Temperature-related impacts on solar assets

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Abstract

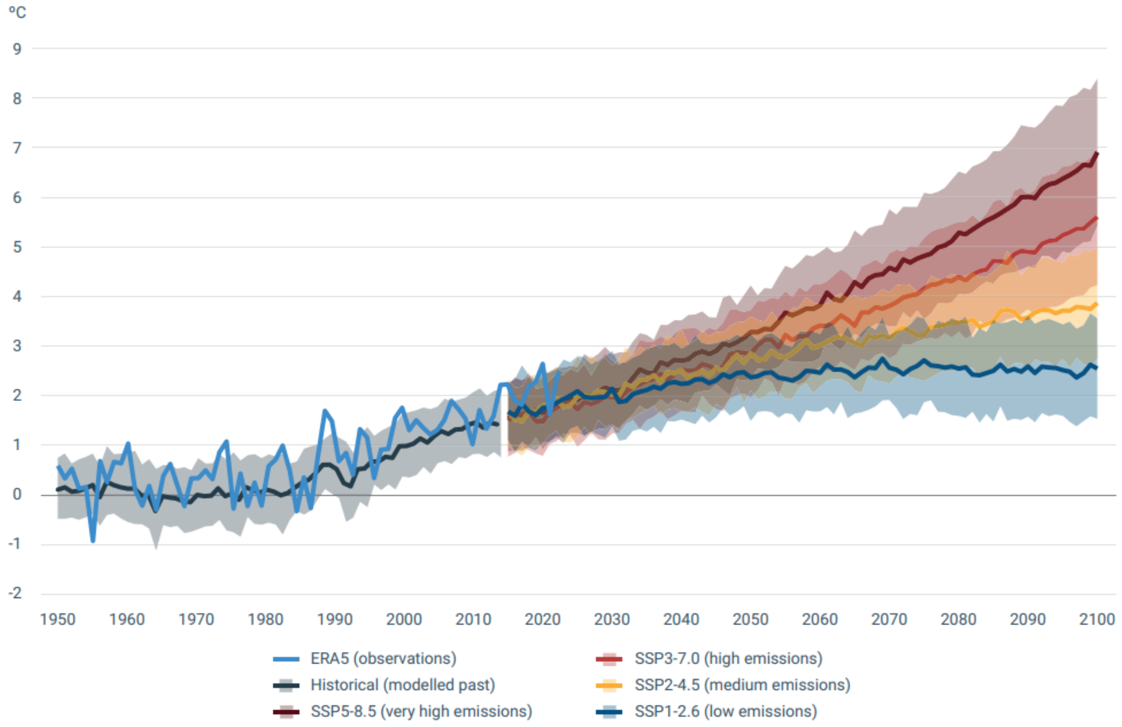
2023 was the warmest year on record over more than 100,000 years globally (European Environmental Agency, 2024). The impact of climate change on asset performance, particularly for alternative energy assets and those based on renewable energy, is increasingly significant. Climate change introduces variability in weather patterns, temperatures, and precipitation, which directly affects the efficiency and output of renewable energy sources such as solar, wind, and hydroelectric power. For instance, solar farms may experience fluctuations in energy production due to changes in solar irradiance and increased incidences of extreme weather events. Similarly, wind farms could be impacted by alterations in wind patterns and speeds. Climate indices, which quantify various aspects of climate variability, play a crucial role in forecasting and assessing these impacts. By integrating climate indices into financial and operational models, investors and operators can better understand, anticipate, and manage the risks associated with climate change. This proactive approach enables more accurate predictions of asset performance, ensuring that renewable energy investments remain viable and sustainable in the face of a changing climate.

The increasing urgency of climate change introduces two principal considerations relevant to this study. First, climate change compels rational investors to reassess vulnerable assets in light of potential financial materiality. Second, climate-related impacts are expected to intensify over time, as global temperatures are projected to rise at an increasing rate in a worst-case scenario, according to the European Environment Agency (see Figure 1). This research is a case study that examines the performance of one solar farm, a renewable energy asset, in relation to fluctuating electricity prices and varying climate conditions. We employ two sophisticated predictive models: a cash-flow model using the internal rate of return (IRR) as the primary performance metric to calculate the asset's return and a generalized additive model (GAM) to analyze and forecast the financial viability of the solar farm by predicting electricity prices, which are critical for determining the cash inflows generated by the farm.

By integrating these models, we aim to provide a comprehensive assessment of the financial viability of solar farms under varying European climate conditions and electricity price scenarios. This dual-model approach not only enhances the predictive accuracy within the European context but also offers valuable insights into the potential risks and opportunities associated with renewable energy investments in this region. Our findings contribute to the broader discourse on sustainable finance and underscore the critical importance of incorporating climate considerations into financial models and investment strategies, particularly within the European framework.

This whitepaper presents a case study focused on a French solar farm, providing a unique, specific example of asset modeling. The performance of this solar farm must be evaluated within the context of its geographical, political, cultural, and economic climate. The study underscores the necessity of considering climate change impacts on renewable energy assets, emphasizing how increased climate variability and rising temperatures could affect both the production efficiency and financial returns of solar farms in Europe. By focusing on a specific French solar farm, this research highlights the importance of region-specific analyses and demonstrates how climate change can materially impact the financial performance of alternative energy assets.

FIGURE 1. DEPARTURES IN TEMPERATURES (EUROPEAN ENVIRONMENTAL AGENCY, 2024)



Source: EEA EUCRA available at https://www.eea.europa.eu/publications/european-climate-risk-assessment

The function used to describe the solar farm's net cash-flow performance at each period modeled or $CF_{t=x}$ is seen in Figure 2:

FIGURE 2. SOLAR FARM NET CASH-FLOW PERFORMANCE

$$\boxed{\text{Cash Flow at time } x = \left(P_x \times \frac{P_{sq} \times A \times \eta}{1{,}000{,}000}\right) - C}$$

Where:

- P_x = Price of energy at time x (in € /MWh)
- P_{sq} = Power produced per square meter (in watts)
- A = Total area of the solar farm (in square meters)
- η = Efficiency of the photovoltaic cells (as a decimal, e.g., 0.20 for 20%)
- C = Total operating costs (in €)

The cash-flow model utilized IRR as a traditional financial metric to determine the profitability of solar farm investments by calculating the expected return rates over a specified investment horizon of 35 years from the start of the investment's cash flows. The solar farm we analyzed was generating electricity as of January 2015. We assumed 35 years or December 2014 to November 2049 was an optimistic and reasonable investment horizon for a solar farm.

To accompany the IRR cash-flow model, a GAM was created to predict energy prices in France. The GAM offers a flexible approach to capture the complex, non-linear relationships between climate variables—such as solar radiance, temperature, dew point temperature, precipitation probability, cloud cover—and electricity prices, which are critical determinants of revenue for solar farms. The GAM also captures the effects of seasonality observed in electricity prices over a time. This is a relevant feature of our predictive model since on average the whole sale electricity price per MWh in France fluctuates from €57.37 at 4 a.m. to €100.68 at 7 p.m. or a daily average increase of ~76% trough to peak daily, according to historical data from France between January 2015 and June 2024.

Combined, the IRR analysis indicates that solar farms can offer competitive returns, while the GAM further expounds the intricate dependencies between climate variables and electricity prices. Together they provide an end-to-end understanding of the risks and opportunities associated with solar farm investments.

By comparing the insights and predictive accuracies of both models, we present a comprehensive framework for evaluating the financial performance of solar farms in the face of climate variability. This research highlights the necessity of integrating climate considerations in investment decision-making processes and demonstrates that advanced predictive models can enhance the strategic planning and risk management of renewable energy assets. While based on a localized case study, our findings contribute to the broader discourse on sustainable investment and underscore the critical role of renewable energy in mitigating climate change impacts.

Introduction

The escalating concerns over climate change and its multifaceted impacts on economic and financial systems have spurred extensive research into the performance of various assets under different climate scenarios. As global temperatures rise and weather patterns become increasingly erratic, the financial viability of assets, particularly those in the energy sector, face heightened uncertainty. This research aims to explore the intersection of climate effects and asset performance, focusing explicitly on the performance of a French solar farm in relation to changes in French energy prices. This research paper quantifies this particular asset's sensitivity to electricity price fluctuations.

The literature on climate change and financial performance is vast and diverse, encompassing studies on the macroeconomic impacts of climate variability, sector-specific analyses, and the development of predictive models to forecast financial outcomes under different climate conditions. Previous research has established that climate change can significantly affect asset values, operational costs, and revenue streams, necessitating the incorporation of climate risk into financial decision-making processes.

Numerous studies have examined the broader economic implications of climate change. For instance, a joint study from the University of Buffalo and Purdue University concluded that mean dew point temperature and extreme maximum temperatures are among the key climate variables relevant to energy price prediction models—namely, they concluded that the mean dew point temperature was one of the most accurate predictor of increased electricity demand (Alipour, Mukherjee, & Nateghi, 2019). Additionally, Burke, Hsiang, and Miguel (2015) highlighted the potential for climate change to reduce global economic output by up to 23% by the end of the century. Similarly, the work of Dietz et al. (2016) underscored the importance of integrating climate risks into economic models to better understand their long-term impacts on growth and productivity. Also, Bressan et al. (2024) provided a model that quantifies physical risks on geolocalized productive assets, considering their exposure to chronic and acute impacts (hurricanes) across the scenarios of the Intergovernmental Panel on Climate Change, and which shows that investor losses are underestimated up to 70% when neglecting asset-level information and up to 82% when neglecting tail acute risks. Robert Lee et al. (2023) in their paper "Climate risk assessment and scenario analysis" reveal how Bayesian network tool is used in n scenario analysis and complex risk analysis aka CRisALIS approach. While there is some indication that physical risks are priced in credit and equity markets, the evidence is preliminary and sometimes mixed. In credit markets, investors seem to pay a premium for corporate bonds that tend to do better when bad news about climate arrives (Huynh and Xia [2020]).

