A framework for evaluating site-specific risks for a climate-neutral energy supply of companies

Masterthesis

submitted on: July 17, 2023

Institute of Economics, University of Ulm

Name: Niklas Steinmann
Course of Studies: Wirtschaftsphysik
1^{st} supervisor: Prof. Dr. Georg Gebhardt
2^{nd} supervisor: Dr.-Ing. Hans-Christian Gils

ABSTRACT

Für eine einzelne Firma ist es in der Theorie immer möglich, die eigenen „Scope-2-Emissionen“ zu verringern. Allerdings ist die Umsetzung dessen durch politische oder physikalische Rahmenbedingungen limitiert. Die Hypothese dieser Arbeit ist also, dass das verfügbare Potential von erneuerbaren Energieträgern nicht ausreichet, um den Energiebedarf jeder Firma an jedem Standort abzudecken, was im Widerspruch zu einer nachhaltigen Zukunft steht. Ein umfassendes Versorgungsrisiko-Management eines Unternehmens muss mit „State-of-the-art“-Forschungsergebnissen aus den Feldern Nachfrage- und Energieinfrastruktur-Modellierung sowie Marktentwicklung dynamisch interagieren.
Forschungsarbeiten in den genannten Felder sind für derartige Anwendung nicht ausgelegt. Die vorliegende Arbeit zielt darauf ab, diese Forschungslücke zu schließen. Forschungsergebnisse der Felder Stromversorgung und -infrastruktur, namentlich das REMix-Model des Deutschen Zentrum für Luft-und Raumfahrts, werden mit unternehmensspezifischen Verbrauchsvorhersagen gekoppelt. In dieser Forschungsarbeit wird eine KPI entwickelt, welche das Versorgungsrisiko mit klimaneutralem Strom auf Basis zukünftiger Energiesysteme direkt bewertet, sowohl auf nationaler als auch auf unternehmensspezifischer Ebene. Das Modell wird an zwei Fallstudien der *BMWGroup* und *WALA Heilmittel GmbH* in Deutschland getestet, die hohe Diskrepanzen in den bundesweiten und lokalen Risikometriken zeigen. Dies dient als Maßstab für den Widerspruch von Forschungsergebnissen bezüglich der Stromversorgung in einer klimaneutralen Energielandschaft und den Wachstumsprognosen für einzelne Unternehmen. Andererseits zeigen lokale Untersuchungen Unternehmensstandorte auf, an denen die Versorgung mit erneuerbaren Energien zuverlässig ist. Das in dieser Forschungsarbeit erstellte Modell hilft somit bei der Entscheidungsfindung in Unternehmen, um eine zukunftsfähige Entwicklung zu gewährleisten.

ABSTRACT

For an individual company it is theoretically always possible to reduce energy-related greenhouse gas emissions, the so-called "Scope 2 emissions". However, this is only possible within certain political or physical limits. The hypothesis of the research is that the available potential of renewable energy sources may not be sufficient to cover all energy demands at every location for a company, which stands in contradiction to a sustainable future. For a holistic supply risk assessment the company's energy management has to dynamically interact with state-of-the-art understanding of energy demand modelling, energy infrastructure modelling and market developments. Research in the latter fields are not tailored to such application.

This thesis aims to bridge that gap. Results for electricity supply and infrastructure research aimed towards a climate neutral economic landscape, namely results from the *REMix* model developed by the *German Aerospace Center*, are combined with company specific demand predictions in the form of regressions. A KPI is developed in this research, which directly assesses the supply risk with climate neutral electricity based on future energy systems, on the nation wide as well as at the company level. The model is tested on two case studies of the *BMWGroup* and *WALA Heilmittel GmbH* in Germany, which show high discrepancies in nation wide and localized risks. This serves as a benchmark of the contradiction between research aimed at electricity supply in a climate neutral energy landscape and growth projections for singular companies. On the other hand, local investigations point out company sites where the supply with renewables is reliable. The model created in this research can in turn aid with executive decisions within companies to ensure guided development in the light of a sustainable future.

Contents

1 Introduction **8**
1.1 Motivation . . . 8
1.2 Research hypothesis . . . 8
1.3 State-of-the-art . . . 9
1.3.1 Energy consumption modelling . . . 9
1.3.2 Energy Management at the company level . . . 9
1.3.3 Supply side analyses on large scales . . . 10
1.3.4 Methods for assessing companies . . . 11
1.4 Research contribution . . . 11

2 Methodology **13**
2.1 Nation wide Model . . . 13
2.1.1 Electricity consumption . . . 13
2.1.2 Electricity supply . . . 16
2.1.3 Riskmetric . . . 19
2.2 Site specific model . . . 22
2.2.1 Local availability of renewables . . . 22
2.2.2 Electricity consumption . . . 26
2.2.3 Riskmetric . . . 27

3 Case study - BMW **30**
3.1 Economic background and sustainability goals . . . 30
3.2 Nation wide analysis . . . 31
3.2.1 GVA and electricity consumption . . . 31
3.2.2 Electricity supply . . . 33
3.2.3 Riskmetric . . . 33
3.3 Local analysis . . . 35
3.3.1 Local availability of renewables . . . 35
3.3.2 Electricity consumption . . . 36
3.3.3 Riskmetric . . . 37
3.4 Sensitivty analysis . . . 38
3.5 Result discussion . . . 41

4 Case study - WALA Heilmittel GmbH **44**
4.1 Economic background and sustainability goals . . . 44
4.2 Nation wide analysis . . . 44
4.2.1 GVA and electricity consumption . . . 44
4.2.2 Electricity supply . . . 47
4.2.3 Riskmetric . . . 47

4.3 Local analysis 49
4.3.1 Local availability of renewables 49
4.3.2 Electricity consumption 50
4.3.3 Riskmetric 50
4.4 Result discussion 51

5 Add-On: Benchmarking 54
5.1 Benchmarking BMW against the automotive sector 54
5.1.1 Automotive sector - overview 54
5.1.2 Comparison - EEI 55
5.2 Benchmarking WALA against the chemical industries sector . 56
5.2.1 Chemical industries sector - overview 56
5.2.2 Comparison - EEI 56

6 Model Improvements and Discussion 59
6.1 Improvements 59
6.1.1 Regression model variations 59
6.1.2 Analytical function for nation wide supply 60
6.1.3 Alternatives to the regression model 61
6.1.4 Localization improvements 62
6.2 Further Discussion 64
6.2.1 Local scenario investigation 64
6.2.2 Internal considerations for companies 65

7 Conclusion 67

8 Bibliography 69

9 Appendix 73
9.1 BMW - Tables, Figures and Data 73
9.2 WALA - Tables, Figures and Data 73

List of Figures

1 Flowchart - company electricity demand forecast. 16
2 Flowchart - nation wide electricity supply forecast. 18
3 Histogram - nation wide electricity supply. 18
4 Histogram - share in renewable electricity generation. 19
5 Histogram - nation wide renewable electricity generation . . . 20
6 Flowchart - consumption comparison 21
7 Flowchart - localized renewable electricity availability 23
8 Geographical regions *BMW* Berlin 25
9 Flowchart - site specific electricity consumption forecast. . . . 27
10 Flowchart - localized site specific risk metric. 28
11 *BMW*'s GVA against the years 32
12 *BMW*'s electricity consumption against the years 33
13 Linear regression for *BMW*'s EEI 34
14 Electricity supply theoretically available to *BMW* 35
15 Local results for share of renewables for *BMW*'s company sites. 37
16 *BMW* - Final results for each company site 38
17 *BMW* - Alternative GVA against the years 39
18 *BMW* - Share of consumption on nation wide consumption. . 40
19 Final result histogram for *BMW*'s nation wide analyses 42
20 *WALA*'s GVA against the years. 45
21 *WALA*'s electricity consumption against the years 46
22 Linear regression for *WALA*'s EEI 47
23 Electricity supply theoretically available to *WALA* 48
24 Geographic regions *WALA* Bad Boll 50
25 Local results for share of renewables for Bad Boll company site 51
26 EEI of *BMW* and the german automotive sector 56
27 EEI difference quotient for *BMW* and automotive sector . . . 57
28 EEI of *WALA* and the german chemical industries sector . . . 58
29 EEI difference quotient for *WALA* and chemical industries sector 58
30 Histogram - density function for nation wide electricity supply. 60
31 Histogram - density function of the share of renewable electricity. 61
32 *UNSEEN* framework parameters for local scenarios 64
33 BMW - Data overview 73
34 BMW - Data overview, GVA 74
35 Automotive Sector - Data overview, electricity consumption . 75
36 Automotive Sector - Data overview, GVA 75
37 Localized scenario validation results for *BMW*'s company sites 76
38 Geographical regions - *BMW* Dingolfing 76
39 Geographical regions - *BMW* Eisenach 77

40 Geographical regions - *BMW* Landshut 77
41 Geographical regions - *BMW* Leipzig 78
42 Geographical regions - *BMW*'s Munich 78
43 Geographical regions - *BMW* Regensburg 79
44 Geographical regions - *BMW* Wackersdorf 79
45 WALA - Data overview 80
46 *WALA* - Local share of renewably produced electricity 80
47 *WALA* - Localized scenario validation results 80

List of Tables

1 Glossary 7
2 Nomenclature 7
3 Technology from *UNSEEN* framework results. 24
4 Result overview for *BMW*'s national analysis. 35
5 *BMW* company sites overview 36
6 Result overview for *BMW*'s alternative national analysis . . . 41
7 *WALA Heilmittel GmbH*'s company site in Germany 49
8 Result overview for *WALA*'s national analysis. 52

Abbreviation	Full Description	Explanation
KPI	Key Performance Indicator	A type of performance measurement. KPIs evaluate the success of an organization in which it engages.
GVA	Gross Value Added	Economic measure. GVA = GDP + subsidies on products - taxes on products, given in mn. EUR or tsd. EUR
XDC-Metric	X Degree Compatability	right. based on science in-house climate performance indicator, see 1.3.4
EEI	Electricity efficiency index	Measure for energy efficient utilization of economic goods. In the context of this thesis: $EEI = \frac{Elec.cons.}{GVA}$, given in $\frac{\text{GWh}}{\text{tsd. EUR}}$. **Note:** In respective literature this quantity is usually defined reciprocal, i.e. $\frac{GVA}{Elec.cons.}$
REMix	Renewable energy mix for a sustainable power supply	DLR Model, see [21].
UNSEEN	REMix model instance	Specified implementation of the REMix model, see [21] and 2.1.2
DLR	*German Aerospace Center*	*Deutsches Zentrum für Luft- und Raumfahrt*, german research institution
BMW	*Bayerische Motoren Werke AG*	German automobile and motorcycle manufacturer. Also referred to as *BMWGroup*
SVR	Sustainable Value Report	*BMW*'s in house reports on climate performance.
WALA	*WALA Heilmittel GmbH*	German drug and cosmetics manufacturer
Net electricity consumption	Total electricity consumption of economic entities	Consumption of electricity computed as generation, plus imports, minus exports, minus transmission and distribution losses

Table 1: Glossary - Explanation of terminology

Abbreviation	Full Description	Explanation
r	Growth rate	Growth rate for GVA of a given company.
FC	Forecast/ forecast year	Considered timeframe for projections and regression. May be used as index to refer to forecast values. In the context of the case studies for this thesis: $t = FC$ is the year 2030.
α_{RE}	Share of renewable sources	The share that describes to which extent the national amount of electricity supply is produced from renewable energy sources in a given scenario. A result from the *UNSEEN* framework.
c	Share of consumption	The share a economic entity (company/ sector) has in nation wide consumption for a given observation period. The observation period is given by the subscript
Comp	Company	Abbreviation (mostly as subscript) to refer to a given economic player in the form of a company.
Sec	Sector	Abbreviation (mostly as subscript) to refer to a given economic entity in the form of an economic sector.
Nat	Nation	Abbreviation (mostly as subscript) to refer to a given economic entity in the form of a nation.
E	Absolute supply of electricity	The absolute supply of electicity for a given econmic entity (company/ sector/ nation). This value exclusively refers to results as given by the *UNSEEN* framework and derived values. It therefore always refers to a value for $t = FC$, i.e. the year 2030, except for values marked with T as exponent. The entity is given by the subscript. The exponent can also refer to renewable energy sources (RE). Given in GWh in this thesis. Subscript may additionally refer to a single geographic region (E_{gr}) as given by the *UNSEEN* framework.
D	Absolute consumption of electicity	The absolute consumption (equiv. to demand) of electricity for a given economic entity (company/ sector/ nation). The entity is given by the exponent. The exponent refers to the considered observation period. Given in GWh in this thesis.
w_{gr}	Weights of geographic regions	Weights of geographic regions to calculate localized results from the *UNSEEN* framework
gr, geo regs	geographical regions	Geographical regions of the *UNSEEN* framework: division of Germany into subregions, see 2.1.2.
$REShare$	share of renewable electricity	Scenario specific share of renewable supply, subscripted with $Comp$ for the company. $REShare_{Nat}$ is equivalent to α_{RE}
scen, scenario	*UNSEEN* framework result instance	A result instance from the DLR *UNSEEN* project (see sec. 2.1.2), taken to be equivalent to a scenario for the renewable electricity infrastructure in Germany in 2030. 1985 nation wide and 5 localized scenarios are available for this research.

Table 2: Nomenclature - Abbreviations and variables as used throughout this thesis

1 Introduction

1.1 Motivation

In order to achieve the climate goals as given by the Paris Agreement, the reduction of greenhouse gas emissions is essential. When evaluating companies from a financial perspective, it is also of central importance to measure their future viability and thus their value based on greenhouse gas emissions caused. One area of expertise in the research field of energy system analysis is macroscopic energy system modeling which provides site specific data about the availability of renewable energy sources and thus about future potentials to reduce energy related greenhouse gas emissions, see the research by Scholz (2010, [1]), and *Prognos* (2021, [2]). From the individual point of view of a company, it is theoretically always possible to reduce energy related greenhouse gas emissions, the so-called "Scope 2 emissions", for example with appropriate energy supply contracts (Teske, 2019, [3]). However, this is only possible within certain political or physical limits. Depending on the sector and the future development of energy demand as well as on the energy infrastructure and renewable potentials at manufacturing sites, there may be an increased competition for the use of renewable energy sources in the future. Early stage business oriented solution to assess a company's Paris alignment already exist, for example the XDC model developed by right. based on science. A KPI which directly assesses the supply risk with climate neutral electricity based on future energy systems is of high desire for executive decisions within companies to ensure guided development in the light of a sustainable future.

1.2 Research hypothesis

The hypothesis is that, if scaled up to a macroscopic level, the available potential of renewable energy sources may not be sufficient to cover all energy demands at every location. Hence, this research aims at answering the following specific question: Is there a site specific risk concerning the access to sufficient renewable energy supply and can this be quantified by an indicator or metric? It is then desirable to create a tool, which allows for such quantification automatically, given the necessary data. On the top-level, the crucial research question to be answered is: How likely is it that the energy consumption of a particular company will be renewables-based in a future when large shares of the economy need to exploit this resource? This question will be explored at different levels of granularity, namely on a national as well as company site based level.

1.3 State-of-the-art

Research is mostly separated between company specific aspects of energy management and broad research in the fields of energy demand modelling, infrastructure and market developments.

1.3.1 Energy consumption modelling

Future energy consumption has to be modelled for a company as well as larger economic entities (sectors, nations) to establish requirements for future supply solutions. This is a complex field with specialized research on different levels of granularity paired with micro- and macroeconomic interaction. G. Erdmann and P. Zweifel (2010, [4]) discuss two general approaches. The bottum up approach is based on a microeconomic view of the economy, starting from the analysis of individual processes. Energy demand is thus a derived variable. In principle, three sources can be determined for changes in energy demand, consisting of long term and short term factors, as well as efficiency improvements, where technological improvements are regarded as the main driving factor. Zweifel models energy demand bottom up by employing classic machine learning methods as regression analyses, neural or networks. The model of this thesis utilizes a similar approach to estimate the future energy demand of singular economic entities, especially in regards to energy efficiency considerations and machine learning methods.
A bottom-up approach for modelling energy demand has many limiting dependencies, which are for example the high difficulty in having detailed data as well as the necessity of assumptions (Erdmann and Zweifel, 2010, [4], p.100).
For a top down approach one models the energy demand according to dependencies w.r.t. macroeconomic variables. The framework developed in this thesis considers variables relevant for macroeconomic modelling, such as the GVA, for the methodology of regression analyses of energy efficiency improvements.

1.3.2 Energy Management at the company level

In general, company specific considerations in the field of energy demand include holistic approaches in analysing all processes within the company. The tasks include risk identification and -mitigation. Official guidelines for setting up such regulatory instruments exist in normative fashion by the *International Organization for Standardization* (2018, [5]). Related academic literature covers risks to be considered in interaction with energy markets, as well as bureaucratic aspects. Important associated risks are: market risk,

price risk, competition risk and supply risk. Also different measures and repurposed KPIs to describe energetic performance are often discussed in this context (Goebel 2007, [6]), (Koppenhoefer et al. 2017, [7]).
Assessments of renewable supply risk are mostly established in-house. Transparency and insights w.r.t. extensivity of supply side availability and development considerations in such assessments is therefore very limited. This stands in strong contrast to their necessity. A company can only achieve sustainable climate neutrality if all contextual facets are covered and climate neutrality is a possibility in a larger economic context. These in-house analyses can therefore be viewed as of limited context and appear insufficient from a system perspective. Peer-reviewed research to enable a climate neutral economy is a matter of public interest.

1.3.3 Supply side analyses on large scales

Such peer-reviewed literature exists in the field of energy market and power grid analyses. This research is of sociopolitical and -economic interest, to ensure sustainable energy supply from renewable resources. In turn, notable and relevant literature is often developed by specialized research teams for large scales. German institutions, such as the *Helmholtz-Institute* in cooperation with the *German Aerospace Center (DLR)* [8], *BMWK* [9], *Agora Energiewende* [10], and the *Fraunhofer-Institutes* [11] regularly publish research papers, software and other academic work on the nation wide transition to renewable energy sources. This literature is aimed at higher granularity than the company level. Often a combination of distinct localization, specific industries or energy carrier utilization is investigated.
Other research aims at specific methodology for energy management on the supply side, see p.e. Demand-Side-Management for electricity grids, as investigated by Ladwig (2017, [12]) and related research, which utilizes demand side analysis to regulate the supply. In similar fashion distinction is here carried out w.r.t. specific market participants (p.e. electric cars, see Dallinger et al (2013, [13])) or other partitions, that are not detailed enough to be employed for the investigation of energy supply for singular companies. The REMix model and the associated *UNSEEN* framework, which is explained in section 2.1.2, offer higher resolution results to be applied to company level analysis.
Research to combine both of the aspects of company specific consumption projections and peer-reviewed research of future electricity infrastructure is lacking, because of multiple reasons: Firstly there is a lack of incentive for research institutes to offer detailed analysis on the company level. It serves no further use than for the management level of the company itself. A given

optimal solution (i.e. a software) may be marketed as a B2B solution and bought for money. On the other hand, there is a lack of incentives for a company's in-house developed solution to be put forward as publicly available research. It is in the stakeholders interest to either keep it from direct competitors or to make it available in exchange for capital.

1.3.4 Methods for assessing companies

Certain B2B solutions for assessing companies based on their alignment to the Paris Agreement already exist. Examples for this are "Climate Neutral Certifications" [14] or government funded solutions such as the "Climate Neutral Now Initiative" by the *United Nations* [15]. An additional example is given by **right. based on science**, which provides ESG related services. Its main advertised product is the *X-Degree Compatibility* (XDC) Model. This methodology, grounded in scientific principles, simplifies the assessment of complex climate impacts across various sectors such as companies, buildings, and financial portfolios into a single temperature benchmark, i.e. a KPI in degrees Celsius.
The subject of company energy consumption, which this thesis is focused on, can be analyzed in similar fashion. In turn the framework of this thesis makes use of concepts established as part of the **right. based on science** XDC-Metric, developed by Helmke et al. (2020, [16]). The focus here is on energy intensity as a predictor for sector wide technological development and the Gross Value added being forecasted under the assumption of exponential growth. This allows for simplistic calculation of an of an economic entity's energy consumption from the investigation of the respective intensity and financial data.

1.4 Research contribution

Company specific solutions may consider limited scopes. While a singular company may be able to provide itself with renewable electricity via existing market entry points, this neglects the greater context of resource shortage if the whole economy demands this resource in equivalence to its consumption. The framework established within this thesis is therefore meant to cover contextual deficiencies of in-house risk assessments while keeping the company specific character.
For a holistic supply risk assessment the company's energy management has to dynamically interact with state-of-the-art understanding of energy demand modelling, infrastructure and market developments. Research in the latter

fields are not tailored to such applications. This research aims to bridge that gap. Results for electricity supply and infrastructure research aimed towards a climate neutral economic landscape are combined with company specific consumption prediction models.
The established framework is tested on case studies with the publicly available data of the companies *WALA Heilmittel GmbH* and *Bayerische Motorenwerk AG* with focus on their economic activities within Germany.

Contents

2 Methodology

This section gibes an overview over the methodology employed in this thesis. It will be divided into two segments. First, a nation level analysis will be conducted to draw conclusions about a company's nationwide supply risk. After proposing this concept to various companies, a strong interest crystallized in a detailed analysis focusing on company site level results, which is developed within the framework of this study. The second part of the methodology overview and each case study therefore aims at this localized analysis. This answers the question of a supply risk with renewable energy sources for individual company sites.
The national as well as the localized consideration will be divided into three aspects. First, the consumer side will be examined, i.e. the companies in detail, after which the supply is evaluated. The final section brings these two considerations together.

