

# ENERGY DATA SCIENCE

## Data Science Lifecycle

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# PREVIOUSLY IN COURSE ...

Key takeaways:

- Energy and information
- Digital transformation
- Smart grids
- Use cases

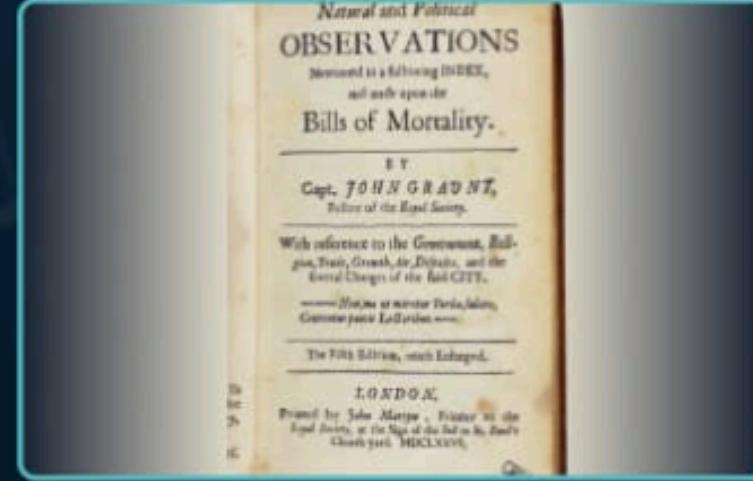
# HISTORY OF DATA

19,000 BC



The [Ishango bone](#) holds the first evidence of data collection and storage.

1600s



John Graunt introduces the [concept of data analysis](#) in 1663.

1800s



Herman Hollerith designs a [machine](#) that helped [complete](#) the US census in 1890.

1900s



Fritz Pfleumer invents the [magnetic tape](#) which later inspired the invention of floppy disks and hard disk drives.

1990s



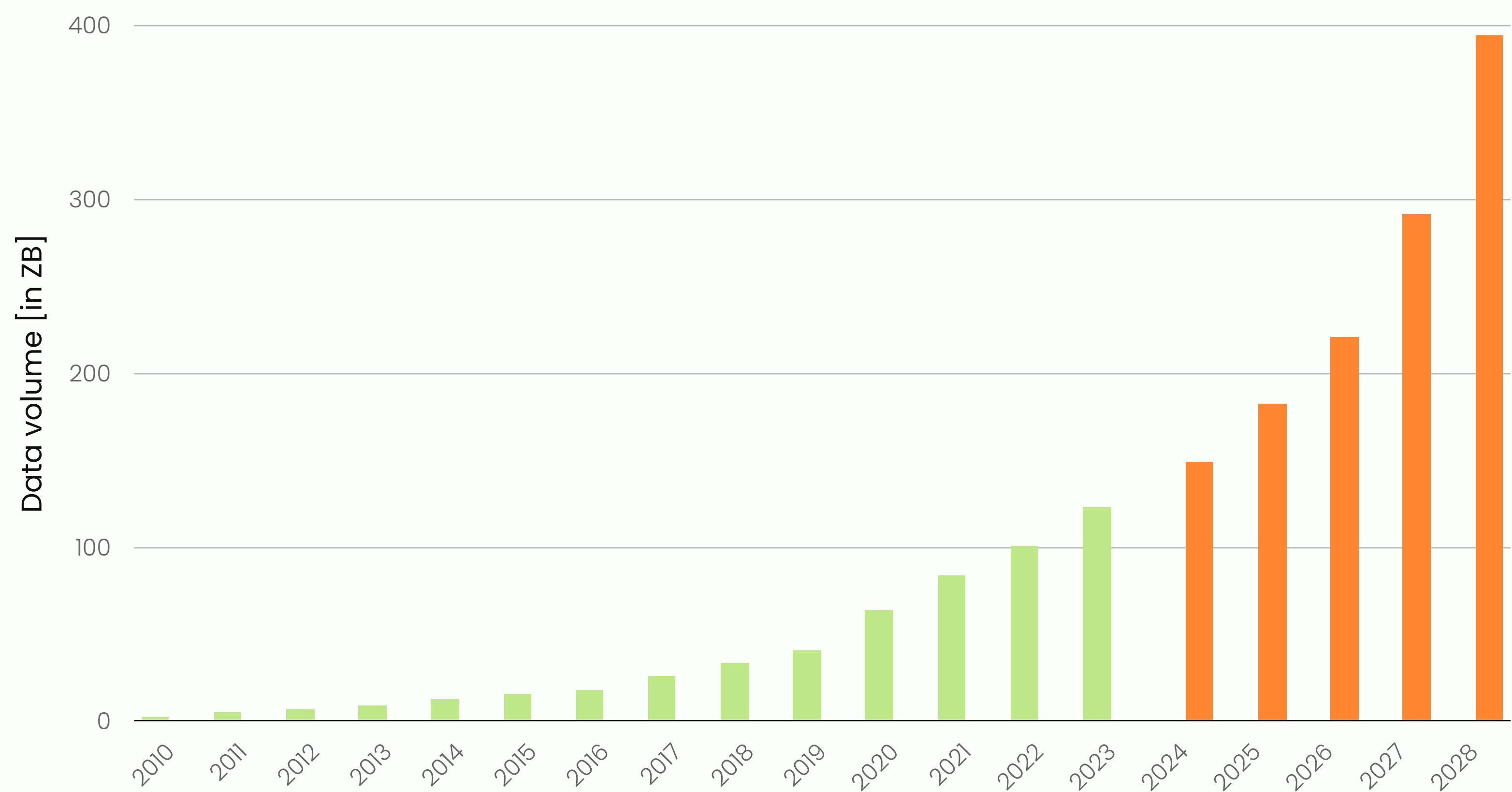
Sir Tim Berners Lee invents the [World Wide Web](#).



More than 50 years ago, John Tukey called for a reformation of academic statistics. In "The Future of Data Analysis," he pointed to the existence of an as-yet unrecognized *science*, whose subject of interest was learning from data, or "data analysis." Ten to 20 years ago, John Chambers, Jeff Wu, Bill Cleveland, and Leo

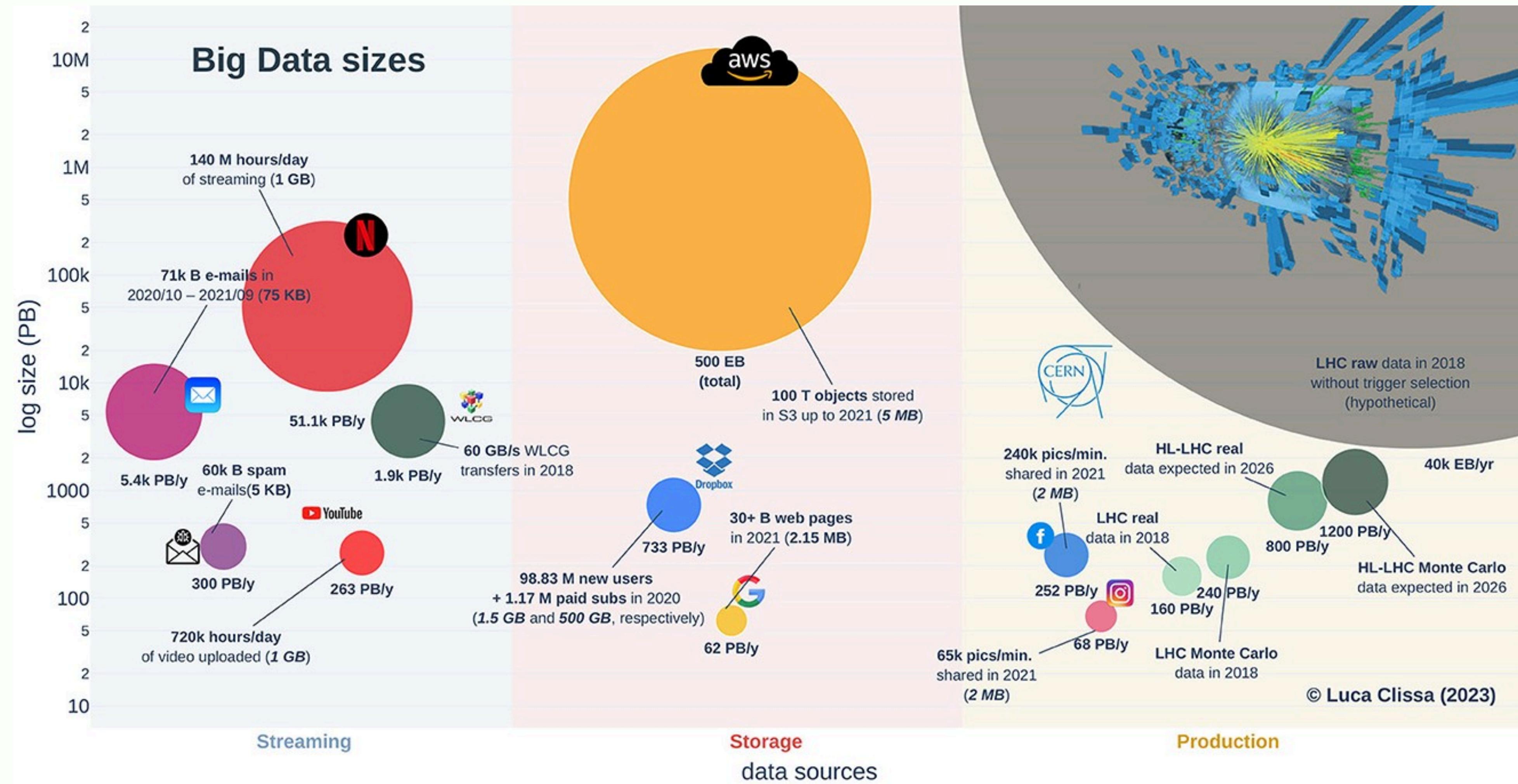
John W. Tukey (1962) The Future of Data Analysis. Ann. Math. Statist. 33(1): 1-67.

# WORLD DATA IN NUMBERS

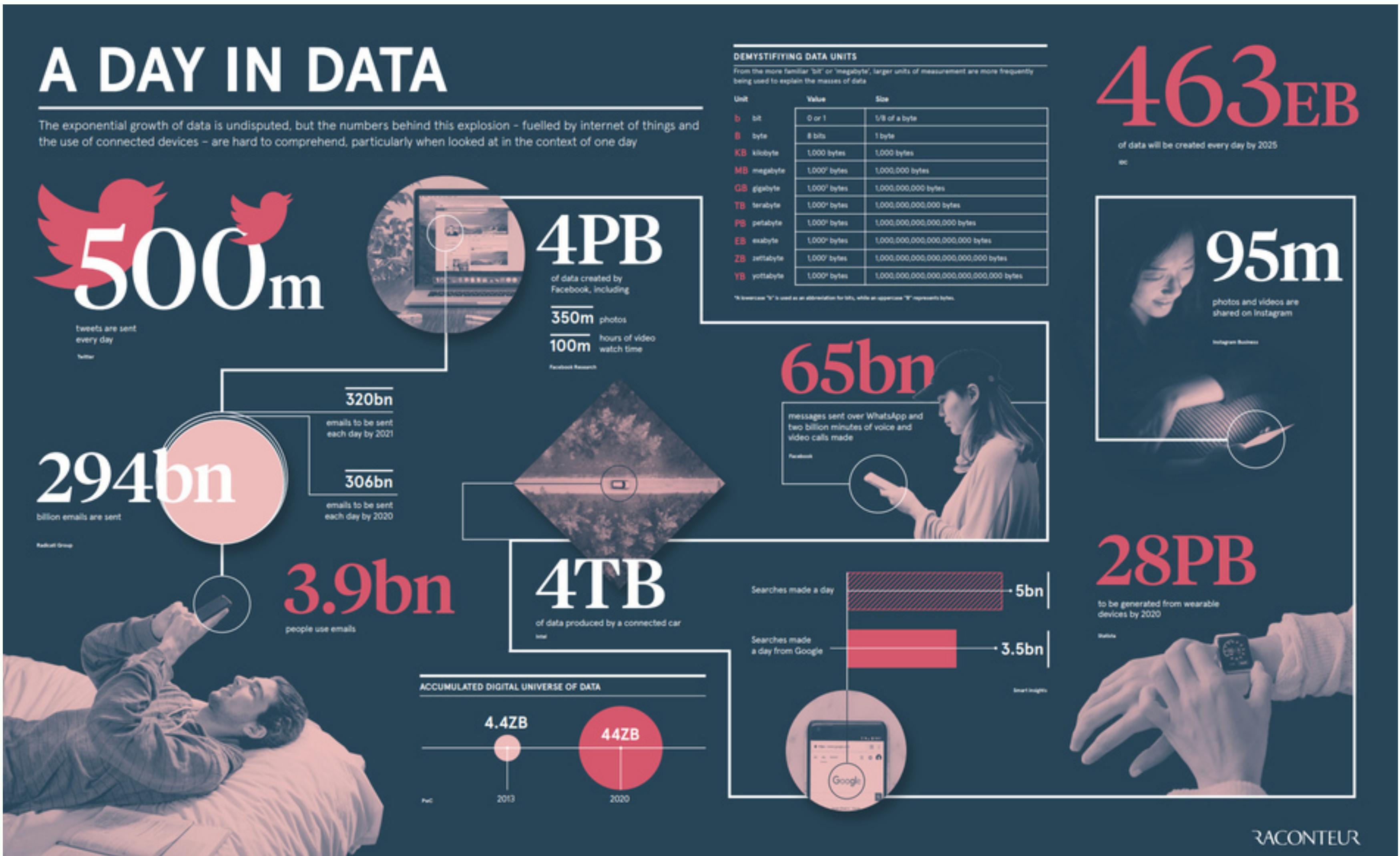


Unit	Value
bit	1
byte	1 bit
kilobyte (kB)	$10^3$ bytes
megabyte (MB)	$10^6$ bytes
gigabyte (GB)	$10^9$ bytes
terabyte (TB)	$10^{12}$ bytes
petabyte (PB)	$10^{15}$ bytes
exabyte (EB)	$10^{18}$ bytes
zettabyte (ZB)	$10^{21}$ bytes
yottabyte (YB)	$10^{24}$ bytes

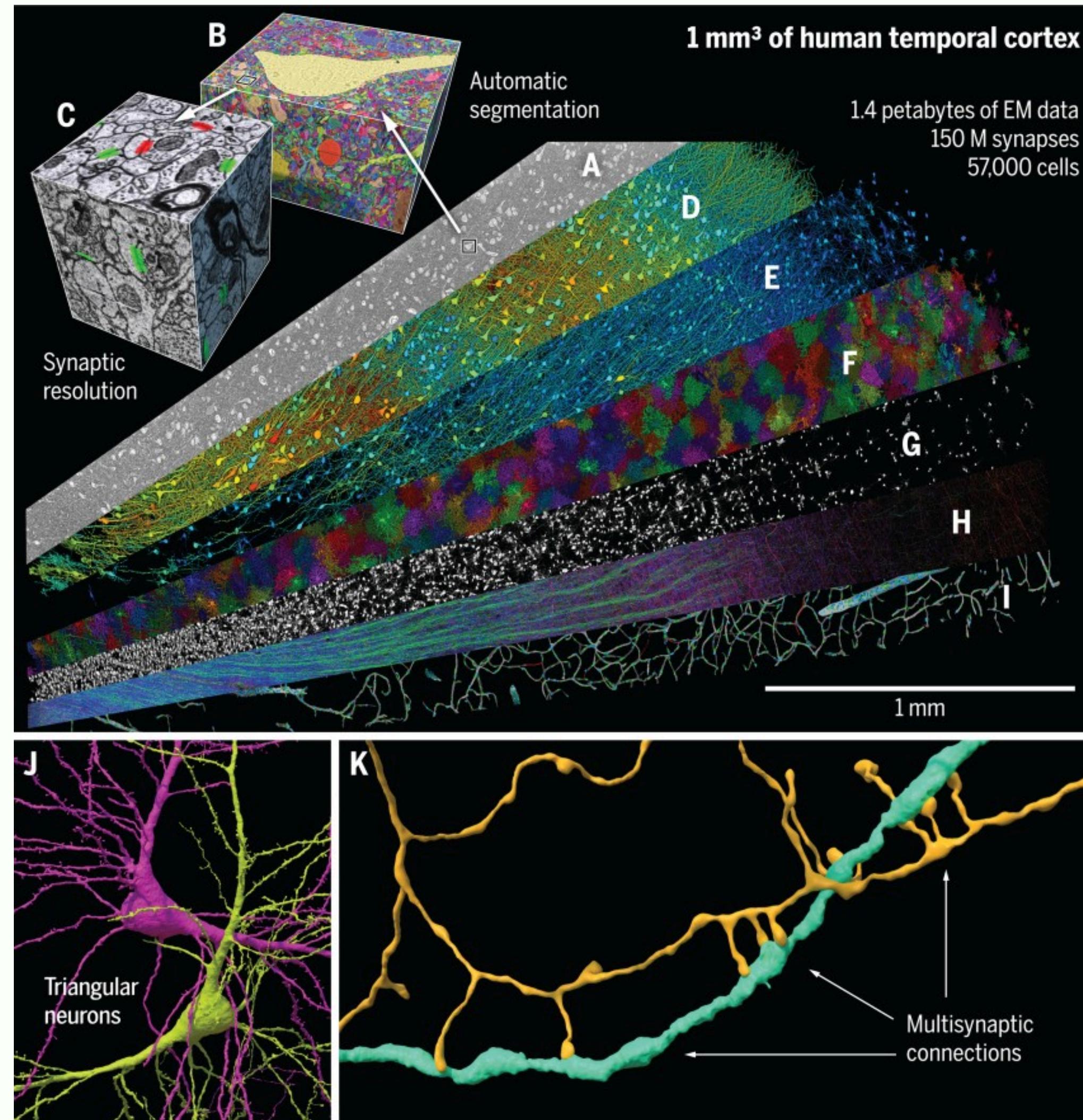
# GETTING PERSPECTIVE



# GETTING PERSPECTIVE (2)



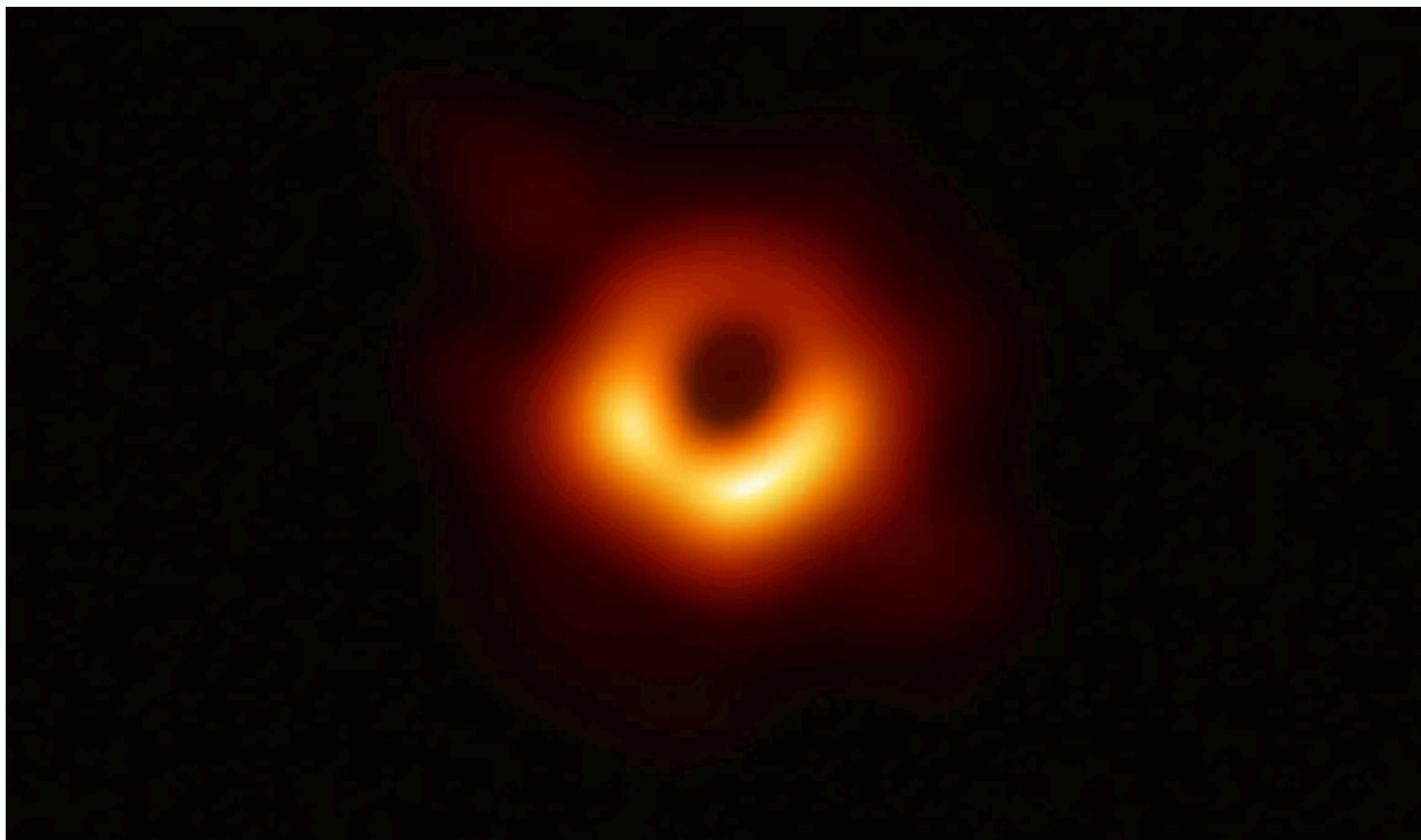
# 3D HUMAN BRAIN MAP



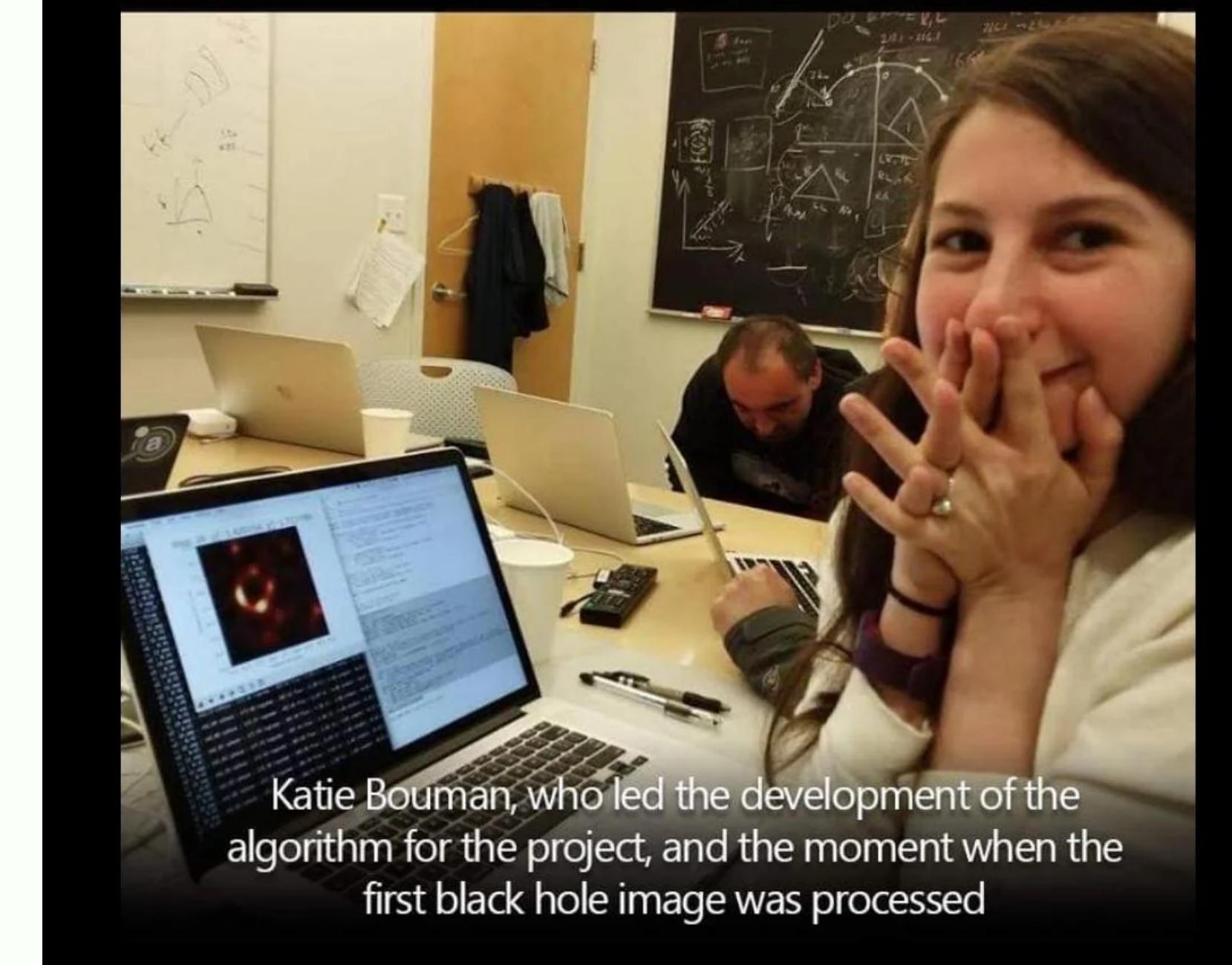
# BLACK HOLE

Home > Extreme

## It Took Half a Ton of Hard Drives to Store the Black Hole Image Data

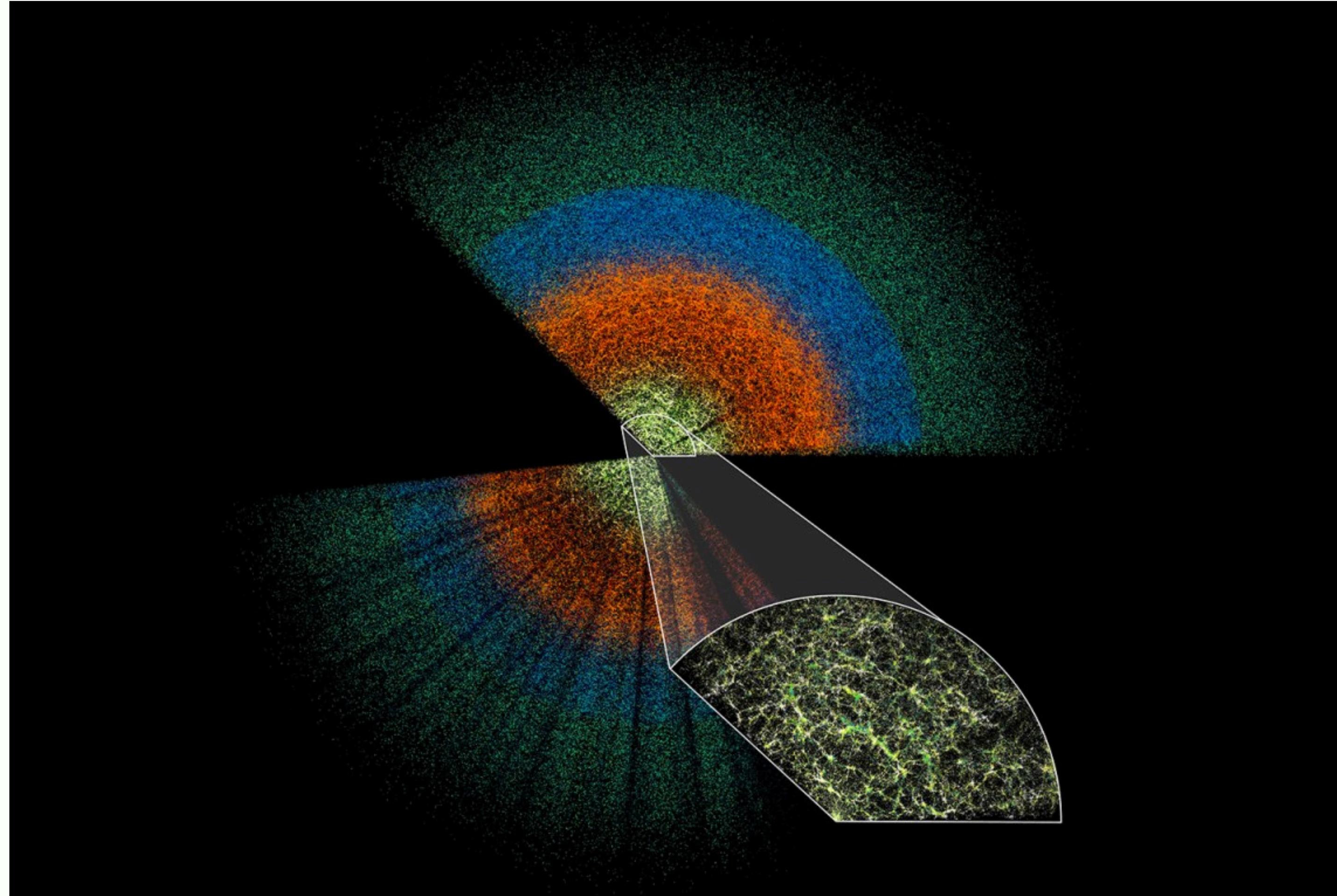


5 petabytes (5,242,880 Gigabytes) of data necessary to image a black hole



Katie Bouman, who led the development of the algorithm for the project, and the moment when the first black hole image was processed

# 3D MAP OF THE UNIVERSE



## Key Takeaways

- The Dark Energy Spectroscopic Instrument collaboration has publicly released the first 13 months of data from its main survey – a treasure trove that will help other researchers investigate big questions in astrophysics.
- Although DESI's Data Release 1 is only a fraction of what the experiment will capture, the **270-terabyte dataset** holds a vast amount of information, including precise distances to millions of galaxies.
- DESI's data release contains more than twice as many unique objects outside our galaxy as in all previous 3D spectroscopic surveys combined.

# DATA CENTRES



APRIL 10, 2025 | 2 MIN READ

## Data Centers Will Use Twice as Much Energy by 2030—Driven by AI

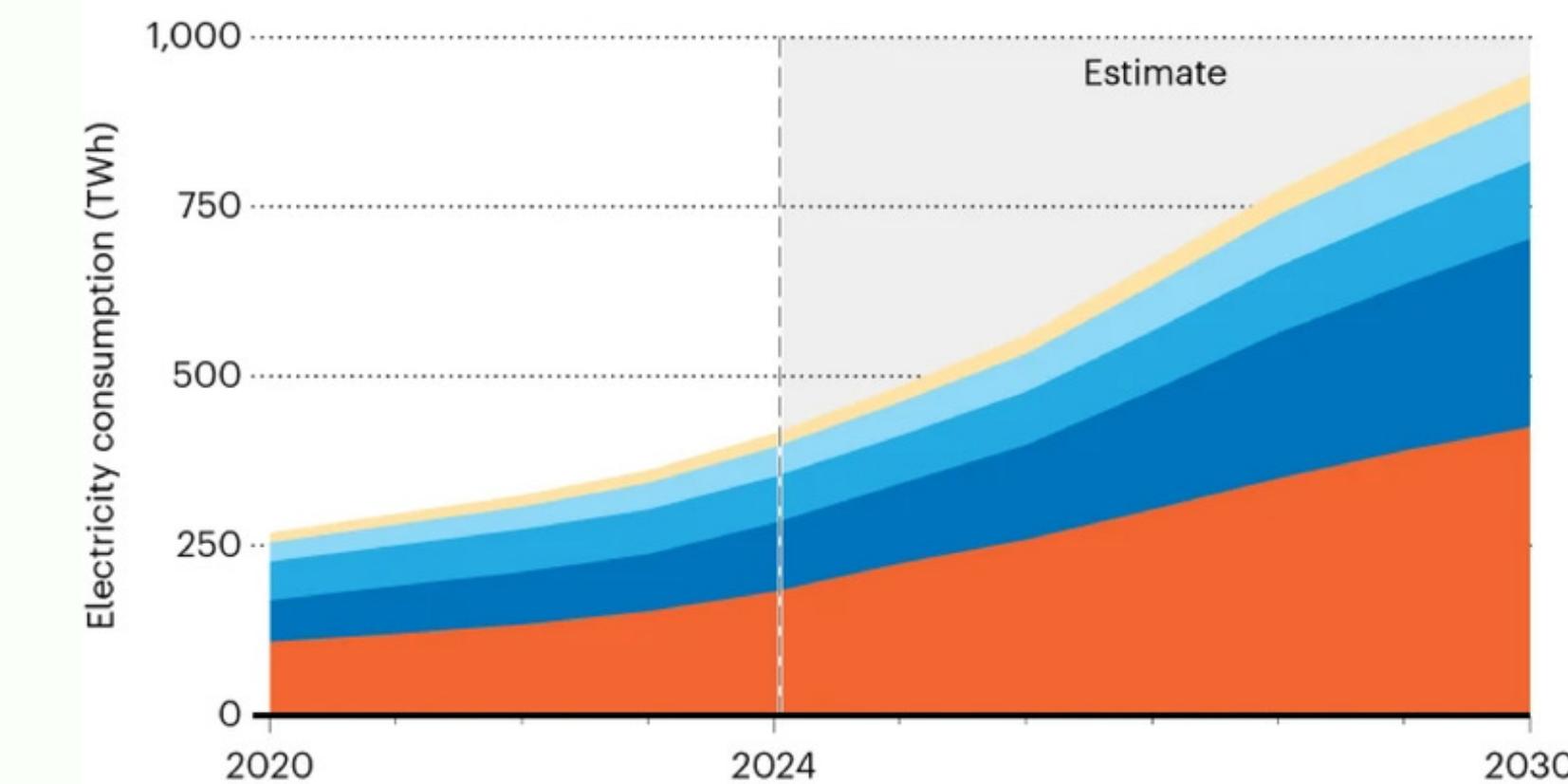
Data centers accounted for about 1.5 percent of global electricity consumption in 2024, an amount expected to double by 2030 because of AI use

BY SOPHIA CHEN & NATURE MAGAZINE

### DATA-CENTRE ENERGY GROWTH

China and the United States are predicted to account for nearly 80% of the global growth in electricity consumption by data centres up to 2030\*.

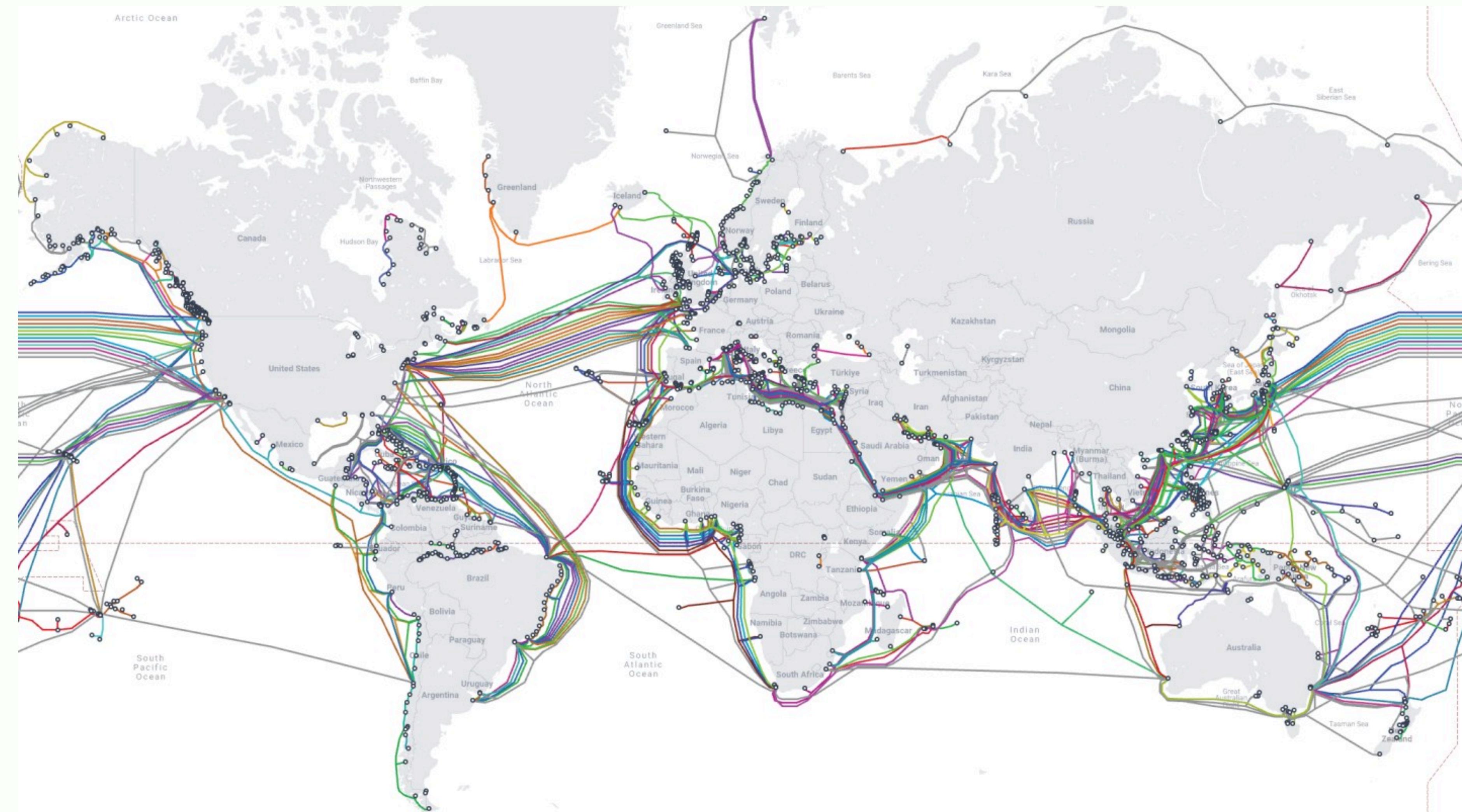
■ United States ■ China ■ Europe ■ Asia excl. China ■ Rest of world



\*Predicted trajectory under current regulatory conditions and industry projections.

©nature

# SUBMARINE CABLE MAP



# DATA ARE THE NEW GOLD NUGGETS



# Data Scientist: The Sexiest Job of the 21st Century

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and DJ Patil

From the Magazine (October 2012)

# **Data Scientist: The Sexiest Job of the 21st Century**

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and DJ Patil

From the Magazine (October 2012)

# **Is Data Scientist Still the Sexiest Job of the 21st Century?**

by Thomas H. Davenport and DJ Patil

July 15, 2022

# WHAT / HOW / WHY?

**WHAT?** Data science is the interdisciplinary field that combines:

**HOW?** ✓ mathematics and statistics,

✓ specialised programming,

✓ advanced analytics,

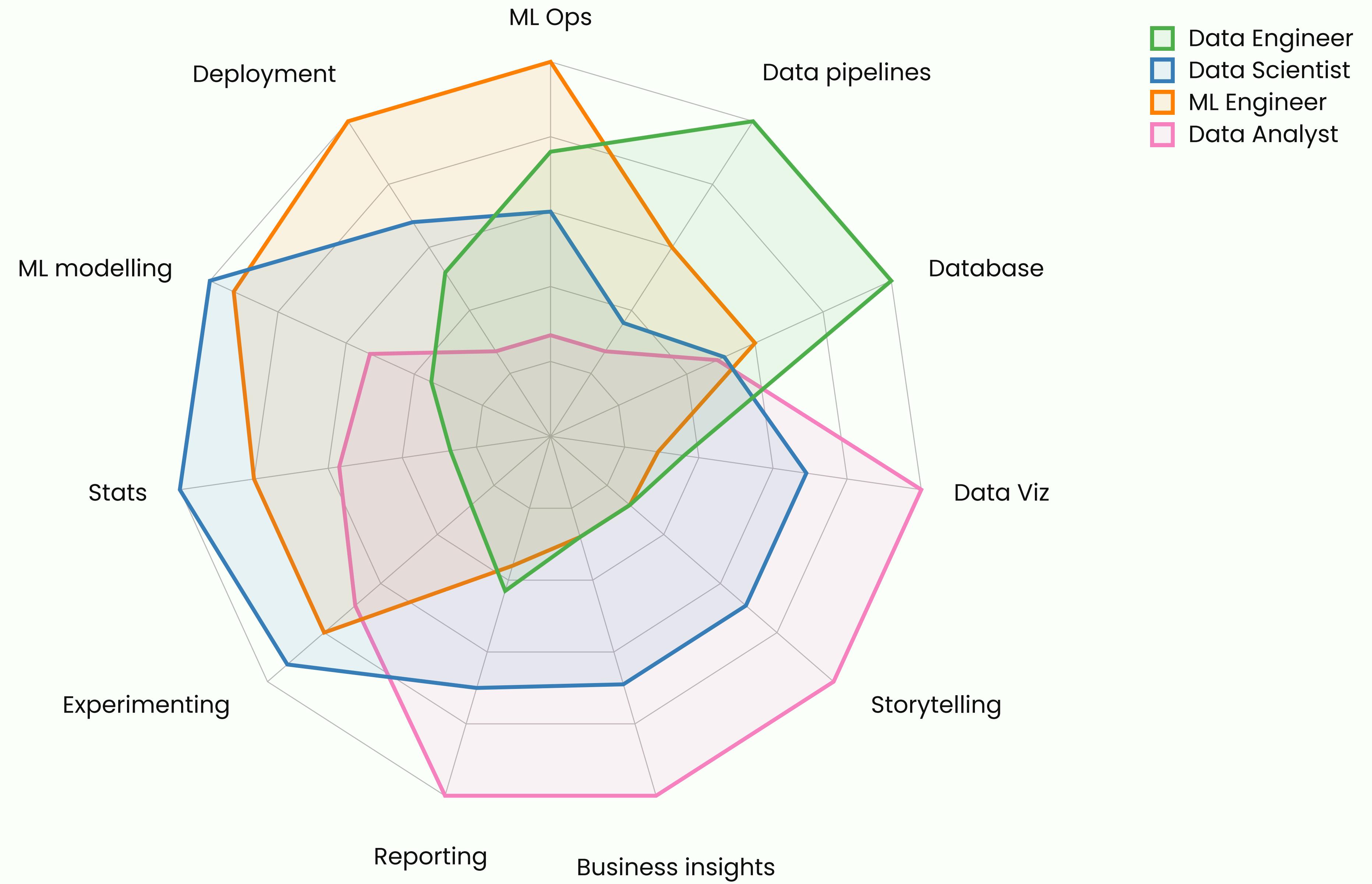
✓ artificial intelligence (AI) and machine learning.

**WHY?** To extract insights and knowledge from data.

With specific subject matter expertise to uncover actionable insights hidden in an organisation's data.

