projected Market Shares Sector** and the **Consumer Familiarity Sector** of the Consumer Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
BEV familiarity delay time	4	year	3	5	No behavioral sensitivity. Some numerical sensitivity, convergent.	Estimated from calibration.
BEV Marketing Fraction of ICEV Revenue	0,001	dmnl	0,00075	0,00125	No behavioral sensitivity. Some numerical sensitivity, convergent.	Assumption.
Marketing Fraction of Revenue	0,004	dmnl	0,003	0,005	No behavioral sensitivity. Very little numerical sensitivity, convergent.	Assumption.
BEV Marketing Effectiveness	4e-03	dmnl/million	3e-03	5e-03	No behavioral sensitivity. Some numerical sensitivity, convergent.	Estimated from calibration.
Effective Contact Rate Drivers	0,06	dmnl/year	0,45	0,75	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].

Table 6 Results from sensitivity testing of selected variables in the **Consumer Utility Sector** of the Consumer Module. The values tested are default weights in a scenario without Carbon Tax.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Range Weight	0,2	dmnl	0,15	0,25	No behavioral sensitivity. Very little numerical sensitivity, slightly convergent.	Estimated from source [15, 16].
Infrastructure Weight	0,11	dmnl	0,0825	0,1375	No behavioral sensitivity. Little numerical sensitivity, slightly convergent.	Estimated from source [15, 16].
Model Selection Weight	0,04	dmnl	0,03	0,05	No behavioral or numerical sensitivity.	Estimated from source [15, 16].
Operating Cost Weight	-0,095	dmnl	-0,07125	-0,11875	No behavioral sensitivity. Little numerical sensitivity, slightly divergent.	Estimated from source [15, 16].
Retail Price Weight	-0,285	dmnl	-0,21375	-0,35625	No behavioral or numerical sensitivity.	Estimated from source [15, 16].
Charge time / Fueling time Weight	-0,27	dmnl	-0,2025	-0,3375	No behavioral sensitivity. Very little numerical sensitivity.	Estimated from source [15, 16].

Table 7 Results from sensitivity testing of selected variables in the **Fleet Turnover sector** of the Vehicles Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Market growth rate	0,025	dmnl	0,01875	0,03125	No behavioral sensitivity. Little numerical sensitivity, divergent.	Estimated from source [25].
New Vehicle Discard Fraction	0,001	dmnl/year	0,00075	0,00125	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Vehicles 5 to 8 Discard Fraction	0,01	dmnl/year	0,0075	0,0125	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Vehicles 9 to 12 Discard Fraction	0,1	dmnl/year	0,075	0,125	No behavioral sensitivity. Very little numerical sensitivity, slightly divergent.	Adopted from Keith et al. [12].
Vehicles Retirement Fraction	0,17	dmnl/year	0,1275	0,2125	Some behavioral and numerical sensitivity, convergent.	Adopted from Keith et al. [12].
Aging Time Lambda	4	year	3	5	No behavioral sensitivity. Some numerical sensitivity, convergent.	Adopted from Keith et al. [12].

Table 8 Results from sensitivity testing of selected variables in the **Vehicle Price and Revenue Sector** of the Vehicles Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Initial IC Engine Cost	3000	$/vehicles	2250	3750	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Initial Base Vehicle Cost	15000	$/vehicles	11250	18750	No behavioral sensitivity. Little numerical sensitivity, slightly convergent.	Adopted from Keith et al. [12].
Initial Battery Cost	10000	$/GGE	7500	12500	No behavioral sensitivity. Very little numerical sensitivity.	Adopted from Keith et al. [12].
Initial Electric Architecture Cost	3000	$/vehicles	2250	3750	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Markup	0,1	dmnl	0,075	0,125	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].

Table 9 Results from sensitivity testing of selected variables in the **OEM Learning Curve Effects sector** of the Vehicles Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Delay time for FE of new ICEVs to impact average FE	8	year	6	10	No behavioral or numerical sensitivity.	Assumption.
Delay time for FE of new BEVs to impact average FE	8	year	6	10	No behavioral or numerical sensitivity.	Assumption.
Initial Gas Fuel Efficiency	20	miles/GGE	15	25	No behavioral sensitivity. Little numerical sensitivity, slightly divergent.	Estimated from source [26].
Initial Electric Fuel Efficiency	90	miles/GGE	67,5	112,5	No behavioral sensitivity. Very little numerical sensitivity, slightly convergent.	Estimated from source [27].
Initial Experience Battery	599000	GGE	149750	748750	No behavioral or numerical sensitivity.	Estimated from other initial values.
Initial Experience Electric Architecture	1e+06	vehicles	7,5E+05	7,5E+07	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Initial Experience Base Vehicle	1e+09	vehicles	7,5E+08	1,25E+09	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Initial Experience IC Engine	1e+09	vehicles	7,5E+08	1,25E+09	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Learning curve rate BEV Auto industry	0,15	dmnl	0,1125	0,1875	No behavioral sensitivity. Little numerical sensitivity, slightly divergent.	Estimated from source [18].
Learning curve rate ICEV Auto industry	0,15	dmnl	0,1125	0,1875	No behavioral sensitivity. Very little numerical sensitivity, slightly divergent.	Estimated from source [18].

Table 10 Results from sensitivity testing of selected variables in the **Fueling Infrastructure Sector** of the Fueling Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Infrastructure in Construction BEV	0	stations	0	482	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Available Infrastructure BEV	482	stations	361,5	602,5	No behavioral or numerical sensitivity.	Estimated from source [2].
Infrastructure in Construction ICEV	10000	stations	7500	12500	No behavioral or numerical sensitivity.	Estimated from source [28].
Available Infrastructure ICEV	159006	stations	119254,5	198757,5	No behavioral or numerical sensitivity.	Estimated from source [28].
Time to Install Infrastructure ICEV	2	year	1,5	2,5	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Supply Line Adjustment Time ICEVS	0,5	year	0,375	0,625	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Infrastructure Life ICEV	20	year	15	25	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Demand delay time ICEV	2	year	1,5	2,5	No behavioral or numerical sensitivity.	Assumption.
Time to Install Infrastructure BEV	1	year	0,75	1,25	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Supply Line Adjustment Time BEV	0,1	year	0,075	0,125	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Infrastructure Life BEV	20	year	15	25	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].
Demand delay time BEV	2	year	1,5	2,5	No behavioral or numerical sensitivity.	Assumption.

Table 11 Results from sensitivity testing of selected variables in the **Fueling metrics Sector** of the Fueling Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Fueling Utilization factor	0,15	dmnl	0,1125	0,1875	No behavioral or numerical sensitivity.	Assumption from source [21].
Initial Dispensing Rate BEV	1,5	GGE/hour	1, 1125	1,1875	No behavioral sensitivity. Little numerical sensitivity, slightly divergent.	Adopted from Keith et al. [12].
Fraction home fueling	graph	dmnl	-25 %	+25 %	No behavioral sensitivity. Little numerical sensitivity, slightly divergent.	Assumption.
Fuel Dispensing Rate ICEV	600	GGE/hour	450	750	No behavioral or numerical sensitivity.	Adopted from Keith et al. [12].

Table 12 Results from sensitivity testing of selected variables in the **Fuel Prices Sector** of the Fueling Module.

Variable name	*Value*	*Unit*	*Testing Range*		*Sensitivity*	*Source model Base Case Value*
			Minimum	*Maximum*		
Gasoline Price Growth rate	0,01	dmnl/year	0,0075	0,0125	No behavioral or numerical sensitivity.	Assumption.
Electricity Price Growth rate	0,01	dmnl/year	0,0075	0,0125	No behavioral or numerical sensitivity.	Assumption.

The results from the sensitivity testing reveal that there are few very sensitive parameters when tested individually, which could be seen as an indication that the model is robust. Five parameters, from the Consumer Familiarity Sector and the Fleet Turnover sector, exhibit more significant numerical changes when tested. From the Consumer Familiarity Sector, the sensitive parameters are BEV familiarity delay time, BEV Marketing Fraction of ICEV Revenue and BEV Marketing Effectiveness. From the Fleet Turnover sector, the sensitive parameters are Vehicles Retirement Fraction and Aging Time Lambda – the Vehicles Retirement Fraction is the only parameter that exhibit slight behavioral changes when tested. The mentioned parameters will be referred to again in the Policy design and Tests chapter of this thesis. Figures 35 and 36 display the confidence intervals for the development in BEV fleet and BEV Sales respectively, when the mentioned sensitive parameters were tested in combination using, Sobol Sequence sampling over 250 runs within a range of ± 25 % from the parameter value used in the model. Similar to the observations when running the parameters individually, the KPIs in figures 28 and 29, do not exhibit behavioral sensitivity when tested in combination. There is, however, significant numerical sensitivity that converges toward the end of the simulation period.

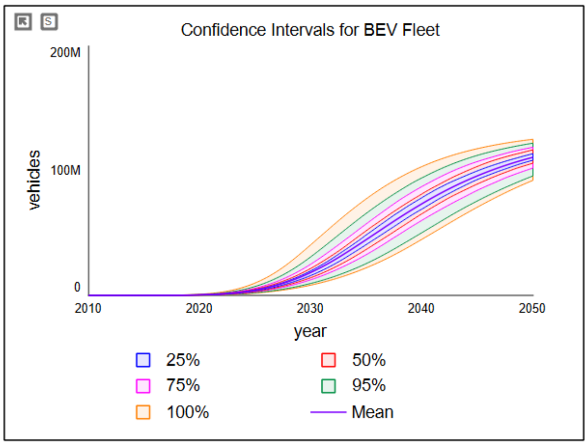

Figure 35 Confidence interval for the development in BEV fleet when running combined sensitivity testing in the most sensitive parameters (axis in vehicles).

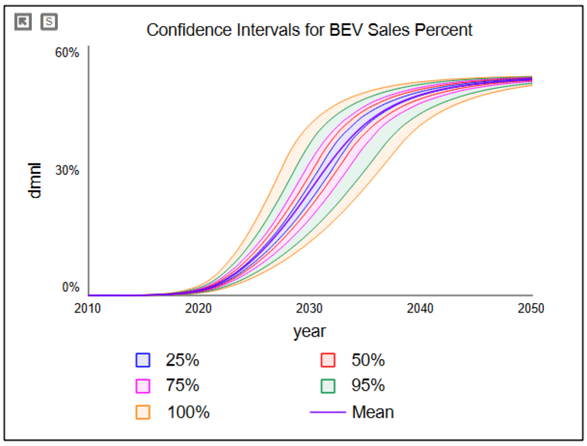

Figure 36 Confidence interval for the development in BEV Sales when running combined sensitivity testing in the most sensitive parameters (axis in percent of market).

4.2.7 Behavior Reproduction and Validation

Validation has been a central part of the iterative process of developing, testing and analyzing the thesis model. The current model is a result of model iterations that have converged toward a plausible model structure that is considered useful for its purpose. In figures 37-39, a selection of key model variables has been compared to historical data [25], [2] from the period 2010-2021, to assess how early model projections compare to the historical development. In figure 40, both historical and projected data made available by the International Energy Agency [2] is compared to the model projection of US BEV Sales.

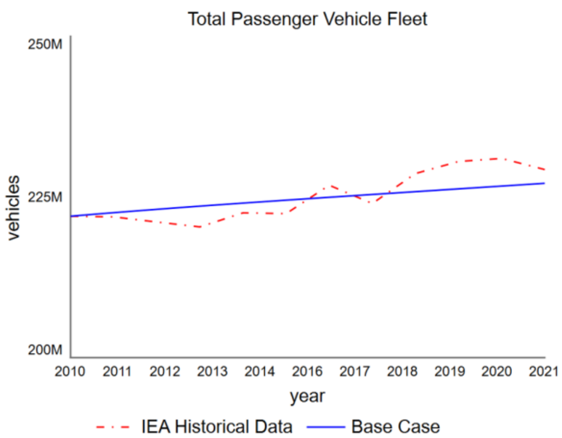

Figure 37 Historical number of passenger vehicles in the US [25] (red dashed) and model projection (blue), in the period 2010-2021.

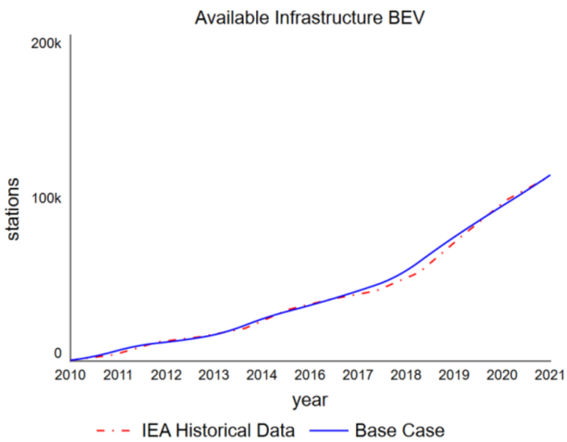

Figure 38 Historical number of charging stations in the US [2] (red dashed) and model projection (blue), in the period 2010-2021.

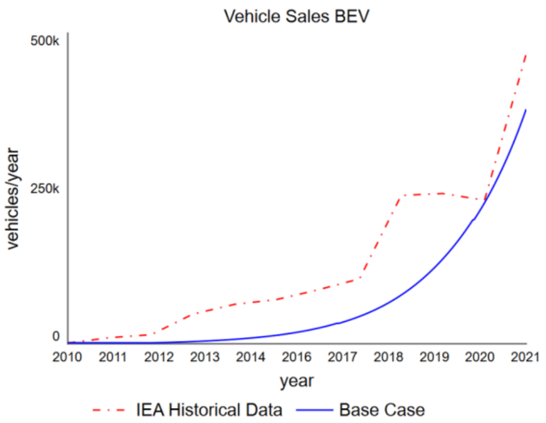

Figure 39 *Historical number of BEV Sales in the US [2] (red dashed) and model projection (blue solid), in the period 2010-2021.*

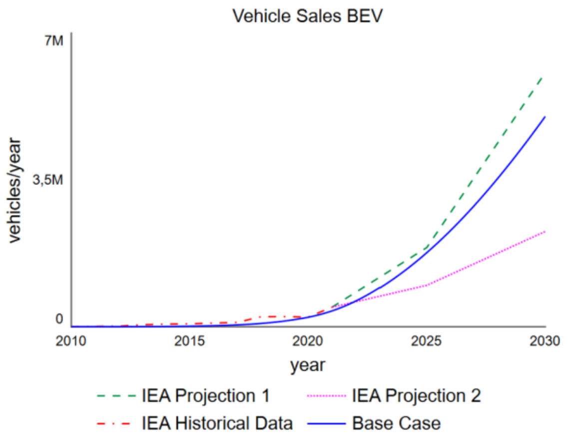

Figure 40 *Historical and projected number of BEV Sales in the US [2] from the reference mode (red dashed, green dashed, pink dotted) and model projection (blue solid), in the period 2010-2030.*

In general, the model produces similar results as the historical data. When looking at the Total Passenger Vehicle Fleet in figure 37, it is clear that short term variations are not revealed by the model, though it does seem to project a satisfactory average approximation. The same is true for the Available Infrastructure BEV or charging station projection in figure 38. However, the very close similarity between historical and projected data for charging stations, is due to the fact that, in addition to endogenous dynamics, historical build-out data was being used in the period 2010-2021.

When looking at the BEV Sales in figure 39, it seems the model is not able to reproduce the historical data accurately. The model underestimates BEV Sales for the duration of the ten-year period and seems to have more of an exponential behavior than can be observed in the historical data. However, when looking at figure 40 and the projected data made available by the International Energy Agency [2], the model projection does display similar behavior as the two projections and is numerically between the two. Overall, the BEV Sales projections are clearly uncertain, and the model behavior seems similar enough to historical data to allow for useful model simulation.

Chapter 5. Policy design and tests

In performing sensitivity testing, five parameters were identified as relatively sensitive which is an indication that they might serve as effective leverage points for interventions. These parameters are:

1. BEV familiarity delay time
2. BEV Marketing Fraction of ICEV Revenue
3. BEV Marketing Effectiveness
4. Vehicles Retirement Fraction
5. Aging Time Lambda

Of the parameters listed above, the three first parameters are related to the BEV familiarity which directly impacts the affinity of BEV technology and thus the market share distribution. The suggested policy to influence BEV familiarity is 'Market Spending'. The two last parameters, among the sensitive parameters listed above, are related to the turnover rate of the vehicle fleet. A more rapid turnover, where vehicles are discarded more frequently, would allow a faster transition from ICEVs to BEVs, though it would also entail dilemmas regarding how the discarded vehicles should be handled and the increased demand for production of new vehicles. There are no policies aimed at these parameters as they are calibrated to fit historical data and because policies would introduce considerable dilemmas.

There are three additional policy categories included in the model – these policy categories have been selected as they have been identified as main policy drivers of BEV adoption to date [4], this applies to Vehicle Purchase Subsidies and Infrastructure Incentives, or are part of emerging global incentives to reduce energy use and shift to cleaner fuels [29], this applies to Carbon tax. The four policy categories are all impacting different parts of the model structure:

1. Marketing Spending
2. Vehicle Purchase Subsidies
3. Infrastructure incentives
4. Carbon Tax

Figures 41 and 42 display the behavior of BEV Fleet and BEV Sales respectively, in the model Base Case and the 'All Policies' scenario, where all policy suggestions are implemented at their most impactful. The settings for the separate policy suggestions are elaborated on in the following subchapters.

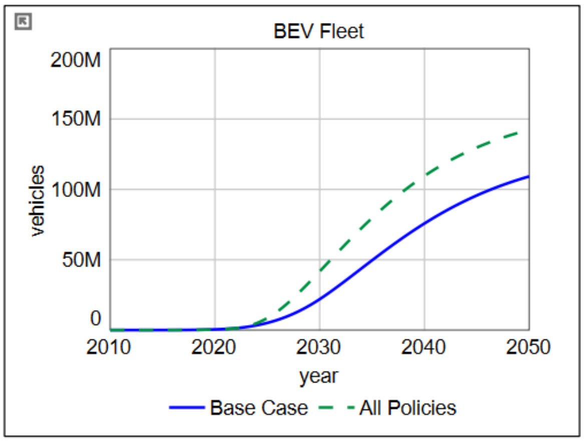

Figure 41 Model Base Case and 'All Policies' Scenario impact on BEV Fleet.

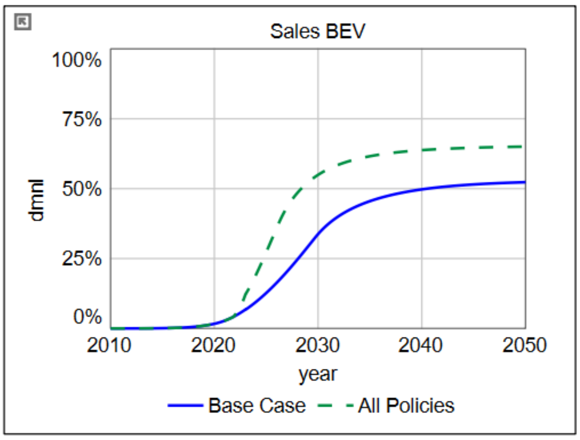

Figure 42 Model Base Case and 'All Policies' Scenario impact on BEV Sales share.

Figure 41 shows that the 'All Policies' scenario projects the size of the US BEV Fleet to be more than 142 million in 2050, an increase of more than 33 million vehicle compared to the Base Case. The market share of BEVs is projected to be around 65 % in the 'All Policies' scenario by 2050, compared to around 52 % in the Base Case. Overall, the 'All Policies' scenario projects an increase of the BEV Fleet and BEV market share of around 23 % and 20 % relative to the Base Case in 2050.

5.1 Marketing Spending

Marketing spending is a promising policy because BEV Marketing Fraction of ICEV Revenue has been identified a sensitive variable along with BEV Marketing Effectiveness – these variables both influence BEV familiarity which in turn directly impacts the affinity of BEV technology and thus the market share distribution.

The market spending for ICEVs and BEVs is set to 4 % of the OEM revenue from the respective technology. 1 % of the OEM revenue from ICEV technology is additionally allocated to BEV Marketing Spending, based on the assumption that most OEMs manufacture both BEV and ICEV technology and might distribute parts of the marketing funds between the two technologies. The regular marketing spending for BEV and ICEV technology is displayed in figure 43. The model also has a structure for additional 'Subsidized Market Spending'. This policy is modelled as an additional yearly marketing allocation of $500 million for the BEV technology from 2022 and for the duration of the simulation period, which was also its setting in the 'All Policies' scenario. Figure 44 displays how the model Base Case and the 'Subsidized Market Spending' Scenario impact on BEV Marketing Spending.

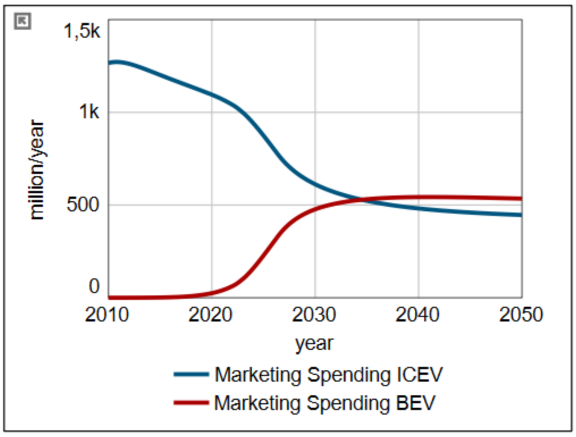

Figure 43 *Regular marketing spending for BEV and ICEV technology.*

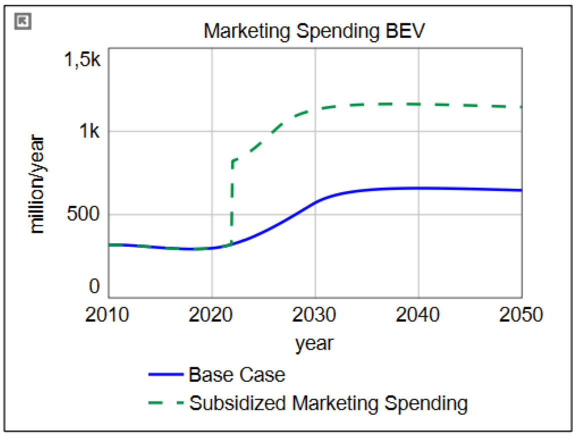

Figure 44 *Model Base Case and the 'Subsidized Market Spending' Scenario impact on BEV Marketing Spending.*

Figures 45 and 46 display the behavior of BEV Fleet and BEV Sales respectively, in the model Base Case and the 'Subsidized Market Spending' scenario. Figure 45 shows that the 'Subsidized Market Spending' scenario projects around an additional 3 million vehicles in the US BEV Fleet by 2050 compared to the Base Case. The market share of BEVs is projected to be around 52 % by 2050 in both the model Base Case and the 'Subsidized Market Spending' scenario. There is, however, a period of around 10 years after the policy deployment in 2022, when the policy seems to have a significant effect – especially during the years 2026-2028, with a peak in 2027 of more than 32 % increase in BEV market share relative to the Base Case. This improvement is caused by a greater increase in familiarity with BEV technology during this period. From around 2040, when familiarity with BEV technology is nearly full, the 'Subsidized Market Spending' policy loses its potential and is no longer effective.

