Forecasting Model for the Integration of Battery Electric Vehicles into the Power Grid using System Dynamics

Dissertation

zur Erlangung des akademischen Grades

Doktoringenieur

(Dr.-Ing.)

von **M. Sc. Mauro dos Santos Ortiz**

geb. am 09.02.1994 in Cruz Alta/RS, Brasilien

genehmigt durch die Fakultät für Elektrotechnik und Informationstechnik
der Otto-von-Guericke-Universität Magdeburg

Gutachter:

Univ.-Prof. Dr. Eng. Daniel Pinheiro Bernardon

Univ.-Prof. Dr.-Ing. habil. Martin Wolter

Promotionskolloquium am 07. November 2024

Res Electricae Magdeburgenses

Magdeburger Forum zur Elektrotechnik, Jg. 22, Band 102, 2024
http://www.mafo.ovgu.de/

IMPRESSUM

Herausgeber:

- Prof. Dr.-Ing. Andreas Lindemann, Lehrstuhl für Leistungselektronik, Institut für Elektrische Energiesysteme
- Prof. Dr.-Ing. habil. Martin Wolter, Lehrstuhl für Elektrische Netze und Erneuerbare Energie, Institut für Elektrische Energiesysteme
- Prof. Dr. rer. nat. Georg Rose, Lehrstuhl für Medizinische Telematik/Medizintechnik, Institut für Medizintechnik
- Prof. Dr.-Ing. Ralf Vick, Lehrstuhl für Elektromagnetische Verträglichkeit, Institut für Medizintechnik

Gründungsherausgeber:

- Prof. Dr. rer. nat. habil. Jürgen Nitsch
- Prof. Dr.-Ing. habil. Zbigniew Antoni Styczynski

alle: Otto-von-Guericke-Universität Magdeburg
Postfach 4120, 39016 Magdeburg

V. i. S. d. P.:
Dr.-Ing. Mauro dos Santos Ortiz
Otto-von-Guericke-Universität Magdeburg, Postfach 4120, 39016 Magdeburg

1. Auflage, Magdeburg, Otto-von-Guericke-Universität, 2024
Zugl.: Magdeburg, Univ., Diss., 2024

Auflage: 20

Redaktionsschluss: November 2024

ISSN: 1612-2526
ISBN: 978-3-948749-53-8
DOI: 10.24352/UB.OVGU-2024-097

Bezug über die Herausgeber

Druck: docupoint GmbH
Otto-von-Guericke-Allee 14, 39179 Barleben

FEDERAL UNIVERSITY OF SANTA MARIA
CENTER OF TECHNOLOGY
GRADUATE PROGRAM IN ELECTRICAL ENGINEERING

Mauro dos Santos Ortiz

FORECASTING MODEL FOR THE INTEGRATION OF BATTERY ELECTRIC VEHICLES INTO THE POWER GRID USING SYSTEM DYNAMICS

Santa Maria, RS
2024

Mauro dos Santos Ortiz

FORECASTING MODEL FOR THE INTEGRATION OF BATTERY ELECTRIC VEHICLES INTO THE POWER GRID USING SYSTEM DYNAMICS

Thesis submitted to the Doctorate Course of the Graduate Program in Electrical Engineering, Concentration Area in Energy Processing, of the Federal University of Santa Maria (UFSM-RS), in cotutelle with the Faculty of Electrical Engineering and Information Technology of the Otto-von-Guericke University Magdeburg (OVGU), as a requirement to obtain the degree of **Doctor in Electrical Engineering**. Thesis defense held over videoconference.

Advisor: Prof. Daniel Pinheiro Bernardon

Advisor: Prof. Martin Wolter

Santa Maria, RS
2024

This study was financied in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001

dos Santos Ortiz, Mauro
Forecasting Model for the Integration of Battery Electric Vehicles into the Power Grid using System Dynamics / Mauro dos Santos Ortiz.- 2024.
148 p.; 30 cm

Orientadores: Daniel Pinheiro Bernardon, Martin Wolter
Tese (doutorado) - Universidade Federal de Santa Maria, Centro de Tecnologia, Programa de Pós-Graduação em Engenharia Elétrica, RS, 2024

1. Analytic hierarchy process. 2. Dinâmica de sistemas. 3. Lógica fuzzy. 4. Modelo de Bass. 5. Modelo de previsão. 6. Veículo elétrico a bateria. I. Bernardon, Daniel Pinheiro II. Wolter, Martin III. Título.

Declaro, MAURO DOS SANTOS ORTIZ, para os devidos fins e sob as penas da lei, que a pesquisa constante neste trabalho de conclusão de curso (Tese) foi por mim elaborada e que as informações necessárias objeto de consulta em literatura e outras fontes estão devidamente referenciadas. Declaro, ainda, que este trabalho ou parte dele não foi apresentado anteriormente para obtenção de qualquer outro grau acadêmico, estando ciente de que a inveracidade da presente declaração poderá resultar na anulação da titulação pela Universidade, entre outras consequências legais.

Mauro dos Santos Ortiz

FORECASTING MODEL FOR THE INTEGRATION OF BATTERY ELECTRIC VEHICLES INTO THE POWER GRID USING SYSTEM DYNAMICS

Thesis submitted to the Doctorate Course of the Graduate Program in Electrical Engineering, Concentration Area in Energy Processing, of the Federal University of Santa Maria (UFSM-RS), in cotutelle with the Faculty of Electrical Engineering and Information Technology of the Otto-von-Guericke University Magdeburg (OVGU), as a requirement to obtain the degree of **Doctor in Electrical Engineering**.

Achim Kienle, Dr.-Ing. (OVGU)
(Comission Chair)

Daniel Pinheiro Bernardon, Dr. Eng. (UFSM)
(Advisor)

Martin Wolter, Dr.-Ing. habil. (OVGU)
(Advisor)

Adriano Peres de Morais, Dr. Eng. (UFSM)

Maurício Sperandio, Dr. Eng. (UFSM)

Thilo Pionteck, Dr.-Ing. (OVGU)

Santa Maria, RS
2024

M.Sc. Mauro dos Santos Ortiz

Forecasting Model for the Integration of Battery Electric Vehicles into the Power Grid using System Dynamics

This doctoral thesis was written as part of a cotutelle procedure between the
Otto-von-Guericke University (OVGU, Germany) and the
Federal University of Santa Maria (UFSM, Brazil)

Diese Doktorarbeit ist entstanden im Rahmen eines Cotutelle-Verfarens zwischen der
Otto-von-Guericke-Universität (OVGU, Deutschland) und der
Bundesuniversität Santa Maria (UFSM, Brasilien)

Esta tese de doutorado foi escrita como parte de um programa de cotutela entre a
Universidade Otto-von-Guericke (OVGU, Alemanha) e a
Universidade Federal de Santa Maria (UFSM, Brasil)

Abstract

Growing discussions about the depletion of natural resources and the environmental risks arising from the extensive use of fossil fuels in the productive sectors are mobilizing public and private agents to rethink strategies for sustainable economic and social development. At the same time, various research projects are being conducted with a focus on generating energy from renewable sources and developing technologies and strategies for the efficient and intelligent use of energy. In the transportation sector, which is responsible for high emissions of greenhouse gases, electric vehicles (EVs) are a promising alternative. The global market for EVs is currently booming, and the outlook is good for a decrease in acquisition costs, especially battery costs. It is also expected that the range of vehicles will increase and the charging infrastructure will improve. Moreover, the formulation of public policies and subsidies for the purchase of EVs represent major incentives for their adoption, especially by residential consumers. However, whether they buy an EV or not depends on the value judgment and subjectivity of each human being. In the literature, studies can be found, that discuss the penetration of EVs in a specific way and are restricted to a few variables. For this reason, the aim of this doctoral thesis is to develop a global model for forecasting the diffusion of battery electric vehicles (BEVs) among residential consumers, analyzing the variables that influence their decision-making. To do this, the system dynamics (SD) technique is used together with the Bass model, considering quantitative and qualitative aspects of decision-making to determine the diffusion of BEVs over time. Additionally, the model encompasses the analytic hierarchy process (AHP) and fuzzy logic to address the uncertainties and region-specific characteristics that influence BEV adoption. Case studies in Brazil and Germany demonstrate the model's flexibility and accuracy in forecasting adoption trends and highlight the different impacts of public policies, infrastructure, market conditions, among others. In addition to the academic and scientific contributions, the developed model can support governments in formulating public policies to promote electric mobility. For companies in the energy sector, it provides important information for studies on the expansion of the electrical energy system. It also helps automotive companies align their sales strategies and expand their business models.

Keywords: Analytic hierarchy process. Bass model. Battery electric vehicle. Forecasting model. Fuzzy logic. System dynamics.

Kurzzusammenfassung

Die zunehmenden Diskussionen über die Erschöpfung der natürlichen Ressourcen und die Umweltrisiken, die sich aus der extensiven Nutzung fossiler Brennstoffe in den Produktionssektoren ergeben, mobilisieren öffentliche und private Akteure, um Strategien für eine nachhaltige wirtschaftliche und soziale Entwicklung zu überdenken. Gleichzeitig werden diverse Forschungsprojekte durchgeführt, die sich auf die Energieerzeugung aus erneuerbaren Quellen und die Entwicklung von Technologien und Strategien für eine effiziente und intelligente Energienutzung konzentrieren. Im Transportsektor, der für hohe Emissionen von Treibhausgasen verantwortlich ist, sind Elektrofahrzeuge (EVs) eine vielversprechende Alternative. Der globale Markt für EVs boomt aktuell, und die Aussichten stehen gut, dass die Anschaffungskosten, insbesondere die Batteriekosten, sinken werden. Zudem wird erwartet, dass die Reichweite der Fahrzeuge steigt und die Ladeinfrastruktur verbessert wird. Darüber hinaus stellen die Formulierung öffentlicher Richtlinien und Subventionen für den Kauf von EVs wichtige Anreize für deren Einführung dar, insbesondere für private Verbraucher. Ob diese ein EV kaufen oder nicht hängt von der Wertvorstellung und Subjektivität jedes einzelnen Menschen ab. In der Literatur finden sich Studien, die die Verbreitung von EVs nicht gesamtheitlich betrachten und sich auf einige wenige Variablen beschränken. Aus diesem Grund ist es das Ziel dieser Doktorarbeit, ein globales Modell zur Vorhersage der Verbreitung von batteriebetriebenen Elektrofahrzeugen (BEVs) bei privaten Verbrauchern zu entwickeln, indem die Variablen analysiert werden, die deren Entscheidungsfindung beeinflussen. Zu diesem Zweck wird der Ansatz der Systemdynamik (SD) zusammen mit dem Bass Modell verwendet, wobei quantitative und qualitative Aspekte der Entscheidungsfindung berücksichtigt werden, um die Verbreitung von BEVs) im Laufe der Zeit zu bestimmen. Des Weiteren umfasst das Modell die Analytic Hierarchy Process (AHP) und Fuzzy Logik, um die Unsicherheiten und regionsspezifischen Merkmale zu berücksichtigen, die die Einführung von BEV beeinflussen. Fallstudien in Brasilien und Deutschland zeigen die Flexibilität und Genauigkeit des Modells bei der Vorhersage von Einführungstrends und heben die unterschiedlichen Auswirkungen unter anderem von Gesetzgebung, Infrastruktur und Marktbedingungen hervor. Zusätzlich zu den akademischen und wissenschaftlichen Beiträgen kann das entwickelte Modell Regierungen bei der Formulierung öffentlicher Maßnahmen zur Förderung der Elektromobilität unterstützen. Für Unternehmen im Energiesektor liefert es wichtige Informationen für Studien zum Ausbau des elektrischen Energiesystems. Zudem hilft es Automobilunternehmen bei der Ausrichtung ihrer Verkaufsstrategien und der Erweiterung von Geschäftsmodellen.

Schlagwörter: Analytic Hierarchy Process. Bass Modell. Batterieelektrisches Fahrzeug. Fuzzy Logik. Prognosemodell. Systemdynamik.

Resumo

As crescentes discussões sobre o esgotamento dos recursos naturais e os riscos ambientais decorrentes do uso extensivo de combustíveis fósseis nos setores produtivos estão mobilizando agentes públicos e privados a repensar estratégias para o desenvolvimento econômico e social de forma sustentável. Paralelamente, diversas pesquisas estão sendo conduzidas com foco na geração de energia por meio de fontes renováveis e no desenvolvimento de tecnologias e estratégias para o uso eficiente e inteligente da energia. No setor de transportes, que é responsável por altas emissões de gases de efeito estufa, os veículos elétricos (VEs) apresentam-se como uma alternativa promissora. O mercado global de VEs está atualmente em expansão, e as perspectivas são boas no que se refere à diminuição nos custos de aquisição, especialmente nos custos das baterias. Espera-se também que a autonomia dos veículos aumente e que a infraestrutura de recarga melhore. Somado a isso, a formulação de políticas públicas e subsídios para aquisição dos VEs representam grandes estímulos para sua adoção, especialmente por parte dos consumidores residenciais. Todavia, se eles compram ou não um VE depende do juízo de valor e da subjetividade de cada ser humano. Na literatura, são encontrados trabalhos que discutem a penetração dos VEs de forma específica e são restritos a poucas variáveis. Por essa razão, o objetivo dessa tese de doutorado é desenvolver um modelo global para projeção da difusão de veículos elétricos a bateria (BEVs) entre consumidores residenciais, analisando as variáveis que influenciam na sua tomada de decisão. Para isso, utiliza-se a técnica de dinâmica de sistemas juntamente com o modelo de Bass, considerando aspectos quantitativos e qualitativos de tomada de decisão para determinar a difusão dos BEVs ao longo do tempo. Além disso, o modelo engloba o *analytic hierarchy process* (AHP) e a lógica fuzzy para lidar com as incertezas e as características específicas de determinada região que influenciam a adoção do BEV. Estudos de caso no Brasil e na Alemanha demonstram a flexibilidade e a precisão do modelo na previsão das tendências de adoção e destacam os diferentes impactos das políticas públicas, infraestrutura, condições de mercado, entre outros. Além das contribuições acadêmicas e científicas, o modelo desenvolvido pode dar suporte aos governos na formulação de políticas públicas para promover a mobilidade elétrica. Para empresas do setor de energia, fornece importantes informações para estudos sobre a expansão do sistema elétrico. Também ajuda as empresas do setor automotivo a alinharem suas estratégias de vendas e a expandirem seus modelos de negócios.

Palavras-chave: *Analytic hierarchy process*. Dinâmica de sistemas. Lógica fuzzy. Modelo de Bass. Modelo de previsão. Veículo elétrico a bateria.

Contents

List of Figures

List of Tables

List of Symbols

Symbols printed in bold depict vectors and matrices.

Greek letters

α	coefficient.
β	fuzzy logic variable.
ϵ	constant.
η	efficiency.
ι	inflection point.
κ	growth rate.
λ	eigenvalue.
μ	membership function.
ν	adjustment coefficient that controls the shape of the curve in the generalized logistic model.
σ	standard deviation.
ξ_1	angular coefficient.
ξ_2	coefficient of the quadratic term.

Indices

aq	acquisition.
bat	battery.
BEV	battery electric vehicle.
d	delay.
DG	distributed generation.
el	electricity.
fb	feedback.
GC	green charger.
G	grouped.
ICEV	internal combustion engine vehicle.
kn	knowledge.
max	maximum.
pop	population.
PV	photovoltaic installation.
R&D	research and development.
rel	relevance.
req	required.
social	social.
WB	wallbox.

Number Sets

A	fuzzy set.
B	fuzzy set.
X	Fuzzy mapping space.

Variables

$\mathbf{M}$	criteria comparison matrix.	
$\mathbf{w}$	vector of criteria weights.	
A	stock of adopters.	
a	fuzzy scalar parameter.	
AA	adoption from advertising.	
AAT	product attractiveness.	
aef	advertising effectiveness.	
Al	decision-making alternatives.	
AR	adoption rate.	
ASE	adoption from social exposure.	
AWM	adoption from word of mouth.	
b	fuzzy scalar parameter.	
C	cost.	
c	fuzzy scalar parameter.	
Cap	capacity.	
CE	cost spent on electricity.	
CF	cash flow.	
CI	consistency index.	
Co	consumption	km/l
CR	consistency ratio.	
Cr	AHP evaluation criterion.	
CSP	number of public CS points.	
CT	vehicle property tax.	
ctr	contact rate.	
D	depreciation.	
d	fuzzy scalar parameter.	
di	distance driven	km
E	energy	kWh
EA	economic aspects.	
Ef	efficiency.	
F	cumulative fraction of reached potential.	
f	sales function density.	
Fi	financing variable.	
Fu	fuel costs.	
G	remaining potential costumers.	
h	expert index.	
H_{own}	number of homeowners.	
I	inflow.	
i	adoption fraction.	
IA	infrastructural aspects.	
In	insurance costs.	
K	saturation level.	
k	eligible population factor.	
L	legislation variable.	
M	models.	
m	stock of potential market.	
MW	mechanic workshops.	
N	total number.	
NPV	net present value.	
O	outflow.	
o	gaussian membership function center.	
$O\&M$	operation and maintenance costs.	
P	stock of potential adopters.	
p	innovation coefficient.	

PA	political aspects.	
PAF	product attractiveness factor.	
PCI	ratio of public charging infrastructure	BEV/CSP
PF	product feedback.	
PK	product knowledge.	
PN	product novelty.	
Pr	probability.	
q	imitation coefficient.	
R	range	km
r	interest rate.	
RI	random consistency index.	
RR	replacement rate.	
Ru^l	fuzzy logic rule.	
S	stock.	
s	total number of experts.	
Sa	savings.	
SAp	social appeal.	
SOC	state of charge.	
Su	subsidies.	
T	tax.	
t	time	s
TA	technical aspects.	
TI	tax incentives variable.	
w	criterion weight.	
x	independent variable.	
Y	cumulative adopter number.	
y	independent variable.	
y'	predicted value.	
z	independent variable.	

Other Symbols

CO_2	Carbon Dioxide.

List of Abbreviations

ABM agent-based model

ADAC Allgemeiner Deutscher Automobil-Club

AHP analytic hierarchy process

ANEEL "Agência Nacional de Energia Elétrica", engl. National Agency of Electric Energy

BEV battery electric vehicle

BNDES "Banco Nacional de Desenvolvimento Econômico e Social”, engl. Brazilian Development Bank

CLD causal loop diagram

CS charging station

CSP charging station point

CI consistency index

CR consistency ratio

COFINS "Contribuição para o Financiamento da Seguridade Social", engl. Contribution for the Financing of Social Security

DER distributed energy resource

DG distributed generation

DS distribution system

EV electric vehicle

EU European Union

FCEV fuel cell electric vehicle

GIS geographic information systems

GHG greenhouse gases

HSAR hierarchical spatial autoregressive

HEV hybrid electric vehicle

HDI human development index

ICMS "Tax on Circulation of Goods and Services", engl. Tax on Circulation of Goods and Services

IOF "Imposto sobre Operações Financeiras", engl. Tax on Financial Operations

IPVA "Imposto sobre a Propriedade de Veículos Automotores", engl. Motor Vehicle Ownership Tax

IPI "Imposto sobre Produtos Industrializados”, engl. Tax on Industrialized Products

ICEV internal combustion engine vehicle

IEA International Energy Agency

ITF International Transport Forum

MAE mean absolute error

NPV net present value

PHEV plug-in hybrid electric vehicle

PV photovoltaic

PIS "Social Integration Program", engl. Programa de Integração Social

R^2 coefficient of determination

RI random consistency index

R&D research and development

RMSE root mean square error

SD system dynamics

SOC state of charge

SFD stock and flow diagram

V2G vehicle-to-grid

VAT value added tax

ZEV zero emission vehicle

1 Introduction

The economic development and progress of society are strongly linked to the transportation sector, which facilitates the delivery of products, raw materials, and the mobility of people for work and leisure [1], [2]. According to the International Transport Forum (ITF), global demand for passenger transport is expected to double by 2050, highlighting the critical role of transportation in economic growth [3]. However, road transport contributes significantly to environmental challenges, accounting for over 23 % of total energy-related CO_2 emissions [2].

Electrification of transportation emerges as a key strategy for decarbonizing and modernizing urban mobility. The relevance of electromobility has increased significantly, with projections indicating higher participation of electric vehicles (EVs) in transportation modes worldwide [4].

Among EVs, battery electric vehicles (BEVs) stand out due to their zero local greenhouse gases (GHG) emissions and reduced noise, as they lack combustion engines. Advances in battery technology have increased driving ranges and reduced costs, making BEVs more appealing to consumers [5], [6].

According to the Global EV Outlook 2024, approximately 14 million EVs (including BEVs and plug-in hybrid electric vehicles (PHEVs)) were registered globally in 2023, totaling 40 million EVs worldwide [7]. Sales increased by 35 % compared to 2022, accounting for 18 % of total car sales in 2023, a significant rise from just 2 % in 2018. Notably, 70 % of these were BEV models. The largest EV stocks are in China, the United States, and Europe, as illustrated in Fig. 1.1.

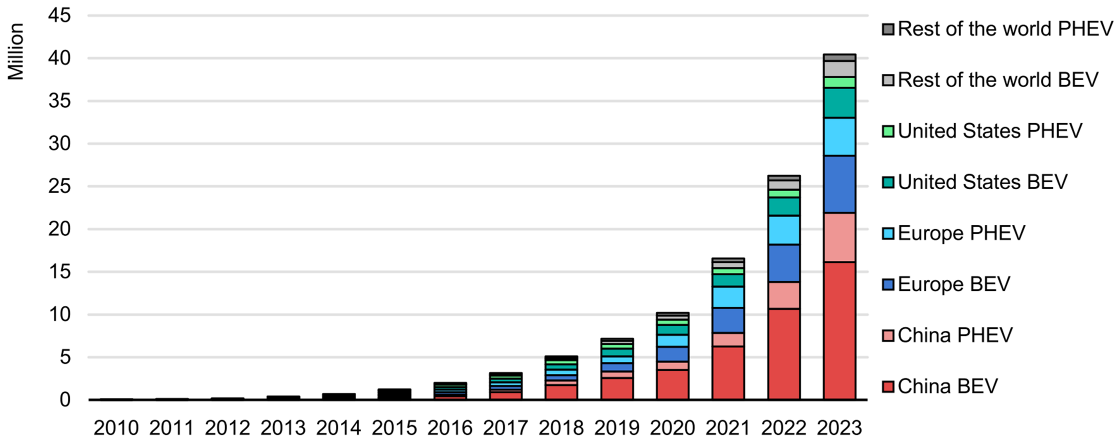


Figure 1.1: Global electric car stock.

The advancements in BEV technology, coupled with supportive global policies, have positioned BEVs as the leading option for decarbonizing the transport sector. However, the rapid adoption of BEVs presents significant challenges for electric power systems. The integration of a large number of BEVs introduces new demands on the grid, affecting voltage stability, increasing peak loads, and potentially impacting power quality [8], [9]. These challenges necessitate careful planning and modeling to ensure that power systems can accommodate the growing number of BEVs without compromising reliability or efficiency.

Therefore, this study aims to develop a comprehensive model for projecting the diffusion of BEVs among residential consumers, considering the various factors influencing adoption. By understanding and forecasting BEV adoption rates, power system operators, policymakers, and other stakeholders can better prepare for the impacts on grid infrastructure, capacity planning, and energy management.

1.1 Background and motivation

In light of what has been discussed in the introductory chapter and considering the forecasts of growing public and private incentives to modernize and develop the transport sector with sustainability, innovation and efficiency, BEVs are expected to play an increasingly important role in transportation. However, the growing diffusion of BEVs presents a set of challenges and opportunities for the electric power sector. As the transportation sector shifts towards electrification, it becomes essential for power system operators and market participants to anticipate how the increasing number of BEVs will affect grid stability, capacity planning, and energy management. This study aims to provide insights into the diffusion dynamics of BEVs, with a focus on the implications for the electric grid.

The rapid and large-scale integration of BEVs introduces a new class of non-linear loads, which can significantly impact the voltage stability of electrical systems [8]. Unlike traditional loads, BEV charging can occur simultaneously across a large number of consumers, resulting in substantial energy consumption over short periods. This characteristic poses a risk to power grids, particularly in regions already operating near the edge of instability and with weaker infrastructure [9], [10]. Moreover, BEV batteries demand significantly higher power levels compared to typical household appliances, which can increase overall energy consumption and demand, leading to further challenges in electricity supply management.

In addition to voltage instability, the integration of BEVs into the grid can also lead to an increase in peak demand. The batteries in these vehicles require a higher level of power compared to the usual household equipment used by residential consumers, which can have an impact on levels of energy consumption and demand and, consequently, changes in aspects of supply. Uncoordinated charging, especially during peak hours, may push the system beyond its generation capacity, requiring significant investments in new generation and transmission infrastructure [11], [12]. Studies have demonstrated that strategies such as time-of-use tariffs and controlled charging can help mitigate these effects, but without proper planning, the additional demand from BEVs could strain the power grid [13]–[15].

Power quality is another area of concern, as the charging of BEVs introduces harmonics and voltage imbalances into the system [9], [11]. Harmonic distortion, which results from the power electronics used in BEV chargers, can reduce the lifespan of transformers and other critical grid infrastructure [6], [16]. Additionally, the charging of BEVs by residential consumers using single-phase connections can cause voltage imbalances in the distribution system (DS), especially when BEVs are charged at the farthest points of the distribution network. This leads to operational limit violations and increases transmission losses in the DS [9], [17].

The massive penetration of BEVs also risks overloading distribution lines and transformers [11], [18]. The electrification of transportation could lead to premature aging of equipment, necessitating additional investments in infrastructure [19]. On the other hand, the integration of renewable energy sources, such as photovoltaic (PV) generation, can mitigate these effects [20], careful planning is required to manage the energy system.

Since BEVs are dynamic loads that can be loaded and unloaded at any time of the day, understanding their diffusion enables their integration with renewable energy sources, which offers potential benefits for both grid operators and consumers. vehicle-to-grid (V2G) technology, for instance, allows BEVs to not only draw energy from the grid but also supply it back (prosumer) during peak demand periods, providing ancillary services such as the possibility of active power support (with energy management, loss minimization, load leveling, peak demand reduction and control of voltage levels), reactive power support (with reactive compensation and voltage control) and support for the integration of renewables (BEVs with PV or wind generation) and frequency regulation [6], [21]–[24]. However, this potential can only be realized if the diffusion of BEVs is well understood and strategically managed.

Therefore, in order to guarantee the inclusion of these new loads, system operators must also include planning and expansion research, seeking resilience, reliability and robustness, so that they are structurally prepared to meet this new demand. As a result, it is important to develop studies, models and methods to analyze the process of BEV adoption by potential users, as well as the impact of these new elements on electricity system. These studies should involve characteristics from infrastructural and technical perspective, such as the DS and its components, to personal factors, such as consumption habits, population mobility patterns, political, market and social aspects, among others, making this a comprehensive and complex task, which is both modern and innovative.

In this sense, this work aims to contribute by proposing a model to analyze the diffusion of BEVs over time in different regions, providing insights into future adoption trends. These insights can be utilized in impact studies of BEV on the power grid to anticipate when undesirable effects may emerge and implement measures to mitigate them.

1.2 Projection of the diffusion of electric vehicles

In 2015, [25] proposed a study on the diffusion of EVs in a region of China from different perspectives of consumer behavior, based on the technique of system dynamics (SD) modeling and agent-based model (ABM). Several scenarios with different conditions were analyzed, including consumer behavior, charging prices, government incentive policies, infrastructure development, and industry technology. The results showed that the sector's growth expectations were initially limited due to the low level of technological infrastructure. However, government incentives such as subsidies and tax exemptions are expected to greatly accelerate the sector's development in the coming years.

In subsequent work, [26] refined their modeling based on SD to more thoroughly explore the relationship between factors that condition the development of the sector, such as EV purchase and maintenance prices, usage performance, technology structure, and incentive policies. The authors deepened their study of consumer behavior profiles through a method based on a quantified survey and used the survey responses to measure the importance of the factors implemented in the system modeling. Based on the models created, a Chinese district was selected to conduct the evaluation, resulting in a scenario similar to that observed in their previous work [25].

In the work of [27], a flexible method was proposed to estimate the diffusion of EVs in the state of California, in the United States of America. The authors used transportation data collected through reports prepared by the state government to formulate their model, which explored the relationship between different factors selected according to three main categories (consumer behavior profile, market context, and vehicle technology characteristics). The methodology implemented two statistical models, logit and probit, to estimate consumer behavior. In addition, the authors used the maximum likelihood approach, which seeks to maximize the probability of correctly classifying the observed data in each category. Based on the results found, the authors concluded that the average level of EV penetration in the state is more related to infrastructure factors, such as public charging station (CS) per capita and fuel price.

In 2019, [28] conducted a study on the diffusion of EVs over time, using the SD technique and the Bass model. The authors were interested in exploring the application of these two methods to estimate consumers' decision to purchase an EV. To do this, they compared the costs of EV and internal combustion engine vehicle (ICEV) by relating the cost of fuel for ICEVs, the increase in energy demand and the price of energy bills (for EVs), the cost of purchasing EVs or ICEVs, the incentive policies for purchasing EVs, the increase in consumer awareness, the development of technology, and the advertising surrounding EVs, in a reference, optimistic, and pessimistic scenario. Finally, the authors conclude that advertising and government support for the purchase of EVs are the main factors for their growth in the market and highlight the great potential of the SD technique to relate variables of different natures (economic, behavioral, technical and strategic) in the same computational model.

Reference [29] presented a spatiotemporal model to estimate the number of EV adopters in the city of Porto, Portugal. The proposed method used a hierarchical spatial autoregressive (HSAR) model and logistic regressions, considering external and internal influences on the projections (coefficient of innovation (p) and imitation (q)). Some socio-economic variables are used in the analysis, such as the location in the city where those who have already adopted EVs live and census data (monthly income, education and number of houses). The results obtained by the authors are presented in the form of spatial databases that can be visualized in geographic information systems (GIS) to observe the regions with the highest predictions of residential EV adopters. In this study, EV adopters were more concentrated in a few sub-areas, but the logistic regression showed a continuous evolution of EV penetration in all regions for the coming years. These results were compared with those estimated by the geographically weighted regression method available in most GIS. The authors did not consider the cost of EV use or the influence of proximity to charging infrastructure.

Reference [30] presents a study using the Bass model to systematically simulate the process of EV (BEV and PHEV) diffusion and charging in France and Germany. The model presented by the authors considered economic and social information, based on a binary logistic regression model, whose variables were the mobility behavior of the users interviewed, their experiences with EVs, household income, frequency of car use, nationality, and number of cars in the household. This way, it is possible to describe the relationship between the user's intention to purchase an EV and the other variables using binary logistic regression. For market development information, the proposed work used the Bass diffusion model with very optimistic innovation (p) and imitation (q) coefficients. The authors assumed that EV adopters have the possibility to charge their cars both at home and at work, and concluded, through sensitive analysis of the variables, that battery size, average charging times, and the amount charged for the average energy consumed influence the number of adopters.

Not just economic, technological, and political factors have an impact on the adoption of EVs. In this regard, [31] carried out a study including the structural characteristics of social networks in the evolution of EVs at scale, using the Bass model. In a two-dimensional socio-spatial study, consumers were divided into two groups: conservatives who seek economic benefits and volatiles who are more susceptible to external influence from people and marketing. The authors considered economic factors (EV price, marketing strategy, public subsidies, fuel price, and energy tariff), technical factors (battery capacity, performance, energy consumption, and technology maturity), and social factors (neighborhood preference, social behavior, and the impact of social networks). A case study was conducted in Changsha, China. The findings showed that social behavior patterns have an impact on customer purchase decisions. Furthermore, it was discovered that different types of social networks cause variances in the diffusion of EVs.

Reference [32] used a variation of the Bass model and SD to analyze the adoption of EVs in Indonesia. In the modified Bass model, in addition to the innovation (p) and imitation (q) coefficients, the authors included a market potential (m) coefficient, which considers EV sales over the course of each year. Three scenarios were implemented (pessimistic, optimistic and ambitious) with variables related to incentive policies for the diffusion of EVs and subsidies for the related sectors (potential adopters, EV manufacturers, and charging infrastructure sectors) in a systemic analysis. Thus, the authors concluded that government support through subsidies and public policies are crucial for the mass diffusion of EVs. In addition, the authors assessed that it is essential to include a tax deduction or direct aid to lower EV prices, along with incentive policies for automakers to guarantee vehicle manufacturing capacity, as well as the development of public charging infrastructure.

According to [33], the main players in the EV industry are consumers, car companies and governments. In this sense, in order to assess the short- and long-term dynamic effects of different policies to promote the adoption of EVs in China, the authors formulated an evolutionary game model using Newman and Watts' small-world networks, establishing a strategic game model between EV and ICEV companies and analyzing their decision-making mechanisms. Thus, in the process of each game, each company node has two strategies, which can be to choose to produce EVs or to choose to produce ICEVs. In the short term, the results presented showed that the government policy of subsidizing the purchase of EVs and restrictions on ICEV travel can stimulate an EV diffusion rate of 60 %. Promoting the construction of charging infrastructure increases the diffusion rate to 70 %. In addition, incentive policies for EV production by automakers had a more significant impact than subsidies for consumer purchases, while low electricity prices and high fuel prices resulted in an EV diffusion rate of 60 % and 70 %, respectively.

In a growing and increasingly complex market, [34] used game theory combined with the technique of evolutionary SD to systematically analyze public policy choices in China, the sales strategies of EV companies and the purchasing preferences of consumers. To do this, the authors considered that the government, companies and consumers have limited rationality and, over the course of several games, continuously learn until they reach the stable evolutionary strategy (or ideal equilibrium). The main results of this study are that the government must maintain subsidies for consumers for a significant period of time, in order to dynamically adapt the rate of subsidy reduction, as well as increasing the cost of purchasing and operating ICEVs. For companies in the electric mobility sector, it is important to intensify their investment in research and technology development in order to boost EV sales.

To assess the impact of public policies on the diffusion of EVs in Brazil, [35] proposed a model based on Beck's adaptation of the Bass model, which considers the final market of potential adopters to be a function of the simple payback time, and no longer a fixed fraction of the preliminary potential market, given in number of adopters. As a result, it was found that policies to subsidize the cost of purchasing EVs accounted for 67 % of total sales, outstripping policies to reduce the operating cost of EVs (33 % of total sales). This is due to the high price of EVs, which is the main barrier to their mass diffusion. On the other hand, the carbon tax accounted for 0.56 % of sales. This is partly due to the high consumption of ethanol in the country. Finally, the increase in the price of ICEVs has led to a 3.11 % share of EV sales. In addition, using a linear regression model and taking into account social and macroeconomic indicators, the authors estimated a total of 2 million car licensing for the upcoming years. The influence of charging infrastructure was not considered in the proposed scenarios.

Reference [12] presented a study of the development of the BEV market up to 2030 in a region of 20 municipalities in northern Portugal. The authors considered three scenarios with different EV sales projections and different grid energy consumption profiles. From this, estimates were made of the energy that will be needed to meet the increase in the EV fleet in the country, as well as a study based on the Monte Carlo Method to assess the probability of occurrence of the negative impacts related to the scenarios analyzed. The results obtained showed a significant possibility that the region's electricity grids will not be able to meet the growth in energy demand by the end of this decade.

In a study based on ABM, [36] analyzed how different public policies can stimulate the diffusion of EVs in Germany, focusing on BEVs and PHEVs. The study evaluates scenarios that include subsidies, infrastructure investments, and fuel price increases, showing that additional policies, such as carbon taxes and more charging points, are necessary to achieve the diffusion targets set for 2030. In the context of the transition to electric mobility, this study provides some important contributions to the formulation of effective policies in Germany.

Reference [37], using ABM, analyzed the importance of financial, political and technical aspects in the diffusion of EVs in a comparison of different types of vehicles: Petrol ICEV, diesel ICEV, hybrid electric vehicle (HEV), PHEV, BEV and fuel cell electric vehicle (FCEV). The choice behavior of the individual agents in the simulations, which is influenced by different factors, was implemented as a utility function using the multinomial logit model. The results obtained were analyzed using techniques such as the response surface methodology, the full factor analysis method and the support vector machine. The authors concluded that public policies, such as subsidies for EV purchases and tax incentives, had a more significant impact on the mass adoption of EVs than technical improvements, such as battery charging time and car range.

Reference [38] simulated the diffusion of EVs in China, focusing on the effects of different incentive policies for reducing GHGs and public health. To do this, the authors used the SD technique, considering multiple variables and agents in an influence mechanism between the government and diffusion policies for consumers, automakers and charging infrastructure operators. Of the variables analyzed in the SD model, the authors concluded that restricting the transit of combustion vehicles, followed by subsidizing the construction of CSs, results in greater adoption of EVs. In addition, it was found that the benefits to the public health of the Chinese population are more significant in increasing the penetration of EVs, followed by a reduction in CO_2 emissions. All government incentives for consumers, automakers and charging infrastructure operators had a positive impact. Another interesting point in this work is that the authors emphasize the importance of improving the efficiency of research and development (R&D) incentives, seeking to intensify the level of industry-university-research cooperation in order to maximize the benefits of government subsidies for electric mobility in the transport sector.

Also in China, in order to determine consumer acceptance of EVs, [39] applied a questionnaire with random sampling in Shanghai with 1,705 valid responses. Then, by means of structural equation modeling using AMOS software, the authors analyzed the influences of five external factors (EV performance, incentive policies, respondents' personal life attitude, presence of CSs and the peer effect) and eight demographic characteristics (gender, age, marital status, education, household income, family size, number of children, and location of residence) on EV purchases in this region. The focus of this study was to analyze the influence of peers on the purchase of EVs, which considered the number of friends of the interviewees with EVs, the influence of friends with and without EVs, word of mouth, the recommendation of close friends and the negative influences of friends with EVs. The authors also carried out an analysis of heterogeneity between consumers who did and did not buy EVs. The main results obtained showed that EV buyers in Shanghai were younger (between 31 and 40 years old); consumers with a high income, high education and who live in the city center were more willing to choose EVs, while large families preferred not to buy them. Consumers who didn't buy EVs were more concerned about their performance. Consumers who had already bought EVs cared about the availability of CSs and related government policies, especially Shanghai's free license plate policy. The peer effect showed that the exchange of information between consumers in the sample interferes with their purchasing decisions.

Recently, [40] published a study of the state of the art of some diffusion models, namely the logistic, Gompertz, Bass and generalized Bass models used in EV adoption analyses (BEV and PHEV) in different countries around the world. The authors compared these models in order to provide new guidelines to help professionals and academics in their research into the diffusion of EVs, taking into account the development of recharging infrastructures and the influence of uncertain scenarios such as the pandemic. The results showed a growth in EV sales as the number of CSs increased. In addition, the countries analyzed that currently have low EV diffusion rates were the most negatively impacted by the pandemic, requiring multiple policies and measures to maintain their estimated diffusion rate. Finally, the authors point out that in order to formulate more assertive forecasting models, the particularities and specific recommendations of each country must be taken into account.

In 2023, [41] conducted a study analyzing the factors driving electric mobility in Brazil, using simulations based on the Bass diffusion model and SD. The study assesses the importance of vehicle purchase prices and public policies for the penetration of EVs in the Brazilian market. The results show that with the adoption of appropriate policies and a reduction in battery costs, the share of EVs in the national fleet could reach up to 36.7 % by 2040, highlighting the relevance of an effective regulatory framework and economic incentives.

The research conducted by [42] evaluates the impact of fiscal policies, particularly the introduction of a CO_2 tax, on the diffusion of BEVs, PHEVs, and FCEVs in Germany, using the ALADIN model (Alternative Automobiles Diffusion and Infrastructure), developed by Fraunhofer-ISI. The authors simulate different scenarios for the application of these environmental public policies until 2050. The simulations indicate that a high CO_2 tax could result in a significant increase in EV adoption, contributing to the reduction of greenhouse gas emissions.

Reference [43] proposes an ABM model along with the Bass model to predict the market penetration of EVs in Brazil. Simulations were conducted for the period from 2021 to 2035, analyzing variables such as acquisition cost, battery capacity, maintenance cost, charging time, and the number of EVs sold. The results highlight acquisition cost as the primary adoption factor, with additional barriers related to battery capacity and charging infrastructure. The model proposed by the authors considers only consumers as agents but acknowledges the importance of future studies to include other agents such as government, manufacturers, and the supply chain in the diffusion process.

Through a literature analysis and a SWOT (Strengths, Weaknesses, Opportunities and Threats) matrix, [44] critically reviewed business models for the adoption of EVs and CSs with a focus on Brazil. The authors identified that high acquisition costs and limited infrastructure are the main barriers, but innovative business models, such as EV sharing and leasing, show promise for the Brazilian context. The research highlights the importance of public policies and coordination between the private and public sectors to develop robust charging infrastructure and accelerate the adoption of EVs in the market.

Another literature review encompassing 54 articles, conducted by [45] reviewed the models and methods used to forecast EV demand for residential consumers (personal use). The research classifies the models into three main categories: bottom-up (ABM models, discrete choice models, evolutionary game theory, etc.), top-down (SD models, aggregate market models, etc.), and mixed models (combination of bottom-up and top-down models), and discusses the strengths and limitations of each. The authors identify that mixed models offer more realistic predictions, although they still face challenges in accuracy due to the need for improvements in input data.

1.3 Objectives and differentials of the proposed work

Main objective

The main objective of this work is to develop an integrated model using system dynamics (SD), the Bass model, analytic hierarchy process (AHP) and fuzzy logic to project the diffusion of BEVs among residential consumers.

Specific objectives

The main objective of this thesis will be achieved through the following specific research tasks:

- Model and analyze the diffusion of BEVs in residential consumers over time;
- Study and review the SD method as well as the Bass model in research for forecasting the diffusion of innovations;
- Identify and characterize the main variables that influence residential consumers (light vehicles) to adopt BEV, considering quantitative and qualitative aspects of decision making;
- Integrate these variables into a unified mathematical model to predict BEV adoption in a given region;
- Contextualize the BEV market in Germany and Brazil, from the perspective of barriers and opportunities for diffusion;
- Define and test different scenarios to validate the proposed model through a model verification, and analyze policy tests, especially those related to policy-making and incentive structures for BEV adoption.

When carrying out this state-of-the-art search in the databases, it can be seen that, in most of the studies found, the SD technique or the Bass model or both has been used in the EV penetration projection studies. In a recent review on forecasting the diffusion of technologies in space and time, [46] pointed out that the Bass model is "well-established and widely used due to its relatively low complexity, as adoption curves are drawn up without the need for expensive and time-consuming empirical research.

In addition, it is noted that there is a lot of research that addresses the diffusion of EVs over time, focusing on economic and technical aspects or incentive policies and the effects of social networks, for example, but never covering this important issue in a holistic way. Therefore, this thesis aims to fill that gap by offering a comprehensive approach that integrates multiple factors and stakeholders, e.g. government, financial institutions, social patterns, companies for after-sale services for BEV, etc. into the analysis of BEV diffusion. The proposed model will contribute to various sectors, including governments, energy suppliers, automotive companies, and power system operators, by providing a deeper understanding of BEV market dynamics.

The specific contributions of this thesis are as follows:

- Develop a global model for projecting the diffusion of BEVs among residential consumers over time, integrating economic, social, technical, political, infrastructural, and market variables;
- Incorporate fuzzy logic and the AHP to systematically evaluate and prioritize the factors that influence BEV adoption;
- Offer valuable insights to governments, power system operators, energy suppliers, and automotive companies by generating different scenarios to study the impacts of BEV adoption on energy demand and infrastructure, helping stakeholders align their strategies with future market trends.

This thesis thus proposes a model that leverages SD modeling combined with the Bass diffusion model, using customized equations and incorporating AHP and fuzzy logic to manage uncertainties. Validated with historical data from Brazil and Germany, the model enables scenario-based analysis of BEV adoption, offering insights that can guide policy, infrastructure planning, and market strategies in preparation for the increasing prevalence of electric vehicles.

1.4 Structure of the work

This work is organized into six chapters, references and appendices. Chapter 1 provides the context and background for the research, outlining the motivations behind the study. It also presents an overview of the transport sector, emphasizing the importance of urban mobility for economic and social development. In addition, it provides various statistics on the transportation sector and previous literature related to the diffusion of EVs.

Chapter 2 introduces the models and theories that form the essential theoretical background for this research. It discusses the concepts related to the SD technique and the Bass model, highlighting their integration for analyzing the projection of BEV penetration as a new technology in society over time. The chapter also describes the AHP method and fuzzy logic, which are employed to determine specific variables within the model.

Chapter 3 details the proposed model and its development. The chapter includes a discussion on the problem formulation and provides an overview of the proposal. Each aspect considered in the model is thoroughly described, along with the conceptual and mathematical modeling involved.

Chapter 4 focuses on the verification of the model. It covers the determination of the model parameters and the historical data used for verification. The study focuses on two regions: Germany and Brazil. This chapter also details the calibration of the Bass coefficients.

Chapter 5 explores future scenarios and examines the impact of various policies that could either encourage or hinder the diffusion of BEVs. It considers different incentives, technological developments, market conditions, and social factors, all of which involve significant uncertainties. The results are analyzed and discussed in detail to understand the potential future impacts of different scenarios.

Finally, Chapter 6 summarizes the research findings, discusses their implications, and suggests directions for future work.

2 Prediction Methods

Estimating the number of BEVs that will be sold in the coming years is of great importance for planning and expanding the electricity system with quality, reliability and safety. In addition, this forecast helps companies in the automotive sector organize their business models, as well as their products and services offered, in view of the possible expansion of electromobility in the transport sector.

Studying the diffusion of BEVs also allows the government to organize its incentive policies to intensify this process to a greater or lesser extent, to articulate public-private partnerships, especially with regard to R&D for the decarbonization and modernization of the transport sector, which is a commitment made by Germany, Brazil and many other countries around the world.

In order to make a technical contribution to these sectors, the model proposed in this thesis uses the SD technique and the Bass model to study the projection of the diffusion of innovations over time. Furthermore, the AHP method and fuzzy logic, which are two distinct methodologies employed for decision-making and solving complex problems, are also presented. Thus, this chapter summarizes some of the main works found in the literature that cover concepts related to the methods and techniques used in the thesis.

2.1 Systems dynamics technique [1]

In order to analyze strategic issues within complex dynamic systems, Jay W. Forrester developed the SD technique in the 1950s [48]. Grounded in control theory and non-linearity, this methodology has been applied for many years to comprehend and predict the processes related to the adoption and diffusion of new products [49]. These investigations are crucial for governments and businesses, aiding in market development through, e.g., policy formulation, reduction of adoption barriers, and investments in infrastructure and new technologies [49], [50].

As discussed in Section 1.2 of this thesis, the SD technique is frequently employed in various studies to examine the diffusion of EVs over time. It is important to highlight that the SD method has also been extensively utilized in studies focusing on analysis, planning, and resource allocation within power systems. This is facilitated by the feedback loops inherent in the modeling process, a key feature of the SD approach [26], [51].

[1]This section has been partially published in [47].

SD employs elements such as inventories, flows, internal feedback loops, tabular functions, and time delays to understand the complex, non-linear behavior of systems over time [52]. [53] reviewed numerous studies within the renewable energy supply sector that implemented SD in their modeling efforts. Likewise, [54] conducted an analysis of a decade's worth of articles, systematically organizing the diverse methodologies and applications of the SD approach to investigate the multifaceted processes of local energy transitions.

Among other studies on the diffusion of new technologies for the electricity sector, SD has also been used to analyze the implementation of smart metering in smart grids, proposing strategies for adequate cost recovery [55]. [56] also presented a model for analyzing the dynamic behavior of the insertion of solar PV micro- and mini-generation in electricity distribution networks, using the SD technique to aid decision-making and policy-making in terms of stimulating PV generation systems. This technique was also used to analyze the diffusion of PV systems in low-voltage residential consumers, considering economic, management, political, social and technical aspects [49], [51].

Furthermore, the integration of distributed energy resource (DER) within a specific region was modeled by [57] using the SD technique, which included demand management. This study investigated a variety of variables and policy tests to facilitate decision-making in the context of microgrid implementation, with an emphasis on financial returns and feasibility. The SD technique's widespread use in energy policy research is a result of its capacity to establish a connection between the macro-energy system and the policy-making process and microstructure.

[45] recently published a review article that offers a critical evaluation of the various methods used in the literature to forecast the number of EVs in the market. The article includes a comprehensive list of studies that have utilized the Bass model and SD. Rather than determining the superior method for generating reliable forecasts in all conditions, the authors focused on assessing the advantages and limitations of each modeling approach, distinguishing the elements that could improve the precision of estimating the demand for EVs.

With these considerations, it can be seen that the SD technique emerges as a consistent and appropriate tool for modeling the diffusion of innovations. It should be noted that this thesis differs from other studies in the literature by integrating the SD technique with an adaptation of the Bass model, incorporating a wide array of factors which affect the consumer's decision to adopt a BEV over time.

2.1.1 Definitions and principles

As previously mentioned, the SD technique was developed by Jay W. Forrester in the 1950s. His book "Industrial Dynamics", published in 1961, is considered a cornerstone in establishing the key concepts and fundamentals of SD. In 1968, Forrester further elaborated on these concepts in his work "Principles of Systems" [58], [59].

The origins of SD studies can also be traced back to Ludwig von Bertalanffy's General Systems Theory. Bertalanffy's theory posits several key assumptions: a clear trend towards the integration of natural and social sciences; this integration seems to be moving towards a theory of systems; and systems theory can be a more comprehensive way of studying non-physical fields of scientific knowledge, especially the social sciences [59]. Building on these foundational analyses and the subsequent evolution of these models, the SD technique emerges as a robust tool for analyzing the behavior of systems, that are defined as sets of functional elements and their interrelationships, which are subject to variations over time [49], [50], [52], [60].

Some of the principal characteristics of the SD technique are identified by [60]:

- Ability to address both long-term and short-term aspects within a single model;
- Thorough representation of complex and non-linear relationships;
- Capability to incorporate social and psychological variables;
- Convenience of testing the impacts of different policy alternatives.

Developing models through the SD technique enables the representation of physical flows, which can be accumulated, and information flows, which are typically observed but cannot be accumulated, as feedback mechanisms among the components of a system. Consequently, variations in external parameters can lead to modifications in the system's state [60]. These alterations can include delays, distortions, system responses, flows, accumulation of flows (stocks), and feedback, which collectively form a dynamic model conceptualized in a systemic manner [50], [58], [60].

The fundamental aspect of SD models is based on the feedback loop of information [48], [58], [60]. Fig. 2.1 represents this feeedback structures. It can be seen that a feedback loop forms a closed path linking the "system level" (state or condition), "information" about the level and a "decision". The latter contains an "action" that is sent to the "system level". The "system level" (true level) is what generates the "information" (apparent level), which may differ from the true level due to delays and/or noise. Despite this, what can be seen is that the foundation of the decision-making process is "information" and not the true level.

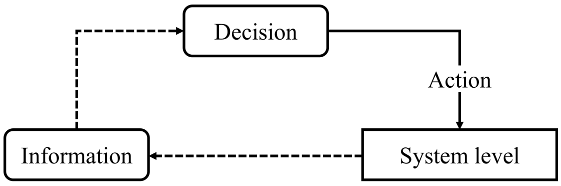


Figure 2.1: Feedback loop [60].

Each feedback loop is made up of two types of elements: level variables and rate variables [60]. These variables will be detailed later in this chapter. Due to the fact that real systems are composed of numerous feedback loops and, thereafter, numerous variables, system analysis becomes increasingly complex as the number of variables and the non-linear and dynamic relationships between them increase, as well as how the system interacts with the environment [48], [58]. This characteristic leads to different behavioral patterns within a given system. Fig. 2.2 illustrates the main graphs depicting the main patterns of variation over time in systems. Additionally, other shapes not shown here can emerge from the combined representation of these patterns.

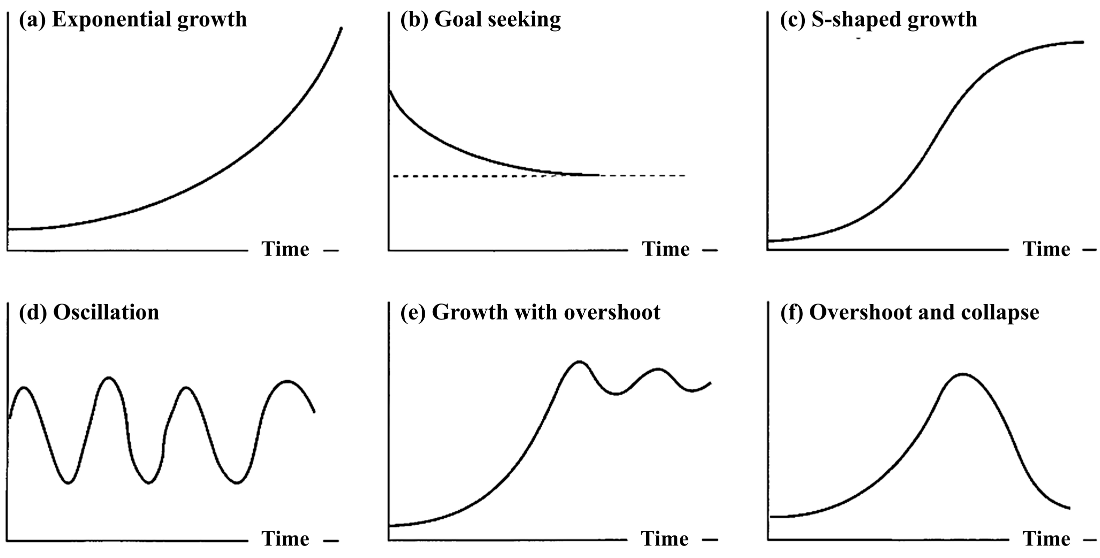


Figure 2.2: Fundamental modes of behavior in SD [48].

In the literature, there are two prominent approaches for modeling a system in the form of SDs [51], [57]: the first, put forth by Ford [58] in his book "Modeling the Environment," and the second, proposed by Sterman [48] in his book "Business Dynamics," consisting of eight and five steps, respectively. Table 2.1 shows these steps.

Table 2.1: Steps for modeling a system using SD

Steps by Ford [58]	Steps by Sterman [48]
1 - A ("Acquainted")	1 - Problem articulation
2 - B ("Be specific")	2 - Dynamic hypothesis
3 - C ("Construct")	3 - Formulation
4 - D ("Draw")	4 - Testing
5 - E ("Estimate")	5 - Policy formulation and evaluation
6 - R ("Run")	
7 - S ("Sensitivity")	
8 - T ("Test")	

The modeling steps described by Ford [58] can be summarized as follows:

1. **Get acquainted with the system:** This stage is fundamental to becoming familiar with the system. The aim is to obtain a comprehensive understanding of the model's purpose, identify the most important variables and parameters, identify key individuals, as well as to outline the dynamic problem.

2. **Be specific about the dynamic problem:** This is possibly the most crucial step in the modeling process. It is necessary to check whether the system shows dynamic behavior. If it does, a graph representing the most important variable over time, known as the reference mode, must be created to define the dynamic behavior of the system in relation to the time horizon of the dynamic problem analysis.

3. **Construct the stock and flow diagram (SFD):** At this stage, it is important to define and distinguish each type of variable in the model. Initially, the stock variables are defined, followed by the flows and finally the other variables and constants in the model. The SFD must include the variable shown in the reference mode. In addition, the mathematical modeling corresponding to each type of variable is carried out, regardless of whether it is input or output.

4. **Draw the causal loop diagram (CLD):** The aim of this step is to construct the CLD. Some systems have a very complicated loop structure; in these cases, the creation of several partial loops is recommended.

Although the modeling steps suggested by Ford [58] indicates building the SFD first, followed by the CLD, this sequence is not a fixed rule. Some modelers may find it interesting to change this sequence.

