Correlation analysis of GHG emissions in the German electricity mix and exchange electricity prices using a sigmoid function

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Abstract— **The hourly greenhouse gas (GHG) emission intensity of German grid electricity shows substantial variability driven by fluctuations in the renewable energy share and electricity prices. This study uses a sigmoid regression model to predict GHG emissions from electricity prices, applying data from 2019 to 2023. The analysis reveals that periods of low and negative prices, often associated with a high renewable share, correspond to low GHG emissions. Higher prices correlate with elevated GHG emissions. The sigmoid function provides asymptotic lower and upper bounds for emission intensity. The model performance is evaluated by comparing two measures: the mean percentage error (MPE) and mean annual percentage error (MAPE). While MAPE across prices ranged from 15% to 19% in a year, the relative error over the year was 3% to 5%. Model accuracy decreased during periods of high volatility, such as the COVID-19 pandemic and geopolitical crises.**

Index Terms — **Sigmoid regression, hourly GHG emissions, electricity price, flexibility, demand response.**

I. Introduction and Motivation

In 2023, 674 million tons of greenhouse gas (GHG) emissions were emitted in Germany as a result of the combustion of fossil energy sources to generate electricity, in industrial processes and livestock farming [1]. The energy sector and the industry are the largest emitters of GHG emissions accounting for 53% of the total emissions [2]. The share of renewable energy sources (RES) in the load of public net electricity generation has increased to 56% in 2024, thus absolute and specific GHG emissions have decreased [3]. The average emission factor of grid electricity is 50% lower in 2023 (380 g CO_2/kWh_{el}) than in 1990 (764 g CO_2/kWh_{el}) [4].

Currently, the calculation of GHG emissions associated with electricity consumption in industry is usually conducted by multiplying the average emission factor of the electricity mix in a year by the annual electricity consumption [5]. The share of RES reduces the GHG emission intensity of the electricity grid on average [6], [7]. However, over time, there are very different electricity generation situations with a high or low share of renewable energy. The proportion, and hence the GHG emission intensity, fluctuates in time based on power market mechanisms and weather conditions. Ideally, in the future, industry (the demand) responds to renewable power generation to lower GHG emissions [8]. A scenario of 100% renewable energy and 0% fossil fuel power plants results theoretically in a zero GHG emission intensity.

Accurately predicting the GHG emissions of the regional grid electricity is an integral part of demand response measures. Most existing research for short-term forecasting focuses on the use of recurrent neural networks [8], [9]. An overview gives [10].

The increasing share of renewable energy has a direct impact on the electricity price. Low marginal costs of solar and wind power reduce the spot prices [11]. In times when the share of renewable energy is high, electricity prices on the stock exchange are low. The potential of temporally resolved GHG emission factors for price and emission-based demand response was investigated by [12]. Due to the continuous daily, seasonal, and annual changes in the German power supply, hourly emission factors are needed to determine GHG emissions from flexible electrification measures. The individual amount of electrical energy drawn from the grid multiplied by the hourly emission factor is a useful indicator of the emissions caused by electricity consumption. [13] has developed a method for calculating GHG emission factors for the German electricity mix on an hourly basis. In the future such emission factors are required for sustainability reporting [14], proof of emission intensity in the electricity grid for RED III and for calculating the GHG footprint of electricity-based downstream products such as green hydrogen from electrolysis [15]–[17]. Industrial consumers can make their electricity procurement more flexible to a certain extent and thus benefit from low electricity prices. The time-resolved GHG emission factors enable electricity to be purchased at times with low GHG emission intensity. The relationship between hourly day-ahead electricity prices and hourly GHG emissions is examined using a sigmoid function. [18] have used the function to develop temperature-dependent standard load profiles for end consumers in the German gas market. [19] applied a sigmoidal function for day-ahead natural gas usage forecasting. An empirical GHG assessment for flexible bioenergy in interaction with the German electricity sector was carried out by [20]. The function is applied to describe the basic relationship between electricity prices and load according to [21].

The research questions guiding this study are:

(1) Can a sigmoidal function serve as an effective model to describe a trend between electricity prices and the GHG emission intensity of grid electricity?

(2) What can be the use of this correlation function?

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II. METHODOLOGY

The aim of this approach is to model the correlation between exchange electricity prices $EP_t = x \in \mathbb{R}$ and hourly GHG emissions $GHG_t = s(x) \in \mathbb{R}$ associated with the German grid electricity mix using a sigmoid function.