In the context of renewable energy, several studies have focused on the performance of solar farms and their economic viability. A study by Branker, Pathak, and Pearce (2011) provided a comprehensive review of solar photovoltaic (PV) levelized cost of electricity (LCOE), emphasizing the sensitivity of solar farm economics to climatic conditions and technological advancements. More recently, Hirth (2013) explored the market value of solar power, noting the significant influence of electricity prices and market dynamics on the profitability of solar energy projects.

The use of a GAM in this article is supported by many studies that have shown this model to be apt for capturing seasonality and nonlinear relationships and interaction terms. Yee, T. W., & Mitchell, N. D. (1991) in their article "Generalized Additive Models in plant ecology" reveal how applying GAM was useful in predicting the distribution of an endangered plant species based on non-linear relationships with climate variables and capturing the non-linear effect of elevation on the presence of a particular tree species using smooth functions in a GAM. In addition, Hastie & Tibshirani (1986) showed how GAMs provide a flexible method for identifying nonlinear covariate effects in exponential family models and other likelihood-based regression models.

However, there remains a gap in the literature regarding the application of advanced predictive models to assess the performance of renewable energy assets, such as solar farms, in the context of climate-induced variability in electricity prices. Solar farms have emerged as a pivotal component of the global transition toward sustainable energy. Their performance, however, is intrinsically linked to climatic factors such as solar radiance, temperature, and weather patterns, which directly influence electricity generation and, consequently, revenue. Additionally, electricity prices, which are subject to market dynamics and regulatory policies, play a crucial role in determining the financial returns of solar farms. An understanding of these complex interdependencies is essential for investors, policymakers, and stakeholders aiming to optimize investment strategies and mitigate risks associated with renewable energy projects.

This research paper seeks to address the gap in understanding European (specifically French) energy prices and solar farm production and performance by employing two sophisticated predictive models: the internal rate of return (IRR) and generalized additive models (GAM). The IRR model is a well-established financial metric used to evaluate the profitability of investments, providing a clear measure of expected return rates. As an accompanying predictive model, the GAM offers a flexible approach to capture the non-linear relationships between French climate variables and regional electricity prices, allowing for a more nuanced analysis of the factors influencing solar farm performance in France. It is important to note that our research is very regionally focused and is not necessarily extendable to other locations. For example, there are cultural and economic factors present in France that may not be applicable in other locations.

By integrating these models, we aim to provide a comprehensive assessment of the financial viability of solar farms under varying climate conditions in France and electricity price scenarios. This dual-model approach not only enhances the predictive accuracy within the French climate context but also offers valuable insights into the potential risks and opportunities associated with renewable energy investments in this region. Our case study and its findings contribute to the broader discourse on sustainable finance and underscore the critical importance of incorporating climate considerations into financial models and investment strategies. It also underscores the importance of looking at climate models and related asset performance on a very localized basis, as findings are difficult to generalize.

In the following sections, we will discuss data preparation and preprocessing, outline the methodology employed in our analysis, present the results of our predictive models, and discuss the implications of our findings for investors and policymakers. Through this research, we aim to advance the understanding of climate-related financial risks and support the development of more resilient and sustainable investment frameworks.

Data preparation and preprocessing

1. Data description

This section includes a brief description of the data set used in the numerical analysis in the subsequent sections. Data on electricity prices and climate variables are collected from reliable sources such as meteorological databases and energy market reports. The data is then preprocessed to handle missing values and outliers, and to ensure consistency in time intervals. The data set comprises a set of electricity prices from Bordeaux that was merged with a climate factor data set that includes temperature, dew temperature, solar radiation, cloud cover, precipitation probability, precipitation, and the time. These two data sets from the different sources were merged using common timestamps given in the two data sets. Alignment was ensured by checking for consistency in the feature definitions and units across the data sets. Both the electricity prices and the climate variables were all given in hours. The data was collected from Visual Crossing's Historical Weather Data, the European Investment Bank, and from Statista regarding the historical wholesale price of electricity in France by the MWh, over the period from January 2015 to June 2024.

The dataset from Visual Crossing comprises 83,136 records with seven features from climate factors and 83,136 records with one feature that is the electricity prices. Each feature is described in Figure 3, including its type.

FIGURE 3. DATA FEATURES

VARIABLE NAME	DESCRIPTION	DATA TYPE	RANGE
Price	The wholesale electricity prices of a MWh in euros per hour.	Numeric	(-134.94,2987.78)
Temperature	The degree Celsius of Temperature per hour.	Numeric	(-7.8,40.1)
Solar radiation	The amount of solar radiation in watts per meter squared per each hour.	Numeric	(0,1176)
Dew	The number of degrees in Celsius at which dew point is reached per each hour.	Numeric	(-29.8,22.8)
Cloud cover	The amount of cloud cover per each hour of the day as a percentage of coverage times 100.	Numeric	(0,100)
Precipitation probability	The chances of precipitation in each hour in a day. With 0 meaning no precipitation and 100 indicating precipitation.	Categorical	0 or 100.
Snow depth	The amount of snow depth in CM in each hour.	Numeric	(0,16)
Precipitation	The amount of precipitation in CM in each hour.	Numeric	(0,45.69)

2. Data cleaning and transformation

Figure 4 shows the energy price against the date from 2015 to 2024 for the complete data set. Energy price increases extremely after October 2021, reaching a maximum amount per MWh of about €3,000 per hour, and as can been seen in Figure 4, starting in October of 2021 the trend continued into 2024. This could be due to the tension and subsequent war between Ukraine and Russia as well as due to electricity demand changes due to a change in consumer habits during COVID lockdowns. To ensure that these extreme values do not alter the performance of the model, we consider only data collected from 2015 to June 2021. Similarly, we filtered out all energy prices that were either below €0 or over €200 per day from 2015 to June 2021 to standardize the data set, as there were unusual and high energy prices recorded from October 2016 to February 2017. The total data cohort size after cleaning was 56,626 discrete data points, out of which 34,904 discrete data points were used as training data while 21,722 discrete data points were used as testing data. The training data are the records obtained from 2015 to 2018, whereas the testing data are the data obtained from 2019 to June 2021. Figure 5 shows the plot of energy price against date from 2015 to 2021 for the cleaned data.

An additional feature, hour, was generated from the date-time variable to determine if electricity price could vary by the time of the day. This feature was created by taking a numeric value of 0 representing 12 a.m. in a day and 23 representing 11 p.m. Precipitation probability was encoded as a factor variable since it populates as only two possible values: 0 or 100.

FIGURE 4. PLOT OF ELECTRICITY PRICE AGAINST DATE FOR THE UNCLEANED DATA

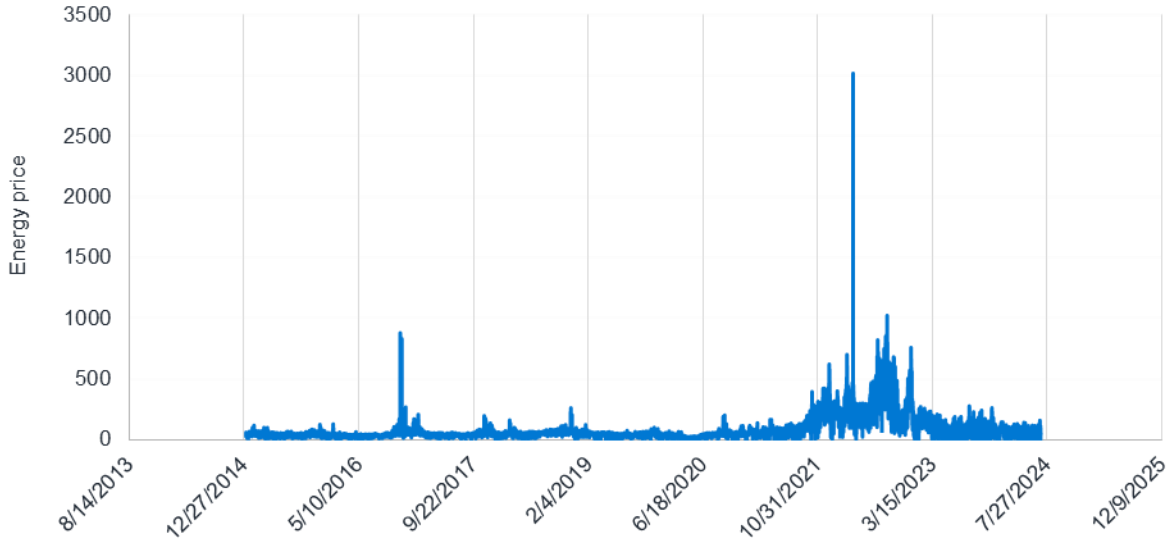
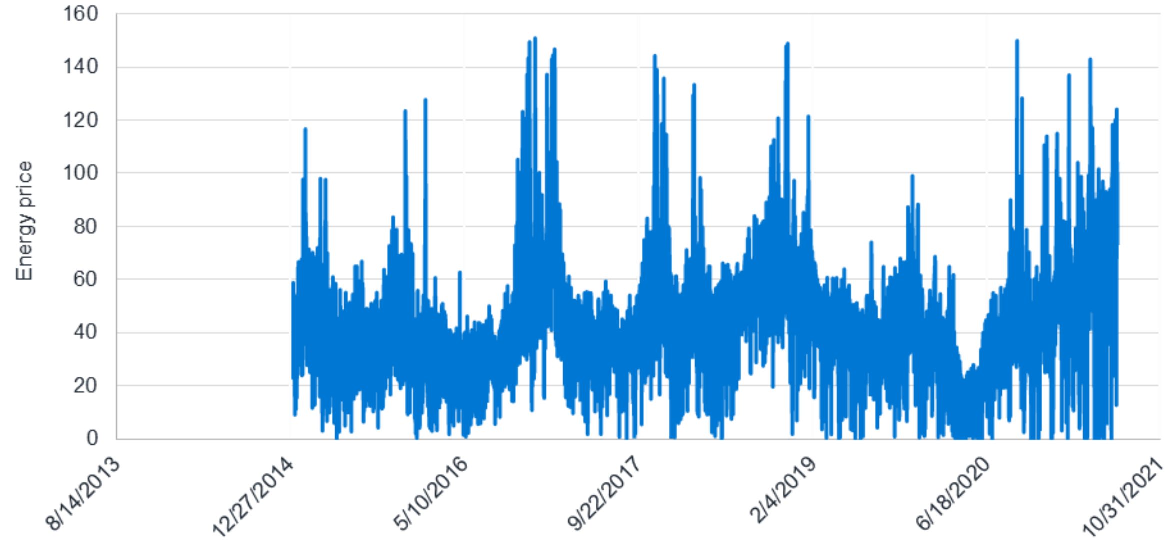