5. **Estimate the parameter values:** This step involves estimating the values of the model parameters individually. Some parameters may be known with complete accuracy, others may have partial accuracy, and others may be completely unknown. Depending on the system being studied, it might be interesting to start processing the data before continuing.

6. **Run the model to get the reference mode:** The aim of this step is to run the model and compare it with the reference mode specified in step 2. At this stage, it is important to analyze whether the consistency of the model is confirmed.

7. **Conduct sensitivity analysis:** In this phase, the aim is to determine if the results are sensitive to changes in the uncertain parameters by changing the parameters controlled by the system. If the reference mode behaves appropriately after each test, the robustness of the model is confirmed. When a model produces the same general pattern despite large uncertainty in the values of the input parameters, it is considered robust. This is the stage of verifying the model and its variables.

8. **Test the impact of policies:** This is the final phase in the process of developing a SD model, whose goal is to evaluate the behavior of the system by changing the estimates of the parameters related to the policy variables and formulating alternative scenarios to test distinct policies.

Sterman [48] proposes the following fundamental steps in the modeling process:

1. **Problem articulation:** This step involves selecting the topic, defining key variables, and specifying the dynamic problem and time horizon. Sterman considers this the most crucial step in modeling.

2. **Formulating a dynamic hypothesis:** The second step is to formulate a dynamic hypothesis, which is the theory that helps understand the dynamics represented by the model. At this stage, subsystems, feedback structures, CLDs, and SFDs are systematically outlined.

3. **Formulating a simulation model:** In the third step, the simulation model is developed. This involves specifying decision parameters, initial conditions, equations, and behavioral relationships. The modeler must be attentive to any

modeling contradictions that were not apparent in the conceptual formulation and address them.

4. **Testing:** In the testing phase, the simulated behavior is compared with the actual system behavior. Additionally, through sensitivity analyses, the proposed model is rigorously tested to identify any deficiencies.

5. **Policy design and evaluation:** Finally, after analyzing the system's behavior, new conditions can be explored to assess how they would affect the system. Similarly, alternative scenarios and new policies can be considered to evaluate the system's response, especially regarding interactions, synergies, or compensations.

As can be observed, the SD modeling methods proposed by Ford [58] and Sterman [48] reveal considerable common characteristics, differing primarily in the level of detail each provides during the modeling process. Given this, the methodology suggested by Ford [58] has been selected for this study due to its more comprehensive detail. The steps for projecting the adoption of BEVs among residential consumers will be presented in Section 3.4 of this work.

Building on this discussion, the SD technique includes two methods for presenting a model: the CLD and the SFD. These diagrams facilitate both quantitative and qualitative representation and analysis of the system, as detailed in the sections 2.1.2 and 2.1.3.

2.1.2 Stock and flow diagram

According to Sterman [48] "stocks and flows, together with feedbacks, are the two central concepts in the theory of DS". Stocks are nothing more than accumulations, which portray the state of the system and provide information, that underpins the model's actions and decisions. The representative elements used to draw up the SFD include:

(a) Stock: Represents everything that is accumulated over time. It is also called a level variable. Stocks cause inertia in systems and provide them with memory. They also generate delays by accumulating the difference between the input and output of a process.

(b) Flow: Represents the quantities that are transferred between points in the system. Flows perform the function of connecting stocks and/or introducing elements from the external environment into the system via clouds.

(c) Valve: A variable responsible for controlling the rate of change of flows between stocks or between stocks and the environment. Valves are affected by internal and external information. The system is controlled by the valves, which can reduce the transport speed of the flow, causing delays and increasing the accumulation of stocks. Similarly, valves can increase the system's flow rate, rapidly reducing stock levels.

(d) Auxiliary variable: Converts or manipulates input data by means of auxiliary calculations and equations, from which the output values are used in another variable.

(e) Constant: Represents the variables whose values remain unchanged during testing and simulation.

(f) Connector: Responsible for linking and relating the variables in the model. Connectors carry information, which can represent a constant, a quantity, a graphical or algebraic relationship, from one element to another.

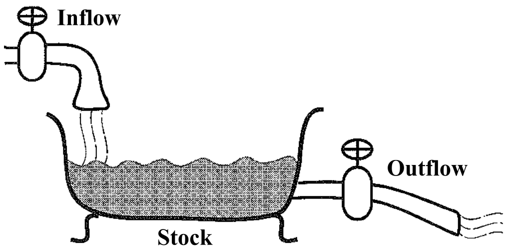
(g) Connector with delay: Symbolized by a connector with two dashes (or the word "delay" written instead of dashes) and used to represent a delay in the information between variables.

(h) Cloud: Used to represent elements that enter (source) or leave (collector) the system. Sources and collectors have infinite receiving or supplying capacity and do not restrict system flows.

In an extremely practical and didactic way, Sterman [48] presents the "hydraulic metaphor", on which SFDs are based and which was proposed by Forrester in 1961. Using this metaphor, Forrester thought of stocks as tubs of water, within which the volume of water varies depending on its flow into and out of the tank. Thus, at any given time, the accumulation of water in the bathtub (stock) is determined by the difference between the water flowing through the tap and that flowing out of the drain. Fig. 2.3 illustrates the aforementioned hydraulic metaphor.

Although simple, this metaphor provides a clear and concrete understanding of the process of formulating SFDs: "stocks accumulate or integrate their flows; the net flow in the stock is the rate of change in the stock" [48]. Mathematically, this relationship can be expressed in integral form (2.1) or differential form (2.2).

$$S(t) = \int_{t_0}^{t} I(t) - O(t)\,\mathrm{d}t + S(t_0) \tag{2.1}$$



(a) Hydraulic representation.

(b) Representation in the form of a SFD.

Figure 2.3: Representation of the hydraulic metaphor for SFDs [48].

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} = I(t) - O(t) \tag{2.2}$$

Where $S(t)$ represents the stock; $S(t_0)$ is the initial stock; $I(t)$ are the inflows at any time between the initial time t_0 and the current time t; and $O(t)$ are the outflows at any time between the initial time t_0 and the current time t.

As demonstrated, the main objective of the SD technique is to represent the dynamic behavior of the system under analysis. This involves characterizing the state variables and their values in order to represent the conditions and elements of the system over time. To do this, the structure of the system is organized in the form of various causal relationships, in which each decision will generate consequences, whether intentional or not, and whether quickly verifiable or not over time. Therefore, it can be seen that through simulations in the context of the SD technique, it is possible to previously analyze the impact of these decisions in the short, medium and long term.

2.1.3 Causal loop diagram

The fourth step of modeling a dynamic problem through SD proposed by Ford [58] consists of drawing up CLDs. In these diagrams, the system's variables and their interrelationships are diagrammed in the form of feedback loops. Therefore, it is necessary to define the cause and effect relationships between the variables in the model, organized in the previous stages, in order to portray the system's behavior.

CLDs are useful and efficient tools for "quickly capturing hypotheses about the causes of dynamics; making explicit and capturing the mental models of individuals or teams; and specifying the important feedbacks that may be responsible for a problem" [48]. They have been used for many years by researchers in academia and industry, as they are an effective representation of the system's feedback structures [48].

(a) **(b)**

Figure 2.4: Representation of loop indicators. (a) Positive or reinforcing loop. (b) Negative or balancing loop. [48].

The connections in the CLD are made by arrows that relate a cause variable to an affected variable. As can be seen in Fig. 2.4, the arrows can be positive feedback (or reinforcing), when the variation between two variables is in the same direction (the variables are directly proportional) or negative feedback (or balancing), when the variation between two variables is in the opposite direction (inversely proportional variables). From a mathematical perspective, the relationship between one variable x and another z can be expressed as shown in (2.3) [48].

$$x \rightarrow^{+} z \implies \frac{\partial z}{\partial x} > 0 \quad \text{and} \quad x \rightarrow^{-} z \implies \frac{\partial z}{\partial x} < 0 \tag{2.3}$$

Upon examination of (2.3), it becomes evident that in the context of positive feedback, an increase in x is accompanied by an increase in z, and vice versa. In the case of negative feedback, a decrease in x is accompanied by a positive variation in z, and vice versa.

CLDs represent the cause-and-effect relationships between the system's variables qualitatively. Therefore, to quantitatively represent the variables analyzed, SFDs are used, which are similar to CLDs. The difference between CLDs and SFDs is that in the latter the variables in the loops are related using logical formulas and/or mathematical equations.

2.2 Rogers' diffusion of innovations theory

According to Sterman [48], the literature on the diffusion of new products and technical and social innovations is vast. A pioneering work on this subject is entitled "Diffusion of Innovations", written by Everett Rogers and originally published in 1962. It is currently in its fifth edition, which was released in 2003.

The adoption of new products or services is a gradual phenomenon that does not occur immediately for all individuals in a social system. In this sense, consumers who adopt an innovation early show distinct characteristics from those who adopt it later [61]. To better understand this, Rogers proposes a distribution into five categories of adopters, as illustrated in Fig. 2.5. The normal frequency distribution of adopter categories, as seen in Fig. 2.5, includes: innovators (2.5 %), early adopters (13.5 %), early majority (34 %), late majority (34 %), and laggards (16 %). Rogers determined this normal distribution of adopter categories using the statistical concepts of mean and standard deviation [61].

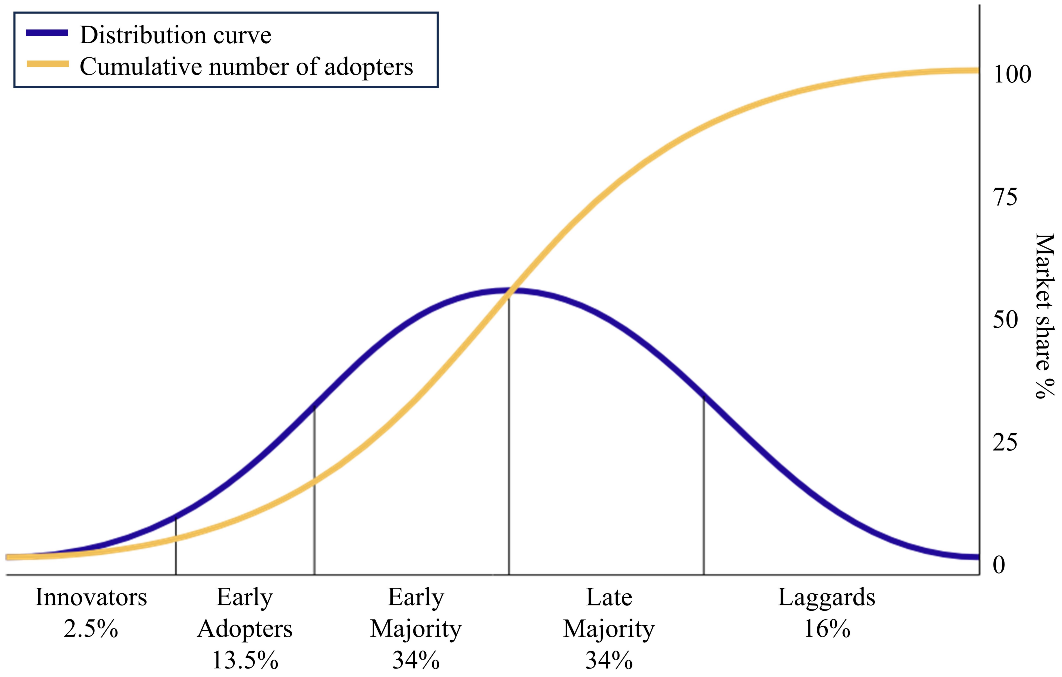


Figure 2.5: Rogers' diffusion of innovations [61].

Basically, *innovators* correspond to the group that wants to be the first to try the innovation, are willing to take risks, have greater contact with scientific information and other innovators and are well-off; *early adopters* are those people who feel comfortable with change and adopting new ideas; the *early majority* is characterized by those who like to adopt new ideas, but need evidence that the innovation works; the *late majority* represents the skeptical part of the population, with low purchasing power, but who will adhere to the new change after it has been widely accepted and adopted by the majority of the population; finally, the *laggards* form the traditional and conservative group of society, who are difficult to appeal to and are the last to acquire the new technology [61].

Thus, it can be seen that the process of diffusion of innovations begins with a slow period of growth, followed by a phase of accelerated growth and culminating in a new period of slowness and decline. For this reason, as illustrated in Fig. 2.5, the number of adopters over time is represented by a bell-shaped curve, while the cumulative number of adopters over time forms an S-shaped curve for the adoption of the innovation under study. Furthermore, according to [61], the diffusion of new technologies is a universal process of social change, regardless of the innovation being studied, but rather of who the potential adopters are.

In addition to Rogers' research, the book "Gestão da Inovação" ("Innovation Management"), published in 2006 by Paulo Bastos Tigre, presents other factors that positively or negatively condition consumer decision-making when it comes to acquiring new technologies. These factors include technical factors, such as the degree of complexity of the technology and its understanding by consumers and positive feedback [62]; economic factors, such as the acquisition and implementing costs of the new technology, expected return on investment, maintenance costs [62]; institutional factors, such as the availability of funding and tax incentives for the innovation, favorable investment conditions in the country, international trade and investment agreements, the intellectual property system and the presence of human capital and support organizations [62]. In addition to the institutional factors, Tigre [62] also considers socio-economic classes differences, religion, culture, and the political and regulatory police framework. It is important to highlight that the latest research on the diffusion of EVs, as discussed in Section 1.2 of this work, addresses some of these aspects.

2.3 Bass model

Frank Bass developed a mathematical model to represent the theory of diffusion of innovations initially proposed by Rogers in 1962, through his article "A New Product Growth for Model Consumer Durables" in 1969 [63]. The Bass forecasting model plays an important role in innovation diffusion studies as it provides satisfactory solutions despite the uncertainty surrounding the insertion of a new product or idea [61]. It has been the most widely used theoretical model in innovation management, marketing, engineering among other areas [49], [61], [64].

According to Sterman [48], a challenge with logistic models of innovation diffusion, including basic growth models like Richards and Weibull, is the issue of initialization. In these models, zero represents equilibrium, which prevents them from explaining the origin of the initial adopters of a new technology. The Bass model addresses this problem by assuming that potential adopters become aware of the innovation through ongoing external information and persuasion sources over time.

The Bass model suggests that the market consists of a homogeneous mix of potential consumers who interact over time. It explains that individuals who are not early adopters eventually adopt the new technology due to two influences: the coefficient of innovation (p), driven by "innovators" and the coefficient of imitation (q), driven by "imitators" [63].

Fig. 2.6 illustrates the adoption of new consumers based on external and internal influences. Innovators are influenced by external factors, such as mass-media, while imitators are influenced by internal social patterns, including "word of mouth" [48], [63], [65].

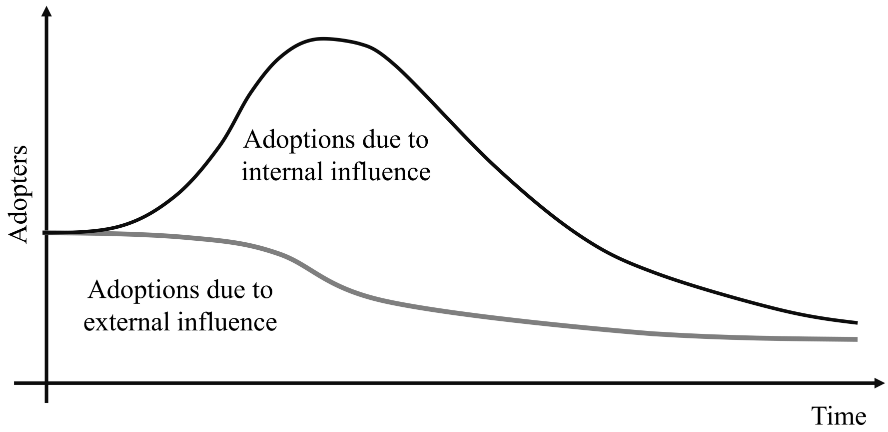


Figure 2.6: Adoption as a function of internal and external factors [65].

In his model, Bass defined that the adoption of technology or innovation begins with the innovators; as new adopters join this group, imitators also emerge, and the model demonstrates growth with a behavior resembling that of logistical models. The mathematical representation of Bass's model is provided in (2.4) [63].

$$Pr(t) = p + q \cdot \frac{Y(t)}{m} \tag{2.4}$$

The variable $Pr(t)$ denotes the probability of adopting the innovation at a specific time t. The innovation coefficient is represented by p, while q indicates the imitation coefficient. $Y(t)$ represents the cumulative number of adopters up to time t and m represents the potential market or the total number of adopters. By analyzing (2.4), it becomes evident that its growth is tied to the increasing number of consumers adopting the market innovation, $\frac{Y(t)}{m}$, and is proportional to the q coefficient.

As $Y(t)$ denotes the cumulative total of adopters at time t, the adoption rate of new consumers at each moment in time will be $\frac{\mathrm{d}Y(t)}{\mathrm{d}t}$. Thus, it is also possible to determine the probability of purchase at time t as the ratio of individuals who have already adopted the innovation at time t to those who have not, as denoted by (2.5).

$$Pr(t) = \left(\frac{1}{m - Y(t)}\right) \cdot \frac{\mathrm{d}Y(t)}{\mathrm{d}t} \tag{2.5}$$

The Bass model is derived in its differential form, as illustrated in (2.6), by combining (2.4) and (2.5) and assuming $G(t) = (m - Y(t))$ as the quantity of potential consumers remaining to purchase the innovation.

$$\frac{\mathrm{d}Y(t)}{\mathrm{d}t} = p \cdot G(t) + q \cdot G(t) \cdot \frac{Y(t)}{m} \tag{2.6}$$

The solution to 2.6 is an S-shaped curve. The asymptotic of the resulting graph corresponds to the maximal market capacity, which is represented by the parameter m, denoting the market potential.

Additionally, (2.7) shows the first-order differential equation that results from replacing $\frac{Y(t)}{m}$ with $F(t)$. This is another frequent representation of the Bass model.

$$\begin{aligned} \frac{\mathrm{d}F(t)}{\mathrm{d}t} &= f(t) = [p + q \cdot F(t)] \cdot [1 - F(t)] \\ &= p + (q - p) \cdot F(t) - q \cdot F^2(t) \end{aligned} \tag{2.7}$$

The sales function density at time t is represented by $f(t)$, while the cumulative fraction of the potential reached by that time is represented by $F(t)$. The cumulative fraction, as denoted in (2.8), is obtained by integrating $f(t)$ over time.

$$F(t) = \frac{1 - \mathrm{e}^{-(p+q)t}}{1 + \left(\frac{p}{q}\right) \mathrm{e}^{-(p+q)t}} \tag{2.8}$$

By examining the equations of the Bass model, it is evident that accurately modeling a system with it requires determining the optimal values of p, q, and m. Various estimation methods are available for calculating these parameters [65]–[69]. However, it should be noted that if just the initial four years of data are available for calibration, the estimates of the Bass model may be compromised [68]. Another study conducted by [70] suggests at least ten years of observations as input data.

As illustrated in equation (2.4), the Bass model is defined by its consideration of macroeconomic factors, including the potential market, innovators, and imitators. This allows for less detailed analyses with a low demand for information. Consequently, the model does not account for factors such as the technological aspects of the product, nor does it consider socio-cultural or economic factors that may drive or hinder the adoption of a new technology. A more detailed study of the diffusion of a specific innovation may be conducted by modifying the Bass model and combining it with other methods, such as the SD technique [41], [48], [50], [60], [71]. This combination permits structural alterations to the system, including modifications to the parameters p and q, as well as the introduction of new variables and loops [50]. Consequently, the model can be expanded to include other aspects of analysis, such as product attributes, specific characteristics of the region under study, among others.

2.3.1 Bass model in the form of a system dynamics model

The SD technique, as previously mentioned, enables the simulation and comprehension of the behavior of complex systems over time by examining the system's structure and its information feedbacks [48], [60]. Also the Bass forecasting model can be implemented in a SD form, as illustrated in Fig. 2.7.

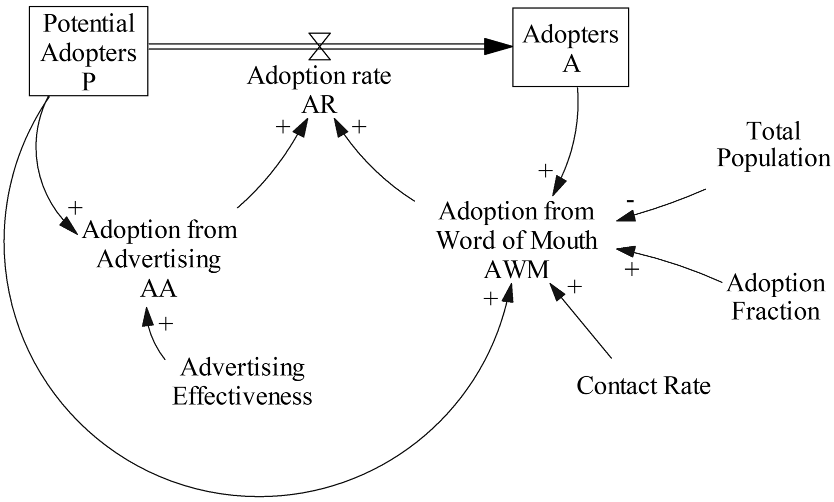


Figure 2.7: Bass model from the perspective of SDs [48].

In Fig. 2.7, it is shown that the adoption rate (AR) is the sum of the adoption from advertising (AA) and the adoption from word of mouth (AWM), as expressed by (2.9)

$$AR(t) = AA(t) + AWM(t) \tag{2.9}$$

Adoption by advertising is the product of advertising effectiveness (aef) by the number of potential adopters (P), according to equation (2.10).

$$AA(t) = aef \cdot P(t) \tag{2.10}$$

Adoption from word of mouth is the product of the contact rate (ctr), the adoption fraction (AF), the number of potential adopters (P) and the number of adopters (A) divided by the total population (N_{pop}), according to equation (2.11).

$$AWM(t) = \frac{ctr \cdot AF \cdot P(t) \cdot A(t)}{N_{\text{pop}}} \tag{2.11}$$

Therefore, the adoption rate can be expressed by equation (2.12).

$$AR(t) = aef \cdot P(t) + \frac{ctr \cdot AF \cdot P(t) \cdot A(t)}{N_{\text{pop}}} \tag{2.12}$$

The parameters aef, ctr and AF are estimated based on specific characteristics of the region of interest, as well as the innovation analyzed. According to [51], when an innovation is introduced into the market, the initial population that will purchase this product is zero and the only source of adoption comes from external information, for example, advertising. These external influences are more significant at the beginning of the customer's decision-making process. Subsequently, they tend to gradually lose relevance as potential adopters begin to adhere to the innovation.

Finally, it should be noted that SD is an interesting technique that allows for modifications to the Bass model, such as altering the coefficients of innovation and imitation, varying the structure of proposed models, and formulating different connections and variables. This flexibility, combined with the mathematical foundation of the Bass model, enables the conduct of consistent diffusion studies over time, facilitating comprehensive analyses as aimed in this thesis.

Furthermore, as previously discussed, the combination of these two methods has been employed in other works and has demonstrated to be very versatile in modeling and understanding the behavior of systems. In this context, given the challenge of modeling the adoption and diffusion of new technologies, such as BEVs, the methodologies mentioned in this section are a notable facilitator of this process.

2.4 Analytic hierarchy process

The AHP method was developed between 1971 and 1975 by Thomas L. Saaty [72]. It is used for multi-criteria decision making and uses logical and mathematical concepts to solve problems with multi-level variables, creating a hierarchy between the possible alternatives. It also involves dividing the different criteria into various hierarchical levels based on judgments and converting the criteria into weights so that the objectives can be ranked through comparisons, and decisions can be made [72]–[74].

In a recent systematic review study, [75] showed that AHP is not only one of the most widely used methods for multi-criteria decision making, but has also gained increasingly popularity in the transportation sector, due to its effectiveness in solving complex problems, ranging from public transport management to logistics planning and the evaluation of sustainable transport strategies. In short, essentially three steps are proposed to implement it [74]:

1. Decomposition of the problem: Goals or objectives broken down into criteria and subcriteria in a hierarchical manner;
2. Comparative judgement: Stage in which comparisons among the criteria are performed and arranged into a matrix;
3. Priority synthesis: Ranked structure based on the defined hierarchical level.

Fig. 2.8 shows a general hierarchical structure of the criteria in the AHP method. Basically, at the top (level 0) is the decision goal or overall purpose. The second level contains the criteria (Cr_1, Cr_2, ..., Cr_n) that influence the decision. This level can be extended into additional levels (level 1, level 2, etc.), where the criteria are further divided into others subcriteria. The final level represents the existing alternatives ($Al_1, Al_2, \ldots, Al_k$) that are suitable for the decision-making process [74].

Moreover, the AHP method is based on the hierarchization of problems and the comparison of various criteria or potential solutions through the use of comparison matrices. This process enables the establishment of a hierarchy vector of alternatives. In other words, the AHP evaluates the importance of the criteria, compares the alternatives pairwise for each criterion and determines a scale in descending order. Thus, each criterion is evaluated according to its degree of importance in relation to another, established according to a numerical scale of values for comparison, proposed by Saaty [73], as shown in Table 2.2.

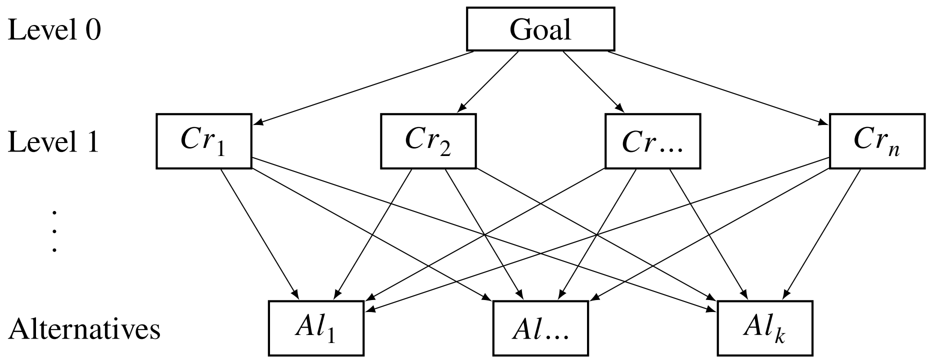


Figure 2.8: Generic diagram of level hierarchy.

Table 2.2: AHP fundamental scale for comparison and judgment [73].

Numerical scale	Importance level	Explanation
1	Equal	Both criteria contribute equally to the goal
3	Moderate	Experience and judgment slightly favor one criterion over the other
5	Strong	Experience and judgment strongly favor one criterion over the other
7	Very strong	One criterion is strongly favored over another and its dominance can be seen in practice
9	Extreme or absolute	The evidence has the highest level of certainty and favors one criteria over another
2, 4, 6, 8	Intermediate values	Intermediate values are assumed when there is no consensus between two adjacent judgments (odd numbers)

Considering the numerical scale in the Table 2.2, the judgments are made by experts who evaluate the criteria and consider how much more important one is in relation to the other, always pair by pair. Thus, a comparison (or judgment) matrix with dimension $n \times n$ for n evaluation criteria is constructed, as can be seen in (2.13).

$$\boldsymbol{M} = \begin{array}{c} \\ Cr_1 \\ Cr_2 \\ \vdots \\ Cr_n \end{array} \begin{array}{c} \begin{array}{cccc} Cr_1 & Cr_2 & \dots & Cr_n \end{array} \\ \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ \dfrac{1}{a_{12}} & 1 & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \dfrac{1}{a_{1n}} & \dfrac{1}{a_{2n}} & \dots & 1 \end{bmatrix} \end{array} \tag{2.13}$$

$\boldsymbol{M}$ represents the criteria comparison matrix; C_1, C_2, Cn indicate the number of evaluation criteria; and a_{ij} is the degree of importance of criterion i over criterion j. For a matrix of order n, the number of required criteria is $\frac{n(n-1)}{2}$ [73]. Furthermore, the main diagonal of the matrix will always have a value of 1, since it reflects the assessment of the C_i criterion itself. According to [73], for consistency requirements reasons, the AHP method considers reciprocal entries $\left(a_{ji} = \frac{1}{a_{ij}}, \forall i, j\right)$ which correspond to the elements below the main diagonal.

Also according to Saaty's theory [72], the comparison matrix $\boldsymbol{M}$ is consistent if it meets the parameter presented in (2.14).

$$a_{ij} \cdot a_{jk} = a_{ik} \quad \forall i, j, k = 1, \dots, n \tag{2.14}$$

In this case, with $a_{ij} > 0$ indicating the extent to which criterion i is preferred over j, and considering the consistency requirement ($a_{ji} = 1/a_{ij}$), each entry of the $\boldsymbol{M}$ accurately reflect the ratio between weight i in relation to j, i.e. $a_{ij} = \frac{w_i}{w_j}, \forall i, j$, so that $\boldsymbol{M}$ can be written as (2.15).

$$M = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \dots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & \frac{w_n}{w_n} \end{bmatrix} \tag{2.15}$$

From the $\boldsymbol{M}$ matrix, the priority or weight of each criterion is calculated, obtained by applying a two-step process. First, all the values in each column are added together, and, in order to normalize them, each value in each column is divided by the sum of the respective column, which will form a new matrix, but normalized according to (2.16).

$$\overline{a}_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{2.16}$$

Subsequently, (2.17) is employed to find the weight or priority of the criterion under consideration and to calculate the mean value of each row of the normalized matrix. Hereby, the vector of priorities is thus determined (2.18). This process must be repeated for each criterion.

$$w_i = \frac{\sum_{j=1}^{n} \bar{a}_{ij}}{n} \tag{2.17}$$

$$\boldsymbol{w}_{\mathrm{i}} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \tag{2.18}$$

Where w_i is the weight of criterion i and n is the number of criteria. The total sum of the criteria weights must equal 1.

The AHP methodology bases its solutions on the opinions of experts. However, this can eventually lead to a certain degree of inconsistency due to the complexity of the problem or the involvement of multiple experts from different fields, each bringing their own perspective [74], [76]. Given this, the AHP method includes the calculation of a consistency ratio (CR) of the judgments [72]–[74], [76]:

$$CR = \frac{CI}{RI} \tag{2.19}$$

As can be seen in (2.19), the CR, which represents the acceptance of the decision-maker's judgment, is determined by the quotient between the consistency index (CI) and the random consistency index (RI). The CI expresses how far the matrix deviates from a consistency matrix. For a matrix of size n, (2.20) is found, where λ_{max} is the maximum eigenvalue of the judgment matrix. The value of the RI can be determined directly by applying the Table 2.3 proposed by Saaty [72], [73], [77].

$$CI = \frac{\lambda_{\text{max}} - n}{n - 1} \tag{2.20}$$

To calculate CI, it is necessary to determine the eigenvalues of the pairwise comparison matrix $\boldsymbol{M}$. This involves multiplying this matrix by the criteria weights to produce a new vector. Each element of this new vector is then divided by its corresponding weight. The results of these divisions are used to calculate the maximum eigenvalue of the comparison matrix, λ_{max}, which corresponds to the average of the values in this final vector. In other words, it is necessary to solve the equation system presented in (2.21) [72], [73], [78].

$$\begin{cases} \boldsymbol{M}\boldsymbol{w} = \lambda_{\text{max}}\boldsymbol{w} \\ \boldsymbol{w}^{\mathrm{T}}\mathbf{1} = 1 \end{cases} \tag{2.21}$$

Where $\boldsymbol{w}$ and λ_{max} correspond to the eigenvector and the maximum eigenvalue of $\boldsymbol{M}$, respectively, $\mathbf{1} = (1, \ldots, 1)^{\mathrm{T}}$.

Table 2.3 shows the RI value based on the number of criteria evaluated, as well as the maximum CR allowed to validate the information provided. This determines the final consistency of the expert's information. Consequently, a higher CR value indicates more dispersed and less consistent information. Generally, a CR of 10 % is acceptable, except for assessments with four and three criteria, which CR is 8 % and 5 %, respectively.

According to [78], the application in (2.22) is another widely used method to calculate w_i. In this equation, each component of w is determined by the geometric mean of the elements in that row divided by a normalization term. In this approach, the terms of w must also sum to 1.

$$w_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \Bigg/ \underbrace{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}_{\text{normalization term}} \tag{2.22}$$

Table 2.3: RI values [77].

Number of criteria	RI value	Maximum CR
1	0.00	0.00
2	0.00	0.00
3	0.52	0.05
4	0.89	0.08
5	1.11	0.10
6	1.25	0.10
7	1.35	0.10
8	1.40	0.10
9	1.45	0.10
10	1.49	0.10
11	1.52	0.10
12	1.54	0.10
13	1.56	0.10
14	1.58	0.10
15	1.59	0.10

Depending on the application of AHP, various areas and experts can be consulted. However, evaluations may differ due to the interests of each sector and the experience of each expert, for example. In such cases, the evaluations of the consulted experts should be aggregated. This is done by applying separate questionnaires and then integrating the judgments that are relevant or most consistent. To achieve this, the comparison matrix is recalculated using the weighted geometric mean [78], as shown in (2.23).

$$a_{ij}^{\mathrm{G}} = \prod_{h=1}^{s} \left(a_{ij}^{(h)} \right)^{\frac{1}{s}} \tag{2.23}$$

Where a_{ij}^{G} is the weighted geometric mean of each a_{ij} term of the comparison matrices; $a_{ij}^{(h)}$ represents the a_{ij} term of the comparison matrices for each expert h; s is the total number of experts considered. The group comparison matrix ($\boldsymbol{M}^{\mathrm{G}}$) can be rewritten as shown in (2.24).

$$
\boldsymbol{M}^{\mathrm{G}} = \begin{array}{c} \\ Cr_1 \\ Cr_2 \\ \vdots \\ Cr_n \end{array}
\begin{array}{c} \begin{array}{cccc} Cr_1 & Cr_2 & \dots & Cr_n \end{array} \\
\begin{bmatrix}
1 & a_{12}^{\mathrm{G}} & \dots & a_{1n}^{\mathrm{G}} \\
\dfrac{1}{a_{12}^{\mathrm{G}}} & 1 & \dots & a_{2n}^{\mathrm{G}} \\
\vdots & \vdots & \ddots & \vdots \\
\dfrac{1}{a_{1n}^{\mathrm{G}}} & \dfrac{1}{a_{2n}^{\mathrm{G}}} & \dots & 1
\end{bmatrix} \end{array} \tag{2.24}
$$

Where Cr_i represents criterion i under analysis; a_{ij}^{G} grouped term representing the preference of criterion i over j; and $\frac{1}{a_{ij}^{\mathrm{G}}}$ grouped term representing the preference of criterion j over i. Saaty [73] emphasizes that "the geometric mean is the only way to combine group judgments and preserve the reciprocal property", i.e., if the experts' analyses result in dispersed judgments, the geometric mean will not preserve this property, leading to results that are not representative.

In this study, the AHP method was chosen because it is easy to use and reliable when it comes to ranking alternatives for the aspects under analysis. Specifically, AHP is used to define the weights of the variables and criteria considered in the analyses for BEV diffusion. The degree of importance of each aspect is also defined using this approach.

2.5 Fuzzy logic

Another method used in the analysis developed in this work is fuzzy logic. Fuzzy logic is a mathematical approach also used for complex multi-criteria decision-making, which differs from the AHP in that it does not rank the opinion of experts. Instead, it offers a more flexible and imprecise evaluation, allowing for different degrees of truth to be considered simultaneously.

In 1965, Lotfi A. Zadeh published a precursor article entitled "Fuzzy Sets", in which he described the assumptions and mathematical foundations of fuzzy logic. In this work, he argues that certain categories, such as "a beautiful woman" or "a tall man", do not fit into traditional mathematical sets or classes [79]. Zadeh emphasizes the importance of these imprecise categories in human thought, especially in areas such as pattern recognition, communication, and abstraction. Through specific mathematical definitions, he lays the necessary foundations for the application of fuzzy logic, offering a new perspective for dealing with uncertainty and subjectivity in various applications [79].

As its main characteristics, fuzzy logic stands out for its flexibility, as well as its ability to evaluate applications although nonlinearities of parameters or incomplete, ambiguous, or imprecise data [80]. This allows, for instance, computer systems to analyze situations that are neither completely false (0) nor completely true (1). Thus, boolean logic, in which only "0" or "1" are possible values, can be interpreted as a particular case of the fuzzy logic, corresponding with what are its extreme cases, i.e. completely true or completely false, as depicted in Fig. 2.9.

(a) Boolean logic. **(b)** Fuzzy logic.

Figure 2.9: Levels of computer evaluation [80].

An important definition of fuzzy logic, as proposed by Zadeh [79], involves mapping a real number to a specific interval, such as [0, 1], to associate an element with a class. In this context, X can be considered a space of points, with x representing a generic element of X, so $X = \{x\}$. A fuzzy set or class A in X is defined by a pertinence (or membership) function $\mu_A(x)$, which assigns each point in X a real value within the interval [0, 1]. This value indicates the degree to which x belongs to A, with values closer to 1 representing a higher degree of membership in A [79]. The typical membership functions are presented in Fig. 2.10 [80].

The triangular membership function (Fig. 2.10a) is defined from three scalar parameters: a, b and c. Its mathematical representation is given by (2.25).

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{for } a < x \leq b \\ \dfrac{c-x}{c-b} & \text{for } b < x \leq c \\ 0 & \text{otherwise} \end{cases} \tag{2.25}$$

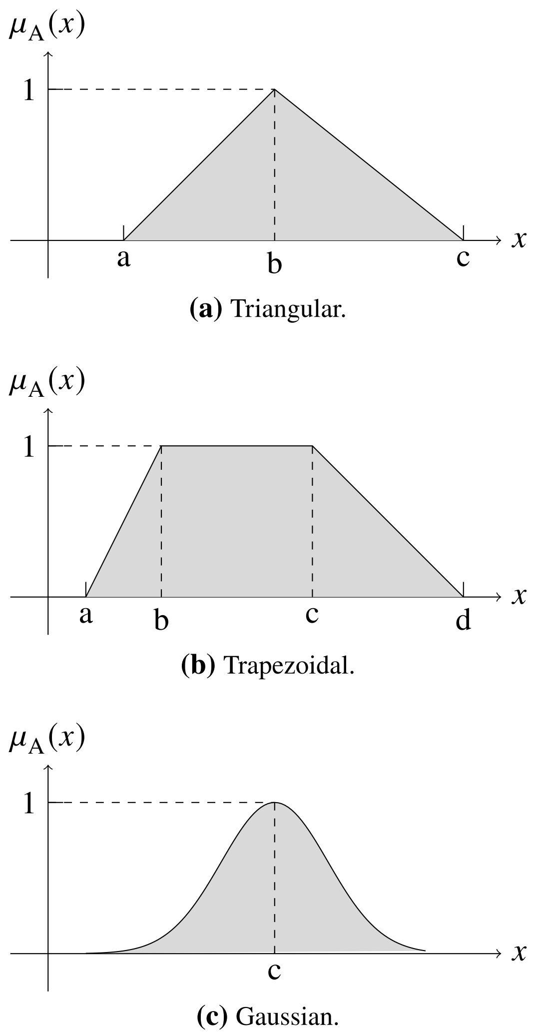


Figure 2.10: Typical membership functions of fuzzy logic [80].

The trapezoidal function (Fig. 2.10b) has four scalar parameters to define its curve: a, b, c and d. Its general formula is expressed as (2.26).

$$\mu_{\mathrm{A}}(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c} & c \le x \le d \\ 0 & \text{otherwise} \end{cases} \tag{2.26}$$

Finally, in the gaussian function (Fig. 2.10c), two parameters are used: o represents the center of the curve and σ (standard deviation) determines its width. Its mathematical representation is given by (2.27).

$$\mu_{\mathrm{A}}(x) = \mathrm{e}^{-\frac{(x-o)^2}{2\sigma^2}} \tag{2.27}$$

Membership functions, for example, those shown in Fig. 2.10, are used to describe how a problem can be interpreted even with imprecise attributes. In this way, by simulating human reasoning, fuzzy logic allows the inputs of a problem to be related to the inferences made. In its classical implementations, fuzzy logic is applied for decision-making processes that use qualitative concepts, for example, excellent, good, bad, important, irrelevant, etc., providing opportunities to quantify these linguistic variables and effectively associate subjective and objective aspects [80]. Therefore, fuzzy systems generally have four principal components: fuzzification, rules, inference engine and defuzzification, as depicted in Fig. 2.11.

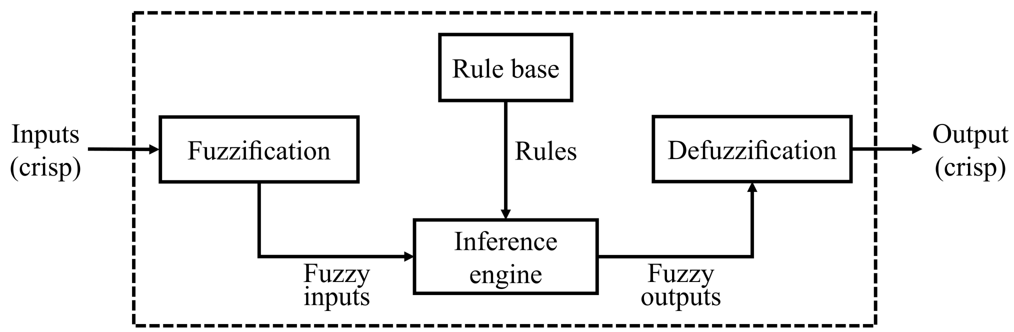


Figure 2.11: Elements of a fuzzy logic system [80].

Each element of this system is described below [80], [81]:

- *Fuzzification*: It is the step that converts a real scalar value into a fuzzy value. In this way, the crisp input data is received and transformed into fuzzy numbers (or sets) that represent certain ranges of belongingness.
- *Rules*: They represent the knowledge base linked to the domain of the analyzed system. This contains all the data and rules of the linguistic fuzzy control.
- *Inference engine*: It is responsible for applying the fuzzy rules to the fuzzy input values to produce fuzzy output values by mapping the fuzzy data into fuzzy sets. It combines the fuzzy rules and calculates the membership degree of the output variables based on the stored expert rules.
- *Defuzzification*: Stage in which a single, suitable value for the output variable is determined from the converted fuzzy outputs.

There are several packages for easy application of fuzzy logic in both commercial and open source software. However, the expert must properly define the rule base and provide the appropriate input data [80]. The construction of the rule base is fundamental and includes defining the universe of each variable, the number of fuzzy sets and the adequate membership functions. In a system based on fuzzy logic, the rules (Ru^l) are implemented using "IF antecedent THEN consequent" logic as shown in (2.28) [82].

$$Ru^l = \text{IF } x_1 \text{ is } Al_1, \ldots, x_n \text{ is } Al_n, \text{ THEN } y \text{ is } B \tag{2.28}$$

Where A_i and B are fuzzy sets; x is the variable of interest (antecedent) with $i = 1, 2, \ldots, n$; y is the output (consequent) value; and j represents the amount of rules for $l = 1, \ldots, j$ in the rule base. In general, the antecedent of a fuzzy system may consist of multiple components that can be combined using "AND" or "OR", and sometimes "NOT" operators. Then, after the fuzzification, the inference engine maps the fuzzy sets by decoding the fuzzy rules. The calculations made by the inference system can be interpreted as a type of interpolation method [82].

An inference system is typically modeled using two approaches: Mamdani-type or Sugeno-type. The first is preferred for implementing rules based on linguistic variables by defining relational operators for antecedents that generate consequents in a fuzzy set. The latter is utilized for constructing and analyzing mathematical models of uncertain systems, and the consequent is a linear combination [82], [83], as shown in (2.29).

$$Ru^l = \text{IF } x_1 \text{ is } Al_1, \ldots, x_n \text{ is } Al_n, \text{ THEN } y = c_0 + \sum_{i=1}^{n} c_i x_i, \tag{2.29}$$

Where c_i is undetermined variable. The Sugeno-type modeling method is better to explain nonlinear associations with linear interpolation than the Mamdani model [82], [83].

In addition, it is through the inference engine that the defuzifier's decision-making strategies are organized [82]. Regarding defuzzification, different techniques can be employed, for instance center of gravity, mean of maxima, first of maxima and last of maxima, and random choice of maxima [17], or even adapted variations of them depending on the study [84].

Reference [81] presented some areas where fuzzy logic has been widely used, for instance, image processing, management, agriculture, industry applications, engineering, among others, emphasizing different works that were developed in these areas. In the context of electromobility, fuzzy logic is also used in different approaches to deal with complex and uncertain variables, such as optimizing the management of battery charging and discharging in EVs, taking into account multiple factors, e.g. temperature and the battery's state of charge (SOC) [85]; improving energy management to increase efficiency and extend battery life by combining supercapacitors and batteries for hybrid storage [83]; improving fuel economy and efficiency of hybrid vehicles [86]; integrating the EV fleet into the smart grid by optimizing battery charging and discharging to ensure economic benefits for the user and to support the operation of the smart grid [87]. Moreover, [88] conducted a study to determine CS locations for EVs in urban areas, integrating AHP and fuzzy logic.

In view of the above, it can be seen that this technique has a wide range of applications with consolidated and reliable results. Therefore, in this work, fuzzy logic will be utilized to determine the values of certain variables for which analytical calculation would be hard. In this context, this approach highlights the flexibility and adaptability of fuzzy logic in complex decision-making scenarios.

3 Proposed Methodology

In Chapter 2, the fundamental theories used to implement the adoption model proposed in this work were presented, namely: system dynamics (SD), Rogers' theory of innovations, the Bass model, the AHP method and fuzzy logic. Each theory has been reviewed in detail, establishing the necessary conceptual basis for the global methodology that is developed in this chapter.

The adoption of BEVs by residential consumers will lead to changes in the planning and operation of the electricity system. Therefore, it is important to understand and determine how this diffusion will occur over time. However, it should be noted that this adoption is challenging and difficult to forecast, since it is linked to the individual decisions of each consumer to purchase a BEV or not, which is associated with the barriers and incentives that reach potential adopters.

3.1 Problem formulation

The global transition to zero emission vehicles (ZEVs) is essential for achieving GHG emission reduction targets and for transport decarbonisation [89]. However, the diffusion of BEVs presents complex challenges that vary significantly across different regions and markets [7], [90]–[93]. Countries like Norway have achieved remarkable success in BEV adoption, with robust policies, comprehensive charging infrastructure, and high environmental awareness leading to market penetration exceeding 80 % of new vehicles sold [94]. In contrast, emerging markets such as Brazil face numerous obstacles, including high acquisition costs, lack of infrastructure, and acceptance that hinder large-scale adoption [43], [44].

Moreover, considering the scope of this thesis, which aims to contribute to the understanding of BEV diffusion specially for the power sector, BEVs have the potential to serve the electric grid as they become more prevalent. By providing ancillary services such as load balancing, voltage regulation, and peak shaving, BEVs can offer significant benefits to power system operators and consumers alike. However, the insertion of BEVs into the power systems without prior estimation and investigation can have undesirable effects on electricity networks, due to the increase in consumer demand for energy, voltage instability, increased peak demand, reduced power quality, increased losses and overloading of lines and transformers in distribution networks [8], [13], [18], [20]. These impacts can vary greatly depending on the different parameters related to EVs, such as penetration levels, charging patterns, vehicle driving patterns, distances traveled, charging strategies, market characteristics, among others.

The complexity of analyzing BEV adoption demands approaches capable of capturing the diverse factors influencing diffusion in diverse and region-specific regional contexts. The Bass model, widely used for forecasting the adoption of new technologies, combined with SD, offers a powerful framework for modeling BEV diffusion on a global scale. These methods allow for the incorporation of both imitation and innovation effects from the Bass theory, as well as the interactions among several quantitative and qualitative variables in a single SD model to study BEV adoption over time.

Despite the advantages of this integrated modeling approach, accurately forecasting BEV adoption across different regional contexts necessitates a detailed understanding of local market conditions. Incorporating methods such as the AHP and fuzzy logic can enhance the model's adaptability and precision by systematically evaluating and weighting the influence of various factors based on regional characteristics. AHP provides a structured technique for organizing and analyzing complex decisions by decomposing them into a hierarchy of importance, i.e. determining the relative importance of each criterion [95]. Fuzzy logic complements this by handling the inherent uncertainties and ambiguities associated with human judgment and qualitative assessments, enabling the model to incorporate expert opinions and subjective evaluations effectively [96]. Together, these methods facilitate comprehensive market analyses and precise mapping of influential variables, ensuring that the model accurately reflects the multifaceted and context-specific nature of BEV adoption.

This study proposes developing a global BEV diffusion model using the integration of the Bass diffusion model, SD, AHP, and fuzzy logic to simulate its adoption in various economic, political, technical, infrastructural, social and business contexts. The model will be applied to case studies in Brazil and Germany, allowing for the exploration of how different factors influence the rate of BEV adoption in emerging and developed economies.

Hence, the objective of this proposal is to provide a robust tool for forecasting BEV adoption and informing policy formulation to accelerate the transition to more sustainable mobility. Additionally, the proposed approach offers several advantages, including enhanced flexibility to adapt the model to diverse regional conditions, improved accuracy in forecasting adoption trends, and the ability to identify and analyze the main factors influencing BEV diffusion. Furthermore, the model can serve as a valuable resource for policymakers and stakeholders by providing insights into effective strategies and interventions adjusted to their specific regions and societies.

3.2 Overview of the proposal

Fig. 3.1 provides an overview of the proposed model for forecasting the rate at which residential consumers are likely to adopt BEVs. The block diagram illustrates the need to first assess the aspects related to the diffusion of BEVs, which are associated with economic, political, social, technical, infrastructural, and market factors. Mapping these aspects helps the development of knowledge and understanding of the system, which is essential for accurate modeling.

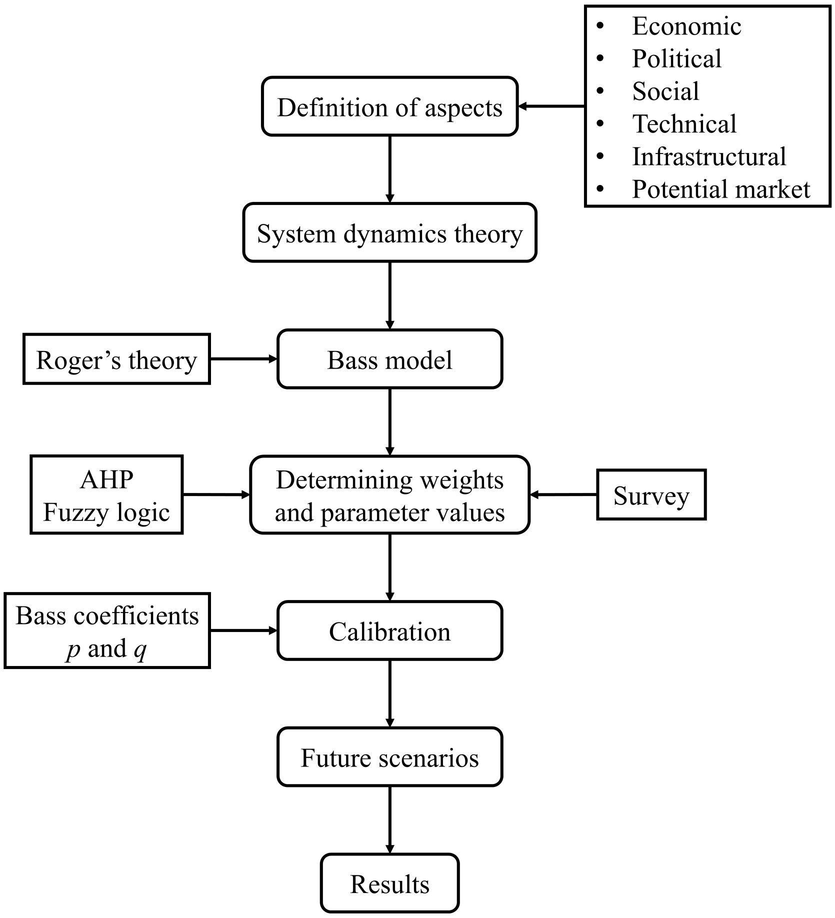


Figure 3.1: Block diagram of the model.

The subsequent phase involves analyzing the spread of BEVs over a period of time, employing the SD approach in conjunction with the Bass model. Moreover, AHP and fuzzy logic are employed to determine the weights and values of some parameters in the model. This analysis encompasses several perspectives of the specified aspects.

Next, a model verification for the available historical data must be performed. At this point, p and q coefficients of the Bass model are calibrated. Finally, future scenarios can be studied, with different policy tests and parameter variations, and the results are analyzed.

3.3 Main aspects influencing the adoption of BEVs

Table 3.1 shows the aspects associated with the diffusion of BEVs among residential consumers. They are divided into six categories: economic, political, technical, infrastructural, social and market.

Table 3.1: Main aspects analyzed for the adoption of BEVs

Economic aspect	**Political aspect**
Net present value (NPV) of ICEV	Legislation
NPV of BEV	Financing opportunities
NPV of BEV and green charger	Tax incentives
Operating costs of the vehicle	Social appeal
Wallbox	
Infrastructural aspect	**Technical aspect**
Mechanic workshops	Range
Public charging infrastructure	Charging time
R&D	BEV models
Social aspect	**Market aspect**
Social appeal	Total population
Knowledge	Potential market
Feedback	Demographic data
Relevance	Human development index (HDI)
DG adopters	Business models

The adoption of BEVs is influenced by several aspects, as outlined in [43], [90]–[92], [97]–[99]. The aspects proposed in this work encompass a range of internal and external factors, which are represented through the dynamic variables and parameters in form of a SD model.

While Table 3.1 provides a general overview, it is important to note that each aspect is intricately detailed through the corresponding equations and interactions in the CLD and SFD within the model, as specified in the next sections. This approach focuses on the main factors related to BEV diffusion, ensuring that the model remains robust and global and avoids becoming overly complex or exhaustive in its parametrization.

During the literature researches, no studies were found that dealt with this issue in a global way, considering the various aspects listed in Table 3.1 in one model. The problem of BEV diffusion in residential consumers is performed over time, taking into account the influence of the proposed aspects categorized using the SD technique together with the Bass model.

Given the complexity of the parameters of these aspects, the model integrates multiple methods to accurately represent their influence on BEV adoption. In particular, the use of AHP method and fuzzy logic provides a robust framework for handling the inherent uncertainty and vagueness associated with certain variables. AHP is employed to determine the weights of various factors, allowing for a region-specific analysis of how each aspect influences BEV adoption. Meanwhile, fuzzy logic is utilized to estimate the imprecise and qualitative aspects of the problem, ensuring that the model captures the characteristics of real-world decision-making processes.

Together, these approaches enable a comprehensive analysis of the factors driving BEV adoption, allowing for a dynamic and regionally tailored model that can adapt to different contexts and scenarios. The combination of these methods not only enhances the accuracy of the model but also provides valuable insights into how various aspects interact to influence the diffusion of BEVs over time in a given country or region.

3.4 Conceptual and mathematical modeling

As mentioned in Section 2.1, the modeling steps suggested by Ford [58] is used to develop the model proposed in this work, which consists of applying the SD technique in conjunction with the Bass model to project the diffusion of BEVs in residential consumers over time. The first stage proposed by [58] refers to knowledge of the system. In this sense, as presented in Section 1.2, research was carried out into the diffusion of EVs. In addition, Table 3.1 shows the different aspects associated with the diffusion of BEVs from five points of view: economic, technical, political, social and market analysis. In this way, knowledge is gained about the technology, the diffusion of which is being studied over time.

The second stage of modeling is related to the dynamic specification of the system under study. Thus, according to Rogers' theory and Bass model, the dynamic behavior for the adoption of BEVs as an innovation is an S-shaped growth curve [61], [65]. The third part of the proposed model is the construction of the SFD, which is detailed in Section 3.4.1.

