IE 360 STATISTICAL FORECASTING AND TIME SERIES

FINAL REPORT

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Introduction

Solar power forecasting plays a pivotal role in optimizing energy production and managing supply in modern energy markets. The Edikli GES, located in Niğde, Turkey (38.29° North, 34.97° East), exemplifies the increasing reliance on solar energy resources. As one of the prominent solar energy facilities in the region, Edikli GES aims to enhance its operational efficiency by predicting hourly solar power output for the subsequent day.

Accurate forecasting is crucial for energy traders who need reliable predictions to make informed decisions. The project simulates real-world conditions where predictions for day **d+1** are made available by 12 PM on day **d**, utilizing data up to day **d-1**. The dataset provided includes historical production values and weather variables from 25 nearby grid points, encompassing various parameters such as solar radiation flux, cloud cover, temperature, and snow cover.

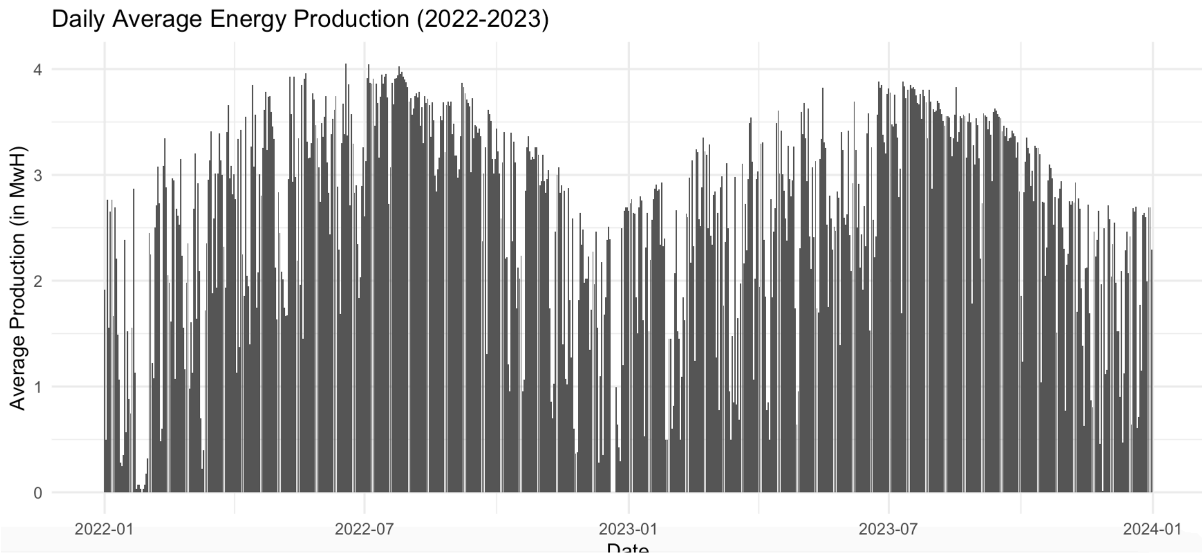


Figure 1 : Hourly Energy Productions

The figure above shows the daily average energy production of the facility for the years 2022 and 2024. One can observe variations in daily production levels, reflecting seasonal changes and operational dynamics. The data indicate periods of increased production, likely corresponding to summer months when daylight hours are longer. In contrast, lower production levels during the winter months can be attributed to shorter daylight hours and potentially adverse weather conditions.

Additionally, the data show that production does not remain constant throughout the day, as the number of daylight hours varies throughout the year in Turkey. For instance, during winter, the sun does not rise until after 4 AM, whereas, in summer, it rises earlier. Similarly, at 7 PM, the sun has already set in winter, while it remains visible in summer. These variations necessitate manual adjustments in the prediction models to account for the changing daylight hours and their impact on solar energy production.

Understanding the relationship between these weather variables and solar power production is essential for developing robust predictive models. By leveraging statistical and machine learning techniques, this project aims to deliver precise hourly forecasts, thereby contributing to the efficient management and integration of solar energy into the power grid. This approach not only supports the operational needs of Edikli GES but also aligns with broader efforts to enhance the sustainability and reliability of energy systems.

3. Modelling Approach

An analysis of the average production rates, as depicted in Table 1, reveals significant insights into the dataset. The table illustrates hourly production rates with two significant digits, highlighting three distinct groups of time periods.

1. **Non-Productive Hours:**
    - Hours from midnight to 4 AM and from 7 PM to midnight exhibit an average production rate of 0. This indicates that no production occurs during these hours, simplifying the forecasting task by allowing the direct assignment of a production value of zero.
2. **Regular Productive Hours:**
    - Hours from 6 AM to 5 PM show varying production rates, typically between 0.03 and 28.23. These hours are the primary productive period and require a sophisticated forecasting model to capture the variability in production accurately.
3. **Critical Hours Affected by Seasons:**
    - Hours with production rates that fall between productive and non-productive times, such as around sunrise and sunset, show average production rates below 0.06. These hours are significantly influenced by seasonal changes and necessitate a nuanced modeling approach to account for this variability.

	hour	avg_production
1	0	0.00
2	1	0.00
3	2	0.00
4	3	0.00
5	4	0.00
6	5	0.06
7	6	0.60
8	7	2.85
9	8	5.54
10	9	7.47
11	10	8.06
12	11	8.17
13	12	8.07
14	13	7.62
15	14	6.53
16	15	4.72
17	16	2.50
18	17	0.93
19	18	0.08
20	19	0.00
21	20	0.00
22	21	0.00
23	22	0.00
24	23	0.00

Table 1: Average production rates (hourly, at two significance)

The delineation of these time periods suggests a divide-and-conquer approach to problem-solving. By breaking down the forecasting task into sub-problems based on production characteristics, the project can apply targeted models that leverage historical patterns and weather variables to deliver precise hourly solar power forecasts. This approach not only meets the operational needs of Edikli GES but also aligns with broader efforts to enhance the sustainability and reliability of energy systems.