FIGURE 5. PLOT OF ELECTRICITY PRICE AGAINST DATE FOR THE CLEANED DATA



Exploratory data analysis

FIGURE 6. TEMPERATURE VERSUS DATE

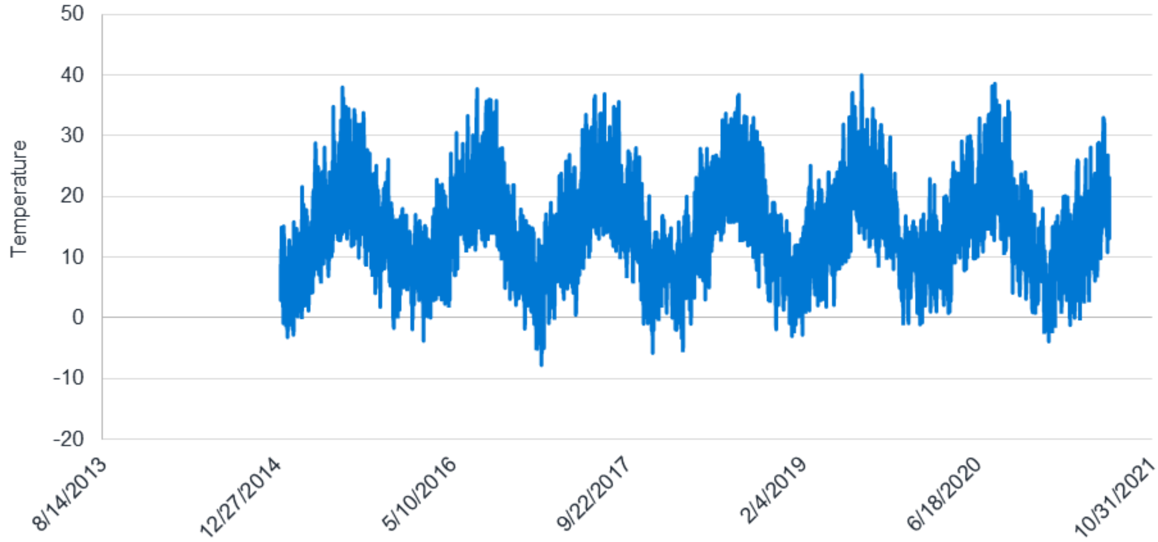


FIGURE 7. SOLAR RADIATION VERSUS DAY

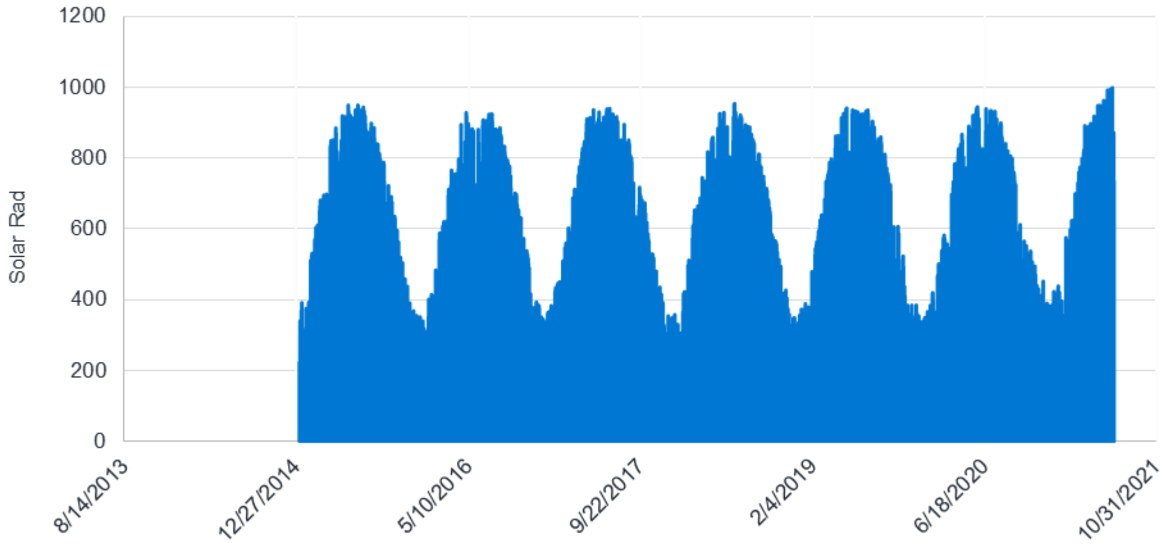


FIGURE 8. ELECTRICITY PRICE VERSUS HOUR OF DAY

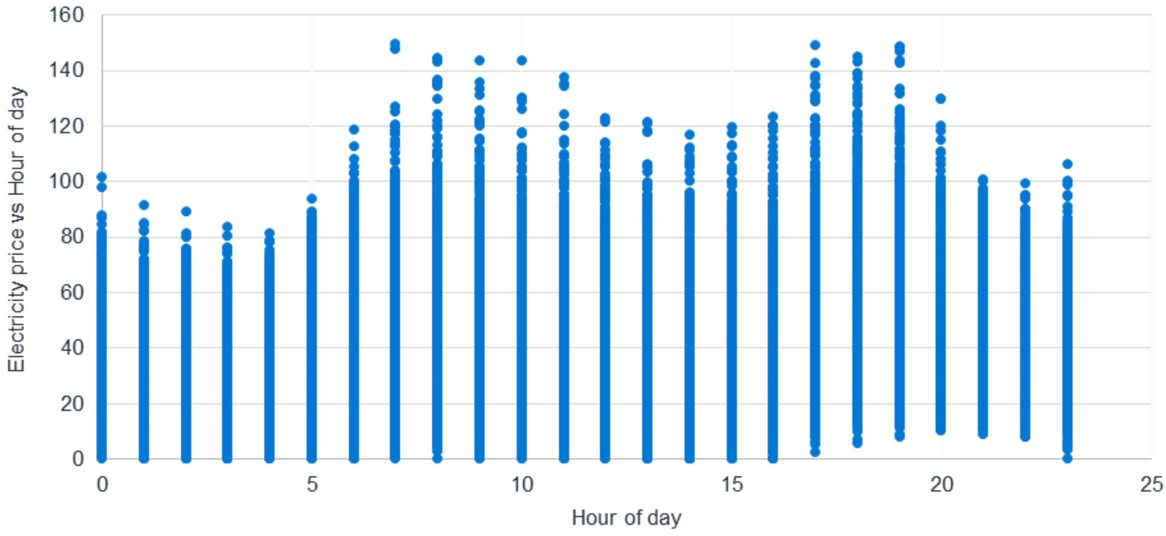


FIGURE 9. ELECTRICITY PRICE VERSUS TEMPERATURE

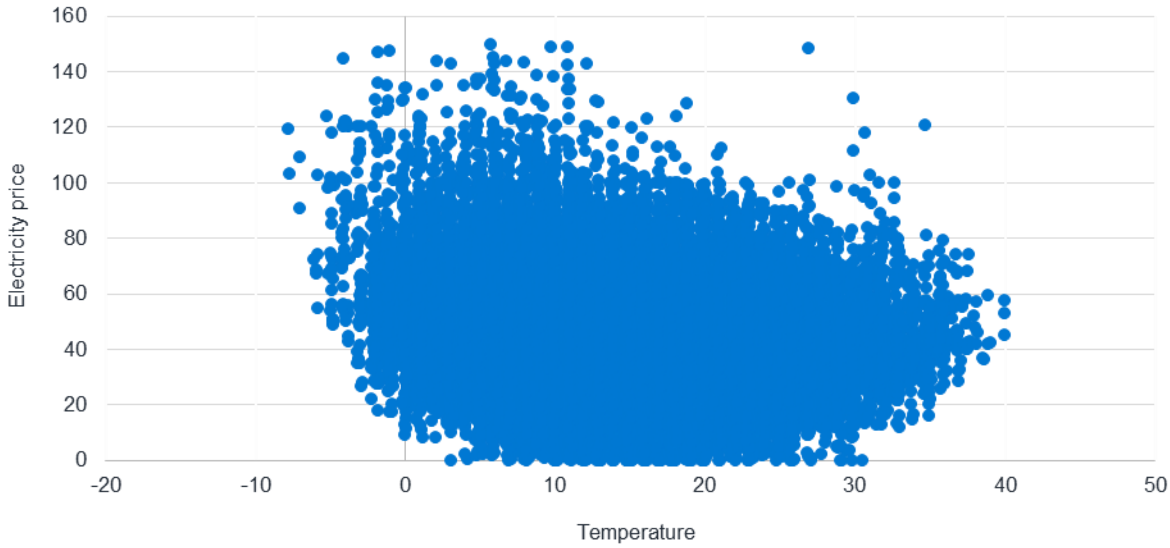


FIGURE 10. ELECTRICITY PRICE VERSUS SOLAR RADIATION

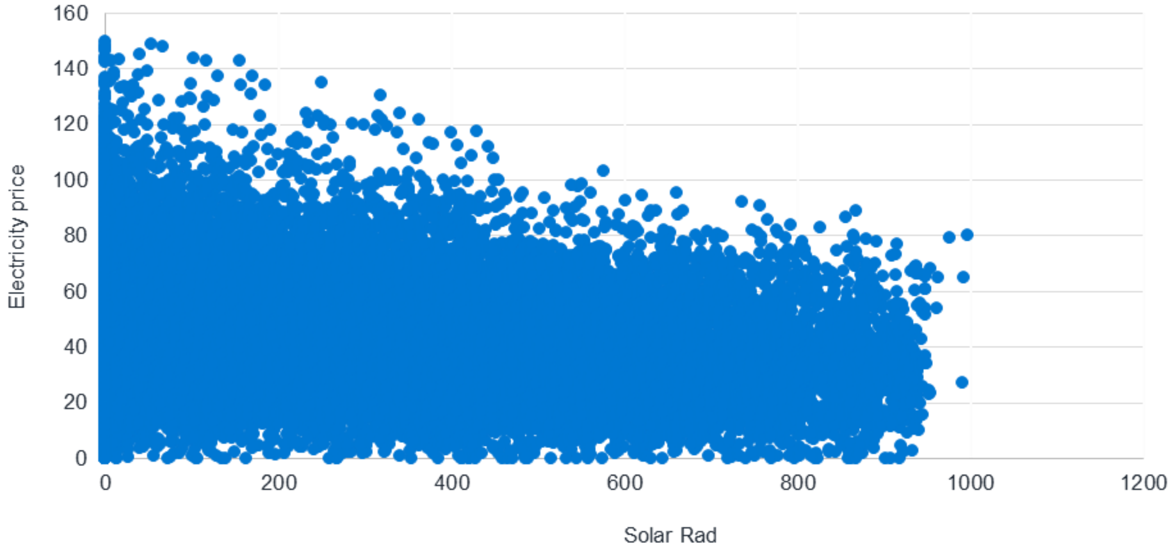


FIGURE 11. ELECTRICITY PRICE VERSUS CLOUD COVER

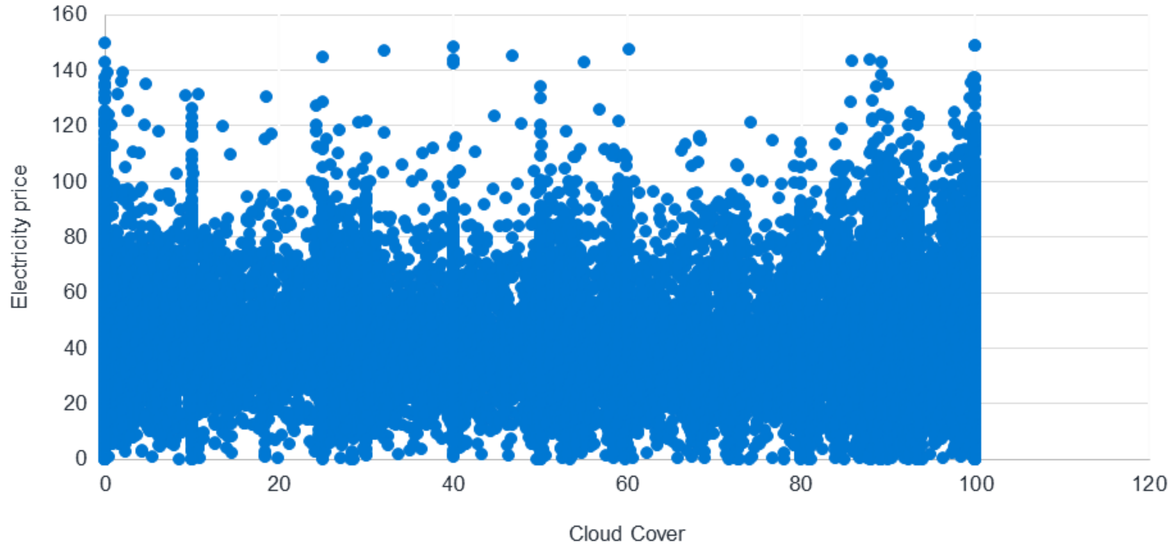


FIGURE 12. ELECTRICITY PRICE VERSUS PRECIPITATION PROBABILITY

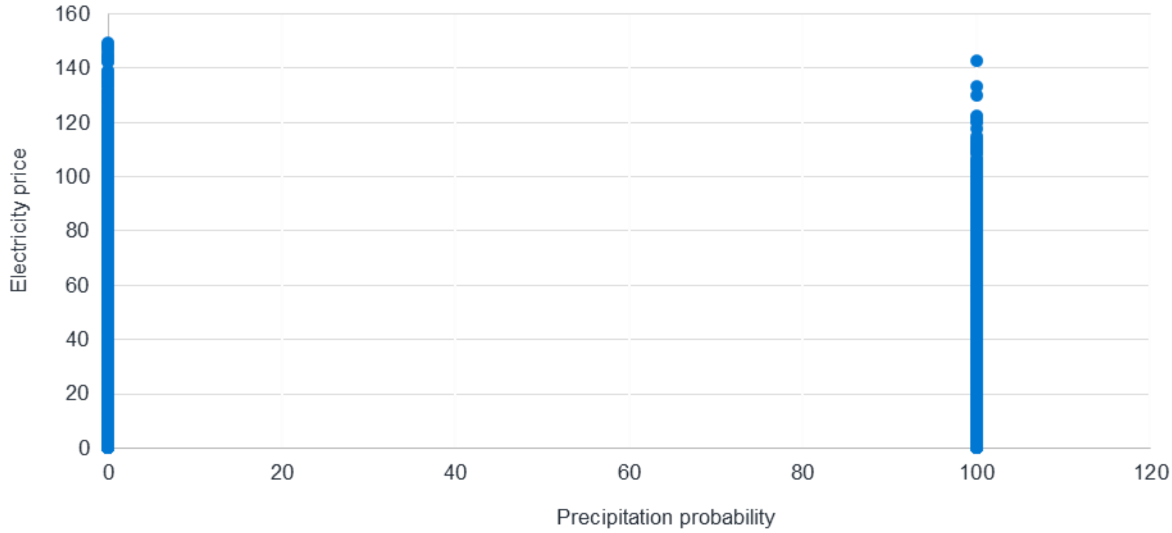


FIGURE 13. ELECTRICITY PRICE VERSUS PRECIPITATION

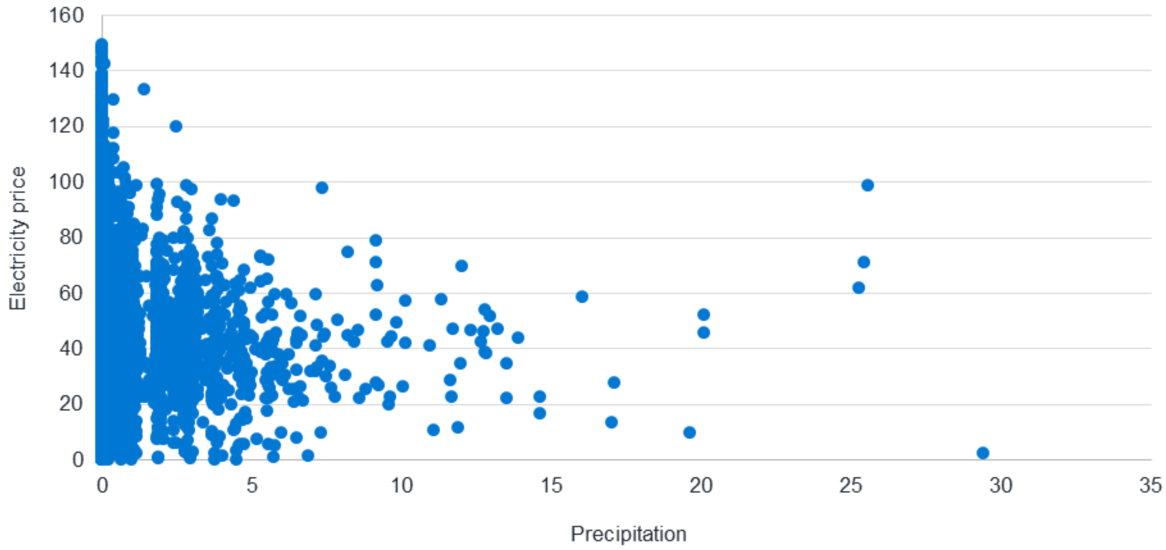


FIGURE 14. ELECTRICITY PRICE VERSUS DEW

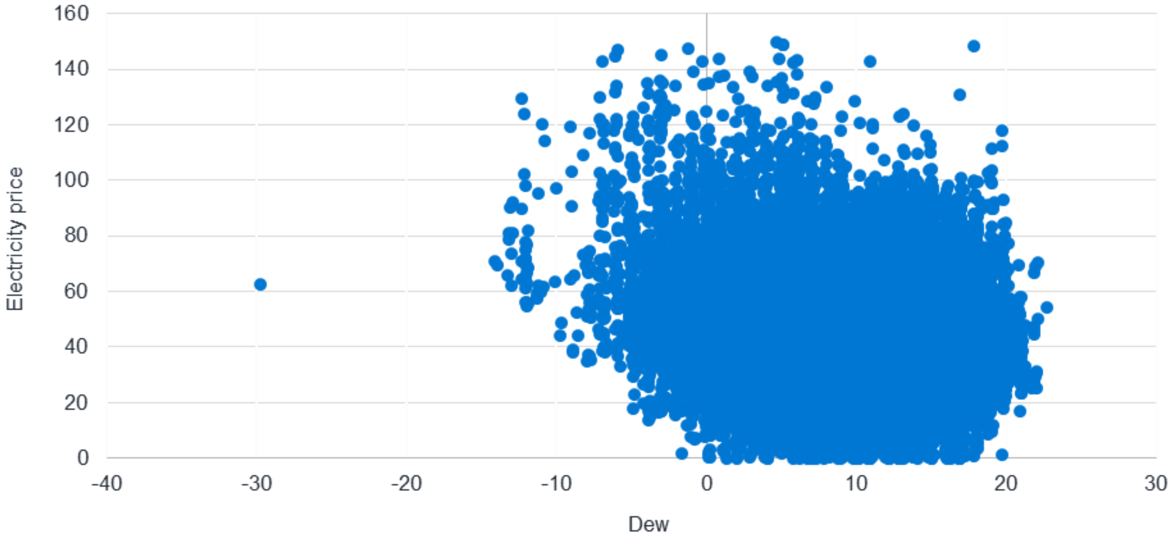
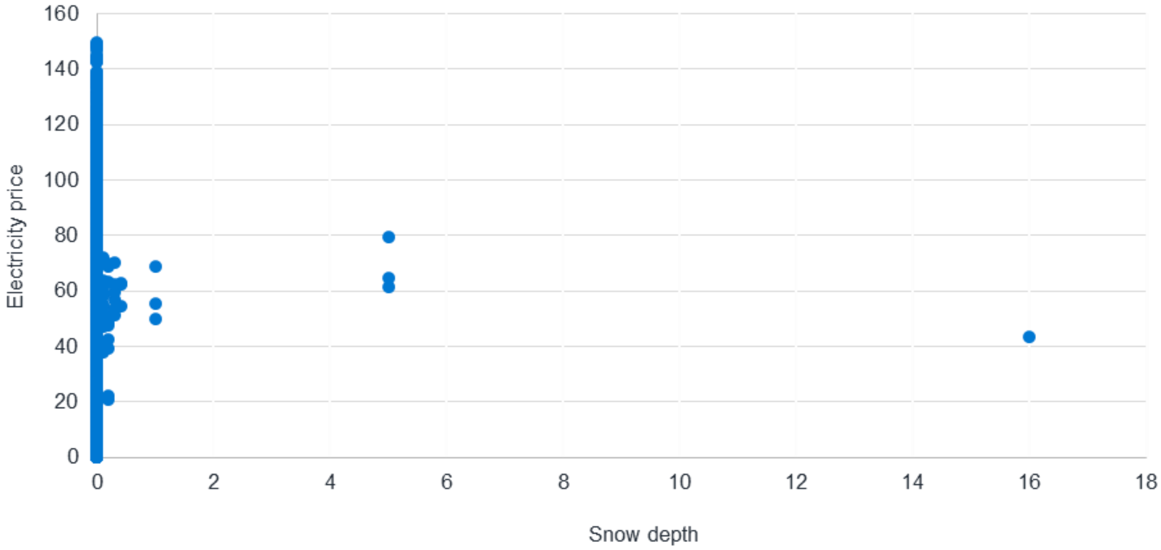


FIGURE 15. ELECTRICITY PRICE VERSUS SNOW DEPTH



Methodology

GENERALIZED ADDITIVE MODEL

Overview of GAM

Generalized additive models (GAMs) are a flexible extension of generalized linear models (GLMs) that allow for the inclusion of non-linear relationships between the dependent variable and independent variables. GAMs achieve this flexibility by using smooth functions to model the non-linear relationships to capture complex and seasonal patterns in the data that linear models might miss.

Model specification

In this research, the dependent variable is the electricity price, while the independent variables include various climate factors such as solar irradiance, temperature, and weather patterns. The GAM can be specified as follows:

$g(E(Y))=\beta_O + s(T) + f(X)$

where $g(.)$ is the link function, E(Y) is the expected value of the response variable electricity price, β_O is the intercept parameter, $f(X) = \sum_i^p \beta_i . X_i$ measures the systematic component where β_i $(i = 1, 2, \dots, p)$ is the regression coefficient or parameter associated with the i-th covariate (climatic variable) of size p, and $s(T) = \sum_j^q \theta_j . B_j(T)$, $j = 1, 2, \dots, q$, is a smooth term or function to capture the seasonal and non-linear patterns of the $j-th$ time periodic depend variable, where $B_j(T)$ $are\ the\ cubic\ B - splines\ basis\ functions,$ and θ_j are the corresponding coefficients to be estimated.

