ENERGY DATA SCIENCE

Andmeteadus energeetikas

Prof. Juri Belikov

Department of Software Science
Tallinn University of Technology
juri.belikov@taltech.ee

LET'S GET ACQUAINTED

Prof. Juri Belikov
Department of Software Science
Tallinn University of Technology
Akadeemia tee 21B, room CYB-319
juri.belikov@taltech.ee

My main research interests lie on the edge of nonlinear control theory, power systems, and computer science (Energy Informatics).

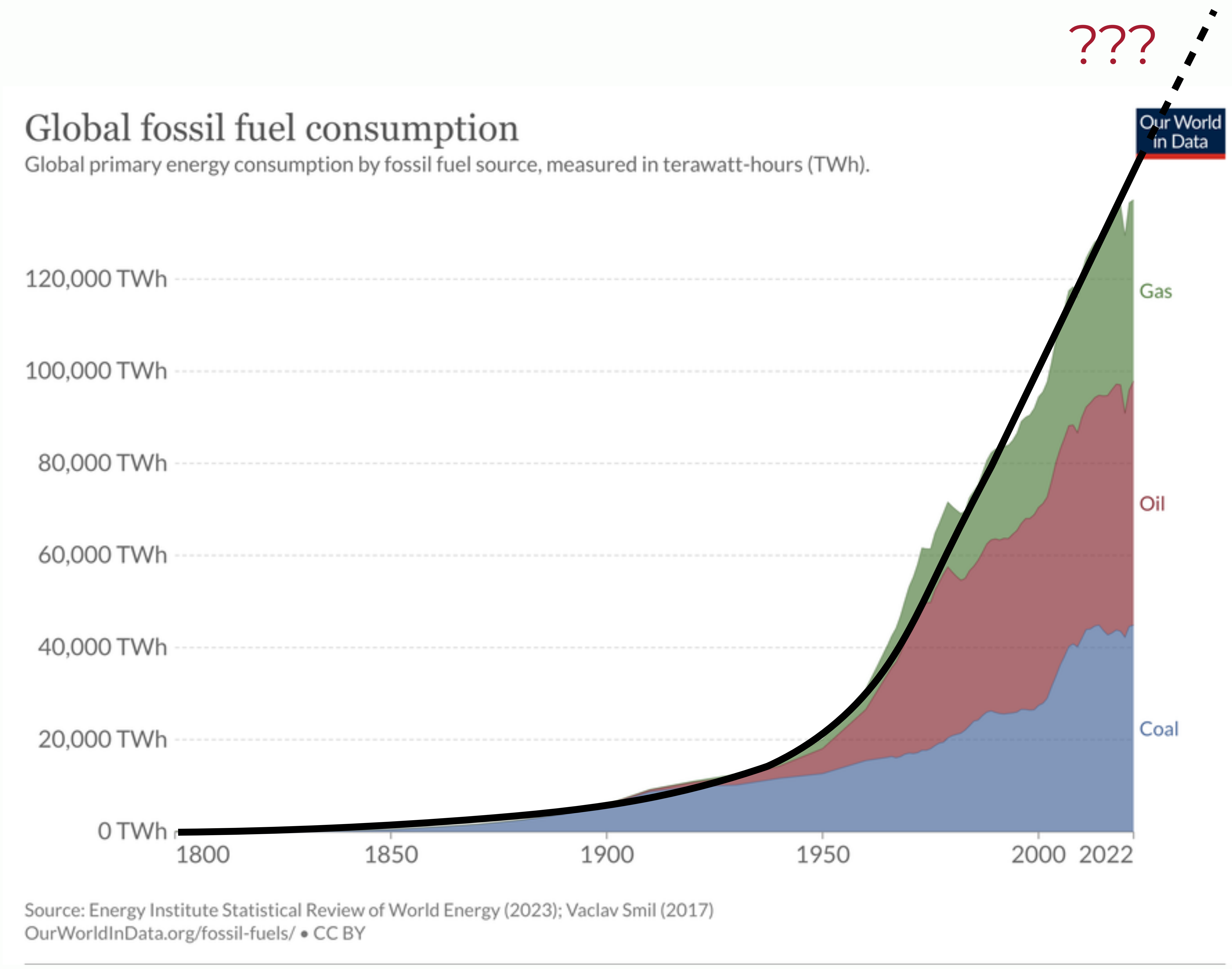
ENERGY & SCIENCE

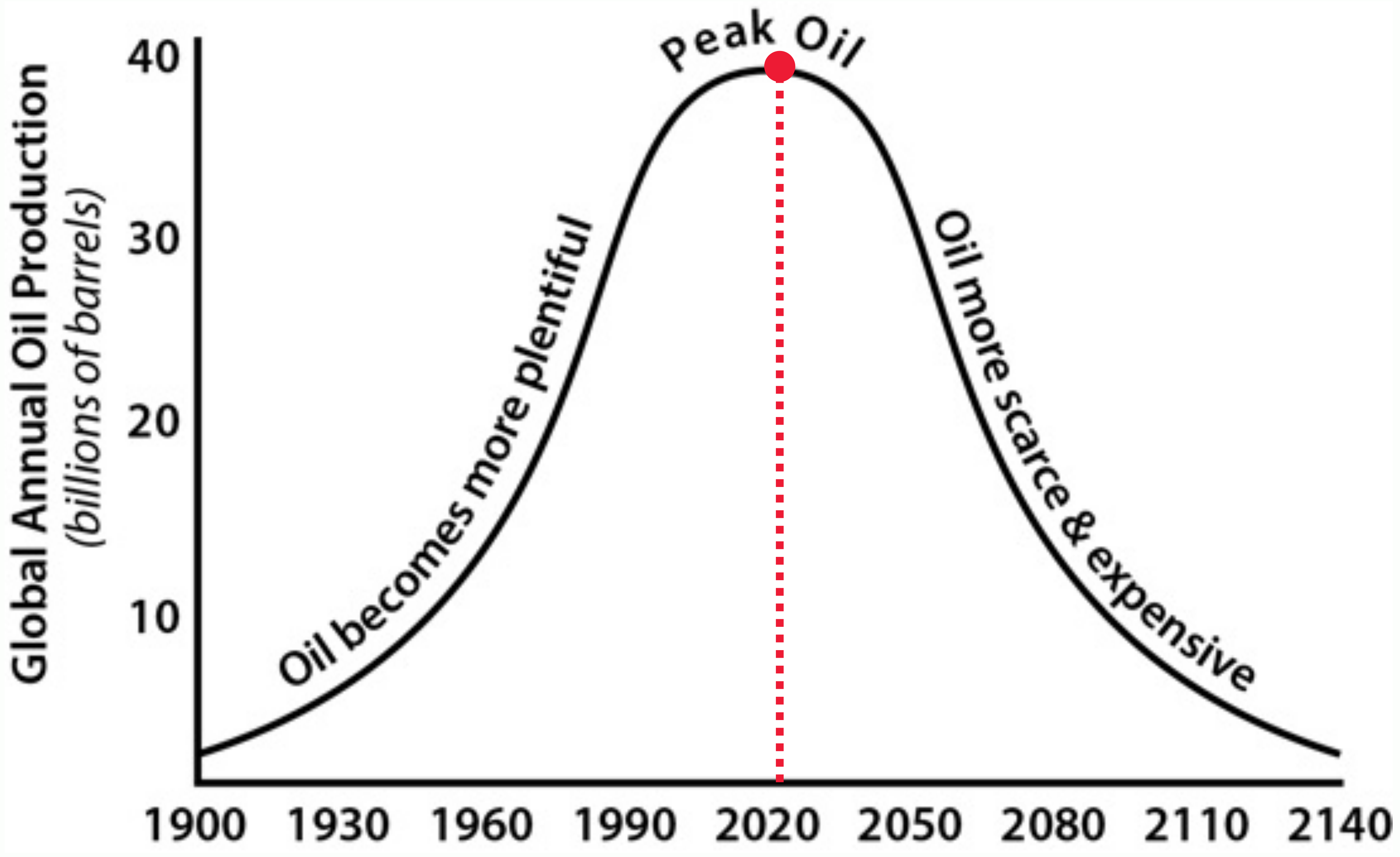
Humans learn to use more energy ...

Progress

HOW LONG?

Such a growth is not sustainable and cannot last forever …





https://www.explainingthefuture.com/peak_oil.html

RENEWABLE ENERGY SOURCES

Renewable energy is the key ...

RENEWABLE ENERGY SOURCES

Renewable energy is the key ...

There is a broader concept of Smart Grids.

SMART GRIDS: LONG STORY SHORT

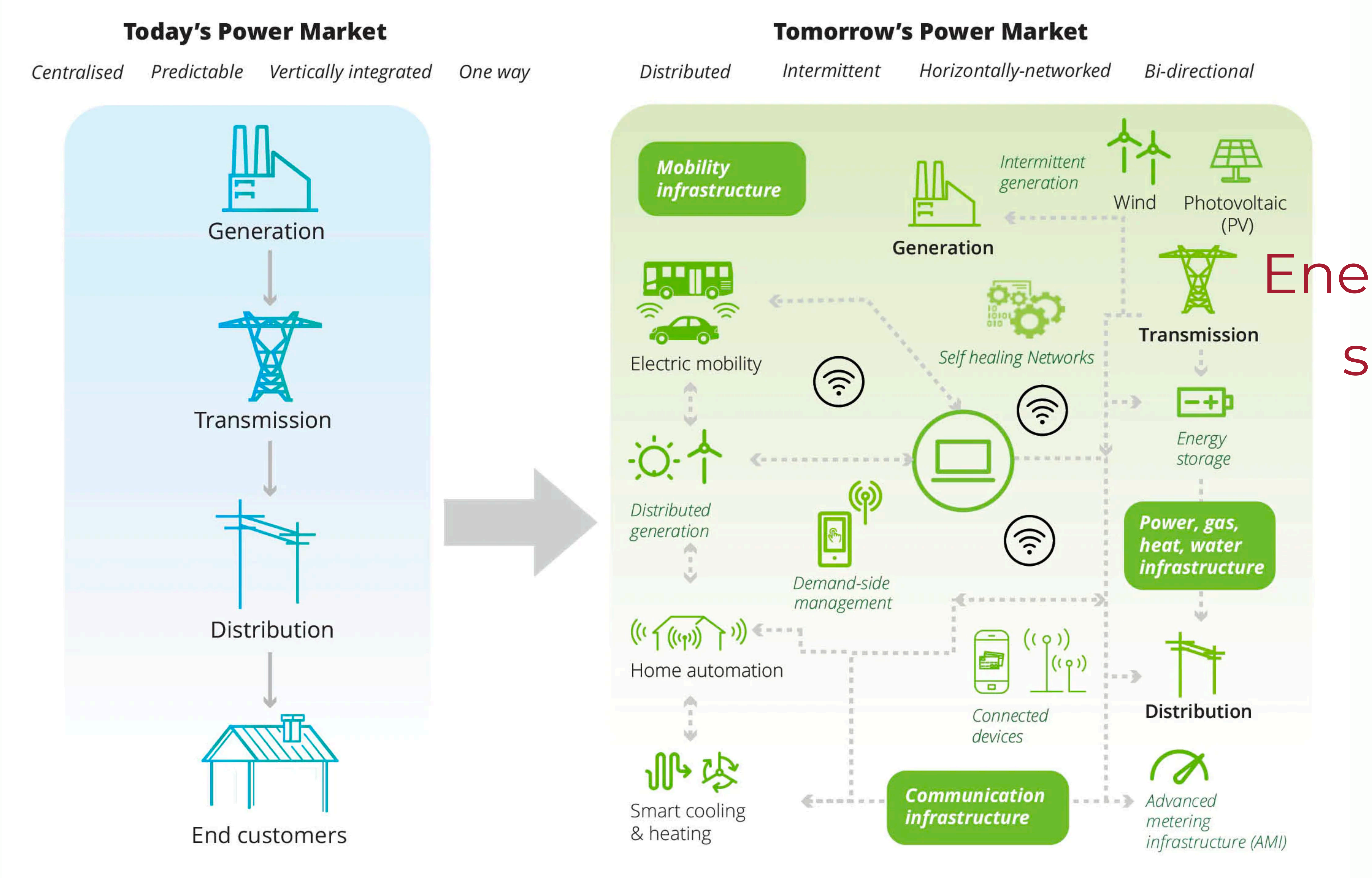
Q: What is Smart Grid?

SMART GRIDS: LONG STORY SHORT

Q: What is Smart Grid?

Short Answer: Smart Grid = IT + Electric Grid

WHAT IS IN THE FUTURE?



Energy-as-a-service

https://www2.deloitte.com/uk/en/pages/energy-and-resources/articles/energy-as-a-service.html

Where is IT and how IT can help?

ENERGY INFORMATICS: ENERGY + INFORMATION

> Energy informatics is a research field covering the use of information and communication technology to address energy utilisation and management challenges.

Core concept

$$\text{Energy} + \boxed{\text{Information}} < \text{Energy}$$

?