2.1 Nation wide Model

2.1.1 Electricity consumption

Before going into the nation level analysis for a company's electricity demand, the discussion focuses on the model choices.

Regression model

To forecast electricity consumption a regression model that assigns the company's financial data set of gross value added (GVA, see 1) to its electricity consumption is established first. With an assumption based derivation of future values for this KPI the electricity consumption is then projected into the future. For this task multiple models can be and have been applied in respective research, see B. Ameyaw and L. Yao (2018, [17]), R. Steinert and F. Ziel (2018 [18]) and V. Srikrishnan et al. (2022, [19]).
Since the focus of this research is on establishing a robust framework, which considers only basic aspects of the future electricity market and combines different statistical approaches for each of them, the decision is made to employ a simple regression model for forecasting future electricity demands.
With publicly available data, a reliable model for predicting future electricity consumption D_{FC}^{Comp} of a company is given by a linear $least - squares$ regression model. There is a variety of reasons why this form of the model

is chosen: Its main advantage lays in its simplicity. It is easy to analyze and one can readily determine the exact effect any change has on the model outcome. The requirements in extensivity of data are comparatively low for the model to stay reliable. The choice as to which exogenous variables are considered here orients along the lines of existing bottom up models and forecast models, see Herbst et al. (2017, [11]), da Silva et al. (2019, [20]). Commonly used data sets for exogenous variables are :

- Number of Employees
- Turnover
- Gross Value Added (GVA)
- Production volume
- Building size

Most of these data sets are expected to show strong correlation. A modification is therefore possible.
In analogy to the **right. based on science** XDC-Metric the framework of this thesis considers the GVA as the explanatory variable of main interest. The modification for this thesis evaluates the evolution of the *electricity efficiency index EEI*

$$EEI_t = \frac{D_t}{GVA_t} \tag{1}$$

over the time t in its regression model, s.t.

$$E\hat{E}I_t = \hat{\beta}_1 \cdot t + \hat{\beta}_0, \tag{2}$$

with the EEI and the years t as defined above and the estimators $\hat{\beta}_1$ and $\hat{\beta}_0$. This reflects the technological development in production processes as described in ([4], p.79ff). A multiplication with the GVA results in the desired electricity consumption forecast.

Forecasting GVA Growth

With the GVA being an independent variable in this model, a predictive value for it is needed to compute a future electricity consumption. **right. based on science** (see 1.3.4) offers multiple approaches for calculating the GVA based on historical values, most notably by assuming exponential growth. A constant growth factor is determined as follows:

$$r = \sqrt[T-t_0]{\frac{GVA_T}{GVA_{t_0}}} - 1, \tag{3}$$

where GVA_T and GVA_{t_0} are the first and last observed value of the company's GVA, respectively. Alternatively one may assume the company to grow in accordance to the global economy, s.t. the values GVA_T and GVA_0 are replaced by values for the economy as a whole.
The future GVA_{FC} is computed as

$$GVA_{FC} = GVA_0 \cdot (1 + r)^{FC - t_0}, \tag{4}$$

where FC refers to the year to project into.

Forecasting electricity consumption

This section discusses how one arrives at future values for a company's electricity consumption. The forecast result and accuracy varies from company to company, due to the differences in data sets, such as

- Granularity (energy carriers, utilization, etc.)
- Survey regulations
- Time resolution
- Geographic resolution
- ...

The model is structured as can be seen in the flowchart fig. 1. In the following each step is explained one by one.
1. First, The electricity efficiency index EEI_t is calculated

$$EEI_t = \frac{D_t}{GVA_t} \tag{5}$$

over the years the t, given by the historically available values for electricity consumption (D_t) and GVA (GVA_t).
2. The EEI is then used as the regressand for a linear regression model, with the regressor being the years t, i.e. a model given by 46. A forecast for the electricity consumption can then be determined by multiplying a value for the GVA with above result for the desired time horizon.
3. To retrieve said GVA the methodology established by **right. based on science** is employed, as described above. A company growth factor r is established from the calculation

$$r = \sqrt[T-t_0]{\frac{GVA_T}{GVA_{t_0}}} - 1, \tag{6}$$

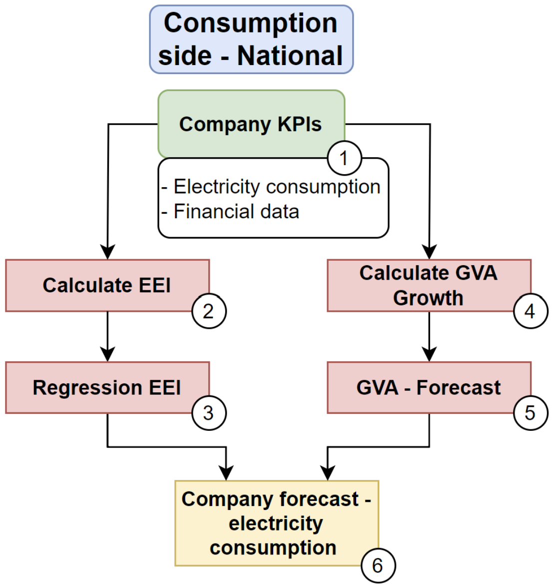


Figure 1: Flowchart to arrive at company's electricity demand forecast. This procedure is divided into 5 steps, explained in section 2.1.1. The colors are coded, s.t. green refers to direct input, with the white boxes giving more information. Red boxes signal calculation steps. Yellow boxes refer to final (section) results, that will be reused later on. All following flowcharts use the same color coding.

where GVA_T and GVA_{t_0} are the first and last available value of the company's GVA, respectively.
4. The growth factor is used to establish the assumption for a future GVA at time $t = FC - t_0$

$$GVA_{FC} = GVA_0 \cdot (1 + r)^{FC - t_0} \tag{7}$$

5. This value is multiplied with the regression result for the EEI_{FC} development, i.e. $\hat{\beta}_1$ to acquire the forecast result for the company electricity consumption in year $t = FC$:

$$D_{FC}^{Comp} = (\hat{\beta}_0 + \hat{\beta}_1 \cdot FC) \cdot GVA_{FC}, \tag{8}$$

where $\hat{\beta}_0$ and $\hat{\beta}_1$ are taken from the regression eq. (46).

2.1.2 Electricity supply

UNSEEN project Description

The second main aspect for the framework of this thesis is the model for renewable electricity supply. This is based on existing DLR scenario studies

([1], [2]). They are used to derive probabilistic descriptions of the infrastructure of renewable electricity supply in different regions. A bottom up potential analysis is used for this approach. For possible renewable resources this framework considers their availability in terms of future capacity expansions and techno-economic improvement scenarios. RES power plant expansions are assumed based on previous DLR publications.
The central *UNSEEN* framework is discussed here in short (Frey et. al, 2020, [21]).
The framework has been developed to delve into the intricacies of scenario development. These scenarios are specifically designed to advance the goal of achieving a decarbonized future, aligning with global efforts to mitigate climate change.
Both best-case and worst-case scenarios are developed within this framework, providing a comprehensive understanding of potential outcomes. To identify optimal solutions, an optimization model is implemented, utilizing constraints. Variable inputs are employed, concerning historical weather years to determine electricity storage from renewable energy sources and techno-economic parameters, such as the costs for building new infrastructure or the price of CO_2 certificates. This input data is then sampled and solved by an optimization model named REMix, implemented in General Algebraic Modeling System (GAMS), a widely used mathematical modeling language. Explicit results are generated, regarding the distribution of energy sources, the amount of total electricity generation per energy source, and the amount of renewable electricity generation per energy source.
The explicit model results are used to establish baseline scenarios for the nation wide renewable electricity supply.

Electricity supply scenarios

Note: In the following all variables concerning the electricity supply side are taken w.r.t. to a singular scenario, i.e. singular result from the *UNSEEN* framework. The describing index will be omitted within this section. This includes the variables: α_{RE}, E_{Nat}, E_{Nat}^{RE}, and $REShare_{Comp}$

The next step of the investigation focuses on the results from the aforementioned *UNSEEN* framework, namely the total nation wide electricity supply E_{Nat} for the forecast horizon, as given by the framework. For this purpose, this value is assumed to be an equivalent predictor to the nation wide electricity supply in the observed periods. In turn, results derived from this value are taken to be the main representative for future supply of electricity markets available to all companies operating within a given nation, see "Net

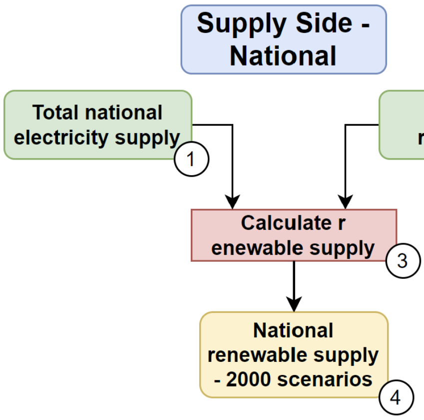


Figure 2: Flowchart to arrive at a nation wide electricity supply forecast. This computation is based on the existing *UNSEEN* model, as described in section 2.1.2. This procedure is divided into 4 steps.

electricity consumption" in tab. 1. It is important to mention here, that these are not a model result but instead an assumed input variable which has been sampled according to a normal distribution. The procedure to then arrive at future renewable supply values is displayed in the flowchart fig. 2. A total of 1985 scenarios are available, the procedure is conducted for each one.

1. The total supply of electricity follows a normal distribution, see figure

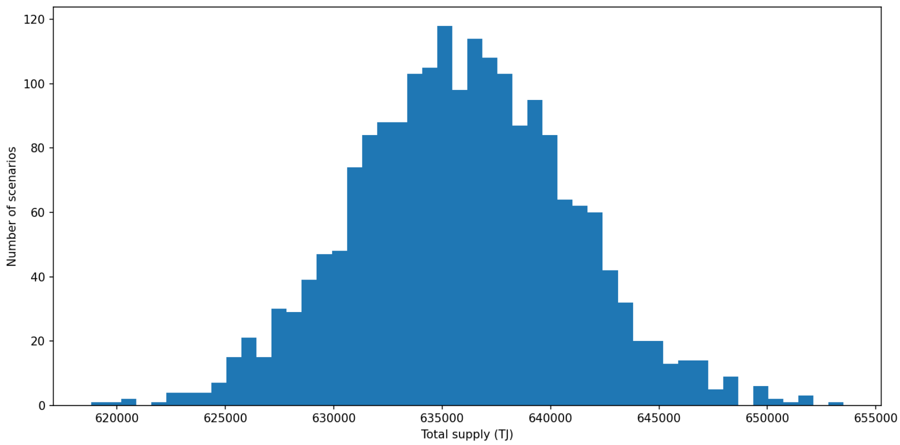


Figure 3: Histogram displaying the sampled input parameters of the *UNSEEN* framework for nation wide electricity supply. These results serve as a baseline to establish a future supply with renewably produced electricity.

3. The original total power supply comprises all sources for electricity gen-

eration, renewables and non-renewables.
The focus of this section is on the supply from renewable electricity sources E_{Nat}^{RE}. This amount is therefore calculated from the total amount of electricity generation

$$E_{Nat}^{RE} = \alpha_{RE} \cdot E_{Nat}, \tag{9}$$

according to a share α_{RE} of renewable electricity sources.
2. α_{RE} is given as a model output, its distinct values can be observed in

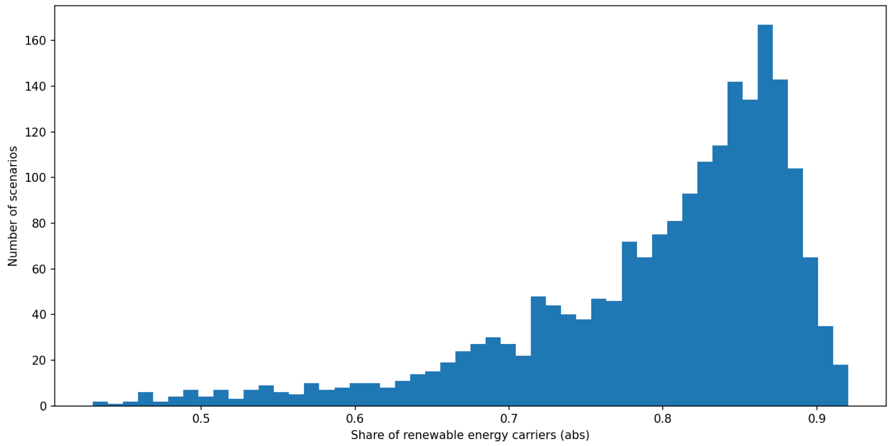


Figure 4: Histogram displaying the number of scenarios for nation wide share in renewable electricity generation. These results serve as a baseline to establish a future supply with renewably produced electricity.

figure 4.
3. The amount of renewable electricity sources E_{Nat}^{RE} is then given by a scenario wise multiplication of the two variables α_{RE} and E_{Nat}.
4. The amount of renewable electricity supply as given by the share α_{RE} multiplied with the total electricity supply is displayed as a histogram for all available scenarios in figure 5. These values constitute the baseline for the renewable electricity supply.
With these considerations, the two aspects of supply and demand will now be brought together in final evaluations, before turning to a localized view.

2.1.3 Riskmetric

With both the electricity consumption of a given company and the theoretically available nation wide supply of renewable electricity supply in the form of different scenarios determined, it is now elaborated on how to bring both sides together for a final comparison on a national level. This is achieved by a down-scaling approach, i.e. down-scaling the nationwide supply per scenario

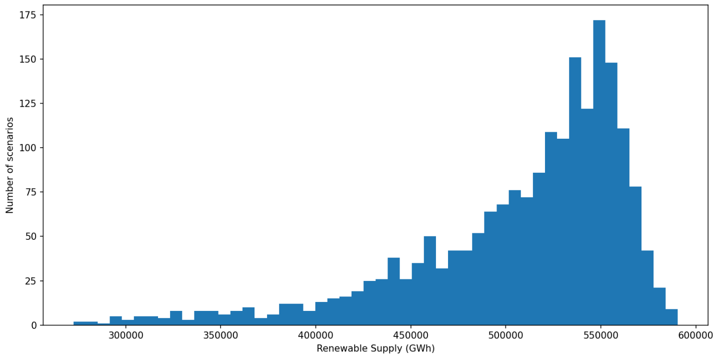


Figure 5: Histogram displaying the absolute amount of *UNSEEN* model results for nation wide renewable electricity generation E^{RE}_{Nat}, as a result of multiplying the absolute amount of electricity generation by the share of renewably generated electricity.

to the company level in a reasonable way. To ensure comparability, a theoretically available amount of future resources for the company is calculated. As a representation an investigation of the share of a company's electricity consumption w.r.t. to the nation wide electricity consumption is conducted. To put it simply: The share of electricity consumption w.r.t. to the nation wide electricity consumption a company had in past years determines the share of future nation wide supply it will receive. The choice for the case studies is to analyze the share as of today in this context, i.e.

$$c_{util} = \frac{D^{Comp}_{T}}{E^{T}_{Nat}}, \tag{10}$$

where D^{Comp}_{T} is the last observed value of the company's electricity demand and E^{T}_{Nat} is the last observed value of nation wide electricity supply. The framework is highly sensitive to the choice made here. Ideally one can therefore individualize the downscaling approach based data at hand and in cooperation with the companies. This is elaborated on in the improvements section 3.4.

After this caveat the final evaluation to receive a national risk metric will now be explained. The procedure for this is shown in the figure 6.

1. and 2. From the previous sections (2.1.2 and 2.1.1) the (forecast) values for the company's electricity consumption, as well as electricity supply related data on the national level are available.

3. Both datasets are utilized to conduct the aforementioned downscaling approach. In this sense, the model of this thesis assigns the company a value of the nation wide supply per scenario.

$$E^{RE}_{Comp} = c_{util} \cdot E^{RE}_{Nat} \tag{11}$$

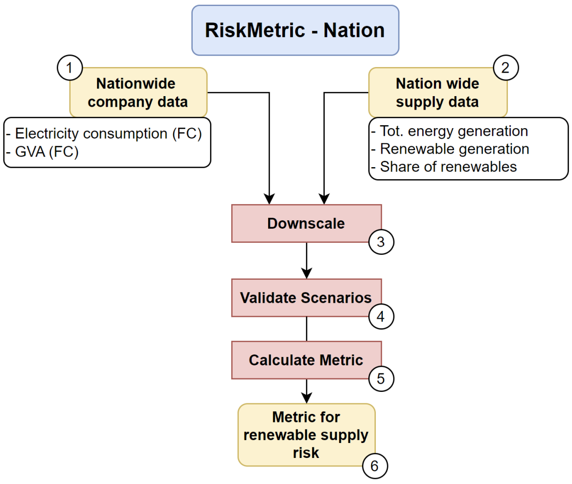


Figure 6: Flowchart on comparing national supply and company wide consumption, including a scenario validation step. The procedure results in a final risk metric on national level

Here E^{RE}_{Nat} is the nation wide amount of renewable electricity supply, as in section 2.1.1, c_{util} is the down-scaling share (which share is used depends on the context, as described above) and E^{RE}_{Comp} is the amount of renewable electricity sources down-scaled to the company level for comparison.

4. With a renewable supply that is comparable to the company's demand, the scenarios can now be validated with the following comparison:

If

$$c_{util} \cdot E^{RE}_{Nat} \geq D^{Comp}_{FC}, \tag{12}$$

this scenario is considered a success and the company can fully provide itself with renewable electricity, i.e. their share of renewable electricity is equal to 1.

Otherwise, if

$$c_{util} \cdot E^{RE}_{Nat} < D^{Comp}_{FC}, \tag{13}$$

this scenario is considered to be a failure for the company and the company can provide itself with renewable electricity to the same extent as the nation, i.e. $REShare_{Comp} = \alpha_{RE}$.

5. With the $REShare$ per scenario , i.e. the share to which extend a given company can be supplied with renewable resources, one can calculate the final risk metric:

$$RiskMetric_{Nat} = 1 - \left(\frac{1}{\#Scens} \left(\sum_{\text{success Scens}} 1 + \sum_{\text{failure Scens}} \alpha_{RE} \right) \right) \tag{14}$$

It results in a number between 0 and 1. The result can be perceived as an assessment of how secure the supply of renewable electricity is. Through the interaction of successful as well as insufficient scenarios, a comprehensive range of supply scenarios is mapped. The prediction of the company wide consumption is of course subject to some assumptions and kept simple, but for the demonstration of the methodology it still meets the requirements.

2.2 Site specific model

Note: In the following section 2.2, all variables concerning the electricity supply side are taken w.r.t. to a singular scenario. The describing index will be omitted within this section. This includes the variables: $REShare_{gr}$, E_{gr}, E_{gr}^{RE} and E_{Site}^{RE}
After the nation wide investigation the next objective is a higher granularity analysis, offering a range of applications for detailed analyses on the company site level.
This localization is based on the existing *UNSEEN* framework. For the purpose of available case studies the description and investigation is limited to Germany. A model instance with higher granularity is employed here. The focus is on higher resolution w.r.t. the electricity transmission grid. Germany is split in geographic sub regions, where each one these contains a high-voltage substation that exists to date. The framework evaluates localized potentials for electricity generation. For the use-case at hand the relevant aspects are the localization and the establishment of electricity generation potentials split into energy carriers.

2.2.1 Local availability of renewables

The site specific investigation starts with explaining how one arrives at a high resolution value for the electricity supply. The localization takes place as follows:
1. Germany is split into a number of sub regions, as can be seen in figure 8. This split does not represent the geopolitical division of this nation, i.e. the government level of counties. A connection between these geographical division could in theory be established via a mapping, see 6.1.4
For each fragment/ geographical region of the division from figure 8 a quantitative result for the electricity generation potential for different energy carriers is given as an *UNSEEN* model framework result. In the table 3 these energy carriers are listed. It is denoted whether they belong to the group of renewable (RE) or non-renewable (FF, for fossil fuels) energy sources. Additional classifications include the demand within the geographical region

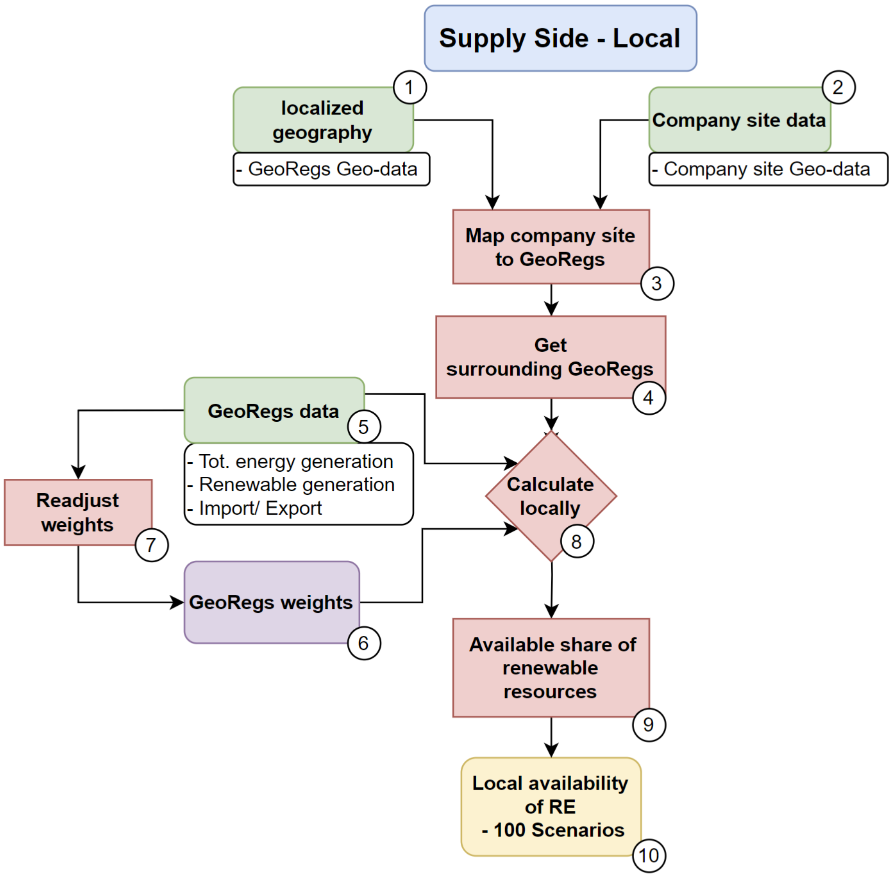


Figure 7: Flowchart to arrive at a localized renewable electricity availability, based on a higher granularity instance of *UNSEEN* model results. This procedure is divided into 10 steps, as explained in section 2.2.1

(DE), export and import (EX), curtailment (CU) and transportation via power transmission lines (Other).