The sigmoid function is a logistic function that is characterized by an exponential increase in a variable, which then appears linear and finally converges asymptotically to a threshold value. A is the maximum value. B is the minimum value. In general, a sigmoid function is a bounded and differentiable function with a consistently positive or consistently negative first derivative. The curve has exactly one inflection point x_0 and is symmetric about it. Parameter k is a scaling parameter controlling the steepness of $s(x)$. The function is described by equation (1).

$$s(x) = \frac{A}{1 + e^{-k\cdot(x-x_0)}} + B \qquad (1)$$

The hourly exchange electricity price EP_t in $€/MWh$ is set as variable x. The hourly GHG emissions GHG_t in $CO_{2\text{-eq.}}$ are the dependent variable to EP_t. Figure 1 illustrates the sigmoid function and its first and second derivative in the context of the approach. The derivative s'(x) shows that the rate of change of the function s(x) depends on the current value of the function itself.

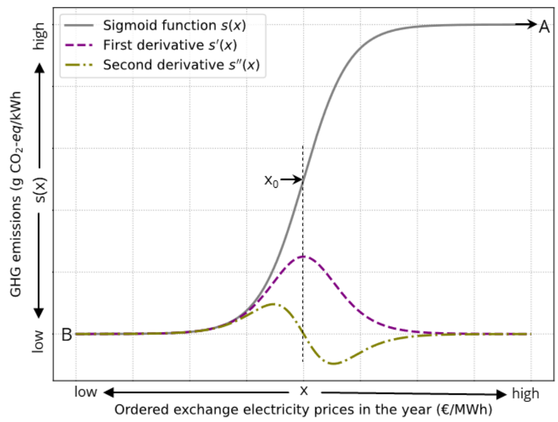

Figure 1: Schematical illustration of the use of the sigmoid function and its derivative within the context of the approach.

The parameters $x0$, k, A, and B of the sigmoid function are determined using a least square method as represented in equation (2). The curve fitting function provided by the SciPy Optimize module in python is used.

$$min \sum_{t=1}^{n} (GHG_t - \frac{A}{1 + \exp(-k \cdot (x_t - x_0))} + B)^2 \qquad (2)$$

For the initial guess of the curve fit, the maximum value of GHG_t is set for the parameter A. The median of the electricity prices EP_{med} is used for x_0. Parameter k is set to 1. The minimum value of the data set is as the lower bound B.

The median EP_{med} for a year with $n = 8{,}760$ values of GHG_t is calculated using equation (3).

$$EP_{med} = \frac{1}{2} \cdot (\frac{EP_t}{2} + \frac{EP_{t+1}}{2}) \qquad (3)$$

The adjusted coefficient of determination R^2 is calculated to evaluate the quality of the sigmoid function as a fitting model for the dependent data GHG_t. The quadratic and exponential function serve as a comparison.

A frequency distribution is calculated in the form of a histogram. The interval widths are chosen with fixed widths w_{GHG} for the time series of GHG emissions and w_{EP} for the time series of exchange electricity prices.The number of intervals I_{THG} or I_{EP} is then calculated from equation (4):

$$I_{GHG} = \frac{GHG_{max} - GHG_{min}}{w_{GHG}} \text{ or } I_{EP} = \frac{EP_{max} - EP_{min}}{w_{EP}} \qquad (4)$$

In order to analyze the adequacy of the sigmoid function in approximating the relationship between hourly GHG emission intensity and exchange electricity prices, the data set is divided into seven price ranges (Table 1).

Table 1: Price ranges for fitting the sigmoid function to the data.

Section	Range of electricity prices $EP_t = x$	Unit
I	-50 > x	€/MWh
II	-50 ≤ x < 0	€/MWh
III	0 ≤ x < 50	€/MWh
IV	50 ≤ x < 100	€/MWh
V	100 ≤ x < 150	€/MWh
VI	150 ≤ x < 200	€/MWh
VII	200 < x	€/MWh

The mean absolute percentage error (MAPE) for n data points is used as an evaluation measure for $s(x)$ and calculated by equation (5). GHG_t is defined as the actual value for the data point. $GHG_{s_t(x)}$ refers to the predicted value for the t-th data point.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{GHG_t - GHG_{s_t(x)}}{GHG_t} \right| \qquad (5)$$

The mean percentage error (MPE) using equation (6) is selected for comparison.

$$MPE = \frac{1}{n} \sum_{t=1}^{n} \frac{GHG_t - GHG_{s_t(x)}}{GHG_t} \qquad (6)$$

The analysis focuses on the relationship in more detail for the year 2023. The optimized parameters of the sigmoid function are also derived for the years 2019-2022. Data of more years is not available. The approximation is evaluated based on Table 1.

III. DATA

The hourly exchange electricity prices for 2023 are selected as the data basis [22]. Information pertaining to the hourly GHG emissions of the German electricity mix (excluding industrial self-generation) is derived from [13]. The German net electricity generation for the public electricity supply is considered, defined as the difference between the gross electricity generation and the power plants' own consumption [23]. The combustion-related emission, in addition to those arising from upstream processes and grid losses, are considered in the analysis. The total GHG emission intensity of the electricity mix is represented over its lifecycle. According to GHG Protocol this incorporates scope 1 and scope 2 emissions [24]–[27], based on the functional unit kWh of electricity provided to the consumer.