But why information is
so important

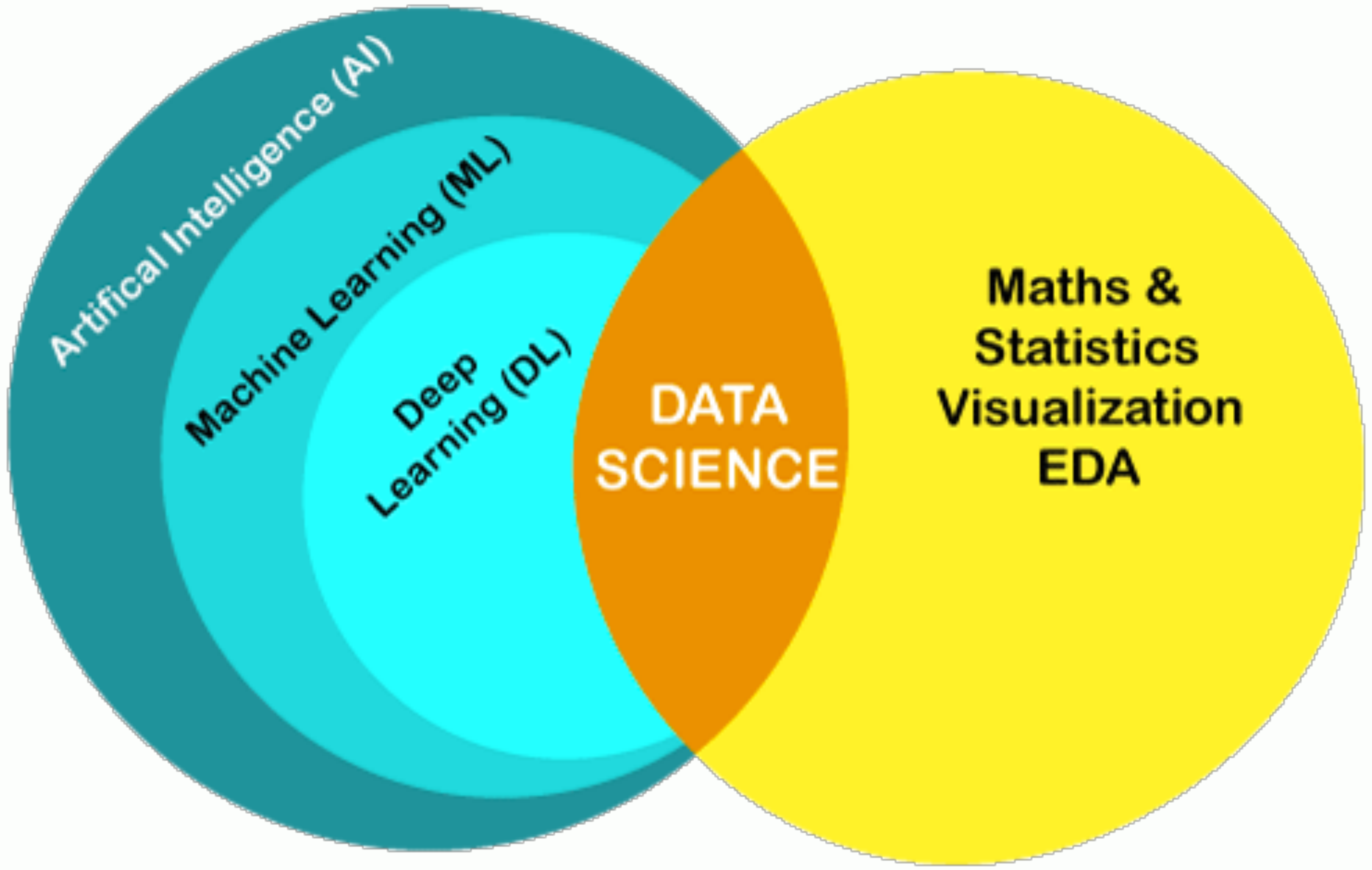
R. T. Watson and M.-C. Boudreau, (August 2011). *Energy Informatics*.

To the World of Data Science

DATA SCIENCE VS MACHINE LEARNING

Data Science is a field to study the approaches to find insights from the raw data.

Machine Learning is a technique used by the group of data scientists to enable the machines to learn automatically from the past data



https://www.javatpoint.com/data-science-vs-machine-learning

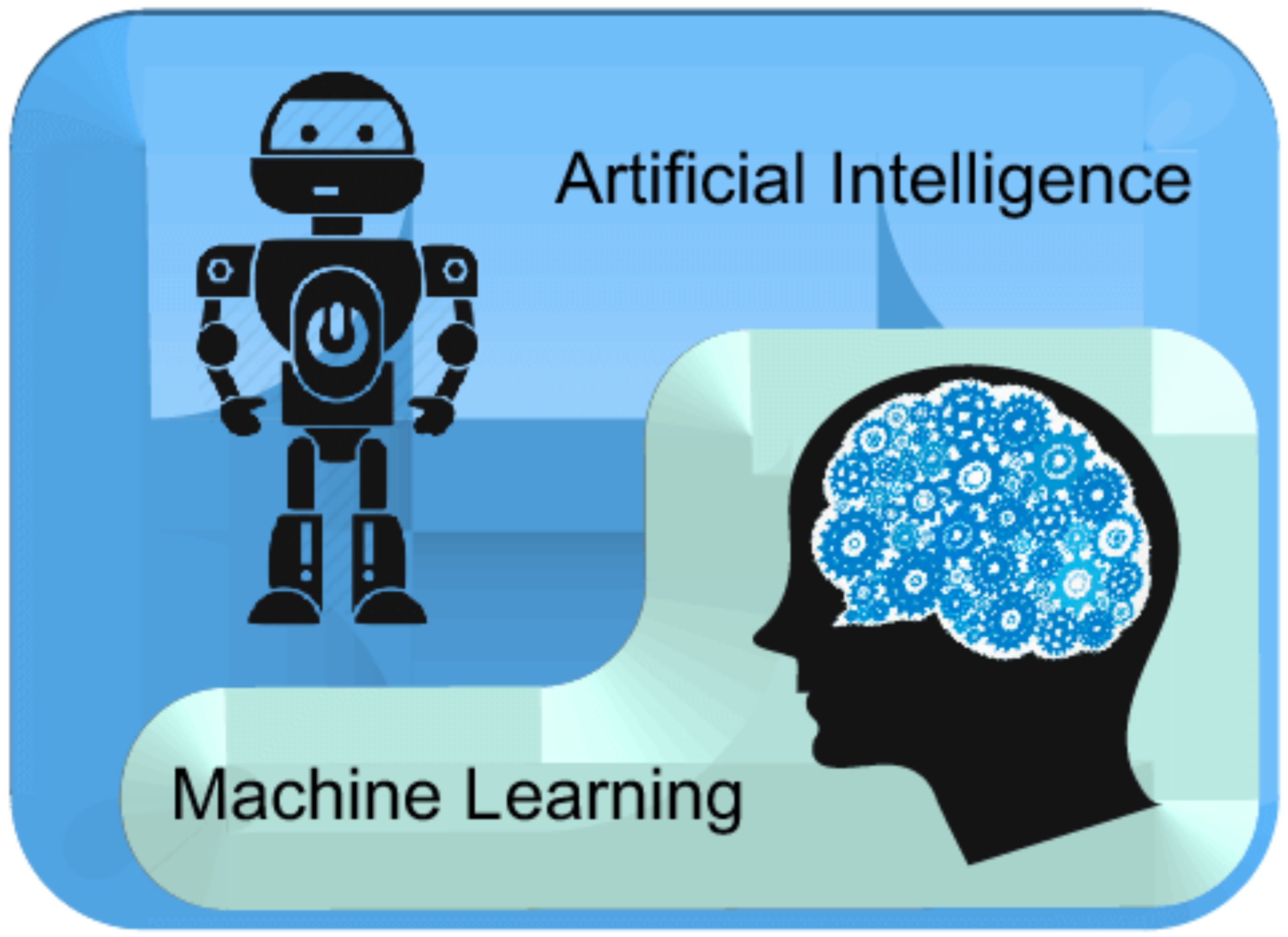
ARTIFICIAL INTELLIGENCE VS MACHINE LEARNING

AI is a technology that enables a machine to simulate human behaviour (decision-making or problem solving).

The **focus** of AI is on solving problems.

ML is a subset of AI which allows a machine to automatically learn from past data without programming explicitly.

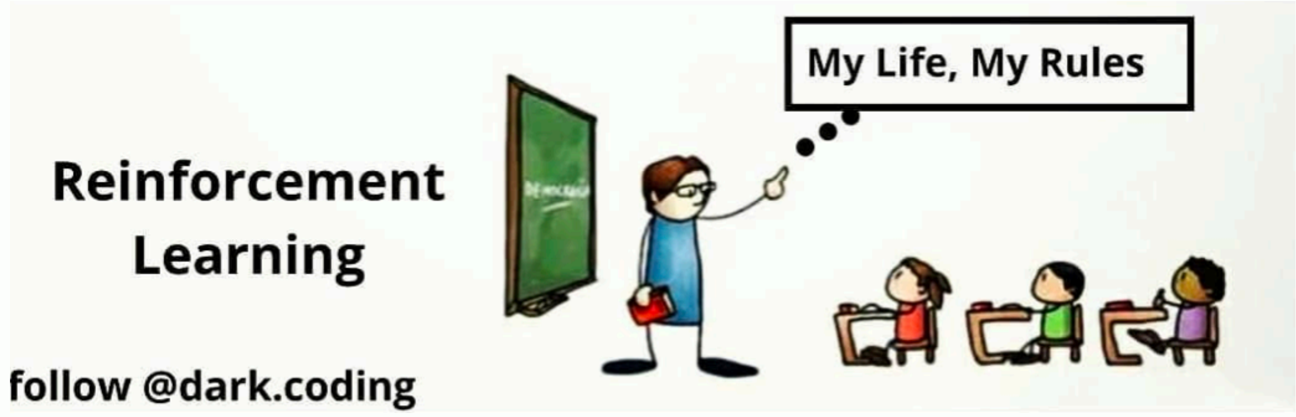
The **focus** of ML is on accuracy.



https://www.javatpoint.com/difference-between-artificial-intelligence-and-machine-learning

TRAINING/LEARNING

SUPERVISED	UNSUPERVISED	REINFORCEMENT
Learning by example	Learning by reasoning	Learning by interacting with the environment
Output is known	Target is not provided	Target is provided
Suitable for classification and regression	Suitable for clusterisation	Output is unknown



https://arshren.medium.com/supervised-unsupervised-and-reinforcement-learning-245b59709f68

ML APPLICATIONS IN POWER SYSTEMS (5)

S: M. Miraftabzadeh, M. Longo, F. Foiadelli, M. Pasetti, R. Igual. Advances in the Application of Machine Learning Techniques for Power System Analytics: A Survey. Energies, 14, 4776, 2021.

ML APPLICATIONS IN POWER SYSTEMS (5)

S: M. Miraftabzadeh, M. Longo, F. Foiadelli, M. Pasetti, R. Igual. Advances in the Application of Machine Learning Techniques for Power System Analytics: A Survey. Energies, 14, 4776, 2021.

Electricity Market:

How are electricity prices formed?

EP FORMATION: THEORY

- Optimisation algorithm finds the cheapest set of power plants (supply) to cover the expected demand in any given hour
- Optimisation typically takes place hourly, but is performed for 24h simultaneously (for next day)
- Mathematically speaking:

$$\begin{aligned} \text{minimize} \qquad & S = P_1Q_1 + P_2Q_2 + \cdots + P_nQ_n, \\ \text{subject to} \qquad & S = D, \end{aligned}$$

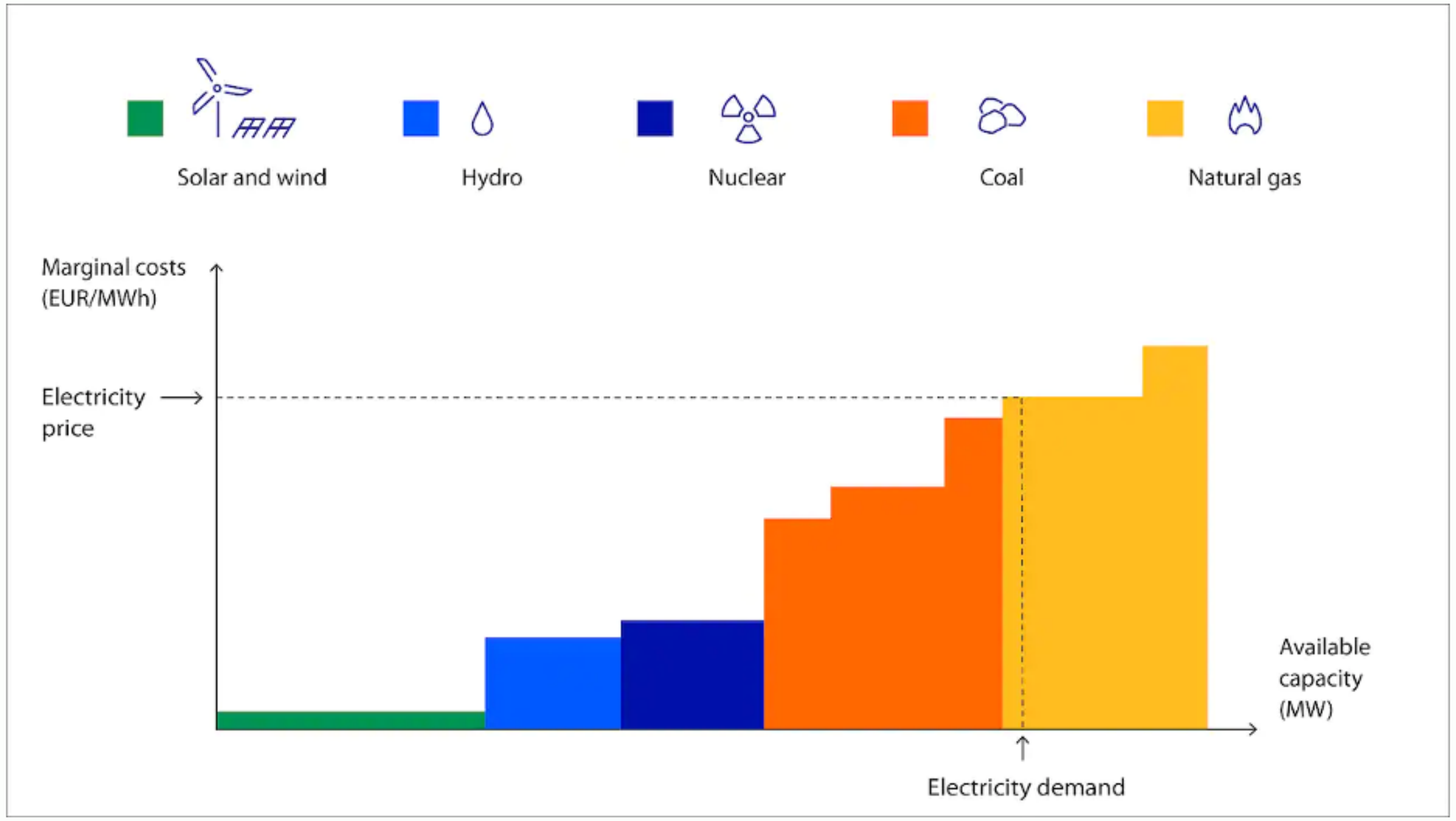
where S is the supply, D is the demand, P is the power plants' production price, and Q is the quantity that the power plant can produce at the offered price .

Power plant with the highest price included in the minimised set, will set the **electricity price**!

