Data Science, Prediction and Forecasting

Course Project

The Relationship Between Wind Energy and Danish Electricity Prices

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Preface

This research article examines the correlation between electricity prices and wind energy specifically within the context of Denmark.

All data manipulation and analysis were conducted in Python and MATLAB.

All codes used for this project can be found at: GitHub Repository

https://github.com/saitsaglam/-Data-Science-Prediction-and-Forecasting-Exam.git

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Abstract

This project aims to investigate the relationship between wind energy generation and electricity prices in Denmark. Denmark is known for its commitment to renewable energy and stands as a global leader in integrating wind power into its electricity grid. The study employs three regression methods, namely the Simple Regression Line, the Robust Regression Line, and Multiple Linear Regression to comprehensively analyze the dynamics between wind energy generation and electricity prices. Additionally, the project explores the relationship between electricity prices and load, which measures the disparity between electricity consumption and the electricity generated by wind turbines. The findings contribute to the understanding of renewable energy integration and its impact on electricity prices, providing valuable insights for policymakers and stakeholders in the energy sector to make informed decisions regarding renewable energy adoption and electricity pricing strategies.

1 Introduction

The utilization of renewable energy sources has gained significant attention in recent years as the world strives to transition towards more sustainable and environmentally friendly energy systems. Denmark, renowned for its commitment to renewable energy, stands out as a global leader in integrating wind power into its electricity grid. Additionally, the project will also explore the relationship between electricity prices and load, which refers to the disparity between electricity consumption and the electricity generated by wind turbines. This analysis aims to provide further insights into the intricate dynamics of the Danish electricity market, shedding light on the factors that influence pricing. To investigate this relationship between wind energy generation and electricity prices in Denmark, two regression methods will be employed: Simple, Robust, and Multiple Linear Regression. These statistical techniques allow for a comprehensive analysis of the dynamics between the variables of interest.

Denmark's wind energy landscape experienced a temporary setback with a decrease in wind-generated electricity to 44 percent due to a poor wind year. However, it is projected that wind energy production will increase significantly in the upcoming years [5]. Given this context, it becomes crucial to explore any potential relationship between wind-generated electricity and electricity prices in Denmark. The primary objective of this project is to contribute to the growing body of knowledge surrounding renewable energy integration and its impact on electricity prices. By gaining a deeper understanding of the relationship between wind energy and Danish electricity prices, policymakers and stakeholders in the energy sector can be better informed when making decisions regarding renewable energy adoption and electricity pricing strategies.

1.1 Introduction to Danish Electricity Market

The Danish day-ahead electricity market, operated by Energinet under Nord Pool, allows electricity producers and consumers to trade for the next day [7]. Bids are submitted before noon, and the spot price is announced at 13:00. Bids are treated as complete packages and either accepted or rejected [3]. The market establishes the electricity price based on supply and demand curves created from bids.

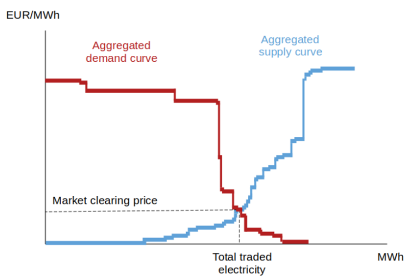

Figure 1.1: Supply-demand curve [8] .

The intersection point of these supply and demand curves becomes the focal point for price determination and quantity traded and this is illustrated in figure 1.1. At this point, the market operator establishes the price and amount of electricity that will be exchanged for the specific hour. It is worth noting that only the bids to the left side of this intersection point are selected for participation in the exchange, ensuring fair and efficient market outcomes.

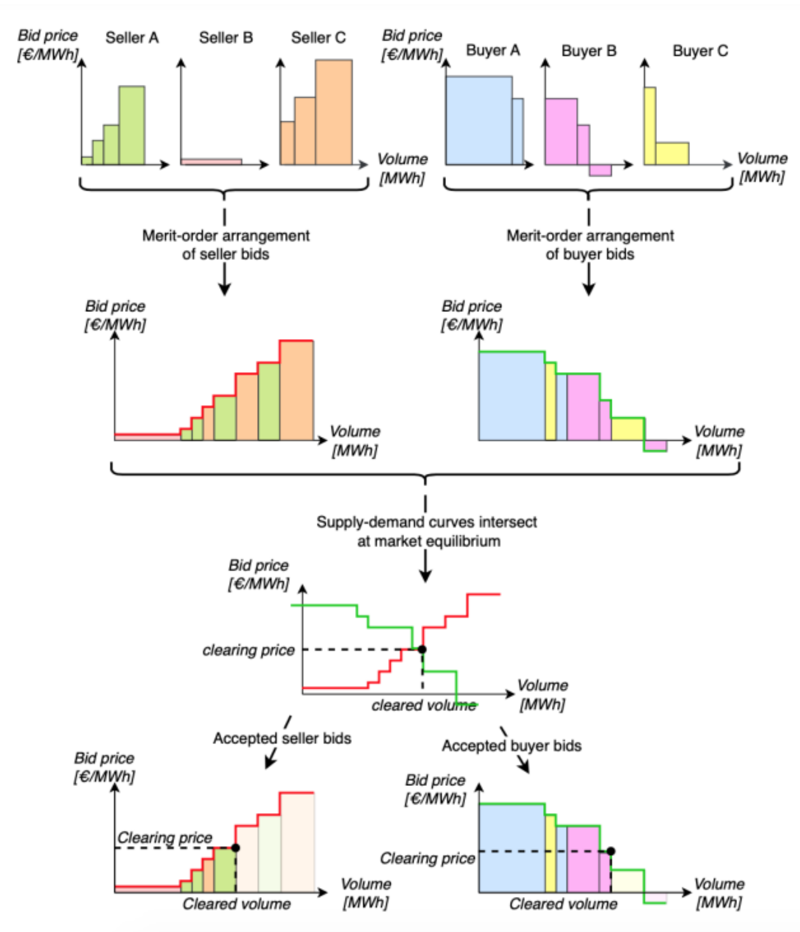

Figure 1.2: Bid and market clearing mechanism of the DA market [9]

By employing this, the day-ahead market enables market forces to determine the price of electricity, promoting competition mechanism and providing a transparent framework for participants to engage in energy trading activities [8]. This process is illustrated in Figure 1.2.

1.2 Simple Linear Regression

Simple linear regression is a statistical method employed to explore and quantify the association between two variables: a dependent variable (y) and an independent variable (x). It assumes a linear connection between the variables, implying that alterations in the independent variable will result in proportional modifications in the dependent variable [4] .

$$y_t = \beta_0 + \beta_1 x_t + \epsilon_t \tag{1.1}$$

This method assumes a linear relationship, where changes in x are associated with proportional changes in y. The goal is to estimate the intercept (β_0) and slope (β_1) that best fit the observed data, allowing for prediction and understanding of the relationship between the variables.

1.3 Robust Regression

Robust regression is an alternative to least squares regression that is particularly useful when the data contains outliers or influential observations. It is also employed for detecting influential observations. This method addresses the concern of potential deviations from the assumptions of traditional linear regression, which assumes a specific distribution for the data and is unaffected by extreme values [6]. Therefore, robust regression is a useful approach when data doesn't meet the assumptions of traditional regression. It provides reliable estimates of the regression coefficients, allowing for more accurate and reliable analysis, particularly in the presence of outliers or non-normal data distributions.

