CHALMERS
UNIVERSITY OF TECHNOLOGY

EV growth in the EU

Probabilistic projections of electric vehicle growth in the EU based on historical data

Degree project report in Complex adaptive systems, MSc

Julia Klaben

Department of Environmental and Energy Sciences

CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2026
www.chalmers.se

Degree project report 2026

EV growth in the EU

Probabilistic projections of electric vehicle growth in the EU based on historical data

Julia Klaben

Department of Environmental and Energy Sciences
Chalmers University of Technology
Gothenburg, Sweden 2026

EV growth in the EU
Probabilistic projections of electric vehicle growth in the EU based on historical data
JULIA KLABEN

Supervisor: Vadim Vinichenko, Department of Environmental and Energy Sciences
Examiner: Jessica Jewell, Department of Environmental and Energy Sciences

Degree project report 2026
Department of Environmental and Energy Sciences
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone +46 31 772 1000

Typeset in LaTeX
Gothenburg, Sweden 2026

EV growth in the EU
Probabilistic projections of electric vehicle growth in the EU based on historical data

JULIA KLABEN
Department of Environmental and Energy Sciences
Chalmers University of Technology

Abstract

While electric vehicles (EVs) are often considered a crucial technology for reducing greenhouse gas emissions emissions in the transport sector, current passenger vehicle sales and stock in the EU are still dominated by emission-producing vehicles. There is a need to understand the feasibility of transitioning from the current status to net-zero transport emissions, and for that reason probabilistic projections are made for electric vehicle growth in the European Union over the next thirty years. This is done using a version of PROLONG [1] that is modified to perform better for the unique case of EVs, a policy driven technology at an early growth stage. The new projection method, Prolong-EV, uses Monte Carlo simulation to create many virtual future worlds in which technology grows according to metrics based on empirically observed growth, following pulsing logistic trajectories. A quantile random forest is trained on the simulation data and is then used to project future EV stock share based on historical country-level EV deployment. Analysis of Prolong-EV using both simulation and empirical data indicates that it performs well with technologies at an early growth stage, but does face some limitations in its projection ability. These limitations, along with the meaning of the probabilistic intervals produced by the projection, are discussed. The resulting projections of EV stock share are consistent with outside projections [2, 3, 4], showing that while EV stock share will grow quickly over the coming decades, it is unlikely that the EU target of net-zero emission transport by 2050 [5] will be achieved through EVs alone.

Acknowledgements

I would like to thank Vadim Vinichenko and Jessica Jewell for their supervisory assistance throughout this project. I would also like to thank Avi Jakhmola for his contributions to this project through the development of PROLONG and guidance he provided in adapting and using the model. I am grateful for my fellow masters students who provided support through the many hours we spent in the office together and for the people at the division of Physical Resource Theory who have shared their ideas and perspectives over lunch and coffee breaks.

Julia Klaben, Gothenburg, June 2026

Contents

List of Figures

List of Tables

1
Introduction

To address the challenge of climate change it is crucial to continue to reduce greenhouse gas emissions [6], which is particularly difficult in the transportation sector due to the reliance on fossil fuel based vehicles [7]. Electric vehicles (EVs) have already begun to play an important role in abating transportation sector emissions, and are expected to continue to do so in the future [2]. There are several types of electric vehicles currently available for sale as passenger vehicles, with the dominant technology being battery electric vehicles (BEVs). Plug-in hybrid electric vehicles (PHEVs) are also available, with stock levels that are comparable to battery electric vehicles [2]. However, plug-in hybrid electric vehicles continue to produce greenhouse gas emissions, with the level highly dependent on driving and charging behavior [8]. Fuel cell electric vehicles are also commercially available, but at much smaller volumes than BEVs and PHEVs. This is in part due to their earlier stage of technological development and the requirement for hydrogen fueling infrastructure [7].

The stock of EVs in the EU has grown significantly over the past five years, in line with EU policies to dramatically reduce vehicle emissions. Nonetheless, EVs are currently at an early growth stage in the EU with a total EV stock share of less than 4% in 2024 [9]. A number of policy measures have been implemented at the national and EU level to reduce vehicle emissions, but in recent years there have been signs of reduced policy ambition [2]. In 2022 the EU enacted legislation to reduce emissions in newly sold passenger vehicles by 100% by 2035 [5], but in 2025 a proposal to decrease the ambition to a 90% reduction was made [10]. Furthermore, the 2025 targets for emission reductions in newly sold passenger vehicles were relaxed so that automotive manufacturers only have to meet the targets on average over the years of 2025 to 2027 [11]. The purchasing cost of EVs in the EU has remained significantly higher than the cost of internal combustion engine vehicles (ICEVs), with subsidies that helped offset this cost differential having been rolled back in several EU countries in 2024 and 2025 [2]. Despite these reductions in policy support, other EU policies to bolster the growth of EVs, such as infrastructure support and consumer-facing labeling systems, remain in place [2].

The dynamic nature of EV policy in the EU highlights some of the difficulties in predicting the rate of EV adoption. There is a wide body of research that has attempted to model mechanisms that affect EV adoption [12, 13, 14, 15, 16, 17] and make projections of future EV growth based on understood mechanisms [18, 19, 4, 20]. However, the complex mechanisms and their interactions within the EU that have led to the creation of ambitious policy followed by proposed reductions demonstrate the shortcomings in attempting to explicitly model observed mechanisms. For example, the changes to EU 2025 emission targets were motivated by reduced European automotive competitiveness [11], which itself is highly unpredictable because of international trade relationships [21]. Public sentiment towards EVs has also proven to follow unexpected patterns [22], demonstrating another example of social, political, and technological mechanisms interacting in a way that can prove too complex to model explicitly. This motivates the need for research that does not attempt to identify or model specific causal relationships, but rather uses data-driven methods to implicitly capture the large range of mechanisms that affect EV growth. In this work, historical time series are used to create projections of future EV deployment. Other research has utilized this data-driven approach due to the advantage of implicitly capturing the complex interaction of technical, political, and economic drivers of technology adoption while avoiding the limitations that arise due to an incomplete understanding of how these mechanisms act and interact explicitly [1]. However, being based on past data, data-driven methods are not able to capture novel mechanisms that emerge in the future and rely on the assumption that the future will be defined by the same forces as the past.

While data-driven methods are advantageous for making projections of future technology growth, creating probabilistic projections as opposed to deterministic provides a number of additional advantages. Probabilistic projections capture the level of uncertainty present in predictions of future trends. This means that if the system encompasses factors that are inherently unpredictable, as in the case of European automotive competitiveness [21], the projection has the capacity to communicate that uncertainty. In addition, the quantity and quality of data available for making projections will impact the results of probabilistic projections, but will not result in transparently higher levels of uncertainty for deterministic projections. This makes probabilistic projections, if produced with skill, a more transparent method for communicating limitations in data. Furthermore, a projection is most useful to its audience if it considers the agency of the audience without "over-constraining their freedom of choice or unrealistically over-extending their agency to factors that are in reality outside of their control" [23]. Presenting future possibilities probabilistically accomplishes this by informing the audience of the level of challenge associated with specific outcomes without explicitly ruling out options.

While a number of probabilistic data-driven methods for projecting green technology growth have been developed [24, 25, 26, 27], this work expands upon the existing body of research by exploring challenges specific to making projections of a technology in an early growth phase. There are clear methodological hurdles in making projections based on historical time series when the time series available are less than a decade long, motivating a detailed analysis of projection performance in the case of limited data. This differs from making projections of more mature technologies, like what was done with PROLONG [1], as there is much less historical deployment data available for making reliable estimates of past growth patterns, and the existing data is harder to interpret as a consequence of technology growth often being more sporadic at an early growth stage. In addition to addressing the challenges associated with making projections of immature technologies, this work begins to answer questions about the meaning of probabilistic intervals produced by probabilistic projections and the relationship between those intervals and uncertainty. Previous probabilistic projections have used a wide range of statistical methods for generating probabilistic intervals, each with a different underlying mathematical interpretation. It is important to consider how the projected intervals relate to the likelihood of future outcomes, how uncertainty of the future is translated to projected probabilistic intervals, and uncertainties that are not captured by the projections.

Projections are made using Prolong-EV, a model based on PROLONG [1] with some modifications made to improve performance for technologies in an early growth stage, as in the case of EVs. PROLONG provides a unique framework for modeling technology growth using logistic curves that exhibit growth pulses, a behavior that is empirically observed in policy-driven technologies [28]. It also employs a quantile random forest [29] to make probabilistic projections.

Three research questions are formulated to reflect on substantive projections for future EV growth in the EU, methodological choices when making projections of technology growth, and the interpretation of projection uncertainty:

1. Will EU EV stock share grow fast enough over the next thirty years to meet targets?
2. How can high quality projections be made for future deployment of a policy-driven technology in an early growth phase?
3. What is the meaning of the probabilities produced by this projection, and how can uncertainty be communicated through a probabilistic projection?

Projections anticipate that EV stock share in the EU will grow rapidly over the coming decades, but not quickly enough to meet the 2050 target for net-zero emissions through EVs alone. The PROLONG-based framework proves valuable in providing a balance of empirically-backed modeling assumptions and flexibility to capture uncertainties in the projection and exhibits a number of advantages compared to other methodologies for making EV projections and forecasts. One specific advantage is the ability to communicate uncertainty through probabilistic intervals, although the projected intervals are not capable of capturing all uncertainty that surrounds technology growth.

2
Literature Review

Modeling a variety of dimensions of EV adoption has long been of interest to researchers, as has previously been established through literature reviews focused on EV forecasting and adoption [30, 31]. This literature review will begin by providing a broad overview of mathematical modeling of electric vehicle growth in section 2.1, with some discussion on scenarios and pathways, electrical infrastructure planning, and understanding mechanisms of EV growth. While this information is useful for understanding EV growth holistically, the literature reviewed in this section does not attempt to project long-term future trends of EV stock or sales. Explicit projections are made in section 2.2, in which a variety of methods for projecting future EV trends will be discussed. This includes one example of a probabilistic projection made of EV growth. Section 2.3 will discuss probabilistic projection methods used for other technologies. While the work discussed in this section does not consider EVs, it provides important theoretical contributions for making probabilistic projections of technology growth.

2.1 Mathematical modeling of EV growth trends

Maybury et al. [30] conducted a systematic literature review to answer research questions about how mathematical modeling has been applied to topics relating to EV adoption. Their results show that there exists a wide breadth of purposes and techniques for EV adoption modeling. Of fifty-three articles considered, they find that twenty-two "investigate factors influencing EV adoption", eleven "predict EV adoption/demand", five "investigate EV business models", four "investigate consumer attitudes", and the remaining eleven articles have a variety of less common purposes. Fifteen unique modeling techniques are identified, with discrete-choice and agent-based modeling the most common. Both of these techniques are often used to understand how individual choice affects outcomes. While Maybury et al. identified a large proportion of EV modeling literature that places choice at the forefront, Domarchi and Cherchi [31] performed a literature review with the specific focus of identifying techniques that have been used to model choice in EV adoption. This choice-based research plays an important role in understanding factors that can impact EV adoption, but diverges from the methodology used in this report which intends to project EU-level trends rather than understand the underlying individual behaviors involved in EV growth. There are a number of other research areas that are well studied and important for understanding EV growth holistically, but are not critical for making EV growth projections. These will be discussed next.

Scenario and pathway modeling aims to present possible trajectories of EV growth. Some research begins by defining potential future EV use and adoption scenarios, and then uses these to model the resulting changes in emissions [32]. Other research models scenarios to fit proposed emission targets, representing pathways to meeting the target. Speizer et al. [33] employ this method through the use of integrated assessment models. Plötz et al. [34] design scenarios based on calculated emission budgets for meeting temperature increase targets, and compare these scenarios to existing policy to demonstrate the global temperature increase implications of policies. These works show that scenario and pathway research can be impactful in its ability to demonstrate the consequences of specific growth trajectories. However, it does not have the ability to make assessments of the feasibility or likelihood of EV growth actually following these trajectories.

There is a rich body of research investigating how to most efficiently plan electrical infrastructure to meet future charging needs of EVs. This research frequently makes projections for future EV use, but on entirely different geographical and temporal scales than done in this report. Projections for EV charging use have repeatedly been made for geographical areas the size of individual cities with temporal resolutions of minutes to hours to provide information critical for charging infrastructure planning in the near future [35, 36, 37]. Other research has made estimates for charging needs in 2050, but also on geographical scales that approximate cities [38, 39]. While there is a clear need for this area of research, it is not intended to project broader trends in EV adoption and necessarily requires many assumptions to be made about long-term, supernational EV growth trends.

Another body of literature studies mechanisms that affect EV growth, for example, location, demographics, and economic factors. One frequently considered mechanism is policy. Axsen and Wolinetz [12] quantify the effect of policies on Canadian EV sales using a discrete choice model and survey data. Brozynski and Leibowicz [13] focus on the way uncertainty affects policy decisions regarding EVs using Markov models. Demographic and economic factors have also been considered. Javid and Nejat [14] use multivariate logistic regression and survey data to understand how a variety of factors can impact the choice to purchase an EV in California. Nazari et al. [15] use a nested logit model to understand factors that can affect EV growth. Besides logit and discrete choice models, another common way to try to understand mechanisms that affect EV growth is through agent-based models. Silvia and Krause [16] employ an agent-based model to determine the impact of policy, while Zhuge et al. [17] use their agent-based model to assess the effect of costs. Although none of this research directly projects vehicle trends, the conclusions can be used to make inferences about general EV growth trends. The next section will discuss research that makes explicit projections of future EV growth.

2.2 Projecting future EV growth

Growth projections have been made both under restrictive assumptions that define a specific scenario for growth and with fewer assumptions so as to provide a more general projection for the type of growth that is expected under current conditions. Projections made under restrictive assumptions will be discussed first. This research has focused on combining an understanding of specific mechanisms, like discussed earlier [12, 13, 14, 15, 16, 17], with numerical projections for future vehicle growth. For example, this has been done by defining specific cost and economic scenarios within which projections can be made. Danielis et al. [18] project EV growth in Italy under a range of subsidy assumptions to quantify both expected EV growth and how subsidies can affect growth. They do this by modeling the total cost of ownership of different types of vehicles using both stochastic and non-stochastic variables. Gnann et al. [19] project EV growth in Germany based on estimations of costs incurred for different types of vehicles and for different driving patterns. Some research expands beyond economic and cost factors. Möring-Martínez et al. [4] consider potential changes in the average age of vehicles in the EU and project expected EV stock in the EU based on different scenarios within their fleet turnover model. Eggers and Eggers [20] use a choice-based model to make projections that are based on consumer preference scenarios. Consumer choice is also strongly incorporated into projections that utilize the Bass diffusion model [40]. Although the Bass model can be fitted on historical data alone, it has also been used to show how projections of EV growth vary with consumer behavior [41, 42].

Models like these that make a number of projections that vary based on scenarios of interest can help shape an understanding of different potential future outcomes and how the chosen variables can influence those outcomes. However, they have limitations when it comes to making probabilistic projections which are intended to inform about likely future EV growth rather than answer questions about how EV growth would develop under specific assumptions. The remainder of this section will be devoted to EV projections that avoid making restrictive assumptions and attempt to project the most likely future trends.

Some of these projections are made using a large quantity of data and attempt to capture all relevant mechanisms explicitly. This can often lead to challenges in being able to collect enough data to forecast over long time periods or large geographical areas. Möring-Martínez et al. [43] encounter this difficulty in their attempt to project EV sales in the EU until 2035, but overcome it by using a statistical clustering algorithm to group all EU countries into seven clusters. They then only explicitly model EV growth in eight total countries and assume that sales patterns are uniform within clusters. Their model is based on utility maximization and uses a variety of economic and policy information as inputs. It assumes that the 2035 EU vehicle emission reduction remains at 100%, as this was the policy at the time of publishing, and finds that the EU as a whole will likely meet the emission reduction target, while some individual countries may struggle to meet the target. Veysi et al. [44] also use a model that requires large quantities of data representing a variety of economic, infrastructure, and policy information, but draw conclusions using three different statistical methods rather than attempting to explicitly model observed mechanisms. Their geographical scope for projections is smaller, covering only the UK, and they also make projections to 2035. Zhang et al. [45] project EV growth in China at a monthly level for one year into the future. They use two methods: one that, similarly to Veysi et al.'s method, employs multiple types of data and statistical analysis to make projections; and a second method that uses only time series data. Their conclusion is that methods requiring large quantities of data

can be more challenging to execute because of the data requirements, but in their case, the more data-heavy method results in more accurate predictions.
Several other research works have made projections of EV growth using only historical time series of deployment, as is done in this article. Wu and Chen [46] make projections for EV growth in China and at a world level up to eight years into the future using time series analysis. Many projections have been made based on the assumption that EV growth will follow an S-curve shaped trajectory. Rietmann et al. [47] fit logistic curves to historical EV growth trends to project EV growth in 26 countries around the world. They assume that the ceiling of the logistic curve will be the current total vehicle market in each country and make projections for the 2035 level of EV deployment. They expect that EV growth within the EU will vary, with some countries growing to very high levels by 2035 and others remaining at lower levels of adoption. Chandra et al. [48] also project EV growth using S-curves, but directly model total vehicle quantities, rather than just EVs, using Gompertz curves, and assume that EV shares will correspond to target shares. Link et al. [49] make probabilistic projections of EV growth in the EU, which contrasts with the deterministic projections made in the majority of cases. They do this by assuming logistic growth, then fitting curves with both historical data and probabilistically defined expected future values. A Monte Carlo simulation is used to create probabilistic projections based on the probabilistic input parameters. In the next section more probabilistic projections will be discussed, with Monte Carlo simulations reappearing as a common tool for incorporating probability into projections.

2.3 Probabilistic projections of technology growth

Although there are few examples of probabilistic projections of EV growth, a number of researchers have made probabilistic projections of technology growth, providing useful guidance for EV projections. These projections employ a wide variety of probabilistic methods and often use S-curve based growth models. Odenweller et al.[50] make probabilistic projections for green hydrogen growth in Europe using a variation on a logistic curve as the growth model and generating probabilistic results using a Monte Carlo simulation. Their logistic curve incorporates a ceiling that increases with time, representing demand pull. The other parameters used to define the curve are initial green hydrogen capacity and growth rate. These two parameters are represented by probability distributions, with the distributions themselves carefully designed based on information about industry plans and historical growth rates of other technologies. A Monte Carlo simulation is used to produce probabilistic green hydrogen growth based on these input parameters.
This method is designed for a technology that is in the formative phase, characterized by unpredictability and a lack of historical data, and for that reason much focus is placed on the level of uncertainty in projections. This ability to not only make a prediction for future technology levels, but to also quantify the level of confidence in the prediction highlights one of the strengths of probabilistic projections. Another strength of Odenweller et al.'s method is that the level of uncertainty in the projections is directly related to the level of uncertainty defined in the input parameters. Since Odenweller et al. clearly describe how they design their parame-

ter distributions, the interpretation of their estimates of uncertainty are transparent and understandable. However, the projection outcomes are highly dependent on the estimation of parameter distributions and demand pull, making it necessary to choose the parameters with skill when utilizing this type of method.

Zielonka and Trutnevyte [24] use a different probabilistic method to forecast a variety of granular green technologies, but also assume technology growth to follow an S-curve based trajectory. They incorporate probability into their projections by running a stochastic curve fitting algorithm 450 different times and use the combination of those 450 projections to represent probability. They perform this procedure on 72 different variants of data length, type of S-curve, and fitting function, then use hindcasting to weight the performance of each variant. The final probabilistic projection is a weighted combination of individual probabilistic projections. Compared to Odenweller et al.'s method, this method requires more historical data for the technology being assessed since it requires hindcasting. It also offers less transparency in the meaning of its probability and uncertainty assessments.

Way et al. [25] project the cost of a variety of green technologies, but use a closed form statistical equation along with historical growth data to assign probabilities to the projections. They model falling technology costs to predict technology growth, with the underlying assumption that technology costs initially decline exponentially before eventually reaching an asymptote. The probabilistic nature is incorporated by assuming that technologies follow this cost trajectory as part of a random walk, and that the uncertainty therefore increases with time according to a statistical equation defining the random walk. Farmer and Lafond [51] established this method in an earlier article using a slightly simplified model for decreasing costs.

Due to the mathematically derived nature of this method, its projections and quantifications of uncertainty are shown to be accurate as long as the underlying modeling assumptions hold. This has the strength of providing real meaning to the uncertainty estimates. However, the assumptions made are relatively rigid and require that technology prices do in fact follow a random walk and that the overall trend follows the defined exponentially decreasing behavior.