The production rates[**Figure 2**] are plotted for these critical hours, revealing notable patterns and trends. For the hours of 5 AM and 7 PM, the production is generally negligible except for brief periods around the summer months, aligning with longer daylight hours during this season. This pattern indicates that these hours experience minimal production for most of the year, with occasional spikes during the summer. The 6 AM hour shows a more pronounced production during the middle months of the year, peaking around the summer solstice. Production rates for 6 AM gradually increase from winter to summer and then decrease back towards winter, mirroring the pattern of daylight duration. Similarly, the 6 PM hour displays significant production during the summer months, with highly variable rates reflecting the changing sunset times. The variability observed in these critical hours suggests a strong sensitivity to seasonal changes, indicating the need for forecasting models to account for these trends and other influencing factors such as weather conditions. This detailed analysis highlights the importance of a targeted approach to accurately predict solar power output during these critical hours, enhancing the overall reliability and accuracy of the forecasting model.

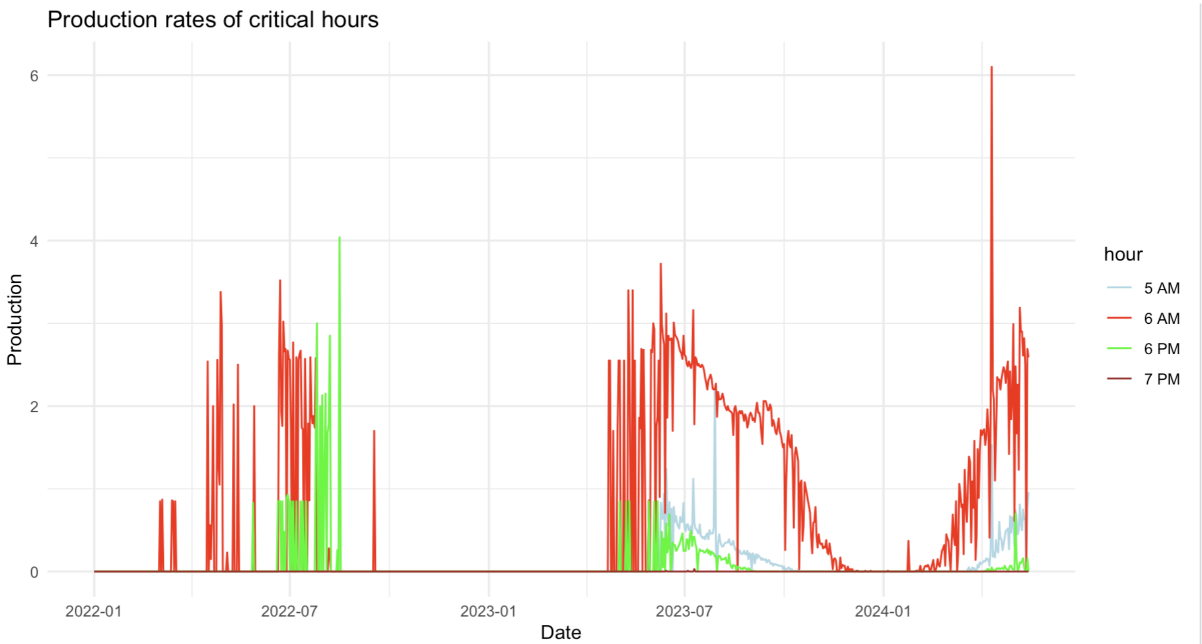


Figure 2. Production rates of critical hours

By some trial and error and heuristic approach, 6 PM is omitted from this list, since in the first days of the prediction period the regular hours model yielded more reasonable results for this hour. From this point on, 5 AM, 6 AM, and 7 PM will be addressed as “critical hours”, and their models will employ different approaches compared to regular hours.

In addition to the sharp transitions between 0-hours and critical hours, and also between critical hours and regular hours in terms of production rates, significant increases and decays occur during intra-critical hour transitions. Thus, the problem can be further split by creating one model for each critical hour.

The common approach for all three critical hours is determining their active periods. What is meant by saying active periods is the part of the year in which production has been seen at these hours and is consequently expected to be seen. To detect these periods, the months or weeks when the investigated critical hour has at least one non-zero production value are filtered.

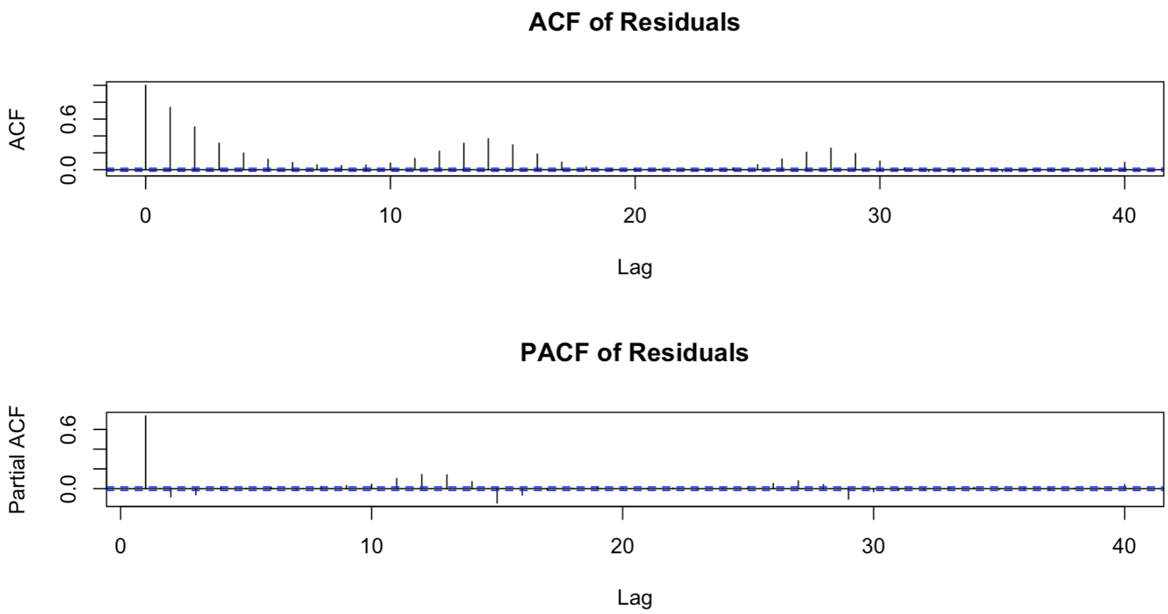


Figure 3.