1.4 Multiple Linear Regression

Multiple linear regression is a statistical method used to model the relationship between a dependent variable and two or more independent variables. The goal is to determine how the predictor variables collectively influence the dependent variable [4]. The general form of the equation:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + ... + \beta_k x_{k,t} + \epsilon_t \tag{1.2}$$

In this equation, y(t) represents the value of the dependent variable at a given time point "t." The term β_0 is the intercept, representing the expected value of y when all predictor variables are zero. The coefficients β_1, β_2, ..., β_k represent the impact or effect of each predictor variable on the dependent variable after accounting for the other predictors in the model and the x values represent the values of predictors at time t.

2 Method

This section of the report focuses on the methods employed to examine the relationship between electricity prices and electricity generated by wind turbines in Denmark. Additionally, it provides an explanation of the data utilized for this analysis.

2.1 Data

This project utilizes hourly data encompassing various key variables. The data employed includes Capacity Factor (CF) values, electricity prices, electricity consumption, and the electricity generated by wind turbines.

2.1.1 Capacity Factor (CF)

The dataset utilized for this project comprises capacity factor data specifically for onshore wind turbines. The data covers the time period from 1979 to 2017, with hourly measurements available. Although the dataset encompasses capacity factor information for various European countries, this analysis focuses solely on the data pertaining to Denmark.

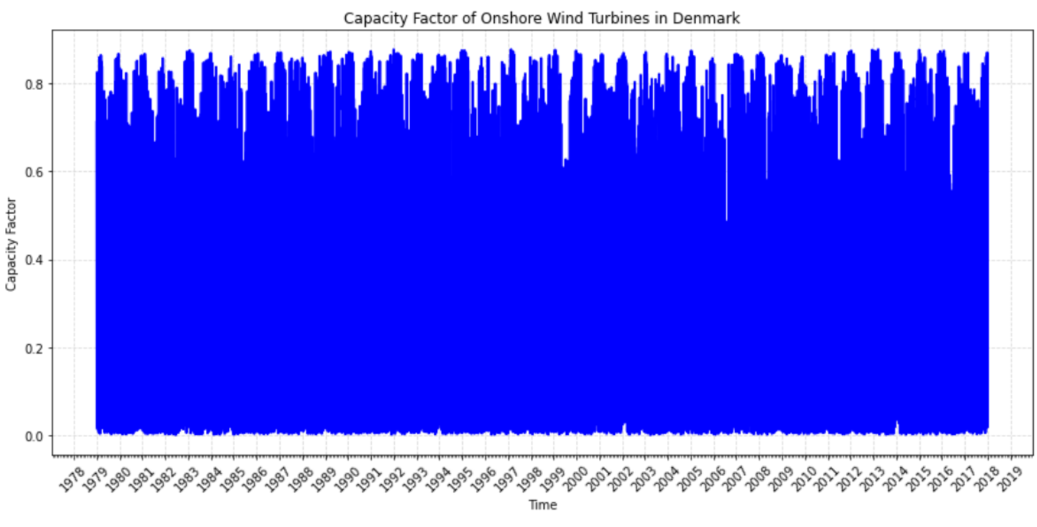

Figure 2.1: Hourly Capacity Factor of Onshore Wind Turbines in Denmark

Figure 2.1 represents the capacity factor data, illustrating the variability and distribution of the values. It can be observed that the data does not exhibit a distinct pattern or discernible behavior. As anticipated, the capacity factor values range between 0 and 1, aligning with expectations for wind turbine performance. Notably, the maximum capacity factor recorded in the data set reaches 0.877.

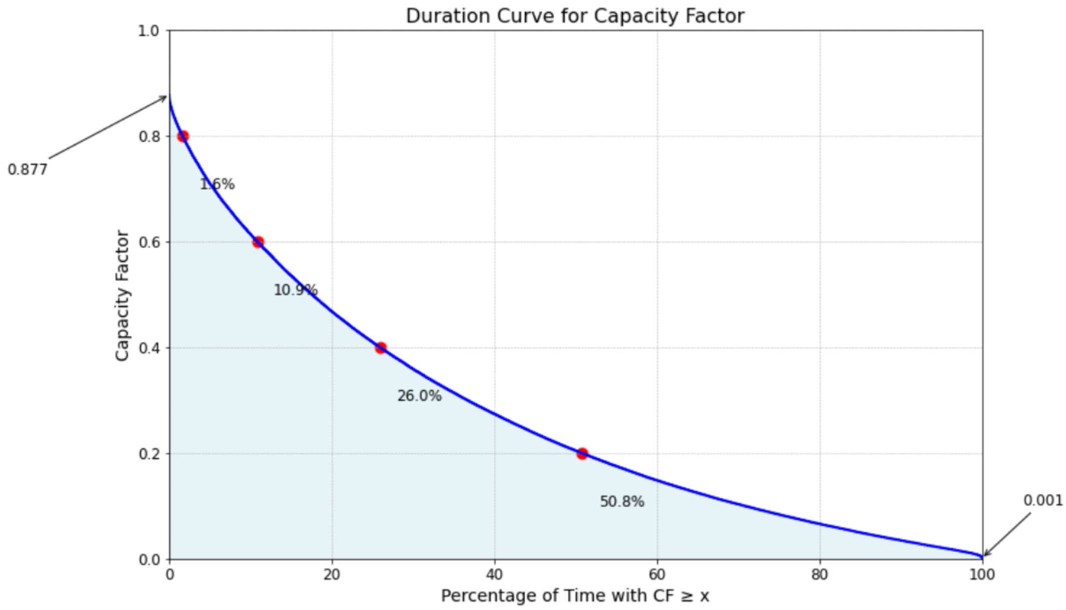

Figure 2.2: Duration Curve for Capacity Factor(CF)

The duration curve figure 2.2 is a useful tool for analyzing time-series data, such as the capacity factor (CF), which represents the impact of wind conditions on wind power generation. CF values range from 0 to 1 and reflect consistent average wind speeds throughout the year. With the duration curve, we can assess the CF dataset's characteristics and determine the percentage of time that exceeds specific CF thresholds. This information is vital for evaluating wind power reliability. By studying the duration curve, we gain insights into the temporal distribution of CF values, enabling us to identify specific conditions or events. This knowledge is valuable for decision-making in wind energy utilization, optimizing energy generation, and identifying periods of high or low wind power availability.

2.1.2 Electricity Price

The Danish electricity market is divided into two regions such as DK1 (Jutland and Funen) and DK2 (Copenhagen). For this project, the focus is solely on the DK1 region's electricity prices and the values measured in euros. The data set comprises hourly data spanning from 2000 to 2017. The price data utilized in this analysis was obtained from Energinet's website [2].