Bayesian inference has also been used to make probabilistic projections of technology growth. Hoffreumon and Labhard [26] use a hierarchical Bayesian approach to make probabilistic projections of digital technology. The benefit of the hierarchical approach is that it allows for information to be learned about a class of objects, so that when a new object belonging to the class appears it is easier to estimate its properties with limited data. In practice this means that Hoffreumon and Labhard are able to learn about characteristics of technology diffusion from technologies that have a long history and apply those learnings to make projections for technologies for which there is less empirical data available.

The growth model used by Hoffreumon and Labhard is a modified Bass diffusion model. Ramírez-Hassan and Montoya-Blandón [27] also use a Bass diffusion model with a Bayesian approach. They employ a different approach to make projections for technologies with limited empirical data by using reference technologies to define priors for newer technologies.

Jakhmola et al. designed PROLONG [1], a method that makes probabilistic projections of solar PV and wind power growth at a world level using historical country level growth data. It first uses a Monte Carlo simulation to generate virtual worlds representing possible trajectories of technology growth. The trajectories generated in the virtual worlds use parameters derived from empirical data and can follow logistic curves or bi-logistic curves. The characteristics of country level growth in these worlds are extracted and used to train quantile random forests to predict future growth at a world level. The trained quantile random forests can then use historical growth data to predict future growth.

One advantage of this method is that it incorporates a more flexible growth model than some other methods which use simple S-curve growth models. This choice is empirically backed by observations of green technologies encountering multiple pulses of growth [28], which can be approximated by bi-logistic growth models. Using quantile random forests to produce probabilistic projections is a reasonable method, as they have been shown to be statistically consistent under reasonable assumptions [29]. Furthermore, the quantile random forests are able to extract information available in country-level trajectories to predict future growth, which could prove useful if some countries are growing faster than others and provide a glimpse into future behavior at a global or regional level. However, sufficient simulated data is needed to train the quantile random forest, with accuracy theoretically increasing with the amount of training data. There are practical limits to how much data can be generated and used for training due to computational requirements.

Of the probabilistic projection methods reviewed, each one uses some form of an S-curve to model technology growth. PROLONG takes a less restrictive approach, allowing curves to take on logistic or bi-logistic forms [1], while Zielonka and Trutnevyte show in their approach that a combination of different types of S-curves performs better than any individual growth model [24]. There is much more variety in the types of methods used to assign probabilities to projections. Most can be clearly understood through statistical theory, providing an important dimension to the projections. The ability to quantify uncertainty is valuable when it comes to interpreting the projection results and can have important policy implications [50].

3 Methodology

The EV growth projections produced are primarily based on PROLONG, with some modifications made to enable the model to function well with EV data. To create these projections, data is obtained and analyzed to calculate early growth metrics that are observed. Next, a naive projection is produced based on these growth metrics and a logistic-curve based growth model to provide a baseline projection that can act as a simple comparison with the main projection. Then, Prolong-EV is implemented. Due to the large number of configurable parameters of Prolong-EV, much time is spent carefully considering how to configure the model to produce the best possible projections. The validity of the projections is evaluated through hindcasting and testing to evaluate how projection performance changes as more historical growth data becomes available. Then the final Prolong-EV projections are compared to EV forecasts and targets. All computational analysis, including the code used to produce projections, is done with R [52].

A critical assumption made throughout this work is that the EV stock share in the EU will at some point reach approximately 100%. Current EU legislation aims to convert the entire stock of passenger vehicles to net-zero emission vehicles by 2050 [5]. While this target could be supported through the use of net-zero fuels with ICEVs or delayed, it is assumed that there is an intention to eventually reach 100% zero-emission vehicles. These vehicles could possibly use a variety of propulsion technologies, but the existing technologies in use today consist of only BEVs and hydrogen-powered vehicles. In the past five years, the sales share of hydrogen-powered passenger vehicles in the EU has never exceeded 0.1% of all zero-emission vehicles, and projections for 2030 continue to be below 0.1% [2]. It is therefore assumed that roughly 100% of all zero-emission passenger vehicles in the EU will continue to be EVs.

Throughout the analysis, EV stock share is considered to have moved from the formative growth phase to accelerating growth when the stock share exceeds 1%. This is an important assumption, since the historical growth trajectories of countries that have not moved beyond the formative phase are not considered in the analysis. While it can be hard to determine the precise end date of the formative phase, choosing a specific stock share as a threshold is an accepted practice [53], and in this case 1% appears to consistently mark a point at which the stock share begins to accelerate and experience less sporadic growth.

3.1 Data used for projections

The scope of data used in this project is limited in several ways to allow for meaningful analysis. Rather than considering PHEV and BEV growth independently, the sum of both of them is considered as total EV growth. While there are several ways to measure EV growth, including number of new registrations, share of new registrations, and total EV stock, the metric that is chosen for this project is stock share. This is because stock share has the helpful properties of almost always increasing monotonically and having a ceiling near 100%. All EU member states are included in the data set, in addition to Norway, Switzerland, and the United Kingdom. The additional three countries are included because they have somewhat advanced EV stock shares which can provide more information about historical EV growth trends while still having characteristics that are similar to EU countries. This makes them good reference cases for informing future EU EV growth trends, but no projections are made for the future EV trends in these countries.

The data is derived from two sources, IEA [2] and Eurostat [9], which provide overlapping and generally consistent data regarding EV stock and sales in Europe. The two data sources are synthesized into one data set that is more complete than either source individually and used for all further analysis. IEA data generally provides a longer history, so in some cases in which IEA and Eurostat data are consistent with each other the IEA data is used for EV stock values. However, only Eurostat data includes values for total vehicle stock, and this information is therefore combined with IEA EV stock values to allow for calculations of EV stock share. In some cases there are significant discrepancies between the two data sources, or reported values that appear to be incorrect. In these cases the data is manually adjusted to reasonable values with the intention of minimizing the impact of data inaccuracies on final results. Table A.1 summarizes which data is used and how it is modified for each country in the data set.

To evaluate the performance of Prolong-EV using hindcasting on empirical data, mobile phone data is used. This data is from World Bank [54] and provides the number of mobile phone subscriptions in many countries from 1970 to 2021. The data is filtered to only EU countries for analysis.

3.2 Empirical growth metrics

In order to make projections of future EV growth, historical growth trends must first be quantified. One way this is done is under the assumption that EV stock share, measured in percent terms, will follow a logistic curve with a ceiling of 100% stock share. Two metrics, growth rate and takeoff timing, are calculated by fitting historical EV stock share data to this logistic curve with a defined ceiling. The growth rate can be interpreted in three different ways which are related to each other through deterministic mathematical relationships: K, a parameter representing the quasi-exponential growth rate of the logistic curve; G, the maximum growth rate at the midpoint of the logistic curve; and ΔT, the time from 10% to 90% of the logistic curve. The takeoff timing and growth rate are calculated for countries in the data set that have passed takeoff, with the takeoff threshold defined as 1% stock share. This results in a total of 22 out of 30 countries in the data set for which metrics are calculated. An additional metric that does not rely on any modeling assumptions for growth is the most recent three year average growth rate, called *R3*. This metric is calculated by assessing the average rate of stock share growth over the past three years for all countries past takeoff. These metrics are included in Table 3.1 and plotted against 2024 EV stock share in Figure A.1. The same metrics are also calculated using data only available in 2020 in order to perform hindcasting, and are included in Table A.2 and Figure A.2.

Country	2024 Stock Share	Takeoff Year	K	G	R3	ΔT
Austria	0.053	2020	0.365	0.091	0.011	12.1
Belgium	0.110	2019	0.472	0.118	0.027	9.3
Denmark	0.165	2020	0.482	0.121	0.038	9.1
Estonia	0.016	2024	0.426	0.106	0.004	10.3
Finland	0.078	2020	0.408	0.102	0.017	10.8
France	0.046	2020	0.360	0.090	0.009	12.2
Germany	0.053	2020	0.357	0.089	0.010	12.3
Hungary	0.017	2023	0.375	0.094	0.004	11.7
Ireland	0.056	2021	0.461	0.115	0.014	9.5
Italy	0.015	2023	0.388	0.097	0.003	11.3
Latvia	0.015	2023	0.505	0.126	0.004	8.7
Lithuania	0.016	2023	0.520	0.130	0.004	8.4
Luxembourg	0.109	2019	0.411	0.103	0.023	10.7
Malta	0.036	2021	0.419	0.105	0.008	10.5
Netherlands	0.106	2015	0.305	0.076	0.021	14.4
Norway	0.332	2014	0.292	0.073	0.041	15.0
Portugal	0.049	2020	0.405	0.101	0.011	10.8
Slovenia	0.016	2023	0.407	0.102	0.004	10.8
Spain	0.017	2023	0.426	0.106	0.004	10.3
Sweden	0.135	2018	0.360	0.090	0.025	12.2
Switzerland	0.069	2019	0.349	0.087	0.013	12.6
United Kingdom	0.066	2020	0.409	0.102	0.015	10.8

Table 3.1: Growth metrics calculated for each country past takeoff in 2024.

Metric	Mean	Standard Deviation
K	0.404	0.059
G	0.101	0.014
ΔT	11.09	1.66

Table 3.2: Summary statistics of calculated growth metrics of 22 countries past takeoff.

The calculated growth metrics of individual countries are analyzed together to determine statistical characteristics that can be used for informing projections. First, the

mean and variance of the growth metrics are calculated. These values are included in Table 3.2. Next, statistical distributions that represent the range of observed values are estimated using the fitdistrplus package in R [55]. Several different types of distributions are considered and compared to each other before the best fit is selected. The selected and empirical distributions are shown in Figure A.3, and the characteristics of the fitted distributions are summarized in Table 3.3.
When considering takeoff timing and K values, a function for fitting distributions with missing values is used. This is because some countries have not yet reached takeoff, leading to uncertainty in their timing, and a K distribution that accounts for the uncertainty in growth metrics due to countries with a low EV stock share is needed for the naive projection. To fit a distribution to takeoff values the function is provided with takeoff years for the 22 countries past takeoff and a lower bound of 2025 for the takeoff years of the remaining eight countries. To fit a distribution to K values it is assumed that in countries with a stock share past 10% the observed value is accurate, while in other countries the observed value provides an upper bound on the range of true values.

Metric	Distribution	First Parameter	Second Parameter
K	Weibull	shape = 7.556	scale = 0.42981
G	Weibull	shape = 7.556	scale = 0.10745
ΔT	Lognormal	meanlog = 2.3956	sdlog = 0.14428
Takeoff year	Normal	mean = 2022.2	sd = 3.8
K with uncertainty	Weibull	shape = 6.335	scale = 0.3806

Table 3.3: Characteristics of distributions fitted to best represent empirical distributions of growth metrics using the fitdistrplus package in R [55]. The first three entries are calculated using fitdist(), while the last two rows are calculated using fitdistcens() which accepts possible ranges of empirical values and accounts for censored data.

3.3 Naive projection

A naive projection for EV growth in the EU, serving as a minimal probabilistic model, is created as a baseline to use in comparison with the Prolong-EV projection created later. It is made using a logistic curve-based growth model and a Monte Carlo simulation to incorporate probabilistic effects, with the process summarized in Figure 3.1. A logistic growth model is chosen due to its simplicity and frequent use in literature modeling green technology growth [47, 49, 50]. The model assumes that country-level EV stock share follows a logistic growth curve and that the total EU EV stock share is the weighted average of individual country stock shares, with the relative total passenger vehicle markets in each country staying constant at 2024 levels. Each country's EV stock share is modeled to grow along a logistic curve that has a ceiling of 100%, consistent with the assumption that nearly all vehicles in the EU will be EVs at some point in the future. The logistic curve also uses a 2024 stock share equal to the empirical value and growth parameter K chosen from an

empirically based distribution. For countries that have not yet reached takeoff in 2024, defined as a stock share of less than 1%, a time delay representing takeoff timing is selected from an empirically based distribution. This delay is applied such that the country's EV stock share remains at the 2024 level for the duration of the takeoff delay before beginning logistic growth.
The Monte Carlo simulation is run 10,000 times, which is sufficient to produce consistent results. The distributions for the growth parameter K and takeoff timing are created based on the fitted probability distributions described earlier and summarized in Table 3.3. K values are chosen from the distribution that incorporates uncertainty, a Weibull distribution with a shape of 6.335 and scale of 0.3806, since it is important that the distributions used for this Monte Carlo simulation represent the empirically expected distributions. It is unlikely that the K values derived from fitting logistic curves to empirical EV growth data represent the true K values that will emerge as growth continues, justifying the use of a K distribution that incorporates this uncertainty. Takeoff timing is chosen from a normal distribution with mean 2022.2 and standard deviation 3.8 which is truncated so that countries that are not past takeoff will be assigned a takeoff year later than 2024.

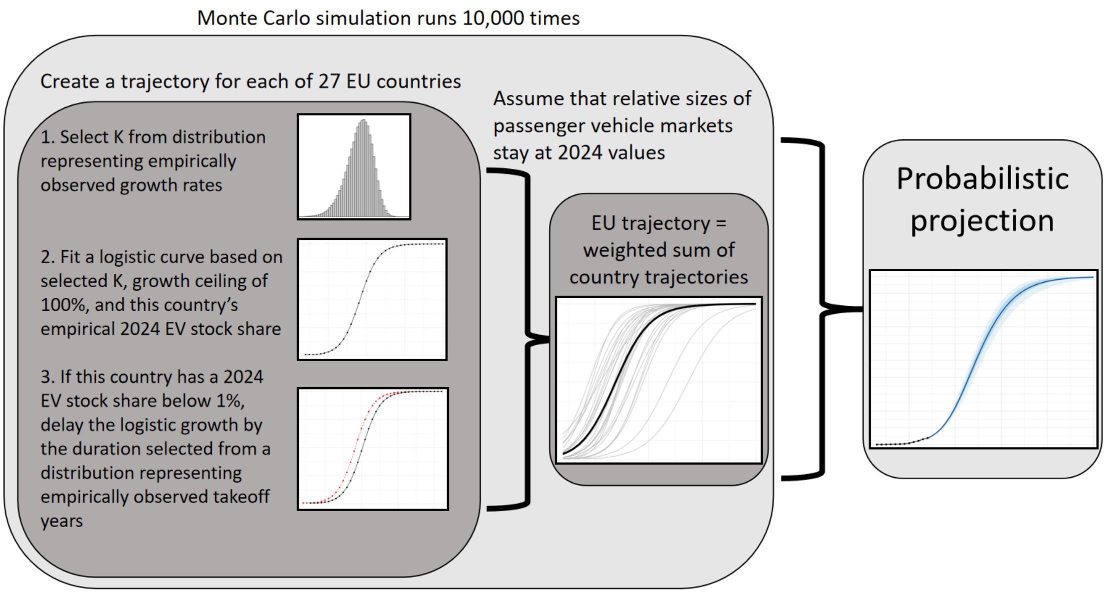


Figure 3.1: Overview of the naive projection method.

3.4 Prolong-EV

This projection method is based on PROLONG [1], with some modifications made to improve the performance when applied to EV growth. The method uses a Monte Carlo simulation to produce a large number of virtual worlds comprised of countries in which technology growth follows a variety of types of trajectories. The data from these virtual worlds is then processed to extract specific features that can be used to predict future EV stock share at an EU level. The extracted features are used train a quantile random forest [29], which, once trained, can be provided with information about early-stage EV growth from an empirical trajectory to project future technology growth. The process is illustrated in Figure 3.2

3.4.1 Simulation of trajectories

The Monte Carlo simulation produces trajectories that are designed to represent possible future trajectories for EV growth. The intention is to produce a wide range of trajectories that can be used to train a machine learning model to identify future EV deployment based on early trends. The trajectories are therefore calibrated to mimic technology growth behaviors observed in empirical cases, but with a wide enough range of growth rates and shapes to capture many possible future trends.

Like in the original version of PROLONG, individual trajectories are produced for each country in the virtual world, with these trajectories following noisy logistic growth with pulses. The technology growth trajectory for the entire virtual world is the combination of these individual country trajectories. In Prolong-EV, the virtual world is made up of the 27 countries in the European Union, as opposed to the original PROLONG which includes many more countries to represent the entire globe. Another difference in Prolong-EV is that trajectories can be configured to have arbitrarily many growth pulses, unlike the original PROLONG which allows for a maximum of one growth pulse.

The country-level trajectories produced by the Monte Carlo simulation include a randomly selected number of pulses, with the distribution for number of pulses being defined during model configuration. The trajectories begin logistic growth at a specified takeoff value and takeoff timing, then continue according to a growth rate, G, and ceiling, L. G and L are chosen from specified distributions, and for growth with no pulses they simply define the logistic curve that growth will follow. For growth with pulses, each pulse is randomly assigned a percentage of the total ceiling that will be reached by the pulse, such that the pulses combined will reach the total L value, and a multiplier of the growth rate G, such that the pulses will have different growth rates which average to the chosen G value. Noise is applied to the final growth curves.

There are a large number of parameters that define the range of trajectories produced by the Monte Carlo simulation. These are carefully selected based on a combination of analysis of historical EV growth trends in Europe and behaviors that have been empirically observed in other policy-driven technologies. Section A.1.3 explains the parameterization process in detail. The parameters used in the final configuration of Prolong-EV are summarized in Table 3.4.

3.4.2 Feature extraction and training

After generating simulated trajectories, these trajectories must be processed to provide training data to the quantile random forest. This training data consists of features and targets, with the target being future EU EV stock share and the features being information extracted from country-level and EU-level trajectories. The trajectories are truncated to imitate the limited availability of empirical data, with features used for training extracted after truncation.

Parameter	Value	Meaning
L	1	Ceiling of growth curves
G	Mean: 0.1, STD: 0.06, Min: 0.01, Max: 0.15	Maximum growth rate
Takeoff Delay Standard Deviation	Mean: 4, STD: 2, Min: 2, Max: 8	The standard deviation of takeoff year within each world
Takeoff stock share	0.01	Stock share value at takeoff of growth curves
Pulses	3	Maximum number of pulses
Pulse probabilities	50%, 30%, 20%	Probability of first, second, and third pulse occurring
Delay	Min: 3, Max: 6	Number of years between the end of one pulse and the beginning of the next pulse
L Pulses	Min: 0.15, Max: 0.8	Percent of total growth curve ceiling reached by each pulse
G Pulses	Meanlog: 0, sdlog: 0.3	Multiplier of base G for each pulse's growth
Pulse takeoff stock share	0.05	Stock share value at each pulse's takeoff
Noise	AR1 with phi: 0.1, amp: 0.3	Additive noise applied to individual country trajectories

Table 3.4: Parameters defining the Monte Carlo simulation used by Prolong-EV to create projections.

The features are selected through a multi-step analysis, which is described in section A.1.3. The selected features include total EU stock share at the last year of data availability and the latest three year average growth rate in the EU. In addition, the countries that are experiencing their first period of accelerating growth are identified and used to calculate additional features. These include the total EU vehicle market of countries that are in the first acceleration period and the median and quartile values of the latest three year average growth for countries experiencing their first period of acceleration.

To train the quantile random forest, feature and target values are calculated for each simulated trajectory for multiple defined levels of truncation. Multiple random forests are trained, with each one learning a specific projection horizon. This means that each random forest is trained on data comprised of the features extracted from all trajectories and the corresponding EV stock share of those trajectories at a specified number of years after truncation.

3.4.3 Making projections

After training these models using data from the Monte Carlo simulation, they are capable of making predictions based on empirical data. Projections are made by extracting the same features from the empirical data as those that were extracted from the training data, then feeding those features into the model to make a projection for each specified horizon.