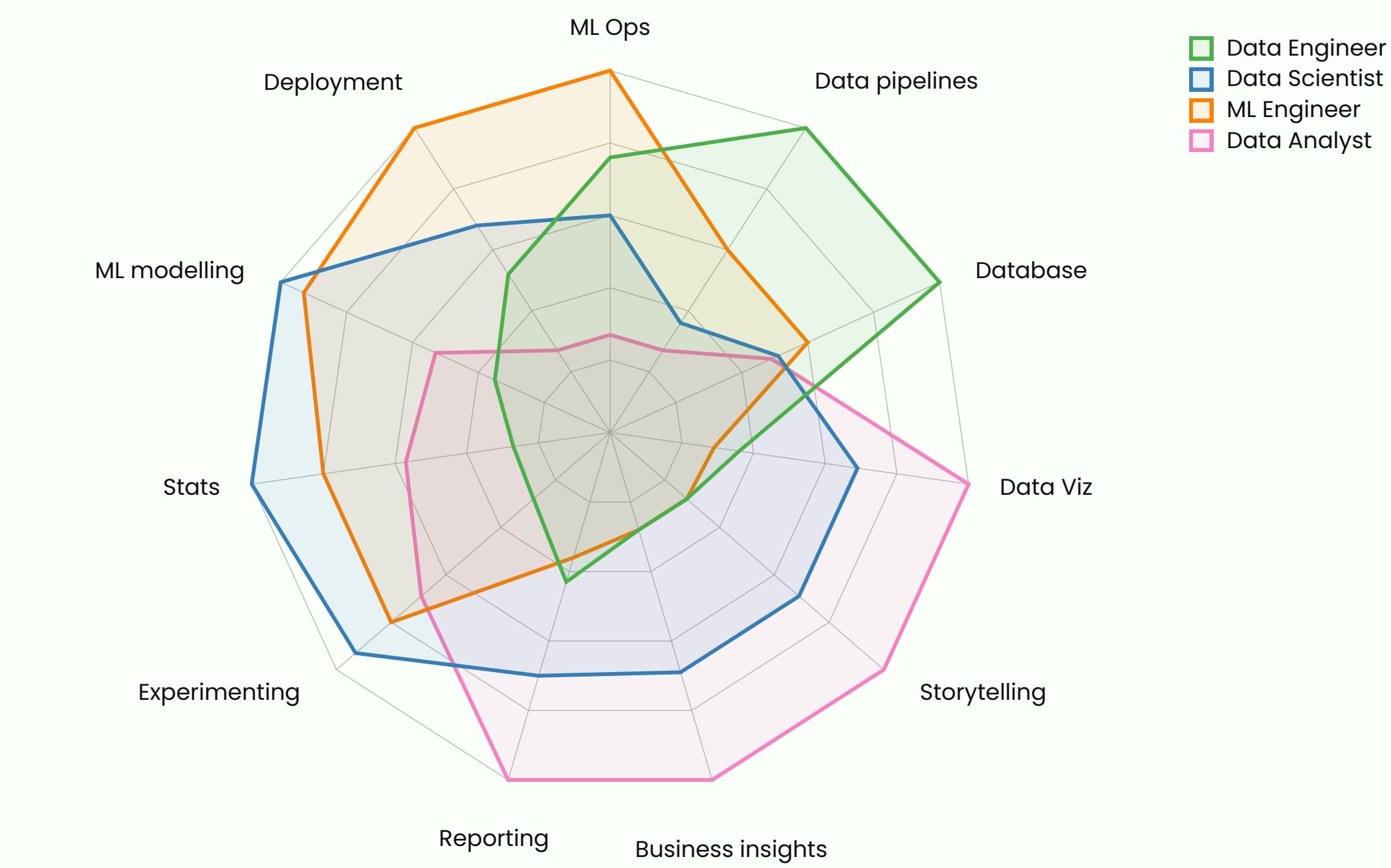
These insights can be used to guide decision making and strategic planning.

*by IBM*





■ Data Scientist

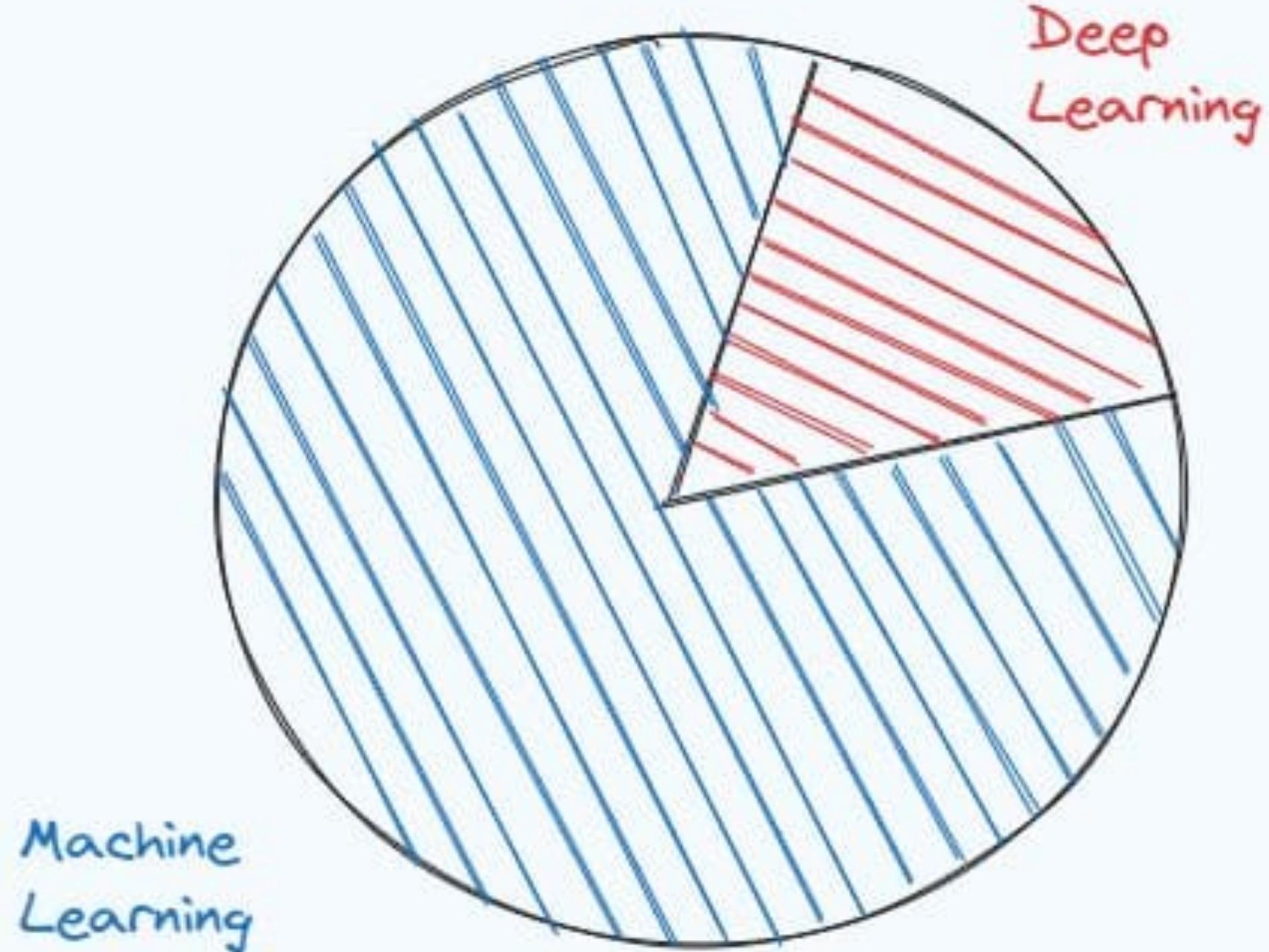


# DATA SCIENCE IN ENERGY INDUSTRY

Illustrative applications:

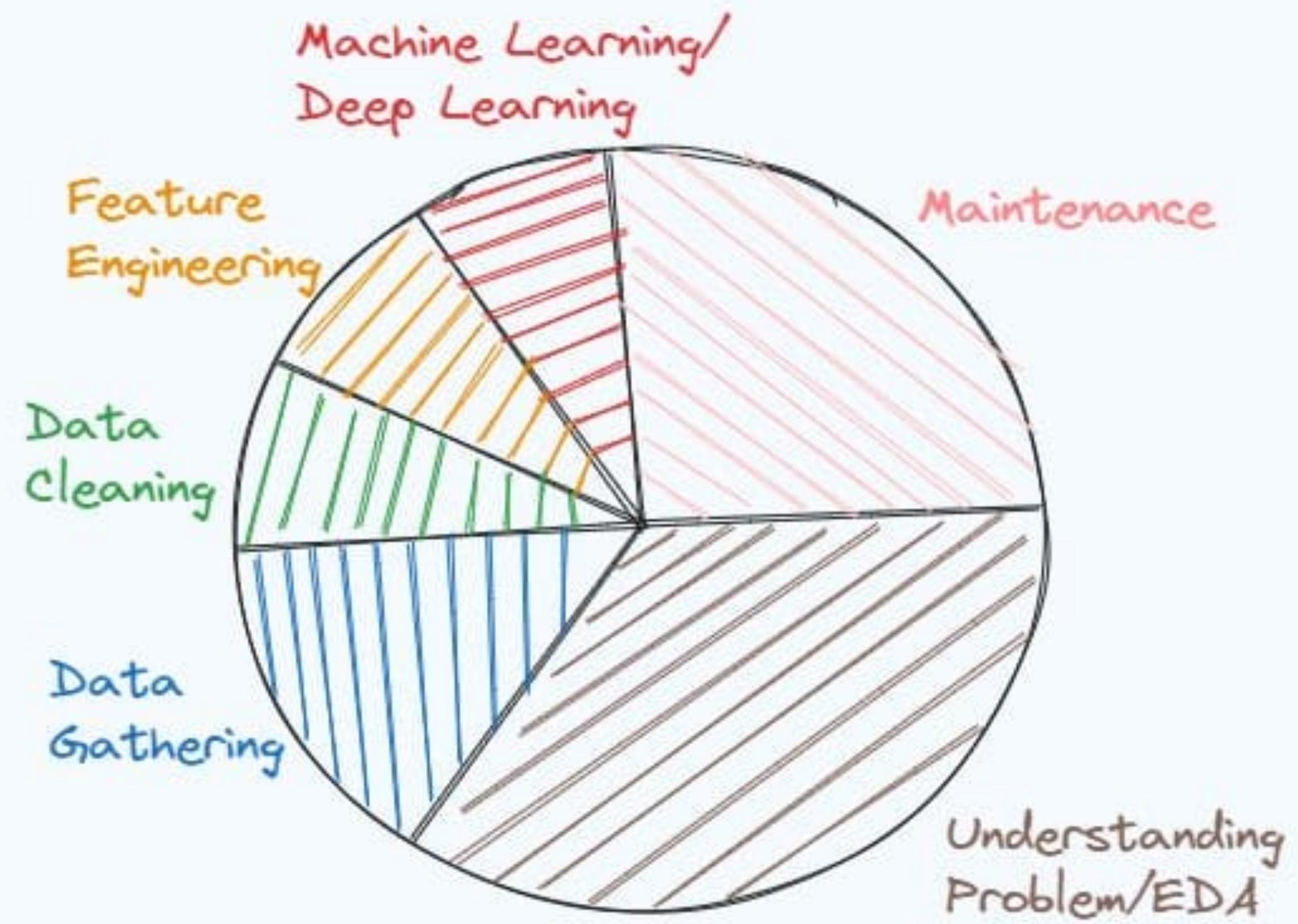
- Asset degradation and failure prediction, anomaly detection
- Recommendations – process and operations, inspection, maintenance
- Classification and clustering – safety incidents, failure modes, similar service
- Forecasting – production, demand, economical analysis
- Process optimisation

EXPECTATIONS

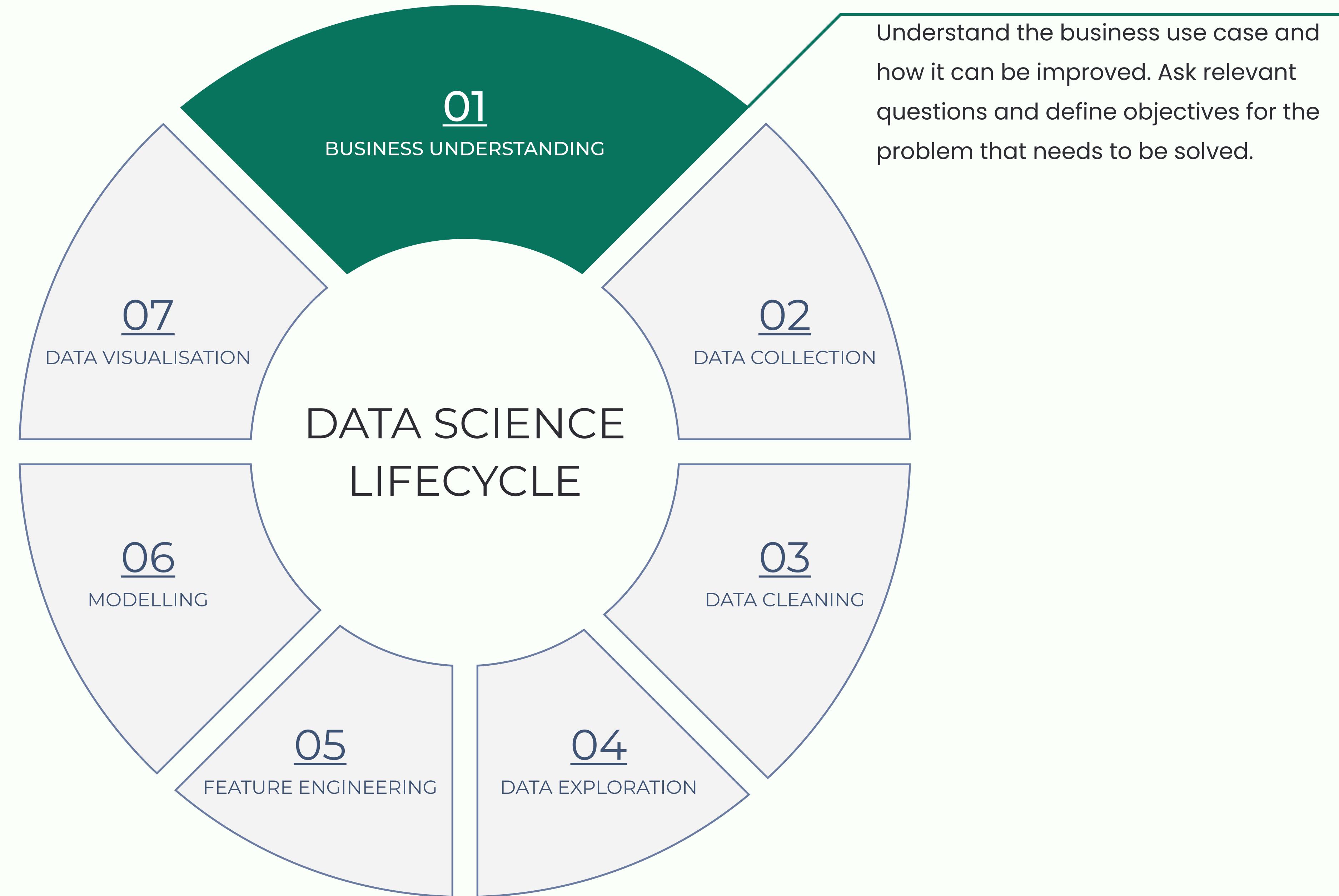


Vs

REALITY



# Step by step Data Science Lifecycle with illustrative example



## 01

### BUSINESS UNDERSTANDING

Understand the business use case and how it can be improved. Ask relevant questions and define objectives for the problem that needs to be solved.

*At this stage, we need to ask: How to solve a problem?*

With this question, Kidlin's law comes into the game. Kidlin's law is a problem-solving theory that says: "*If you write the problem down clearly, then the matter is half solved.*" It may sound as a simple sentence at first, but it has a significant depth in meaning.

# BUSINESS UNDERSTANDING

Consider a problem of developing  
a day-ahead electricity demand  
forecast model.

# NORDPOOL DAY-AHEAD MARKET

Daily at 12:00 CET, all purchase and sell orders are aggregated into two curves for each delivery hour.

Optimisation algorithm finds the cheapest set of power plants (supply) to cover the expected demand for all 24h (next day):

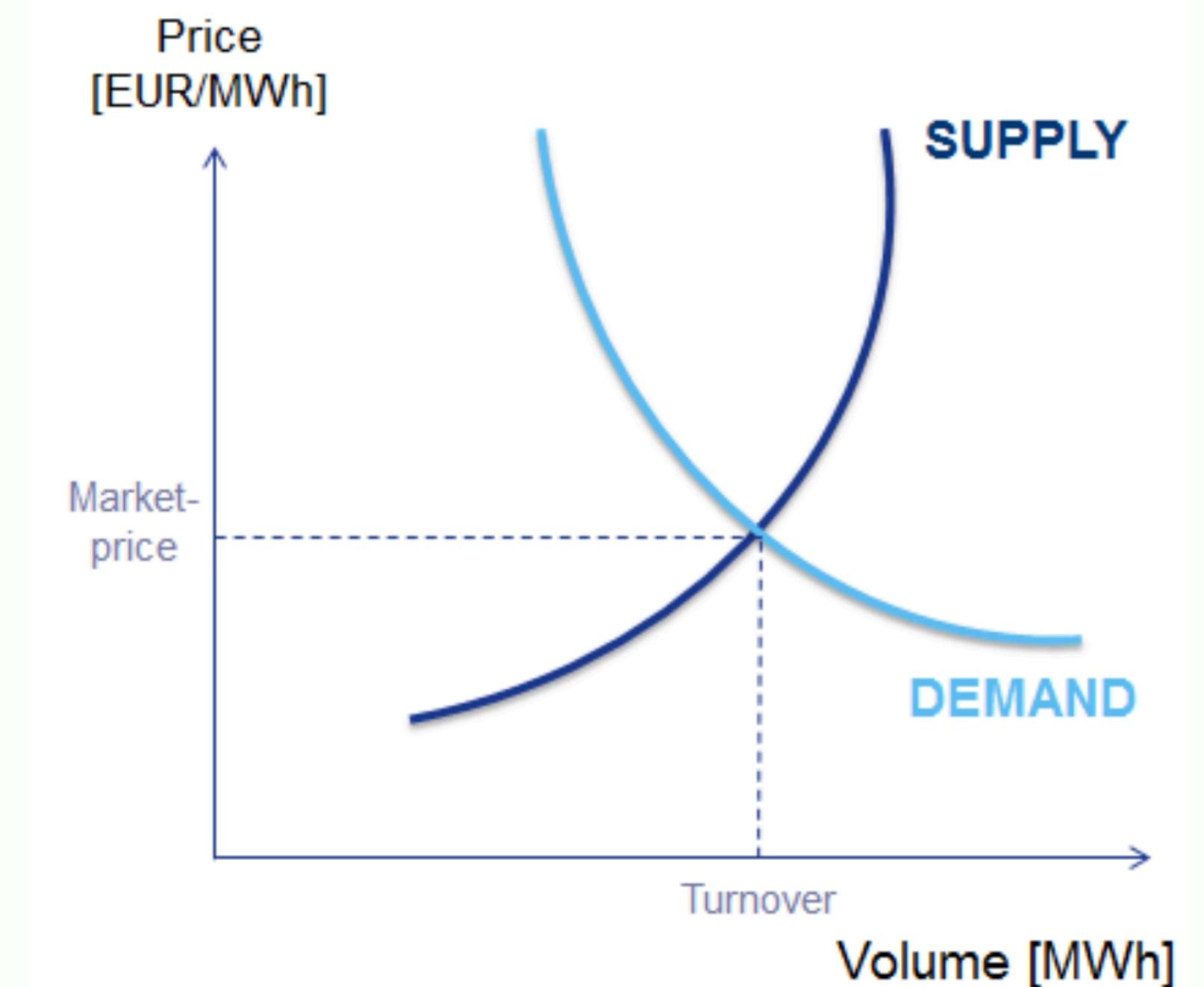
$$\begin{aligned} \min S &= P_1 Q_1 + \dots + P_n Q_n, \\ \text{s.t. } S &= D \end{aligned}$$

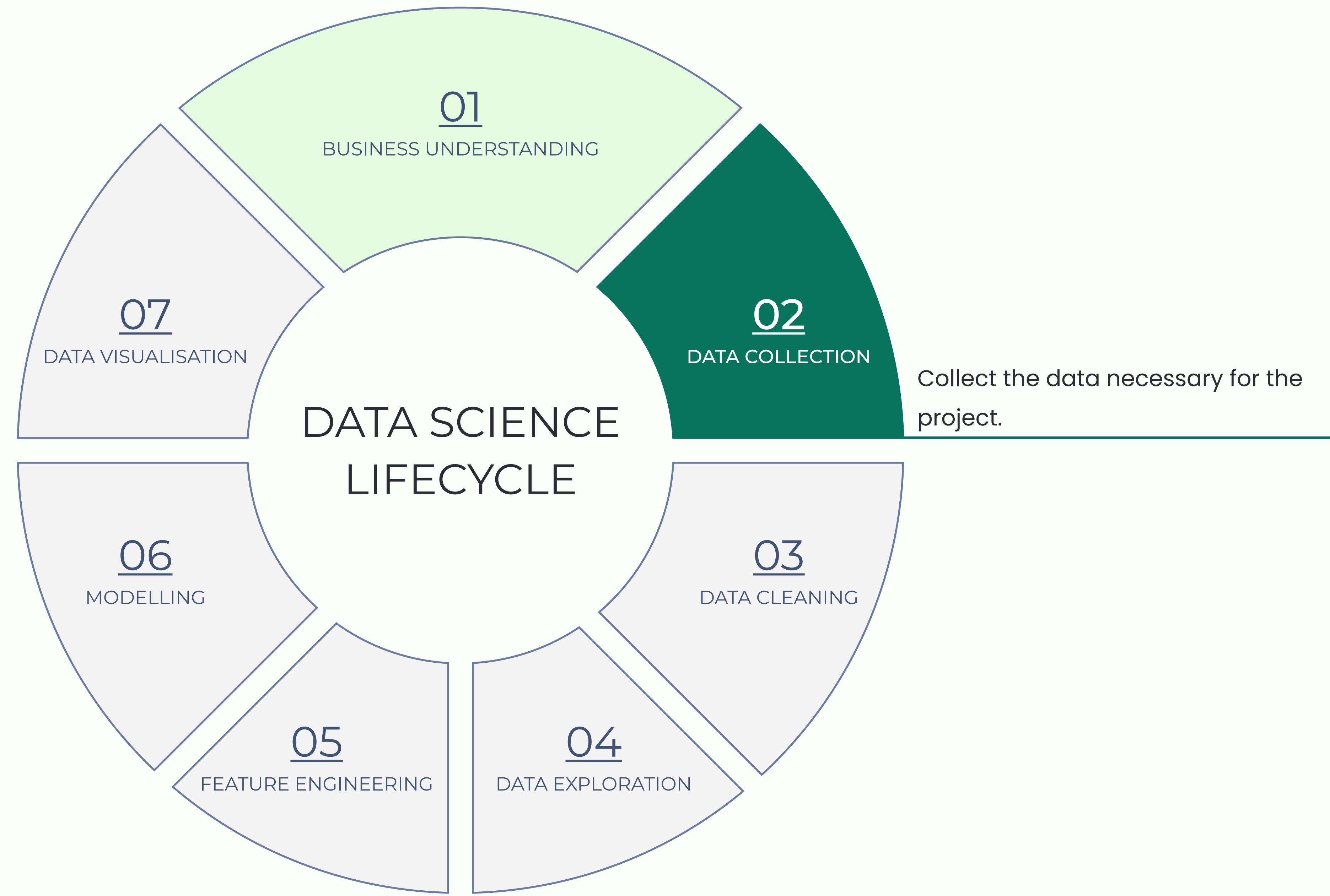
$S$  is supply

$D$  is demand

$P$  is power plants' production price

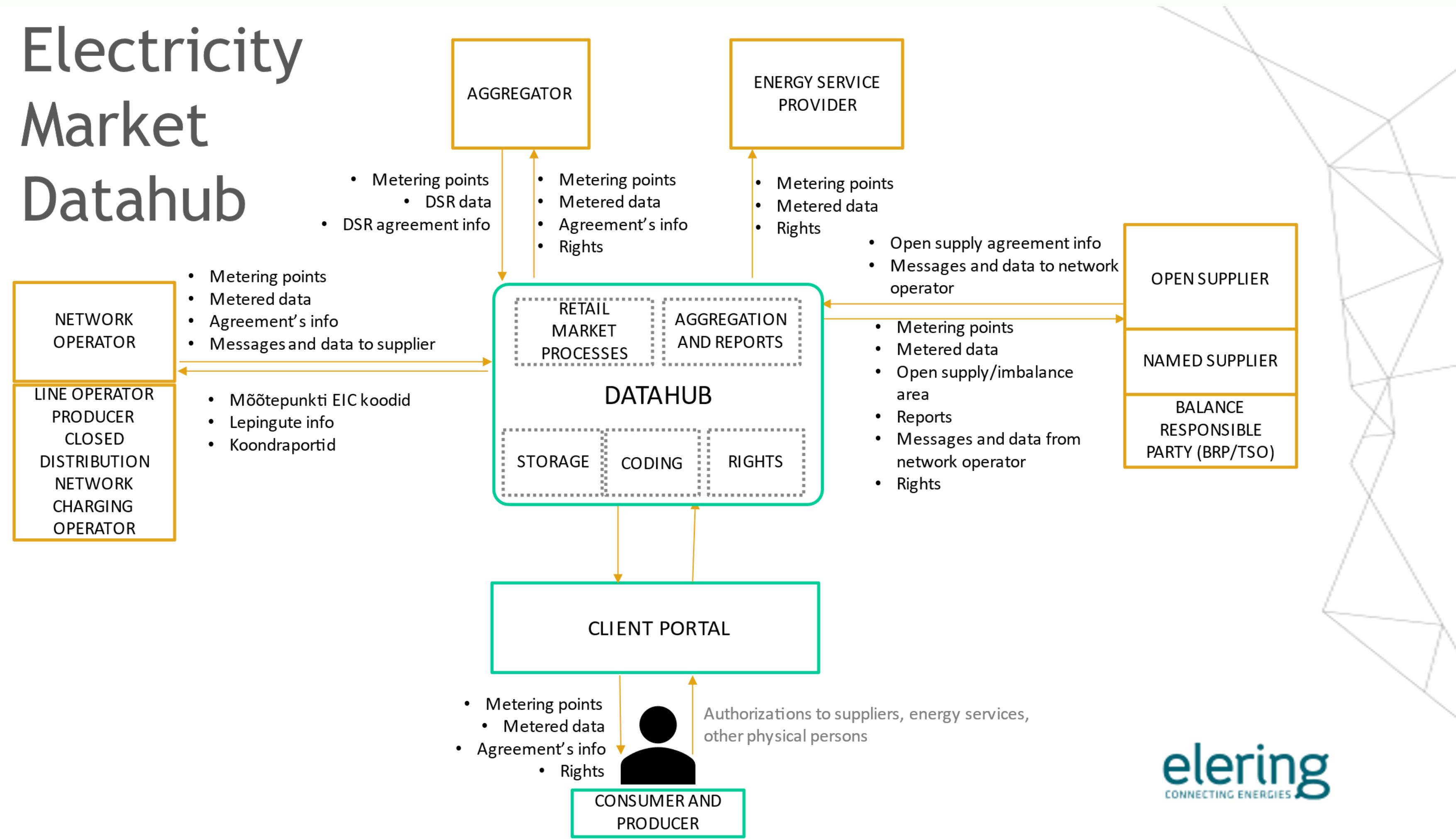
$Q$  quantify that the power plan can produce at the offered price





# ELERING DATAHUB

## Electricity Market Datahub



# ELECTRICITY DATA

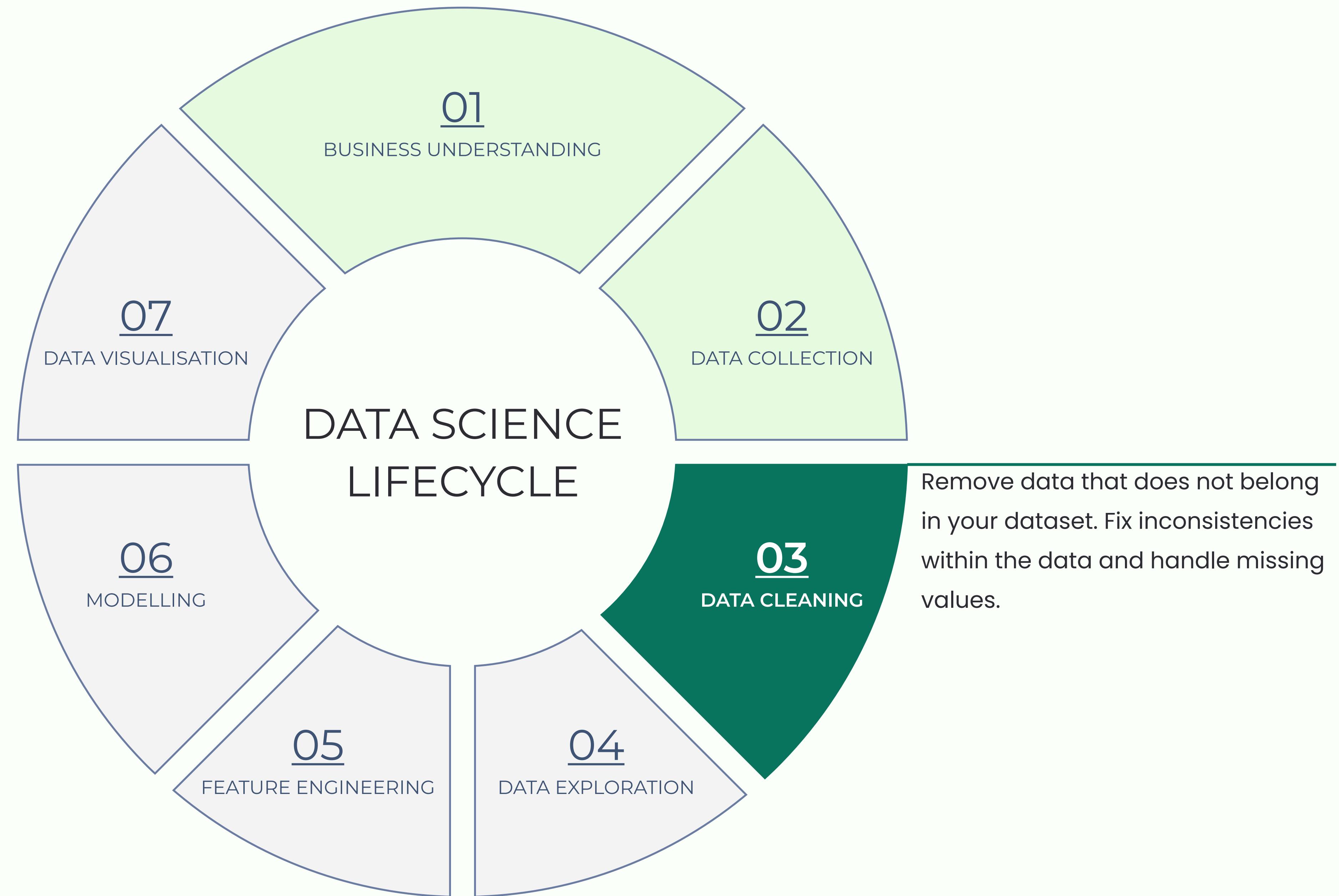
## Sample of electricity production/demand data (in MWh)

Timestamp (UTC)	Date (Estonia time)	Demand	Production	Planned demand	Planned production
1672524000	01.01.2023 00:00	798,2	543,1	830,6	549,3
1672527600	01.01.2023 01:00	793,4	552,8	816,3	556,8
1672531200	01.01.2023 02:00	776,5	546,5	848,6	528,3
1672534800	01.01.2023 03:00	757	545,3	814,2	516,5
1672538400	01.01.2023 04:00	743,7	503,1	832,1	497,2
1672542000	01.01.2023 05:00	737,6	483,5	818	478,4
1672545600	01.01.2023 06:00	749,4	455,6	834,2	457

# WEATHER DATA

## Sample of weather related data

Local time in Tallinn (airport)	T	Po	P	Pa	U	DD	Ff	ff10	ff3	N	WW	W1	W2	Tn	Tx	Cl	Nh	H	Cm	Ch	VV	Td	RRR	tR
01.01.2023 00:00	5.8	744.1	747.1	-0.3	91	Wind blowing from the south- west	4	8	9	100%	Precipitation	Showers or intermittent precipitation	No significant weather observed	3.2	6.0		100%	200-300			35.0	4.5	0.1	3
01.01.2023 01:00	5.8	744.0	747.1	-0.3	88	Wind blowing from the west- southwest	5		9	60%	No significant weather observed	Showers or intermittent precipitation	No significant weather observed	3.6	6.0		60%	300-600			35.0	4.0	No precipitati on	3
01.01.2023 02:00	5.2	744.4	747.5	0.3	91	Wind blowing from the west- southwest	4		9	90 or more, but not 100%	State of sky on the whole unchanged	Shower(s)	Cloud covering more than 1/2 of the sky throughout the appropriate period	4.1	6.0	Stratus nebulosus or Stratus fractus other than of bad weather, or both	90 or more, but not 100%	300-600	No Altocumulus, Altostratus or Nimbostratus	No Cirrus, Cirrocumulus or Cirrostratus	35.0	3.8	No precipitati on	3
01.01.2023 03:00	4.8	744.8	747.8	0.7	89	Wind blowing from the west	4		9	60%	No significant weather observed.	No significant weather observed.	No significant weather observed.	4.5	6.0		10% or less, but not 0	300-600			35.0	3.1	No precipitati on	3
01.01.2023 04:00	4.1	745.3	748.3	1.3	91	Wind blowing from the west	4		9	90 or more, but not 100%	No significant weather observed.	No significant weather observed.	No significant weather observed.	4.1	6.0		90 or more, but not 100%	2500 or more, or no clouds			35.0	2.7	No precipitati on	3
01.01.2023 05:00	3.3	745.6	748.6	1.2	93	Wind blowing from the west- southwest	3		9	60%	State of sky on the whole unchanged.	Cloud covering more than 1/2 of the sky throughout the appropriate period.	Cloud covering more than 1/2 of the sky throughout the appropriate period.	3.3	6.0	No Stratocumulus, Stratus, Cumulus or Cumulonimbus	40%	2500 or more, or no clouds	Altocumulus translucidus at a single level	Cirrocumulus alone, or Cirrocumulus accompanied by Cirrus or Cirrostratus or both, but Cirrocumulus is predominant	35.0	2.2	No precipitati on	3



# DATA QUALITY

**Variables** may be:

- ▶ **Qualitative** variables are those that express a qualitative attribute such as cloudiness, hair colour, gender, etc. They are also referred to as categorical variables.
- ▶ **Quantitative** variables are those variables that are measured in terms of numbers.
  - **Discrete** variables can take only certain values.
  - **Continuous** variables can take any value within the range of the scale.

# DATA CLEANING

**Sample of weather related data**

Local time in Tallinn (airport)	T	Po	U	DD	N	Tn	Tx	Nh	Cm	Ch
01.01.2023 00:00	5.8	744.1	91	Wind blowing from the south-west	100%	3.2	6.0	100%		
01.01.2023 01:00	5.8	744.0	88	Wind blowing from the west-southwest	60%	3.6	6.0	60%		
01.01.2023 02:00	5.2	744.4	91	Wind blowing from the west-southwest	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%	No Altocumulus, Altocstratus or Nimbostratus	No Cirrus, Cirrocumulus or Cirrostratus
01.01.2023 03:00	4.8	744.8	89	Wind blowing from the west	60%	4.5	6.0	10% or less, but not 0		
01.01.2023 04:00	4.1	745.3	91	Wind blowing from the west	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%		
01.01.2023 05:00	3.3	745.6	93	Wind blowing from the west-southwest	60%	3.3	6.0	40%	Altocumulus translucidus at a single level	Cirrocumulus alone, or Cirrocumulus accompanied by Cirrus or Cirrostratus or both, but Cirrocumulus is predominant

# DATA CLEANING

Sample of weather related data

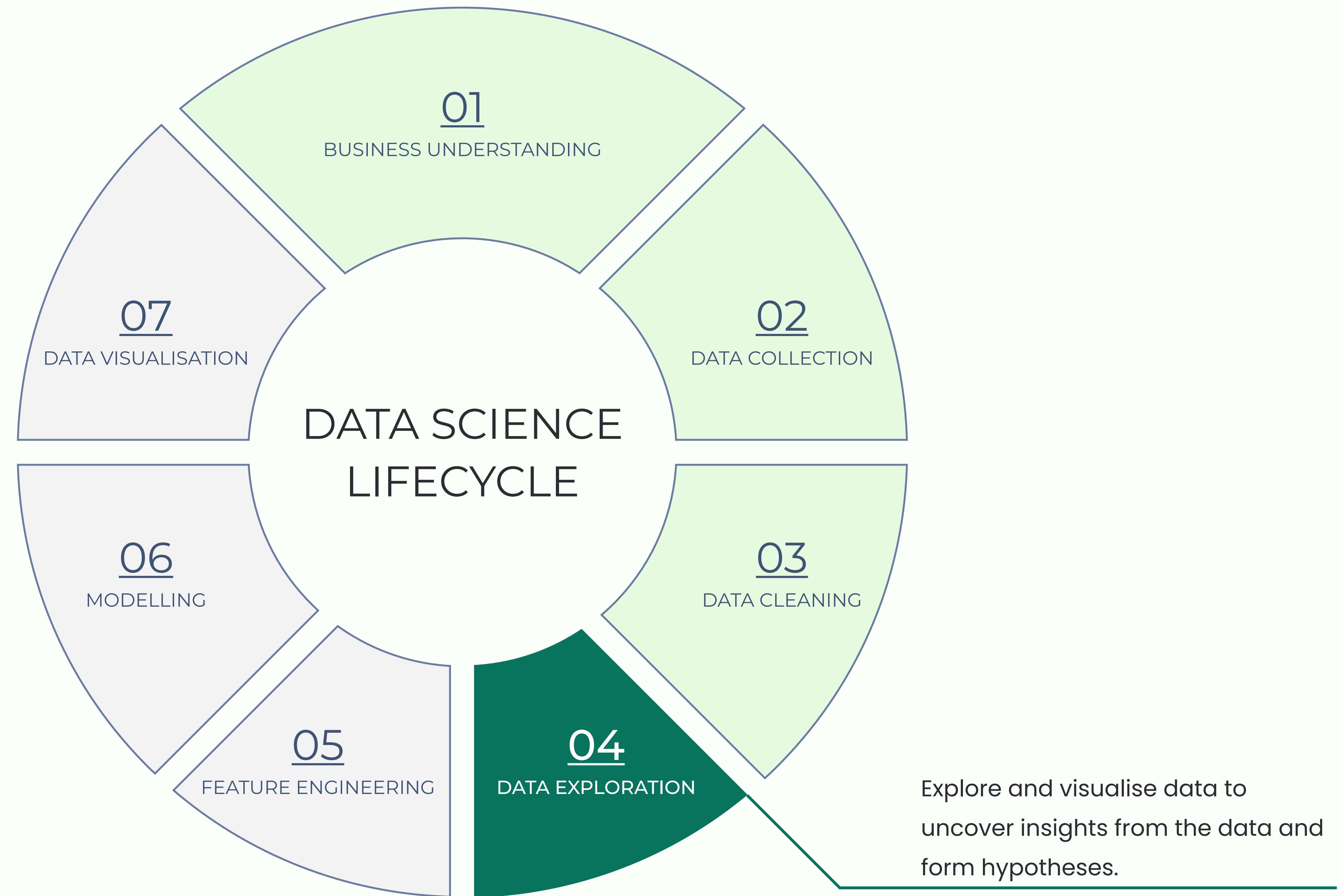
Local time in Tallinn (airport)	T	Po	U	DD	N	Tn	Tx	Nh	Cm	Ch
01.01.2023 00:00	5.8	744.1	91	Wind blowing from the south-west	100%	3.2	6.0	100%		
01.01.2023 01:00	5.8	744.0	88	Wind blowing from the west-southwest	60%	3.6	6.0	60%		
01.01.2023 02:00	5.2	744.4	91	Wind blowing from the west-southwest	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%	No Altocumulus, Altocumulus or Nimbostratus	No Cirrus, Cirrocumulus or Cirrostratus
01.01.2023 03:00	4.8	744.8	89	Wind blowing from the west	60%	4.5	6.0	10% or less, but not 0		
01.01.2023 04:00	4.1	745.3	91	Wind blowing from the west	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%		
01.01.2023 05:00	3.3	745.6	93	Wind blowing from the west-southwest	60%	3.3	6.0	40%	Altocumulus translucidus at a single level	Cirrocumulus alone, or Cirrocumulus accompanied by Cirrus or Cirrostratus or both, but Cirrocumulus is predominant

Still there may remain some **anomalies** that cannot be easily seen from the table, and further exploration is needed.

# HOW TO CLEAN YOUR DATA

While the techniques used for data cleaning may vary according to the types of data, you can still follow these basic steps:

1. Remove duplicates
2. Remove irrelevant observations
3. Fix structural errors
4. Handle unwanted outliers
5. Convert and unify data types
6. Clear formatting
7. Handle missing data



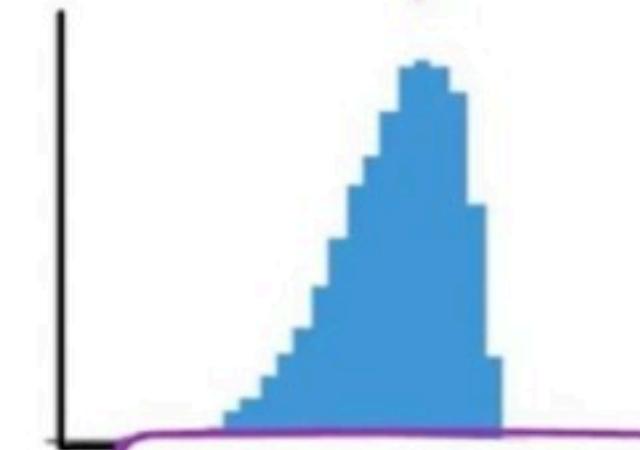
## 04

### DATA EXPLORATION

Explore and visualise data to uncover insights from the data and form hypotheses.