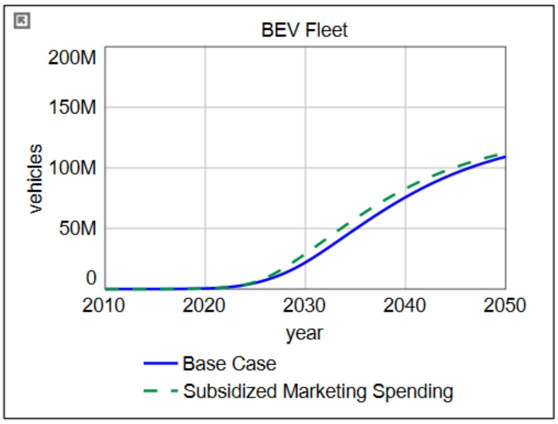

Figure 45 *Model Base Case and the 'Subsidized Market Spending' Scenario impact on BEV Fleet.*

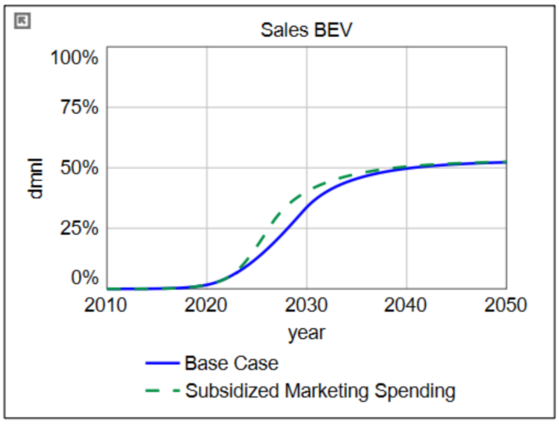

Figure 46 *Model Base Case and the 'Subsidized Market Spending' Scenario impact on BEV Market Share.*

An alternative policy, which was not included in the 'All Policies' scenario, could be to impose an allocation of minimum half the marketing budget towards BEV technology, on OEMs. This might mean a marketing spending for ICEVs and BEVs at 2.5 % of revenue from the respective technology and an additional 2.5 % of ICEV revenue allocated to BEV Marketing Spending. The effect of the '2.5 % BEV Marketing fraction' alternative scenario is displayed in figures 47 and 48. This alternative projects around an additional 5 million BEVs by 2050 compared to the Base Case which is 2 million more than in the 'Subsidized Market Spending' scenario – it also projects the transition would be slightly expedited compared to both the Base Case and the 'Subsidized Market Spending' scenario. The '2.5 % BEV Marketing fraction' policy is effective in that it also reduces the strength of the reinforcing feedback loops for the incumbent ICEV technology.

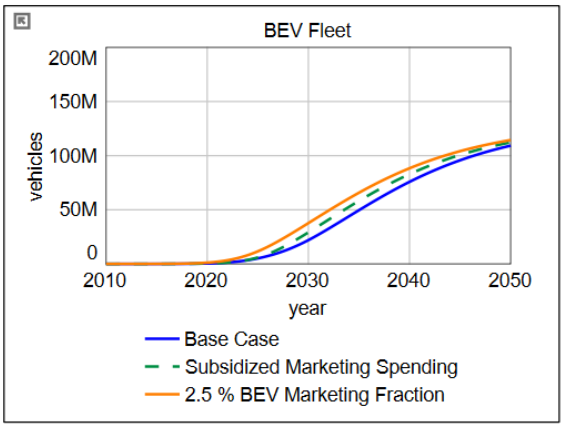

Figure 47 *Model Base Case, 'Subsidized Market Spending' Scenario and '2.5 % BEV Marketing fraction' alternative scenario impact on BEV Fleet.*

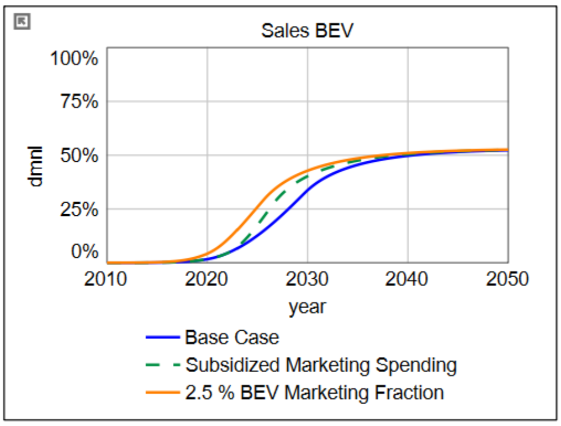

Figure 48 *Model Base Case, 'Subsidized Market Spending' Scenario and '2.5 % BEV Marketing fraction' alternative scenario impact on BEV Market Share.*

5.2 Vehicle Purchase Subsidies

The model contains one default BEV purchase subsidy policy which is included in the model Base Case, namly the 2010 BEV Tax Credit that was part of the American Recovery and Reinvestment Act of 2009 and was effective in the US from 2010 [20]. The tax credit ranged from $2500 to $7500 per vehicle based on battery capacity and vehicle weight. The tax credit was made available until a manufacturer had sold 200000 EVs, at which point the credit was phased out for vehicles sold by that manufacturer. In the phase-out period, the credit was first halved for the six months following the sale of the 200000th vehicle and then halved again for the next six months, and finally phased out entirely [5] [20].

As part of the governmental 2022 Jobs initiative, a new BEV Tax Credit policy was proposed and will be effective from 2023, replacing the 2010 Tax Credit – in the model this policy is called the 2023 BEV Tax Credit. The new tax credit will remove manufacturer sales caps, expand the scope of eligible vehicles and add sourcing requirements for critical mineral extraction, processing and recycling, as well as battery component requirements. Vehicles meeting either the mineral sourcing requirements or the battery component requirements will be eligible for a tax credit of up to $3750, while vehicles meeting both requirements will be eligible for a total tax credit of $7500 [30], [31].

At the federal level, the US has taken less of a supportive approach through BEV purchase subsidies than China and Europe, however, over half of the states in the US are using additional measures to incentivize EV purchases [4] [5]. In 2020, only 30% of electric cars sold in the US benefitted from the federal tax credits [4]. The Obama Administration tried to increase the tax credit to $10000 and replace it with a point-of-sale rebate, but the proposal was not passed by Congress [5]. In Norway, where the BEV market share recently exceeded 80 % [32], BEVs have been exempt from registration tax since 1990, which has meant an effective 25 % point-of-sale rebate for more than 30 years [4].

In the thesis model, the 2010 BEV Tax Credit and the 2023 BEV Tax Credit have been modeled as point-of-sale rebates, though in reality they would rather give the option to claim a tax credit after the purchase and not affect the retail price directly as modeled. They have also been simplified as the details of the policies would require significant additional model structure. Figure 49 display the 2010 BEV Tax Credit and 2023 BEV Tax Credit as modelled, while figure 50 displays the effective purchase prices of ICEVs and BEVs when the default 2010 BEV Tax Credit and the '2023 BEV Tax Credit' scenario is applied. The same settings for '2023 BEV Tax Credit' scenario' as shown here, were also used in the 'All Policies' scenario.

Figure 50 shows that the initial ICEV price is around $20000 and the BEV price is around $19000 with the full compensation of the 2010 BEV Tax Credit – without this compensation the initial BEV price would be around $26500. The BEV price later exceeds the ICEV price for a period before the '2023 BEV Tax Credit' is introduced and the BEV price drops well below the ICEV price.

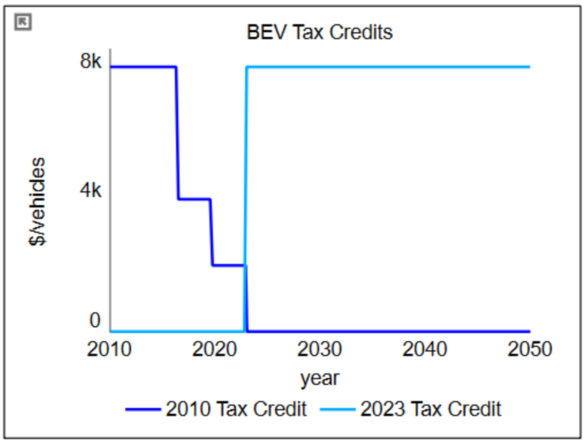

Figure 49 Modelled 2010 BEV Tax Credit and the 2023 BEV Tax Credit

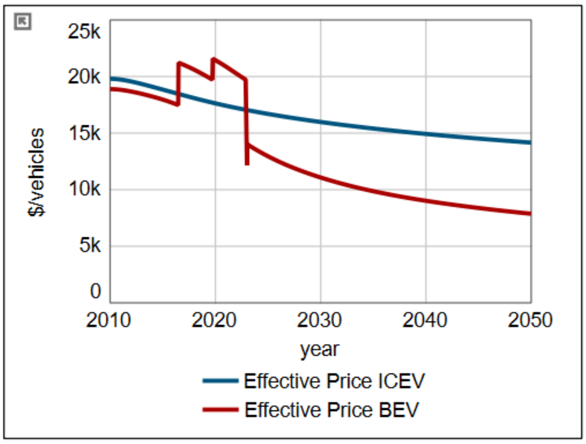

Figure 50 Model Base Case and the '2023 BEV Tax Credit' Scenario impact on BEV Market Share.

Figures 51 and 52 display the model Base Case and the '2023 BEV Tax Credit' scenario impact on BEV Fleet and BEV Market Share, respectively. The '2023 BEV Tax Credit' scenario projects the size of the US BEV Fleet would increase by around 6 million vehicles and the BEV market share by around 3 percentage points by 2050, compared to the Base Case. This corresponds to an improvement for both the BEV Fleet and BEV market share of close to 5 % relative to the Base Case in 2050. The relatively low effectiveness of this policy is due to the rather small difference beween BEV and ICEV Retail Price Utility in comparison to other utility attributes.

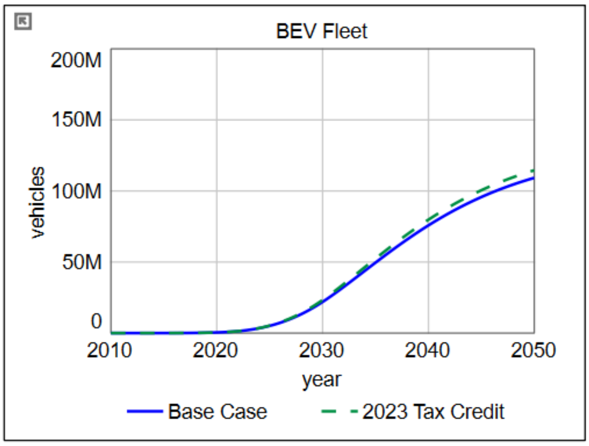

Figure 51 Model Base Case and the '2023 BEV Tax Credit' Scenario impact on BEV Fleet.

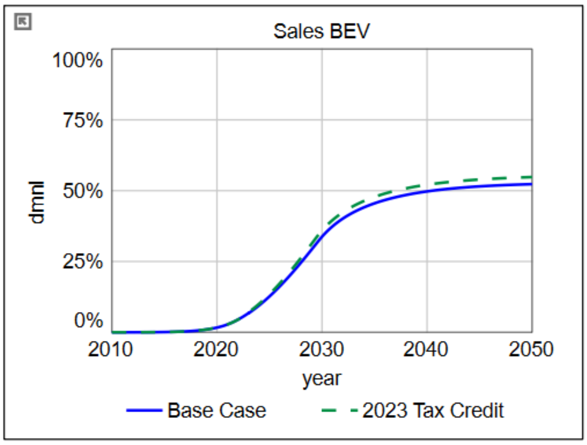

Figure 52 Model Base Case and the '2023 BEV Tax Credit' Scenario impact on BEV Market Share.

There are three additional purchase subsidy options in the model; a manufacturer point-of-sale rebate (OEM POS Rebate) and governmental point-of-sale rebates in form of either an absolute discount (Absolute POS Rebate) or a percentagewise discount (% POS Rebate). These policies were modelled as listed below, which were also their settings in the ‘All Policies’ scenario, however the ‘Absolute POS Rebate’ was not included in the ‘All Policies’ scenario to avoid overlap with the similar ‘2023 BEV Tax Credit’ policy:

1. OEM POS Rebate: $5000 rebate prior to adding markup and determining Manufacturer's Suggested Retail Price (MSRP) from 2023 and for the duration of the simulation period
2. Absolute POS Rebate: $10000 rebate on effective retail price from 2023 and for the duration of the simulation period
3. % POS Rebate: 5.75 % tax exemption rebate on effective retail price from 2023 and for the duration of the simulation period

Figures 53 and 54 display the model Base Case, the ‘OEM POS Rebate’, ‘Absolute POS Rebate’ and ‘% POS Rebate’ scenarios, and their impacts on BEV Fleet and BEV Market Share respectively. The ‘OEM POS Rebate’ scenario projects a BEV fleet increase of around 3 million vehicles and a BEV market share increase of around 2 percentage points by 2050, compared to the Base Case. The ‘Absolute POS Rebate’ scenario projects a BEV fleet increase of around 7 million vehicles and a BEV market share increase of around 3 percentage points by 2050, compared to the Base Case. The ‘% POS Rebate’ scenario projects a BEV fleet increase of around 1 million vehicles and a BEV market share increase of around 1 percentage points by 2050, compared to the Base Case.

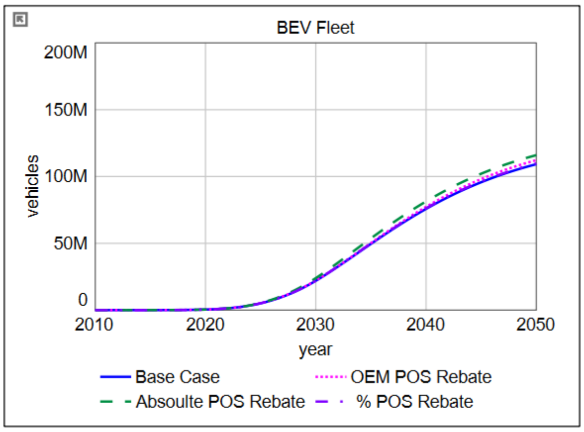

Figure 53 *Model Base Case and the ‘2023 BEV Tax Credit’ Scenario impact on BEV Fleet.*

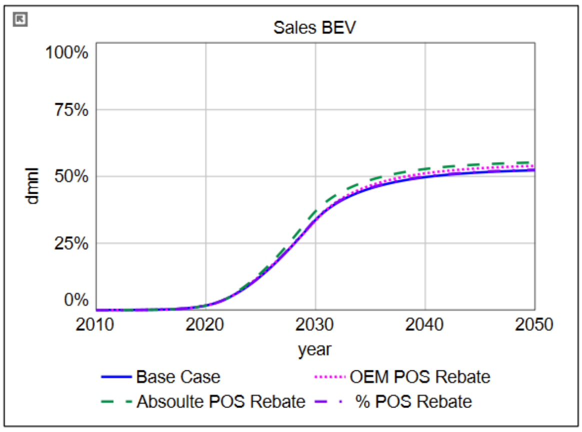

Figure 54 *Model Base Case and the ‘2023 BEV Tax Credit’ Scenario impact on BEV Market Share.*

5.3 Infrastructure Incentives

In 2010, there were 482 charging points available in the US [2]. The following years were dominated by governmental and private build-out incentives aimed at making charging infrastructure available prior to demand. Tesla built out its charging infrastructure significantly during this period. In 2022 there are more than 140,000 charging points available in the US, of which more than 27,000 or around 20 % are Tesla chargers [33].

In the model, the charging infrastructure build-out takes input from historical data. Future development in build-out relies on demand estimated from the size and growth rate of the BEV fleet. This means that without incentives charging infrastructure will be available sometime after the demand is a fact.

In early 2021, the US government proposed an infrastructure plan that will establish grant and incentive programs to install 500,000 chargers by 2030 [34], [35]. This incentive program is modelled as an addition of 62,500 chargers per year in the period 2022-2030, as displayed in figure 55, which also were its setting in the 'All Policies' scenario. Figure 56 displays the behavior of BEV Charging Infrastructure in the '2022 Infrastructure Incentive' scenario, described above and the model Base Case.

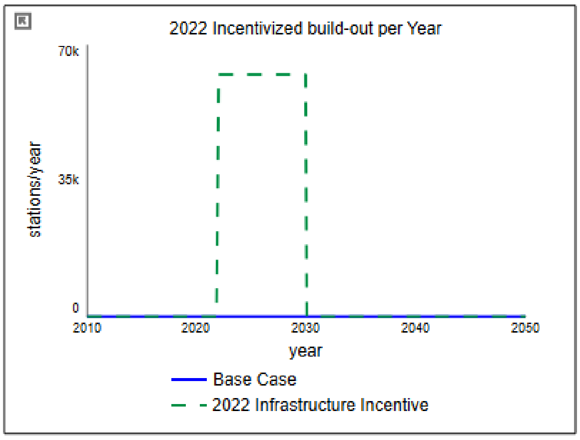

Figure 55 *Additional chargers from the '2022 Infrastructure Incentive'.*

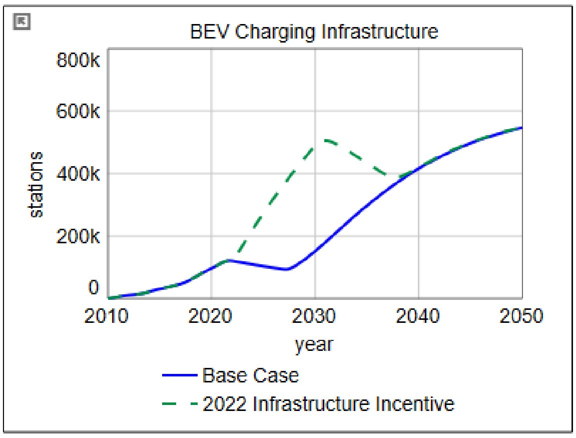

Figure 56 *Model Base Case and the '2022 Infrastructure Incentive' Scenario impact on Available Infrastructure BEV.*

Figure 56 shows the how the 2022 Infrastructure Incentive will serve to prolong the growth in Charging Infrastructure from 2022, a period from which the Base Case projects an approximate 5-year decline before demand compels further build-out. A similar period of decline occurs in '2022 Infrastructure Incentive' scenario as well, from when the incentive is planned to end 8 years later. From figure 47, it is clear the Infrastructure Incentive does not impact the BEV market share. Though the incentive does improve the Utility Infrastructure BEV, as seen in figure 58, the utility of BEV Charging Infrastructure is still much lower that the utility of ICEV Fueling Infrastructure in this period, and is not projected to reach a level where it can compete with ICEV technology until 2040.

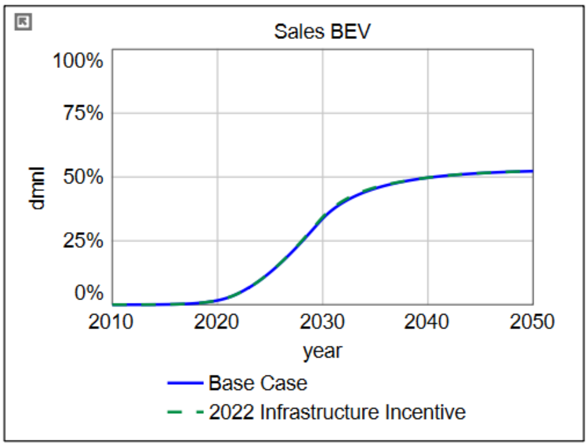

Figure 57 *Model Base Case and the '2022 Infrastructure Incentive' Scenario impact on BEV Sales share.*

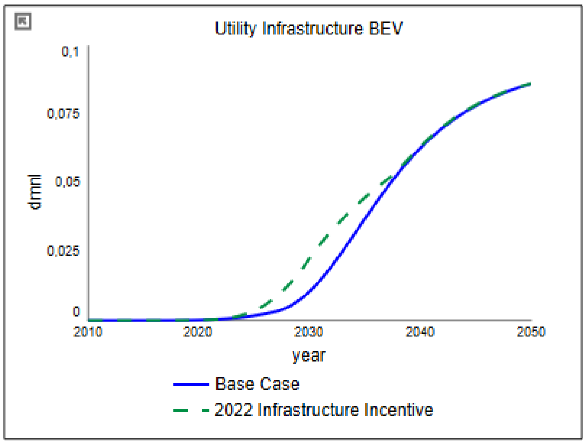

Figure 58 *Model Base Case and the '2022 Infrastructure Incentive' Scenario impact on Utility Infrastructure BEV.*

The model also has a structure for additional 'Subsidized Charging Points'. This policy is modelled as an addition of 30,000 chargers per year from 2022 and for the duration of the simulation period – in the 'All Policies' scenario the start time for this policy was set to 2030 when the 2022 Infrastructure Incentive is planned to be phased out. Like for the '2022 Infrastructure Incentive' scenario, the 'Subsidized Charging Points' scenario does improve the Utility Infrastructure BEV, as seen in figure 59, but not enough to impact the BEV market share. Figure 60 displays the behavior of BEV Charging Infrastructure in the 'Subsidized Charging Points' scenario and the in model Base Case. The 'Subsidized Charging Points' scenario allows for a smoother build-up of charging Infrastructure without the period of decline that the '2022 Infrastructure Incentive' scenario projects.

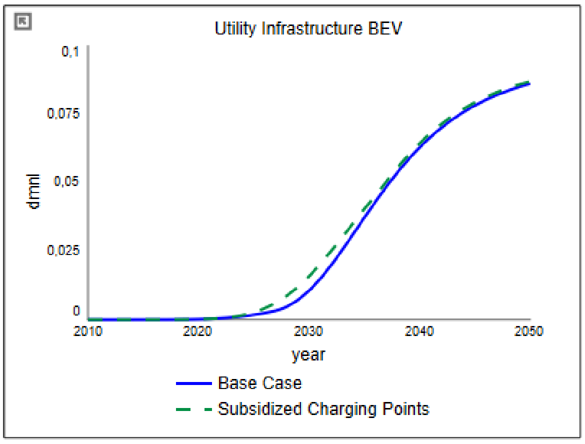

Figure 59 Model Base Case and the 'Subsidized Charging Points' Scenario impact on Utility Infrastructure BEV.