EP FORMATION: THEORY (2)

For example, in one single hour:

- Demand = 1000 MWh
- Producer 1: 500 MWh, Price = 30 EUR/MWh
- Producer 2: 300 MWh, Price = 40 EUR/MWh
- Producer 3: 300 MWh, Price = 50 EUR/MWh



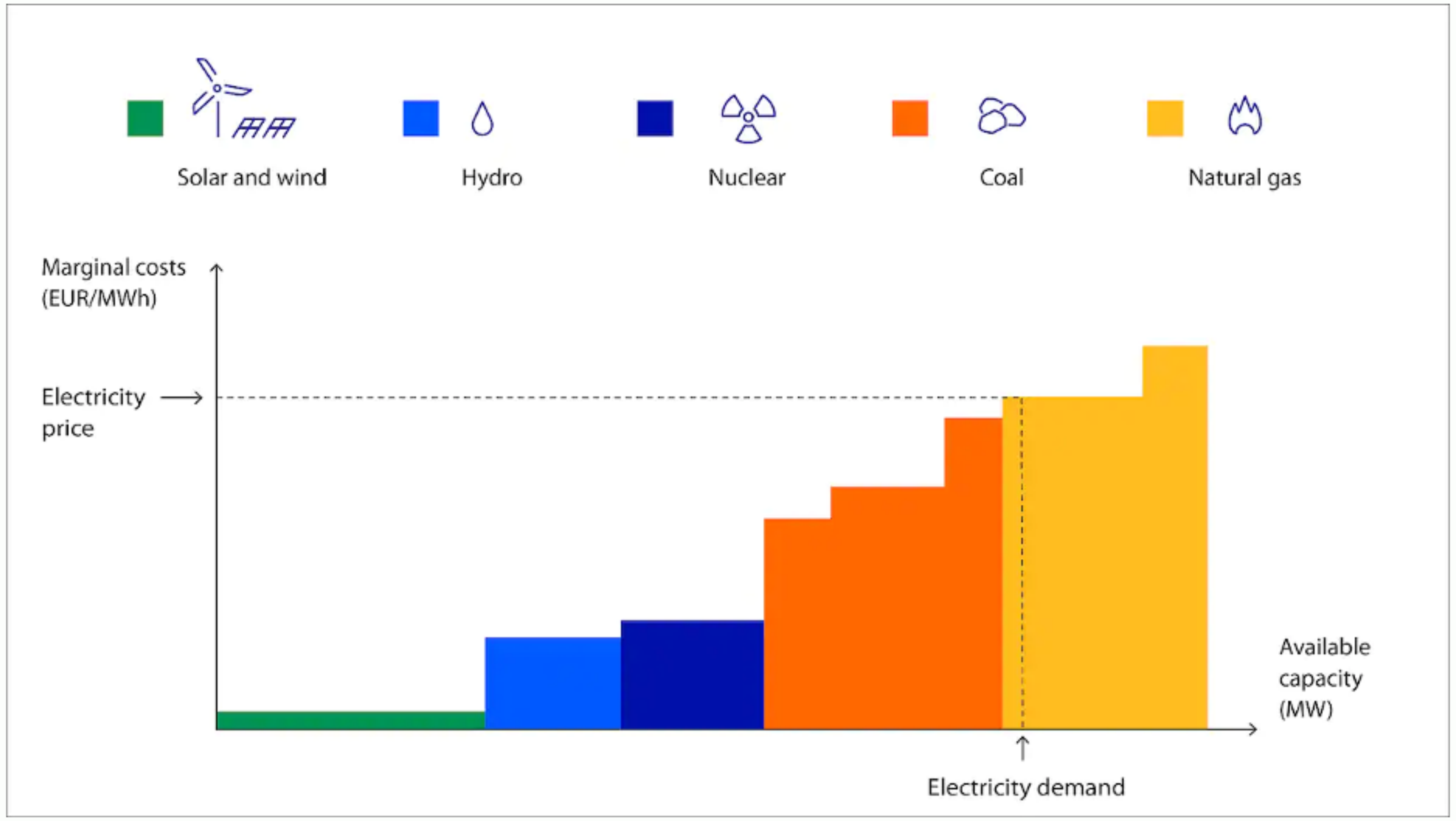
Let's find 1000 MWh of cheapest supply:

- Producer 1, producing 500 MWh
- Producer 2, producing 300 MWh
- Producer 3, producing 200 MWh

EP FORMATION: THEORY (2)

For example, in one single hour:

- Demand = 1000 MWh
- Producer 1: 500 MWh, Price = 30 EUR/MWh
- Producer 2: 300 MWh, Price = 40 EUR/MWh
- Producer 3: 300 MWh, Price = 50 EUR/MWh



Let's find 1000 MWh of cheapest supply:

- Producer 1, producing 500 MWh
- Producer 2, producing 300 MWh
- Producer 3, producing 200 MWh

Producer 3, being the last in the set, will set the electricity price to 50 EUR/MWh.

ELECTRICITY PRICE CAN BE NEGATIVE!

EUR/MWh

26-05-2023	EE	NL	FI	LV
00 - 01	62,94	88,11	0,01	62,94
01 - 02	61,86	76,40	-0,04	61,86
02 - 03	60,46	74,53	-0,08	60,46
03 - 04	4,09	74,00	-0,09	4,09
04 - 05	4,09	77,69	-0,02	4,09
05 - 06	22,05	87,44	1,36	22,05
06 - 07	128,08	102,42	2,15	128,08
07 - 08	103,06	103,06	40,15	103,06
08 - 09	95,00	95,00	52,47	95,00
09 - 10	74,90	74,90	28,68	74,90
10 - 11	38,54	38,54	14,70	38,54
11 - 12	4,02	4,02	3,97	4,02
12 - 13	4,05	-3,91	2,11	4,05
13 - 14	0,97	-25,34	0,97	0,97
14 - 15	0,00	-19,90	0,00	0,00
15 - 16	4,05	-10,01	0,07	4,05
16 - 17	9,42	-3,90	1,38	9,42
17 - 18	43,12	44,90	1,78	43,12
18 - 19	80,90	80,90	2,43	80,90
19 - 20	83,26	80,49	3,21	83,26
20 - 21	112,85	113,98	3,44	112,85
21 - 22	110,00	109,46	3,97	110,00
22 - 23	99,50	99,50	3,45	99,50
23 - 00	90,28	92,50	2,21	90,28

WHAT IS A DATA SCIENCE?

Data science combines:

✓ math and statistics,

✓ specialised programming,

✓ advanced analytics,

✓ artificial intelligence (AI), and machine learning

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.

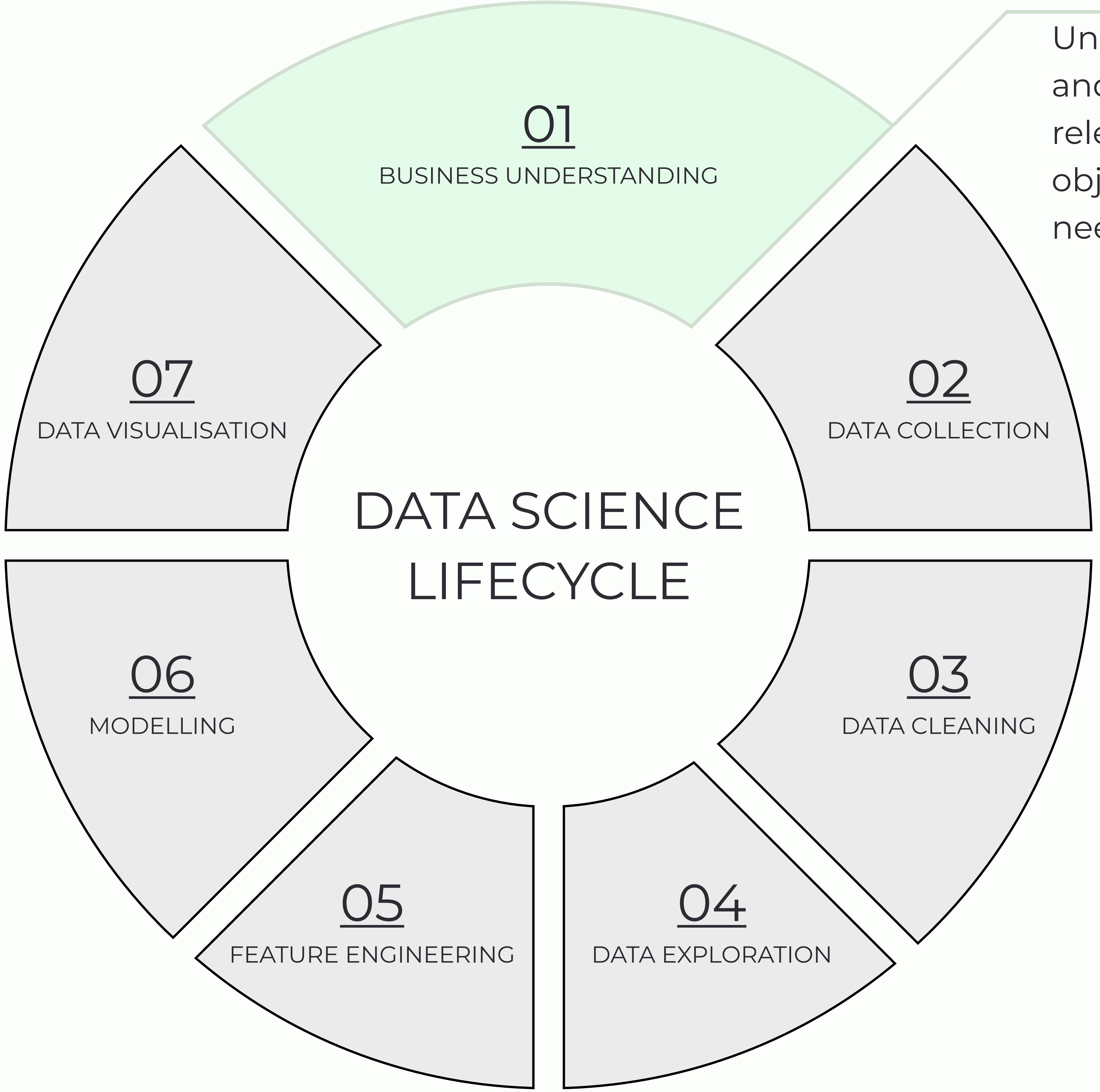
by IBM

https://www.ibm.com/topics/data-science

Step by step

Data Science Lifecycle

with illustrative example

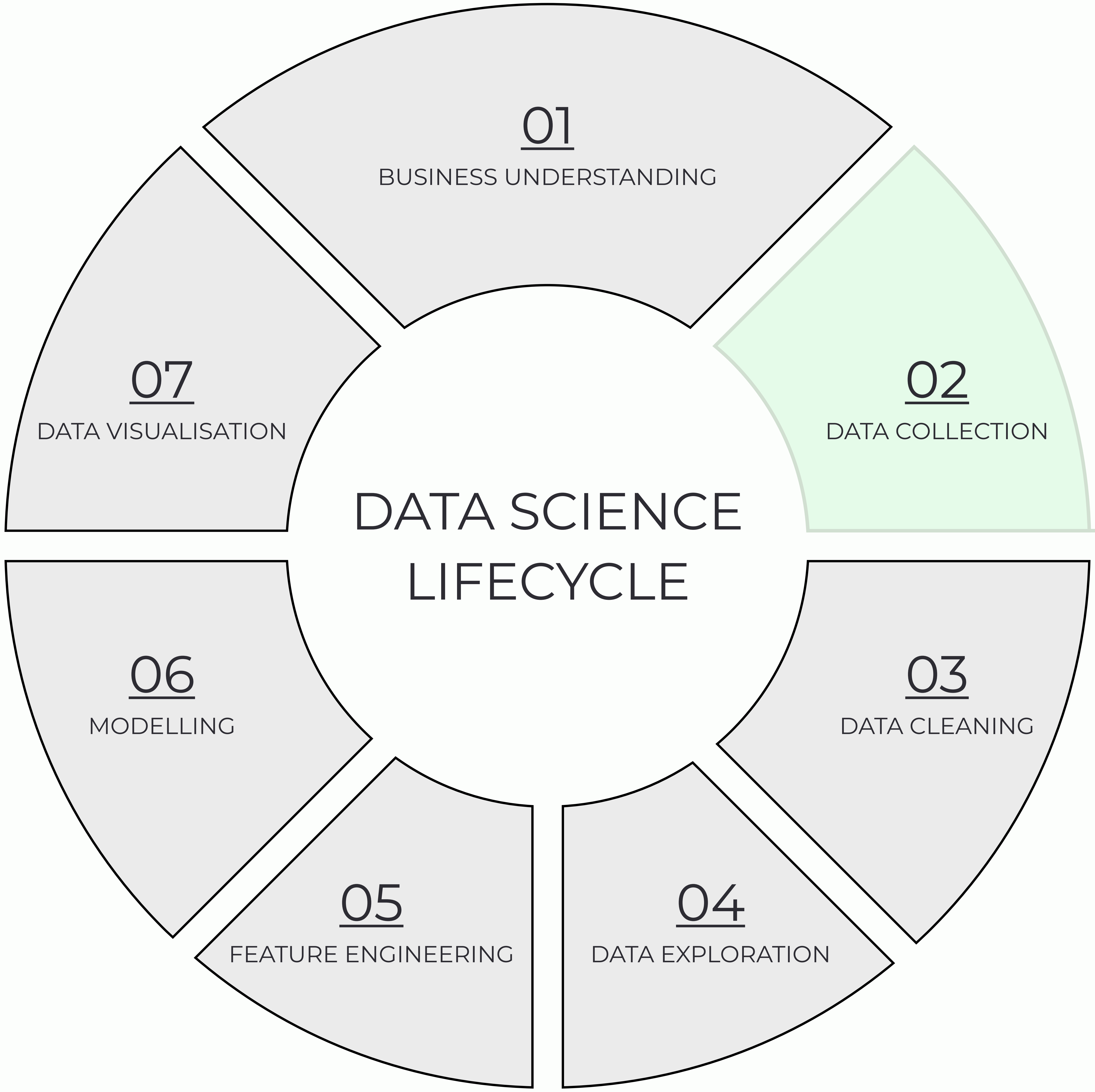


Understand the business use case and how it can be improved. Ask relevant questions and define objectives for the problem that needs to be solved.