The overall ACF and PACF plots for the residuals across all hours reveal that most autocorrelations and partial autocorrelations fall within the significance threshold, indicating that the residuals are largely uncorrelated and the model fits well for the majority of the data. When compared to the critical hours, it is evident that the residuals at 5 AM and 6 AM display significant autocorrelation at initial lags, suggesting the need for further model adjustments by incorporating additional lagged values. In contrast, the residuals for 7 PM showed no significant autocorrelation, indicating that the model sufficiently captures the data structure for this hour. The comprehensive ACF and PACF plots reinforce these findings, showing minor autocorrelations at initial lags across all hours, but nothing substantial enough to undermine the model's overall performance. These insights guided the construction of our model, ensuring it effectively captures the production data's underlying patterns while highlighting areas, particularly in the early morning hours, where additional refinement can enhance accuracy.

ACF (Autocorrelation Function) Plot

The ACF plot for the residuals at 5 AM shows the autocorrelation of the residuals at various lags:

- The ACF plot shows significant spikes at several lags, indicating autocorrelation in the residuals.
- The fact that several lags are above the significance threshold suggests that the residuals are not entirely random and there may still be some patterns or structure left unexplained by the model.

PACF (Partial Autocorrelation Function) Plot

The PACF plot for the residuals at 5 AM shows the partial autocorrelation of the residuals at various lags:

- Significant spikes at initial lags (e.g., lag 1, lag 2) indicate that including these lagged values as predictors might help in further reducing the autocorrelation in the residuals.
- The fact that the partial autocorrelation decreases and becomes non-significant beyond a few lags indicates that the dependencies are mostly explained by the initial lag values.

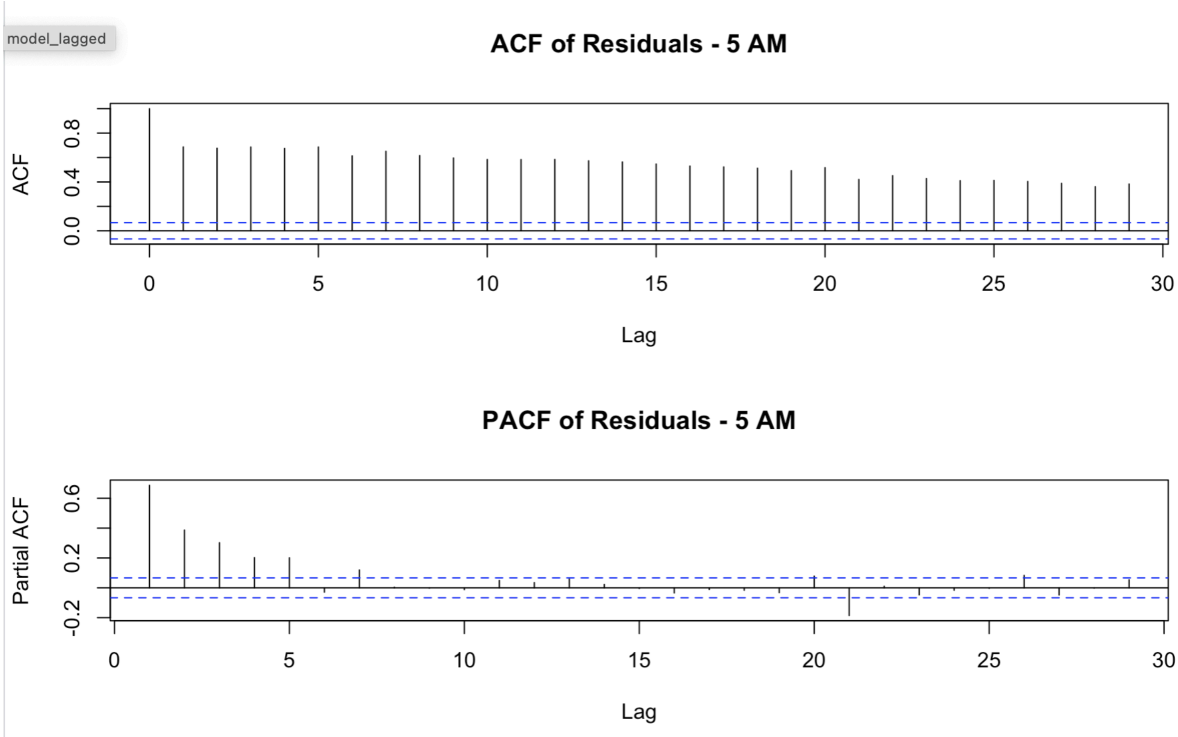


Figure 4

ACF (Autocorrelation Function) Plot:

The ACF plot for the residuals at 6 AM shows the autocorrelation of the residuals at various lags:

- The ACF plot shows significant spikes at several lags, indicating autocorrelation in the residuals.
- Similar to the 5 AM residuals, the fact that several lags are above the significance threshold suggests that the residuals are not entirely random and there may still be some patterns or structure left unexplained by the model.

PACF (Partial Autocorrelation Function) Plot:

The PACF plot for the residuals at 6 AM shows the partial autocorrelation of the residuals at various lags:

- Significant spikes at initial lags (e.g., lag 1, lag 2) indicate that including these lagged values as predictors might help in further reducing the autocorrelation in the residuals.

- The fact that the partial autocorrelation decreases and becomes non-significant beyond a few lags indicates that the dependencies are mostly explained by the initial lag values.