2. A given company has one or multiple production sites. A single site is given as a geographical coordinate, in the form of longitude and latitude, analogous to the definition of the geographical region corners.
3. Therefore, each company site is located within a geographical region. The localized availability of renewable electricity can in turn directly be deducted from calculatable quantities, see eq. (15) in step **5.**, by mapping the company site to a geographical region.
4. This consideration not only includes the geographical region in which the company site is located, but all adjacent geographical regions as well.
5. For each geographical region one can in turn calculate the total amount

Technology	**Classification**
Biopower	RE
Demand	DE
Hydropower - Rivers	RE
Lithium-ion battery	RE
Photovoltaic	RE
Wind - Onshore	RE
High voltage AC transmission lines	Other
High voltage DC transmission lines	Other
Slack	FF
Pump storages	RE
Combined cycle gas turbine	FF
Gasturbines - natural gas	FF
Wind - Offshore	RE
ST_Coal	FF
Export to germany	EX
ST_Lignite	FF
Curtailment	CU
Fuelimports	EX

Table 3: Technology from *UNSEEN* framework results.

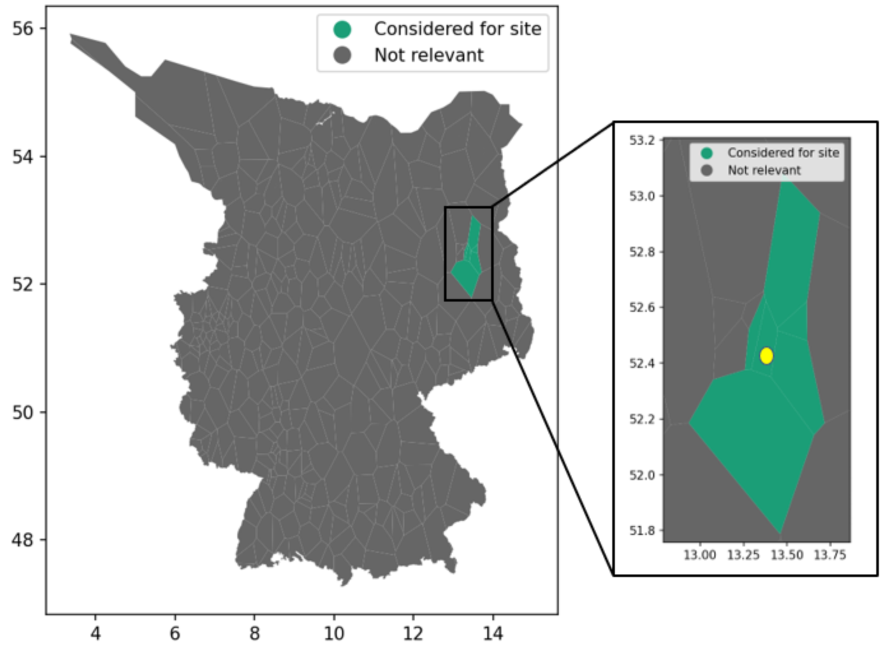


Figure 8: On the left, the localized view of Germany divided into geographical regions. On the right, as a first example, the geographical regions relevant to *BMW*'s company site in Berlin, see step **5.** and onwards in figure 7 and section 2.2.1. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

of electricity generation potential E_{gr} (the gr index signifies that this variable is defined w.r.t. a single geographical sub region), the total amount of renewable electricity generation E_{gr}^{RE} and the share of renewable electricity generation potential $REshare_{gr}$

$$REshare_{gr} = \frac{E_{gr}^{RE}}{E_{gr}}. \tag{15}$$

These three quantities are used to establish a calculation for the localized share of electricity generated from renewable energy sources for companies.
6. All considered geographic regions, adjacent and the one containing the company site, are weighted. This is done to merge individual geographic regions quantities into one. The weights are set as model parameters and sum up to 1. They are set artificially: The weight of the geographic region containing the site is set to be $w_{gr,main} = 0,4$, while all the bordering geographic regions receive the weights

$$w_{gr,border} = \frac{0,6}{\#georegs - 1}, \tag{16}$$

i.e. the remaining $0,6$ are evenly distributed between the bordering geographic regions.
7. Being set artificially, methodology to adjust the weights in useful. This achieved by considering the in- and outflow of electricity across the geographic region borders. The weights are reevaluated as follows:
For every geographic region the amount of in- and outflowing electricity via high voltage transmission lines $E_{gr}^{Other,FC}$ (see table 3, marked as "Other") is evaluated. The transmission of electricity between geographical regions are result outcomes of the *UNSEEN* framework. The weights are then recalculated via an activation function:

$$w_{gr} = w_{gr} \cdot \left(1 - \tanh \left(0,2 \cdot \frac{E_{gr}^{Other,FC}}{E_{gr}^{RE}} \right) \right). \tag{17}$$

The factor $0,2$ is set artificially. The weights are also renormalized after this step, s.t. they again add up to 1.
This approach is chosen so that transport of generated electricity in and out of the considered geographic regions is depicted, since not all of the electricity is consumed locally. The model at hand is a national model (see 2.1.2), that also generates localized results and in turn it makes sense to treat it as such. Alternative approaches to this weight readjustment are possible, see the improvements section.
8.-9. The main result of interest is the share of renewable electricity available according to eq. (15), mapped from the considered geographic region down to a final value representing the localized share for a company site. This is then a weighted average of the share in geographic region containing the site and all adjacent geographic regions.
10. The next step is to calculate calculate the localized site specific share of renewable electricity supply per scenario

$$REshare_{Site}^{Scen} = \sum_{gr \in \text{geo regs}} w_{gr}\, REshare_{gr}, \tag{18}$$

The *geo regs* considered here are the geographic region containing the site and all bordering geographic regions. The $REshare_{Site}^{scen}$ then stands as an intermediate result for this section, before being investigated further in the next.

2.2.2 Electricity consumption

In this section the discussion returns to the already calculated result from eq. (8), namely the forecast of a company's electricity consumption. The

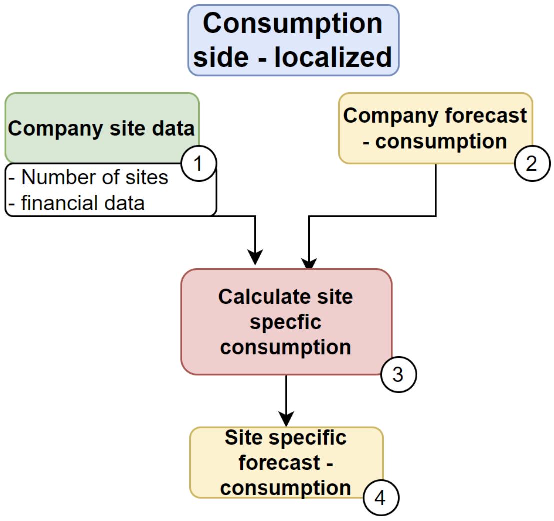


Figure 9: Flowchart to arrive at a company site specific electricity consumption forecast. This procedure is divided into 4 steps, as explained in section 2.2.2

procedure to arrive at a company site specific electricity consumption forecast is depicted in figure 9
1. The goal is to integrate the companies projected growth into the localized model. For this every company site is attributed with a specific future electricity consumption.
2. and see above This is based on the projection for the company as a whole.
3. The simplest approach is to split the projection equally by the number of a company's sites within a country

$$D_{FC}^{Site} = \frac{1}{\#Sites} D_{FC}^{Comp}. \tag{19}$$

This is the site specific electricity consumption for the case studies.
Other alternatives rely on higher data quality. This is elaborated on in the improvements section, see 6.1.4.

2.2.3 Riskmetric

The goal here is to assert whether a scenario is suitable for the local consideration, i.e. whether the company site's electricity requirements are fulfilled locally. If this not the case, it is assumed instead that the company sites can only be provided with a share of renewables equivalent to the nation wide supply. The procedure is depicted in figure 10

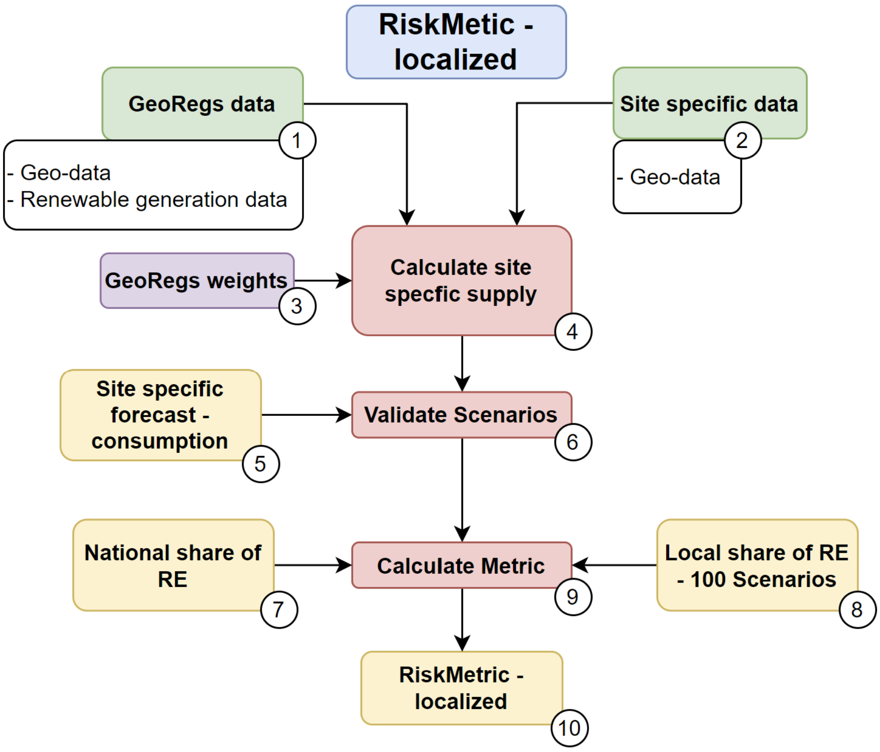


Figure 10: Flowchart to arrive at the final localized site specific risk metric. This procedure is divided into 10 steps, as explained in section 2.2.3

Analogously to the national scenario validation procedure, a methodology is implemented to compare the site specific consumption forecast D_{FC}^{Site} to a theoretically available supply for the site.

1.-4. The site specific supply is established similarly to the site specific share of renewable supply, using the total amount of electricity generation in each surrounding geographic region E_{gr}^{RE}, instead of the share of renewables. This leads to the site specific renewable supply E_{Site}^{RE} per scenario:

$$E_{Site}^{RE} = \sum_{gr \in \text{geo regs}} w_{gr} \, E_{gr}^{RE} , \tag{20}$$

where the weights w_{gr} are the same as in eq. (17) and the sum is over all geographic regions considered for the site.

5.-6. As mentioned in the introduction to this section, the goal here is to assert the validity of each scenario. For this a comparison is drawn between E_{Site}^{RE} and D_{FC}^{Site}: If

$$E_{Site}^{RE} \geq D_{FC}^{Site} , \tag{21}$$

the scenarios local renewable share $(1 - REshare^{Scen}_{Site})$ from eq. (18) is used to calculate $RiskMetric_{site}$. Otherwise, if

$$E^{RE}_{Site} < D^{Site}_{FC}, \tag{22}$$

the scenario is considered to be a failure for the company site and $RiskMetric_{Nat}$ is used in place of $(1-REshare^{Scen}_{Site})$, as seen in eq. (23). The model therefore dynamically considers the company's growth expectations on a local level. If they exceed corresponding local limitations, the national riskmetric applies.
7.-10. The final result is the average over all failure and success scenarios, s.t. the calculation for the final risk metric is:

$$RiskMetric_{site} = \frac{1}{\#Scens}\left(\sum_{\text{success Scens}} (1 - REShare^{Scen}_{Site}) + \sum_{\text{failure Scens}} RiskMetric_{Nat}\right) \tag{23}$$

It results in a number between 0 and 1. The result can be perceived as an assessment of how insecure the supply of renewably produced electricity for specific company sites is, in analogy to the national riskmetric $RiskMetric_{Nat}$. Further improvements are discussed in section6

3 Case study - BMW

3.1 Economic background and sustainability goals

Sustainibility Goals

BMW Group is convinced of striving for firm sustainability goals. This is reflected for example in their answers to the CDP questionnaire in 2021: "The BMW Group is firmly convinced that the fight against climate change and the responsible use of resources will determine the future of our society – and thus also that of the BMW Group. [...] The BMW Group has a direct influence on the carbon emissions generated at its own plants and locations and has therefore been a leader in terms of resource efficiency in this field for many years. Its underlying aspiration is even more ambitious than the international pursuing efforts of limiting global warming to 1.5 degrees celsius."(*BMWGroup*, 2021, [23] p.62) True to these statements, one sees a steadily progressing development in associated variables, especially the EEI. These facts make *BMW* an interesting candidate for the case studies in this paper.

Company Data

All relevant company data is taken from the "*Sustainable Value Report*"'s (SVRs) [22]. These reports are published on a yearly basis, dating back to 2002, and contain thorough information on *BMW*'s performance in regard to ESG-related topics. While only a fraction of the provided data is used, these elaborations offer interesting insights on the company's values, drivers for decisions and climate neutrality developments. The additionally published *CDP Questionnaire*'s contain further information [23]. The 2021 value electricity consumption is taken from this report.
Further notes:
The first *SVR* was published in 2002, the second one in 2004, the third one in 2006. The 2003 and 2005 values for external electricity consumption are therefore calculated by linear interpolation, same for the GVA values for 2003 and 2005.
The values given by the *SVR*'s are almost always in relation to the global performance, i.e. the data refers to worldwide company data. Since national values are required, they are scaled down employing the share of employees working in Germany in 2021:

$$x_{Nation,t} = \frac{e_{Nat,T}}{e_{World,T}} \cdot x_{World,t}. \tag{24}$$

Here $x_{World,t}$ is a given data point of BMW's worldwide statistics in year t, $e_{World,t}$ is the number of worldwide employees in year t. $e_{Nation,t}$, the number of employees in a particular nation, is broken down as part of the SVR's [22] and lacks availability for the years 2009 to 2016. This calculation is conducted for all data series used here, namely the GVA and the electricity consumption. The implications of this are discussed in section 3.5

3.2 Nation wide analysis

3.2.1 GVA and electricity consumption

GVA

BMW is an evergrowing company in german automotive sector with a long history. Its development is reflected in analyses of the GVA, see figure 11. One can see growth in comparison to the previous year for almost every data point, with the only exceptions being in the years 2008-09 and 2019-21, which may be due to worldwide economic crises, namely the 2007-2008 financial crisis and the corona pandemic, without going into further detail. To forecast the GVA the methodology established by right. based on science is employed, as described in 2.1.1. The GVA development is in turn modelled via exponential growth. This growth factor r is retrieved from the calculation

$$r = \sqrt[T-t_0]{\frac{GVA_T}{GVA_0}} - 1 = 4,24\,\%, \tag{25}$$

where $T - t_0 = 2021 - 2002$ and GVA_T and GVA_0 are the first and last available value from Tab. 34 respectively. The growth factor is utilized to establish the assumption for a future GVA at time $t = FC - t_0$

$$GVA_{FC} = GVA_0 \cdot (1 + r)^{FC - t_0} = 45679,91\text{mn. EUR} \tag{26}$$

Figure 11 displays how this model holds up against the real values, where one can see deviations mostly due to missing functionality of considering the collapse at the start of the Covid pandemic. This is explained more in later sections. The value is multiplied by the regression result for the EEI_{FC}. This results in a forecast value for the company electricity consumption in year $t = FC$.

Electricity consumption

In the figure 12 a plot w.r.t. BMW's historic electricity demands can be seen, including a linear fit. The electricity consumption is steadly rising,

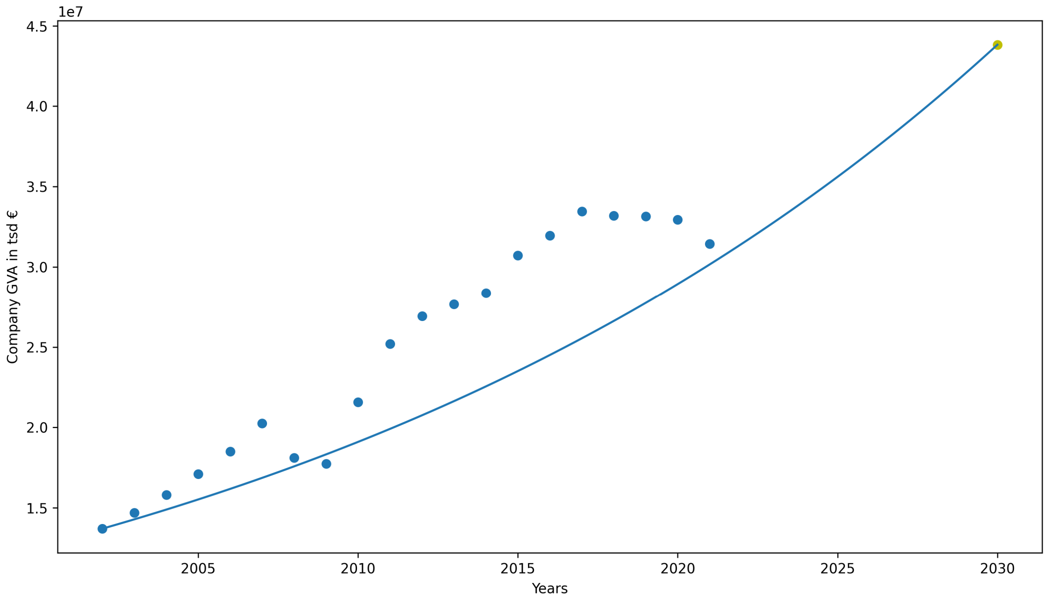


Figure 11: BMW's GVA (in blue) against the years In green the forecast value for the year $t = FC$ is marked, as calculated in 26. The values for BMW's GVA are taken from 34.

which one may attribute to company growth.
According to the methodology from 2.1.1, a linear regression of the EEI is conducted to receive a forecast value for BMW's electricity consumption. For the context of this case study the company's consumption D_t refers strictly to the electricity supplied to the company from outside sources, i.e. electricity bought from the market and fed into the in house grid (see 33, column "electricity external"). The values are taken directly from the aforementioned SVRs. The regression is defined as

$$E\hat{E}I_t = \hat{\beta}_1 \cdot t + \hat{\beta}_0, \tag{27}$$

where $EEI_t = \frac{D_t}{GVA_t}$ depicts the regressand and the regressor is the absolute years t, for which data is available, i.e. $t \in [2002, 2021]$. The regression result is shown in figure 13. With the estimators plugged into eq. (27) one receives

$$E\hat{E}I_t = -7,1 \cdot 10^{-7} \frac{\text{GWh}}{\text{year} \cdot \text{tsd. EUR}} \cdot t + 1,4953 \cdot 10^{-3} \frac{\text{GWh}}{\text{tsd. EUR}}, \tag{28}$$

The final result for the EEI in the year FC is therefore

$$EEI_{FC} = 4,14 \cdot 10^{-5} \frac{\text{GWh}}{\text{tsd. EUR}} \tag{29}$$

Figure 12: *BMW*'s electricity consumption against the years, including a fit for the linear trend. The values for *BMW*'s electricity consumption are taken from 33 (column "electricity external")

With the previous result for the GVA forecast (see eq. (26)), the forecast for the electricity consumption of *BMW* within the nation of Germany in the year *FC* is

$$D_{FC}^{Comp} = EEI_{FC} \cdot GVA_{FC} = 1892,71\,\text{GWh} \tag{30}$$

3.2.2 Electricity supply

The values for future energy supply are taken directly from project results calculated with the DLR model *REMix* in the project UNSEEN, referring to section 2.1.2. Reiterating the central information from this chapter, the electricity supply is given as an *UNSEEN* framework input variable sampled from a normal distribution. The amount of electricity produced via renewable energy carriers is of main interest. The share of renewable electricity for the model results is again distributed according to figure 4. For the total amount of electricity from renewable sources see the histogram 5.