Adopted from https://nearlearn.com/blog/machine-learning-data-science-life-cycle-whats-the-difference/

PROBLEM STATEMENT

Develop a model for forecasting day-ahead consumption based on past consumption and weather data



Collect the data necessary for the project

ELECTRICITY DATA

Sample of electricity production/consumption data (in MWh)

Timestamp (UTC)	Date (Estonia time)	Consumption	Production	Planned consumption	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
1672549200	01.01.2023 07:00	763,5	435,9	848,1	447,9
1672552800	01.01.2023 08:00	782,7	425,4	877,2	436,7
1672556400	01.01.2023 09:00	797,2	423,9	902,7	428,8
1672560000	01.01.2023 10:00	841,1	430,3	914,1	427,9

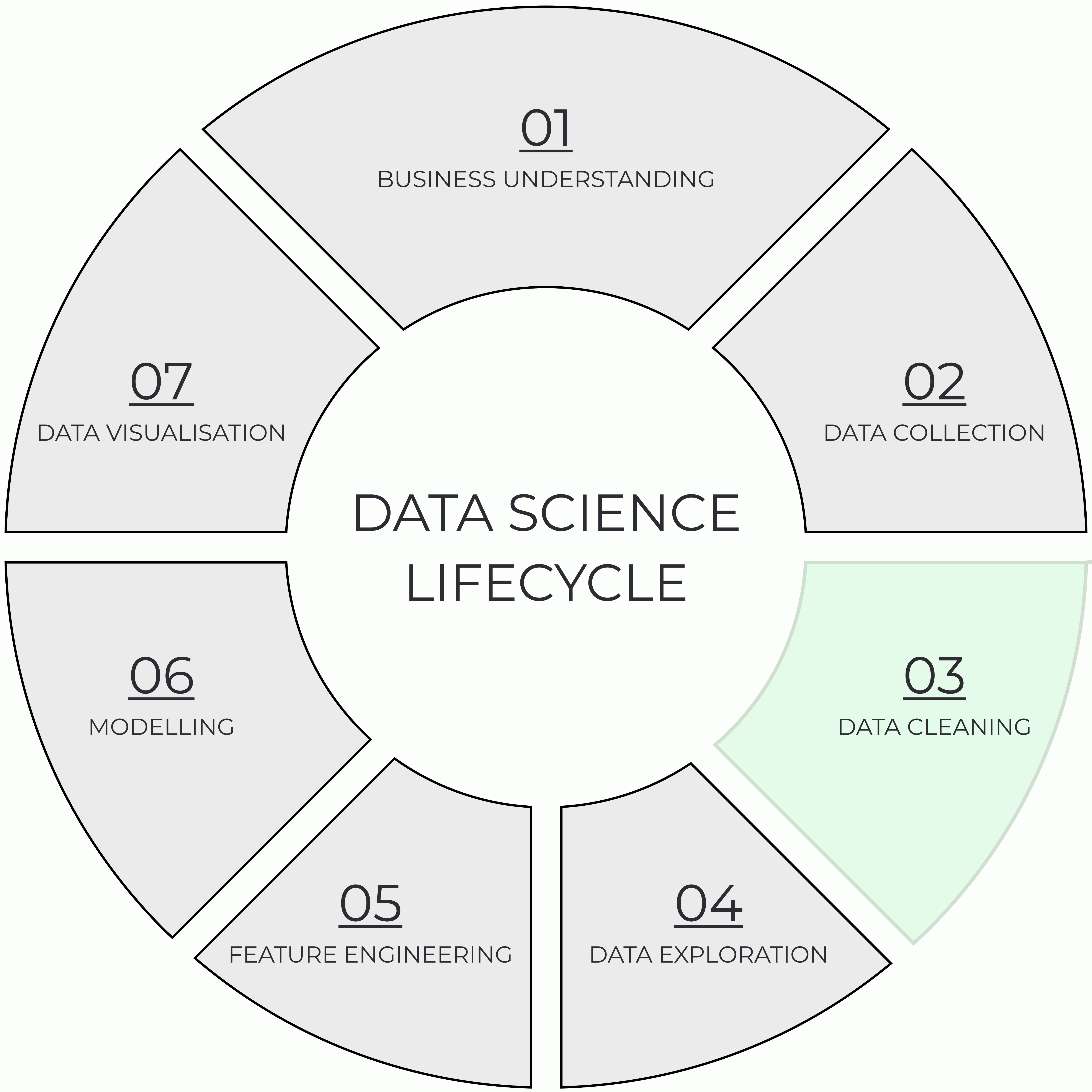
https://dashboard.elering.ee/en/system/with-plan/production-consumption

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 precipitation	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 precipitation	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 precipitation	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 precipitation	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 precipitation	3

https://rp5.ru/Weather_archive_in_Tallinn_(airport)



Remove data that does not belong in your dataset. Fix inconsistencies within the data and handle missing values.

DATA CLEANING

Sample of weather related data

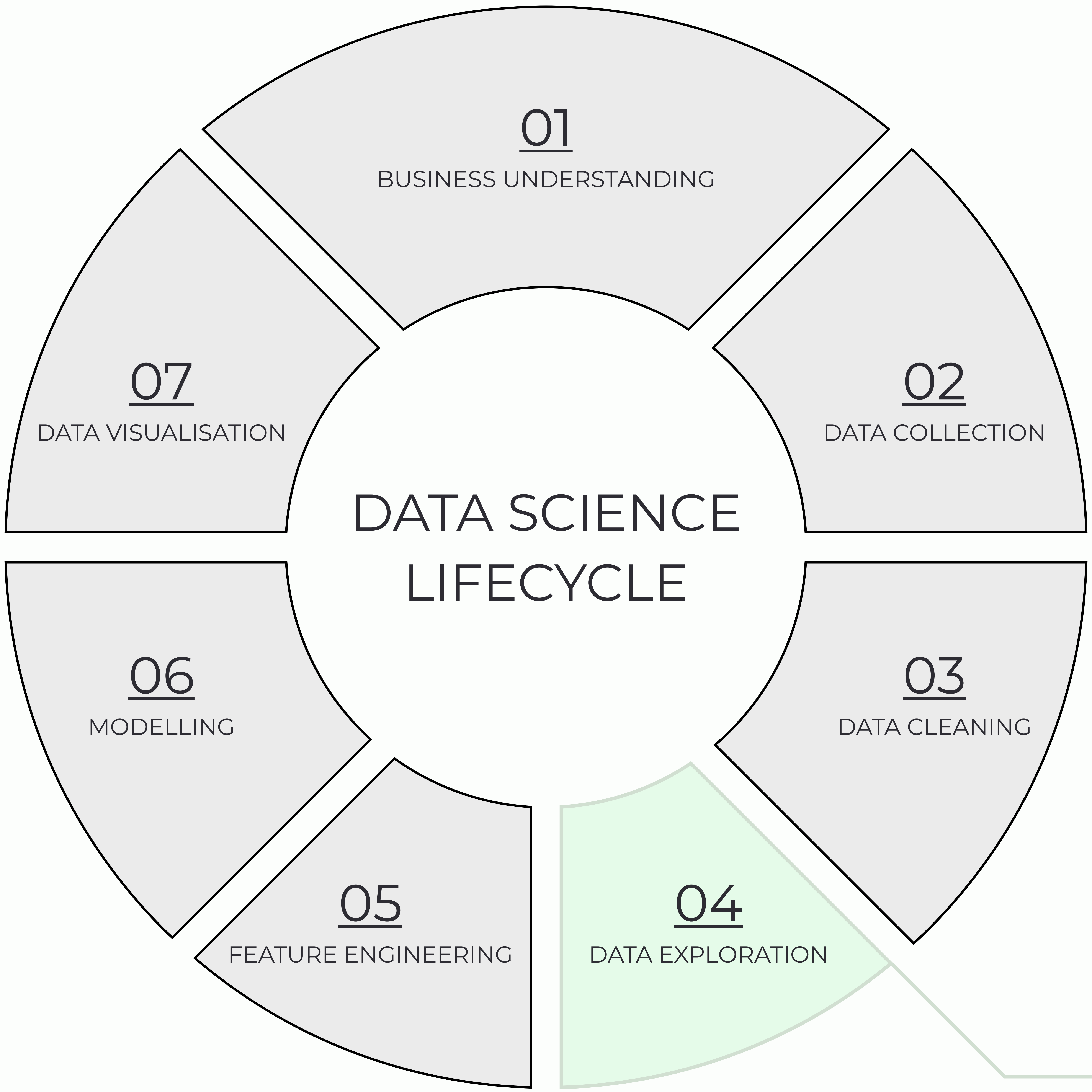
Local time in Tallinn (airport)	T	Po	U	DD	N	Tn	Tx	Nh	Cm	Ch
01.01.2023 00:00	5.8	744.1	91	Wind blowing from the south-west	100%	3.2	6.0	100%		
01.01.2023 01:00	5.8	744.0	88	Wind blowing from the west-southwest	60%	3.6	6.0	60%		
01.01.2023 02:00	5.2	744.4	91	Wind blowing from the west-southwest	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%	No Altocumulus, Altostratus 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

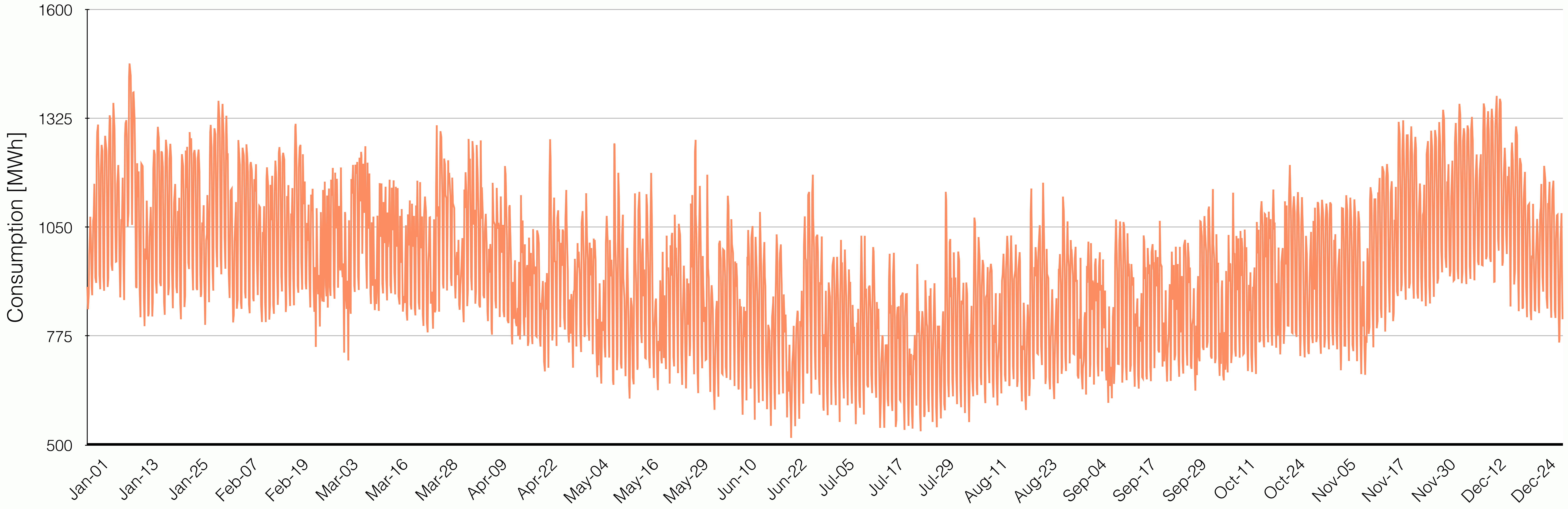
Local time in Tallinn (airport)	T	Po	U	DD	N	Tn	Tx	Nh	Cm	Ch
01.01.2023 00:00	5.8	744.1	91	Wind blowing from the south-west	100%	3.2	6.0	100%		
01.01.2023 01:00	5.8	744.0	88	Wind blowing from the west-southwest	60%	3.6	6.0	60%		
01.01.2023 02:00	5.2	744.4	91	Wind blowing from the west-southwest	90 or more, but not 100%	4.1	6.0	90 or more, but not 100%	No Altocumulus, Altostratus 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.

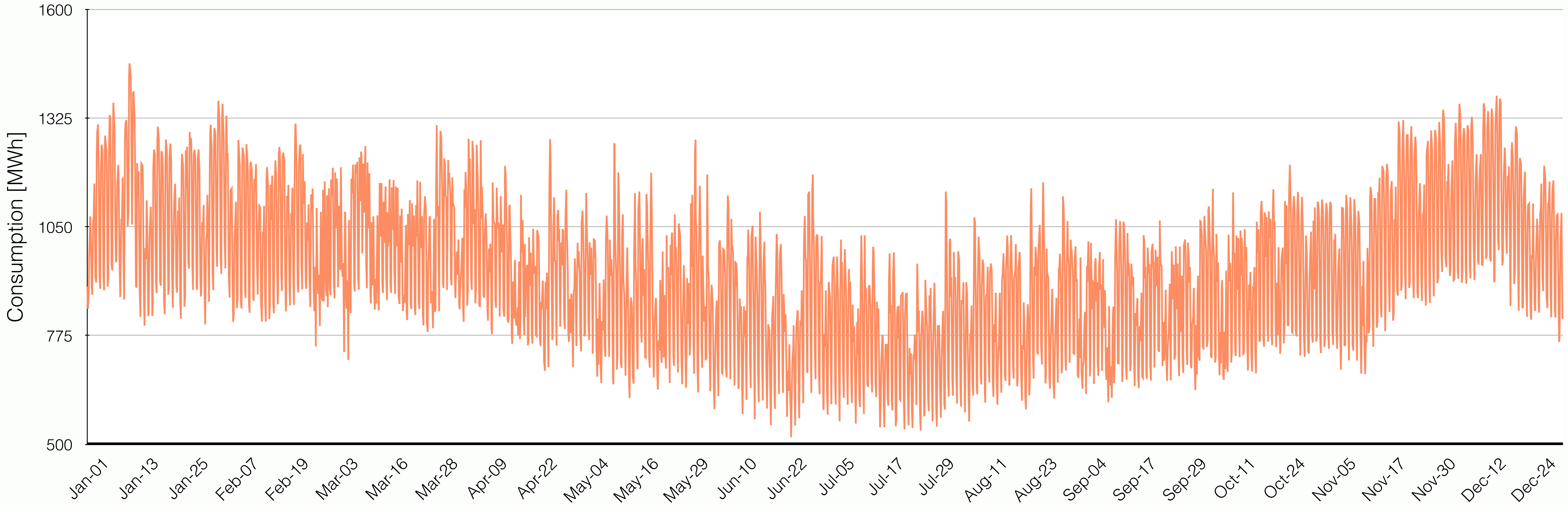


Explore and visualise data to uncover insights from the data and form hypotheses.