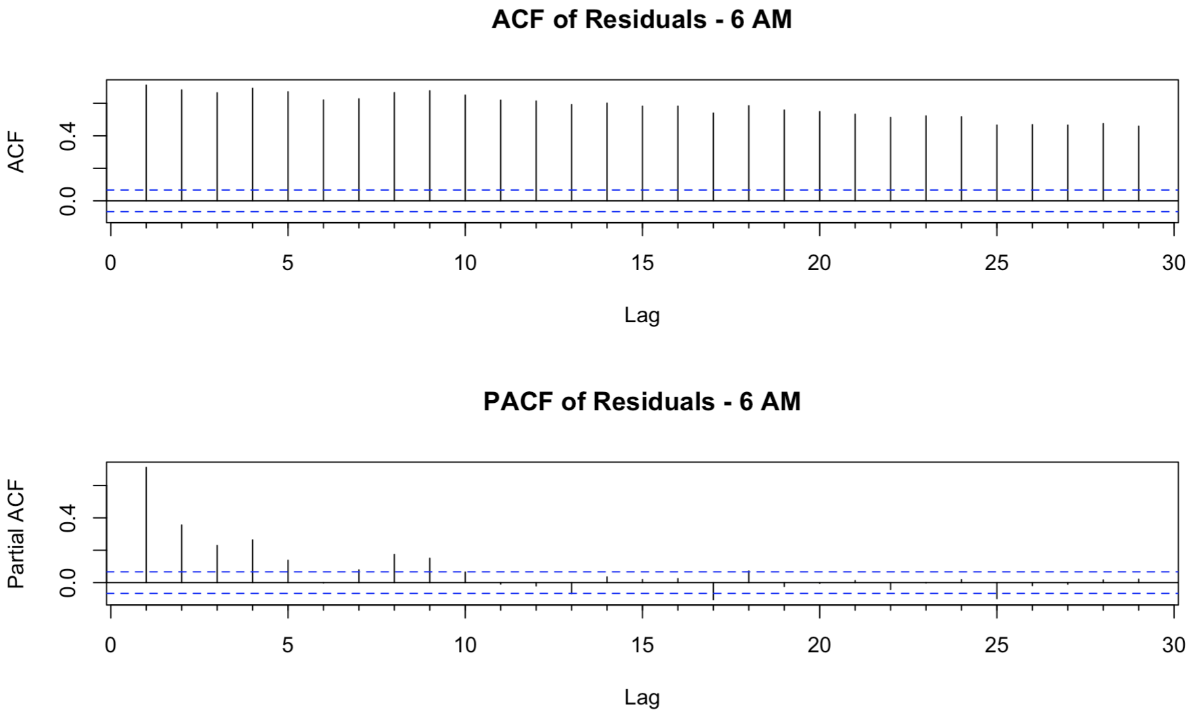


Figure 5

ACF (Autocorrelation Function) Plot

The ACF plot for the residuals at 7 PM shows the autocorrelation of the residuals at various lags:

- The ACF plot shows that most of the lags fall within the significance threshold, indicating that the autocorrelation in the residuals is mostly insignificant.
- A few spikes are present, but they are not substantial enough to indicate strong autocorrelation patterns.

PACF (Partial Autocorrelation Function) Plot

The PACF plot for the residuals at 7 PM shows the partial autocorrelation of the residuals at various lags:

- Similar to the ACF plot, the PACF plot shows that most lags fall within the significance threshold.
- A few initial lags show slight spikes, suggesting some minor partial autocorrelation, but they are not substantial enough to indicate strong patterns.

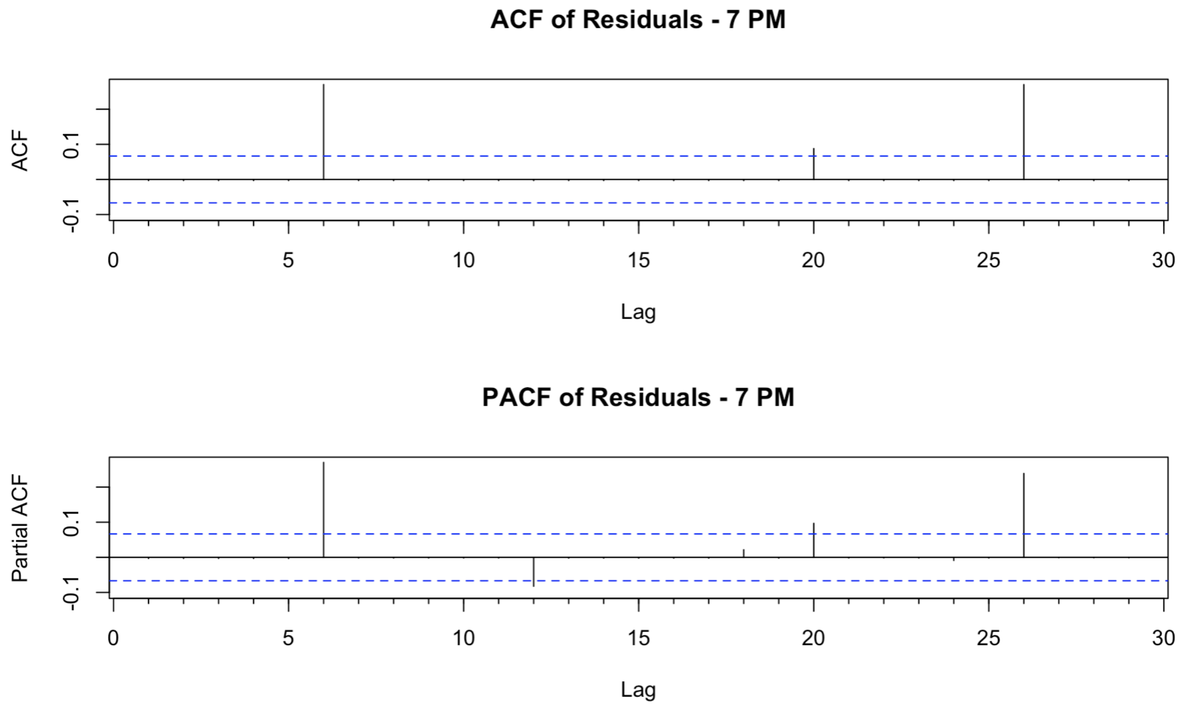


Figure 6

c. Predictions

Given the introduction section, the predictions for the Edikli GES solar power output take into account various critical factors and adjustments to ensure accuracy and reliability.