## EDA

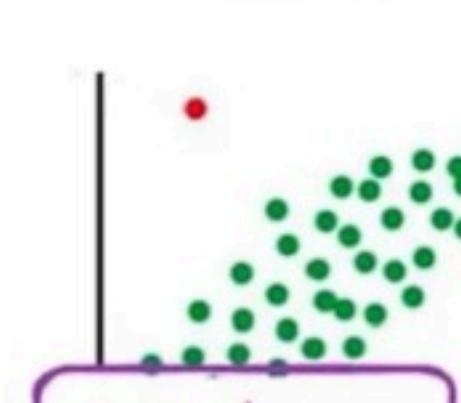
### Exploratory Data Analysis



Data distribution

	F	G	H	I	J
A	0.620576	0.140053	1.352728	NaN	0.808078
B	NaN	0.526829	NaN	NaN	0.170902
C	NaN	0.458827	1.406713	0.071119	NaN
D	NaN	2.307197	NaN	NaN	NaN
E	0.203402	0.259913	NaN	0.505811	1.516755

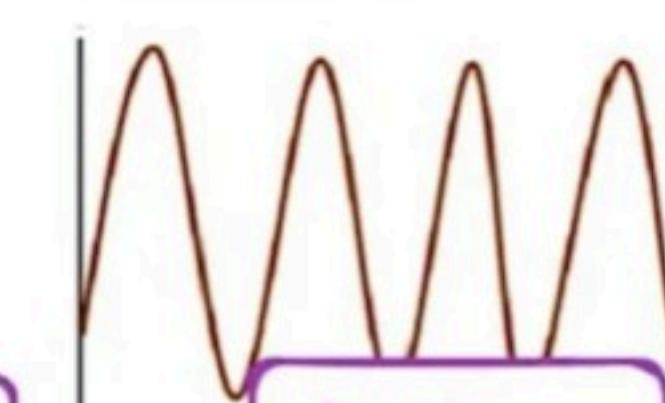
Missing data



Outliers



Correlation

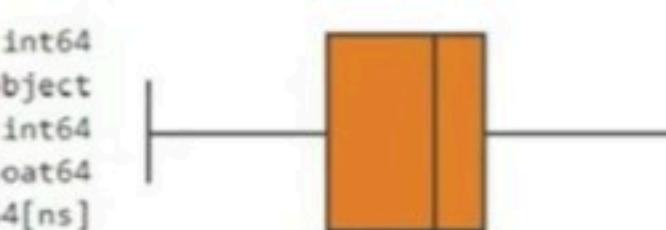


Patterns

Cust\_No  
Cust\_Name  
Product\_id  
Product\_cost  
Purchase\_Date  
dtype: object

int64  
object  
int64  
float64  
datetime64[ns]

Data types

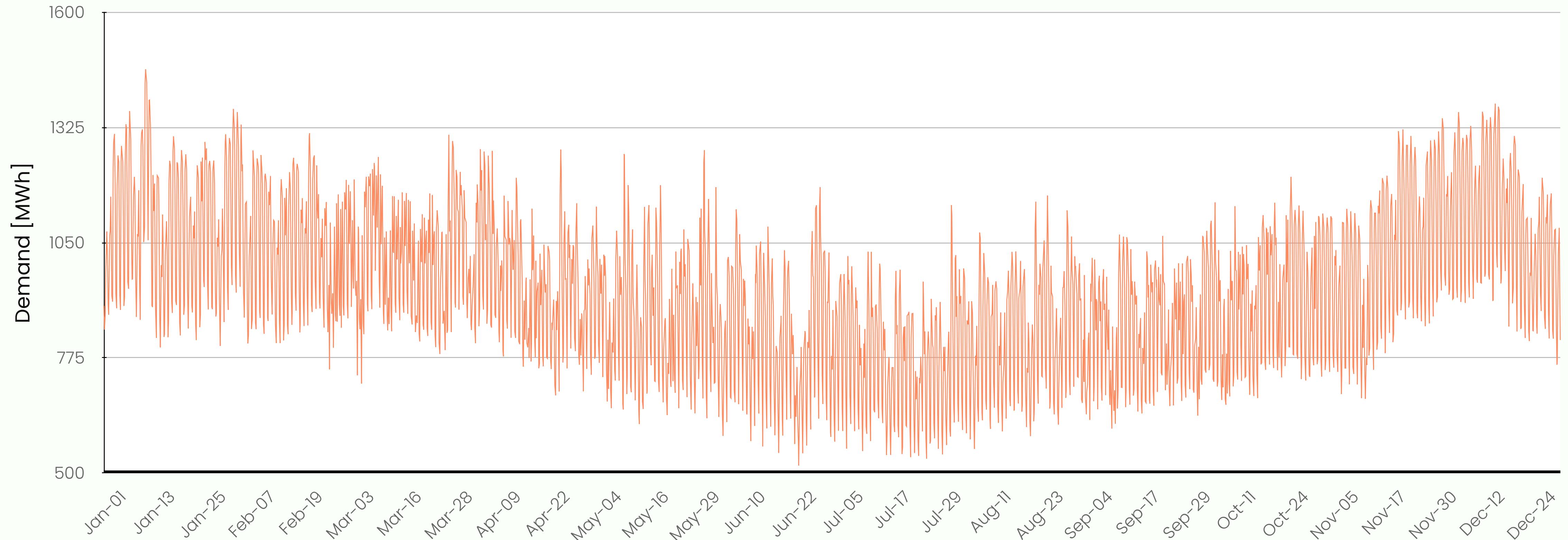


Data visualization



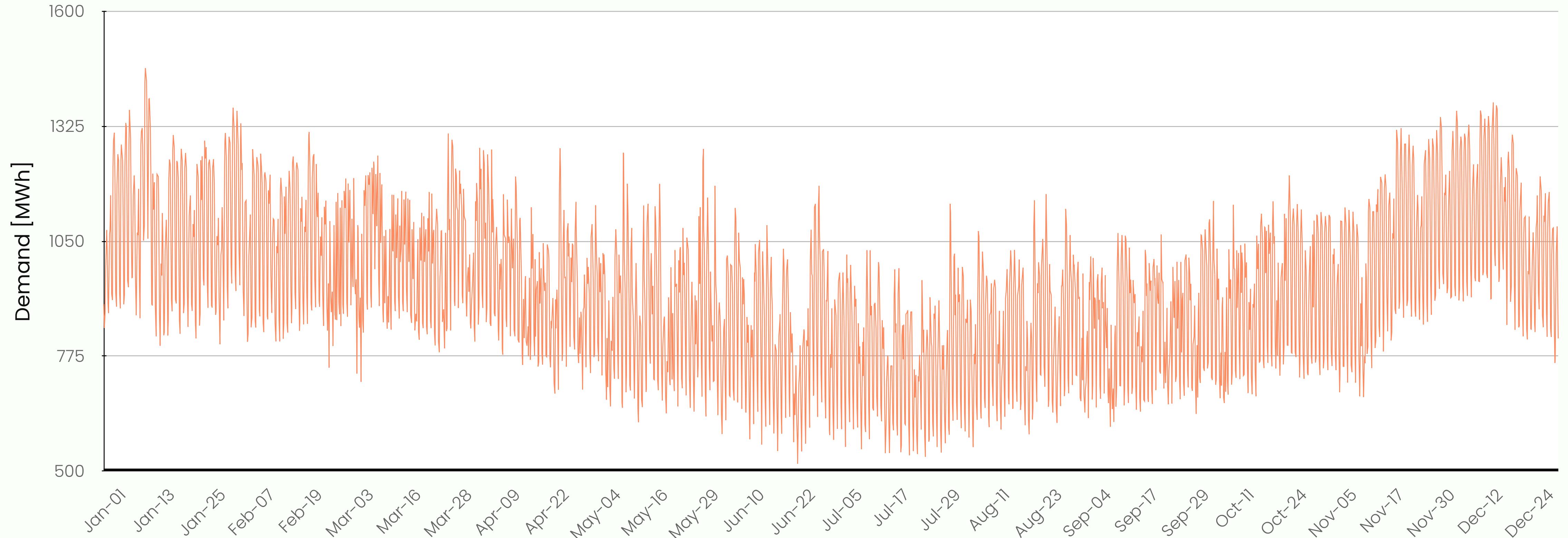
Data quality

# ELECTRICITY DEMAND IN ESTONIA, 2022



Any observations?

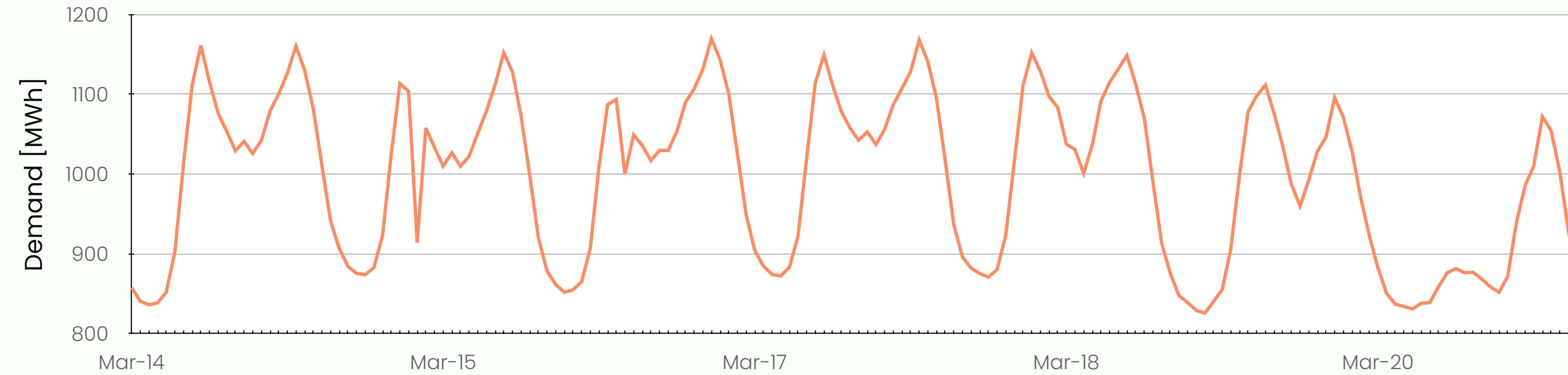
# ELECTRICITY DEMAND IN ESTONIA, 2022



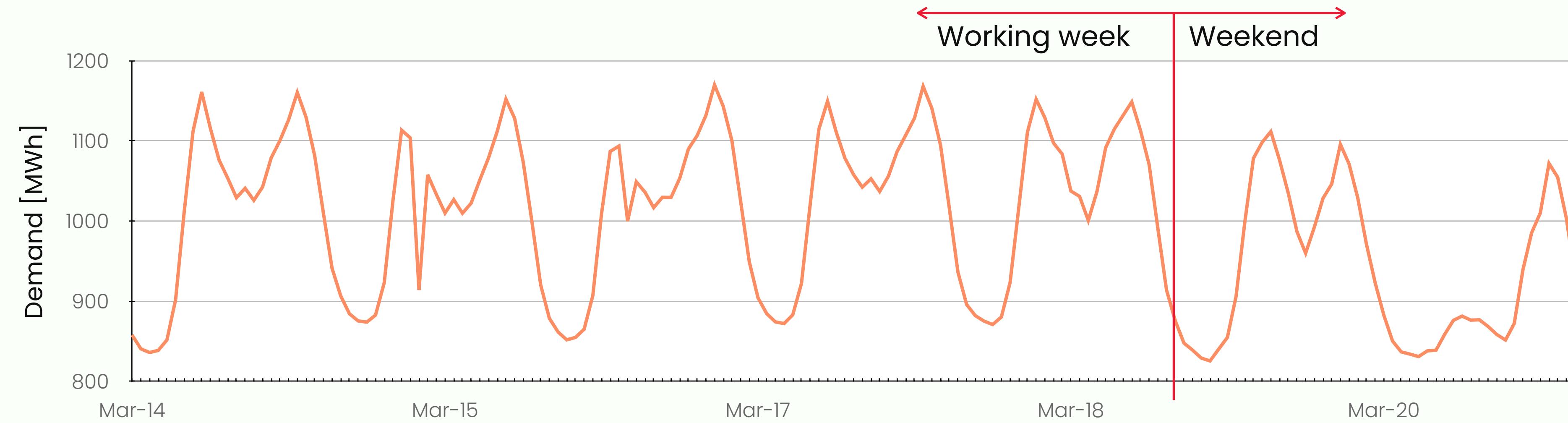
Any observations?

Seasonality!

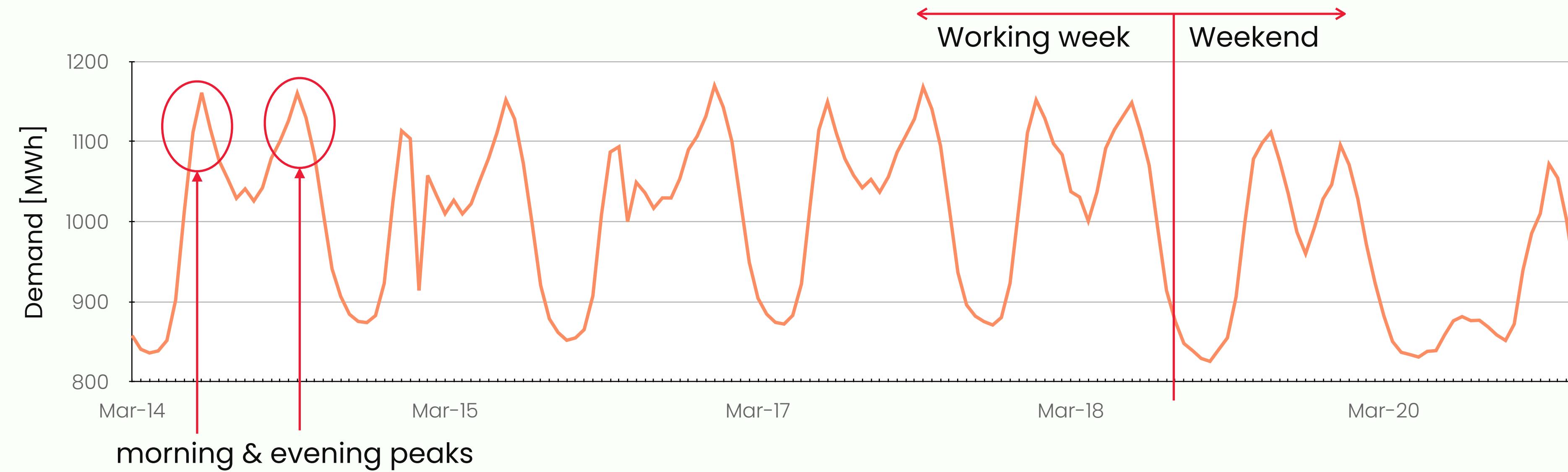
# IT'S ALL ABOUT PATTERNS



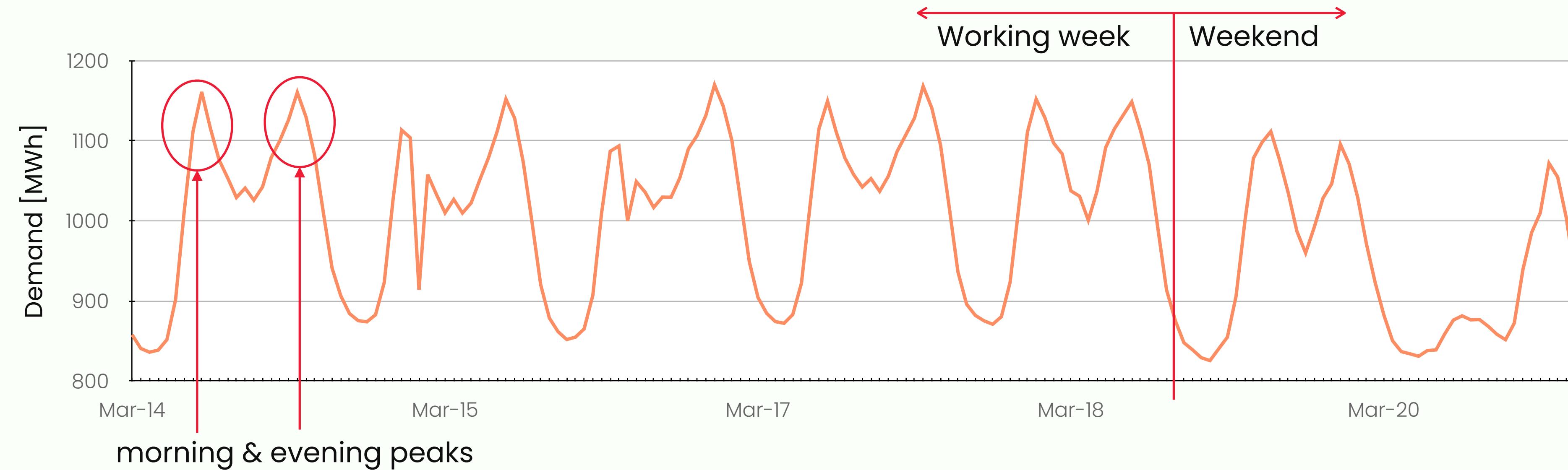
# IT'S ALL ABOUT PATTERNS



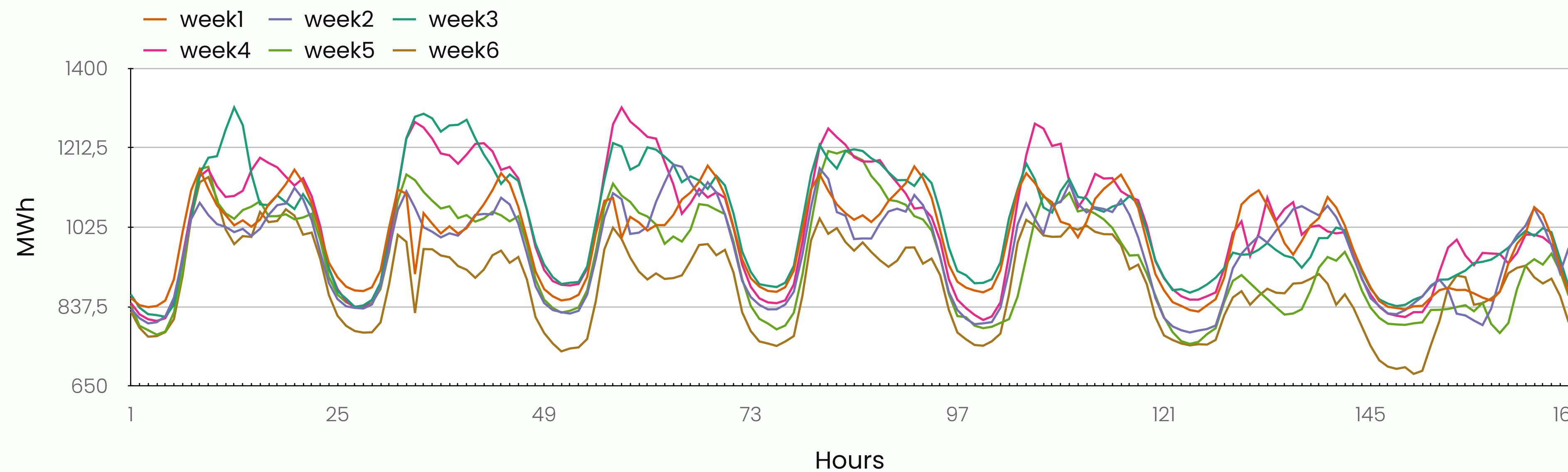
# IT'S ALL ABOUT PATTERNS



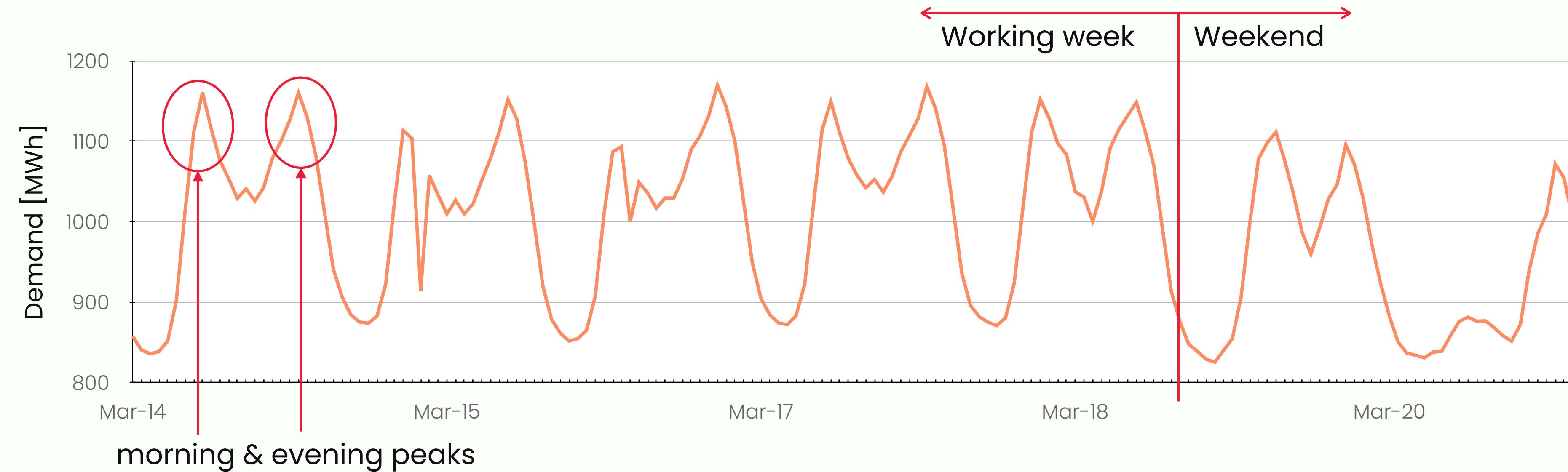
# IT'S ALL ABOUT PATTERNS



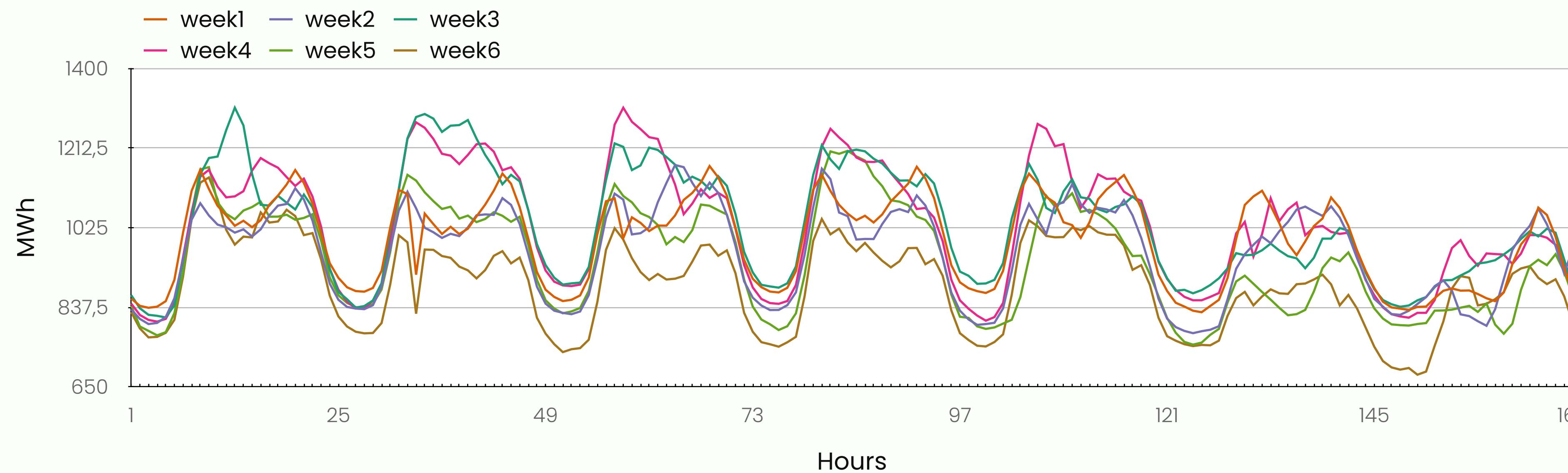
Let's plot  
several  
weeks



# IT'S ALL ABOUT PATTERNS



Let's plot  
several  
weeks

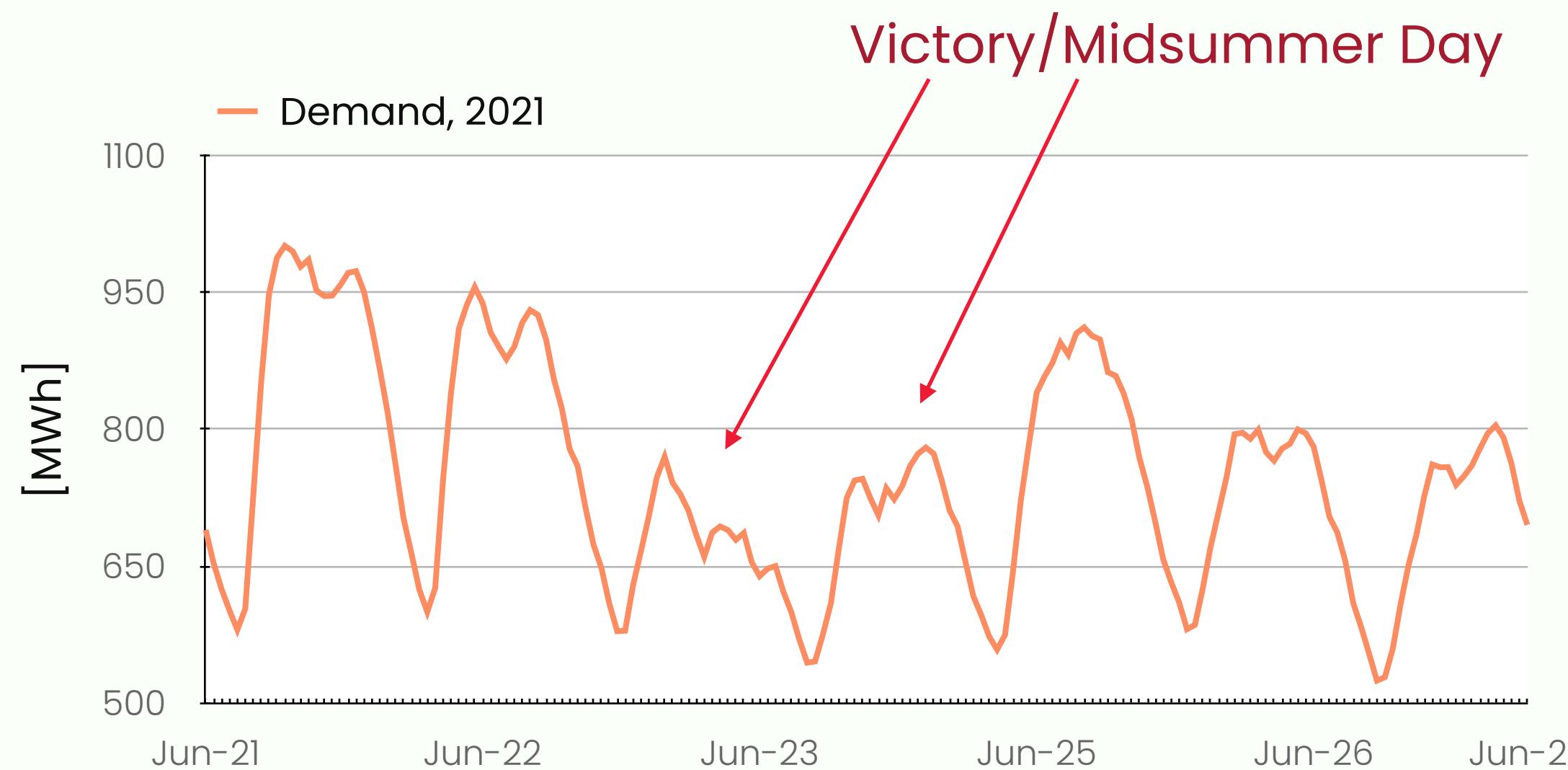


What can  
go wrong?

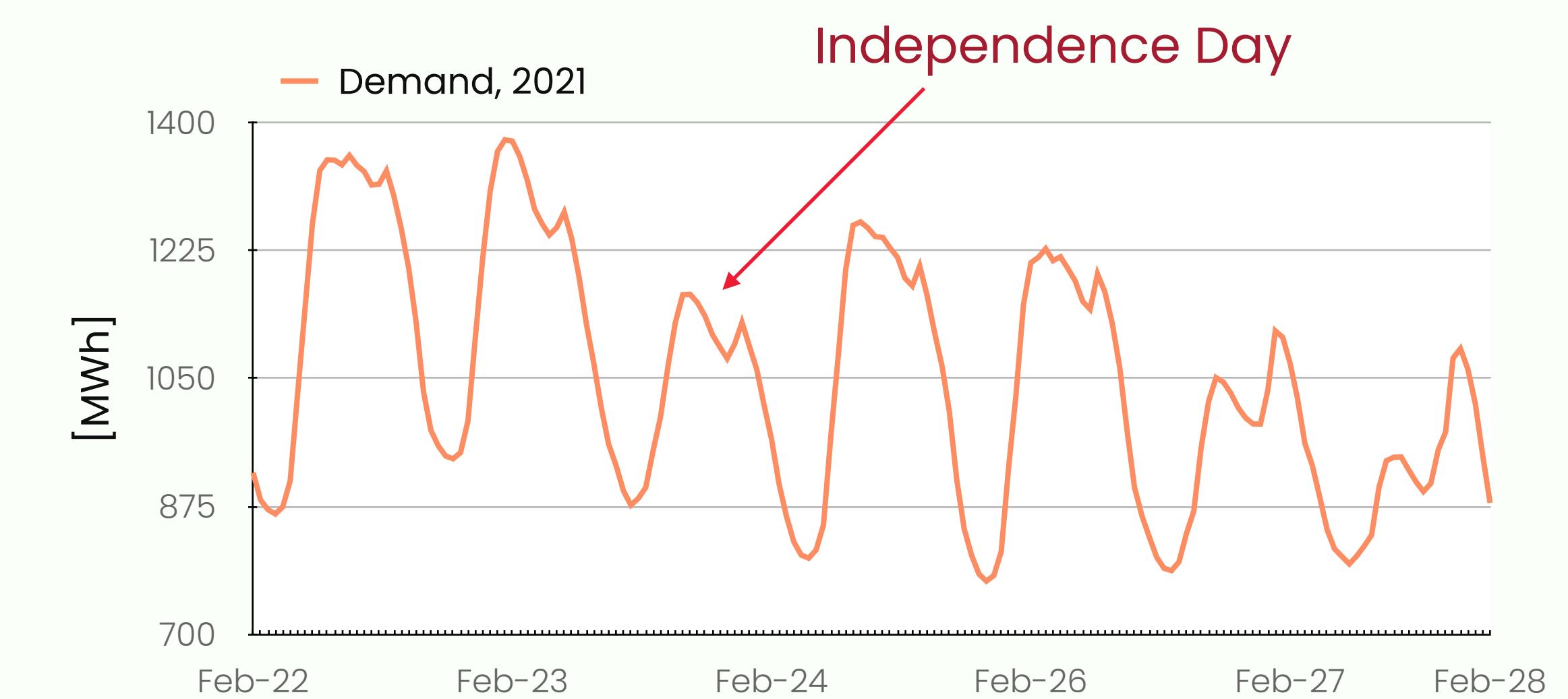
# HOLIDAYS



# HOLIDAYS



# HOLIDAYS



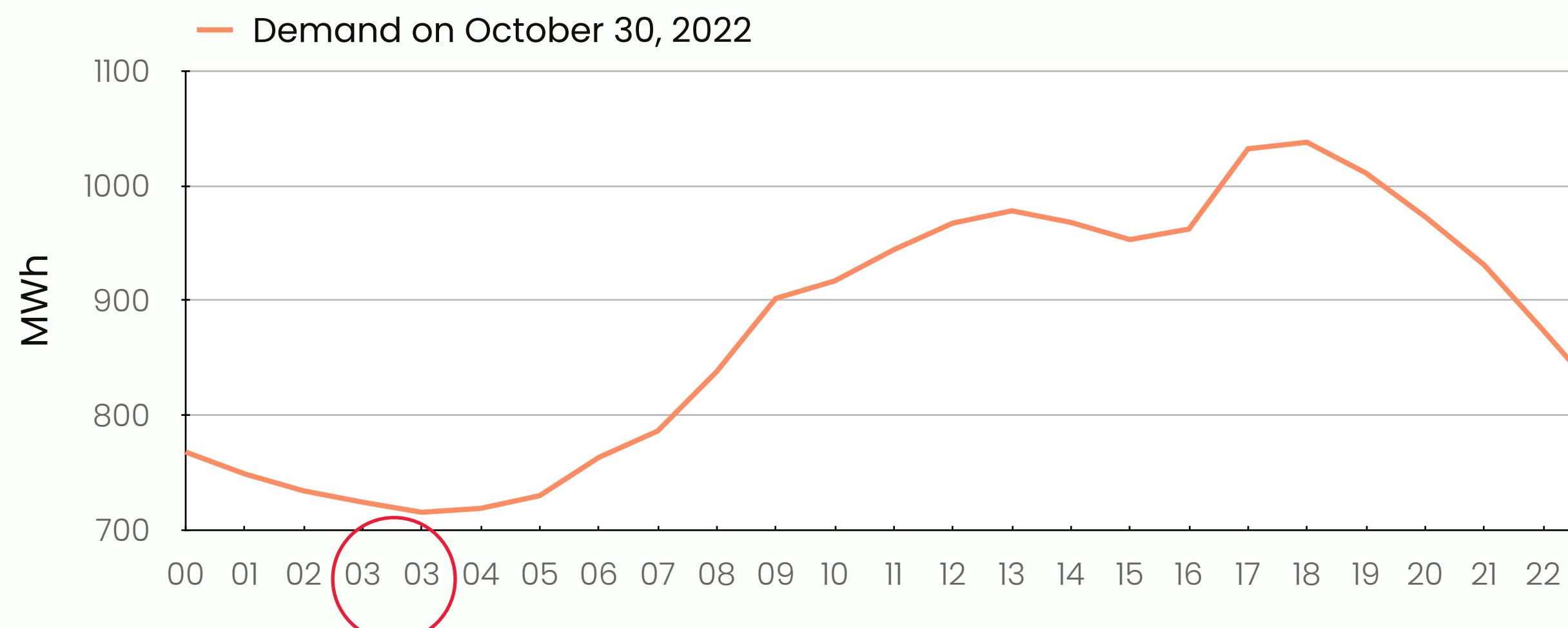
# DAYLIGHT SAVING TIME



# DAYLIGHT SAVING TIME



# DAYLIGHT SAVING TIME



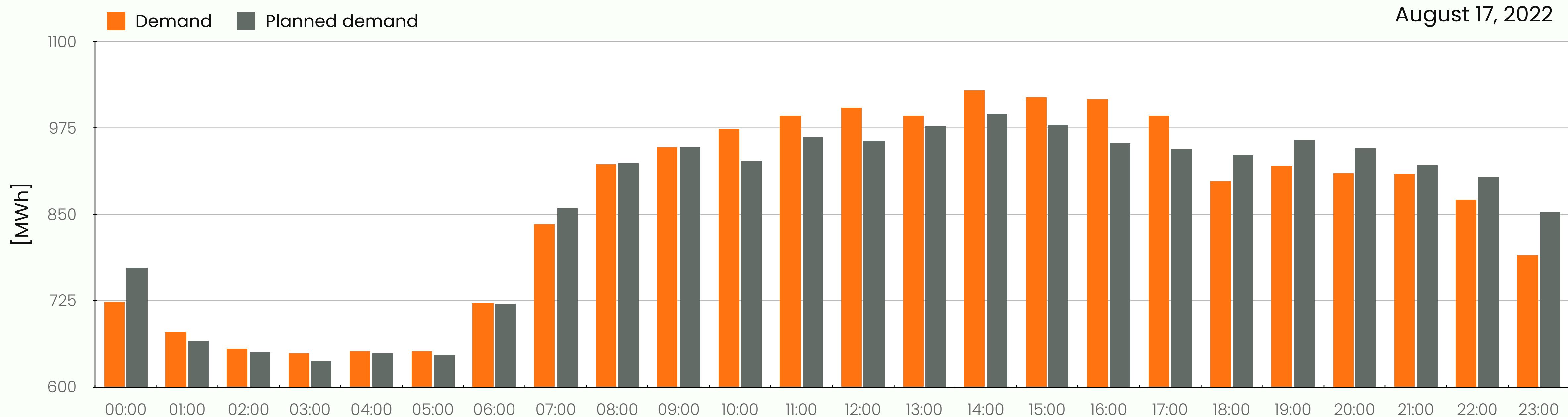
Sample of electricity production/demand data

Timestamp (UTC)	Date (Estonia time)	Consumption	Production	Planned consumption	Planned production
1648332000	27.03.2022 00:00	857	554,1	903,8	570,3
1648335600	27.03.2022 01:00	838,9	574,4	913,5	569,5
1648339200	27.03.2022 02:00	821,3	528,9	882,4	537,5
1648342800	27.03.2022 04:00	819,5	547	943,7	593,2
1648346400	27.03.2022 05:00	829,1	512,3	881,2	536
1648350000	27.03.2022 06:00	845,1	520,3	915,4	530

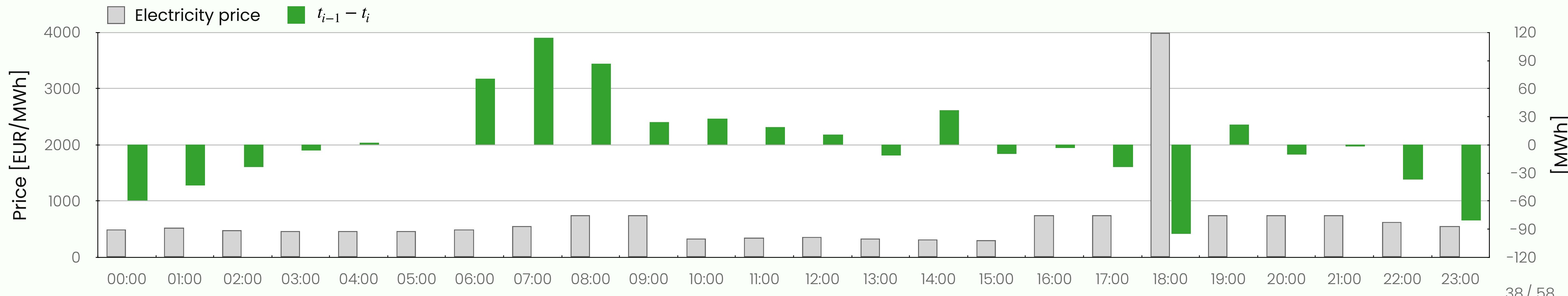
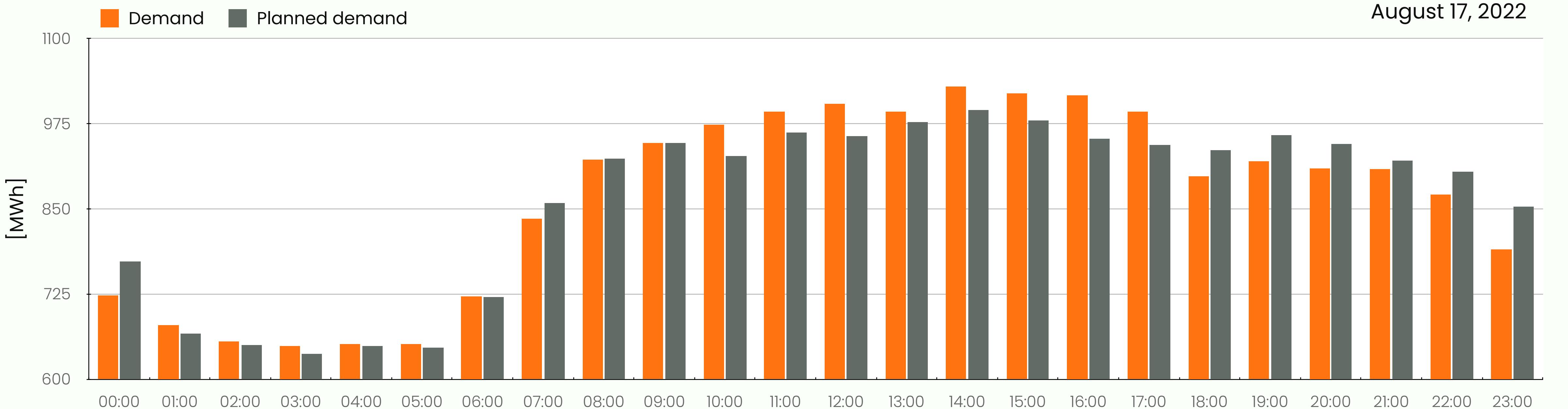
Sample of electricity production/demand data

Timestamp (UTC)	Date (Estonia time)	Consumption	Production	Planned consumption	Planned production
1667077200	30.10.2022 00:00	768	641,2	747,8	638,2
1667080800	30.10.2022 01:00	748,9	640,2	732,4	635,2
1667084400	30.10.2022 02:00	734,1	631	720,6	623,5
1667088000	30.10.2022 03:00	724,2	625,3	708,8	626,3
1667091600	30.10.2022 03:00	715,4	620,9	695,4	614,8
1667095200	30.10.2022 04:00	718,8	624,4	673,2	619,2

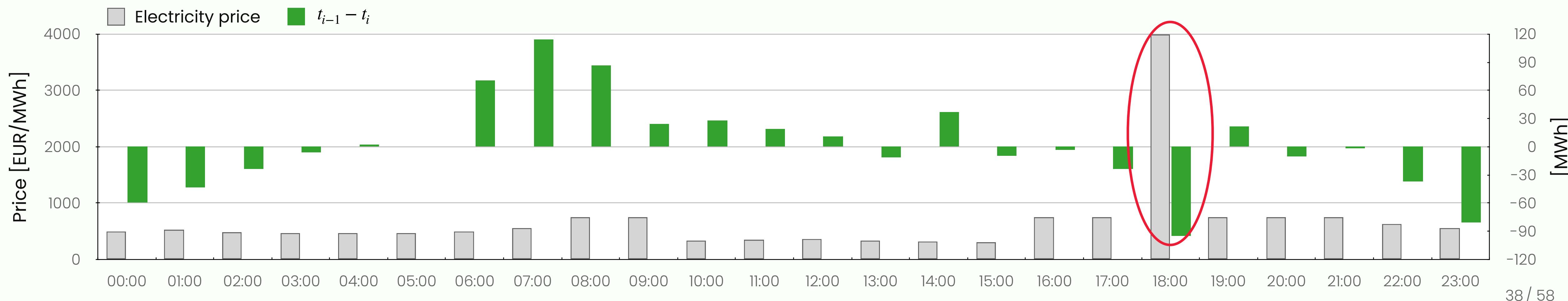
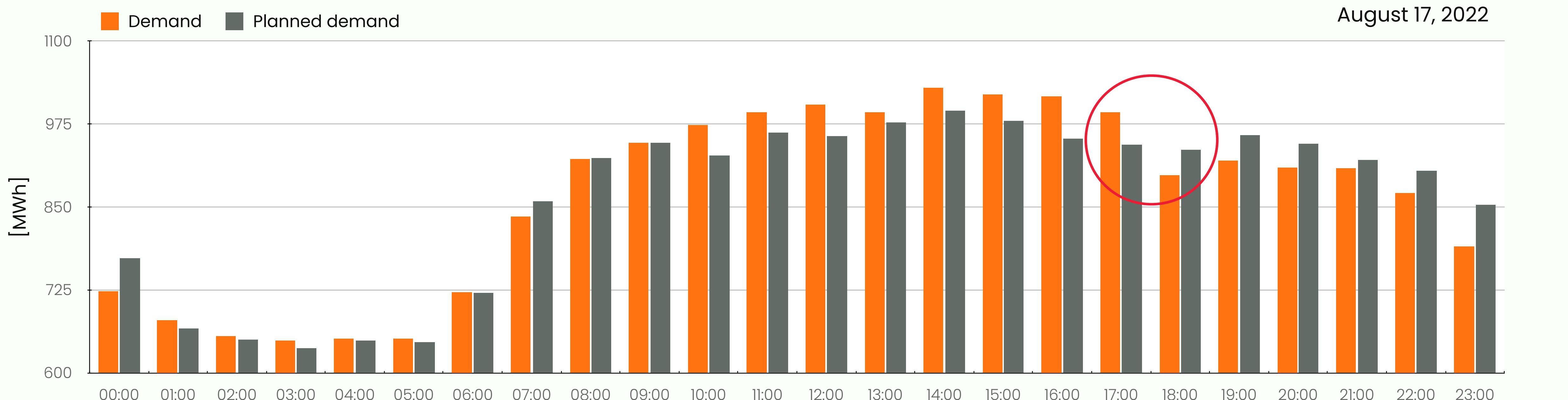
# ELECTRICITY PRICES AND MASS MEDIA