For purposes of demonstration, we assumed electricity price to follow a normal distribution and model the relationship between electricity price and the set of predictors based on a linear identity link function. However, we consider the cyclic cubic regression spline basis to capture the non-linear and seasonal effects in energy price over time.

To construct cyclic cubic splines, we consider a combination of cubic B-splines and additional constraints to ensure periodicity.

1. **Cubic B-splines:** These are piecewise polynomials of degree 3. For a set of knots, the cubic B-spline basis functions $B_j(T)$ are defined such that each $B_j(T)$ is non-zero only over a limited range of T.

2. **Periodicity constraints:** To ensure the spline is cyclic, we impose constraints such that the spline and its first and second derivatives match at the boundaries a and b

$$f(a) = f(b), f'(a) = f'(b), f''(a) = f''(b).$$

To fit the GAM with cyclic cubic splines, we typically use penalized likelihood to control the smoothness of the spline. To derive the penalized likelihood function, we consider the distribution of the response variable to follow a Gaussian distribution with an identity link function, thus, we have: $Y \sim N(\mu_{i,\ \sigma^2}$), where $\sigma^2$is the variance of the Gaussian distribution.

Likelihood function

Given that the linear predictor $\eta_i = \mu_i = \beta_O + s(T) + f(X)$, the log-likelihood function becomes:

$$l(\theta, \beta, \sigma^2) = \sum_i^n (-\frac{1}{2}\log(2\pi\sigma^2) - \frac{(y_i - (\beta_O + s(T) + f(X)))^2}{2\sigma^2}$$

To estimate the smooth functions, $s(T)$, we use a penalized log-likelihood to control the smoothness. The penalized log-likelihood function is expressed as:

$$l_p(\theta, \beta, \sigma^2) = l(\theta, \beta, \sigma^2) - \sum_j^q \lambda_j . \int (s_j''(t))^2 dt,$$