IV. RESULTS

A. Describing GHG emissions with electricity prices concidering renewable energy share

The hourly GHG emission factors are subject to seasonal and daily variations. Figure 2 shows the hourly resolved GHG emission intensity in g $CO_{2\text{-eq.}}$/kWh of the German electricity mix in 2023 [23]. The dashed line marks the average GHG emissions GHG_{mean} of 380.9 g $CO_{2\text{-eq.}}$/kWh.

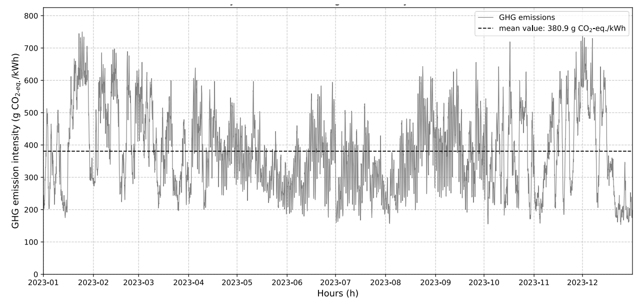

Figure 2: Hourly resolved GHG emission intensity of German electricity mix in 2023.

Figure 3 shows the hourly GHG emissions over the day-ahead electricity prices within the range of $> -50\,€/MWh$ and $< 300\,€/MWh$ (outliers are excluded).

GHG emissions are low (range) in times of low and negative electricity prices. However, the GHG emission intensity of grid electricity tends to increase as electricity prices rise. A high share of renewable energy in the load is associated with low electricity prices.

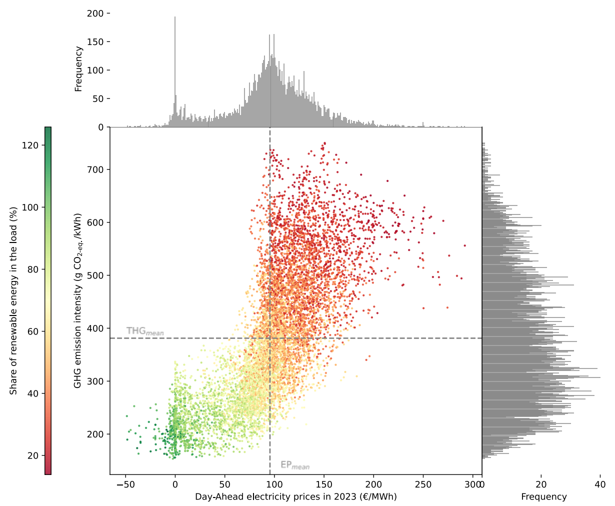

Figure 3: Hourly GHG emissions of the electricity mix depending on the sorted day-ahead electricity prices (without outliers) in 2023.

The renewable energy share in the load, indicated by the color scheme, shows the relation between electricity production from renewable energy and domestic electricity consumption (load). As Figure 3 illustrates, while the renewables share exceeds 100%, the GHG emission intensity remains at a minimum of around 150 $g\ CO_{2eq}/kWh$ and do not exceed zero. Figure 4 shows the power plant deployment for public net electricity production in Germany during such period with a high share of renewables. Fossil power plants were still in operation, resulting in remaining GHG emissions. Minimum GHG emissions could be achieved through the deployment of storage options and more flexible electricity use on the consumer side [22].

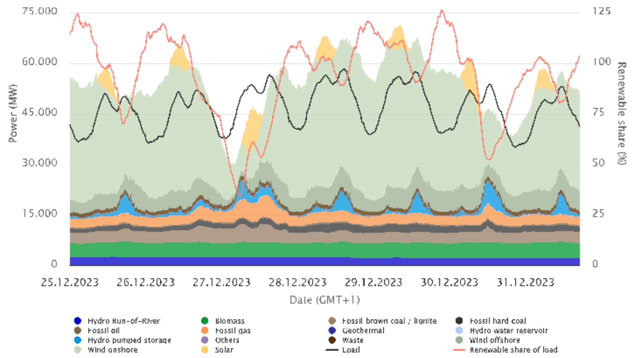

Figure 4: Public net electricity generation in Germany with high feed-in of renewable energy plants at the load [23].

The x-axis histogram in Figure 3 shows that day-ahead prices are relatively symmetrically distributed, with a mean of $95.19\,€/MWh$ and a median at $98.83\,€/MWh$. Extreme outliers are rare and hardly affect the mean price.