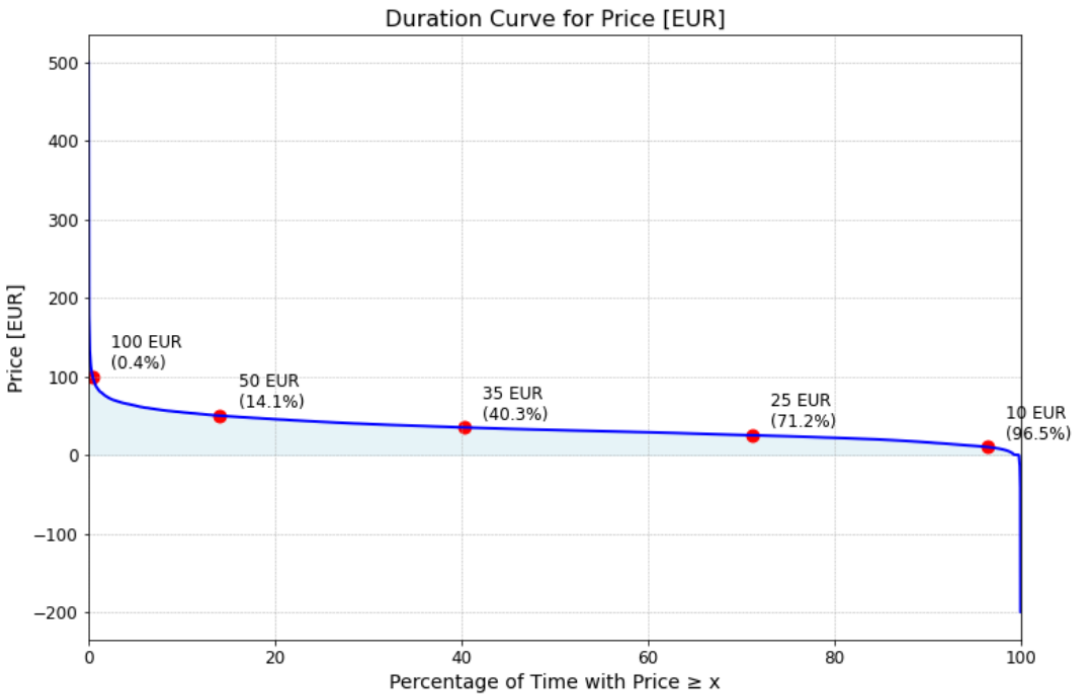

Figure 2.3: Duration Curve for Electricity Price

The duration curve (Figure 2.3) reveals insights about the distribution and characteristics of electricity prices in DK1. Most of the time, prices are below 500 EUR, with just 9 values exceeding this threshold. The curve shows a steep initial decline, indicating that lower prices are more common. As the curve progresses, higher prices become less frequent.

The red dots on the curve represent specific price levels (100 EUR, 50 EUR, 35 EUR, 25 EUR, and 10 EUR) and their corresponding percentages of time. Although wind turbine farm owners could offer slightly below zero for selling all generated electricity (Figure 1.2), current regulations mandate prices above zero. Out of the 157,789 data points used in the project, only 364 are below zero.

Overall, the price duration curve provides a comprehensive visual representation of electricity price distribution in Denmark. It emphasizes the prevalence of lower prices and allows for the identification of specific price levels and their occurrence percentages. This aids in analyzing and understanding price dynamics in the Danish electricity market.

2.1.3 Consumption

Consumption data is hourly and taken from the Energinet website [10]. The data set is from the beginning of 2005 to the end of 2017. The unit of consumption is MWh.

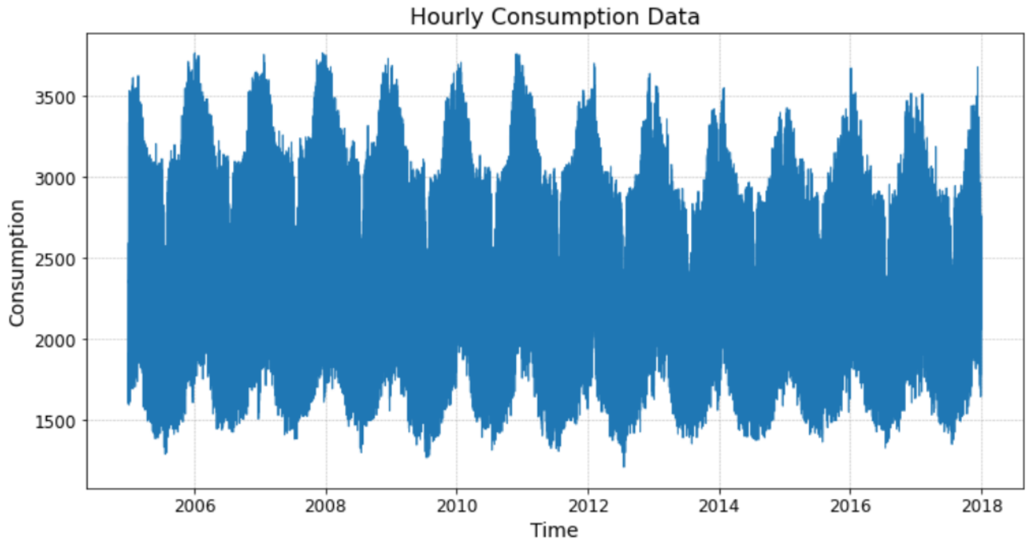

Figure 2.4: Hourly Electricity Consumption from 2005 to 2017

Figure 2.4 presents the hourly electricity consumption data spanning the years 2005 to 2017. The plot depicts the variation in electricity usage throughout the given time period, providing a comprehensive view of consumption patterns over the years. Peaks and valleys in the line indicate periods of higher and lower electricity usage, respectively.

2.1.4 | Electricity Generated by Wind Turbines

The wind-generated electricity data presented in this analysis is derived from the same dataset as the electricity consumption data [10].

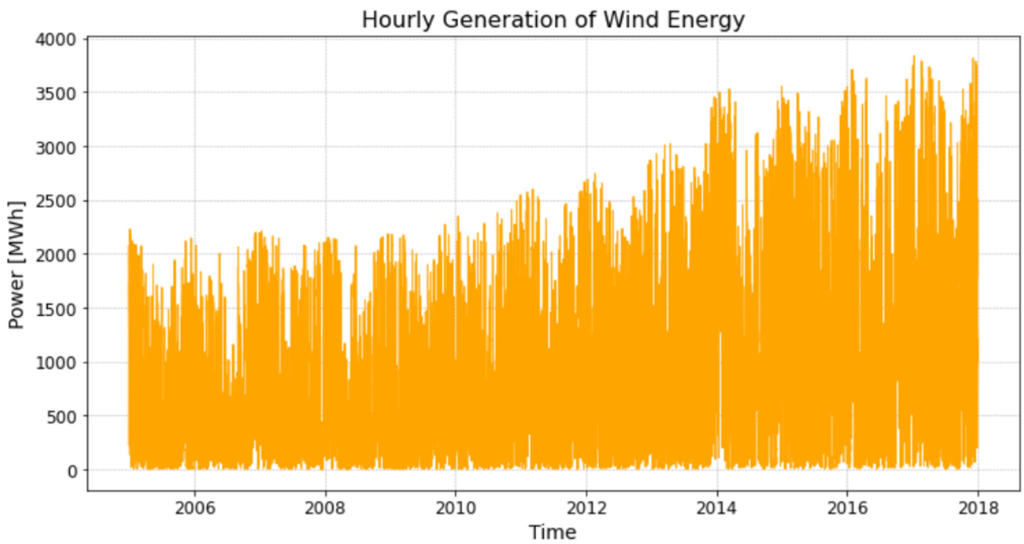

Figure 2.5: Hourly Generation of Wind Energy from 2005 to 2017

Figure 2.5 shows the hourly generation of wind energy over a specific time period. The plot displays the variation in power output in megawatt-hours (MWh) as a function of time. The x-axis represents time, while the y-axis represents the power output. As can see from the figure there is an increase in power over time and the reason is the increasing number of installed wind turbines over the years. Also, new turbines that are installed have higher capacity than the old ones. This relation can see in figure 2.6.