where λ_j are the smoothing parameters that control the trade-off between fit and smoothness, and $\int (s_j''(t))^2 dt$ is the roughness penalty for the smoothness function of $s(T)$. We obtain the basis dimensions based on a random search approach, whiles the smoothing parameter (λ) is obtained using grid search cross-validation. Expanding the log-likelihood function:

$$l(\theta, \beta, \sigma^2) = -\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(y_i - \left(\beta_O + \sum_j^q \theta_j . B_j(T) + \sum_i^p \beta_i . X_i\right))^2$$

Including the penalty term:

$$l(\theta, \beta, \sigma^2) = -\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(y_i - \left(\beta_O + \sum_j^q \theta_j . B_j(T) + \sum_i^p \beta_i . X_i\right))^2 - \sum_j^q \lambda_j . \int (s_j''(t))^2 dt$$

To estimate the parameters β, the smooth functions θ, and the variance σ^2, we maximize the penalized log-likelihood function. This is done using iterative algorithms like the backfitting algorithm or penalized iteratively reweighted least squares (P-IRLS).

MODEL FITTING

To fit the GAM, we made used of the R software package "mgcv," which is readily available in R. Figure 3.1 reports the results of the estimated coefficients, standard errors, t-values, and the p-values for the GAM based on the set of predictors. Based on the small p-values associated with each predictor, we can conclude that all the climatic variables are statistically significant at less than a 0.01 significance level. This means that there is strong evidence to suggest that climatic conditions such as temperature, solar radiation, dew temperature, cloud cover, and precipitation probability have meaningful association with energy costs and that this association is unlikely to be due to random chance. The p-value corresponding to snow depth was greater than 0.05, suggesting a non-statistical significance relationship between energy price and snow depth. Snow depth was therefore removed from the model.

By substituting the estimated coefficients, the GAM can be expressed as follows:

Expected Electricity Price ≈ $50.035 + s(Date) + s(Hour) - 0.283.Temperature - 0.010.Solar\ Rad - 0.148.Dew - 0.007.Cloud\ cover - 1.364.Precipitation\ Probability$.

FIGURE 16. APPROXIMATE SIGNIFICANCE OF THE SMOOTH TERM.