In times with GHG emissions below $\sim 300\ g\ CO_{2eq}/kWh$, the renewable energy share is often high (green dots). At these times, negative electricity prices occur in 301 hours in 2023. In the range from 0 to 100 €/MWh, a greater spread is evident, with both low ($< 200\ g\ CO_{2eq}/kWh$) and very high GHG emission values ($> 700\ g\ CO_{2eq}/kWh$) occurring. The correlation between increasing GHG emissions (red dots) and a reduced share of renewable energies indicates a predominance of fossil energy sources in times where the share of renewable energies is low.

When electricity prices are low up to $\sim 50\,€/MWh$, there is a tendency for a low GHG emission intensity, which is consistent with the high share of renewable energies in these periods. Conversely, as electricity prices rise to levels greater than $100\,€/MWh$, there is an increase in GHG emissions (red-orange dots), suggesting that conventional power plants with higher emission factors are utilized during these periods. The histogram on the y-axis shows the distribution of GHG emissions. The values are concentrated in the range $200 - 600\ g\ CO_{2eq}/kWh$, which is typical for an energy mix with a high share of fossil fuels [28].

The GHG_{mean} is with 3.2% slightly above GHG_{med}. This shows the slightly right-skewed distribution on the second y-axis of Figure 3. This indicates that there are some periods with very high emissions that raise the mean.

The GHG_{mean} shows that although the electricity mix in 2023 contained a considerable amount of renewable energies (on average 56% [23]), fossil power plants (mainly coal with 26.1% and natural gas with 13.6%) still had a significant share in electricity generation [29].

The lower GHG_{med} value indicates that in more than half of the period, emissions were lower. Consequently, renewable energy plays a more significant role in the electricity supply, thereby reducing emissions.

B. Correlation with the sigmoid function for the year 2023

Figure 5 shows the year 2023 with outliers and the fitted sigmoid function. Table 2 lists the optimized parameters and the error measures (MAPE and MPE) for the model predictions. Table 4 and Table 5 in the appendix show the errors for the years 2019-2022. The function shows a lower and upper bound of 203.4 and 556.0 $g\ CO_{2eq}/kWh$. The data points ranging from $153.4 - 750.0\ g\ CO_{2eq}/kWh$.

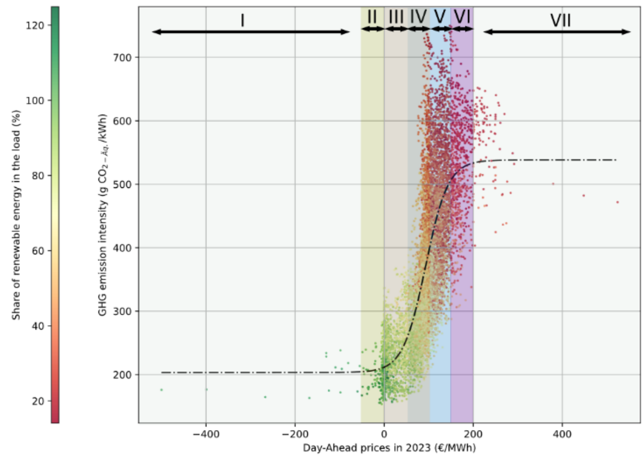

Figure 5: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2023.

In ranges I and VII (Figure 5), there are few data points compared to the other price ranges. These show a broad range of values (range I from -500 $€/MWh$ to -50 $€/MWh$; range VII from 200 $€/MWh$ to 524 $€/MWh$. Range I is characterized by low and negative electricity prices, the data points are evenly distributed above and below the sigmoid function (Figure 6 with Table 3).

Range VII is characterized by high electricity prices. Two-thirds of the data points exceed the sigmoid function. The data points in range I fluctuate from a minimum of 163.0 $g\ CO_{2eq}/kWh$ to a maximum of 238.2 $g\ CO_{2eq}/kWh$. The values of the sigmoid function are asymptotic around the lower limit B. This results in an absolute error of up to 40.3 $g\ CO_{2eq}/kWh$ (25%). The deviance of the predictive values from the data points leads to a MAPE for range I of 0.14. The relative difference (MPE) is 0.07. The values almost compensate each other and slightly overestimate the data points.

In range II – VI the data points account for 98% of the total. In range II, the data points are distributed from 153.4 $g\ CO_{2eq}/kWh$ to 324.0 $g\ CO_{2eq}/kWh$, representing the data point with the lowest GHG emission intensity. The MAPE value is 0.11, with the maximum deviation between a predicted and a data point being 37%. Range III is comparable to II. The data points vary from 156.7 $g\ CO_{2eq}/kWh$ to 369.1 $g\ CO_{2eq}/kWh$. The absolute error in Range III is 0.14 (MAPE), the relative error is -0.02 (MPE). The maximum discrepancy is overestimated by +52% or 81.7 $g\ CO_{2eq}/kWh$.