3.4.1 Proposed stock and flow diagram

SFDs are responsible for mathematically relating the equations and assumptions involved in formulating the behavior of the factors that influence the decision of residential consumers to purchase a BEV or not over time. Fig. 3.2 shows the SFD of the proposed model considering the aspects under analysis.

As can be seen in Fig. 3.2, the model includes three stocks: the BEV population (m), potential adopters (P), and adopters (A). m represents the total number of individuals eligible to purchase a BEV, specifically those who possess a valid driver's license for cars. These individuals constitute the total potential market.

Unlike the general structure of the Bass model in the form of SD (see Fig. 2.7), the proposed model considers, in addition to the adoption rate (AR), a replacement rate (RR) for the diffusion of BEVs. This is because the Bass model is described as a model to represent the behavior of first sales, relating the stock of potential adopters (P) to that of adopters (A). However, in the context of EV usage, as with other durable goods, vehicles may be discarded, or the consumer may decide to upgrade after some time, among other reasons that lead them to purchase another vehicle [48]. In this way, at certain intervals the BEV can be replaced, causing BEV adopters to return to the pool of potential adopters again, being susceptible to buying a new vehicle depending on attractiveness of the product or social exposure. In the proposed model, this $AR(t)$ can be expressed as the sum of adoption from BEV attractiveness ($AAT(t)$) and adoption from social exposure ($ASE(t)$), as shown in (3.1).

$$AR(t) = AAT(t) + ASE(t) \tag{3.1}$$

The replacement rate $RR(t)$, by contrast, can be conceptualized as a time-delayed version of the adoption rate, with the delay corresponding to the average useful life of the BEV (t_{BEV}), in years, as expressed in (3.2).

$$RR(t) = AR(t - t_{\text{BEV}}) \tag{3.2}$$

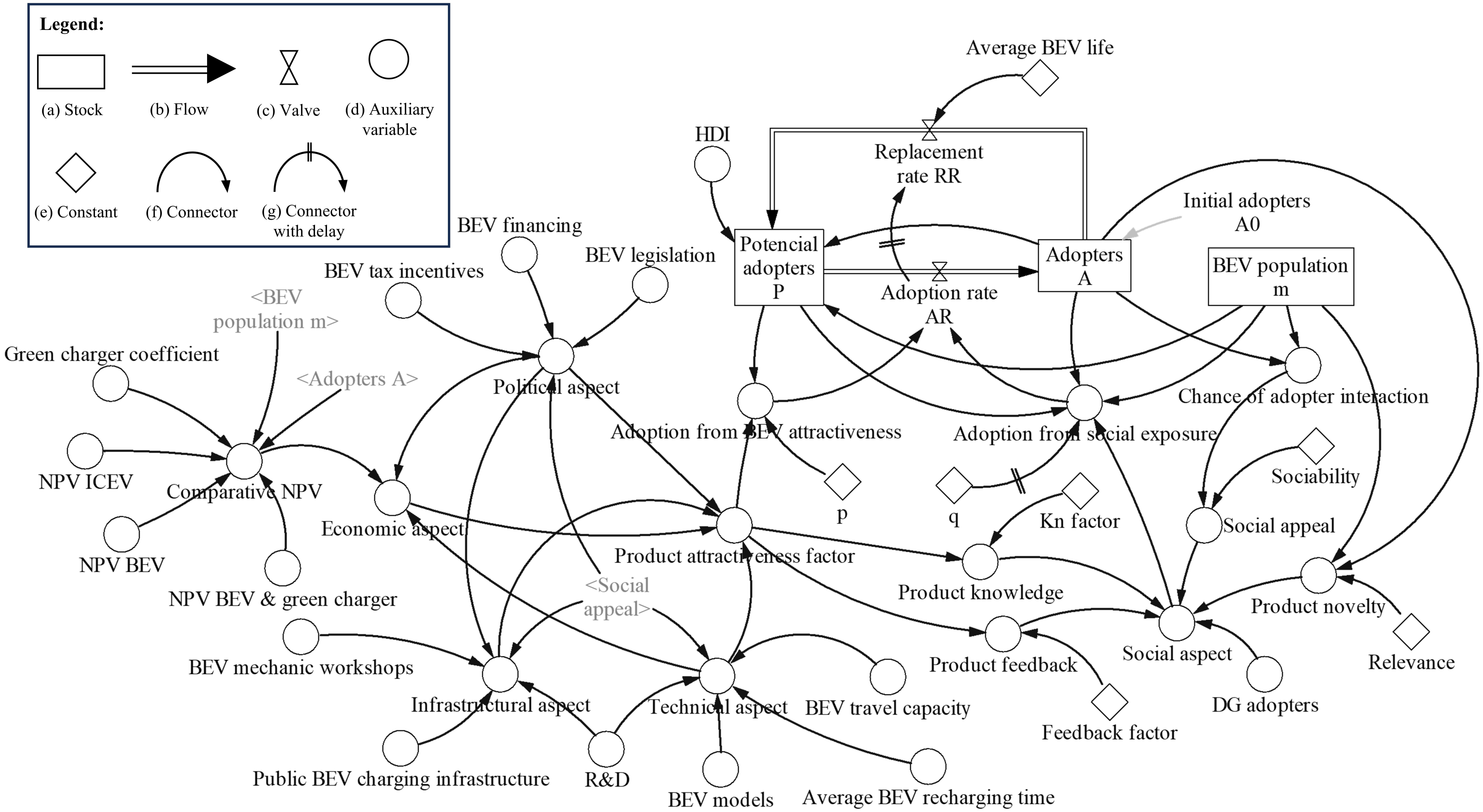


Figure 3.2: SFD of the complete model.

The stock of adopters A is modeled as an integral of the adoption and replacemente rate, reflecting the flow of individuals transitioning from potential adopters to actual BEV owners over time. The equation for A is given by (3.3). $A(t_0)$ represents possible early adopters in the study region.

$$A(t) = \int_{t_0}^{t} (AR(t) - RR(t))\ \mathrm{d}t + A(t_0) \tag{3.3}$$

From the perspective of SFD in a SD analysis, the variable AR represents the rate at which potential adopters become BEV adopters based on the dynamic relationships in the model. A positive variation of this variable increases the stock of BEV adopters and decreases the stock of potential adopters.

Potential adopters (P) are calculated as a subset of the BEV population (m), adjusted by the HDI to reflect the socioeconomic conditions of a specific region. The pool of potential adopters is further modified by accounting for the current number of adopters (A), which reduces the number of individuals who are still in the market to adopt a BEV. Additionally, the replacement rate (RR) reintroduces individuals back into the pool of potential adopters as they become eligible to purchase a new BEV after replacing their previous one. This dynamic relationship is expressed as:

$$\begin{aligned} P(t) &= \max\left(0, m(t) \cdot HDI(t) - A(t)\right) \\ &= \max\left(0, m(t) \cdot HDI(t) + \int_{t_0}^{t} (-AR(t) + RR(t))\ \mathrm{d}t - A(t_0)\right) \end{aligned} \tag{3.4}$$

Here, $P(t)$ represents the potential adopters at time t, ensuring that the value cannot be negative even under extreme variations.

From (3.1), $AAT(t)$ is defined according to (3.5), where p is the Bass innovation coefficient, and $PAF(t)$ represents the product attractiveness factor.

$$AAT(t) = p \cdot P(t) \cdot PAF(t) \tag{3.5}$$

PAF is a variable that influences BEV attractiveness. It is directly determined by technical (TA), infrastructural (IA), economic (EA) and political (PA) aspects, together with their respective weights, w_1, w_2, w_3 and w_4, as presented in (3.6). Indirectly, as depicted in the model, factors such as recharging infrastructure development, public policies, BEV characteristics, and market dynamics also influence it.

$$PAF(t) = w_1 \cdot TA(t) + w_2 \cdot IA(t) + w_3 \cdot EA(t) + w_4 \cdot PA(t) \tag{3.6}$$

Within the Bass model, the innovation coefficient p is multiplied by the PAF to adjust the initial adoption rate of the BEV from the perspective of its attractiveness. This approach enables the model to capture not only the tendency of innovators to adopt the BEV as an innovation or novelty initially, but also how its relative attractiveness influences the diffusion process throughout the time.

The technical aspect depends on the travel capacity of the BEV, its recharging time, the number of models available on the market and R&D into this technology. In addition, the proposed model accounts for the impact of social influences on the development of the technical aspects.

The travel capacity of the BEV, denoted by Cap_{travel}, is defined as a normalized measure of the vehicle's range. This measure relates the effective range of the BEV, in kilometers, to a standard normalization base value, denoted by Cap_{max}, in km. Mathematically, the travel capacity can be expressed by the following equation:

$$C\hat{a}p_{\text{travel}}(t) = \begin{cases} \dfrac{R_{\text{BEV}}(t)}{Cap_{\text{max}}} & \text{if } R_{\text{BEV}(t)} \leq Cap_{\text{max}} \\ 1 & \text{otherwise} \end{cases} \tag{3.7}$$

where R_{BEV} represents the range, in km, that the BEV can travel on a full charge. The choice of C_{max} depends on the specific context and should reflect a relevant standard or industry average to facilitate objective comparisons between different BEV categories.

The calculation of the BEV recharging time begins with determining the required energy (E_{req}). This is calculated by taking the battery capacity (Cap_{bat}), in kWh, and multiplying it by the difference between the target SOC (SOC_{target}) and the current SOC (SOC_{current}), expressed as a percentage. This value is then divided by the charging efficiency (η_{charge}) to account for energy losses during charging:

$$E_{\text{req}}(t) = \frac{Cap_{\text{bat}}(t) \cdot (SOC_{\text{target}} - SOC_{\text{current}})}{100 \cdot \eta_{\text{charge}}} \tag{3.8}$$

Finally, the recharging time (t_{charge}) is obtained by dividing the required energy (E_{req}) by the charging power (P_{charge}) of the charging station (CS), in kW, which can be a wallbox, a fast-charging station, or another type of charger:

$$t_{\text{charge}}(t) = \frac{E_{\text{req}}(t)}{P_{\text{charge}}} \tag{3.9}$$

To integrate the recharging time into the technical aspects of the model, t_{charge} is further normalized by a base recharging time (t_{min}), in hours or minutes, providing a dimensionless measure that can be compared across different scenarios:

$$\hat{t}_{\text{charge}}(t) = \begin{cases} \dfrac{t_{\text{min}}}{t_{\text{charge}}(t)} & \text{if } t_{\text{charge}}(t) \geq t_{\text{min}} \\ 1 & \text{otherwise} \end{cases} \tag{3.10}$$

The variable M_{BEV} represents the current number of BEV models available in the market, normalized by a reference number of models M_{max}, which reflects a well-supplied market condition considered favorable for consumer choice. The idea is that a larger selection of available models increases the attractiveness of BEVs, providing consumers with more options and potentially boosting adoption. Mathematically, this can be expressed as:

$$\hat{M}_{\text{BEV}}(t) = \begin{cases} \dfrac{M_{\text{BEV}}(t)}{M_{\text{max}}} & \text{if } M_{\text{BEV}}(t) \leq M_{\text{max}} \\ 1 & \text{otherwise} \end{cases} \tag{3.11}$$

$\hat{M}_{\text{BEV}}$ is the normalized value of the number of BEV models, used in the technical aspects of the model to assess market influence. This normalization allows $\hat{M}_{\text{BEV}}$ to be dimensionless and comparable across different market scenarios, helping to evaluate how the availability of models influences consumer decisions.

The R&D variable ($\beta_{\text{R\&D}}$) represents the research and development efforts surrounding BEV technology over time. This variable is determined using a fuzzy logic approach, which allows for handling the inherent uncertainty and vagueness in the evaluation of R&D effectiveness. The specific implementation of this fuzzy logic model was carried out in Python, and the corresponding code is provided in the Appendix B with the exact details of the inputs and the logic rules applied.

The social appeal variable $SAp(t)$ is related to the ratio between the population that has already adopted BEVs and the total BEV population $m(t)$. This variable is included in the model because, as the number of adopters increases, it is expected to drive further technical improvements in BEV technology. The detailed equation for $SAp(t)$ is presented alongside other variables related to the social aspects, specifically in (3.38).

Finally, the technical aspect is calculated using (3.12). Each variable is multiplied by its corresponding weight, reflecting its relative importance in the overall technical aspect.

$$TA(t) = w_5 \cdot \hat{Cap}_{\text{travel}}(t) + w_6 \cdot \hat{t}_{\text{charge}}(t) + w_7 \cdot \hat{M}_{\text{BEV}}(t) + w_8 \cdot \beta_{\text{R\&D}}(t) + SAp(t) \tag{3.12}$$

The infrastructural aspect of the model is shaped by both R&D related to BEV technology and social appeal. R&D not only drives advancements in BEV technology but also supports the development and expansion of charging infrastructure, including more efficient and accessible CSs. Additionally, the model accounts for the effect of the growing number of BEV adopters on infrastructure, acknowledging the increased demand for charging facilities as adoption rates rise.

Another variable of the infrastructural aspect, namely the public charging infrastructure (PCI) is defined as the ratio of the number of BEVs (N_{BEV}) to the number of public CS points (CSP) in a given region:

$$PCI(t) = \frac{N_{\mathrm{BEV}}(t)}{CSP(t)} \tag{3.13}$$

Then this ratio is normalized to assess the existing and the development of public charging infrastructure:

$$\hat{PCI}(t) = \begin{cases} \dfrac{PCI(t)}{PCI_{\max}} & \text{if } PCI(t) \leq PCI_{\max} \\ 1 & \text{otherwise} \end{cases} \tag{3.14}$$

Within the infrastructural aspect of the model, the variable BEV mechanic workshops (MW_{BEV}) represents the number of companies available for the maintenance of BEVs, availability of parts, inspections, and other after-sales services. Basically, this variable captures the shift from ICEVs services to those required by BEVs, until this market becomes saturated, i.e. it reaches 100 %, representing the market maturity for this sector. The evolution of the number of these businesses is modeled using a logistic function, represented by (3.15).

$$MW_{\mathrm{BEV}}(t) = \frac{1}{1 + \mathrm{e}^{-\kappa(t-t_\iota)}} \tag{3.15}$$

Where t is time (years); κ is the growth rate of the curve, indicating how quickly BEV workshops approach market saturation; and t_ι is the inflection point, representing the year in which the growth of workshops begins to accelerate significantly. The parameters κ and t_ι require calibration based on market data or related studies to accurately reflect trends in the adoption of BEV after-sales services.

The final component of the infrastructural aspect of the model includes the influence of political decisions on infrastructure development. This variable represents the weight of political factors and their impact on the expansion of the infrastructure supporting BEVs.

The overall infrastructural aspect over time, $IA(t)$, is then calculated as shown in (3.16).

$$IA(t) = w_9 \cdot \beta_{\text{R\&D}}(t) + w_{10} \cdot \hat{PCI}(t) + w_{11} \cdot MW_{\text{BEV}}(t) + w_{12} \cdot PA(t) + SAp(t) \quad (3.16)$$

Where w_9, w_{10}, w_{11}, and w_{12} represent the weights associated with R&D, normalized public BEV charging infrastructure ($\hat{PCI}$), BEV mechanic workshops (MW_{BEV}), and political aspects (PA), respectively. These weights are calibrated using expert judgment through the AHP method.

Modeling political aspects for the study of BEV diffusion involves analyzing policies that impact various stakeholders, including government entities, policymakers, industry leaders, and end users [91], [100]. Developing public policies that promote BEV adoption is essential, benefiting not only direct consumers but the entire supply chain [101]. Such policies can motivate the automotive industry, financial institutions, and energy companies to support the transition to BEVs, creating an environment conducive to widespread adoption. Together with the development of political measures, awareness campaigns and dissemination can increase the acceptance of BEV among the population [92], [102].

By establishing clear targets and standards for the transportation sector, legislation drives the adoption of BEVs and contributes to broader environmental objectives. Policies focused on reducing GHG emissions, improving air quality, and promoting the transition to renewable energy are central to these agendas [4], [102]. Aligning BEV adoption with climate policies supports the decarbonization of the transportation sector [89]. Moreover, policy frameworks provide the necessary structure to guide the interventions and strategies to move BEVs into the main stream market through actions such as the development of recharging facilities, targets for reducing CO_2 emissions in the transport sector, financial subsidies, tax reductions and exemptions [7], [42], [89], [100].

To promote BEV adoption, it is essential to establish a robust supply chain that supports the production and distribution of EVs [90]. This involves providing incentives for manufacturers to develop new BEV models and ensuring that the necessary infrastructure, such as CSs and maintenance services, is in place [91]. Additionally, financial institutions must be encouraged to offer attractive financing options for consumers, which can be facilitated, for instance, through government-backed loan programs, new business models and tax incentives [12], [37], [103].

The energy sector supports BEV adoption by establishing a robust regulatory framework. Policies that revise energy tariffs and introduce innovative pricing models can make BEV ownership more appealing to consumers [14], [15]. Additionally, integrating V2G technology allows BEVs to provide ancillary services to the grid, offering financial incentives to owners and enhancing grid efficiency and stability [23], [104].

However, political aspects are generally qualitative variables inherently qualitative rather than quantitative. In this work, these dynamics are quantified to enable simulations. To this end, the following variables are proposed: BEV legislation ($L_{\text{BEV}}(t)$), BEV financing ($Fi_{\text{BEV}}(t)$) and BEV tax incentives ($TI_{\text{BEV}}(t)$). These variables are subdivided into parameters, each assigned a weight based on its importance, and are evaluated on a scale proposed in Table 3.2.

Table 3.2: Political variables with their parameters and weights.

Variable	Parameter	Weight
Legislation	Mandates for vehicle emissions standards	0.20
	Public charging infrastructure investment	0.20
	Grid integration and smart charging regulations	0.20
	Clean energy targets and renewable energy mandates	0.20
	BEV supply chain support	0.20
Financing	Grants/subsidies	0.40
	Solar power funding program for BEV	0.20
	Low-interest loans	0.40
Tax incentives	Reduction in annual car tax	0.30
	Grid connection and tariff incentives (V2G)	0.30
	Reduction in purchase tax	0.20
	Tax reduction on renewable source installation	0.20

Finally, the political aspect (PA) is also influenced by social appeal $SAp(t)$, as the collective behavior and attitudes of the population can impact policy decisions. Thus, the increase in the number of adopters tends to influence not only individual consumer choices but also the political framework. This integration of qualitative assessments and social dynamics ensures a comprehensive evaluation of the political factors affecting BEV adoption. $PA(t)$ is calculated as shown in (3.17).

$$PA(t) = w_{16} \cdot L_{\text{BEV}}(t) + w_{17} \cdot Fi_{\text{BEV}}(t) + w_{18} \cdot TI_{\text{BEV}}(t) + SAp(t) \tag{3.17}$$

Where w_{16}, w_{17} and w_{18} are the weights associated with BEV legislation, BEV financing and BEV tax incentives, respectively. Variations in the parameters of the political aspect scale directly influence economic and infrastructural factors, affecting variables such as NPV calculations and public charging infrastructure, as discussed earlier. It is crucial to determine the values of each parameter through a thorough analysis of legislation, financial incentives, and tax incentives. For accurate modeling, it is recommended to consult with experts and stakeholders in the sector, ensuring that the parameters are appropriately calibrated for the region under study.

In the economic aspect of the model, the NPV calculations are used to evaluate the financial viability of different vehicle purchase options. Specifically, the comparative NPV variable (NPV_{comp}) analyzes which NPV is most attractive between the NPV of an ICEV (NPV_{ICEV}), the NPV of a BEV (NPV_{BEV}), and the NPV of a BEV with a green charger [2] ($NPV_{\text{BEV, GC}}$). The logic used to define NPV_{comp} is as follows:

$$NPV_{\text{comp}}(t) = \begin{cases} 0 & \text{if } NPV_{\text{ICEV}}(t) > NPV_{\text{BEV}}(t) \text{ AND } NPV_{\text{ICEV}}(t) > NPV_{\text{BEV, GC}}(t) \\ 1 & \text{if } NPV_{\text{BEV, GC}}(t) > NPV_{\text{BEV}}(t) \text{ AND } A(t) \leq \alpha_{\text{GC}}(t) \cdot m(t) \\ 1 & \text{otherwise} \end{cases} \tag{3.18}$$

Where $NPV_{\text{ICEV}}(t)$, $NPV_{\text{BEV}}(t)$ and $NPV_{\text{BEV, GC}}(t)$ represent the NPV of purchasing and operating an ICEV, a BEV or a BEV along with the installation of a green charger, respectively. $A(t)$ is the current number of BEV adopters, and $\alpha_{\text{GC}}(t)$ is the green charger coefficient.

α_{GC} is a factor representing the proportion of the population eligible for installing a green charger when purchasing a BEV. It is defined as the ratio between the number of home-owners (H_{own}) — those who own a house with land — and the total population ($N_{\text{pop}}(t)$) of the region under study. α_{GC} is determined as follows:

$$\alpha_{\text{GC}}(t) = \frac{H_{\text{own}}(t)}{N_{\text{pop}}(t)} \tag{3.19}$$

The (NPV_{ICEV}) is calculated using (3.20), which relates the ICEV's annual cash flow ($CF_{\text{ICEV}}(t)$), the interest rate (r) used to calculate the present value of the cash flows, and the ICEV acquisition cost ($C_{\text{ICEV, aq}}$) in the year the investment begins.

$$NPV_{\text{ICEV}}(t) = \sum_{t=1}^{n} \frac{CF_{\text{ICEV}}(t)}{(1+r)^t} - C_{\text{ICEV, aq}}(t) \tag{3.20}$$

[2] A green charger refers to a charging technology that charges EVs using renewable energy sources. As the focus of this work is the adoption of BEVs to residential consumers, it is considered a green charger powered by solar energy.

The acquisition cost of the ICEV is calculated, as shown in (3.21), considering

$$C_{\text{ICEV, aq}}(t) = C_{\text{ICEV}} \cdot (1 + T_{\text{ICEV}}(t)) \tag{3.21}$$

Where C_{ICEV} represents the purchase price of the ICEV, to which purchase taxes T_{ICEV}, e.g. value added tax (VAT), are added at the time of acquisition.

The cash flow for the consumer purchasing the ICEV is given by (3.22), which accounts for the operation and maintenance costs of the ICEV ($O\&M_{\text{ICEV}}(t)$), annual fuel expenses ($Fu_{\text{ICEV}}(t)$), vehicle property tax (car tax) ($CT_{\text{ICEV}}(t)$), insurance costs ($In_{\text{ICEV}}(t)$), and the depreciation ($D_{\text{ICEV}}(t)$) of the vehicle over time. The sum of these costs also represent the operating costs of the vehicle.

$$CF_{\text{ICEV}}(t) = -O\&M_{\text{ICEV}}(t) - Fu_{\text{ICEV}}(t) - CT_{\text{ICEV}}(t) - In_{\text{ICEV}}(t) - D_{\text{ICEV}}(t) \tag{3.22}$$

$Fu_{\text{ICEV}}(t)$ represents the cost spent on fuel in the ICEV, which corresponds to the product of the distance (di_{annual}) driven annually by the consumer, in km, with the average consumption of the ICEV's combustion engine (Co_{ICEV}), in km/l, and the cost of fuel (C_{fuel}), in the local currency per liter, paid by the consumer, including taxes. Equation (3.23) shows the relationship between these variables.

$$Fu_{\text{ICEV}}(t) = \frac{di_{\text{annual}}(t)}{Co_{\text{ICEV}}(t)} \cdot C_{\text{fuel}}(t) \tag{3.23}$$

Similarly, the NPV_{BEV} is calculated using (3.24), which accounts for the BEV's annual cash flow ($CF_{\text{BEV}}(t)$), the interest rate (r) used to calculate the present value of the cash flows, the BEV acquisition cost ($C_{\text{BEV, aq}}$), the cost of installing a wallbox (C_{WB}), and any subsidies ($Su_{\text{BEV}}(t)$) applied at the time of purchase.

$$NPV_{\text{BEV}}(t) = \sum_{t=1}^{n} \frac{CF_{\text{BEV}}(t)}{(1+r)^t} - \Big(C_{\text{BEV, aq}}(t) - Su_{\text{BEV}}(t) + C_{\text{WB}}(t)\Big) \tag{3.24}$$

The acquisition cost of the BEV is calculated as shown in (3.25), considering:

$$C_{\text{BEV, aq}}(t) = C_{\text{BEV}} \cdot (1 + T_{\text{BEV}}(t)) \tag{3.25}$$

Where C_{BEV} represents the purchase price of the BEV, to which purchase taxes, T_{BEV}, are added at the time of acquisition. It is important to note that tax rates for acquiring BEVs can vary significantly, especially as many countries offer more favorable rates for environmentally friendly technologies. In this context, subsidies may also play a crucial role in reducing the effective purchase cost of BEVs, thereby influencing consumer decision-making.

The cash flow for the consumer purchasing the BEV is given by (3.26), which accounts for the operation and maintenance costs of the BEV ($O\&M_{\mathrm{BEV}}(t)$) and of the wall-box ($O\&M_{\mathrm{WB}}(t)$), annual electricity costs ($CE_{\mathrm{BEV}}(t)$), vehicle property tax ($CT_{\mathrm{BEV}}(t)$), insurance costs ($In_{\mathrm{BEV}}(t)$), and the depreciation ($D_{\mathrm{BEV}}(t)$) of the vehicle over time.

$$CF_{\mathrm{BEV}}(t) = -O\&M_{\mathrm{BEV}}(t) - O\&M_{\mathrm{WB}}(t) - CE_{\mathrm{BEV}}(t) - CT_{\mathrm{BEV}}(t) - In_{\mathrm{BEV}}(t) - D_{\mathrm{BEV}}(t) \tag{3.26}$$

$CE_{\mathrm{BEV}}(t)$ represents the cost spent on electricity for recharging the BEV, which corresponds to the product of the distance driven annually by the consumer ($di_{\mathrm{annual}}(t)$), the average efficiency of the BEV ($Ef_{\mathrm{BEV}}(t)$) in kilowatt-hours per kilometer, and the cost of electricity ($C_{\mathrm{el}}(t)$) in the local currency per kilowatt-hour, including taxes. Equation (3.27) shows the relationship between these variables.

$$CE_{\mathrm{BEV}}(t) = di_{\mathrm{annual}}(t) \cdot Ef_{\mathrm{BEV}}(t) \cdot C_{\mathrm{el}}(t) \tag{3.27}$$

Where Ef_{BEV} can also be calculated as:

$$Ef_{\mathrm{BEV}}(t) = \frac{Cap_{\mathrm{bat}}(t)}{R_{\mathrm{BEV}}(t)} \tag{3.28}$$

In this study, the green charger scenario is included to account for the additional investment required for solar BEV charging. The decreasing costs of solar energy have made it a viable option for many residential consumers. Therefore, this scenario is analyzed to assess its impact on the overall costs.

Similarly, the $NPV_{\mathrm{BEV,\,GC}}$ is calculated using (3.29), which accounts for the annual cash flow ($CF_{\mathrm{BEV,\,GC}}(t)$) for purchasing BEV and green charger. In comparison to the calculation of the NPV_{BEV}, in this case, the cost of acquiring the green charger (C_{GC}) is added at the time of purchase.

$$NPV_{\mathrm{BEV,\,GC}}(t) = \sum_{t=1}^{n} \frac{CF_{\mathrm{BEV,\,GC}}(t)}{(1+r)^t} - \left(C_{\mathrm{BEV,\,aq}}(t) - Su_{\mathrm{BEV,\,GC}}(t) + C_{\mathrm{WB}}(t) + C_{\mathrm{GC}}(t)\right) \tag{3.29}$$

The acquisition cost of the BEV is calculated according to (3.25). The cost of purchasing a green charger depends on the power required, which is determined by the efficiency of the BEV considered (Ef_{BEV}), in kWh/km, and the average annual distance traveled by the consumer (di_{annual}) in km. This cost is calculated using (3.30), where C_{PV} represents the average cost of purchasing and installing a solar power system in the local currency per kW, and $\alpha_{\text{PV, avg}}$ denotes the estimated average annual productivity factor for this system in the study region in kWh/kW.

$$C_{\text{GC}}(t) = \frac{Ef_{\text{BEV}}(t) \cdot di_{\text{annual}}(t) \cdot C_{\text{PV}}(t)}{\alpha_{\text{PV, avg}}} \tag{3.30}$$

The cash flow for the consumer purchasing the BEV with a green charger is given by (3.31). This calculation is similar to that of $CF_{\text{BEV}}(t)$ in (3.26), but with the addition of the operation and maintenance costs of the green charger ($O\&M_{\text{GC}}(t)$), and the savings from energy produced by the green charger, which offsets the cost of electricity that would otherwise be purchased from the grid ($Sa_{\text{GC}}(t)$).

$$CF_{\text{BEV, GC}}(t) = CF_{\text{BEV}}(t) - O\&M_{\text{GC}}(t) + Sa_{\text{GC}}(t) \tag{3.31}$$

Where:

$$Sa_{\text{GC}}(t) = CE_{\text{BEV}}(t) \tag{3.32}$$

The economic aspect also considers the effects and developments of the political and technical aspects to promote the diffusion of BEVs. This aspect is calculated as expressed in (3.33).

$$EA(t) = w_{13} \cdot NPV_{\text{comp}}(t) + w_{14} \cdot PA(t) + w_{15} \cdot TA(t) \tag{3.33}$$

Where w_{13}, w_{14} and w_{15} are the weights associated with the comparative NPV ($NPV_{\text{comp}}(t)$), political aspect ($PA(t)$) and technical aspect ($TA(t)$), respectively.

The equations presented so far influence the adoption rate $AR(t)$ considering adoption by BEV attractiveness (AAT). Another important part of AR calculation (3.1) refers to adoption from social exposure $ASE(t)$, which is calculated according to (3.34).

$$ASE(t) = q(t - t_{\text{d}}) \cdot SA(t) \cdot P(t) \cdot \frac{A(t)}{m(t)} \tag{3.34}$$

Where $P(t)$, $A(t)$, and $m(t)$ are the stocks representing the potential adopters, the adopters, and the total potential market of the model. $SA(t)$ represents the social aspects, and q is the imitation coefficient of the Bass model with a delay of t_d in years.

As illustrated in Fig. 3.2, the social aspect is influenced by five auxiliary variables: product knowledge, product feedback, social appeal, product novelty, and the adoption of distributed generation (DG). This aspect encompasses relevant variables that shape the development of actions and practices influencing social dynamics and individual behavior within society, as well as their perceptions of using BEVs to decarbonize the transport sector and promote electromobility.

Product knowledge ($PK(t)$) represents the dissemination of knowledge about the BEV, affected by the knowledge coefficient (β_{kn}) and the product attractiveness factor ($PAF(t)$).

$$PK(t) = \beta_{\text{kn}} \cdot (1 + PAF(t)) \tag{3.35}$$

Product feedback ($PF(t)$) measures the impact of social feedback on the BEV, influenced by the product attractiveness factor ($PAF(t)$) over time and the feedback coefficient (β_{fb}), which is a fuzzy variable.

$$PF(t) = (1 + \beta_{\text{fb}}) \cdot (PAF(t) - 1) \tag{3.36}$$

From (3.35) and (3.36), it can be seen that as the PAF, which relates the technical, infrastructure, economic and political aspects, increases over time, these variables also increase, so that feedback improves and knowledge about the characteristics of the BEV also spreads in society.

Product novelty ($PN(t)$) quantifies the perceived novelty of the BEV, driven by the relevance coefficient (β_{rel}). This variable is modeled in such a way that, as time passes and more adopters adopt BEV, this product ceases to be an innovation or a novelty on the market. $PN(t)$ is calculated as shown in (3.37).

$$PN(t) = \beta_{\text{rel}} \cdot \left(1 + \ln\left(\frac{m(t)}{A(t)}\right)\right) \tag{3.37}$$

Social appeal ($SAp(t)$) is influenced by a social coefficient (sociability), (β_{social}), and the interaction rate between adopters and total market, which is the ratio of the total BEV population ($m(t)$) to the current adopters ($A(t)$).

$$SAp(t) = \frac{A(t)}{m(t)} \cdot \beta_{\text{social}} \tag{3.38}$$

The variable $\alpha_{\text{DG}}(t)$ represents the proportion of DG adopters in relation to the total population ($N_{\text{pop}}(t)$), serving as a factor to evaluate population's exposure to DG.

$$\alpha_{\text{DG}}(t) = \frac{N_{\text{DG}}(t)}{N_{\text{pop}}(t)} \tag{3.39}$$

Finally, the social aspect ($SA(t)$) is calculated as presented in (3.40).

$$SA(t) = w_{19} \cdot PK(t) + w_{20} \cdot PF(t) + w_{21} \cdot PN(t) + w_{22} \cdot SAp(t) + \alpha_{\mathrm{DG}}(t) \quad (3.40)$$

Where w_{19}, w_{20}, w_{21} and w_{22} are the weights for product knowledge ($PK(t)$), product feedback ($PF(t)$), product novelty ($PN(t)$) and social appeal ($SAp(t)$), respectively.

To determine the values of the β coefficients (fuzzy variables), and w_i (AHP weights), a survey was applied in collaboration with experts from the sector, presented in Appendix A. The algorithm for calculating the fuzzy values, as well as the details of this modeling and everything else, are presented in Appendix B.

The SFD presented in this work encompasses all relevant variables and interactions necessary for a comprehensive analysis of BEV adoption. The fourth stage of the proposed modeling is the construction of the CLD, which is described in Section 3.4.2.

3.4.2 Proposed causal loop diagram

To construct the CLD, all the variables in the model must be known and are now correlated. According to Sterman [48], the CLD is of great importance in systems modeling and its purpose is to represent the model's causal hypotheses in the form of a sketch, as well as to allow assumptions about the model's structural correlations to be interconnected and tested by varying its parameters.

The CLD is constructed based on the relationships between the selected variables, with the aim of highlighting the cause-and-effect connections that emerge when defining causal hypotheses based on their interdependencies. Fig. 3.3 presents the general CLD model proposed in this work. It captures the dynamics of how main different factors interact to influence BEV adoption, considering both the positive (amplifying) and negative (limiting) effects that may arise in the process. The general CLD features three balancing loops and one reinforcing loop.

The first balancing loop (B1) is related to market saturation, determined by the number of potential adopters. This loop illustrates how an increase in adoption, driven by the BEV's attractiveness — primarily influenced by the innovation coefficient (p) — leads to a higher adoption rate, turning potential adopters into BEV adopters. Additionally, as the number of adopters increases, the pool of potential adopters decreases, creating a balancing feedback loop. The second balancing loop (B2) demonstrates that the adoption rate is influenced by adoption through social exposure and BEV attractiveness, yet it

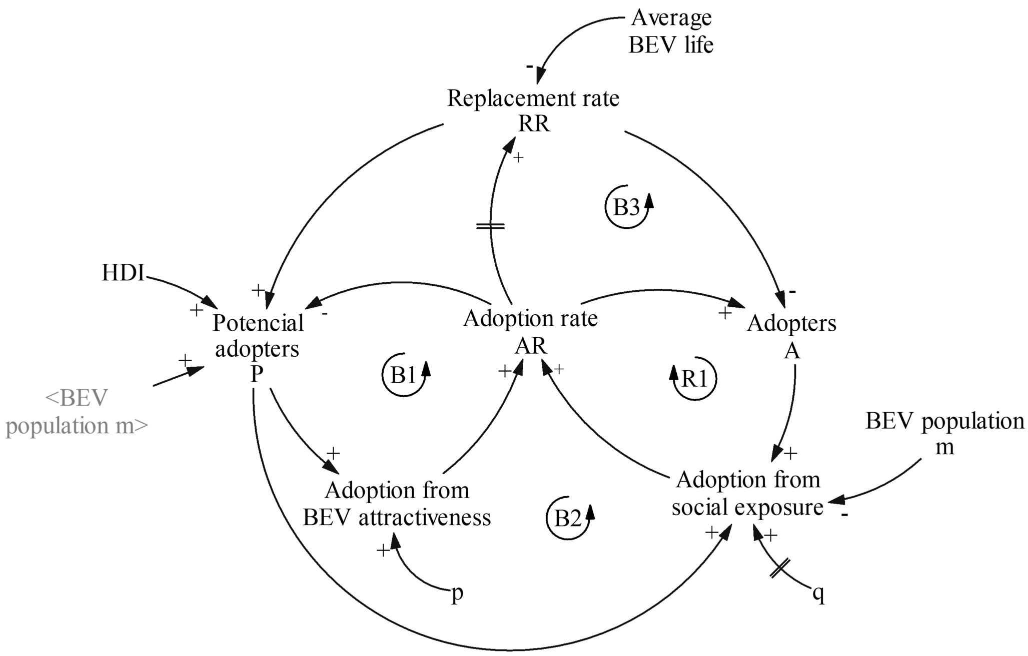


Figure 3.3: General CLD of the proposed model.

is constrained by the potential market size (m). Therefore, this loop also represents market saturation.

The reinforcing loop (R1) correlates to an increase in the number of adopters due to social exposure among both adopters and potential adopters, with the primary influencing factor being the imitation coefficient (q) from the Bass model. Another balancing loop (B3) depicted in this diagram relates to the replacement of BEVs, where former adopters return to the pool of potential adopters, controlled by a replacement rate, which is modeled as a delay in the adoption rate, determined by BEV's average lifespan. Thus, this consumer is once again influenced by all the decision-making factors examined in this study, namely the adoption from BEV attractiveness and social exposure.

Another significant factor to highlight is the HDI, an important socioeconomic indicator that reflects the levels of health, education, and income (standard of living) in a given country or region. The HDI is a value ranging from 0 to 1; the closer to zero, the lower the indicator for the specified criteria, and the closer to one, the better the conditions in these areas [105]. In the context of the proposed model, the HDI is used as a socioeconomic variable to determine the proportion of the potential market (BEV population) considered eligible to become potential adopters.

Starting from the macromodel shown in Fig. 3.3, the analysis is expanded by incorporating the considered aspects and their respective variables, with the aim of deepening the understanding of the cause-and-effect relationships between adoption from BEV attractiveness and social exposure. Fig. 3.4 presents the CLD for the complete model.

Throughout the construction of this model, various tests were conducted to verify the correlations between the variables. Finally, the mathematical equations that establish the relationships among the variables were modeled in the SFD.

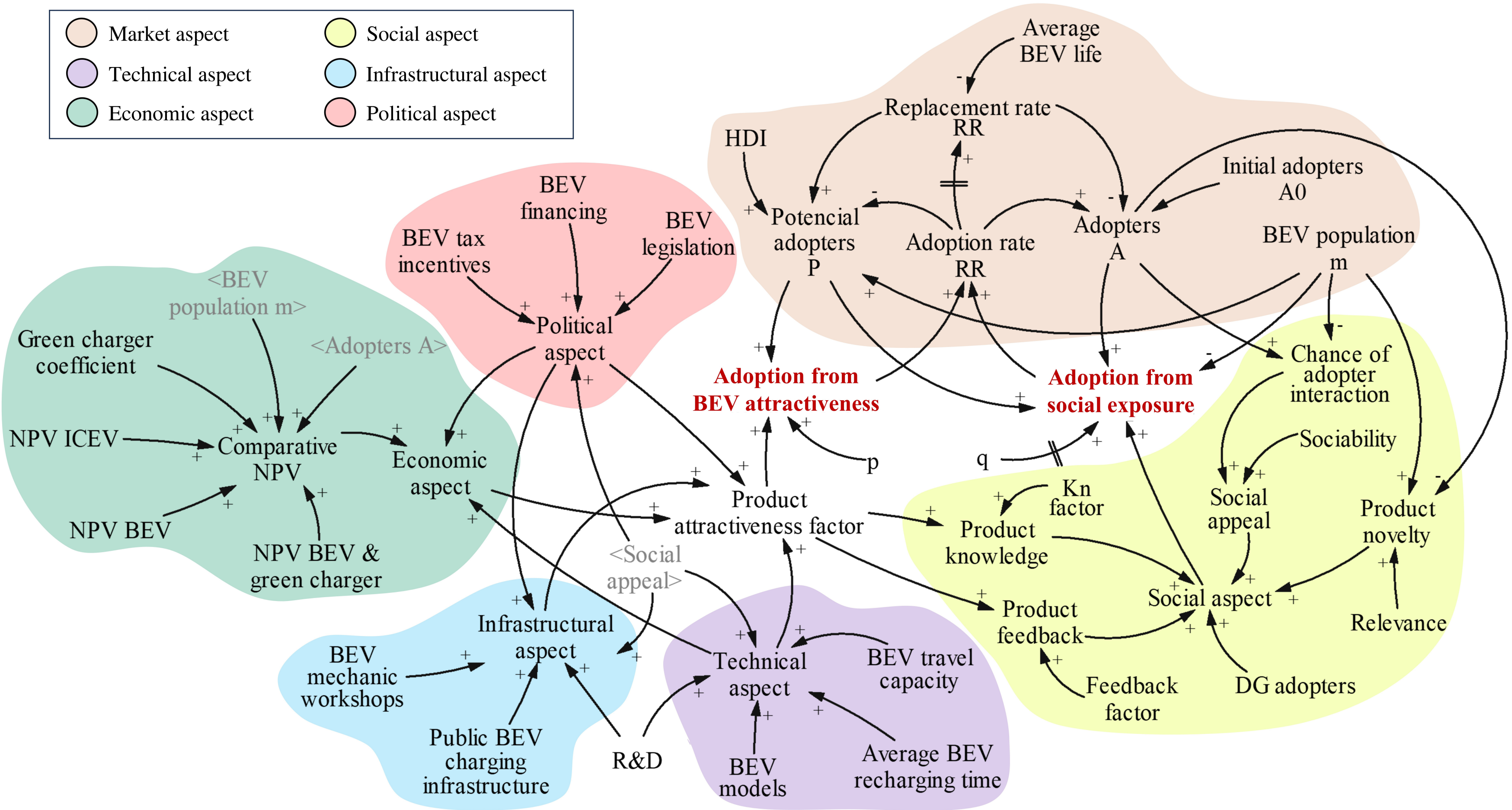


Figure 3.4: CLD of the complete model.

By expanding the factors related to adoption from BEV attractiveness and social exposure, new and significant relationships have been established between the aspects, as illustrated in Fig. 3.4. In this context, the influence of the political aspect on the economic aspect stands out, reflecting political decisions and the development of public policies, such as tax incentives, advances in legislation and financing policies. The interaction of political variables on the infrastructural aspect is also observed, which is further influenced by the business models of companies operating with BEVs, alongside R&D efforts and the development of public charging infrastructure.

In the technical aspect, especially with regard to EV technology, variables such as travel capacity, recharging time and R&D advances in this sector stand out. Another relevant variable in this context is the number of BEV models available on the market, which might also influence consumer decisions due to market growth and availability of different options.

Furthermore, regarding social issues and word of mouth, it is observed that feedback and knowledge about BEVs are dependent of the product's attractiveness factor, which functions to interconnect the political, economic, infrastructural and technical aspects. Both feedback and product knowledge, along with social appeal, BEV as an innovation in the transportation sector, and the fraction of the population already owning a DG system, exert influence on social factors.

Moreover, social appeal among individuals within a given region also play a crucial role in the dynamics of BEV diffusion over time. As the number of adopters of BEVs increases, it is anticipated that the resulting social pressure will impact political, infrastructural, and technical aspects, as represented in the model. Consequently, this may lead to the development of public charging infrastructure, new business models, public financing policies, tax reductions, and advancements in research related to this technology.

These characteristics are thoroughly evaluated in the proposed model. The analysis of the interactions between variables is performed through dynamic simulations, which allow observing how changes in specific variables can reverberate throughout the system, influencing other variables and, consequently, the overall behavior of the model. This approach not only facilitates the identification of the main drivers of BEV adoption, but also helps to forecast how different policies or interventions might impact the diffusion of BEVs over time.

4 Model Verification and Application

Chapter 3 presented the proposed model to be simulated in this work, including the complete SFD and the CLD. Additionally, all the parameters and variables to be modeled and parameterized were detailed. In this chapter, the verification and calibration of the model are discussed. To achieve this, it is necessary to collect historical data and apply expert questionnaires to determine the parameter values. As proposed by Ford [58], estimating the values of the model parameters corresponds to step five.

Once the model is parameterized, verification and calibration simulations can be conducted, focusing on verifying the sensitivity of the model and adjusting its delays and calibrating the coefficients of the Bass diffusion model. The aim is to ensure that the model accurately reflects the real-world dynamics of BEV adoption and can be reliably used for future scenario analysis.

4.1 Determination of parameters

The determination of parameters for the proposed model involved an extensive search for historical data and the identification of variables introduced in the previous chapter (see Section 3.4). This research focused on both Brazil and Germany, aiming to gather comprehensive data that accurately reflects the different realities of these countries. The process of collecting historical data was particularly challenging, especially in the case of Brazil, where obtaining consistent and detailed information proved difficult.

The historical data collected was essential for parameterizing various aspects of the model, such as market potential, BEV range, public charging infrastructure, NPV calculations, etc. This data enabled the establishment of baseline values for the model's variables, ensuring that the simulation reflects realistic conditions in both countries.

In addition to historical data, determining the weights of variables required the application of a structured survey. This questionnaire was designed to gather expert opinions on the relative importance of different variables within the model, particularly for quantifying their weights determined through the AHP method. For qualitative variables, a fuzzy logic approach is employed. This method enables experts to provide their assessments on a scale from 0 to 10, representing crisp input values. These inputs are then processed through the fuzzy algorithm. Finally, the output values generated by the fuzzy algorithm are averaged to produce a final value for each variable.

The complete survey, including the sub-questionnaires used for determining the weights for both AHP and fuzzy logic values, is provided in Appendix A. The fuzzy algorithm, including its input variables, rule sets, and defuzzyfication method, is detailed in Appendix B.

The questionnaire included the participation of 30 experts from different sectors and areas of expertise, with 20 participants from Brazil and 10 from Germany. Responses were collected via Microsoft Forms, and participants were asked to evaluate the relative importance of each variable using the AHP method, as well as provide input for the fuzzy logic algorithm. For the AHP, participants followed the structured scale proposed by Saaty [72]–[74], which includes pairwise comparisons with values of 1, 3, 5, etc., along with intermediate values. The fuzzy logic questions were based on a scale from 0 to 10 (crisp input values), where 0, depending on the variable, represents no importance, influence, familiarity, etc. and 10 is very important, relevant, etc.

To ensure the accuracy and consistency of the data collected, responses were carefully evaluated. In cases where responses did not meet consistency criteria, particularly in the AHP method, or where the answers were not fully completed, the responses were invalidated. In Brazil, five evaluations were partially invalidated, and two were completely invalidated. In Germany, one evaluation was partially invalidated, and two were completely invalidated. The validated results of the fuzzy logic values and AHP weights are presented in Table Table 4.1 and 4.2, respectively.

Table 4.1: Fuzzy variable values.

Parameter	Brazil	Germany
R&D (current)	0.74	0.57
R&D (next 10 years)	0.87	0.81
R&D (next 20 years)	0.86	0.84
Knowledge	0.75	0.54
Feedback	0.89	0.49
Relevance	0.79	0.79
Sociability	0.73	0.24

As can be seen in Table 4.1, the variable $\beta_{\mathrm{R\&D}}$ is represented by three distinct values. This is due to the fuzzy analysis conducted, which considers current levels of investment, quality, and public acceptance associated with R&D for BEVs, and also projections of these values over the next 10 and 20 years.

Table 4.2: Weight of variables determined by AHP.

Parameter	Brazil	Germany
Product attractiveness factor		
Technical aspect	0.221	0.294
Infrastructural aspect	0.301	0.305
Economic aspect	0.303	0.254
Political aspect	0.175	0.147
Consistency (CR)	0.007	0.014
Technical aspect		
BEV travel capacity	0.297	0.392
Average BEV charging time	0.437	0.386
BEV models	0.094	0.156
R&D	0.172	0.065
Consistency (CR)	0.036	0.002
Infrastructural aspect		
R&D	0.138	0.148
Public BEV charge infrastructure	0.432	0.401
BEV mechanic workshops	0.203	0.199
Political aspect	0.227	0.252
Consistency (CR)	0.004	0.006
Economic aspect		
Comparative NPV	0.366	0.154
Political aspect	0.368	0.540
Technical aspect	0.266	0.306
Consistency (CR)	0.016	0.002
Political aspect		
BEV legislation	0.204	0.326
BEV financing	0.397	0.261
BEV tax incentives	0.399	0.413
Consistency (CR)	0.049	0.011
Social aspect		
Product knowledge	0.174	0.252
Product feedback	0.361	0.163
Product novelty	0.221	0.286
Social appeal	0.244	0.299
Consistency (CR)	0.035	0.040

4.2 Case study data

An extensive research effort was conducted to gather data on the electric mobility market, with a specific focus on the integration of BEVs into the German and Brazilian markets. This phase of the study involved engaging with various stakeholders in the sector, consulting different databases, and referencing information from ministries, as well as consulting with agencies to obtain critical data.

The following subsections present the collected data for each country, along with the references used. The study horizon for the historical BEV diffusion analysis in Germany is considered from 2013 to 2023, and for Brazil from 2019 to 2023.

4.2.1 Germany

Considering the general CLD of the proposed model (see Fig. 3.3), the parameterization begins with the definition of the stock that represents the total potential market (m). This stock is composed of consumers who have a driving license for cars. For the analysis in this work, the considered consumers are those between 18 and 70 years old, holding a driving license for categories B, B96, or BE. This data is obtained from [106] and is illustrated in Fig. 4.1.

The stock of potential consumers (P), as already defined, takes into account socio-economic factors in the region in question. The criterion selected to determine this is the HDI. The HDI values for Germany were obtained from [105].

Furthermore, the average BEV life is assumed to be 8 years. This figure is in line with the average guarantee offered by the market. In general, manufacturers provide an 8-year battery warranty and 160,000 km [107].

For the technical aspects, the model considers the average BEV range, determined using data from [7], [108] and depicted in Fig. 4.2. To normalize the value of travel capacity, a base value of 400 km is used. This value is chosen based on a study by [109], which indicates that 400 km covers more than 98 % of consumers' daily journeys, thereby reducing range anxiety. With the continued improvement of charging infrastructure, this distance is sufficient to balance performance, cost, and convenience [109].

The average BEV charging time is calculated based on the average battery capacity observed in recent years, as detailed in [110], [111], for the global market, and presented in Table 4.3. The SOC_{target} and SOC_{current} considered are between 0 % and 80 % [112].

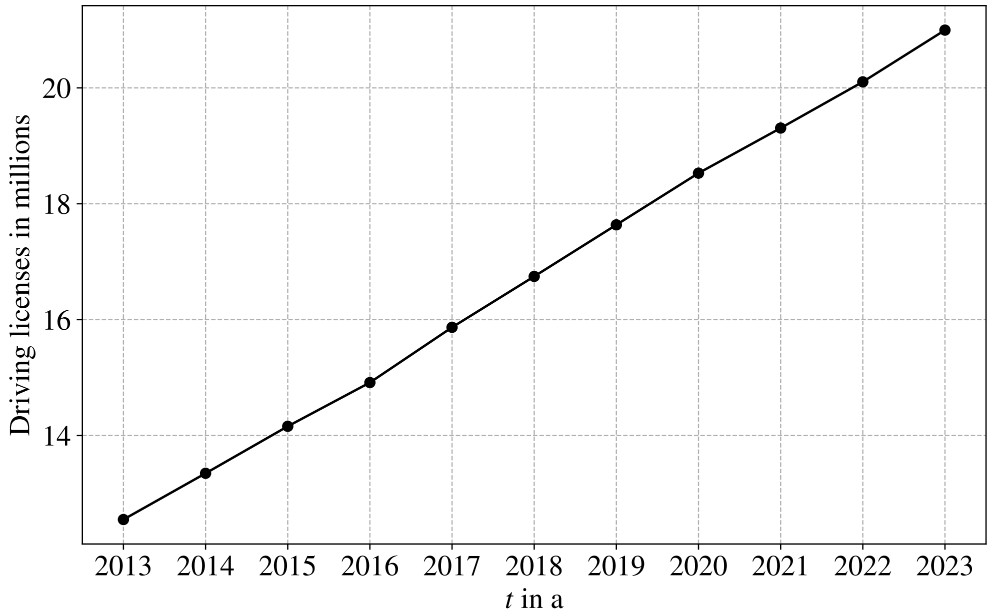


Figure 4.1: Number of driving licenses for cars in Germany [106].

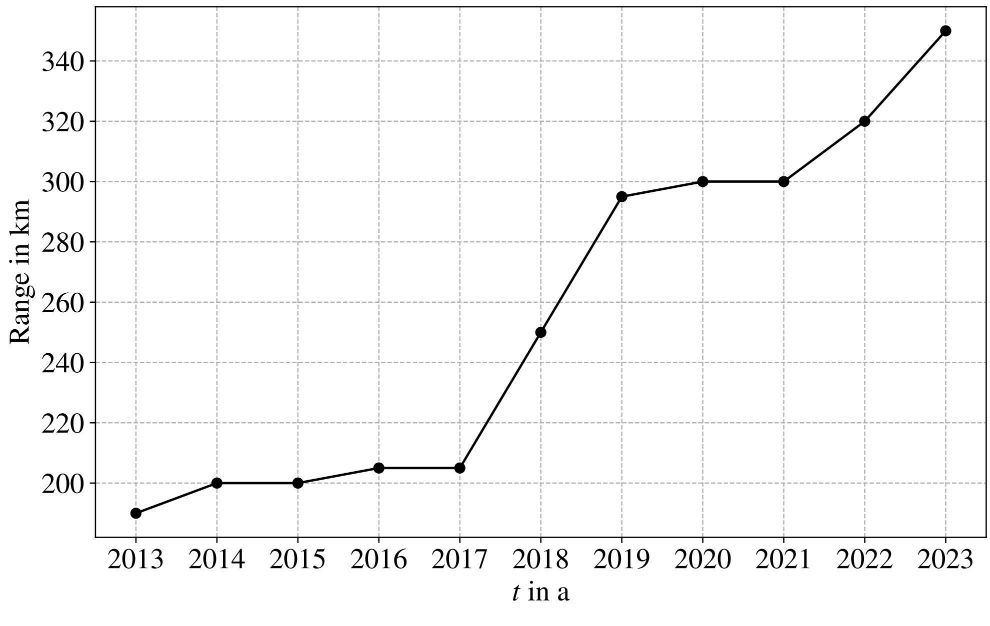


Figure 4.2: Evolution of average BEV range worldwide [7], [108].

The charging power assumed is for a home wallbox with 7.4 kW and a charging efficiency of 90 % [112]. For normalization purposes, a charging time of 3 hours is used as a base value for an average residential consumer [113]. Generally, residential consumers charge their vehicles in the evening [23], after returning from work, which is more than enough time to ensure a full recharge before the next use. Furthermore, shorter charging times are crucial for encouraging the adoption of EVs [113].

Table 4.3: Evolution of average battery capacity worldwide [110], [111].

Year	Cap_{bat} in kWh
2013	30
2014	29
2015	33
2016	37
2017	36
2018	44
2019	53
2020	54
2021	54
2022	60
2023	71

Information on specific BEV models available in Germany over the years is obtained from [114]–[116] and presented in Table 4.4. To normalize the number of BEV models available, a figure of one thousand models is used, reflecting the broad range of options available in the ICEV market, which signifies the maturity and diversity of that segment. For instance, in 2019, there were 1,561 petrol and diesel ICEV models available [114]. A trend observed in the German market is the reduction in the number of ICEV models, alongside a significant increase in electrified vehicles, particularly BEVs. Between 2019 and 2022, the number of petrol and diesel vehicle models decreased by 26 % and 46 %, respectively, while the number of BEV models grew by 382 % over the same period [114]. This shift reflects the growing prevalence of electrification in the automotive market.