CLIMATIC VARIABLE	COEFFICIENT ESTIMATE	STD. ERROR	T-VALUE	P-VALUE
INTERCEPT TERM	50.035	0.256	195.56	$2X10^{-16}$
TEMPERATURE	-0.283	0.023	-12.10	$2X10^{-16}$
SOLAR RAD	-0.010	0.001	-18.17	$2X10^{-16}$
DEW	-0.148	0.025	-6.01	$2X10^{-09}$
CLOUD COVER	-0.007	0.002	-4.50	$2X10^{-06}$
PRECIPITATION PROBABILITY	-1.364	0.163	-8.35	$2X10^{-16}$

FIGURE 17. APPROXIMATE SIGNIFICANCE OF THE SMOOTH TERM.

SMOOTH TERM	EFFECTIVE DF	REF. DF	F-STATISTIC	P-VALUE
DATE	117.95	118	492.2	$2X10^{-16}$
HOUR OF DAY	19.83	22	765.8	$2X10^{-16}$

Interpretation of model coefficients

- *β_0* = 50.03: The baseline value of energy price when all other variables are zero.
- *β_1 = 0.28*: For each unit increase in temperature, the price decreases by approximately 0.28 units, holding all other variables fixed. All climate factors and supply factors held constant the region seemingly experiences higher demand for electricity when temperatures go down. The demand explanation is that the region experiences a greater demand shock (whereby demand increases at a higher rate than the supply can be shocked by without an increase in prices) during the winter since there is a considerable rate of use of electrical heaters. The region does not experience as great of a demand shock during the summer, as the region does not use as much energy to cool itself as it does to heat itself. This hypothesis is borne out by the evidence that roughly 39% of homes in France have electrical heaters (Vollmuth & Pellinger). This demand-side explanation expects that there is not a considerable rate of use of air conditioners compared to heating units in France, and this is borne out by evidence. Only ~25% of French households have air conditioning, this data point stands in contrast to the United States, where roughly 90% of homes have air conditioning (Pauline, 2024), (Ross & Bill, 2024).
- *β_2 = 0.01*: For each unit increase in solar radiation, the price decreases by approximately 0.01 units, holding all other variables fixed. This is likely due to an increased amount of electricity supplied from solar arrays. As solar radiation increases, likewise, the amount of electricity supplied to the grid increases.
- *β_3 = 0.15*: For each unit increase in dew point, the price decreases by approximately 0.15 units, holding other variables fixed. Dew temperature should have a directional relationship with temperature. As temperature increases then usually so does dew temperature. Therefore, the same reasons that an increase in temperature relates to a decrease in price can be thought to apply to dew temperature.
- *β_4 = 0.007*: For each unit increase in cloud cover, the price decreases by approximately 0.007 units, holding other variables fixed. There is a decrease of supply that is most likely due to a decrease in solar array productivity during a period of increased cloud cover. In 2023, 15% of France's electricity production came from solar power (Electricity Transmission Network, 2024).
- *β_5 = 1.36*: The price decreases by approximately 1.36 units (36%) when there is 100% probability of precipitation as compared to when there 0% probability of precipitation, holding all other variables constant. If supplied electricity remains roughly constant regardless of the probability of precipitation, then it seems that precipitation has an impact on demand. When rain is occurring then the demand of electricity goes down. This causes the price of electricity to decrease, all other factors held constant.

MODEL VALIDATION AND DIAGNOSTICS

The fitted GAM is validated using a testing data set to assess its predictive accuracy. Performance metrics such as the R-square adjusted, the proportion of deviance explained, and the root mean squared error (RMSE) are used to evaluate the model. Figure 18 is a graph of the line of best fit on the train data. Observe that the fitted line approximately captures the seasonal patterns in the training data. Similarly, Figure 19 shows the corresponding line of best fit on the testing data. The line of best fit approximately captures the seasonal patterns in the testing data, indicating the superiority of the GAM to capture both linear and non-linear patterns in data.

FIGURE 18. PLOT OF THE BEST FIT LINE FOR THE TRAINING DATA

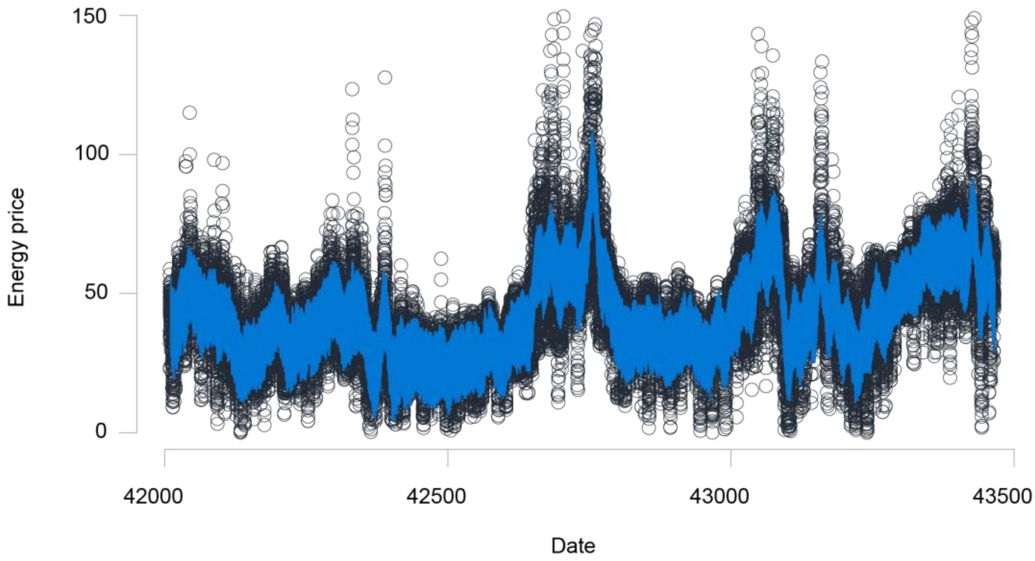
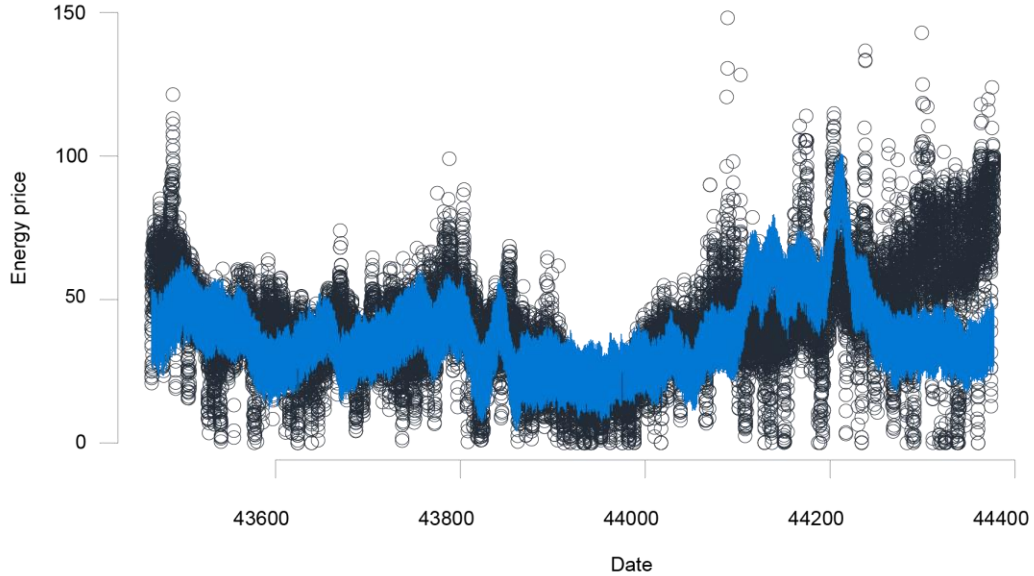


FIGURE 19. PLOT OF THE BEST FIT LINE FOR THE TESTING DATA



As a parametric distribution, the GAM assumes that the residuals are normality distributed with a constant variance. Figures 20 and 21 are used to check the normality of the residuals. The Q-Q plot indicates a systematic deviation from the line in later values, which may be due to the many outliers recorded in the recent observations. For future studies, we may recommend using lighter tail distributions than the normal distribution considered in this study.

To check for non-linearity and heteroscedasticity, we presented a plot of residuals against the predictors in Figure 23. The plot shows a systematic pattern, funnel shape, where the spread of residuals increases with fitted/predictor values and indicates heteroscedasticity (non-constant variance). This indicates that the smooth term may not have captured the relationship adequately, suggesting the need for a more flexible smooth term. The test for the significance of the smooth terms in the model are statistically significant at 5% alpha level. This clearly shows that date and hour of day both have significant non-linear relationship with electricity prices. However, observe that increasing the smooth term or the flexibility comes at cost for computational efficiency and overfitting. Figure 22 suggests that the GAM with cyclic basis function captures the underlying structure of the data well since the points lie approximately on a 45-degree diagonal line where the response equals the fitted values.