In particular, the price is between $50 - 150\ €/MWh$ (range IV and V), each representing 38% of the total data points. Both price ranges show a large spread from 161.4 $g\ CO_{2eq}/kWh$ to 736.8 $g\ CO_{2eq}/kWh$ (range IV) and 211.8 $g\ CO_{2eq}/kWh$ to 750.0 $g\ CO_{2eq}/kWh$ – the highest GHG emission intensity of the year (range V). The error for the predicted sigmoidal values within the ranges are largest with $MAPE = 0.19$ and $MPE = 0.05$. Predicted sigmoidal values deviate from the data points by up to 96% or 323.4 $g\ CO_{2eq}/kWh$. In range VI, fossil fuels are dominant. GHG emissions range from 287.6 $g\ CO_{2eq}/kWh$ to 748.2 $g\ CO_{2eq}/kWh$. The predicted values deviate in absolute with 0.14 (MAPE) and 0.03 (MPE)in relative terms across range VI. There are high outliers in range VII, with the data points situated between 403.4 $g\ CO_{2eq}/kWh$ and 652.1 $g\ CO_{2eq}/kWh$. Most values are located above the function. This results in a value for MAPE of 0.10 and MPE of -0.04. The data points are underestimated.

The mean deviation of the predicted GHG emissions, as determined by the sigmoid function, from the GHG_{mean} of the data points is equal in all ranges.

Table 2 shows the optimized parameters and data of the sigmoid function and the measure of prediction accuracy MAPE for the years 2019–2023. The Figure 7 to Figure 11 for subsequent years can be found in the appendix.

Table 2: Comparison of optimized parameters, data and regressions measure "MAPE" for the years 2019-2023.

	B	A	k	x_0	y_0	MAPE	MPE
2023	203.4	538.3	0.04	92.9	370.8	0.17	0.04
2022	197.2	528.3	0.02	104.6	362.8	0.15	0.03
2021	102.0	498.1	0.03	24.5	295.0	0.19	0.05
2020	147.2	556.0	0.08	28.0	351.6	0.17	0.04
2019	199.7	530.9	0.11	30.1	365.3	0.17	0.04

C. *Correlation with the sigmoid function for the years 2019–2022*

The lower limit B of the fitted sigmoid function ranges from 102.0 to 197.2 $g\ CO_{2eq}/kWh$ in the years 2019–2022. The upper limit value A ranges between 498.1– 556 $g\ CO_{2eq}/kWh$. The parameter k is used to indicate the global trend of the sigmoid function. A low value (e.g. 0.02–0.04 in 2021–2023) indicates a rather gradual transition. Whereas higher values (0.08–0.11 in 2019 and 2020) suggest a steep increase. The value of the point of inflection x_0 has tripled from around 30 to 93 $€/MWh$ between 2019 and 2023. The value of the GHG emissions y_0 has slightly increased by 1.5%.

The mean absolute percentage error (MAPE) for the years ranges from 0.15–0.19. For a MAPE value range of [0;1], a result below 0.2 can be considered adequate according to [24] and [25]. However, its significance depends on various factors, including the field of application and price range, which is to be discussed.

Figure 6 shows a comparison of the distribution of datapoints above and below the sigmoidal function of the years. The distribution is approximately equal above and below. There is a shift in prices from low prices in 2019/2020 (price range III) to heterogeneous prices with a wider price range and increasingly negative prices in 2023. In general, for all years, price ranges III, IV, and V – which cover 0 to 150 $€/MWh$ – tend to capture most of the data. The most significant price ranges, covering 97% of all data in 2019 and 2020, are price range III ($0 \leq x < 50\ €/MWh$) and price range IV ($50 \leq x < 100\ €/MWh$). The ranges can be well represented by the sigmoid function. Price range III (green) demonstrates a balanced distribution number, indicating that most data points (88%) are concentrated within this price range. In 2021, 48% of the data is in price range IV. In 2022, prices are heterogeneous, with the highest prices recorded in price range VII (53%). In 2021 to 2023, the distribution across the ranges is more balanced, with the main price ranges being III, IV and V ($100 \leq x < 150\ €/MWh$). The increase in price variability is consistent with the decreasing parameter k in Table 2 over the years.

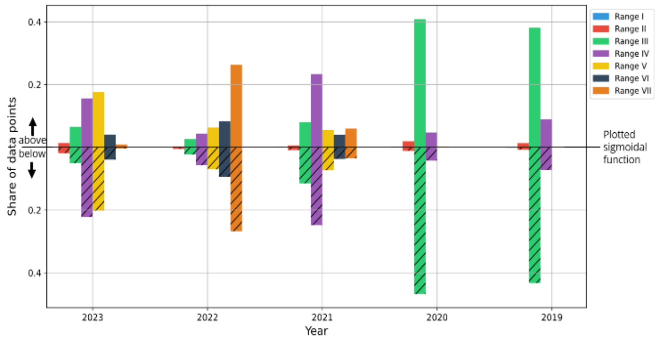

Figure 6: Distribution of data points for a year around the sigmoid function.