3.2.3 Riskmetric

In this section an intermediate step is conducted followed by a comparison of the results for the theoretically available renewably produced electricity with the forecast for the company wide demand. The intermediate step is scaling down the national supply for comparability with the company using

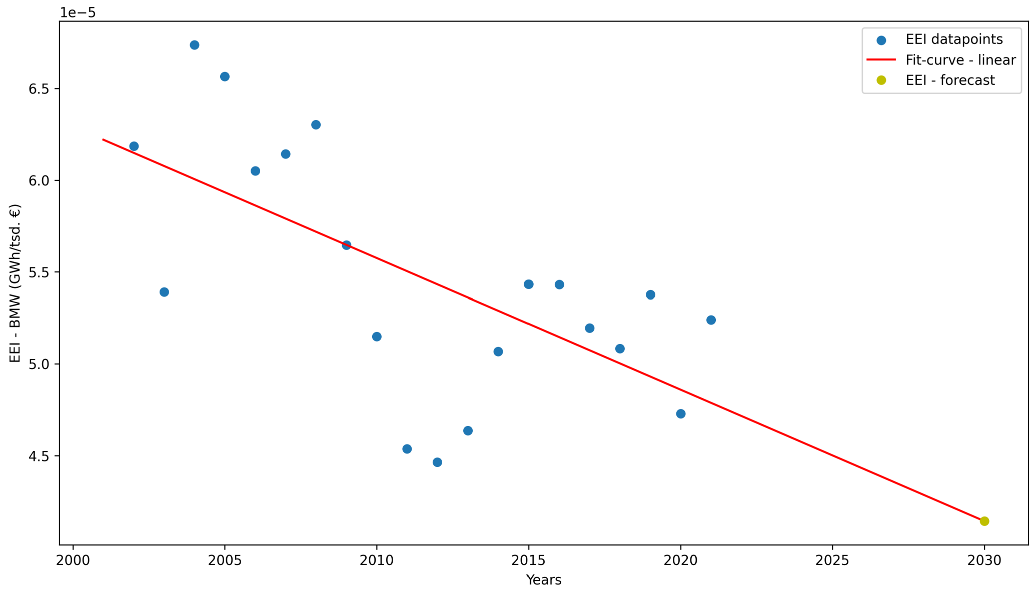


Figure 13: Linear regression for *BMW*'s EEI, as defined in 47 the years in blue. The forecast value as calculated in is marked in green.

the share of the company's demand on the nation wide electricity supply. As explained in section 2.1.3, the last available value $c^T_{Comp} = 0,244\,\%$ is used to downscale the nation wide demand.
The according downscaled values are displayed in figure 14. For every scenario result from the *UNSEEN* model a comparison is conducted as follows:

If

$$E^{RE}_{Nat} \cdot c^T_{Comp} \geq D^{Comp}_{FC}, \tag{31}$$

this scenario is a success and the company can fully provide itself with renewable electricity, i.e. their share of renewable electricity is equal to 1. Otherwise, if

$$E^{RE}_{Nat} \cdot c^T_{Comp} < D^{Comp}_{FC}, \tag{32}$$

this scenario is a failure for the company and the company can provide itself with renewable electricity to the same extent as the nation, i.e. $REShare_{Comp} = \alpha_{RE}$. Statistics on these evaluations can be found in table 4.
The national risk factor of *BMW* being able to supply all its german sites is given as the scenario average:

$$RiskMetric_{Nat} = 1 - \frac{1}{\#Scens}\left(\sum_{\text{success Scens}} 1 + \sum_{\text{failure Scens}} REshare\right) = 20,19\,\% \tag{33}$$

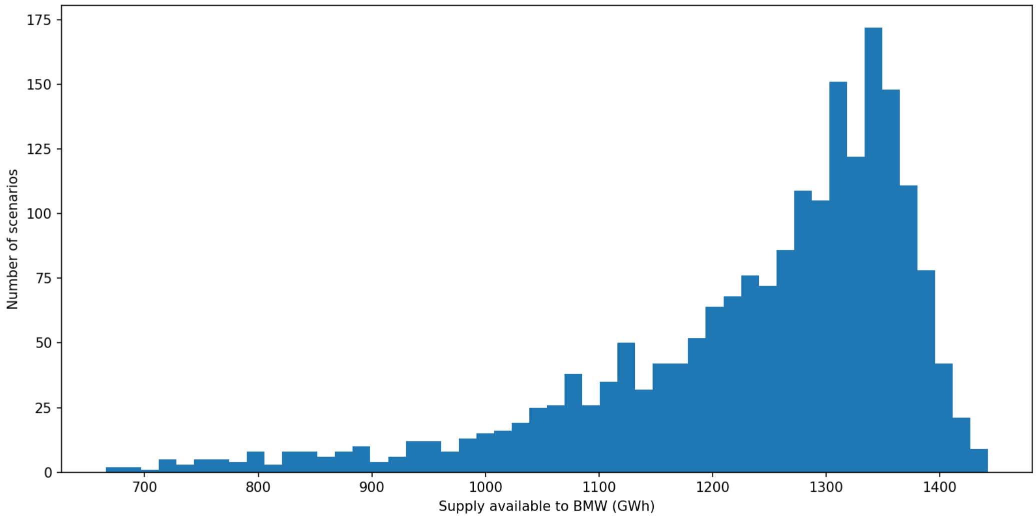


Figure 14: Electricity supply theoretically available to *BMW*, downscaled from nation wide supply. The values are given by $E_{Comp} = c^T_{Comp} \cdot E^{RE}_{Nat}$

Identifier	**Data**
Number of Scenarios	1985
Nat. wide comp. cons. forecast	1892,71 GWh
Average renew. supply for company	1239.96 GWh
Standard deviation	140.60 GWh
Number of failures	1985
Average renew. share for failures	79,81 %

Table 4: Result overview for *BMW*'s national analysis.

A full result data overview on the national analysis of *BMW* can be seen in tab. 4. This result will be used further down the line as a benchmark result to be compared to localized riskmetrics.

3.3 Local analysis

3.3.1 Local availability of renewables

Up next is the localized analysis of *BMW*'s company sites. These are: München, Dingolfing, Berlin, Leipzig, Landshut, Regensburg, Eisenach and Wackersdorf. Their geographical coordinates can be seen in table 5. Following the procedure as described in section 2.2.1, for each company site the geographic regions containing and surrounding the site are established. This number is displayed in table 5, see column "Num. of surrounding geographic

Site Location	Coordinates (Lon,Lat)	Num. of surrounding geographic regions
München	11.5753, 48.1371	7
Dingolfing	12.4977, 48.6300	5
Berlin	13.3888, 52.5170	6
Leipzig	12.3747, 51.3406	7
Landshut	12.1516, 48.5362	8
Regensburg	12.0974, 49.0195	6
Eisenach	10.3193, 50.9747	11
Wackersdorf	12.1938, 49.3123	6

Table 5: *BMW* company sites in Germany and their respective geographical coordinates

regions". In the Appendix (see fig 38 and following) one can find geographic maps displaying the location of the main and the surrounding geographic regions for each company. Data on all considered geographic regions can be found in tabular form in [25].
Weights are assigned to the geographic regions, where

$$w_{gr,main} = 0,4 \tag{34}$$

is given as the main weight for the geographic region in which the company site is located and

$$w_{gr,border} = \frac{0,6}{\#Sites - 1} \tag{35}$$

for all geographic regions bordering on the main geographic region. The weights are readjusted as described in section 2.2.1. The data to calculate $REshare_{gr} = \frac{E_{gr}^{RE}}{E_{gr}}$ per geographic region is gathered and used to calculate the intermediate result per scenario:

$$REshare_{Site}^{Scen} = \sum_{gr \in \text{geo regs}} w_{gr} \, REshare_{gr} \tag{36}$$

The results are displayed in figure 15.

3.3.2 Electricity consumption

As described in section 2.2.2, the company's nation wide electricity consumption (eq. (30)) is distributed to all production sites.
No further information that could be used to tune this electricity demand distribution to the sites is publicly available. This includes financial data

Scenario	München	Dingolfing	Berlin	Leipzig	Landshut	Regensburg	Eisenach	Wackersdorf
0	0,4430	0,6111	0,0738	0,2566	0,7468	0,6727	0,3638	0,7547
1	0,7894	0,9895	0,9898	0,4796	0,9952	0,9960	0,6395	0,9921
2	0,5395	0,7914	0,1362	0,2681	0,9406	0,8878	0,5157	0,9056
3	0,7730	0,9655	0,8687	0,3472	0,9855	0,9909	0,5536	0,9871
4	0,5956	0,9464	0,6107	0,3816	0,9730	0,9671	0,5501	0,9703

Nationwide Result
0,7981

Figure 15: Local results for $REshare_{Site}^{Scen}$ per scenario and company site. This represents the intermediate result for section 3.3.1.

(GVA, sales volume, etc.), production volumes, employees and building size. The company wide electricity consumption is therefore split equally among the sites:

$$D_{FC}^{Site} = \frac{D_{FC}^{Comp}}{\#Sites} = 236,589\,\text{GWh} \tag{37}$$

This result is used in the following section to evaluate scenario plausibility, this time on a local level.

3.3.3 Riskmetric

A value for the renewable electricity supply theoretically available to each company site is established next. The steps described in the following refer to a singular site and are repeated to gather results for every site.
Each site is located within a geographic region, and has a number of surrounding geographic regions. The renewable electricity generation $E_{Site,gr}^{RE}$ for each surrounding geographic region is taken directly from the model. With these values one can directly calculate the assumption of available renewable electricity for a singular site E_{Site}^{RE}:

$$E_{Site}^{RE} = \sum_{gr \in \text{ geo regs}} w_{gr} E_{Site,gr}^{RE}, \tag{38}$$

where the weights w_{gr} are the same as the readjusted weights from section 3.3.1.
This value is used to evaluate how the localized demand side calculations compare to the supply side calculations, i.e. a plausibility check for the scenarios. It is conducted as described in 2.1.3: If

$$E_{Site}^{RE} \geq D_{FC}^{Site}, \tag{39}$$

the scenarios local renewable share ($1-REshare_{Site}^{Scen}$) is employed to calculate $RiskMetric_{Site}$. Otherwise, if

$$E_{Site}^{RE} < D_{FC}^{Site}, \tag{40}$$

this scenario is considered to be a failure for the company site. The nation wide $RiskMetric_{Nat} = 20,19\,\%$ is then assumed for this company site and scenario. This may alter the result substantially, depending on the site. Statistics on these analyses can found in the Appendix, see figure 37. In a final step the local riskmetric is calculated from the share of renewable electricity sources per scenario, local in case of scenario success or the national riskmetric in case of scenario failure. The average over all scenarios is

$$RiskMetric_{site} = \frac{1}{\#Scens}\left(\sum_{\text{success Scens}} (1 - REShare_{Site}^{Scen}) + \sum_{\text{failure Scens}} RiskMetric_{Nat}\right) \tag{41}$$

The riskfactors per company site of *BMW* can be taken from figure 16.

	München	Dingolfing	Berlin	Leipzig	Landshut	Regensburg	Eisenach	Wackersdorf
RiskFactor	0,3718	0,1391	0,1868	0,6533	0,0717	0,097	0,4754	0,0779

Nationwide Result
0,2019

Figure 16: *BMW* - Final results for each company site, as calculated from 41

3.4 Sensitivty analysis

In this section a limited scope sensitivity analysis is conducted to evaluate the model choices. This considers methodology for GVA forecasting and the down-scaling of nation wide supply.

GVA forecasting

The fit to forecast the GVA for companies is established according to the **right. based on science** approach (see sec. 2.1.1). An alternative is given by simply fitting the GVA GVA_t against the years t in a classic manner, i.e.

$$\hat{GVA}_t = \hat{\beta}_0 + \hat{\beta}_1 \cdot (1+r)^t + \hat{\beta}_2 \cdot t. \tag{42}$$

This model still assumes exponential growth, but all parameters are fitted. The fit is conducted for BMW to receive

$$GVA_t = 13,19\text{mn EUR} + (1-4,76 \cdot 10^{-6})^t \cdot 0,37\text{mn EUR} + t \cdot 1,16\text{mn EUR} \tag{43}$$

The resulting fit is displayed in figure 17. As can be seen from the figure, it is

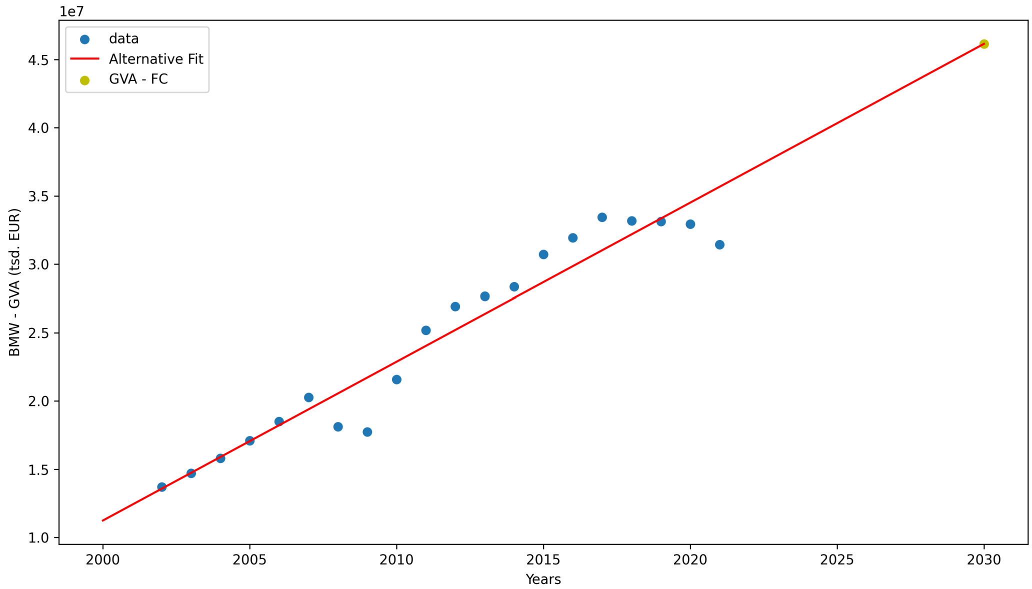


Figure 17: BMW - GVA against the years. In blue historical values for available years, in orange the forecast value for $t = FC$. In red an alternative regression fit according to eq. (43).

equivalent to a linear fit. The final forecast result of $GVA_{FC} = 46142,18$mn EUR is not notably different from the original result of $45679,91$mn EUR, see eq 26. The alternative approach makes no qualitative difference for this case study.

National downscaling

As mentioned in the respective sections (2.1.3, 3.2.3) the aspect of downscaling nation wide supply to the company level within this framework undergoes only superficial analysis. An in depth model to establish comparability is conceivable. Different choices may be illustrated by a given narrative of

a company's development and are therefore context reliant. The choice of the down-scaling approach is considered to be a model assumption, which is ideally set case-by-case.
Within the case studies, the last available value for this share is used. Examplary values for different approaches will now be given, based on the data available from *BMW*. In figure 18 the historical values for c^t_{Comp} are displayed, with $t \in [2002, 2021]$. The last available value for *BMW*, which is used throughout this thesis is given by $c^T_{Comp} = 0,244\,\%$.

Historical values of the share - Mean Value
The average from all historical values displayed in figure 18 results in $c^{avg}_{Comp} = 0,204\,\%$ and is in turn around 20 % less than the used value $c^T_{Comp} = 0,244\,\%$

Future projection with linear fit

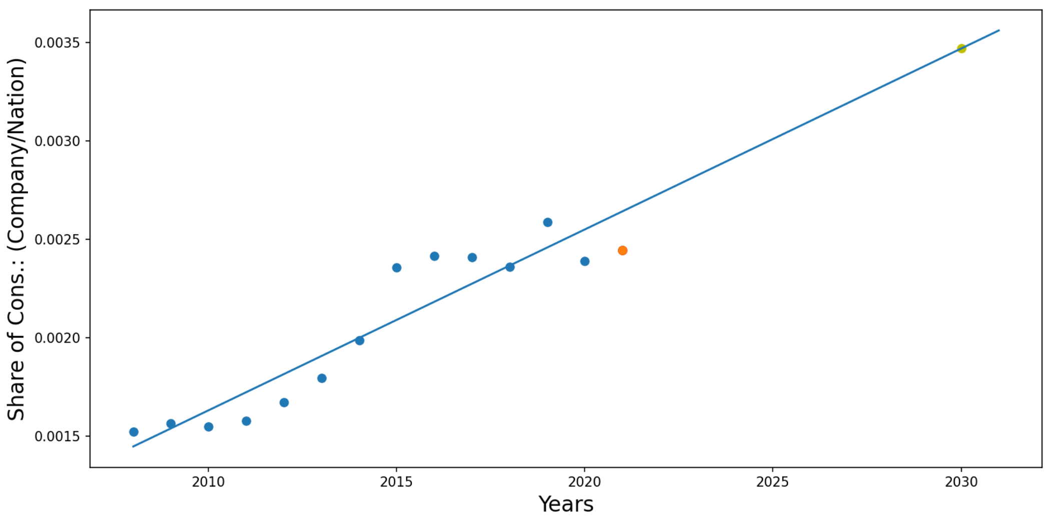


Figure 18: *BMW* - Share of electricity consumption w.r.t. nation wide consumption. In blue: historical values for available years, including a linear fit. In orange: the value c^T_{Comp} used throughout this thesis. In yellow: a forecast value $c^{FC}_{Comp} = 0,346\,\%$, as calculated from the linear fit.

In figure 18 a linear fit for the historical values is displayed. Using this fit to forecast a share for the year $t = FC$, one receives $c^{FC}_{Comp} = 0,346\,\%$, which is equal to around 140 % of c^T_{Comp}. Employing this value for the downscaling approach reduces the amount of scenarios that fail down to 1399 from 1985. Only 70 % of the scenarios fail, instead of 100 %. Tab. 6 displays a full result data overview. See also fig. 19, where the cut-off point, i.e. the amount of renewable electricity supply below which the scenarios fail, is displayed.

Identifier	**Data**
Number of Scenarios	1985
Nat. wide comp. cons. forecast	1892,718 GWh
Average renew. supply for company	1760,56 GWh
Standard deviation	199,63 GWh
Number of failures	1399
Average renew. share for failures	76,45 %
Final riskmetric	**16,59 %**

Table 6: Result overview for *BMW*'s alternative national analysis. A different downscaling share is employed here: $c_{Comp}^{FC} = 0,346\,\%$

3.5 Result discussion

The topic of discussion is now whether the results for this case study are reasonable within the context of this framework, starting with the national result.

National values via share of employees

To receive national values, i.e. values to applied to a german analysis in the context of this case study, the global values as given by the *SVR*s are scaled down using the share of employees in Germany, see section 3.1. Equating the share of the GVA generated and electricity consumed in Germany with the share of employees is a consequential assumption. However, the data is lacking any further insight regarding electricity consumption and GVA in Germany. It is therefore necessary make this assumption for the conducted case study.

EEI Decrease

The projected EEI decrease is reasonable considering that technological improvements are the main driver for such a development. *BMW* regularly releases press reports ([22]) commenting on how they target every facet of their business and try to improve in terms of energy efficiency. Whether the assumed linear decrease is sustainable long-term or whether it is going to converge remains to be seen.

Result Discussion - Country level

As the table 4 suggests, the national approach fails *BMW* for every scenario. W.r.t. to the statistical analysis the discussions of the general model and can

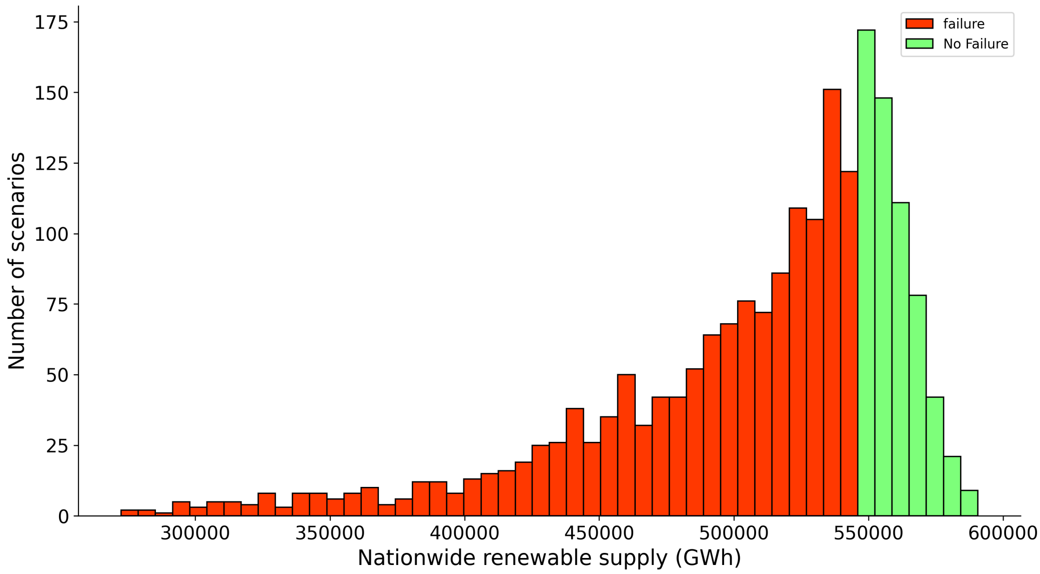


Figure 19: Final result histogram for *BMW*'s nation wide analyses: Displayed are the nation wide renewable electricity supplies for all scenarios. In red, scenarios for which receive a failure as described in 3.2.3. In green the success scenarios are marked. This leads to a clear cut-off point: Scenarios below a threshold fail, while the ones above the threshold are a success. The scenarios are evaluated with an alternative downscaling approach of $c^{FC}_{Comp} = 0,346\,\%$

be found in sections sections 2.1.1 and 6.1.3.
The economical aspects remain to be analysed:
The data suggests a decrease in nation wide electricity supply from 674214 GWh [26] to an average renewable supply of 507554 GWh in the year $t = FC$ (see fig. 3), i.e. a decrease down to 75 %, of which 0, 244% are available to *BMW*, same as in 2021.
On the other hand the forecast results in an increase in *BMW*'s electricity consumption from 1647, 11 GWh in year 2021 to 1892, 71 GWh in the year $t = FC$, i.e. an increase of 14 %. In light of this contrasting development the results are thoroughly explainable and reasonable. In no *UNSEEN* scenario enough renewable electricity is provided to cover the growth projections for *BMW*. On the contrary, the amount of renewable electricity supply is decreasing compared to the total supply available in 2021. This restricts growth projects, provided they are to be carried out using renewable resources. The latter is in the interest of climate protection and is regulated by legal provisions. This results in an unsolvable contradiction for the national investigation of the case study *BMW*.
Potential improvements, which may be sufficient to align the supply scenarios

with the demand projections are discussed in section 6.