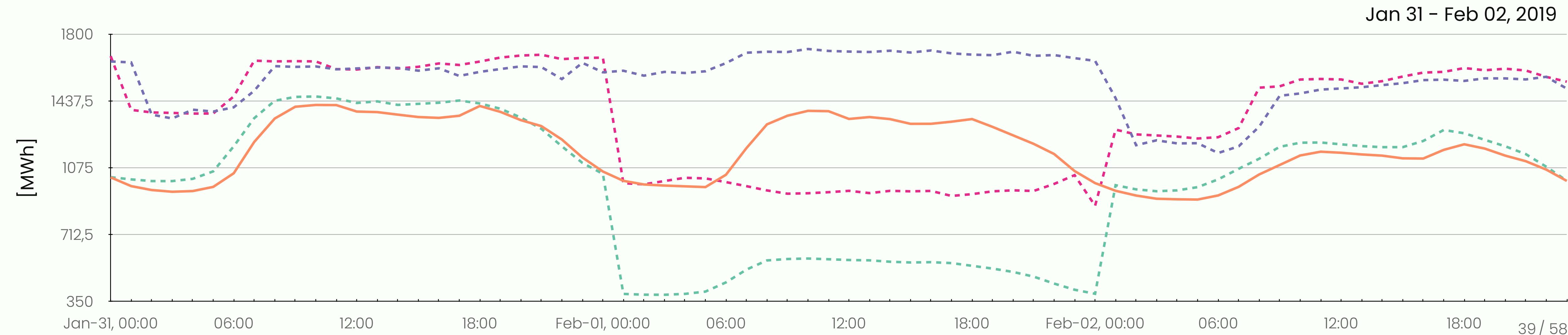
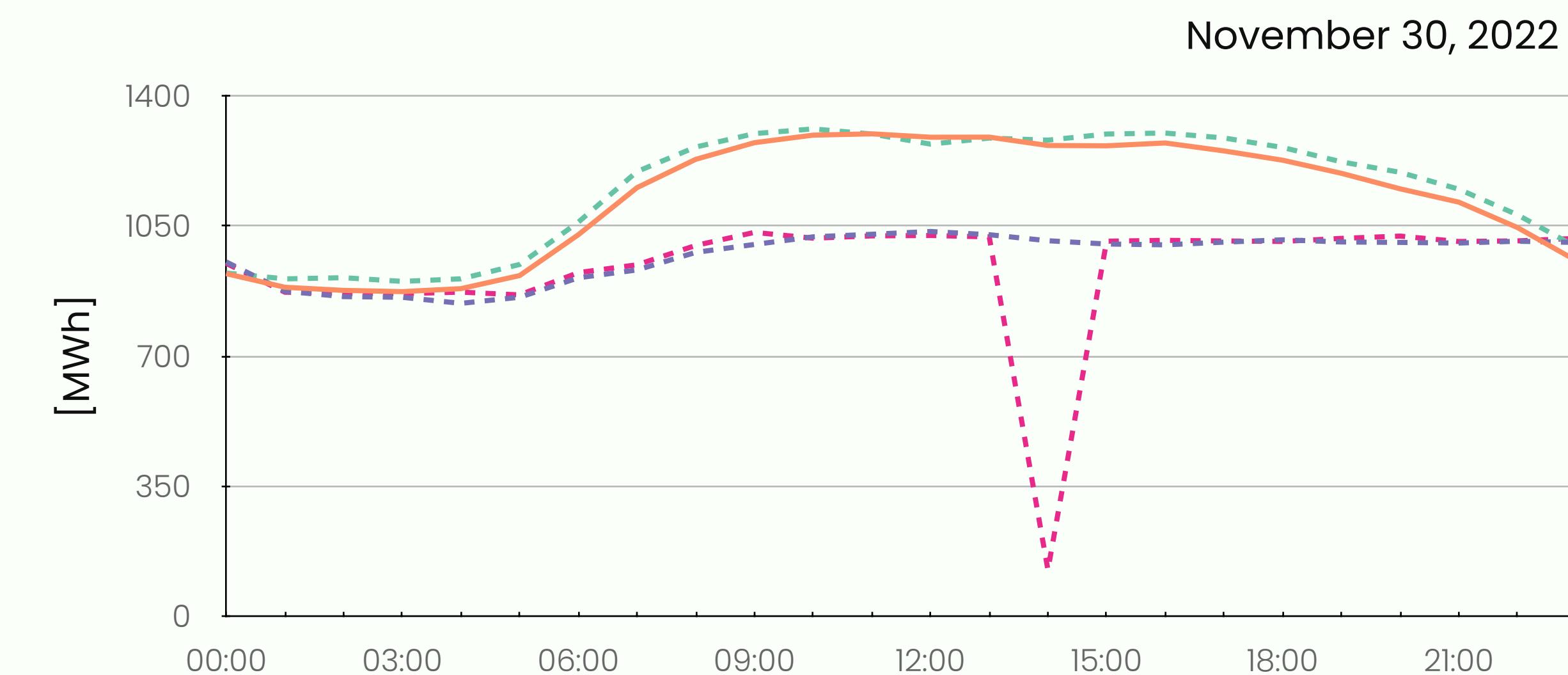
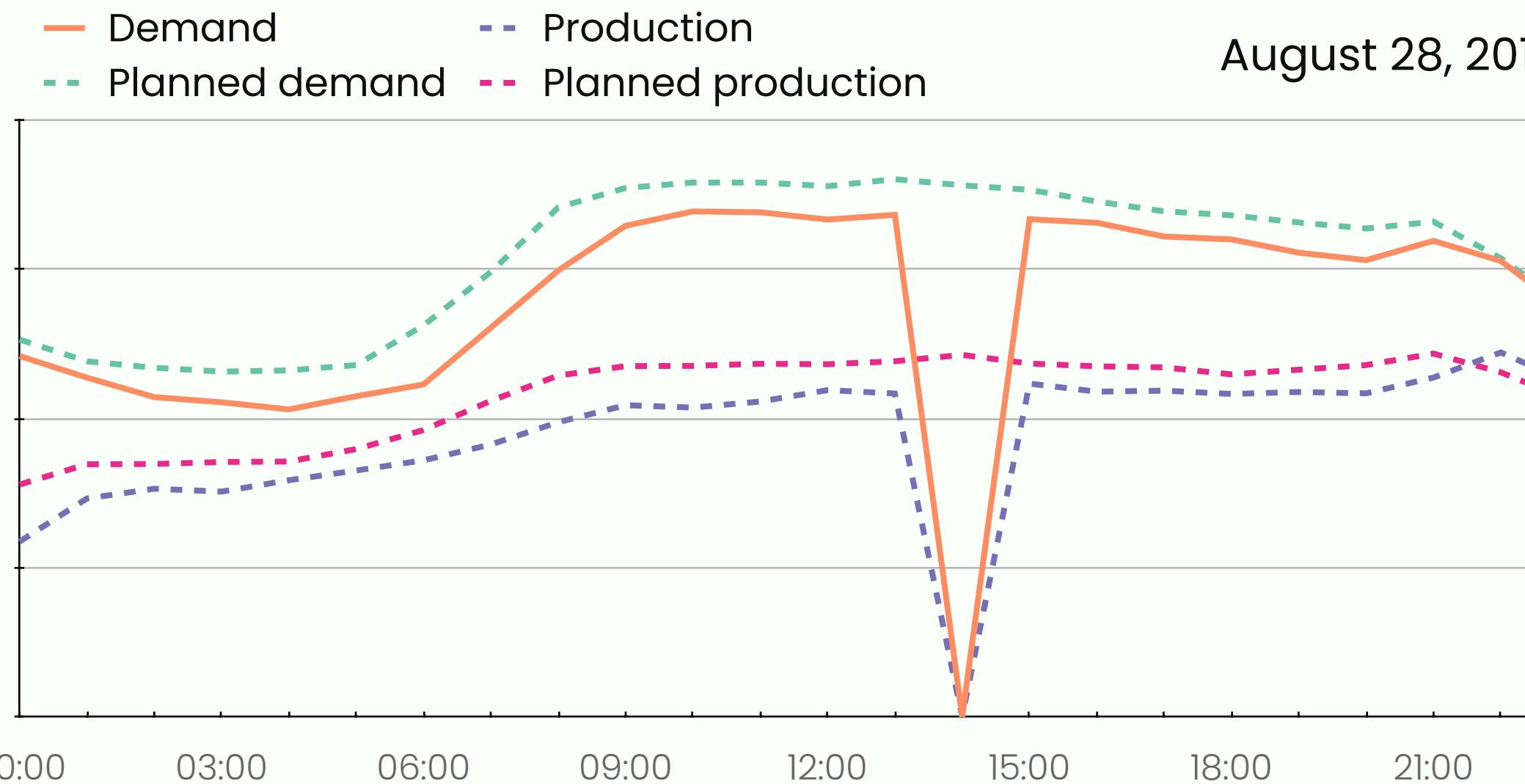
# ELECTRICITY PRICES AND MASS MEDIA

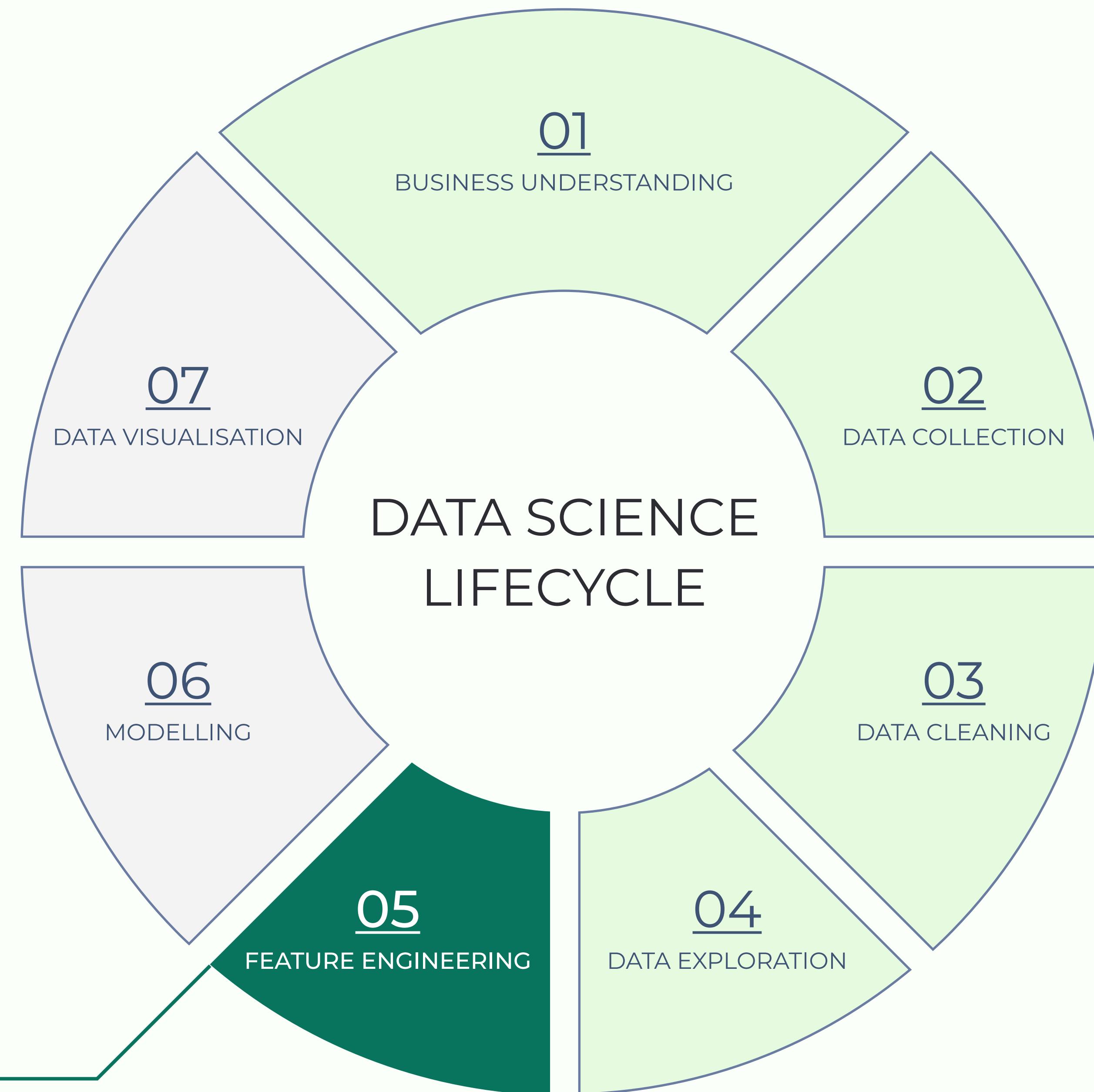


# ELECTRICITY PRICES AND MASS MEDIA



# SUSPICIOUS DATA/OUTLIERS





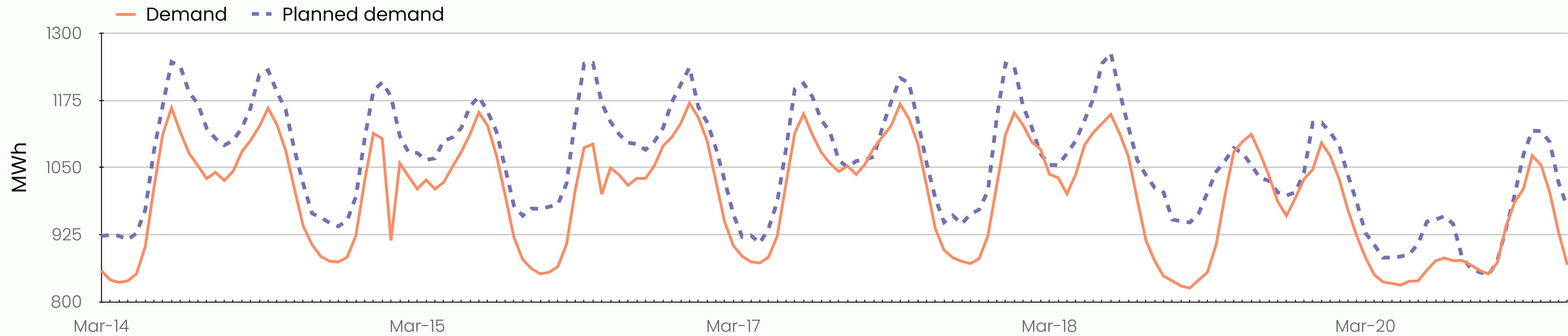
Select important features and  
construct more meaningful ones.

# SUMMARY OF FEATURE ENGINEERING

Feature engineering involves the following main steps:

1. Data exploration and understanding to identify relevant features and potential issues.
2. Data preprocessing, including handling missing values, scaling, normalisation, and encoding categorical features.
3. Feature selection to identify the most relevant features for the model.
4. Feature transformation to create new features or derive more meaningful features from existing ones.

# WHAT FEATURES CAN BE RELEVANT?



A shot list on possible features:

- ▶ Previous electricity consumption: a day, a week ago
- ▶ Weather: temperature, irradiation, wind direction/speed, humidity
- ▶ Day length: sunset/sunrise
- ▶ Weekday
- ▶ Hour of the day
- ▶ Electricity price



# GENERATE NEW FEATURES

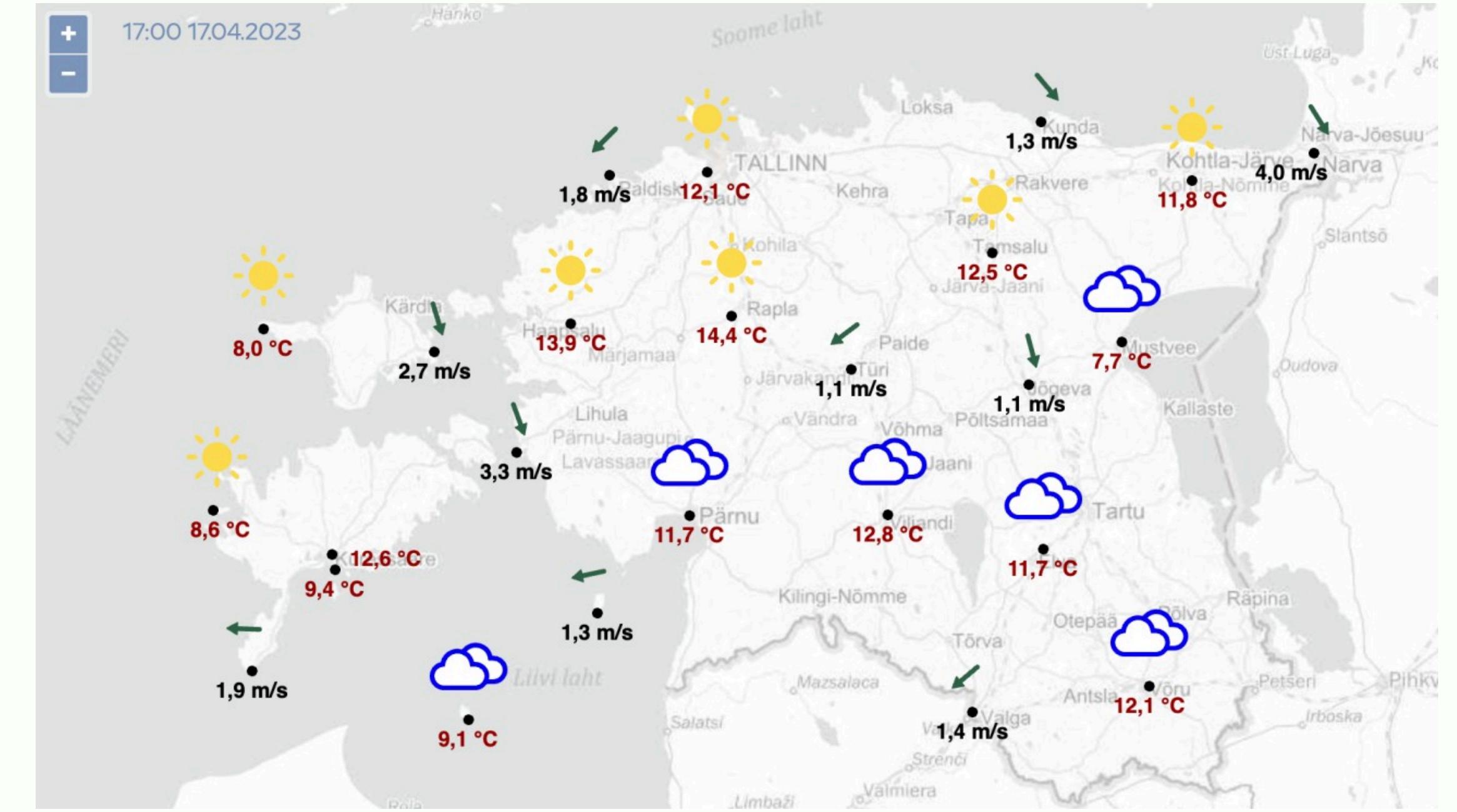
Temperature:

- average
- average + difference
- weighted average (population, correlation)
- heating/cooling degree-day

Wind:

- windchill (temperature + wind)
- FeelsLike (RealFeel):  
temperature + wind + humidity + pressure

Clouds + Sun

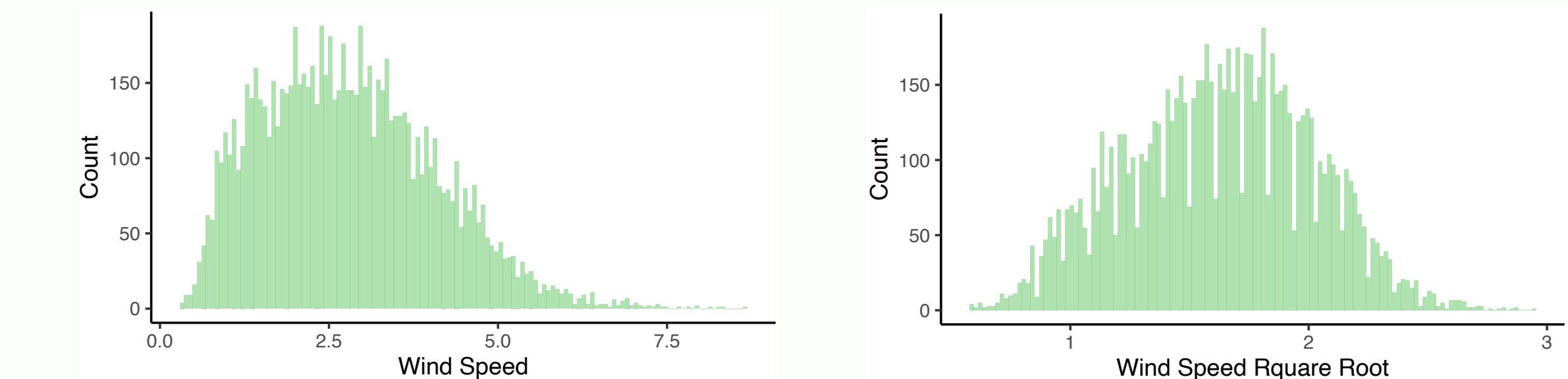
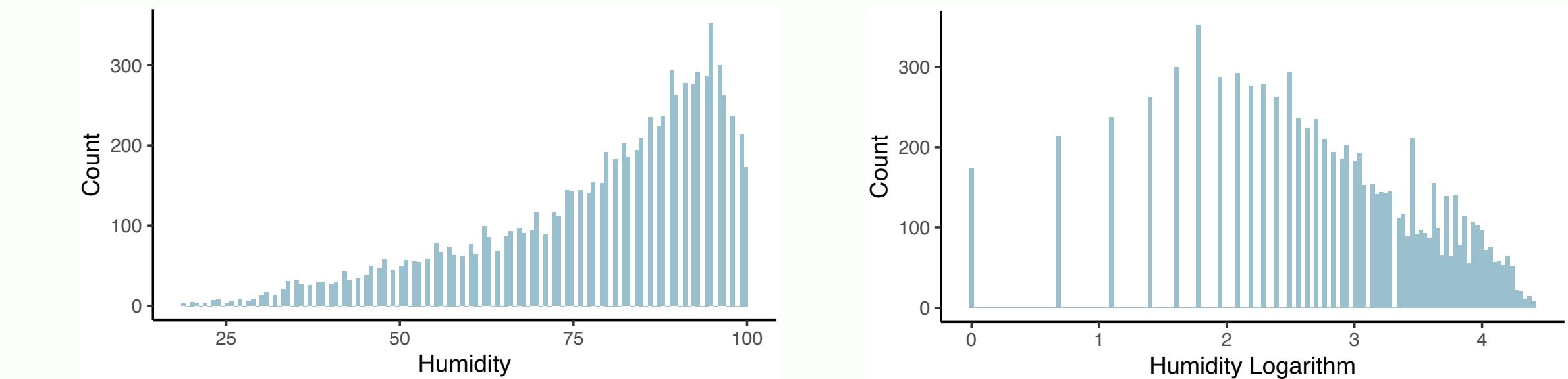
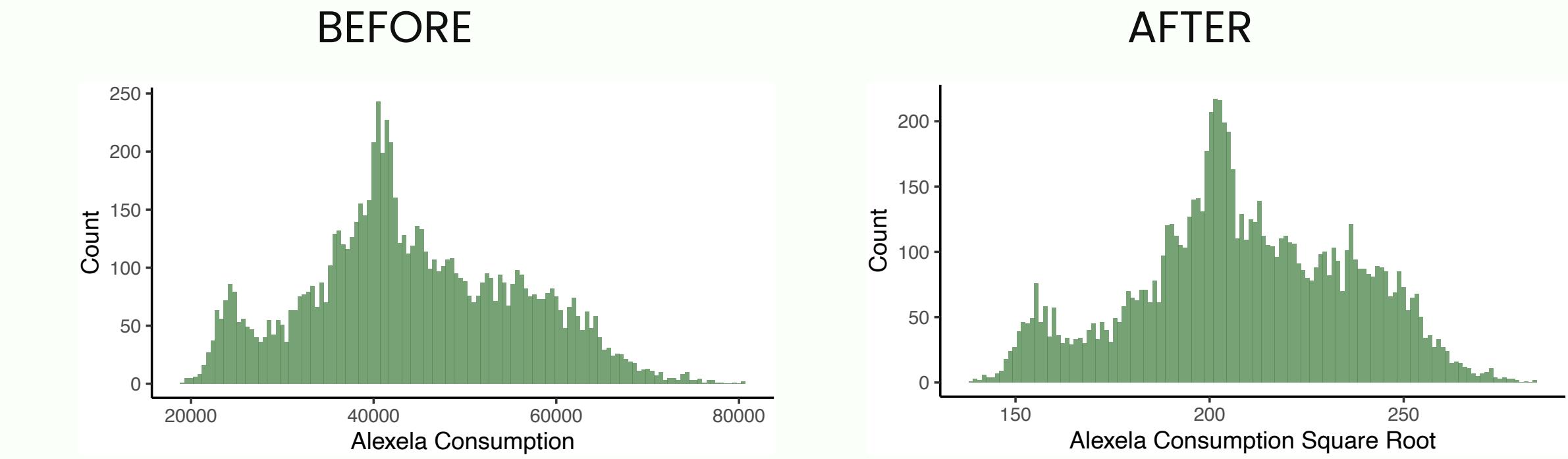


# DATA TRANSFORMATION

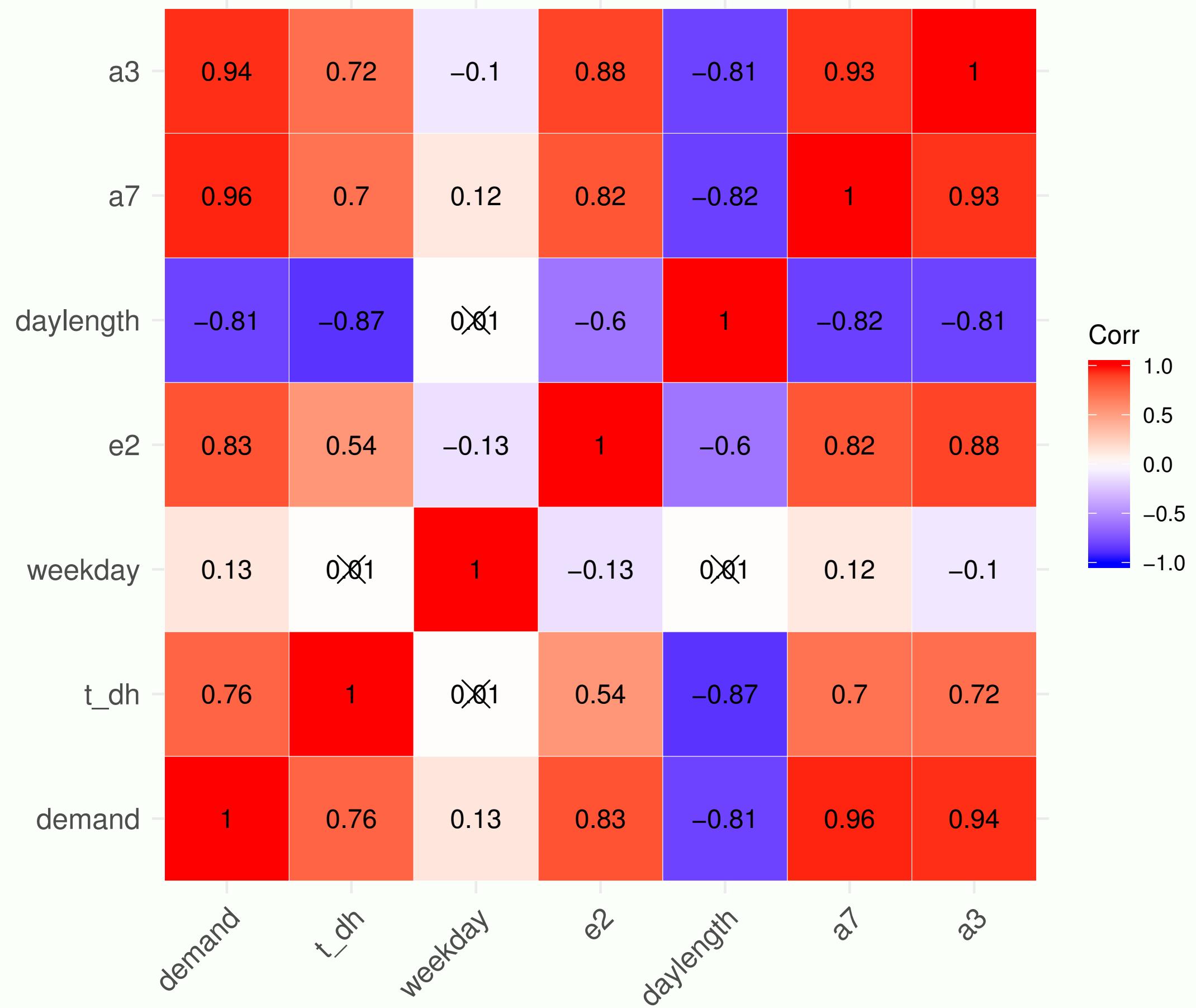
Data transformation is the process of converting raw data into a format or structure more appropriate for model building and data exploration.

Popular methods include, but not limited to:

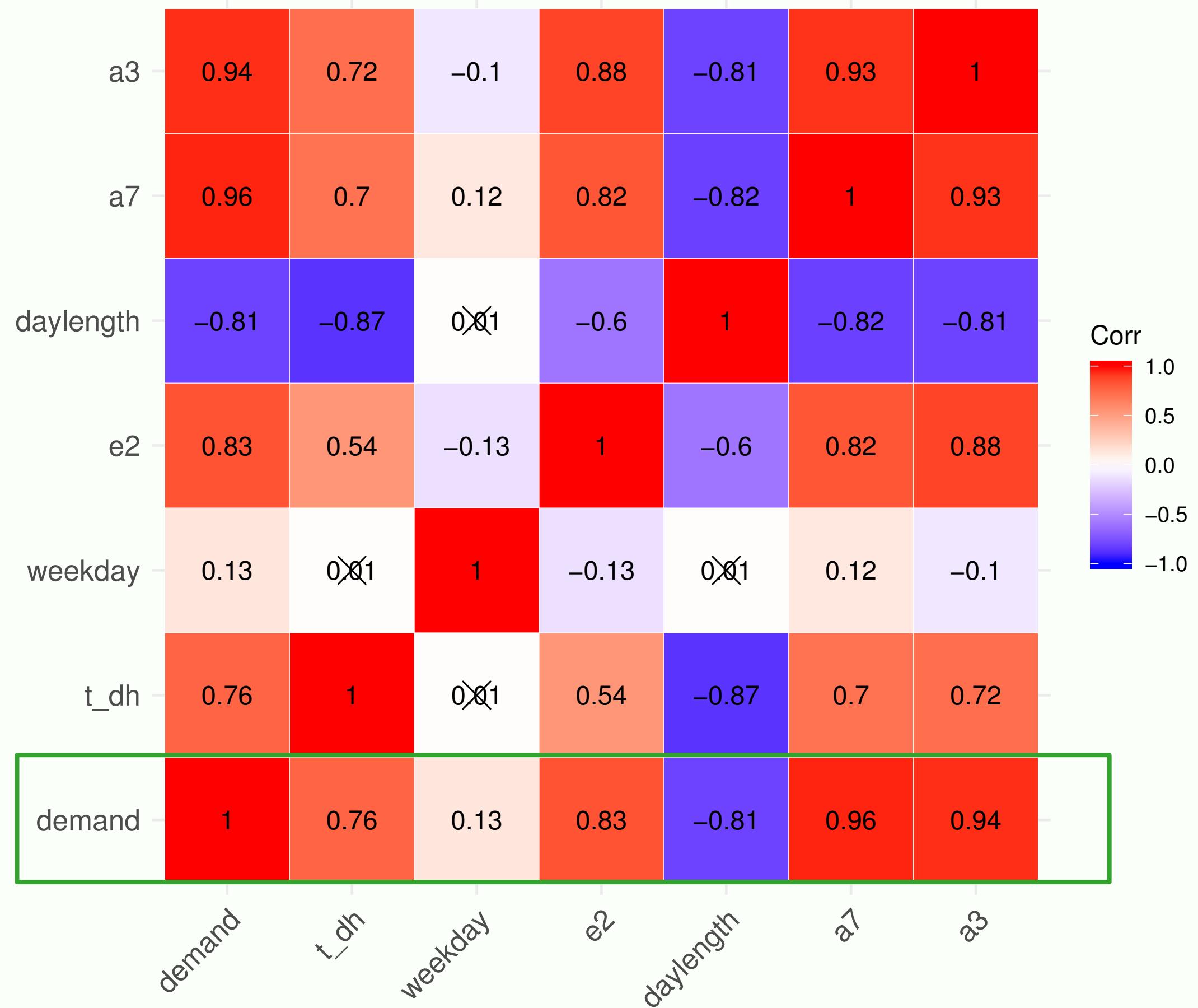
- Log transform
- Square transform
- Square root transform
- Box Cox transform
- Scaling: min-max, standardisation, robust scaler, decimal