ELECTRICITY CONSUMPTION IN ESTONIA, 2022

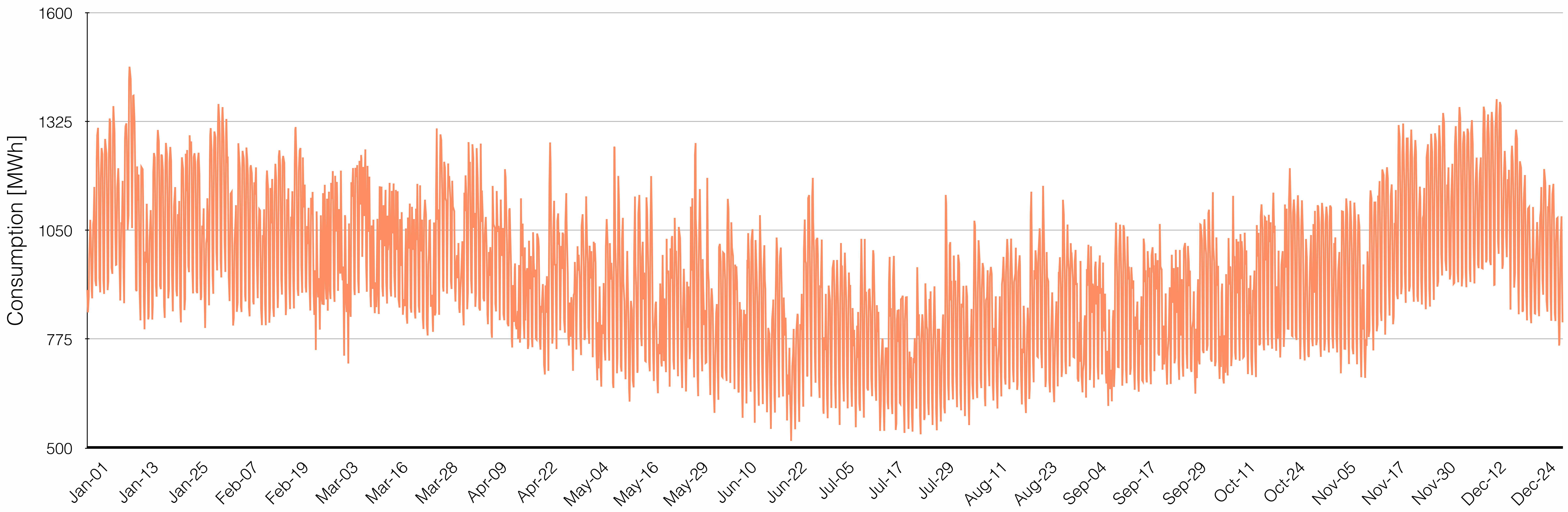


ELECTRICITY CONSUMPTION IN ESTONIA, 2022



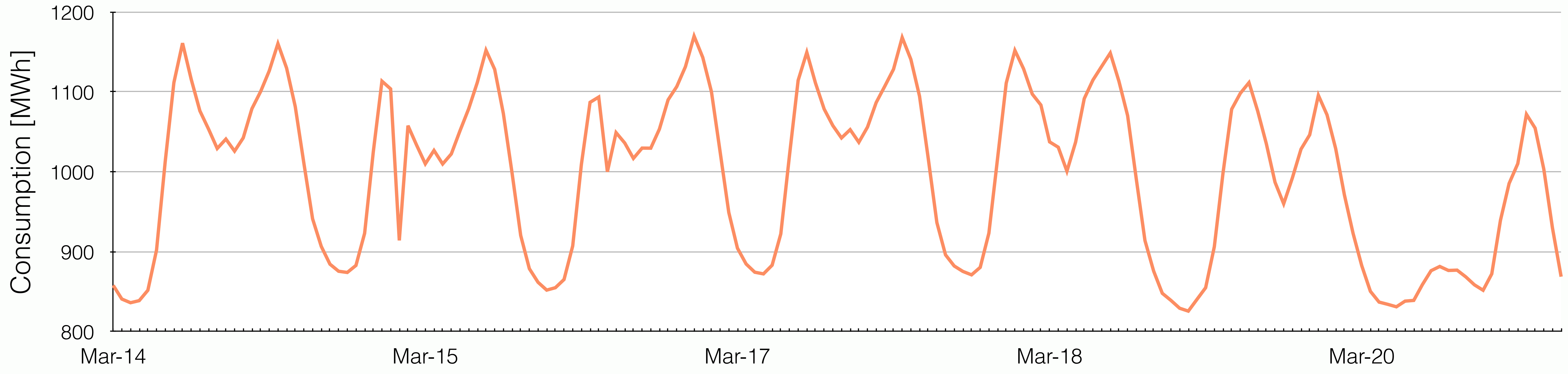
Any observations?

ELECTRICITY CONSUMPTION IN ESTONIA, 2022

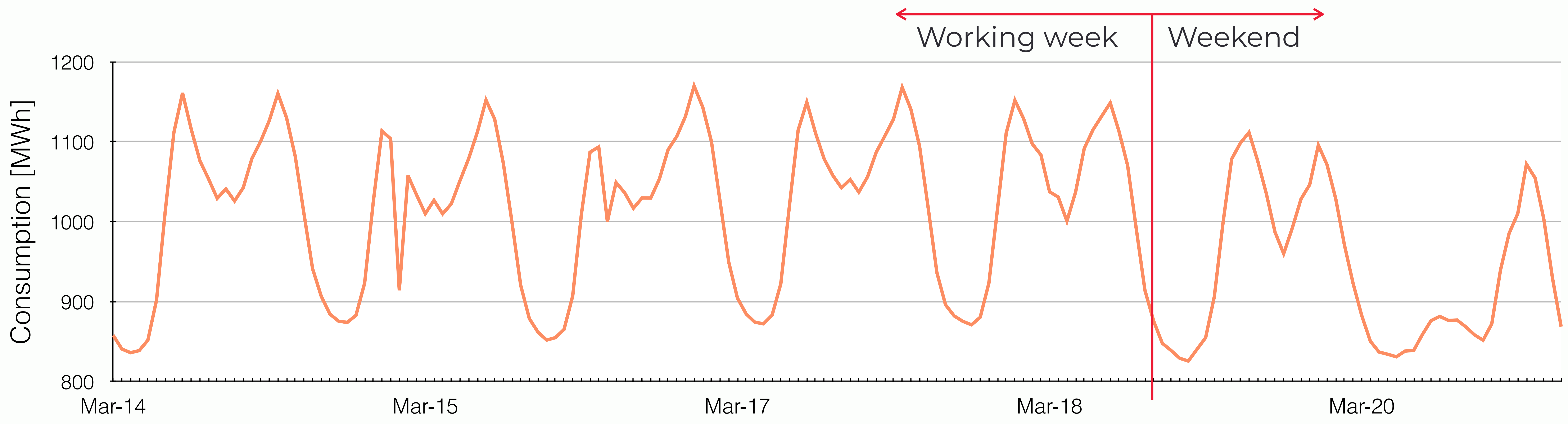


Any observations? Seasonality!