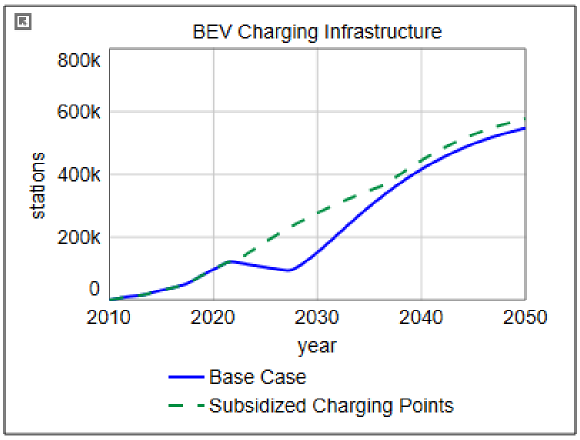

Figure 60 Model Base Case and the 'Subsidized Charging Points'' Scenario impact on Available Infrastructure BEV.

5.4 Carbon Tax

Currently, 33 countries have implemented Carbon Tax at rates ranging from under $1 to $137 per tonne CO_2 equivalent (CO_2e) – however, the number of countries adopting Carbon tax and the associated tax rates are expected to rise [29]. An example is Norway where it is outlined to increase taxes from $69 to $233 by 2030 [36].

The proposed Carbon tax in this model ranges from $0 to $500 per tonne CO_2e, with an introduction time earliest in 2023. The tax is modelled to be introduced over period in which the tax increases steadily from $0 to the proposed value. The model assumes that significant carbon taxation will shift the utility weights. The tax will not affect the positive weight attributes Model Selection, Infrastructure Availability or Range. It will, however, affect the negative weight attributes; increasing the significance of Operating Cost relative to Retail Price and Charge time / Fueling time as described in the Model Overview – Modules and Sectors chapter.

Of the Carbon Tax options modelled, a Carbon Tax of $100 with an introduction time of 20 years would be the most lenient, while a Carbon Tax of $500 with an introduction time of 2 years would be the most aggressive and is the chosen setting for Carbon Tax in the 'All Policies' scenario.

Figure 61 displays the option of $100 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods. Figure 62 displays this options impact on projected gasoline price, while figures 63 and 64 display this option along with the Base Case, and the impacts on BEV Fleet and BEV Market Share respectively.

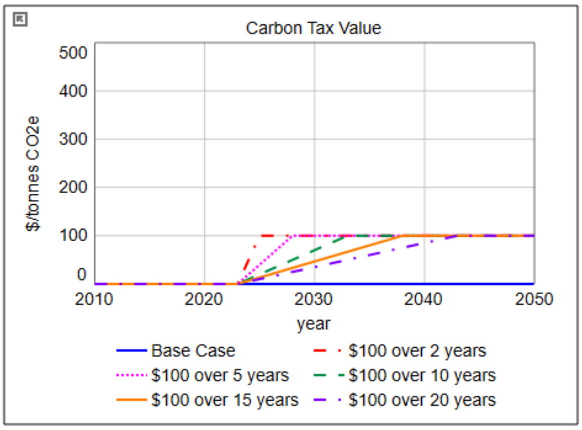

Figure 61 *$100 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

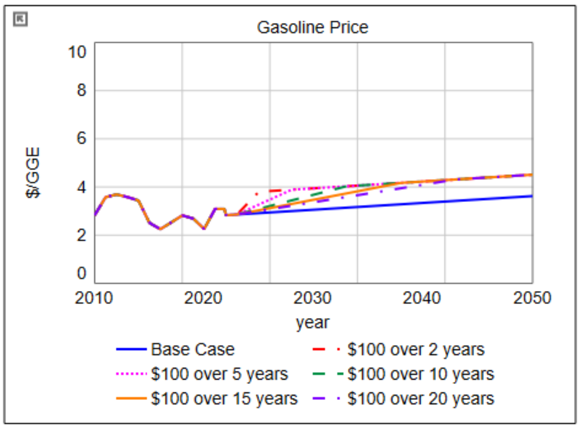

Figure 62 *Projected gasoline price in scenario with $100 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

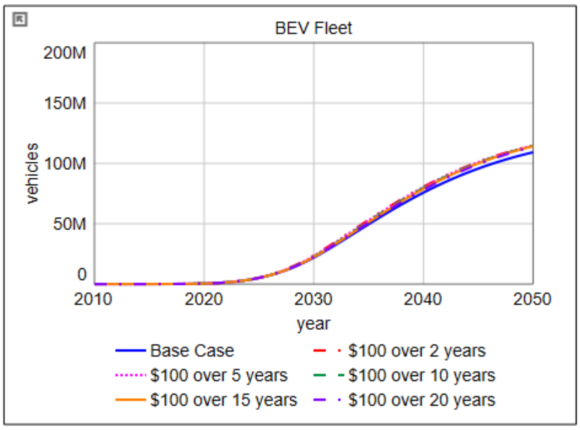

Figure 63 *Projected BEV Fleet in scenario with $100 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

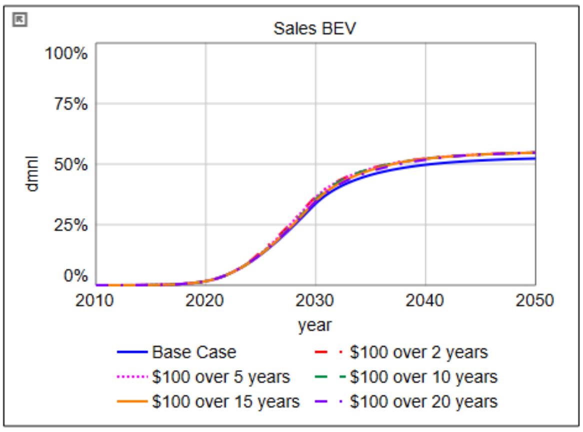

Figure 64 *Projected BEV Market share in scenario with $100 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods..*

The $100 Carbon Tax scenario projects a BEV fleet increase of around 5-6 million vehicles and a BEV market share increase of around 3 percentage points by 2050, compared to the Base Case – this would mean an approximate 4-5 percent improvement on the Base Case by introducing $100 Carbon Tax.

Figures 65 displays the option of $500 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods. Figures 66 displays this options impact on projected gasoline price, while figures 67 and 68 display this option along with the Base Case, and the impacts on BEV Fleet and BEV Market Share respectively.

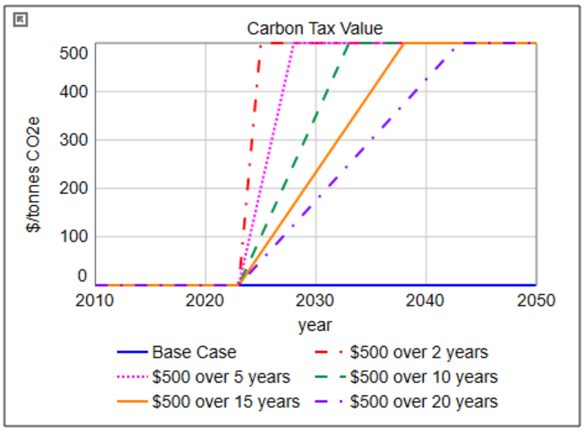

Figure 65 *$500 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

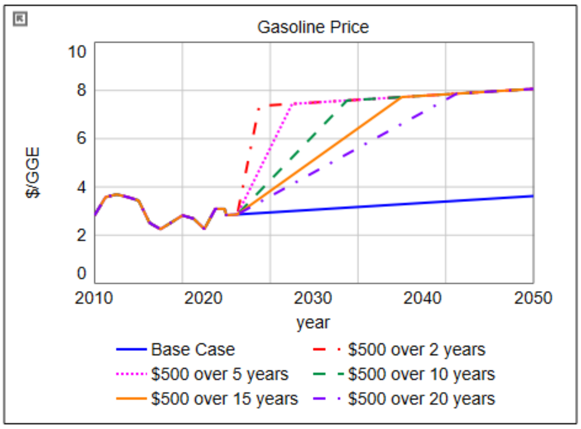

Figure 66 *Projected gasoline price in scenario with $500 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

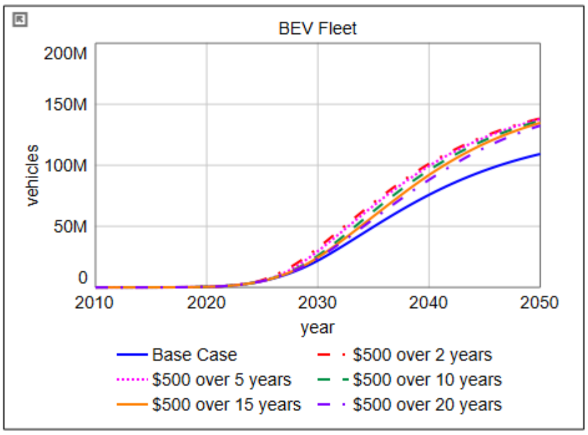

Figure 67 *Projected BEV Fleet in scenario with $500 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

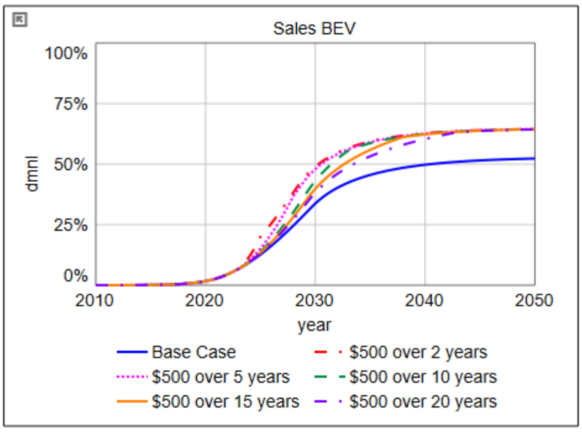

Figure 68 *Projected BEV Market share in scenario with $500 Carbon Tax with 2-year, 5-year, 10-year, 15-year and 20-year introduction periods.*

The $500 Carbon Tax scenario projects a BEV fleet increase of around 23-29 million vehicles and a BEV market share increase of around 12 percentage points by 2050, compared to the Base Case – this would mean an approximate 19-20 percent improvement on the Base Case by introducing $500 Carbon Tax.

Figures 69 displays $100, $200, $300, $400 and $500 Carbon Tax options with 7-year introduction period in order to reach the goals set for 2030. Figure 70 displays these options impact on projected gasoline price, while figures 71 and 72 display these options along with the Base Case, and the impacts on BEV Fleet and BEV Market Share respectively. Impacts on BEV Fleet and BEV Market Share under scenarios with $100, $200, $300, $400 and $500 Carbon Tax with 7-year introduction period are listed in table 13. As expected, the efficiency the of Carbon Tax increases with the tax rate level which makes the $500 Carbon Tax the most effective of the options included here. The length of the introduction period is important for the short-term development, and a long introduction period will delay the transition but still enable similar long-term results.

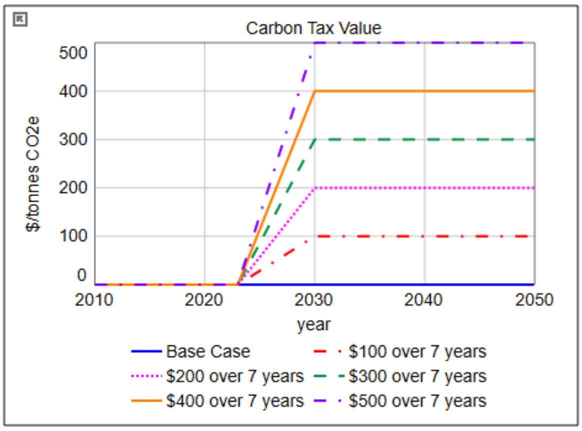

Figure 69 *$100, $200, $300, $400 and $500 Carbon Tax options with 7-year introduction period*

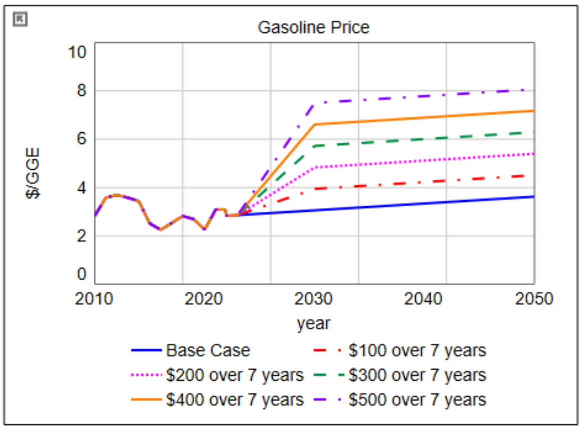

Figure 70 *Projected gasoline price in scenarios with $100, $200, $300, $400 and $500 Carbon Tax with 7-year introduction period.*

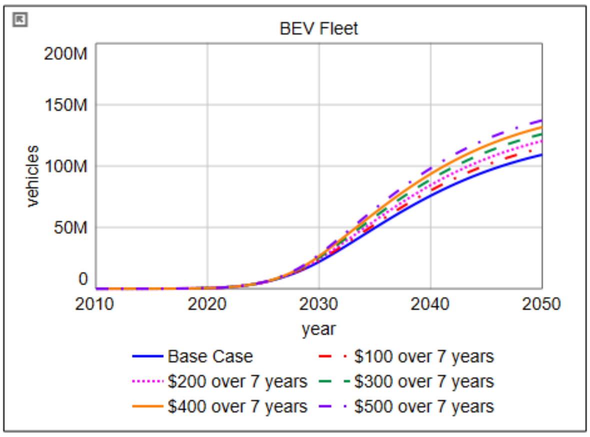

Figure 71 *Projected BEV Fleet in scenarios with $100, $200, $300, $400 and $500 Carbon Tax with 7-year introduction period.*

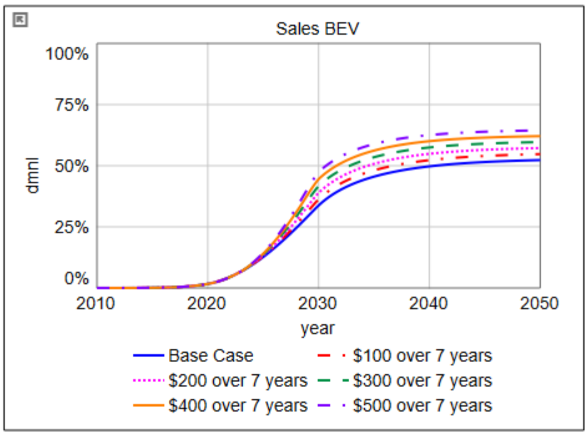

Figure 72 *Projected BEV Market share in scenarios with $100, $200, $300, $400 and $500 Carbon Tax with 7-year introduction period.*

Table 13 Impacts on BEV Fleet and BEV Market Share under scenarios with $100, $200, $300, $400 and $500 Carbon Tax with 7-year introduction period.

Carbon Tax Value	***BEV Fleet by 2050***	***Improvement in BEV Fleet Relative to Base Case***	***Market Share by 2050***	***Improvement in BEV Market Share Relative to Base Case***
$100	115M	6M (4.8 %)	55 %	3 pp (4.5 %)
$200	120M	11M (9.3 %)	57 %	5 pp (8.6 %)
$300	126M	17M (13.4 %)	60 %	8 pp (12.3 %)
$400	132M	23M (17.1 %)	62 %	10 pp (15.8 %)
$500	137M	28M (20.4 %)	64 %	12 pp (18.8 %)

Chapter 6. Insight Communication – Interactive Learning Environment

Simulation modeling is a powerful tool in exploring and analyzing structural aspects of complex systems and has proven useful in trying to develop understanding about, among other things, the learning curve effects that develop from the cumulation of sales and manufacturing experience and the cumulation of familiarity with technology, which are not intuitive to grasp without modeling. For experienced modelers, the iterative process of building, testing and analyzing a model, can lead them to deep insights about the dynamic interactions at play in the system the model has set out to represent. However, the usefulness of any model can be seen as the product of the simulation model power and the effectiveness of results and insights communication. If the results and insights of a model cannot or are not communicated, they ultimately have little value and though simulation modeling might be useful for experienced modelers, it is not necessarily easily understood by non-modelers. An interactive learning environment is a way of communicating the results and key insights of a system dynamics model to an audience, without the audience having to go through the modeling process themselves.

Several interactive interfaces focusing on alternative fuel vehicle transition, have been created in the past. Among these, is an interface developed by Forio which is based on the Keith et al. model [37] [38]. It focuses on the competition between a range of technologies and includes eight separate alternative fuel technologies as displayed in figure 73.

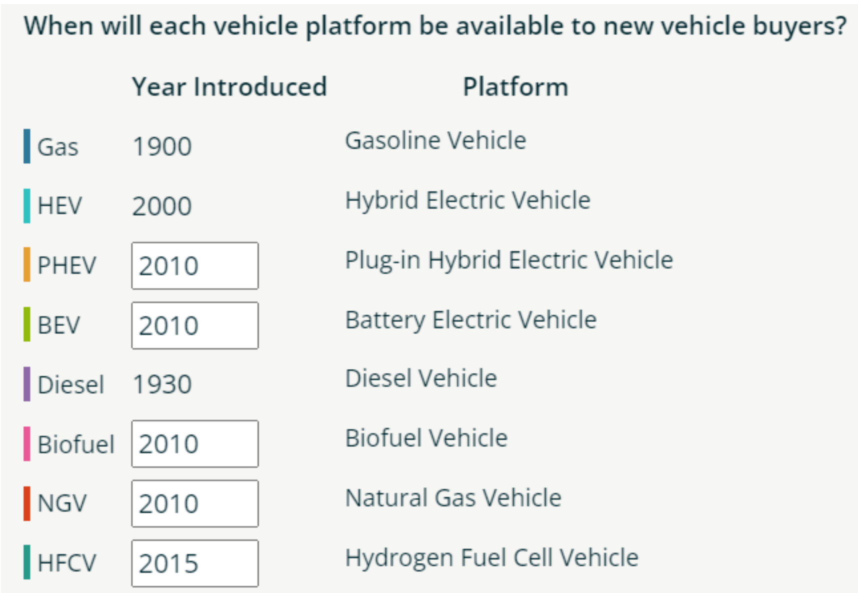

Figure 73 *From interface developed by Forio which focuses on the competition between a range of technologies [38].*

Anther interface has been made available by Energy Policy Solutions [7] and has a wider scope – focusing on US polices aimed towards a range of sectors in addition to the transportation sector as displayed in figure 74, like the Forio interface, it includes a range of alternative fuel vehicle technologies. A valuable feature of the Energy Policy Solutions interface is that it links to pages with information about how policies were modelled, as well as to pages with additional information on the policies per se. An interactive learning environment (ILE), powered by the thesis model, has been created and goes beyond linking to other content by adding more context on the dynamic hypothesis in the ILE itself.

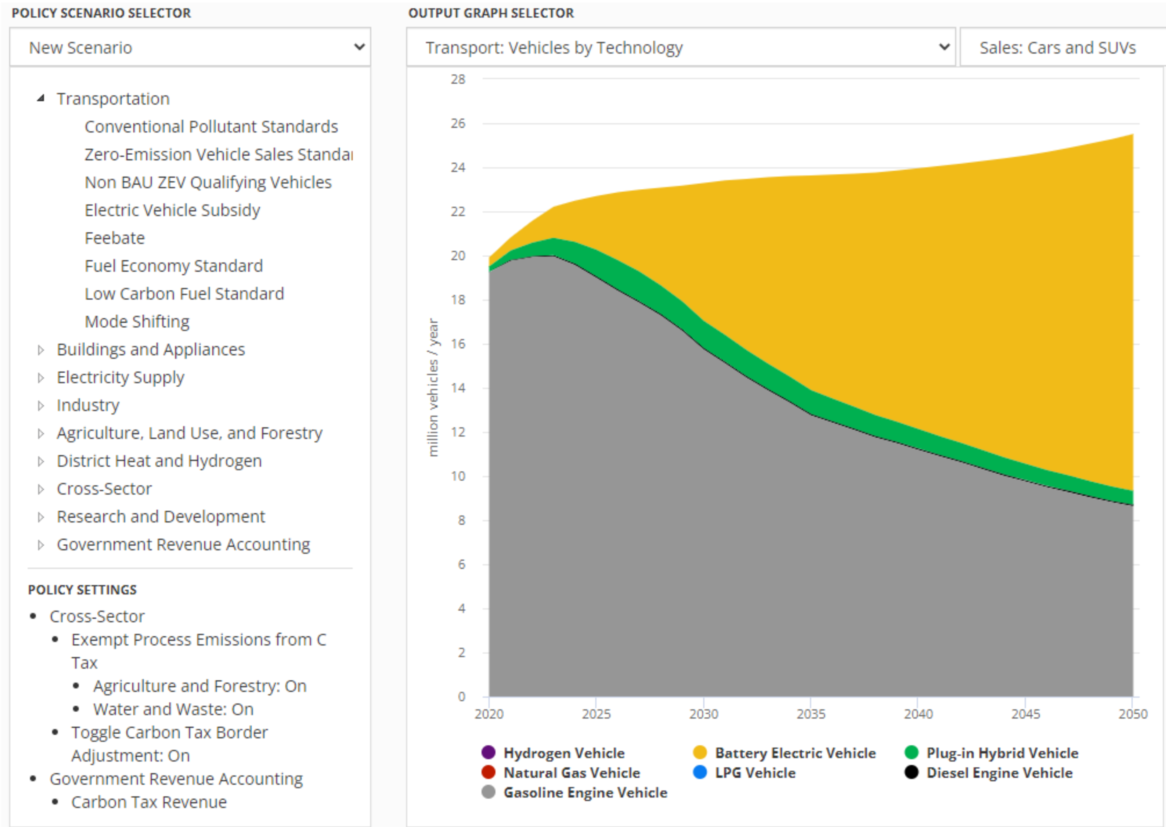

Figure 74 From interface made available by Energy Policy Solutions focusing on polices aimed towards a range of sectors including the transportation sector [7].

The thesis ILE has the objective to communicate a selection of insights from the model, in a way that makes them accessible to a non-SD audience. The ILE is an analysis tool that aims to provide greater understanding of the dynamics at play when transitioning from a vehicle fleet consisting of predominantly ICEVs to a more diverse vehicle fleet. The tool allows users to experiment with a selection of policies that might accelerate the development in BEV adoption and explore impacts of adjusting a selection of underlying model assumptions – the ILE aspires to communicate structural model insights by providing ample context and not merely enable interaction with model metrics. The ILE is accessible via any internet browser and does not require users to acquire any subscriptions or software licenses. The tool aims to reach an audience interested in systems thinking and system dynamics but does not require prior knowledge or skills in the method. The ILE can be accessed from the isee systems exchange domain: https://exchange.iseesystems.com/public/tonelowi/adoption-of-battery-electric-vehicles-in-the-us/index.html

The ILE has a **Landing Page (figure 75)** that presents statistics related to the status of electric vehicle adoption in the US and in a selection of other comparable markets. It also presents central questions related to electric vehicle adoption in the US and prompts users to enter the analysis tool.