Figure 7 to Figure 13 with Table 4 and Table 5 in the appendix show that the sigmoid function predicts the GHG emissions with an absolute error of about 0.12 and an relative error of about 0.04 in the selected prices ranges over the years. In the years 2019 and 2020, the ranges I-V are almost evenly distributed across the yearly price distribution. Most data points are located in ranges III and IV (96% and 98% respectively; high k values). Some negative prices (3%) exist. There are a few high prices. In 2020, ranges VI and VII each have only one data point.

A significant change shows range VII for the years 2021 and 2022. 10% and 53% of the total data points are located here, respectively. The price range for this outlier range extends from 200 to 620 or 871 $€/MWh$. The GHG emissions range between 300 to 777 $g\ CO_{2eq}/kWh$

In 2021, range I has an error of -0.25 and range III has an error of 0.1 relative (MPE) to the data points. The absolute error (up to 0.26) is the highest of all years. Individual data points are up to 292 $g\ CO_{2eq}/kWh$ higher than predicted. The sigmoid prediction for 2021 is the least accurate.

D. Correlation using alternative functions

For comparison: The quadratic regression approach yields the accuracy measure MAPE between 0.18 to 0.64. The exponential function yields MAPE between 0.20 to 0.26 for the years 2019-2023.

V. DISCUSSION

The objective to construct a sigmoidal trend in electricity prices that describes the GHG emission intensity of grid electricity can be achieved to a limited extent. Even though several methodical limitations exist at the different calculation steps, the findings demonstrated a sigmoidal correlation between electricity prices and GHG emissions, with the analysis incorporating the mean deviation within a price range. In addition to the visual correlation analysis, a first robust statistical significance was demonstrated using the measures MAPE and MPE. The model demonstrates a reasonable ability to represent the years 2019, 2020 and 2023, despite certain limitations. In these years, ranges I, II and VI, VII can be modelled with good accuracy on average (Figure 12 and Figure 13) using the sigmoid function. However, the price ranges in the middle are challenging, due to the high level of volatility in GHG emissions. The MAPE and MPE measures must be evaluated within the context of the specified price ranges, depending on the spread of prices and GHG emissions. A divergent conclusion may be drawn from the same value. A confidence interval and other and more statistical measures could provide more information. This speaks for the complexity of the underlying system. In periods of crisis, such as the Corona pandemic (2020-2022) and the war of aggression against Ukraine (2022), there has been an increased distribution of data. In these years, modeling with the sigmoid function shows weaknesses.

There are price ranges and years in which the function over- or underestimates the data points. The quality of the fitted function depends on the input data and the initial and estimated parameters A, k, B and x_0. A good spread of the x-values (electricity prices) is important to detect the sigmoid shape. If x-values are too close together, the curve could be fitted too flat or too steep. In these ranges, a linear regression might be more appropriate. If the relationship does not exactly follow a sigmoid function, poor fits may occur (e.g. if multiple inflection points exist). For very high/low values, the sigmoid function shows asymptotic behavior. Therefore, a larger data set and several years might be helpful for further analysis. In order to formulate a generalized sigmoid function for the purpose of forecasting GHG emissions based on electricity prices, data from multiple years could be considered simultaneously.

Over the years, electricity prices have become more heterogeneous with larger outliers, increasing the price amplitude. In contrast, the hourly GHG emission amplitude remained constant (around 600 $g\ CO_{2eq}/kWh$). This is why the parameter k (Table 2) decreased over time. A higher k means high variation in GHG emissions to comparatively modest price ranges. Conversely, as k decreases, prices are heterogeneous, and the curve becomes flatter.

A rise in negative electricity prices, linked to high and inflexible generation and low demand, is becoming more common. This often happens during periods of substantial wind and/or solar feed-in [32]. Other factors not considered in the model could also have an influence. GHG emissions may depend on local weather conditions, grid restrictions, and transmission system operator's power plant deployment planning. High electricity prices often arise when there is low renewable energy share and expensive fossil power plants (e.g. gas power plants) step in. However, GHG emission intensity can decrease when gas power plants displace coal power plants. A correlation with the residual load could provide more information.

The question arises whether it makes sense to set price signals to encourage electricity consumption in times of low GHG emission intensity.

VI. CONCLUSION AND OUTLOOK

The present study investigates the correlation between hourly day-ahead electricity prices and hourly GHG emissions of grid electricity in Germany. The optimal parameters A, k, x_0 and B of the sigmoid function were determined by minimizing the squared deviations between the function and the data set. In consideration of the data available and the selected approach, a measure of uncertainty is associated with the forecast of hourly GHG emissions, due to the distribution of the GHG data points for each electricity price within the price ranges. The forecast average of GHG emissions is equal to the mean of the data points. A company could use a generalized sigmoid function and day-ahead electricity prices to forecast its hourly GHG emissions with a certain bias. The approach of mapping the GHG emissions of grid electricity with the electricity prices using a sigmoid function requires further research work. Other factors can influence the relationship and need to be considered in further research. More years and data sets might be enhancing the results.