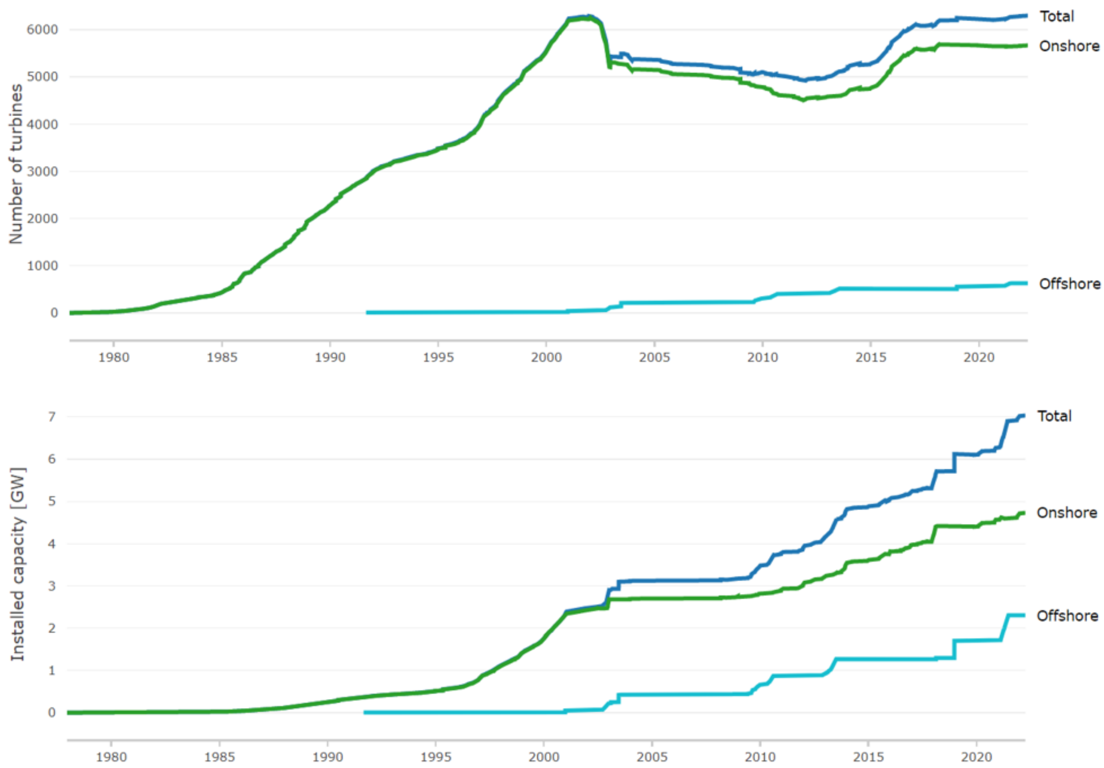

Figure 2.6: Number of turbines and installed capacity over time [12].

2.1.5 Load

The load is determined by subtracting the electric power generated by wind turbines from the total electricity supply. This calculation is performed for each hour and the results are plotted. Figure 2.7 illustrates this relationship, with the blue line representing consumption and the orange line representing generated power.

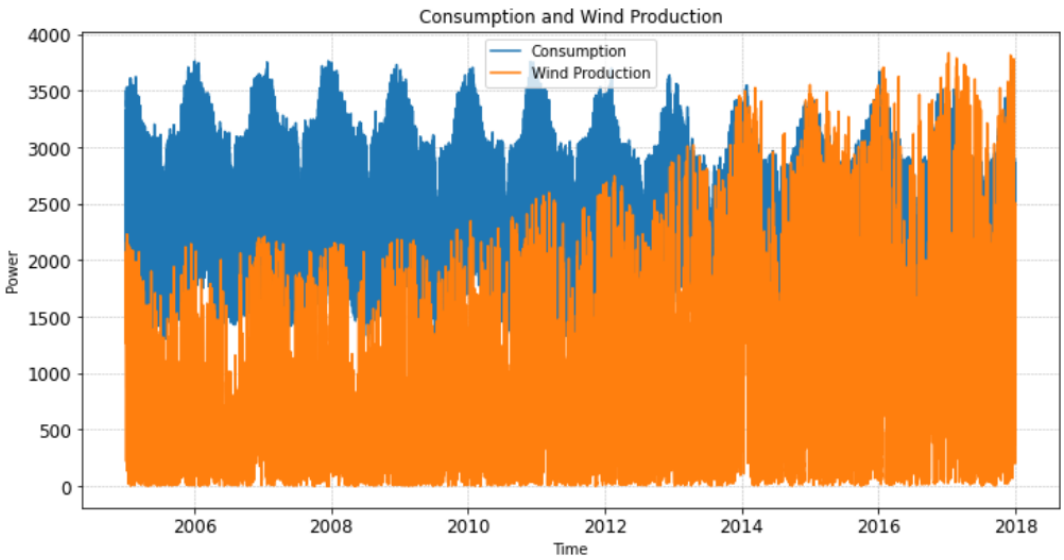

Figure 2.7: Hourly Generation of Wind Energy and Consumption from 2005 to 2017

Notably, starting from 2014, there are instances where the generated power exceeds consumption during certain hours. Furthermore, figure 2.8 demonstrates that values below zero indicate instances where the generated power surpasses consumption. This outcome aligns with expectations due to the observed increase in the number of wind turbines and installed capacity depicted in figure 2.6 after 2014. Therefore, it can be anticipated that the impact of wind energy on prices would be more significant after 2014.

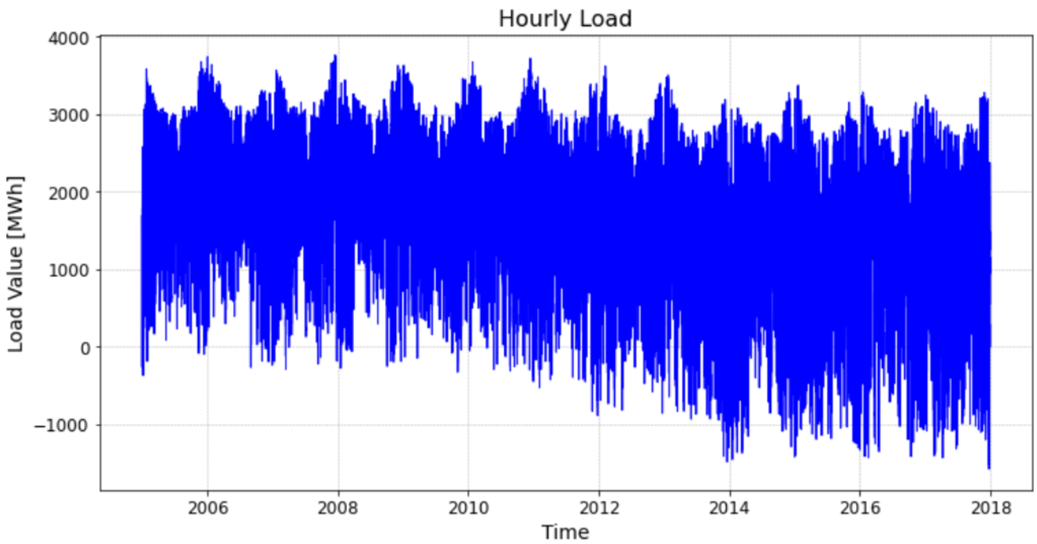

Figure 2.8: Hourly Load from 2005 to 2017

The duration curve for the load offers valuable insights into the distribution and characteristics of the dataset. Figure 2.9 highlights the maximum and minimum values with arrows and corresponding labels. Additionally, three dots are positioned on the curve to indicate the values for 1000, 2000, and 3000 MWh. The percentages of time where the load is higher than these values are as follows: 2.6 percent, 29.9 percent, and 74.9 percent, respectively.