Table 4.4: Number of BEV models available in Germany [114]–[116].

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
BEV models	18	27	32	36	47	55	68	73	129	217	300

Next, the infrastructural aspect considers the public BEV charging infrastructure ratio. To calculate this variable, it is necessary to determine the number of registered BEVs and the number of public charging station points (CSPs) in Germany, as presented in Table 4.5. The number of CSs in Germany for each year is gathered from [117], [118], while the number of registered BEVs is obtained from [119].

Table 4.5: Parameters for calculating the ratio of PCI for BEVs in Germany [117]–[119].

Year	**Registered BEVs**	**Public CSPs**	PCI
2013	7,114	4,454	2
2014	12,156	5,553	2
2015	18,948	5,894	3
2016	25,502	7,407	3
2017	34,022	9,108	4
2018	53,861	15,695	3
2019	83,175	26,746	3
2020	136,617	38,058	4
2021	309,083	53,447	6
2022	618,460	77,602	8
2023	1,013,009	108,266	9

A study conducted be Harrison [120] suggests that the optimal ratio of EVs to CSPs typically ranges between 5 and 25 EVs/CSP. This range is significant because maintaining this ratio ensures a balance between infrastructure availability and cost efficiency while reducing range anxiety. For this analysis, a normalized value of 15 BEVs/CSP has been selected. According to [120], an excessively high ratio of EVs to CSPs (beyond 25) tends to show diminishing returns in terms of market impact, while lower ratios can lead to disproportionately high infrastructure costs without corresponding benefits in EV adoption rates. The EU Directive on alternative fuels infrastructure (Directive 2014/94/EU) suggests having at least 10 EVs/CSP [121].

As previously discussed, a logistic function is employed to model the number of BEV mechanic workshops, representing the market's maturation trend concerning services provided to BEV consumers. The estimated coefficients for this function were $\kappa = 0.2$ and $t_\iota = 2035$.

Political factors influence not only legislation but also financing opportunities and tax incentives at the federal, state, and municipal levels. As a result, modeling and parameterizing these values can be a complex task. Additionally, such policies can be driven by societal pressures or actions from private industry sectors.

However, based on recent studies, scales for financing, legislation, and tax incentives for BEVs have been defined, as presented in Table 4.6. This phase of the research focused on federal public policies in each country and on state-level policies. In cases where certain policies are not implemented uniformly across all states but are present in only a few, an average value was applied as a proportion to account for these variations.

Table 4.6: Weights for legislation, financing and tax incentives for BEV in Germany.

Year	Legislation	Financing	Tax incentives
2013	0.20	0.00	0.35
2014	0.25	0.00	0.40
2015	0.25	0.00	0.40
2016	0.50	0.30	0.40
2017	0.55	0.30	0.45
2018	0.55	0.30	0.45
2019	0.60	0.35	0.45
2020	0.60	0.45	0.45
2021	0.60	0.45	0.45
2022	0.60	0.45	0.45
2023	0.60	0.55	0.50

Based on specific laws and incentive programs within society, these weight values are allocated annually for each country. It is also important to emphasize that these variables impact the NPV calculations due to their direct correlation. In this work, these variations over time are incorporated as inputs into the model.

For Germany, an overview of the political framework can be found in [121]–[123]. In summary, with regard to assigning weights to the political aspects, the analysis for Germany considered the following key strategies [124]–[136]:

- "Integrated Energy and Climate Program (IEKP)" of 2007, which converts European Union (EU)'s targets for 2020 into German policies, including the role of BEVs in managing renewable energy intermittency.
- "Konjunkturpaket II" (2009), an economic stimulus package that allocated 500 million euros to promote electric mobility through R&D and market preparation.

- "Directive 2009/28/EC (Renewable Energy Directive)", which encourages the consumption of renewable energy in the transport sector, including renewable electricity for EVs.
- "National Development Plan for Electric Mobility (NEPE)", adopted in 2009, aimed to have 1 million EVs deployed by 2020, without distinction between BEVs, PHEVs, and FCEVs.
- "Government Program for Electric Mobility" of 2011, which doubled spending on BEVs and PHEVs related to R&D from 2009 to 2013.
- Motor tax exemptions for BEVs since 2012.
- "EU Directive on Alternative Fuels Infrastructure (Directive 2014/94/EU)", which requires member states to implement infrastructure for EVs, setting standards for fast and slow charging.
- "European Council Conclusions on 2030 Climate and Energy Policy Framework" (2014), which sets binding targets to reduce GHG emissions by at least 40 % by 2030, increase the share of renewable energy to at least 27 %, and improve energy efficiency by at least 27 %, directly impacting the adoption and infrastructure development for EVs.
- "Renewable Energy Sources Act (EEG)" (2014, 2023), which set electricity prices, target 80 % renewable energy generation, reduce dependence on fossil fuels, and to contain the increase in temperature to 1.5 ºC.
- "Electric Mobility Act (EmoG)", introduced in 2015, which regulates the labeling of BEVs and PHEVs.
- Germany's participation as a signatory to the Paris Agreement since 2016, committed to metrics for reducing GHG.
- "Purchase grant (Umweltbonus/Kaufprämie)" from 2016 to 2023 to purchase a PHEV or BEV.
- "German Climate Cabinet Agreement 2030 (Klimaschutzprogramm 2030)" (2019), which sets a target of 7 to 10 million EVs in Germany by 2030, along with a master plan for public CS infrastructure aiming for 1 million CSs by 2030.
- "Ladeinfrastruktur für Elektrofahrzeuge in Deutschland" (2017-2020), dedicated to the installation of CSs, including 100 million euros for standard CSs and 200 million euros for fast CSs.

- "Fit für 55" program (2021), which aims to ban all combustion vehicles by 2035.

In addition to the aforementioned legislations and programs, it is important to note that, at the federal level, Germany does not have a dedicated national program specifically for offering loans to support the adoption of BEVs. However, various private banks and financial institutions have developed their own loan schemes to promote electromobility, offering favorable terms to consumers interested in purchasing BEVs. Moreover, regarding advanced technologies such as V2G and smart charging, they require further technological and regulatory advancements [15].

The "Policies Database" by International Energy Agency (IEA) is another essential resource, offering access to a wide range of legislation from Germany, the EU, and other countries. This platform provides a comprehensive overview of policies supporting BEVs and clean energy, making it a valuable tool for understanding and comparing legislative frameworks across different regions [136].

The economic aspect in this study compares the NPV of an ICEV, a BEV, and a BEV with a green charger. The NPV is calculated over a 10-year analysis horizon, serving as the primary economic criterion for this analysis. Thus, a direct comparison of the long-term financial viability of each vehicle option can be analyzed.

For the case of Germany, the interest rate is considered 7 % based on [137]. Tables 4.7 and 4.8 present, respectively, the purchase price and annual operating costs of medium-sized light vehicles for the ICEVs and BEVs considered in this analysis. These vehicles are chosen to represent the needs of an average consumer, ensuring that the results are applicable to a broad demographic of potential BEV adopters. For the calculations of annual operational costs and cash flow, the values from the Allgemeiner Deutscher Automobil-Club (ADAC) tables in Germany are used. These tables provide comprehensive data on all relevant costs, including fuel or electricity cost, operation and maintenance, depreciation, insurance, and car tax (Kfz-Steuer), which are integrated into the analysis.

In the NPV analysis of the BEV, the cost of acquiring a wallbox is included. Table 4.9 shows the acquisition cost of a 7.4 kW wallbox. An installation fee of € 1,250.00 is also considered in the NPV calculation. Additionally, scheduled maintenance of the wallbox is accounted for every four years, at a cost of € 200.00 per maintenance cycle [149].

Table 4.7: Purchase cost and annual operating costs for the ICEV in Germany [138]–[148].

Year	Brand	Model	Purchase cost	Operational cost
2013	VW	Golf TDI	€ 22,675.00	€ 5,976.00
2014	VW	Golf 1.2 TSI	€ 19,175.00	€ 6,348.00
2015	VW	Golf Variant TSI	€ 24,025.00	€ 6,636.00
2016	VW	Golf 1.2 TSI	€ 19,675.00	€ 6,492.00
2017	VW	Golf 1.0 TSI	€ 19,900.00	€ 6,456.00
2018	VW	Golf Variant 1.0 TSI	€ 24,200.00	€ 6,636.00
2019	VW	Golf 1.5 TSI	€ 25,630.00	€ 7,896.00
2020	VW	Golf Variant 1.5 TSI	€ 26,840.00	€ 7,692.00
2021	VW	Golf GTI Clubsport	€ 42,265.00	€ 10,248.00
2022	VW	Golf GTI Clubsport	€ 44,645.00	€ 10,896.00
2023	VW	Golf GTI Clubsport	€ 46,480.00	€ 11,328.00

Table 4.8: Purchase cost and annual operating costs for the BEV in Germany [138]–[148].

Year	Brand	Model	Purchase cost	Operational cost
2013	Nissan	Leaf	€ 33,990.00	€ 7,848.00
2014	Renault	Zoe Z.E. Life	€ 21,700.00	€ 6,480.00
2015	Kia	Soul EV	€ 30,790.00	€ 7,440.00
2016	Renault	Zoe Life	€ 21,500.00	€ 6,828.00
2017	Renault	Zoe	€ 22,100.00	€ 6,360.00
2018	Renault	Zoe	€ 21,900.00	€ 6,336.00
2019	Renault	Zoe R135	€ 25,900.00	€ 7,776.00
2020	Renault	Zoe R135	€ 25,900.00	€ 7,212.00
2021	Tesla	Model 3 Standard	€ 45,560.00	€ 8,760.00
2022	VW	ID.5 Pro	€ 47,935.00	€ 9,600.00
2023	Tesla	Model 3	€ 47,560.00	€ 9,564.00

Table 4.9: Average wallbox prices for Germany [149]–[153].

Year	Wallbox price
2013 - 2016	€ 1,000.00
2017 - 2019	€ 850.00
2020 - 2021	€ 700.00
2022 - 2023	€ 600.00

Additionally, in Germany, the environmental bonus ("Umweltbonus") program, which ran from 2016 to 2023, represented an important subsidy, reducing the purchase cost of BEVs. The changes and adjustments to the "Umweltbonus" over the years are detailed in Table 4.10. This subsidy program has been canceled by the German government for the year 2024 [133].

Table 4.10: Variations in environmental bonus in Germany over time [130]–[133].

Year	Vehicle price	
	up to € 40,000	€ 40,000 – € 60,000
2016 – 2020	€ 4,000	
2021 – 2022	€ 6,000	€ 5,000
2023	€ 6,750	€ 4,500

For the NPV calculation of the BEV with a green charger, firstly, the acquisition cost of the green charger must be determined. To do this, the annual distance traveled is set at 15,000 km, as this is the value used by ADAC in its reports for an average driver in Germany. The average acquisition costs for PV systems, in €/kW, are sourced from [154]. The estimated average annual productivity ($\alpha_{\text{PV, avg}}$) for a green charger in Germany is considered to be 1,000 kWh/kW [155]. Table 4.11 details the BEV efficiency, in kWh/km, the acquisition cost of the green charger based on solar power, in €/kW, and the annual savings, in €, used in the NPV calculation for this scenario.

Table 4.11: Parameters for calculating the NPV of the BEV and green charger for the German scenario [138]–[148], [154].

Year	Ef_{BEV} in kWh/km	C_{PV} in €/kW	Savings in €
2013	0.126	2,100.00	453.60
2014	0.111	2,000.00	432.90
2015	0.147	1,900.00	617.40
2016	0.133	1,700.00	558.60
2017	0.133	1,600.00	598.50
2018	0.133	1,500.00	598.50
2019	0.177	1,450.00	929.25
2020	0.177	1,350.00	955.80
2021	0.143	1,400.00	772.20
2022	0.139	1,350.00	917.40
2023	0.132	1,450.00	871.20

For the cash flow calculation, the savings from using the green charger are determined based on the electricity costs provided in the ADAC reports [138]–[148], [154]. The operating costs of the green charger are estimated to be 1 % of its acquisition cost [129]. Fig. 4.3 presents the results of the NPV analysis over a 10-year horizon for the acquisition of an ICEV, BEV, or BEV with a green charger in Germany.

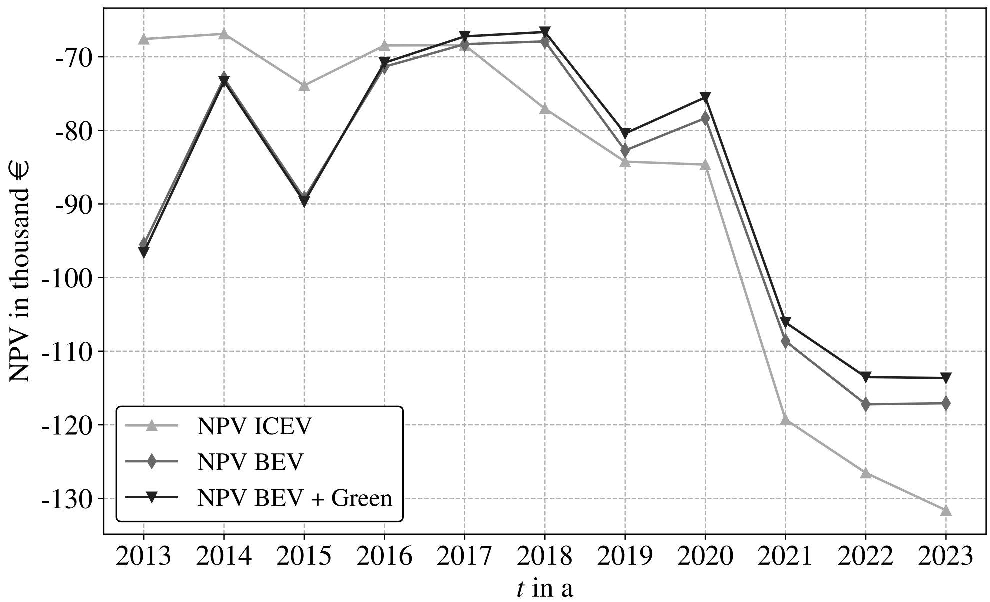


Figure 4.3: Result of the NPV calculation for historical values in Germany.

Analyzing Fig. 4.3, it is possible to note that, from 2013 to 2016, the ICEV remained the most economical option. However, starting in 2017, a significant shift occurred, where both BEV options — particularly the BEV with a green charger — became more financially attractive. This shift can likely be attributed to the introduction or enhancement of subsidies for BEVs around this period, making BEVs more appealing. Additionally, the declining costs of PV systems, which are integral to green chargers, further contributed to the improved NPV for the BEV and green charger option.

By 2020, the NPV of both BEV options became notably more favorable compared to ICEVs, reflecting the combined effects of economic incentives and advancements in technology. From 2021 onward, the BEV with a green charger consistently outperformed the ICEV in terms of NPV, demonstrating the economic shift towards electrification driven by supportive policies and the increasing cost-effectiveness of renewable energy solutions. This analysis underscores the critical role of government policies and market trends in accelerating the adoption of BEVs, particularly when complemented by green technologies like solar systems for EV charging.

However, while the BEV with a green charger proves to be the most economical option, it is not viable for all consumers due to demographic factors. To address this, the developed model incorporates the green charger coefficient (α_{GC}) as a limiting factor, representing the portion of the population capable of installing a green charger at home. This coefficient, which saturates at a certain value, is derived from the demographic data of the study region. For Germany, this involves analyzing the proportion of people living in their own homes (H_{own}) alongside general population (N_{pop}) data. (α_{GC}) then multiplies the potential market (m) in the diffusion model to realistically limit the adoption of the BEV with a green charger based on regional demographics. Table 4.12 presents these demographic data for Germany.

Table 4.12: Demographic data for Germany and green charger coefficient [156]–[158].

Year	**Home ownership**	**Population**	α_{GC}
2013	29,840,000	80,767,463	0.37
2014	29,530,000	81,197,537	0.36
2015	29,050,000	82,175,684	0.35
2016	28,980,000	82,521,653	0.35
2017	28,980,000	82,792,351	0.35
2018	29,200,000	83,019,213	0.35
2019	28,990,000	83,166,711	0.35
2020	28,880,000	83,155,031	0.35
2021	28,670,000	83,237,124	0.34
2022	28,710,000	84,358,845	0.34
2023	27,870,000	84,669,326	0.33

Finalizing the presentation of the historical data collected for Germany, the social aspect is introduced. The parameters within the social aspect are primarily fuzzy variables, as presented in Section 3.4 and in Table 4.1. However, one variable, the DG adopters coefficient (α_{DG}), which establishes a population exposure factor concerning the diffusion of DG units, must be calculated. In this study, only PV systems are considered, representing the extent to which individuals in German society are exposed to this technology. Table 4.13 presents the current number of PV installations in Germany and the corresponding α_{DG}. Fig. 4.4 illustrates the historical growth in these installations.

Table 4.13: Number of PV system installations and DG adopters coefficient for Germany [129], [159].

Year	PV installations	α_{DG}
2013	1,436,115	0.018
2014	1,507,364	0.019
2015	1,564,083	0.019
2016	1,623,467	0.020
2017	1,688,801	0.020
2018	1,759,902	0.021
2019	1,872,255	0.023
2020	2,047,751	0.025
2021	2,275,880	0.027
2022	2,651,773	0.031
2023	3,664,000	0.043

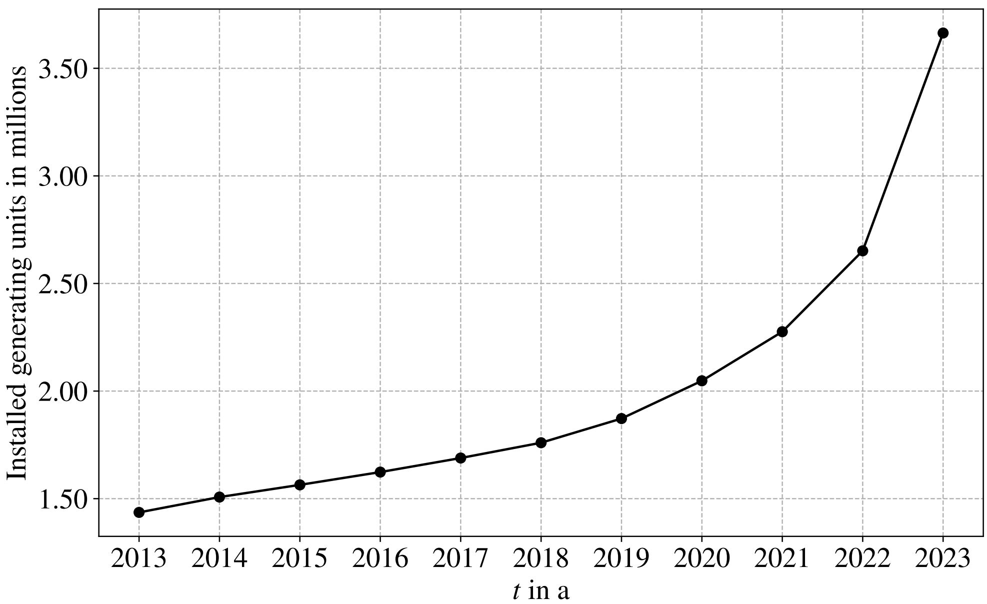


Figure 4.4: Number of PV systems installed in Germany.

4.2.2 Brazil

For Brazil, the total potential market (m) is also composed of consumers between 18 and 70 years old, who have a driving license for cars, namely categories AB (motorcycle/car) and B (only car). This data is obtained from [160] and is illustrated in Fig. 4.5.

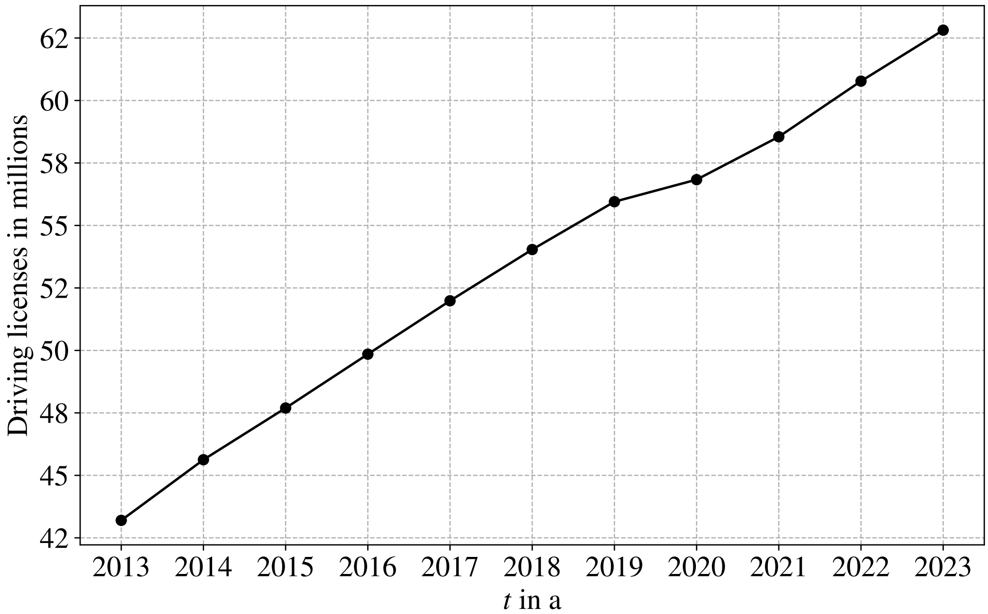


Figure 4.5: Number of driving licenses for cars in Brazil [160].

Regarding the socio-economic factors, HDI, used to specify the pool of potential adopters $P(t)$, is obtained from [105]. Furthermore, the average BEV life in Brazil is assumed to be 8 years, similar to Germany.

In the technical aspect, the BEV range determined for Germany already considers a global average range and a normalization value based on [109]. Therefore, this same value is used for Brazil. Similarly, for the calculation of the BEV charging time, the same charging times described for Germany are considered. In general, for these parameters that use global averages, the same values are applied to both Brazil and Germany.

However, for the number of BEV models available in the Brazilian market, data were sourced from [161], [162]. For normalization, a base value of 1,000 models, similar to Germany, is used. Table 4.14 presents the data on the BEV models considered in the simulations for the Brazilian scenario.

Table 4.14: Number of BEV models available in Brazil [161], [162].

Year	2018	2019	2020	2021	2022	2023
BEV models	3	3	13	32	60	106

To determine the rate of public BEV charging infrastructure in Brazil, the number of registered BEVs and the number of public CSPs are considered. These values are sourced from [162] for CSs and [163] for registered BEVs and presented with the resulting rate in Table 4.15. For normalization purposes, 15 BEVs/CSP are also considered.

Table 4.15: Parameters for calculating the ratio of PCI for BEVs in Brazil [163].

Year	**Registered BEVs**	**Public CSPs**	PCI
2019	538	220	2
2020	801	400	2
2021	2,851	800	4
2022	8,458	3,000	3
2023	19,310	3,800	5

The variable BEV mechanic workshops, modeled using a logistic function, was adjusted for Brazil with parameters $\kappa = 0.15$ and $t_\iota = 2045$. These values are an estimate to represent the pattern of evolution of the after-sales services provided for BEV owners in Brazil from 2019 to 2023.

Modeling and parameterizing political factors in a diffusion model is particularly challenging in a country of continental dimensions like Brazil. The diversity of public policies that can be implemented at different levels of government—federal, state, and municipal—increases the complexity of capturing all the variables involved. Each level of government has its own priorities and resources, leading to a variety of approaches and outcomes that complicate the modeling process. In this context, even with a thorough literature review, consultation with experts is essential for understanding and properly incorporating these factors into the model. Alternatively, to minimize these uncertainties, a study of the diffusion of innovations, such as BEV, can be regionalized, allowing for a more precise analysis adapted to the specificities of each region.

However, based on recent studies, scales for financing, legislation, and tax incentives for BEVs have been defined, as presented in Table 4.16. This phase of the research focused on federal public policies in Brazil and on state-level policies. In cases where certain policies are not uniformly implemented across all states, an average value was applied as a proportion to account for these variations.

Table 4.16: Weights for legislation, financing and tax incentives for BEV in Brazil.

Year	Legislation	Financing	Tax incentives
2019	0.20	0.00	0.20
2020	0.20	0.00	0.20
2021	0.25	0.10	0.25
2022	0.25	0.15	0.25
2023	0.30	0.15	0.42

In the analysis period from 2019 to 2023, the following legislations, programs, and incentives were considered to estimate these weights for Brazil [1], [91], [162], [164]–[167]:

- "Motor Vehicle Air Pollution Control Program (PROCONVE)" (1986): Focuses on controlling and reducing the emission of pollutants by motor vehicles.
- "National Policy on Climate Change (PNMC)" (2009): Establishes targets for the reduction of GHG emissions.
- "Banco Nacional de Desenvolvimento Econômico e Social", engl. Brazilian Development Bank (BNDES) Climate Fund Program (2011): Provides financing for sustainability projects.
- Law No. 13.755 (2018): Introduces the "Rota 2030" program (2018 - 2033), which focuses on promoting research and development for innovation and efficiency in the automotive sector.
- "Agência Nacional de Energia Elétrica", engl. National Agency of Electric Energy (ANEEL) Resolution No. 819 (2018): Regulates the provision of EV charging services, allowing any entity to choose the business model that best suits them for providing EV charging services.
- "National Electric Mobility Plan (PNME)" (2021): A strategic plan to promote electric mobility in Brazil, mapping opportunities for expanding technological competencies in the country.
- "Inova Energy" program by BNDES: Supports projects by companies for technological innovation involving electric mobility and DG, such as solar photovoltaic energy for EVs.

- Tax exemptions (IPI, IPVA, ICMS): Various fiscal policies have been implemented to incentivize the purchase of EVs in Brazil, including exemptions from "Imposto sobre Produtos Industrializados”, engl. Tax on Industrialized Products (IPI), "Imposto sobre a Propriedade de Veículos Automotores", engl. Motor Vehicle Ownership Tax (IPVA), and "Tax on Circulation of Goods and Services", engl. Tax on Circulation of Goods and Services (ICMS) for EVs.
- R&D incentives: There are incentives aimed at developing technologies related to EVs through government programs and private initiatives.

In 2017, Brazil also had Bill No. 454/2017, which proposed a ban on the sale of new ICEVs from 2060. This bill was shelved in 2022 [168].

Despite the progress made in electromobility in Brazil, the country still faces significant challenges. Regulatory, governance and acceptance obstacles need to be overcome to promote electric mobility effectively [166]. Other challenges include high vehicle purchase prices, limited range of available models in the Brazilian market and insufficient charging infrastructure. The scarcity of government incentives and subsidies compared to other countries also hinders the mass adoption of these vehicles. Therefore, for electromobility to take hold in Brazil, continued investment in technology, public policies to encourage and expand recharging infrastructure, and the creation of an effective regulatory framework are essential [162], [168].

For the economic aspect of Brazil, a 10-year analysis horizon is also used, considering the acquisition of an ICEV, BEV, or BEV with a green charger. The interest rate considered is 11 % [169]. Tables 4.17 and 4.18 present the specifications of the ICEVs and BEVs, respectively, considered for the Brazilian market. Unlike in Germany, where data is readily available from comprehensive sources such as ADAC, collecting the necessary data for Brazil required consulting various platforms and databases. This approach was essential due to the lack of a single institution providing all the relevant information, which required a broader search across multiple sources to obtain the technical and economic specifications of the vehicles and calculate their operating costs and NPV.

With the information from Tables 4.17 and 4.18, it is possible to calculate the fuel expenses for the ICEV, using the fuel prices provided in [184]. Similarly, the electricity costs for the BEV are calculated based on the values reported in [185]. The average annual distance traveled by residential consumers in Brazil is considered to be 14,300 km, as indicated in [35]. For the operational and maintenance costs, 0.5 % of the purchase price is considered for the BEV and 1.5 % for the ICEV, as suggested by [7]. The insurance cost for both vehicles in Brazil is approximately 4 % of the vehicle’s value per

Table 4.17: ICEV specifications for Brazil [170]–[175].

Year	Brand	Model	Consumption in km/l	Purchase cost
2019	Chevrolet	Onix 1.4 LT	11.7	R$ 49,280.00
2020	Chevrolet	Onix Turbo 1.0	13.0	R$ 55,590.00
2021	Fiat	Argo 1.3 Trekking	12.1	R$ 57,480.00
2022	Hyundai	HB20 Sense 1.0	12.8	R$ 58,890.00
2023	VW	Polo TSI	14.0	R$ 95,990.00

Table 4.18: BEV specifications for Brazil [176]–[183].

Year	Brand	Model	Cap_{bat} in kWh	Range in km	Purchase cost
2019	Renault	Zoe	41	300	R$ 149,990.00
2020	JAC	iEV 20	41	320	R$ 142,990.00
2021	JAC	iEV 20	41	320	R$ 159,900.00
2022	Renault	Kwid E-Tech	26.8	282	R$ 146,990.00
2023	BYD	Dolphin	44.9	291	R$ 149,800.00

year, according to market data [186]. The depreciation rate for the BEV is assumed to be 9 % of the purchase price, while for the ICEV, it is 6 % [187]. This difference in depreciation negatively impacts the NPV calculation for the BEV.

For the Brazilian car tax (IPVA), which is a state tax in Brazil, a survey of various state laws was conducted to calculate the average value across the country. In 2023, BEVs were exempt from this tax in 9 states, including Bahia (exemption for BEVs up to R$ 300,000.00), Ceará, Distrito Federal, Maranhão, Minas Gerais (exemption for BEVs manufactured in this state), Paraná, Pernambuco, Rio Grande do Norte, and Rio Grande do Sul, and have differentiated aliquots in Alagoas (reduced rate of 2 % on the BEV's market value), Mato Grosso do Sul (50 % reduction for BEV), Rio de Janeiro (50 % reduction for BEV), and São Paulo (without specific legislation for the whole state, São Paulo has advantages for some cities). The average values for IPVA are presented in Table 4.19. The annual operational costs for ICEVs and BEVs are presented in Tables 4.20 and 4.21, respectively.

In the NPV analysis of the BEV in Brazil, the acquisition cost of a 7.4 kW wallbox is considered, with the average prices presented in Table 4.22. An installation cost of R$ 3,150 is also factored in [188], [189], along with average operation and maintenance costs of R$ 500 every four years.

Table 4.19: Average IPVA rates for ICEV and BEV by year in Brazil.

Year	ICEV average	BEV average
2019	3.03 %	2.06 %
2020	3.01 %	1.95 %
2021	3.01 %	1.99 %
2022	3.01 %	1.88 %
2023	3.03 %	1.88 %

Table 4.20: ICEV operational costs for Brazil.

Year	O&M	Fuel cost	Insurance	IPVA	Depreciation	Total
2019	R$ 739.20	R$ 5,352.01	R$ 1,971.20	R$ 1,492.09	R$ 2,956.80	R$ 12,511.30
2020	R$ 833.85	R$ 4,707.84	R$ 2,223.60	R$ 1,672.85	R$ 3,335.40	R$ 12,773.54
2021	R$ 862.20	R$ 6,831.80	R$ 2,299.20	R$ 1,729.72	R$ 3,448.80	R$ 15,171.72
2022	R$ 883.35	R$ 6,829.93	R$ 2,355.60	R$ 1,772.15	R$ 3,533.40	R$ 15,374.43
2023	R$ 1,439.85	R$ 5,622.11	R$ 3,839.60	R$ 2,906.36	R$ 5,759.40	R$ 19,567.33

Table 4.21: BEV operational costs for Brazil.

Year	O&M	Fuel cost	Insurance	IPVA	Depreciation	Total
2019	R$ 749.95	R$ 1,662.20	R$ 5,999.60	R$ 3,097.02	R$ 13,499.10	R$ 25,007.87
2020	R$ 714.95	R$ 1,464.65	R$ 5,719.60	R$ 2,793.60	R$ 12,869.10	R$ 23,561.90
2021	R$ 799.50	R$ 1,266.76	R$ 6,396.00	R$ 3,183.19	R$ 14,391.00	R$ 26,036.45
2022	R$ 734.95	R$ 956.98	R$ 5,879.60	R$ 2,762.87	R$ 13,229.10	R$ 23,563.50
2023	R$ 749.00	R$ 1,673.33	R$ 5,992.00	R$ 2,815.69	R$ 13,482.00	R$ 24,712.02

Table 4.22: Average wallbox prices for Brazil [189]–[193]

Year	Wallbox price
2019	R$ 7,000.00
2020 – 2021	R$ 6,499.00
2022 – 2023	R$ 5,500.00

Unlike in Germany, Brazil does not offer a direct subsidy for consumers to purchase a BEV. Using the provided information, it is possible to determine the cash flow and calculate the NPV for both the BEV and ICEV.

For the BEV with a green charger, the estimated average annual productivity ($\alpha_{\text{PV, avg}}$) for a green charger in Brazil is assumed to be 1,200 kWh/kW [194], with operation and maintenance costs also set at 1 %. Table 4.23 presents the average costs for solar PV systems in Brazil, as well as the associated savings when purchasing a BEV with a green charger.

Table 4.23: Parameters for calculating the NPV of the BEV and green charger for the Brazilian scenario [195]–[197].

Year	C_{PV} **in R$/kW**	**Savings in R$**
2019	6,265.00	1,662.20
2020	6,015.00	1,464.65
2021	6,180.00	1,266.76
2022	6,170.00	956.98
2023	4,950.00	1,673.33

Additionally, similar to the analysis conducted for Germany, the necessary data for calculating the BEV green charger coefficient in Brazil are also included. Table 4.24 provides data on home ownership and population in Brazil, which are used to determine this coefficient.

Table 4.24: Demographic data for Brazil and green charger coefficient [198], [199].

Year	**Population**	**Home ownership**	α_{GC}
2019	211,782,878	183,549,000	0.87
2020	213,196,304	183,549,000	0.86
2021	214,326,223	183,549,000	0.86
2022	215,313,498	186,536,000	0.87
2023	216,422,446	186,536,000	0.86

The resulting NPV calculations for Brazil are detailed in Fig. 4.6. As observed, traditional ICEVs continue to dominate the Brazilian market, largely due to the absence of direct subsidies and the higher initial costs associated with BEVs. Additionally, although integrating a green charger could provide long-term savings, it does not substantially change the short-term economic outlook under the analyzed conditions.

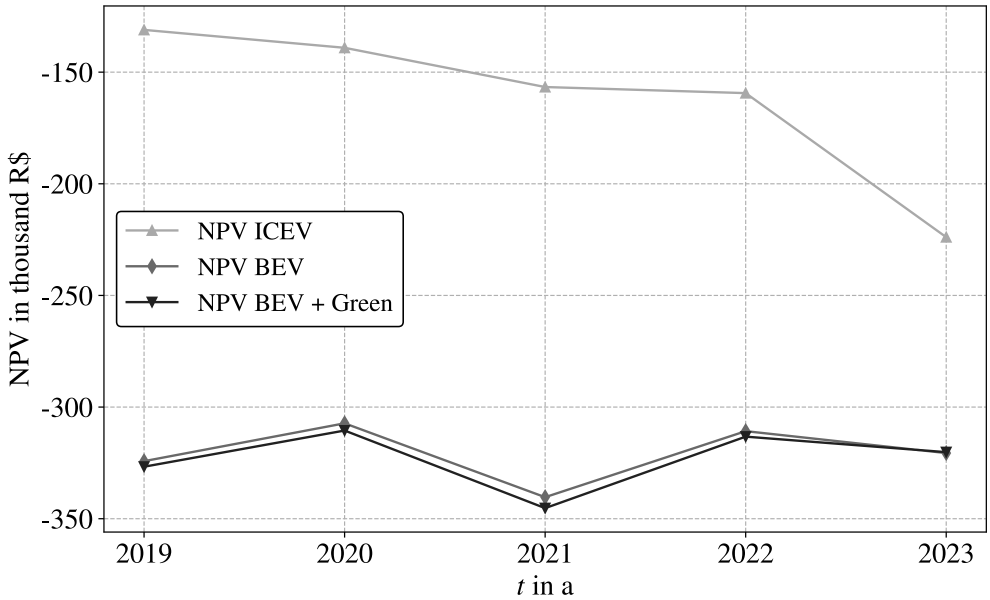


Figure 4.6: Result of the NPV calculation for historical values in Brazil.

Finalizing the presentation of the historical data collected for Brazil, the data for calculating the DG adopters coefficient (α_{DG}) from the social aspect is presented. Table 4.25 shows the evolution of the number of installed PV generating units in Brazil and the resulting α_{DG} values between 2019 and 2023. The growth in the number of installed PV systems is also depicted in Fig. 4.7. These data is used in future scenarios to perform analyses based on the regression of these values show in the figure.

Table 4.25: Number of PV system installations and DG adopters coefficient for Brazil [200].

Year	**PV installations**	α_{DG}
2019	1,81,014	0.001
2020	4,07,460	0.002
2021	8,65,279	0.004
2022	1,662,532	0.008
2023	2,345,847	0.011

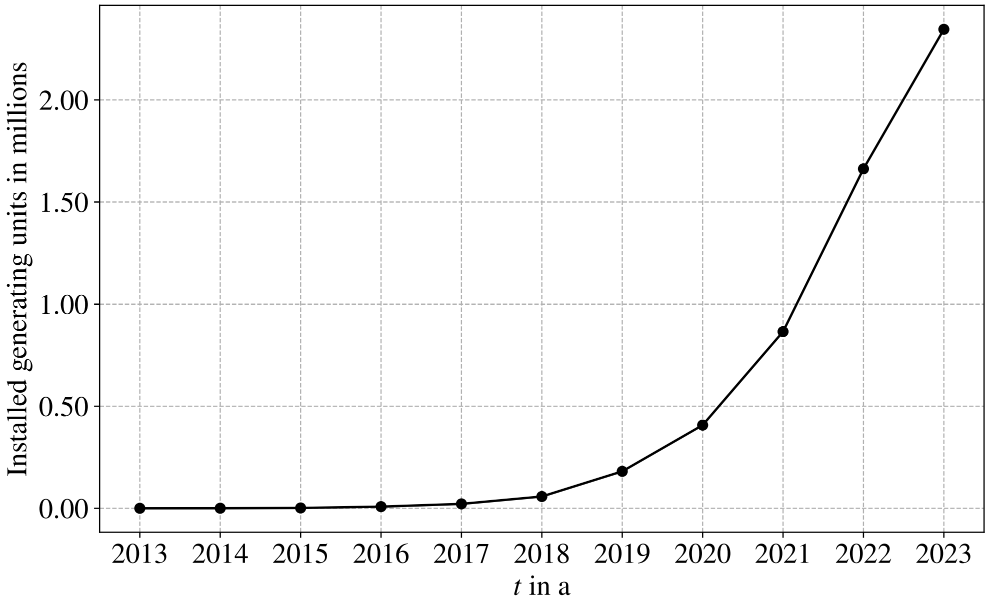


Figure 4.7: Number of PV systems installed in Brazil.

4.3 Calibration and verification of the model

After extensive data collection, parameterization, application of the questionnaire, calculation of AHP weights, and estimation of fuzzy variables through multiple consultations with experts, the next step involves running the model to obtain a reference mode, as proposed by Ford [58]. This corresponds to the sixth step in Ford's methodology. In this study, the Vensim software is used to implement the model with all the defined variables in a single simulation. To simulate the model, 7,114 registered BEVs in Germany and 538 in Brazil are considered as initial adopters $(A(t_0))$, as presented in Tables 4.5 and 4.15, respectively.

As mentioned in Section 2.3, simulating a diffusion model requires at least four years of historical data [68], with ten years being ideal [70]. Due to the lack of historical data to fully parameterize the model for Brazil, the model verification simulations are carried out with data from 2019 to 2023, while for Germany data from 2013 to 2023 are used.

Next, the calibration of the p and q values for the Bass model is performed. For Germany, the values obtained are 0.00146 and 0.5469, respectively, with a delay of five years for q. For Brazil, the corresponding values are 0.0001 for p and 0.7982 for q, which has a delay of one year. The results of the simulations are presented in Figures 4.8 for Germany and 4.9 for Brazil.

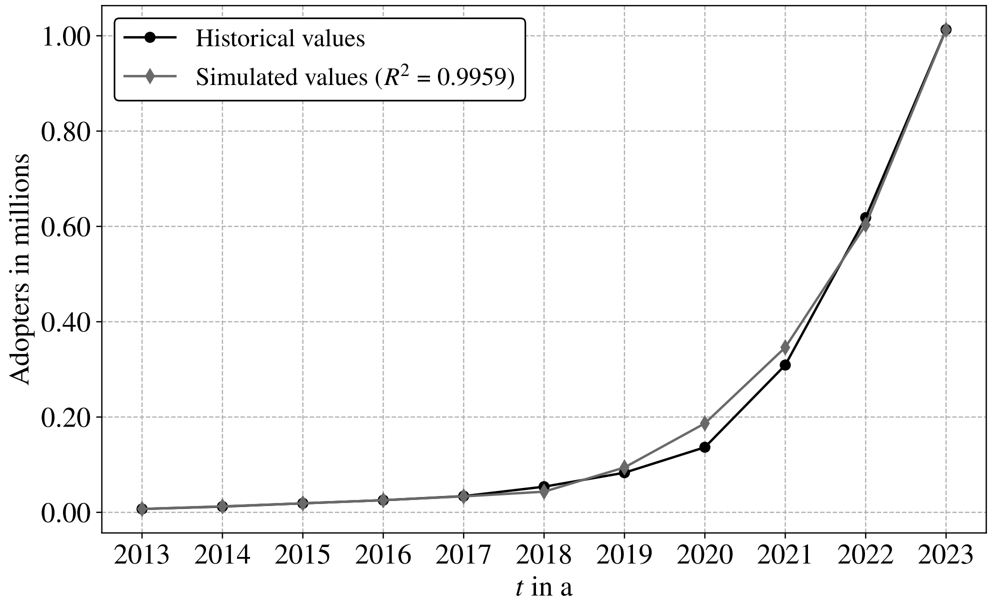


Figure 4.8: Verification of the proposed model compared with historical data for Germany.

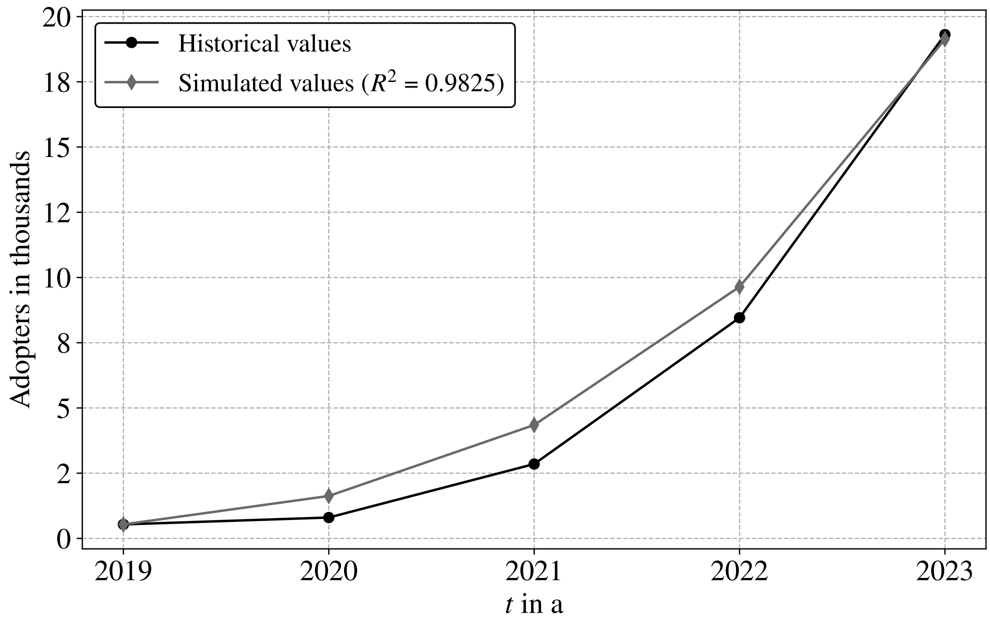


Figure 4.9: Verification of the proposed model compared with historical data for Brazil.

The p value, which reflects the initial "innovators" who adopt the product or technology independently of other adopters, i.e. before the majority, is small in relation to the q value, which represents social influence, such as word-of-mouth, the probability of adoption through interaction with individuals who have already adopted the innovation or through social pressures, as can be seen in previous innovation diffusion studies [30], [35], [49], [51], [63], [67]. In this sense, diffusion tends to depend much more on imitation than on independent innovation, unless it is a disruptive technology in a highly innovative market, which is not the case with BEVs, since there is an effort by various stakeholders to promote their diffusion.

In addition, the values obtained also reflect the maturity of these markets. In the case of Germany, innovation still plays a relatively more significant role than in Brazil, where adoption seems to be almost entirely dependent on social factors and the influence of previous adopters. The low p coefficient for Brazil also indicates barriers related to this innovation, such as cost, lack of infrastructure or unfamiliarity with the technology.

Finally, in the verification process of the model, statistical metrics are used, and they are the coefficient of determination (R^2), the root mean square error (RMSE) and the mean absolute error (MAE), to evaluate the model. The appendix C provides the equations for calculating these parameters. These metrics are presented in the Table 4.26.

Table 4.26: Model performance metrics/results for the proposed model.

Country	R^2	$RMSE$	MAE
Germany	0.9959	19,878	11,391
Brazil	0.9825	934	738

The results indicate a strong model performance for both Germany and Brazil. For Germany, the R^2 value is 0.9959, reflecting a very high level of agreement between the historical and simulated data. The RMSE and MAE values are 19,878 and 11,391 registered BEVs, respectively, indicating a relatively low average error, considering the large number of adopters in the country (over one million). The high R^2 and the low error metrics demonstrate that the model is well-calibrated for the German market, accurately capturing the dynamics of BEV adoption.

The results for Brazil also show good model performance, with an R^2 value of 0.9825, which is slightly lower than that of Germany but still indicates a strong correlation between the simulated and historical data. The RMSE and MAE values for Brazil are significantly lower at 934 and 738 registered BEVs, respectively, reflecting the smaller scale of BEV adoption in the country. However, the lower RMSE and MAE do not necessarily imply better model accuracy but rather correspond to the smaller population of BEV adopters in Brazil.

These results validate the model's robustness in simulating BEV adoption in two distinct markets, demonstrating its flexibility and adaptability to different contexts and adoption patterns. Thus, after defining a reference scenario to assess the possibilities of BEV spreading in Brazil and Germany, two other alternative future scenarios are simulated using the proposed model.

5 Future Scenarios

In Chapter 4, the identification and parameterization of proposed variables that influence BEV diffusion in Germany and Brazil was presented. These variables were classified into social, economic, technical, infrastructural, political and market aspects. The chapter covered the collection of historical data, the estimation of parameters using the AHP method, and the calculation of fuzzy variables with the assistance of expert consultations. Additionally, the coefficients of the Bass diffusion model were calibrated for each country, considering the initial adopters and the specific market characteristics of Germany and Brazil. Finally, the model's verification was performed by comparing simulated values with historical data, using evaluation metrices like the R-squared, RMSE, and MAE.

In this chapter, future scenarios for the diffusion of BEVs in both Brazil and Germany are analyzed. The purpose is to define a reference scenario as a baseline, followed by simulations for two alternative scenarios, which are described in detail. The analysis period spans from 2024 to 2050, with the objective of evaluating potential diffusion pathways for BEVs under varying conditions. The simulations will provide insights into how the market might evolve in each country, considering different factors such as technological advancements, policy incentives, social appeal, and consumer behavior.

Some variables remain invariable throughout future analysis. The HDI is not varied, and the values from 2023 (0.950 for Germany and 0.760 for Brazil) are used for the entire simulation period. Similarly, the green charger coefficient (α_{GC}) also utilized the value from the last available year. For the variables requiring normalization, the same normalized values as presented in Chapter 4 are maintained. Additionally, the fuzzy variable factors remained constant over time, except for the R&D variable, which varies according to Table 4.1 for the reference scenario and some other assumptions for future scenarios. Furthermore, the calibrated p and q values for the Bass model, as well as the delay for q and the average BEV life t_{BEV}, also remained invariant throughout the simulations until 2050. The variations of all other variables are presented in the following sections of this chapter.

5.1 Reference scenario

The reference scenario establishes a baseline for further comparisons with alternative futures. Initially, the potential market is defined. In both countries, a linear growth trend was observed based on the historical data for driver licenses (see Fig. 4.1 for Germany and Fig. 4.5 for Brazil). Therefore, a linear regression method is employed, utilizing these data and projecting the potential market size forward to 2050 for both Germany and Brazil, using (5.1).

$$y_{\mathrm{i}}^{'} = \xi_1 \cdot t + \epsilon \tag{5.1}$$

Where $y_{\mathrm{i}}^{'}$ is the predicted i^{th} value (dependent variable), ξ_1 is the angular coefficient (slope of the line), t is the time (independent variable), and ϵ is a constant, which represents the intercept of the line with the y-axis. The coefficients of the linear regression, along with R^2, RMSE, and MAE, are presented in Table 5.1.

Table 5.1: Estimation of the number of driving licenses for future scenarios.

Country	ξ_1	ϵ	R^2	$RMSE$	MAE
Germany	851,748	12,483,053	0.9996	54,103	40,285
Brazil	1,901,449	43,885,051	0.9946	441,170	375,062

In the technical aspect, the travel capacity varies according to the BEV range. Based on [201], the range is expected to reach 600 km by the end of the analysis period in 2050. This evolution of the range is considered for both Brazil and Germany, with the range values progressively increasing up to 600 km throughout the simulations.

The recharging time variable is influenced by battery capacity. Based on [202], the average battery capacity is expected to reach 100 kWh in the coming years. For this study, it is assumed that this value will be achieved by 2033, and this battery capacity is used in all future simulations, as well as the charging efficiency of 90 %. In the reference scenario, the recharging time is calculated considering residential charging at 11 kW. Differentiations in charging technology will be explored in other scenarios to evaluate variations in recharging times.

For the variable BEV models, the variations are performed using non-linear regression. A logistic regression model is used for Germany, as shown in (5.2), while a generalized logistic model is employed for Brazil, as shown in (5.3). The model is fitted using historical data, assuming a saturation point of 1,000 BEV models. This value is based on the projection in [7], which estimates that the number of electric car models will reach 1,000 by 2028. The resulting parameter values and regression evaluation metrics are presented in Table 5.2.

$$y_{\mathrm{i}}^{'} = \frac{K}{1 + \mathrm{e}^{-\kappa(t-t_\iota)}} \tag{5.2}$$

$$y_{\mathrm{i}}^{'} = \frac{K}{\left(1 + \nu \cdot \mathrm{e}^{-\kappa \cdot (t - t_{\iota})}\right)^{\frac{1}{\nu}}} \tag{5.3}$$

Where K represents the saturation level, or the maximum number of BEV models that can be reached; κ is the growth rate parameter that defines how fast the market will reach saturation; t_{ι} refers to the inflection point in the curve, indicating when half of the market potential is reached; ν in the generalized logistic model controls the shape of the curve, providing greater flexibility for the non-linear regression in the case of Brazil.

Table 5.2: Coefficients and evaluation metrics of the regression for BEV models in the reference scenario.

Country	K	κ	t_{ι}	ν	R^2	$RMSE$	MAE
Germany	1,000	0.4295	2,025.08	–	0.9656	16	14
Brazil	1,000	0.1459	2,029.19	0.0199	0.9220	10	9

Fig. 5.1 shows the results of the forecasting regression for BEV models in Germany under the reference scenario. Similarly, the projection for the number of BEV models in Brazil, which is expected to reach 953 models by 2050, is represented in Fig. 5.2.

The variable $\beta_{\mathrm{R\&D}}$, which represents the efforts related to R&D in the reference scenario, uses the values calculated through fuzzy algorithm. Table 5.3 presents the variations for this variable in the reference scenario.

Table 5.3: Variations in $\beta_{\mathrm{R\&D}}$ for the reference scenario.

Period	**Germany**	**Brazil**
2013 – 2024	0.57	0.74
2025 – 2035	0.81	0.87
2036 – 2050	0.84	0.86

In the reference scenario, the variable public charging infrastructure (PCI) varies from 10 to 15 BEVs/CSP from 2024 to 2050. In the case of Brazil, this variable is set to range from 5 BEVs/CSP in 2024 to 15 in 2050. For the variable BEV mechanic workshops, which is modeled by a logistic function, the values of κ and t_{ι} remain unchanged from the historical data simulations. The same values are maintained for Germany ($\kappa = 0.20$, $t_{\iota} = 2035$) and for Brazil ($\kappa = 0.15$, $t_{\iota} = 2045$).

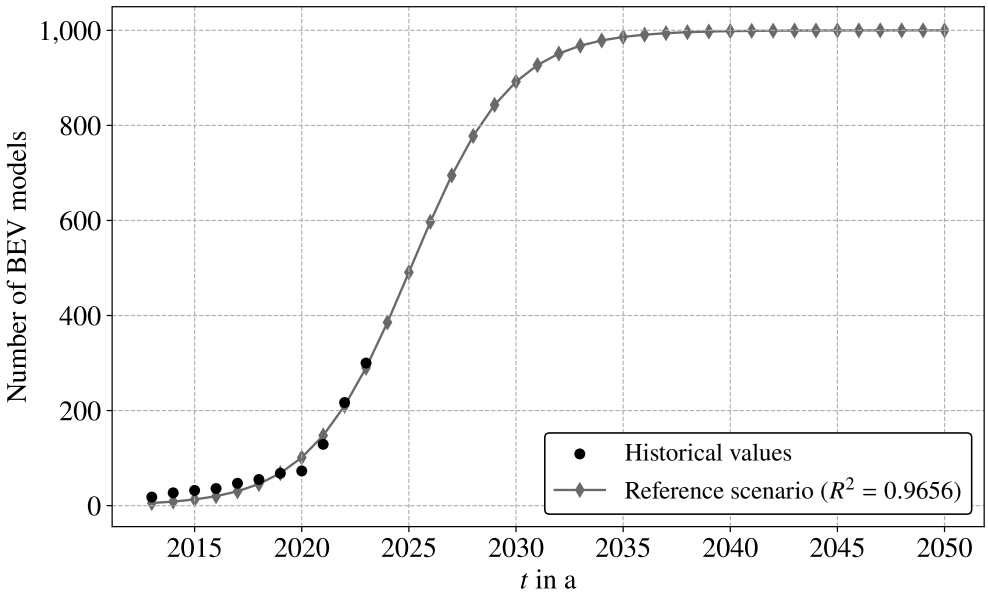


Figure 5.1: BEV models for reference scenario in Germany.

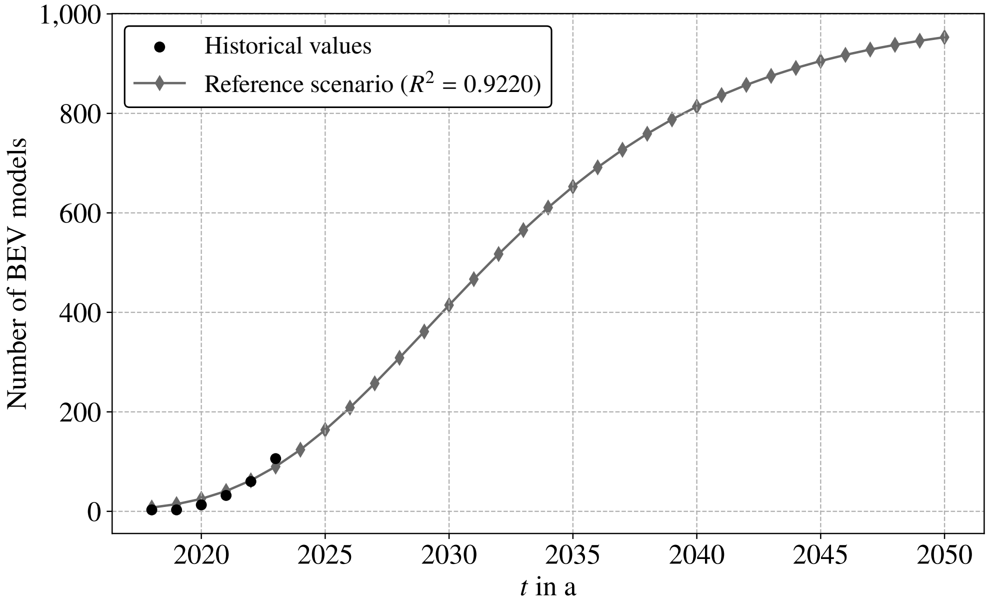


Figure 5.2: BEV models for reference scenario in Brazil.