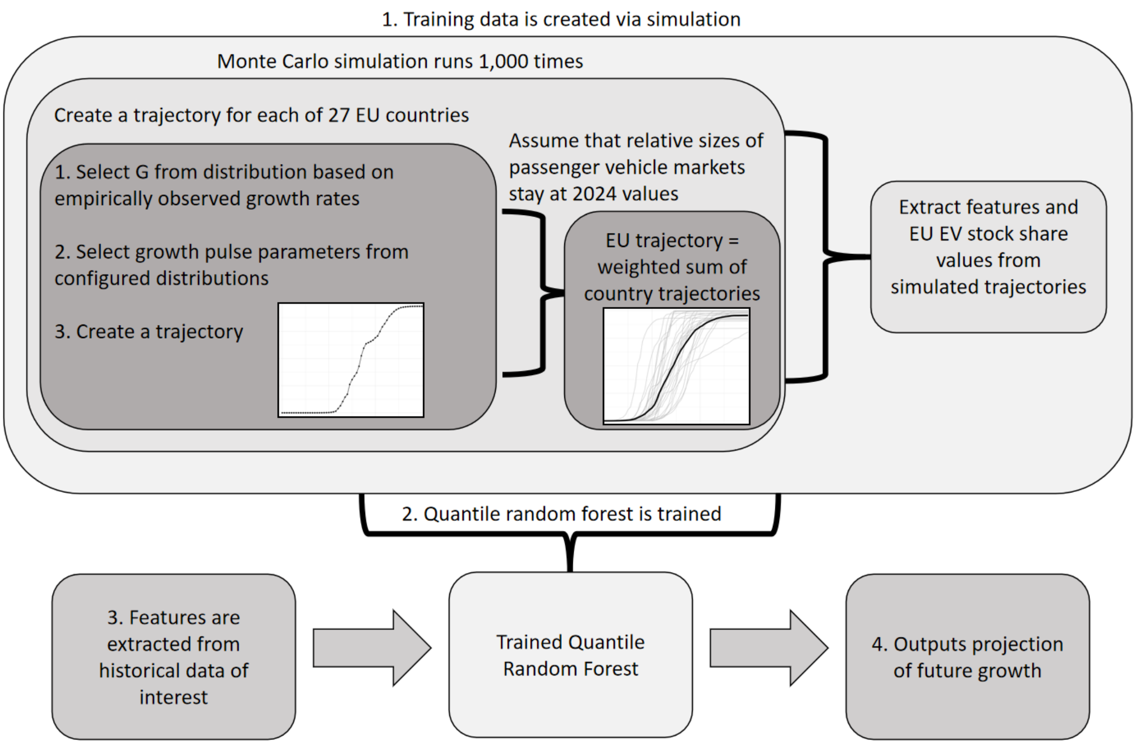


Figure 3.2: Overview of the Prolong-EV projection method.

3.5 Evaluation of projection performance

The performance of Prolong-EV is evaluated from multiple perspectives to gain a greater understanding of its applicability in different contexts and identify best practices for producing high-quality results. It is tested using out-of-sample simulation data, mobile phone subscription data, and hindcasting with EV data. This enables analysis of the general quality of projections, how projection performance changes with increased data availability, and possible limitations. The specific experiments performed are summarized in Table 3.5.

Test	**Name**	**Data**	**Description**
1	Data truncation performance	Out-of-sample simulation and mobile phone data	Evaluating how projection performance varies with number of years of data available
2	Varying trajectory characteristics	Out-of-sample simulation data	Evaluating how projection performance varies for trajectories with different characteristics
3	2020 hindcasting	EV data	Evaluating projection performance over 2021-2024 based on 2020 projection
4	Growth metric parameterization	Mobile phone data	Evaluating how projection performance varies with accuracy in parameterization of growth parameters for simulated trajectories

Table 3.5: Summary of tests run on Prolong-EV for evaluation of performance.

Several metrics are used to evaluate the performance of the probabilistic projections. These metrics are used while configuring Prolong-EV, to compare the performance in different contexts, and to evaluate the model results. The metrics are summarized in Table 3.6. A discussion of best practices for using these metrics in assessing probabilistic projections of early growth stage technologies is included in Section A.2.

3.5.1 Evaluation using out-of-sample simulation data

Out-of-sample simulation data is used to evaluate the effects of the length of available data on model performance. This is first done by generating trajectories using the Monte Carlo simulation used in Prolong-EV's training, but with different parameterizations than those used during model training. Five differently parameterized sets of trajectories are created, with the characteristics that differentiate the trajectories described in Table A.4.

To test the effects of the length of data available, the simulation data is truncated at eight different points, ranging from two to ten years past takeoff. Projections are made based on the truncated data, and the performance of these projections is calculated using the metrics described in Table 3.6.

Metric	Description	Interpretation
Symmetric mean absolute percent error (sMAPE)	Mean absolute percentage error between projection mean and empirical value	Quantification of error in projection
Symmetric mean percent error (sMPE)	Mean percentage error between projection mean and empirical value	Quantification of systematic bias in projection
Continuously ranked probability score (CRPS)	Metric that combines evaluation of accuracy and uncertainty	Lower values indicate a higher quality projection, with zero being a perfect projection with no uncertainty
Interval width	Upper bound of uncertainty minus lower bound (i.e. third quartile minus first quartile for 50% interval)	Magnitude of range of uncertainty for the projection
Normalized interval width	Interval width divided by projection mean	When greater than one, the level of uncertainty dominates the projection
Coverage rate	Percentage of projection values that fall into uncertainty interval	Uncertainty values represent probabilities of the true value falling into that range if the coverage rate approximates the interval of uncertainty in consideration (i.e. 50% coverage rate for the interval from first quartile to third quartile)

Table 3.6: Metrics used to evaluate the performance of probabilistic projections.

3.5.2 Evaluation using mobile phone data

The process for making Prolong-EV projections for mobile phone growth is very similar to making projections for EVs. The first step is to identify empirically observed growth metrics that can be used to parameterize the Monte Carlo simulation. The growth metrics are calculated for the complete mobile phone growth trajectories, then for a number of earlier years in which the growth is not yet complete and the growth metrics are therefore not yet certain. The results reveal that early growth metric calculations yield faster growth estimates on average than those seen with the complete trajectory, but the early estimates are still somewhat accurate.

Next, projections are made from 1997 with different growth metric parameterizations to study the effects of inaccurate growth metrics on projections. Nine different configurations of L values are tested, as well as nine different configurations of G values. The resulting projections are compared visually.

Mobile phone data is also used to evaluate how projection performance varies with the amount of empirical data available for making a projection. One model is trained based on early observed mobile phone growth metrics, then it makes projections for mobile phone growth based on ten different truncated empirical data series, ending in 1993 to 2003. These projections are compared and evaluated based on the performance metrics described in Table 3.6.

3.5.3 EV hindcasting

Hindcasting using EV data is performed on both the naive projection and Prolong-EV to create projections starting in 2020. Similar processes are used to configure the models, but using only data available in 2020. Figure A.2 and Table A.2 show the data that is available for hindcasting. For the naive projection, this data is used to generate K and takeoff year distributions. For Prolong-EV, a similar process is performed to set parameters for the model. One difference is that the distribution for G used to generate training data is significantly wider than in the standard configuration. This is done because all countries except for Norway have a 2020 stock share below 4%, meaning that the G values calculated from empirical data are highly uncertain. Figures A.8 and A.9 show some examples of trajectories generated with this parameterization, which have a wider range of growth rate than the trajectories produced for the 2024 projection, as shown in Figures A.4 and A.5.

In order to be able to directly compare projections at specific future years while also comparing projections at specific horizons, a larger number of horizons are projected for the hindcasting projection. Besides this and the change to G parameterization, the configuration of the Prolong-EV hindcasting model is the same as that done with 2024 data and described in Table 3.4.

4

Results

4.1 Naive projection

Two projections for EV growth in the EU are made using the naive projection method. For these projections, as well as the Prolong-EV projections, the 90% probabilistic interval is shown in light blue, the 50% interval is shown in darker blue, and the mean projection value is shown as a dark blue line. The first projection, as seen in Figure 4.1, is made using 2024 data and and shows mean projections of EV stock share of approximately 22% in 2030, 53% in 2035, and 78% in 2040. It is projected that EV stock share will likely be above 90% by 2047. The range of uncertainty in the projection is consistently narrow, with an 90% interval width of 7% in 2030 and the largest range of uncertainty occurring around 2040 with a 90% interval width of 15%.

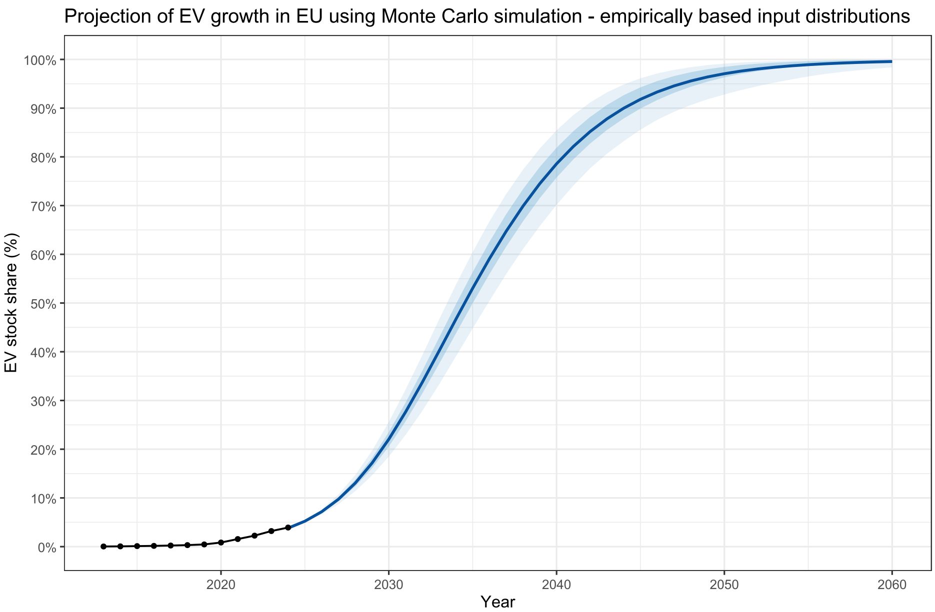


Figure 4.1: Projection of EV stock share in the EU made using naive projection methodology with data from 2024 and earlier.

The second projection, as seen in Figure 4.2, is made using 2020 data and uses

hindcasting to compare the projected stock shares from 2021 to 2024 with the empirical values. The projected stock share matches the empirical data well from 2021 to 2023, but in 2024 a slight slowdown in growth is observed in the empirical data while continued acceleration is projected. From 2021 to 2024, the projection uncertainty remains so low that the empirically observed slowdown in growth falls outside of the 50% interval of the probabilistic projection.
Overall, the range of uncertainty in the 2020 based projection is much higher than in the 2024 based projection. The 90% interval width is 22% in 2030 and reaches a maximum of 24% around 2035. The 2020 based projection also shows much more rapid growth, with mean projections of stock share of approximately 35% in 2030, 66% in 2035, and 86% in 2040.

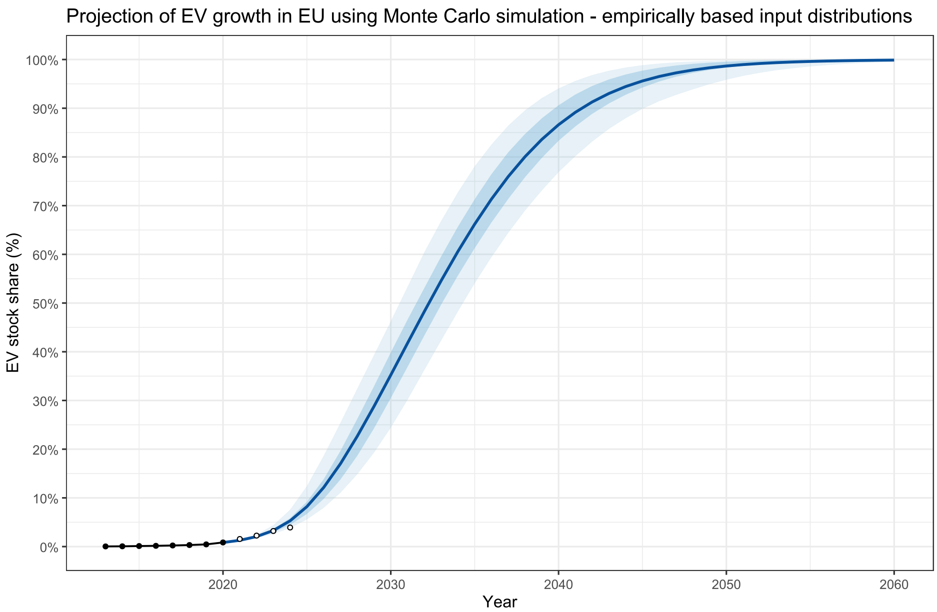


Figure 4.2: Results of hindcasting from 2020 with naive projection methodology.

4.2 Prolong-EV projections

2020 and 2024 based projections are also made using the Prolong-EV projection method. This projection method results in considerably slower growth and larger ranges of uncertainty than the naive projection method. The 2024 based projection, shown in Figure 4.3, shows mean projections of EV stock share of approximately 23% in 2030, 43% in 2035, and 61% in 2040. The mean projected stock share does not reach 90% before 2064, the last projected year. The 90% interval width is 18% in 2030, and the largest 90% interval width is observed around 2040 with a magnitude of 32%.

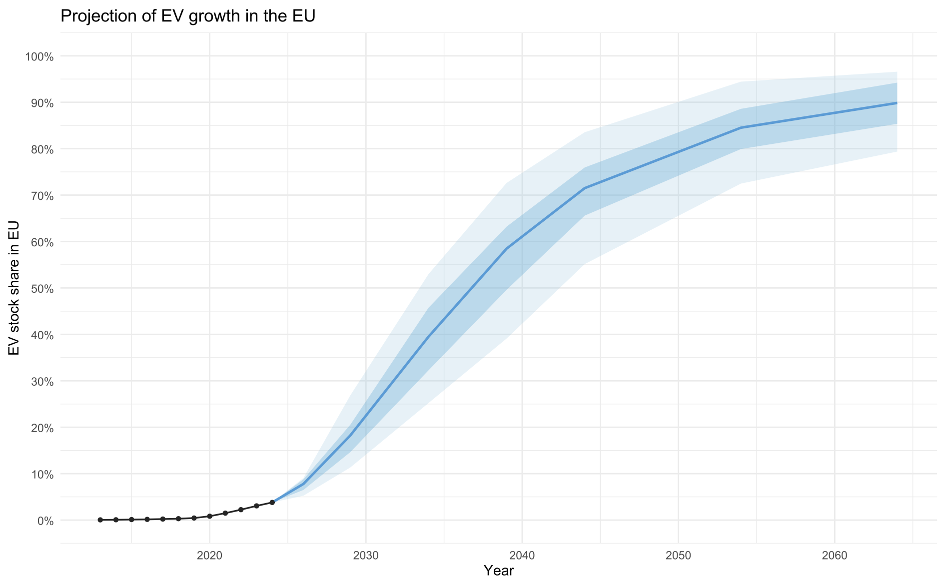


Figure 4.3: Projection of EV stock share in the EU made using Prolong-EV with data from 2024 and earlier.

The 2020 based projection, shown in Figure 4.4 exhibits even slower mean growth projections and larger uncertainty. Mean projections of EV stock share are approximately 22% in 2030, 38% in 2035, and 56% in 2040. The 90% interval width is 21% in 2030, and the largest 90% interval width is observed around 2040 with a magnitude of 35%. The 2020 based projections are compared with the 2024 based projections in Table 4.1 and Figure 4.5. The mean projected stock share before 2030 is very similar in the two projections, but after 2030 the 2024 based projection shows consistently higher mean stock share. The 50% interval range of the 2024 projection stays within the 90% interval range of the 2020 projection, showing consistency between the two projections. Figure 4.6 shows that the normalized interval widths of the 2020 based projection are always larger than those of the 2024 based projection, exemplifying how the 2024 projection exhibits a narrower range of uncertainty.

	2024 projection						2020 projection					
Year	Mean	Q05	Q25	Q50	Q75	Q95	Mean	Q05	Q25	Q50	Q75	Q95
2026	0.076	0.053	0.065	0.078	0.088	0.091	0.089	0.038	0.064	0.083	0.110	0.166
2029	0.185	0.113	0.146	0.182	0.205	0.269	0.180	0.077	0.135	0.179	0.229	0.265
2034	0.400	0.252	0.322	0.395	0.457	0.530	0.353	0.192	0.280	0.338	0.432	0.495
2039	0.575	0.391	0.496	0.585	0.632	0.726	0.536	0.357	0.457	0.534	0.592	0.710
2044	0.704	0.551	0.656	0.715	0.760	0.835	0.667	0.483	0.581	0.671	0.729	0.835
2054	0.833	0.725	0.799	0.845	0.886	0.944	0.785	0.631	0.728	0.786	0.853	0.900
2064	0.884	0.794	0.854	0.899	0.942	0.966	0.846	0.714	0.797	0.867	0.907	0.947

Table 4.1: Projections of EV stock share in the EU made by Prolong-EV based on data available in 2024 compared to projections based on data available in 2020.

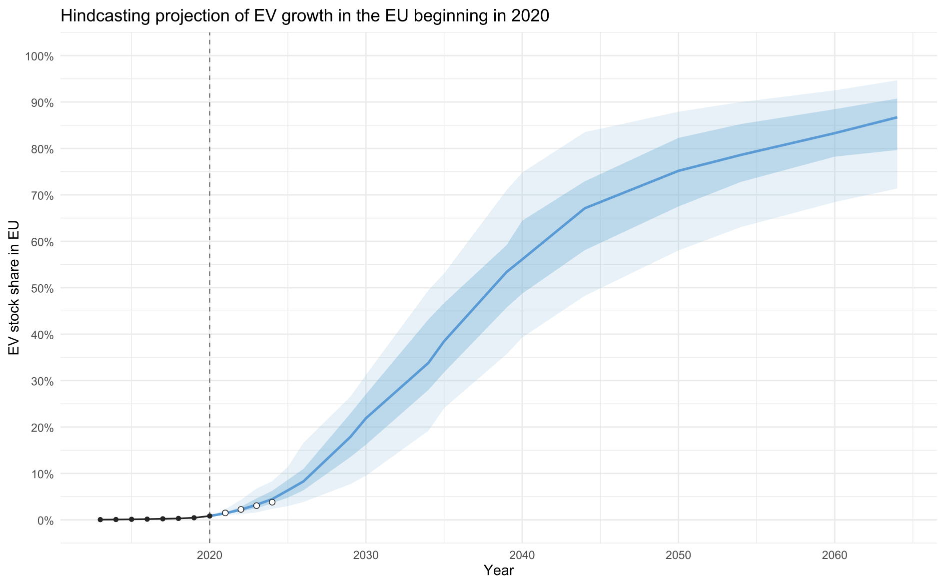


Figure 4.4: Results of hindcasting from 2020 with Prolong-EV.

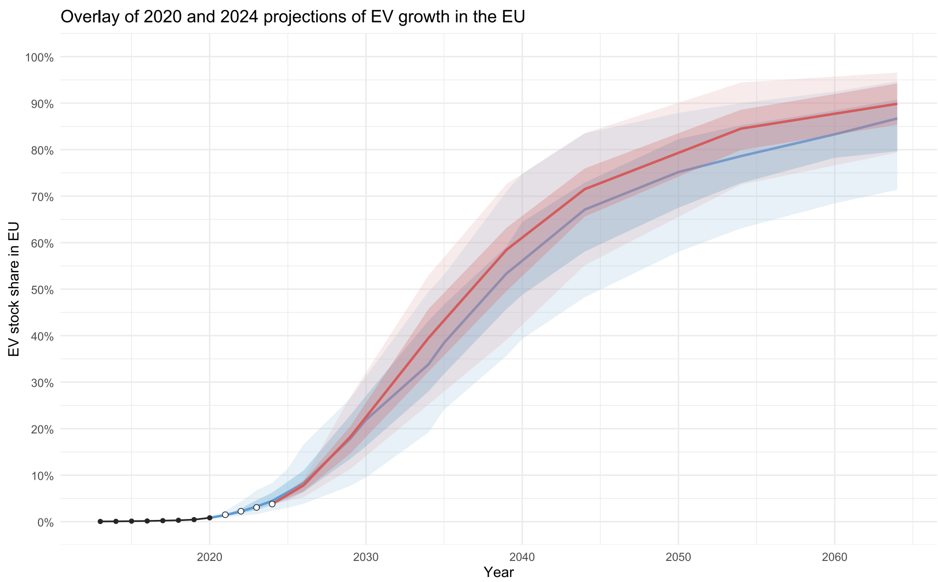


Figure 4.5: Overlay of 2020 and 2024 projections made by Prolong-EV. The 2020 projection is shown in blue and the 2024 projection is shown in red.