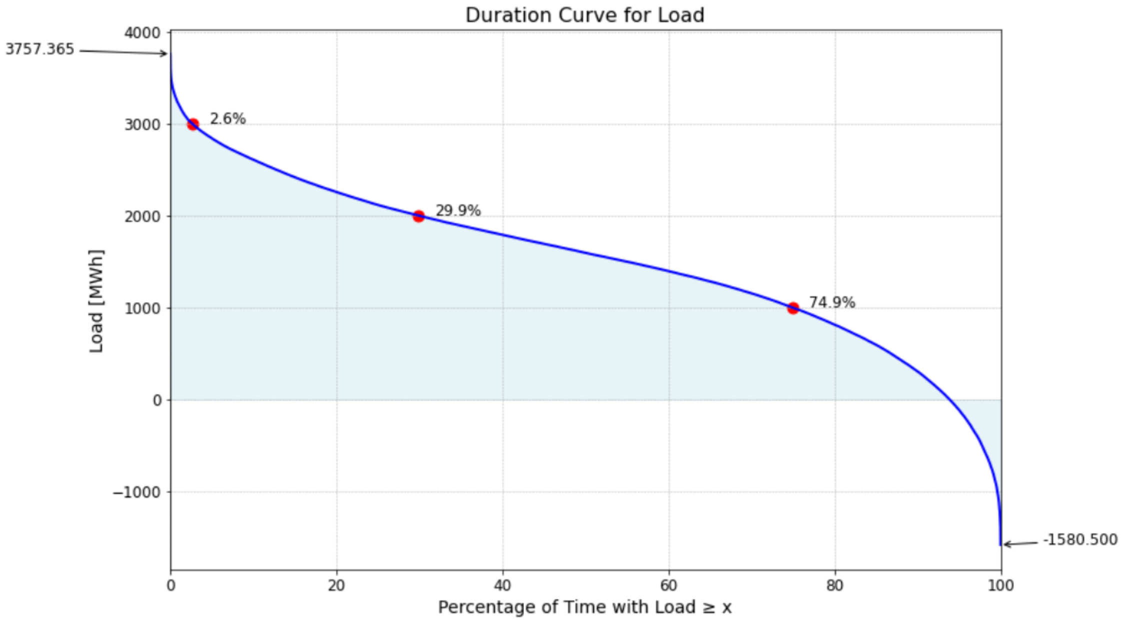

Figure 2.9: Duration Curve for Load

2.2 Simple Regression

Simple linear regression is employed in this analysis to examine the association between the capacity factor (CF) and the corresponding price values. Python is utilized as the programming language for implementing this method, making use of the LinearRegression function from the sklearn library's linear model module. The regression results, including the slope and other relevant statistics, are then presented and discussed in the subsequent section of the report.

2.3 Robust Regression

Robust regression, specifically the RANSAC (Random Sample Consensus) algorithm from sklearn linear model library, is employed in this analysis to examine the relationship between the capacity factor (CF) and the corresponding price values. The CF array is reshaped if necessary to ensure compatibility with the RANSACRegressor model. The RANSACRegressor model is then instantiated, and the CF data is fitted to the model. From the RANSAC regressor, the inliers and outliers are obtained using the inlier mask and outlier mask, respectively. The CF and Price data points are plotted and then presented and discussed in the subsequent section of the report. Additionally, the RANSAC regression line is plotted, representing the robust fit to the data. The resulting plot provides visual insight into the relationship between CF and Price, highlighting the inliers and outliers identified by the RANSAC algorithm.

2.4 Multiple Linear Regression

To analyze the relationship between the predictor variables CF and load and the target variable Price, a multiple linear regression model was constructed. The dataset was divided into training and testing sets, with 80% of the data assigned to the training set and the remaining 20% to the testing set. The training set, comprising the predictor variables train data (CF and load) and the target variable train target (Price), was used to train the linear regression model. The model was fitted using the LinearRegression class from the sklearn linear model library. Once trained, the model was applied to the testing set (test data) to generate predictions for the target variable. These predictions (stored in the 'predictions' variable) were then utilized to evaluate the model's performance and compare it against the actual Price values.

3 Results and Discussion

This chapter of the report presents and discusses the results. It consists of two sections: an analysis of price change based on the capacity factor (CF) and load. These two factors provide distinct perspectives on the electricity generated by wind turbines.

3.1 Analysis Using Capacity Factor (CF)

This section focuses on analyzing prices using two different regression techniques: simple linear regression and robust linear regression, both applied solely to the capacity factor (CF).

3.1.1 Simple Linear Regression for CF and Electricity Price

The relationship between the capacity factor (CF) and price was analyzed using the simple linear regression method. The results are visualized in Figure 3.1, which presents a scatter plot. In the left subplot of Figure 3.1, the data and regression line are depicted. However, due to the distribution of the data, it is difficult to observe the behavior of the regression line, as it appears almost parallel to the x-axis. To facilitate a more effective examination of the results, the regression line is presented alone in the right subplot.

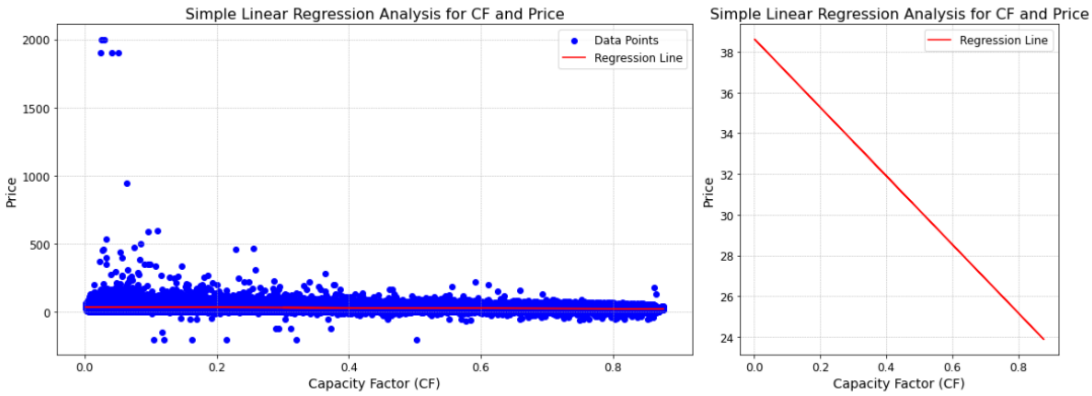

Figure 3.1: Simple Linear Regression Between CF and Electricity Prices

The regression line figure (right) clearly indicates a significant decline in the line, suggesting that as the capacity factor (CF) increases, electricity prices decrease. Notably, when the CF is below 0.2, the price exceeds 35 EUR, whereas when the CF hovers around 0.8, the price drops below 26 EUR. This finding holds significance in addressing the research question concerning the relationship between Denmark's wind energy and electricity prices.

3.1.2 | Robust Regression for CF and Electricity Price

The robust regression method was utilized to analyze the relationship between the capacity factor (CF) and price. The results are depicted in Figure 3.2, presenting a scatter plot. However, due to the presence of outliers, the behavior of the inliers data becomes difficult to discern as the regression line appears nearly parallel to the x-axis.