Result discussion - Local

Data for input parameters and values w.r.t. electricity supply are given by the *UNSEEN* framework methodology and results. Detailed explanations on the model are not feasible here and can be looked up in the respective literature (Frey et. al, 2020, [21]).
A comparison of the localized results with the nation wide results shows interesting trends.
Firstly, no scenario fails for any company sites, except for Berlin (figure 37). This is attributed to the ambitious attribution of localized supply. For each company site the weights of all considered geographic regions add up to 1, see eq 17. One can think of the amount of theoretically available renewable supply per site E^{RE}_{Site} as being equivalent to the theoretically available renewable supply of a whole geographic region in terms of magnitude. In this analysis, the whole supply within one of the 391 geographical regions is assigned to a singular site, while there are more than 3 million companies registered nation wide [27]. This is an insufficient consideration of the economical landscape in Germany. The steps undertaken in this context are an attempt to make the localized geographic region data comparable to company site data. For this a mapping of the geographic regions to geopolitical entities and detailed company data are necessities. Both of these aspects lie outside of the scope of this thesis. A theoretical workflow is suggested, given these two procedures can be implemented, in the improvements section 6.1.4.
Secondly, one can see high variances for the different company sites, not only in terms of final riskmetrics, but also within the singular scenarios (figure 15) (see also section 6.2.1). While this reflects on the wide range of *UNSEEN* scenarios, a higher number of scenarios is desirable to ensure consistent end results.
Thirdly, a comparison of the localized results per company site with the nation wide company results leads to the following conclusions: For long-term expansion plans of production three sites are highly desirable, namely Landshut, Wackersdorf and Regendsburg, with a riskmetric of7.17 %, 7.79 %, and 9.70 %, respectively. Additionally, Dingolfing and Berlin posses a lower riskmetric than the national average. However, these sites also show high variances in singular scenario results w.r.t. $REShare^{Scen}_{Site}$, which limit their suitability for increased production reliant on renewable resources.

4 Case study - WALA Heilmittel GmbH

Due to the nature of this framework and the case studies both the actual procedure for this case study as well as the discussion part show high similarities and analogies w.r.t. to previously discussed case study for *BMW*.

4.1 Economic background and sustainability goals

Sustainability Goals

WALA's commitment to sustainability is evident through its efforts to achieve climate neutrality goals. Through implementation of eco-friendly practices and adoption of renewable energy sources, the company has significantly reduced its carbon footprint. By prioritizing sustainability at every level of operation, the company shows its dedication to combatting climate change. Official statements regarding this topic can be found in their "Environmental Statement" (*WALA*, 2021, [24]).

Company Data

While *WALA* has supplied data for this research, the supplied data is also publicly available. *WALA* as a economic entity conglomerates multiply companies, with *WALA Heilmittel GmbH* being one of their subcompanies. The data was provided on only this subcompany, which has one production site, located in Bad Boll. Data series provided are electricity consumption, energy consumption, employees, turnover and gross value added. They range in availability from 1991 to 2021. The GVA is an exception here, since its collection started only in 2010.
Note: From this point onward any mention of *WALA* directly refers to the subcompany *WALA Heilmittel GmbH.*

4.2 Nation wide analysis

4.2.1 GVA and electricity consumption

GVA

WALA as a company has shown interesting developments. It has managed to establish itself as a company in the chemical industry sector, showing an overall growth in GVA on average. The GVA development is dominated by 3 big jumps in 2011, 2013 and 2016. During these timeframes it is apparent that prior expansion investments have paid of, be it in the number of employees, production investments or electricity efficiency improvements, where one can

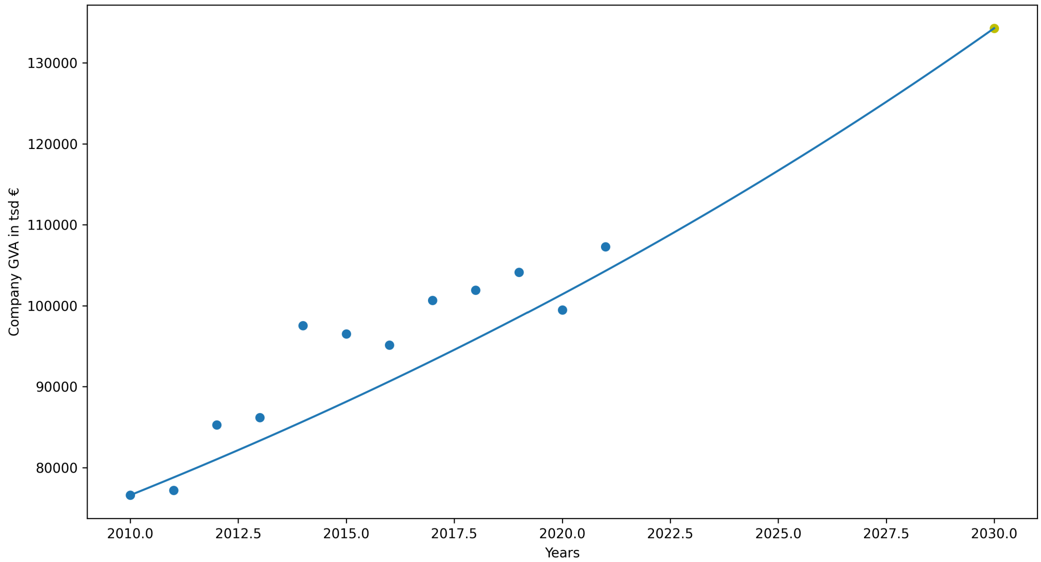


Figure 20: *WALA*'s GVA (in blue) against the years. In green the forecast value for the year FC is marked, as calculated in 45. The values for *WALA*'s GVA are taken from 45

see similar developments.
The forecast for the GVA is established using the methodology established by right. based on science, as described in 2.1.1. The growth factor r is

$$r = \sqrt[T-t_0]{\frac{GVA_T}{GVA_0}} - 1 = 0,284, \tag{44}$$

where $T - t_0 = 2021 - 2010$ and GVA_T and GVA_0 are the first and last available value from Tab. 45 respectively. The forecast value for the GVA is then given by

$$GVA_{FC} = GVA_0 \cdot (1 + r)^{FC - t_0} = 138095\,\text{tsd. EUR} \tag{45}$$

In figure 20 one can see how this model compares to the real values. The exponential growth assumption deviates from the real values, slightly undercutting them. The outliers in the years 2015 and 2016, which show regression in the GVA growth, are to be marked as cause for this. This forecast value will be used in the framework to establish a value for *WALA*'s electricity consumption in year $t = FC$.

Electricity consumption

WALA's historic electricity demands are displayed in figure 21 including a linear fit. Similar to the GVA, it is dominated by three major jumps, with

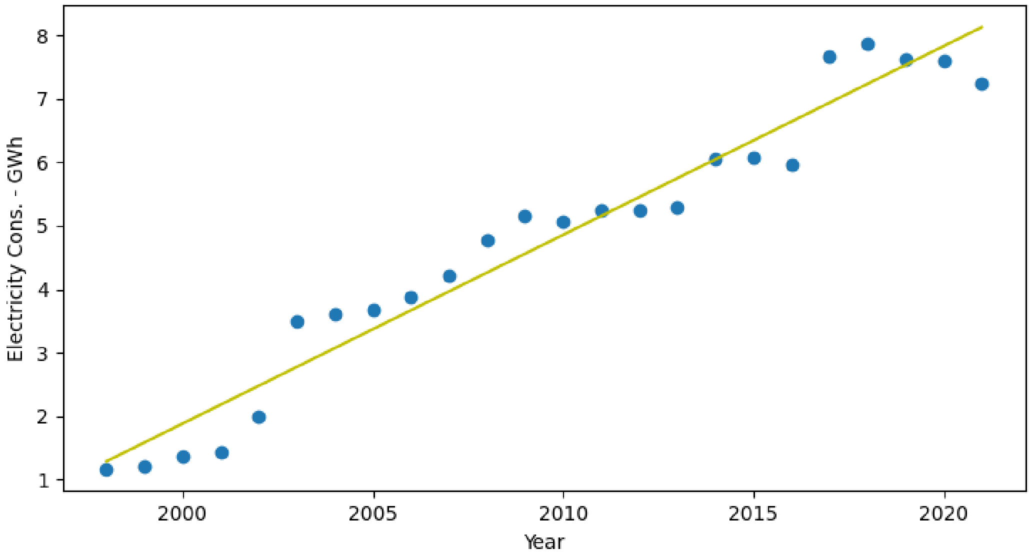


Figure 21: *WALA*'s electricity consumption against the years, including a fit for the linear trend. The values for *WALA*'s electricity consumption are shown in figure 45

the first one dating back to 2003.
As described in section 2.1.1, a linear regression is conducted to receive a forecast value for *WALA*'s EEI. The regression is defined as

$$E\hat{E}I_t = \hat{\beta}_1 \cdot t + \hat{\beta}_0, \tag{46}$$

where $EEI_t = \frac{D_t}{GVA_t}$ depicts the regressand and the years t are the regressor. The company's consumption D_t and GVA (GVA_t) refer to the values that have been supplied directly by the company, see 45, column "Stromverbrauch" and "Gross value added", respectively. The regressor is given by the years t. Since GVA is only available from 2010 onwards only 11 values (from 2010 to 2021) are available for the EEI. The regression results as a figure is shown in 22. The received result for the EEI is

$$E\hat{E}I_t = 1,02 \cdot 10^{-6} \frac{\text{GWh}}{\text{y} \cdot \text{tsd. EUR}} \cdot t - 1,988 \cdot 10^{-3} \frac{\text{GWh}}{\text{tsd. EUR}}, \tag{47}$$

The EEI shows an increase of 1,02 $10^{-6} \frac{\text{GWh}}{\text{tsd. EUR}}$ p.a. as determined from the linear regression, indicating a rising trend. From this a forecast for the EEI can be calculated as

$$EEI_{FC} = 8,24 \cdot 10^{-5} \frac{\text{GWh}}{\text{tsd. EUR}} \tag{48}$$

With the previous result for the GVA forecast (see 45), $WALA$'s electricity consumption within the nation Germany in the year $t = FC$ is evaluated to

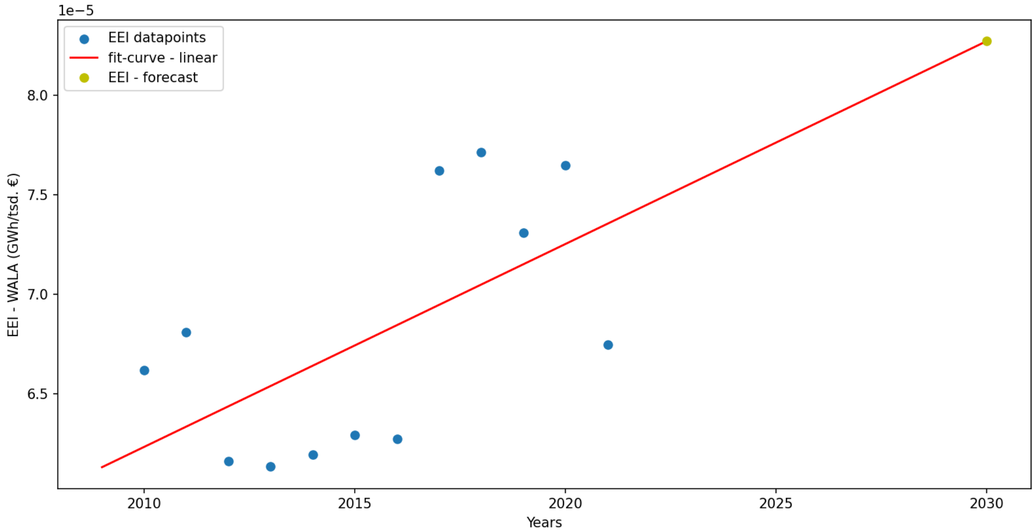


Figure 22: Linear regression for *WALA*'s EEI, as defined in 47. The singular values for given years is marked in blue. The forecast value as calculated in is marked in yellow.

be

$$D_{FC}^{Comp} = EEI_{FC} \cdot GVA_{FC} = 11,42\,\text{GWh} \quad (49)$$

This is a 55 % increase from the 2021 value.

4.2.2 Electricity supply

The values for future electricity supply are taken directly from the DLR framework *UNSEEN*, referring to section 2.1.2, where samples from a normal distribution are given. In fig 4 the share of renewable electricity is displayed, whereas the total amount of electricity with renewable sources can be seen in the histogram 5.

4.2.3 Riskmetric

In this section the intermediate downscaling step is performed again, resulting in a theoretically available renewable electricity supply for the company of this case study. The last available value for the company's share of consumption on the nation wide consumption $c_{Comp}^{T} = 0,001073\,\%$ is used for this.
When now comparing the downscaled nation wide supply with the forecast for the company's consumption, the values considered are the nationwide

supply E_{Nat} multiplied with the share c^T_{Comp}, see figure 23 for the respective histogram. The next step is to conduct a comparison, according to the

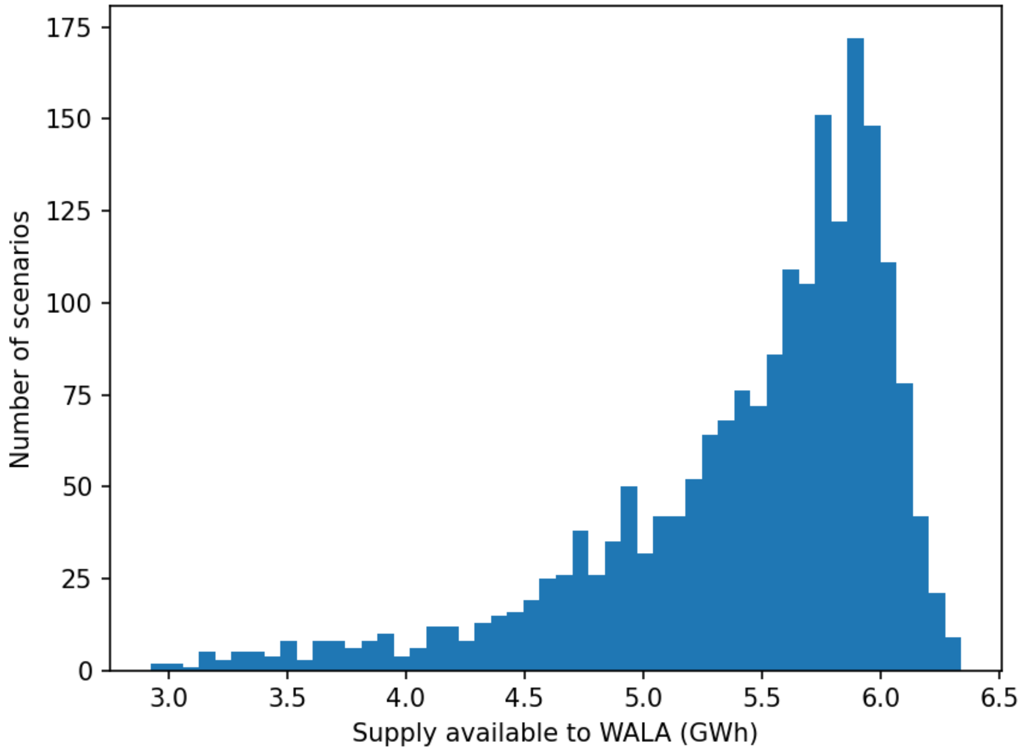


Figure 23: Electricity supply theoretically available to *WALA*, downscaled from nation wide supply. The values are given by $E_{Comp} = c^T_{Comp} \cdot E^{RE}_{Nat}$

methodology described in section 2.1.3

If

$$E^{RE}_{Nat} \cdot c^T_{Comp} \geq D^{Comp}_{FC}, \tag{50}$$

then the company can fully provide itself with renewable electricity, i.e. their share of renewable electricity is equal to 1. This is then referred to as a success scenario. Otherwise, if

$$E^{RE}_{Nat} \cdot c^T_{Comp} < D^{Comp}_{FC}, \tag{51}$$

this is considered a failure scenario. The company's share of renewable electricity for this scenario will be equivalent to the nation wide share, i.e. $REShare_{Comp} = \alpha_{RE}$. Statistics on these evaluations can be found in table 8.

Site Location	Coordinates (Lon,Lat)	Num. of surrounding geographic regions
Bad Boll	9.5947, 48.6382	10

Table 7: *WALA Heilmittel GmbH*'s company site in Germany, its respective geographical coordinates and number of surrounding geographic regions.

The average over all scenarios then results in the national riskmetric, describing the risk of *WALA* being able to supply all its german sites :

$$RiskMetric_{Nat} = 1 - \frac{1}{\#Scens} \left(\sum_{\text{success Scens}} 1 + \sum_{\text{failure Scens}} REshare \right) = 20,19\,\% \tag{52}$$

This result will be used further down the line as a benchmark result to be compared to localized riskmetric.

4.3 Local analysis

4.3.1 Local availability of renewables

The localized analysis for *WALA Heilmittel GmbH*'s company site in Bad Boll is conducted next. Its geographical coordinates can be seen in tab. 7. A graphical display of the companies location and all surrounding geographic regions within Germany is shown in figure 24. Data for all geographical regions considered can be found online in tabular form, including the total amount renewably generated electricity, the total generated electricity and the in-/outflow of electricity. See the citation [25] for this. Following the procedure as described in section 2.2.1, weights are assigned to the geographic regions, s.t.

$$w_{p,main} = 0,4 \tag{53}$$

is given as the main weight for the geographic region in which the company site is located and

$$w_{p,border} = \frac{0,6}{10-1} \tag{54}$$

for all geographic regions bordering on the main geographic region The weights are readjusted depending on import and export of electricity with transmission lines. The data to calculate $REshare_{gr} = \frac{E_{gr}^{RE}}{E_{gr}}$ per geographic region is gathered and used to calculate the intermediate result per scenario:

$$REshare_{Site}^{Scen} = \sum_{gr\,\in \text{geo regs}} w_{gr}\, REshare_{gr} \tag{55}$$

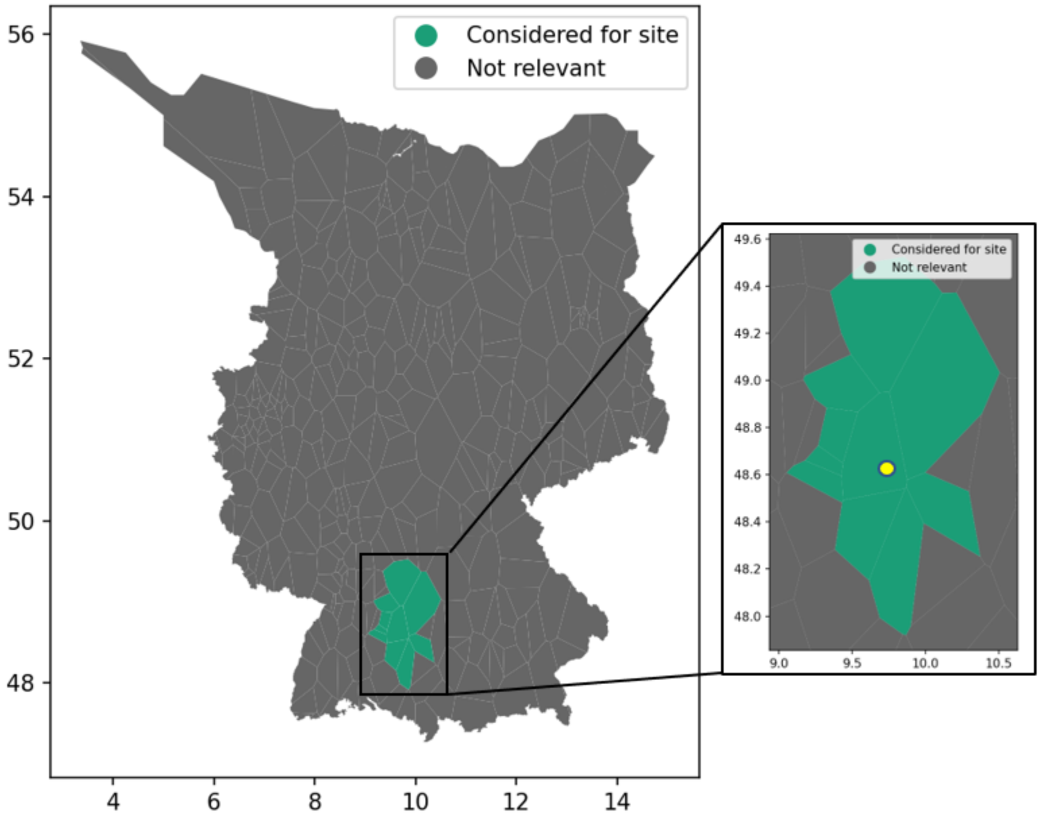


Figure 24: Left: geographical representation of BadBoll as located within Germany. Right: Zoom onto considered geographic regions, with the location the of company site marked in yellow

The results are displayed in figure 25.