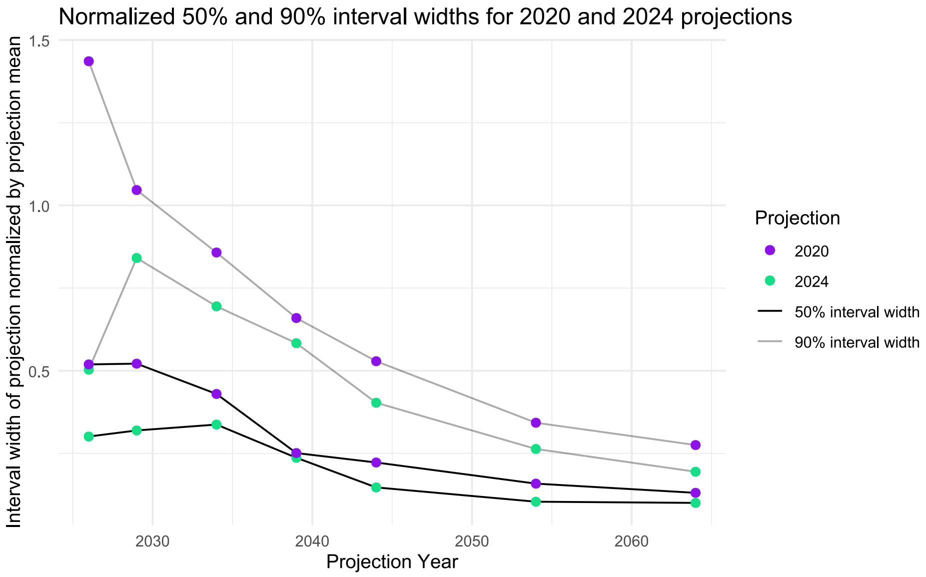


Figure 4.6: Comparison of the interval widths between Prolong-EV projections made with data from 2020 and 2024.

The 2020 based projection is used to evaluate Prolong-EV's performance by comparing it with empirical data from 2021 to 2024. Table 4.2 summarizes the hindcasting performance using a number of different metrics for evaluation. The empirical values fall within the 50% interval for all four years, indicating that the projection is accurate. The degree of accuracy, as measured by CRPS and sAPE, decreases with increasing projection horizon. The interval widths increase with projection horizon, with 90% normalized interval widths being above one in 2022 to 2024. This indicates that the uncertainty may dominate the projection, but due to the very low stock share values seen in 2021 to 2024 the normalized interval widths easily exceed one.

Year	CRPS	sAPE	sPE	50% interval width (stock share)	normalized 50% interval width	90% interval width (stock share)	normalized 90% interval width
2021	0.001	0.026	0.026	0.3%	0.184	1.3%	0.872
2022	0.002	0.086	-0.089	1.0%	0.416	3.1%	1.262
2023	0.003	0.167	-0.182	2.1%	0.591	5.1%	1.418
2024	0.005	0.267	-0.309	2.7%	0.533	6.0%	1.198

Table 4.2: Performance of Prolong-EV projection from 2020 compared with empirical data from 2021 to 2024.

4.3 Evaluation of performance with out-of-sample simulation trajectories

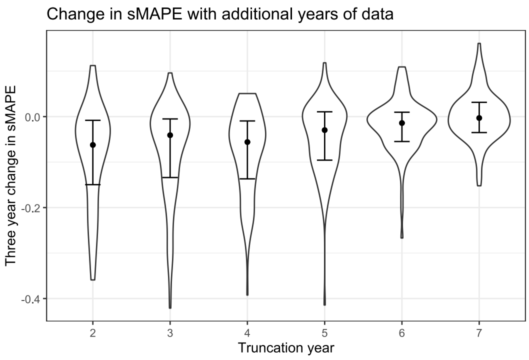
In order to test how Prolong-EV performs across a variety of possible trajectories and with different quantities of available data, projections are made using 100 simulated trajectories that are truncated at 2 to 10 years after they first reach a stock share of 1%. This is done as described in section 3.5.1 with five groups of twenty trajectories, each group parameterized as described in Table A.4.

The change in performance of projections with a later truncation year is calculated for each trajectory individually, and these results are summarized in Figure 4.7. Here it can be seen that for approximately 75% of the trajectories, sMAPE improves when Prolong-EV makes a projection based on truncation five years after takeoff rather than only two years after takeoff. A similar level of improvement is seen when truncation is done at six rather than three years, and at seven rather than four years. The beneficial effects of more available data diminish once 6-7 years after takeoff are available.

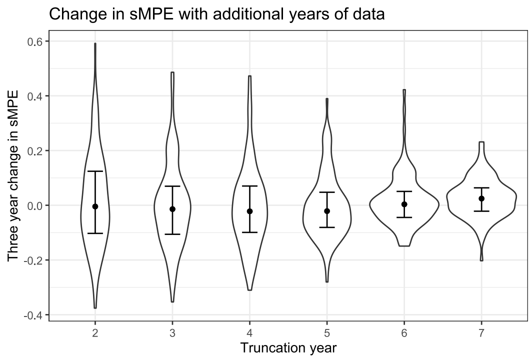
The change in interval width is even more dramatic than that of sMAPE, with nearly all trajectories showing a reduction in projection interval width when an additional three years of data are provided to Prolong-EV. This effect diminishes somewhat with initial truncation year, indicating that the most change is seen when the initial truncation is very short. CRPS shows a more subtle trend, with the majority of trajectories seeing improved CRPS performance of projections as additional years of data are available only by a slim margin and only when the initial truncation was less than five years after takeoff.

Performance metrics for each simulation trajectory are compared to the trajectory's growth duration to reveal correlations between model performance and trajectory characteristics. Figure 4.8 shows how the correlations between sMAPE and sMPE and the trajectory's growth duration change as trajectories are truncated at later years. With early truncation, a strong correlation between projection performance and trajectory growth rate is seen. sMPE reveals that slow growing trajectories are systematically projected to be faster than they actually are, while the opposite is true of fast growing trajectories. sMAPE shows that there is high error for both slow and fast trajectories, with average trajectories having the lowest error. As additional years of data are made available to Prolong-EV the strength of these trends becomes weaker. From a two year truncation to five year truncation, a dramatic change is seen in how strongly performance correlates to trajectory growth duration. Beyond a six year truncation, additional years of data availability do not result in a significant change.

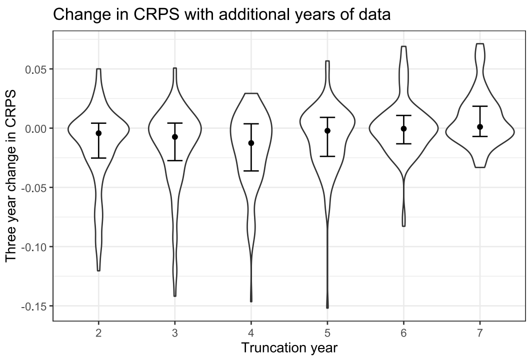
The coverage rates of projections within each trajectory group are measured to evaluate how the observed frequency of simulation trajectories falling within uncertainty intervals compares to the theoretical probability associated with that interval. The different trajectory groups show significantly different results, as summarized in Table 4.3. Trajectory group one has very low coverage rates, indicating either that the projected interval ranges are too narrow or that the projected values are inaccurate for group one trajectories. Groups five two also exhibit low coverage rates, while groups three and four have coverage rates that correspond closely to their associated



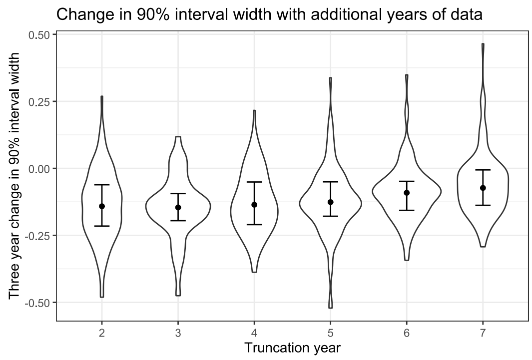
(a) sMAPE



(b) sMPE

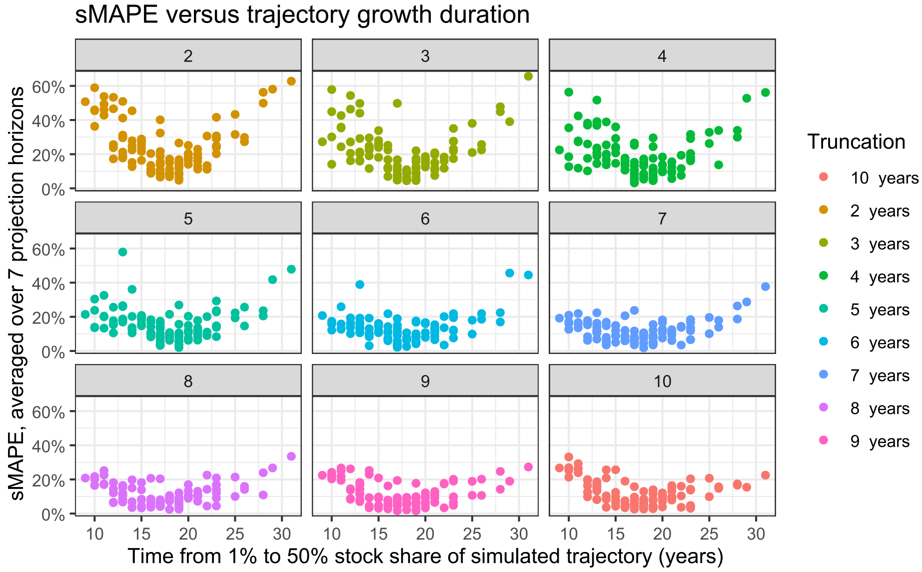


(c) CRPS

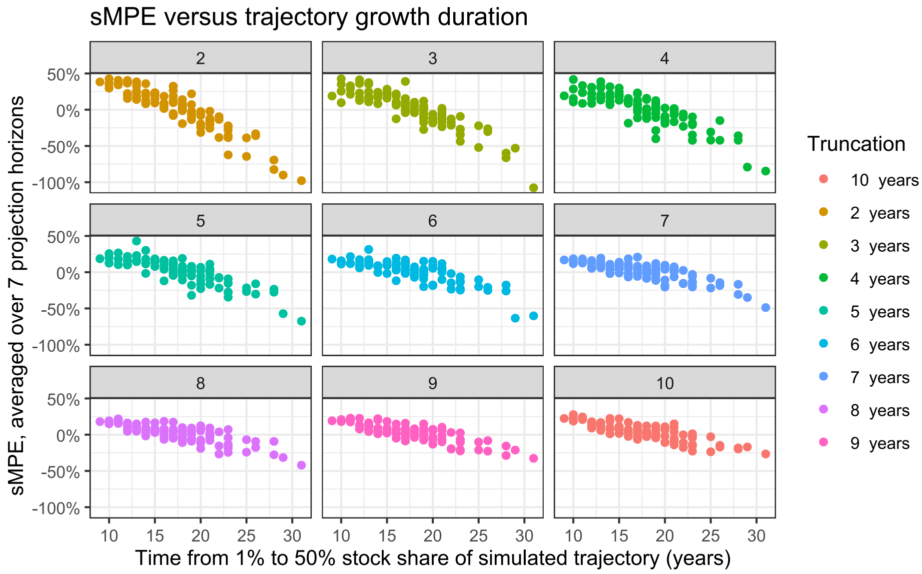


(d) 90% interval width

Figure 4.7: Change in hindcasting performance on out-of-sample simulation trajectories when an additional three years of data is provided. The performance metrics seen here include sMAPE, sMPE, CRPS, and the 90% interval width. The x-axis shows the initial year of data truncation and the y-axis shows the change in each metric's value with an additional three years of data provided. The change is measured in each individual trajectory then presented as violin plots that show the range of differences seen across all 100 trajectories.



(a) sMAPE



(b) sMPE

Figure 4.8: Plots of hindcasting performance metrics vs the ΔT values of out-of-sample simulation trajectories for different years of data truncation. The x-axis shows the time from 1% to 50% of the trajectory and the y-axis shows the sMAPE or sMPE for each trajectory. The plots are faceted by truncation year, ranging from two to 10 years after takeoff.

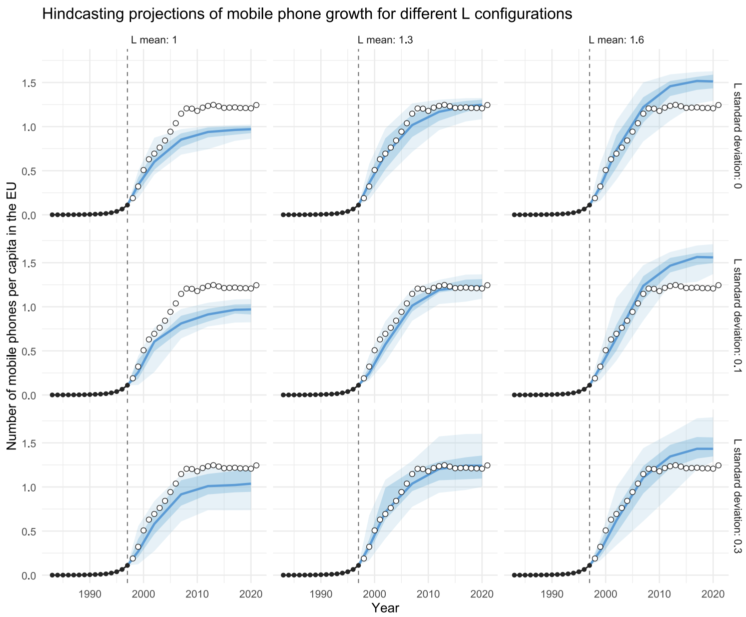
intervals.

Trajectory group	Average 50% coverage rate	Average 90% coverage rate
1	12.4%	35.5%
2	41.2%	86.8%
3	47.5%	90.4%
4	51.5%	85.2%
5	37.2%	77.5%

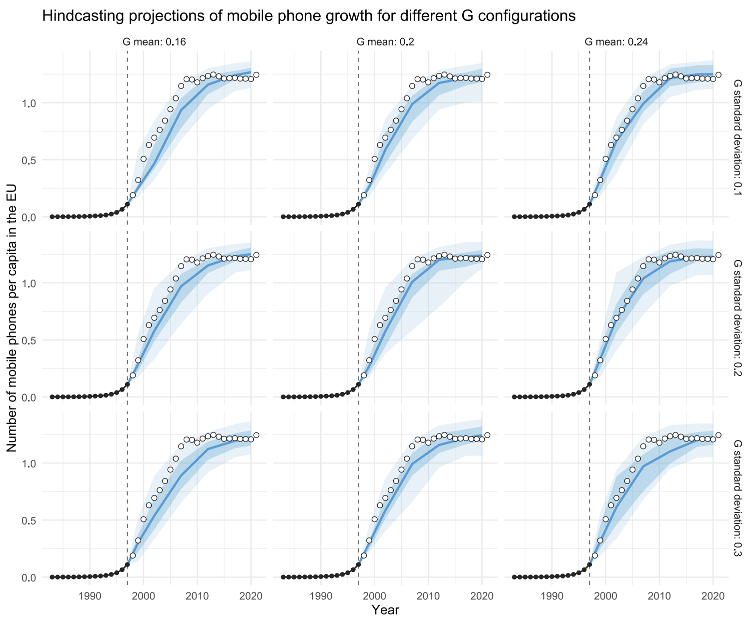
Table 4.3: Coverage rates of different simulation trajectory groups.

4.4 Evaluation of performance with mobile phone subscription data

Prolong-EV is also used to make projections of mobile phone subscriptions in the EU. Hindcasting is performed with data from 1997, as this is four years after takeoff and the 2024 EV projection is also four years after takeoff. The importance of accurate parameterization of Prolong-EV is tested by making mobile phone projections using nine different values of L and nine different values of G. Figure 4.9 shows the resulting projections with the distributions of L and G configured with three different means and three different standard deviations. The projections made always show an asymptotic behavior that mirrors the distribution of L that is used. The projections are more flexible to different G configurations, with the projected growth rate being similar in all nine G configurations.
Prolong-EV is used to make projections of mobile phone subscriptions in the EU with data that is truncated from takeoff year to ten years after takeoff. The resulting projections are evaluated, and it is found that performance is significantly better when data after 1996 is available compared to trajectories truncated in 1996 or earlier. However, for all years of truncation, projections have high performance in the first three years of the projection and particularly low performance for the years of 2008 and 2009. Figure 4.10 shows these results as a heatmap of CRPS across different truncation years and projection years. Additional heatmaps of how performance varies with truncation year are shown in Figure A.11
Performance evaluation with different years of data truncation from out-of-sample simulation trajectories is combined with an evaluation of how different years of truncation impact mobile phone projection performance. Figure 4.12 shows how accuracy and bias change with additional years of data available, while Figure 4.11 shows how the normalized interval width changes as more data becomes available. The mobile phone projections and simulation trajectory projections show consistent results, with sMAPE, CRPS, and interval width decreasing significantly with increasing truncation year, and the largest improvements in performance occurring at earlier years of truncation. Improvements are also seen in sMPE with later truncation.



(a) Varying L configuration



(b) Varying G configuration

Figure 4.9: Grids of Prolong-EV projections of mobile phone subscriptions starting in 1997 compared to empirical values while using different configurations of L and G in the Monte Carlo simulation parameterization. Columns include different mean values of the parameter and rows include different standard deviation values for the parameter.

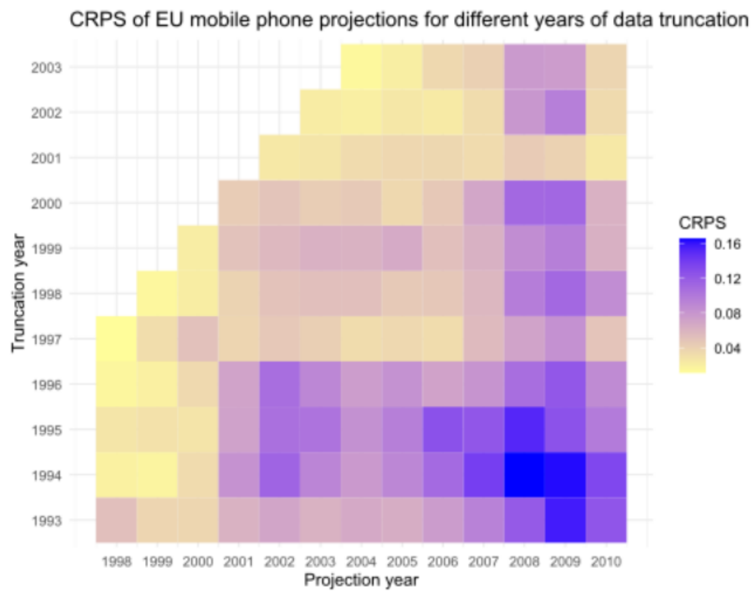


Figure 4.10: Heatmap of CRPS of Prolong-EV projections of mobile phone subscriptions for a range of truncation years and projection years.