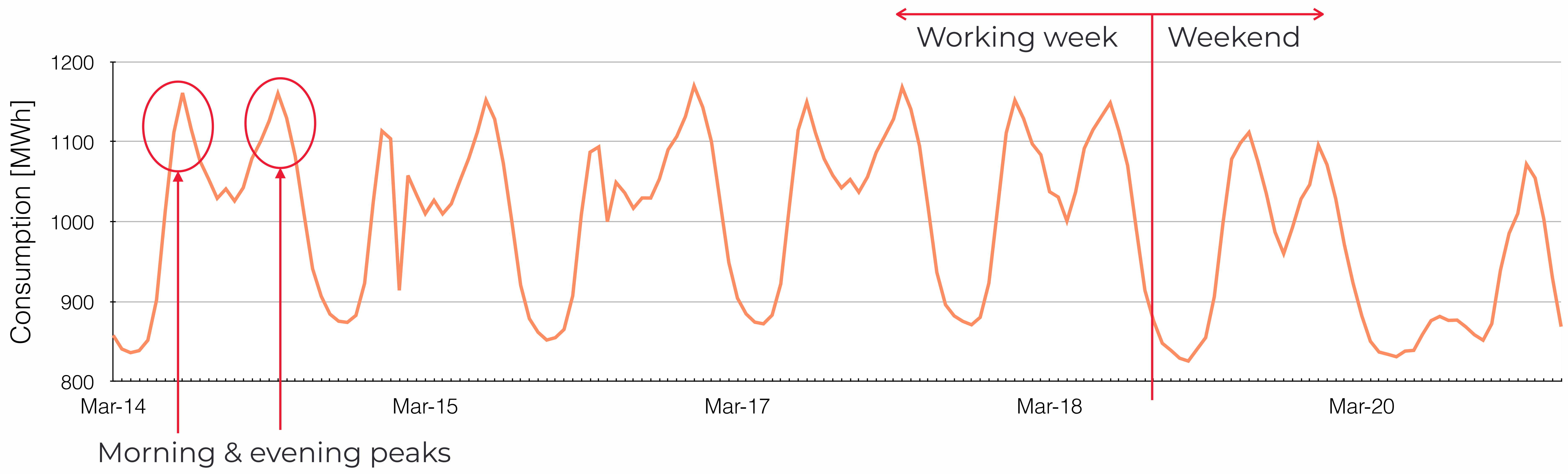
IT'S ALL ABOUT PATTERNS



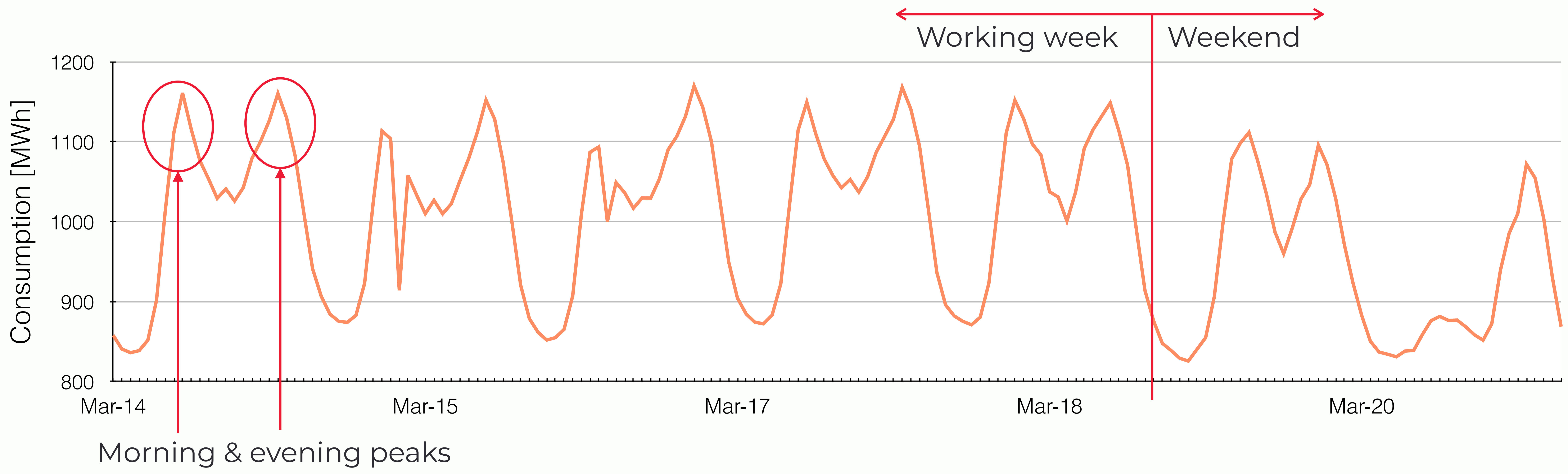
IT'S ALL ABOUT PATTERNS



IT'S ALL ABOUT PATTERNS

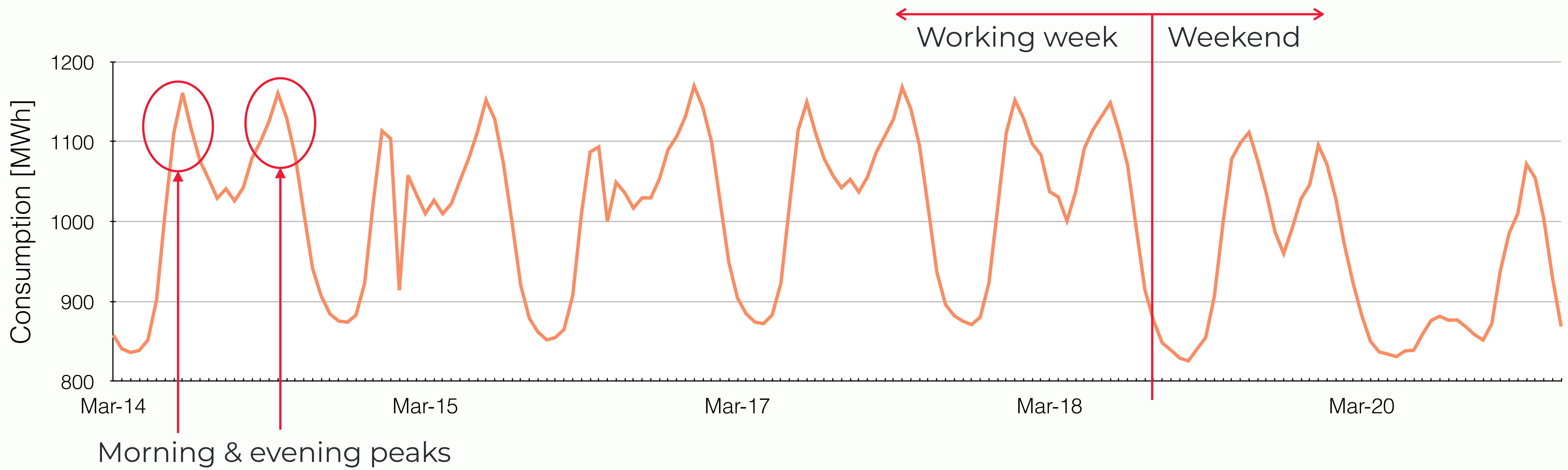


IT'S ALL ABOUT PATTERNS

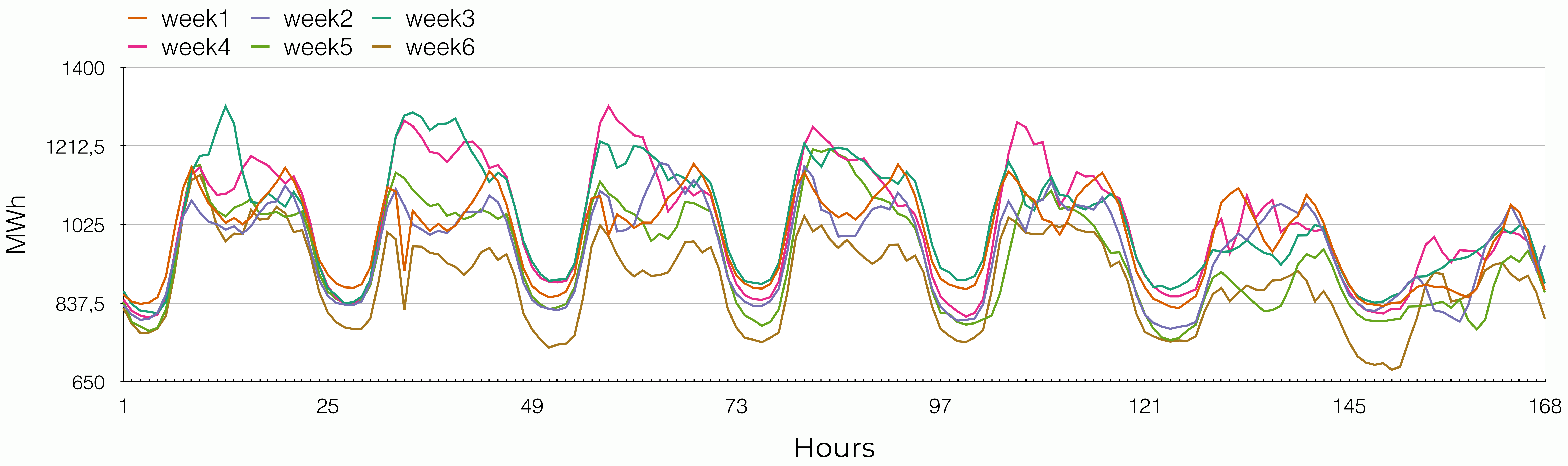


Let's plot several weeks

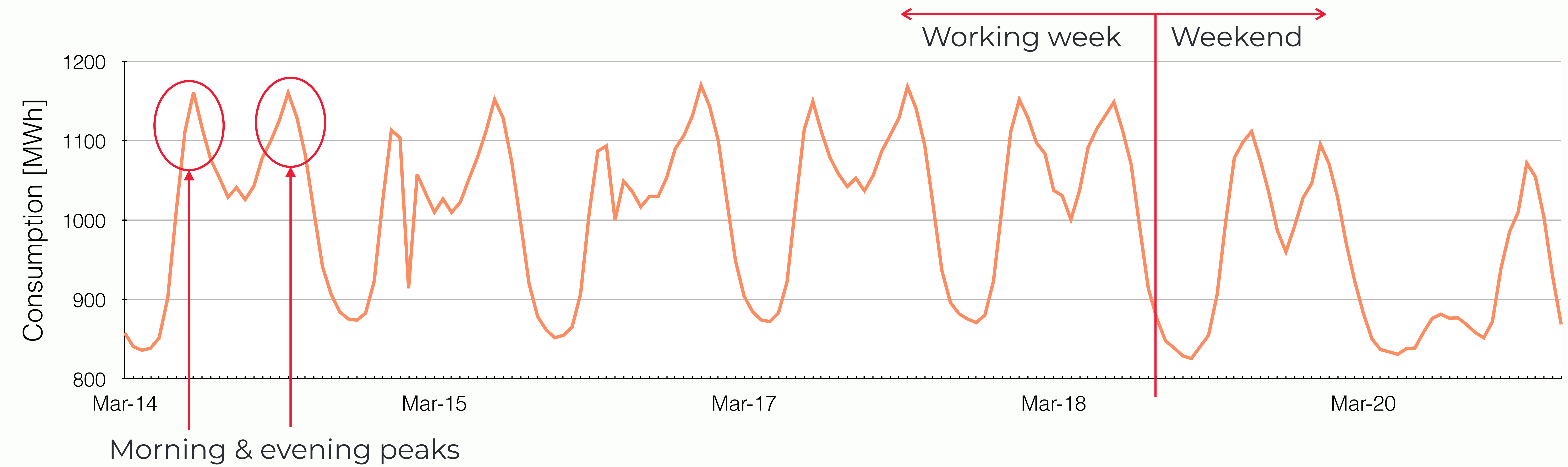
IT'S ALL ABOUT PATTERNS



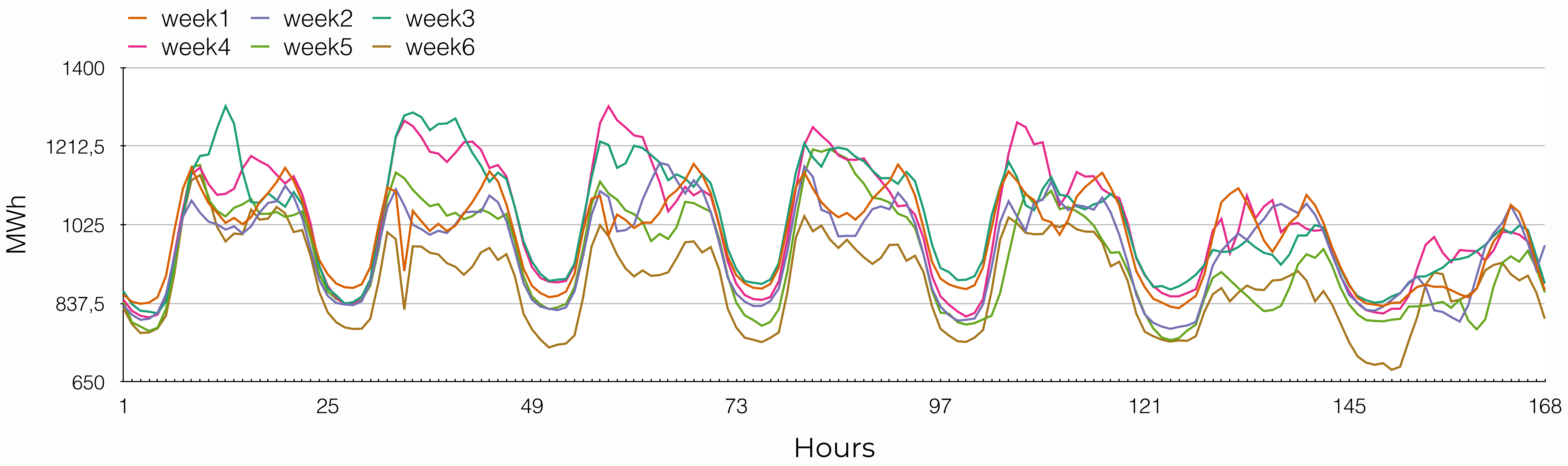
Let's plot several weeks



IT’S ALL ABOUT PATTERNS

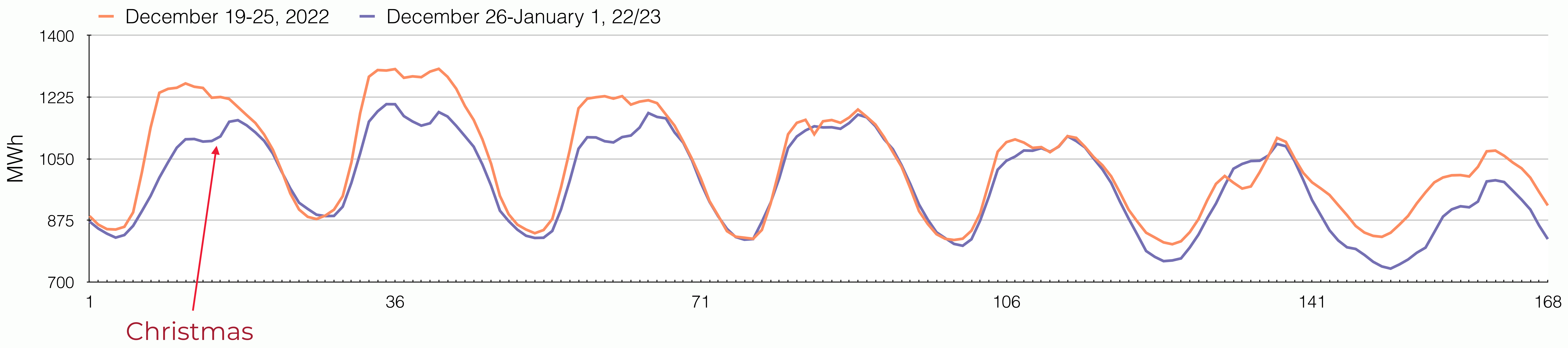


Let’s plot several weeks



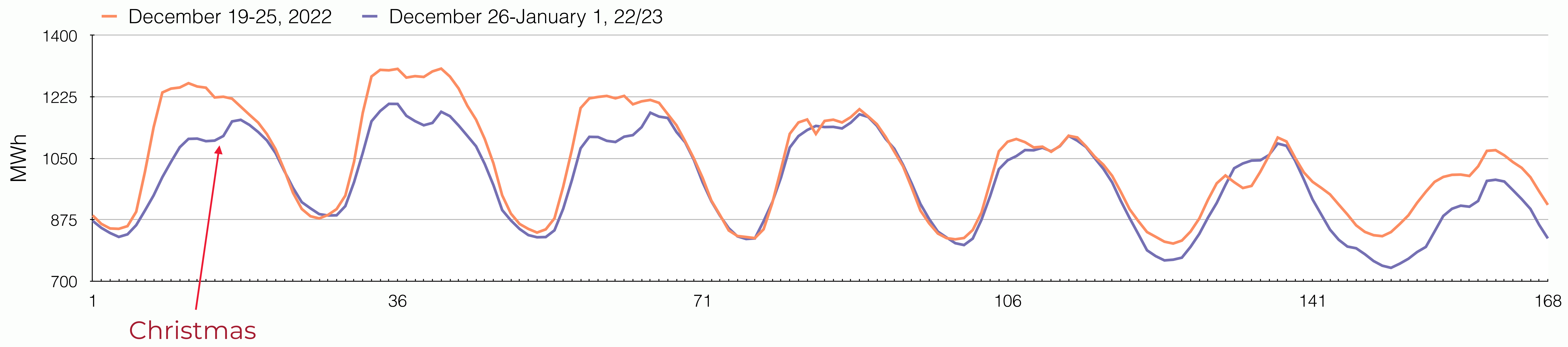
What can go wrong?

HOLIDAYS

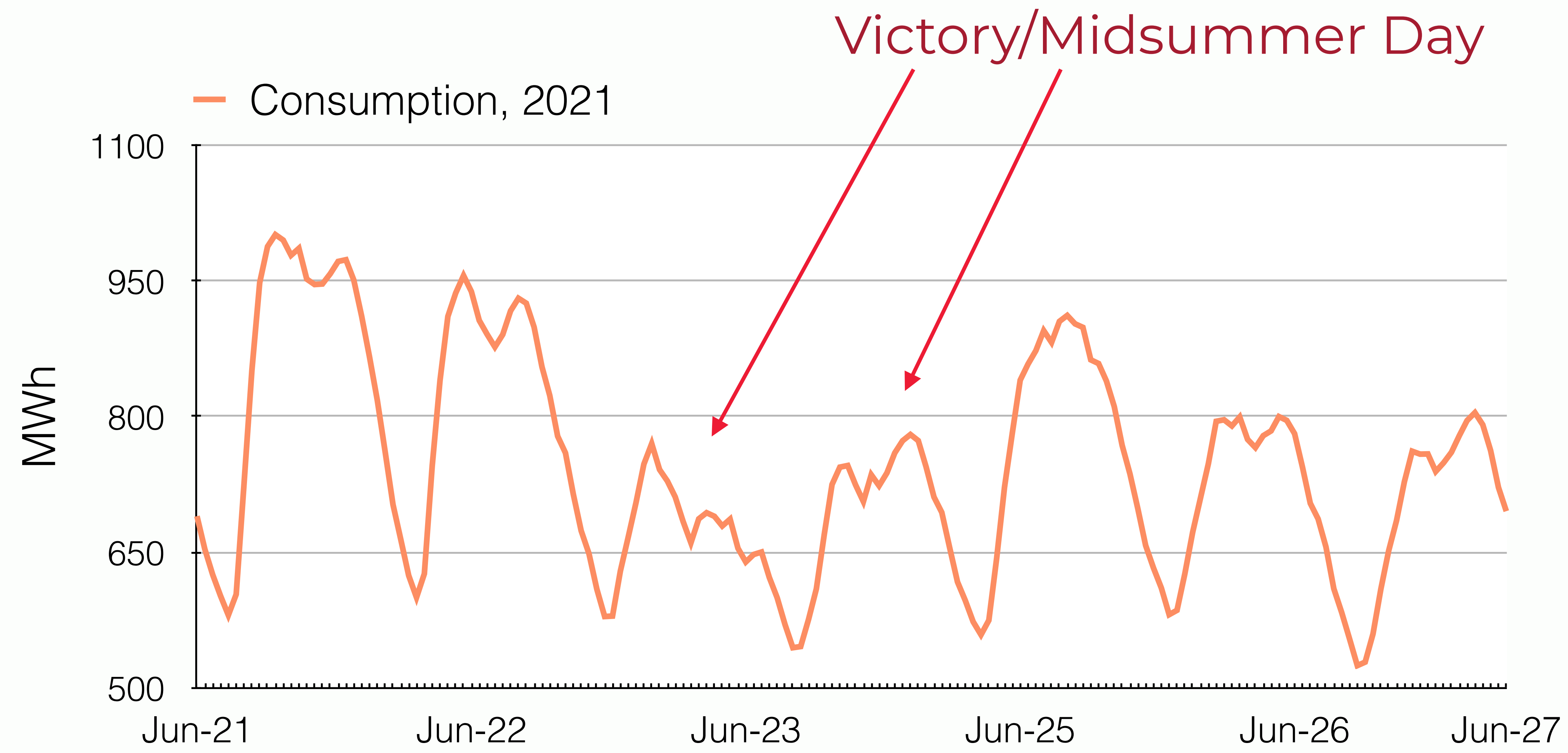


December 19-25, 2022
December 26-January 1, 22/23
MWh
1400
1225
1050
875
700
1
36
71
106
141
168
Christmas

HOLIDAYS

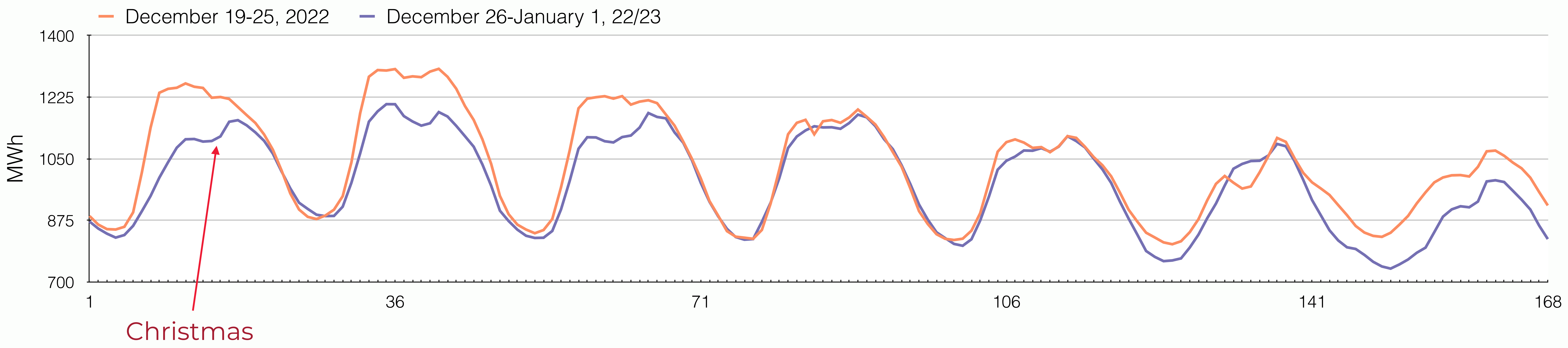


December 19-25, 2022
December 26-January 1, 22/23
MWh
1400
1225
1050
875
700
1
36
71
106
141
168
Christmas