In the political scenario, variations in the parameters include the variables BEV legislation, financing, and tax incentives. Overall, a scenario is considered where government and industry actions work towards enhanced BEV diffusion in both countries. Tables 5.4 and 5.5 present the variations of these parameters for Germany and Brazil, respectively.

In Brazil, the tax system on car purchases is more complex than in Germany. While in Germany the primary tax is the VAT, which has a standard rate of 19 %, in Brazil different taxes affect the final price. Vehicle purchases in Brazil are subject to both federal and state taxes. Among the federal taxes, the IPI stands out, with a rate ranging from 7 % to 18 %, depending on the vehicle's energy efficiency and weight. The "Imposto sobre Operações Financeiras", engl. Tax on Financial Operations (IOF) is also applied, though there are exemptions for specific groups such as taxi drivers and people with disabilities, as established by Law 13,755/2018. Another federal tax is the "Social Integration Program", engl. Programa de Integração Social (PIS)/"Contribuição para o Financiamento da Seguridade Social", engl. Contribution for the Financing of Social Security (COFINS), which applies a 9.25 % rate to new vehicles. At the state level, the ICMS tax has rates that vary depending on the state and applies to the sale of vehicles [35]. For the analyses in this work, variations in VAT for Germany and IPI for Brazil are considered.

When considering variations in these policies, particularly subsidies, tax reductions, and car tax variations ("Kfz-Steuer" for Germany and IPVA for Brazil), there is a direct impact on the economic variables. These changes notably influence the NPV calculations, as they alter the initial investment and operational costs associated with BEVs and ICEVs. Thus, these policy-driven variations are integrated into the economic analysis conducted in this work, reflecting their influence on the adoption of BEVs.

In the economic aspect of the reference scenario for calculating the NPV, several economic and political factors are considered for both Brazil and Germany. The vehicles considered in this analysis are the 2023 models, with their respective prices for fuel and energy. The energy price for BEVs remains constant throughout the analysis, while the fuel price for ICEVs varies due to the addition of the fossil fuel tax.

For Brazil, the ICEV price is projected in two phases: a 10 % increment from 2024 to 2030, based on [203], followed by a 2 % increment until 2050. In Germany, a 10.5 % increase is projected by 2035.

Regarding BEV subsidies, Germany ended its grant program in December 2023 [204]. However, for the reference scenario, a new grant of € 3,375 is assumed from 2026 to 2035 to support BEV adoption, in line with the EU's decision to ban ICEVs by 2035 [127]. After this period, the grant is withdrawn.

Table 5.4: Political aspects in reference scenario for Germany.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2023: 0.20	2050: 0.20
	Public charging infrastructure investment	2023: 0.20	2050: 0.10
	Grid integration and smart charging regulations	2023: 0.00	2050: 0.10
	Clean energy targets and renewable energy mandates	2023: 0.20	2050: 0.00
	BEV supply chain support	2023: 0.00	2050: 0.10
Financing	Grants for BEV	2026: 0.20	2035: 0.20
	Solar power funding program for BEV	2026: 0.20	2050: 0.10
	Low-interest loans	2023: 0.15	2050: 0.30
Tax Incentives	Annual BEV car tax	2035: 0.30	2050: 0.15
	Grid connection and tariff incentives (V2G)	2024: 0.00	2050: 0.10
	VAT to purchase a BEV	2024: 0.00	2050: 0.00
	Tax reduction on renewable source installation	2035: 0.20	2050: 0.10

Table 5.5: Political aspects in reference scenario for Brazil.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2026: 0.10	2050: 0.15
	Public charging infrastructure investment	2026: 0.05	2050: 0.10
	Grid integration and smart charging regulations	2024: 0.00	2050: 0.10
	Clean energy targets and renewable energy mandates	2026: 0.15	2050: 0.10
	BEV supply chain support	2024: 0.00	2050: 0.10
Financing	Grants for BEV	2026: 0.30	2050: 0.30
	Solar power funding program for BEV	2026: 0.10	2050: 0.05
	Low-interest loans	2023: 0.05	2050: 0.15
Tax Incentives	Annual BEV car tax (IPVA)	2026 to 2035: 0.30	2050: 0.15
	Grid connection and tariff incentives (V2G)	2023: 0.00	2050: 0.20
	IPI to purchase a BEV	2026: 0.10	2050: 0.05
	Tax reduction on renewable source installation	2026: 0.15	2050: 0.20

Meanwhile, in Brazil, a grant of 7.5 % of the BEV purchase price is consistently provided from 2026 to 2050, influencing the financing parameters related to BEV adoption. Vehicle prices are expected to decrease by 2050, with a 35 % reduction for BEVs in Germany (30 % until 2030), and 30 % in Brazil, based on sources [203] and [205].

For operational costs, the BEV car tax exemption in Germany is valid until 2035, after which a tax of € 62 is applied. In both countries, carbon taxes[3] are introduced, with fossil fuel taxes increasing by 5 % annually until 2050, and ICEV carbon taxes rising by 3 % in Brazil and 1.15 % in Germany by 2035. These changes reflect broader mandates for emissions reduction and the promotion of clean energy [35].

Changes in subsidies, car taxes (IPVA in Brazil and KfZ-Steuer in Germany), and VAT directly impact the NPV calculations. In Brazil, the IPVA is exempt from 2026 to 2034, after which it gradually increases to 1.5 % of the BEV price by 2050.

For wallbox prices, a reduction of 50 % is considered for Germany and 40 % for Brazil by 2050. In both countries, the green charger price is expected to drop significantly, with Brazil's prices decreasing by 40 % by 2050 [206] and and Germany's green charger prices reaching an average of 315 €/kW by 2050 [207] The green charger coefficient remains stable throughout the analysis period, as historical data shows minimal variation in this factor for both countries.

Table 5.6 summarizes the variations for calculating the NPV in the reference scenario for Germany, and Fig. 5.3 presents the results of the NPV calculation for the German scenario. For Brazil, Table 5.7 provides the variations considered in the NPV calculation, while Fig. 5.4 shows the NPV projection for the Brazilian scenario.

In Germany, as illustrated in Fig. 5.3, the NPV for ICEV remains negative throughout the analysis period. The results indicate that ICEV steadily worsens as investment over time, driven primarily by price increment applied from the 2023 baseline, and rising fuel costs and carbon taxes. Notably, by 2017 (Fig. 4.3), the NPV of the BEV with a green charger had already surpassed the ICEV, making it the more economically viable option. This shift highlights that, under the assumptions made in this analysis, the BEV with a green charger becomes the most favorable option in terms of economic performance, particularly as subsidies and reductions in PV prices for solar BEV charging are factored in, although this option remains limited by the green charger coefficient.

[3] This tax is applied annually and calculated as a percentage of the vehicle's price. It is based on the Norwegian policy, where the tax reaches up to 11 %, as reported by [35].

Table 5.6: Variation of the parameters for calculating NPV in reference scenario for Germany.

Parameter	Change	Start year	End year
Grant/Subsidy	Half of 2023 grant (€ 3,375)	2026	2035
BEV price	30 % reduction of 2023 price	2024	2030
	35 % reduction of 2023 price	2031	2050
ICEV price	10.5 % increment on 2023 price	2024	2035
Wallbox price	50 % reduction of average price of 2023	2024	2050
VAT	19 %	2024	2050
BEV car tax	Exemption	2024	2035
	€ 62	2031	2050
Carbon tax on ICEV	1 % linear increment	2026	2035
Fossil fuel tax	5 % linear increment	2026	2050
Green charger price	Reduce linearly to 315 €/kW by 2050	2024	2050

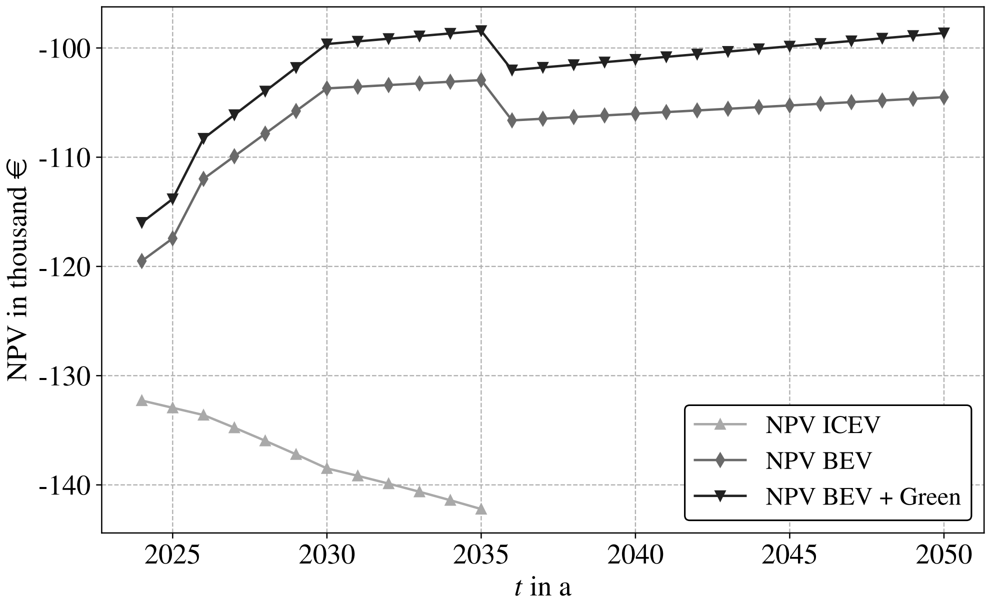


Figure 5.3: NPV result for the reference scenario in Germany.

Table 5.7: Variation of the parameters for calculating NPV in reference scenario for Brazil.

Parameter	Change	Start year	End year
Grant/Subsidy	7.5 % of BEV purchase price	2026	2050
BEV price	30 % reduction of 2023 price	2024	2050
ICEV price	10 % increment on 2023 price	2024	2030
	12 % increment on 2023 price	2031	2050
Wallbox price	48 % reduction of average price of 2023	2024	2050
IPI	7 %	2026	2050
IPVA	Exemption	2026	2034
	0 – 1.5 % of the BEV price	2035	2050
Carbon tax on ICEV	3 % linear increment	2026	2050
Fossil fuel tax	5 % linear increment	2027	2050
Green charger price	40 % reduction of 2023 price	2024	2050

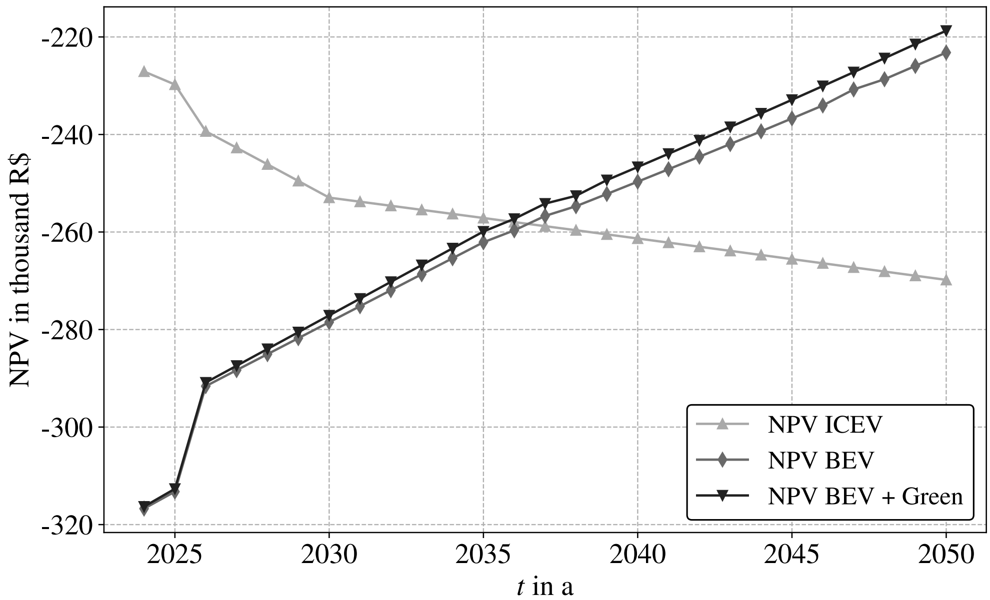


Figure 5.4: NPV result for the reference scenario in Brazil.

The NPV results for Brazil, shown in Fig. 5.4, indicate that the NPV for ICEV also remains consistently negative, reflecting the increment on ICEV acquisition prices, higher operational costs, and the growing impact of the carbon tax on ICEV and fossil fuel tax until 2050. However, for BEV, the NPV improves over time, with the BEV and green charger becoming the most economical option by 2036, highlighting the importance of subsidies and the reduction in BEV acquisition costs.

To determine the DG adopters coefficient in the social aspect, it is necessary to account for the impact of increasing distributed PV generation over time. For Germany, projections from [208] in a reference scenario are considered. To estimate the number of future PV system installations, the installed capacity determined by [208] is multiplied by a factor obtained from [209]. Since [208] only provides values until 2045, a linear regression is used to project data through 2050. The R-squared (R^2) for this regression is 0.9751, with $\xi_1 = 633,084$ and $\epsilon = 1,892,817$.

The population growth in a moderate scenario for Germany is proposed by [210], and is illustrated in Fig. 5.5. These population values remain constant throughout the subsequent simulations for the total population of Germany. However, in other scenarios, variations in the increase of PV generation are considered.

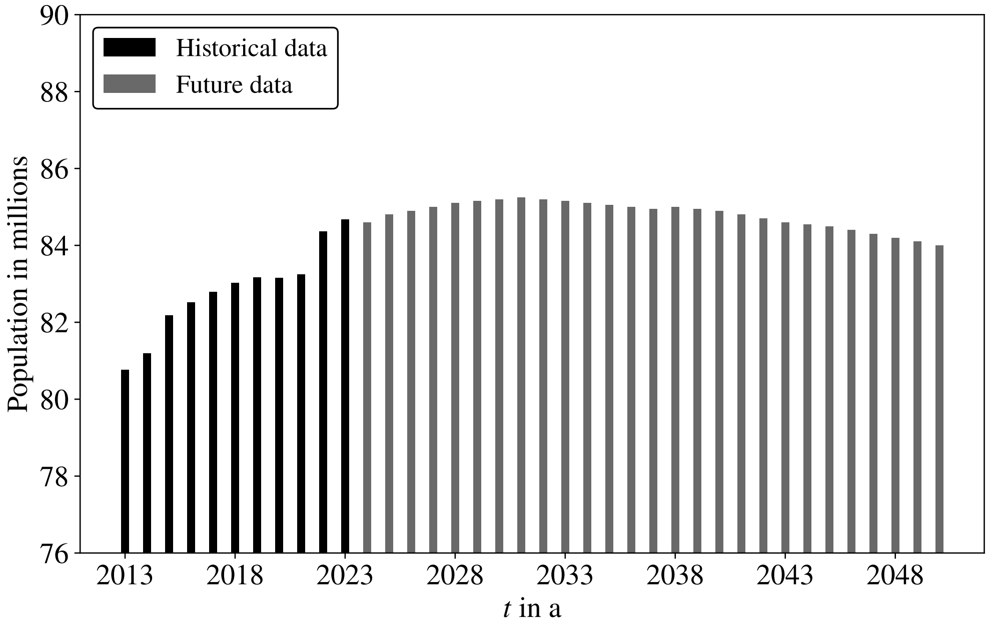


Figure 5.5: Future population projections for Germany [210].

For Brazil, the study by [211] with data up to 2024 serves as a reference for examining the growth trend of PV generation units. After analyzing these data, a second-degree polynomial regression, represented by equation (5.4), is applied to predict the future number of installed PV systems in Brazil.

$$y_{\mathrm{i}}^{'} = \xi_2 \cdot t^2 + \xi_1 \cdot t + \epsilon \tag{5.4}$$

Where $y_{\mathrm{i}}^{'}$ is the predicted i^{th} value (dependent variable), ξ_1 is the coefficient of the linear term, ξ_2 is the coefficient of the quadratic term, t is the time (independent variable), and ϵ is a constant representing the error term. Table 5.8 provides the coefficients obtained from the polynomial regression for the Brazilian system. The graphical result of this regression is presented in Fig. 5.6.

Table 5.8: Coefficients of polynomial regression for number of PV systems in reference scenario for Brazil.

Scenario	ξ_2	ξ_1	ϵ	R^2	$RMSE$	MAE
Reference	27,885	-83,976	-52,755	0.9193	216,917	179,929

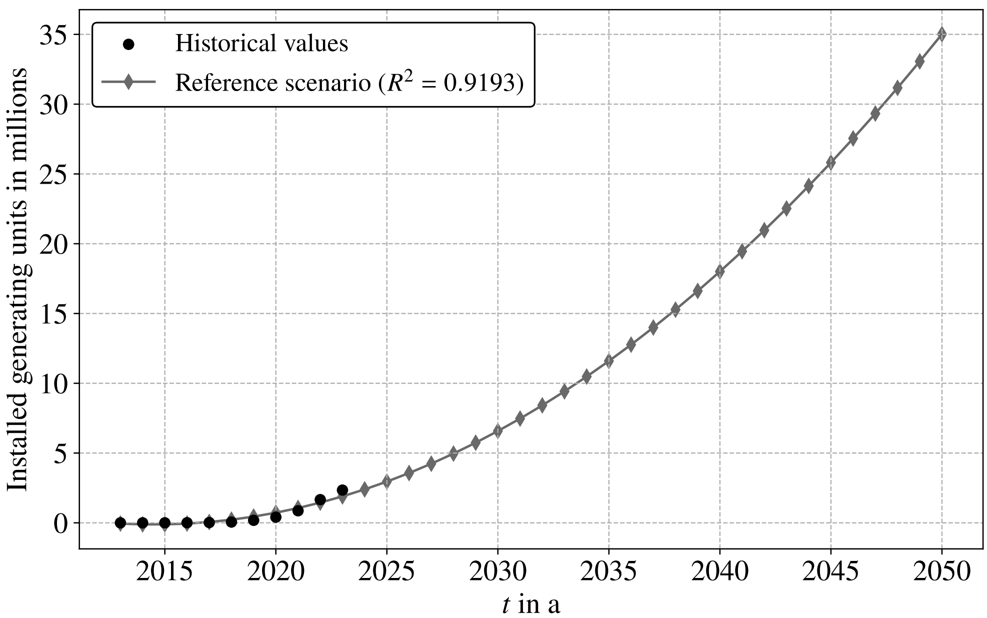


Figure 5.6: Projection of the expansion of PV systems for the reference scenario in Brazil.

For population growth in Brazil, studies conducted by [212] were considered, and the results are shown in Fig. 5.7. The DG adopters' coefficient (α_{DG}) is then calculated based on these values throughout the performed simulations.

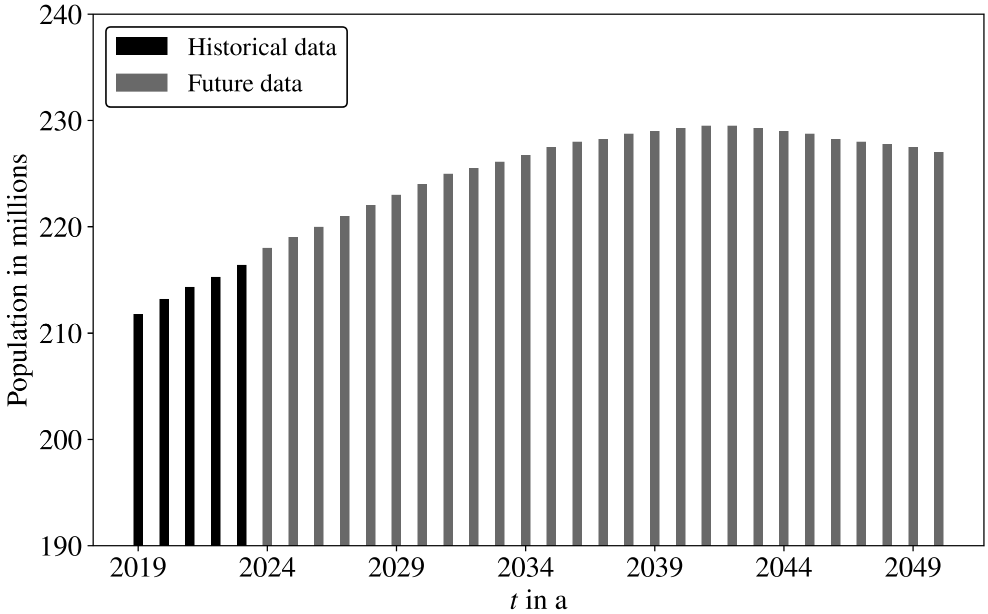


Figure 5.7: Future population projections for Brazil [212].

5.2 Investigation of alternative scenarios

In this research, two alternative future scenarios are explored, building up assumptions made in the reference scenario. These scenarios represent different potential trajectories for the diffusion of BEVs in Germany and in Brazil. These scenarios are described as following:

- **Alternative scenario 1:** It envisions rapid BEV diffusion, driven by favorable policies and robust financial incentives for BEV owners. This scenario assumes significant governmental and industrial support, leading to accelerated market growth and widespread use of BEV in a relatively short time.
- **Alternative scenario 2:** A more conservative outlook, where minimal changes to the current BEV market are considered. In this scenario, limited developments and efforts from stakeholders result in a slower rate of BEV adoption.

As all variables have been thoroughly discussed in previous sections, this section presents a more streamlined overview of the parameter variations for both Germany and Brazil in parallel.

For alternative scenario 1, in the technical aspect, the evolution of the average BEV range is considered, reaching 800 km for light vehicles aimed at average consumers. In alternative scenario 2, there is a reduction of 200 km in the average vehicle range, such that only by 2050 does the range reach a value of 1, considering the normalization value of 400 km.

Regarding recharging time, there is no variation in the average battery capacity considered in the reference scenario. However, these future analysis explore different charging technologies, with 22 kW for alternative scenario 1 and 7.4 kW for alternative scenario 2. This approach allows for the exploration of charging times considering possible wallboxes for residential consumers.

For the variable BEV models, the results of the non-linear regressions are presented in Table 5.9 for Germany (logistic model) and for Brazil (generalized logistic model). The corresponding graphical results are shown in Fig. 5.8 for Germany and Fig. 5.9 for Brazil.

Table 5.9: Coefficients and evaluation metrics of the regression for BEV models in the reference scenario.

Country	**Scenario**	K	κ	t_ι	ν	R^2	$RMSE$	MAE
Germany	Alternative 1	1,200	0.4162	2,025.73	–	0.9676	15	14
	Alternative 2	800	0.2933	2,026.08	–	0.8943	28	19
Brazil	Alternative 1	1,000	0.2245	2,026.69	0.0166	0.9990	1	1
	Alternative 2	600	0.1900	2,027.65	0.1874	0.8732	13	11

The results in Table 5.9 show that the non-linear regressions for the BEV models perform well, particularly in alternative scenario 1 for both Germany and Brazil. The high R^2 values and low error metrics in scenario 1 indicate accurate fits to the projected data. In alternative scenario 2, the results are less accurate, with lower R^2 and higher error values. However, the models still provide sufficient accuracy for varying this parameter in the diffusion studies being conducted.

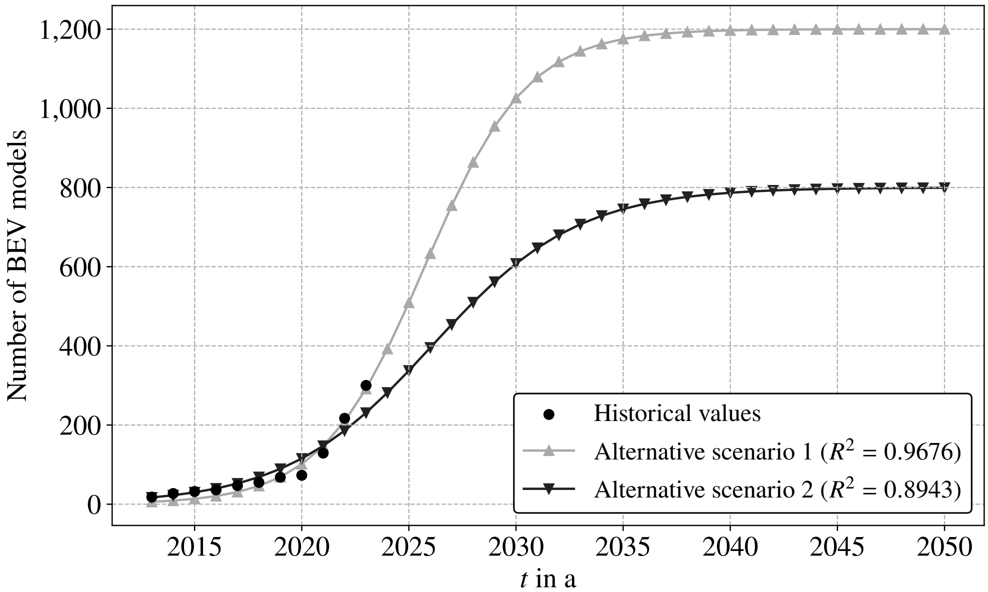


Figure 5.8: BEV models for alternative scenarios in Germany.

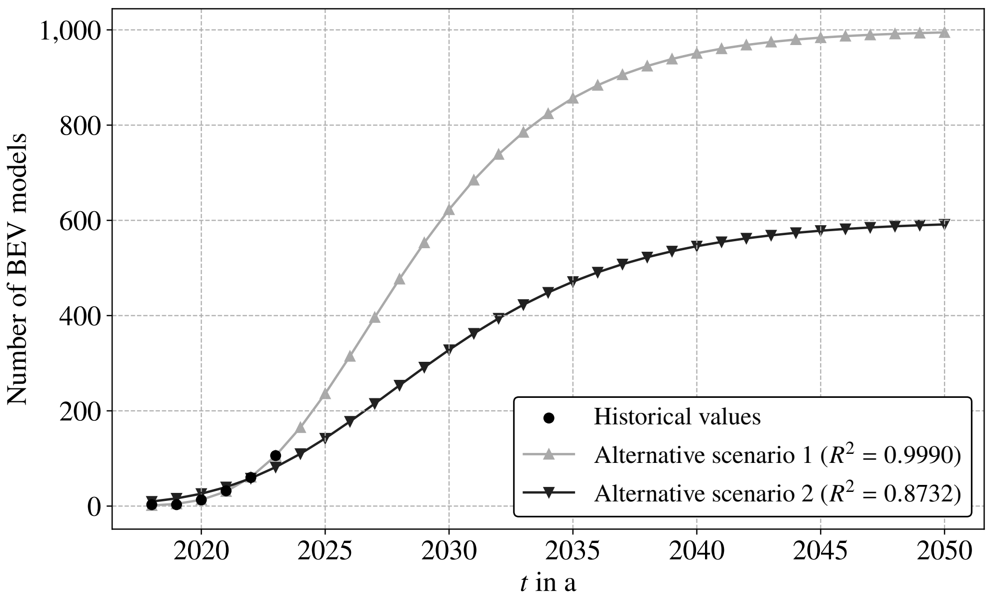


Figure 5.9: BEV models for alternative scenarios in Brazil.

Table 5.10 presents the variations in $\beta_{\mathrm{R\&D}}$ for Brazil and Germany across the two alternative scenarios. In alternative scenario 1, there is a steady increase in R&D investments, reflecting a strong focus on innovation and technological advancements. In contrast, alternative scenario 2 shows a more conservative increase in R&D, with Brazil and Germany both maintaining a constant value of 0.50 after 2025. This scenario suggests limited breakthroughs and slower technological progress.

Table 5.10: Variations in $\beta_{\mathrm{R\&D}}$ for the alternative scenarios.

Scenario	Period	Germany	Brazil
Alternative 1	2013 – 2024	0.57	0.74
	2025 – 2035	0.81	0.87
	2036 – 2050	0.90	1.00
Alternative 2	2013 – 2024	0.57	0.74
	2025 – 2035	0.50	0.50
	2036 – 2050	0.50	0.50

In terms of public charging infrastructure development, alternative scenario 1 assumes that by 2035, the normalization value of 15 BEVs/CSP will be reached in both Germany and Brazil. This reflects an accelerated effort to expand the charging network in line with the growing adoption of BEVs. In contrast, alternative scenario 2 keeps the PCI variable unchanged for Brazil (5 BEVs/CSP), while in Germany, a reduction to 5 BEVs/CSP is assumed by 2035, with this value remaining constant until the end of the simulation. This scenario implies a slower expansion of the public charging infrastructure.

The variable BEV mechanic workshops follows different coefficients for each scenario in both Brazil and Germany. Table 5.11 presents the proposed coefficients for each country across the scenarios. The variation in the coefficients of this logistic function represents different trajectories for market maturation.

Table 5.11: BEV mechanic workshop parameters for alternative scenarios in Germany and Brazil.

Country	Scenario	κ	t_ι
Germany	Alternative 1	0.35	2030
	Alternative 2	0.11	2045
Brazil	Alternative 1	0.45	2030
	Alternative 2	0.15	2050

In the political aspect, in alternative scenario 1 for both Germany and Brazil, there is an intensification of policies supporting electric mobility, with a focus on legislation, financing, and tax incentives aimed at promoting the adoption of BEVs. Tables 5.12 and 5.13 present these variations for Germany and Brazil, respectively.

The changes in the political landscape, have significant impacts on the economic aspect of the NPV calculation. The intensified support through legislation, financing options, and tax incentives for BEVs contributes to a more favorable economic environment for BEV adoption. These changes affect several variables in the model, such as the reduction in the initial purchasing cost of BEVs, the decrease in the IPVA in Brazil, and the extension of grants and subsidies in both countries. The specific variations to calculate the NPV are summarized in Table 5.14. The results of the NPV calculation are shown in figures 5.10 and 5.11 for Germany and Brazil, respectively.

The results for the NPV calculation in the alternative scenario 1 show that the improved policies lead to a more positive NPV for BEVs and BEVs with green chargers, making them a more competitive option than ICEV. The support provided by financial incentives, reductions in operational costs, and technological advancements contribute to the economic viability of BEVs in this scenario. Meanwhile, the NPV for ICEV continues to deteriorate over time due to rising fuel costs and taxes, further highlighting the benefits of adopting BEVs. In Germany, the improved policies in the alternative scenario 1 further enhance the attractiveness of BEVs. In Brazil, while in the reference scenario the NPV of BEVs is projected to surpass ICEV around 2036, in the alternative scenario 1, this crossover is expected to occur earlier, by the mid-2020s, reflecting the positive impact of the accelerated policy measures.

In the alternative scenario 2, both Brazil and Germany experience reduced support for BEV adoption, with fewer financial incentives and a general lack of movement from both governments and manufacturers to promote BEVs. In this more conservative scenario, lower levels of government-backed incentives are considered, including reduced or absent subsidies, limited access to low-interest loans, and fewer tax breaks for consumers. Additionally, there is minimal involvement from the manufacturing industry in providing financial support or encouraging the adoption of BEVs. The tables 5.15 and 5.16 summarize the key variations in the factors of the political aspect under alternative scenario 2 for Brazil and Germany, respectively.

Table 5.12: Political aspects in alternative scenario 1 for Germany.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2023: 0.20	2050: 0.20
	Public charging infrastructure investment	2023: 0.20	2050: 0.20
	Grid integration and smart charging regulations	2023: 0.00	2050: 0.20
	Clean energy targets and renewable energy mandates	2023: 0.20	2050: 0.20
	BEV supply chain support	2023: 0.00	2050: 0.20
Financing	Grants for BEV	2026 to 2035:0.40	2050:0.20
	Solar power funding program for BEV	2026: 0.20	2050: 0.20
	Low-interest loans	2023: 0.15	2050: 0.35
Tax Incentives	Annual BEV car tax	2035: 0.30	2050: 0.30
	Grid connection and tariff incentives (V2G)	2023: 0.00	2050: 0.20
	VAT to purchase a BEV	2026: 0.15	2050: 0.00
	Tax reduction on renewable source installation	2035: 0.20	2050: 0.15

Table 5.13: Political aspects in alternative scenario 1 for Brazil.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2024: 0.10	2050: 0.20
	Public charging infrastructure investment	2023: 0.05	2050: 0.20
	Grid integration and smart charging regulations	2023: 0.00	2050: 0.15
	Clean energy targets and renewable energy mandates	2024: 0.15	2050: 0.20
	BEV supply chain support	2023: 0.00	2050: 0.15
Financing	Grants for BEV	2026: 0.40	2050: 0.40
	Solar power funding program for BEV	2026: 0.10	2050: 0.15
	Low-interest loans	2023: 0.05	2050: 0.35
Tax Incentives	Annual BEV car tax (IPVA)	2026: 0.30	2050: 0.30
	Grid connection and tariff incentives (V2G)	2023: 0.00	2050: 0.20
	IPI to purchase a BEV	2026: 0.10	2050: 0.10
	Tax reduction on renewable source installation	2024: 0.15	2050: 0.20

Table 5.14: Parameter variations for NPV calculation in alternative scenario 1 for Germany and Brazil.

Parameter	Germany	Brazil
Grant/Subsidy	€ 6,750 for BEV (2026 to 2035) € 3,375 (from 2036 to 2050)	11.5 % of BEV price (2026 to 2050)
BEV price	35 % reduction of 2023 price (2024 to 2030) 40 % reduction of 2023 price (2031 to 2050)	35 % reduction of 2023 price (2024 to 2035) 40 % reduction of 2023 price (2036 to 2050)
ICEV price	15.5 % increment on 2023 price (2024 to 2035)	15 % increment on 2023 price (2024 to 2030) 17 % increment on 2023 price (2031 to 2050)
Wallbox price	50 % price reduction (2024 to 2050)	41 % price reduction (2024 to 2050)
VAT / IPI	9.50 % – 19 % (2026 to 2050)	0 % – 7 % (2026 to 2050)
Car tax / IPVA	Exemption (until 2050)	IPVA exemption (2026 to 2050)
Carbon tax on ICEV	5 % linear increment (2026 to 2050)	5 % linear increment (2026 to 2050)
Fossil fuel tax	7 % linear increment (2026 to 2050)	7 % linear increment (2026 to 2050)
Green charger price	Reduce linearly to 270 €/kW by 2050	80 % reduction of 2023 price by 2050

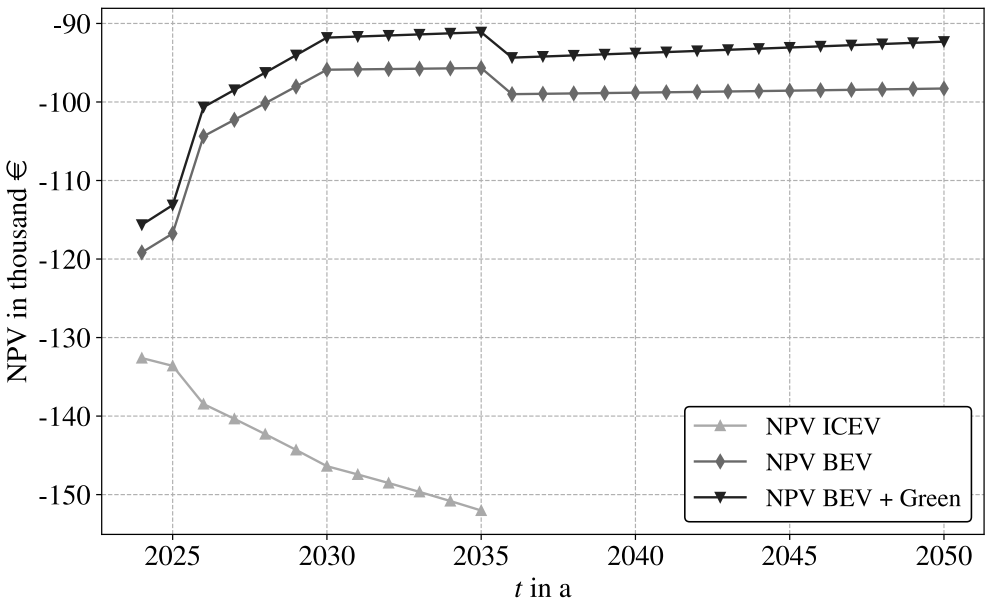


Figure 5.10: NPV result for the alternative scenario 1 in Germany.

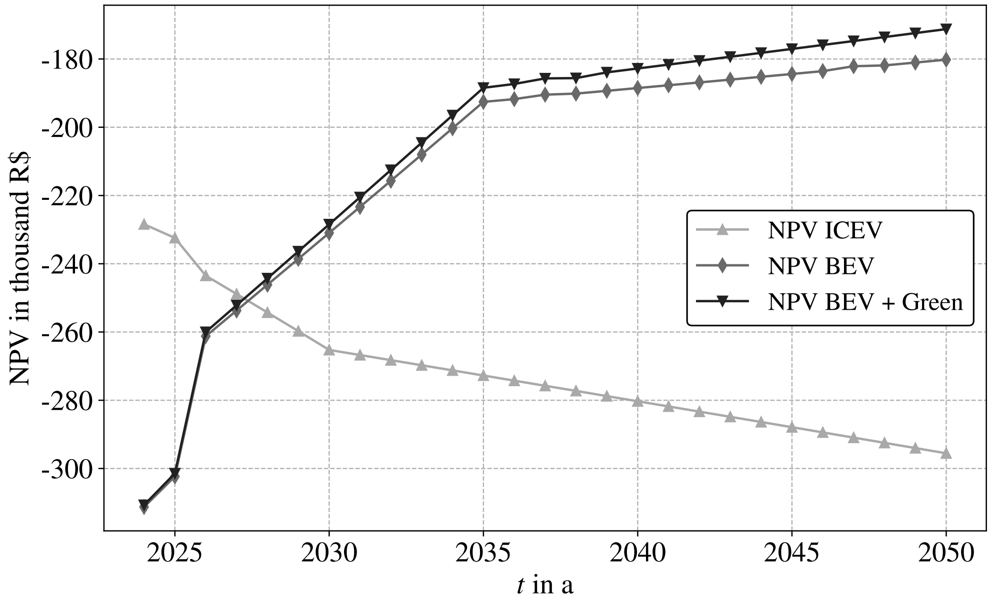


Figure 5.11: NPV result for the alternative scenario 1 in Brazil.

Table 5.15: Political aspects in alternative scenario 2 for Germany.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2026: 0.20	2050: 0.05
	Public charging infrastructure investment	2024-2025: 0.20	2026-2050: 0.00
	Grid integration and smart charging regulations	2024: 0.00	2050: 0.05
	Clean energy targets and renewable energy mandates	2026: 0.20	2050: 0.05
	BEV supply chain support	2024: 0.00	2050: 0.05
Financing	Grants for BEV	2026:0.00	2050:0.00
	Solar power funding program for BEV	2026: 0.00	2050: 0.00
	Low-interest loans	2024-2025: 0.15	2026-2050: 0.00
Tax Incentives	Annual BEV car tax	2024-2025: 0.30	2026-2050: 0.00
	Grid connection and tariff incentives (V2G)	2026: 0.00	2050: 0.10
	VAT to purchase a BEV	2024: 0.00	2050: 0.00
	Tax reduction on renewable source installation	2026: 0.20	2050: 0.10

Table 5.16: Political aspects in alternative scenario 2 for Brazil.

Variable	Parameter	Year: Weight	Year: Weight
Legislation	Mandates for vehicle emissions standards	2026: 0.10	2050: 0.10
	Public charging infrastructure investment	2025: 0.05	2050: 0.00
	Grid integration and smart charging regulations	2024: 0.00	2050: 0.00
	Clean energy targets and renewable energy mandates	2026: 0.15	2050: 0.15
	BEV supply chain support	2024: 0.00	2050: 0.00
Financing	Grants for BEV	2025: 0.00	2050: 0.00
	Solar power funding program for BEV	2024: 0.05	2050: 0.05
	Low-interest loans	2024: 0.00	2050: 0.10
Tax Incentives	Annual BEV car tax (IPVA)	2026: 0.17	2050: 0.15
	Grid connection and tariff incentives (V2G)	2023: 0.00	2050: 0.10
	IPI to purchase a BEV	2024: 0.10	2050: 0.00
	Tax reduction on renewable source installation	2024: 0.15	2050: 0.10

For alternative scenario 2, a 25 % reduction in BEV prices is applied between 2024 and 2050, with the first 20 % decrease occurring by 2030 [213]. On the other hand, ICEV prices are considered to rise by 7 % until 2050, with an initial 5 % increase taking place by 2030 [203]. Additionally, the car tax, set at € 62 in the reference scenario [214], is expected to double and be applied from 2026 to 2050. For green chargers, the price range provided by [215] with the cost of PV systems in Germany assumed to reach 360 €/kW in alternative scenario 2. In Brazil, the percentage price variation suggested by [216] is considered for solar BEV charging. Table 5.17 summarizes the other variations used to calculate the NPV, and the results of the NPV calculation are shown in figures 5.12 and 5.13 for Germany and Brazil, respectively.

The NPV results for alternative scenario 2 show a clear distinction in the economic viability of BEVs compared to ICEV for both Germany and Brazil. In Germany, as illustrated in Fig. 5.12, the NPV for BEVs and BEVs with green chargers shows a modest improvement over time. However, the financial benefits are less pronounced than in alternative scenario 1. The ICEV NPV continues to decline, largely due to the rising fuel costs and taxes. The NPV for BEVs remains superior to ICEV throughout the simulation period, reinforcing that even with limited incentives, BEVs maintain an advantage over ICEV under the given conditions.

Table 5.17: Parameter variations for NPV calculation in alternative scenario 2 for Germany and Brazil.

Parameter	Germany	Brazil
Wallbox price	No variation	10 % price reduction (2024 to 2050)
VAT/IPI	19 %	0 % – 7 % (2026 to 2050)
Car tax/IPVA	€ 124 (2026 to 2050)	1.84 % – 1.5 % (2026 to 2050)
Carbon tax on ICEV	1 % fixed (2026 to 2050)	0 % – 1 % (2026 to 2050)
Fossil fuel tax	1 % – 3 % (2026 to 2050)	0 % – 3 % (2026 to 2050)
Green charger price	Reduce linearly to € 360/kW by 2050	10 % reduction of 2023 price by 2050

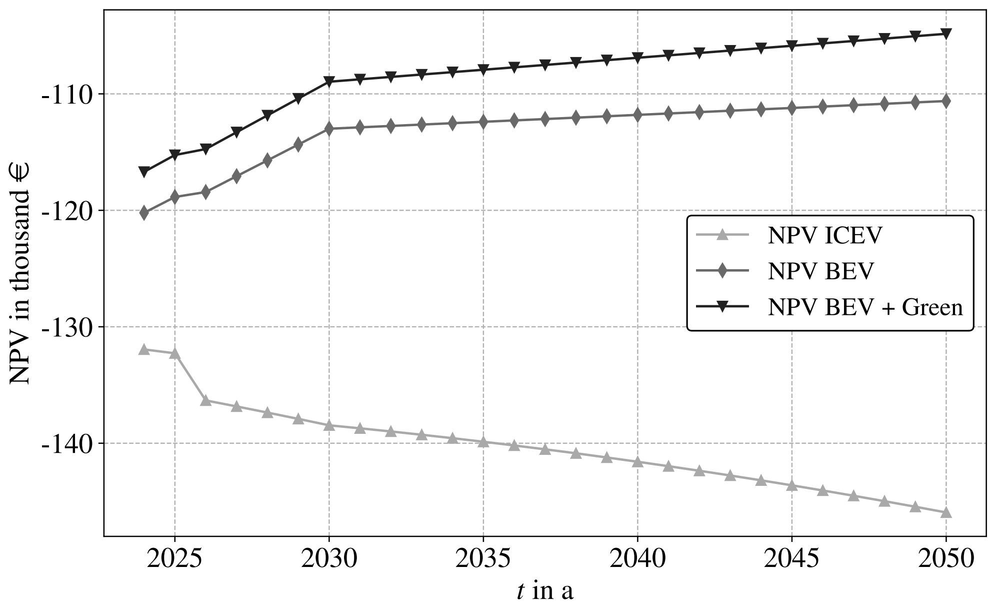


Figure 5.12: NPV result for the alternative scenario 2 in Germany.

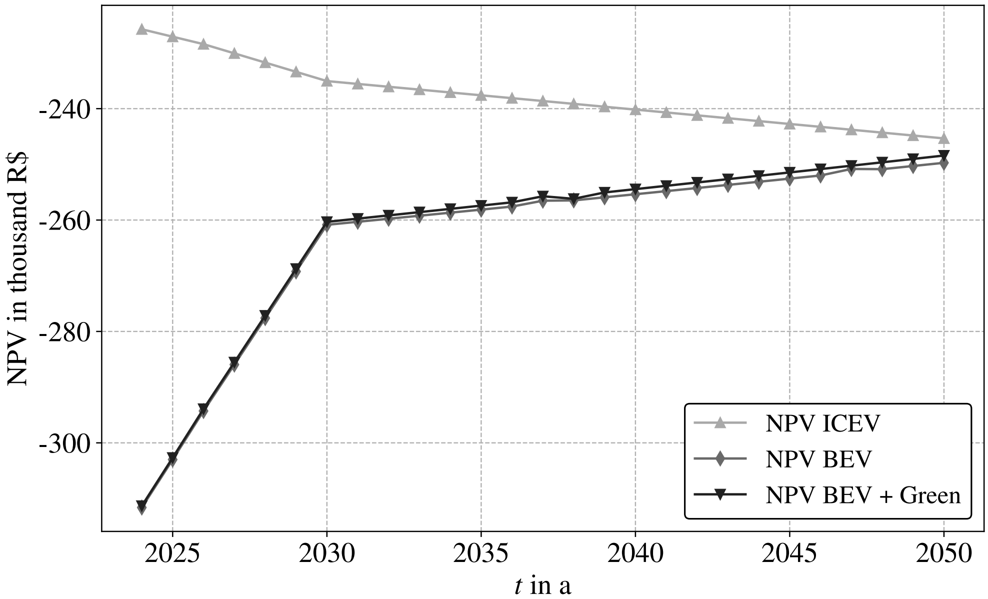


Figure 5.13: NPV result for the alternative scenario 2 in Brazil.

For Brazil, the NPV calculation in Fig. 5.13 shows a different result. The ICEV still exhibits a negative trend due to price increases and carbon taxes. However, the price reductions applied to BEVs in this scenario are not sufficient to make them a more competitive option than ICEV. The NPV for BEVs, even with a green charger, does not surpass the ICEV by 2050, reflecting the more conservative nature of the policy measures and the higher operational and acquisition costs for BEVs in Brazil. As a result, BEVs do not emerge as the most economically viable option in the long term under this scenario.

The population in each region (Brazil and Germany) is assumed to remain constant across all future scenarios. For Brazil, the number of PV system installations is projected using a second-degree polynomial regression, with different parameter values compared to the reference scenario, as detailed in Table 5.18 and illustrated in Fig. 5.14.

Table 5.18: Coefficients of polynomial regression for number of PV systems in alternative scenarios for Brazil.

Scenario	ξ_2	ξ_1	ϵ	R^2	$RMSE$	MAE
Alternative 1	45,927	-259,946	197,045	0.9632	146,513	130,627
Alternative 2	13,220	59,071	-255,818	0.8190	324,900	275,923

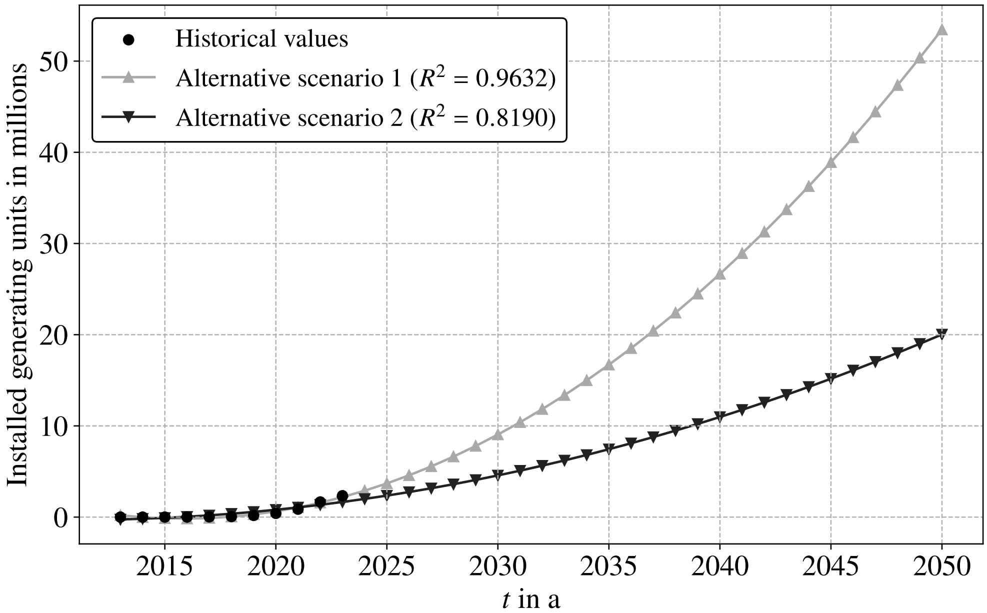


Figure 5.14: Projection of the expansion PV systems in alternative scenarios for Brazil.

In contrast, the PV system installations for Germany are based on data from [208] under the non-acceptance and sufficiency scenarios for alternative scenarios 1 and 2, respectively. Future projections of PV installed capacity are adjusted using a scaling factor derived from [209]. Since the projections in [208] only extend to 2045, a second-degree polynomial regression is employed to extend the analysis to 2050 for alternative scenario 1, yielding an R^2 value of 0.9939, with parameters $\xi_2 = 24,433$, $\xi_1 = 130,370$, and $\epsilon = 256,926$. For alternative scenario 2, a linear regression model is applied, producing parameters $\xi_1 = 488,378$, $\epsilon = 951,462$, and an R^2 value of 0.9849. These values allow for the calculation of α_{DG} in the alternative future scenarios.

5.3 Analysis of results and discussions

The main output variables of the model include the number of adopters and the adoption rate over the years. These results are presented in Figures 5.15 and 5.16 for Germany, and in Figures 5.17 and 5.18 for Brazil, respectively. These figures illustrate the diffusion of BEVs across the scenarios presented previously. In addition to the presentation of these results, Table 5.19 summarizes the maximum market shares recorded in each scenario for both Germany and Brazil.

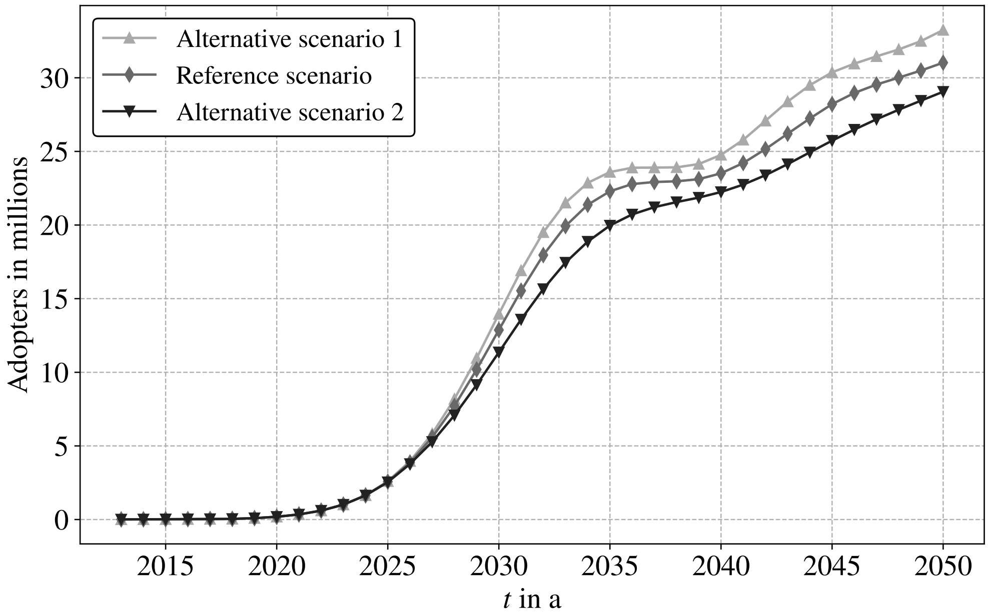


Figure 5.15: Simulation results for forecasting BEV adopters in Germany.

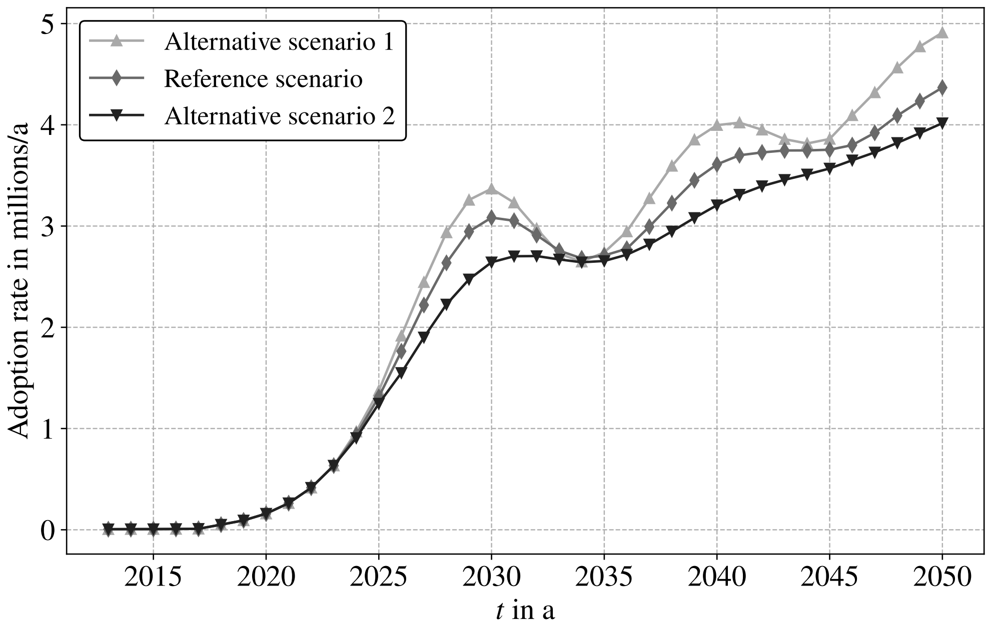


Figure 5.16: BEV adoption rate in Germany for future scenarios.