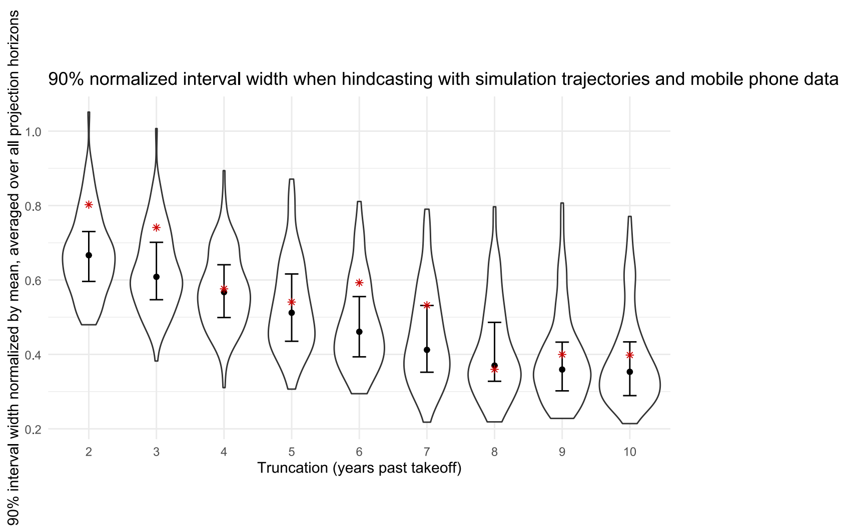
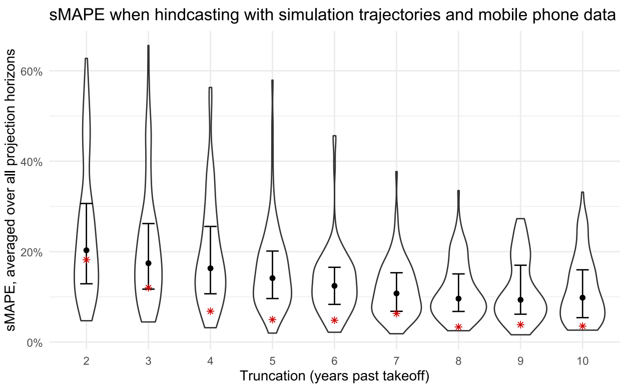
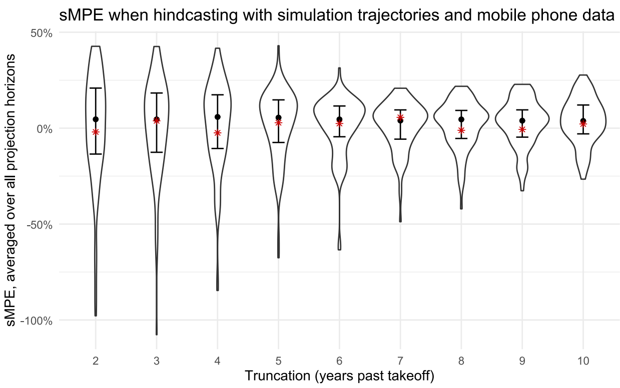


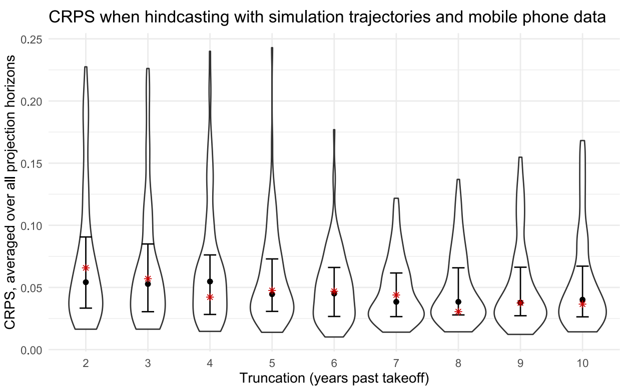
Figure 4.11: Interval width of hindcasting projections with out-of-sample simulation data and mobile phone data for different years of data truncation. Results based on simulation data are shown as violins that capture 100 different simulated trajectories, while results based on mobile phone data are shown as red stars.



(a) sMAPE



(b) sMPE



(c) CRPS

Figure 4.12: Metrics of accuracy and bias of hindcasting with out-of-sample simulation data and mobile phone data for different years of data truncation. Results based on simulation data are shown as violins that capture 100 different simulated trajectories, while results based on mobile phone data are shown as red stars.

5 Discussion

5.1 RQ1: Projections for EV growth in EU

The projections made by Prolong-EV anticipate growth similar to that predicted by other sources, with expectations that EV stock share will continue accelerating for several years then grow at a steady rate until around 2040. This will result in an EV stock share of around 55% to 70% by 2040, which is a dramatic increase from the 2024 stock share of less than 4%. However, the anticipated rate of growth is not fast enough for the 2050 EU net-zero target to be achieved through EVs alone. The anticipated growth is certainly not sufficient to reach the earlier 2044 to 2048 date for net-zero transport emissions in the EU proposed by Plötz et al. [34] without significant use of other emission reduction strategies, such as replacing fossil-based fuels with biofuels. These results can be observed in Figure 5.1, which shows the Prolong-EV projection together with projections made by Enerdata [3], IEA [2], and Möring-Martínez et al. [4]. Targets set by the EU [5] and suggested by Plötz et al. [34] are also included in the figure.

Two Enerdata projections are shown in the figure, both of which project only BEV stock share in the EU. Enerblue is a scenario in which countries meet their existing targets, while Energreen is a scenario in which more ambitious targets that enable global warming to stay below 2°C are reached [3]. The IEA's projected 2030 stock share for EVs in Europe [2] is shown as a rhombus, but it should be noted that this projection includes countries outside of the EU. The IEA projection is a STEPS scenario based on stated initiatives. Three of Möring-Martínez et al.'s projections for EU BEV stock share [4] are included in the figure. These were developed based on earlier work projecting BEV sales share in the EU [43], which is used in combination with different passenger fleet turnover rates to estimate stock share. The three scenarios included in Figure 5.1 show projections for when turnover rate remains the same as the most recently observed empirical rate, 20% faster than the empirical baseline, and 20% slower than the empirical baseline. Two targets are included in the figure, with one being the existing EU target for net-zero emissions by 2050. The other target shows the range of dates proposed by Plötz et al. by which total transportation greenhouse gas emissions in the EU need to reach net zero in order to limit global warming to below 1.5°C [34]. This could be done without replacing all ICEVs, as other technologies, such as biofuels, can also be used to achieve net-zero emissions.

Projections made by both Enerdata and Möring-Martínez et al. are for BEVs alone, which differs from the Prolong-EV projection that also includes PHEVs. This can

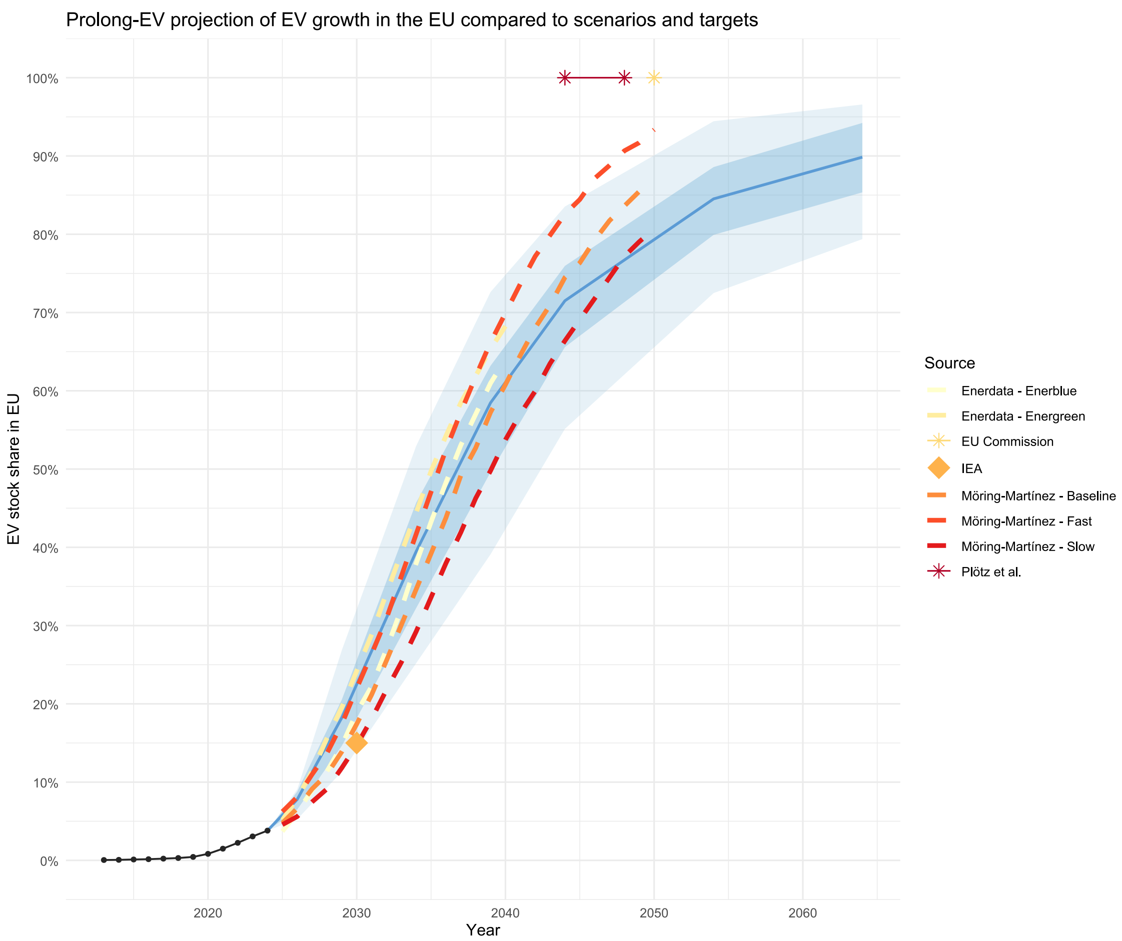


Figure 5.1: Figure of Prolong-EV projections with other projections and targets overlayed. Projections are shown as dotted lines and targets are shown as stars. The IEA projection for 2030 is shown as a rhombus.

explain Prolong-EV's higher projected stock share in the near-term, but should cause less of a discrepancy in the long-term as BEVs are expected to replace PHEVs entirely [2]. Furthermore, both Enerdata and Möring-Martínez et al. make projections based on the assumption that existing EU emission targets will remain in place, although a proposal has been made to reduce the current policy ambition [10]. Prolong-EV, on the other hand, does not make any explicit assumptions about future EU legislation. This could explain how long-term projections made by Enerdata and Möring-Martínez et al. surpass the Prolong-EV mean projection. However, as demonstrated in Figure 4.9, Prolong-EV is more prone to error near the growth ceiling, with the most reliable results produced before the projected or empirical growth begins to stagnate. The discrepancy between the growth rate of Möring-Martínez et al.'s projections from 2040 to 2050 and the growth rate projected by Prolong-EV in that time period could therefore be a result of Prolong-EV's reduced performance near the growth ceiling. Regardless of which projected 2050 stock share values are most accurate, it is clear that a significant effort will be needed to reach the EU's 2050 target.

5.2 RQ2: Making probabilistic projections for technology in an early growth phase

5.2.1 Capabilities and limitations of Prolong-EV

While projections made by Enerdata [3] and Möring-Martínez et al. [4] corroborate Prolong-EV's projections, Prolong-EV also shows promising performance across a variety of tested projection conditions. Good projection performance is even seen when trajectories are truncated to just a few years after takeoff, indicating the Prolong-EV can be used to make projections of technologies that are in an early growth stage. This is observed in all three data sets used for testing: out-of-sample simulation test data, mobile phone data (Figure 4.12), and 2020 EV data (Figure 4.4 and Table 4.2). Furthermore, when EV projections made with 2020 data are compared with 2024 projections, the 2024 projection values are primarily contained within the 90% interval of the 2020 projection (Figure 4.5 and Table 4.1). This consistency is further evidence that the projections are accurate beyond 2024. However, when exploring Prolong-EV's performance with mobile phone and simulation data, some specific areas of limitation emerge.

The error, bias, and uncertainty associated with the projections all decrease on average with additional years of data available, as shown in Figures 4.10, 4.11, and 4.12. It is important to note that the configuration used to train Prolong-EV remains constant in these experiments, and the additional time series data provided as an input to the trained quantile random forest is the sole cause of the improvement in performance. The performance improvement would likely be greater if the additional available data were also used to parameterize the model more accurately. However, not all out-of-sample simulation trajectories show an improvement in performance with later truncation. As shown in Figure 4.7, around a quarter of out-of-sample simulation trajectories either have similar or slightly worsened performance when an additional three years of data is made available. This evidence supports the conclusion that when making projections with very early empirical data, it is likely, but not guaranteed, that the quality of the projection will improve within a few years when more data becomes available.

Accurate parameterization of the model is important for producing accurate projections, with the parameterization of L, the growth ceiling, of much higher importance than the parameterization of G, the growth rate. This is clearly seen in Figure 4.9 where the projections made with incorrectly parameterized L values are very inaccurate near the growth ceiling, while the projections made with incorrectly parameterized G values are all relatively accurate. The effects of inaccurate L parameterization are fortunately limited to the period where growth begins to saturate, meaning that even with somewhat inaccurate parameterization, technology deployment during periods of accelerating and steady growth can be accurately predicted by Prolong-EV. However, G parameterization does have an impact on the accuracy and bias of projections. Figure 4.8 shows how this effect becomes less significant as the truncation year increases, indicating that when the quantile random forest is provided with more data it is capable of adjusting its projections to compensate for an inaccurate parameterization. This effect, combined with the increased likelihood of parameterizing the model well when more data is available, suggests that, in practice, projections will often show large improvements with just a few additional years of data available.

5.2.2 Advantages of Prolong-EV's methodology

Despite some limitations, the performance of Prolong-EV with early data is strong enough to provide a useful methodology for making projections. It also has specific advantages compared to other projection methods. None of the other methods shown in Figure 5.1 create probabilistic projections, limiting their ability to communicate uncertainty. The probabilistic nature of Prolong-EV provides transparency around the level of uncertainty associated with projections of early phase technology. This can be clearly seen in Figure 4.6, which shows that the projection made in 2024 has a significantly decreased level of uncertainty compared to the 2020 projection. Deterministic projections cannot communicate the level of confidence associated with a projection as easily, making them less suitable for cases of immature technologies in which the uncertainty can be very high.

Another advantage of Prolong-EV is that it is data driven, using only historical trajectories to project future growth. The mechanisms that affect EV growth in the EU do not need to be explicitly understood or modeled in order to make a projection with Prolong-EV. Rather, mechanisms and their interactions are implicitly captured, like in PROLONG [1]. Using historical deployment data as the basis for projections also results in a methodology that is easier to implement, as mechanism-driven methods frequently require more data in order to model how each individual mechanism functions. This can be particularly challenging for early phase technology where markets are not as developed and data relating to mechanisms can be missing, as Möring-Martínez et al. observed while attempting to model EV sales share in the EU [43]. Data-driven projections also differ significantly from policy-based projections, like those made by Enerdata [3] and IEA [2], and from IAM-based scenarios, like those made by Speizer et al. [33]. Data-driven projections have the ability to assess the feasibility of targets by implicitly incorporating information about sociotechnical, political, and techno-economic mechanisms, and their interactions, into the projection. On the contrary, policy-driven projections fail to consider factors that could make policy infeasible or lead to a future reduction in policy ambition, while IAMs primarily address technological feasibility but fail to consider social and political aspects. This makes it possible for Prolong-EV to provide a more holistic assessment of likely future EV growth in the EU.

Beyond the general advantages of data-driven, probabilistic projection methodologies, Prolong-EV exhibits several unique features that enable as much information as possible to be utilized when making projections of early phase, policy-driven technologies. The Monte Carlo simulation utilized by Prolong-EV is an efficient way to extract information from limited data. By creating many virtual worlds that have characteristics chosen from distributions modeled on empirical observations, it is possible to simulate a situation in which much larger quantities of data are available. Useful modeling assumptions, in the form of pulsing logistic growth curves that have been empirically observed in other policy-driven technologies [28], bolster the limited data. Prolong-EV is also capable of extracting information present in countries that are front-runners in technology growth and using those trends to inform future regional growth [1].

Finally, Prolong-EV has clear advantages when compared to a minimalist data-driven, probabilistic projection method. The 2020 projections made by Prolong-EV and the naive projection (Figures 4.4 and 4.2) demonstrate how a projection methodology where technology growth is modeled as a simple logistic curve is not able to account for a slight growth stagnation seen in 2024. Prolong-EV's use of pulsing logistic growth solves this problem by providing flexibility for growth to slow temporarily. Furthermore, the 2024 naive projection (Figure 4.1) shows a very narrow band of uncertainty in the first five years of projection which grows significantly from 2025 to 2040. This trend of quickly increasing uncertainty is inherent to the naive projection methodology, and if input distribution variance were to be increased to create more reasonable near-term projection uncertainty, then the long-term projections would be dominated by uncertainty (Figure A.10). The quantile random forest utilized by Prolong-EV to generate probabilistic ranges has a high degree of flexibility and shows uncertainty that has a more intuitive increase in which projections before 2030 show significant levels of uncertainty without distant projections being entirely dominated by uncertainty.

It should be noted that there are other ways to adapt the standard logistic growth model to make probabilistic projections that avoid these pitfalls. Odenweller et al.'s logistic curve with a ceiling that varies as a function of time [50] is another way in which a logistic curve can be modified to create probabilistic projections for early stage technology growth. There are a large number of variations possible when using s-curve growth models [24], with one example being the Richards model [56]. Therefore, it is worthwhile to consider other types of models that can avoid the challenges associated with projections made using the naive methodology. In addition, a large number of methods exist for incorporating probabilistic aspects into projections [24, 25, 26, 27], encompassing a variety of mathematical frameworks for representing uncertainty, and these can be adapted to provide a useful measure of uncertainty to projections.

5.3 RQ3: Understanding uncertainty

One of the key strengths of Prolong-EV is its ability to communicate uncertainty, but communicating uncertainty in an interpretable way requires more than simply assigning probabilities to projected values. To understand the meaning behind probabilistic intervals produced by Prolong-EV, it can be helpful to consider how metrics of uncertainty behave under different conditions. It is consistently observed that interval widths decrease with additional years of data available (Figures 4.11 and 4.6). Furthermore, when considering the EV projections made in 2020 and 2024, the 2024 projection's probabilistic intervals are mostly contained within the 2020 projection's intervals (Figure 4.5), demonstrating that there is a decrease in uncertainty but not a significant change in the expected future stock share values. These results show that the intuitively expected behavior of uncertainty decreasing as more data becomes available is demonstrated through projected probabilistic intervals. However, it is harder to gain an understanding of the practical or mathematical meaning of the probabilistic intervals.
One intuitive interpretation of the probabilistic intervals could be that they represent the likelihood that a future empirical value will fall into that range. The metric of *coverage rate* presents a way to assess whether the probabilistic intervals correspond to that definition, being calculated as the percentage of trajectory values that fall into the projection's interval. Quantile random forests have the helpful property of producing probabilistic intervals that correspond to the coverage rates (i.e. the coverage rate for the 50% interval will be 50%) when trained with ideal training data [29]. In reality, it is not possible to have an ideal training set with infinite samples of training data, and, in the case of Prolong-EV, it is not possible to know with certainty the set that future possible trajectories belong to, as this would require knowledge of the future. This creates a different type of scenario in which the meaning of the probabilistic intervals is not entirely clear, but can be tested by assessing coverage rates of hindcasting performance of test data.
Out-of-sample simulation trajectories are used for this testing, as there are a large number of trajectories, reducing the noisiness of measured coverage rates, and the five different trajectory groups are used to assess how performance changes as a result of trajectory characteristics. It is seen that coverage rates for some out-of-sample simulation trajectory groups are significantly lower than the 50% and 90% interval values, while other trajectory groups have coverage rates close to 50% and 90% (Table 4.3). This demonstrates that the probabilistic intervals produced by Prolong-EV do not always correspond to the frequency with which trajectories fall into that range and reflects the different types of uncertainty that are present in the projection. Trajectories from group one in Table 4.3 exhibit high parameterization uncertainty, as they are generated with a growth rate that is significantly faster than the growth rate Prolong-EV is parameterized with, explaining why they show such low coverage rates. This type of situation can also occur with empirical trajectories,

where uncertainty due to limited data and inherent randomness in the system results in an inaccurate parameterization of Prolong-EV. For this reason, it is important to understand that the probabilistic intervals are not guaranteed to capture all uncertainty present in the system, and that accurate parameterization of Prolong-EV significantly reduces the uncertainties that are not able to be communicated through the probabilistic intervals of the projection itself.

The concept of parameterization uncertainty can be generalized, with all uncertainty regarding technology growth split into two groups: uncertainty that is visible to the projection model and uncertainty that is invisible to the model. The uncertainty that is visible to Prolong-EV is the uncertainty present in the training data. This is affected by parameterization, but also by other modeling assumptions, like the shape of growth curves and total number of passenger vehicles in each country. In the case of simulation trajectory group one, which has low coverage rates (Table 4.3), it is clear that the trajectories used for projection have a significantly different growth rate than the trajectories used for training, resulting in a model that is unaware of the possibility of growth rates as high as those of the test trajectories. In the empirical case, growth rates that fall outside of the distributions used to train Prolong-EV could also result in a situation in which there is uncertainty that is not visible to the model. In addition, there are a large number of real life factors that could affect future technology growth in a way that is not captured through modeling assumptions and parameterization. This model uncertainty exists as an additional layer of unknown factors that extends beyond the uncertainty communicated by Prolong-EV's projections.