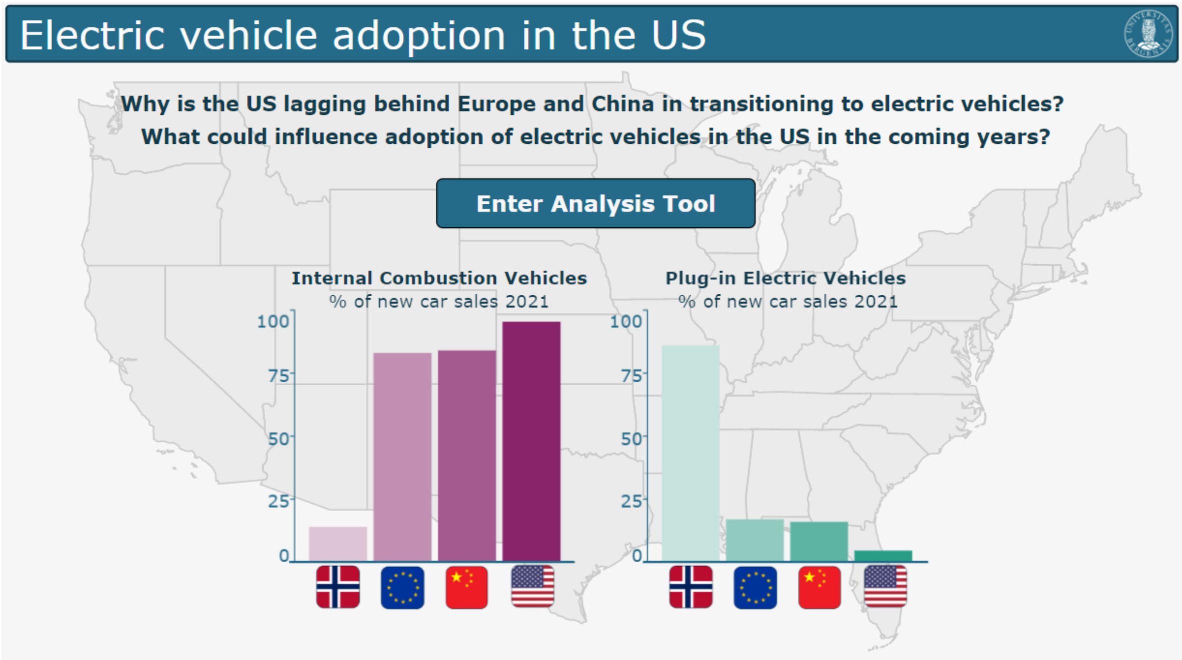

Figure 75 ILE Analysis Tool Landing Page.

Once users enter the analysis tool, they arrive in the **Tool Guide (figure 76)**, where they can read about how to navigate the analysis tool and test how to operate the controls and how to manipulate or interact with assumptions and policies.

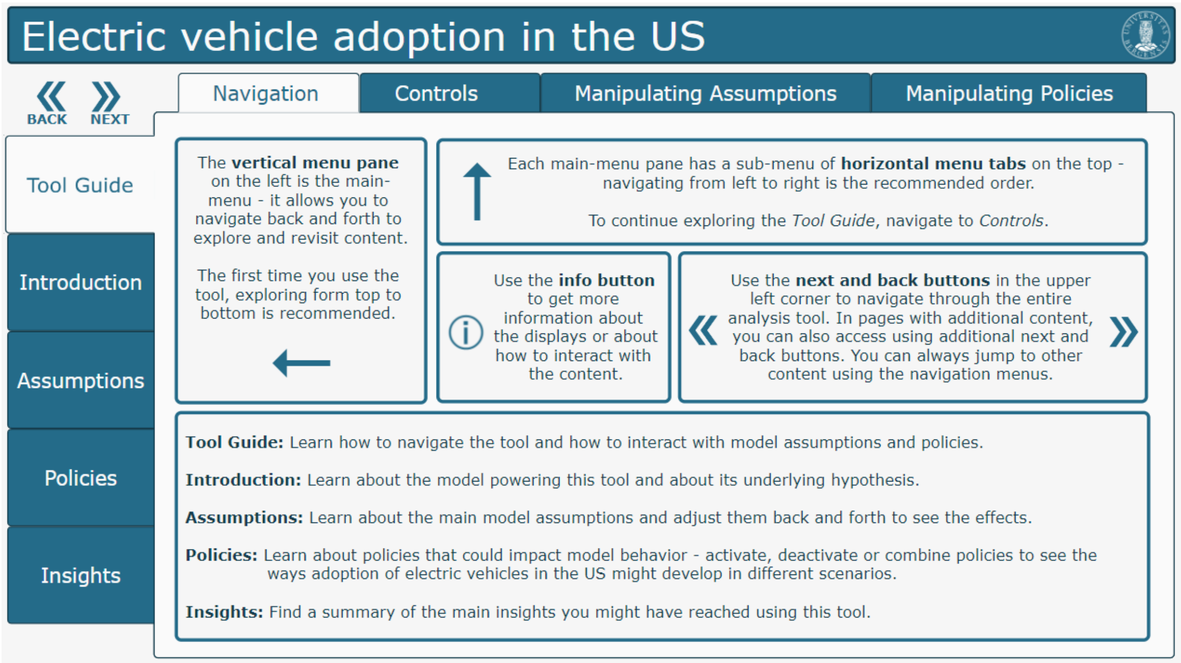

Figure 76 ILE Analysis Tool Guide, Navigation page.

The **Introduction section (figure 77)** provides an elaborated overview of the current status of electric vehicle adoption in the US in the context of comparison with other major markets. It moves on to present an interpretation of the problem at hand.

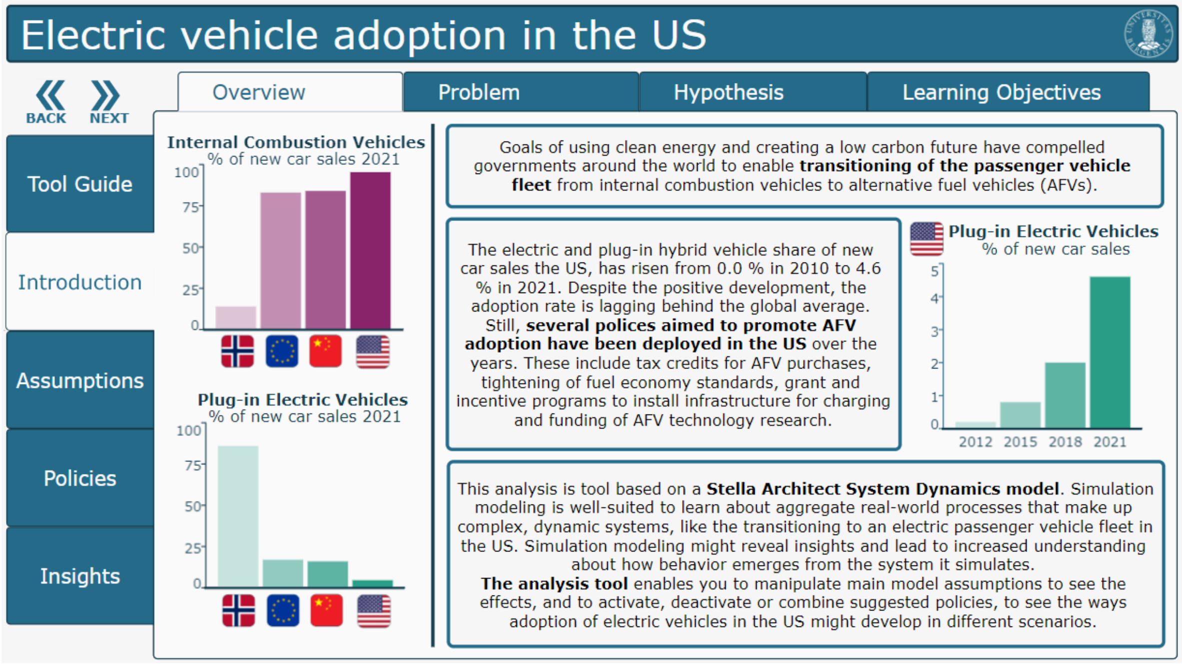

Figure 77 *ILE Analysis Tool Introduction section, Overview page.*

Further, the introduction section presents a selection of essential model features and assumptions and moves on to elaborate on the dynamic hypothesis of the underlying model as exemplified in figure 78. The introduction finishes by presenting a selection of learning objectives, to make the user aware and attentive to the insights that might be taken away from engaging with the tool.

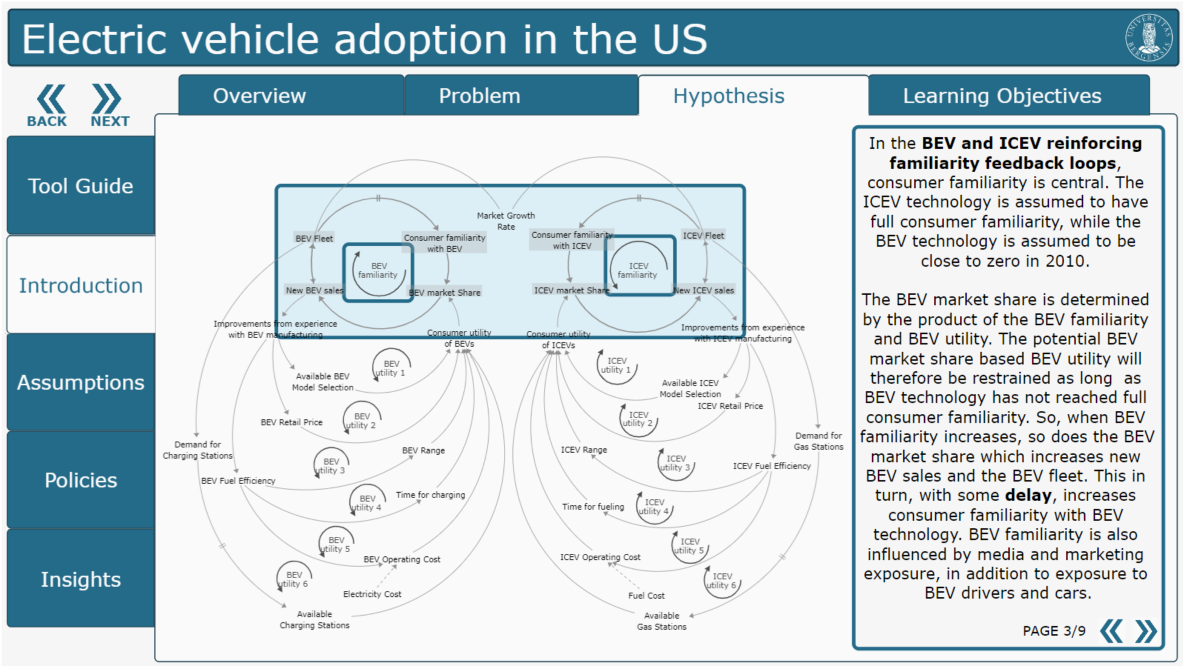

Figure 78 *ILE Analysis Tool Introduction section, Hypothesis page 3/9.*

The **Assumptions section (figure 79)** allows the user to interact with model and edit assumptions to see the effects. The ILE focuses on the most central assumptions like the BEV Familiarity and the Utility Weights. It also facilitates revisiting the Hypothesis section to possibly raise user awareness of the model context and interconnections.

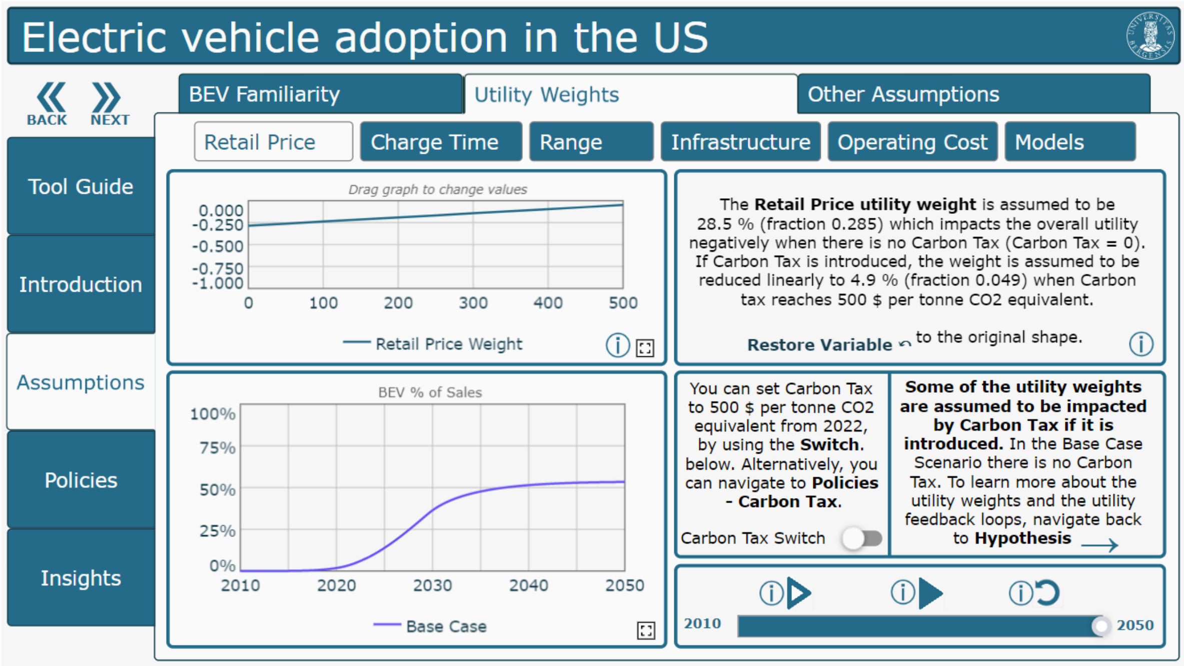

Figure 79 *ILE Analysis Tool Assumptions section, Utility Weights page.*

The **Policies section (figure 80)** allows the user to interact with model and apply policies to see how they impact key performance indicators. The controls allow for seeing the live changes as variables are being adjusted and to compare the performance user defined run with the base run.

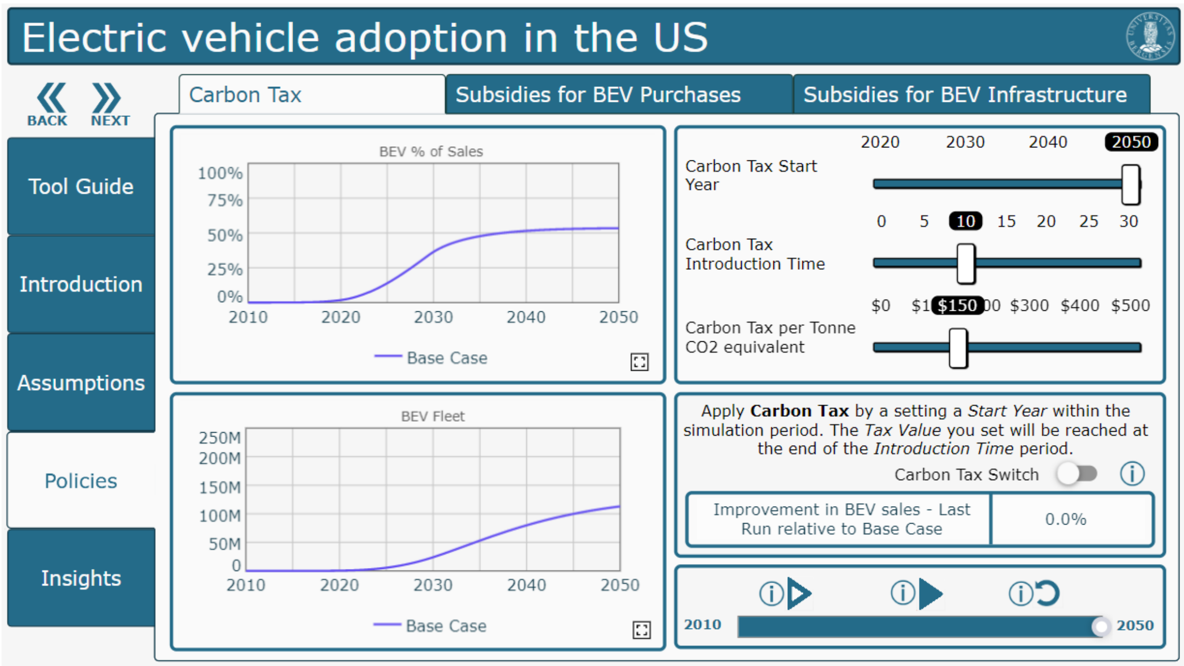

Figure 80 *ILE Analysis Tool Policies section, Carbon Tax page.*

The **Insights section (figure 81)** revisits the learning objectives and relate them back to the dynamic hypothesis. In this section, selected interactive content is linked to selected parts of a causal loop diagram in an effort to guide users to the distilled dynamic insights.

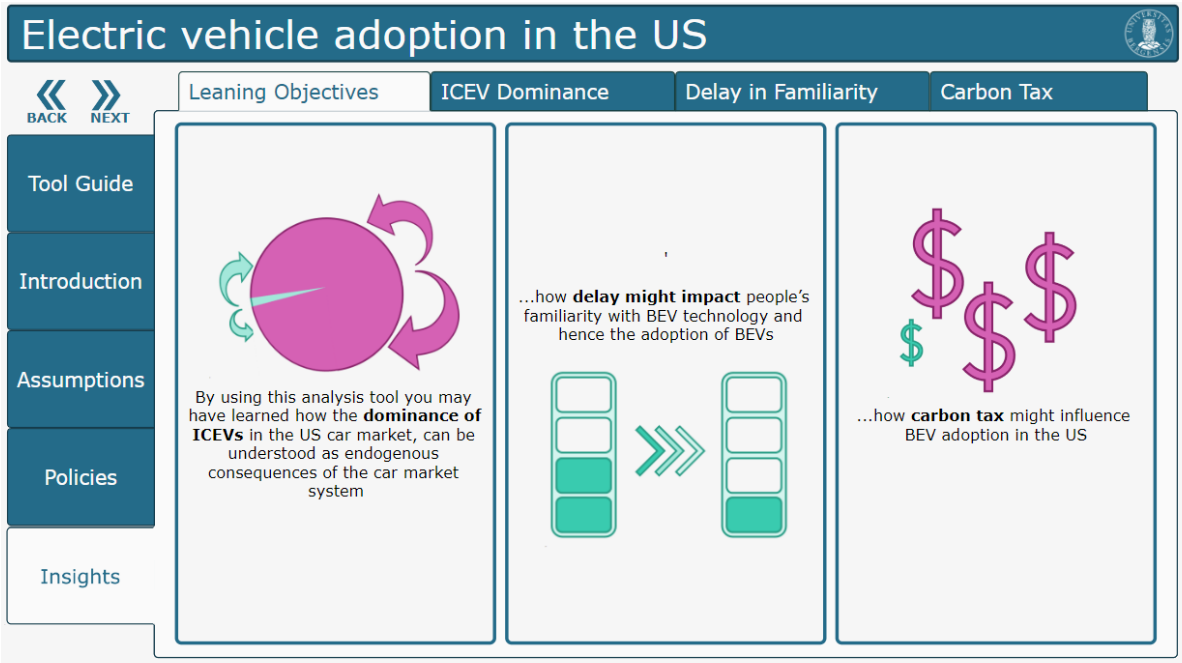

Figure 81 *ILE Analysis Tool Insights section, Learning Objectives page.*

The thesis ILE has been beta tested and all reported bugs on the interface have been resolved – the published version should be accessible and without technical shortcomings.

Chapter 7. Conclusions

This thesis paper set out to investigate dynamic interactions that have been holding back adoption of electric vehicles in the US, to try and identify policies with potential to accelerate adoption in the coming years and to communicate insights from systems thinking and system dynamics modelling in a way that makes them accessible to a non-SD audience. It formulated three research questions:

- What are the processes driving adoption of battery electric vehicles in the US?
- Which policies have the potential to accelerate adoption in the coming years?
- How can insights from systems thinking and system dynamic modelling be communicated, to be made accessible to non-SD audiences?

What are the processes driving adoption of battery electric vehicles in the US?

In general, the fate of alternative technologies will always be at the mercy of early adopters and how early adopters in turn influence others to adopt. As mentioned earlier, Sterman attributes the historic failure of alternatives to endogenous consequences of the dominance of the ICEV technology and its associated industries and networks [3], which still might limit the number of potential early adopters in the US. This thesis finds it is the increased familiarity with BEV technology and the learning curve effects on overall BEV utility, that is driving adoption of BEVs in the US. The development in familiarity and utility is onset by the global development – i.e. early adopters in other countries where the ICEV technology dominance is less powerful or has been outweighed by successful BEV incentives. The thesis model reveals the importance of considering possible influences from other markets for assumed isolated markets that are relatively underdeveloped. This is a process that, to the best of my knowledge, has not been described in the literature yet.

Which policies have the potential to accelerate adoption in the coming years?

There are four policy categories included in the model – these policy categories have been selected as a result of sensitivity testing, because they have been identified as main policy drivers of BEV adoption to date or because they are part of emerging global incentives to reduce energy use and shift to cleaner fuels:

1. Marketing Spending
2. Vehicle Purchase Subsidies
3. Infrastructure Incentives
4. Carbon Tax

The tests performed on these policy categories revealed Market Spending is a feasible policy option, especially in the coming years when familiarity with BEV technology has yet to reach its full potential. Imposing a given allocation of marketing budget towards BEV technology on OEMs is also effective in reducing the strength of the reinforcing feedback loops for the incumbent ICEV technology. Vehicle Purchase Subsidies also showed to have an effect on key performance indicators due to the improvement in the overall utility of BEV relative to ICEV technology, though not significantly. The tests revealed that the Infrastructure Incentives has little potential to influence key performance indicators. Though the incentives do improve the utility of BEV charging infrastructure, relative to the utility of gas fueling infrastructure it remains below a level where it can compete with ICEV technology until the BEV market is more significant.