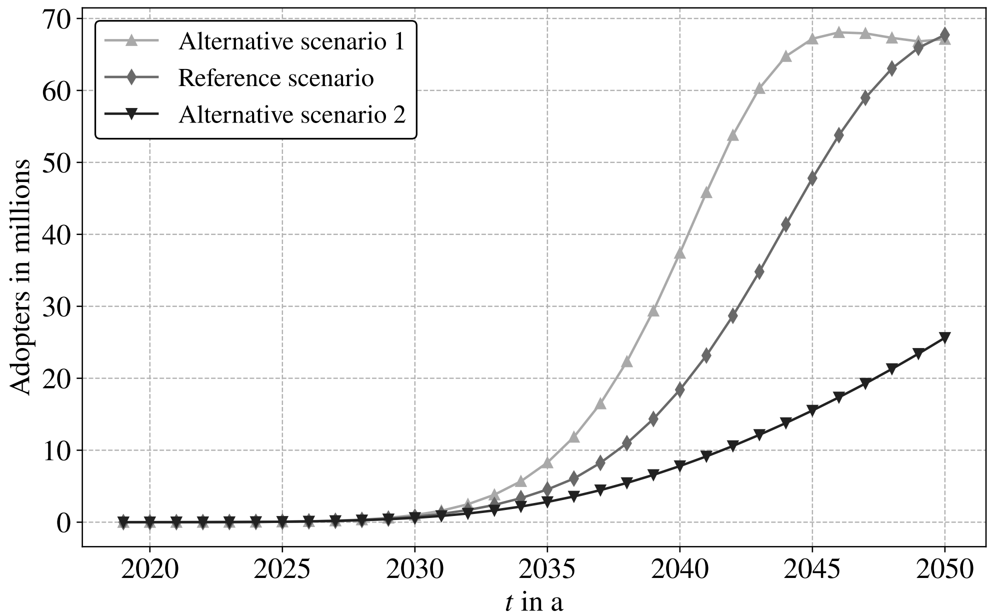


Figure 5.17: Simulation results for forecasting BEV adopters in Brazil.

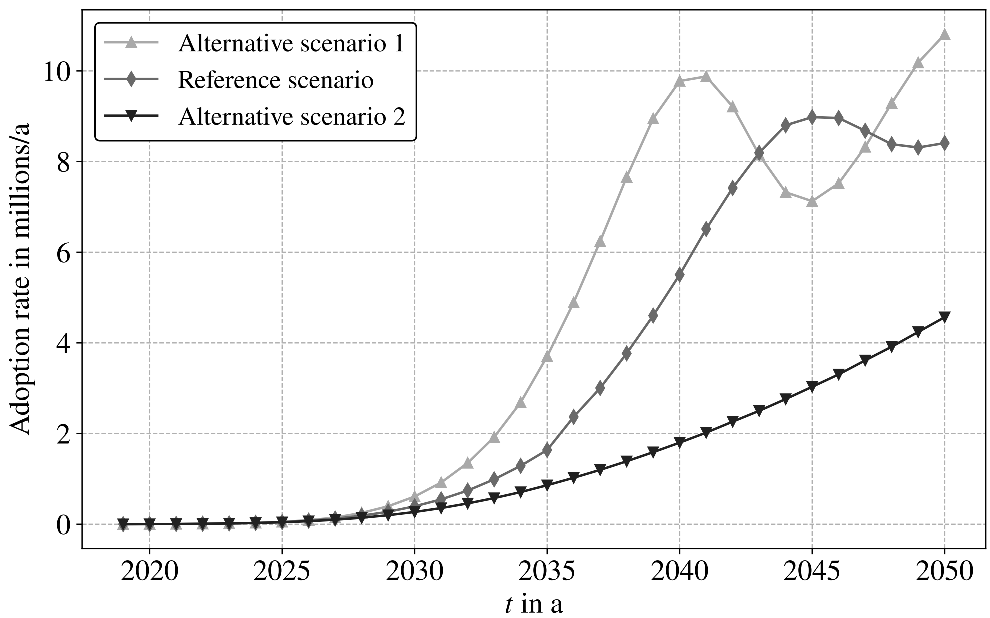


Figure 5.18: BEV adoption rate in Brazil for future scenarios.

Table 5.19: Maximum market share of BEV adopters relative to the potential market *m* in each scenario for Brazil and Germany.

Scenario	Germany	Brazil
Alternative 1	75.44 %	58.68 % (2046)
Reference	70.40 %	58.39 %
Alternative 2	65.93 %	22.10 %

For the reference scenario, where moderate policies, financial incentives, technical and infrastructural developments are gradually implemented, the results indicate sustained, though less accelerated, growth in BEV adoption in both Germany and Brazil. This scenario highlights the importance of consistent policies and improvements, but also emphasizes that, without intensifying such measures, the BEV market does not reach its full potential, especially in emerging economies like Brazil. In the case of Germany, it is expected that no more ICEVs will be sold by 2035, thus achieving a market share of 70.40 % for BEVs. In Brazil, the projection is 58.39 %, considering that the simulations of this work focus on the diffusion of BEVs, as they are ZEVs and have more positive environmental impact.

Thus, the ultimate goal, as discussed in the introduction, is to achieve the complete electrification of transport modes, which justifies the focus on BEVs. However, it should be noted that the market may vary depending on other technological or economic scenarios, e.g. reduction in acquisition costs with FCEV, which would impact the market share of BEV and other technologies. In this sense, if necessary, the proposed model can be adapted to include these analyses.

In alternative scenario 1, where more aggressive incentive policies, robust subsidies and faster technological and infrastructural advancements are introduced, an acceleration in BEV adoption is observed. In Germany, market share reaches 75.44 % by 2050. This significant fraction of the potential market can be attributed to the higher-weighted factors determined through AHP analysis. For Germany, infrastructural (30.5 %) and technical aspects (29.4 %) carry the most weight in influencing the adoption of BEVs, as seen in Table 4.2. These factors are particularly crucial in ensuring a robust and accessible charging network, along with improvements in charging times and vehicle travel capacity, as well as ensuring reliable post-sale services, as modeled in this study, significantly enhance the overall attractiveness of BEVs for German consumers.

In Brazil, the impact of alternative scenario 1 is also evident, with BEV market share reaching 58.68 % by 2046. While this represents only a slight increase over the reference scenario, it highlights that, even with more aggressive policies, the market tends to achieve this maximum due to socioeconomic factors. Unlike in Germany, where the market continues to grow steadily, Brazilian adopters reach a high point by 2046. This is likely due to the country's economic challenges. Additionally, while the alternative scenario 1 introduces important incentives, such as subsidies and cost reductions, these measures are not enough to overcome the broader economic constraints of the country. Even as technology advances and infrastructure improves, the BEV market suffers a slight reduction in the number of adopters, unlike Germany, where continuous development in infrastructure and economic factors allows for ongoing growth. Thus, while the aggressive policies in alternative scenario 1 do stimulate adoption, their observed effects differ between developed and emerging markets, as observed in the results.

Additionally, a notable characteristic in both countries is the behavior of the adoption rate over time, which is higher in alternative scenario 1, especially after 2030 for Germany. Additionally, the effect of the replacement rate in the system is also worth noting. This delay, representing the lifetime of BEVs, causes the BEV adoption rate variation to be influenced by the return of consumers to the potential adopter pool after the lifespan of BEVs, causing fluctuations in the adoption curves in both countries. The slowdown in the adoption rate shows that many of the consumers most likely to adopt have already done so. The lifespan of the BEV also influences these oscillations, since after reaching this period, early adopters of BEVs could be replacing their vehicles, which drives adoption again. Furthermore, the changes made to the variables considering incentives and reductions also have an impact on the adoption rate, leading to further oscillations.

Alternative scenario 2 presents a significant contrast to the other two scenarios. Here, support policies are limited, and there is an absence of strong incentives from both the government and private companies. Subsidies are reduced, and tax incentives are less generous, resulting in a much slower diffusion of BEVs. In Germany, with a market share of 65.93 %, the market still achieves good penetration, but this is clearly a slower growth trajectory, especially when compared to alternative scenario 1. The more gradual development can be attributed to the existing infrastructure and and favorable NPV for BEVs, in addition to the high taxation of ICEVs.

In Brazil, alternative scenario 2 presents an even more challenging outlook. BEV market share reaches only 22.10 %, reflecting the country's extreme dependence on incentive policies to promote the adoption of BEVs. The lack of adequate infrastructure, combined with the absence of other policies and advancements, causes the BEV market to grow very slowly, with a limited number of consumers willing to adopt the new technology. Furthermore, as seen before, the NPV of this scenario continues to be more attractive to ICEVs, demonstrating the importance of the financial aspect in the diffusion of BEVs in Brazil.

5.4 Scenario comparisons

Comparing the three scenarios, it can be noted that alternative scenario 1 provides the best outcomes in terms of BEV adoption in both Germany and Brazil, with faster adoption rates and higher market penetration. In the reference scenario, an intermediate future diffusion of BEVs is observed, which, although positive, could be accelerated with additional policies. Meanwhile, alternative scenario 2 demonstrates the slowly impact of limited support policies and small developments in technical and infrastructural aspects, with adoption slowing considerably, especially in Brazil. Thus, the absence of incentives in alternative scenario 2 makes these consumers more inclined to postpone their acquisition of a BEV, while in alternative scenario 1, the transition is accelerated by favorable conditions.

The simulations and analyses carried out in this study provide a projection of potential BEV market share developments in both Brazil and Germany. However, these results should be interpreted with caution due to the inherent uncertainties associated with modeling variables and scenarios. The assumptions made throughout this work may deviate from future realities. While various simulations were conducted to explore the impacts of different variable changes, the outcomes remain subject to the limitations and uncertainties of this type of study.

Despite these considerations, the comparative analyses remain valid within the simulated scenarios, offering insight into the influence of key factors on BEV diffusion. By simulating variations in blocks of different aspects—such as economic, technological, and political factors—it becomes clear that price reductions, technological advancements, infrastructure development, and favorable political environments significantly enhance the market potential for BEVs. Consequently, the visibility of BEVs within society grows, further stimulating adoption. Additionally, it is important to note that many other scenarios could be explored. The global model proposed in this study allows for future investigations to focus on specific analyses, further contributing to the understanding of BEV diffusion dynamics.

6 Conclusions and Future Work

Transition processes bring about significant changes in society, which substantially alter the course of technological adoption over time. When it comes to the diffusion of new technologies, particularly BEVs, it is not only important to understand how this substitution occurs, but also to simulate how such innovations are being integrated into the market and what their impacts are on society, especially regarding economic, environmental, and technical aspects.

In this context, although electric mobility offers promising solutions to reduce greenhouse gas emissions and advance the decarbonization of the transport sector, widespread adoption of BEVs still requires substantial study and investment. BEVs function as an additional load on the electric grid, meaning the system must ensure that the energy supplied to charge these vehicles comes from renewable sources. Therefore, understanding how this diffusion will happen over time is crucial for energy planning and to guarantee sustainable power generation. Additionally, in the context of V2G technologies, BEVs have the potential to offer ancillary services to the power grid, further integrating the transportation and energy sectors.

Thus, this work deals with the development of a global model for analyzing the diffusion process of BEVs among residential consumers in both Brazil and Germany over time. In addition, this research assesses the market adoption of BEVs, providing insights into how the electric sector can prepare for and support this transition. Accurate modeling of BEV adoption is crucial for ensuring that these vehicles contribute positively to the stability and reliability of the electrical system.

The analyses are conducted using SD technique, combined with the Bass model. This approach accounted for main variables in the economic, technical, political, social, market and infrastructural aspects, as well as innovation and imitation coefficients from the Bass model, which influence consumer decision-making processes. To further refine the model and handle both qualitative and quantitative variables, the AHP and fuzzy logic are used, allowing for the calculation of specific parameters and weighting of the various aspects considered.

The simulation results indicate that the proposed model adequately captures the diffusion dynamics in both Brazil and Germany. However, each country presents distinct characteristics regarding market maturity, political incentives, and technological development. This highlights the versatility of the model in adapting to different market conditions, providing a comprehensive analysis of the factors influencing BEV adoption in each scenario. Thus, the model allows for scenario generation to explore future adoption patterns under diverse conditions.

The studies conducted in this thesis used block variations of the aspects and variables considered to evaluate the impact of different changes on the adoption rates of BEVs. These analyses clearly reveal the influence of more aggressive policies, reductions in acquisition costs, improvements in charging infrastructure, and technological advancements, including increased range and reduced charging times, on the diffusion of BEVs. However, these findings should be interpreted with caution due to the inherent uncertainties associated with modeling assumptions and scenario development. Although several simulations were conducted to account for these variations, additional studies could provide further refinements.

In general, the analysis of the adoption growth curves for each scenario studied shows that they follow the reference model proposed by Everett Rogers, especially in the reference and alternative scenario 1, with a growth in S, due to the greater number of incentives. The fact that the curve continues to grow and oscillate is due to the linear increase in the potential market and the oscillations caused by the incentives simulated over the years, as well as the effects of replacement rates.

Finally, this thesis aims to contribute to the development of public policies that promote the electrification of transportation and incentives for BEVs adoption. It also provides valuable insights for electricity distributors in their planning for distribution system expansion and for automotive companies to guide their sales strategies and innovative business models. In this sense, the variables studied and the proposed scenarios serve as a robust tool for future studies on the dissemination and consolidation of BEVs in society and their integration into the power sector.

Thus, the main scientific contribution of this work lies in proposing a representative model to forecast the adoption of BEVs among residential consumers. The advantage of this model is its ability to comprehensively analyze the influence of a broad set of variables, including economic, technical, social, political, and infrastructural aspects, within a single system dynamics framework. Moreover, the developed model allows for a deeper understanding of how these variables impact the prediction of BEV penetration over time, providing robust insights for governments, power system operators, and other stakeholders in formulating public policies and planning within the energy sector, considering the diffusion trends and their implications for power systems.

6.1 Future work

Although this thesis has provided significant insights into the diffusion of BEVs and their potential impacts on the electric power sector, there are several areas that could benefit from further investigation.

While the current work focuses on the temporal aspect of BEV diffusion, future studies could examine the spatial diffusion of BEVs, particularly identifying which regions within Brazil and Germany are likely to see higher rates of adoption. Such studies could use GIS or other spatial analysis techniques to determine where BEVs penetration might be more concentrated, considering factors like population density, infrastructure development, and regional policies.

The development of a comprehensive platform for tracking data on BEV penetration, battery capacity, renewable energy progress, public charging infrastructure, etc. in each country would be beneficial. Such a platform would aggregate critical information for both academic and industrial studies of BEV diffusion, offering real-time, transparent access to the key variables driving the electric mobility transition to parameterize the model.

Additionally, future work could delve deeper into analyzing the impact of improvements in public transport infrastructure or car sharing on car ownership, and consequently, on BEV diffusion. For instance, the number of new driver's license registrations in Germany and Brazil shows a linear growth, but changes in public transportation could significantly alter the potential market for BEVs. Exploring such scenarios could help better understand how urban transport policies impact BEV adoption.

Deeper exploration of the integration between BEVs and the electric grid is crucial, particularly with respect to V2G technology. Future research could simulate the potential of BEVs to not only draw power from the grid but also to return it during peak demand periods, providing ancillary services to the electric grid and enhancing grid stability.

Incorporating the results of this thesis into algorithms to assess the impact of increased BEV penetration on electric power systems could also be explored. This could assist electric system operators in planning mitigation strategies to accommodate BEVs as a load, while also studying the flexibility of the growing BEV fleet to provide ancillary services.

The model already presents satisfactory results, according to simulations carried out. Furthermore, modeling specific regional impacts can also be an important alternative. Studying how the diffusion of BEVs can vary in different regions and which strategies can be adopted to meet the specific local needs of different stakeholders.

Additionally, regarding the development of electric charging stations on highways, fast charging times can be explored.

Lastly, while this thesis has explored the role of PV system adoption as a driver for BEV diffusion, future studies could investigate more closely the integration of BEVs with renewable energy systems, particularly in smart grid contexts. Exploring how BEVs could optimize energy usage and minimize costs in conjunction with PV systems, wind energy, and other renewables could provide further insights intoBEV diffusion and its challenges and opportunities in the power system.

References

[1] B. Borba, “Cenários para acelerar a penetração de veículos elétricos leves no Brasil Big Push para a Mobilidade Sustentável,” in *Documentos de Projetos (LC/TS.2020/50; LC/BRS/TS.2020/2), Santiago, Comissão Econômica para a América Latina e o Caribe (CEPAL)*, 2020.

[2] International Transport Forum - ITF, *ITF Transport Outlook 2023*. ITF Transport Outlook, OECD, May 2023.

[3] International Transport Forum - ITF, *ITF Transport Outlook 2021*. ITF Transport Outlook, OECD, May 2021.

[4] International Energy Agency - IEA, “Global EV Outlook 2021 - Accelerating ambitions despite the pandemic.” [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2021, Accessed on: 02/25/2022, 2021.

[5] M. Ehsani, K. V. Singh, H. O. Bansal, and R. T. Mehrjardi, “State of the Art and Trends in Electric and Hybrid Electric Vehicles,” *Proceedings of the IEEE*, vol. 109, pp. 967–984, Jun. 2021.

[6] I. Husain, B. Ozpineci, M. S. Islam, E. Gurpinar, G.-J. Su, W. Yu, S. Chowdhury, L. Xue, D. Rahman, and R. Sahu, “Electric Drive Technology Trends, Challenges, and Opportunities for Future Electric Vehicles,” *Proceedings of the IEEE*, vol. 109, pp. 1039–1059, Jun. 2021.

[7] International Energy Agency - IEA, “Global EV Outlook 2024 - Moving towards increased affordability.” [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2024, Accessed on: 05/07/2024, 2024.

[8] M. A. Sayed, R. Atallah, C. Assi, and M. Debbabi, “Electric vehicle attack impact on power grid operation,” *International Journal of Electrical Power & Energy Systems*, vol. 137, p. 107784, May 2022.

[9] M. R. Khalid, M. S. Alam, A. Sarwar, and M. Jamil Asghar, “A Comprehensive review on electric vehicles charging infrastructures and their impacts on power-quality of the utility grid,” *eTransportation*, vol. 1, p. 100006, Aug. 2019.

[10] C. Dharmakeerthi, N. Mithulananthan, and T. Saha, “Impact of electric vehicle fast charging on power system voltage stability,” *International Journal of Electrical Power & Energy Systems*, vol. 57, pp. 241–249, May 2014.

[11] S. Deb, A. K. Goswami, P. Harsh, J. P. Sahoo, R. L. Chetri, R. Roy, and A. S. Shekhawat, "Charging Coordination of Plug-In Electric Vehicle for Congestion Management in Distribution System Integrated with Renewable Energy Sources," *IEEE Transactions on Industry Applications*, vol. 56, pp. 5452–5462, Sep. 2020.

[12] T. Nogueira, J. Magano, E. Sousa, and G. R. Alves, "The Impacts of Battery Electric Vehicles on the Power Grid: A Monte Carlo Method Approach," *Energies*, vol. 14, p. 8102, Dec. 2021.

[13] N. K. Neto and L. Piotrowski, "Methodology for Analysis of the Impact of Residential Charging of Electric Vehicles," *IEEE Latin America Transactions*, vol. 17, pp. 953–961, Jun. 2019.

[14] J. Hildermeier, J. Burger, A. Jahn, and J. Rosenow, "A Review of Tariffs and Services for Smart Charging of Electric Vehicles in Europe," *Energies*, vol. 16, p. 88, Dec. 2022.

[15] M. Helferich, J. Tröger, A. Stephan, S. Preuß, S. Pelka, J. Stute, and P. Plötz, "Tariff option preferences for smart and bidirectional charging: Evidence from battery electric vehicle users in Germany," *Energy Policy*, vol. 192, p. 114240, Sep. 2024.

[16] S. Deb, K. Tammi, K. Kalita, and P. Mahanta, "Impact of electric vehicle charging station load on distribution network," *Energies*, vol. 11, p. 178, Jan. 2018.

[17] S. Hussain, M. A. Ahmed, K. B. Lee, and Y. C. Kim, "Fuzzy Logic Weight Based Charging Scheme for Optimal Distribution of Charging Power among Electric Vehicles in a Parking Lot," *Energies 2020, Vol. 13, Page 3119*, vol. 13, p. 3119, Jun. 2020.

[18] A. Palomino and M. Parvania, "Data-driven risk analysis of joint electric vehicle and solar operation in distribution networks," *IEEE Open Access Journal of Power and Energy*, vol. 7, no. 1, pp. 141–150, 2020.

[19] A. Dubey and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations," *IEEE Access*, vol. 3, pp. 1871–1893, 2015.

[20] J. H. Angelim and C. d. M. Affonso, "Probabilistic assessment of voltage quality on solar-powered electric vehicle charging station," *Electric Power Systems Research*, vol. 189, p. 106655, Dec. 2020.

[21] M. N. B. Arias, *Integração de veículos elétricos no planejamento da expansão dos sistemas de distribuição*. PhD thesis, Tese (Doutorado em Engenharia Elétrica) -

Universidade Estadual Paulista, Ilha Solteira, 2019.

[22] N. Banol Arias, S. Hashemi, P. B. Andersen, C. Traeholt, and R. Romero, "Distribution System Services Provided by Electric Vehicles: Recent Status, Challenges, and Future Prospects," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, pp. 4277–4296, Dec. 2019.

[23] O. Sadeghian, A. Oshnoei, B. Mohammadi-ivatloo, V. Vahidinasab, and A. Anvari-Moghaddam, "A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges," *Journal of Energy Storage*, vol. 54, p. 105241, Oct. 2022.

[24] Y. Wu, Z. Wang, Y. Huangfu, A. Ravey, D. Chrenko, and F. Gao, "Hierarchical Operation of Electric Vehicle Charging Station in Smart Grid Integration Applications — An Overview," *International Journal of Electrical Power & Energy Systems*, vol. 139, p. 108005, Jul. 2022.

[25] W. Yang, H. Zhou, J. Liu, S. Dai, Z. Ma, and Y. Liu, "Market evolution modeling for electric vehicles based on system dynamics and multi-agents," in *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, pp. 133–138, IEEE, Sep. 2015.

[26] Y. Xiang, H. Zhou, W. Yang, J. Liu, Y. Niu, and J. Guo, "Scale Evolution of Electric Vehicles: A System Dynamics Approach," *IEEE Access*, vol. 5, pp. 8859–8868, 2017.

[27] R. J. Javid and A. Nejat, "A comprehensive model of regional electric vehicle adoption and penetration," *Transport Policy*, vol. 54, pp. 30–42, Feb. 2017.

[28] A. E. Cenci, G. Bordin, R. P. Homrich, and L. T. Loureiro, "Estimation of Electric Vehicles in Dynamic Environment," *2019 IEEE PES Conference on Innovative Smart Grid Technologies, ISGT Latin America 2019*, Sep. 2019.

[29] J. L. Rodrigues, H. M. Bolognesi, J. D. Melo, F. Heymann, and F. Soares, "Spatiotemporal model for estimating electric vehicles adopters," *Energy*, vol. 183, pp. 788–802, Sep. 2019.

[30] A. Ensslen, C. Will, and P. Jochem, "Simulating Electric Vehicle Diffusion and Charging Activities in France and Germany," *World Electric Vehicle Journal*, vol. 10, p. 73, Nov. 2019.

[31] Z. Zhou, Y. Cai, S. Su, X. Tang, and Y. Cao, "Electric vehicles scale evolution model considering social attributes," *IEEE Access*, vol. 8, pp. 168784–168792,

2020.

[32] E. S. Lonan and R. Ardi, “Electric Vehicle Diffusion in the Indonesian Automobile Market: A System Dynamics Modelling,” in *2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, vol. 2020-Decem, pp. 43–47, IEEE, Dec. 2020.

[33] Y. Hu, Z. Wang, and X. Li, “Impact of policies on electric vehicle diffusion: An evolutionary game of small world network analysis,” *Journal of Cleaner Production*, vol. 265, p. 121703, Aug. 2020.

[34] H. Sun, Y. Wan, and H. Lv, “System Dynamics Model for the Evolutionary Behaviour of Government Enterprises and Consumers in China’s New Energy Vehicle Market,” *Sustainability*, vol. 12, p. 1578, Feb. 2020.

[35] L. Bitencourt, T. Abud, R. Santos, and B. Borba, “Bass Diffusion Model Adaptation Considering Public Policies to Improve Electric Vehicle Sales—A Brazilian Case Study,” *Energies*, vol. 14, p. 5435, Sep. 2021.

[36] T. Buchmann, P. Wolf, and S. Fidaschek, “Stimulating E-Mobility Diffusion in Germany (EMOSIM): An Agent-Based Simulation Approach,” *Energies 2021, Vol. 14, Page 656*, vol. 14, p. 656, Jan. 2021.

[37] A. S. Ebrie and Y. J. Kim, “Investigating Market Diffusion of Electric Vehicles with Experimental Design of Agent-Based Modeling Simulation,” *Systems*, vol. 10, p. 28, Mar. 2022.

[38] J. Li, V. Nian, and J. Jiao, “Diffusion and benefits evaluation of electric vehicles under policy interventions based on a multiagent system dynamics model,” *Applied Energy*, vol. 309, p. 118430, Mar. 2022.

[39] X. Zhao, Y. Ma, S. Shao, and T. Ma, “What determines consumers’ acceptance of electric vehicles: A survey in Shanghai, China,” *Energy Economics*, vol. 108, p. 105805, Apr. 2022.

[40] R. R. Kumar, P. Guha, and A. Chakraborty, “Comparative assessment and selection of electric vehicle diffusion models: A global outlook,” *Energy*, vol. 238, p. 121932, Jan. 2022.

[41] C. Grangeia, L. Santos, D. V. Ferreira, R. Guimarães, L. de Magalhães Ozorio, and A. Tavares, “Energy transition scenarios in the transportation sector in Brazil: Contributions from the electrical mobility,” *Energy Policy*, vol. 174, p. 113434, Mar. 2023.

[42] T. L. Cao Van, L. Barthelmes, T. Gnann, D. Speth, and M. Kagerbauer, "Enhancing electric vehicle market diffusion modeling: A German case study on environmental policy integration," *Energy Strategy Reviews*, vol. 50, p. 101244, Nov. 2023.

[43] R. F. de Assis, F. M. Guerrini, L. A. Santa-Eulalia, and W. de Paula Ferreira, "An agent-based model for regional market penetration of electric vehicles in Brazil," *Journal of Cleaner Production*, vol. 421, p. 138477, Oct. 2023.

[44] L. Bitencourt, B. Dias, T. Soares, B. Borba, J. Quirós-Tortós, and V. Costa, "Understanding Business Models for the Adoption of Electric Vehicles and Charging Stations: Challenges and Opportunities in Brazil," *IEEE Access*, vol. 11, pp. 63149–63166, 2023.

[45] C. Domarchi and E. Cherchi, "Electric vehicle forecasts: a review of models and methods including diffusion and substitution effects," *Transport Reviews*, vol. 43, pp. 1118–1143, Nov. 2023.

[46] F. Heymann, F. vom Scheidt, F. J. Soares, P. Duenas, and V. Miranda, "Forecasting Energy Technology Diffusion in Space and Time: Model Design, Parameter Choice and Calibration," *IEEE Transactions on Sustainable Energy*, vol. 12, pp. 802–809, Apr. 2021.

[47] M. d. S. Ortiz, P. H. Eisenkraemer, D. P. Bernardon, and M. Wolter, "Methodology for Projection of the Diffusion of Electric Vehicles in Residential Consumers ," in *24. Dresdener Kreis*, pp. 25–30, 2023.

[48] J. D. Sterman, *Business dynamics: Systems thinking and modeling for a complex world*. Boston: McGraw-Hill, 2000.

[49] L. dos Santos, L. Canha, and D. Bernardon, "Projection of the diffusion of photovoltaic systems in residential low voltage consumers," *Renewable Energy*, vol. 116, pp. 384–401, Feb. 2018.

[50] D. Neumann, L. A. d. Santa-Eulalia, R. T. Yoshino, and J. Klasen, "Um novo modelo de previsão de demanda para inovações radicais," *Production*, vol. 24, pp. 605–617, Sep. 2013.

[51] L. L. C. dos Santos, *Projeção da difusão de sistemas fotovoltaicos em consumidores residenciais de baixa tensão*. PhD thesis, Tese (Doutorado em Engenharia Elétrica) - Universidade Federal de Santa Maria, Santa Maria, 2018.

[52] Z. Ding, W. Gong, S. Li, and Z. Wu, "System Dynamics versus Agent-Based Modeling: A Review of Complexity Simulation in Construction Waste Management,"

Sustainability 2018, Vol. 10, Page 2484, vol. 10, p. 2484, Jul. 2018.

[53] M. R. Saavedra M., C. H. de O. Fontes, and F. G. M. Freires, “Sustainable and renewable energy supply chain: A system dynamics overview,” *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 247–259, Feb. 2018.

[54] S. Selvakkumaran and E. O. Ahlgren, “Review of the use of system dynamics (SD) in scrutinizing local energy transitions,” *Journal of Environmental Management*, vol. 272, p. 111053, Oct. 2020.

[55] A. Dehdarian, “Scenario-based system dynamics modeling for the cost recovery of new energy technology deployment: The case of smart metering roll-out,” *Journal of Cleaner Production*, vol. 178, pp. 791–803, Mar. 2018.

[56] C. Baumgarten, *Modelo para análise da inserção de pequenas fontes solares fotovoltaicas em sistemas de distribuição: Uma abordagem multivariável*. PhD thesis, Dissertação (Mestrado em Engenharia Elétrica) - Universidade Federal do Rio Grande do Sul, Porto Alegre, 2016.

[57] P. S. Ebert, *Modelo de dinâmica de sistemas aplicado a integração de recursos energéticos distribuídos considerando a operação em uma microrrede*. PhD thesis, Tese (Doutorado em Engenharia Elétrica) - Universidade Federal de Santa Maria, Santa Maria, 2019.

[58] A. Ford, *Modeling the environment: An introduction to system dynamics models of environmental systems*. Washington D.C.: Island Press, 1st ed., 1999.

[59] M. Schwaninger, “System dynamics in the evolution of the systems approach.,” *Encyclopedia of complexity and systems science*, vol. 9, pp. 8974–87, 2009.

[60] G. B. Schuch, *Um modelo para estudos da demanda de energia elétrica em ambiente competitivo*. PhD thesis, Tese (Doutorado em Engenharia Elétrica) - Universidade Federal de Santa Catarina, Florianópolis, 2000.

[61] E. M. Rogers, *Diffusion of Innovations*. New York: Free Press, 5th ed., 2003.

[62] P. B. Tigre, *Gestão da inovação: a economia da tecnologia do Brasil*. Rio de Janeiro: Elsevier, 7 ed., 2006.

[63] F. M. Bass, “A New Product Growth for Model Consumer Durables,” *Management Science*, vol. 15, pp. 215–227, Jan. 1969.

[64] T. Dhakal and K.-S. Min, “Macro Study of Global Electric Vehicle Expansion,” *Foresight and STI Governance*, vol. 15, pp. 67–73, Mar. 2021.

[65] V. Mahajan, E. Muller, and F. M. Bass, “New Product Diffusion Models in Marketing: A Review and Directions for Research,” *The Journal of Marketing*, vol. 54, no. 1, pp. 1–26, 1990.

[66] R. Venkatesan, T. V. Krishnan, and V. Kumar, “Evolutionary Estimation of Macro-Level Diffusion Models Using Genetic Algorithms: An Alternative to Nonlinear Least Squares,” *Marketing Science*, vol. 23, pp. 451–464, Aug. 2004.

[67] J. Massiani and A. Gohs, “The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies,” *Research in Transportation Economics*, vol. 50, pp. 17–28, Aug. 2015.

[68] V. Srinivasan and C. H. Mason, “Nonlinear Least Squares Estimation of New Product Diffusion Models,” *Marketing Science*, vol. 5, no. 2, pp. 169–178, 1986.

[69] Z.-X. Xiao, J.-W. Jia, X.-Y. Liu, H.-K. Bai, Q.-Y. Li, and Y.-P. Hua, “Medium- and Long-Term Electric Vehicle Ownership Forecasting for Urban Residents,” *World Electric Vehicle Journal*, vol. 15, p. 212, May 2024.

[70] R. M. Heeler and T. P. Hustad, “Problems in Predicting New Product Growth for Consumer Durables,” *Management Science*, vol. 26, pp. 1007–1020, Oct. 1980.

[71] L. M. M. Benvenutti, A. B. Ribeiro, and M. Uriona, “Long term diffusion dynamics of alternative fuel vehicles in Brazil,” *Journal of Cleaner Production*, vol. 164, pp. 1571–1585, Oct. 2017.

[72] R. Saaty, “The analytic hierarchy process—what it is and how it is used,” *Mathematical Modelling*, vol. 9, pp. 161–176, Jan. 1987.

[73] T. L. Saaty, “Priority setting in complex problems,” *IEEE Transactions on Engineering Management*, vol. EM-30, pp. 140–155, Aug. 1983.

[74] T. L. Saaty and L. G. Vargas, *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*, vol. 175 of *International Series in Operations Research & Management Science*. Boston, MA: Springer US, 2012.

[75] S. Moslem, M. K. Saraji, A. Mardani, A. Alkharabsheh, S. Duleba, and D. Esztergar-Kiss, “A Systematic Review of Analytic Hierarchy Process Applications to Solve Transportation Problems: From 2003 to 2022,” *IEEE Access*, vol. 11, pp. 11973–11990, 2023.

[76] T. L. Saaty, "How to make a decision: The analytic hierarchy process," *European Journal of Operational Research*, vol. 48, pp. 9–26, Sep. 1990.

[77] T. L. Saaty and L. T. Tran, "On the invalidity of fuzzifying numerical judgments in the Analytic Hierarchy Process," *Mathematical and Computer Modelling*, vol. 46, pp. 962–975, Oct. 2007.

[78] M. Brunelli, *Introduction to the Analytic Hierarchy Process*. SpringerBriefs in Operations Research, Cham: Springer International Publishing, 2015.

[79] L. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338–353, Jun. 1965.

[80] V. Profillidis and G. Botzoris, "Fuzzy Methods," in *Modeling of Transport Demand*, pp. 383–417, Elsevier, Jan. 2019.

[81] R. Kaur and A. Singh, "Fuzzy Logic: An Overview of Different Application Areas," *Advances and Applications in Mathematical Sciences*, vol. 18, pp. 677–689, Jun. 2019.

[82] W. Zeng, Y. Zhao, and Q. Yin, "Sugeno fuzzy inference algorithm and its application in epicentral intensity prediction," *Applied Mathematical Modelling*, vol. 40, pp. 6501–6508, Jul. 2016.

[83] M. Şen, M. Özcan, and Y. R. Eker, "Fuzzy Logic-Based Energy Management System for Regenerative Braking of Electric Vehicles with Hybrid Energy Storage System," *Applied Sciences*, vol. 14, p. 3077, Apr. 2024.

[84] W. Zhang, "A new defuzzification method and ranking method for type-2 fuzzy numbers," *Information Sciences*, vol. 682, p. 121275, Nov. 2024.

[85] M. A. A. Viegas and C. T. da Costa, "Fuzzy Logic Controllers for Charging/Discharging Management of Battery Electric Vehicles in a Smart Grid," *Journal of Control, Automation and Electrical Systems*, vol. 32, pp. 1214–1227, Oct. 2021.

[86] H. Maghfiroh, O. Wahyunggoro, and A. I. Cahyadi, "Energy Management in Hybrid Electric and Hybrid Energy Storage System Vehicles: A Fuzzy Logic Controller Review," *IEEE Access*, vol. 12, pp. 56097–56109, Apr. 2024.

[87] G. C. Lazaroiu and M. Roscia, "Fuzzy Logic Strategy for Priority Control of Electric Vehicle Charging," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, pp. 19236–19245, Oct. 2022.

[88] W. Morocho-Chicaiza, A. Barragán-Escandón, E. Zalamea-León, D. Ochoa-Correa, J. Terrados-Cepeda, and X. Serrano-Guerrero, "Identifying locations

for electric vehicle charging stations in urban areas through the application of multicriteria techniques," *Energy Reports*, vol. 12, pp. 1794–1809, Aug. 2024.

[89] International Energy Agency - IEA, "Global EV Outlook 2023: Catching up with climate ambitions." [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2023, Accessed on: 07/20/2023, 2023.

[90] B. Rathore, V. Kumar, R. Gupta, P. Verma, S. Bag, and K. P. Tagarakis, "Demystifying the barriers for electric vehicle acceptance: Multiple stakeholders' perspective," *Research in Transportation Business & Management*, vol. 53, p. 101090, Mar. 2024.

[91] M. A. Schvartz, A. Lange Salvia, L. Londero Brandli, W. Leal Filho, and L. Veiga Avila, "The Electric Vehicle Market in Brazil: A Systematic Literature Review of Factors Influencing Purchase Decisions," *Sustainability*, vol. 16, p. 4594, May 2024.

[92] T. Munshi, S. Dhar, and J. Painuly, "Understanding barriers to electric vehicle adoption for personal mobility: A case study of middle income in-service residents in Hyderabad city, India," *Energy Policy*, vol. 167, p. 112956, Aug. 2022.

[93] R. Chhikara, R. Garg, S. Chhabra, U. Karnatak, and G. Agrawal, "Factors affecting adoption of electric vehicles in India: An exploratory study," *Transportation Research Part D: Transport and Environment*, vol. 100, p. 103084, Nov. 2021.

[94] E. Figenbaum, "An Empirical Study of the Policy Processes behind Norway's BEV-Olution," *World Electric Vehicle Journal*, vol. 15, p. 37, Jan. 2024.

[95] D. P. Bernardon, M. Sperandio, V. J. Garcia, L. N. Canha, A. D. R. Abaide, and E. F. B. Daza, "AHP decision-making algorithm to allocate remotely controlled switches in distribution networks," *IEEE Transactions on Power Delivery*, vol. 26, pp. 1884–1892, Jul. 2011.

[96] B. Feng, Q. Ye, and B. J. Collins, "A dynamic model of electric vehicle adoption: The role of social commerce in new transportation," *Information & Management*, vol. 56, pp. 196–212, Mar. 2019.

[97] A. Pamidimukkala, S. Kermanshachi, J. M. Rosenberger, and G. Hladik, "Evaluation of barriers to electric vehicle adoption: A study of technological, environmental, financial, and infrastructure factors," *Transportation Research Interdisciplinary Perspectives*, vol. 22, p. 100962, Nov. 2023.

[98] B. Lebrouhi, Y. Khattari, B. Lamrani, M. Maaroufi, Y. Zeraouli, and T. Kousksou, “Key challenges for a large-scale development of battery electric vehicles: A comprehensive review,” *Journal of Energy Storage*, vol. 44, p. 103273, Dec. 2021.

[99] M. Adhikari, L. P. Ghimire, Y. Kim, P. Aryal, and S. B. Khadka, “Identification and Analysis of Barriers against Electric Vehicle Use,” *Sustainability*, vol. 12, p. 4850, Jun. 2020.

[100] G. Z. d. Rubens, L. Noel, J. Kester, and B. K. Sovacool, “The market case for electric mobility: Investigating electric vehicle business models for mass adoption,” *Energy*, vol. 194, p. 116841, Mar. 2020.

[101] A. C. Ruoso and J. L. D. Ribeiro, “An assessment of barriers and solutions for the deployment of electric vehicles in the Brazilian market,” *Transport Policy*, vol. 127, pp. 218–229, Oct. 2022.

[102] International Energy Agency - IEA, “World Energy Outlook 2021.” [Online]. Available: www.iea.org/weo, Accessed on: 06/10/2024, 2021.

[103] H. E. Hafdaoui and A. Khallaayoun, “Mathematical Modeling of Social Assessment for Alternative Fuel Vehicles,” *IEEE Access*, vol. 11, pp. 59108–59132, 2023.

[104] G. Chen and Z. Zhang, “Control Strategies, Economic Benefits, and Challenges of Vehicle-to-Grid Applications: Recent Trends Research,” *World Electric Vehicle Journal*, vol. 15, p. 190, Apr. 2024.

[105] United Nations Development Programme - UNDP, “Human Development Report 2023-24.” [Online]. Available: https://hdr.undp.org/content/human-development-report-2023-24, Accessed on: 06/10/2024, 2024.

[106] Kraftfahrt-Bundesamt - KBA, “Fahrerlaubnisbestand im Zentralen Fahrerlaubnisregister.” [Online]. Available: https://www.kba.de/DE/Statistik/Kraftfahrer/Fahrerlaubnisse/Fahrerlaubnisbestand/fahrerlaubnisbestand_node.html;jsessionid=56DEE3FC7FDFDA58C0911B1A2A73FE9B.live11294?yearFilter=2023, Accessed on: 08/12/2024, 2023.

[107] ADAC e.V., “Elektroauto-Batterie: Lebensdauer, Garantie, Reparatur.” [Online]. Available: https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/laden/elektroauto-batterie/, Accessed on: 08/07/2024, 2022.

[108] International Energy Agency - IEA, “Global EV Outlook 2022: Securing supplies for an electric future.” [Online]. Available: https://www.iea.org/reports/global-ev-

outlook-2022, Accessed on: 02/20/2023, 2022.

[109] X. Liu, F. Zhao, J. Geng, H. Hao, and Z. Liu, “Comprehensive assessment for different ranges of battery electric vehicles: Is it necessary to develop an ultra-long range battery electric vehicle?,” *iScience*, vol. 26, p. 106654, Jun. 2023.

[110] European Transport and Energy Research Centre, “Trends in the Global Vehicle Fleet 2023: Managing the SUV Shift and the EV Transition.” [Online]. Available: https://www.globalfueleconomy.org/media/792523/gfei-trends-in-the-global-vehicle-fleet-2023-spreads.pdf, Accessed on: 08/12/2024, Nov. 2023.

[111] EV Database, “Useable battery capacity of full electric vehicles cheatsheet.” [Online]. Available: https://ev-database.org/cheatsheet/useable-battery-capacity-electric-car, Accessed on: 08/12/2024, 2024.

[112] M. N. Tasnim, S. Akter, M. Shahjalal, T. Shams, P. Davari, and A. Iqbal, “A critical review of the effect of light duty electric vehicle charging on the power grid,” *Energy Reports*, vol. 10, pp. 4126–4147, Nov. 2023.

[113] M. S. Mastoi, S. Zhuang, H. M. Munir, M. Haris, M. Hassan, M. Usman, S. S. H. Bukhari, and J.-S. Ro, “An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends,” *Energy Reports*, vol. 8, pp. 11504–11529, Nov. 2022.

[114] Landesagentur für neue Mobilitätslösungen und Automotive Baden-Württemberg, “Transformation der Automobil-und Nutzfahrzeugindustrie in Baden-Württemberg durch Elektrifizierung, Digitalisierung und Automatisierung.” [Online]. Available: https://verkehrsforschung.dlr.de/public/documents/2023/e-mobil_BW_Strukturstudie_BW_2023.pdf, Accessed on: 08/12/2024, 2023.

[115] Statista, “Elektromobilität - Anzahl der Fahrzeugmodelle in Deutschland bis 2022.” [Online]. Available: https://de.statista.com/statistik/daten/studie/1076875/umfrage/anzahl-der-modelle-an-elektrofahrzeugen-in-deutschland/, Accessed on: 08/12/2024, 2022.

[116] EV Database, “Neue und bald verfügbare E-Autos für 2024 und 2025.” [Online]. Available: https://ev-database.org/de/vergleich/neue-bald-erhaeltliche-elektroauto#sort:path~type~order=.id~number~desc|rs-price:prev~next=10000~100000|rs-range:prev~next=0~1000|rs-fastcharge:prev~next=0~1500|rs-acceleration:prev~next=2~23|rs-topspeed:prev~next=110~350|rs-battery:prev~next=10~200|rs-towweight:prev~next=0~2500|rs-eff:prev~next=100~300|rs-safety:prev~next=-1~5|paging:currentPage=0|paging:number=10,

Accessed on: 08/12/2024, 2024.

[117] BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., "Ausbau der öffentlich zugänglichen Ladepunkte." [Online]. Available: https://www.bdew.de/media/documents/PI_20171024_Anlage_Grafiken-Erhebung-Ladeinfrastruktur.pdf, Accessed on: 08/12/2024, 2017.

[118] Statista, "Anzahl der öffentlichen ladepunkte in deutschland von januar 2017 bis märz 2024." [Online]. Available: https://de.statista.com/statistik/daten/studie/1190896/umfrage/ladesaeulen-in-deutschland/, Accessed on: 08/12/2024, 2024.

[119] Kraftfahrt-Bundesamt - KBA, "Der Fahrzeugbestand im Überblick." [Online]. Available: https://www.kba.de/DE/Statistik/Fahrzeuge/Bestand/Jahrebilanz_Bestand/fz_b_jahresbilanz_node.html?yearFilter=2023%20(28.03.2023)%20(Excel%20file=%20No.%20of%20BEV), Accessed on: 08/12/2024, 2023.

[120] G. Harrison and C. Thiel, "An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe," *Technological Forecasting and Social Change*, vol. 114, pp. 165–178, Jan. 2017.

[121] E. Künle and C. Minke, "Macro-environmental comparative analysis of e-mobility adoption pathways in France, Germany and Norway," *Transport Policy*, vol. 124, pp. 160–174, Aug. 2022.

[122] Bundesministerium für Digitales und Verkehr, "Regulatory landscape for electric mobility Key strategies, acts, and statutory instruments." [Online]. Available: https://www.now-gmbh.de/wp-content/uploads/2022/09/Regulatory-landscape-for-electric-mobility.pdf, Accessed on: 08/12/2024, 2022.

[123] Bundesminiterium für Wirtschaft und Klimaschutz - BMWK, "Regulatory environment and incentives for using electric vehicles and developing a charging infrastructure." [Online]. Available: https://www.bmwk.de/Redaktion/EN/Artikel/Industry/regulatory-environment-and-incentives-for-using-electric-vehicles.html, Accessed on: 03/07/2024, 2024.

[124] C. Böhringer, F. Landis, and M. A. T. Reaños, "Economic impacts of renewable energy promotion in germany," *The Energy Journal*, vol. 38, pp. 189–209, 2017.

[125] European Council, "EUCO 169/14." [Online]. Available: https://data.consilium.europa.eu/doc/document/ST-169-2014-INIT/en/pdf, Accessed on: 08/12/2024, 2014.

[126] Bundesministerium für Verkehr und digitale Infrastruktur, "Bekanntmachung: Förderrichtlinie Ladeinfrastruktur für Elektrofahrzeuge in Deutschland." [Online]. Available: https://www.bundesanzeiger.de/pub/publication/4aI9atiwTiPchGbnKa0/content/4aI9atiwTiPchGbnKa0/BAnz%20AT%2015.02.2017%20B4.pdf?inline, Accessed on: 08/12/2024, Feb. 2017.

[127] Rat der Europäischen Union, "„Fit für 55" – Der EU-Plan für den grünen Wandel - Consilium." [Online]. Available: https://www.consilium.europa.eu/de/policies/green-deal/fit-for-55/, Accessed on: 04/18/2024, 2024.

[128] Bundesministerium für Wirtschaft und Energie, "Bekanntmachung: Förderung von stationären und dezentralen Batteriespeichersystemen zur Nutzung in Verbindung mit Photovoltaikanlagen." [Online]. Available: https://www.bundesanzeiger.de/pub/publication/gzg77aamFZqPuY9O2LM/content/gzg77aamFZqPuY9O2LM/BAnz%20AT%2029.02.2016%20B1.pdf?inline, Accessed on: 08/12/2024, Feb. 2016.

[129] H. Wirth, "Recent Facts about Photovoltaic in Germany." [Online]. Available: https://www.ise.fraunhofer.de/en/publications/studies/recentfacts-about-pv-in-germany.html, Accessed on: 08/12/2024, 2024.

[130] Bundesministerium für Wirtschaft und Energie, "Bekanntmachung: Richtlinie zur Förderung des Absatzes von elektrisch betriebenen Fahrzeugen (Umweltbonus)." [Online]. Available: https://www.bundesanzeiger.de/pub/publication/uac5zLC7s9z2ctgOMA3/content/uac5zLC7s9z2ctgOMA3/BAnz%20AT%2001.07.2016%20B1.pdf?inline, Accessed on: 08/12/2024, Jun. 2016.

[131] Bundesministerium für Wirtschaft und Energie, "Bekanntmachung: Richtlinie zur Förderung des Absatzes von elektrisch betriebenen Fahrzeugen (Umweltbonus)." [Online]. Available: https://www.bundesanzeiger.de/pub/publication/Ofji6LqnwwhUMGo0TGA/content/Ofji6LqnwwhUMGo0TGA/BAnz%20AT%2005.06.2019%20B1.pdf?inline, Accessed on: 08/12/2024, May 2019.

[132] Bundesministerium für Wirtschaft und Energie, "Bekanntmachung: der Richtlinie zur Förderung des Absatzes von elektrisch betriebenen Fahrzeugen (Umweltbonus)." [Online]. Available: https://www.bundesanzeiger.de/pub/publication/iea6RMvfSkVO348LK4c/content/iea6RMvfSkVO348LK4c/BAnz%20AT%2007.07.2020%20B2.pdf?inline, Accessed on: 08/12/2024, Jun. 2020.

[133] ADAC e.V., "Umweltbonus: Plötzliches Aus für die Förderung von E-Autos." [Online]. Available: https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/

elektroauto/foerderung-elektroautos/, Accessed on: 08/12/2024, Jan. 2024.

[134] Bundesamt für Justiz, "EEG 2023 - Gesetz für den Ausbau erneuerbarer Energien." [Online]. Available: https://www.gesetze-im-internet.de/eeg_2014/BJNR106610014.html, Accessed on: 08/12/2024, 2014.

[135] Bundesgesetzblatt BGBl. Online-Archiv 1949 - 2022 | Bundesanzeiger Verlag, "Gesetz zur Änderung des Versicherungsteuergesetzes und des Kraftfahrzeugsteuergesetzes (Verkehrsteueränderungsgesetz – VerkehrStÄndG)." [Online]. Available: https://www.bgbl.de/xaver/bgbl/start.xav?startbk=Bundesanzeiger_BGBl&start=//*%255B@attr_id=%27bgbl112s2431.pdf%27%255D#__bgbl__%2F%2F*%5B%40attr_id%3D%27bgbl112s2431.pdf%27%5D__1724072887143, Accessed on: 08/12/2024, 2012.

[136] International Energy Agency - IEA, "Policy database – Data & Statistics - Germany." [Online]. Available: https://www.iea.org/policies?country%5B0%5D=Germany&page=3, Accessed on: 03/07/2024, 2024.

[137] Deutsche Bundesbank, "Effektivzinssätze Banken DE / Neugeschäft / Konsumentenkredite an private Haushalte, anfängliche Zinsbindung über 1 bis 5 Jahre." [Online]. Available: https://www.bundesbank.de/de/statistiken/geld-und-kapitalmaerkte/zinssaetze-und-renditen/konsumentenkredite-an-private-haushalte-ratenkredite-615046, Accessed on: 08/07/2024, 2024.

[138] ADAC e.V., "Autokosten 2013," Apr. 2013.

[139] ADAC e.V., "Autokosten 2014," Apr. 2014.

[140] ADAC e.V., "Autokosten 2015," May 2015.

[141] ADAC e.V., "Autokosten 2016," Apr. 2016.

[142] ADAC e.V., "Autokosten 2017," Nov. 2017.

[143] ADAC e.V., "Autokosten Herbst/Winter 2018/2019," Oct. 2018.

[144] ADAC e.V., "Autokosten 2019," Oct. 2019.

[145] ADAC e.V., "Autokosten Frühjahr/Sommer 2020," Apr. 2020.

[146] ADAC e.V., "Autokosten Herbst/Winter 2021/22," Oct. 2021.

[147] ADAC e.V., "Autokosten Herbst/Winter 2022/23," Oct. 2022.

[148] ADAC e.V., "Autokosten Frühjahr/Sommer 2023," Apr. 2023.

[149] C. Madina, I. Zamora, and E. Zabala, “Methodology for assessing electric vehicle charging infrastructure business models,” *Energy Policy*, vol. 89, pp. 284–293, Feb. 2016.

[150] Focus Online, “Technische Daten BMW i3.” [Online]. Available: https://www.focus.de/auto/fahrberichte/fahrbericht-bmw-i3-nie-wieder-tanken-trotzdem-vollgas-rollendes-iphone-mit-power-der-bmw-i3-im-ersten-test_id_3276293.html, Accessed on: 19/12/2023, 2013.

[151] Wohnglück, “Elektroauto zuhause laden: Alles über Ladestationen, Installation und Kosten.” [Online]. Available: https://wohnglueck.de/artikel/elektroauto-zuhause-laden-alles-ueber-ladestationen-wallbox-installation-und-kosten-597, Accessed on: 19/12/2023, 2020.

[152] Amazon, “Price history - Wallbox Pulsar Plus Electric Vehicle Charger,” Mar. 2024.

[153] P. Plötz, T. Gnann, A. Kühn, and M. Wietschel, “Markthochlaufszenarien für Elektrofahrzeuge – Langfassung.” Fraunhofer-Institut für System- und Innovationsforschung ISI, Sep. 2013.

[154] Gruenes Haus, “Preisentwicklung Photovoltaik: Preise im Überblick (2024).” [Online]. Available: https://gruenes.haus/photovoltaik-preisentwicklung/, Accessed on: 06/10/2024, 2024.

[155] P. Olczak, “Evaluation of degradation energy productivity of photovoltaic installations in long-term case study,” *Applied Energy*, vol. 343, p. 121109, Aug. 2023.

[156] Statista, “Housing situation germany from 2014 to 2018.” [Online]. Available: https://qph.cf2.quoracdn.net/main-qimg-129ba1d14782c69a079c41281e767db6, Accessed on: 08/12/2024, 2018.

[157] Statista, “Housing situation germany from 2019 to 2023.” [Online]. Available: https://www.statista.com/statistics/961085/housing-situation-population-germany/, Accessed on: 08/12/2024, 2023.

[158] Statistisches Bundesamt, “Bevölkerung nach dem Gebietsstand und Durchschnittsalter 1990 bis 2023.” [Online]. Available: https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-gebietstand.html#249750, Accessed on: 08/12/2024, 2023.

[159] Statista, "Anzahl der Photovoltaikanlagen in Deutschland in den Jahren von 2009 bis 2022." [Online]. Available: https://de.statista.com/statistik/daten/studie/1448887/umfrage/anzahl-photovoltaikanlagen-in-deutschland/, Accessed on: 08/12/2024, 2022.

[160] Ministério dos Transportes, "Registro Nacional de Condutores Habilitados 2019 - 2023." [Online]. Available: https://www.gov.br/transportes/pt-br/assuntos/transito/conteudo-Senatran/estatisticas-quantidade-de-habilitados-denatran, Accessed on: 08/12/2024, 2024.

[161] Qualidade e Tecnologia - INMETRO Instituto Nacional de Metrologia, "Veículos Automotivos (PBE veicular) 2019 - 2023." [Online]. Available: https://www.gov.br/inmetro/pt-br/assuntos/avaliacao-da-conformidade/programa-brasileiro-de-etiquetagem/tabelas-de-eficiencia-energetica/veiculos-automotivos-pbe-veicular, Accessed on: 08/12/2024, 2023.

[162] Plataforma Nacional de Mobilidade Elétrica - PNME, "3º Anuário Brasileiro da Mobilidade Elétrica." [Online]. Available: https://pnme.org.br/biblioteca/3o-anuario-brasileiro-da-mobilidade-eletrica/, Accessed on: 06/10/2024, 2023.

[163] Associação Brasileira do Veículo Elétrico - ABVE, "BEV: Evolução de Vendas no Brasil." [Online]. Available: https://abve.org.br/, Accessed on: 08/12/2024, 2024.

[164] Plataforma Nacional de Mobilidade Elétrica - PNME, "1º Anuário Brasileiro da Mobilidade Elétrica." [Online]. Available: https://pnme.org.br/biblioteca/1o-anuario-brasileiro-da-mobilidade-eletrica/, Accessed on: 06/10/2024, 2021.

[165] Plataforma Nacional de Mobilidade Elétrica - PNME, "2º Anuário Brasileiro da Mobilidade Elétrica." [Online]. Available: https://www.pnme.org.br/biblioteca/2o-anuario-brasileiro-da-mobilidade-eletrica-pnme/, Accessed on: 06/10/2024, 2022.