An intuitive frequentist meaning of probabilities is also challenged when there is only a single sample available, like in the case of making projections for EVs in the EU. Here there will only ever be one empirical trajectory, so the coverage rate cannot be meaningfully calculated even thirty years in the future when all empirical values are known. This is a hurdle in the interpretation of probabilistic projections, but should not be a reason to abandon any attempt to clarify their meaning. This work makes a contribution by establishing that the probabilistic projections made by Prolong-EV consistently demonstrate decreased uncertainty in the case of greater data availability and are capable of capturing some, but not all, of the uncertainty that exists in future EV stock share.

5.4 Limitations and future work

There are several limitations of this work, regarding both the quality of the EV projections and the analysis of the methodology itself. The short history of EV adoption limits how well future growth can be predicted. Furthermore, hindcasting analysis of EV projections is constrained to four years due to the limited data. The type of data used also presents some limitations. Since only historical stock share data is used to make future projections, it is not possible to account for unprecedented shifts in the mechanisms that have historically driven EV growth.

There are a number of assumptions made about EV growth that can reduce the validity of the projections. Prolong-EV utilizes the assumption that the relative shares of total passenger vehicle stock among countries in the EU will remain approximately constant in EU countries over the next thirty years, which would not hold if there are major structural changes to the way that passenger vehicles are used, possibly as a mitigation strategy to limit global warming [34]. In addition, Prolong-EV does not account for the possibility of restrictions to future EV sales in the EU as a result of supply shortages, but the minerals required to manufacture batteries and the local manufacturing capacity of batteries are both possible, but not highly likely, limitations to future EV supply in the EU [57, 49]. Furthermore, EVs are reliant on charging infrastructure, which itself needs to be deployed at a fast enough rate to enable EV stock growth [58].

The analysis of Prolong-EV's projection performance faces some limitations which could be addressed with more thorough experiments in future work. While EV projections based in 2020 and 2024 are created after a detailed parameterization process, projections made with the intention of testing Prolong-EV's performance on simulation and mobile phone data do not involve such a thorough parameterization process. In some cases this is done intentionally to test the effects of poor parameterization on projection performance, but in other cases the analysis could be made more complete by carrying out more detailed calibration.

There are additional aspects of Prolong-EV that could be improved and expanded upon in future work. An important, but potentially challenging, improvement is to incorporate historical trajectories of sales share data into the model, so that sales share can be used in conjunction with stock share to make projections. There are also a number of smaller improvements that could be made to the model. The quantile random forest could be tuned carefully to potentially increase its performance. In addition, the training data produced via Monte Carlo simulation could potentially be improved through a more detailed analysis of how to create a set of virtual trajectories that are sufficiently broad while not overwhelming the quantile random forest with irrelevant data.

Future work could also advance a general understanding of probabilistic projections of immature technologies. The theory of being able to predict future growth from information available in early trends can be further validated and understood through a detailed statistical analysis of the information available in early data that most strongly predicts future growth. Finally, the theoretical understanding of the meaning and interpretation of projection uncertainty in this context can be explored with the goal of improving the usability and understandability of probabilistic projections.

6
Conclusion

Prolong-EV expands upon existing bodies of research making projections for EV growth and probabilistic projections for technology growth. The methodology used to make projections is chosen to be data-driven because of the advantages associated with implicitly capturing a wide range of mechanisms of growth. The probabilistic nature of the projections provides benefits in the form of increased transparency regarding uncertainty of the projection and an increased ability for the audience to understand the level of effort required to achieve specific targets. Prolong-EV is based off of PROLONG [1], but is adapted to meet the unique situation presented by a technology in a very early growth stage that is policy-driven and has an expected saturation of around 100% stock share.

EV stock share projections made by Prolong-EV are largely consistent with projections made by Enerdata [3], IEA [2], and Möring-Martínez et al. [4]. None of these projections indicate that EU EV stock share could reach close to 100% by 2050, presenting a challenge for the EU target for net-zero emissions. However, EV stock share is expected to grow quickly over the next two decades, with accelerating growth until around 2030 followed by a steady yearly growth rate of around 5% per year for at least a decade. While this will be an important step toward meeting climate targets, additional action would be needed to constrain the greenhouse gas emissions of passenger vehicles in order to limit global warming to 1.5°C [34].

These conclusions highlight the importance of making projections of green technology growth. In this case, it becomes clear that more aggressive policy interventions will be needed to meet existing climate goals. The probabilistic nature of the projection also plays an important role in communicating the wide range of uncertainty associated with this projection that has been made at a point when EU EV stock share is still below 4%. It is transparent to the audience that the 2040 and 2050 levels of EV deployment are not certain, while also communicating that the 2050 EU target is out of reach without significant complementary technologies or policies.

There is a need for further research to explore probabilistic projections, as they are an underutilized, yet important, tool for planning climate change mitigation efforts. Existing probabilistic projection methods demonstrate a range of different strategies for calculating uncertainty, motivating research of the practical implications of the probabilities presented by projections as well as a unified understanding of how uncertainty can best be communicated to be both interpretable and meaningful. The range of methods used to capture uncertainty in projections also motivates continued research of different types of methodologies and the establishment of best practices.

Bibliography

[1] Avi Jakhmola et al. "Probabilistic projections of global wind and solar power growth based on historical national experience". In: *Nature Energy* (Apr. 2026). ISSN: 2058-7546. DOI: `10.1038/s41560-026-02021-w`. URL: `https://doi.org/10.1038/s41560-026-02021-w`.

[2] IEA. *Global EV Outlook 2025*. Paris, 2025. URL: `https://www.iea.org/reports/global-ev-outlook-2025`.

[3] Pacco Bailly and Jacques Despres. *Electric Vehicles' deployment: will it reach expected targets?* Tech. rep. Enerdata, Apr. 2024.

[4] Gabriel Möring-Martínez et al. "Quantifying the impact of fleet turnover on electric vehicle uptake in Europe". In: *Transportation Research Part D: Transport and Environment* 147 (Oct. 2025), p. 104945. ISSN: 1361-9209. DOI: `10.1016/j.trd.2025.104945`. URL: `https://www.sciencedirect.com/science/article/pii/S1361920925003554`.

[5] European Commission. *Setting CO2 emission performance standards for new passenger cars and for new light commercial vehicles, and repealing Regulations (EC) No 443/2009 and (EU) No 510/2011*. 2022. URL: `http://data.europa.eu/eli/reg/2019/631/2023-12-03`.

[6] IPCC. *Climate Change 2023: Synthesis Report*. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)] Geneva, Switzerland. DOI: `10.59327/IPCC/AR6-9789291691647`.

[7] Steven J. Davis et al. "Net-zero emissions energy systems". In: *Science* 360.6396 (June 2018), eaas9793. DOI: `10.1126/science.aas9793`. URL: `https://doi.org/10.1126/science.aas9793`.

[8] Patrick Plötz et al. "From lab-to-road: Real-world fuel consumption and CO2 emissions of plug-in hybrid electric vehicles". In: 16.5 (2021). DOI: `10.1088/1748-9326/abef8c`.

[9] Eurostat. *Passenger cars, by type of motor energy and size of engine*. DOI: `https://doi.org/10.2908/ROAD_EQS_CARMOT`. (Visited on 02/01/2026).

[10] European Commission. *Commission takes action for clean and competitive automotive sector*. Press Release. Strasbourg, Dec. 2025. URL: `https://ec.europa.eu/commission/presscorner/detail/en/ip_25_3051`.

[11] European Parliament. *CO2 emissions: EP adopts flexibility measures for carmakers*. Press Release. May 2025. URL: `https://www.europarl.europa.eu/news/en/press-room/20250502IPR28225/co2-emissions-ep-adopts-flexibility-measures-for-carmakers`.

[12] Jonn Axsen and Michael Wolinetz. “Reaching 30% plug-in vehicle sales by 2030: Modeling incentive and sales mandate strategies in Canada”. In: *Transportation Research Part D: Transport and Environment* 65 (Dec. 2018), pp. 596–617. ISSN: 1361-9209. DOI: 10.1016/j.trd.2018.09.012. URL: https://www.sciencedirect.com/science/article/pii/S1361920918301809.

[13] Max T. Brozynski and Benjamin D. Leibowicz. “Markov models of policy support for technology transitions”. In: *European Journal of Operational Research* 286.3 (Nov. 2020), pp. 1052–1069. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2020.03.066. URL: https://www.sciencedirect.com/science/article/pii/S037722172030299X.

[14] Roxana J. Javid and Ali Nejat. “A comprehensive model of regional electric vehicle adoption and penetration”. In: *Transport Policy* 54 (Feb. 2017), pp. 30–42. ISSN: 0967-070X. DOI: 10.1016/j.tranpol.2016.11.003. URL: https://www.sciencedirect.com/science/article/pii/S0967070X16303584.

[15] Fatemeh Nazari, Abolfazl (Kouros) Mohammadian, and Thomas Stephens. “Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure”. In: *Transportation Research Part D: Transport and Environment* 72 (July 2019), pp. 65–82. ISSN: 1361-9209. DOI: 10.1016/j.trd.2019.04.010. URL: https://www.sciencedirect.com/science/article/pii/S1361920918311866.

[16] Chris Silvia and Rachel M. Krause. “Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model”. In: *Energy Policy* 96 (Sept. 2016), pp. 105–118. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2016.05.039. URL: https://www.sciencedirect.com/science/article/pii/S0301421516302695.

[17] Chengxiang Zhuge et al. “The potential influence of cost-related factors on the adoption of electric vehicle: An integrated micro-simulation approach”. In: *Journal of Cleaner Production* 250 (Mar. 2020), p. 119479. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.119479. URL: https://www.sciencedirect.com/science/article/pii/S0959652619343495.

[18] Romeo Danielis, Marco Giansoldati, and Lucia Rotaris. “A probabilistic total cost of ownership model to evaluate the current and future prospects of electric cars uptake in Italy”. In: *Energy Policy* 119 (Aug. 2018), pp. 268–281. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2018.04.024. URL: https://www.sciencedirect.com/science/article/pii/S0301421518302404.

[19] Till Gnann et al. “What is the market potential of plug-in electric vehicles as commercial passenger cars? A case study from Germany”. In: *Transportation Research Part D: Transport and Environment* 37 (June 2015), pp. 171–187. ISSN: 1361-9209. DOI: 10.1016/j.trd.2015.04.015. URL: https://www.sciencedirect.com/science/article/pii/S1361920915000474.

[20] Felix Eggers and Fabian Eggers. “Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model”. In: *Technological Forecasting and Social Change* 78.1 (Jan. 2011), pp. 51–62. ISSN: 0040-1625. DOI: 10.1016/j.techfore.2010.06.014. URL: https://www.sciencedirect.com/science/article/pii/S0040162510001356.

[21] Kjeld van Wieringen. *The future of European electric vehicles.* Tech. rep. Brussels: European Parliamentary Research Service, 2024. DOI: 10.2861/1724777. URL: https://www.europarl.europa.eu/RegData/etudes/IDAN/2024/762873/EPRS_IDA(2024)762873_EN.pdf.

[22] Janna Hoppe, Tim Tröndle, and Anthony Patt. ""I didn't like them from the beginning, and I hate them now." Changes in attitudes towards electric vehicles and phase-out policies for conventional cars". In: *Energy Policy* 205 (Oct. 2025), p. 114715. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2025.114715. URL: https://www.sciencedirect.com/science/article/pii/S0301421525002228.

[23] Jessica Jewell and Aleh Cherp. "The feasibility of climate action: Bridging the inside and the outside view through feasibility spaces". In: *WIREs Climate Change* 14.5 (Sept. 2023), e838. ISSN: 1757-7780. DOI: 10.1002/wcc.838. URL: https://doi.org/10.1002/wcc.838 (visited on 02/13/2026).

[24] Nik Zielonka and Evelina Trutnevyte. "Probabilities of reaching required diffusion of granular energy technologies in European countries". In: *iScience* 28.2 (Feb. 2025). ISSN: 2589-0042. DOI: 10.1016/j.isci.2025.111825. URL: https://doi.org/10.1016/j.isci.2025.111825.

[25] Rupert Way et al. "Empirically grounded technology forecasts and the energy transition". In: *Joule* 6.9 (Sept. 2022), pp. 2057–2082. ISSN: 2542-4351. DOI: 10.1016/j.joule.2022.08.009. URL: https://www.sciencedirect.com/science/article/pii/S254243512200410X.

[26] Charles Hoffreumon and Vincent Labhard. *Cross-country cross-technology digitalisation: a Bayesian hierarchical model perspective.* Tech. rep. European Central Bank, 2022. URL: https://ideas.repec.org/p/ecb/ecbwps/20222700.html.

[27] Andrés Ramírez-Hassan and Santiago Montoya-Blandón. "Forecasting from others' experience: Bayesian estimation of the generalized Bass model". In: *International Journal of Forecasting* 36.2 (Apr. 2020), pp. 442–465. ISSN: 0169-2070. DOI: 10.1016/j.ijforecast.2019.05.016. URL: https://www.sciencedirect.com/science/article/pii/S0169207019301943.

[28] Jessica Jewell et al. "Policy-driven growth of technologies to accelerate climate action". In: *Nature Reviews Earth & Environment* (Mar. 2026). ISSN: 2662-138X. DOI: 10.1038/s43017-026-00765-3. URL: https://doi.org/10.1038/s43017-026-00765-3.

[29] Nicolai Meinshausen. "Quantile Regression Forests". In: *Journal of Machine Learning Research* 7 (June 2006), pp. 983–999. URL: https://www.jmlr.org/papers/volume7/meinshausen06a/meinshausen06a.pdf.

[30] Lucy Maybury, Padraig Corcoran, and Liana Cipcigan. "Mathematical modelling of electric vehicle adoption: A systematic literature review". In: *Transportation Research Part D: Transport and Environment* 107 (June 2022), p. 103278. ISSN: 1361-9209. DOI: 10.1016/j.trd.2022.103278. URL: https://www.sciencedirect.com/science/article/pii/S1361920922001067.

[31] Cristian Domarchi and Elisabetta Cherchi. "Electric vehicle forecasts: a review of models and methods including diffusion and substitution effects". In: *Transport Reviews* 43.6 (Nov. 2023), pp. 1118–1143. ISSN: 0144-1647. DOI:

10.1080/01441647.2023.2195687. URL: https://doi.org/10.1080/01441647.2023.2195687.

[32] Matteo Muratori et al. "Electrification pathways for U.S. passenger vehicles". In: *npj Sustainable Mobility and Transport* 2.1 (July 2025), p. 33. ISSN: 3004-8664. DOI: 10.1038/s44333-025-00052-6. URL: https://doi.org/10.1038/s44333-025-00052-6.

[33] Simone Speizer et al. "Integrated assessment modeling of a zero-emissions global transportation sector". In: *Nature Communications* 15.1 (May 2024), p. 4439. ISSN: 2041-1723. DOI: 10.1038/s41467-024-48424-9. URL: https://doi.org/10.1038/s41467-024-48424-9.

[34] Patrick Plötz et al. "Greenhouse gas emission budgets and policies for zero-Carbon road transport in Europe". In: *Climate Policy* 23.3 (Mar. 2023), pp. 343–354. ISSN: 1469-3062. DOI: 10.1080/14693062.2023.2185585. URL: https://doi.org/10.1080/14693062.2023.2185585.

[35] Jingbo Wang et al. "Spatiotemporal planning of electric vehicle charging infrastructure: Demand estimation and grid-aware optimization under uncertainty". In: *iScience* 28.9 (Sept. 2025), p. 113368. ISSN: 2589-0042. DOI: 10.1016/j.isci.2025.113368. URL: https://www.sciencedirect.com/science/article/pii/S2589004225016293.

[36] Mohannad Kabli et al. "A stochastic programming approach for electric vehicle charging station expansion plans". In: *International Journal of Production Economics* 220 (Feb. 2020), p. 107461. ISSN: 0925-5273. DOI: 10.1016/j.ijpe.2019.07.034. URL: https://www.sciencedirect.com/science/article/pii/S0925527319302713.

[37] S.A. MirHassani, A. Khaleghi, and F. Hooshmand. "Two-stage stochastic programming model to locate capacitated EV-charging stations in urban areas under demand uncertainty". In: *EURO Journal on Transportation and Logistics* 9.4 (Dec. 2020), p. 100025. ISSN: 2192-4376. DOI: 10.1016/j.ejtl.2020.100025. URL: https://www.sciencedirect.com/science/article/pii/S2192437620301552.

[38] Noémie Jeannin et al. "Mapping the charging demand for electric vehicles in 2050 from mobility habits". In: *Sustainable Energy, Grids and Networks* 39 (Sept. 2024), p. 101468. ISSN: 2352-4677. DOI: 10.1016/j.segan.2024.101468. URL: https://www.sciencedirect.com/science/article/pii/S2352467724001978.

[39] Jiaman Wu et al. "Planning charging stations for 2050 to support flexible electric vehicle demand considering individual mobility patterns". In: *Cell Reports Sustainability* 1.1 (Jan. 2024), p. 100006. ISSN: 2949-7906. DOI: 10.1016/j.crsus.2023.100006. URL: https://www.sciencedirect.com/science/article/pii/S294979062300006X.

[40] Frank M. Bass. "A New Product Growth for Model Consumer Durables". In: *Management Science* 15.5 (1969), pp. 215–227. ISSN: 00251909, 15265501. URL: http://www.jstor.org/stable/2628128.

[41] Leonardo Bitencourt et al. "Bass Diffusion Model Adaptation Considering Public Policies to Improve Electric Vehicle Sales—A Brazilian Case Study". In: *Energies* 14.17 (2021), p. 5435. ISSN: 1996-1073. DOI: 10.3390/en14175435.

[42] Anqi Chen et al. "A Sustainable Road Transport Decarbonisation: The Scenario Analysis of New Energy Vehicle in China." eng. In: *International journal of environmental research and public health* 20.4 (Feb. 2023). ISSN: 1660-4601 1661-7827. DOI: 10.3390/ijerph20043406.

[43] Gabriel Möring-Martínez, Murat Senzeybek, and Patrick Jochem. "Clustering the European Union electric vehicle markets: A scenario analysis until 2035". In: *Transportation Research Part D: Transport and Environment* 135 (Oct. 2024), p. 104372. ISSN: 1361-9209. DOI: 10.1016/j.trd.2024.104372. URL: https://www.sciencedirect.com/science/article/pii/S1361920924003298.

[44] Shima Veysi et al. "Electric Vehicle Sales Forecast for the UK: Integrating Machine Learning, Time Series Models, and Global Trends". In: *Algorithms* 18.7 (2025), p. 430. ISSN: 1999-4893. DOI: 10.3390/a18070430.

[45] Yong Zhang et al. "Forecasting electric vehicles sales with univariate and multivariate time series models: The case of China". In: *PLOS ONE* 12.5 (May 2017), e0176729. DOI: 10.1371/journal.pone.0176729. URL: https://doi.org/10.1371/journal.pone.0176729.

[46] Minfeng Wu and Wen Chen. "Forecast of Electric Vehicle Sales in the World and China Based on PCA-GRNN". In: *Sustainability* 14.4 (2022), p. 2206. ISSN: 2071-1050. DOI: 10.3390/su14042206.

[47] Nele Rietmann, Beatrice Hügler, and Theo Lieven. "Forecasting the trajectory of electric vehicle sales and the consequences for worldwide CO2 emissions". In: *Journal of Cleaner Production* 261 (July 2020), p. 121038. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2020.121038. URL: https://www.sciencedirect.com/science/article/pii/S0959652620310854.

[48] Minal Chandra et al. "Paths of progress: Forecasting global electric vehicle demand amidst demographic and economic growth". In: *Transportation Research Part D: Transport and Environment* 147 (Oct. 2025), p. 104928. ISSN: 1361-9209. DOI: 10.1016/j.trd.2025.104928. URL: https://www.sciencedirect.com/science/article/pii/S1361920925003384.

[49] Steffen Link et al. "Feasibility of meeting future battery demand via domestic cell production in Europe". In: *Nature Energy* 10.4 (Apr. 2025), pp. 526–534. ISSN: 2058-7546. DOI: 10.1038/s41560-025-01722-y. URL: https://doi.org/10.1038/s41560-025-01722-y.

[50] Adrian Odenweller et al. "Probabilistic feasibility space of scaling up green hydrogen supply". In: *Nature Energy* 7.9 (Sept. 2022), pp. 854–865. ISSN: 2058-7546. DOI: 10.1038/s41560-022-01097-4. URL: https://doi.org/10.1038/s41560-022-01097-4.