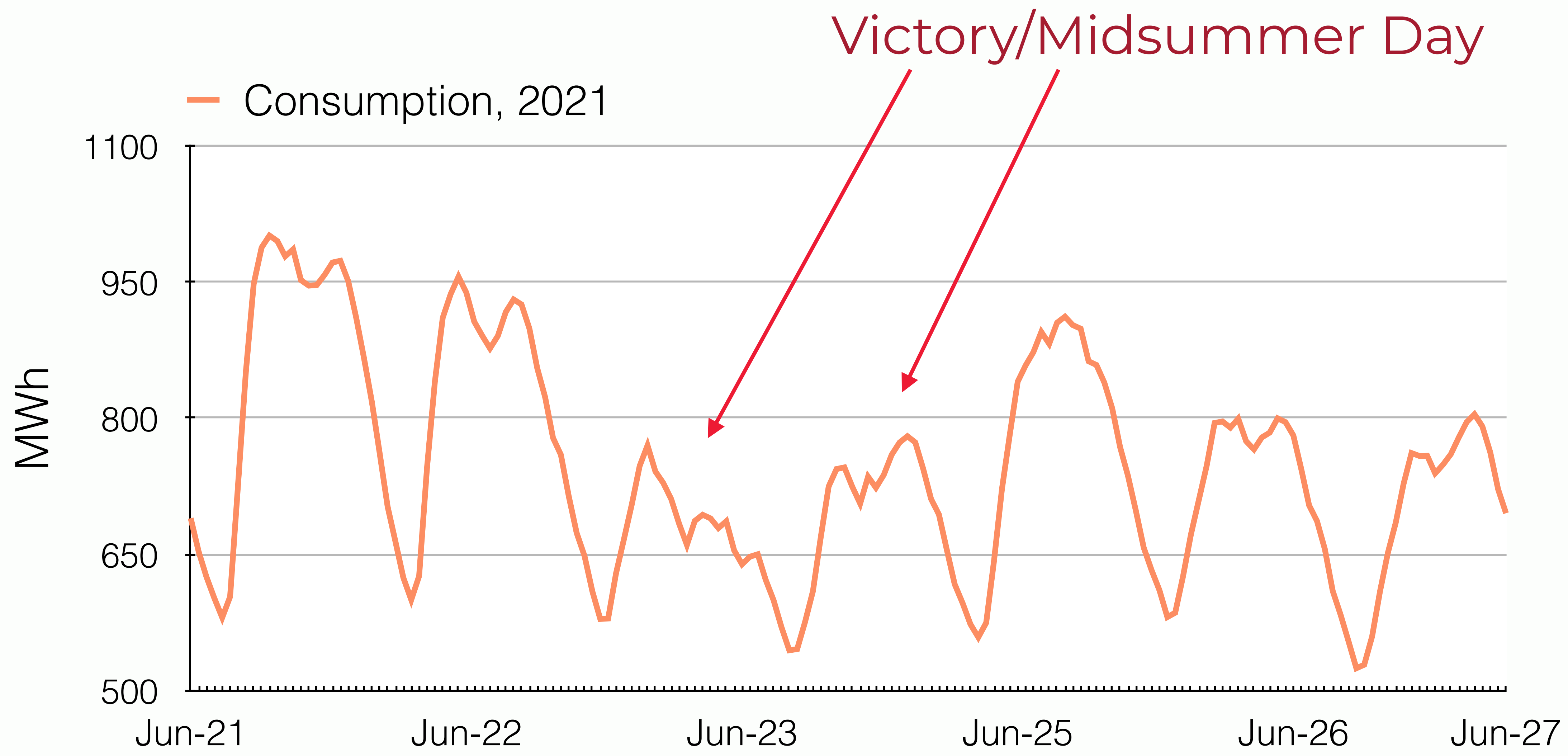


Victory/Midsummer Day
Consumption, 2021
MWh
1100
950
800
650
500
Jun-21
Jun-22
Jun-23
Jun-25
Jun-26
Jun-27

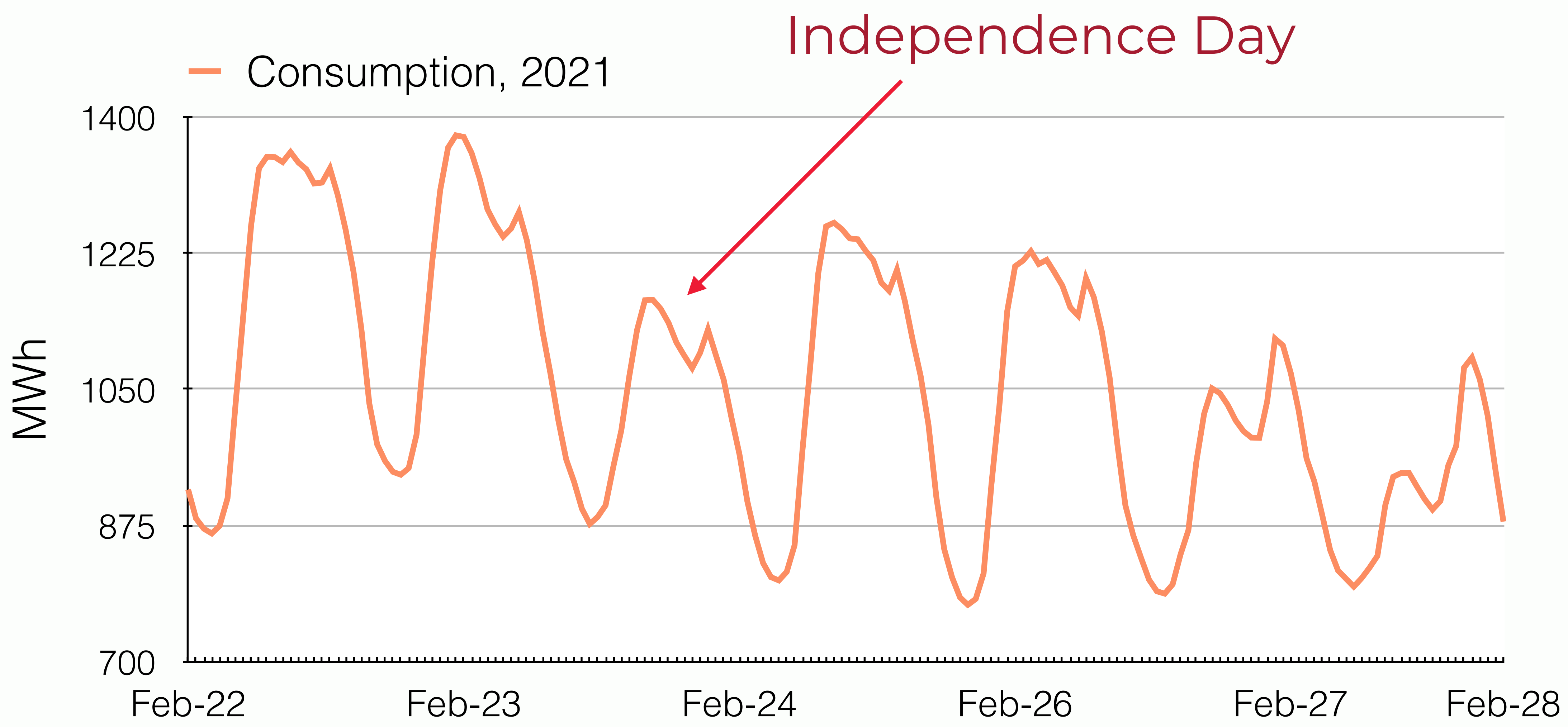
HOLIDAYS



December 19-25, 2022
December 26-January 1, 22/23
MWh
1400
1225
1050
875
700
1
36
71
106
141
168
Christmas

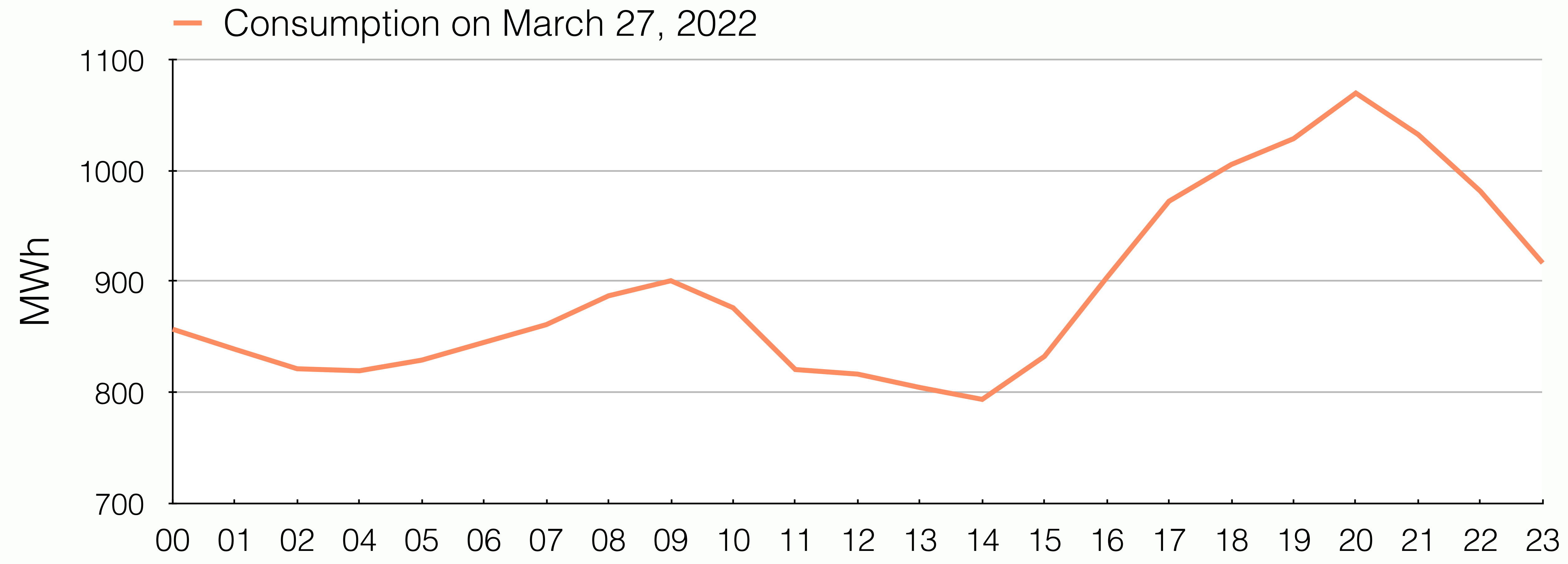


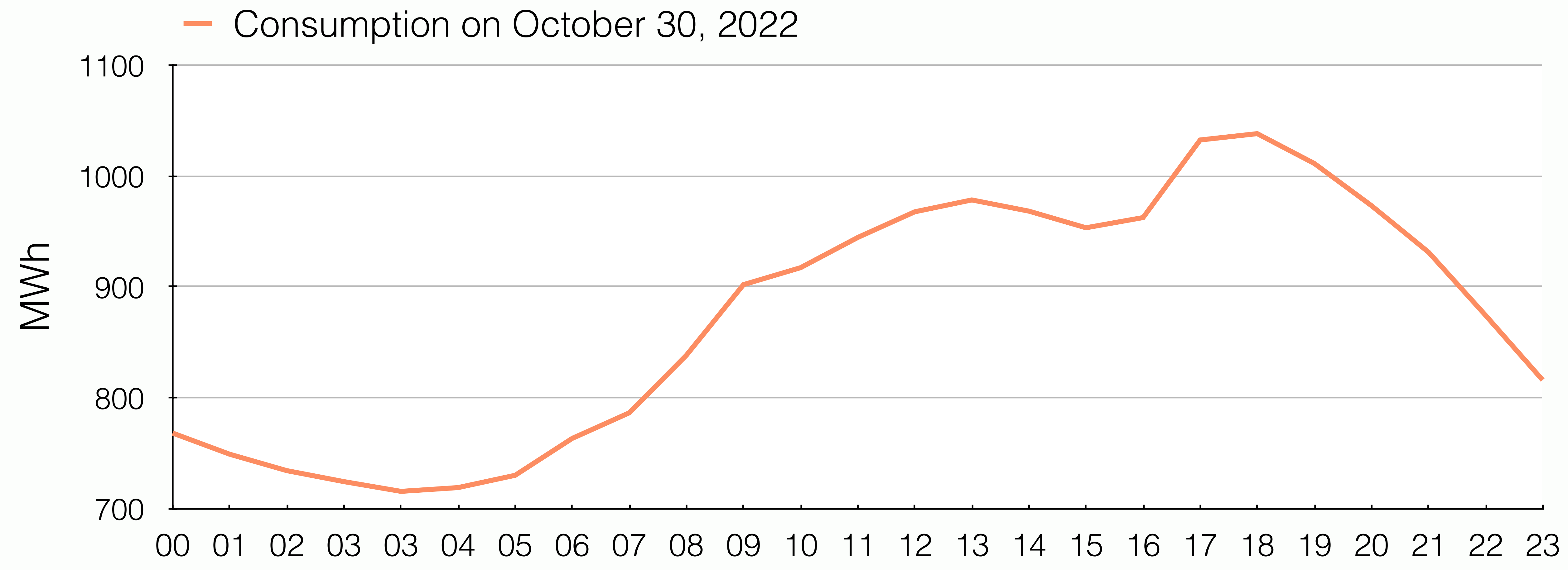
Victory/Midsummer Day
Consumption, 2021
MWh
1100
950
800
650
500
Jun-21
Jun-22
Jun-23
Jun-25
Jun-26
Jun-27