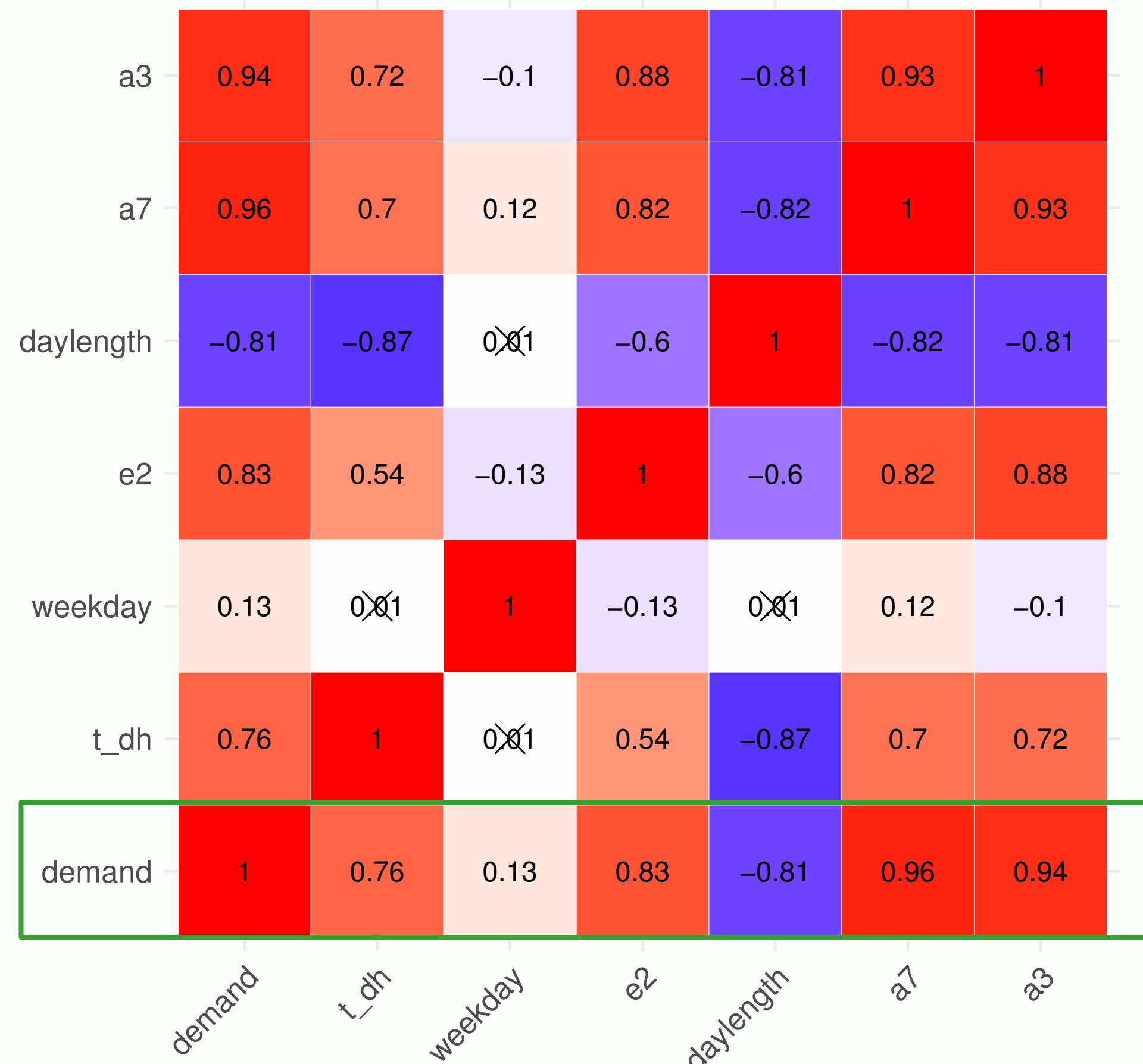
# CHECK WHICH FEATURES ARE IMPORTANT



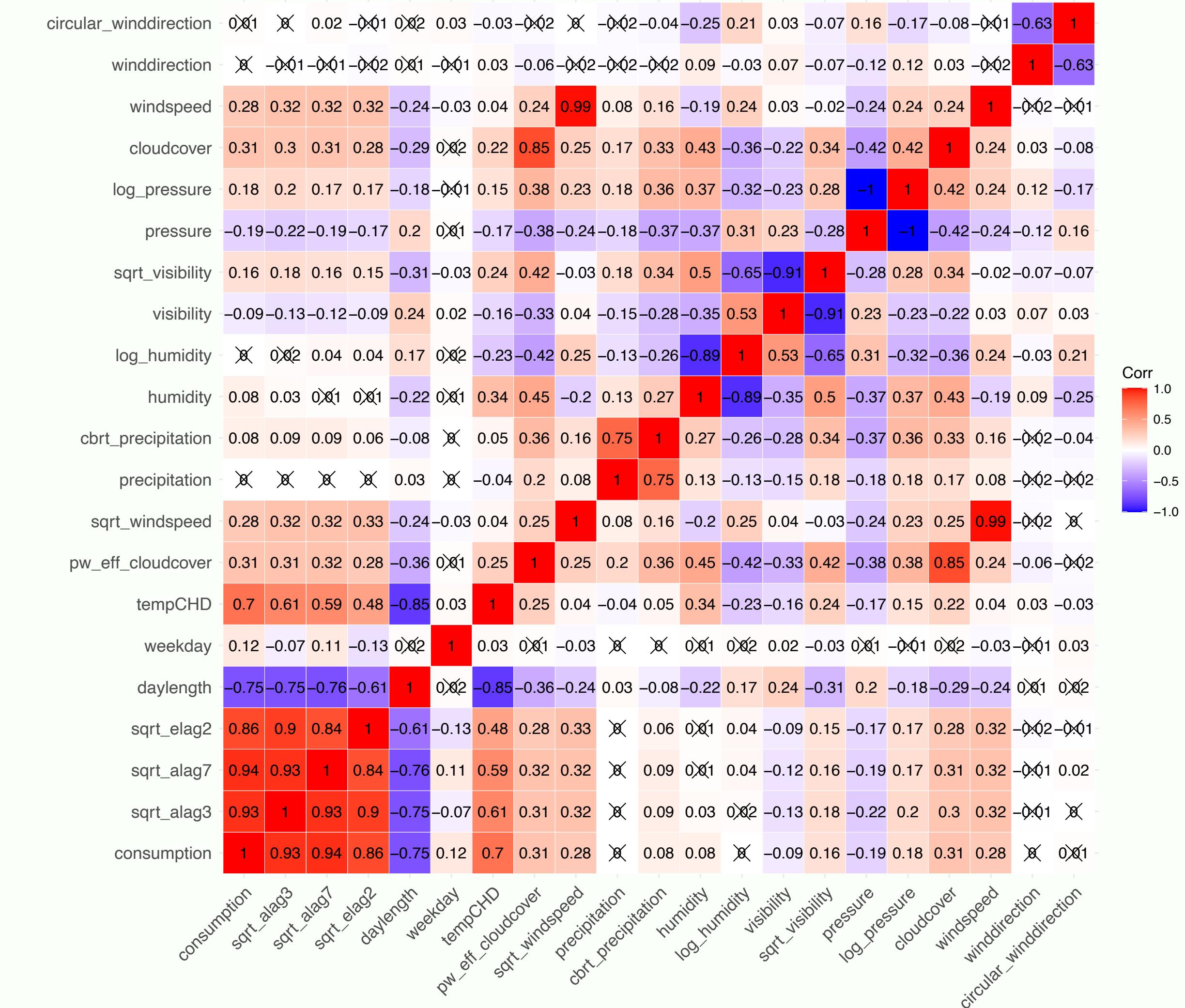
# CHECK WHICH FEATURES ARE IMPORTANT

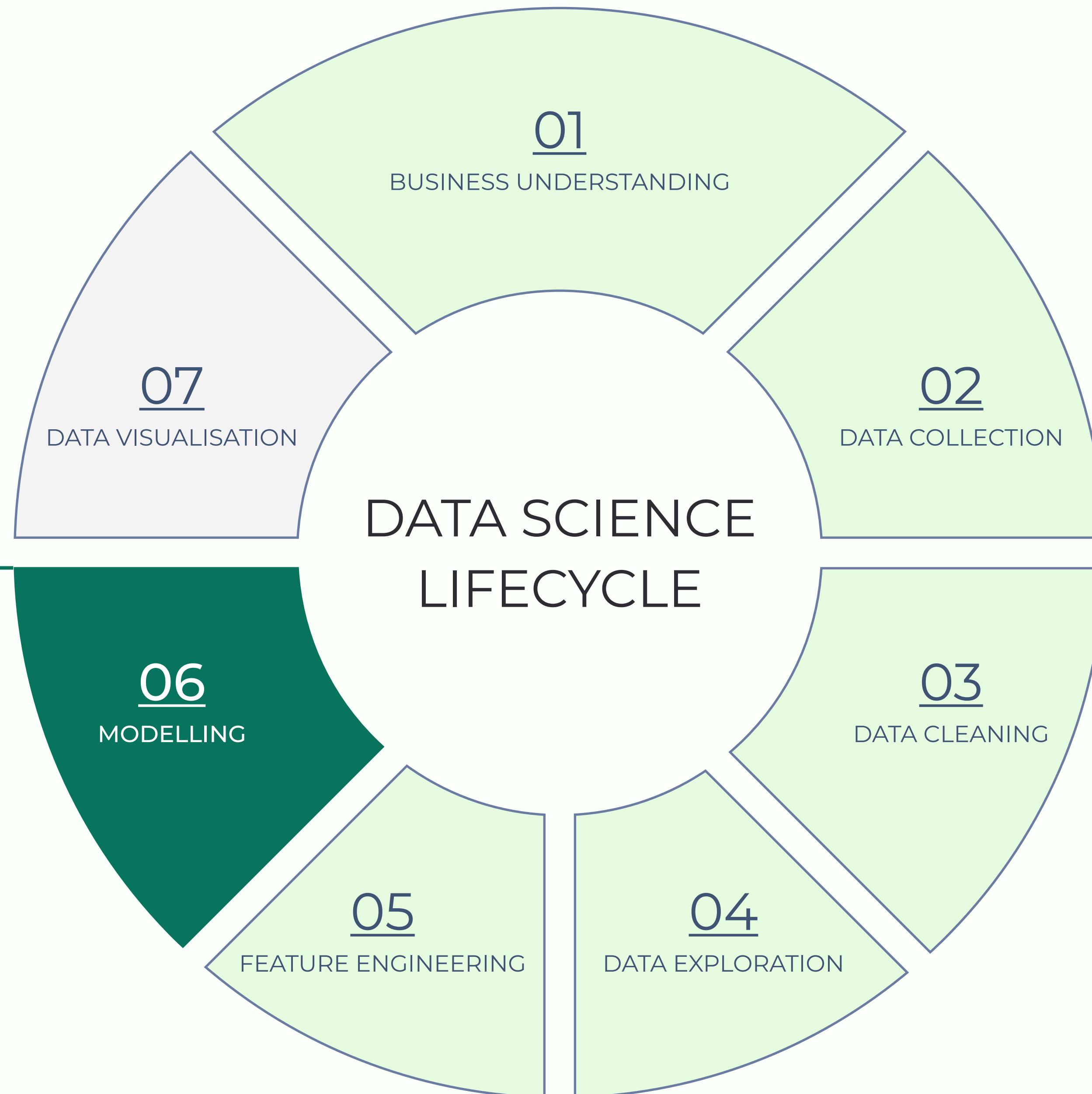


# CHECK WHICH FEATURES ARE IMPORTANT

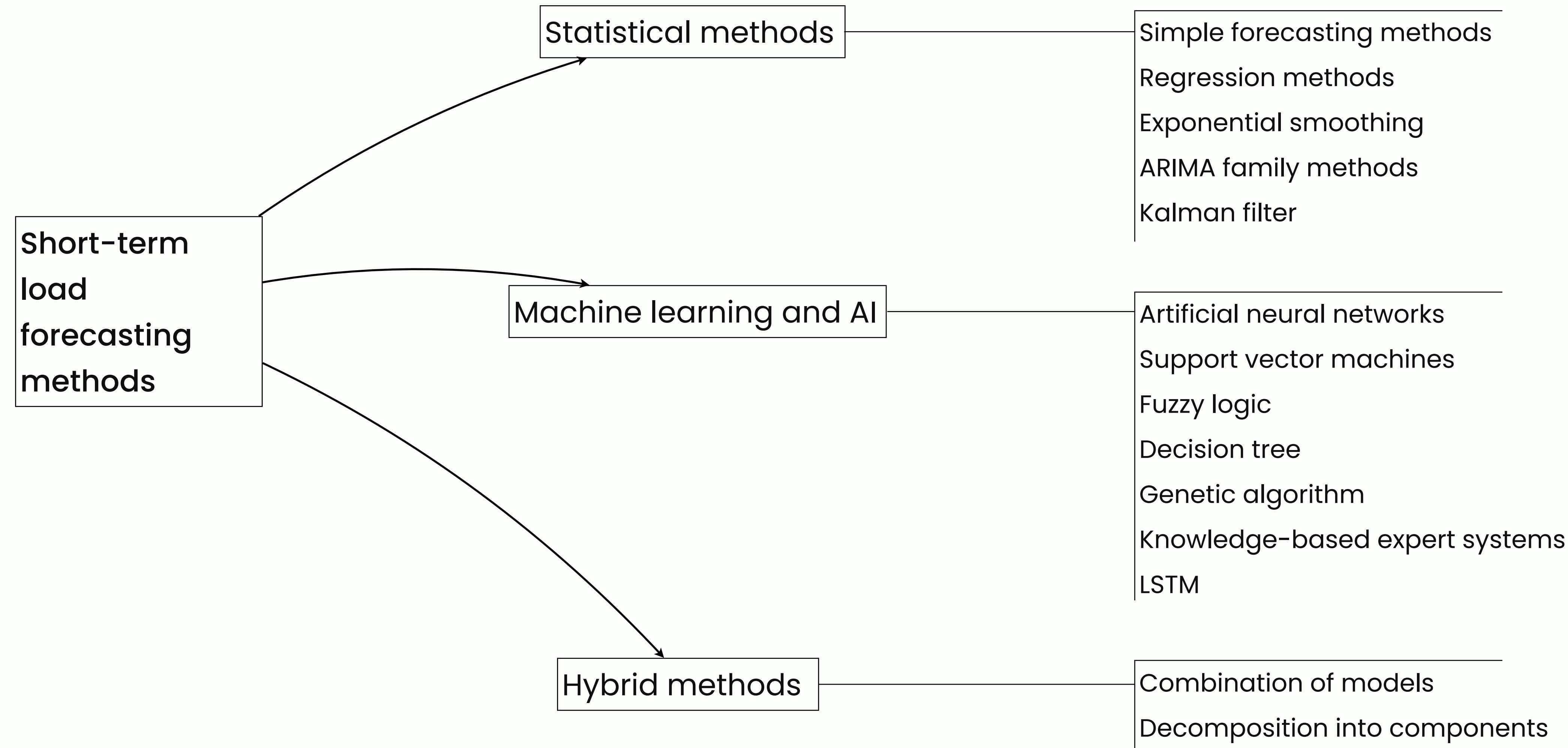


Corr





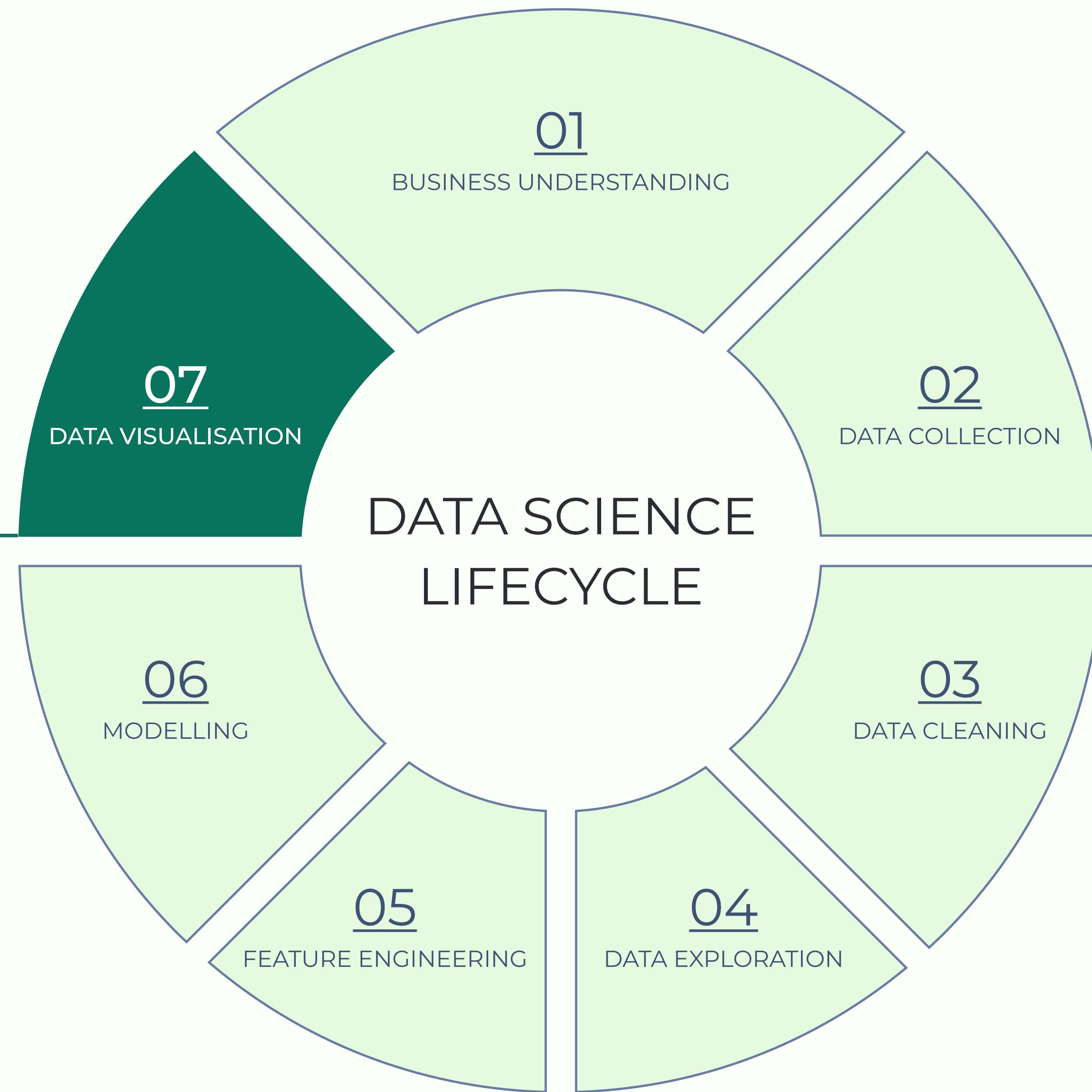
# OVERVIEW OF THE MODELLING TECHNIQUES



# MODELLING

We will skip this step for now  
and will return to it in the  
upcoming lectures.

Communicate the findings with key people using plots and interactive visualisations.



# COMMUNICATE YOUR RESULTS

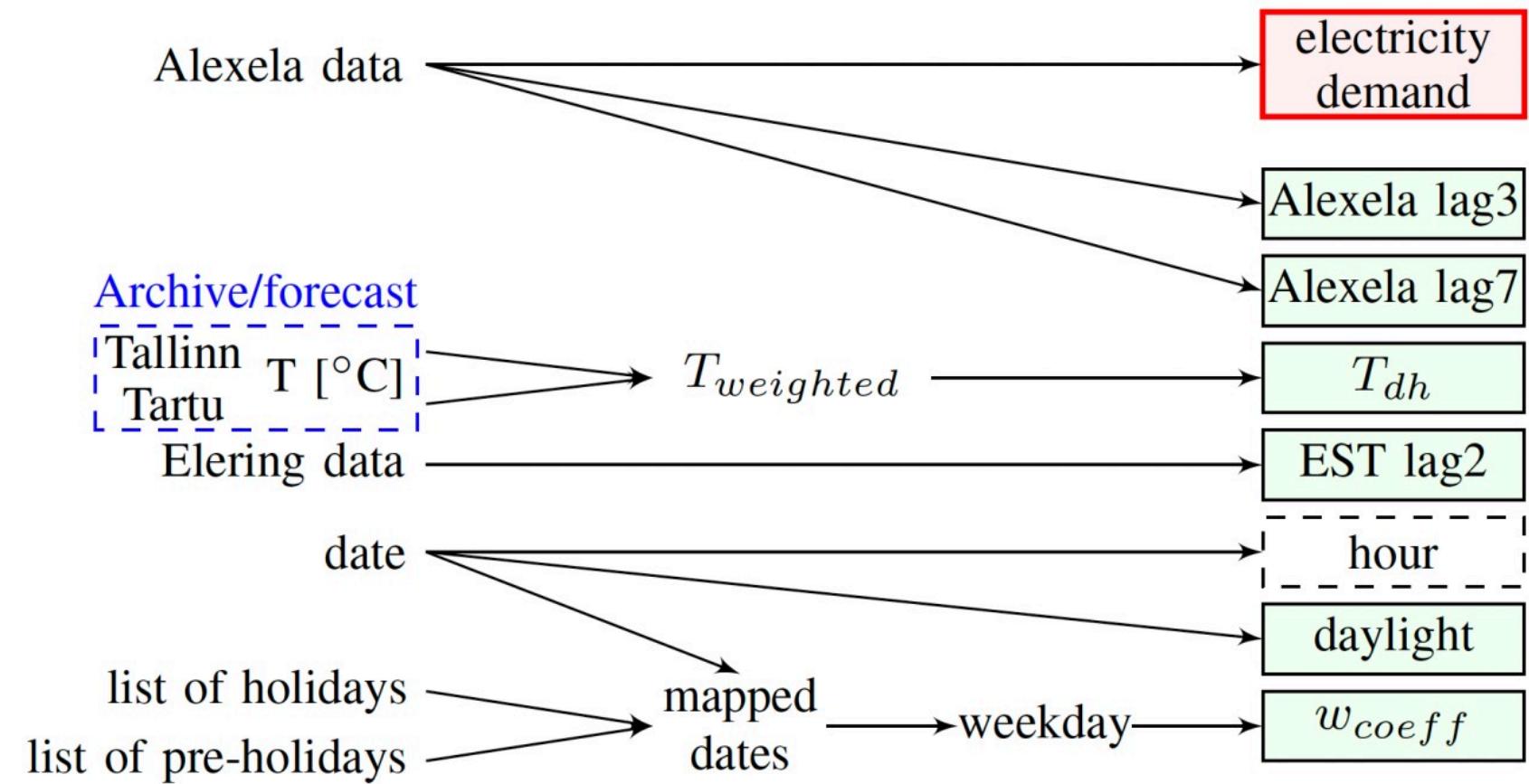


Fig. 5: Relations between different factors revealed by the feature analysis.

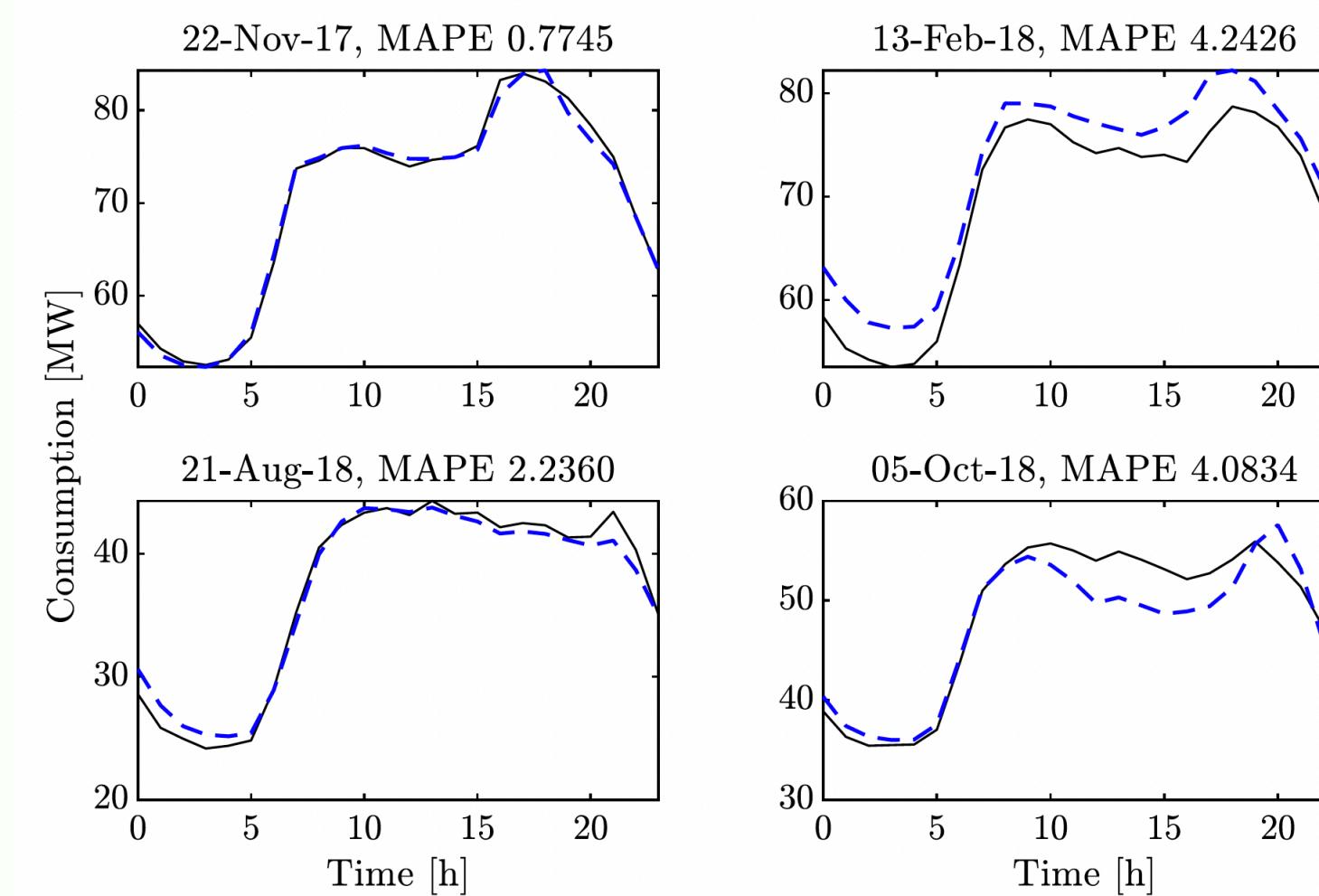


Fig. 8: Real ('—') and predicted ('---') electricity consumption for several representative days within the test set.

TABLE II: Validation Results: Monthly MAPE

Year/Month		Proposed	Var1	Var2	Var3	Var4
2017	November	1.959	2.589	2.562	2.578	3.791
	December	2.358	3.39	3.104	3.39	4.009
2018	January	2.829	4.561	4.782	4.561	7.183
	February	4.412	4.654	4.444	4.654	5.808
	March	4.217	5.046	5.236	5.046	8.779
	April	2.73	3.823	3.725	3.951	8.563
	May	3.235	4.066	4.065	4.722	4.453
	June	4.001	4.376	4.635	4.474	4.246
	July	3.779	4.282	4.509	4.177	4.317
	August	2.949	3.735	4.081	3.95	3.661
	September	3.968	4.498	4.71	4.497	4.964
	October	3.629	4.172	4.43	4.663	7.744
	Total	<b>3.339</b>	<b>4.099</b>	<b>4.19</b>	<b>4.222</b>	<b>5.626</b>

<sup>a</sup>Var1 has all 6 features, except  $w_{tln} = w_{trt} = 0.5$  in  $T_{dh}$ .

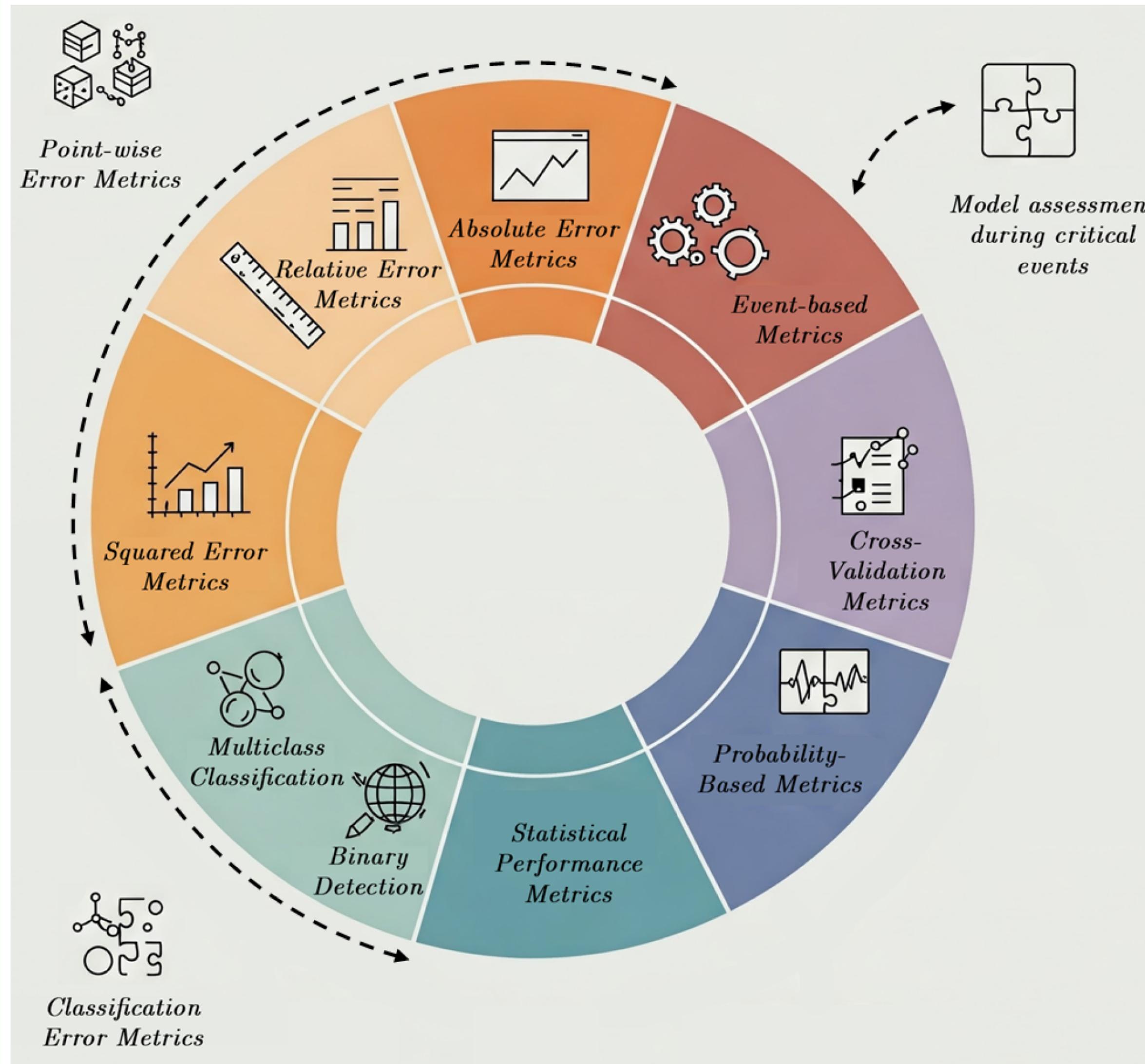
<sup>b</sup>Var2 has 5 features:  $a_3$ ,  $a_7$ ,  $e_2$ ,  $T_{dh}$ , and daylight.

<sup>c</sup>Var3 has all 6 features, but  $T_{dh}$  is replaced by  $(T_{tln} + T_{trt})/2$ .

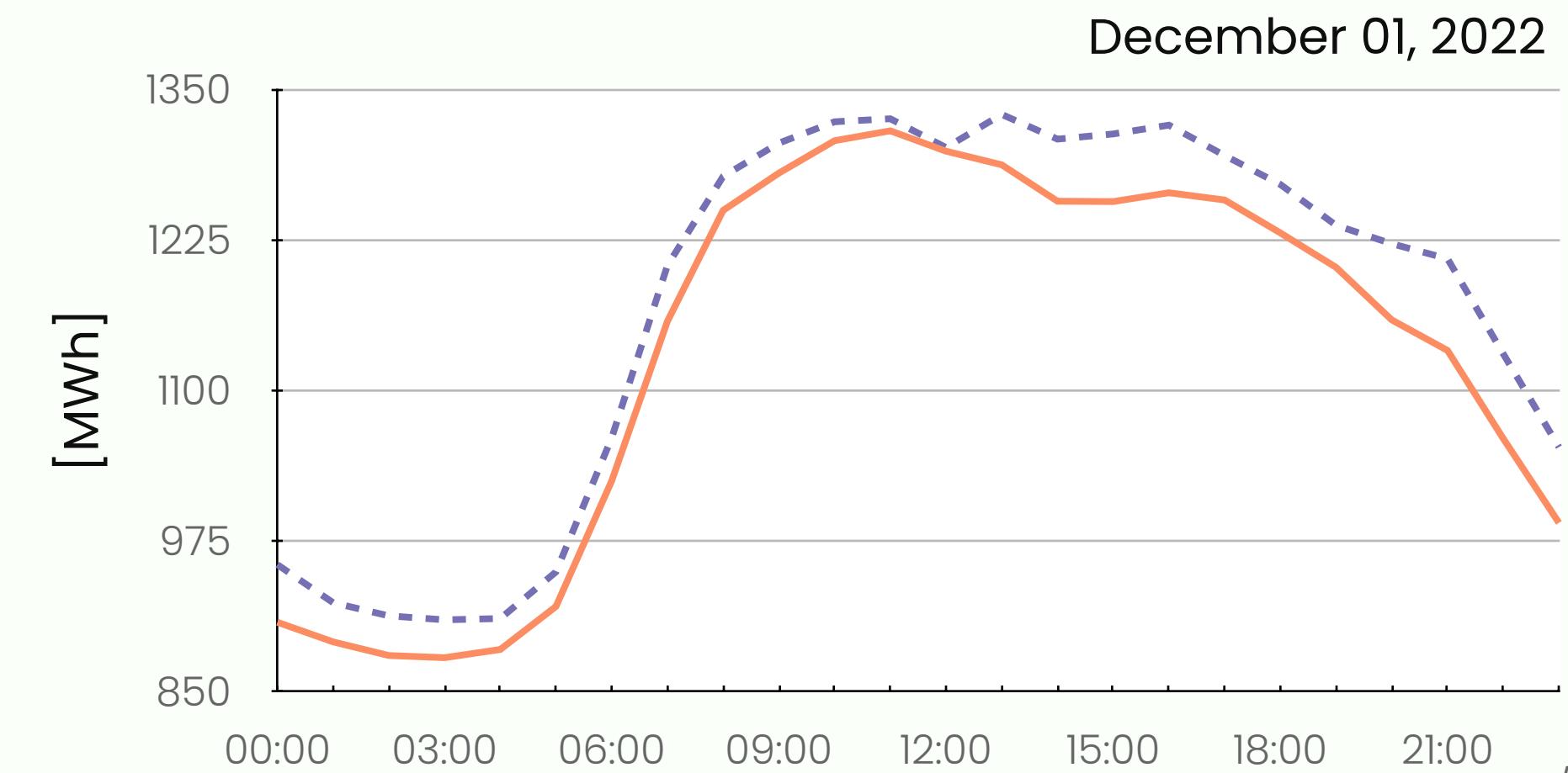
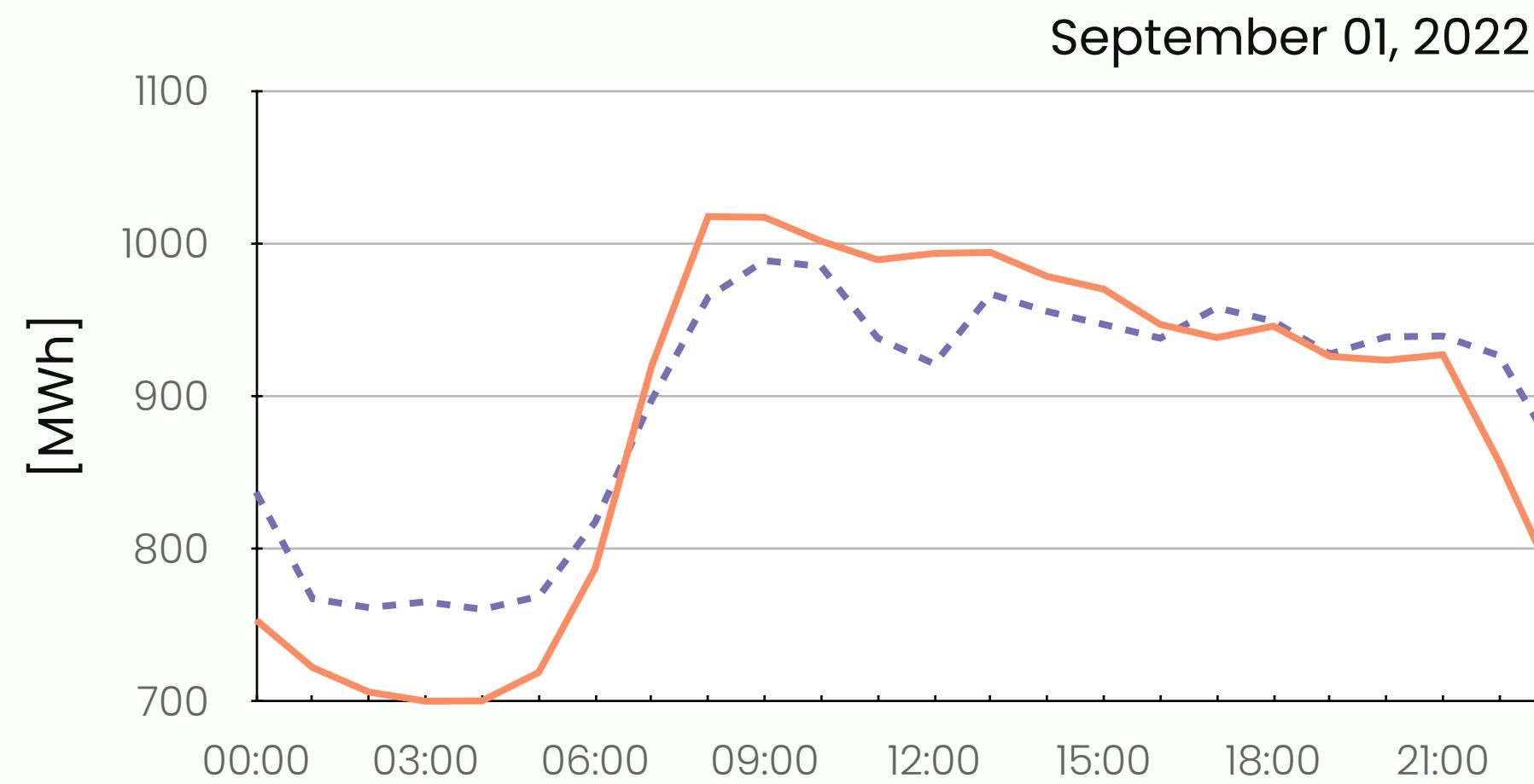
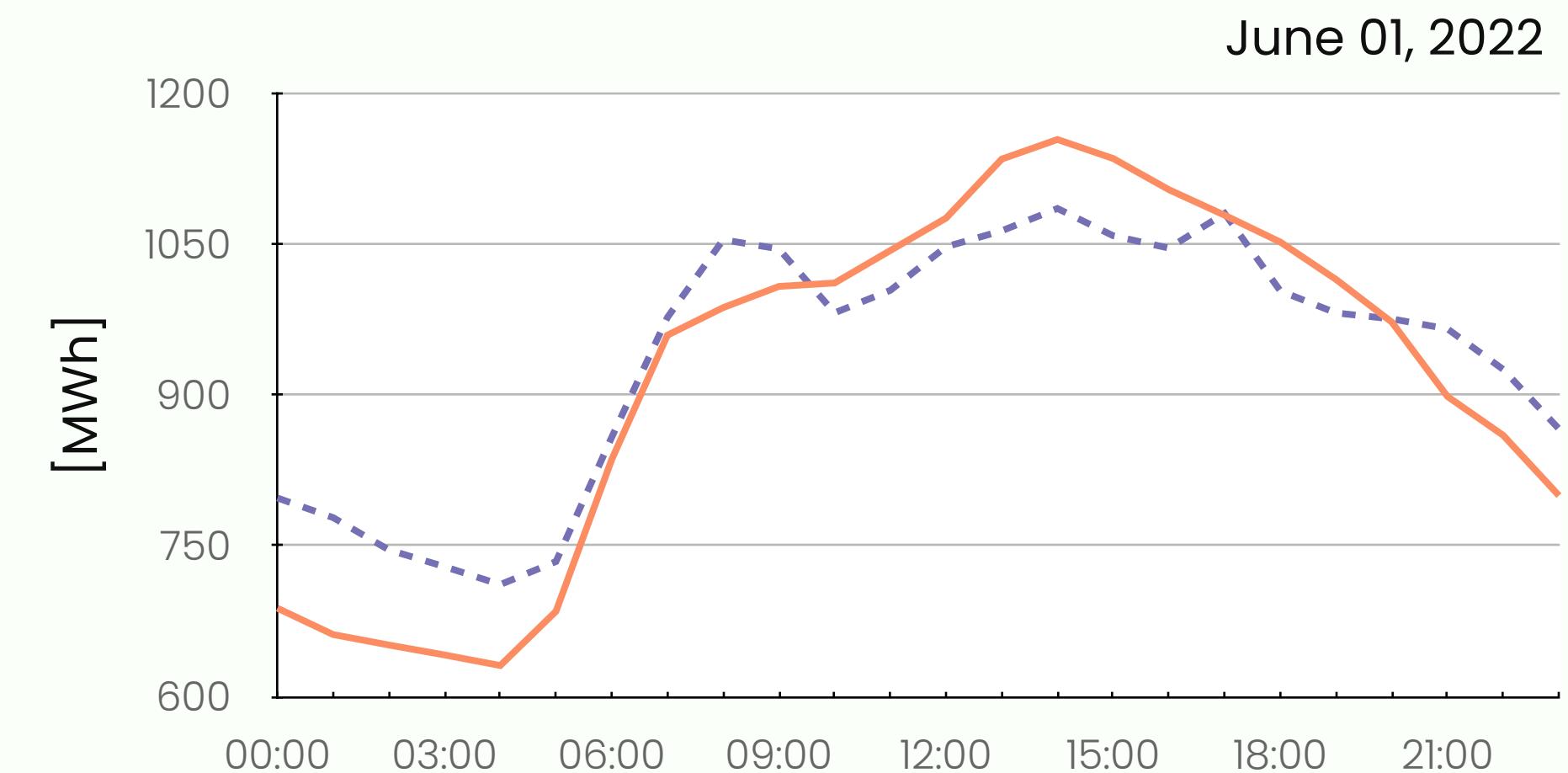
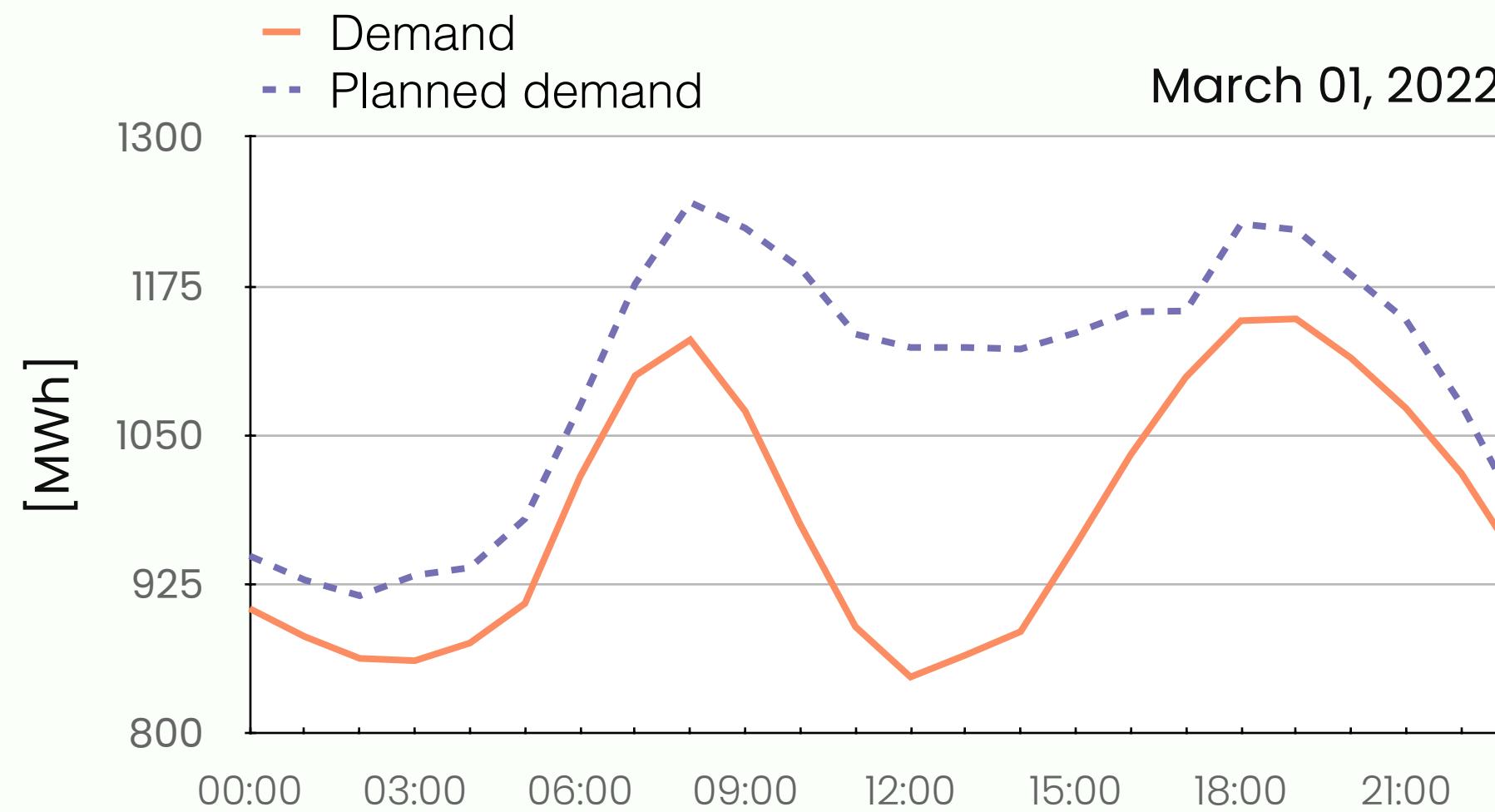
<sup>d</sup>Var4 has 2 features:  $a_7$  and  $T_{dh}$ .