Hourly Prediction Thresholds: Similar to previous regulations, any predicted solar power output that exceeds a practical threshold due to factors like peak solar radiation or unexpected weather conditions will be capped at a maximum value. For instance, predictions that exceed a certain upper limit will be rounded to this maximum threshold to maintain operational stability. This threshold may vary seasonally, reflecting longer daylight hours in summer and shorter hours in winter.

Zero Production Adjustments: Predictions that result in near-zero outputs, potentially due to nighttime hours or extreme weather conditions such as heavy cloud cover or snow, will be rounded to zero. This adjustment ensures that non-productive periods are accurately represented, preventing false positives in the energy forecasts.

Handling Poor Model Performance: During certain hours where the model's performance historically shows higher residuals, these periods will be identified, and past residuals will be incorporated into the current predictions. This method of residual correction helps in minimizing forecast errors and enhances the overall prediction accuracy.

Incorporating Weather Variability: The model accounts for weather variability by incorporating data from 25 nearby grid points, including parameters such as solar radiation flux, cloud cover, temperature, and snow cover. These variables are crucial in understanding the daily and seasonal patterns of solar power production.

Daylight Hours Adjustments: Since daylight hours significantly influence solar power output, manual adjustments will be applied to the model to reflect the changes in sunrise and sunset times throughout the year. For example, during winter months, predictions will be adjusted to account for later sunrises and earlier sunsets, whereas in summer, the model will be adjusted for earlier sunrises and later sunsets.

Seasonal Production Patterns: Historical data indicating seasonal variations in production will be leveraged to refine predictions. The model will incorporate patterns of increased production during summer months and decreased production during winter months, reflecting the natural variations in daylight hours and weather conditions.

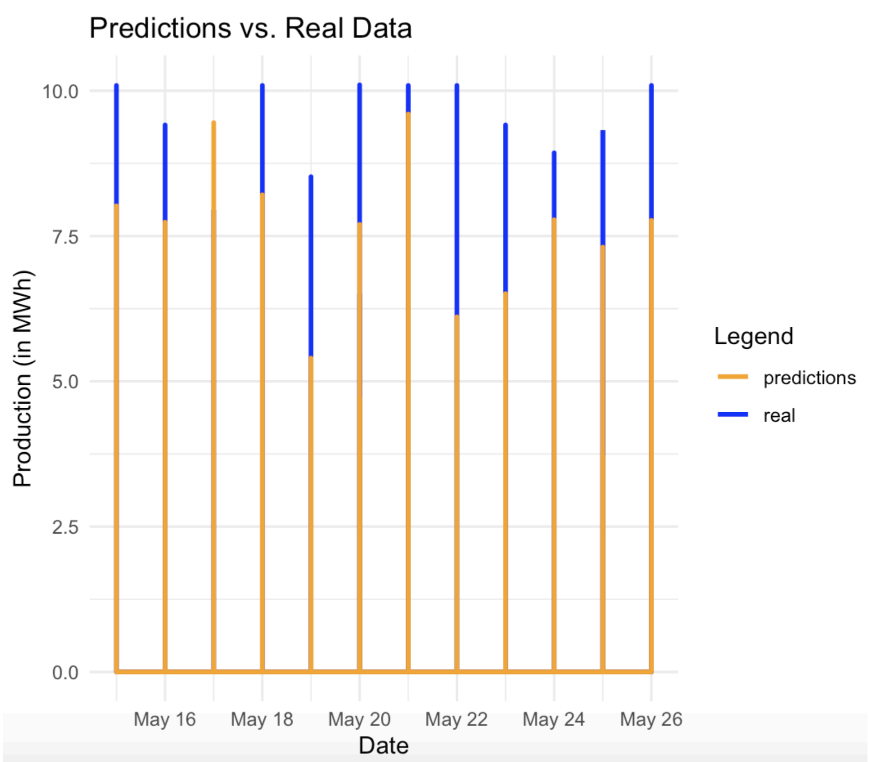
Prediction Schedule: The model will provide predictions for day d+1 by 12 PM on day d, using data up to day d-1. This timely prediction process ensures that energy traders and operational managers at Edikli GES can make informed decisions based on the most recent and relevant data.

By applying these methodologies, the project aims to deliver accurate and reliable hourly solar power forecasts for Edikli GES, supporting efficient energy production and supply management in the modern energy market. This approach not only aids in optimizing the operations of Edikli GES but also contributes to the broader goal of enhancing the sustainability and reliability of solar energy integration into the power grid.

d. Results

Following the mentioned approaches the predictions and the real observations occurred as the following. Submitted predictions and real production data can be investigated at *Appendix 1.*

Predictions vs Real Data



5. Code

Links for the codes has been added to the journal page.

6.Appendices

i. Code for Figure 1

```
# Filter data to include only the years 2022 and 2023
data_filtered <- data %>%
  filter(format(date, "%Y") %in% c("2022", "2023"))

# Calculate the daily average production
daily_avg <- data_filtered %>%
  group_by(date) %>%
  summarise(avg_production = mean(production, na.rm = TRUE))

# Create the plot as a bar graph
ggplot(daily_avg, aes(x = date, y = avg_production)) +
  geom_col() +
  labs(title = "Daily Average Energy Production (2022-2023)",
       x = "Date",
       y = "Average Production (in MwH)") +
  theme_minimal()
```

ii. Code for Table 1

```
# Calculation the hourly average production
hourly_avg <- data_filtered %>%
  group_by(hour) %>%
  summarise(avg_production = mean(production, na.rm = TRUE)) %>%
  mutate(avg_production = round(avg_production, 2)) # Round to two decimal places
```

iii. Code for Figure 2

```
# Select critical hours (5 AM, 6 AM, 6 PM, 7 PM)
critical_hours <- c(5, 6, 18, 19)

# Filter data to include only the critical hours
data_critical_hours <- data %>%
  filter(hour %in% critical_hours) %>%
  mutate(hour = factor(hour, levels = c(5, 6, 18, 19), labels = c("5 AM", "6 AM", "6 PM", "7 PM")))

# Create the plot
p <- ggplot(data_critical_hours, aes(x = date, y = production, color = hour)) +
  geom_line() +
  labs(title = "Production rates of critical hours",
       x = "Date",
       y = "Production") +
  theme_minimal() +
  scale_color_manual(values = c("5 AM" = "lightblue", "6 AM" = "red", "6 PM" = "green", "7 PM" = "brown"))
```