FIGURE 20. HISTOGRAM OF THE RESIDUALS FROM THE TRAINING DATA

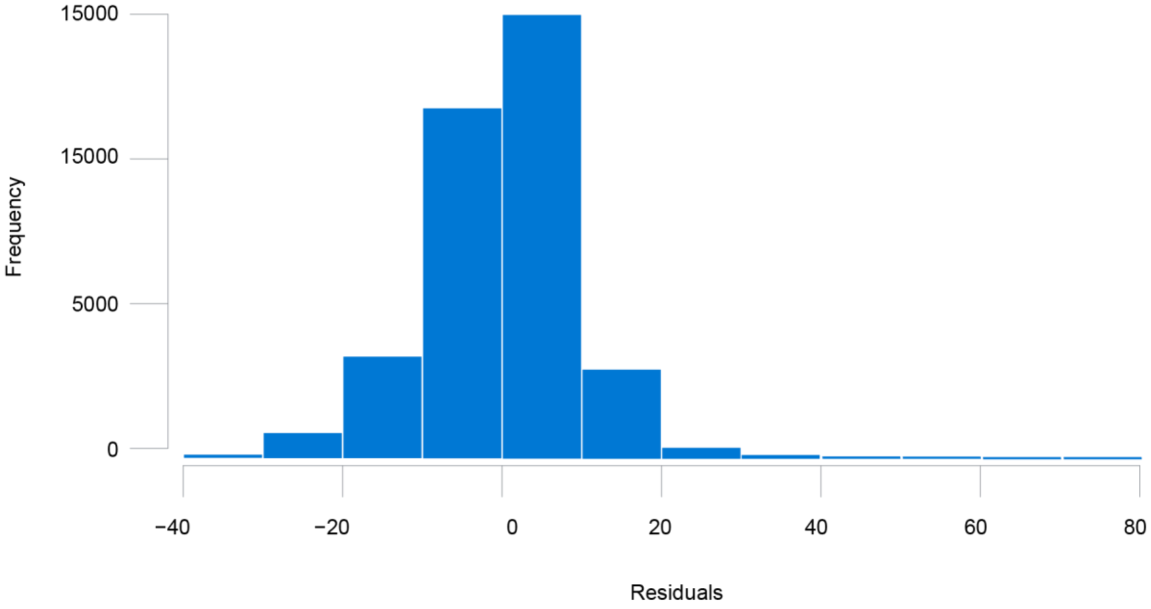


FIGURE 21. Q-Q PLOT FOR THE TEST OF NORMALITY OF THE DEVIANCE RESIDUALS

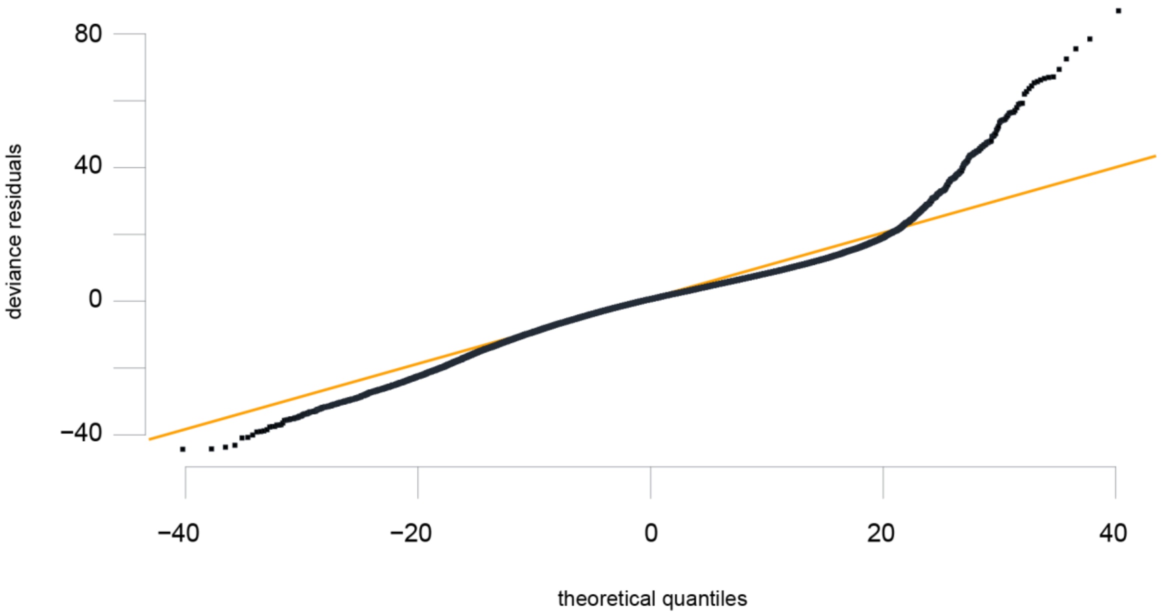


FIGURE 22. Q-Q PLOT FOR THE TEST OF NORMALITY OF THE DEVIANCE RESIDUALS

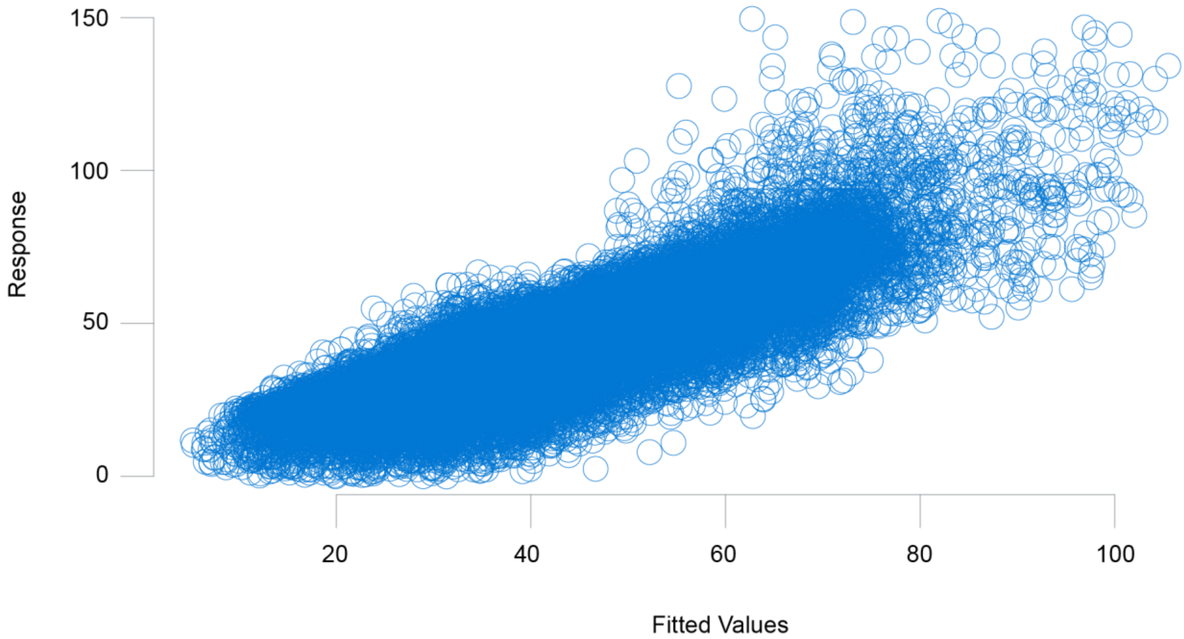
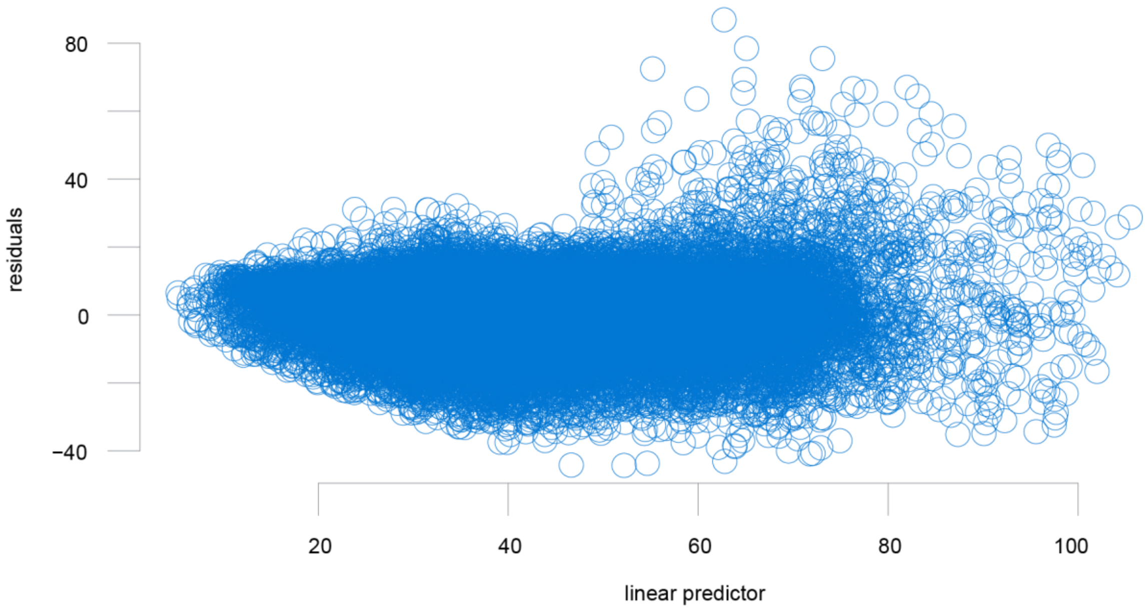


FIGURE 23. PLOT OF THE RESIDUALS AGAINST THE LINEAR PREDICTORS



MODEL PERFORMANCE

- R-sq.(adj) = 0.712: This means that approximately 71.2% of the variability in price is explained by the model. This is a good fit.
- Deviance explained = 71.3%: Like R-squared, this indicates how well the model explains the data.
- RMSE: The RMSE on the training data is 9.60, while the testing RMSE data is 17.20**.** The high RMSE is highly attributed to the many extremely large outliers recorded in the data.