Taxation of CO_2 emissions from fossil fuel combustion is identified as the most effective among the policies tested. This policy works to increase the overall relative utility of BEVs and cancels out some of the strength of the ICEV dominance. As expected, the efficiency the of Carbon Tax increases with the tax rate level which makes the $500 Carbon Tax the most effective of the options included here. The length of the introduction period is important for the short-term development, and a long introduction period will delay the transition but still enable similar long-term results. Though identified as effective policy, it might prove difficult to implement Carbon Tax in the US due to its traditions of low gas pricing and low taxation – introducing Carbon Tax could potentially cause significant social disturbance. The current values of Carbon Tax around the world are mostly well below $200 at which level, it would have little effect in the US market and might not be worth the political fight for its introduction.

How can insights from systems thinking and system dynamic modelling be communicated, to be made accessible to non-SD audiences?

The deployment of an ILE Analysis Tool has the potential to help its users gain understanding of the dynamics at play when transitioning from a vehicle fleet consisting of predominantly ICEVs to a more diverse vehicle fleet. In an accommodating way, that does not require prior knowledge or skills, nor any subscriptions or software licenses, it allows users to experiment with policies that might accelerate the development in BEV adoption and explore impacts of adjusting underlying model assumptions. Not only does the ILE allow for interaction with model metrics, it also aims to communicate structural model insights, which sets it apart from many other available projection tools.

7.1 Implications

Overall, the thesis model is an example of the archetype 'Success to the Successful' [39], where the market distribution among BEV and ICEV technology is highly dependent on initial conditions and the initial conditions favor the successful, in this case the rooted ICEV technology. The enormous scale of the ICEV dominated passenger car industry, establish a set of powerful positive feedback processes that give substantial advantage to ICEV relative to BEV technology – while the negative externalities of the massive ICEV fleet are not accounted for. This dynamic might be typical in cases of sustainability transitions in general.

A general observation from testing policy options, is that policies that penalize incumbent technology, like Carbon tax and imposed Marketing Allocation, seem to be more adept as they reduce the strength of the reinforcing feedback loops for the incumbent technology.

The current model and ILE can provide insights into the dynamics at play in a market transitioning to BEVs and can also serve as a starting point for further work. The model structure is fairly generic and could be adjusted to other contexts – an interesting model development would be to adapt it to Norwegian or Chinese settings, where the development in BEV adoption has followed a very different trajectory the past decade. Structurally, the model should be scalable to other contexts by editing input parameter values and calibrating key assumptions like average BEV familiarity delay.

7.2 Model limitations and future research

There are ample opportunity to further improve the thesis model beyond the completion of this thesis. The model was developed with the purposes to identify non-essential structures in the Keith et al. model, replace overly complex formulations and to simplify the model so as to make the core processes driving market transformation more easily accessible to non-SD audiences. A central model feature is the weighted structure of the utility attributes – this feature could be modelled in several alternative ways. As a consequence of the modelling choice of this structure in the thesis model, as discussed in the Direct Extreme-Condition Testing subchapter, the model is unsensitive to extreme developments in any particular utility attribute as their contribution to overall utility are structurally dictated and limited.

References

[1] United Nations. "THE 17 GOALS." https://sdgs.un.org/goals (accessed 26.07, 2022).

[2] International Energy Agency. *Global EV Data Explorer*, 28.07.2022. [Online]. Available: https://www.iea.org/articles/global-ev-data-explorer

[3] J. Sterman, "Stumbling towards Sustainability: Why organizational learning and radical innovation are necessary to build a more sustainable world—but not sufficient," in *Leading Sustainable Change*, R. Henderson, M. Tushman, and R. Gulati Eds. Oxford UK: Oxford University Press, 2015, pp. 51-80.

[4] International Energy Agency, "Policies to promote electric vehicle deployment," no. Global EV Outlook 2021. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2021/policies-to-promote-electric-vehicle-deployment

[5] Environmental and Energy Study Institute, "Comparing U.S. and Chinese Electric Vehicle Policies," 28.02.2018. [Online]. Available: https://www.eesi.org/articles/view/comparing-u.s.-and-chinese-electric-vehicle-policies

[6] J. Rissman, "The Future of Electric Vehicles in the U.S.," 09.2017. [Online]. Available: https://energyinnovation.org/wp-content/uploads/2017/09/2017-09-13-Future-of-EVs-Research-Note_FINAL.pdf

[7] Energy Innovation Policy & Technology LLC. "Energy Policy Solutions." https://us.energypolicy.solutions/ (accessed 05.12.2022, 2022).

[8] U.S. Energy Information Administration. "Annual Energy Outlook 2017." (accessed 01.06, 2022).

[9] Bloomberg New Energy Finance, "Electric Vehicle Outlook 2017," 01.07.2017. [Online]. Available: https://data.bloomberglp.com/bnef/sites/14/2017/07/BNEF_EVO_2017_ExecutiveSummary.pdf

[10] V. d. Gooyert, "Developing dynamic organizational theories; three system dynamics based research strategies," *Quality & quantity,* vol. Vol.53 (2), pp. p.653-666, 2019, doi: 10.1007/s11135-018-0781-y.

[11] A. K. Saysel and T. Barlas, "Model simplification and validation with indirect structure validity tests," *System dynamics review,* vol. Vol.22 (3), pp. p.241-262, 2006, doi: 10.1002/sdr.345.

[12] D. R. Keith, J. J. R. Struben, and S. Naumov, "The Diffusion of Alternative Fuel Vehicles: A Generalised Model and Future Research Agenda," *Journal of Simulation,* vol. 14:4, pp. 260-277, 2020, doi: 10.1080/17477778.2019.1708219.

[13] D. Brownstone, D. S. Bunch, and K. Train, "Joint mixed models of stated and revealed preferences for alternative fuel vehicles," *Transportation Research Part B,* vol. 34, pp. 315-338, 2000.

[14] C. McKerracher, "Plug-In Hybrid Cars Are Running Out of Road," 28.07.2022. [Online]. Available: https://www.bloomberg.com/news/articles/2022-07-28/plug-in-hybrid-cars-are-running-out-of-road?leadSource=uverify%20wall

[15] Castrol. "Accelerating the EVolution: The tipping points to mainstream electric vehicle adoption." https://www.castrol.com/content/dam/castrol/master-

site/en/global/home/technology-and-innovation/electric-vehicle-adoption/accelerating_the_evolution_study.pdf (accessed 15.10, 2022).
[16] M. Lu, "Mainstream EV Adoption: 5 Speedbumps to Overcome," 29.09.2020. [Online]. Available: https://www.visualcapitalist.com/mainstream-ev-adoption-5-speedbumps-to-overcome/
[17] H. Rahmandad and J. D. Sterman, "Reporting guidelines for simulation-based research in social sciences," *System dynamics review,* vol. Vol.28 (4), 2012, doi: 10.1002/sdr.1481.
[18] S. Korus, "Wright's Law Predicted 109 Years of Auto Production Costs, and Now Tesla's." [Online]. Available: https://ark-invest.com/articles/analyst-research/wrights-law-predicts-teslas-gross-margin/
[19] A. Z. Martin Weissa, Eckard Helmersb, "Fully electric and plug-in hybrid cars - An analysis of learning rates, user costs, and costs for mitigating CO2 and air pollutant emissions," *Journal of Cleaner Production,* vol. 212, pp. 1478-1489, 2019, doi: https://doi.org/10.1016/j.jclepro.2018.12.019.
[20] *American Recovery and Reinvestment Act of 2009: Tax-Based Provisions,* I. I. R. P. Database, 2017.
[21] M. Gilleran *et al.*, "Impact of electric vehicle charging on the power demand of retail buildings," *Advances in Applied Energy,* vol. Vol.4, 2021, doi: 10.1016/j.adapen.2021.100062.
[22] United States Environmental Protection Agency. "Greenhouse Gases Equivalencies Calculator - Calculations and References." https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references (accessed 01.09, 2022).
[23] Internal Revenue Service. "IRC 30D New Qualified Plug-In Electric Drive Motor Vehicle Credit." https://www.irs.gov/businesses/irc-30d-new-qualified-plug-in-electric-drive-motor-vehicle-credit (accessed 01.10, 2022).
[24] Internal Revenue Service. "Plug-In Electric Drive Vehicle Credit (IRC 30D)." https://www.irs.gov/businesses/plug-in-electric-vehicle-credit-irc-30-and-irc-30d (accessed 01.10, 2022).
[25] Bureau of Transportation Statistics. *Number of U.S. Aircraft, Vehicles, Vessels, and Other Conveyances*, U.S. DEPARTMENT OF TRANSPORTATION. [Online]. Available: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
[26] Oak Ridge National Laboratory. "Fuel Economy of 2010 Midsize Cars." U.S. Department of Energy. https://www.fueleconomy.gov/feg/byclass/midsize_cars2010.shtml (accessed 09.10, 2022).
[27] MPG Buddy. "2011 Nissan Leaf MPG and Fuel Economy." MPG Buddy. https://mpgbuddy.com/cars/nissan/leaf/2011 (accessed 09.10, 2022).
[28] Alternative Fuels Data Center. *Public Retail Gasoline Stations by State and Year*, U.S. Department of Energy, 09.10.2022. [Online]. Available: https://afdc.energy.gov/files/u/data/data_source/10333/10333_gasoline_stations_year.xlsx
[29] The World Bank Group, "State and Trends of Carbon Pricing 2022," in "State and Trends of Carbon Pricing," The World Bank Group, 2022. [Online]. Available: https://openknowledge.worldbank.org/handle/10986/37455

[30] Alternative Fuels Data Center. "Search Federal and State Laws and Incentives." U.S. Department of Energy. https://afdc.energy.gov/laws/search (accessed 15.10, 2022).
[31] International Energy Agency. "Policies database." https://www.iea.org/policies (accessed 15.10.2022, 2022).
[32] Opplysningsrådet for veitrafikken (OFV). "Bilsalget i november 2022." https://ofv.no/bilsalget/bilsalget-i-november-2022-2-2 (accessed 10.12.2022, 2022).
[33] Alternative Fuels Data Center. "Alternative Fueling Station Locator." https://afdc.energy.gov/stations/#/analyze?fuel=ELEC&ev_levels=all&country=US&access=public&access=private (accessed 01.09, 2022).
[34] U. S. D. o. Transportation. "President Biden, U.S. Department of Transportation Releases Toolkit to Help Rural Communities Build Out Electric Vehicle Charging Infrastructure." U.S. DEPARTMENT OF TRANSPORTATION. https://www.transportation.gov/briefing-room/president-biden-us-department-transportation-releases-toolkit-help-rural-communities#:~:text=President%20Biden's%20Bipartisan%20Infrastructure%20Law,make%20these%20projects%20a%20reality. (accessed 01.09.2022, 2022).
[35] International Energy Agency. "Infrastructure and Jobs act: Nationwide network of EV chargers." https://www.iea.org/policies/14978-infrastructure-and-jobs-act-nationwide-network-of-ev-chargers (accessed 01.09.2022, 2022).
[36] Organisation for Economic Cooperation and Development (OECD), "OECD Environmental Performance Reviews: Norway 2022," in "OECD Environmental Performance Reviews," Organisation for Economic Cooperation and Development (OECD), OECD iLibrary, 2022. [Online]. Available: https://www.oecd-ilibrary.org/sites/59e71c13-en/index.html?itemId=/content/publication/59e71c13-en
[37] D. R. Keith, S. Naumov, and J. Sterman, "Driving the Future A Management Flight Simulator of the US Automobile Market," *Simulation & Gaming*, vol. 48 (6), pp. 735–769, 2017, doi: 10.1177/1046878117737807.
[38] MIT and Forio. "Driving the Future." https://forio.com/work/mit-alternative-fuel-vehicle-simulator/ (accessed 29.07, 2022).
[39] W. Braun, "The System Archetypes." [Online]. Available: https://www.albany.edu/faculty/gpr/PAD724/724WebArticles/sys_archetypes.pdf

Appendix A – Model Documentation

	Equation	Properties	Units	Documentation
Consumer.Consumer_Familiarity:				
Consumer."Global_BEV_stock_excl._U.S."	GRAPH(TIME) Points(51): (2000,00, 600), (2001,00, 1300), (2002,00, 2600), (2003,00, 3900), (2004,00, 5200), (2005,00, 6500), (2006,00, 7800), (2007,00, 9100), (2008,00, 10400), (2009,00, 11700), ...		vehicles	Global stock of BEVs, excluding the US. Set to constant from 2021. Source: https://www.iea.org/articles/global-ev-data-explorer
Consumer.Additional_Marketing_Spending_BEV	Vehicles.OEM_Revenue_ICEV/Dollars_per_Million*BEV_Marketing_Fraction_of_ICEV_Revenue		million/year	Additional marketing spending on BEVs from ICEV revenue by OEMs manufacturing both BEVs and ICEVs.
Consumer.BEV_Marketing_Effectiveness	4e-03		dmnl/million	Effectiveness of advertising activities in reducing the gap to full familiarity with BEVs per million dollar spent.
Consumer.BEV_Marketing_Fraction_of_ICEV_Revenue	0,001		dmnl	Fraction of ICEV revenue dedicated to additional marketing spending on BEVs by OEMs manufacturing both BEVs and ICEVs.
Consumer.BEV_marketing_spending_duration	30		year	Duration of additional marketing spending to promote BEVs.
Consumer.BEV_marketing_spending_start	2100		year	Start year for additional marketing spending to promote BEVs.
Consumer.BEV_marketing_spending_value	500		million/year	Potential additional marketing spending to promote BEVs.

Consumer.Cumulative_BEV_Familiarity(t)	Cumulative_BEV_Familiarity(t - dt) + (Familiarity_Sales + Familiarity_Exposure) * dt	INIT Consumer.Cumulative_BEV_Familiarity = Vehicles.BEV_Fleet	vehicles	Cumulative familiarity with BEVs.
Consumer.Dollars_per_Million	1e+06		$/million	Amount of dollars in one million dollars. Dummy variable to correct for units.
Consumer.Effective_Contact_Rate_Drivers	0,06		dmnl/year	Average strength of contacts with BEV drivers to build familiarity with BEVs. Calculated as the rate of reducing the gap to full familiarity per year.
Consumer.Exposure_from_BEV_Drivers	Effective_Contact_Rate_Drivers*Probability_of_Contact_with_BEV_Drivers		dmnl/year	Effective strength of a contact with a BEV driver. Measures the effective rate of reducing the gap to full familiarity with BEVs per year.
Consumer.Familiarity_Exposure	IF Vehicles.Global_influence_Switch = 1 THEN MAX(0; (1-Average_Familiarity_BEV)*Total_Social_Exposure_to_BEV*(Vehicles.BEV_Fleet+"Global_BEV_stock_excl._U.S.")) ELSE MAX(0; (1-Average_Familiarity_BEV)*Total_Social_Exposure_to_BEV*(Vehicles.BEV_Fleet))		vehicles/year	Increase in familiarity with BEVs per year. The impact of total social exposure is high when average familiarity is low and is approaches zero as full familiarity is approached.
Consumer.Familiarity_Sales	Vehicles.Vehicle_Sales_BEV		vehicles/year	Increase in familiarity with BEVs per year due to sales.
Consumer.Marketing_Fraction_of_Revenue	0,004		dmnl	OEM revenue fraction dedicated to marketing on a regular basis.

Consumer.Marketing_Spending_BEV	Regular_Marketing_Spending_BEV+Subsidized_BEV_marketing_spending+Additional_Marketing_Spending_BEV		million/year	Total marketing spending to promote BEVs.
Consumer.Probability_of_Contact_with_BEV_Drivers	Vehicles.BEV_Fleet/Vehicles.Total_Passenger_Vehicle_Fleet		dmnl	Probability of a random contact to be with the driver of BEVs.
Consumer.Regular_Marketing_Spending_BEV	Vehicles.OEM_Revenue_BEV/Dollars_per_Million*Marketing_Fraction_of_Revenue		million/year	Actual marketing spending of BEV OEMs.
Consumer.Regular_Marketing_Spending_ICEV	Vehicles.OEM_Revenue_ICEV/Dollars_per_Million*Marketing_Fraction_of_Revenue		million/year	Actual marketing spending of ICEV OEMs.
Consumer.Subsidized_BEV_marketing_spending	(BEV_marketing_spending_value*(IF TIME >= (BEV_marketing_spending_start) AND TIME < ((BEV_marketing_spending_start) + MAX(DT;BEV_marketing_spending_duration)) THEN 1 ELSE 0))		million/year	Actual additional marketing spending to promote BEVs.
Consumer.Total_BEV_Marketing_Exposure	Marketing_Spending_BEV*(MAX(BEV_Marketing_Effectiveness; 4e-04))		dmnl/year	Effective strength of the advertising to promote the BEVs. Measures the effective rate of reducing the gap to full familiarity with BEVs per year.
Consumer.Total_Social_Exposure_to_BEV	Total_BEV_Marketing_Exposure+ Exposure_from_BEV_Drivers		dmnl/year	Total effective rate of reducing the gap to full familiarity of platform i with BEVs per year.
Consumer.Consumer_Utility:				
Consumer."\"Normalize_Abs.\"_Utility_Range"	"Abs._Utility_Range_BEV"+"Abs._Utility_Range_ICEV"		dmnl	The sum of the absolute Range Utility.

Consumer."Abs._Utility_ Models_Available_BEV"	(Vehicles.BEV_Projected_Models_Available/Models_Available_Peak_Utility)+(Vehicles.BEV_Luxury_makes /Impact_of_available_Luxury_makes)		dmnl	The absolute BEV Available Models Utility taking input from both overall model availability and availability in the luxury segment.
Consumer."Abs._Utility_ Models_Available_ICEV"	(Vehicles."ICEV_Models_Available_- _Saturated_level"/Models_Available_Peak_Utility)+(Vehicles.ICEV_Luxury_makes/Impact_of_available_Luxury_makes)		dmnl	The absolute ICEV Available Models Utility taking input from both overall model availability and availability in the luxury segment.
Consumer."Abs._Utility_ Range_BEV"	(IF Fueling.Range_BEV>= Range_at_Peak_Utility THEN Max_Utility_from_Range ELSE Range_A*(Fueling.Range_BEV/Vehicle_Range_Normalizer)- Range_B*(Fueling.Range_BEV/Vehicle_Range_Normalizer)^2)		dmnl	BEV range component of von Neumann-Morgenstern utility function.
Consumer."Abs._Utility_ Range_ICEV"	(IF Fueling.Range_ICEV >= Range_at_Peak_Utility THEN Max_Utility_from_Range ELSE Range_A*(Fueling.Range_ICEV/Vehicle_Range_Normalizer)- Range_B*(Fueling.Range_ICEV/Vehicle_Range_Normalizer)^2)		dmnl	Range component of von Neumann-Morgenstern utility function.
Consumer."Abs._Utility_ Refuel_Time_BEV"	(Fueling.Weekly_refueling_time_BEV/Refueling_Time _Peak_Utility)		dmnl	The absolute BEV Refuel time Utility.
Consumer."Abs._Utility_ Refuel_Time_ICEV"	(Fueling.Weekly_refueling_time_ICEV/Refueling_Time_Peak_Utility)		dmnl	The absolute ICEV Refuel time Utility.
Consumer."Abs._Utility_ Retail_Price_BEV"	((Vehicles.Effective_Price_BEV)/1000)/"Ln(Household_Income)"		$/vehicles	BEV purchase price component of von Neumann-Morgenstern utility function.

Consumer."Abs._Utility_Retail_Price_ICEV"	((Vehicles.Effective_Price_ICEV)/1000)/"Ln(Household_Income)"		$/vehicles	ICEV purchase price component of von Neumann-Morgenstern utility function.
Consumer."Normalize_Abs._Refuel_Time"	"Abs._Utility_Refuel_Time_BEV"+"Abs._Utility_Refuel_Time_ICEV"		dmnl	The sum of the absolute Refuel time Utility.
Consumer."Normalize_Abs._Utility_Infrastructure"	Fueling.Charging_availability+Fueling.Fueling_availability		pump/Miles	The sum of the absolute Infrastructure Utility.
Consumer."Normalize_Abs._Utility_Model_Selection"	"Abs._Utility_Models_Available_BEV"+"Abs._Utility_Models_Available_ICEV"		dmnl	The sum of the absolute Available models Utility.
Consumer."Normalize_Abs._Utility_Retail_Price"	"Abs._Utility_Retail_Price_BEV"+"Abs._Utility_Retail_Price_ICEV"		$/vehicles	The sum of the absolute Retail Price Utility.
Consumer.Cents_per_Dollar	100		cents/$	How many cents are in a dollar.
Consumer."Charge_time_/_Fueling_time_Weight"	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, -0,270), (50,0, -0,2476), (100,0, -0,2252), (150,0, -0,2028), (200,0, -0,1804), (250,0, -0,158), (300,0, -0,1356), (350,0, -0,1132), (400,0, -0,0908), (450,0, -0,0684), ...		dmnl	The weight of Refuel time Utility in the overall Utility.
Consumer.Impact_of_available_Luxury_makes	7		models	Number of luxury models available assumed to have be sufficient to impact the luxury car segment.
Consumer.Infrastructure_Weight	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, 0,110), (50,0, 0,110), (100,0, 0,110), (150,0, 0,110), (200,0, 0,110), (250,0, 0,110), (300,0, 0,110), (350,0, 0,110), (400,0, 0,110), (450,0, 0,110), ...		dmnl	The weight of Infrastructure Utility in the overall Utility.