ix Code For Figure 3,4,5,6,7

```
# Generation ACF and PACF plots for each critical hour
for (critical_hour in levels(data_critical_hours$hour)) {
  # Filter data for the specific critical hour
  data_specific_hour <- data_critical_hours %>%
    filter(hour == critical_hour)

  #  to fit a linear model for the specific critical hour
  model <- lm(production ~ date, data = data_specific_hour)

  # Calculation residuals
  residuals <- residuals(model)

  # Plot ACF
  acf_res <- Acf(residuals, main = paste("ACF of Residuals -", critical_hour))
  # Save ACF plot
  acf_plot_file <- paste0("acf_residuals_", gsub(" ", "_", tolower(critical_hour)), ".png")
  png(acf_plot_file, width = 800, height = 600)
  plot(acf_res, main = paste("ACF of Residuals -", critical_hour))
  dev.off()

  # Plot PACF
  pacf_res <- Pacf(residuals, main = paste("PACF of Residuals -", critical_hour))
  # Save PACF plot
  pacf_plot_file <- paste0("pacf_residuals_", gsub(" ", "_", tolower(critical_hour)), ".png")
  png(pacf_plot_file, width = 800, height = 600)
  plot(pacf_res, main = paste("PACF of Residuals -", critical_hour))
  dev.off()

  # Display plots in R
  plot(acf_res, main = paste("ACF of Residuals -", critical_hour))
  plot(pacf_res, main = paste("PACF of Residuals -", critical_hour))
}
```

```
# Load necessary libraries
```

```r
library(ggplot2)

library(readxl)

# Load the data

file_path <- "Users/ufukozkan/Desktop/360_final/comparison_real_predicted.xlsx"

comparison_data <- read_excel(file_path)

# Convert date column to Date type

comparison_data$date <- as.Date(comparison_data$date)

# Create the plot

p <- ggplot(comparison_data, aes(x = date)) +

  geom_line(aes(y = production, colour = "real"), size=1) +

  geom_line(aes(y = predicted, colour = "predictions"), size=1) +

  labs(y = "Production (in MWh)", x = "Date", title = "Predictions vs. Real Data") +

  scale_colour_manual(values = c("real" = "blue", "predictions" = "orange"), name = "Legend") +

  theme_minimal()

# Save the plot

ggsave("comparison_plot.png", plot = p, width = 10, height = 6)

# Display the plot

print(p)
```

May 15

date	hour	production	predicted
2022-05-15 00:00:00	0	0	0
2022-05-15 00:00:00	1	0	0
2022-05-15 00:00:00	2	0	0
2022-05-15 00:00:00	3	0	0
2022-05-15 00:00:00	4	0	0,37
2022-05-15 00:00:00	5	0	0,72

2022-05-15 00:00:00	6	0	1,43
2022-05-15 00:00:00	7	3	3,87
2022-05-15 00:00:00	8	2,5	6,05
2022-05-15 00:00:00	9	8,93	8,02
2022-05-15 00:00:00	10	1	5,31
2022-05-15 00:00:00	11	6,27	6,01
2022-05-15 00:00:00	12	5,55	6,02
2022-05-15 00:00:00	13	10,09	5,8
2022-05-15 00:00:00	14	10,09	4,73
2022-05-15 00:00:00	15	2	3,34
2022-05-15 00:00:00	16	0,15	0
2022-05-15 00:00:00	17	3	0
2022-05-15 00:00:00	18	0	0
2022-05-15 00:00:00	19	0	0
2022-05-15 00:00:00	20	0	0
2022-05-15 00:00:00	21	0	0
2022-05-15 00:00:00	22	0	0
2022-05-15 00:00:00	23	0	0

May 16

date	hour	production	predicted
2022-05-16 00:00:00	0	0	0
2022-05-16 00:00:00	1	0	0
2022-05-16 00:00:00	2	0	0
2022-05-16 00:00:00	3	0	0
2022-05-16 00:00:00	4	0	0,08
2022-05-16 00:00:00	5	0	1,64
2022-05-16 00:00:00	6	0	2,6
2022-05-16 00:00:00	7	2,79	5,13
2022-05-16 00:00:00	8	9	6,33

2022-05-16 00:00:00	9	8,95	7,23
2022-05-16 00:00:00	10	7,47	7,72
2022-05-16 00:00:00	11	9,41	7,74
2022-05-16 00:00:00	12	8,99	7,3
2022-05-16 00:00:00	13	7,03	6,49
2022-05-16 00:00:00	14	7,64	5,43
2022-05-16 00:00:00	15	7,54	4,29
2022-05-16 00:00:00	16	7,32	0
2022-05-16 00:00:00	17	4,16	0
2022-05-16 00:00:00	18	0	0
2022-05-16 00:00:00	19	0	0
2022-05-16 00:00:00	20	0	0
2022-05-16 00:00:00	21	0	0
2022-05-16 00:00:00	22	0	0
2022-05-16 00:00:00	23	0	0

May 17

date	hour	production	predicted
2022-05-17 00:00:00	0	0	0
2022-05-17 00:00:00	1	0	0
2022-05-17 00:00:00	2	0	0
2022-05-17 00:00:00	3	0	0
2022-05-17 00:00:00	4	0	0,08
2022-05-17 00:00:00	5	0	0,85
2022-05-17 00:00:00	6	0	2,09
2022-05-17 00:00:00	7	0	3,18
2022-05-17 00:00:00	8	7,94	6,5