# Model Validation

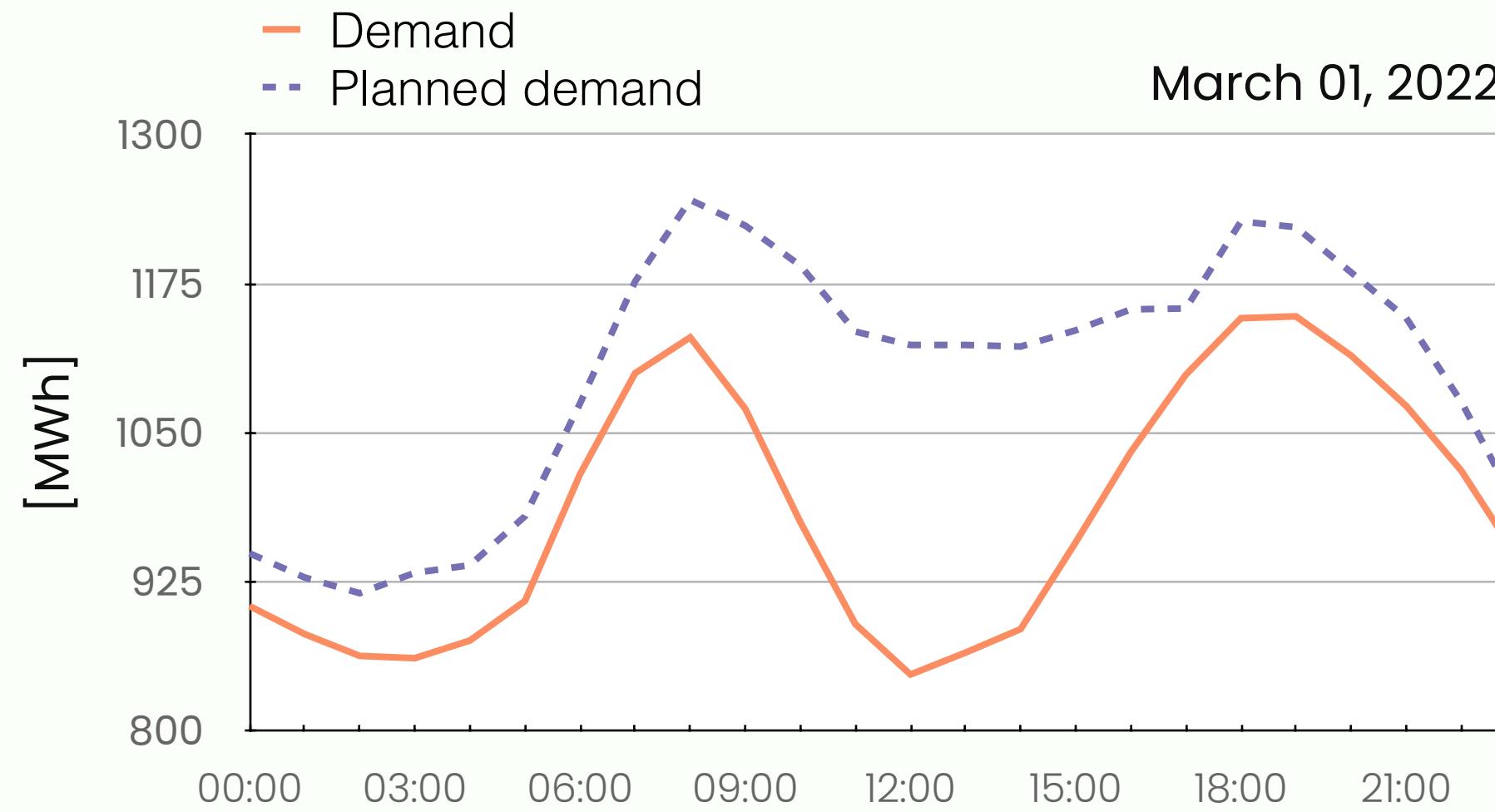
# PERFORMANCE METRICS



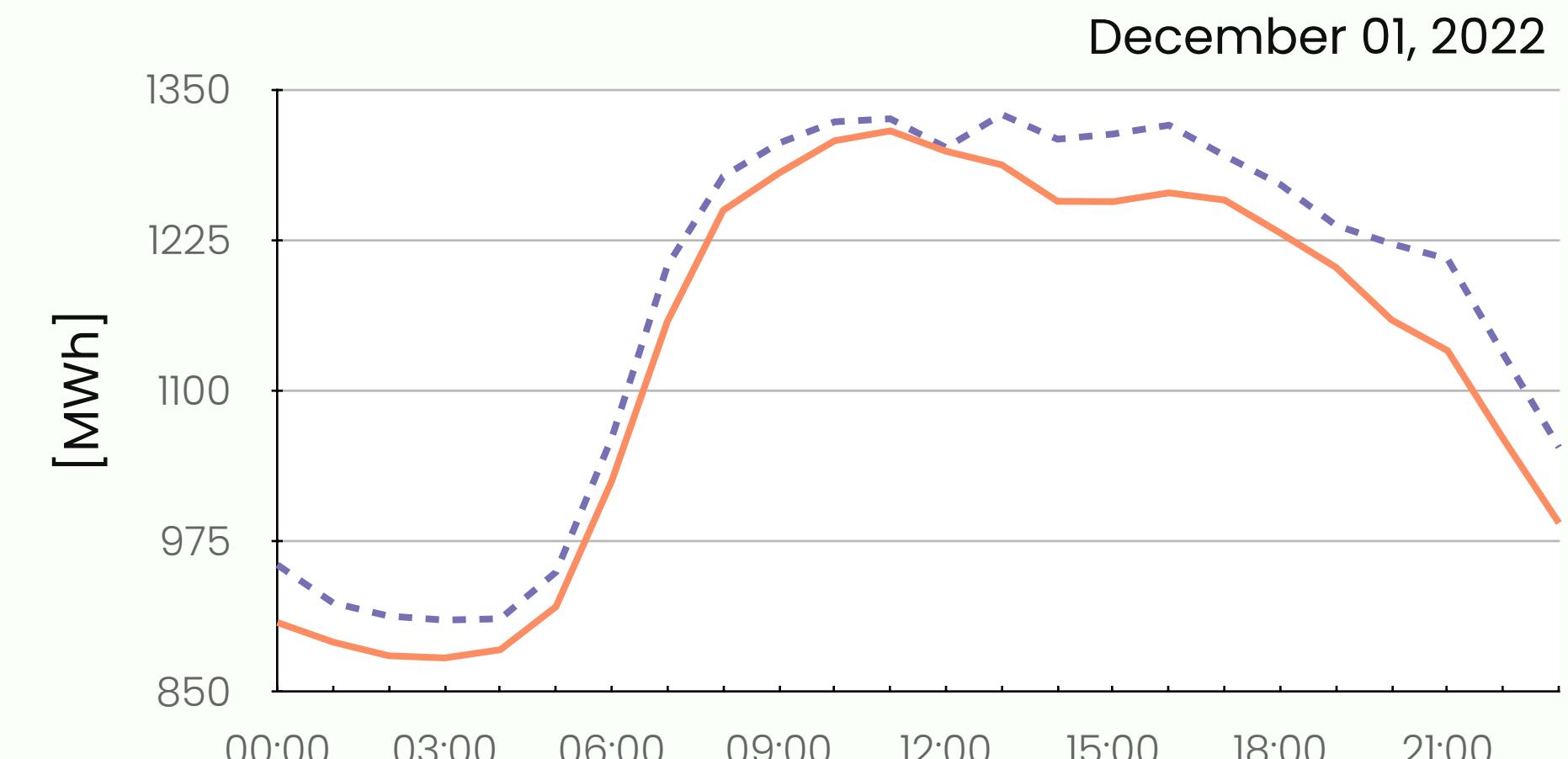
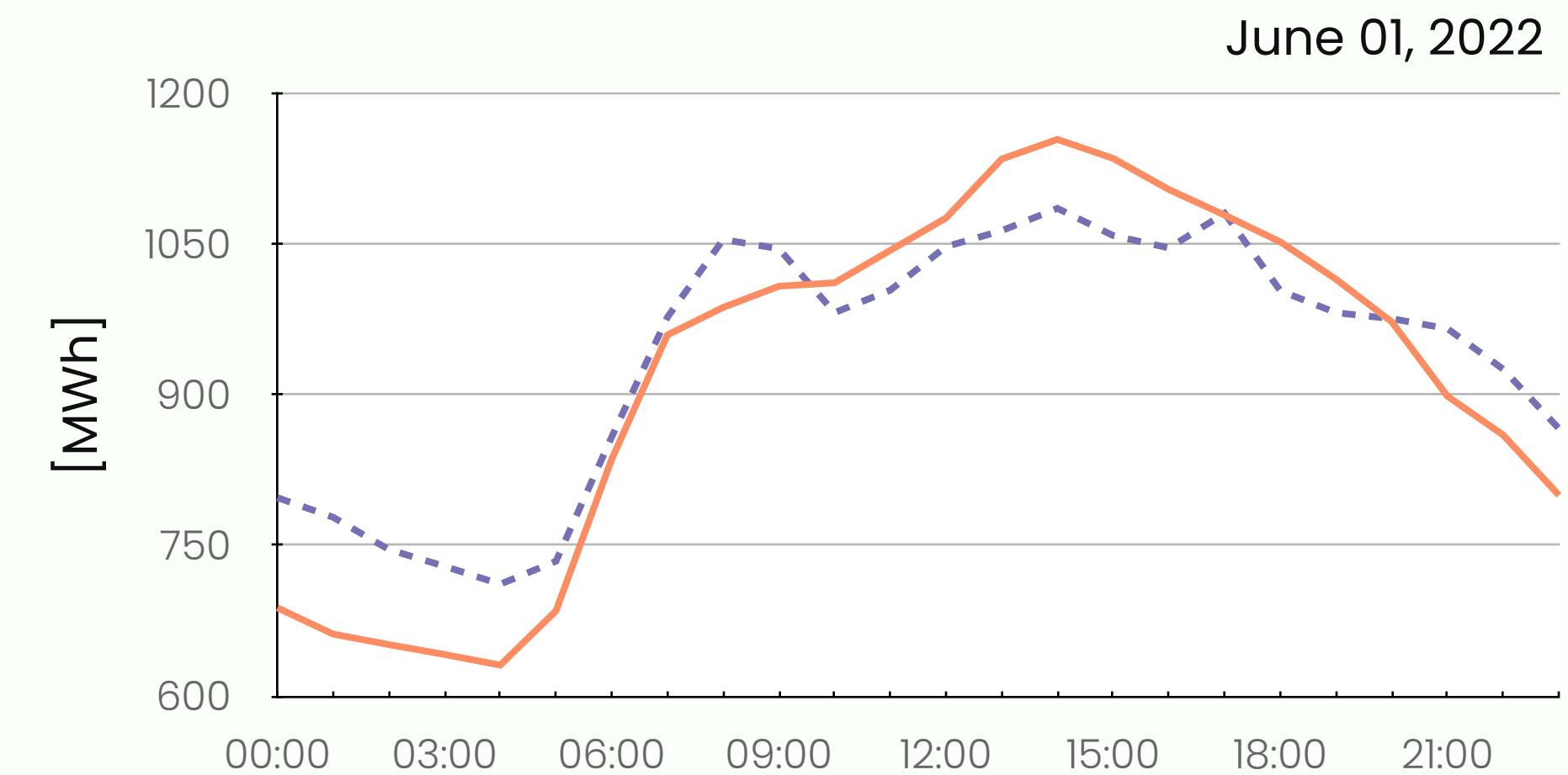
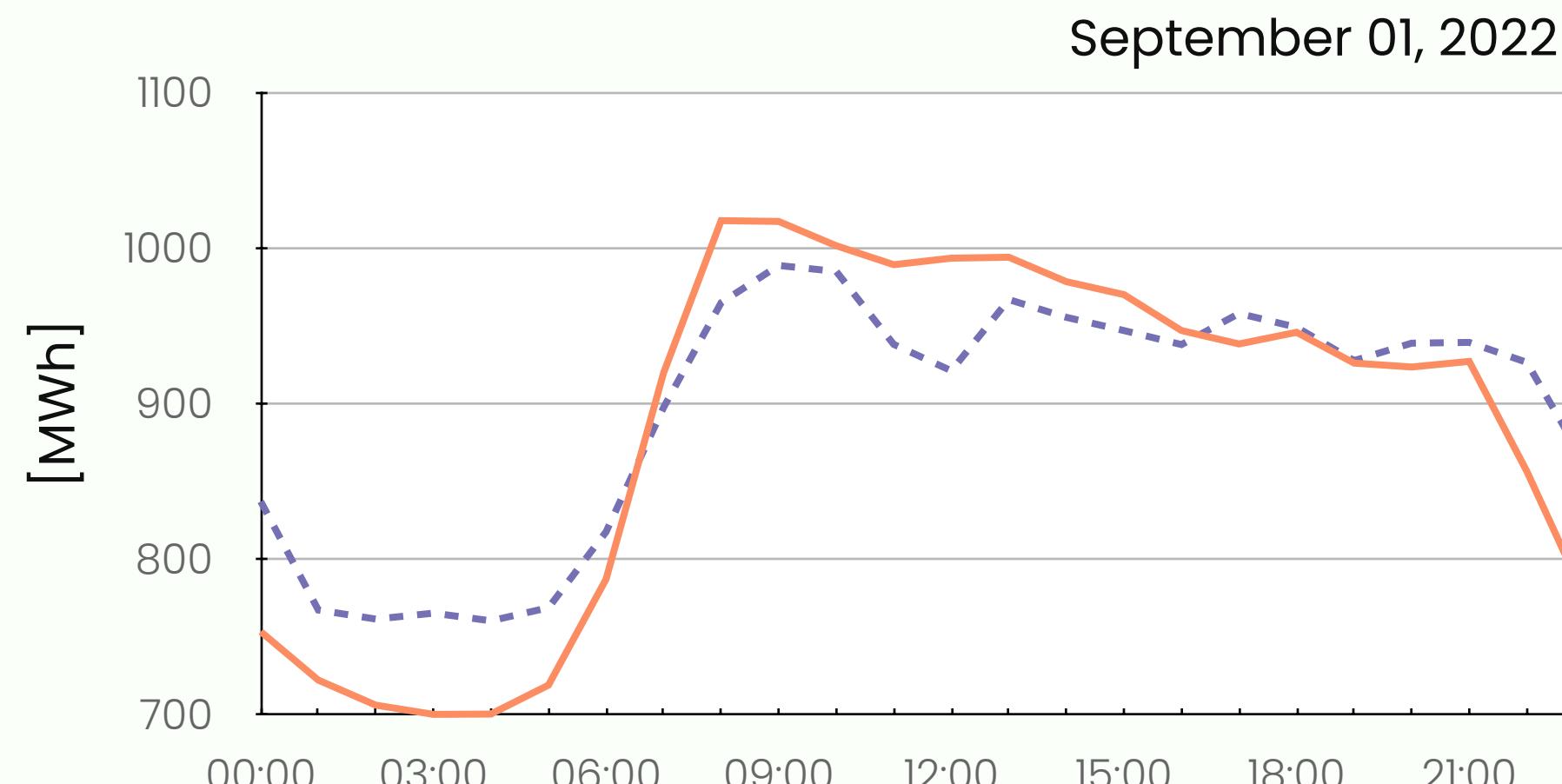
# UNDERSTANDING ACCURACY



# UNDERSTANDING ACCURACY



How to  
understand  
which prediction  
result is better?



# COMMON METRICS

Metrics	Formula
Mean squared error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^n (y_i^{obs} - y_i^{pred})^2$
Root mean squared error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i^{obs} - y_i^{pred})^2}$
Mean absolute error (MAE)	$MAE = \frac{1}{n} \sum_{i=1}^n  y_i^{obs} - y_i^{pred} $
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n} \sum_{i=1}^n \left  \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right  \times 100\%$

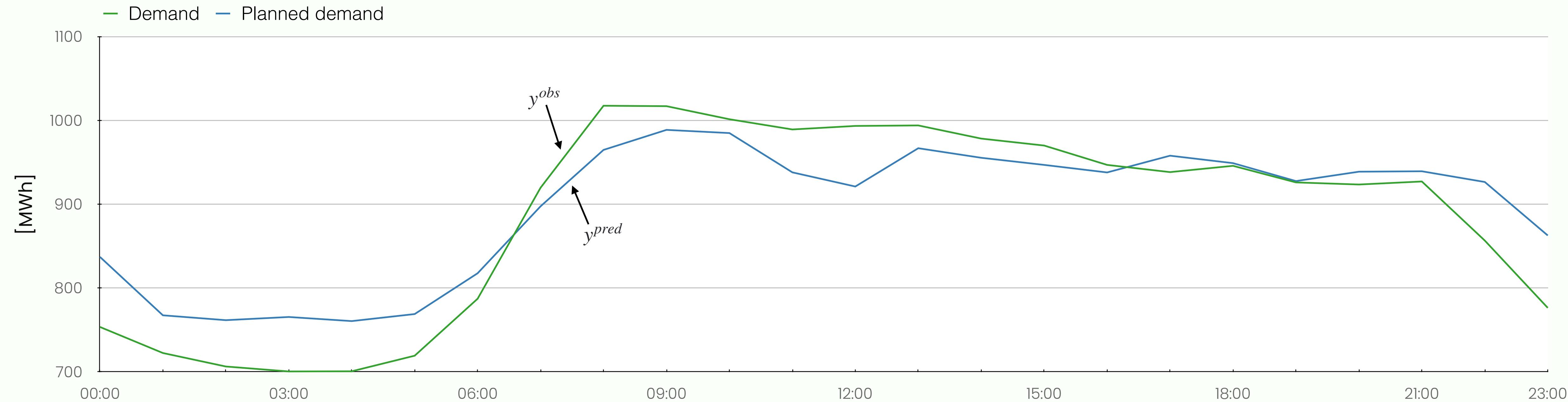
$y_i^{obs}$  is the observed value

$y_i^{pred}$  is the predicted value

$i$  is the  $i$ th data point

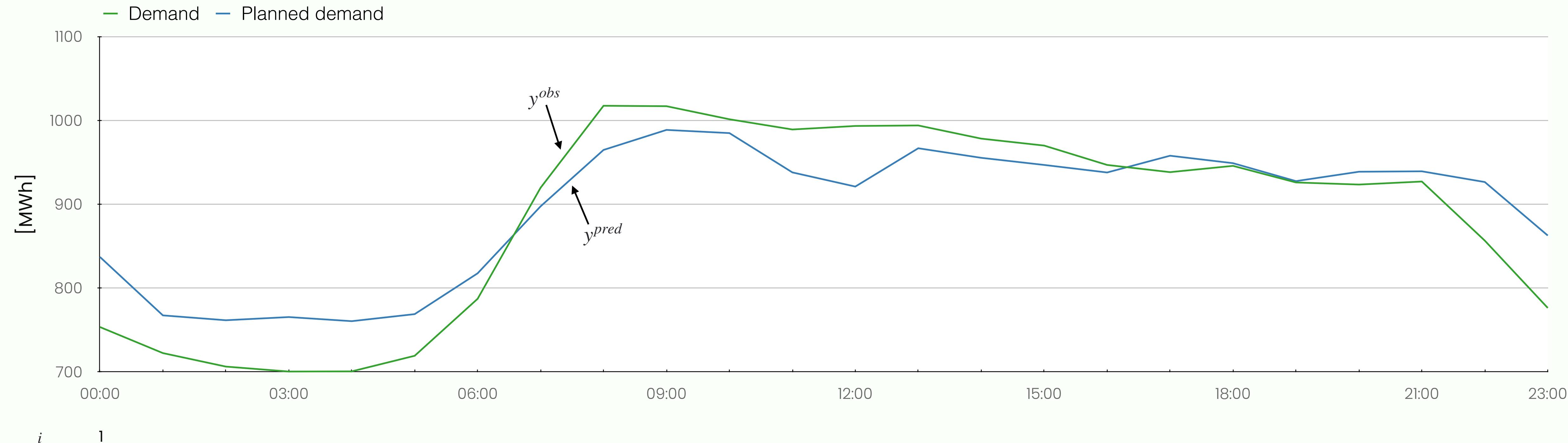
$n$  is the total number of data points

# ONE-DAY EXAMPLE (01.09.2022)



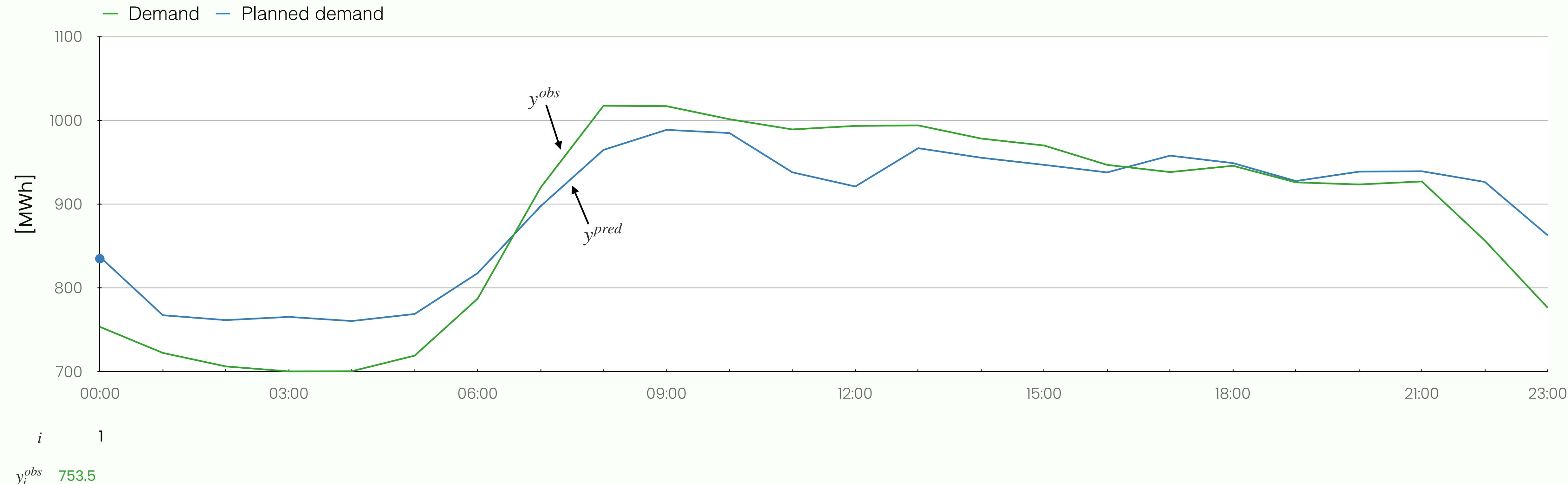
$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



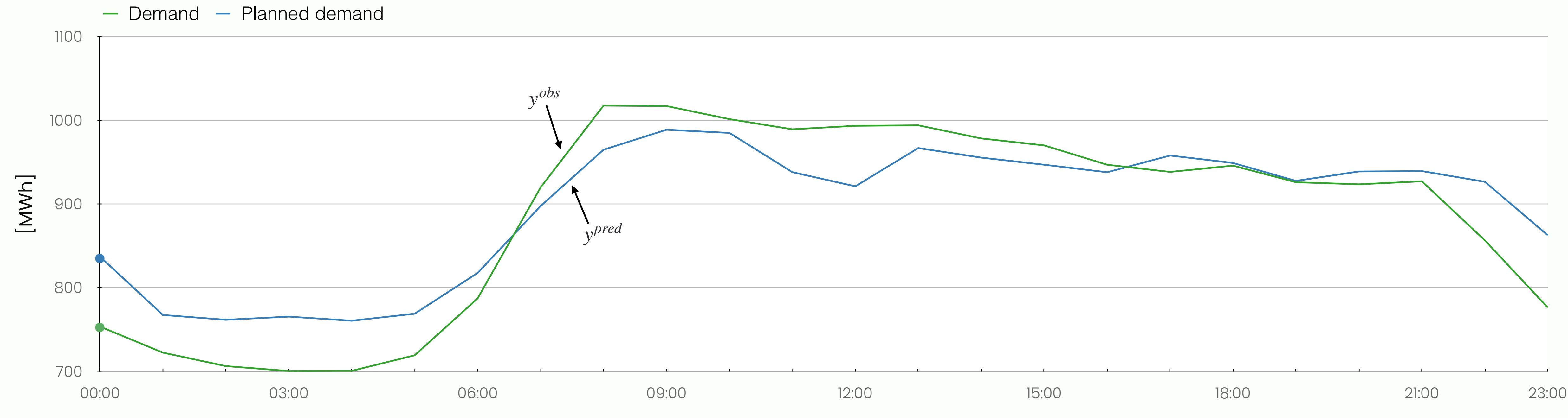
$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



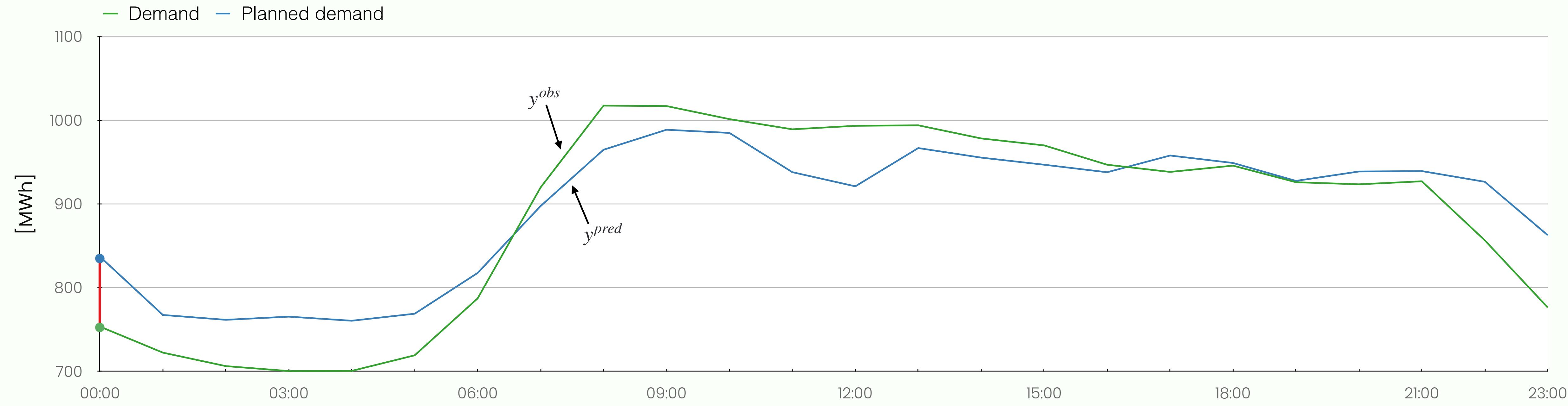
$i = 1$

$y_i^{obs} = 753.5$

$y_i^{pred} = 837.1$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$

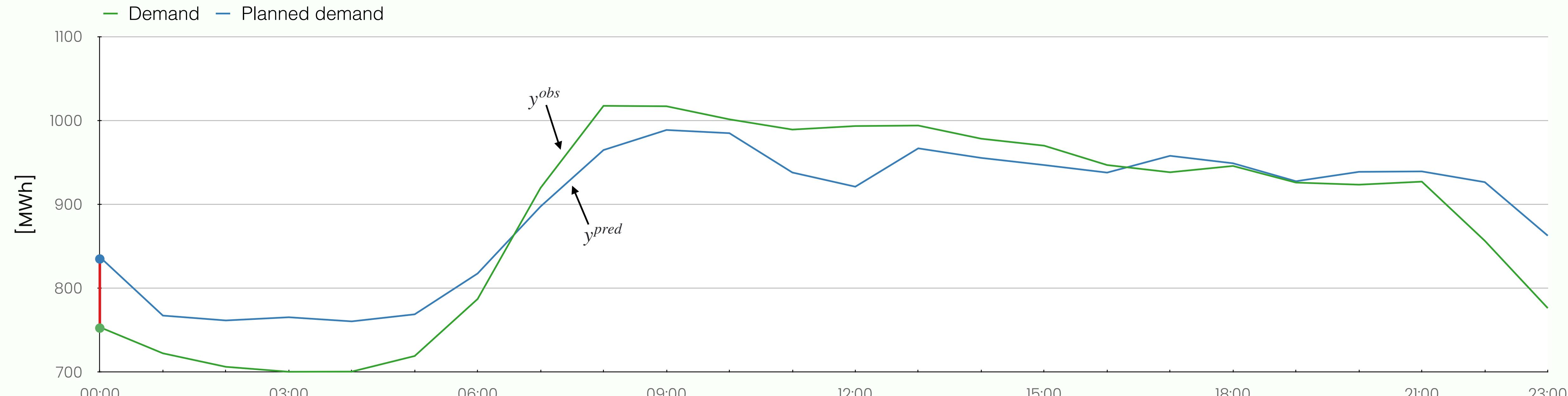
$y_i^{obs}$  753.5

$y_i^{pred}$  837.1

$y_i^{obs} - y_i^{pred}$  -83.6

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i \quad 1 \quad 2$

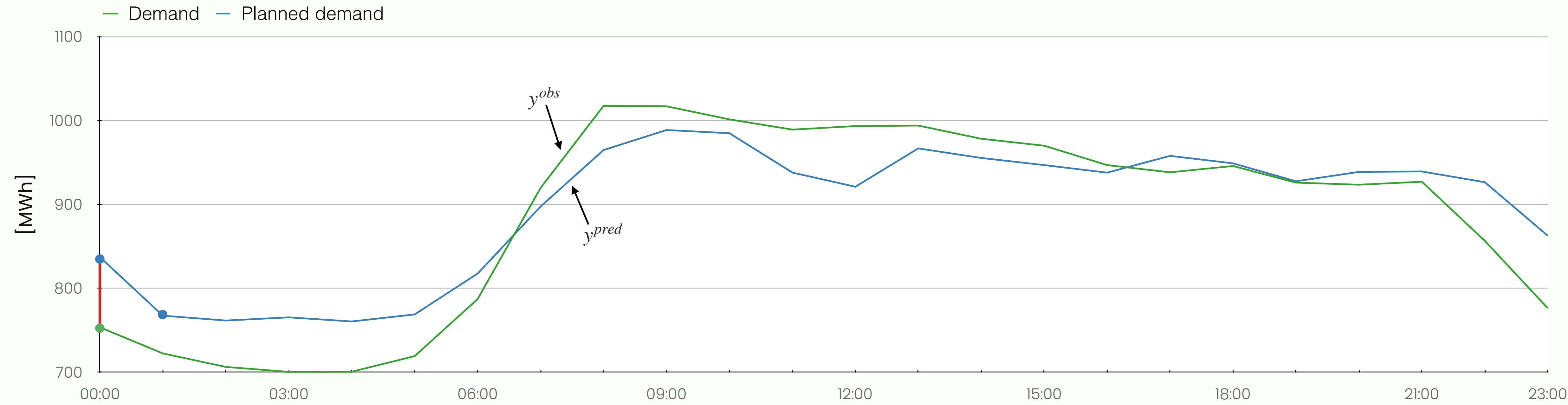
$$y_i^{obs} \quad 753.5$$

$$y_i^{pred} \quad 837.1$$

$$y_i^{obs} - y_i^{pred} \quad -83.6$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i \quad 1 \quad 2$

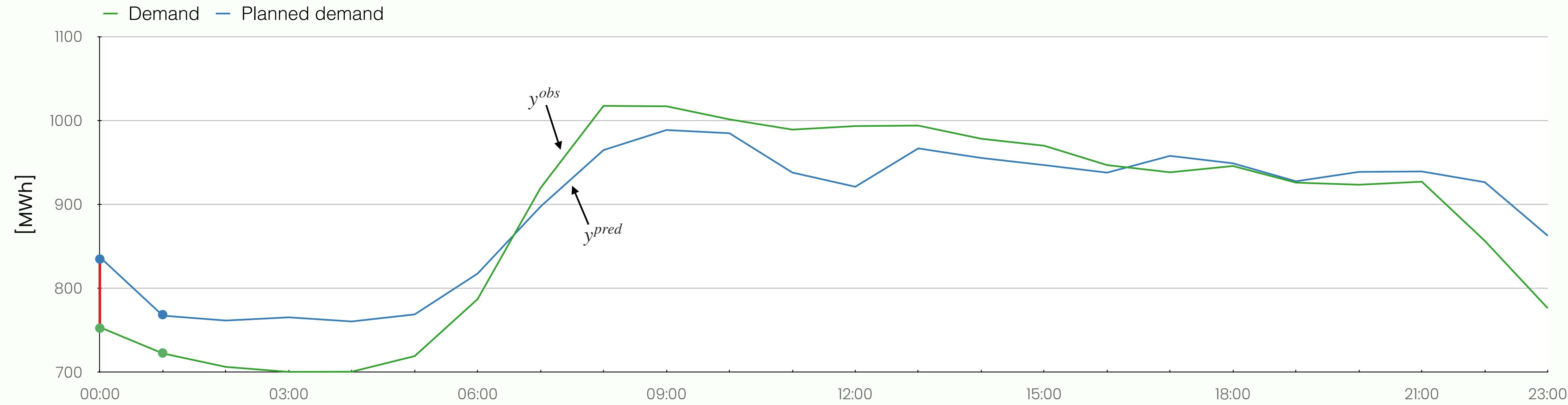
$y_i^{obs} \quad 753.5 \quad 722.4$

$y_i^{pred} \quad 837.1$

$y_i^{obs} - y_i^{pred} \quad -83.6$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$       1      2

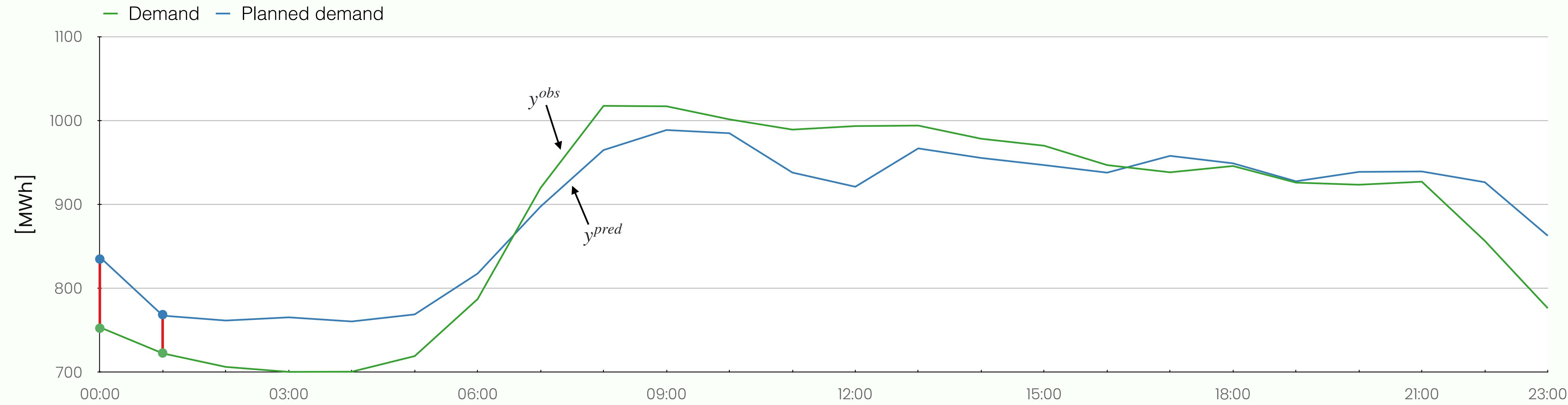
$y_i^{obs}$     753.5    722.4

$y_i^{pred}$     837.1    767.4

$y_i^{obs} - y_i^{pred}$     -83.6

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$  1 2

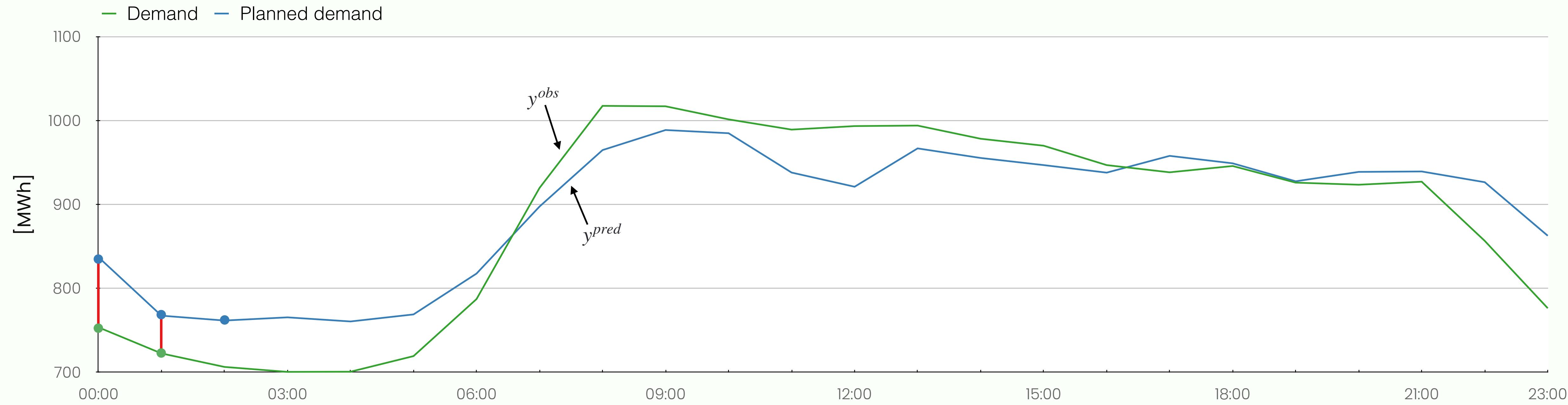
$y_i^{obs}$  753.5 722.4

$y_i^{pred}$  837.1 767.4

$y_i^{obs} - y_i^{pred}$  -83.6 -45

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$  1 2 3

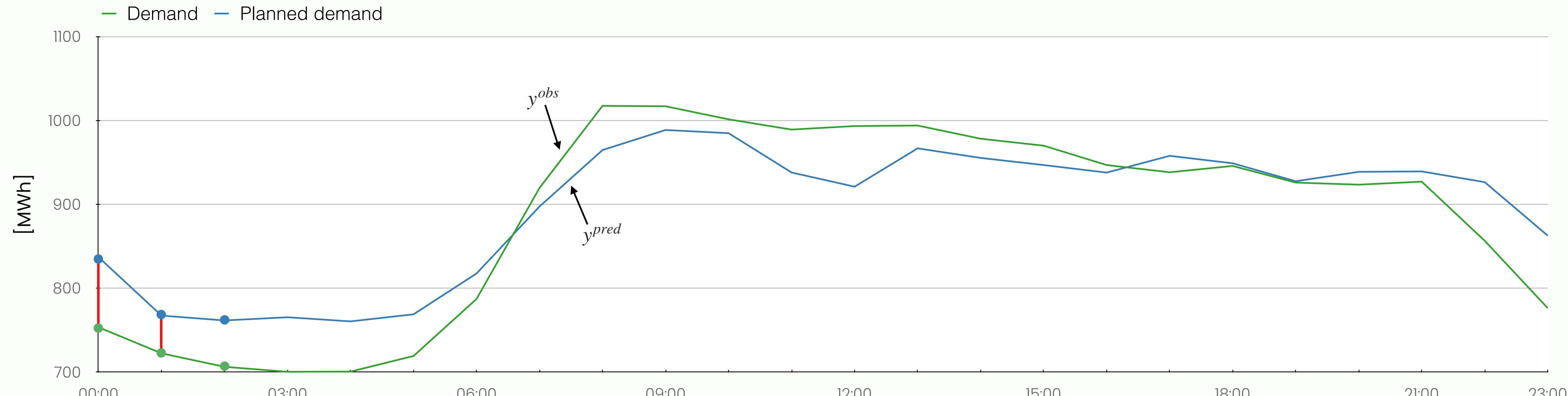
$y_i^{obs}$  753.5 722.4 706.3

$y_i^{pred}$  837.1 767.4

$y_i^{obs} - y_i^{pred}$  -83.6 -45

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$  1 2 3

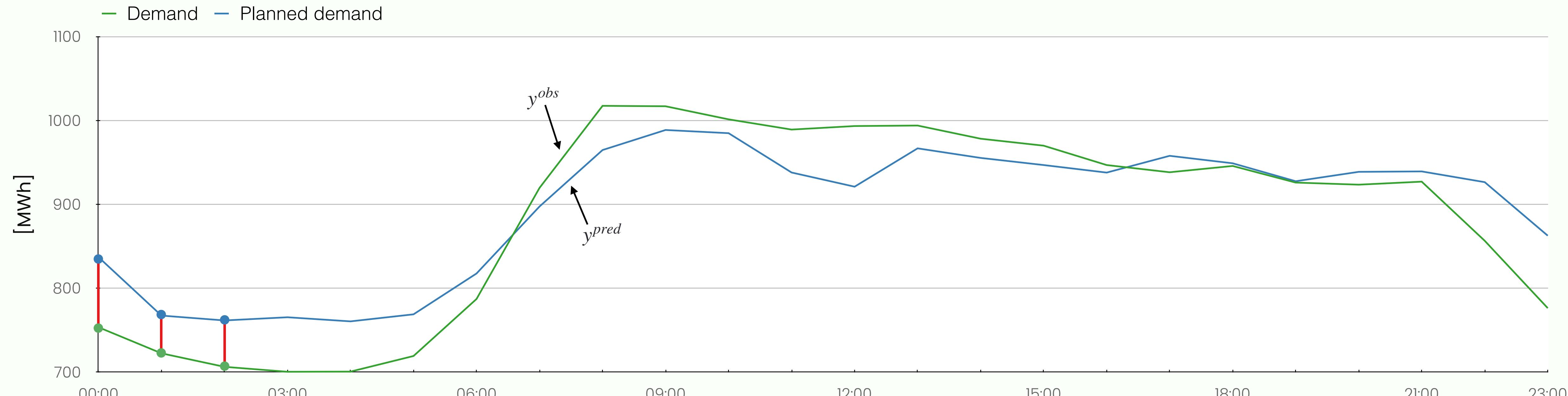
$y_i^{obs}$  753.5 722.4 706.3

$y_i^{pred}$  837.1 767.4 761.6

$y_i^{obs} - y_i^{pred}$  -83.6 -45

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

# ONE-DAY EXAMPLE (01.09.2022)



$i$  1 2 3

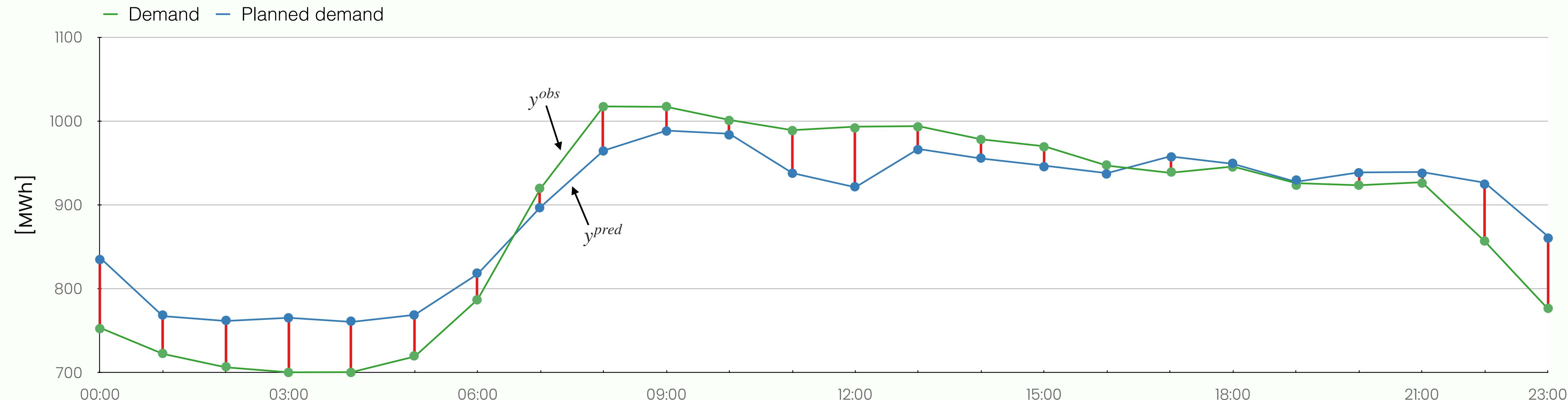
$y_i^{obs}$  753.5 722.4 706.3

$y_i^{pred}$  837.1 767.4 761.6

$y_i^{obs} - y_i^{pred}$  -83.6 -45 -55.3

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

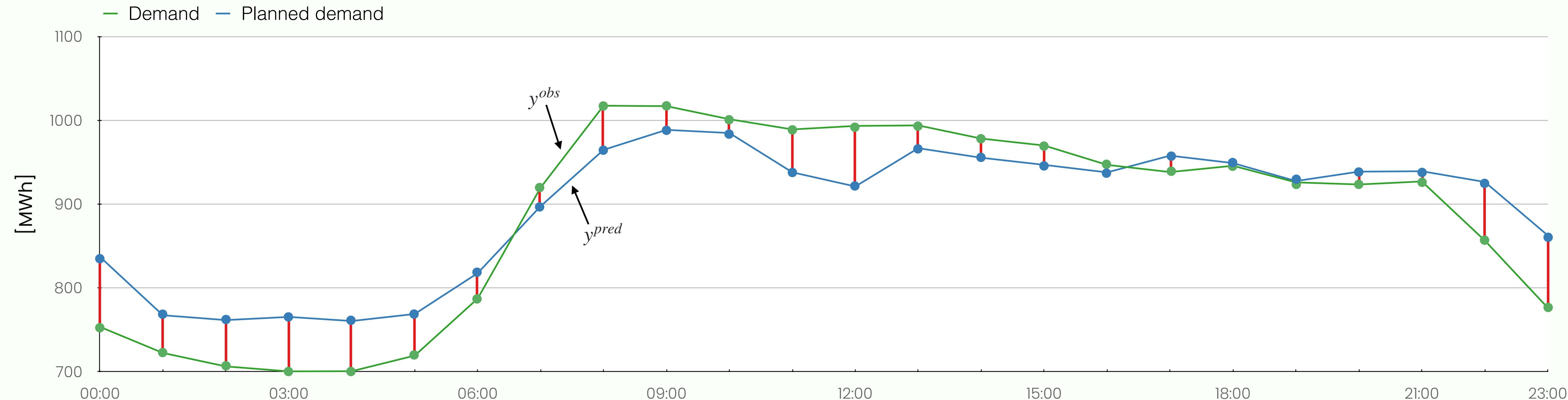
# ONE-DAY EXAMPLE (01.09.2022)



$i$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$y_i^{obs}$	753.5	722.4	706.3	700.4	700.6	719.2	787.2	919.7	1017.5	1017	1001.4	989.2	993.4	994	978.3	970	946.9	938.3	945.8	926	923.5	927.1	856.6	776.3
$y_i^{pred}$	837.1	767.4	761.6	765.4	760.5	768.9	817.6	897.5	964.8	988.7	984.9	938	921.1	966.8	955.4	946.9	937.9	957.9	949	927.6	938.8	939.3	926.5	862.7
$y_i^{obs} - y_i^{pred}$	-83.6	-45	-55.3	-65	-59.9	-49.7	-30.4	22.2	52.7	28.3	16.5	51.2	72.3	27.2	22.9	23.1	9	-19.6	-3.2	-1.6	-15.3	-12.2	-69.9	-86.4

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \%$$

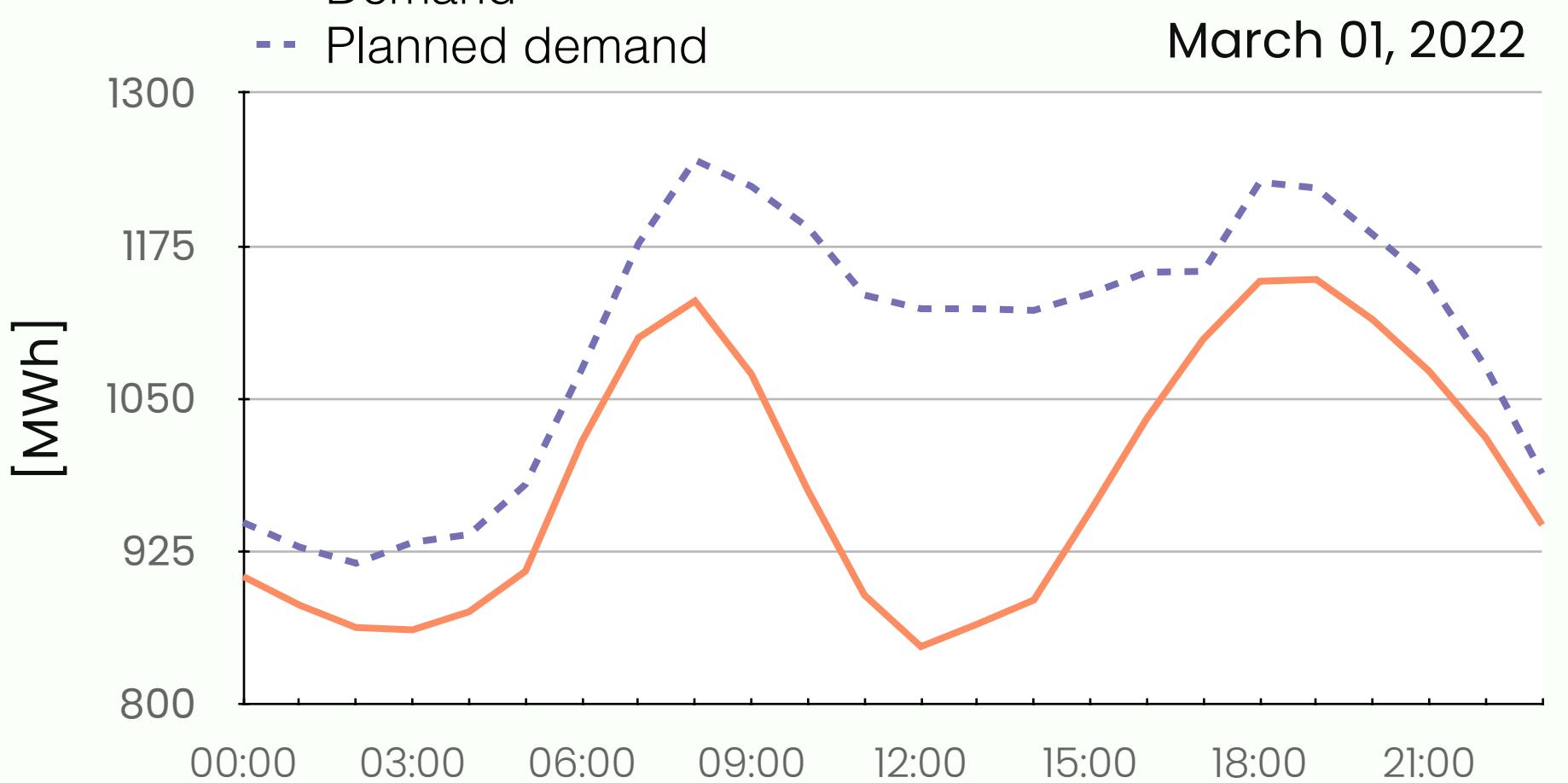
# ONE-DAY EXAMPLE (01.09.2022)