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ANNEX

Figure 7 to Figure 11 show the analyzed years with the electricity price ranges selected and fitted sigmoid functions.

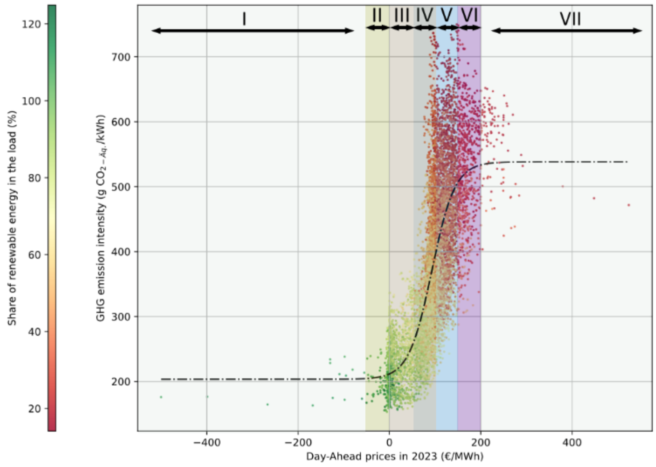

Figure 7: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2023.

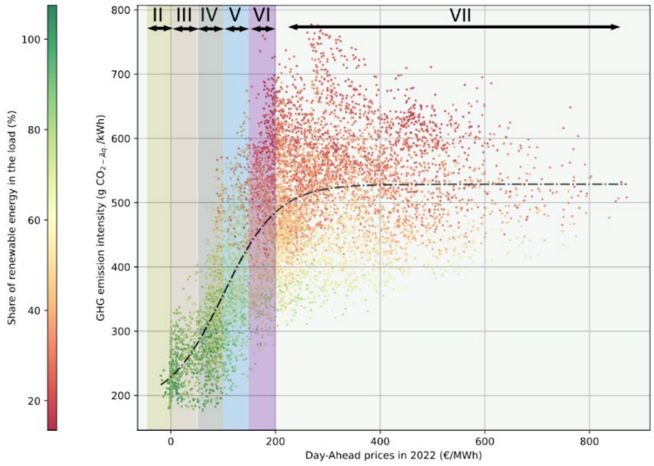

Figure 8: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2022.

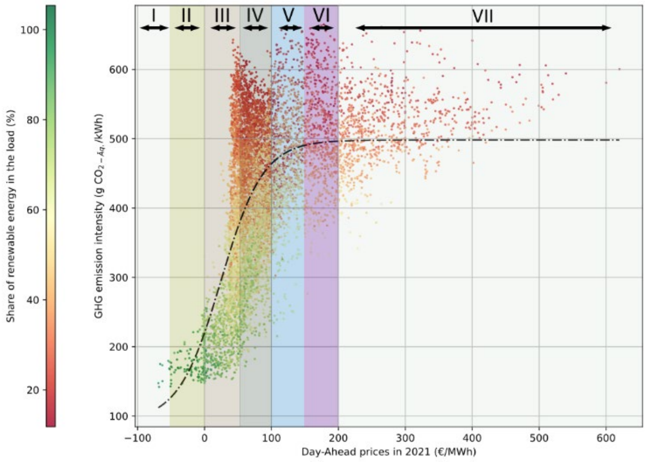

Figure 9: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2021.

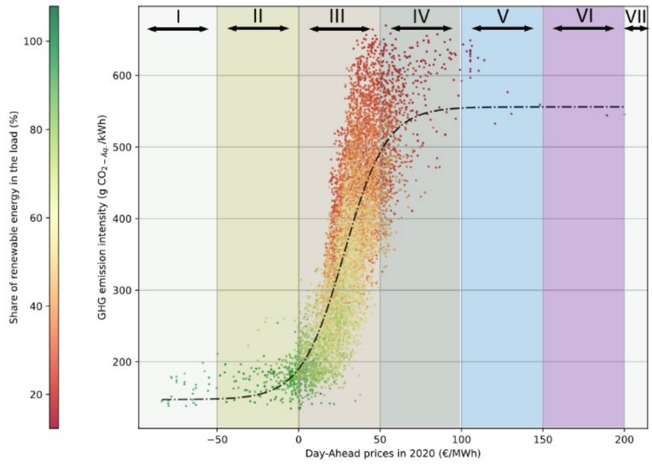

Figure 10: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2020.