2022-05-17 00:00:00	9	6,78	7,92
2022-05-17 00:00:00	10	5,08	8,95
2022-05-17 00:00:00	11	2,75	9,45
2022-05-17 00:00:00	12	4,17	9,36
2022-05-17 00:00:00	13	1,65	8,73
2022-05-17 00:00:00	14	2,52	7,65
2022-05-17 00:00:00	15	7,8	6,32
2022-05-17 00:00:00	16	5,45	4,92
2022-05-17 00:00:00	17	2,94	3,68
2022-05-17 00:00:00	18	0	2,72
2022-05-17 00:00:00	19	0	0
2022-05-17 00:00:00	20	0	0
2022-05-17 00:00:00	21	0	0
2022-05-17 00:00:00	22	0	0
2022-05-17 00:00:00	23	0	0

May 18

date	hour	production	predicted
2022-05-18 00:00:00	0	0	0
2022-05-18 00:00:00	1	0	0
2022-05-18 00:00:00	2	0	0
2022-05-18 00:00:00	3	0	0
2022-05-18 00:00:00	4	0	0,85
2022-05-18 00:00:00	5	0	1,05
2022-05-18 00:00:00	6	0	1,56
2022-05-18 00:00:00	7	1,11	3,81
2022-05-18 00:00:00	8	10,02	6,15

2022-05-18 00:00:00	9	9,05	8,21
2022-05-18 00:00:00	10	10,08	5,76
2022-05-18 00:00:00	11	10,09	6,53
2022-05-18 00:00:00	12	10,09	6,47
2022-05-18 00:00:00	13	9,95	6,03
2022-05-18 00:00:00	14	10,02	4,62
2022-05-18 00:00:00	15	9,11	3,38
2022-05-18 00:00:00	16	8,26	2,23
2022-05-18 00:00:00	17	4,69	0,99
2022-05-18 00:00:00	18	0	0
2022-05-18 00:00:00	19	0	0
2022-05-18 00:00:00	20	0	0
2022-05-18 00:00:00	21	0	0
2022-05-18 00:00:00	22	0	0
2022-05-18 00:00:00	23	0	0

May 19

date	hour	production	predicted
2022-05-19 00:00:00	0	0	0
2022-05-19 00:00:00	1	0	0
2022-05-19 00:00:00	2	0	0
2022-05-19 00:00:00	3	0	0
2022-05-19 00:00:00	4	0	0,71
2022-05-19 00:00:00	5	0	0,57
2022-05-19 00:00:00	6	0	2,5
2022-05-19 00:00:00	7	0	3,4
2022-05-19 00:00:00	8	2	4,25

2022-05-19 00:00:00	9	5,2	4,92
2022-05-19 00:00:00	10	8,52	5,32
2022-05-19 00:00:00	11	6,48	5,4
2022-05-19 00:00:00	12	5,42	5,15
2022-05-19 00:00:00	13	0,96	4,63
2022-05-19 00:00:00	14	1,15	3,93
2022-05-19 00:00:00	15	1,5	3,14
2022-05-19 00:00:00	16	1,04	2,4
2022-05-19 00:00:00	17	2,59	0,84
2022-05-19 00:00:00	18	0	0,05
2022-05-19 00:00:00	19	0	0
2022-05-19 00:00:00	20	0	0
2022-05-19 00:00:00	21	0	0
2022-05-19 00:00:00	22	0	0
2022-05-19 00:00:00	23	0	0

May 20

date	hour	production	predicted
2022-05-20 00:00:00	0	0	0
2022-05-20 00:00:00	1	0	0
2022-05-20 00:00:00	2	0	0
2022-05-20 00:00:00	3	0	0
2022-05-20 00:00:00	4	0	0,6
2022-05-20 00:00:00	5	0	0,46
2022-05-20 00:00:00	6	0	3,45
2022-05-20 00:00:00	7	6,5	4,73
2022-05-20 00:00:00	8	6,95	5,95

2022-05-20 00:00:00	9	8,79	6,93
2022-05-20 00:00:00	10	9,94	7,54
2022-05-20 00:00:00	11	9,77	7,7
2022-05-20 00:00:00	12	10,1	5,77
2022-05-20 00:00:00	13	10,1	5,45
2022-05-20 00:00:00	14	10,09	4,58
2022-05-20 00:00:00	15	10,06	2,76
2022-05-20 00:00:00	16	8,48	1,58
2022-05-20 00:00:00	17	3	0,84
2022-05-20 00:00:00	18	0	0,08
2022-05-20 00:00:00	19	0	0
2022-05-20 00:00:00	20	0	0
2022-05-20 00:00:00	21	0	0
2022-05-20 00:00:00	22	0	0
2022-05-20 00:00:00	23	0	0

May 21

date	hour	production	predicted
2022-05-21 00:00:00	0	0	0
2022-05-21 00:00:00	1	0	0
2022-05-21 00:00:00	2	0	0
2022-05-21 00:00:00	3	0	0
2022-05-21 00:00:00	4	0	0,06
2022-05-21 00:00:00	5	0	0,88
2022-05-21 00:00:00	6	0	2,34
2022-05-21 00:00:00	7	0	5,85
2022-05-21 00:00:00	8	9	7,37

2022-05-21 00:00:00	9	10,09	8,61
2022-05-21 00:00:00	10	10,09	9,39
2022-05-21 00:00:00	11	10,09	9,6
2022-05-21 00:00:00	12	10,09	9,25
2022-05-21 00:00:00	13	10,09	8,39
2022-05-21 00:00:00	14	10,09	7,18
2022-05-21 00:00:00	15	9,5	5,8
2022-05-21 00:00:00	16	10,09	4,46
2022-05-21 00:00:00	17	5,86	3,37
2022-05-21 00:00:00	18	0	2,67
2022-05-21 00:00:00	19	0	0,42
2022-05-21 00:00:00	20	0	0
2022-05-21 00:00:00	21	0	0
2022-05-21 00:00:00	22	0	0
2022-05-21 00:00:00	23	0	0

May 22

date	hour	production	predicted
2022-05-22 00:00:00	0	0	0
2022-05-22 00:00:00	1	0	0
2022-05-22 00:00:00	2	0	0
2022-05-22 00:00:00	3	0	0
2022-05-22 00:00:00	4	0	0,65
2022-05-22 00:00:00	5	0	0,44
2022-05-22 00:00:00	6	0	3,02
2022-05-22 00:00:00	7	5	4,06
2022-05-22 00:00:00	8	8	5