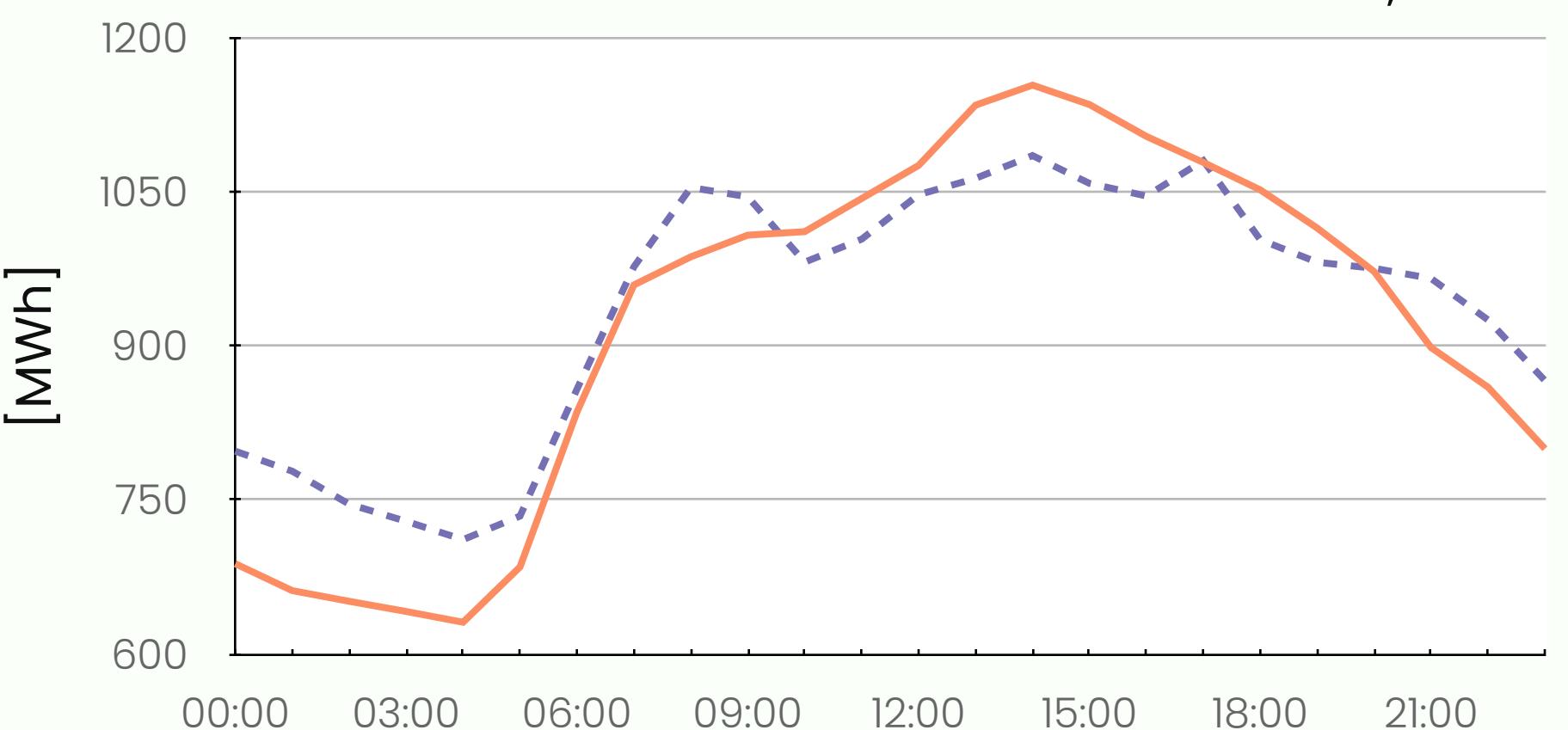
$i$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$y_i^{obs}$	753.5	722.4	706.3	700.4	700.6	719.2	787.2	919.7	1017.5	1017	1001.4	989.2	993.4	994	978.3	970	946.9	938.3	945.8	926	923.5	927.1	856.6	776.3
$y_i^{pred}$	837.1	767.4	761.6	765.4	760.5	768.9	817.6	897.5	964.8	988.7	984.9	938	921.1	966.8	955.4	946.9	937.9	957.9	949	927.6	938.8	939.3	926.5	862.7
$y_i^{obs} - y_i^{pred}$	-83.6	-45	-55.3	-65	-59.9	-49.7	-30.4	22.2	52.7	28.3	16.5	51.2	72.3	27.2	22.9	23.1	9	-19.6	-3.2	-1.6	-15.3	-12.2	-69.9	-86.4

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}} \right| \times 100 \% \xrightarrow{n=24} \text{MAPE} = \frac{1}{24} \left( \frac{83.6}{753.5} + \frac{45}{722.4} + \frac{55.3}{706.3} + \dots + \frac{12.2}{927.1} + \frac{69.9}{856.6} + \frac{86.4}{776.3} \right) \times 100 \% \\ = \frac{1}{24} (11.09\% + 6.22\% + 7.83\% + \dots + 1.32\% + 8.16\% + 11.13\%) \\ \approx 4.65\%$$

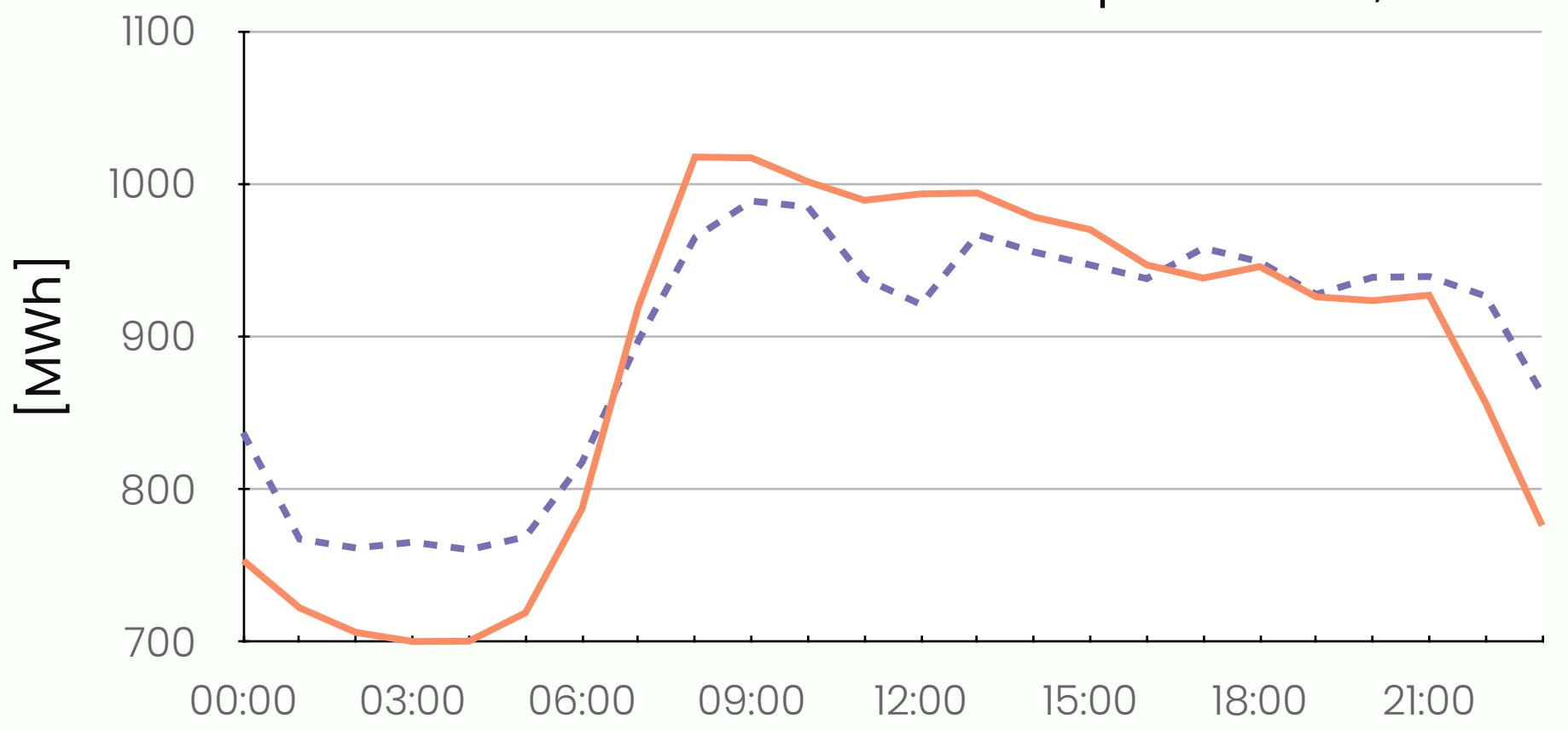
Demand  
Planned demand



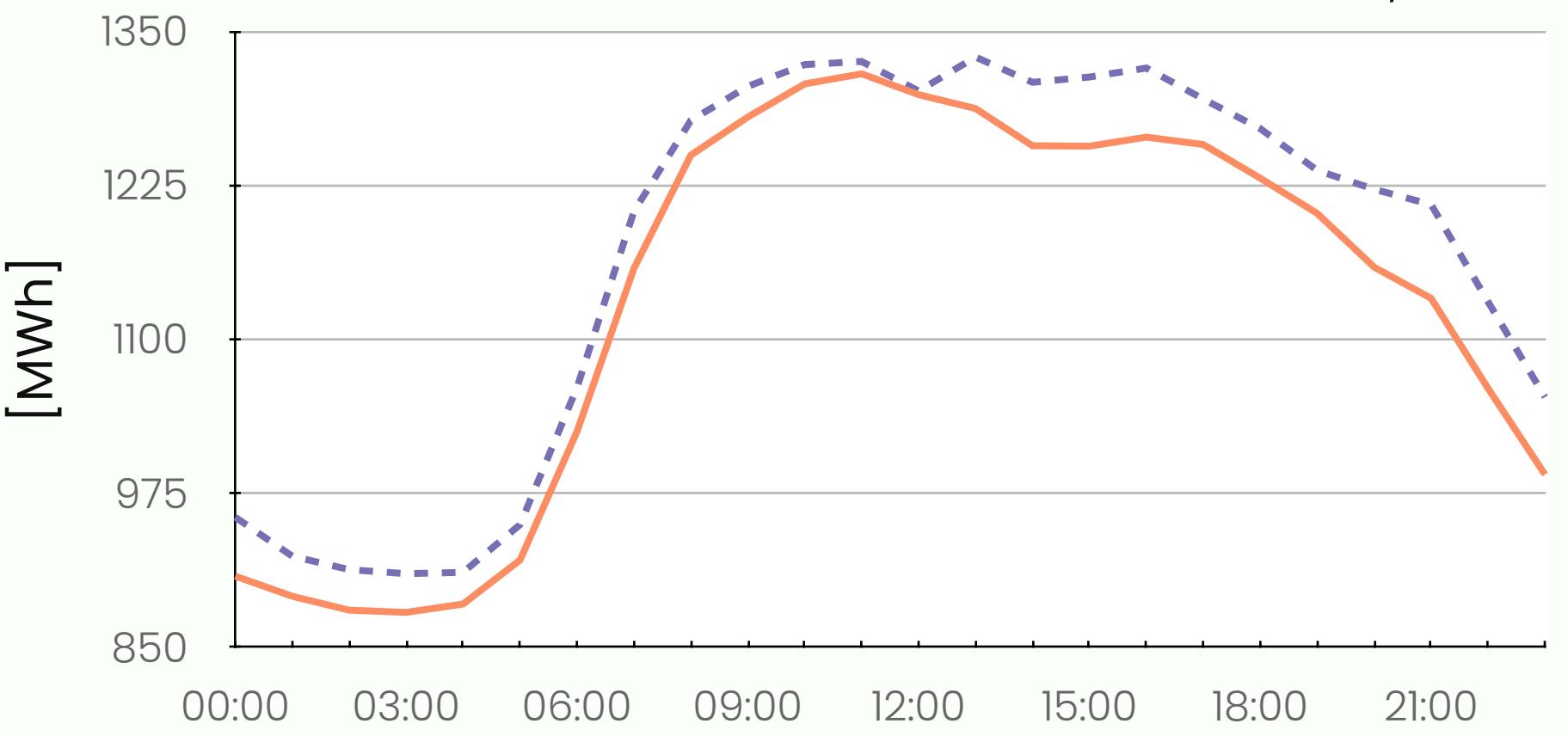
June 01, 2022



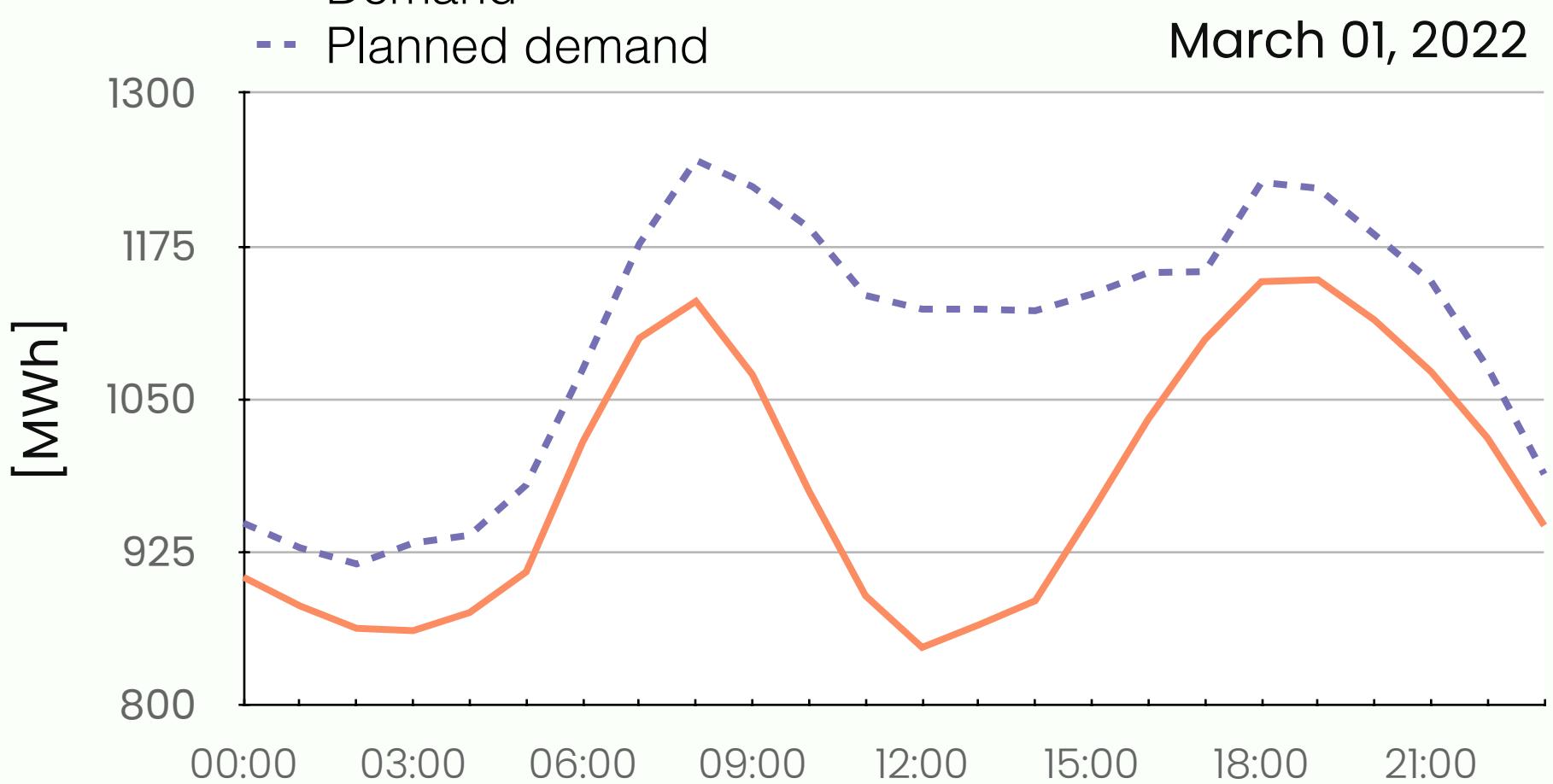
September 01, 2022



December 01, 2022

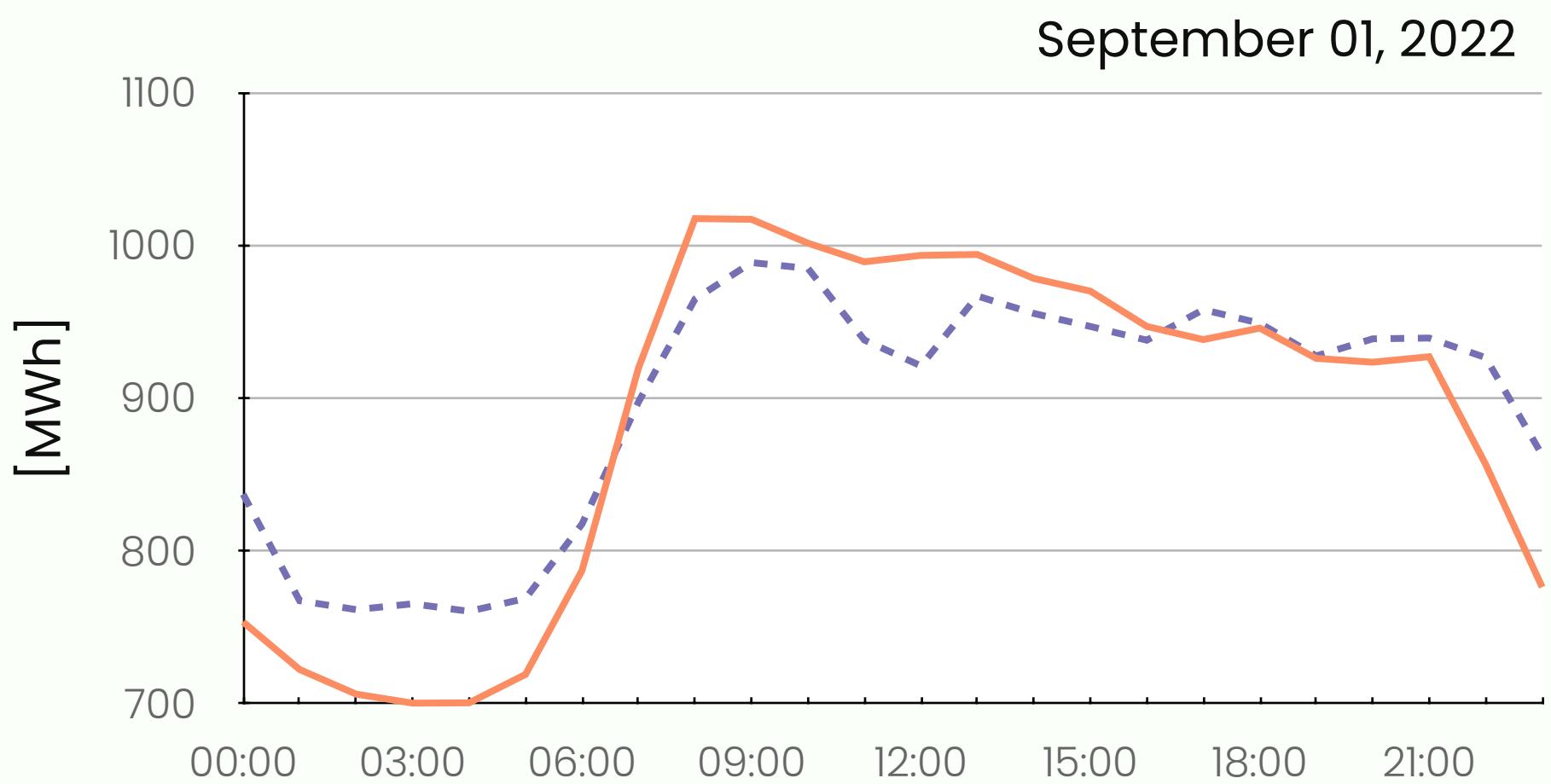
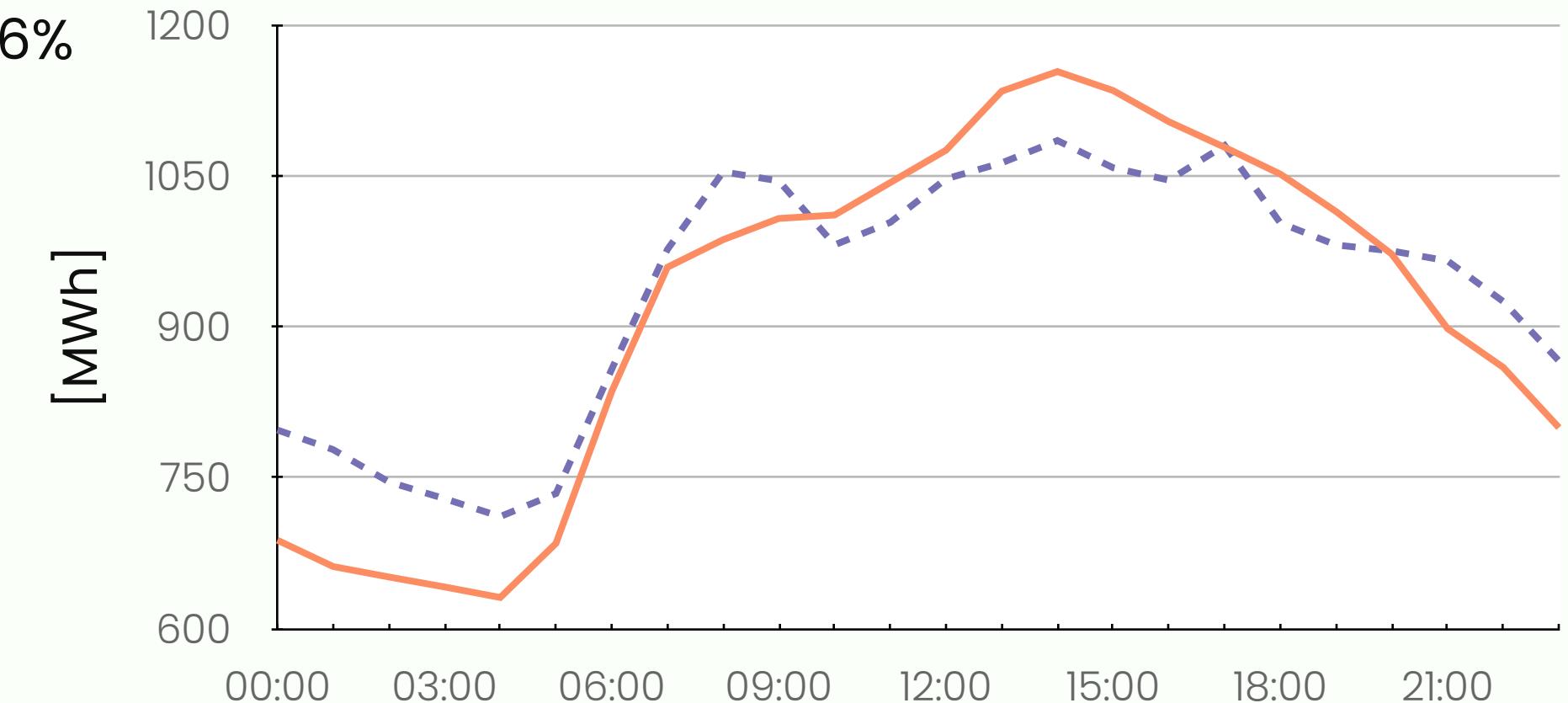