Consumer.Ln_Units_Correction	1		$/year	Dummy variable for LN unit correction.
Consumer."Ln(Household_Income)"	LN(US_Median_Household_Income/Ln_Units_Correction)		dmnl	Log of the income of the median household in the US.
Consumer.Max_Utility_from_Range	Range_A^2/(4*Range_B)		dmnl	The maximum utility a consumer gets from increased vehicle range.
Consumer.Model_Selection_Weight	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, 0,040), (50,0, 0,040), (100,0, 0,040), (150,0, 0,040), (200,0, 0,040), (250,0, 0,040), (300,0, 0,040), (350,0, 0,040), (400,0, 0,040), (450,0, 0,040), ...		dmnl	The weight of Available models Utility in the overall Utility.
Consumer.Models_Available_Peak_Utility	100		models	Model availability that yields the max utility.
Consumer.Normalize_Operating_Cost	Vehicle_Operating_Cost_BEV+Vehicle_Operating_Cost_ICEV		cents/miles	The sum of the absolute Operating cost Utility.
Consumer.Operating_Cost_Weight	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, -0,095), (50,0, -0,141), (100,0, -0,187), (150,0, -0,233), (200,0, -0,279), (250,0, -0,325), (300,0, -0,371), (350,0, -0,417), (400,0, -0,463), (450,0, -0,509), ...		dmnl	The weight of Operating cost Utility in the overall Utility.
Consumer.Range_A	1,268		dmnl	Brownstone Bunch and Train estimate an attribute formulation for range, the upward sloping segment of a negative quadratic: 1.268*Range-0.116*(Range^2). Source: http://www.uctc.net/papers/597.pdf

Consumer.Range_at_Peak_Utility	Range_A/(2*Range_B)*Vehicle_Range_Normalizer		miles/vehicles	Range that yields the max utility given the weights.
Consumer.Range_B	0,116		dmnl	Brownstone Bunch and Train estimate an attribute formulation for range, the upward sloping segment of a negative quadratic: 1.268*Range-0.116*(Range^2). Source: http://www.uctc.net/papers/597.pdf
Consumer.Range_Weight	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, 0,200), (50,0, 0,200), (100,0, 0,200), (150,0, 0,200), (200,0, 0,200), (250,0, 0,200), (300,0, 0,200), (350,0, 0,200), (400,0, 0,200), (450,0, 0,200), ...		dmnl	The weight of Range Utility in the overall Utility.
Consumer.Refueling_Time_Peak_Utility	31		Minutes/(vehicle*Weeks)	Refuel time that yields the max utility - 'tipping point ' charge time. Source: https://www.visualcapitalist.com/mainstream-ev-adoption-5-speedbumps-to-overcome/
Consumer.Retail_Price_Weight	GRAPH(Fueling.Carbon_Tax_Price) Points(11): (0,0, -0,285), (50,0, -0,2614), (100,0, -0,2378), (150,0, -0,2142), (200,0, -0,1906), (250,0, -0,167), (300,0, -0,1434), (350,0, -0,1198), (400,0, -0,0962), (450,0, -0,0726), ...		dmnl	The weight of Retail Price Utility in the overall Utility.
Consumer.US_Median_Household_Income	40000		$/year	Income of the median household in the US.

Consumer.Utility_Infrastructure_BEV	Infrastructure_Weight*(Fueling.Charging_availability/"Normalize_Abs._Utility_Infrastructure")		dmnl	The BEV share of Infrastructure Utility.
Consumer.Utility_Infrastructure_ICEV	Infrastructure_Weight*(Fueling.Fueling_availability/"Normalize_Abs._Utility_Infrastructure")		dmnl	The ICEV share of Infrastructure Utility.
Consumer.Utility_Model_Selection_BEV	Model_Selection_Weight*("Abs._Utility_Models_Available_BEV"/"Normalize_Abs._Utility_Model_Selection")		dmnl	The BEV share of Available models Utility.
Consumer.Utility_Model_Selection_ICEV	Model_Selection_Weight*("Abs._Utility_Models_Available_ICEV"/"Normalize_Abs._Utility_Model_Selection")		dmnl	The ICEV share of Available models Utility.
Consumer.Utility_Operating_Cost_BEV	Operating_Cost_Weight*(Vehicle_Operating_Cost_BEV/Normalize_Operating_Cost)		dmnl	Operating cost component of von Neumann-Morgenstern utility function.
Consumer.Utility_Operating_Cost_ICEV	Operating_Cost_Weight*(Vehicle_Operating_Cost_ICEV/Normalize_Operating_Cost)		dmnl	Operating cost component of von Neumann-Morgenstern utility function.
Consumer.Utility_Range_BEV	("Abs._Utility_Range_BEV"/"\"Normalize_Abs.\"_Utility_Range")*Range_Weight		dmnl	The BEV share of Range Utility.
Consumer.Utility_Range_ICEV	("Abs._Utility_Range_ICEV"/"\"Normalize_Abs.\"_Utility_Range")*Range_Weight		dmnl	The ICEV share of Range Utility.
Consumer.Utility_Refuel_Time_BEV	"Charge_time_/_Fueling_time_Weight"*("Abs._Utility_Refuel_Time_BEV"/"Normalize_Abs._Refuel_Time")		dmnl	BEV share of Refuel time Utility.
Consumer.Utility_Refuel_Time_ICEV	"Charge_time_/_Fueling_time_Weight"*("Abs._Utility_Refuel_Time_ICEV"/"Normalize_Abs._Refuel_Time")		dmnl	ICEV share of Refuel time Utility.
Consumer.Utility_Retail_Price_BEV	("Abs._Utility_Retail_Price_BEV"/"Normalize_Abs._Utility_Retail_Price")*Retail_Price_Weight		dmnl	BEV share of Retail Price Utility.

Consumer.Utility_Retail_Price_ICEV	("Abs._Utility_Retail_Price_ICEV"/"Normalize_Abs._Utility_Retail_Price")*Retail_Price_Weight		dmnl	ICEV share of Retail Price Utility.
Consumer.Vehicle_Operating_Cost_BEV	(SAFEDIV(Fueling.Retail_Fuel_Price_BEV; Vehicles.Fuel_Efficiency_of_New_BEVs))*Cents_per_Dollar		cents/miles	Operating cost of BEVs.
Consumer.Vehicle_Operating_Cost_ICEV	(SAFEDIV(Fueling.Retail_Fuel_Price_ICEV; Vehicles.Fuel_Efficiency_of_New_ICEVs))*Cents_per_Dollar		cents/miles	Operating cost of ICEVs.
Consumer.Vehicle_Range_Normalizer	100		miles/vehicles	Dummy variable for unit corrections.
Consumer.Projected_Market_Shares:				
Consumer."Exp._Utility_BEV"	EXP(Utility_BEV)		dmnl	Exponent of the utility of BEVs.
Consumer."Exp._Utility_ICEV"	EXP(Utility_ICEV)		dmnl	Exponent of the utility of ICEVs.
Consumer.Affinity_BEV	Average_Familiarity_BEV*"Exp._Utility_BEV"		dmnl	Combined effect of familiarity and consumer utility reflecting the propensity of drivers to purchase BEVs.
Consumer.Affinity_ICEV	Saturated_Familiarity_ICEV*"Exp._Utility_ICEV"		dmnl	Combined effect of familiarity and consumer utility reflecting the propensity of drivers to purchase ICEVs.
Consumer.Average_Familiarity_BEV	MAX(0,0001; (SMTHN(MIN(1; SAFEDIV(Cumulative_BEV_Familiarity; Vehicles.Total_Passenger_Vehicle_Fleet)); BEV_familiarity_delay_time; 1)))		dmnl	Average familiarity with BEVs.

Consumer.BEV_familiarity_delay_time	4		year	Time for BEV familiarity to mature.
Consumer.BEV_Share	SAFEDIV(Affinity_BEV; Combined_Affinity)		dmnl	Share of drivers choosing BEVs.
Consumer.Combined_Affinity	Affinity_ICEV +Affinity_BEV		dmnl	Total of affinities of drivers looking to purchase a new vehicle.
Consumer.ICEV_Share	SAFEDIV(Affinity_ICEV; Combined_Affinity)		dmnl	Share of drivers choosing ICEVs.
Consumer.Saturated_Familiarity_ICEV	1 { IF SW_Endogenous_Familiarity = 0 THEN Exogenous_Familiarity_Value ELSE Average_Familiarity_ij[Technology; TechnologyTo]		dmnl	Current level of familiarity with ICEVs.
Consumer.Utility_BEV	Utility_Retail_Price_BEV+Utility_Operating_Cost_BEV+Utility_Range_BEV+Utility_Model_Selection_BEV+Utility_Refuel_Time_BEV+Utility_Infrastructure_BEV		dmnl	Total utility BEVs.
Consumer.Utility_ICEV	Utility_Retail_Price_ICEV+Utility_Operating_Cost_ICEV+Utility_Range_ICEV+Utility_Model_Selection_ICEV+Utility_Refuel_Time_ICEV+Utility_Infrastructure_ICEV		dmnl	Total utility ICEVs.
Fueling.Fuel_Prices:				
Fueling.Carbon_Tax_ICEV	Carbon_Tax_Price*GHG_Emissions_Factor_Gasoline_GGE		$/GGE	Carbon tax on gasoline based on emission impact.
Fueling.Carbon_Tax_introduction_time	7		year	Carbon Tax regime duration.
Fueling.Carbon_Tax_Price	IF TIME > 2022 AND Carbon_Tax_Switch >0 THEN 500 ELSE IF TIME < Carbon_Tax_start THEN 0 ELSE 0+RAMP(Carbon_Tax_Value/(MAX((1/365); Carbon_Tax_introduction_time)); Carbon_Tax_start; Carbon_Tax_start+(MAX((1/365); Carbon_Tax_introduction_time)))		$/tonnes CO2e	Current carbon Tax price per tonne CO2 equivalent.

Fueling.Carbon_Tax_start	2100		year	Carbon Tax regime start.
Fueling.Carbon_Tax_Switch	0		dmnl	Carbon Tax Switch.
Fueling.Carbon_Tax_Value	400		$/tonnes CO2e	Potential carbon Tax price per tonne CO2 equivalent. Currently 33 countries have implemented Carbon Tax, ranging from <1 to 137 USD per tonne CO2e. The number of countries adopting the tax and the tax levels are expected to increase. An example is Norway where it is planned to increase taxes from USD 69 to USD 233 by 2030. Sources: https://openknowledge.worldbank.org/handle/10986/37455 https://www.oecd-ilibrary.org/sites/59e71c13-en/index.html?itemId=/content/publication/59e71c13-en
Fueling.Electricity_Price (t)	Electricity_Price(t - dt) + (Electricity_Price_Rate) * dt	INIT Fueling.Electricity_Price = Initial_Price_Electricity	$/GGE	Current price of electricity GGE.
Fueling.Electricity_Price_Growth_rate	0,01		dmnl/year	Yearly growth rate in price of electricity.

Fueling.Electricity_Price_Rate	IF TIME < 2022 THEN 0 ELSE Initial_Price_Electricity*Electricity_Price_Growth_rate		$/(GGE*year)	Change in electricity price.
Fueling.Fuel_Price_BEV	Electricity_Price		$/GGE	Electricity price without taxes.
Fueling.Fuel_Price_ICEV	Gasoline_Price		$/GGE	Gasoline price without taxes.
Fueling.Gasoline_Price(t)	Gasoline_Price(t - dt) + (Gasoline_Price_Rate) * dt	INIT Fueling.Gasoline_Price = Initial_Price_Gasoline	$/GGE	Current price of gasoline.
Fueling.Gasoline_Price_Growth_rate	0,01		dmnl/year	Yearly growth rate in price of gasoline.
Fueling.Gasoline_Price_Rate	IF TIME < 2022 THEN 0 ELSE Initial_Price_Gasoline*Gasoline_Price_Growth_rate		$/GGE/year	Change of price of gasoline.
Fueling.GHG_Emissions_Factor_Gasoline_GGE	0,008887		tonnes CO2e/GGE	Emissions factor for gasoline per GGE consumed. Source: http://www.epa.gov/energy/ghg-equivalencies-calculator-calculations-and-references
Fueling.Historical_Electricity_Price_GGE	Historical_Electricity_Price_kwh*Native_units_to_GGE_Electricity		$/GGE	Retail Price of electricity in the period from 2000 to 2022 (yearly average) converted to GGE. Source:

				https://www.statista.com/statistics/183700/us-average-retail-electricity-price-since-1990/
Fueling.Historical_Electricity_Price_kwh	GRAPH(TIME) Points(12): (2010,00, 0,0983), (2011,00, 0,099), (2012,00, 0,0984), (2013,00, 0,1007), (2014,00, 0,1044), (2015,00, 0,1041), (2016,00, 0,1027), (2017,00, 0,1048), (2018,00, 0,1053), (2019,00, 0,1054), ...		$/kwh	Retail Price of electricity in the period from 2000 to 2022 (yearly average). Source: https://www.statista.com/statistics/183700/us-average-retail-electricity-price-since-1990/
Fueling.Historical_Gasoline_Price	GRAPH(TIME) Points(12): (2010,00, 2,830), (2011,00, 3,580), (2012,00, 3,690), (2013,00, 3,580), (2014,00, 3,440), (2015,00, 2,510), (2016,00, 2,250), (2017,00, 2,530), (2018,00, 2,820), (2019,00, 2,690), ...		$/GGE	Retail Price of gasoline in the period from 2010 to 2021 (yearly average). Source: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPM0_PTE_NUS_DPG&f=M
Fueling.Initial_Price_Electricity	INIT(Historical_Electricity_Price_GGE)		$/GGE	Price of electricity at the beginning of simulation. Source: https://www.statista.com/statistics/183700/us-average-retail-electricity-price-since-1990/
Fueling.Initial_Price_Gasoline	INIT(Historical_Gasoline_Price)		$/GGE	Price of gasoline at the beginning of simulation. Source: https://www.eia.gov/dnav/pet/hist/L

				eafHandler.ashx?n=PET&s=EMM_EPM0_PTE_NUS_DPG&f=M
Fueling.Native_units_to_GGE_Electricity	33,4		kwh/GGE	Conversion from native capacity units for the electricity (kwh) to Gasoline gallon equivalent (GGE). 1 GGE ≈ 33.40 kWh Source: https://grcc.us/measuring-fuels-understanding-and-using-gasoline-gallon-equivalents/
Fueling.Retail_Fuel_Price_BEV	IF TIME < 2022 THEN Historical_Electricity_Price_GGE ELSE Fuel_Price_BEV		$/GGE	Retail price of electricity.
Fueling.Retail_Fuel_Price_ICEV	IF TIME < 2022 THEN Historical_Gasoline_Price ELSE Fuel_Price_ICEV +Carbon_Tax_ICEV		$/GGE	Retail price of gasoline.
Fueling.Fueling_infrastructure:				
Fueling."2022_Incentivized_build-out_per_Year"	IF TIME < "2022_Infrastructure_Incentive_start" THEN 0 ELSE IF TIME > "2022_Infrastructure_Incentive_start"+"2022_Infrastructure_Incentive_duration" THEN 0 ELSE "2022_Infrastructure_Incentive_stations"		stations/year	2022 incentive program for additional number of stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling."2022_Infrastructure_Incentive_duration"	8		year	Duration of 2022 incentive program additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling."2022_Infrastructure_Incentive_start"	2100		year	Start year for 2022 incentive program additional number of charging stations

				being introduced (bypassing economic considerations of infrastructure evolution).
Fueling."2022_Infrastructure_Incentive_stations"	62500		stations /year	Potential value of 2022 incentive program additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling.Available_Gas_Pumps	Available_Infrastructure_ICEV*Pumps_per_Station_ICEV		pump	Total available gas pumps.
Fueling.Available_Infrastructure_BEV(t)	Available_Infrastructure_BEV(t - dt) + (Infrastructure_Acquisition_Rate_BEV + "Historical_Infrastructure_build-out" - Infrastructure_Exits_BEV) * dt	INIT Fueling.Available_Infrastructure_BEV = 482	stations	Number of charging stations available.
Fueling.Available_Infrastructure_ICEV(t)	Available_Infrastructure_ICEV(t - dt) + (Infrastructure_Acquisition_Rate_ICEV - Infrastructure_Exits_ICEV) * dt	INIT Fueling.Available_Infrastructure_ICEV = 159006	stations	Number of gas refueling stations available. 159 006 stations in 2010 and on the decline for more than a decade. Source initialization: https://afdc.energy.gov/files/u/data/data_source/10333/10333_gasoline_stations_year.xlsx
Fueling.Average_Distance_to_Gas_Station	SQRT(SAFEDIV(1; Density_of_Stations_ICEV*Average_Distance_Unit_Correction; 1e+20))/2		miles/vehicles	Average distance to a gas station.

Fueling.Average_Distance_to_Station_BEV	SQRT(SAFEDIV(1; Density_of_Stations_BEV*Average_Distance_Unit_Correction; 1e+20))/2		miles/vehicles	Average distance to a charging station.
Fueling.Average_Distance_Unit_Correction	1		vehicles*vehicles/pump	Dummy variable to correct unit errors.
Fueling.Buffer_Adjust_Time	DT*2		year	Time to change the buffer.
Fueling.Buffer_Change_Rate_BEV	(Suggested_Buffer_BEV-Fuel_Buffer_BEV)/(Buffer_Adjust_Time)		miles/(vehicles*year)	Rate of change of fuel buffer. Information delay structure.
Fueling.Buffer_Change_Rate_ICEV	(Suggested_Buffer_ICEV-Fuel_Buffer_ICEV)/(Buffer_Adjust_Time)		miles/(vehicles*year)	Rate of change of fuel buffer. Information delay structure.
Fueling.Buffer_miles_per_Distance_to_Stations_parameter	20		miles/vehicles	A parameter scaling distance to stations curve to buffer miles.
Fueling.Charging_availability	Density_of_Stations_BEV*Vehicles.BEV_Fleet*Fuel_Buffer_BEV		pump/Miles	A variable that is used to assess availability of fueling a BEV.
Fueling.Clustering_factor_BEV	1,5{6		dmnl	Factor affecting density of charging stations due to clustering, <1 = more density.
Fueling.Clustering_factor_ICEV	10		dmnl	Factor affecting density of refueling stations due to clustering, <1 = more density.
Fueling.Delayed_demand_BEV	SMTH1(Demand_for_Infrastructure_BEV; Demand_delay_time_BEV)		stations	Delayed total number of charging stations demanded by the BEV fleet.

Fueling.Delayed_demand_ICEV	SMTH1(Demand_for_Infrastructure_ICEV; Demand_delay_time_ICEV)		stations	Delayed total number of charging stations demanded by the ICEV fleet.
Fueling.Demand_delay_time_BEV	2		year	Delay time in years to assess a change in demand.
Fueling.Demand_delay_time_ICEV	2		year	Delay time in years to assess a change in demand.
Fueling.Demand_for_Infrastructure_BEV	Minimum_demand_for_Infrastructure_by_Charging_plugs_BEV/Fueling_utilization_factor		stations	Total number of charging stations demanded by the BEV fleet.
Fueling.Demand_for_Infrastructure_ICEV	(SAFEDIV(Minimum_demand_for_Infrastructure_by_Pumps_ICEV; Pumps_per_Station_ICEV))/Fueling_utilization_factor		stations	Total number of refueling stations demanded by the ICEV fleet.
Fueling.Density_of_Stations_BEV	SAFEDIV(Available_Infrastructure_BEV*Pump_equivalent_per_Station_BEV; Useful_Station_Land_Area*Clustering_factor_BEV)		pump/(miles*miles)	Average density of charging stations.
Fueling.Density_of_Stations_ICEV	SAFEDIV(Available_Infrastructure_ICEV*Pumps_per_Station_ICEV; Useful_Station_Land_Area*Clustering_factor_ICEV)		pump/(miles*miles)	Average density of gas refueling stations.
Fueling.Desired_Infrastructure_Acquisition_Rate_BEV	MAX(0; (Infrastructure_Stock_Level_Adjustment_BEV +Infrastructure_Loss_Rate_BEV) *Recent_change_in_demand_BEV) +Subsidized_Charging_Point_per_Year +"2022_Incentivized_build-out_per_Year"		stations /year	Desired rate of orders for new charging stations.
Fueling.Desired_Infrastructure_Acquisition_Rate_ICEV	MAX(0; (Infrastructure_Stock_Level_Adjustment_ICEV+Infrastructure_Loss_Rate_ICEV)*Recent_change_in_demand_ICEV)		stations /year	Desired rate of orders for new stations.

Fueling.Desired_Infrastructure_Under_Construction_BEV	Time_to_Install_Infrastructure_BEV*Desired_Infrastructure_Acquisition_Rate_BEV		stations	Desired level of charging stations being built.
Fueling.Desired_Infrastructure_Under_Construction_ICEV	Time_to_Install_Infrastructure_ICEV*Desired_Infrastructure_Acquisition_Rate_ICEV		stations	Desired level of stations being built.
Fueling.Distance_to_Gas_Station_to_Buffer	SQRT(Average_Distance_to_Gas_Station/Unit_conversion_for_distance_to_station_to_buffer)*Buffer_miles_per_Distance_to_Stations_parameter		miles/vehicles	A convex function that describes relation between average distance to refueling station and buffer (amount of miles left on a remaining fuel when drivers begin search for a refueling station) drivers choose. Square root provides a good fit to the observed behavior.
Fueling.Distance_to_Station_to_Buffer_BEV	SQRT(Average_Distance_to_Station_BEV/Unit_conversion_for_distance_to_station_to_buffer)*Buffer_miles_per_Distance_to_Stations_parameter		miles/vehicles	A convex function that describes relation between average distance to refueling station and buffer (amount of miles left on a remaining fuel when drivers begin search for a refueling station) drivers choose. Square root provides a good fit to the observed behavior.
Fueling.Fuel_Buffer_BEV(t)	Fuel_Buffer_BEV(t - dt) + (Buffer_Change_Rate_BEV) * dt	INIT Fueling.Fuel_Buffer_BEV = New_Buffer_BEV	miles/vehicles	Perceived fuel buffer (amount of miles left on a remaining fuel when drivers begin search for a refueling station).
Fueling.Fuel_Buffer_ICEV(t)	Fuel_Buffer_ICEV(t - dt) + (Buffer_Change_Rate_ICEV) * dt	INIT Fueling.Fuel_Buffer_ICEV =	miles/vehicles	Perceived fuel buffer (amount of miles left on a remaining fuel when drivers begin search for a refueling station).

		New_Buffer_ICEV		
Fueling.Fueling_availability	Density_of_Stations_ICEV*Vehicles.ICEV_Fleet*Fuel_Buffer_ICEV		pump/ Miles	A variable that is used to assess availability of fueling an ICEV.
Fueling."Historical_build-out"	GRAPH(TIME) Points(41): (2010,00, 3421,0), (2011,00, 7792,0), (2012,00, 3295,0), (2013,00, 5125,0), (2014,00, 11559,0), (2015,00, 8494,0), (2016,00, 9869,0), (2017,00, 11463,0), (2018,00, 22858,0), (2019,00, 21623,0), ...		stations /year	Historical charging point build out - calibrated to match development in the period 2010-2022. Sources: According to IEA, there were 113527 charging point available in the US in 2021: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer According to the Alternative Fuels Data Center, the estimation is 138,492 of which 123,538 are public and 14954 are private: https://afdc.energy.gov/stations/#/analyze?fuel=ELEC&ev_levels=all&country=US&access=public&access=private
Fueling."Historical_Infrastructure_build-out"	"Historical_build-out"		stations /year	Additional rate of introduction of new charging stations from private investments.
Fueling.Infrastructure_Acquisition_Rate_BEV	SAFEDIV(Infrastructure_in_Construction_BEV; Time_to_Install_Infrastructure_BEV)		stations /year	Rate of construction completion and turning on of new charging stations.