2022-05-22 00:00:00	9	10,02	5,71
2022-05-22 00:00:00	10	10,09	6,1
2022-05-22 00:00:00	11	10,09	6,11
2022-05-22 00:00:00	12	10,09	5,77
2022-05-22 00:00:00	13	9,71	5,12
2022-05-22 00:00:00	14	5	4,28
2022-05-22 00:00:00	15	4,45	3,38
2022-05-22 00:00:00	16	6	0
2022-05-22 00:00:00	17	1,06	0
2022-05-22 00:00:00	18	0	0
2022-05-22 00:00:00	19	0	0
2022-05-22 00:00:00	20	0	0
2022-05-22 00:00:00	21	0	0
2022-05-22 00:00:00	22	0	0
2022-05-22 00:00:00	23	0	0

May 23

date	hour	production	predicted
2022-05-23 00:00:00	0	0	0
2022-05-23 00:00:00	1	0	0
2022-05-23 00:00:00	2	0	0
2022-05-23 00:00:00	3	0	0
2022-05-23 00:00:00	4	0	0,49
2022-05-23 00:00:00	5	0	0,33
2022-05-23 00:00:00	6	0	0,88
2022-05-23 00:00:00	7	4	2,91
2022-05-23 00:00:00	8	6,23	4,86

2022-05-23 00:00:00	9	8,19	6,51
2022-05-23 00:00:00	10	9,39	3,49
2022-05-23 00:00:00	11	9,41	4,41
2022-05-23 00:00:00	12	8,74	4,75
2022-05-23 00:00:00	13	5,4	4,75
2022-05-23 00:00:00	14	3,71	4,02
2022-05-23 00:00:00	15	8,26	2,94
2022-05-23 00:00:00	16	8,02	0
2022-05-23 00:00:00	17	4,35	0
2022-05-23 00:00:00	18	0	0
2022-05-23 00:00:00	19	0	0
2022-05-23 00:00:00	20	0	0
2022-05-23 00:00:00	21	0	0
2022-05-23 00:00:00	22	0	0
2022-05-23 00:00:00	23	0	0

May 24

date	hour	production	predicted
2022-05-24 00:00:00	0	0	0
2022-05-24 00:00:00	1	0	0
2022-05-24 00:00:00	2	0	0
2022-05-24 00:00:00	3	0	0
2022-05-24 00:00:00	4	0	1,2
2022-05-24 00:00:00	5	0	1,07
2022-05-24 00:00:00	6	0	1,67
2022-05-24 00:00:00	7	4	4,02
2022-05-24 00:00:00	8	6,44	6,17

2022-05-24 00:00:00	9	8,72	7,78
2022-05-24 00:00:00	10	7,64	4,94
2022-05-24 00:00:00	11	5,65	5,51
2022-05-24 00:00:00	12	7,47	5,25
2022-05-24 00:00:00	13	7,47	3,78
2022-05-24 00:00:00	14	8,93	3,09
2022-05-24 00:00:00	15	8,54	2,46
2022-05-24 00:00:00	16	5,96	0
2022-05-24 00:00:00	17	5,05	0
2022-05-24 00:00:00	18	0	0
2022-05-24 00:00:00	19	0	0
2022-05-24 00:00:00	20	0	0
2022-05-24 00:00:00	21	0	0
2022-05-24 00:00:00	22	0	0
2022-05-24 00:00:00	23	0	0

May 25

date	hour	production	predicted
2022-05-25 00:00:00	0	0	0
2022-05-25 00:00:00	1	0	0
2022-05-25 00:00:00	2	0	0
2022-05-25 00:00:00	3	0	0
2022-05-25 00:00:00	4	0	0,33
2022-05-25 00:00:00	5	0	1,85
2022-05-25 00:00:00	6	0	2,61
2022-05-25 00:00:00	7	5	5,08
2022-05-25 00:00:00	8	6,67	7,31

2022-05-25 00:00:00	9	9,1	6,73
2022-05-25 00:00:00	10	8,83	6,16
2022-05-25 00:00:00	11	7,94	5,82
2022-05-25 00:00:00	12	8,77	4,38
2022-05-25 00:00:00	13	8,65	3,6
2022-05-25 00:00:00	14	9,32	3,73
2022-05-25 00:00:00	15	6,85	3,52
2022-05-25 00:00:00	16	5,56	0
2022-05-25 00:00:00	17	2,55	0
2022-05-25 00:00:00	18	0	0
2022-05-25 00:00:00	19	0	0
2022-05-25 00:00:00	20	0	0
2022-05-25 00:00:00	21	0	0
2022-05-25 00:00:00	22	0	0
2022-05-25 00:00:00	23	0	0

May 26

date	hour	production	predicted
2022-05-26 00:00:00	0	0	0
2022-05-26 00:00:00	1	0	0
2022-05-26 00:00:00	2	0	0
2022-05-26 00:00:00	3	0	0
2022-05-26 00:00:00	4	0	1,97
2022-05-26 00:00:00	5	0	1,8
2022-05-26 00:00:00	6	0	2,25
2022-05-26 00:00:00	7	5	3,66
2022-05-26 00:00:00	8	6,5	5,08

2022-05-26 00:00:00	9	8,98	6,77
2022-05-26 00:00:00	10	10,09	5,83
2022-05-26 00:00:00	11	10,09	7,28
2022-05-26 00:00:00	12	10,09	7,77
2022-05-26 00:00:00	13	9,7	7,65
2022-05-26 00:00:00	14	8,87	6,59
2022-05-26 00:00:00	15	8,31	5,39
2022-05-26 00:00:00	16	7,96	3,96
2022-05-26 00:00:00	17	4,88	3,28
2022-05-26 00:00:00	18	0	2,57
2022-05-26 00:00:00	19	0	0
2022-05-26 00:00:00	20	0	0
2022-05-26 00:00:00	21	0	0
2022-05-26 00:00:00	22	0	0
2022-05-26 00:00:00	23	0	0