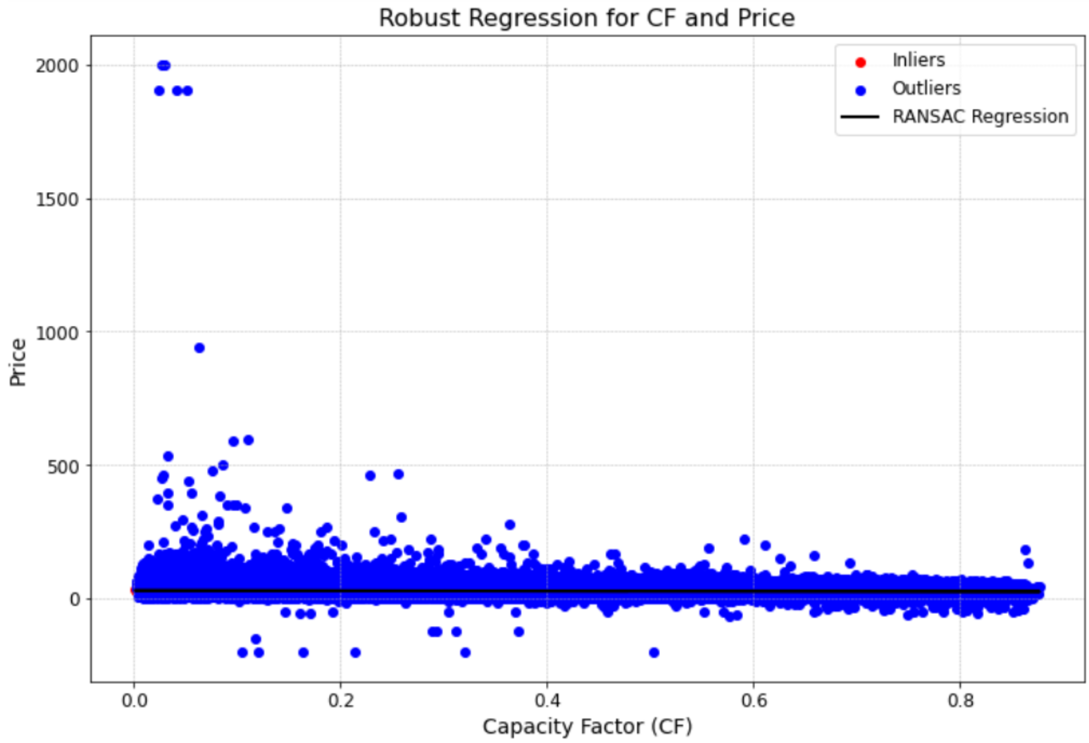

Figure 3.2: Robust Regression Between CF and Electricity Prices

In order to address this issue, Figure 3.3 is created. In the left subplot, the inliers and regression line are plotted, allowing for a clearer observation of the data's behavior. Meanwhile, the right subplot exclusively displays the regression line, providing precise values for CF and their corresponding price to facilitate a comprehensive discussion of the results.

The regression line 3.3 (right) figure clearly illustrates that when the capacity factor (CF) falls below 0.2, the electricity price exceeds 27 EUR, whereas when the CF exceeds 0.8, the price drops below 25 EUR. This finding provides evidence that as wind power increases, electricity prices decrease. Furthermore, when employing the robust regression method, the price range for the regression line is between 29 to 24 EUR. In contrast, for simple linear regression, this range extends from 39 to 23 EUR. This outcome aligns with expectations since robust regression reduces the impact of outliers, resulting in a narrower price range and more reliable estimates.

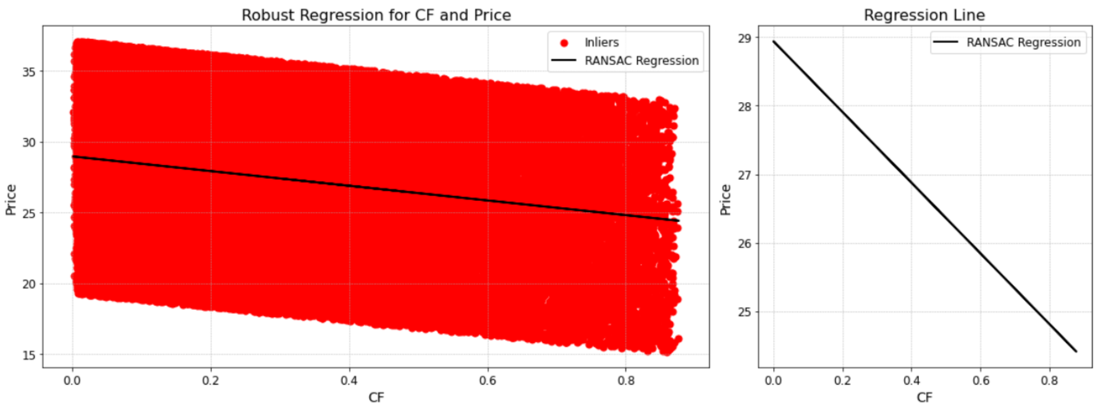

Figure 3.3: Robust Regression Line Between CF and Electricity Prices, with inliers and regression line(left) and just with regression line(right)

3.2 | Analysis Using Load

In this section, the emphasis is placed on analyzing prices by employing two distinct regression techniques: simple linear regression and robust linear regression. Both methods are exclusively applied to the load variable to find the relation between prices.

3.2.1 | Simple Linear Regression for Load and Electricity Price

The simple linear regression method was employed to analyze the relationship between the load and price variables. The results are presented graphically in Figure 3.4 as a scatter plot. In the left subplot of Figure 3.4, both the data points and the regression line are depicted. However, due to the distribution of the data, the behavior of the regression line is indistinct, as it appears almost parallel to the x-axis. To enhance the clarity of the results, the right subplot exclusively displays the regression line, enabling a more focused examination.

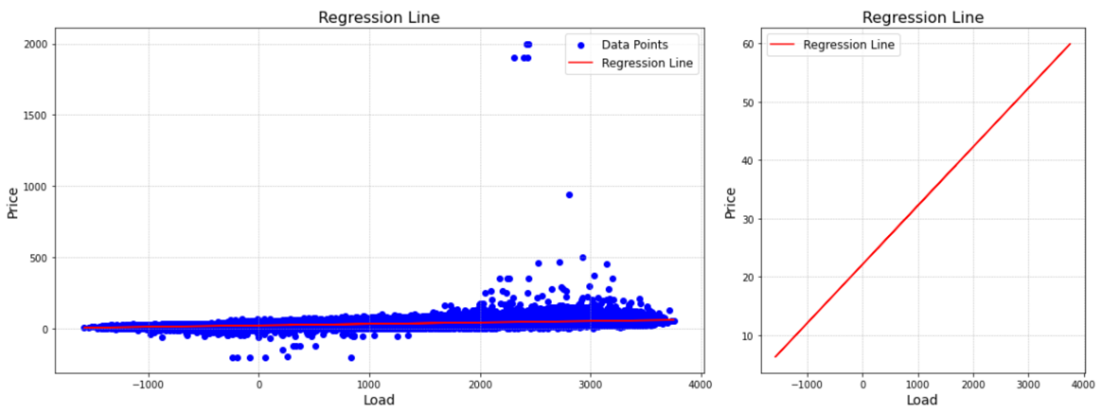

Figure 3.4: Simple Linear Regression Between Load and Electricity Prices

The regression line figure 3.4 (right) clearly demonstrates a substantial rise in the line, indicating that as the load increases, electricity prices also tend to rise. Remarkably, when the load is below -1000 MWh, the price remains below 15 EUR, while for loads exceeding 3000 MWh, the price exceeds 50 EUR. This finding reveals that when the consumption significantly surpasses the power generated by wind turbines, prices escalate. Conversely, as the disparity between consumption and wind power diminishes, prices decline. Moreover, when the power generated by wind exceeds consumption, resulting in a negative load value, price drops below 25 EURO, as indicated by the regression line. This discovery holds substantial significance in addressing the research question concerning the correlation between Denmark's wind energy and electricity prices.

3.2.2 Robust Regression for Load and Electricity Price

The relationship between the load and price was examined using the robust regression method. Figure 3.5 presents a scatter plot, visualizing the results. However, the presence of outliers poses challenges in interpreting the behavior of the inliers data, as the regression line appears nearly parallel to the x-axis.