[51] J. Doyne Farmer and François Lafond. "How predictable is technological progress?" In: *Research Policy* 45.3 (Apr. 2016), pp. 647–665. ISSN: 0048-7333. DOI: 10.1016/j.respol.2015.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0048733315001699.

[52] R Core Team. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing, 2025. URL: https://www.R-project.org/.

[53] Nuno Bento and Charlie Wilson. "Measuring the duration of formative phases for energy technologies". In: *Environmental Innovation and Societal Transitions* 21 (Dec. 2016), pp. 95–112. ISSN: 2210-4224. DOI: 10.1016/j.eist.2016.04.004. URL: https://www.sciencedirect.com/science/article/pii/S2210422416300284.

[54] World Bank Group. *Mobile cellular subscriptions*. 2026. URL: https://data.worldbank.org/indicator/IT.CEL.SETS.P2.

[55] Marie Laure Delignette-Muller and Christophe Dutang. "fitdistrplus: An R Package for Fitting Distributions". In: *Journal of Statistical Software* 64.4 (2015), pp. 1–34. DOI: 10.18637/jss.v064.i04.

[56] Wenxin Ye et al. "Probabilistic analysis of tripling global renewables based on Bayesian-inferred growth dynamics model". In: *Renewable Energy* 256 (Jan. 2026), p. 124496. ISSN: 0960-1481. DOI: 10.1016/j.renene.2025.124496. URL: https://www.sciencedirect.com/science/article/pii/S0960148125021603.

[57] Eyal Li, Georg Bieker, and Arijit Sen. *Electrifying road transport with less mining: A global and regional battery material outlook*. Tech. rep. ICCT, 2024. URL: http://theicct.org/publication/EV-battery-materials-demand-supply-dec24.

[58] Simon Árpád Funke et al. "How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison". In: *Transportation Research Part D: Transport and Environment* 77 (Dec. 2019), pp. 224–242. ISSN: 1361-9209. DOI: 10.1016/j.trd.2019.10.024. URL: https://www.sciencedirect.com/science/article/pii/S136192091930896X.

[59] Tilmann Gneiting and Adrian E Raftery. "Strictly Proper Scoring Rules, Prediction, and Estimation". In: *Journal of the American Statistical Association* 102.477 (Mar. 2007), pp. 359–378. ISSN: 0162-1459. DOI: 10.1198/016214506000001437. URL: https://doi.org/10.1198/016214506000001437.

A
Appendix

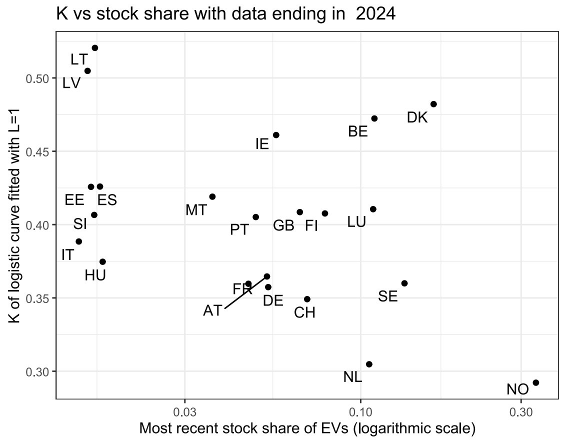
A.1 Methods

A.1.1 Data used for projections

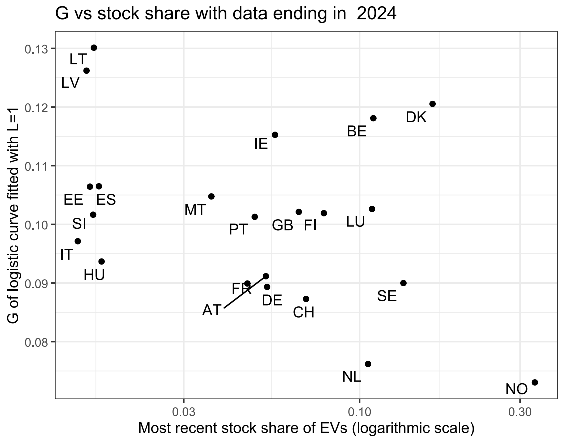
Countries	Data source used for EV stock values	Modifications made to data
Austria, Bulgaria, Cyprus, Denmark, Estonia, Finland, France, Germany, Luxembourg, Malta, Poland, Portugal, Slovakia, Spain, Sweden	Eurostat	None
Belgium, Greece, Italy, Netherlands, Switzerland	IEA	None
Croatia	Eurostat	Extrapolated PHEV values from 2021-2023 by assuming linear growth
Czechia, Lithuania	Eurostat	Extrapolated 2022 PHEV value by assuming linear growth
Hungary	Eurostat	Interpolated PHEV values from 2019-2022 by assuming linear growth
Ireland	Eurostat	Extrapolated 2021 and 2022 PHEV values by assuming linear growth
Latvia, Slovenia	Eurostat	Extrapolated 2021 PHEV value by assuming linear growth
Norway	IEA	Imputed 2010-2012 total vehicle stock values with 2013 vehicle stock reported by Eurostat
Romania	Eurostat	Removed erroneous BEV values from before 2018 and extrapolated 2022 PHEV value by assuming linear growth
United Kingdom	IEA	Filled in missing total vehicle stock values from Eurostat with data from UK Vehicle Licensing and Statistics

Table A.1: Source of data and modifications made for each country used in synthesized data set. All countries use total passenger vehicle stock values provided by Eurostat without modifications, unless otherwise specified.

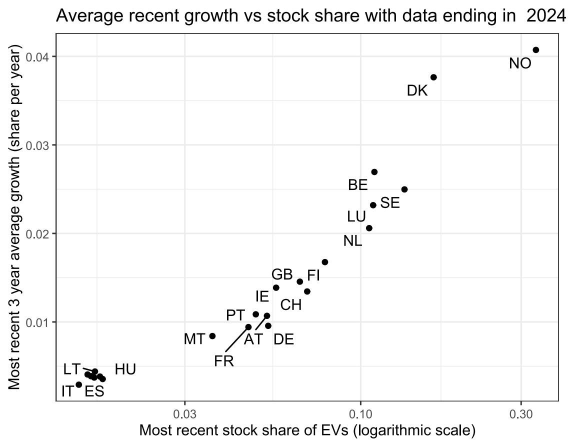
A.1.2 Empirical growth metrics



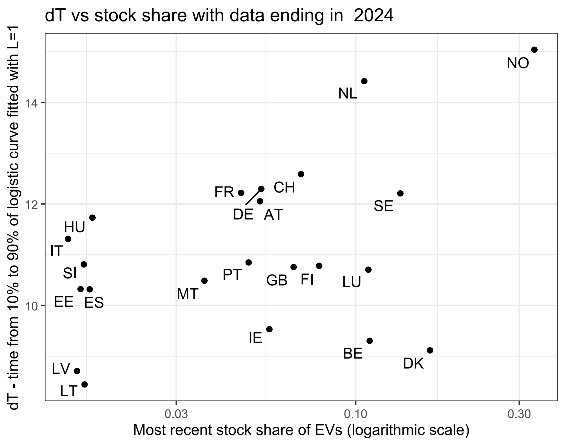
(a) K



(b) G

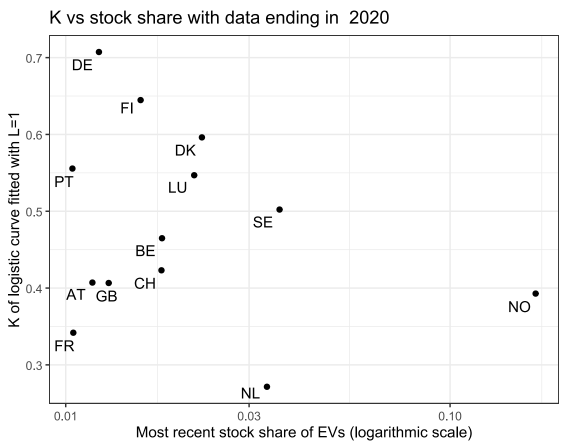


(c) R3

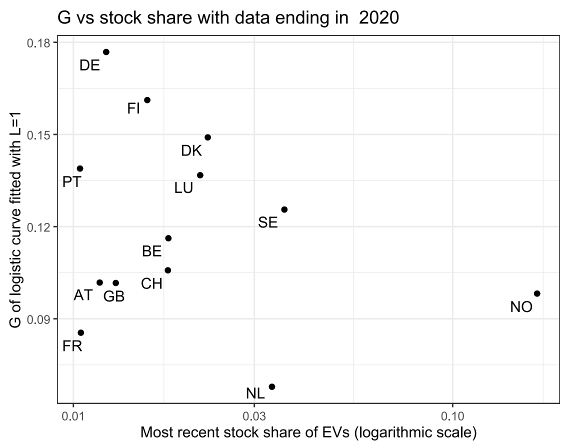


(d) ΔT

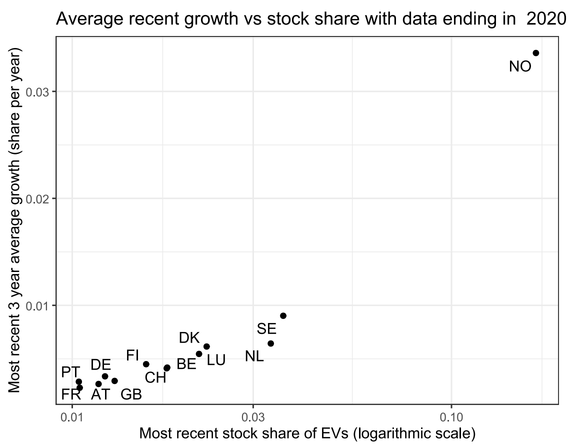
Figure A.1: Growth metrics versus 2024 stock share for EU27 countries that have passed takeoff in addition to Norway, Switzerland, and the United Kingdom.



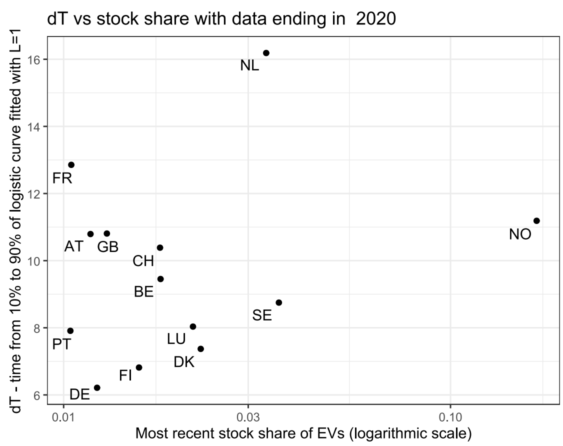
(a) K



(b) G



(c) R3



(d) ΔT

Figure A.2: Growth metrics from data available in 2020 versus 2020 stock share.

Country	2024 Stock Share	Takeoff Year	K	G	R3	ΔT
Austria	0.012	2020	0.407	0.102	0.003	10.8
Belgium	0.018	2019	0.465	0.116	0.004	9.5
Denmark	0.023	2020	0.596	0.149	0.006	7.4
Finland	0.016	2020	0.645	0.161	0.004	6.8
France	0.010	2020	0.342	0.085	0.002	12.9
Germany	0.012	2020	0.707	0.177	0.003	6.2
Luxembourg	0.022	2019	0.547	0.137	0.005	8.0
Netherlands	0.033	2015	0.271	0.068	0.006	16.2
Norway	0.167	2014	0.393	0.098	0.034	11.2
Portugal	0.010	2020	0.556	0.139	0.003	7.9
Sweden	0.036	2018	0.502	0.126	0.009	8.8
Switzerland	0.018	2019	0.423	0.106	0.004	10.4
United Kingdom	0.013	2020	0.407	0.102	0.003	10.8

Table A.2: Growth metrics calculated for each country past takeoff using only data available in 2020.

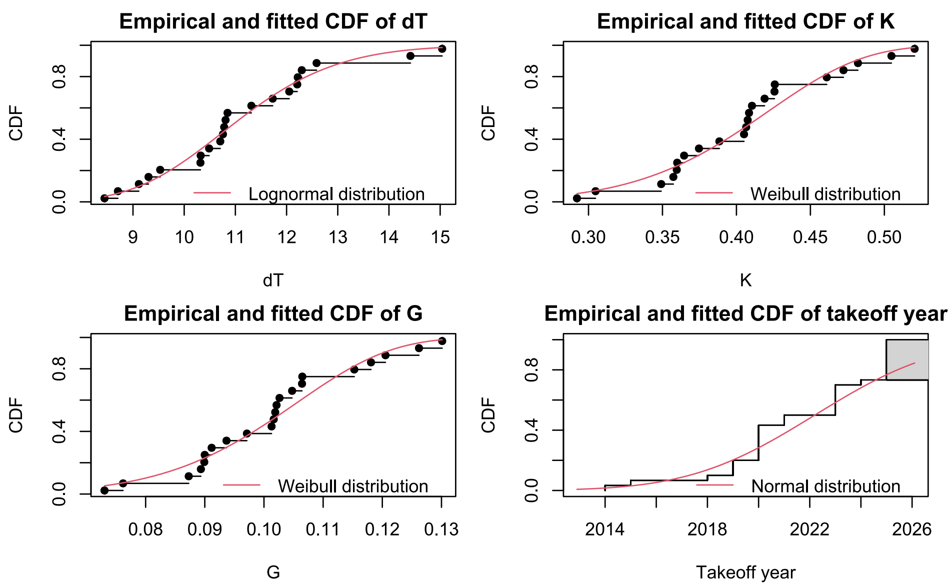


Figure A.3: Empirical and fitted distributions for calculated values of ΔT, K, G, and takeoff year. Distributions are plotted as Cumulative Distribution Functions, which show the probability (on the y-axis) that a random variable will be equal to or less than the value on the x-axis.

A.1.3 Configuring Prolong-EV

There are a large number of configurable parameters that define the behavior of Prolong-EV. These are carefully chosen through analysis and experiments with out-of-sample simulated test data with the goal of producing well-calibrated results based on robust analysis wherever possible. This section describes some of the most important decisions made during the calibration of Prolong-EV for use with EV data from 2024 and earlier. A summary of the tests used to configure Prolong-EV are listed in Table A.3

Test	Name	Data	Description
1	Feature importance	Simulation training data	Comparing importance values produced by random forest when trained using all possible features
2	Feature correlation	Simulation training data	Identifying correlations between potential features
3	Feature configuration	Out-of-sample simulation data	Comparing hindcasting performance for different feature configurations
4	Number of Monte Carlo runs	Out-of-sample simulation data	Comparing hindcasting performance with number of runs of Monte Carlo simulation
5	Cutoff configuration	Out-of-sample simulation data	Comparing hindcasting performance for different cutoff configurations

Table A.3: Summary of tests run on Prolong-EV for configuration.

The trajectories produced in the Monte Carlo simulation are defined by a number of parameters that are based on the growth trends observed in empirical data. These growth metrics were calculated as discussed in an Section 3.2 and are described in Tables 3.1 and 3.2. However, the distributions used in the Monte Carlo simulation have a higher variance than trends seen empirically, as it is important to train the quantile random forest with a sufficiently broad set of data. This distinguishes Prolong-EV from the naive projection, since in the case of the naive projection the results of the Monte Carlo simulation are being used directly to draw conclusions about likely outcomes and levels of uncertainty. In Prolong-EV the results of the Monte Carlo simulation do not represent expected outcomes or uncertainty, but rather are a tool to train the machine learning algorithm to distinguish possible future outcomes based on early observed trends. Figures A.4 and A.5 show some examples of the resulting trajectories.

The chosen growth metrics that define these trajectories are summarized in Table 3.4. L is set to 1, like in the naive projection, due to the expectation that EVs will eventually make up nearly 100% of the passenger vehicle market in the EU. G is chosen to have a mean matching the empirically observed mean of 0.1, but a much larger standard deviation so that all empirically observed values lie within one standard deviation and ensure that the range of trajectories produced represents a

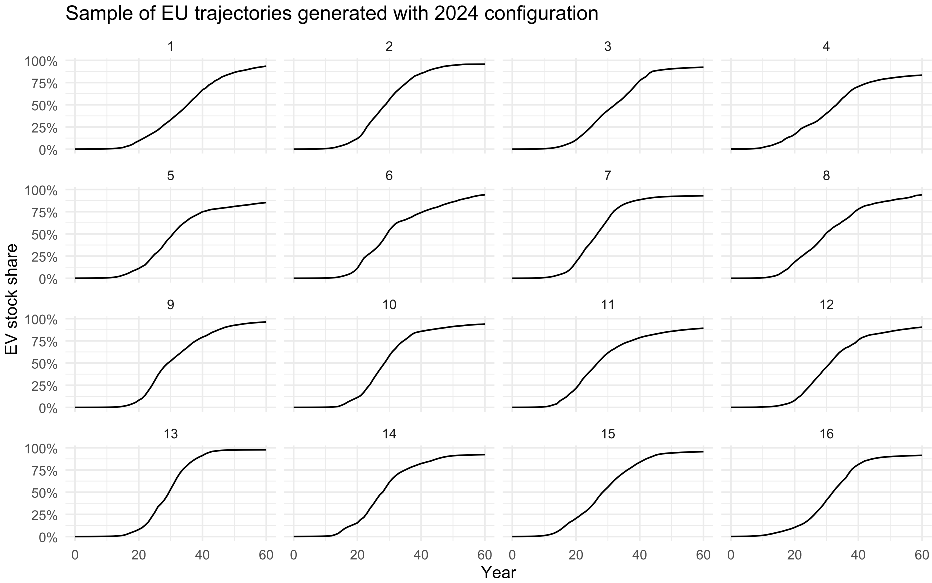


Figure A.4: Several examples of EU stock share trajectories produced by the Monte Carlo simulation that generates training data for Prolong-EV.

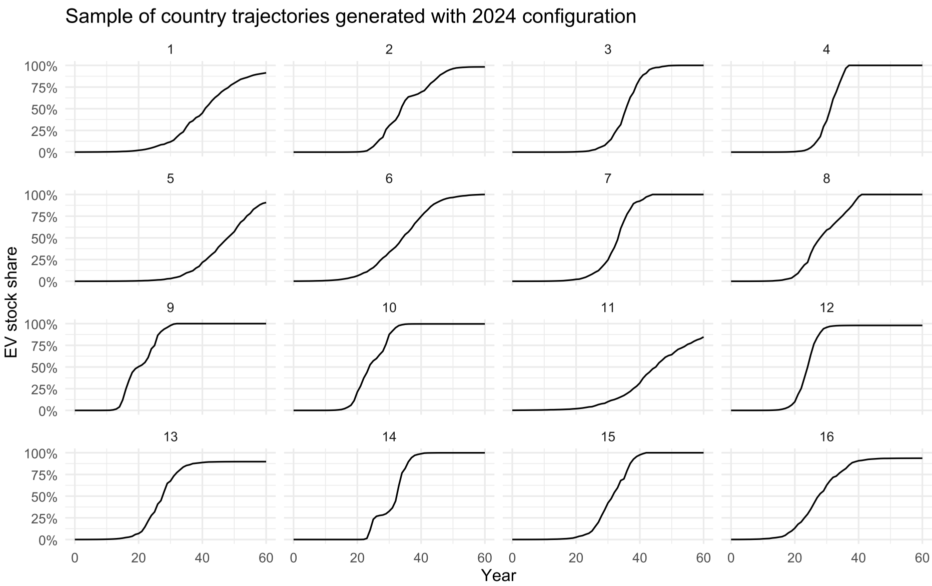


Figure A.5: Several examples of individual country stock share trajectories produced by the Monte Carlo simulation that generates training data for Prolong-EV.

sufficiently broad range of possibilities. The minimum and maximum values are set based on an understanding of particularly fast growth being very unlikely, while slow outliers are more likely. The value for takeoff delay has a standard deviation that is itself a distribution so as to create some worlds in which countries are tightly clustered in their takeoff and some worlds in which there is a large range of takeoff years. The pulse parameters are chosen to create pulses that have similar behavior as pulses that have been observed in other policy-driven technologies [28], while allowing for a wide range of possible trajectories.

In addition to calibrating the trajectories produced, the selection of features used to train the quantile random forest is chosen through a multi-step process. First, potential features are considered based on a subjective understanding of the information they provide about technology growth. Next, a quantile random forest is trained using all of those features, resulting in an importance value for each feature. A few features show significantly higher importance values than the others, including the latest EU EV stock share and three year average EU EV stock share growth rate, indicating that these features may be some of the most helpful for classifying future growth based on early trends. However, feature importance is not a clear indicator of which features will function better than others and can also indicate statistical properties of the feature instead of indicating that the feature causes the model to perform well. For that reason, feature importance is not considered beyond identifying the few features that have particularly high importance values.