Fueling.Infrastructure_Acquisition_Rate_ICEV	SAFEDIV(Infrastructure_in_Construction_ICEV; Time_to_Install_Infrastructure_ICEV)		stations/year	Rate of construction completion and turning on of new stations.
Fueling.Infrastructure_Exits_BEV	SAFEDIV(Available_Infrastructure_BEV; Infrastructure_Life_BEV)		stations/year	Number of charging stations discarded every year.
Fueling.Infrastructure_Exits_ICEV	SAFEDIV(Available_Infrastructure_ICEV; Infrastructure_Life_ICEV)		stations/year	Number of refueling stations discarded every year.
Fueling.Infrastructure_in_Construction_BEV(t)	Infrastructure_in_Construction_BEV(t - dt) + (Infrastructure_Order_Rate_BEV - Infrastructure_Acquisition_Rate_BEV) * dt	INIT Fueling.Infrastructure_in_Construction_BEV = 0	stations	Number of charging stations being built.
Fueling.Infrastructure_in_Construction_ICEV(t)	Infrastructure_in_Construction_ICEV(t - dt) + (Infrastructure_Order_Rate_ICEV - Infrastructure_Acquisition_Rate_ICEV) * dt	INIT Fueling.Infrastructure_in_Construction_ICEV = 10000	stations	Number of gas stations in construction. Source initialization: https://afdc.energy.gov/files/u/data/data_source/10333/10333_gasoline_stations_year.xlsx
Fueling.Infrastructure_Life_BEV	20		year	Average lifetime of a charging station.
Fueling.Infrastructure_Life_ICEV	20		year	Average lifetime of a station.
Fueling.Infrastructure_Loss_Rate_BEV	Infrastructure_Exits_BEV		stations/year	Rate of charging stations exiting the stock of available stations.
Fueling.Infrastructure_Loss_Rate_ICEV	Infrastructure_Exits_ICEV		stations/year	Rate of stations exiting the stock of available stations.

Fueling.Infrastructure_Order_Rate_BEV	MAX(0; Desired_Infrastructure_Acquisition_Rate_BEV+Infrastructure_Supply_Line_Adjustment_BEV)		stations /year	Order rate of new charging stations.
Fueling.Infrastructure_Order_Rate_ICEV	MAX(0; Desired_Infrastructure_Acquisition_Rate_ICEV+Infrastructure_Supply_Line_Adjustment_ICEV)		stations /year	Order rate of new refueling stations.
Fueling.Infrastructure_Stock_Level_Adjustment_BEV	SAFEDIV(Demand_for_Infrastructure_BEV - Available_Infrastructure_BEV ; Time_to_Install_Infrastructure_BEV)		stations /year	Adjustment for the rate of orders for new charging stations from comparing current and desired stock level.
Fueling.Infrastructure_Stock_Level_Adjustment_ICEV	SAFEDIV(Demand_for_Infrastructure_ICEV-Available_Infrastructure_ICEV; Time_to_Install_Infrastructure_ICEV)		stations /year	Adjustment for the rate of orders for new stations from comparing current and desired stock level.
Fueling.Infrastructure_Supply_Line_Adjustment_BEV	MAX(0; (Desired_Infrastructure_Under_Construction_BEV-Infrastructure_in_Construction_BEV)/Supply_Line_Adjustment_Time_BEV)		stations /year	Adjustment for the new orders for charging stations by accounting for the supply line of stations being built.
Fueling.Infrastructure_Supply_Line_Adjustment_ICEV	MAX(0; (Desired_Infrastructure_Under_Construction_ICEV-Infrastructure_in_Construction_ICEV)/Supply_Line_Adjustment_Time_ICEVS)		stations /year	Adjustment for the new orders for refueling stations by accounting for the supply line of stations being built.
Fueling.Maximum_Buffer	0,99		dmnl	Maximum fraction of a full range of the vehicle that drivers could use as a buffer. It is a complement to 1 of a minimum useful driving range drivers are expecting from a car.
Fueling.New_Buffer_BEV	MIN(Range_BEV*Maximum_Buffer; Distance_to_Station_to_Buffer_BEV)		miles/vehicles	Buffer bound by maximum buffer size.

Fueling.New_Buffer_ICEV	MIN(Range_ICEV*Maximum_Buffer; Distance_to_Gas_Station_to_Buffer)		miles/vehicles	Buffer bound by maximum buffer size.
Fueling.Number_of_Refuels_per_Year_BEV	VMT_per_Year/(Range_BEV-Fuel_Buffer_BEV)		1/year	Number of refuels an average vehicle of platform i needs per year.
Fueling.Number_of_Refuels_per_Year_ICEV	VMT_per_Year/(Range_ICEV-Fuel_Buffer_ICEV)		1/year	Number of refuels an average vehicle of platform i needs per year.
Fueling.Pump_equivalent_per_Station_BEV	1		pump/stations	Number of chargers per station - set to 1.
Fueling.Pumps_per_Station_ICEV	8		pump/stations	Average number of pumps per refueling station.
Fueling.Recent_change_in_demand_BEV	Demand_for_Infrastructure_BEV/Delayed_demand_BEV		dmnl	Variable that accounts for recent change in demand for BEVs. When above 1 demand is on the rise and when below it is on the decline.
Fueling.Recent_change_in_demand_ICEV	Demand_for_Infrastructure_ICEV/Delayed_demand_ICEV		dmnl	Variable that accounts for recent change in demand for ICEVs. When above 1 demand is on the rise and when below it is on the decline.
Fueling.Subsidized_Charging_Point_per_Year	IF TIME < Subsidized_Charging_Points_start THEN 0 ELSE IF TIME > Subsidized_Charging_Points_start+Subsidized_Charging_Points_duration THEN 0 ELSE Subsidized_Charging_Points_value		stations/year	Subsidized additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling.Subsidized_Charging_Points_duration	30		year	Duration of subsidized additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).

Fueling.Subsidized_Charging_Points_start	2100		year	Start year of subsidized additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling.Subsidized_Charging_Points_value	30000		stations/year	Potential subsidized additional number of charging stations being introduced (bypassing economic considerations of infrastructure evolution).
Fueling.Suggested_Buffer_BEV	New_Buffer_BEV		miles/vehicles	The buffer suggested by the model bound and adjusted for the platform introduction.
Fueling.Suggested_Buffer_ICEV	New_Buffer_ICEV		miles/vehicles	The buffer suggested by the model bound and adjusted for the platform introduction.
Fueling.Supply_Line_Adjustment_Time_BEV	0,1		year	Time to adjust orders for new stations.
Fueling.Supply_Line_Adjustment_Time_ICEVS	0,5		year	Time to adjust orders for new stations.
Fueling.Time_to_Install_Infrastructure_BEV	1		year	Time required to install a charging station.
Fueling.Time_to_Install_Infrastructure_ICEV	2		year	Time required to install a gas refueling station.
Fueling.Unit_conversion_for_distance_to_station_to_buffer	1		miles/vehicles	Dummy variable to correct for unit errors.

Fueling.Useful_Station_Land_Area	3,79e+06		miles*miles	Total area of land useful for building refueling stations - the land area captures the total land useful in the U.S.
Fueling.Fueling_metrics:				
Fueling.Fleet_Refuels_Required_per_Year_BEV	Public_refuels_per_Year_for_BEVs*Vehicles.BEV_Fleet		vehicles/year	Yearly number of refuels required for BEVs.
Fueling.Fleet_Refuels_Required_per_Year_ICEV	Refuels_per_Year_ICEV*Vehicles.ICEV_Fleet		vehicles/year	Yearly number of refuels required for ICEVs.
Fueling.Fraction_home_charging	GRAPH(Range_BEV) Points(11): (60,0, 0,3000), (114,0, 0,33060351228), (168,0, 0,364425624043), (222,0, 0,401804838351), (276,0, 0,443115258945), (330,0, 0,488770334399), (384,0, 0,539226996053), (438,0, 0,594990231137), (492,0, 0,656618136849), (546,0, 0,724727505984), ...		dmnl	The home refueling fraction has been set to be between 30 and 80 %. As the range of BEVs increase, so does the home refueling fraction. Sources: 1. https://elbil.no/slik-lader-elbileierne/ 2. https://www.mckinsey.com/industries/public-and-social-sector/our-insights/building-the-electric-vehicle-charging-infrastructure-america-needs
Fueling.Fuel_Dispensing_Rate_BEV	Initial_Dispensing_Rate_BEV+Initial_Dispensing_Rate_BEV*(1-(Vehicles."Effect_of_Experience_on_Unit_Battery_Cost,_Capacity_&_Charging"))		GGE/hour	Rate of recharging a BEV battery.
Fueling.Fuel_Dispensing_Rate_ICEV	600		GGE/hour	Rate of filing the storage tank of a ICEV from the pump.

				32 lpm -500 gge/h https://www.quora.com/What-is-the-flow-rate-of-gasoline-station-fuel-dispensers-in-liters-per-second
Fueling.Fuel_Dispensing_Utilization_per_Plug_BEV	Maximum_Fuel_Dispensing_Capacity_per_Plug_BEV*Fueling_utilization_factor		GGE/(year*stations)	Amount of GGEs a charging plug is serving per year adjusted with utilization factor.
Fueling.Fuel_Dispensing_Utilization_per_Pump_ICEV	Maximum_Fuel_Dispensing_Capacity_per_Pump_ICEV*Fueling_utilization_factor		GGE/(year*pump)	Amount of GGEs a pump is serving per year adjusted with utilization factor.
Fueling.Fueling_utilization_factor	0,15		dmnl	The fraction of time any pump is in actual service. Source: https://www.sciencedirect.com/science/article/pii/S2666792421000548
Fueling.Initial_Dispensing_Rate_BEV	1,5		GGE/hour	Initial recharging rate.
Fueling.Maximum_Fuel_Dispensing_Capacity_per_Plug_BEV	Fuel_Dispensing_Rate_BEV*Operating_Hours_per_Year_BEV		GGE/(year*stations)	Maximum possible amount of GGEs a charging plug is serving per year.
Fueling.Maximum_Fuel_Dispensing_Capacity_per_Pump_ICEV	Fuel_Dispensing_Rate_ICEV*Operating_Hours_per_Year_ICEV		GGE/(year*pump)	Maximum possible amount of GGEs a gas pump is serving per year.
Fueling.Minimum_demand_for_Infrastructure_by_Charging_plugs_BEV	SAFEDIV(Fleet_Refuels_Required_per_Year_BEV;(Refueling_Capacity_BEV_per_Year))		stations	Total demand for charging plugs for BEVs.

Fueling.Minimum_demand_for_Infrastructure_by_Pumps_ICEV	SAFEDIV(Fleet_Refuels_Required_per_Year_ICEV; (Refueling_Capacity_ICEV_per_Year))		pump	Total demand for pumps from ICEVs.
Fueling.Minutes_conversion	1/60		hour/minute	Number of hours in a minute.
Fueling.Operating_Hours_per_Year_BEV	8766		hour/(year*stations)	Total number of hours a charging plug can theoretically operates per year. Additional information: One year has 8766 hours
Fueling.Operating_Hours_per_Year_ICEV	8766		hour/(year*pump)	Total number of hours a pump can theoretically operates per year. Additional information: One year has 8766 hours
Fueling.Public_refuels_per_Year_for_BEVs	SAFEDIV(VMT_Public_per_Year; Range_BEV)		dmnl/year	Number of refuels for BEVs per year.
Fueling.Range_BEV	Vehicles.Battery_Capacity_GGE*Vehicles.Average_FE_BEV		miles/vehicles	Nominal driving range of BEVs.
Fueling.Range_ICEV	Vehicles.Average_FE_ICEV*Tank_ICEV_GGE		miles/vehicles	Nominal driving range of ICEVs.
Fueling.Refueling_Capacity_BEV	Range_BEV/Vehicles.Average_FE_BEV		GGE/vehicles	Amount of fuel required by a BEV per one refueling.
Fueling.Refueling_Capacity_BEV_per_Year	SAFEDIV(Operating_Hours_per_Year_BEV; Refueling_Time_BEV)		vehicles/(stations*year)	Number of BEVs demanding fuel per charging plug per year.

Fueling.Refueling_Capacity_ICEV_per_Year	SAFEDIV(Operating_Hours_per_Year_ICEV; Refueling_Time_ICEV)		vehicles/(pump*year)	Number of vehicles of ICEVs demanding fuel per pump per year.
Fueling.Refueling_Time_BEV	MAX (0,167; SAFEDIV(Refueling_Capacity_BEV; Fuel_Dispensing_Rate_BEV))		hour/vehicles	Total time in hours to complete refueling of a BEV.
Fueling.Refueling_Time_ICEV	MAX (0,167; SAFEDIV(Tank_ICEV_GGE; Fuel_Dispensing_Rate_ICEV))		hour/vehicles	Total time to complete refueling of a ICEV - the minimum time to refuel has been set to 10 minutes (0,167 hours).
Fueling.Refuels_per_Year_ICEV	SAFEDIV(VMT_per_Year; Range_ICEV)		dmnl/year	Number of ICEV refuels year.
Fueling.Tank_ICEV_GGE	14		GGE/vehicles	Average capacity of a gasoline tank in gallon gas equivalent (GGE).
Fueling.VMT_per_Year	11520		miles/(vehicles*year)	Miles traveled per year by an average vehicle - both BEVs and ICEVs. Source: https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references
Fueling.VMT_Public_per_Year	Fraction_home_charging*VMT_per_Year		miles/(vehicles*year)	Miles traveled per year by an average BEV fueled by public infrastructure rather than home fueling.
Fueling.Weekly_refueling_time_BEV	Yearly_refueling_time_BEV/Weeks_conversion		Minutes/(vehicle*Weeks)	Total time in minutes a BEV needs to charge in the course of a week.
Fueling.Weekly_refueling_time_ICEV	Yearly_refueling_time_ICEV/Weeks_conversion		Minutes/(vehicl	Total time in minutes a ICEV needs to refill in the course of a week.

			e*Weeks)	
Fueling.Weeks_conversion	52		weeks/year	Number of weeks in a year.
Fueling.Yearly_refueling_time_BEV	(Refueling_Time_BEV/Minutes_conversion)*Public_refuels_per_Year_for_BEVs		Minutes/(vehicle*Years)	Total time in minutes a BEV needs to charge in the course of a year.
Fueling.Yearly_refueling_time_ICEV	(Refueling_Time_ICEV/Minutes_conversion)*Refuels_per_Year_ICEV		Minutes/(vehicle*Years)	Total time in minutes a ICEV needs to refill in the course of a year.
Vehicles.Fleet_Turnover:				
Vehicles.Aging_Time_Lambda	4		year	Average time a vehicle spends in each of the aging chain stocks.
Vehicles.BEV_Fleet	Vehicles_0_to_4_years_BEV+Used_Vehicles_BEV		vehicles	Total number of BEVs on the road.
Vehicles.Cumulative_Order_Fulfillment_BEV(t)	Cumulative_Order_Fulfillment_BEV(t - dt) + (Order_Fulfillment_BEV) * dt	INIT Vehicles.Cumulative_Order_Fulfillment_BEV = 0	vehicles	Cumulative number of BEVs manufactured by OEMs.
Vehicles.Cumulative_Order_Fulfillment_ICEV(t)	Cumulative_Order_Fulfillment_ICEV(t - dt) + (Order_Fulfillment_ICEV) * dt	INIT Vehicles.Cumulative_Order_Fulfillment_ICEV = 0	vehicles	Cumulative number of ICEVs manufactured by OEMs.

Vehicles.Demand_BEVs	(Vehicle_Discards_BEV+Vehicle_Discards_GAS)*(1+Market_Growth_Rate)*Consumer.BEV_Share		vehicles/year	Total demand of BEVs.
Vehicles.Demand_ICEVs	(Vehicle_Discards_GAS+Vehicle_Discards_BEV)*(1+Market_Growth_Rate)*Consumer.ICEV_Share		vehicles/year	Total demand of ICEVs.
Vehicles.ICEV_Fleet	Vehicles_0_to_4_years_ICEV+Used_Vehicles_ICEV		vehicles	Total number of ICEVs on the road.
Vehicles.Market_Growth_Rate	0,025		dmnl	Growth rate of auto sales. Source: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
Vehicles.New_Vehicle_Discard_Fraction	0,001		dmnl/year	Discard fraction of new vehicles.
Vehicles.Order_Fulfillment_BEV	Demand_BEVs		vehicles/year	Number of BEVs manufactured per year.
Vehicles.Order_Fulfillment_ICEV	Demand_ICEVs		vehicles/year	Number of ICEVs manufactured per year.
Vehicles.Total_Passenger_Vehicle_Fleet	BEV_Fleet + ICEV_Fleet		vehicles	Total number of vehicles on the road.
Vehicles.Used_Vehicles_BEV	"Vehicles_13+_years_BEV" + Vehicles_5_to_8_years_BEV + Vehicles_9_to_12_years_BEV		vehicles	Total number of used BEVs on the road.
Vehicles.Used_Vehicles_ICEV	"Vehicles_13+_years_ICEV" + Vehicles_5_to_8_years_ICEV + Vehicles_9_to_12_years_ICEV		vehicles	Total number of used ICEVs on the road.
Vehicles."Vehice_Aging_9-12_BEV"	Vehicles_9_to_12_years_BEV/Aging_Time_Lambda		vehicles/year	Rate of aging of used BEVs (9 to 12 years).

Vehicles."Vehice_Aging_9-12_ICEV"	Vehicles_9_to_12_years_ICEV/Aging_Time_Lambda		vehicles/year	Rate of aging of used ICEVs (9 to 12 years).
Vehicles."Vehicle_Aging_0-4_BEV"	Vehicles_0_to_4_years_BEV/Aging_Time_Lambda		vehicles/year	Rate of aging of new BEVs (0 to 4 years).
Vehicles."Vehicle_Aging_0-4_ICEV"	Vehicles_0_to_4_years_ICEV/Aging_Time_Lambda		vehicles/year	Rate of aging of new ICEVs (0 to 4 years)
Vehicles."Vehicle_Aging_5-8_BEV"	Vehicles_5_to_8_years_BEV/Aging_Time_Lambda		vehicles/year	Rate of aging of used BEVs (5 to 8 years).
Vehicles."Vehicle_Aging_5-8_ICEV"	Vehicles_5_to_8_years_ICEV/Aging_Time_Lambda		vehicles/year	Rate of aging of used ICEVs (5 to 8 years).
Vehicles.Vehicle_Discards_BEV	Vehicles_0_to_4_Retirements_BEV + Vehicles_13_plus_Retirements_BEV + Vehicles_5_to_8_Retirements_BEV + Vehicles_9_to_12_Retirements_BEV		vehicles/year	Total discard rate of used BEVs.
Vehicles.Vehicle_Discards_GAS	Vehicles_0_to_4_Retirements_ICEV + Vehicles_13_plus_Retirements_ICEV + Vehicles_5_to_8_Retirements_ICEV + Vehicles_9_to_12_Retirements_ICEV		vehicles/year	Total discard rate of used ICEVs.
Vehicles.Vehicle_Sales_BEV	Demand_BEVs		vehicles/year	Sales of new BEVs.
Vehicles.Vehicle_Sales_ICEV	Demand_ICEVs		vehicles/year	Sales of new ICEVs.
Vehicles.Vehicle_Sales_Percent_BEV	Vehicle_Sales_Share_BEV*100		dmnl	BEV percent market share of sales.
Vehicles.Vehicle_Sales_Percent_ICEV	Vehicle_Sales_Share_ICEV*100		dmnl	ICEV percent market share of sales.

Vehicles.Vehicle_Sales_Share_BEV	Vehicle_Sales_BEV/(Vehicle_Sales_BEV+Vehicle_Sales_ICEV)		dmnl	BEV market share of sales.
Vehicles.Vehicle_Sales_Share_ICEV	Vehicle_Sales_ICEV/(Vehicle_Sales_ICEV+Vehicle_Sales_BEV)		dmnl	ICEV market share of sales..
Vehicles.Vehicles_0_to_4_Retirements_BEV	New_Vehicle_Discard_Fraction*Vehicles_0_to_4_years_BEV		vehicles/year	Discard rate of new BEVs (0 to 4 years).
Vehicles.Vehicles_0_to_4_Retirements_ICEV	New_Vehicle_Discard_Fraction*Vehicles_0_to_4_years_ICEV		vehicles/year	Discard rate of new ICEVs (0 to 4 years).
Vehicles.Vehicles_0_to_4_years_BEV(t)	Vehicles_0_to_4_years_BEV(t - dt) + (Vehicle_Sales_BEV - Vehicles_0_to_4_Retirements_BEV - "Vehicle_Aging_0-4_BEV") * dt	INIT Vehicles.Vehicles_0_to_4_years_BEV = 1872	vehicles	New BEVs (0 to 4 years).
Vehicles.Vehicles_0_to_4_years_ICEV(t)	Vehicles_0_to_4_years_ICEV(t - dt) + (Vehicle_Sales_ICEV - Vehicles_0_to_4_Retirements_ICEV - "Vehicle_Aging_0-4_ICEV") * dt	INIT Vehicles.Vehicles_0_to_4_years_ICEV = 55499055	vehicles	New ICEVs (0 to 4 years) Source: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
Vehicles.Vehicles_13_plus_Retirements_BEV	"Vehicles_13+_years_BEV"*Vehicles_Retirement_Fraction		vehicles/year	Discard rate of used BEVs (13+ years).
Vehicles.Vehicles_13_plus_Retirements_ICEV	"Vehicles_13+_years_ICEV"*Vehicles_Retirement_Fraction		vehicles/year	Discard rate of used ICEVs (13+ years).
Vehicles."Vehicles_13+_years_BEV"(t)	"Vehicles_13+_years_BEV"(t - dt) + ("Vehice_Aging_9-12_BEV" - Vehicles_13_plus_Retirements_BEV) * dt	INIT Vehicles."Vehicles_13+_years_BEV" = 312	vehicles	Used BEVs (13+ years).