[166] C. B. Rosa, M. B. Francescatto, A. L. Neuenfeldt Júnior, D. P. Bernardon, and L. L. C. dos Santos, "Regulatory analysis of E-mobility for Brazil: A comparative review and outlook," *Utilities Policy*, vol. 84, p. 101638, Oct. 2023.

[167] M. F. Bento, "Process of import of hybrid and electric cars by individual," *International Journal of Regional Development*, vol. 10, p. 14, Dec. 2022.

[168] M. A. Schvartz, A. Lange Salvia, L. Londero Brandli, W. Leal Filho, and L. Veiga Avila, "The Electric Vehicle Market in Brazil: A Systematic Literature Review of Factors Influencing Purchase Decisions," *Sustainability*, vol. 16, p. 4594,

May 2024.

[169] Banco Central do Brasil, “Taxa Selic.” [Online]. Available: https://www.bcb.gov.br/controleinflacao/taxaselic, Accessed on: 06/10/2023, 2024.

[170] iCarros, “Ficha técnica: Chevrolet Onix 2019.” [Online]. Available: https://www.icarros.com.br/chevrolet/onix/2019/ficha-tecnica/28802, Accessed on: 08/10/2023, 2019.

[171] Autoo, “Chevrolet Onix 2020 Turbo 1.0 12V flex automático 4p.” [Online]. Available: https://www.autoo.com.br/chevrolet/onix/2020/turbo-10-12v-flex-automatico-4p/, Accessed on: 08/10/2023, 2020.

[172] Motor 1, “Crítica: Chevrolet Onix 1.0 Turbo Premier.” [Online]. Available: https://ar.motor1.com/reviews/479867/critica-chevrolet-onix-1-0-turbo-premier/, Accessed on: 08/10/2023, 2020.

[173] iCarros, “Ficha técnica: Fiat Argo 2021.” [Online]. Available: https://www.icarros.com.br/fiat/argo/2021/ficha-tecnica/30496, Accessed on: 09/10/2023, 2021.

[174] Garagem 360, “Hyundai HB20 2022 ganha novos itens de série em todas as versões.” [Online]. Available: https://garagem360.com.br/hyundai-hb20-2022/, Accessed on: 09/01/2024, 2024.

[175] Garagem 360, “VW Polo 2023 TSI: ficha técnica, preço e itens de série.” [Online]. Available: https://garagem360.com.br/vw-polo-tsi-2023/, Accessed on: 09/12/2023, 2023.

[176] UOL, “Teste: Renault Zoe mostra que ser elétrico é normal.” [Online]. Available: https://insideevs.uol.com.br/reviews/379177/teste-renault-zoe-eletrico/, Accessed on: 05/10/2023, 2019.

[177] W. L. d. Lima and I. C. Branquinho, “A Viabilidade de Veículos Elétricos no Brasil,” *Gestão da Cadeia de Suprimentos no Agronegócio: Desafios e Oportunidades no Contexto Atual - XII FATECLOG*, 2021.

[178] Auto Esporte, “Teste: dirigimos o JAC IEV20, o elétrico mais barato do Brasil.” [Online]. Available: https://autoesporte.globo.com/testes/noticia/2020/01/teste-dirigimos-o-jac-iev20-o-eletrico-mais-barato-do-brasil.ghtml, Accessed on: 06/10/2023, 2020.

[179] Auto Esporte, “Confira quais são os 10 carros elétricos mais baratos do Brasil.” [Online]. Available: https://autoesporte.globo.com/um-so-planeta/noticia/2021/10/confira-quais-sao-os-10-carros-eletricos-mais-baratos-do-brasil.ghtml, Accessed on: 06/10/2023, 2021.

[180] Auto Esporte, “Vídeo: Renault Kwid E-Tech é o elétrico mais barato do Brasil, que custa o dobro da versão a combustão.” [Online]. Available: https://autoesporte.globo.com/videos/noticia/2022/05/video-renault-kwid-e-tech-e-o-eletrico-mais-barato-do-brasil-que-custa-o-dobro-da-versao-a-combustao.ghtml, Accessed on: 06/10/2023, 2022.

[181] Jornal do Carro, “Renault Kwid E-Tech elétrico chega às lojas com preço de R$ 146.990.” [Online]. Available: https://jornaldocarro.estadao.com.br/carros/renault-lanca-novo-kwid-e-tech-no-brasil-pelo-preco-de-r-146-990-em-andamento/, Accessed on: 06/10/2023, 2022.

[182] Quatro Rodas, “BYD Dolphin: preços, versões e equipamentos do carro elétrico mais vendido.” [Online]. Available: https://quatrorodas.abril.com.br/carros-eletricos/byd-dolphin-precos-versoes-e-equipamentos-do-carro-eletrico-mais-vendido, Accessed on: 09/12/2023, 2023.

[183] BYD, “BYD Dolphin.” [Online]. Available: https://www.byd.com/br/car/dolphin?gad_source=1, Accessed on: 09/12/2023, 2023.

[184] Agência Nacional do Petróleo, Gás Natural e Biocombustíveis, “Série histórica do levantamento de preços.” [Online]. Available: https://www.gov.br/anp/pt-br/assuntos/precos-e-defesa-da-concorrencia/precos/precos-revenda-e-de-distribuicao-combustiveis/serie-historica-do-levantamento-de-precos, Accessed on: 08/10/2023.

[185] Agência Nacional de Energia Elétrica - ANEEL, “Tarifa residencial: Evolução por função de custo.” [Online]. Available: https://app.powerbi.com/view?r=eyJrIjoiOTY0NWQzOGItMmQ3ZS00MWUzLTllNmMtNTA5NTYxODdhYTk-zIiwidCI6IjQwZDZmOWI4LWVjYTctNDZhMi05MmQ0LWVhNGU5YzAxNzB-lMSIsImMiOjR9, Accessed on: 06/10/2023.

[186] Associação Brasileira de Planejamento Financeiro, “Seguro automotivo: faz sentido se custa quase 10% do valor do veículo?.” [Online]. Available: https://planejar.org.br/seguro-automotivo-faz-sentido-se-custa-quase-10-do-valor-do-veiculo/, Accessed on: 08/07/2023.

[187] Bright Consulting, "A desvalorização dos eletrificados." [Online]. Available: https://brightisd.com/project/a-desvalorizacao-dos-eletrificados/, Accessed on: 06/10/2024, 2024.

[188] Inside EVs, "Veja quanto custa a instalação técnica de um wallbox residencial." [Online]. Available: https://insideevs.uol.com.br/news/726956/preco-instalacao-carregador-eletrico-residencial/, Accessed on: 06/10/2023.

[189] InsideEVs, "Intelbras lança carregador para carro elétrico com preço inicial de R$ 3.200." [Online]. Available: https://insideevs.uol.com.br/news/652917/carregadores-intelbras-cvemini-cvehome/, Accessed on: 19/10/2023, 2023.

[190] Auto Esporte, "Quanto custa carregar um carro elétrico em casa?." [Online]. Available: https://autoesporte.globo.com/carros/noticia/2019/10/quanto-custa-carregar-um-carro-eletrico-em-casa.ghtml, Accessed on: 19/10/2023, 2019.

[191] InsideEVs, "Volvo lança carregador para elétricos e híbridos plug-in por R$ 6.499." [Online]. Available: https://insideevs.uol.com.br/news/444534/volvo-carregador-eletricos-hibridos-plug-in-brasil/, Accessed on: 19/10/2023, 2020.

[192] Mobility Now, "Comparativo: os principais carregadores do mercado para seu carro elétrico." [Online]. Available: https://automotivebusiness.com.br/pt/posts/mobility-now/comparativo-os-principais-carregadores-do-mercado-para-seu-carro-eletrico/, Accessed on: 19/10/2023, 2021.

[193] Auto Papo, "Confira os principais modelos de Wallbox para seu elétrico não falhar na hora H." [Online]. Available: https://autopapo.uol.com.br/noticia/wallbox-carro-eletrico/, Accessed on: 19/10/2023, 2023.

[194] J. Urbanetz, C. D. Zomer, and R. Rüther, "Compromises between form and function in grid-connected, building-integrated photovoltaics (BIPV) at low-latitude sites," *Building and Environment*, vol. 46, pp. 2107–2113, Oct. 2011.

[195] Greener, "Strategic market research - distributed generation (dg): Photovoltaic (pv) market." [Online]. Available: https://www.greener.com.br/wp-content/uploads/2021/10/Summary-Strategic-Market-Research-PV-Solar-Market-Distributed-Generation-1H-2021.pdf, Accessed on: 08/12/2024, 2021.

[196] Greener, "Strategy report - distributed generation: Solar photovoltaic market 2023 | brazil." [Online]. Available: https://www.greener.com.br/wp-content/uploads/2023/03/Strategic-Market-Report-PV-Solar-Market-Distributed-Generation-2H2022.pdf, Accessed on: 08/12/2024, 2023.

[197] Greener, “Strategic market research - distributed generation: Photovoltaic solar power market.” [Online]. Available: https://www.greener.com.br/wp-content/uploads/2024/04/Greener-Strategic-Market-Research-Distributed-Generation-2024-V1.0-1.pdf, Accessed on: 08/12/2024, Mar. 2024.

[198] Macrotrends, “Brazil Population 1950-2024.” [Online]. Available: https://www.macrotrends.net/global-metrics/countries/BRA/brazil/population, Accessed on: 08/12/2024, 2024.

[199] Instituto Brasileiro de Geografia e Estatística - IBGE, “Tabela 6820: Domicílios e Moradores, por tipo de domicílio.” [Online]. Available: https://sidra.ibge.gov.br/tabela/6820#resultado, Accessed on: 08/12/2024, 2022.

[200] Agência Nacional de Energia Elétrica - ANEEL, “Geração Distribuída 2013 - 2023.” [Online]. Available: https://app.powerbi.com/view?r=eyJrIjoiY2VmMmUwN2QtYWFiOS00ZDE3LWI3NDMtZDk0NGI4MGU2NTkxIiwidCI6IjQwZDZmOWI4LWVjYTctNDZhMi05MmQ0LWVhNGU5YzAxNzBlMSIsImMiOjR9, Accessed on: 08/12/2024, 2023.

[201] T. Grube, S. Kraus, J. Reul, and D. Stolten, “Passenger car cost development through 2050,” *Transportation Research Part D: Transport and Environment*, vol. 101, p. 103110, Dec. 2021.

[202] M. Etxandi-Santolaya, L. Canals Casals, and C. Corchero, “Estimation of electric vehicle battery capacity requirements based on synthetic cycles,” *Transportation Research Part D: Transport and Environment*, vol. 114, p. 103545, Jan. 2023.

[203] N. Lutsey and M. Nicholas, “Update on electric vehicle costs in the United States through 2030,” in *The International Council on Clean Transportation (ICCT)*, 2019.

[204] ADAC e.V., “Umweltbonus: Plötzliches Aus für die Förderung von E-Autos.” [Online]. Available: https://www.adac.de/rund-ums-fahrzeug/elektromobilitaet/elektroauto/foerderung-elektroautos/, Accessed on: 02/09/2024, 2024.

[205] U. S. Departament of Energy, “An Extensive Study on Sizing, Energy Consumption, and Cost of Advanced Vehicle Technologies.” [Online]. Available: https://publications.anl.gov/anlpubs/2018/08/145412.pdf, Accessed on: 08/10/2023, 2018.

[206] Associação Brasileira de Energia Solar Fotovoltaica - ABSOLAR, “Energia solar será 40% mais barata em 2050, aponta BNEF.” [Online]. Avail-

able: https://www.absolar.org.br/noticia/energia-solar-sera-40-mais-barata-em-2050-aponta-bnef/, Accessed on: 03/20/2023, 2021.

[207] Fraunhofer ISE, "Current and Future Cost of Photovoltaics. Long-term Scenarios for Market Development, System Prices and LCOE of Utility-Scale PV Systems." [Online]. Available: https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/AgoraEnergiewende_Current_and_Future_Cost_of_PV_Feb2015_web.pdf, Accessed on: 06/09/2023, 2015.

[208] Fraunhofer ISE, "Transformation Paths | Installed capacity of variable renewables (VRE) for electricity generation in Germany." [Online]. Available: https://www.energy-charts.info/charts/remod_installed_power/chart.htm?l=en&c=DE&legendItems=2w3&scenario=reference, Accessed on: 03/17/2024, 2021.

[209] Fraunhofer ISE, "Aktuelle Fakten zur Photovoltaik in Deutschland." [Online]. Available: https://www.ise.fraunhofer.de/de/veroeffentlichungen/studien/aktuelle-fakten-zur-photovoltaik-in-deutschland.html, Accessed on: 05/07/2024, 2024.

[210] Statistisches Bundesamt, "Bevölkerungspyramide: Altersstruktur Deutschlands von 1950 - 2070." [Online]. Available: https://service.destatis.de/bevoelkerungspyramide/#!y=2024&v=2, Accessed on: 03/18/2024, 2024.

[211] Agência Nacional de Energia Elétrica - ANEEL, "Nota Técnica n° 0056/2017-SRD/ANEEL." [Online]. Available: https://www.solarize.com.br/downloads/ANEEL_Nota_Tecnica_estimativa_GD_0056-2017-SRD-ANEEL.pdf, Accessed on: 06/04/2023, 2017.

[212] Empresa de Pesquisa Energética - EPE, "Cenário Econômico 2050." [Online]. Available: https://www.epe.gov.br/sites-pt/publicacoes-dados-abertos/publicacoes/PublicacoesArquivos/publicacao-227/topico-458/PNE2050_Premissas%20econ%C3%B4micas%20de%20longo%20prazo.pdf, Accessed on: 03/20/2024, 2015.

[213] N. Goetzel and M. Hasanuzzaman, "An empirical analysis of electric vehicle cost trends: A case study in Germany," *Research in Transportation Business & Management*, vol. 43, p. 100825, Jun. 2022.

[214] ADAC e.V., "Tesla Model 3." [Online]. Available: https://assets.adac.de/image/upload/Autodatenbank/Autotest/AT6375_tesla-model-3/tesla-model-3.pdf, Accessed on: 01/17/2024, 2023.

[215] Fraunhofer ISE, "Current and Future Cost of Photovoltaics. Long-term Scenarios for Market Development, System Prices and LCOE of Utility-Scale PV Systems." [Online]. Available: https://www.ise.fraunhofer.de/content/dam/ise/de/documents/publications/studies/AgoraEnergiewende_Current_and_Future_Cost_of_PV_Feb2015_web.pdf, Accessed on: 09/08/2023, 2015.

[216] International Renewable Energy Agency - Irena, "Future of Solar Photovoltaic: Deployment, investment, technology, grid integration and socio-economic aspects." [Online]. Available: www.irena.org/publications., Accessed on: 09/02/2024, 2019.

[217] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Computer Science*, vol. 7, pp. 1–24, Jul. 2021.

[218] R. Willink, "The role of the sample standard deviation in the analysis of measurement data," *Accreditation and Quality Assurance*, vol. 14, pp. 353–358, Jul. 2009.

A Survey

Battery Electric Vehicle (BEV) Diffusion Research

Welcome to our BEV Diffusion Research! Your insights are crucial in understanding the factors influencing residential consumers in adopting BEVs. Please take a moment (around 20 minutes) to answer the following questions. Thank you for your valuable time; we appreciate your participation!

Statement of Consent

Dear participant,

You are being invited to take part in the research "Diffusion of BEVs among residential consumers" carried out by Mauro dos Santos Ortiz, a PhD student at the Federal University of Santa (UFSM, Brazil) and the Otto-von-Guericke University (OVGU, Germany), under the guidance of Prof. Dr. Eng. Daniel Pinheiro Bernadon and Prof. Dr.-Ing. habil. Martin Wolter.

The main objective of this study is to analyze the factors that impact residential consumers' decisions to purchase a BEV. This research is part of a comprehensive binational study on the dissemination of BEVs in the context of electric mobility and the energy transition. The use of this instrument aims to determine the technical, legal, organizational, and market barriers encountered in the BEV adoption scenario, providing a comprehensive view of the issue and drawing up perspectives for the future.

Your participation is voluntary, i.e., it is not compulsory, and you have full autonomy to decide whether or not to participate, as well as to withdraw your participation at any time. You will not be penalized in any way if you decide not to consent to your participation or withdraw from it. However, it is very important for the research to be carried out.

The confidentiality and privacy of the information you provide will be guaranteed.

Any data that could identify you will be omitted from the research, and the material will be stored in the Drive of the researchers associated with the UFSM and OVGU institutions. At the end of five years, the data will be permanently deleted.

At any time during the research or afterwards, you can ask the researcher for information about your participation and/or the research, which can be done through the means of contact explained in this Agreement. Your participation will consist of answering questions in the form of a questionnaire using Microsoft Forms. The answers will be recorded in digital files and will only be used by the researchers. It will take approximately twenty minutes to answer the questionnaire.

The indirect benefit related to your collaboration in this research is to gain knowledge regarding the study of the diffusion of BEVs as an innovation. The risks are minimal, only those related to the time taken for the interview. The results will be published in the form of a scientific article and a presentation to the doctoral thesis evaluation board.

As the Consent Term is in electronic format, your answers in this form will be saved upon clicking on the option "I accept the terms set out in the CONSENT TERM for participation in this research".

If you have any doubts about the ethical conduct of the study, please contact the researchers.

Researchers contact information:

- Mauro dos Santos Ortiz - mauro.dossantosortiz@ovgu.de - Phone: +49 391 67-51071.

- Pedro Henrique Eisenkraemer - peisenkr@ttu.edu - Phone: +1 806 224 4298.

- Prof. Dr. Eng. Daniel Pinheiro Bernardon - dpbernardon@ufsm.br - Phone: +55 55 3220-8877.

- Prof. Dr.-Ing. habil. Martin Wolter - martin.wolter@ovgu.de - Phone: +49 391 67-57012.

1. Do you consent with the terms and conditions of this research?

○ I ACCEPT the terms set out in the CONSENT TERM for participation in this research.

○ I DO NOT accept the terms set out in the CONSENT TERM for participation in this research.

Personal information

2. Current country of residency

○ Brazil

○ Germany

○ United States of America

○ Other: ____________________

3. Highest degree already achieved
- ◯ High school
- ◯ Undergraduate
- ◯ Masters
- ◯ Ph.D.
- ◯ Post-doctorate

4. Current occupation

____

5. Work experience
- ◯ Less than 1 year
- ◯ 1 to 2 years of experience
- ◯ 2 to 5 years of experience
- ◯ 5 to 10 years of experience
- ◯ 10+ years of experience

6. Field of expertise
- ◯ Behavioral sciences
- ◯ Business
- ◯ Computer sciences
- ◯ Economy
- ◯ Engineering
- ◯ Other: ______________________________

A.1 Aspects weight evaluation through the analytic hierarchy process

Dear evaluator, AHP is a decision-making method that helps break down complex problems into a hierarchy of criteria and alternatives through the assignment of weight factors, allowing for a systematic and structured evaluation. The main characteristic of the method is the decomposition of the problem into hierarchical levels, in which comparative judgments of the criteria are made in pairs.

In this initial phase of our analysis, we will focus on global aspects that play a significant role in the decision of residential consumers to purchase a BEV in their region. Please refer to the following list of variables during your assessment:

1 - **Economic viability:** This variable interferes with potential adopters' intention to purchase a BEV. This aspect reflects consumers' critical consideration of the economic costs and benefits associated with purchasing a BEV.

2 - **Infrastructure:** This variable is another point of analysis, seeking to understand the extent to which the development of infrastructure related to BEVs influences the consumer's decision to acquire one.

3 - **Public policies:** We would like you to consider the weight of this component in consumer decision-making, considering how government policies can impact the adoption of BEVs.

4 - **Technological development:** This variable assess the extent to which the improvement and development of innovative technologies for BEVs can influence the decision of potential adopters.

In the following stages of this questionnaire, these general aspects will be explored in greater depth, by means of more specific variables.

Consider the following table for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

Table A.1: Numerical scale for the AHP method

Numerical scale	**Importance level**
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values

7. How important are **public policies** in relation to **economical variables** for the diffusion of BEVs?

- ◯ Public policies are more important.
- ◯ Economical variables are more important.
- ◯ They have equal importance.

8. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

9. How important are **public policies** in relation to **infrastructure** for the diffusion of BEVs?

- ◯ Public policies are more important.
- ◯ Infrastructure is more important.
- ◯ They have equal importance.

10. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

11. How important are **public policies** in relation to **technical viability** for the diffusion of BEVs?

- ◯ Public policies are more important.
- ◯ Technical viability is more important.
- ◯ They have equal importance.

12. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

13. How important are **economic variables** in relation to **infrastructure** for the diffusion of BEVs?

◯ Economic variables are more important.
◯ Infrastructure is more important.
◯ They have equal importance.

14. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

15. How important are **economic variables** in relation to **technical viability** for the diffusion of BEVs?

◯ Economic variables are more important.
◯ Technical viability is more important.
◯ They have equal importance.

16. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

17. How important is **infrastructure** in relation to **technical viability** for the diffusion of BEVs?

◯ Infrastructure is more important.
◯ Technical viability is more important.
◯ They have equal importance.

18. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

AHP - Technical development

Dear evaluator, in this stage of the evaluation of the diffusion of BEVs, we take a comprehensive look at some variables related to technological development that influence the decision of residential consumers to purchase a BEV in their region. Please refer to the following list of variables during your assessment:

1 - **Average BEV recharging time:** Refers to the period needed to charge the BEVs battery to 100 %, enabling a trip to be made.

2 - **Distance range:** Refers to the travel capacity, indicating how many kilometers the BEV can travel on a full charge before needing to be recharged.

3 - **BEV model diversity:** Refers to the impact of the increase and diversity of BEV models and manufacturers on the market in terms of the development of innovative technologies.

4 - **BEV research and development (BEV R&D):** Addresses the influence of this criterion on the advancement of BEV technologies.

Consider Table A.1 for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

19. How important is **BEV recharging time** in relation to **distance range** for the diffusion of BEVs?

○ BEV recharging time is more important.
○ Distance range is more important.
○ They have equal importance.

20. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

21. How important is **BEV recharging time** in relation to **BEV model diversity** for the diffusion of BEVs?

○ BEV recharging time is more important.
○ BEV model diversity is more important.
○ They have equal importance.

22. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

23. How important is **BEV recharging time** in relation to **BEV R&D** for the diffusion of BEVs?

○ BEV recharging time is more important.
○ BEV R&D is more important.
○ They have equal importance.

24. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

25. How important is **distance range** in relation to **BEV model diversity** for the diffusion of BEVs?

○ Distance range is more important.
○ BEV model diversity is more important.
○ They have equal importance.

26. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

27. How important is **distance range** in relation to **BEV R&D** for the diffusion of BEVs?

○ Distance range is more important.
○ BEV R&D is more important.
○ They have equal importance.

28. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

29. How important is **BEV model diversity** in relation to **BEV R&D** for the diffusion of BEVs?

- ◯ BEV model diversity is more important.
- ◯ BEV R&D is more important.
- ◯ They have equal importance.

30. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

AHP - Infrastructure

Dear evaluator, in this phase of the evaluation of the diffusion of BEVs, we are investigating the impact of variables related to local infrastructure on the decision of residential consumers to purchase a BEV in their region. Please refer to the following list of variables during your assessment:

1 - **BEV mechanic workshops:** Refers to the number of companies offering maintenance services and supplying parts for BEVs, assessing the importance given by potential adopters to the presence of this support.

2 - **BEV research and development (BEV R&D):** Refers to the extent to which the development of research and new technologies can impact on infrastructure and improvements related to BEVs.

3 - **Public charging infrastructure:** Reflects how much the construction and development of public charging networks for BEVs influences consumers, especially in situations of recharging for long journeys.

4 - **Public policies:** Refers to the evaluation of the impact of the development of public policies by the government in your region on infrastructure and general development related to BEVs.

Consider Table A.1 for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

31. How important is the **number of BEV mechanic workshops** in relation to **BEV R&D** for the diffusion of BEVs?

○ Number of BEV mechanic workshops is more important.
○ BEV R&D is more important.
○ They have equal importance.

32. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

33. How important is the **number of BEV mechanic workshops** in relation to **public BEV charging infrastructure** for the diffusion of BEVs?

○ Number of BEV mechanic workshops is more important.
○ Public BEV charging infrastructure is more important.
○ They have equal importance.

34. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

35. How important is the **number of BEV mechanic workshops** in relation to **public policies** for the diffusion of BEVs?

○ Number of BEV mechanic workshops is more important.
○ Public policies are more important.
○ They have equal importance.

36. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

37. How important is **BEV R&D** in relation to **public BEV charging infrastructure** for the diffusion of BEVs?

- ◯ BEV R&D is more important.
- ◯ Public BEV charging infrastructure is more important.
- ◯ They have equal importance.

38. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

39. How important is **BEV R&D** in relation to **public BEV charging infrastructure** for the diffusion of BEVs?

- ◯ BEV R&D is more important.
- ◯ Public policies are more important.
- ◯ They have equal importance.

40. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

41. How important is **public BEV charging infrastructure** in relation to **public policies** for the diffusion of BEVs?

- ◯ Public BEV charging infrastructure is more important.
- ◯ Public policies are more important.
- ◯ They have equal importance.

42. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

AHP - Economic viability

Dear evaluator, in this crucial phase of the evaluation of the diffusion of BEVs, we explore the impact of economic variables on the decision of residential consumers to purchase a BEV in their region. Please refer to the following list of variables during your assessment:

1 - **Net present value (NPV):** Evaluates the weight attributed to this economic variable in the consumer's decision to purchase a BEV. The NPV considers the present value of future costs and benefits, reflecting the financial importance in decision-making.

2 - **Public policies:** Considers the impact of the development of public policies on economic decision-making variables. It assesses how policies can influence factors such as tax incentives, financing and other relevant economic aspects for consumers when purchasing BEVs.

3 - **Technological development:** Examines the importance of technological progress, especially in reducing the price of batteries, in the consumer's decision to purchase a BEV. It also reflects how technological progress can influence economic factors and, consequently, consumer decisions.

Consider Table A.1 for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

43. How important is the **NPV** in relation to **public policies** for the diffusion of BEVs?

◯ NPV is more important.
◯ Public policies are more important.
◯ They have equal importance.

44. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

45. How important is the **NPV** in relation to **technological development** for the diffusion of BEVs?

◯ NPV is more important.
◯ Technological development is more important.
◯ They have equal importance.

46. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

47. How important are **public policies** in relation to **technological development** for the diffusion of BEVs?

○ Public policies are more important.
○ Technological development is more important.
○ They have equal importance.

48. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

AHP - Public policies

Dear evaluator, in this phase of the evaluation of the diffusion of BEVs, we are focusing our analysis on the impact of public policies on the decision-making process of residential consumers to purchase a BEV in their region. Please refer to the following list of variables during your assessment:

1 - **BEV financing opportunities:** This criterion explores the impact of government financing policies for electric vehicles, assessing how such measures can influence consumers' decisions.

2 - **BEV legislation:** Refers to the development of local legislation related to charging standards, electrification of the transport sector, tariff models and vehicle-to-grid (V2G), analyzing how these regulations can affect the adoption of BEVs.

3 - **BEV tax incentives:** Investigates the role of fiscal incentives, such as tax reductions for BEV owners compared to other vehicles, and how these incentives can influence consumer decisions.

Consider Table A.1 for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

49. How important are **BEV financing opportunities** in relation to the **BEV legislation** for the diffusion of BEVs?

◯ BEV financing opportunities are more important.
◯ BEV legislation is more important.
◯ They have equal importance.

50. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

51. How important are **BEV financing opportunities** in relation to **BEV tax incentives** for the diffusion of BEVs?

◯ BEV financing opportunities are more important.
◯ BEV tax incentives are more important.
◯ They have equal importance.

52. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

53. How important is **BEV legislation** in relation to **BEV tax incentives** for the diffusion of BEVs?

◯ BEV legislation is more important.
◯ BEV tax incentives are more important.
◯ They have equal importance.

54. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

AHP - Social aspects

Dear evaluator, at this crucial stage of the modeling, we are asking for your valuable assessment regarding the diffusion of BEVs, considering some of the social variables that impact people's decision whether or not to adopt a BEV in your region. Please refer to the following list of variables during your assessment:

1 - **BEV feedback:** Examines the impact of the experiences of consumers who already own a BEV in the region, especially in terms of influencing other potential adopters.

2 - **BEV knowledge:** Highlights the importance of potential adopters' understanding of BEV characteristics, including environmental benefits, costs and technology.

3 - **BEV relevance:** Investigates the importance of economic and environmental aspects, such as greenhouse gas emission reductions, carbon footprint and low operational costs of the BEV.

4 - **Social appeal:** Analyzes the influence of the opinions of BEV users in the region, considering the importance given to image, status and social interaction when owning a BEV, as well as how communication from users who already own BEVs can influence the decision of potential adopters.

Consider Table A.1 for evaluating the weights of the aspects that influence the diffusion of BEV using AHP.

55. How important is **BEV feedback** in relation to **BEV technical knowledge** for the diffusion of BEVs?

◯ BEV feedback is more important.
◯ BEV technical knowledge is more important.
◯ They have equal importance.

56. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

57. How important is **BEV feedback** in relation to **BEV relevance** for the diffusion of BEVs?

○ BEV feedback is more important.
○ BEV relevance is more important.
○ They have equal importance.

58. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

59. How important is **BEV feedback** in relation to **social appeal** for the diffusion of BEVs?

○ BEV feedback is more important.
○ Social appeal is more important.
○ They have equal importance.

60. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

61. How important is **BEV technical knowledge** in relation to **BEV relevance** for the diffusion of BEVs?

○ BEV technical knowledge is more important.
○ BEV relevance is more important.
○ They have equal importance.

62. How much more important?

○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9

63. How important is **BEV technical knowledge** in relation to **social appeal** for the diffusion of BEVs?

◯ BEV technical knowledge is more important.
◯ Social appeal is more important.
◯ They have equal importance.

64. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

65. How important is **BEV relevance** in relation to **social appeal** for the diffusion of BEVs?

◯ BEV relevance is more important.
◯ Social appeal is more important.
◯ They have equal importance.

66. How much more important?

◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9

A.2 Fuzzy variables in BEV diffusion aspects

67. How much do you consider the opinion of friends, family and social groups when making important decisions, such as purchasing a BEV?

◯ 0 ◯ 1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9 ◯ 10
Not important Very important

68. How often do you discuss the possibility of buying a BEV with people in your social circle?

◯ 0 ◯ 1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7 ◯ 8 ◯ 9 ◯ 10
Never Very often

69. Do you believe that having a BEV can improve your social interaction, your image or your status among your acquaintances?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Strongly disagree Strongly agree

70. How important is it for you to share the experience of owning a BEV with others?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

71. How much does the experience of other BEV owners influence your purchasing decision?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Does not influence Influences a lot

72. How reliable do you consider the opinions of other consumers when evaluating a BEV?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not reliable Very reliable

73. To what extent do technician or expert evaluations of BEV affect your purchasing decision?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Does not influence Influences a lot

74. How much does the reputation of a BEV brand affect your purchasing decision?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Does not influence Influences a lot

75. To what extent are you aware of the differences in maintenance and operating costs between BEVs and combustion vehicles?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not aware Very aware

76. How much do you think you know about the different battery technologies and charging types used in BEVs?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Little knowledge Extensive knowledge

77. How informed do you feel about the environmental benefits of BEVs?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not informed Very well informed

78. Are you aware of the public and private charging networks available in your region?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not aware Very aware

79. How important is protecting the environment and reducing carbon emissions to you when choosing a BEV over a combustion vehicle?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

80. How familiar are you with the tax incentives and benefits available to BEV owners in your area?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not familiar Very familiar

81. How much do you value economic benefits such as fuel savings and lower maintenance costs when considering purchasing a BEV?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Do not value Value a lot

82. How important is independence from fluctuations in fossil fuel prices to you?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

83. How do you rate the current level of investment and quality of BEV R&D?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

84. How do you rate the current public acceptance of the results of BEV R&D in your region?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

85. How do you rate the level of investment and quality of BEV R&D over the next ten years?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

86. How do you rate the public acceptance of the results of BEV R&D in your region over the next ten years?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

87. How do you rate the level of investment and quality of BEV R&D over the next twenty years?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

88. How do you rate the public acceptance of the results of BEV R&D in your region over the next twenty years?

○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10
Not important Very important

B Python Implementation of Fuzzy Logic for Model Variables

This appendix presents the Python code for the five model variables that are implemented using fuzzy logic. The codes provide the detailed implementation of this approach.

1. Variable: $\beta_{\text{R\&D}}$

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl

# Create the fuzzy input variables
research_level = ctrl.Antecedent(np.arange(0, 11, 1), 'research_level
    ')
acceptance = ctrl.Antecedent(np.arange(0, 11, 1), 'acceptance')

# Create fuzzy variables for the consequent outputs
bev_research = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'bev_research'
    , defuzzify_method='mom')

# Define membership functions for antecedents
research_level['low'] = fuzz.trapmf(research_level.universe, [0, 0,
    2, 4] )
research_level['medium'] = fuzz.trapmf(research_level.universe, [2,
    4, 6, 8])
research_level['high'] = fuzz.trapmf(research_level.universe, [6, 8,
    10, 10])

acceptance['low'] = fuzz.trapmf(acceptance.universe, [0, 0, 2, 4] )
acceptance['medium'] = fuzz.trapmf(acceptance.universe, [2, 4, 6, 8])
acceptance['high'] = fuzz.trapmf(acceptance.universe, [6, 8, 10, 10])

# acceptance.view()

# Define membership functions for the consequent outputs
bev_research['very low'] = fuzz.trimf(bev_research.universe, [0, 0,
    0.2])
bev_research['low'] = fuzz.trimf(bev_research.universe, [0.0, 0.2,
    0.4])
bev_research['medium'] = fuzz.trimf(bev_research.universe, [0.3, 0.5,
     0.7])
bev_research['high'] = fuzz.trimf(bev_research.universe, [0.6, 0.8,
    1.0])
```

```
bev_research['very high'] = fuzz.trimf(bev_research.universe, [0.8,
    1.0, 1.0])

# bev_research.view()

# Define fuzzy rules for the consequent outputs
rule_01 = ctrl.Rule(research_level['high'] & acceptance['high'],
    bev_research['very high'])
rule_02 = ctrl.Rule(research_level['high'] & acceptance['medium'],
    bev_research['high'])
rule_03 = ctrl.Rule(research_level['high'] & acceptance['low'],
    bev_research['low'])
rule_04 = ctrl.Rule(research_level['medium'] & acceptance['high'],
    bev_research['very high'])
rule_05 = ctrl.Rule(research_level['medium'] & acceptance['medium'],
    bev_research['medium'])
rule_06 = ctrl.Rule(research_level['medium'] & acceptance['low'],
    bev_research['very low'])
rule_07 = ctrl.Rule(research_level['low'] & acceptance['high'],
    bev_research['high'])
rule_08 = ctrl.Rule(research_level['low'] & acceptance['medium'],
    bev_research['low'])
rule_09 = ctrl.Rule(research_level['low'] & acceptance['low'],
    bev_research['very low'])

# Create the control system
bev_research_ctrl = ctrl.ControlSystem([rule_01, rule_02, rule_03,
    rule_04, rule_05, rule_06, rule_07, rule_08, rule_09])

# Create the simulation
bev_research_control = ctrl.ControlSystemSimulation(bev_research_ctrl
    )

# Generate Brazilian experts inputs for current BEV research level
research_level = [7, 9, 5, 10, 6, 8, 8, 9, 8, 8, 8, 10, 5, 4]
acceptance = [7, 5, 6, 10, 5, 6, 7, 8, 5, 6, 9, 7, 5, 3]
inputs = list(zip(research_level, acceptance))

# Generate Brazilian experts inputs for BEV research level in 10
    years from now
# research_level = [8, 10, 6, 10, 8, 8, 7, 7, 9, 8, 7, 10, 8, 6]
# acceptance = [8, 9, 5, 10, 9, 8, 6, 8, 7, 6, 8, 8, 8, 6]
# inputs = list(zip(research_level, acceptance))
```

```
# Generate Brazilian experts inputs for BEV research level in 20
    years from now
# research_level = [9, 9, 5, 10, 9, 8, 7, 6, 7, 7, 9, 10, 8, 8]
# acceptance = [9, 10, 5, 10, 9, 8, 7, 5, 9, 6, 5, 10, 8, 8]
# inputs = list(zip(research_level, acceptance))

# Generate German experts inputs for current BEV research level
# research_level = [5, 3, 7, 7, 5, 8, 4]
# acceptance = [5, 5, 5, 5, 6, 6, 4]
# inputs = list(zip(research_level, acceptance))

# Generate German experts inputs for BEV research level in 10 years
    from now
# research_level = [4, 8, 7, 9, 10, 9, 6]
# acceptance = [6, 8, 7, 10, 8, 9, 5]
# inputs = list(zip(research_level, acceptance))

# Generate German experts inputs for BEV research level in 20 years
    from now
# research_level = [7, 9, 6, 8, 8, 9, 7]
# acceptance = [8, 8, 6, 8, 6, 8, 6]
# inputs = list(zip(research_level, acceptance))

# Initialize a list to store the resulting relevance values
resulting_bev_researchs = []

# Calculate recommended speeds for the random scenarios
for i, (research_level_val, acceptance_val) in enumerate(inputs, 1):
    bev_research_control.input['research_level'] = research_level_val
    bev_research_control.input['acceptance'] = acceptance_val
    bev_research_control.compute()
    resulting_bev_research = bev_research_control.output['
        bev_research']
    resulting_bev_researchs.append(resulting_bev_research)

    # Determine the relevance category based on the membership
        functions
    relevance_category = fuzz.interp_membership(bev_research.universe
        , bev_research['very low'].mf,
                                              resulting_bev_research
                                                  ), \
        fuzz.interp_membership(bev_research.universe, bev_research['
            low'].mf, resulting_bev_research), \
        fuzz.interp_membership(bev_research.universe, bev_research['
            medium'].mf, resulting_bev_research), \
```

```
        fuzz.interp_membership(bev_research.universe, bev_research['
            high'].mf, resulting_bev_research), \
        fuzz.interp_membership(bev_research.universe, bev_research['
            very high'].mf, resulting_bev_research)
    categories = ["very low", "low", "medium", "high", "very high"]
    category = categories[relevance_category.index(max(
        relevance_category))]

    print(f"Participant {i}: research_level={research_level_val:.2f},
        acceptance={acceptance_val:.2f}, "
          f"bev_research={resulting_bev_research:.2f}, bev_research
            Category={category}")

# Calculate and print the average of resulting
average_bev_research = np.mean(resulting_bev_researchs)
print(f"Average BEV research: {average_bev_research:.2f}")
```

2. Variable: β_{kn}

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl

# Create the fuzzy input variables
cost = ctrl.Antecedent(np.arange(0, 11, 1), 'cost')
technology = ctrl.Antecedent(np.arange(0, 11, 1), 'technology')
environment = ctrl.Antecedent(np.arange(0, 11, 1), 'environment')
charging_network = ctrl.Antecedent(np.arange(0, 11, 1), '
    charging_network')

# Create fuzzy variables for the consequent outputs
knowledge = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'knowledge',
    defuzzify_method='mom')

# Define membership functions for antecedents
cost['low'] = fuzz.trapmf(cost.universe, [0, 0, 2, 4] )
cost['medium'] = fuzz.trapmf(cost.universe, [2, 4, 6, 8])
cost['high'] = fuzz.trapmf(cost.universe, [6, 8, 10, 10])

technology['low'] = fuzz.trapmf(technology.universe, [0, 0, 2, 4] )
technology['medium'] = fuzz.trapmf(technology.universe, [2, 4, 6, 8])
technology['high'] = fuzz.trapmf(technology.universe, [6, 8, 10, 10])

environment['low'] = fuzz.trapmf(environment.universe, [0, 0, 2, 4] )
```

```
environment['medium'] = fuzz.trapmf(environment.universe, [2, 4, 6,
    8])
environment['high'] = fuzz.trapmf(environment.universe, [6, 8, 10,
    10])

charging_network['low'] = fuzz.trapmf(charging_network.universe, [0,
    0, 2, 4] )
charging_network['medium'] = fuzz.trapmf(charging_network.universe,
    [2, 4, 6, 8])
charging_network['high'] = fuzz.trapmf(charging_network.universe, [6,
     8, 10, 10])

# Define membership functions for the consequent outputs
knowledge['very low'] = fuzz.trimf(knowledge.universe, [0, 0, 0.2])
knowledge['low'] = fuzz.trimf(knowledge.universe, [0.0, 0.2, 0.4])
knowledge['medium'] = fuzz.trimf(knowledge.universe, [0.3, 0.5, 0.7])
knowledge['high'] = fuzz.trimf(knowledge.universe, [0.6, 0.8, 1.0])
knowledge['very high'] = fuzz.trimf(knowledge.universe, [0.8, 1.0,
    1.0])

# Define fuzzy rules for the consequent outputs
rule_01 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    high'] & charging_network['high'], knowledge['very high'])
rule_02 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    high'] & charging_network['medium'], knowledge['very high'])
rule_03 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    high'] & charging_network['low'], knowledge['very high'])
rule_04 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    medium'] & charging_network['high'], knowledge['very high'])
rule_05 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    medium'] & charging_network['medium'], knowledge['very high'])
rule_06 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    medium'] & charging_network['low'], knowledge['high'])
rule_07 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    low'] & charging_network['high'], knowledge['very high'])
rule_08 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    low'] & charging_network['medium'], knowledge['very high'])
rule_09 = ctrl.Rule(cost['high'] & technology['high'] & environment['
    low'] & charging_network['low'], knowledge['high'])
rule_10 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['high'] & charging_network['high'], knowledge['very high'])
rule_11 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['high'] & charging_network['medium'], knowledge['high'])
rule_12 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['high'] & charging_network['low'], knowledge['high'])
```

```
rule_13 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['medium'] & charging_network['high'], knowledge['very high'])
rule_14 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['medium'] & charging_network['medium'], knowledge['high'])
rule_15 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['medium'] & charging_network['low'], knowledge['high'])
rule_16 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['low'] & charging_network['high'], knowledge['high'])
rule_17 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['low'] & charging_network['medium'], knowledge['high'])
rule_18 = ctrl.Rule(cost['high'] & technology['medium'] & environment
    ['low'] & charging_network['low'], knowledge['medium'])
rule_19 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    high'] & charging_network['high'], knowledge['high'])
rule_20 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    high'] & charging_network['medium'], knowledge['high'])
rule_21 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    high'] & charging_network['low'], knowledge['medium'])
rule_22 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    medium'] & charging_network['high'], knowledge['high'])
rule_23 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    medium'] & charging_network['medium'], knowledge['medium'])
rule_24 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    medium'] & charging_network['low'], knowledge['medium'])
rule_25 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    low'] & charging_network['high'], knowledge['high'])
rule_26 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    low'] & charging_network['medium'], knowledge['medium'])
rule_27 = ctrl.Rule(cost['high'] & technology['low'] & environment['
    low'] & charging_network['low'], knowledge['low'])
rule_28 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['high'] & charging_network['high'], knowledge['very high'])
rule_29 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['high'] & charging_network['medium'], knowledge['high'])
rule_30 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['high'] & charging_network['low'], knowledge['high'])
rule_31 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['medium'] & charging_network['high'], knowledge['high'])
rule_32 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['medium'] & charging_network['medium'], knowledge['high'])
rule_33 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['medium'] & charging_network['low'], knowledge['medium'])
rule_34 = ctrl.Rule(cost['medium'] & technology['high'] & environment
    ['low'] & charging_network['high'], knowledge['high'])
```

```
rule_35 = ctrl.Rule(cost['medium'] & technology['high'] & environment['low'] & charging_network['medium'], knowledge['high'])
rule_36 = ctrl.Rule(cost['medium'] & technology['high'] & environment['low'] & charging_network['low'], knowledge['medium'])
rule_37 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['high'] & charging_network['high'], knowledge['high'])
rule_38 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['high'] & charging_network['medium'], knowledge['medium'])
rule_39 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['high'] & charging_network['low'], knowledge['medium'])
rule_40 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['medium'] & charging_network['high'], knowledge['high'])
rule_41 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['medium'] & charging_network['medium'], knowledge['medium'])
rule_42 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['medium'] & charging_network['low'], knowledge['low'])
rule_43 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['low'] & charging_network['high'], knowledge['medium'])
rule_44 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['low'] & charging_network['medium'], knowledge['medium'])
rule_45 = ctrl.Rule(cost['medium'] & technology['medium'] & environment['low'] & charging_network['low'], knowledge['low'])
rule_46 = ctrl.Rule(cost['medium'] & technology['low'] & environment['high'] & charging_network['high'], knowledge['medium'])
rule_47 = ctrl.Rule(cost['medium'] & technology['low'] & environment['high'] & charging_network['medium'], knowledge['low'])
rule_48 = ctrl.Rule(cost['medium'] & technology['low'] & environment['high'] & charging_network['low'], knowledge['low'])
rule_49 = ctrl.Rule(cost['medium'] & technology['low'] & environment['medium'] & charging_network['high'], knowledge['medium'])
rule_50 = ctrl.Rule(cost['medium'] & technology['low'] & environment['medium'] & charging_network['medium'], knowledge['low'])
rule_51 = ctrl.Rule(cost['medium'] & technology['low'] & environment['medium'] & charging_network['low'], knowledge['low'])
rule_52 = ctrl.Rule(cost['medium'] & technology['low'] & environment['low'] & charging_network['high'], knowledge['low'])
rule_53 = ctrl.Rule(cost['medium'] & technology['low'] & environment['low'] & charging_network['medium'], knowledge['low'])
```

```
rule_54 = ctrl.Rule(cost['medium'] & technology['low'] & environment['low'] & charging_network['low'], knowledge['very low'])
rule_55 = ctrl.Rule(cost['low'] & technology['high'] & environment['high'] & charging_network['high'], knowledge['high'])
rule_56 = ctrl.Rule(cost['low'] & technology['high'] & environment['high'] & charging_network['medium'], knowledge['medium'])
rule_57 = ctrl.Rule(cost['low'] & technology['high'] & environment['high'] & charging_network['low'], knowledge['low'])
rule_58 = ctrl.Rule(cost['low'] & technology['high'] & environment['medium'] & charging_network['high'], knowledge['medium'])
rule_59 = ctrl.Rule(cost['low'] & technology['high'] & environment['medium'] & charging_network['medium'], knowledge['medium'])
rule_60 = ctrl.Rule(cost['low'] & technology['high'] & environment['medium'] & charging_network['low'], knowledge['low'])
rule_61 = ctrl.Rule(cost['low'] & technology['high'] & environment['low'] & charging_network['high'], knowledge['medium'])
rule_62 = ctrl.Rule(cost['low'] & technology['high'] & environment['low'] & charging_network['medium'], knowledge['low'])
rule_63 = ctrl.Rule(cost['low'] & technology['high'] & environment['low'] & charging_network['low'], knowledge['low'])
rule_64 = ctrl.Rule(cost['low'] & technology['medium'] & environment['high'] & charging_network['high'], knowledge['medium'])
rule_65 = ctrl.Rule(cost['low'] & technology['medium'] & environment['high'] & charging_network['medium'], knowledge['low'])
rule_66 = ctrl.Rule(cost['low'] & technology['medium'] & environment['high'] & charging_network['low'], knowledge['low'])
rule_67 = ctrl.Rule(cost['low'] & technology['medium'] & environment['medium'] & charging_network['high'], knowledge['low'])
rule_68 = ctrl.Rule(cost['low'] & technology['medium'] & environment['medium'] & charging_network['medium'], knowledge['low'])
rule_69 = ctrl.Rule(cost['low'] & technology['medium'] & environment['medium'] & charging_network['low'], knowledge['very low'])
rule_70 = ctrl.Rule(cost['low'] & technology['medium'] & environment['low'] & charging_network['high'], knowledge['low'])
rule_71 = ctrl.Rule(cost['low'] & technology['medium'] & environment['low'] & charging_network['medium'], knowledge['low'])
rule_72 = ctrl.Rule(cost['low'] & technology['medium'] & environment['low'] & charging_network['low'], knowledge['very low'])
rule_73 = ctrl.Rule(cost['low'] & technology['low'] & environment['high'] & charging_network['high'], knowledge['low'])
rule_74 = ctrl.Rule(cost['low'] & technology['low'] & environment['high'] & charging_network['medium'], knowledge['very low'])
rule_75 = ctrl.Rule(cost['low'] & technology['low'] & environment['high'] & charging_network['low'], knowledge['very low'])
```

```
rule_76 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    medium'] & charging_network['high'], knowledge['low'])
rule_77 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    medium'] & charging_network['medium'], knowledge['very low'])
rule_78 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    medium'] & charging_network['low'], knowledge['very low'])
rule_79 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    low'] & charging_network['high'], knowledge['very low'])
rule_80 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    low'] & charging_network['medium'], knowledge['very low'])
rule_81 = ctrl.Rule(cost['low'] & technology['low'] & environment['
    low'] & charging_network['low'], knowledge['very low'])


# Create the control system
knowledge_ctrl = ctrl.ControlSystem([rule_01, rule_02, rule_03,
    rule_04, rule_05, rule_06, rule_07, rule_08, rule_09,
                                        rule_10, rule_11, rule_12,
                                            rule_13, rule_14, rule_15,
                                            rule_16, rule_17, rule_18,
                                        rule_19, rule_20, rule_21,
                                            rule_22, rule_23, rule_24,
                                            rule_25, rule_26, rule_27,
                                        rule_28, rule_29, rule_30,
                                            rule_31, rule_32, rule_33,
                                            rule_34, rule_35, rule_36,
                                        rule_37, rule_38, rule_39,
                                            rule_40, rule_41, rule_42,
                                            rule_43, rule_44, rule_45,
                                        rule_46, rule_47, rule_48,
                                            rule_49, rule_50, rule_51,
                                            rule_52, rule_53, rule_54,
                                        rule_55, rule_56, rule_57,
                                            rule_58, rule_59, rule_60,
                                            rule_61, rule_62, rule_63,
                                        rule_64, rule_65, rule_66,
                                            rule_67, rule_68, rule_69,
                                            rule_70, rule_71, rule_72,
                                        rule_73, rule_74, rule_75,
                                            rule_76, rule_77, rule_78,
                                            rule_79, rule_80, rule_81])

# Create the simulation
knowledge_control = ctrl.ControlSystemSimulation(knowledge_ctrl)
```

```python
# Generate Brazilian experts inputs
cost = [5, 10, 7, 9 ,8 ,7 ,6 ,9 ,2, 7, 5, 9, 6 , 6]
technology = [5, 10, 7, 10, 10, 6, 9, 8, 2, 6, 6, 10, 5, 8]
environment = [6, 10, 7, 10, 6, 6, 10, 9, 9, 8, 8, 10, 5, 8]
charging_network = [4, 10, 3, 10, 9, 8, 6, 10, 9, 6, 4, 5, 3, 4]
inputs = list(zip(cost, technology, environment, charging_network))

# Generate German experts inputs
# cost = [7, 2, 9, 9, 2, 3, 3]
# technology = [4, 4, 6, 7, 7, 3, 6]
# environment = [4, 8, 10, 8, 7, 7, 7]
# charging_network = [3, 6, 1, 8, 9, 7, 3]
# inputs = list(zip(cost, technology, environment, charging_network))

# Initialize a list to store the resulting knowledge values
resulting_knowledges= []

# Calculate recommended speeds for the random scenarios
for i, (cost_val, technology_val, environment_val, sharing_val) in
    enumerate(inputs, 1):
     knowledge_control.input['cost'] = cost_val
     knowledge_control.input['technology'] = technology_val
     knowledge_control.input['environment'] = environment_val
     knowledge_control.input['charging_network'] = sharing_val
     knowledge_control.compute()
     resulting_knowledge = knowledge_control.output['knowledge']
     resulting_knowledges.append(resulting_knowledge)

     # Determine the knowledge category based on the membership
         functions
     knowledge_category = fuzz.interp_membership(knowledge.universe,
         knowledge['very low'].mf,
                                                         resulting_knowledge),
                                                             \
         fuzz.interp_membership(knowledge.universe, knowledge['low'].
             mf, resulting_knowledge), \
         fuzz.interp_membership(knowledge.universe, knowledge['medium'
             ].mf, resulting_knowledge), \
         fuzz.interp_membership(knowledge.universe, knowledge['high'].
             mf, resulting_knowledge), \
         fuzz.interp_membership(knowledge.universe, knowledge['very
             high'].mf, resulting_knowledge)
     categories = ["very low", "low", "medium", "high", "very high"]
     category = categories[knowledge_category.index(max(
         knowledge_category))]
```

```
    print(f"Participant {i}: cost={cost_val:.2f}, technology={
        technology_val:.2f}, "
           f"environment={environment_val:.2f}, charging_network={
              sharing_val:.2f},  knowledge={resulting_knowledge:.2f},
              knowledge Category={category}")

# Calculate and print the average of resulting
average_knowledge = np.mean(resulting_knowledges)
print(f"Average knowledge: {average_knowledge:.2f}")
```

3. Variable: β_{fb}

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl

# Create the fuzzy input variables
experience = ctrl.Antecedent(np.arange(0, 11, 1), 'experience')
trust = ctrl.Antecedent(np.arange(0, 11, 1), 'trust')
specialist_experience = ctrl.Antecedent(np.arange(0, 11, 1), '
    specialist_experience')
brand = ctrl.Antecedent(np.arange(0, 11, 1), 'brand')

# Create fuzzy variables for the consequent outputs
feedback = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'feedback',
    defuzzify_method='mom')

# Define membership functions for antecedents
experience['low'] = fuzz.trapmf(experience.universe, [0, 0, 2, 4] )
experience['medium'] = fuzz.trapmf(experience.universe, [2, 4, 6, 8])
experience['high'] = fuzz.trapmf(experience.universe, [6, 8, 10, 10])

trust['low'] = fuzz.trapmf(trust.universe, [0, 0, 2, 4] )
trust['medium'] = fuzz.trapmf(trust.universe, [2, 4, 6, 8])
trust['high'] = fuzz.trapmf(trust.universe, [6, 8, 10, 10])

specialist_experience['low'] = fuzz.trapmf(specialist_experience.
    universe, [0, 0, 2, 4] )
specialist_experience['medium'] = fuzz.trapmf(specialist_experience.
    universe, [2, 4, 6, 8])
specialist_experience['high'] = fuzz.trapmf(specialist_experience.
    universe, [6, 8, 10, 10])
```

```
brand['low'] = fuzz.trapmf(brand.universe, [0, 0, 2, 4] )
brand['medium'] = fuzz.trapmf(brand.universe, [2, 4, 6, 8])
brand['high'] = fuzz.trapmf(brand.universe, [6, 8, 10, 10])

# Define membership functions for the consequent outputs
feedback['very low'] = fuzz.trimf(feedback.universe, [0, 0, 0.2])
feedback['low'] = fuzz.trimf(feedback.universe, [0.0, 0.2, 0.4])
feedback['medium'] = fuzz.trimf(feedback.universe, [0.3, 0.5, 0.7])
feedback['high'] = fuzz.trimf(feedback.universe, [0.6, 0.8, 1.0])
feedback['very high'] = fuzz.trimf(feedback.universe, [0.8, 1.0,
    1.0])

# Define fuzzy rules for the consequent outputs
rule_01 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['high'] & brand['high'], feedback['very high
    '])
rule_02 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['high'] & brand['medium'], feedback['very
    high'])
rule_03 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['high'] & brand['low'], feedback['high'])
rule_04 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['medium'] & brand['high'], feedback['very
    high'])
rule_05 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['medium'] & brand['medium'], feedback['high'
    ])
rule_06 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['medium'] & brand['low'], feedback['high'])
rule_07 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['low'] & brand['high'], feedback['very high'
    ])
rule_08 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['low'] & brand['medium'], feedback['high'])
rule_09 = ctrl.Rule(experience['high'] & trust['high'] &
    specialist_experience['low'] & brand['low'], feedback['medium'])
rule_10 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['high'] & brand['high'], feedback['very high
    '])
rule_11 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['high'] & brand['medium'], feedback['very
    high'])
rule_12 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['high'] & brand['low'], feedback['high'])
```