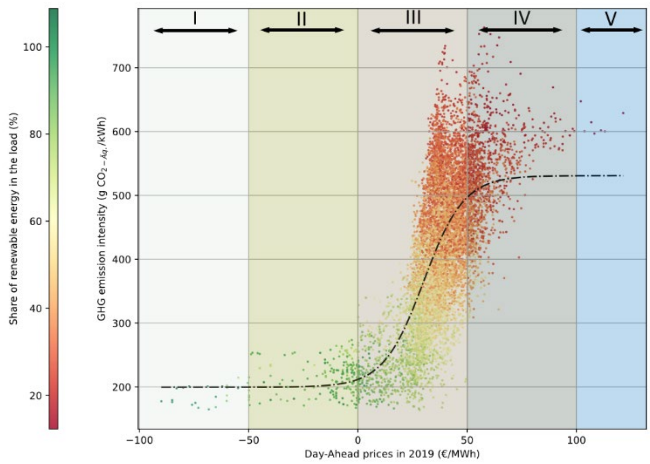

Figure 11: Hourly GHG emissions of the electricity mix depending on day-ahead exchange electricity prices (with outliers) in 2019.

Table 3: Distribution of points around the sigmoid function.

Above	Electricity price area						
Below	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**
2023	7	120	572	1366	1546	357	79
	8	*165*	*447*	*1946*	*1768*	*343*	*36*
2022	0	24	233	385	554	728	2307
	0	*46*	*200*	*496*	*613*	*828*	*2345*
2021	10	52	706	2047	481	355	526
	0	*77*	*1009*	*2174*	*639*	*323*	*307*
2020	19	170	3579	415	21	0	0
	8	*101*	*4096*	*370*	*2*	*1*	*1*
2019	6	119	3339	779	7	0	0
	15	*71*	*3790*	*633*	*0*	*0*	*0*

Table 4: Comparison of regression measure "MAPE" for individual price ranges in the years 2019-2023.

	Electricity price range						
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
2023	0.140	0.109	0.140	0.188	0.192	0.139	0.102
2022	0	0.096	0.124	0.177	0.172	0.165	0.141
2021	0.295	0.161	0.261	0.137	0.137	0.115	0.081
2020	0.106	0.098	0.177	0.120	0.095	0.022	0.020
2019	0.081	0.105	0.183	0.120	0.133	0	0

Table 5: Comparison of regression measure "MPE" for individual price ranges in the years 2019-2023.

	Electricity price range						
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
2023	0.07	0.02	-0.02	0.06	0.05	0.03	-0.04
2022	0	0.08	0.00	0.05	0.04	0.04	0.03
2021	-0.26	0.05	0.10	0.06	0.05	0.00	-0.03
2020	-0.08	-0.03	0.05	0.02	-0.09	0.02	0.02
2019	0.07	-0.04	0.05	0.01	-0.13	0	0

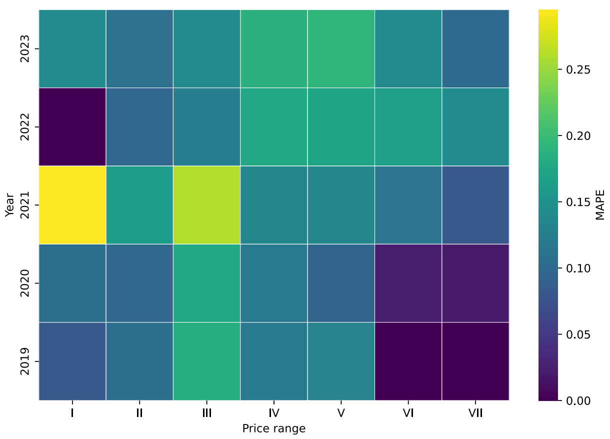

Figure 12: Heatmap of regression measure "MAPE" for individual price ranges in the years 2019-2023.

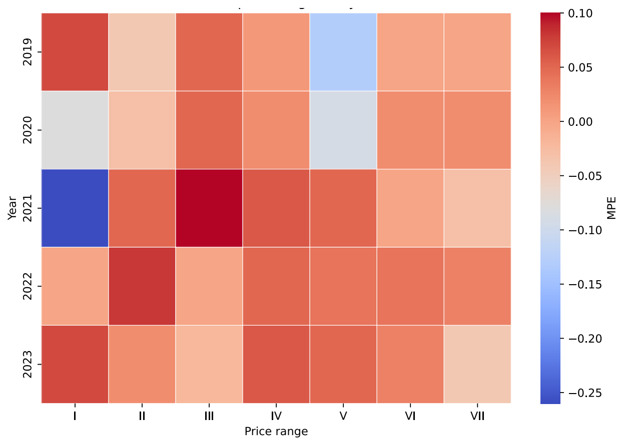

Figure 13: Heatmap of regression measure "MPE" for individual price ranges in the years 2019-2023.