Vehicles."Vehicles_13+_years_ICEV"(t)	"Vehicles_13+_years_ICEV"(t - dt) + ("Vehice_Aging_9-12_ICEV" - Vehicles_13_plus_Retirements_ICEV) * dt	INIT Vehicles."Vehicles_13+_years_ICEV" = 55499056	vehicles	Used ICEVs (13+ years). Source: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
Vehicles.Vehicles_5_to_8_Discard_Fraction	0,01		dmnl/year	Discard fraction of vehicles 5 to 8 years.
Vehicles.Vehicles_5_to_8_Retirements_BEV	Vehicles_5_to_8_years_BEV*Vehicles_5_to_8_Discard_Fraction		vehicles/year	Discard rate of used BEVs (5 to 8 years).
Vehicles.Vehicles_5_to_8_Retirements_ICEV	Vehicles_5_to_8_years_ICEV*Vehicles_5_to_8_Discard_Fraction		vehicles/year	Discard rate of used ICEVs (5 to 8 years).
Vehicles.Vehicles_5_to_8_years_BEV(t)	Vehicles_5_to_8_years_BEV(t - dt) + ("Vehicle_Aging_0-4_BEV" - "Vehicle_Aging_5-8_BEV" - Vehicles_5_to_8_Retirements_BEV) * dt	INIT Vehicles.Vehicles_5_to_8_years_BEV = 936	vehicles	Used BEVs (5 to 8 years).
Vehicles.Vehicles_5_to_8_years_ICEV(t)	Vehicles_5_to_8_years_ICEV(t - dt) + ("Vehicle_Aging_0-4_ICEV" - "Vehicle_Aging_5-8_ICEV" - Vehicles_5_to_8_Retirements_ICEV) * dt	INIT Vehicles.Vehicles_5_to_8_years_ICEV = 55499056	vehicles	Used ICEVs (5 to 8 years) Source: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
Vehicles.Vehicles_9_to_12_Discard_Fraction	0,1		dmnl/year	Discard fraction of vehicles 9 to 12 years.
Vehicles.Vehicles_9_to_12_Retirements_BEV	Vehicles_9_to_12_years_BEV*Vehicles_9_to_12_Discard_Fraction		vehicles/year	Discard rate of used BEVs (9 to 12 years).
Vehicles.Vehicles_9_to_12_Retirements_ICEV	Vehicles_9_to_12_years_ICEV*Vehicles_9_to_12_Discard_Fraction		vehicles/year	Discard rate of used ICEVs (9 to 12 years).

Vehicles.Vehicles_9_to_12_years_BEV(t)	Vehicles_9_to_12_years_BEV(t - dt) + ("Vehicle_Aging_5-8_BEV" - "Vehice_Aging_9-12_BEV" - Vehicles_9_to_12_Retirements_BEV) * dt	INIT Vehicles.Vehicles_9_to_12_years_BEV = 624	vehicles	Used BEVs (9 to 12 years).
Vehicles.Vehicles_9_to_12_years_ICEV(t)	Vehicles_9_to_12_years_ICEV(t - dt) + ("Vehicle_Aging_5-8_ICEV" - "Vehice_Aging_9-12_ICEV" - Vehicles_9_to_12_Retirements_ICEV) * dt	INIT Vehicles.Vehicles_9_to_12_years_ICEV = 55499056	vehicles	Used ICEVs (9 to 12 years). Source: https://www.bts.gov/content/number-us-aircraft-vehicles-vessels-and-other-conveyances
Vehicles.Vehicles_Retirement_Fraction	0,17		dmnl/year	Discard fraction of vehicles 13+ years. Adjusted to stabilize the stocks.
Vehicles.OEM_Learning_Curve_Effects:				
Vehicles."Global_BEV_sales_excl._U.S."	GRAPH(TIME) Points(51): (2000,00, 20), (2001,00, 40), (2002,00, 80), (2003,00, 160), (2004,00, 320), (2005,00, 640), (2006,00, 1280), (2007,00, 2560), (2008,00, 3700), (2009,00, 4200), ...		vehicles/year	Yearly number of BEVs sold globally, excluding the US. Source: https://www.iea.org/articles/global-ev-data-explorer
Vehicles."Global_ICE_sales_excl._U.S."	GRAPH(TIME) Points(51): (2000,00, 33230758,42), (2001,00, 35157717,13), (2002,00, 37084655,85), (2003,00, 39011554,56), (2004,00, 40938373,28), (2005,00, 42865031,99), (2006,00, 45589353,53), (2007,00, 49252713,31), (2008,00, 48907667,25), (2009,00, 49986793,78), ...		vehicles/year	Yearly number of vehicles sold globally, excluding the US. Source: https://www.iea.org/data-and-statistics/charts/global-car-sales-by-key-markets-2005-2020

Vehicles.Average_FE_BEV	SMTH1(Fuel_Efficiency_of_New_BEVs; Delay_time_for_FE_of_new_BEVs_to_impact_average_FE)		miles/GGE	Average fuel efficiency of BEVs.
Vehicles.Average_FE_ICEV	SMTH1(Fuel_Efficiency_of_New_ICEVs; Delay_time_for_FE_of_new_ICEVs_to_impact_average_FE)		miles/GGE	Average fuel efficiency of ICEVs.
Vehicles.Averaging_time_BEV_Predicted_Models	1		year	Averaging time for available BEV models prediction.
Vehicles.Battery_Capacity_GGE	(Initial_Battery_Capacity/Fueling.Native_units_to_GGE_Electricity)+(Initial_Battery_Capacity/Fueling.Native_units_to_GGE_Electricity)*(1-"Effect_of_Experience_on_Unit_Battery_Cost,_Capacity_&_Charging")		GGE/vehicles	Capacity of BEV batteries.
Vehicles.BEV_Luxury_makes	BEV_Projected_Models_Available*BEV_Luxury_makes_share		models	Number of BEV luxury models.
Vehicles.BEV_Luxury_makes_share	0,05		dmnl	Share of BEV models that are luxury makes.
Vehicles.BEV_Projected_Models_Available	MAX(2; (SMTH1 (MIN(((Order_Fulfillment_BEV+"Global_BEV_sales_excl._U.S.")*Ratio_Models_to_Order_Fulfillment); 250); Averaging_time_BEV_Predicted_Models; 2)))		models	Predicted number of BEV models available based on BEV order fulfillment assuming the same ratio of models to order fulfillment as for ICEVs.
Vehicles."Cumulative_Experience_-_Base_Vehicle"(t)	"Cumulative_Experience_-_Base_Vehicle"(t - dt) + ("Experience_Gain_-_Base_Vehicle") * dt	INIT Vehicles."Cumulative_Experience_-_Base_Vehicle" = Initial_Experie	vehicles	Cumulative experience with base vehicle architecture.

		nce_Base_Vehicle		
Vehicles."Cumulative_Experience_-_Battery"(t)	"Cumulative_Experience_-_Battery"(t - dt) + ("Experience_Gain_-_Battery") * dt	INIT Vehicles."Cumulative_Experience_-_Battery" = Initial_Experience_Battery	GGE	Cumulative experience with battery technology.
Vehicles."Cumulative_Experience_-_Electric_Architecture"(t)	"Cumulative_Experience_-_Electric_Architecture"(t - dt) + ("Experience_Gain_-_Electric_Architecture") * dt	INIT Vehicles."Cumulative_Experience_-_Electric_Architecture" = Initial_Experience_Electric_Architecture	vehicles	Cumulative experience with BEV architecture.
Vehicles."Cumulative_Experience_-_IC_Engine"(t)	"Cumulative_Experience_-_IC_Engine"(t - dt) + ("Experience_Gain_-_IC_Engine") * dt	INIT Vehicles."Cumulative_Experience_-_IC_Engine" = Initial_Experience_IC_Engine	vehicles	Cumulative experience with internal combustion engine technology.
Vehicles.Delay_time_for_FE_of_new_BEVs_to_impact_average_FE	8		year	Delay in years for FE of new BEVs to impact average FE.

Vehicles.Delay_time_for_FE_of_new_ICEVs_to_impact_average_FE	8		year	Delay in years for FE of new ICEVs to impact average FE.
Vehicles.Effect_of_Experience_on_Base_Vehicle_Cost	SMTH1((("Cumulative_Experience_-_Base_Vehicle"/Initial_Experience_Base_Vehicle)^-Experience_Beta_ICEV); 2)		dmnl	Effect of experience on base vehicle architecture cost.
Vehicles.Effect_of_Experience_on_Electric_Architecture_Cost	SMTH1((("Cumulative_Experience_-_Electric_Architecture")/(Initial_Experience_Electric_Architecture))^-Experience_Beta_BEV; 2)		dmnl	Effect of experience on BEV architecture cost.
Vehicles.Effect_of_Experience_on_IC_Engine_Cost	SMTH1(("Cumulative_Experience_-_IC_Engine"/Initial_Experience_IC_Engine)^-Experience_Beta_ICEV; 2)		dmnl	Effect of experience on internal combustion engine cost.
Vehicles."Effect_of_Experience_on_Unit_Battery_Cost,_Capacity_&_Charging"	SMTH1((("Cumulative_Experience_-_Battery")/(Initial_Experience_Battery))^-Experience_Beta_BEV; 2)		dmnl	Effect of experience on on unit battery cost, capacity and charging.
Vehicles.Experience_Beta_BEV	-(LN(1-Learning_curve_rate_BEV_Auto_industry) / LN(2))		dmnl	Experience learning curve strength BEVs.
Vehicles.Experience_Beta_ICEV	-(LN(1-Learning_curve_rate_ICEV_Auto_industry) / LN(2))		dmnl	Experience learning curve strength ICEVs.
Vehicles."Experience_Gain_-_Base_Vehicle"	IF Global_influence_Switch = 1 THEN Order_Fulfillment_ICEV+Order_Fulfillment_BEV+"Global_ICE_sales_excl._U.S." + "Global_BEV_sales_excl._U.S." ELSE Order_Fulfillment_ICEV+Order_Fulfillment_BEV		vehicles/year	Change in experience with base vehicle architecture.
Vehicles."Experience_Gain_-_Battery"	IF Global_influence_Switch = 1 THEN Order_Fulfillment_BEV*Battery_Capacity_GGE+"Glob		GGE/year	Change in experience with battery technology.

	al_BEV_sales_excl._U.S."*Battery_Capacity_GGE ELSE Order_Fulfillment_BEV*Battery_Capacity_GGE			
Vehicles."Experience_Gain_-_Electric_Architecture"	IF Global_influence_Switch = 1 THEN Order_Fulfillment_BEV+"Global_BEV_sales_excl._U.S." ELSE Order_Fulfillment_BEV		vehicles/year	Change in experience with BEV architecture.
Vehicles."Experience_Gain_-_IC_Engine"	IF Global_influence_Switch = 1 THEN Order_Fulfillment_ICEV+"Global_ICE_sales_excl._U.S." ELSE Order_Fulfillment_ICEV		vehicles/year	Change in experience with internal combustion engine technology.
Vehicles.Fuel_Efficiency_of_New_BEVs	1/(Reference_Fuel_Efficiency_BEV*"Effect_of_Experience_on_Unit_Battery_Cost,_Capacity_&_Charging")		miles/GGE	Average fuel efficiency of new BEVs.
Vehicles.Fuel_Efficiency_of_New_ICEVs	1/(Reference_Fuel_Efficiency_ICEV*Effect_of_Experience_on_IC_Engine_Cost)		miles/GGE	Average fuel efficiency of new ICEVs.
Vehicles.Global_influence_Switch	1		dmnl	Global influence Switch allows choosing 1 to take in the influence from global development, and choosing 0 to disregard it.
Vehicles.ICEV_Luxury_makes	"ICEV_Models_Available_-_Saturated_level"*ICEV_Luxury_makes_share		models	Number of ICEV luxury models available - assumed to be a share if the overall models available.
Vehicles.ICEV_Luxury_makes_share	0,025		dmnl	Share of ICEV models that are luxury makes.
Vehicles."ICEV_Models_Available_-_Saturated_level"	250		Models	The number of ICEV models available assumed to be sufficient for a full range in choice of model. Source: https://www.statista.com/statistics/2

				00097/number-of-existing-car-models-on-the-us-market-since-1990/
Vehicles.Initial_Battery_Capacity	20		kwh/vehicles	Capacity of a BEV battery at the start of the simulation. Source: https://www.fueleconomy.gov/feg/byclass/midsize_cars2010.shtml
Vehicles.Initial_Electric_Fuel_Efficiency	90		miles/GGE	Initial fuel efficiency of BEVs. Source: https://mpgbuddy.com/cars/nissan/leaf/2011
Vehicles.Initial_Experience_Base_Vehicle	1e+09		vehicles	Initial experience with base vehicle architecture.
Vehicles.Initial_Experience_Battery	1e+06*0,599		GGE	Initial experience with battery technology. Based on Initial Experience Electric Architectureand initial Battery Capacity GGE.
Vehicles.Initial_Experience_Electric_Architecture	1e+06		vehicles	Initial experience with BEV architecture.
Vehicles.Initial_Experience_IC_Engine	1e+09		vehicles	Initial experience with internal combustion engine technology.
Vehicles.Initial_Gas_Fuel_Efficiency	20		miles/GGE	Initial fuel efficiency of a ICEV. Source: https://www.fueleconomy.gov/feg/byclass/midsize_cars2010.shtml

Vehicles.Learning_curve_rate_BEV_Auto_industry	0,15		dmnl	Technology learning curve rate. Indicates fractional increase in principal variable with every doubling of experience - set to 15 % for the auto industry. Source: https://ark-invest.com/articles/analyst-research/wrights-law-predicts-teslas-gross-margin/
Vehicles.Learning_curve_rate_ICEV_Auto_industry	0,15		dmnl	Technology learning curve rate. Indicates fractional increase in principal variable with every doubling of experience - set to 15 % for the auto industry. Source: https://ark-invest.com/articles/analyst-research/wrights-law-predicts-teslas-gross-margin/
Vehicles.Ratio_Models_to_Order_Fulfillment	INIT("ICEV_Models_Available_-_Saturated_level"/(Order_Fulfillment_ICEV))		Models*Years/vehicle	Ratio of ICEV models to order fulfillment.
Vehicles.Reference_Fuel_Efficiency_BEV	1/Initial_Electric_Fuel_Efficiency		GGE/miles	Reference inverted fuel efficiency of BEVs.
Vehicles.Reference_Fuel_Efficiency_ICEV	1/Initial_Gas_Fuel_Efficiency		GGE/miles	Reference inverted fuel efficiency of ICEVs.

Vehicles.Vehicle_Price_and_Revenue:				
Vehicles."2010_BEV_Tax_Credit_Duration"	13		year	Duration of government 2010 Tax Credit incentive for BEVs.
Vehicles."2010_BEV_Tax_Credit_Start"	2010		year	Start of government 2010 Tax Credit incentive for BEVs.
Vehicles."2010_BEV_Tax_Credit_Value"	IF TIME < "2010_BEV_Tax_Credit_Start" THEN 0 ELSE IF TIME > "2010_BEV_Tax_Credit_Start"+"2010_BEV_Tax_Credit_Duration" THEN 0 ELSE IF TIME < "2010_BEV_Tax_Credit_Start"+"2010_BEV_Tax_Credit_Duration"*1/2 THEN 7500 ELSE IF TIME < "2010_BEV_Tax_Credit_Start"+"2010_BEV_Tax_Credit_Duration"*3/4 THEN 7500/2 ELSE 7500/4		$/vehicles	Value of government 2010 Tax Credit incentive for BEVs This variable reduces the effective price customers pay for the vehicle. The tax credit was effective from 2010 and ranges from $2,500 to $7,500 for each vehicle based on battery capacity and vehicle weight. The tax credit is available until a manufacturer sells 200,000 EVs, at which point the credit begins to phase out over time for vehicles sold by that company. The credit halves for the six months following the sale of the 200,000th vehicle, and then halves again for the next six months, and finally disappears entirely. Source: https://www.irs.gov/businesses/irc-30d-new-qualified-plug-in-electric-drive-motor-vehicle-credit
Vehicles."2023_BEV_Tax_Credit_Duration"	30		year	Duration of government 2023 Tax Credit incentive for BEVs.

Vehicles."2023_BEV_Tax_Credit_Start"	2100		year	Start of government 2023 Tax Credit incentive for BEVs.
Vehicles."2023_BEV_Tax_Credit_Value"	7500		$/vehicles	Value of Government 2023 Tax Credit incentive for BEVs This variable reduces the effective price customers pay for the vehicle. The tax credit will be effective from 2023, and remove manufacturer sales caps, expand the scope of eligible vehicles to include both EVs and FCEVs, require a traction battery that has at least seven kilowatt-hours (kWh), and establish criteria for a vehicle to be considered eligible that involve sourcing requirements for critical mineral extraction, processing, and recycling and battery component manufacturing and assembly. Vehicles that meet critical mineral requirements are eligible for $3,750 tax credit, and vehicles that meet battery component requirements are eligible for a $3,750 tax credit. Vehicles meeting both the critical mineral and the battery component requirements are eligible for a total tax credit of up to $7,500. Source: https://afdc.energy.gov/laws/search Search Selection:

				Jurisdiction: Federal Technology/Fuel: EVs Incentive/Regulation: N/A User: Personal Vehicle Owner or Driver Title in Search: Electric Vehicle (EV) and Fuel Cell Electric Vehicle (FCEV) Tax Credit
Vehicles.Base_Vehicle_Cost	Initial_Base_Vehicle_Cost*Effect_of_Experience_on_Base_Vehicle_Cost {Initial_Base_Vehicle_Cost_i*SW_Learning		$/vehicles	Base cost of a vehicle.
Vehicles.Battery_Cost	Battery_Capacity_GGE*Unit_Battery_Cost		$/vehicles	Cost of the battery per vehicle.
Vehicles.Effective_Price_BEV	MAX(Vehicle_Cost_BEV/2; IF TIME < "2010_BEV_Tax_Credit_Start" THEN MSRP_BEV-Government_2023_Tax_Credit-Government_BEV_Subsidy ELSE IF TIME > "2010_BEV_Tax_Credit_Start"+"2010_BEV_Tax_Credit_Duration" THEN MSRP_BEV-Government_2023_Tax_Credit-Government_BEV_Subsidy ELSE MSRP_BEV-"2010_BEV_Tax_Credit_Value"-Government_BEV_Subsidy-Government_2023_Tax_Credit)		$/vehicles	Retail price of BEVs.
Vehicles.Effective_Price_ICEV	MSRP_ICEV		$/vehicles	Retail price of ICEVs.
Vehicles.Electric_Architecture_Cost	Initial_Electric_Architecture_Cost*Effect_of_Experience_on_Electric_Architecture_Cost		$/vehicles	Cost of the electric vehicle architecture.

Vehicles.Government_2023_Tax_Credit	IF TIME < "2023_BEV_Tax_Credit_Start" THEN 0 ELSE IF TIME > "2023_BEV_Tax_Credit_Start"+"2023_BEV_Tax_Credit_Duration" THEN 0 ELSE "2023_BEV_Tax_Credit_Value"		$/vehicles	Government BEV Subsidy
Vehicles.Government_BEV_Purchase_Subsidy_Duration	30		year	Duration of government BEV subsidy provided by government.
Vehicles.Government_BEV_Purchase_Subsidy_Start	2100		year	Start of government BEV subsidy provided by government.
Vehicles.Government_BEV_Purchase_Subsidy_Value	10000		$/vehicles	Value of Government BEV subsidy provided by government. This variable reduces the effective price customers pay for the vehicle.
Vehicles.Government_BEV_Sales_Tax_Cut_Duration	30		year	Duration of Government BEV Sales Tax Cut.
Vehicles.Government_BEV_Sales_Tax_Cut_Start	2100		year	Start of Government BEV Sales Tax Cut.
Vehicles.Government_BEV_Sales_Tax_Cut_Value	0,0575		dmnl	Fraction of Government BEV Sales Tax Cut provided by government. This variable reduces the effective price customers pay for the vehicle. The Average national sales tax on cars is 5,75 %, it is proposed to cut the entire sales tax. Source:

				https://auto.howstuffworks.com/under-the-hood/cost-of-car-ownership/cost-of-taxes-on-your-car1.htm
Vehicles.Government_BEV_Subsidy	(IF TIME < Government_BEV_Sales_Tax_Cut_Start THEN 0 ELSE IF TIME > Government_BEV_Sales_Tax_Cut_Start+Government_BEV_Sales_Tax_Cut_Duration THEN 0 ELSE Government_BEV_Sales_Tax_Cut_Value*MSRP_BEV) + (IF TIME < Government_BEV_Purchase_Subsidy_Start THEN 0 ELSE IF TIME > Government_BEV_Purchase_Subsidy_Start+Government_BEV_Purchase_Subsidy_Duration THEN 0 ELSE Government_BEV_Purchase_Subsidy_Value)		$/vehicles	Government BEV Subsidy
Vehicles.IC_Engine_Cost	Initial_IC_Engine_Cost*Effect_of_Experience_on_IC_Engine_Cost		$/vehicles	Cost of the internal combustion engine in a vehicle.
Vehicles.Initial_Base_Vehicle_Cost	15000		$/vehicles	Initial cost of base vehicle architecture.
Vehicles.Initial_Battery_Cost	10000		$/GGE	Initial cost of battery.
Vehicles.Initial_Electric_Architecture_Cost	3000		$/vehicles	Initial cost of electric vehicle architecture.
Vehicles.Initial_IC_Engine_Cost	3000		$/vehicles	Initial cost of internal combustion engine.
Vehicles.Manufacturer_BEV_Subsidy_Duration	30		year	Duration of BEV subsidy provided by manufacturer.

Vehicles.Manufacturer_BEV_Subsidy_Start	2100		year	Start year of BEV subsidy provided by manufacturer.
Vehicles.Manufacturer_BEV_Subsidy_Value	5000		$/vehicles	BEV subsidy provided by manufacturer. This variable reduces the effective price customers pay for the vehicle.
Vehicles.Markup	0,1		dmnl	OEM manufacturer margin.
Vehicles.MSRP_BEV	IF TIME < Manufacturer_BEV_Subsidy_Start THEN (1+Markup)*Vehicle_Cost_BEV ELSE IF TIME > Manufacturer_BEV_Subsidy_Start+Manufacturer_BEV_Subsidy_Duration THEN (1+Markup)*Vehicle_Cost_BEV ELSE (1+Markup)*(Vehicle_Cost_BEV - Manufacturer_BEV_Subsidy_Value)		$/vehicles	BEV recommended price by manufacturer.
Vehicles.MSRP_ICEV	(1+Markup)*Vehicle_Cost_ICEV		$/vehicles	ICEV recommended price by manufacturer.
Vehicles.OEM_Revenue_BEV	Order_Fulfillment_BEV*MSRP_BEV		$/year	Revenue of BEV OEMs.
Vehicles.OEM_Revenue_ICEV	Order_Fulfillment_ICEV*MSRP_ICEV		$/year	Revenue of ICEV OEMs.
Vehicles.Unit_Battery_Cost	Initial_Battery_Cost*"Effect_of_Experience_on_Unit_Battery_Cost,_Capacity_&_Charging"		$/GGE	Cost of the battery per GGE.
Vehicles.Vehicle_Cost_BEV	Base_Vehicle_Cost+Electric_Architecture_Cost+Battery_Cost		$/vehicles	Total cost of BEVs.
Vehicles.Vehicle_Cost_ICEV	Base_Vehicle_Cost+IC_Engine_Cost		$/vehicles	Total cost of a ICEV.