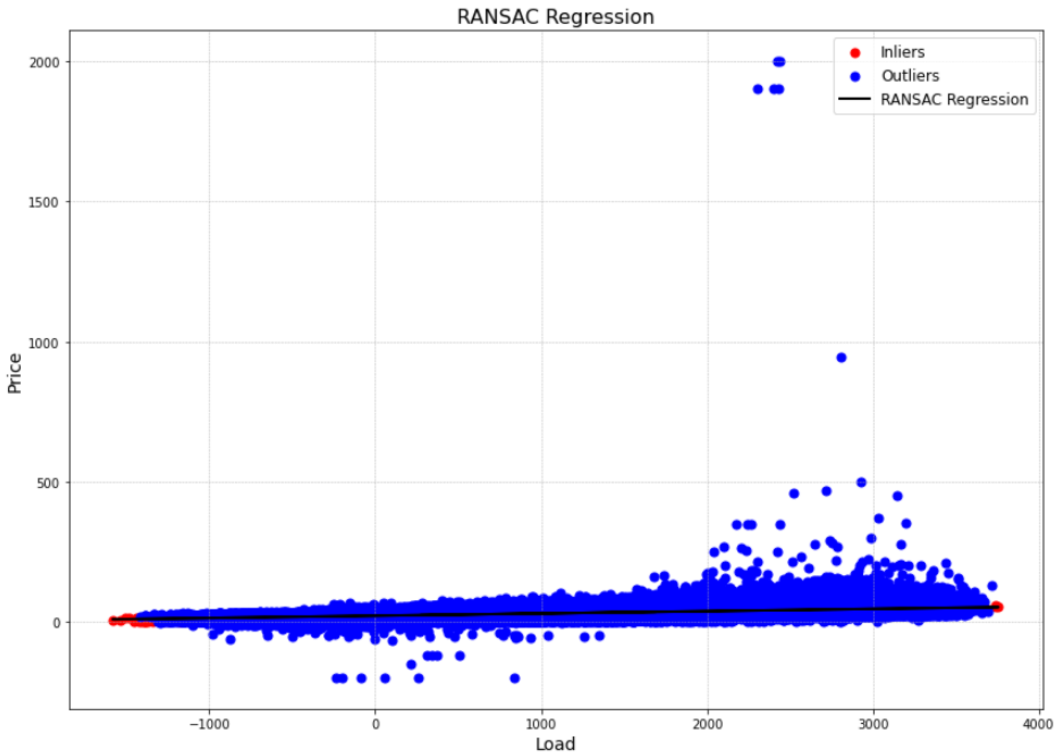

Figure 3.5: Robust Regression Between Load and Electricity Prices

To mitigate this concern, Figure 3.6 was generated, providing a solution. The left subplot of this figure exhibits the inliers along with the regression line, enabling a more distinct assessment of the data's behavior. Conversely, the right subplot exclusively presents the regression line, offering precise values for the load and its corresponding price. This segregation aids in facilitating a comprehensive analysis and discussion of the results.

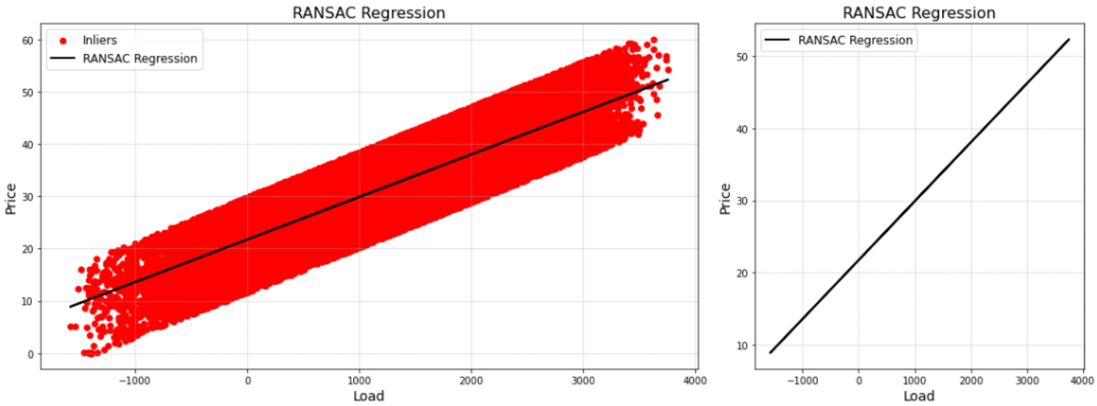

Figure 3.6: Robust Regression Line Between Load and Electricity Prices, with inliers and regression line(left) and just with regression line(right)

The regression line depicted in Figure 3.6 (right) exhibits a noticeable upward trend, indicating a positive relationship between the load and electricity prices. Notably, for load values below -1000 MWh, the corresponding prices remain below 15 EUR, while for loads exceeding 3000 MWh, prices surpass 45 EUR. These results suggest that when the demand for electricity significantly exceeds the power generated by wind turbines, prices tend to rise. Conversely, as the disparity between consumption and wind power diminishes, prices decline. Furthermore, when the power generated by wind exceeds consumption, resulting in a negative load value, the price drops below 25 EUR, as indicated by the regression line. This discovery holds considerable significance in addressing the research inquiry regarding the relationship between Denmark's wind energy and electricity prices.

3.3 Analysis Using Multiple Linear Regression

The multiple linear regression method is employed to examine the relationship between wind energy and electricity prices. Specifically, it investigates how two predictor variables, the capacity factor (CF) and the load, are associated with the variable of interest, which is the forecasted price of electricity. By utilizing multiple linear regression, can evaluate the influence of the CF and load on electricity prices and gain insights into their predictive capability in determining price fluctuations.

Figure 3.7 illustrates the comparison between the actual price values and the predicted price values over time using the Multiple Linear Regression model, providing insights into the model's performance and accuracy in price prediction.

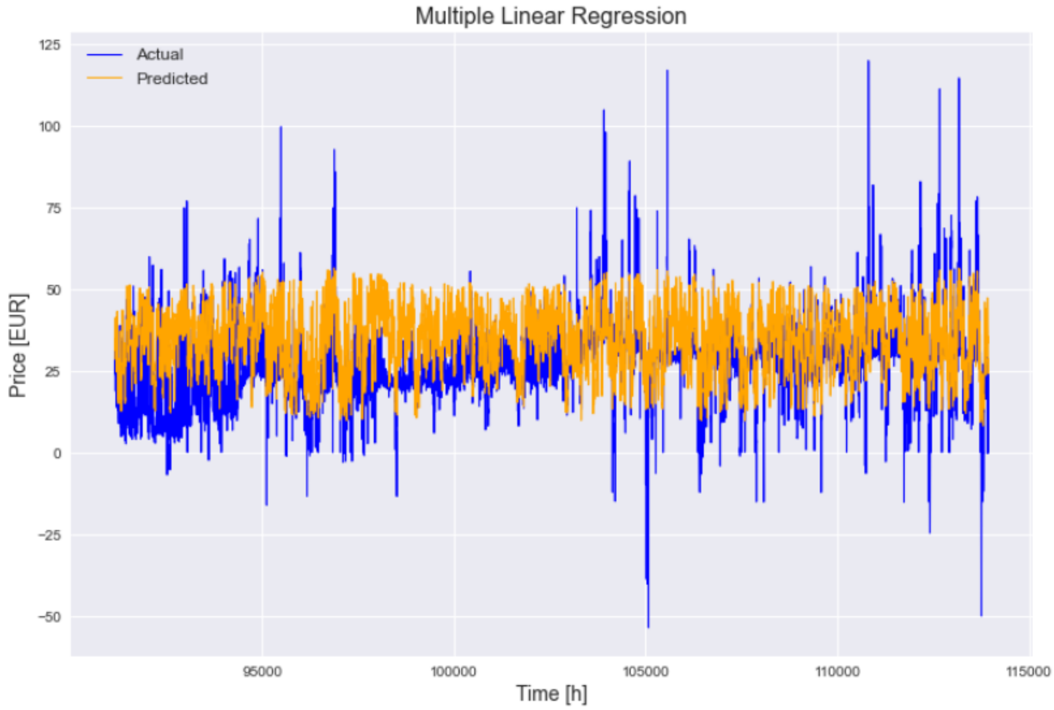

Figure 3.7: Comparison of Actual and Predicted Price Values over Time using Multiple Linear Regression

According to results, it is observed that, apart from extreme values such as peak prices, the forecast of electricity prices can be predicted using CF and load data. In other words, the capacity factor and load variables demonstrate the potential to provide reliable predictions for electricity prices, with the exception of instances involving extreme price fluctuations, such as peak prices.