Demand  
Planned demand



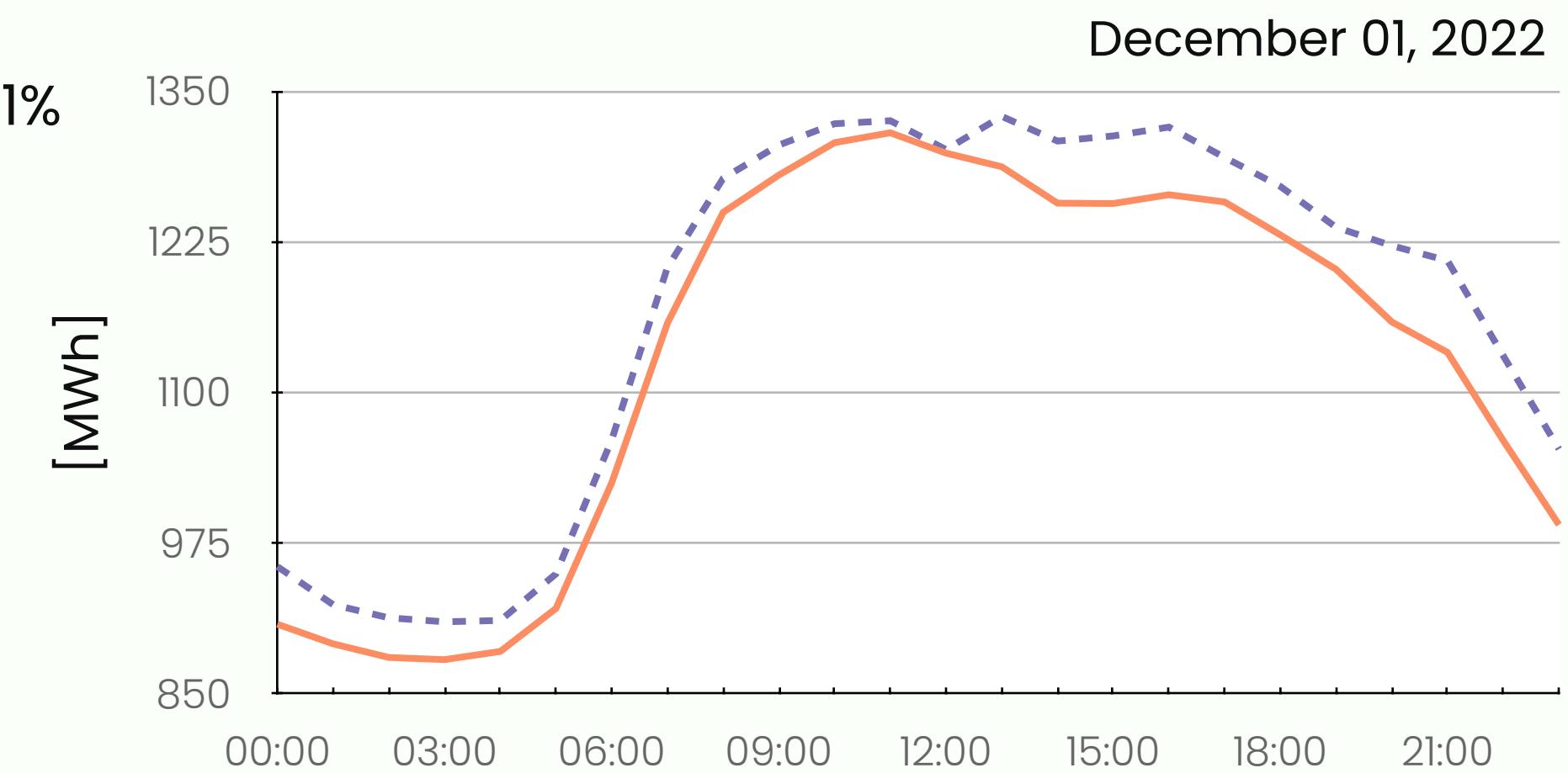
MAPE1 = 12%

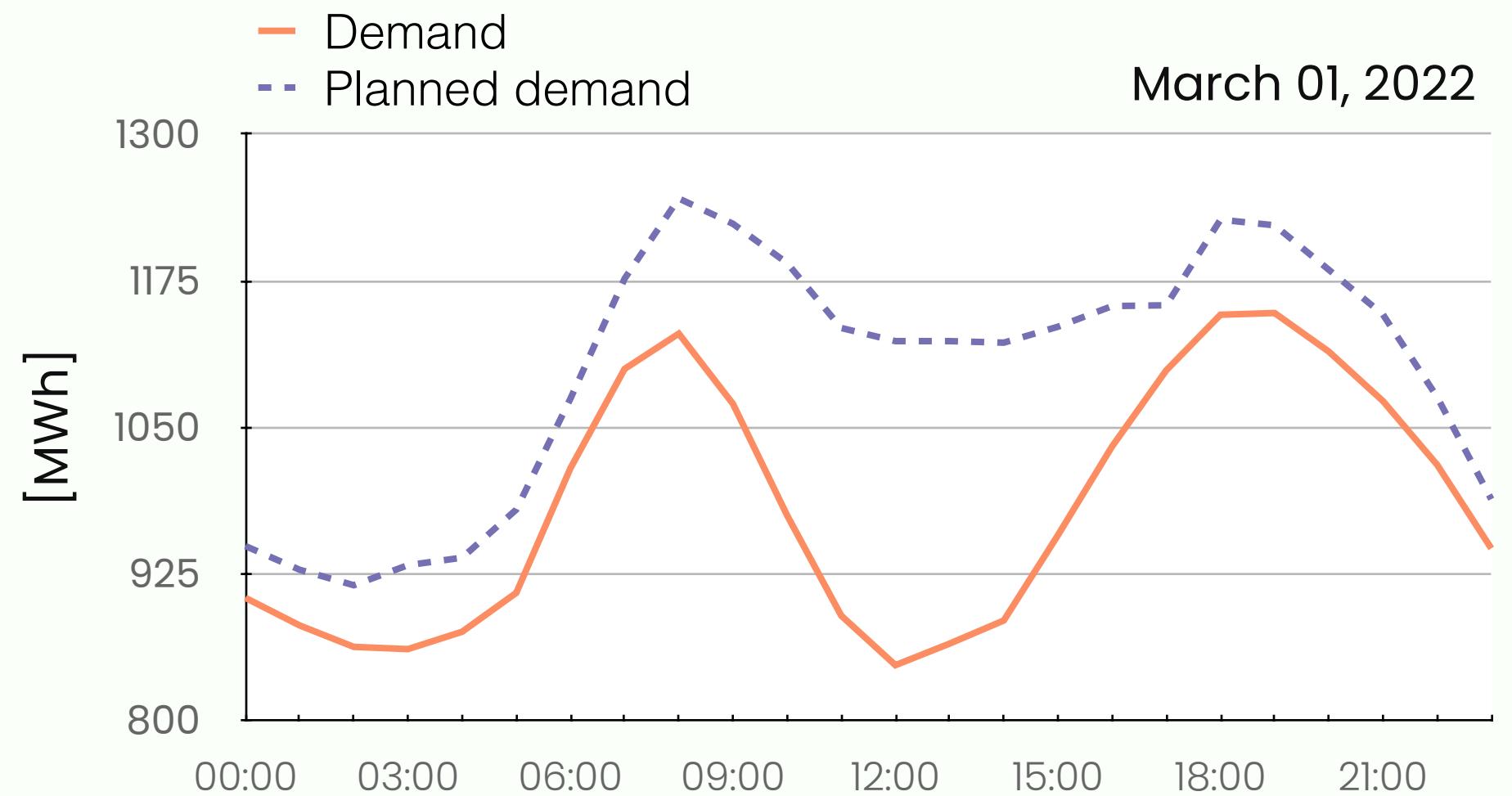
MAPE2 = 6.76%



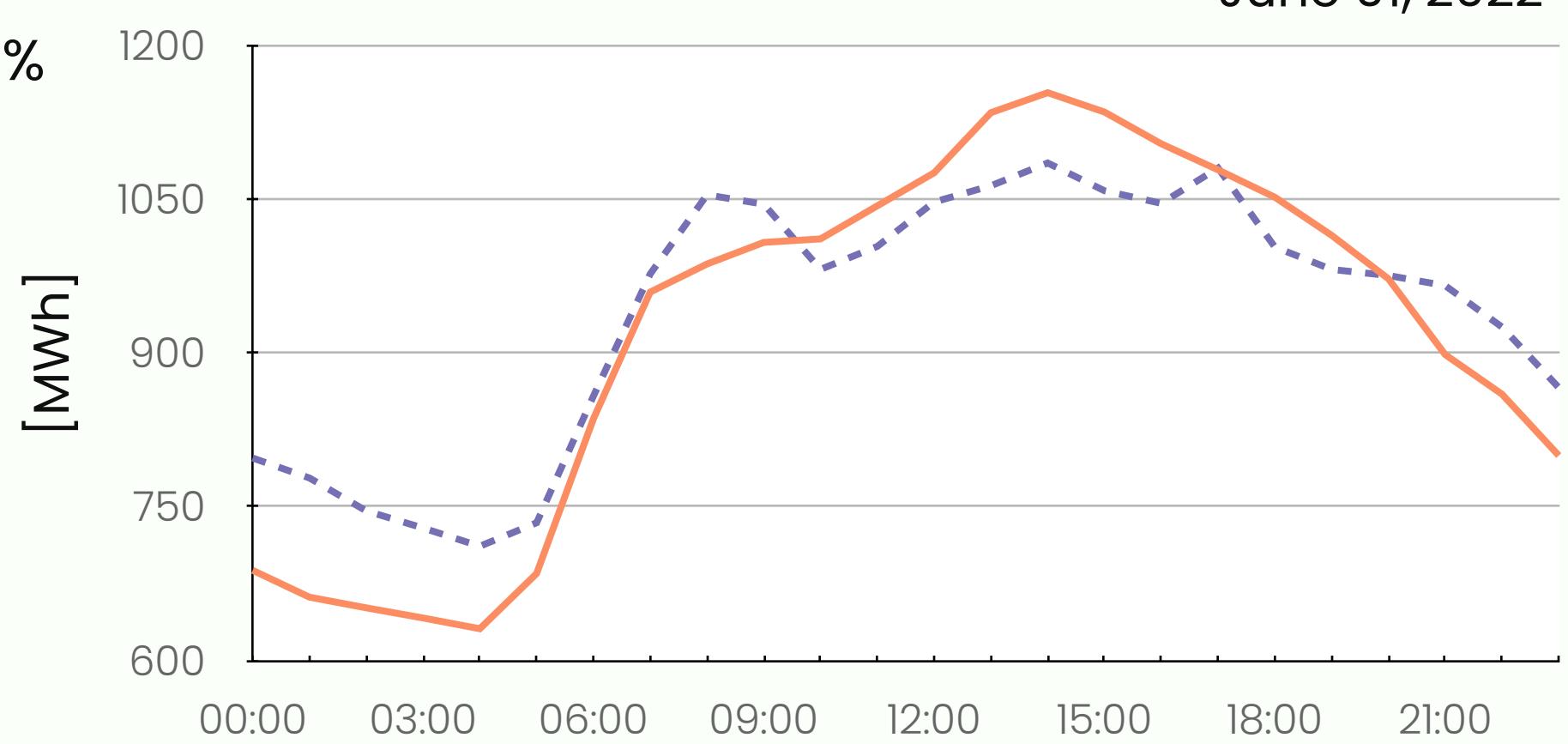
MAPE3 = 4.65%

MAPE4 = 3.61%



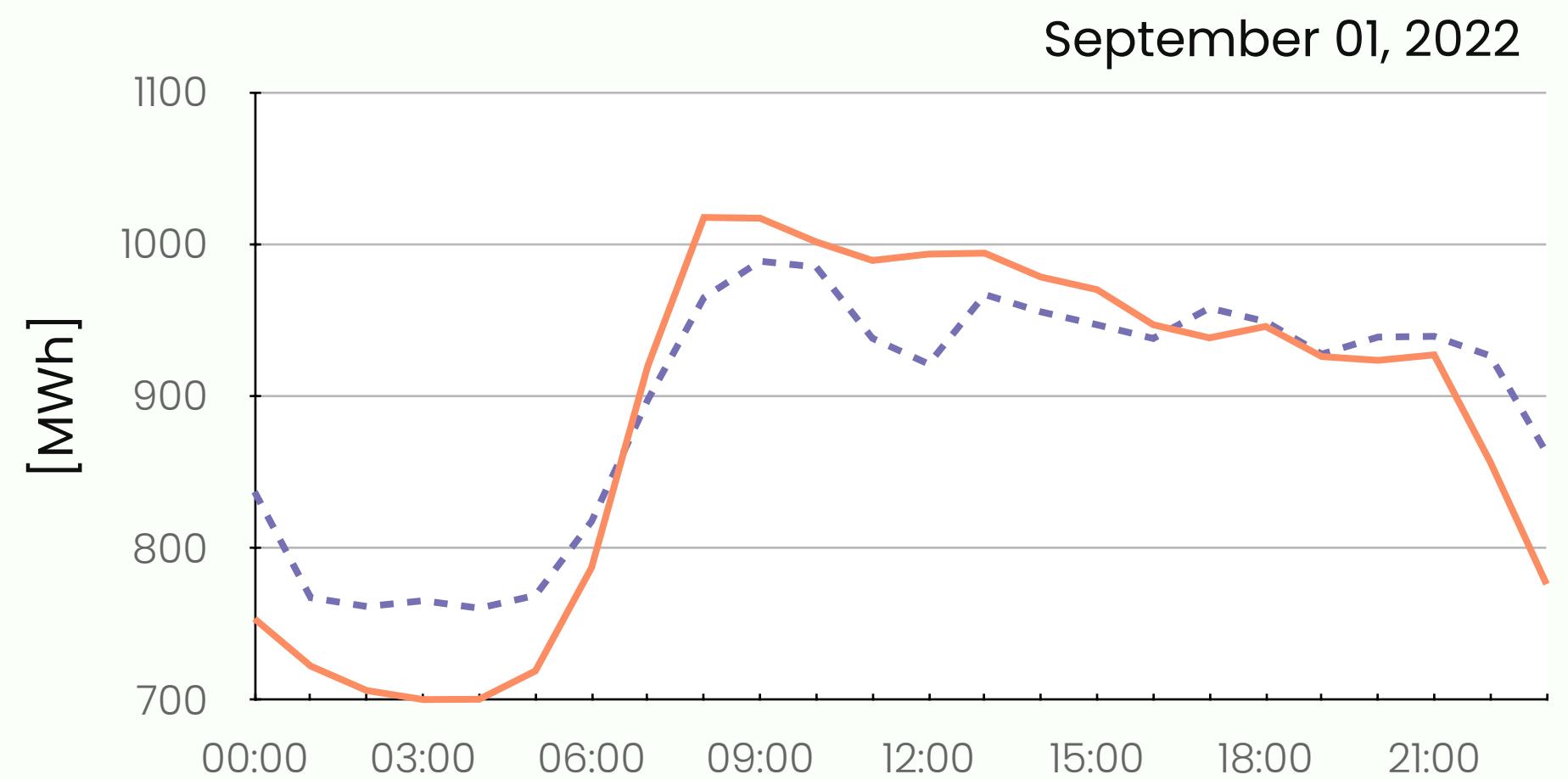


MAPE1 = 12%

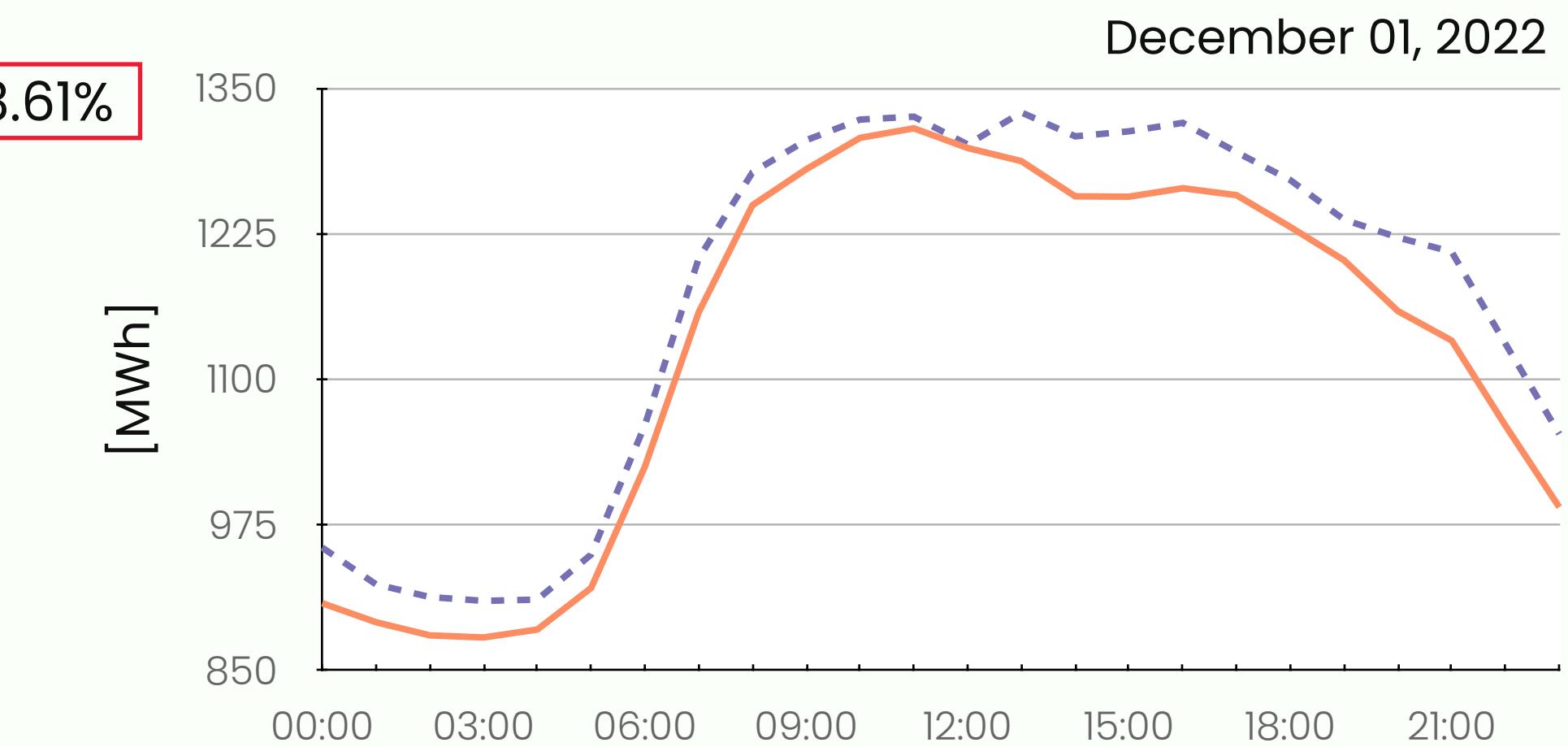


MAPE2 = 6.76%

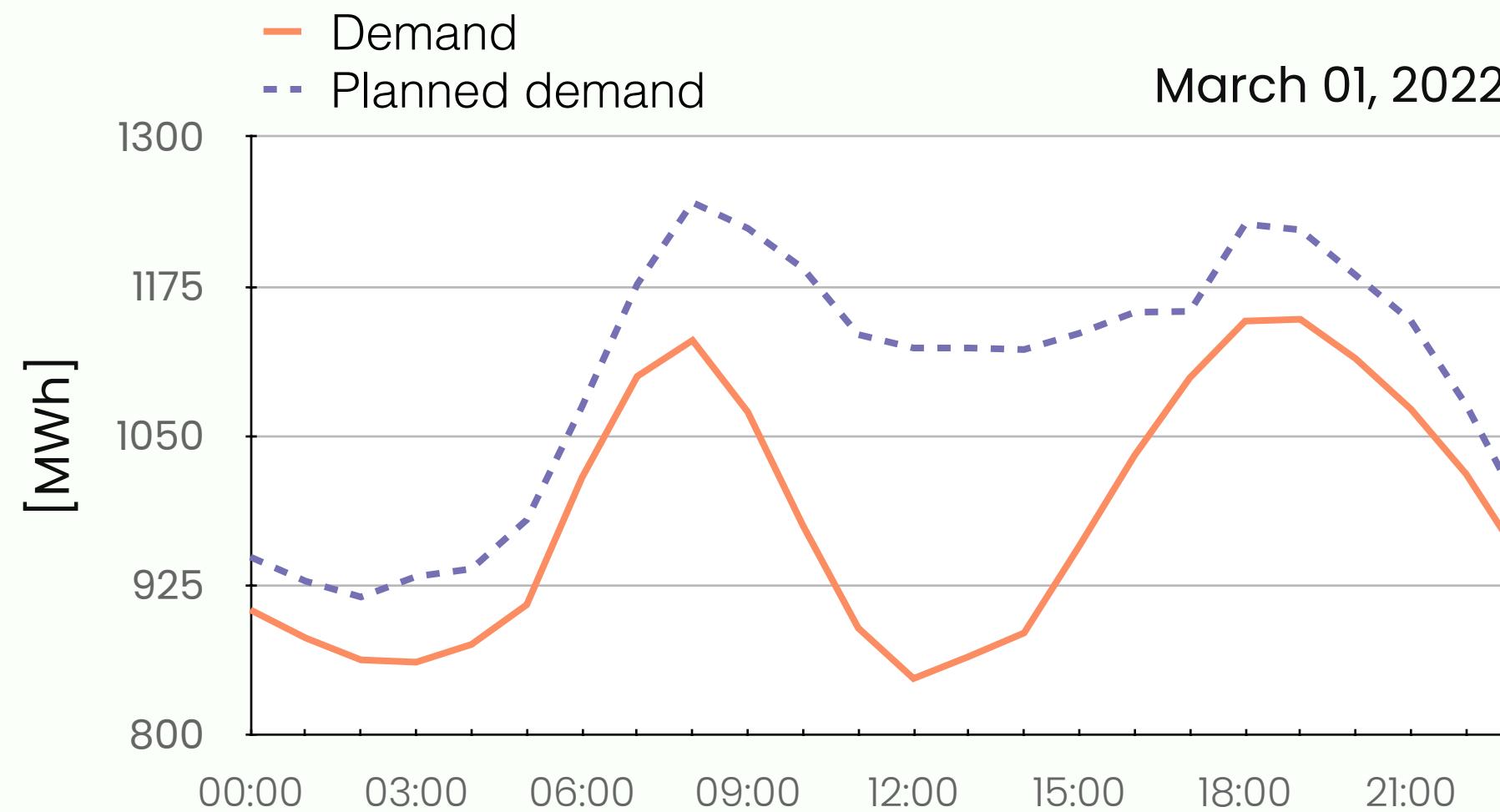
We have a  
clear winner  
- MAPE4



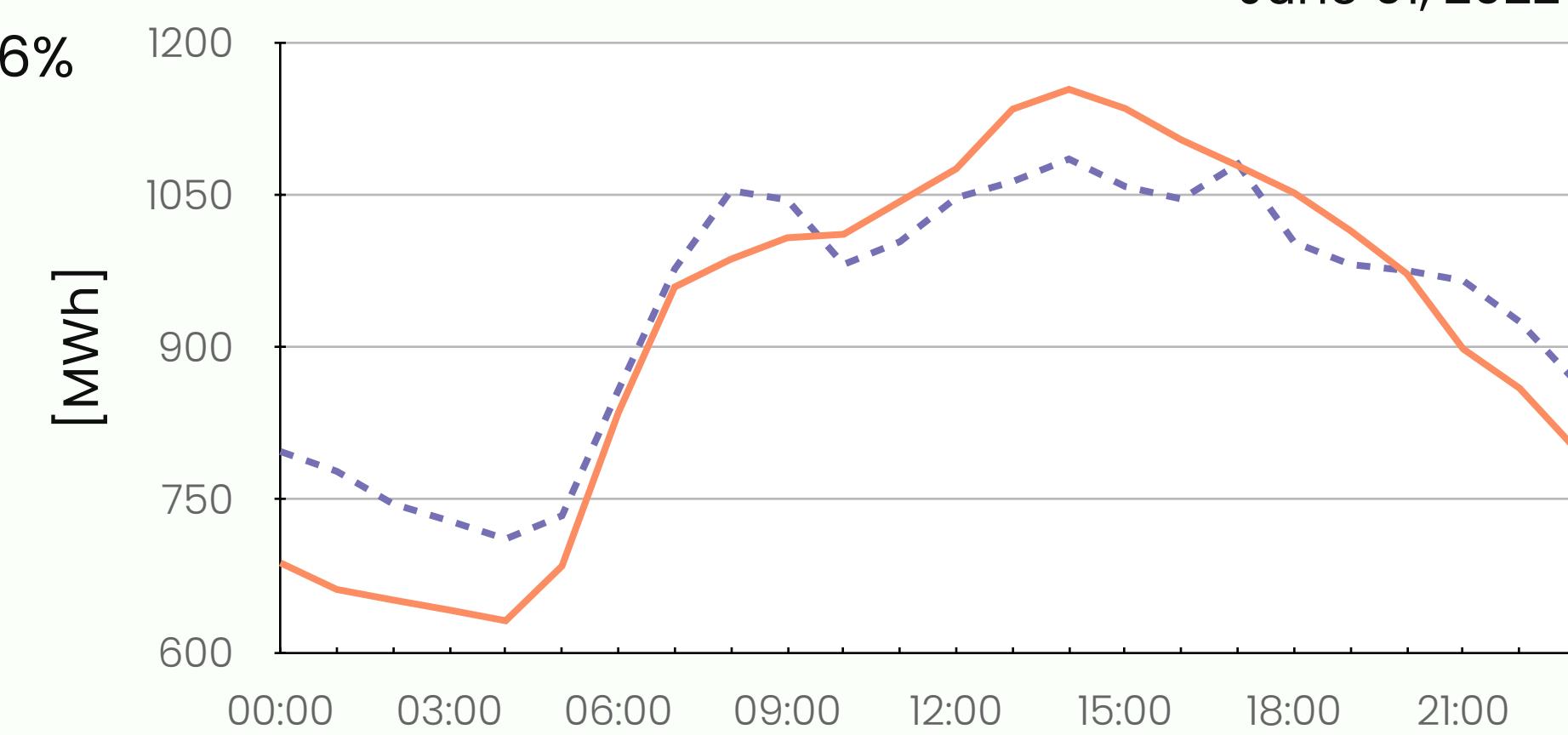
MAPE3 = 4.65%



MAPE4 = 3.61%

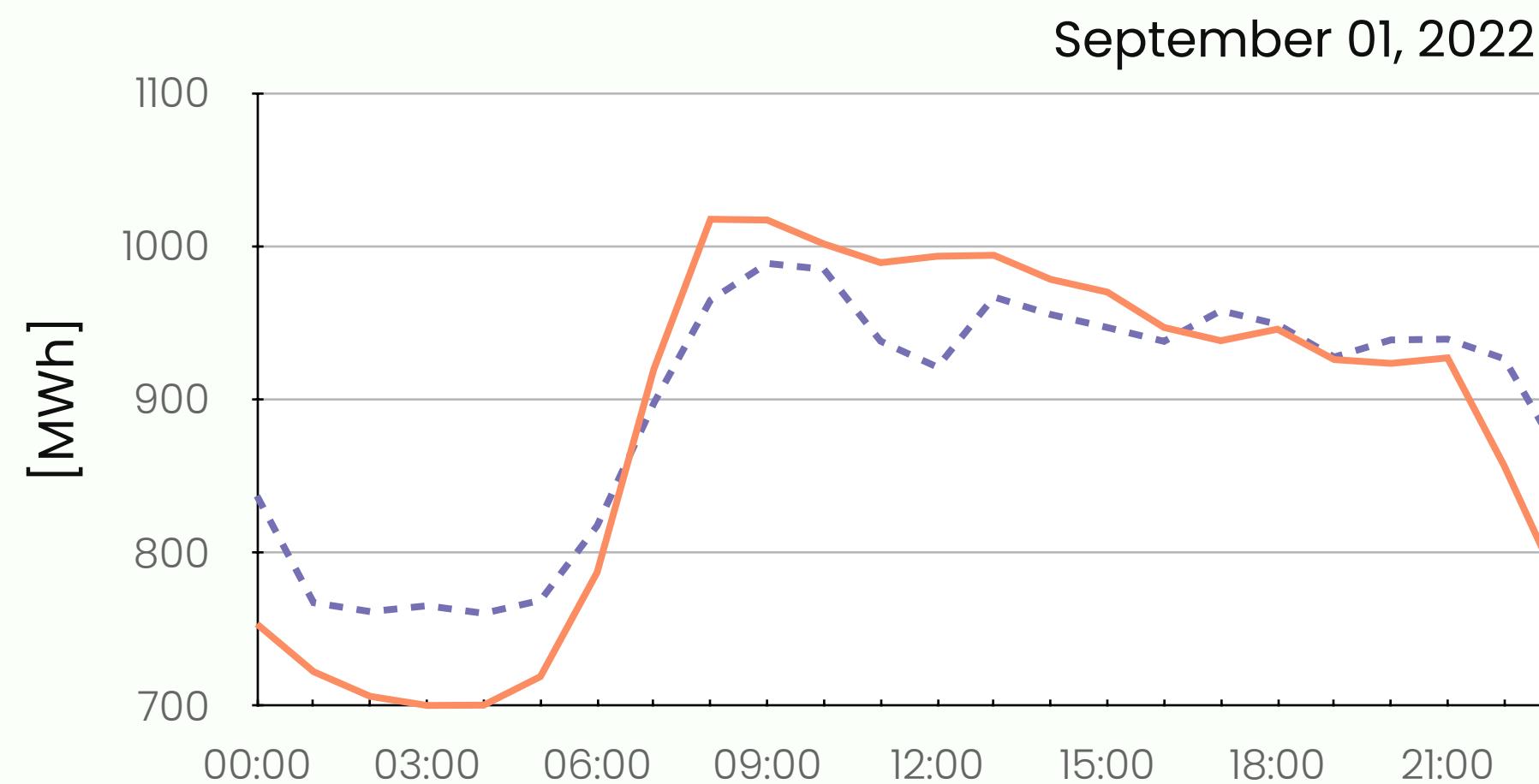


MAPE1 = 12%



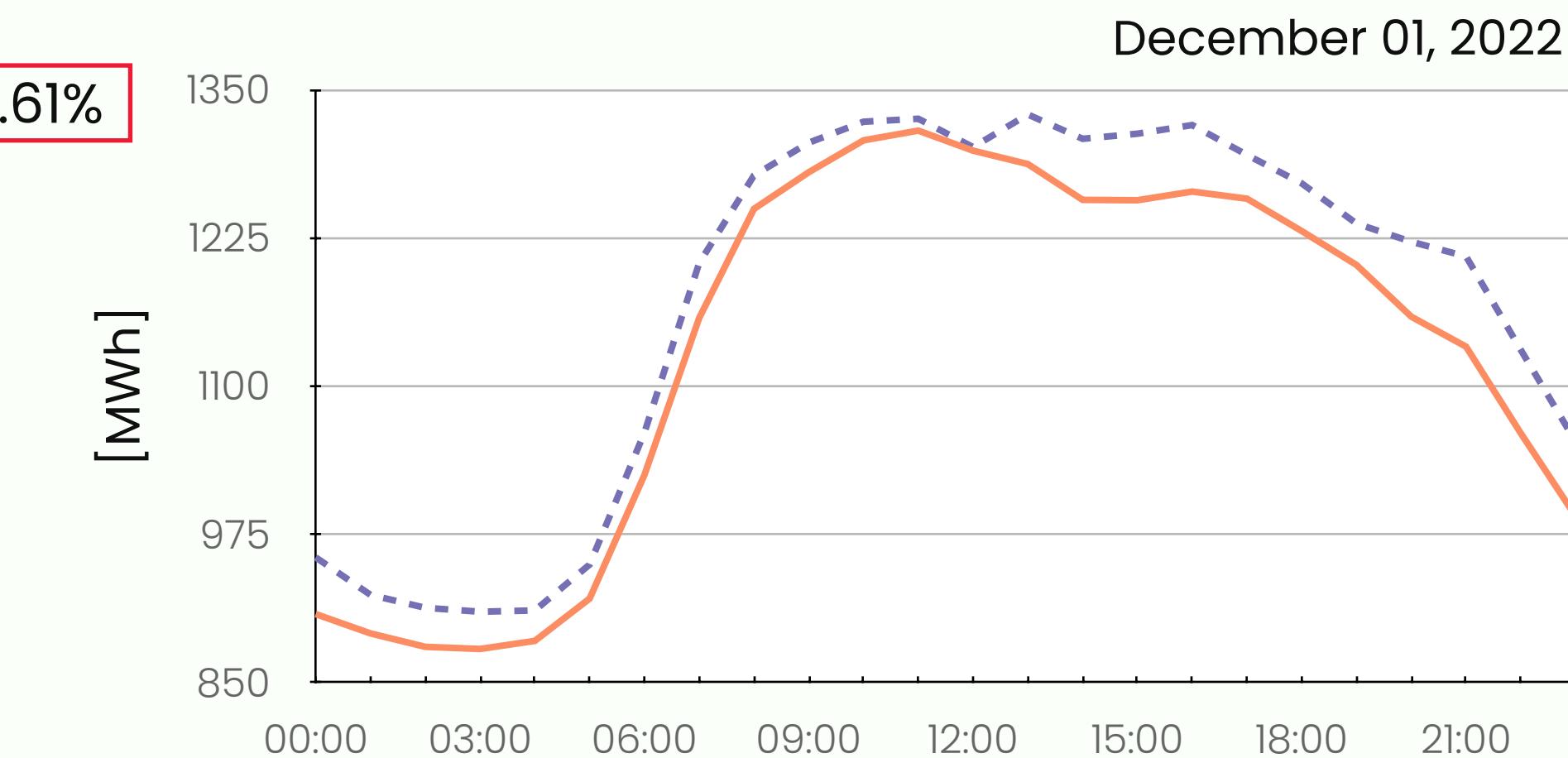
MAPE2 = 6.76%

We have a  
clear winner  
– MAPE4



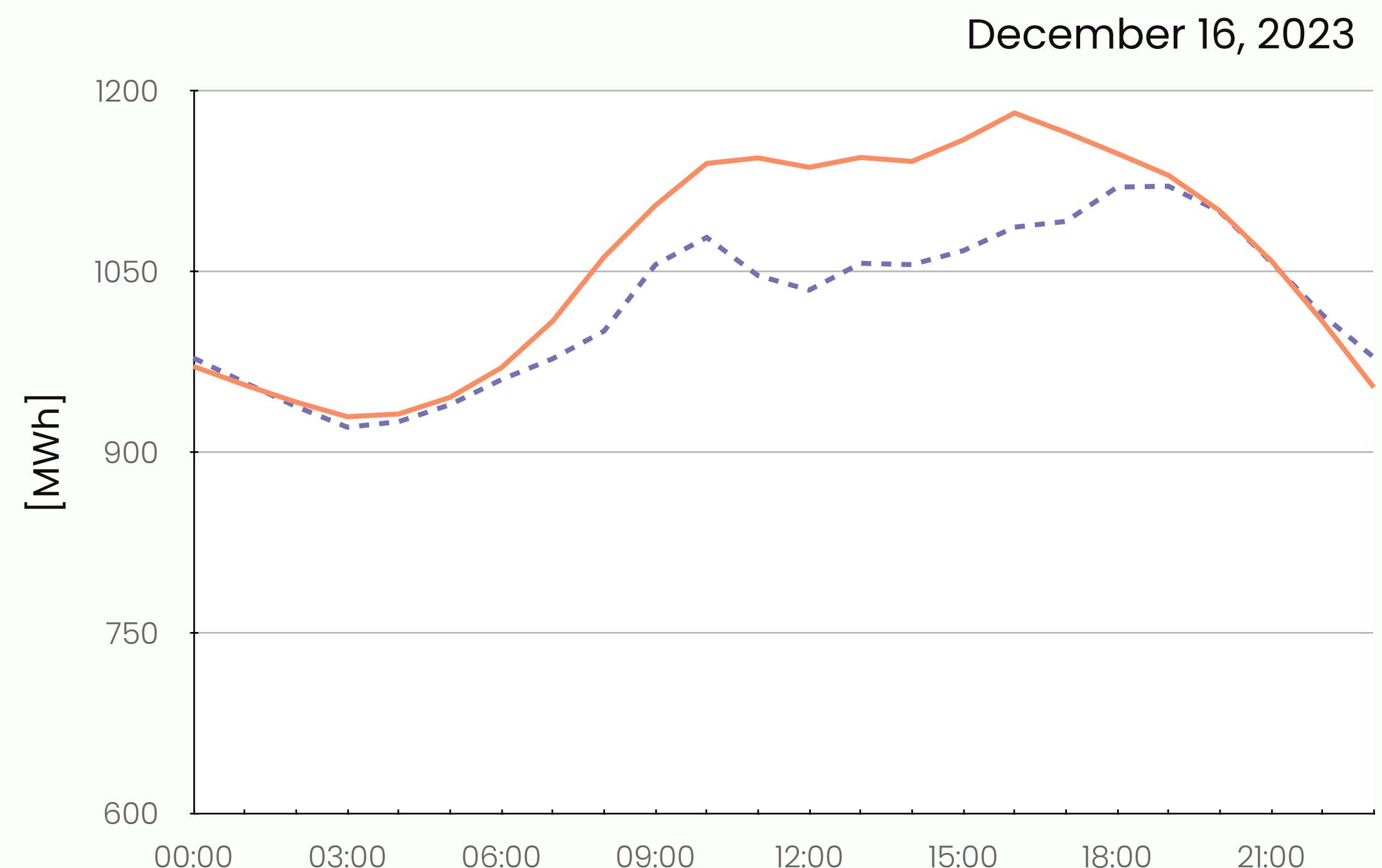
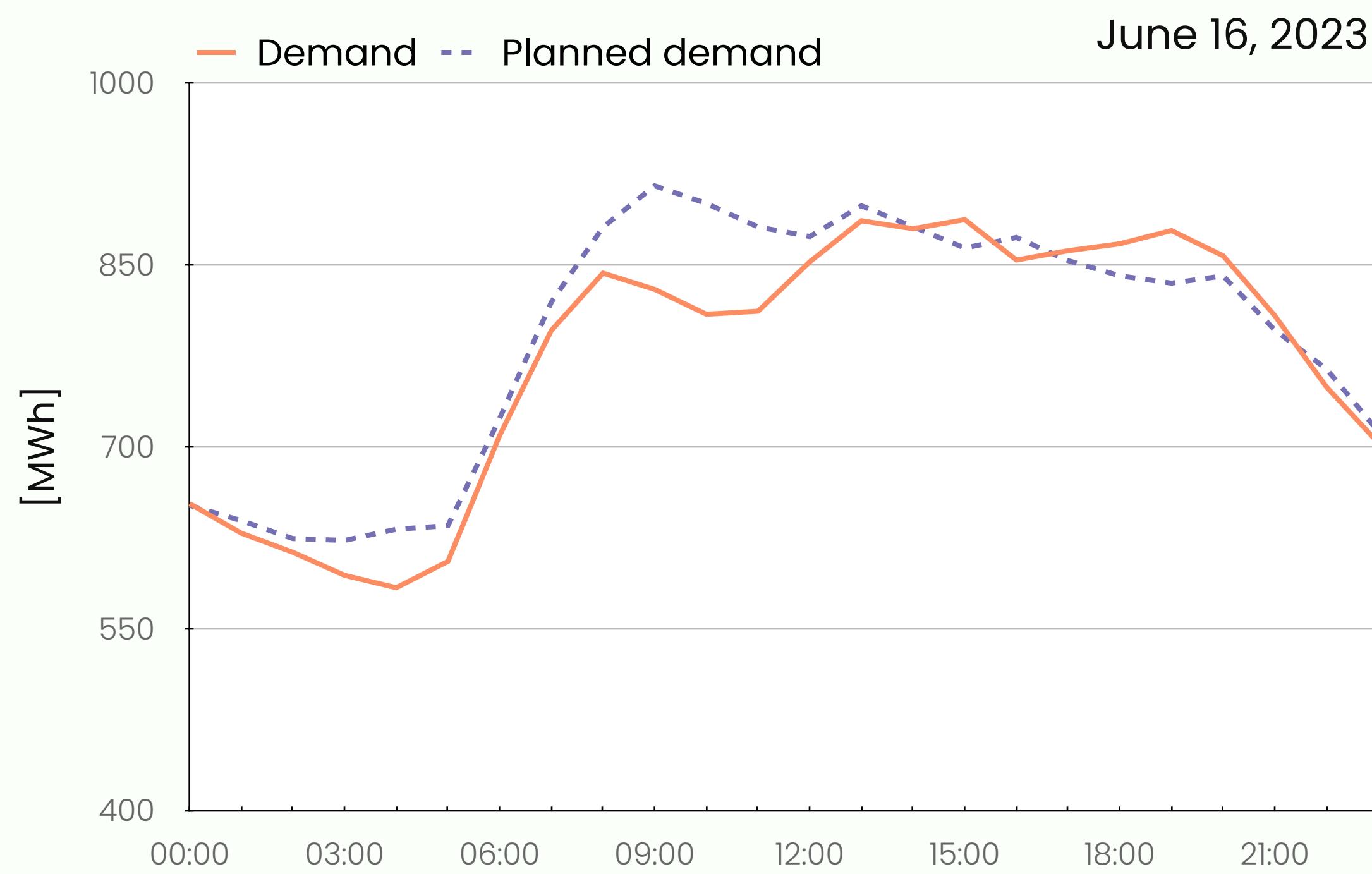
MAPE3 = 4.65%

How about  
others?

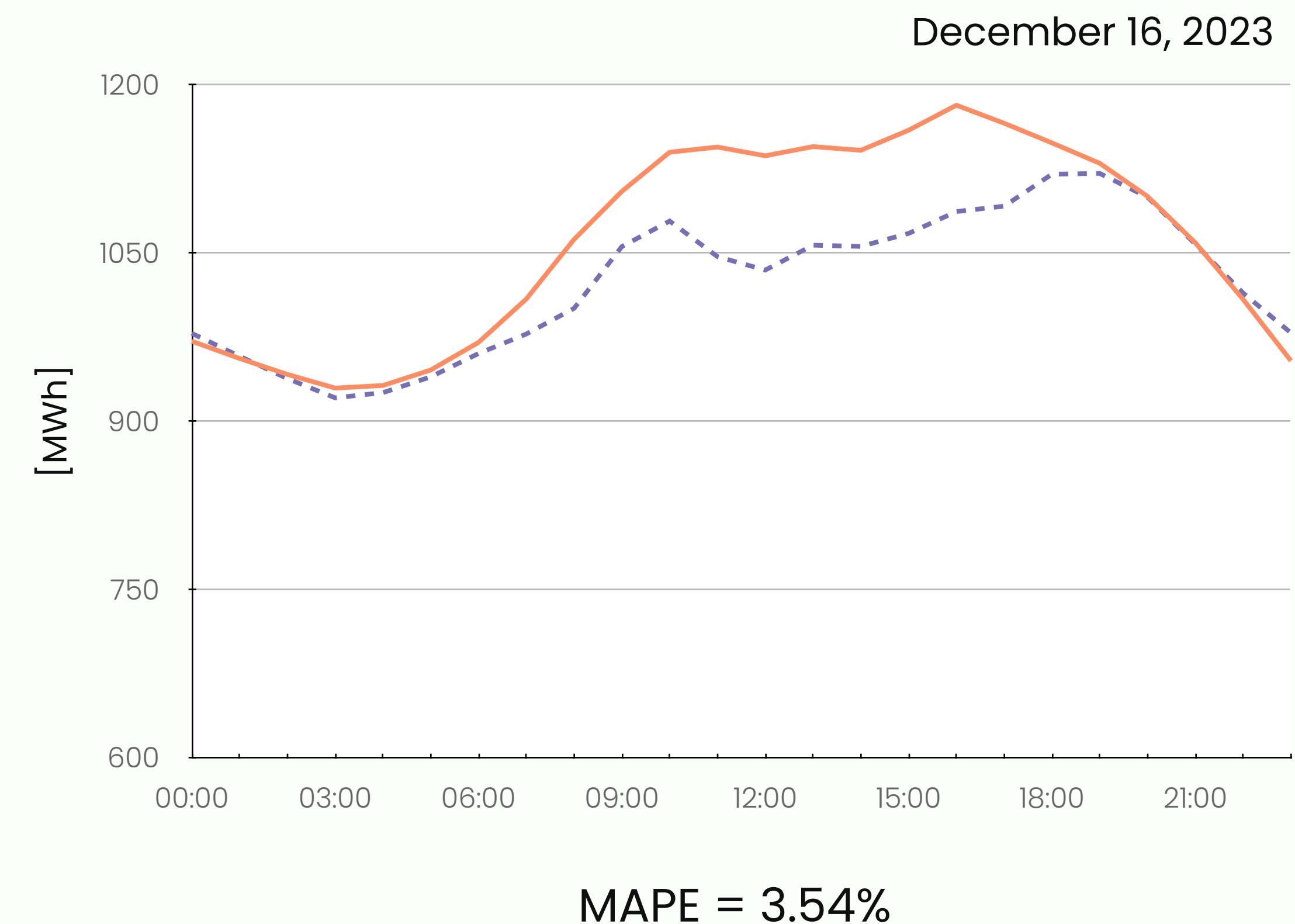
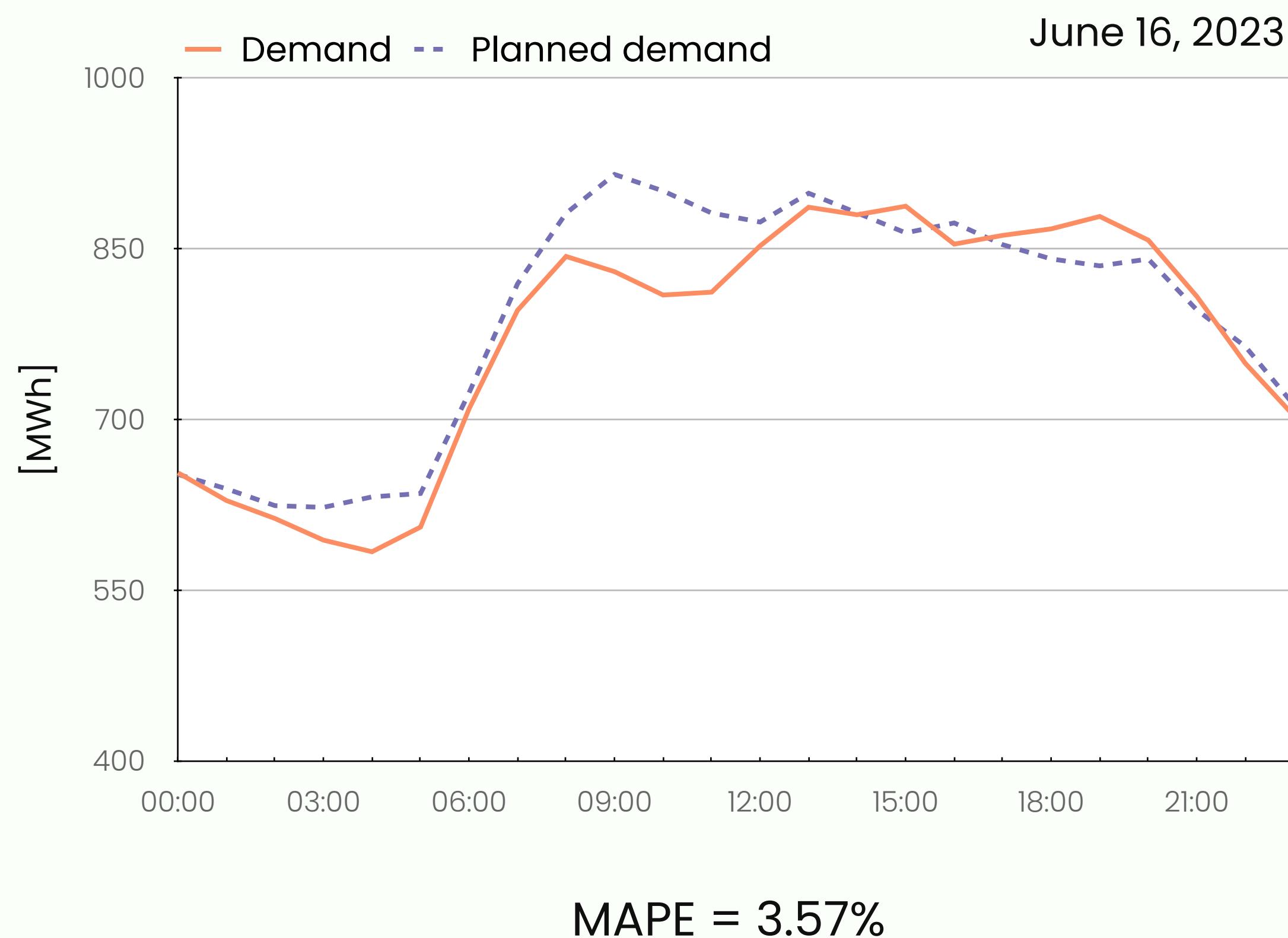


**MAPE4 = 3.61%**

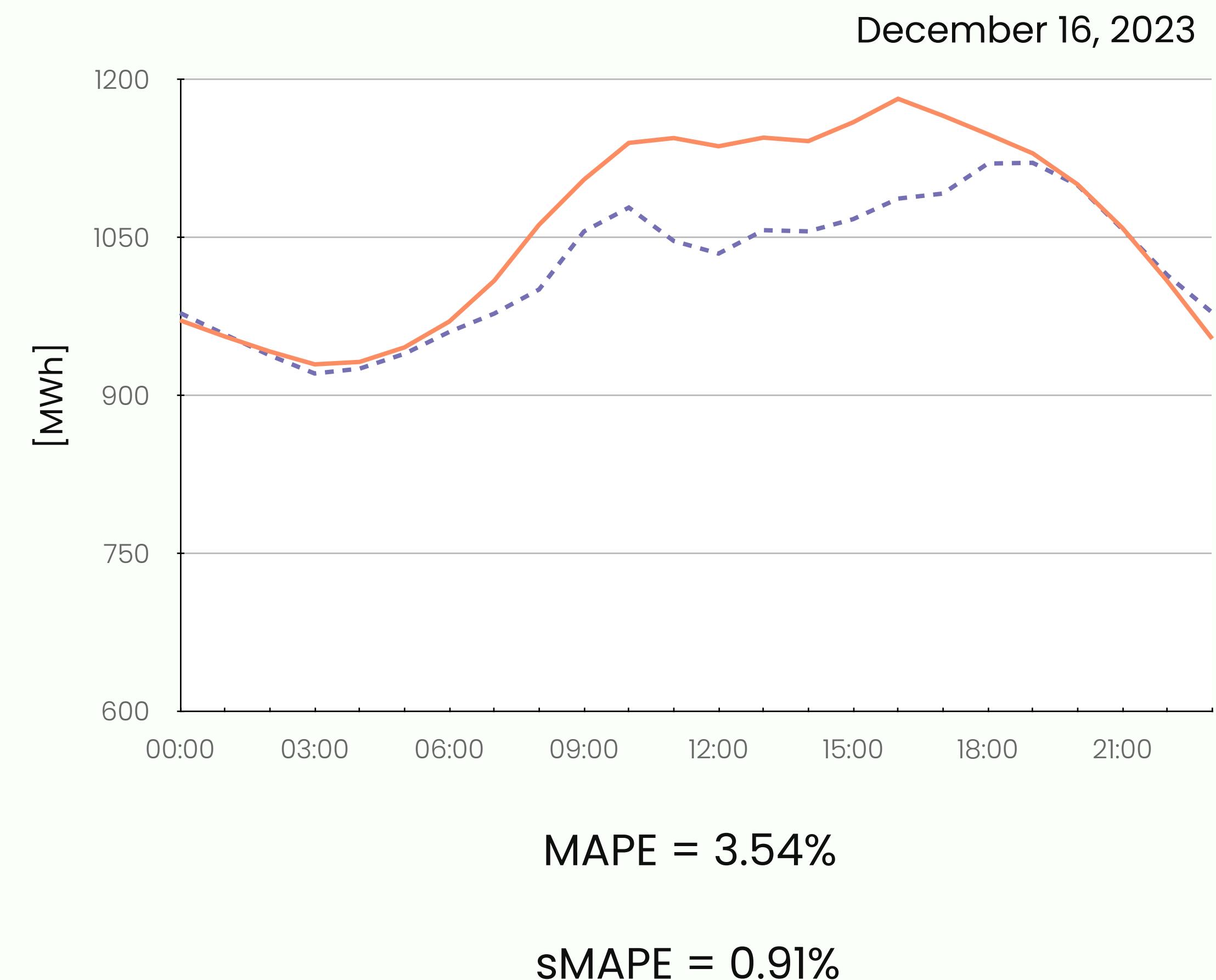
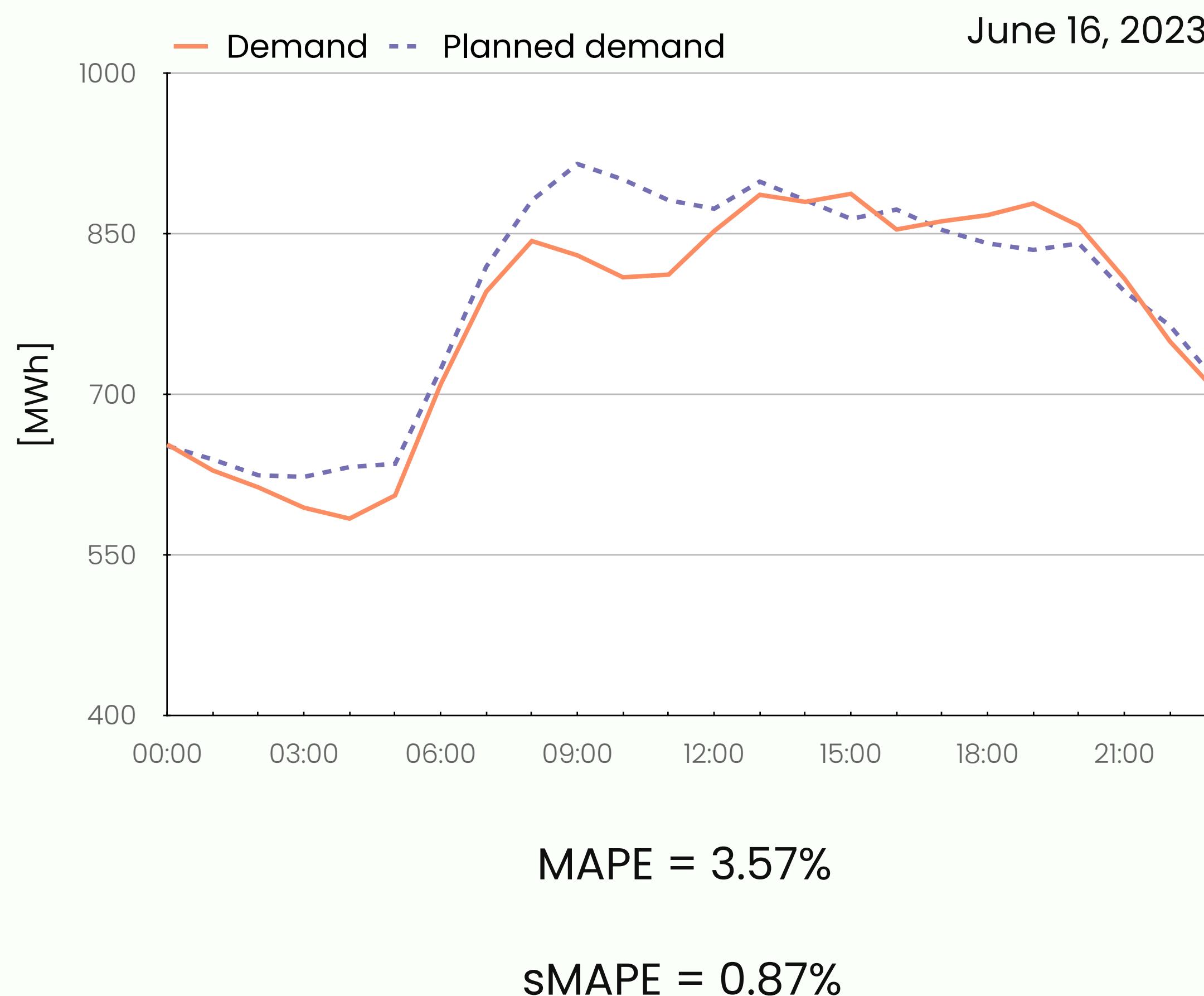
# FINAL REMARKS



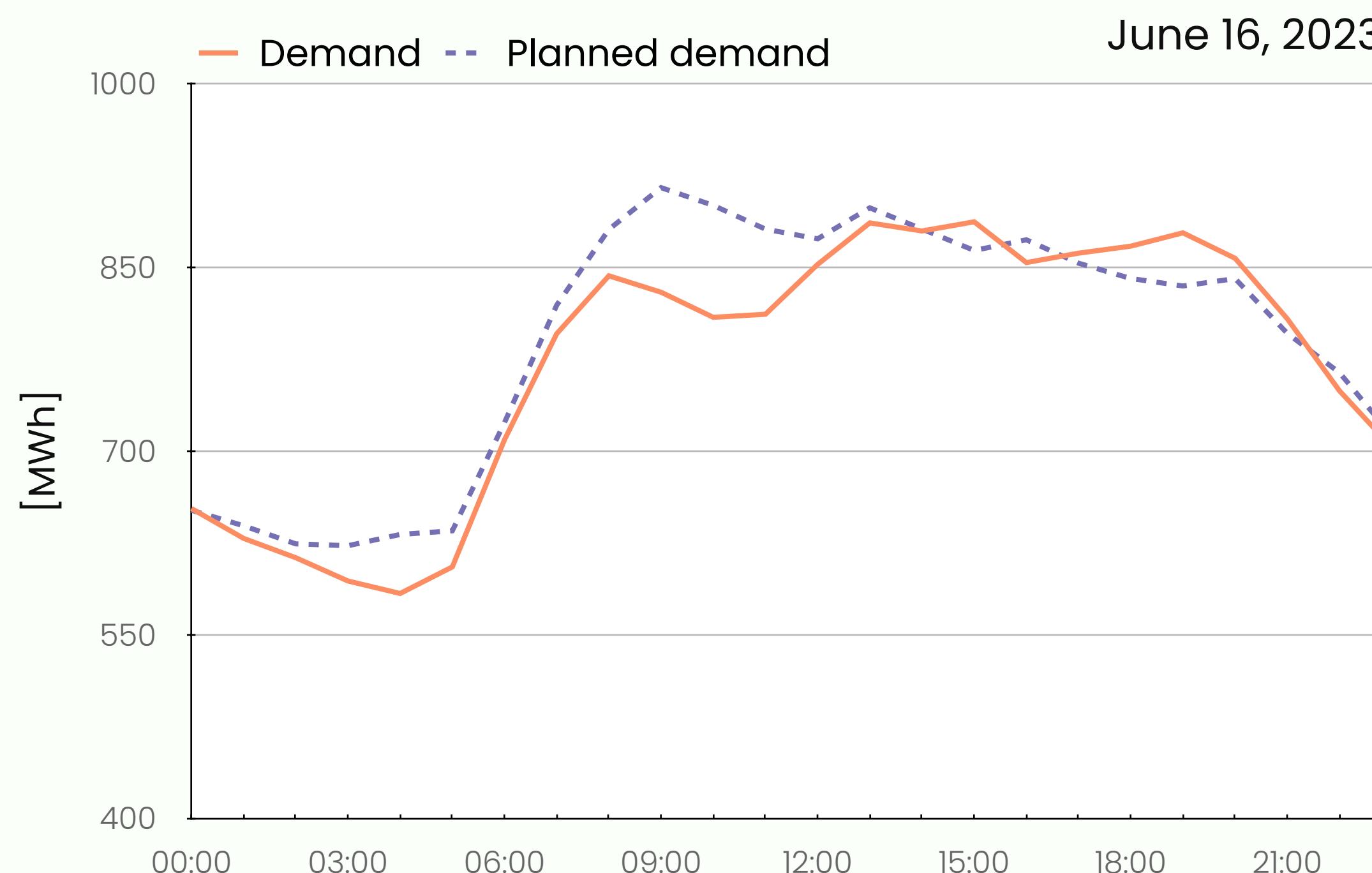
# FINAL REMARKS



# FINAL REMARKS



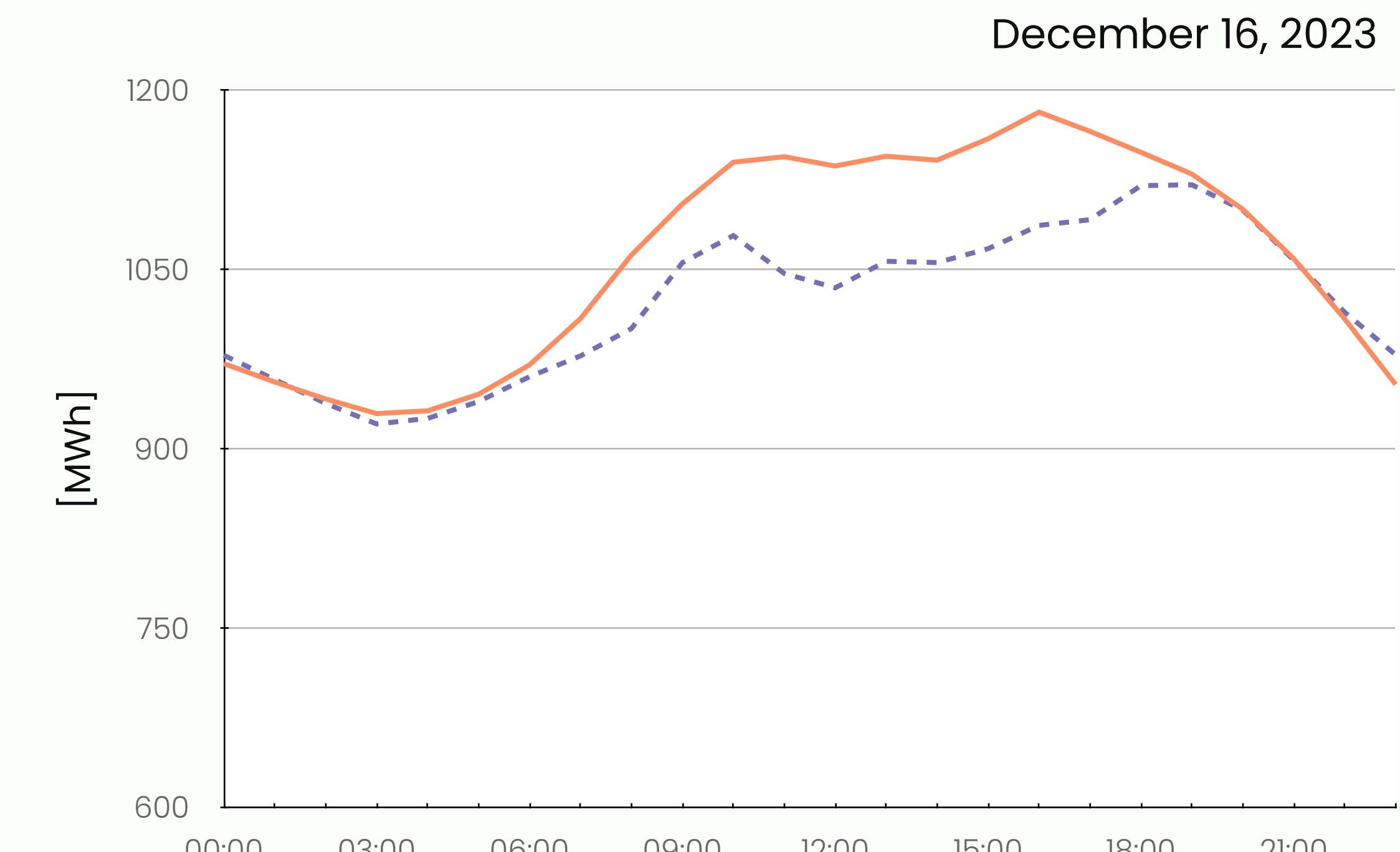
# FINAL REMARKS



MAPE = 3.57%

sMAPE = 0.87%

R<sup>2</sup> = 0.91



MAPE = 3.54%

sMAPE = 0.91%

R<sup>2</sup> = 0.84

Thank you!

Questions?