In summary, this GAM is used to predict the price based on several factors, including time-related variables (date and hour of day), and weather-related variables (temperature, solar radiation, dew, cloud cover, and precipitation probability). The model captures both linear and non-linear relationships, explaining a significant portion of the variability in the electricity price. The results show that all the included variables significantly impact the price, with the model fitting the data quite well.

CONSTRUCTING THE CASH-FLOW MODEL USING IRR

1. **Predictive electricity prices from GAM:** The validated GAM provides predictive values of electricity prices based on the following climate variables. These predicted electricity prices are crucial inputs for the cash flow model of the solar farm.
2. **Cash-flow model components/assumptions of the cash-flow inputs**: The cash-flow model includes several components:
   - **Revenue:** Calculated based on the predicted electricity prices and the expected electricity generation from the solar farm
   - **Operating costs:** Includes maintenance, labor, and other operational expenses
   - **Capital expenditures:** Initial investment required to set up the solar farm
   - **Depreciation:** Accounting for the wear and tear of the solar farm equipment over time
   - **Tax considerations:** Including potential tax benefits and liabilities
3. **Revenue calculation:** Revenue is calculated using the formula:

   Revenue = Sum of all the predicted hourly electricity price in each month
   where the predicted electricity price is obtained from the GAM.
4. **Cash-flow projection:** The cash flow for each month is projected by subtracting the operating costs and other expenses from the revenue at the end of each month. The net cash flow for each month is given by:

   Net cash flow = Revenue − Operating costs − Other expenses
5. **IRR calculation:** The IRR is calculated using the projected cash flows. IRR is the discount rate that makes the net present value (NPV) of the cash flows equal to zero. It is computed using the formula:

   $$\text{NPV}=\sum_{t=0}^{T}\frac{Net\ Cashflow_t}{(1+IRR)^t}=0$$

   where t is the time period, and T is the total number of periods.
6. **Sensitivity analysis:** A sensitivity analysis is conducted to understand how changes in key assumptions, operating cost, and other assumptions affect the IRR. This analysis helps in identifying the most critical factors influencing the financial performance of the solar farm.
7. **Model inputs and variables:** See Figure 2 in the abstract for more details about how the values presented below are used to calculate a net monthly cashflow for the asset.

FIGURE 24. CASH-FLOW MODEL ASSUMPTIONS

Model start date	12/31/2014
Cost to develop asset	€ 352,080,000
Temperature increases during scenario analysis	Variable (+0 ℃, +.5 ℃, +1 ℃)
Efficiency	Variable (11.35%, 16%, 17%, 18%, 19%, 20%, 21%, 22%)
Solar depreciation factor	0.25%
Investment horizon	35 Yrs.

FIGURE 25. CASH-FLOW MODEL FEES

Monthly Maintenance Fee	1% of monthly Gross Cashflow
Management Fee	2% of monthly Cashflow net of Maintenance

Additional considerations:

1. **Taxes** - All results are provided on a pre-tax basis.
2. **Purchased** – All solar panels at the farm are modeled as purchased and not leased. Therefore, no ongoing lease rate was modeled.
3. **Solar panel replacement rate** – The solar panels are modeled with a 0% replacement rate.
4. **Solar panel efficiency depreciation rate** – The solar panels are modeled with a 0.25% annual depreciation rate.

INTEGRATION AND ANALYSIS

Comparative analysis**:** The IRR values from different scenarios are compared to assess the robustness of the solar farm's financial performance under varying climate conditions. This comparative analysis provides insights into the potential risks and opportunities associated with the investment.

Key findings

FIGURE 26. IRR NET OF ASSUMED 1% FEES MONTHLY AND A 2% MANAGEMENT FEE WITH 35-YEAR INVESTMENT HORIZON USING PROJECTED AND HISTORICAL WHOLESALE PRICE PER MWH IN EUROS

Avg. Solar Cell Efficiency	Scenario 1: With Historical Wholesale Price and Projected Temp +0 degree Celsius Increase	Scenario 2: With Historical Wholesale Price and Projected Temp +.5 degree Celsius Increase	Scenario 3: With Historical Wholesale Price and Projected Temp +1 degree Celsius Increase	Scenario 4: With Historical Wholesale Price and Projected Temp +1 degree Celsius Increase, Projected Dew Temp +1 degree Celsius Increase, and Projected Cloud Cover reduction of 15%
11.35%	4.26%	4.25%	4.23%	4.22%
16%	7.47%	7.46%	7.45%	7.44%
17%	8.12%	8.11%	8.10%	8.09%
18%	8.76%	8.75%	8.74%	8.73%
19%	9.39%	9.38%	9.36%	9.35%
20%	10.00%	9.99%	9.98%	9.97%
21%	10.61%	10.60%	10.59%	10.58%
22%	11.21%	11.20%	11.19%	11.18%

FIGURE 27. COMPARISON OF A DOLLAR VALUE OF A BASIS POINT (DV01) AND A SENSATIVITY VALUE OF A BASIS POINT (SV01) BETWEEN SCENARIOS 1 AND 3

Avg. Solar Cell Efficiency	DV01 (Scenario 1 - Scenario 3)	SV01 (Scenario 1 - Scenario 3)
11.35%	€ 2,378,689	0.024%
16%	€ 3,353,414	0.023%
17%	€ 3,563,002	0.023%
18%	€ 3,772,591	0.023%
19%	€ 3,982,179	0.023%
20%	€ 4,191,767	0.022%
21%	€ 4,401,356	0.022%
22%	€ 4,610,944	0.022%

FIGURE 28. TOTAL CASH FLOW NET OF ASSET DEVELOPMENT COST AND FEES IN EUROS OVER A 35-YEAR TIME HORIZON

Avg. Solar Cell Efficiency	Scenario 1: With Historical Wholesale Price and Projected Temp +0 degree Celsius Increase	Scenario 2: With Historical Wholesale Price and Projected Temp +.5 degree Celsius Increase	Scenario 3: With Historical Wholesale Price and Projected Temp +1 degree Celsius Increase
11.35%	€ 287,424,216	€ 286,234,872	€ 285,045,527
16%	€ 549,476,386	€ 547,799,679	€ 546,122,972
17%	€ 605,823,660	€ 604,042,159	€ 602,260,658
18%	€ 662,170,934	€ 660,284,639	€ 658,398,343
19%	€ 718,518,208	€ 716,527,119	€ 714,536,029
20%	€ 774,865,482	€ 772,769,599	€ 770,673,715
21%	€ 831,212,756	€ 829,012,078	€ 826,811,401
22%	€ 887,560,030	€ 885,254,558	€ 882,949,086

Solar panels used at solar farms have increased in efficiency over time. While this research team found that the solar farm modeled has an efficiency of roughly 11.35%, we analyzed greater efficiencies to determine the materiality of this variable on the asset's performance over the 35-year investment horizon at an efficiency more representative of solar arrays produced today (see rows 2-8 in Figure 28). In conclusion of this section there are two points of note. First, when running our scenario analysis, the historical average (Jan 2015 to June 2024) temperature (the temp variable) at a given hour at a given day during the year was applied as the temperature value for the annual projected electricity prices; it is possible that another team could derive more accurate projected temperature values, but this is beyond the scope of this paper. Likewise, the average MWh per meter squared (or the solarrad variable) over the period of January 2015 to June of 2024 at a given hour at a given day during the year was applied as the solarrad value for the annual projected electricity price; for the variables cloudcover, precipprob, precip, and dew point temperature or (dew), 2023 values were used for projecting electricity prices. Again, we imagine that other teams may use different methods to derive projection values for these climate variables. Second, several additional model runs were performed in order to observe the GAM's predicted impact on IRR in a case where several climate variables experienced changes. This would be an enhancement to the scenarios run in the figures above since in scenarios 1 to 3 only experienced an air temperature shock. We noted a de minimis impact when stressing the projected cash flows using multiple climate variables. For example, the gap in IRR between scenario 3 noted above in Figure 26 and scenario 4 is ~1 basis point, where in addition to a temperature variable stress of one degree Celsius, we applied an increase to the dew variable at each hour of one degree Celsius as well as a 15% cloud cover reduction at each hour.

RESULTS

The cash-flow model indicates that the impact of future temperature change on solar array assets is not material. At worst ~-0.024% and at best ~-0.022% performance reductions would have occurred in terms of IRR due to an increase in temperatures of 1℃ from day one of the projection period which was July 2024 until the end of the projection in November 2049. Factors much more relevant than temperature to the performance of this asset include the solar efficiency of the solar system used, the investment horizon used to model the assets performance, and the fee assumptions applied to the projected asset performance.

LIMITATIONS

There are three key limitations to the analysis.

1. Regarding the GAM, the dataset used to create this model was of limited relevance to the French wholesale energy market. The weather variables we observed did not directly relate to the energy market; however, the limited data provided was statistically significant (for setting an electricity price) and allowed our team to produce a GAM with an acceptable goodness of fit based on historical electricity prices. It was a sufficient data set for our purposes. We could imagine that a team with access to the electricity demand or supply sourced from a government authority, or with access to much more detailed information about the specific solar park's energy output, would be capable of producing a more apt GAM.
2. Electricity prices in France are based on demand, and the research must be considered with this relationship in mind and may not be extendible to areas where demand pricing is not done.
3. The research would be more robust and the IRR cash-flow model more refined if the research team had access to data on the solar array efficiency at energy production start date, the full land leasing agreement, the solar array efficiency depreciation year over year, and specific maintenance fee schedule for the solar array we were modeling.

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