4.3.2 Electricity consumption

As described in section 2.2.2, a value for the company site specific consumption forecast is to be established. Since there is only one company site available for this case study, the specific energy consumption D_{FC}^{Site} forecast is equivalent to the nation wide forecast from equation (49), i.e.

$$D_{FC}^{Site} = 11,42\,\mathrm{GWh} \tag{56}$$

4.3.3 Riskmetric

Referencing the localized DLR model described in section 2.2.3, the local renewable electricity generation is analyzed to establish a value for the renewably generated electricity theoretically available to the company site in

Scenario	BadBoll
0	0,6986
1	0,9881
2	0,8711
3	0,9731
4	0,9392

Figure 25: Local results for $REshare_{Site}^{Scen}$ per scenario for Bad Boll company site. This represents the intermediate result for section 4.3.1.

Bad Boll. The renewable generation $E_{Site,gr}^{RE}$ for each surrounding geographic region is taken directly from the model. This allows for direct calculation of the desired quantity E_{Site}^{RE}:

$$E_{Site}^{RE} = \sum_{gr \in \text{geo regs}} w_{gr} E_{Site,gr}^{RE}, \tag{57}$$

where the weights w_{gr} are the same as the readjusted weights from section 4.3.1.
With E_{Site} calculated a plausibility check for the scenarios can be conducted. Said plausibility check consists of a localized comparison between the consumption side and supply side calculations, as described in 2.2.3: If

$$E_{Site}^{RE} \geq D_{FC}^{Site}, \tag{58}$$

the scenarios local share $(1 - REshare_{Site}^{Scen})$ will be used to calculate the riskmetric. Else, if

$$E_{Site}^{RE} < D_{FC}^{Site}, \tag{59}$$

the nation wide riskmetric $RiskMetric_{Nat} = 20,19\,\%$ is considered for this scenario. Statistics on these analyses can be found in the Appendix, see 47.
In a final step the calculation of the riskmetric from the share of renewable electricity sources per scenario is conducted, with either $(1-REShare_{Site}^{Scen})$ in case of scenario success or the national riskmetric in case of scenario failure. The average over all scenarios is given by eq. (23) The result received from averaging over all scenarios is

$$RiskMetric_{\text{ Bad Boll}} = 10,57\,\%. \tag{60}$$

4.4 Result discussion

The topic of discussion is now whether the assumptions and results for this case study are reasonable within the context of this framework, starting with the national result.

Identifier	Data
Number of Scenarios	1985
Company wide consumption forecast	11,42 GWh
Average renew. supply for company	5,44 GWh
Std. Dev.	0,61 GWh
Number of failures	1985
Average renew. share for failures	79,81 %

Table 8: Result overview for *WALA*'s national analysis.

EEI Increase

The increasing trend for the EEI, as established in eq. (47), contradicts the anticipated decrease attributed to expected technological advancements and efficiency improvements. Additionally, the regression analysis shows high variance with respect to the data points. The data series in electricity consumption and GVA exhibit multiple jumps.
The limited number of data points may not fully capture the long-term patterns and is subject to fluctuations, which negatively affect the regression result.

WALA's share on nation wide demand

The assumption on $WALA$'s future share of energy demand remains to be discussed. This methodology is a central part of this framework. A sensitivity analysis of this assumption conducted for *BMW* in the previous case study shows how much of an influence the down-scaling approach has. Similar deviations in with alternative approaches are expected for *WALA*.

Result discussion - Country level

As the table 8 suggests, the national approach fails $WALA$ in every scenario. The discussion now focuses on the reasonability of these observations within the context of this framework, focusing on economic assumptions.
Several important aspects related to the data sets provided by the company need to be considered in order to assess the analysis.
The data suggests a decrease in nation wide energy supply from 674214 GWh [26] to an average renewable supply of 507554 GWh in the year $t = FC$ (see fig. 3) in $t = FC$, i.e. a decrease down to 75 %. The share available to *WALA* is limited to $0,001073\,\%$.
The framework shows an increase in *WALA*'s energy consumption from

$7,237\,\text{GWh}$ in year 2021 to $11,42\,\text{GWh}$ in $t = FC$, i.e. an increase of more than 55 %. These contrasting developments lead to a contradiction in the context of this framework. Growth projects, provided they are to be carried out using renewable resources, can not be covered by the projected amount of renewable electricity resources in any given scenarios. The resulting contradiction stands as an examplary case study for misalignment of energy consumption projections and scientific studies concerning supply scenarios.

Result discussion - Local

Investigation of REMix model results cannot be explained in detail here, see reference Frey et. al, (2020, [21]) for elaborations.
The comparison of national and localized result offers interesting insights.
No scenario fails for the company site in Bad Boll (figure 47). This is again attributed to the allocation of localized supply of localized supply, i.e. the company site receiving an amount of renewable supply which is in magnitude as high as the supply for a whole geographic region. An in depth analysis is necessary to guarantee comparability, including a mapping of geopolitical entities to the assumed geographic regions. In the case of Bad Boll the following information is relevant here: Bad Boll belongs to the "Landkreis" of Göppingen, which contains 27 top companies ([30]). One may therefore potentially only attribute a respective share of the resources from geographic regions intersecting with Göppingen.
Still, there exists a noteable difference of 9, 62 % between the localized and nation wide riskmetric, which leads to the conclusion that the localized supplication with renewable electricity for *WALA Heilmittel GmbH*'s company site in Bad Boll is more secure than than in the nation wide average. The nation wide riskmetric is almost twice as high as the local riskmetric. *WALA* should therefore aim to cover its future electricity demand with direct delivery agreements from local suppliers.

5 Add-On: Benchmarking

In this section it is investigated how a company's electricity intensity predictions hold up against its direct economic competitors in the form of its respective sector. While forecasting sector electricity consumption and comparing this forecast to a companies consumption is an option, the intensities allow for interpretation of efficient resource utilization, and are therefore of higher interest.
The sector specific EEI development is established by determining the parameters of a regression model, that assigns a sector's GVA to its electricity consumption, in analogy to the company's EEI regression model:

$$E\hat{E}I_t^{Sec} = \hat{\beta}_0 + \hat{\beta}_1 \cdot t \tag{61}$$

with a machine learning *least-squares regression* model. The company-specific electricity intensity will then be compared to a sector-specific energy intensity projection to complement a benchmark framework, similar to the XDC-Model. Multiple different approaches of benchmarking the company against the sector present themselves One can look at...

- ... the EEIs as of today,
- ... the EEIs as given by forecast/projection values,
- ... the EEI growth (change rate) between today and the forecast horizon - compared by time developement,
- ... the values of the analytical derivative of the EEI between today and the forecast horizon.

The choice here is to analyze the EEI and the difference quotient of the EEI between today and the forecast horizon as follows: A first analysis considers the EEI in its raw values to draw preliminary conclusions. Afterwards the difference quotient is investigated year by year.

5.1 Benchmarking BMW against the automotive sector

5.1.1 Automotive sector - overview

The automotive sector plays a pivotal role in the german economy, contributing significantly to its growth, employment, and international competitiveness. As one of the leading global producers of automobiles, Germany has established itself as a powerhouse in the automotive industry. The sector encompasses a wide range of activities, including vehicle manufacturing, parts

production, research and development, and related services. With BMW being a key company among the industry's global players the ability to stay competitive is of highest importance. Efficiency plays a vital role here, not only in the company's production but also in products themselves being efficient in resource utilization. The focus of this investigation is on electricity efficiency represented by the EEI as described in the prior section.
The data on the auotmotive sector is taken from Destatis ([28], [29]) and displayed in the figures 36 and 35, with the 2021 value being interpolated for comparability.

5.1.2 Comparison - EEI

Both the EEI's for *BMW* and the automotive sector are displayed in figure 26. Calculations show that, averaging over all available values, *BMW*'s historic EEI has been 39% of the sectors EEI. This ratio has increased to 55% in 2021. One can see that *BMW*'s EEI has remained comparatively stagnant. While smaller jumps occur, a particular trend is not noticeable. In contrast, the sector shows a clear downward trend. In the observed periods, the EEI has more than halved, with the linear trend suggesting an approach to a third of the first observed value. This signals a remarkable improvement in the sectors electricity efficiency. This stark difference in EEI changes and development trends is attributed to *BMW*'s overall low EEI, and, in turn, high efficiency of value creation with energy usage. While the company still prides itself in efficiency improvements (see 3.1), the effective gain has little impacts on the EEI. It is important to note that the sectors shows convergence and stagnation over the last 5 observed values, with the ratio of $\frac{EEI_{BMW}}{EEI_{Sector}}$ remaining constant at around 55%. It is therefore reasonable to assume that *BMW* keeps the competitive lead against the sector average w.r.t. energy efficiency in the years to come.
Figure 27 underlines this further. It displays the difference quotient, i.e.

$$\Delta EEI_t = \frac{EEI_t - EEI_{t-1}}{EEI_t}. \tag{62}$$

While *BMW*'s development of the ΔEEI_t is inconsistent, with values fluctuating around 0, this solidifies its stagnation of the actual EEI, with the trend being showing an increase. The whole sector shows improvements over the years. The fluctuations over the last 5 years, similar to the ones for *BMW* explain the stagnation in $\frac{EEI_{BMW}}{EEI_{Sector}}$.

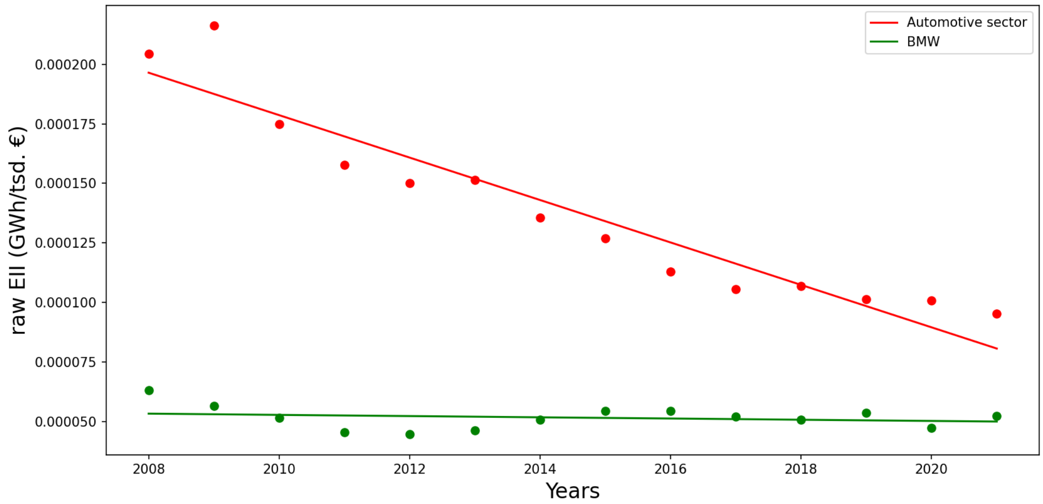


Figure 26: The EEI of *BMW* in green and the german automotive sector in red. This comparative view is used to benchmark the electricity efficiency performance of *BMW* against its respective sector.

5.2 Benchmarking WALA against the chemical industries sector

5.2.1 Chemical industries sector - overview

The chemical industries sector plays a vital role in the German economy, serving as a cornerstone of its industrial landscape and contributing significantly to economic growth, employment, innovation, and international trade. Germany has long been recognized as a global leader in chemical production, boasting a diverse range of sub-sectors including basic chemicals, specialty chemicals, pharmaceuticals, and plastics. While *WALA Heilmittel GmbH* is a comparatively small company within this industry its energy policies and related performance is remarkable compared to the sectoral average, as will be discussed in the following. The data on the chemical industries sector is taken from Destatis ([28], [29]), with the 2021 value being interpolated for comparability.

5.2.2 Comparison - EEI

Both the EEI's for *WALA* and the chemical industries sector are displayed in figure 28. One directly sees that the two data sets are barely comparable. The sectors average is around 1,5 magnitudes higher than *WALA*'s EEI. This is due to the aforementioned wide variety of products and services within the

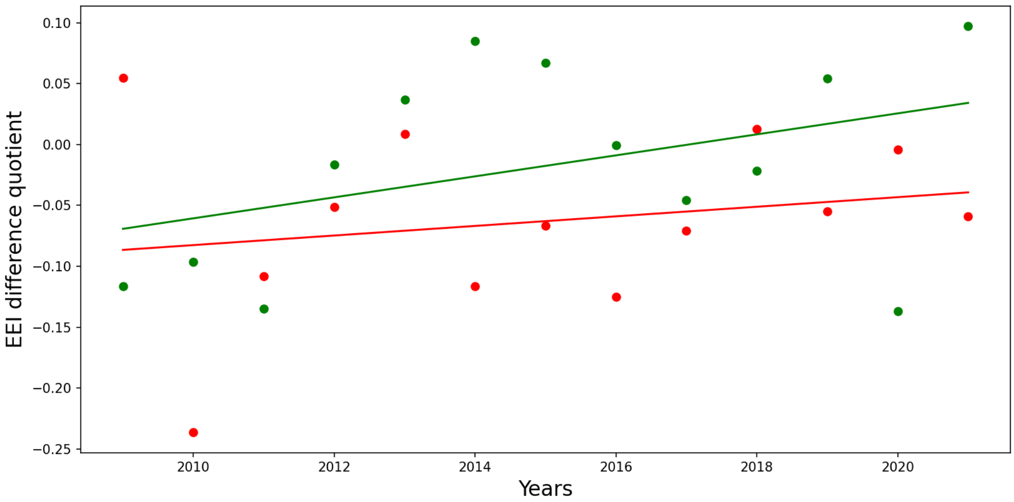


Figure 27: Difference quotient of the EEI's as defined in eq. (62) for *BMW* in green and the german automotive sector in red.

chemical industry sector. *WALA* provides products with comparatively low energy cost in production. On the contrary many competitors specialize in production processes with high energy intensity. These data series are therefore of limited interest and provide few insights.

The difference quotient according to eq. (62) paints a different picture worthy of investigation, see figure 29: From these graphs both EEI developments seem very comparable. They show similar trends, with both data series fluctuating around the 0-mark. The data suggests, that over the years neither the sector nor *WALA* were able to establish lasting energy efficiency improvements, that were not upended by a counteracting development in latter years. Still, the sector has taken more actionable steps. Almost all data points lie below the 0-mark, which means at least minor improvements every year. Multiple outliers suggest bigger improvements in these periods (2015, 2016 and 2020). While *WALA* shows two big outliers in 2012 and 2021, the majority of data points lie above the 0-mark, which equates to higher electricity consumption per value added.

The sector average and *WALA* remain difficult to compare. The EEI is separated by magnitudes due to the difference in provided services and products. The change rate of the EEI suggest a better performance in EEI-improvement by the sector, if only slightly.

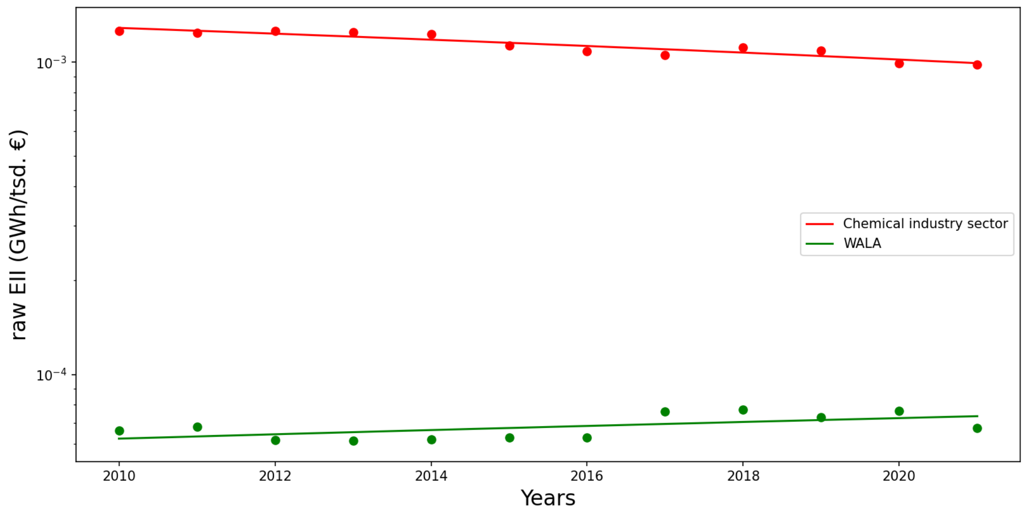


Figure 28: The EEI of *WALA* in green and the german chemical industries sector in red. The y-scale is logarithmic.

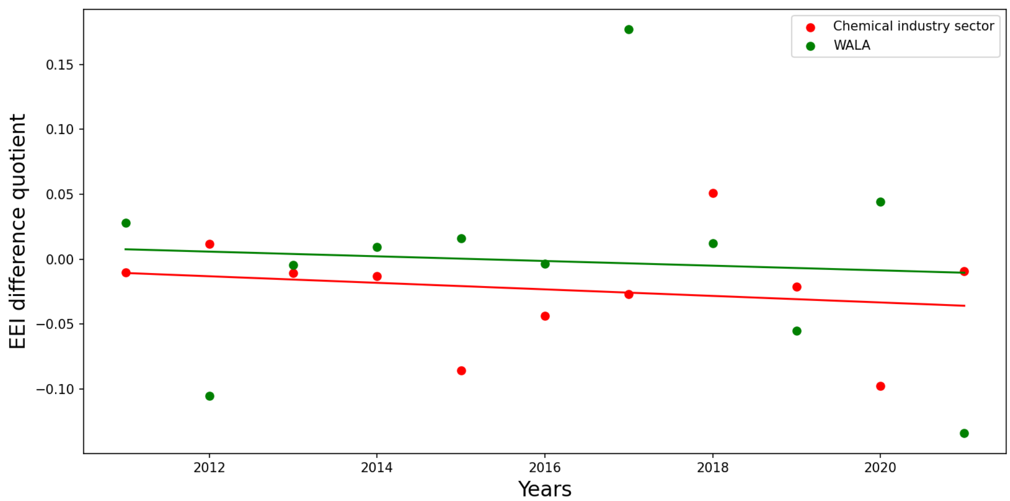


Figure 29: Difference quotient of the EEI's as defined in eq. (62) for *WALA* in green and the german chemical industries sector in red.

6 Model Improvements and Discussion

6.1 Improvements

This section focuses on possible improvements of the framework established in this thesis and how they fit into the state-of-the-art scientific context. The first aspect to be discussed is an investigation and possible variations of statistical approaches used throughout this thesis. The second topic is improving interactions of the company specific forecast with the *UNSEEN* framework results.

6.1.1 Regression model variations

Due to certain downsides of the linear regression model used throughout this thesis, this section discusses alternatives. The simplicity is also the model's main pitfall. Modelling expected macroeconomic effects, such as a convergence of electricity consumption w.r.t. economic growth, is strictly not possible. This is a generally expected effect in modern day technological landscapes, as described in 1.3.1, referring to Erdmann and Zweifel (2010, [4], p.92ff).

Logarithmic model

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_3 \cdot x + \hat{\beta}_1 \ln(\hat{\beta}_2 \cdot x), \tag{63}$$

It allows for consistent comparison and forecasting of appropriate data. This non-linear regression model offers notable advantages, i.e. the capability to depict non-linear growth when necessary. With the additional introduction of a difference of logs ($\Delta \ln$) this model can used as a general approach for time series models. Potential drawbacks associated lie in the introduction of additional complexity into the analysis process.

Exponential model

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_3 \cdot x + \hat{\beta}_1 \exp\Big\{(\hat{\beta}_2 \cdot x)\Big\}, \tag{64}$$

For the exponential model one significant advantage is its ability to model the expected convergence property for the Energy Efficiency Index (EEI). It has the potential to provide insights into the macroeconomic effects associated with energy systems. Drawbacks lie again within the added complexity.