Table 3.1: Correlation Matrix

	Price	CF	load
Price	1.000000	-0.192119	0.414462
CF	-0.192119	1.000000	-0.509986
load	0.414462	-0.509986	1.000000

Additionally, correlation values are calculated and tabulated as shown in table 3.1. Positive correlation refers to a situation where two variables tend to change in the same direction. This means that as one variable increases, the other variable also tends to increase, and as one variable decreases, the other variable tends to decrease. According to table 3.1, there is positive correlation between load and price and the same trend can see from figure 3.6 and figure 3.4.

On the other hand, negative correlation refers to a situation where two variables tend to change in opposite directions. This means that as one variable increases, the other variable tends to decrease, and vice versa. According to table 3.1, there is negative correlation between CF and price and the same trend can see from figure 3.3 and figure 3.1.

4 Conclusion

Based on the analyses conducted in this project report, several key findings have emerged regarding the relationship between Denmark's wind energy and electricity prices.

Firstly, the examination of price changes based on the capacity factor (CF) revealed a significant inverse relationship. As the CF, which represents the efficiency of wind turbines, increased, electricity prices tended to decrease. This suggests that higher levels of wind power generation were associated with lower electricity prices.

Furthermore, the analysis of the relationship between load and price using regression techniques provided insights into the dynamics between these variables. The findings revealed a direct relationship between the load, which represents the disparity between electricity consumption and power generated by wind turbines, and the corresponding electricity prices. As the load increased, there was a corresponding increase in electricity prices. This positive correlation suggests that higher load leads to higher prices.

Moreover, the application of robust regression, which accounts for outliers in the data, helped to better understand the relationship between load and price. By minimizing the influence of outliers, the analysis revealed a clearer pattern in the data and improved the accuracy of price estimation.

Lastly, the utilization of multiple linear regression with the capacity factor (CF) and load as predictors enables the prediction of price values. According to results, except for extreme values such as peak prices, the CF and load data exhibit a dependable capability to forecast electricity prices. This indicates a promising potential for accurately anticipating price fluctuations, thus enhancing decision-making and planning within the energy sector. The application of multiple linear regression with CF and load variables as predictors offers valuable insights and practical implications for the effective management of electricity pricing dynamics.

In conclusion, this study reveals a clear relationship between Denmark's wind energy and electricity prices. As wind power generation increases (measured by the CF), electricity prices tend to decrease. Similarly, higher loads lead to higher prices, while the presence of outliers can affect price estimation. These findings contribute to a better understanding of the dynamics between wind energy generation and electricity pricing, providing valuable insights for policymakers, energy stakeholders, and researchers in the field.

5 Appendix

Due to space constraints, additional pertinent information could not be included within the allotted page limits. However, it is important to note that there is further relevant information available that could enhance the understanding and context of the subject matter.

5.1 Capacity Factor

The capacity factor (CF) of a wind turbine represents the ratio of its average power output to its maximum power capability [11]. The CF value ranges between 0 and 1 and is predominantly influenced by wind conditions. When the wind speed reaches the turbine's rated speed (v_r), the turbine generates its maximum power, resulting in a CF of 1. This relationship between power output and wind speed is illustrated in Figure 5.1.

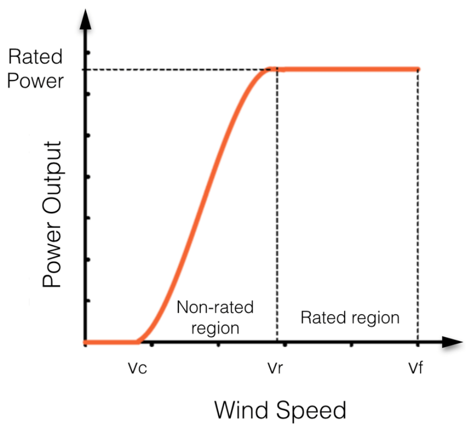

Figure 5.1: Wind turbine power curve [1]

The capacity factor (CF) of a wind turbine is a valuable metric for estimating wind power generation. By multiplying the CF with the maximum power capacity of the turbine, the actual power output generated by the turbine can be calculated. This makes the CF a useful indicator for understanding and predicting the amount of power that can be harnessed from the wind turbine.

5.2 Load

In this project, the load is the difference between the electricity consumption of DK1 and electricity generation by wind turbines in DK1. Where Dk1 means Electricity Grid Price Area for West Denmark (Jutland and Funen).

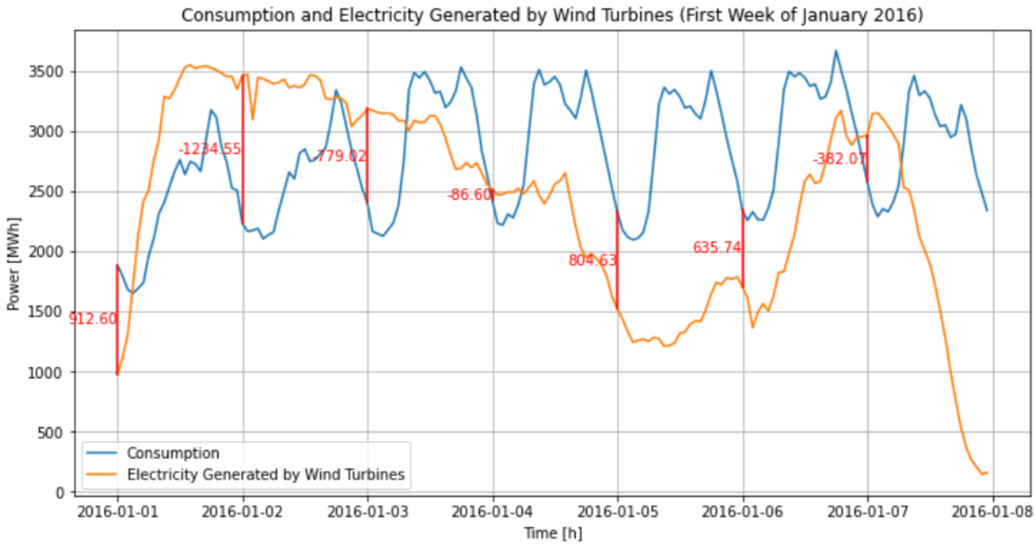

Figure 5.2: Comparison of consumption and electricity generated by wind turbines (First Week of January 2016) and representation of load

Figure 5.2 presents a comparison of electricity consumption and electricity generated by wind turbines for the first week of January 2016. The blue line represents the electricity consumption, indicating the amount of power consumed during each hour, while the orange line depicts the wind energy, illustrating the power generated by wind turbines over the same time period. To describe load, red lines are included. These red lines extend vertically from the consumption value to the wind production value for the first hour of each day. The length of these lines represents the discrepancy between the two variables, with longer lines indicating a larger difference between consumption and wind production. Additionally, the numeric values of these differences are displayed alongside the red lines. Positive values indicate that electricity consumption exceeds the electricity generated by wind turbines, resulting in a shortfall of renewable energy supply. Negative values, on the other hand, indicate that wind-generated electricity exceeds consumption, leading to a surplus of renewable energy

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