Next, correlations between the considered features are examined to ensure that redundant features are not included together in one feature configuration. Some features are found to have strong correlations, such as the maximum growth rate and the most recent growth rate, but most are uncorrelated or weakly correlated. Next, 24 different feature configurations are designed based on earlier findings and an understanding of which features could complement the information provided by each other. The different feature configurations are tested using 50 simulated test trajectories to compare the performance of the configurations on data that could plausibly represent different EV growth trajectories. Based on an analysis of accuracy, bias, and uncertainty intervals resulting from the different feature configurations, as seen in Figure A.6, the final configuration is chosen.

The years at which simulation data is truncated are also chosen based on a combination of analysis and testing. First, a selection of cutoff years is chosen based on these values being sufficiently broad while also being centered around the number of years of EV growth observed in empirical data. Several variations of this configuration are created and tested using simulated hindcasting with out-of-sample trajectories. The results indicate that as long as the values chosen resemble that of the empirical data there is not a large difference in error, but the selection of values does have a significant impact on bias of the results, as seen in Figure A.7. This highlights the importance of configuring Prolong-EV with training data truncation that matches the length that is being used to make a projection.

The number of trajectories produced by the Monte Carlo simulation is also explored, and it is found that increasing the number beyond 1000 trajectories does not result in a significant increase in performance. For that reason, 1000 trajectories are produced by the simulation in the configured model.

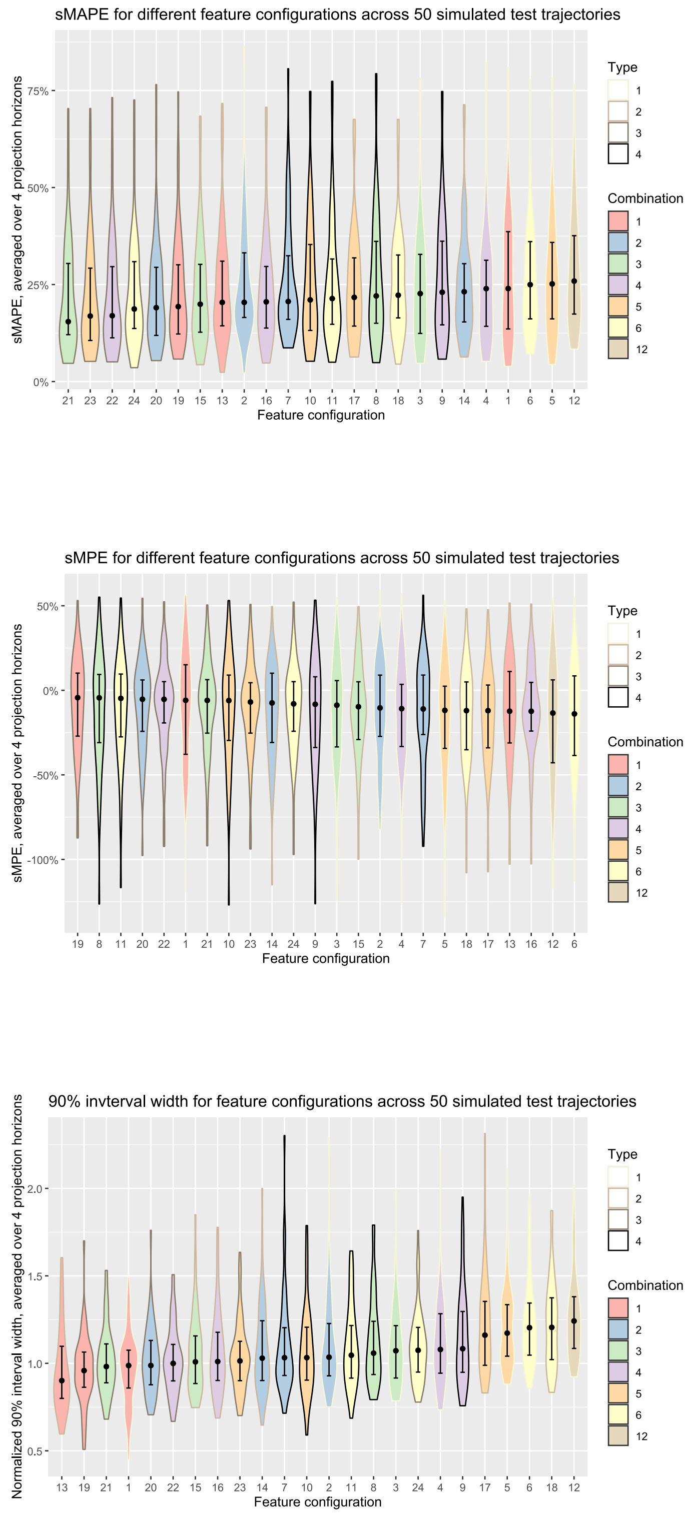
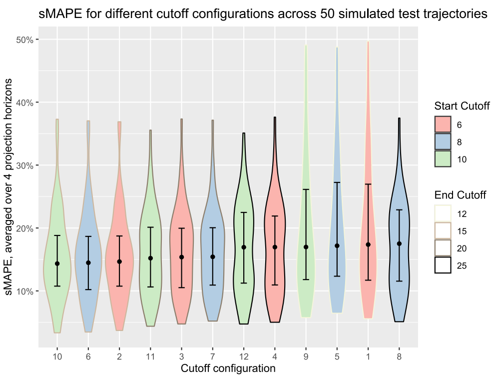
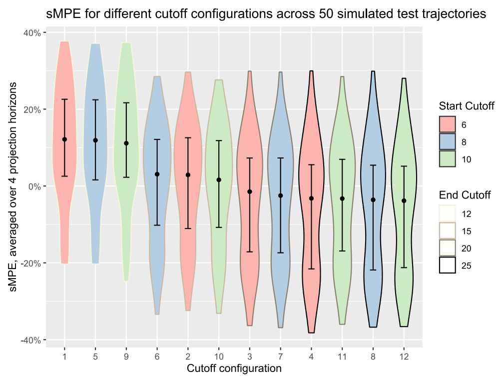


Figure A.6: Metrics of accuracy, bias, and uncertainty compared between 24 different feature configurations. The outline color indicates which primary features were included while the fill color indicates a certain combination of additional features.



(a) Error



(b) Bias

Figure A.7: Metrics of accuracy and bias comparing different configurations of truncation values for simulated training data. Fill color indicates the minimum cutoff year in the configuration while outline color indicates the maximum cutoff year in the configuration, which possible cutoff year values being 6, 8, 10, 12, 15, 20, and 25.

A.1.4 Evaluating performance with out-of-sample simulation data

Configuration	Modifications from base configuration
1	Trajectories have faster growth with mean G increased from 0.1 to 0.2
2	Trajectories have slower growth with mean G decreased from 0.1 to 0.08
3	More distinct growth pulses with delay between pulses increased by 3 years and the stock share at which the pulse begins decreased to 0.01
4	Less distinct growth pulses with delay between pulses decreased by 3 years and the stock share at which the pulse begins increased to 0.1
5	ΔT parameterization rather than G parameterization

Table A.4: Parameterizations used for creating out-of-sample simulation test data. Twenty trajectories are generated from each of these five configurations to create a total of 100 test trajectories.

A.1.5 EV hindcasting

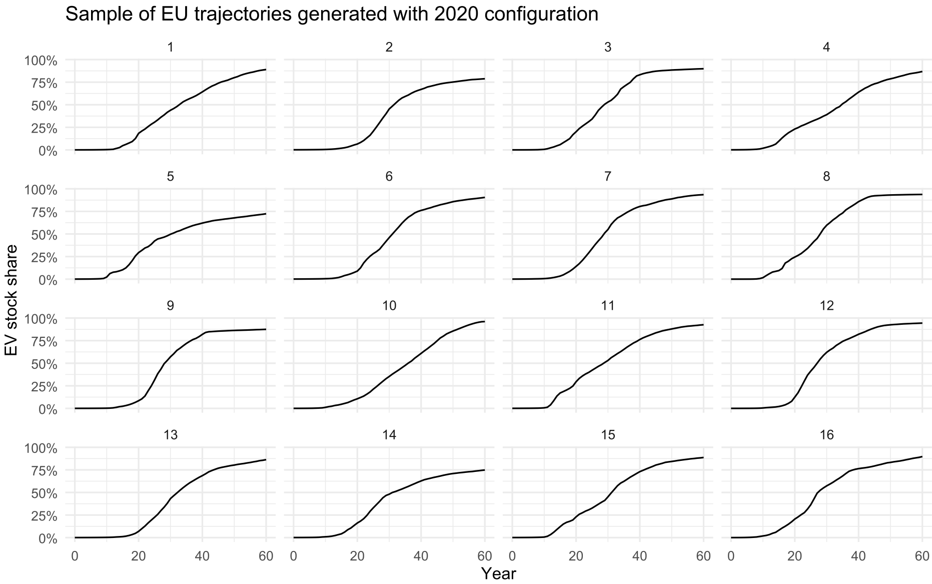


Figure A.8: Several examples of EU stock share trajectories produced by the Monte Carlo simulation that generates training data for Prolong-EV as part of hindcasting.

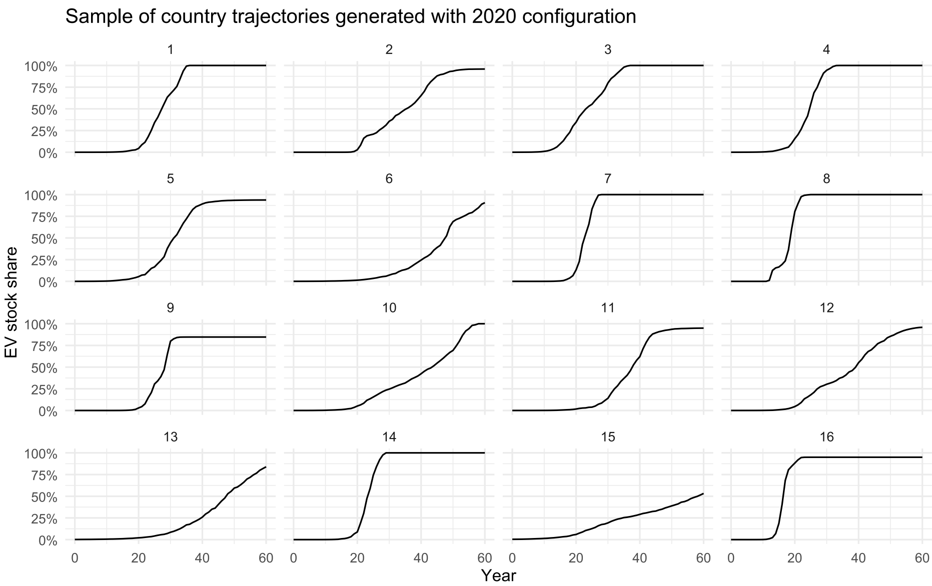


Figure A.9: Several examples of individual country stock share trajectories produced by the Monte Carlo simulation that generates training data for Prolong-EV as part of hindcasting.

A.2 Metrics for assessing probabilistic projections

A number of metrics can be used to assess the quality of projections when comparing against empirical data. The different metrics (Table 3.6) quantify different aspects of performance, with sMAPE measuring accuracy, sMPE measuring bias, CRPS quantifying accuracy and uncertainty together as an index [59], coverage rates providing information about the frequency with which empirical data falls into uncertainty intervals, and interval widths quantifying the magnitude of uncertainty. sMAPE and sMPE both compare empirical values to only the projection mean, and therefore cannot be used to assess uncertainty. They also quantify error and bias as a percentage of the empirical value, meaning that when the empirical value is very low, sMAPE and sMPE become large. On the other hand, the magnitude of CRPS decreases with the empirical value. This is important to consider when comparing sMAPE, sMPE, and CRPS across different time horizons when the empirical values have significantly different magnitudes. CRPS can be challenging to interpret in any case, as it does not have units but is an index that can take on any positive value. However, observations that are consistent between all three metrics provide confidence that the trends seen are not merely artifacts of the methods used to calculate the metrics, so it is recommended to use all three of these metrics together to best assess the performance of the model.

The coverage rate is a metric that can provide important insight into the meaning of projected uncertainty. It is the percentage of trajectory values that fall into the projection's uncertainty interval. When a quantile random forest is trained with ideal training data and then used to make predictions for data from that set, the coverage rate corresponds to the percentage associated with that prediction interval (i.e. the 50% coverage rate will be 50%) [29]. This holds true for many other machine learning models, therefore making coverage rate a useful metric for evaluating how well the training data captures the uncertainty of trajectories that can be used to test a model. However, coverage rate values are noisier when there are a smaller number of true values to compare against, making it hard to use in the case of individual empirical trajectories.

The projected uncertainty intervals can be useful in evaluating projections. Interval widths, unlike the other metrics discussed, can be used to evaluate projections even when there is no empirical data available to compare against. The interval width can be normalized by the mean of the projection value to provide a metric for evaluating how much the uncertainty dominates the projection. As a rule of thumb, a normalized interval width greater than one indicates a situation in which uncertainty dominates the projection. However, when projection mean values are very small it becomes easy for the normalized interval width to exceed one, and for this reason the values should be considered more carefully when making projections for early technology growth with low values of deployment projected. In the case of EVs, the interval width can be compared to the total range of possible values for EV deployment, meaning that a 25% interval width covers one quarter of the total possible future values of EV stock share. This can be intuitively understood as a large range of uncertainty.

A.3 Results

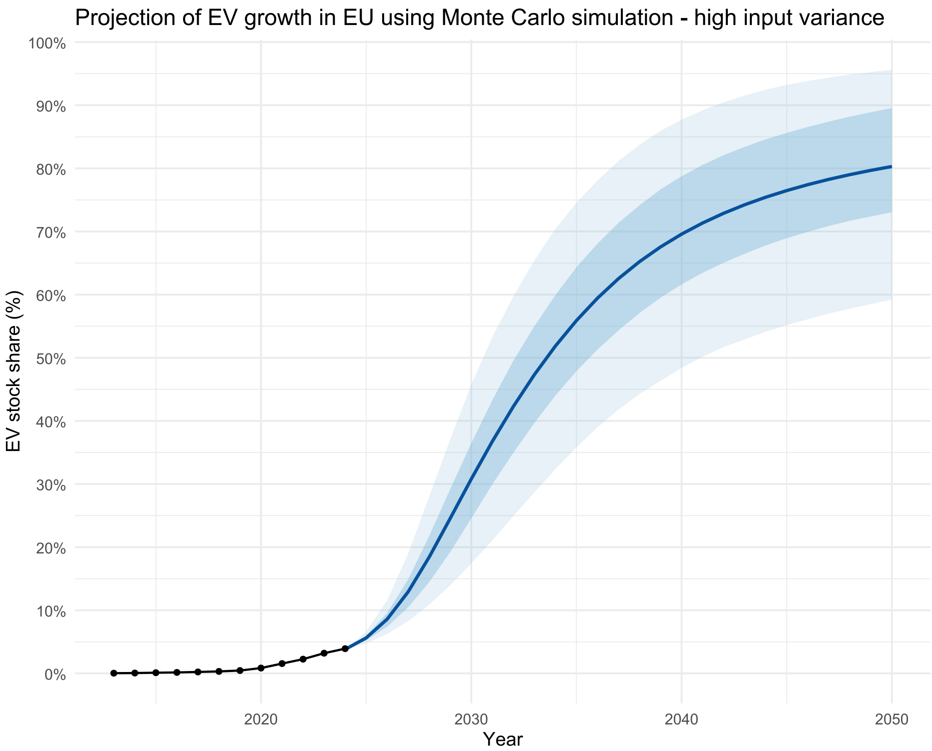
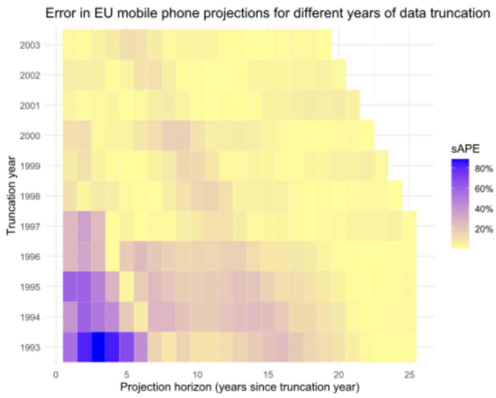
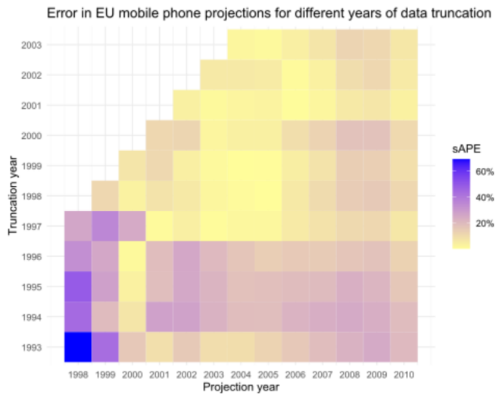


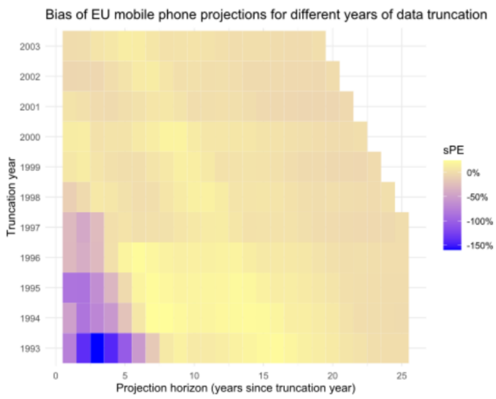
Figure A.10: Naive projection of EV stock share in the EU made using 2024 data and an input distribution of K with a five times higher variance than the empirical variance used in the original projection (Figure 4.1).



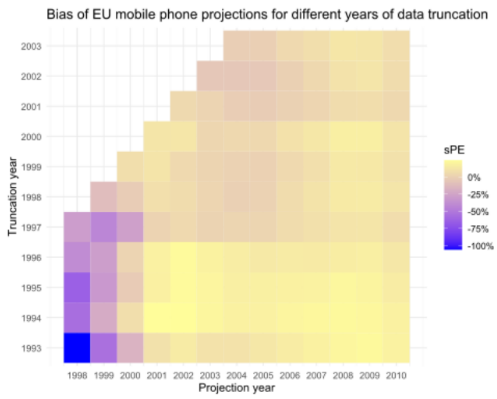
(a) sAPE



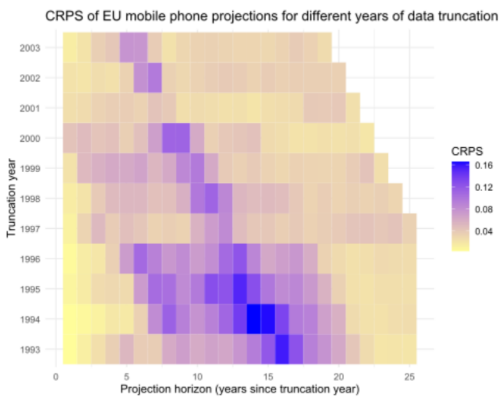
(b) sAPE



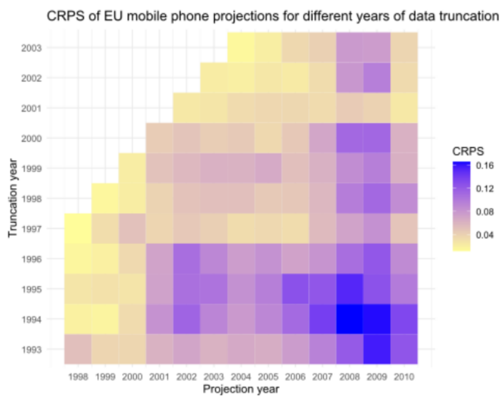
(c) sPE



(d) sPE



(e) CRPS



(f) CRPS

Figure A.11: Heatmaps of hindcasting performance of Prolong-EV using mobile phone subscription data. X-axes show either the projection year or projection horizon and y-axes show the year at which data is truncated.

DEPARTMENT OF ENVIRONMENTAL AND ENERGY SCIENCES
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden
www.chalmers.se

CHALMERS
UNIVERSITY OF TECHNOLOGY