Quadratic model

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_2 \cdot x + \hat{\beta}_1 x^2 \tag{65}$$

The quadratic model offers similar advantages as the exponential model, being able to model the expected convergence property for the Energy Efficiency Index (EEI) and incorporating both non-linear and linear growth patterns. Despite this advantage, this non-linear regression model remain relatively simplistic in its approach. The main downside for this model is that limit may be nonsensical. If $\hat{\beta}_1 < 0$ then the limit is $\propto -\infty$.

6.1.2 Analytical function for nation wide supply

The national supply of electricity, as given by the *UNSEEN* framework is sampled from a normal distribution. From the respective fit (fig. 31) one can see that

$$E_{Nat} \sim \mathcal{N}(635951, 28;\ 4982, 91) \tag{66}$$

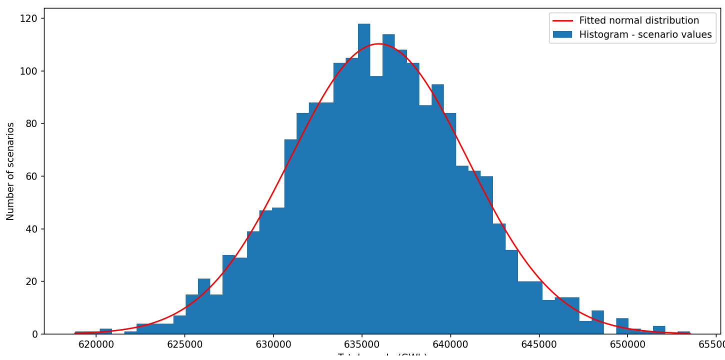


Figure 30: Histogram displaying the density function of *UNSEEN* framework result for nation wide electricity supply. Additionally, a normal distribution has been fitted onto the values. The y-axis is therefore scaled down to represent a density. These results can be used to establish an analytical density function for the nation wide renewable electricity supply.

For the purpose of an analytical investigation of the renewable supply, a Burr-distribution is fitted on the histogram of α_{RE}, which results in

$$\alpha_{RE} \sim Burr(160, 49;\ 0, 084), \tag{67}$$

and therefore

$$E_{Nat}^{RE} \sim \mathcal{N}(635951, 28;\ 4982, 91) \cdot Burr(160, 49;\ 0, 084), \tag{68}$$

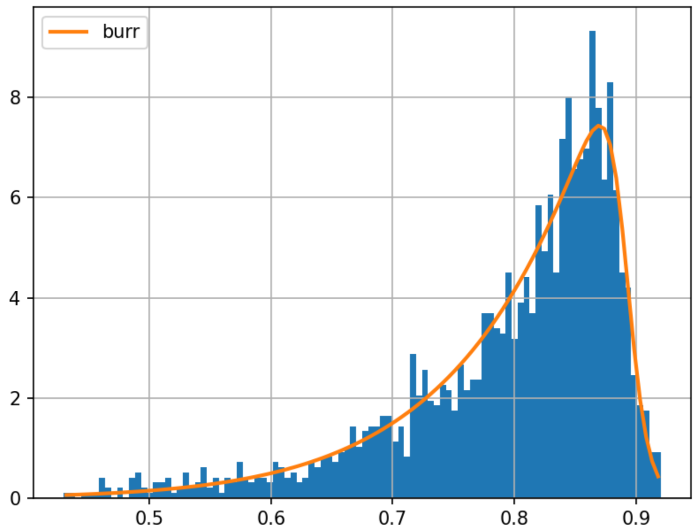


Figure 31: Histogram displaying the density function of *UNSEEN* model result for nation wide α_{RE}, i.e. the share of renewable electricity. Additionally, a Burr-distribution has been fitted onto the values. The y-axis is therefore scaled down to represent a density. These results can be used to establish an analytical density function for the nation wide renewable electricity supply.

The implementation of a continuous supply distribution can be used to sample further values for the supply of renewable electricity. The amount of nation wide scenarios can therefore be scaled up as desired. A similar distribution can be established for the localized scenario results, enabling scenario scaling on a local level. Alternatively one can directly replace the scenario values by continuous functions.
This further underlines this frameworks results to be used as probabilistic company KPIs. They may be used in analogy or addition to other supply risk assessment methodology like the VaR for energy management (Goebel, (2007) [6] p.212-215).

6.1.3 Alternatives to the regression model

For this thesis forecasts are established utilizing regression models, whereas other choices present themselves. Methodology to incorporate advanced models into energy consumption forecasting has been proven to be feasible in different research:
Hadjout et al. (2021, [31]), Mirsoltan and Akhavan (2013, [32]) and Wang et al. (2018, [33]) apply deep learning networks to the different industry sectors

in Algeria, Iran and China.
Da Silva et al. (2019, [20]) and Firsova et al. (2019, [34]) show how time series models such as ARIMA models and probabilistic approaches can be applied to the topic.
The common denominator is high data quality in longevity and accuracy due to public data sets released by official institutes or research groups. This stands in stark contrast to data sets available for the case studies of this thesis.
The scope of application in this thesis is limited and simplistic models for a robust framework are chosen. Bad data quality (i.e. annual data, low granularity, generally small data sets) allows only for simple regression models (such as linear regression algorithms) to be robust, while high data quality may allow for the implementation of time series forecasting algorithms used in scientific approaches, such as ARIMA models or more complex machine learning models (neural networks, etc.).
More complex models offer a deep insight into electricity market mechanics and how this affects the company. Different models may also offer further relevant results and be usable for applications (variational analysis, Monte-Carlo-simulations, etc.), which are strictly not considered in this research. Generally speaking the best solution for developing a model to forecast a company's financial and energy related KPIs is to establish such a model with the company itself. This also includes the choice of data series to be used as inputs, which is left out of the discussion for the reason of lacking communication with the case study companies.

6.1.4 Localization improvements

Site consumption split

The site specific consumption (see 2.2.2) can be optimized further. This requires higher data quality, i.e. site specific values on GVA and electricity consumption. The consumption is then ideally established by site specific forecasting, instead of splitting the company wide forecast equivalently between the site. Another simplistic alternative is a an alignment of the split with the company's site-specific development plans or establishing a partition of the consumption forecast which is in line with the today's split between the sites:

$$D_{FC}^{Site} = \frac{D_T^{Site}}{D_T^{Comp}} D_{FC}^{Comp}. \tag{69}$$

Mapping of geographic regions to geopolitical entities

For the theoretical improvement of accurately downscaling local *UNSEEN* results to the company site level a mapping of geographic region coordinates to geopolitical entities (In Germany: government level of "Landkreise") can be of use. If one can establish how much electricity has been consumed previously within these entities one could determine how this amount compares to the renewable supply given by the *UNSEEN* framework results, and draw conclusions w.r.t. to future developments by mapping the geographic regions accordingly. This in turn directly sets the boundary conditions for localized growth expectations for company sites.
In the following an examplary discussion will be conducted: Assume a mapping of geographic regions to such governmental entities is established. The data on local electricity consumption is known, (see p.e. [35] for *WALA*'s company site in BadBoll). The data for future renewable electricity supply is given by the REMix model results for the mapped geographic region. Assume a decrease of 20 % between the two values.
If a company plans to increase its GVA without reduction in *EEI* these values are again contradictory.
The localized comparison in this scenario directly considers localized geopolitical electricity infrastructure and relates it to the company's demand. Additionally, governmental data offers in depth differentiation in terms of sector, energy usage, etc. This enables a wider range of possible analyses (benchmarking, sectoral development), also in the context of the previous discussion in nation wide downscaling.

In- and outflow improvement

Equation (17) describes how the weights for considered geographic regions per site are readjusted, using data w.r.t. to the in- and outflow of electricity over geographic region borders. A theoretical improvement in this regard could be constructed as follows:
In the result files from the *UNSEEN* framework data is available on direct in- and outflow from one geographic region to another. This information can be used to restructure the geographic region weight adjustment, s.t. it does not simply just consider the total in- and outflow. Instead one inserts into eq. (17) the inflow from the bordering geographic regions into main geographic region, with the the outflow out of the main geographic region subtracted. This would ensure a more accurate representation of the role the electricity generation in the bordering geographic regions plays for the main geographic region and in turn the company site.

Szenario	Amount CO2	Total Supply
0	74139.4991	640106.299
1	32636.8765	619406.551
2	49641.2691	637547.911
3	38348.5038	647645.054
4	53822.9452	638120.33

Figure 32: Overview of *UNSEEN* framework parameters for the five local scenarios, that where investigated in the local analysis of the case studies. The parameters are given as input data for the *UNSEEN* framework and are used as targets for the optimization model. Displayed are the total amount of CO_2 emission per year in metric tons and the annual demand of electricity in GWh.

6.2 Further Discussion

6.2.1 Local scenario investigation

As mentioned throughout the thesis specific aspects of the *UNSEEN* framework necessary for detailed understanding of the causalities leading to the different scenario results is out-of-scope for this research. However, a general overview over the central parameters for the investigated local scenarios can be given. While this does not offer insights into the overall results for singular company sites, it enables a better understanding of the variances between the scenarios.

In figure 32 the input parameters "Amount CO_2" (total amount of CO_2 emission per year in metric tons) and "Annual Demand" (annual demand of electricity, equivalent to nation wide supply, in GWh) are displayed per scenario. While a lower amount of overall supply may directly result in a lower amount of renewable supply, there is no notable difference in the total supply. On the other hand the total amount of CO_2 emission shows a higher variance. A comparison between *scenario 0* and *scenario 3* leads to the conclusion:
Both have similar values in "Annual Demand", the amount of that has to be met by the national electricity generation. In *scenario 0* the parameter "Amount CO_2" has a higher value. Therefore more CO_2 can be emitted in electricity generation to meet the goal given by the "Annual Demand" parameter. In turn, less renewable electricity is generated. The overall share $REShare_{Nat} = \frac{E_{Nat}^{RE}}{E_{Nat}}$ is therefore lower than in *scenario 3*. This directly reflects on the $REShare_{Site}$'s for *scenario 0* compared to *scenario 3*, which are lower for all company sites, as seen in fig. 15 and fig. 25.

6.2.2 Internal considerations for companies

Both the datasets for company data (*BMW* SVRs and *WALA* "Environmental Statements") as well as the national electricity supply (*UNSEEN* framework) are given beforehand. Their extensivity and accuracy is investigated in this research, but the actual data quality remains outside of the researcher's control. Consequently, mitigating potential biases or inaccuracies resulting from these limitations is hindered. Of particular significance is the need for a higher quality and larger dataset for variables such as Gross Value Added (GVA) and electricity usage per value added. The data sets for GVA's are excessively short, which has a profound impact on further analyses.
The additional consideration of companies having preexisting entry points into the renewable energy market is out of scope for this thesis. With connections to direct suppliers a company can hedge itself against renewable supply shortages beforehand. Relevant information has to be provided by the company.
The case studies for the framework of this thesis are therefore ideally undertaken in direct cooperation with the companies. In this context **right.** aided with establishing and guiding exchanges with company representatives. The companies with which cooperation was considered are

- Porsche AG,
- Rolls Royce Power Systems,
- WALA Heilmittel GmbH,
- GFT Technologies SE,
- LaBiosthétique,
- BASF,
- Viessmann

Many of these companies have in-house teams working on similar questions and in turn see no value added in the work of this thesis. Unfortunately, no data was made available over the course of this research. The case studies therefore rely on publicly available data.

Microgrids

Preexisting infrastructure within the electricity market can be given by a *microgrid*. Literature in this aspect focuses on small scale electricity supply to the point of autonomy for the economic entities that are a part of the grid system. Research on microgrids is also adapted to represent fully climate neutral electricity production(García et al. 2019, [36]). Solutions like these are options for companies if the preceding step of establishing renewable over the public grid has failed. This therefore falls into the category of executive energy management decisions as discussed in the introductory literature section.

Rüdiger-Bachmann model

During the development of the war between Russia and Ukraine, Germany's dependency on russian gas was of high interest for economical research. Concepts and models that had been established in different context were refined and reapplied to investigate potential consequences of a gas supply shortage due to the political situation. Of particular interest is the model considered by Bachmann et al. (2022, [37]), based on the original work by Baqaee and Farhi (2019, [38]). It offers a framework for estimation of socio-economic effects due to resource shortages, among other factors. With a wholistic approach the model covers a broad range of possible applications to similar research questions and may therefore also be applied to the question of this research thesis. However, the task of employing a modified version of this model to evaluate site specific supply risks for single companies is beyond the scope of this thesis and has been omitted here. It may be integrated into the company's response strategy in the case of high supply risk.

7 Conclusion

The risk assessment model for renewable energy supply developed for companies offers throughout functionality in forecasting company electricity consumption and financial data. By relying on key performance indicators such as the EEI, Gross Value Added, and the calculated electricity consumption derived from GVA and EEI, the model provides reliable forecasts. These forecasts are based on analytical software solutions that have been developed, tested, and established using real-world data, see the **right based on science** XDC-metric. Furthermore, the model encapsulates a state-of-the-art framework for evaluating the future German electricity supply landscape, namely the *UNSEEN* framework. It incorporates both a nationwide model and a localized model, ensuring a comprehensive understanding in different detailing.

The nationwide analysis contains optimization results for total electricity generation, renewable electricity generation and the share of renewable energy sources at a national level, employing statistical analysis and a scenario based approach.

The localized model treats Germany as a conglomeration of 300+ geographic regions, allowing for a detailed analysis of electricity generation information per geographic region. By bringing together consumption and supply aspects, the risk assessment model provides a holistic evaluation. It undergoes scenario validation to ensure alignment with company specific consumption patterns, enhancing the relevance and applicability of the results. Finally, the model establishes a risk metric that serves as a representative measure for assessing the potential insufficiency of renewable energy supply.

This model aids companies in mitigating risks, optimizing energy utilization, and embracing a sustainable future.

The scenario studies offer deeper insights into applicability on the company level.

For *BMW* the result comprises of the company's energy consumption and associated risks. The analysis reveals several key findings. The nationwide consumption forecast for *BMW* indicates a projected increase of 14 % from 2021, with a total estimated consumption of 1892.71 GWh. However, the calculated nationwide risk metric of 20.19 % highlights potential challenges in meeting renewable supply availability. Model assumptions contributing to this specific result include the assumed growth in GVA and the downscaling approach for the nationwide supply to the company level. On the localized level, the results suggest alternative conclusions. Specific *BMW* company sites of high interest, such as Landshut, Wackersdorf, and Regensburg, exhibit substantially lower riskmetrics of 7.17 %, 7.79 %, and 9.70 %

respectively. These localized risk metrics suggest expansion plans should be carried out at these sites.
These findings underscore the importance of site specific strategies in the integration of renewable energy sources to achieve sustainable growth for *BMW*.

The second case study, that of *WALA Heilmittel GmbH*, shows equally interesting results. The nationwide consumption forecast projects a total of 11,42 GWh, representing a substantial 55 % increase from 2021. The calculated nationwide risk metric stands at 20,19 %, primarily driven by the increasing trend in EEI and the downscaling approach employed in the analysis.
From the localized analysis the company site in Bad Boll exhibits a reduced risk metric of 10,57 %. This finding suggests a potential incentive for *WALA* to establish local electricity delivery contracts at this site. Therefore, strategically establishing such contracts can mitigate potential risks and ensure a more reliable renewable electricity supply for the company's future operations.
Several key areas remain to be improved upon, including enhancing the regression model and data series used for forecasting company consumption, refining the downscaling of nationwide supply, accurately mapping geographic regions to geopolitical entities, and further investigation of interdependencies in terms of regional electricity transfer. With the already established functionality and the proposed theoretical improvements, this framework serves as a tool for assessing and mitigating risks associated with renewable energy supply. It enables companies to make choices regarding their energy sources, specifically in determining whether to rely on local supply contracts or opt for the free market alternative, and in turn contribute to a sustainable and climate-friendly future with informed decisions.

8 Bibliography

References

[1] Y. Scholz (2012) *Renewable energy based electricity supply at low costs : development of the REMix model and application for Europe*, PhD thesis, Universität Stuttgart.

[2] Prognos (2021) *Entwicklung des Bruttostromverbrauchs bis 2030 (bmwk.de)*, Bundesministerium für Wirtschaft und Energie, https://www.prognos.com/de/projekt/entwicklung-des-bruttostromverbrauches-bis-2030, accessed July 17, 2023.

[3] S. Teske (2019) *Achieving the Paris Climate Agreement Goals*, Springer Nature

[4] G. Erdmann, P. Zweifel (2010) *Energieökonmik - Theorie und Anwendungen* (2nd Edition), Springer Verlag

[5] Umweltbundesamt (2021) *Internationale Energiemanagementnorm ISO 50001*, https://www.umweltbundesamt.de/energiemanagementsysteme-iso-50001iso-50001-aufbau-und-anwendung, accessed July 17, 2023

[6] D. Goebel (2007) *Betriebliches Energiemanagement*, PhD thesis, Universität Duisburg-Essen

[7] C. Koppenhoefer, J. Fauser, D. Hertweck (2017) *Managing and Controlling Decentralized Corporate Energy Systems. Transferring Best-practice Methods to the Energy Domain* , ICEIS 2017, Volume 3, pages 532-540

[8] Helmholtz Climate Initiative (2023), *Publications*, Helmholtz-Institute, https://www.helmholtz-klima.de/en/projects/publications, accessed July 17, 2023

[9] Bundesministerium für Wirtschaft und Klimaschutz (2023) *Langfrist- und Klimaszenarien*, https://www.bmwk.de/Redaktion/DE/Artikel/Energie/langfrist-und-klimaszenarien.html, accessed July 17, 2023

[10] Agora Energiewende (2023) *Die Energiewende in Deutschland: Stand der Dinge 2022. Rückblick auf die wesentlichen Entwicklungen sowie Ausblick auf 2023*

[11] A. Herbst, U. Reiter, M. Rehfeldt, R. Elsland, T. Fleiter (2017), *Benchmarking the EU reference scenario 2016: An alternative bottom-up analysis of long-term energy consumption in Europe*, eceee 2017 Summer Study on Energy Efficiency. Consumption, efficiency and limits

[12] T. Ladwig (2017) *Demand Side Management in Deutschland zur Systemintegration erneuerbarer Energien*, PhD thesis, Technische Universität Dresden

[13] D. Dallinger, S. Gerda, M. Wietschel (2013) *Integration of intermittent renewable power supply using grid-connected vehicles - A 2030 case study for California and Germany.* Applied Energy, Vol. 104, S. 666–682.

[14] Climate Neutral (2023) *Climateneutral.org*, https://www.climateneutral.org/, accessed July 17, 2023

[15] Climate Neutral Now Initiative (2023) *Climate Neutral Now*, United Nations, https://unfccc.int/climate-neutral-now,accessed July 17, 2023

[16] H. Helmke, H.-P. Hafner, F. Gebert, A. Pankiewicz (2020) Provision of Climate Services - The XDC Model. In W. Filho, D. Jacob (Eds.) *Handbook of Climate Services* (pp.223-249) Springer Nature Switzerland AG

[17] B. Ameyaw, L. Yao (2018) *Sectoral Energy Demand Forecasting under an Assumption-Free Data-Driven Technique* Sustainability 2018, 10(7), 2348.

[18] R. Steinert, F. Ziel (2018) *Probabilistic Mid- and Long-Term Electricity Price Forecasting* Renewable and Sustainable Energy Reviews, 32.3 (2018) 251-266.

[19] V. Srikrishnan, Y. Guan, R. Tol, K. Keller (2022) *Probabilistic projections of baseline twenty-first century* CO_2 *emissions using a simple calibrated integrated assessment model* Climatic Change 170, 37 (2022).

[20] F.ḋa Silva, F. Cyrino Oliveira, R. Souza (2019) *A bottom-up bayesian extension for long term electricity consumption forecasting* Energy 167, p. 198-210 .

[21] U. Frey, K. -K. Cao, T. Breuer, M. Wetzel, S. Sasanpour, J. Buschmann, K. v. Krbek, A. Böhm (2022) *A multi-perspective approach for exploring the scenario space of future power systems*, International Conference on Operations Research - OR 2022

[22] Bayerische Motorenwerke AG (2023) *BMW GROUP. DOWNLOADCENTER.*, https://www.bmwgroup.com/de/downloadcenterpage.html?area=responsibility, accessed July 17, 2023

[23] Carbon Disclosure Project (2021) *BMW - CDP Climate Change Questionnaire 2021*, Bayerische Motorenwerke AG, https://www.bmwgroup.com/content/dam/grpw/websites/bmwgroup _com/ir/downloads/de/2022/bericht/CDP-Fragebogen-2021.pdf, accessed July 17, 2023

[24] WALA Heimittel GmbH (2021) *WALA Environmental Statement 2021* WALA, https://www.wala.world/files/wala/footer/fakten/Umwelterklaerung _2021.pdf, accessed July 17, 2023

[25] N. Steinmann, K.-K. Cao, N. Wulff (2023) *Masterthesis - Niklas Steinmann - Supplementary Material - Data*, Deutsches Zentrum für Luft- und Raumfahrt, Institut für Vernetzte Energiesysteme, Stuttgart, https://doi.org/10.23728/B2SHARE.6AF126683CF6452EB8E1DF50017D16FB, accessed July 17, 2023

[26] Statistisches Bundesamt (2022) *43331-0001: Stromabsatz und Erlöse der Elektrizitätsversorgungsunternehmen: Deutschland, Jahre, Abnehmergruppen*, https://www-genesis.destatis.de/genesis//online?operation=tablecode=43331-0001bypass=truelevelindex=0levelid=1689270309409abreadcrumb, accessed July 17, 2023

[27] Statistisches Bundesamt (2022) *Statistisches Unternehmensregister*, https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Unternehmen/Unternehmensregister/$_i$*nhalt.html*, accessed July 17, 2023

[28] Statistisches Bundesamt (2022) *81000-0103: VGR des Bundes - Bruttowertschöpfung (nominal/ preisbereinigt): Deutschland, Jahre, Wirtschaftsbereiche*, https://www-genesis.destatis.de/genesis//online?operation=tablecode=81000-0103bypass=truelevelindex=0levelid=1689270531291abreadcrumb, accessed July 17, 2023

[29] Statistisches Bundesamt (2022) *43531-0002: Stromerzeugung, Strombezug, Stromabgabe, Stromverbrauch:*

Deutschland, Jahre, Wirtschaftszweige, https://www-genesis.destatis.de/genesis//online?operation=tablecode=43531-0002bypass=truelevelindex=0levelid=1689270709365abreadcrumb, accessed July 17, 2023

[30] Die deutsche Wirtschaft (2023) *Standortprofil Göppingen: Wirtschaft und die größten Unternehmen*, https://die-deutsche-wirtschaft.de/standort/goeppingen, accessed July 17, 2023.