```
rule_13 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['medium'] & brand['high'], feedback['very
    high'])
rule_14 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['medium'] & brand['medium'], feedback['high'
    ])
rule_15 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['medium'] & brand['low'], feedback['medium'
    ])
rule_16 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['low'] & brand['high'], feedback['high'])
rule_17 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['low'] & brand['medium'], feedback['high'])
rule_18 = ctrl.Rule(experience['high'] & trust['medium'] &
    specialist_experience['low'] & brand['low'], feedback['medium'])
rule_19 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['high'] & brand['high'], feedback['very high
    '])
rule_20 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['high'] & brand['medium'], feedback['high'])
rule_21 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['high'] & brand['low'], feedback['high'])
rule_22 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['medium'] & brand['high'], feedback['very
    high'])
rule_23 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['medium'] & brand['medium'], feedback['high'
    ])
rule_24 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['medium'] & brand['low'], feedback['medium'
    ])
rule_25 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['low'] & brand['high'], feedback['high'])
rule_26 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['low'] & brand['medium'], feedback['medium'
    ])
rule_27 = ctrl.Rule(experience['high'] & trust['low'] &
    specialist_experience['low'] & brand['low'], feedback['low'])
rule_28 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['high'] & brand['high'], feedback['very high
    '])
rule_29 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['high'] & brand['medium'], feedback['high'])
rule_30 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['high'] & brand['low'], feedback['medium'])
```

```
rule_31 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['medium'] & brand['high'], feedback['high'])
rule_32 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['medium'] & brand['medium'], feedback['
    medium'])
rule_33 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['medium'] & brand['low'], feedback['low'])
rule_34 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['low'] & brand['high'], feedback['high'])
rule_35 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['low'] & brand['medium'], feedback['medium'
    ])
rule_36 = ctrl.Rule(experience['medium'] & trust['high'] &
    specialist_experience['low'] & brand['low'], feedback['low'])
rule_37 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['high'] & brand['high'], feedback['high'])
rule_38 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['high'] & brand['medium'], feedback['high'])
rule_39 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['high'] & brand['low'], feedback['medium'])
rule_40 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['medium'] & brand['high'], feedback['high'])
rule_41 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['medium'] & brand['medium'], feedback['
    medium'])
rule_42 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['medium'] & brand['low'], feedback['low'])
rule_43 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['low'] & brand['high'], feedback['medium'])
rule_44 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['low'] & brand['medium'], feedback['low'])
rule_45 = ctrl.Rule(experience['medium'] & trust['medium'] &
    specialist_experience['low'] & brand['low'], feedback['low'])
rule_46 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['high'] & brand['high'], feedback['high'])
rule_47 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['high'] & brand['medium'], feedback['medium'
    ])
rule_48 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['high'] & brand['low'], feedback['low'])
rule_49 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['medium'] & brand['high'], feedback['high'])
rule_50 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['medium'] & brand['medium'], feedback['
    medium'])
```

```
rule_51 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['medium'] & brand['low'], feedback['low'])
rule_52 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['low'] & brand['high'], feedback['medium'])
rule_53 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['low'] & brand['medium'], feedback['low'])
rule_54 = ctrl.Rule(experience['medium'] & trust['low'] &
    specialist_experience['low'] & brand['low'], feedback['very low'])
rule_55 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['high'] & brand['high'], feedback['high'])
rule_56 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['high'] & brand['medium'], feedback['medium'
    ])
rule_57 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['high'] & brand['low'], feedback['low'])
rule_58 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['medium'] & brand['high'], feedback['medium'
    ])
rule_59 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['medium'] & brand['medium'], feedback['low'
    ])
rule_60 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['medium'] & brand['low'], feedback['very low
    '])
rule_61 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['low'] & brand['high'], feedback['low'])
rule_62 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['low'] & brand['medium'], feedback['low'])
rule_63 = ctrl.Rule(experience['low'] & trust['high'] &
    specialist_experience['low'] & brand['low'], feedback['very low'])
rule_64 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['high'] & brand['high'], feedback['medium'])
rule_65 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['high'] & brand['medium'], feedback['low'])
rule_66 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['high'] & brand['low'], feedback['low'])
rule_67 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['medium'] & brand['high'], feedback['medium'
    ])
rule_68 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['medium'] & brand['medium'], feedback['low'
    ])
rule_69 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['medium'] & brand['low'], feedback['very low
    '])
```

```
rule_70 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['low'] & brand['high'], feedback['low'])
rule_71 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['low'] & brand['medium'], feedback['very low
    '])
rule_72 = ctrl.Rule(experience['low'] & trust['medium'] &
    specialist_experience['low'] & brand['low'], feedback['very low'])
rule_73 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['high'] & brand['high'], feedback['medium'])
rule_74 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['high'] & brand['medium'], feedback['low'])
rule_75 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['high'] & brand['low'], feedback['very low'
    ])
rule_76 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['medium'] & brand['high'], feedback['low'])
rule_77 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['medium'] & brand['medium'], feedback['low'
    ])
rule_78 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['medium'] & brand['low'], feedback['very low
    '])
rule_79 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['low'] & brand['high'], feedback['low'])
rule_80 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['low'] & brand['medium'], feedback['very low
    '])
rule_81 = ctrl.Rule(experience['low'] & trust['low'] &
    specialist_experience['low'] & brand['low'], feedback['very low'])


# Create the control system
feedback_ctrl = ctrl.ControlSystem([rule_01, rule_02, rule_03,
    rule_04, rule_05, rule_06, rule_07, rule_08, rule_09,
                                   rule_10, rule_11, rule_12,
                                       rule_13, rule_14, rule_15,
                                       rule_16, rule_17, rule_18,
                                   rule_19, rule_20, rule_21,
                                       rule_22, rule_23, rule_24,
                                       rule_25, rule_26, rule_27,
                                   rule_28, rule_29, rule_30,
                                       rule_31, rule_32, rule_33,
                                       rule_34, rule_35, rule_36,
```

```
                                                    rule_37, rule_38, rule_39,
                                                        rule_40, rule_41, rule_42,
                                                        rule_43, rule_44, rule_45,
                                                    rule_46, rule_47, rule_48,
                                                        rule_49, rule_50, rule_51,
                                                        rule_52, rule_53, rule_54,
                                                    rule_55, rule_56, rule_57,
                                                        rule_58, rule_59, rule_60,
                                                        rule_61, rule_62, rule_63,
                                                    rule_64, rule_65, rule_66,
                                                        rule_67, rule_68, rule_69,
                                                        rule_70, rule_71, rule_72,
                                                    rule_73, rule_74, rule_75,
                                                        rule_76, rule_77, rule_78,
                                                        rule_79, rule_80, rule_81])

# Create the simulation
feedback_control = ctrl.ControlSystemSimulation(feedback_ctrl)

# Generate Brazilian experts inputs
experience = [5, 9, 8, 9, 9, 6, 6, 6, 9, 8, 8, 9, 8, 3]
trust = [6, 9, 7, 7, 8, 7, 6, 6, 8, 8, 9, 9, 7, 4]
specialist_experience = [8, 8, 6, 10, 9, 8, 9, 6, 9, 9, 8, 9, 10 , 4]
brand = [7, 8, 8, 10, 10, 8, 9, 8, 6, 9, 7, 8, 8, 5]
inputs = list(zip(experience, trust, specialist_experience, brand))

# Generate german experts inputs
# experience = [6, 3, 2, 5, 1, 7, 6]
# trust = [4, 4, 5, 8, 2, 7, 5]
# specialist_experience = [7, 5, 6, 6, 5, 9, 7]
# brand = [4, 4, 4, 7, 3, 8, 7]
# inputs = list(zip(experience, trust, specialist_experience, brand))

# Initialize a list to store the resulting feedback values
resulting_feedbacks = []

# Calculate recommended speeds for the random scenarios
for i, (experience_val, trust_val, specialist_experience_val,
    sharing_val) in enumerate(inputs, 1):
    feedback_control.input['experience'] = experience_val
    feedback_control.input['trust'] = trust_val
    feedback_control.input['specialist_experience'] =
        specialist_experience_val
    feedback_control.input['brand'] = sharing_val
    feedback_control.compute()
```

```
    resulting_feedback = feedback_control.output['feedback']
    resulting_feedbacks.append(resulting_feedback)

    # Determine the feedback category based on the membership
        functions
    feedback_category = fuzz.interp_membership(feedback.universe,
        feedback['very low'].mf,
                                                resulting_feedback)
                                                    , \
        fuzz.interp_membership(feedback.universe, feedback['low'].mf,
            resulting_feedback), \
        fuzz.interp_membership(feedback.universe, feedback['medium'].
            mf, resulting_feedback), \
        fuzz.interp_membership(feedback.universe, feedback['high'].mf
            , resulting_feedback), \
        fuzz.interp_membership(feedback.universe, feedback['very high
            '].mf, resulting_feedback)
    categories = ["very low", "low", "medium", "high", "very high"]
    category = categories[feedback_category.index(max(
        feedback_category))]

    print(f"Participant {i}: experience={experience_val:.2f}, trust={
        trust_val:.2f}, "
          f"specialist_experience={specialist_experience_val:.2f},
            brand={sharing_val:.2f}, feedback={resulting_feedback
            :.2f}, feedback Category={category}")

# Calculate and print the average of resulting
average_feedback = np.mean(resulting_feedbacks)
print(f"Average feedback: {average_feedback:.2f}")
```

4. Variable: β_{rel}

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl

# Create the fuzzy input variables
environment = ctrl.Antecedent(np.arange(0, 11, 1), 'environment')
incentive = ctrl.Antecedent(np.arange(0, 11, 1), 'incentive')
benefits = ctrl.Antecedent(np.arange(0, 11, 1), 'benefits')
independence = ctrl.Antecedent(np.arange(0, 11, 1), 'independence')

# Create fuzzy variables for the consequent outputs
```

```
relevance = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'relevance',
    defuzzify_method='mom')

# Define membership functions for antecedents
environment['low'] = fuzz.trapmf(environment.universe, [0, 0, 2, 4] )
environment['medium'] = fuzz.trapmf(environment.universe, [2, 4, 6,
    8])
environment['high'] = fuzz.trapmf(environment.universe, [6, 8, 10,
    10])

incentive['low'] = fuzz.trapmf(incentive.universe, [0, 0, 2, 4] )
incentive['medium'] = fuzz.trapmf(incentive.universe, [2, 4, 6, 8])
incentive['high'] = fuzz.trapmf(incentive.universe, [6, 8, 10, 10])

benefits['low'] = fuzz.trapmf(benefits.universe, [0, 0, 2, 4] )
benefits['medium'] = fuzz.trapmf(benefits.universe, [2, 4, 6, 8])
benefits['high'] = fuzz.trapmf(benefits.universe, [6, 8, 10, 10])

independence['low'] = fuzz.trapmf(independence.universe, [0, 0, 2, 4]
     )
independence['medium'] = fuzz.trapmf(independence.universe, [2, 4, 6,
     8])
independence['high'] = fuzz.trapmf(independence.universe, [6, 8, 10,
    10])

# Define membership functions for the consequent outputs
relevance['very low'] = fuzz.trimf(relevance.universe, [0, 0, 0.2])
relevance['low'] = fuzz.trimf(relevance.universe, [0.0, 0.2, 0.4])
relevance['medium'] = fuzz.trimf(relevance.universe, [0.3, 0.5, 0.7])
relevance['high'] = fuzz.trimf(relevance.universe, [0.6, 0.8, 1.0])
relevance['very high'] = fuzz.trimf(relevance.universe, [0.8, 1.0,
    1.0])

# Define fuzzy rules for the consequent outputs
rule_01 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['high'] & independence['high'], relevance['very high'])
rule_02 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['high'] & independence['medium'], relevance['very high'])
rule_03 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['high'] & independence['low'], relevance['very high'])
rule_04 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['medium'] & independence['high'], relevance['very high'])
rule_05 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['medium'] & independence['medium'], relevance['high'])
```

```
rule_06 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['medium'] & independence['low'], relevance['high'])
rule_07 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['low'] & independence['high'], relevance['high'])
rule_08 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['low'] & independence['medium'], relevance['medium'])
rule_09 = ctrl.Rule(environment['high'] & incentive['high'] &
    benefits['low'] & independence['low'], relevance['medium'])
rule_10 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['high'] & independence['high'], relevance['very high'])
rule_11 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['high'] & independence['medium'], relevance['very high'])
rule_12 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['high'] & independence['low'], relevance['very high'])
rule_13 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['medium'] & independence['high'], relevance['high'])
rule_14 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['medium'] & independence['medium'], relevance['high'])
rule_15 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['medium'] & independence['low'], relevance['high'])
rule_16 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['low'] & independence['high'], relevance['medium'])
rule_17 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['low'] & independence['medium'], relevance['medium'])
rule_18 = ctrl.Rule(environment['high'] & incentive['medium'] &
    benefits['low'] & independence['low'], relevance['low'])
rule_19 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['high'] & independence['high'], relevance['very high'])
rule_20 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['high'] & independence['medium'], relevance['high'])
rule_21 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['high'] & independence['low'], relevance['high'])
rule_22 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['medium'] & independence['high'], relevance['high'])
rule_23 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['medium'] & independence['medium'], relevance['medium'])
rule_24 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['medium'] & independence['low'], relevance['medium'])
rule_25 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['low'] & independence['high'], relevance['low'])
rule_26 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['low'] & independence['medium'], relevance['low'])
rule_27 = ctrl.Rule(environment['high'] & incentive['low'] & benefits
    ['low'] & independence['low'], relevance['low'])
```

```
rule_28 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['high'] & independence['high'], relevance['very high'])
rule_29 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['high'] & independence['medium'], relevance['very high'])
rule_30 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['high'] & independence['low'], relevance['high'])
rule_31 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['medium'] & independence['high'], relevance['high'])
rule_32 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['medium'] & independence['medium'], relevance['high'])
rule_33 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['medium'] & independence['low'], relevance['medium'])
rule_34 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['low'] & independence['high'], relevance['medium'])
rule_35 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['low'] & independence['medium'], relevance['low'])
rule_36 = ctrl.Rule(environment['medium'] & incentive['high'] &
    benefits['low'] & independence['low'], relevance['low'])
rule_37 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['high'] & independence['high'], relevance['high'])
rule_38 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['high'] & independence['medium'], relevance['high'])
rule_39 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['high'] & independence['low'], relevance['high'])
rule_40 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['medium'] & independence['high'], relevance['medium'])
rule_41 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['medium'] & independence['medium'], relevance['medium'])
rule_42 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['medium'] & independence['low'], relevance['medium'])
rule_43 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['low'] & independence['high'], relevance['low'])
rule_44 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['low'] & independence['medium'], relevance['low'])
rule_45 = ctrl.Rule(environment['medium'] & incentive['medium'] &
    benefits['low'] & independence['low'], relevance['low'])
rule_46 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['high'] & independence['high'], relevance['high'])
rule_47 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['high'] & independence['medium'], relevance['high'])
rule_48 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['high'] & independence['low'], relevance['medium'])
rule_49 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['medium'] & independence['high'], relevance['medium'])
```

```
rule_50 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['medium'] & independence['medium'], relevance['low'])
rule_51 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['medium'] & independence['low'], relevance['low'])
rule_52 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['low'] & independence['high'], relevance['low'])
rule_53 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['low'] & independence['medium'], relevance['very low'])
rule_54 = ctrl.Rule(environment['medium'] & incentive['low'] &
    benefits['low'] & independence['low'], relevance['very low'])
rule_55 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['high'] & independence['high'], relevance['high'])
rule_56 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['high'] & independence['medium'], relevance['high'])
rule_57 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['high'] & independence['low'], relevance['high'])
rule_58 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['medium'] & independence['high'], relevance['medium'])
rule_59 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['medium'] & independence['medium'], relevance['medium'])
rule_60 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['medium'] & independence['low'], relevance['low'])
rule_61 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['low'] & independence['high'], relevance['low'])
rule_62 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['low'] & independence['medium'], relevance['low'])
rule_63 = ctrl.Rule(environment['low'] & incentive['high'] & benefits
    ['low'] & independence['low'], relevance['very low'])
rule_64 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['high'] & independence['high'], relevance['high'])
rule_65 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['high'] & independence['medium'], relevance['medium'])
rule_66 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['high'] & independence['low'], relevance['medium'])
rule_67 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['medium'] & independence['high'], relevance['low'])
rule_68 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['medium'] & independence['medium'], relevance['low'])
rule_69 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['medium'] & independence['low'], relevance['low'])
rule_70 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['low'] & independence['high'], relevance['very low'])
rule_71 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['low'] & independence['medium'], relevance['very low'])
```

```
rule_72 = ctrl.Rule(environment['low'] & incentive['medium'] &
    benefits['low'] & independence['low'], relevance['very low'])
rule_73 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'high'] & independence['high'], relevance['medium'])
rule_74 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'high'] & independence['medium'], relevance['medium'])
rule_75 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'high'] & independence['low'], relevance['low'])
rule_76 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'medium'] & independence['high'], relevance['low'])
rule_77 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'medium'] & independence['medium'], relevance['low'])
rule_78 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'medium'] & independence['low'], relevance['very low'])
rule_79 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'low'] & independence['high'], relevance['very low'])
rule_80 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'low'] & independence['medium'], relevance['very low'])
rule_81 = ctrl.Rule(environment['low'] & incentive['low'] & benefits[
    'low'] & independence['low'], relevance['very low'])


# Create the control system
relevance_ctrl = ctrl.ControlSystem([rule_01, rule_02, rule_03,
    rule_04, rule_05, rule_06, rule_07, rule_08, rule_09,
                                        rule_10, rule_11, rule_12,
                                            rule_13, rule_14, rule_15,
                                            rule_16, rule_17, rule_18,
                                        rule_19, rule_20, rule_21,
                                            rule_22, rule_23, rule_24,
                                            rule_25, rule_26, rule_27,
                                        rule_28, rule_29, rule_30,
                                            rule_31, rule_32, rule_33,
                                            rule_34, rule_35, rule_36,
                                        rule_37, rule_38, rule_39,
                                            rule_40, rule_41, rule_42,
                                            rule_43, rule_44, rule_45,
                                        rule_46, rule_47, rule_48,
                                            rule_49, rule_50, rule_51,
                                            rule_52, rule_53, rule_54,
                                        rule_55, rule_56, rule_57,
                                            rule_58, rule_59, rule_60,
                                            rule_61, rule_62, rule_63,
```

```
                                           rule_64, rule_65, rule_66,
                                              rule_67, rule_68, rule_69,
                                              rule_70, rule_71, rule_72,
                                           rule_73, rule_74, rule_75,
                                              rule_76, rule_77, rule_78,
                                              rule_79, rule_80, rule_81])

# Create the simulation
relevance_control = ctrl.ControlSystemSimulation(relevance_ctrl)

# Generate Brazilian experts inputs
environment = [7, 7, 4, 10, 6, 9, 9, 9, 8, 9, 5, 10, 3, 10]
incentive = [5, 10, 5, 7, 2, 5, 5, 9, 5, 7, 4, 5, 3, 4]
benefits = [7, 10, 5, 7, 3, 9, 9, 9, 8, 9, 6, 10, 7, 9]
independence = [7, 10, 8, 7, 1, 8, 9, 7, 9, 9, 7, 10, 7, 10]
inputs = list(zip(environment, incentive, benefits, independence))

# Generate German experts inputs
# environment = [3, 8, 9, 9, 9, 6, 8]
# incentive = [1, 8, 8, 8, 9, 3, 6]
# benefits = [6, 7, 9, 8, 9, 8, 6]
# independence = [6, 6, 9, 9, 7, 9, 8]
# inputs = list(zip(environment, incentive, benefits, independence))

# Initialize a list to store the resulting relevance values
resulting_relevancies = []

# Calculate recommended speeds for the random scenarios
for i, (environment_val, incentive_val, benefits_val, sharing_val) in
     enumerate(inputs, 1):
    relevance_control.input['environment'] = environment_val
    relevance_control.input['incentive'] = incentive_val
    relevance_control.input['benefits'] = benefits_val
    relevance_control.input['independence'] = sharing_val
    relevance_control.compute()
    resulting_relevance = relevance_control.output['relevance']
    resulting_relevancies.append(resulting_relevance)

    # Determine the relevance category based on the membership
       functions
    relevance_category = fuzz.interp_membership(relevance.universe,
       relevance['very low'].mf,
                                                 resulting_relevance),
                                                    \
```

```
        fuzz.interp_membership(relevance.universe, relevance['low'].
            mf, resulting_relevance), \
        fuzz.interp_membership(relevance.universe, relevance['medium'
            ].mf, resulting_relevance), \
        fuzz.interp_membership(relevance.universe, relevance['high'].
            mf, resulting_relevance), \
        fuzz.interp_membership(relevance.universe, relevance['very
            high'].mf, resulting_relevance)
    categories = ["very low", "low", "medium", "high", "very high"]
    category = categories[relevance_category.index(max(
        relevance_category))]

    print(f"Participant {i}: environment={environment_val:.2f},
        incentive={incentive_val:.2f}, "
          f"benefits={benefits_val:.2f}, independence={sharing_val:.2
            f},  relevance={resulting_relevance:.2f}, relevance
            Category={category}")

# Calculate and print the average of resulting
average_relevance = np.mean(resulting_relevancies)
print(f"Average relevance: {average_relevance:.2f}")
```

5. Variable: β_{social}

```
import numpy as np
import skfuzzy as fuzz
from skfuzzy import control as ctrl

# Create the fuzzy input variables
opinion = ctrl.Antecedent(np.arange(0, 11, 1), 'opinion')
transmission = ctrl.Antecedent(np.arange(0, 11, 1), 'transmission')
status = ctrl.Antecedent(np.arange(0, 11, 1), 'status')
sharing_importance = ctrl.Antecedent(np.arange(0, 11, 1), '
    sharing_importance')

# Create fuzzy variables for the consequent outputs
sociability = ctrl.Consequent(np.arange(0, 1.1, 0.1), 'sociability',
    defuzzify_method='mom')

# Define membership functions for antecedents
opinion['low'] = fuzz.trapmf(opinion.universe, [0, 0, 2, 4] )
opinion['medium'] = fuzz.trapmf(opinion.universe, [2, 4, 6, 8])
opinion['high'] = fuzz.trapmf(opinion.universe, [6, 8, 10, 10])
```

```
transmission['low'] = fuzz.trapmf(transmission.universe, [0, 0, 2, 4] )
transmission['medium'] = fuzz.trapmf(transmission.universe, [2, 4, 6, 8])
transmission['high'] = fuzz.trapmf(transmission.universe, [6, 8, 10, 10])

status['low'] = fuzz.trapmf(status.universe, [0, 0, 2, 4] )
status['medium'] = fuzz.trapmf(status.universe, [2, 4, 6, 8])
status['high'] = fuzz.trapmf(status.universe, [6, 8, 10, 10])

sharing_importance['low'] = fuzz.trapmf(sharing_importance.universe, [0, 0, 2, 4] )
sharing_importance['medium'] = fuzz.trapmf(sharing_importance.universe, [2, 4, 6, 8])
sharing_importance['high'] = fuzz.trapmf(sharing_importance.universe, [6, 8, 10, 10])

# Define membership functions for the consequent outputs
sociability['very low'] = fuzz.trimf(sociability.universe, [0, 0, 0.2])
sociability['low'] = fuzz.trimf(sociability.universe, [0.0, 0.2, 0.4])
sociability['medium'] = fuzz.trimf(sociability.universe, [0.3, 0.5, 0.7])
sociability['high'] = fuzz.trimf(sociability.universe, [0.6, 0.8, 1.0])
sociability['very high'] = fuzz.trimf(sociability.universe, [0.8, 1.0, 1.0])

# Define fuzzy rules for the consequent outputs
rule_01 = ctrl.Rule(opinion['high'] & transmission['high'] & status['high'] & sharing_importance['high'], sociability['very high'])
rule_02 = ctrl.Rule(opinion['high'] & transmission['high'] & status['high'] & sharing_importance['medium'], sociability['very high'])
rule_03 = ctrl.Rule(opinion['high'] & transmission['high'] & status['high'] & sharing_importance['low'], sociability['high'])
rule_04 = ctrl.Rule(opinion['high'] & transmission['high'] & status['medium'] & sharing_importance['high'], sociability['very high'])
rule_05 = ctrl.Rule(opinion['high'] & transmission['high'] & status['medium'] & sharing_importance['medium'], sociability['high'])
rule_06 = ctrl.Rule(opinion['high'] & transmission['high'] & status['medium'] & sharing_importance['low'], sociability['medium'])
rule_07 = ctrl.Rule(opinion['high'] & transmission['high'] & status['low'] & sharing_importance['high'], sociability['very high'])
```

```
rule_08 = ctrl.Rule(opinion['high'] & transmission['high'] & status['
    low'] & sharing_importance['medium'], sociability['high'])
rule_09 = ctrl.Rule(opinion['high'] & transmission['high'] & status['
    low'] & sharing_importance['low'], sociability['low'])
rule_10 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['high'] & sharing_importance['high'], sociability['very high'])
rule_11 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['high'] & sharing_importance['medium'], sociability['high'])
rule_12 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['high'] & sharing_importance['low'], sociability['medium'])
rule_13 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['medium'] & sharing_importance['high'], sociability['high'])
rule_14 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['medium'] & sharing_importance['medium'], sociability['medium'])
rule_15 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['medium'] & sharing_importance['low'], sociability['low'])
rule_16 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['low'] & sharing_importance['high'], sociability['high'])
rule_17 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['low'] & sharing_importance['medium'], sociability['medium'])
rule_18 = ctrl.Rule(opinion['high'] & transmission['medium'] & status
    ['low'] & sharing_importance['low'], sociability['low'])
rule_19 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    high'] & sharing_importance['high'], sociability['high'])
rule_20 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    high'] & sharing_importance['medium'], sociability['medium'])
rule_21 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    high'] & sharing_importance['low'], sociability['low'])
rule_22 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    medium'] & sharing_importance['high'], sociability['high'])
rule_23 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    medium'] & sharing_importance['medium'], sociability['low'])
rule_24 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    medium'] & sharing_importance['low'], sociability['very low'])
rule_25 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    low'] & sharing_importance['high'], sociability['medium'])
rule_26 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    low'] & sharing_importance['medium'], sociability['low'])
rule_27 = ctrl.Rule(opinion['high'] & transmission['low'] & status['
    low'] & sharing_importance['low'], sociability['very low'])
rule_28 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['high'] & sharing_importance['high'], sociability['very high'])
rule_29 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['high'] & sharing_importance['medium'], sociability['high'])
```

```
rule_30 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['high'] & sharing_importance['low'], sociability['medium'])
rule_31 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['medium'] & sharing_importance['high'], sociability['very high'])
rule_32 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['medium'] & sharing_importance['medium'], sociability['high'])
rule_33 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['medium'] & sharing_importance['low'], sociability['medium'])
rule_34 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['low'] & sharing_importance['high'], sociability['high'])
rule_35 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['low'] & sharing_importance['medium'], sociability['medium'])
rule_36 = ctrl.Rule(opinion['medium'] & transmission['high'] & status
    ['low'] & sharing_importance['low'], sociability['low'])
rule_37 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['high'] & sharing_importance['high'], sociability['very
    high'])
rule_38 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['high'] & sharing_importance['medium'], sociability['high'
    ])
rule_39 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['high'] & sharing_importance['low'], sociability['low'])
rule_40 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['medium'] & sharing_importance['high'], sociability['high'
    ])
rule_41 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['medium'] & sharing_importance['medium'], sociability['
    medium'])
rule_42 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['medium'] & sharing_importance['low'], sociability['low'])
rule_43 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['low'] & sharing_importance['high'], sociability['high'])
rule_44 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['low'] & sharing_importance['medium'], sociability['low'])
rule_45 = ctrl.Rule(opinion['medium'] & transmission['medium'] &
    status['low'] & sharing_importance['low'], sociability['very low'
    ])
rule_46 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'high'] & sharing_importance['high'], sociability['high'])
rule_47 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'high'] & sharing_importance['medium'], sociability['medium'])
rule_48 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'high'] & sharing_importance['low'], sociability['low'])
rule_49 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'medium'] & sharing_importance['high'], sociability['medium'])
```

```
rule_50 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'medium'] & sharing_importance['medium'], sociability['low'])
rule_51 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'medium'] & sharing_importance['low'], sociability['very low'])
rule_52 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'low'] & sharing_importance['high'], sociability['medium'])
rule_53 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'low'] & sharing_importance['medium'], sociability['low'])
rule_54 = ctrl.Rule(opinion['medium'] & transmission['low'] & status[
    'low'] & sharing_importance['low'], sociability['very low'])
rule_55 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    high'] & sharing_importance['high'], sociability['very high'])
rule_56 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    high'] & sharing_importance['medium'], sociability['high'])
rule_57 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    high'] & sharing_importance['low'], sociability['medium'])
rule_58 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    medium'] & sharing_importance['high'], sociability['very high'])
rule_59 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    medium'] & sharing_importance['medium'], sociability['high'])
rule_60 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    medium'] & sharing_importance['low'], sociability['low'])
rule_61 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    low'] & sharing_importance['high'], sociability['high'])
rule_62 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    low'] & sharing_importance['medium'], sociability['medium'])
rule_63 = ctrl.Rule(opinion['low'] & transmission['high'] & status['
    low'] & sharing_importance['low'], sociability['low'])
rule_64 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'high'] & sharing_importance['high'], sociability['high'])
rule_65 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'high'] & sharing_importance['medium'], sociability['medium'])
rule_66 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'high'] & sharing_importance['low'], sociability['low'])
rule_67 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'medium'] & sharing_importance['high'], sociability['high'])
rule_68 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'medium'] & sharing_importance['medium'], sociability['medium'])
rule_69 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'medium'] & sharing_importance['low'], sociability['low'])
rule_70 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'low'] & sharing_importance['high'], sociability['medium'])
rule_71 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'low'] & sharing_importance['medium'], sociability['low'])
```

```
rule_72 = ctrl.Rule(opinion['low'] & transmission['medium'] & status[
    'low'] & sharing_importance['low'], sociability['very low'])
rule_73 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    high'] & sharing_importance['high'], sociability['high'])
rule_74 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    high'] & sharing_importance['medium'], sociability['low'])
rule_75 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    high'] & sharing_importance['low'], sociability['very low'])
rule_76 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    medium'] & sharing_importance['high'], sociability['medium'])
rule_77 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    medium'] & sharing_importance['medium'], sociability['low'])
rule_78 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    medium'] & sharing_importance['low'], sociability['very low'])
rule_79 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    low'] & sharing_importance['high'], sociability['low'])
rule_80 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    low'] & sharing_importance['medium'], sociability['very low'])
rule_81 = ctrl.Rule(opinion['low'] & transmission['low'] & status['
    low'] & sharing_importance['low'], sociability['very low'])


# Create the control system
sociability_ctrl = ctrl.ControlSystem([rule_01, rule_02, rule_03,
    rule_04, rule_05, rule_06, rule_07, rule_08, rule_09,
                                       rule_10, rule_11, rule_12,
                                          rule_13, rule_14, rule_15,
                                          rule_16, rule_17, rule_18,
                                       rule_19, rule_20, rule_21,
                                          rule_22, rule_23, rule_24,
                                          rule_25, rule_26, rule_27,
                                       rule_28, rule_29, rule_30,
                                          rule_31, rule_32, rule_33,
                                          rule_34, rule_35, rule_36,
                                       rule_37, rule_38, rule_39,
                                          rule_40, rule_41, rule_42,
                                          rule_43, rule_44, rule_45,
                                       rule_46, rule_47, rule_48,
                                          rule_49, rule_50, rule_51,
                                          rule_52, rule_53, rule_54,
                                       rule_55, rule_56, rule_57,
                                          rule_58, rule_59, rule_60,
                                          rule_61, rule_62, rule_63,
```

```
                                                rule_64, rule_65, rule_66,
                                                    rule_67, rule_68, rule_69,
                                                    rule_70, rule_71, rule_72,
                                                rule_73, rule_74, rule_75,
                                                    rule_76, rule_77, rule_78,
                                                    rule_79, rule_80, rule_81])

# Create the simulation
sociability_control = ctrl.ControlSystemSimulation(sociability_ctrl)

# Generate Brazilian experts inputs
opinion = [6, 5, 9, 10, 7, 7, 7, 2, 0, 4, 2, 10, 8, 6]
transmission = [4, 5, 8, 8, 10, 2, 10, 7, 2, 6, 4, 7, 7, 3]
status = [6, 6, 8, 9, 9, 8, 8, 4, 0, 6, 7, 10 , 8, 8]
sharing_importance = [6, 8, 5, 10 ,9, 6, 10, 10, 0, 6, 7, 10, 7, 4]
inputs = list(zip(opinion, transmission, status, sharing_importance))

# Generate German experts inputs
# opinion = [4, 6, 1, 4, 3, 3, 4]
# transmission = [2, 4, 5, 8, 1, 2, 3]
# status = [4, 1, 2, 7, 1, 7, 2]
# sharing_importance = [4, 2, 4, 9, 0, 2, 6]
# random_inputs = list(zip(opinion, transmission, status,
    sharing_importance))

# Initialize a list to store the resulting sociability values
resulting_sociabilities = []

# Calculate recommended speeds for the random scenarios
for i, (opinion_val, transmission_val, status_val, sharing_val) in
    enumerate(inputs, 1):
     sociability_control.input['opinion'] = opinion_val
     sociability_control.input['transmission'] = transmission_val
     sociability_control.input['status'] = status_val
     sociability_control.input['sharing_importance'] = sharing_val
     sociability_control.compute()
     resulting_sociability = sociability_control.output['sociability']
     resulting_sociabilities.append(resulting_sociability)

     # Determine the sociability category based on the membership
         functions
     sociability_category = fuzz.interp_membership(sociability.
         universe, sociability['very low'].mf, resulting_sociability),
         \
```

```
        fuzz.interp_membership(sociability.universe, sociability['low
            '].mf, resulting_sociability), \
        fuzz.interp_membership(sociability.universe, sociability['
            medium'].mf, resulting_sociability), \
        fuzz.interp_membership(sociability.universe, sociability['
            high'].mf, resulting_sociability), \
        fuzz.interp_membership(sociability.universe, sociability['
            very high'].mf, resulting_sociability)
    categories = ["very low", "low", "medium", "high", "very high"]
    category = categories[sociability_category.index(max(
        sociability_category))]

    print(f"Participant {i}: opinion={opinion_val:.2f}, transmission
        ={transmission_val:.2f}, "
          f"status={status_val:.2f}, sharing_importance={sharing_val
              :.2f},  Sociability={resulting_sociability:.2f},
              Sociability Category={category}")

# Calculate and print the average of results
average_sociability = np.mean(resulting_sociabilities)
print(f"Average Sociability: {average_sociability:.2f}")
```

C Model Evaluation Metrics

In this appendix, the metrics utilized to assess the performance and accuracy of the model predictions are presented. The evaluation metrics considered for the model include the mean ($\bar{y}$), sample standard deviation (σ_s), coefficient of determination (R^2), root mean square error ($RMSE$), and mean absolute error (MAE) [217], [218].

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_\mathrm{i} \tag{C.1}$$

$$\sigma_\mathrm{s} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(y_\mathrm{i} - \bar{y}\right)^2} \tag{C.2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_\mathrm{i} - y_\mathrm{i}^{'})^2}{\sum_{i=1}^{n}\left(y_\mathrm{i} - \bar{y}\right)^2} \tag{C.3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_\mathrm{i} - y_\mathrm{i}^{'})^2} \tag{C.4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_\mathrm{i} - y_\mathrm{i}^{'}| \tag{C.5}$$

Where:

- y_i is the actual i^{th} value;
- $y_\mathrm{i}^{'}$ is the predicted i^{th} value;
- R^2 is the coefficient of determination or R-squared;

Res Electricae Magdeburgenses

MAgdeburger FOrum zur Elektrotechnik

OTTO VON GUERICKE UNIVERSITÄT MAGDEBURG

MAFO-01 ORTHS, A.: *Multikriterielle, optimale Planung von Verteilungsnetzen im liberalisierten Energiemarkt unter Verwendung von spieltheoretischen Verfahren*, 2003. ISBN 3-929757-57-5.

MAFO-02 PURMANN, M.: *Optimierung des Betriebsverhaltens von PEM-Brennstoffzellen unter Berücksichtigung von elektrischem und Gesamtwirkungsgrad bei unterschiedlichen Lastanforderungen und Betriebsparametern*, 2004. ISBN 3-929757-63-X.

MAFO-03 AL-HAMID, M.: *Extraktion von höheren Moden in TEM-Wellenleitern*, 2004. ISBN 3-929757-64-8.

MAFO-04 HAASE, H., J. NITSCH, and T. STEINMETZ: *Transmission-Line Super Theory – A new Approach to an Effective Calculation of Electromagnetic Interference*, 2004. ISBN 3-929757-67-2.

MAFO-05 BACHRY, A.: *Power Quality Studies in Distribution Systems Involving Spectral Decomposition*, 2004. ISBN 3-929757-68-0.

MAFO-06 STYCZYNSKI, Z. A.: *Power Network and Renewables – A Scientific Report*, 2004. ISBN 3-929757-69-9.

MAFO-07 BLUME, E.: *Numerische Analyse der Kopplung linearer Antennen innerhalb eines Resonators*, 2004. ISBN 3-929757-71-0.

MAFO-08 HANDSCHIN, E. and Z. A. STYCZYNSKI: *Power System Application of the Modern Battery Storage*, 2004. ISBN 3-929757-75-3.

MAFO-09 HAASE, H.: *Full-Wave Field Interactions of Nonuniform Transmission Lines*, 2005. ISBN 3-929757-78-8.

MAFO-10 NITSCH, D.: *Die Wirkung eingekoppelter ultrabreitbandiger elektromagnetischer Impulse auf komplexe elektronische Systeme*, 2005. ISBN 3-929757-79-6.

MAFO-11 HADZI-KOSTOVA, B.: *Protection Concepts in Distribution Networks with Decentralized Energy Resources*, 2005. ISBN 3-929757-84-2.

MAFO-12 STEINMETZ, T.: *Ungleichförmige und zufällig geführte Mehrfachleitungen in komplexen technischen Systemen*, 2006. Nummerierung geändert, ISBN 3-929757-98-2.

MAFO-13 STYCZYNSKI, Z. and J. HAUBROCK: *Influence of Distributed and Renewable Generation on Power System Security – Proceedings of the CRIS Workshop 2006*, 2006. ISBN 3-929757-99-0.

MAFO-14 HEIDECK, G.: *Ein autonomes Brennstoffzellensystem: Optimierungsansätze*, 2006. ISBN 3-929757-94-X.

MAFO-15 STYCZYNSKI, Z. und H.-D. MUSIKOWSKI: *Dresdener Kreis Elektroenergieversorgung 7*, 2006. ISBN 3-929757-85-0.

MAFO-16 GRONWALD, F.: *Antenna Theory in Resonating Systems derived from Fundamental Electromagnetism*, 2007. ISBN 3-929757-93-1.

MAFO-17 KRAUTHÄUSER, H.G.: *Grundlagen und Anwendungen von Modenverwirbelungskammern*, 2007. ISBN 978-3-929757-43-9.

MAFO-18 DZIENIS, C.: *Ersatzmodelle nichtlinearer Lasten in elektrischen Verteilungsnetzen*, 2007. ISBN 978-3-929757-07-1.

MAFO-19 Styczynski, Z. and J. Haubrock: *Renewable and Dispersed Power Generation in Power Systems*, 2007. ISBN 978-3-929757-44-6.

MAFO-20 Haubrock, J.: *Parametrierung elektrischer Äquivalentschaltbilder von PEM-Brennstoffzellen*, 2008. ISBN 978-3-940961-02-0.

MAFO-21 Angelov, A. N.: *Rechnergestütztes Lernen im Bereich der Regenerativen Energien (Ausgewählte Aspekte)*, 2008. ISBN 978-3-940961-03-7.

MAFO-22 Komarnicki, P.: *Anwendung hochgenauer, synchroner Messungen zur Verbesserung des Betriebs von Verteilungsnetzen*, 2008. ISBN 978-3-940961-04-4.

MAFO-23 Roggatz, C.: *Trainingssimulator für die Führung von elektrischen Systemen mit dezentralen Energieeinspeisungen – Trainingsszenarien und Umsetzung*, 2008. ISBN 978-3-940961-05-1.

MAFO-24 Rudion, K.: *Aggregated Modelling of Wind Farms*, 2008. ISBN 978-3-940961-14-3.

MAFO-25 Ganjavi, M. R.: *Protection System Coordination Using Expert System*, 2008. ISBN 978-3-940961-15-0.

MAFO-26 Bofinger, S.: *Energieversorgungsnetze mit einem hohen Anteil an photovoltaischer Solarenergie: Standortbestimmung, Solarstromprognose, Netzintegration*, 2008. ISBN 978-3-940961-25-9.

MAFO-27 Styczynski, Z. and P. Komarnicki: *Distributed and Renewable Power Generation*, 2008. ISBN 978-3-940961-26-6.

MAFO-28 Kochetov, S. V.: *Time- and Frequency-Domain Modeling of Passive Interconnection Structures in Field and Circuit Analysis*, 2008. ISBN 978-3-940961-27-3.

MAFO-29 Magdowski, M.: *Entwicklung und Validierung eines Werkzeugs zur Berechnung der elektromagnetischen Einkopplung von stochastischen Feldern in Leitungsstrukturen*, 2008. ISBN 978-3-940961-28-0.

MAFO-30 Sonnemann, F.: *Elektromagnetische Effekte an elektrischen Zündmitteln (EED) mit angeschlossener Zündkreiselektronik (ZKE) bei impulsförmiger, breitbandiger Bestrahlung*, 2009. ISBN 978-3-940961-32-7.

MAFO-31 Smieja, T.: *Multikriterielle Planung interregionaler Elektrizitätsnetze im liberalisierten Energiemarkt*, 2009. ISBN 978-3-940961-35-8.

MAFO-32 Heyde, C. O.: *Dynamic Voltage Security Assessment for On-Line Control Room Application*, 2010. ISBN 978-3-940961-40-2.

MAFO-33 Styczynski, Z. A. and N. I. Voropai (Editors): *Renewable Energy Systems Fundamentals, Technologies, Techniques and Economics*, 2010. ISBN 978-3-940961-42-6.

MAFO-34 Styczynski, Z. A. и N. I. Voropai (Editors): Renewable Energy Systems Fundamentals, Technologies, Techniques and Economics (Russian Version), 2010. ISBN 978-3-940961-44-0.

MAFO-35 Styczynski, Z. A. and A. Lindemann (Editors): *Integration of Renewable Energies into the Grid / Proceedings of the Power & Energy Student Summit 2010*, 2010. ISBN 978-3-940961-47-1.

MAFO-36 Styczynski, Z. A. und H.-D. Musikowski (Editors): *Dresdener Kreis Elektroenergieversorgung 11*, 2010. ISBN 978-3-940961-51-8.

MAFO-37 Gurbiel, M. A.: *Definition and Testing of a Digital Interface of a Power Substation*, 2011. ISBN 978-3-940961-54-9.

MAFO-38 Lombardi, P.: *Multi Criteria Optimization of an Autonomous Virtual Power Plant*, 2011. ISBN 978-3-940961-55-6.

MAFO-39 Powalko, M.: *Beobachtbarkeit eines elektrischen Verteilungsnetzes – Ein Beitrag zum Smart Grid*, 2011. ISBN 978-3-940961-62-4.

MAFO-40 Styczynski, Z. A., K. Rudion, and C. Nguyen-Mau (Editorial Board): *Power System Dynamic Security Assessment*, 2011. ISBN 978-3-940961-61-7.

MAFO-41 Käbisch, M: *Optimale Dimensionierung und Betriebsführung einer brennstoffzellenbasierten Auxiliary Power Unit im Fahrzeug*, 2011. ISBN 978-3-940961-67-9.

MAFO-42 Styczynski, Z. A. und N. I. Voropai (Editors): *Special Issue Grant 220 Russian Federation SSmart Grid for Efficient Energy Power System for the Future", Proceedings Volume I*, 2012. ISBN 978-3-940961-74-7.

MAFO-43 Styczynski, Z. A., P. Komarnicki und A. Naumann (Editors): *Abschlussbericht Harz.ErneuerbareEnergien-mobility*, 2012. ISBN 978-3-940961-71-6.

MAFO-44 Heuer, M.: *Diagnosetool für stationär betriebene PEM-Brennstoffzellensysteme*, 2012. ISBN 978-3-940961-77-8.

MAFO-45 Stötzer, M.: *Demand Side Integration in elektrischen Verteilnetzen – Potenzialanalyse und Bewertung*, 2012. ISBN 978-3-940961-78-5.

MAFO-46 Magdowski, M.: *Vergleich der Einkopplung deterministischer und statistischer elektromagnetischer Felder in Leitungen*, 2012. ISBN 978-3-940961-75-4.

MAFO-47 Naumann, A.: *Leitwarte im Smart Grid*, 2012. ISBN 978-3-940961-81-5.

MAFO-48 Rudion, K.: *Offshore Power System Planning – Selected Aspects*, 2012. ISBN 978-3-940961-82-2.

MAFO-49 Nguyen-Mau, C.: *Electric Power System Stability Enhancement by Voltage Source Converter based High Voltage Direct Current Technology*, 2012. ISBN 978-3-940961-84-6.

MAFO-50 Guo, H.: *Measurement-Based Load Modeling for Smart Grid Planning*, 2012. ISBN 978-3-940961-86-0.

MAFO-51 Styczynski, Z. A.: *Proceedings No. 2 in the Scope of Mega Grant Baikal*, 2013. ISBN 978-3-940961-95-2.

MAFO-52 Styczynski, Z. A.: *Proceedings No. 3 in the Scope of Mega Grant Baikal*, 2013. ISBN 978-3-940961-98-3.

MAFO-53 Wenge, C.: *Optimaler Betrieb von mobilen Speichern im Smart Grid. -Mobilitätsleitwarte-*, 2013. ISBN 978-3-944722-01-6.

MAFO-54 Röhrig, C.: *Smart Distribution Planung unter Berücksichtigung von residualen Lasten*, 2014. ISBN 978-3-944722-06-1.

MAFO-55 Middelstädt, F.: *Research of SEM Poles of Complex Wire Structures*, 2014. ISBN 978-3-944722-07-8.

MAFO-56 Styczynski, Z. A. (Editor): *Power Network and Renewables – A Scientific Report – 15 Years Research*, 2014. ISBN 978-3-944722-08-5.

MAFO-57 Solonina, N. N., V. S. Stepanov, and K. V. Suslov: *Information technology in intelligent power networks*, 2014. ISBN 978-3-944722-13-9.

MAFO-58 Krebs, R.: *Fundamentals of Power System Protection*, 2014. ISBN 978-3-944722-15-3.

MAFO-59 Moskalenko, N.: *Optimal Dynamic Energy Management System in Smart Homes*, 2014. ISBN 978-3-944722-16-0.

MAFO-60 Hauer, I.: *Optimale Last- und Erzeugungsanpassung bei kritischen Netzzuständen – Algorithmen und deren Bewertung*, 2014. ISBN 978-3-944722-18-4.

MAFO-61 Richter, M.: *Dresdner Kreis Elektroenergieversorgung 15, Begleitband zum Workshop 2014*, 2014. ISBN 978-3-944722-21-4.

MAFO-62 Styczynski, Z. A., A. Richter und P. Kühne: *Second ELECON Workshop – Begleitband zum Workshop 2014*, 2014. ISBN 978-3-944722-23-8.

MAFO-63 Bernstein, P.: *Modellgestützte optimale Betriebsführung von PEM-Brennstoffzellen für autonome Anlagen*, 2015. ISBN 978-3-944722-24-5.

MAFO-64 Rabe, S.: *Betrieb einer Zweipunkt-Offshore-HGÜ-Verbindung – Modelluntersuchungen*, 2015. ISBN 978-3-944722-31-3.

MAFO-65 Arendarski, B.: *Reliability Assessment of Smart Grids*, 2015. ISBN 978-3-944722-32-0.

MAFO-66 Pan, X.: *Numerisches EMV-Simulationsverfahren zur Berechnung der Störaussendung elektrischer Antriebssysteme in Hybridfahrzeugen*, 2016. ISBN 978-3-944722-34-4.

MAFO-67 Richter, M.: *PMU-basierte Zustandsabschätzung in Smart Distribution*, 2016. ISBN 978-3-944722-43-6.

MAFO-68 Bielchev, I.: *Adaptiver Distanzschutz im Standard IEC 61850*, 2016. ISBN 978-3-944722-45-0.

MAFO-69 Hassan, A.: *Modeling of Single and Double-Shielded Cables for EMC Applications*, 2016. ISBN 978-3-944722-41-2.

MAFO-70 Liu, X.: *Control of Voltage Source Converter Based High Voltage Direct Current Transmission Systems for Grid Code Compliance*, 2016. ISBN 978-3-944722-46-7.

MAFO-71 Kaiser, M.: *Fusion of Interventional Ultrasound & X-ray*, 2016. ISBN 978-3-944722-51-1.

MAFO-72 Grieger, F.: *Ein Beitrag zur Bestimmung der Zuverlässigkeit von Leistungshalbleiterbauelementen unter Berücksichtigung der Anwendung*, 2016. ISBN 978-3-944722-52-8.

MAFO-73 Li, M.: *Towards a Robust Electromagnetic Tracking System for Use in Medical Applications*, 2018. ISBN 978-3-944722-66-5.

MAFO-74 Klabunde, C., J. Dancker, N. Gast, T. Schröter, F. Schulz, J. Rossberg und A. Richter: *Statusbericht der Otto-von-Guericke-Universität Magdeburg zum Verbundprojekt: Intelligentes Multi-Energie-System (SmartMES)*, 2018. ISBN 978-3-944722-69-6.

MAFO-75 Schröter, T.: *19. Dresdner Kreis Elektroenergieversorgung, Begleitband zum Workshop 2018 in Magdeburg*, 2018. ISBN 978-3-944722-79-5.

MAFO-76 Klabunde, C., J. Dancker, N. Gast, T. Schröter, F. Schulz und J. Rossberg: *Intelligentes Multi-Energie-System (SmartMES) – Statusbericht der Otto-von-Guericke-Universität Magdeburg zum Verbundprojekt, 2. Statusseminar 04. April 2019 in Magdeburg*, 2019. ISBN 987-3-944722-80-1.

MAFO-77 Helm, S., J. Dancker, M. Fritsch und T. Schröter: *Power and Energy Student Summit 2019, 09.–11. Juli*, 2019. ISBN 978-3-944722-84-9.

MAFO-78 Chychykina, I.: *Comparison of Different Redispatch Optimization Strategies*, 2019. ISBN 978-3-944722-89-4.

MAFO-79 Balischewski, S.: *Multifunktionaler Einsatz von Batteriespeichern in elektrischen Verteilnetzen*, 2020. ISBN 978-3-944722-92-4.

MAFO-80 Petzold, J.: *Analytische Beschreibung der Kopplung elektromagnetischer Felder durch Aperturen in Resonatoren*, 2020. ISBN 978-3-944722-91-7.

MAFO-81 Middelstädt, L.: *Transiente Effekte in leistungselektronischen Schaltungen mit schnellschaltenden Leistungshalbleitern unter besonderer Berücksichtigung der elektromagnetischen Verträglichkeit*, 2020. ISBN 978-3-944722-95-5.

MAFO-82 Liu, Y.: *Contribution to Improve the EMI Performance of Electrical Drive Systems in Vehicles With Special Consideration of Power Semiconductor Modules*, 2021. ISBN 978-3-948749-01-9.

MAFO-83 Gerlach, A.: *Regelung von direktangetriebenen elektrischen Maschinen für Verbrennungsmotoren*, 2021. ISBN 978-3-948749-03-3.

MAFO-84 Zhang, Y.: *Analysis and Control of Resonances in HVDC Connected DFIG-Based Offshore Wind Farms*, 2021. ISBN 978-3-948749-05-7.

MAFO-85 Pannicke, E.: *Empfangsspulen für bildgeführte Eingriffe mittels Magnetresonanztomographie*, 2021. ISBN 978-3-948749-12-5.

MAFO-86 Kasper, J.: *Analysis of the Stochastic Electromagnetic Field Coupling to Single and Multiconductor Transmission Line Structures*, 2021. ISBN 978-3-948749-13-2.

MAFO-87 Hauer, I.: *Abschlussbericht zum Projekt InKola: Infrastrukturkopplung – Platzierung und Betrieb von Ladestationen aus Verkehrs- und Energienetzsicht*, 2022. ISBN 978-3-948749-15-6.

MAFO-88 Raya, M.: *Circuit Models of Shielded Single and Multiconductor Cables for EMC Analyses*, 2022. ISBN 978-3-948749-16-3.

MAFO-89 Pribahsnik, F.: *GaN-Specific Mechanical Phenomena and Their Influence on Reliability in Power HEMT Operation*, 2022. ISBN 978-3-948749-17-0.

MAFO-90 Willmann, B.: *Elektromagnetische Umweltverträglichkeit eines Elektrofahrzeugs mit kontaktlosem Ladesystem*, 2022. ISBN 978-3-948749-19-4.

MAFO-91 Dancker, J.: *Sensitivity Factors for Integrated Energy Systems: A Joined Quasi-Steady-State Approach*, 2022. ISBN 978-3-948749-24-8.

MAFO-92 Tayyab, M.: *Holistic Approach for Microgrid Planning and Operation for E-Mobility Infrastructure Under Consideration of Multi-Type Uncertainties*, 2022. ISBN 978-3-948749-25-5.

MAFO-93 Richter, A.: *Virtuelle Kraftwerke im Verteilnetz – Systemstützender Betrieb im wirtschaftlichen Kontext – Eine gesamtheitliche Betrachtung virtueller Kraftwerke*, 2022. ISBN 978-3-948749-28-6.

MAFO-94 Woldu, T.: *Modeling and Simulation of Power System Dynamics for Studying the Impacts of Increasing Wind Power in a Weak Grid System*, 2022. ISBN 978-3-948749-31-6.

MAFO-95 Könneke, N.: *Entwurf eines Testbetts für Assistenzsysteme in der Netz- und Systemführung*, 2023. ISBN 978-3-948749-32-3.

MAFO-96 Glende, E. und M. Gebhardt: *23. Dresdner Kreis Elektroenergieversorgung, Begleitband zum Workshop 2022 in Magdeburg*, 2022. ISBN 978-3-948749-33-0.

MAFO-97 Kempiak, C.: *Lastwechselmethoden für Siliziumkarbid-MOSFETs unter Berücksichtigung von deren Schwellspannungsinstabilität*, 2023. ISBN 978-3-948749-38-5.

MAFO-98 Fritsch, M.: *Measurement of Partial Discharges on Power Cables: A Step Towards Successful Online Monitoring*, 2024. ISBN 978-3-948749-43-9.

MAFO-99 Middelstädt, F.: *Electromagnetic Field Coupling to Thin Wires Above a Ground*, 2024. ISBN 978-3-948749-43-9.

MAFO-100 Helm, S.: *Optimiertes Lademanagement von E-Kfz zur Spannungsstabilisierung im Niederspannungsnetz*, 2024. ISBN 978-3-948749-48-4.

MAFO-101 Wilhelmi, F.: *On the characteristic electrical and thermal properties of beta-phase gallium oxide (β–Ga2O3) Schottky diodes in view of their potential application in power*, 2024. ISBN 978-3-948749-49-1.