[31] D. Hadjout, J.F. Torres, A. Troncoso, A. Sebaa, F. Martínez-Alvarez (2021) *Electricity consumption forecasting based on ensemble deep learning with application to the Algerian market*, Energy 243 (2022) 123060

[32] S. Mirsoltan, NST. Akhavan (2013) *Forecasting energy price and consumption for Iranian industrial sectors using ANN and ANFIS.* Iranian Journal of Economic studies, 2013.

[33] Z-X. Wang, Q. Lei, L-L. Pei (2018) *A seasonal GM (1, 1) model for forecasting consumption of the primary energy sectors.* Energy 2018;154:522-34

[34] I. Firsova, D. Vasbieva, N. Kosarenko, M. Khvatova, L. Klebanov (2018) *Energy Consumption Forecasting for Power Supply Companies.* International Journal of Energy Economics and Policy, 2019, 9(1), 1-6

[35] Statisches Landesamt Baden-Württemberg *Erzeugung und Verwendung - Energieverbrauch der Industrie seit 2003*, https://www.statistik-bw.de/Energie/ErzeugVerwend/EV-Industrie.jsp, accessed July 17, 2023

[36] Y. García Vera,R. Dufo-López 2, J. Bernal-Agustín (2019) *Energy Management in Microgrids with Renewable Energy Sources: A Literature Review*, Appl. Sci. 2019, 9(18), 3854

[37] R. Bachmann, D. Baqaee, C., M. Kuhn, A. Löschel, B. Moll, A. Peichl, K. Pittel, M. Schularick (2022) *What if? The Economic Effects for Germany of a Stop of Energy Imports from Russia*, EconPol Policy Report 36, ifo Institute

[38] D. Baqaee, E. Farhi (2019) *Networks, Barriers and Trade* Working Paper 26108, National Bureau of Economic Research, accessed July 17, 2023

9 Appendix

9.1 BMW - Tables, Figures and Data

	Energy Consumption total (MWh)	Electricity external (MWh)	Electr inhouse (MWh)	Employees NonGer	Employees Ger	Employees total
1996	2517758	958651	105962	51876	64236	116112
1997	2527577	951711	114870	52198	65426	117624
1998	2517528	1043051	120908	50828	67661	118489
1999	2581423	1086358	117168	46104	68848	114952
2000	2636565	1163233	94757	24719	68905	93624
2001	2788126	1163233	83331	24412	72863	97275
2002	3503102	1262232	95057	25252	76143	101395
2003	3295277	1180217	115323	25773	78569	104342
2004	3672212	1586457	127981	25967	80005	105972
2005	3861253	1671928	125229	25778	80020	105798
2006	3959908	1667122	125414	26679	79896	106575
2007	4283922	1853961	125182	27411	80128	107539
2008	4034442	1700828	136963	26125	73916	100041
2009	3635755	1491182	152578	NA	NA	96239
2010	4072217	1654956	177671	NA	NA	95453
2011	4278582	1702157	NA	NA	NA	100306
2012	4549788	1790534	NA	NA	NA	105876
2013	4721174	1910065	NA	NA	NA	110351
2014	4867094	2141222	NA	NA	NA	116324
2015	5479002	2485881	NA	NA	NA	122244
2016	5783841	2584570	NA	NA	NA	124729
2017	5852666	2588409	NA	NA	NA	129932
2018	5788965	2513308	NA	NA	92333	134682
2019	6348009	2653855	NA	NA	NA	126000
2020	6040824	2320314	NA	NA	81367	122874
2021	6476955	2453215	NA	NA	79647	118626

Figure 33: BMW - Data overview, 2002-2021, including energy consumption, electricity consumption (divided into inhouse production and external sources), employees (divided into german employees and non-german employees). Taken from [22]

9.2 WALA - Tables, Figures and Data

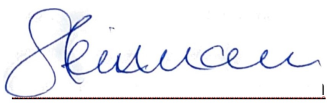
	GVA (tsd. €)
2002	13700
2003	14700
2004	15808,7732
2005	17100
2006	18501
2007	20260
2008	18120
2009	17733
2010	21580
2011	25189
2012	26930
2013	27660,3024
2014	28362,6877
2015	30714,5455
2016	31943,6518
2017	33452
2018	33187
2019	33143
2020	32938
2021	31435

Figure 34: BMW - Data overview GVA, 2002-2021. Taken from [22] and [23].

Ehrenwörtliche Erklärung

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbständig angefertigt habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Ich bin mir bewusst, dass eine unwahre Erklärung rechtliche Folgen haben wird.



Ulm, den 17.07.2023

Unterschrift Niklas Steinmann

Wirtschaftszweig	Jahr	Eigene Stromerzeugung (netto)	Strombezug	Stromabgabe (einschließlich Ausland)	Stromverbrauch	Gesamter Verbrauch
WZ08-30	2008	50174	1417861	68433	1399602	3539915
WZ08-30	2009	59810	1361140	67297	1353652	3338125
WZ08-30	2010	61990	1384729	78046	1368673	3343313
WZ08-30	2011	72681	1458379	103089	1427971	3451729
WZ08-30	2012	123524	1423454	118463	1428515	3519448
WZ08-30	2013	204714	1364876	151379	1418210	3464941
WZ08-30	2014	194889	1369672	139407	1425154	3442295
WZ08-30	2015	209882	1378888	135515	1453255	3508602
WZ08-30	2016	213952	1340724	129170	1425506	3471142
WZ08-30	2017	173259	1245789	103682	1315365	3315922
WZ08-30	2018	191025	1336587	121954	1405659	3439798
WZ08-30	2019	206779	1356282	118235	1444825	3465907
WZ08-30	2020	234051	1191532	123927	1301656	3334746
WZ08-30	2021	227963	1170506	103977	1294492	3357189

Figure 35: Automotive Sector - Data overview electricity consumption in different measures, all values in MWh, 2008-2021. Taken from [29]

Wirtschaftsbereiche (WZ2008)	WZ08-29-01	WZ08-29	WZ08-30
	Fahrzeugbau	Herstellung von Kraftwagen und Kraftwagenteilen	Sonstiger Fahrzeugbau
1991	54,56	46,843	7,717
1992	57,428	49,028	8,4
1993	47,866	41,274	6,592
1994	50,88	44,719	6,161
1995	53,224	47,725	5,499
1996	53,75	47,335	6,415
1997	58,916	51,72	7,196
1998	63,671	56,122	7,549
1999	64,776	56,383	8,393
2000	63,708	55,807	7,901
2001	73,88	65,029	8,851
2002	74,697	66,098	8,599
2003	78,545	70,388	8,157
2004	77,03	69,739	7,291
2005	77,809	68,915	8,894
2006	86,382	77,544	8,838
2007	92,748	83,31	9,438
2008	83,823	73,887	9,936
2009	67,003	57,693	9,31
2010	94,16	83,376	10,784
2011	106,153	95,35	10,803
2012	110,023	98,117	11,906
2013	111,661	100,005	11,656
2014	126,222	113,36	12,862
2015	134,283	120,785	13,498
2016	146,95	132,551	14,399
2017	156,099	138,378	17,721
2018	152,965	137,823	15,142
2019	153,386	136,614	16,772
2020	131,938	118,601	13,337
2021	142,562	127,803	...

Figure 36: Automotive Sector - Data overview GVA, all values in bn. EUR, 1991-2021. Taken from [28]

Scenario	München	Dingolfing	Berlin	Leipzig	Landshut	Regensburg	Eisenach	Wackersdorf
0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure 37: Overview of localized scenario validation results for *BMW*'s company sites, see section 3.3.3. A 0 represents scenario success, a 1 stands for failure. Only Berlin shows scenario failures, in stark contrast to the national results.

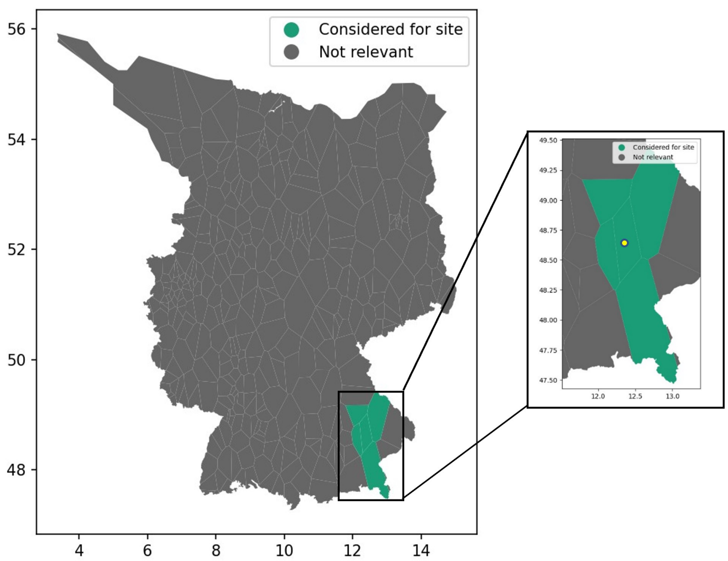


Figure 38: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Dingolfing. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

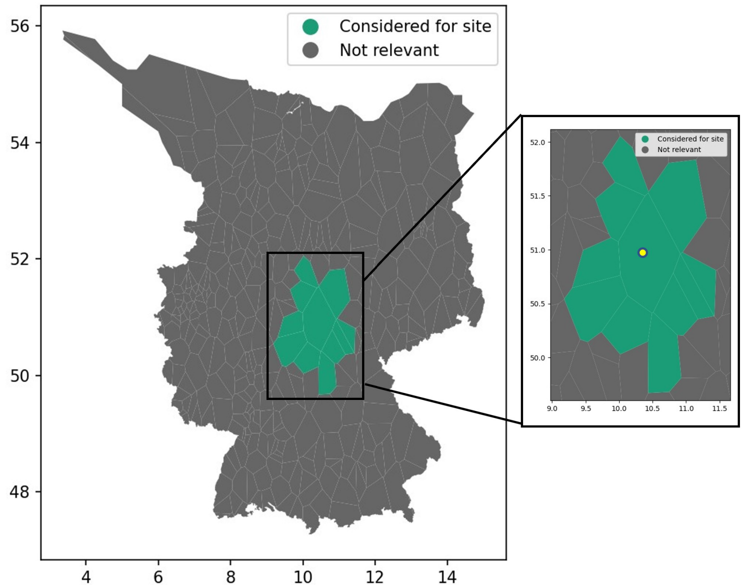


Figure 39: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Eisenach. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

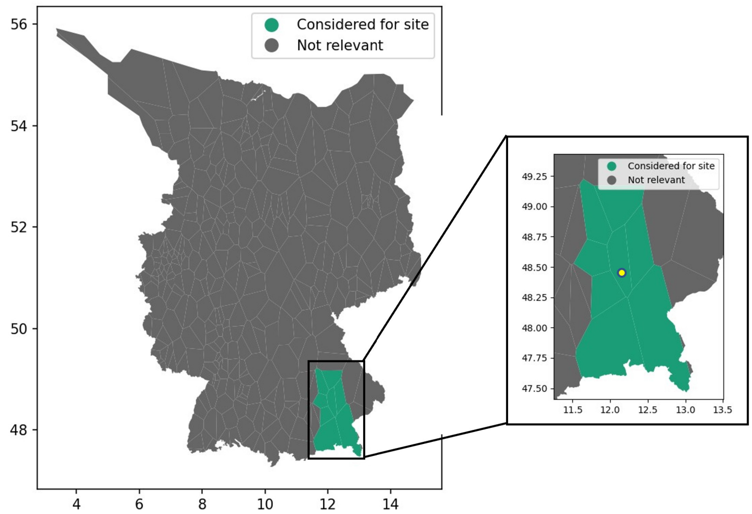


Figure 40: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Landshut. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

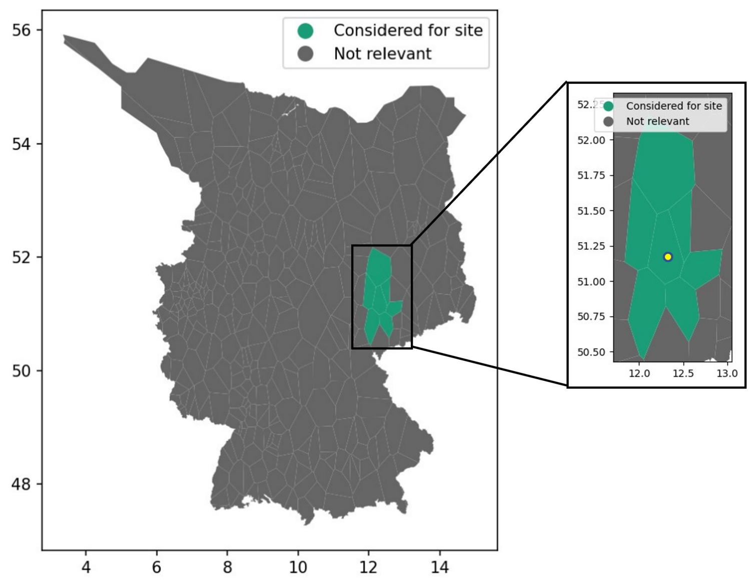


Figure 41: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Leipzig. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

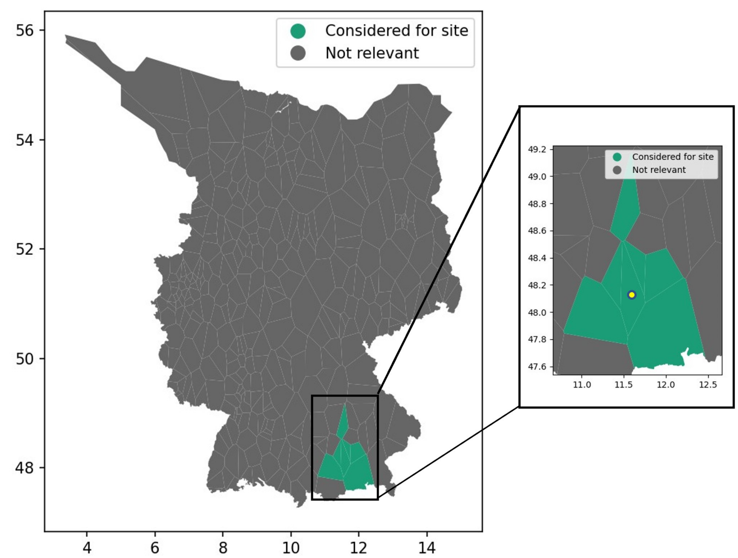


Figure 42: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Munich. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

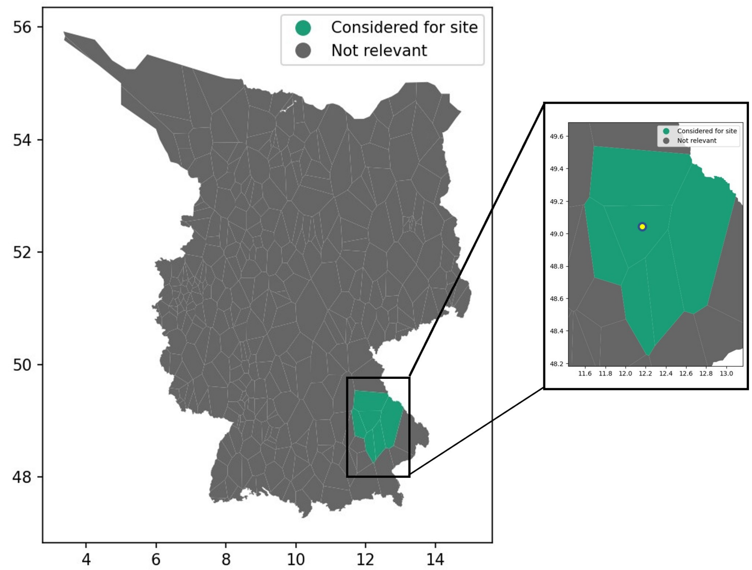


Figure 43: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Regensburg. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

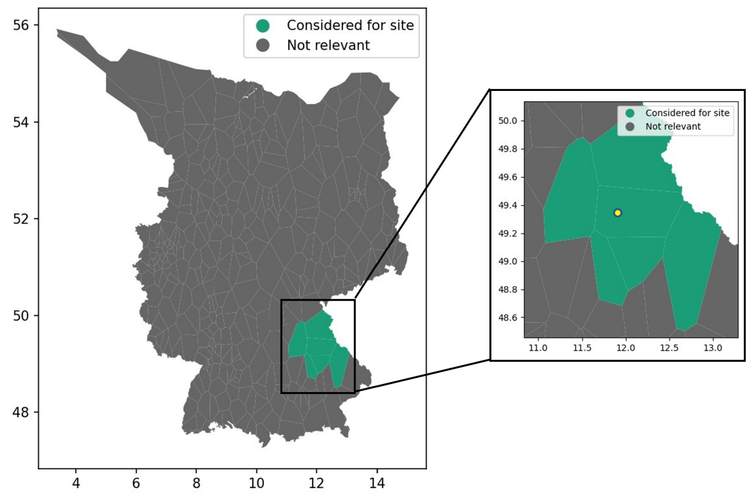


Figure 44: On the left, the localized view of Germany divided into geographical regions. On the right the geographical regions relevant to *BMW*'s company site in Wackersdorf. The relevant geographical regions are marked in green, the ones not considered are marked in grey. The company site is shown in yellow.

Datenreihen	Stromverbrauch in Mwh	Energieverbrauch in MWh	Employees (Vollzeitstellen)	Turnover in TEUR	Gross value added in TEUR
1998	1.171	2.675	400	26.133	0
1999	1.217	2.427	400	31.802	0
2000	1.359	2.332	400	36.515	0
2001	1.442	2.611	446	43.438	0
2002	2.005	3.222	446	53.274	0
2003	3.500	5.480	446	58.901	0
2004	3.610	5.596	470	65.598	0
2005	3.672	5.896	470	75.733	0
2006	3.882	5.929	530	86.575	0
2007	4.221	5.320	760	96.264	0
2008	4.785	7.690	760	103.921	0
2009	5.164	8.921	760	98.157	0
2010	5.071	9.285	806	102.894	76.604
2011	5.256	8.823	855	107.357	77.183
2012	5.256	9.247	861	112.438	85.294
2013	5.287	9.948	834	118.387	86.173
2014	6.042	9.585	847	129.495	97.556
2015	6.077	10.063	878	129.921	96.538
2016	5.968	10.714	881	132.056	95.127
2017	7.674	12.874	901	143.943	100.672
2018	7.866	12.973	925	141.299	101.943
2019	7.615	12.530	898	143.546	104.147
2020	7.611	12.335	882	133.686	99.486
2021	7.237	13.195	874	137.250	107.272

Figure 45: WALA - Data overview, 1998-2021, including Energy consumption, electricity consumption, Employees, Turnover and GVA. This data has been provided directly from inhouse sources.

Scenario	N0109	N0265	N0266	N0267	N0111	N0268	N0112	N0216	N0316	N0127
0	0.5452	0.9999	0.9191	0.9998	0.9995	0.9994	0.0843	0.6798	0.9998	0.9996
1	0.9903	0.9999	0.8772	0.9999	0.9999	0.9999	0.9530	0.9914	0.9999	0.9999
2	0.8678	0.9999	0.8805	0.9999	0.9999	0.9999	0.4223	0.6999	0.9999	0.9999
3	0.9975	0.9999	0.9123	0.9999	0.9999	0.9999	0.8445	0.8497	0.9999	0.9999
4	0.9663	0.9999	0.8285	0.9999	0.9999	0.9999	0.5525	0.8524	0.9999	0.9999

Figure 46: Share of renewably produced electricity for *WALA*'s company site in Bad Ball. Overview for all considered geographic regions per Scenario.

Scenario	BadBoll
0	0
1	0
2	0
3	0
4	0

Figure 47: Overview of localized scenario validation results for *WALA*'s company site in Bad Boll, see section 4.3.3. A 0 represents scenario success, a 1 stands for failure. No scenarios fail.

Ehrenwörtliche Erklärung

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Arbeit selbständig angefertigt habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Ich bin mir bewusst, dass eine unwahre Erklärung rechtliche Folgen haben wird.

Ulm, den 17.07.2023

Unterschrift Niklas Steinmann