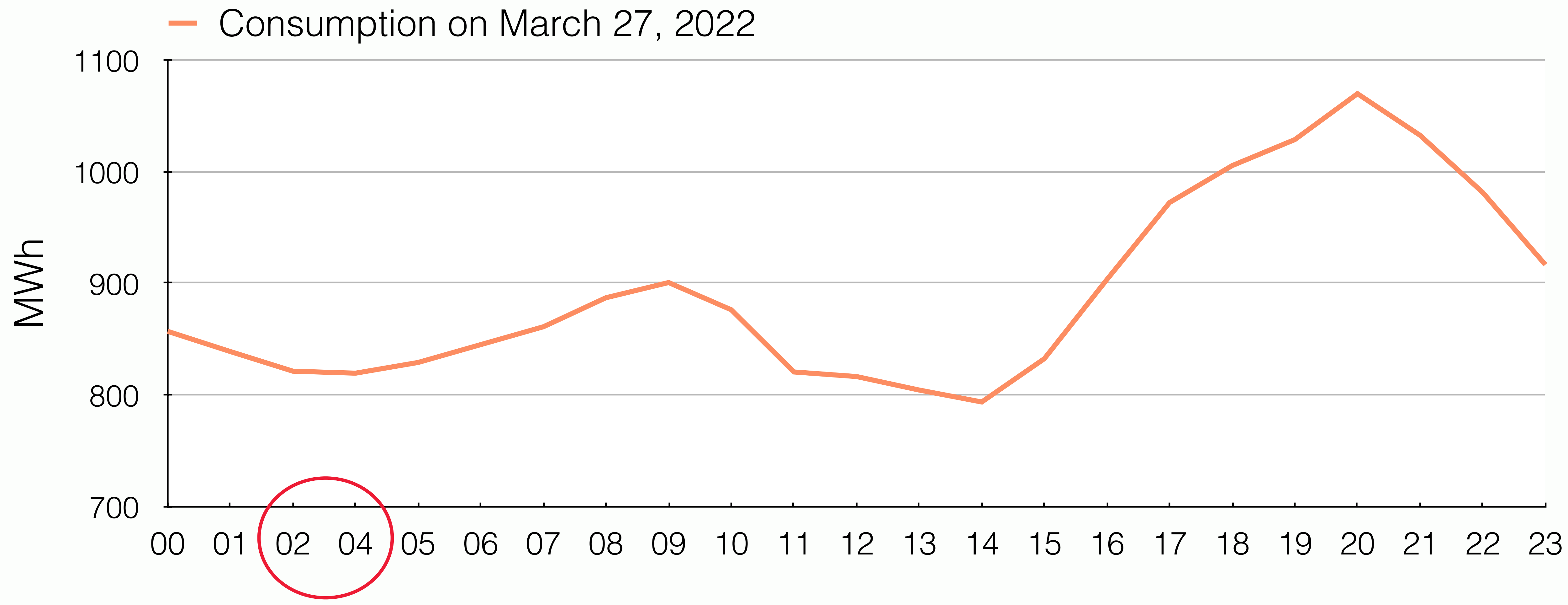
Independence Day
Consumption, 2021
MWh
1400
1225
1050
875
700
Feb-22
Feb-23
Feb-24
Feb-26
Feb-27
Feb-28

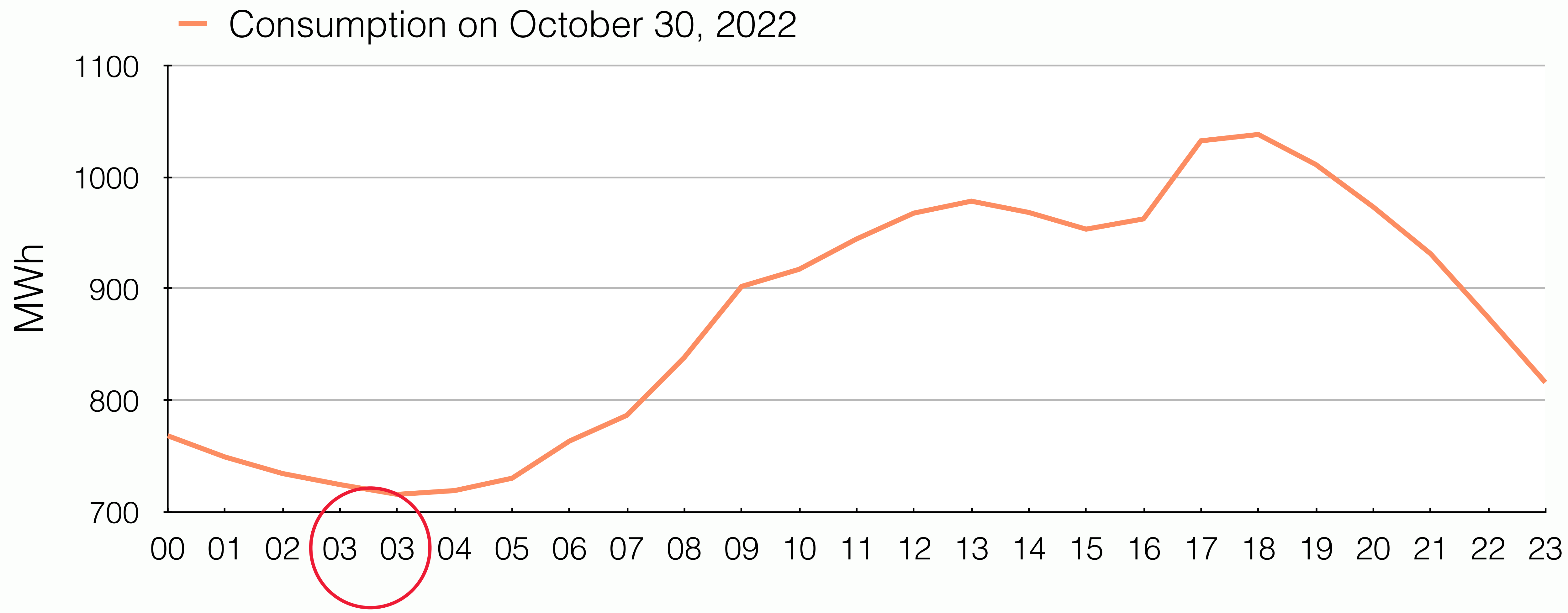
DAYLIGHT SAVING TIME



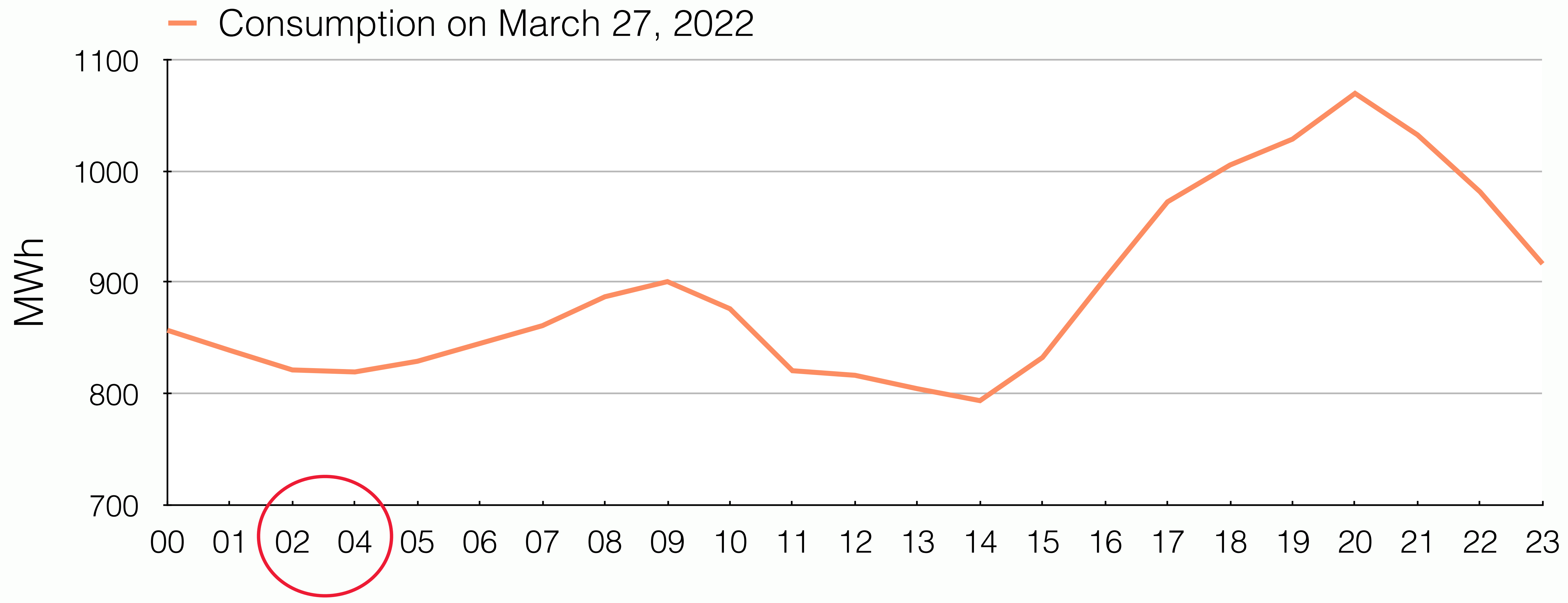


DAYLIGHT SAVING TIME



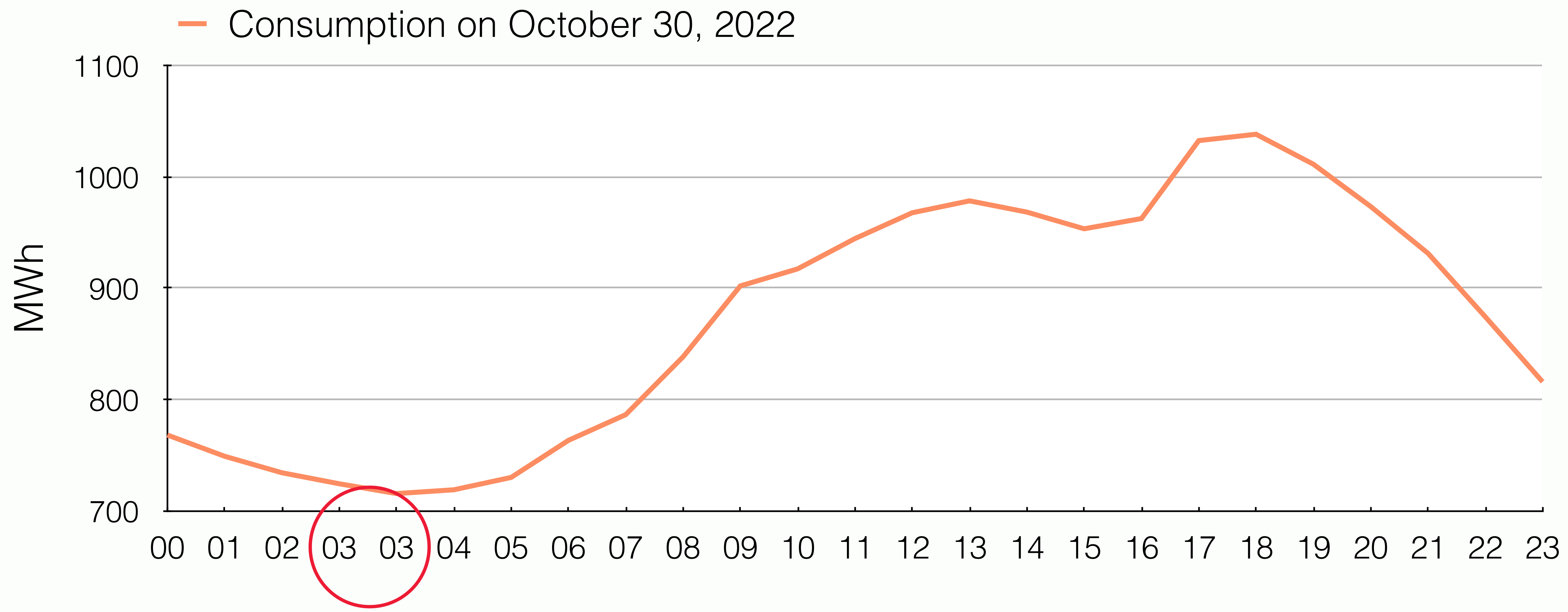


DAYLIGHT SAVING TIME



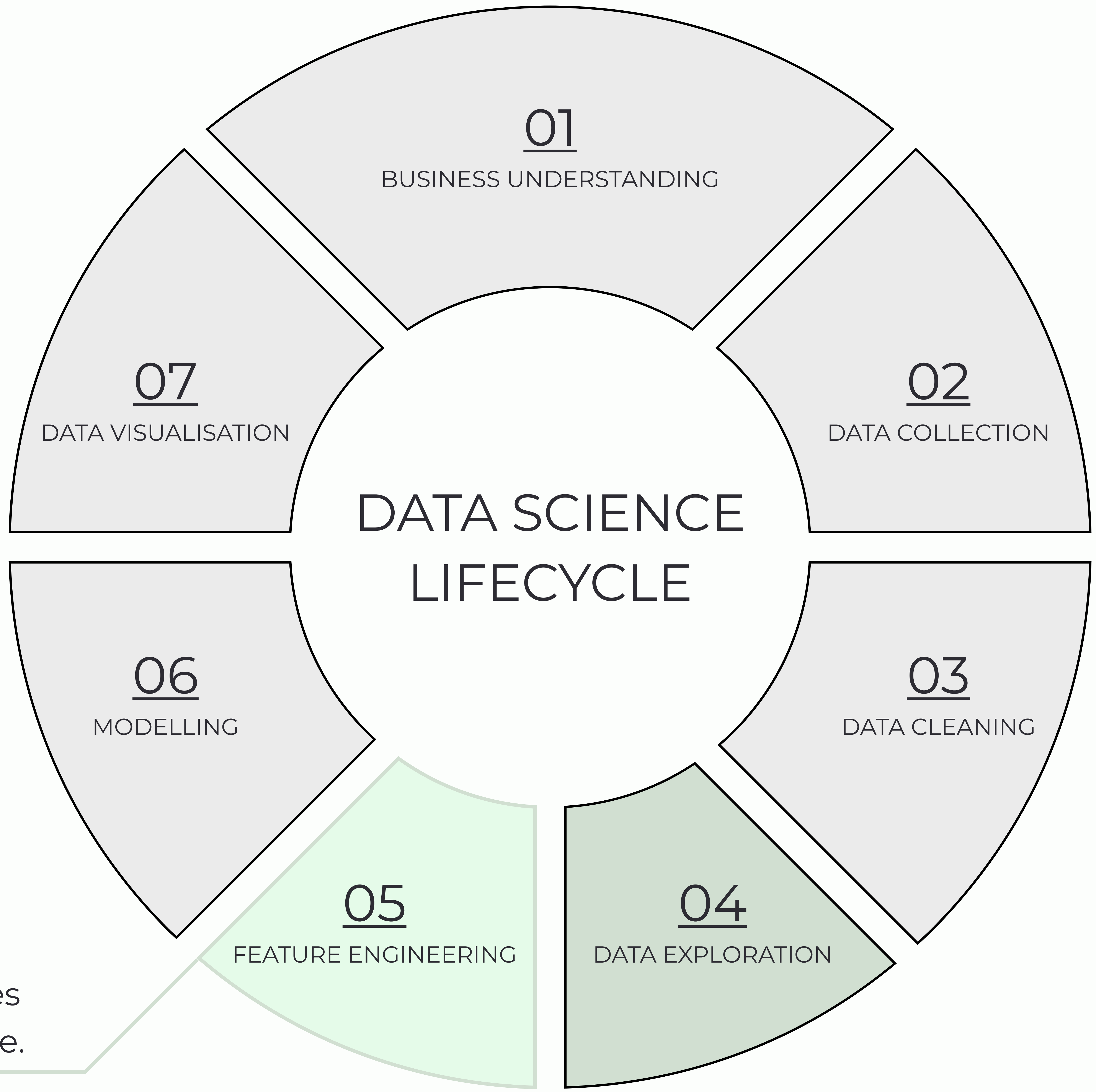
Sample of electricity production/consumption data

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/consumption 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



Select important features and construct more meaningful ones using the raw data that you have.

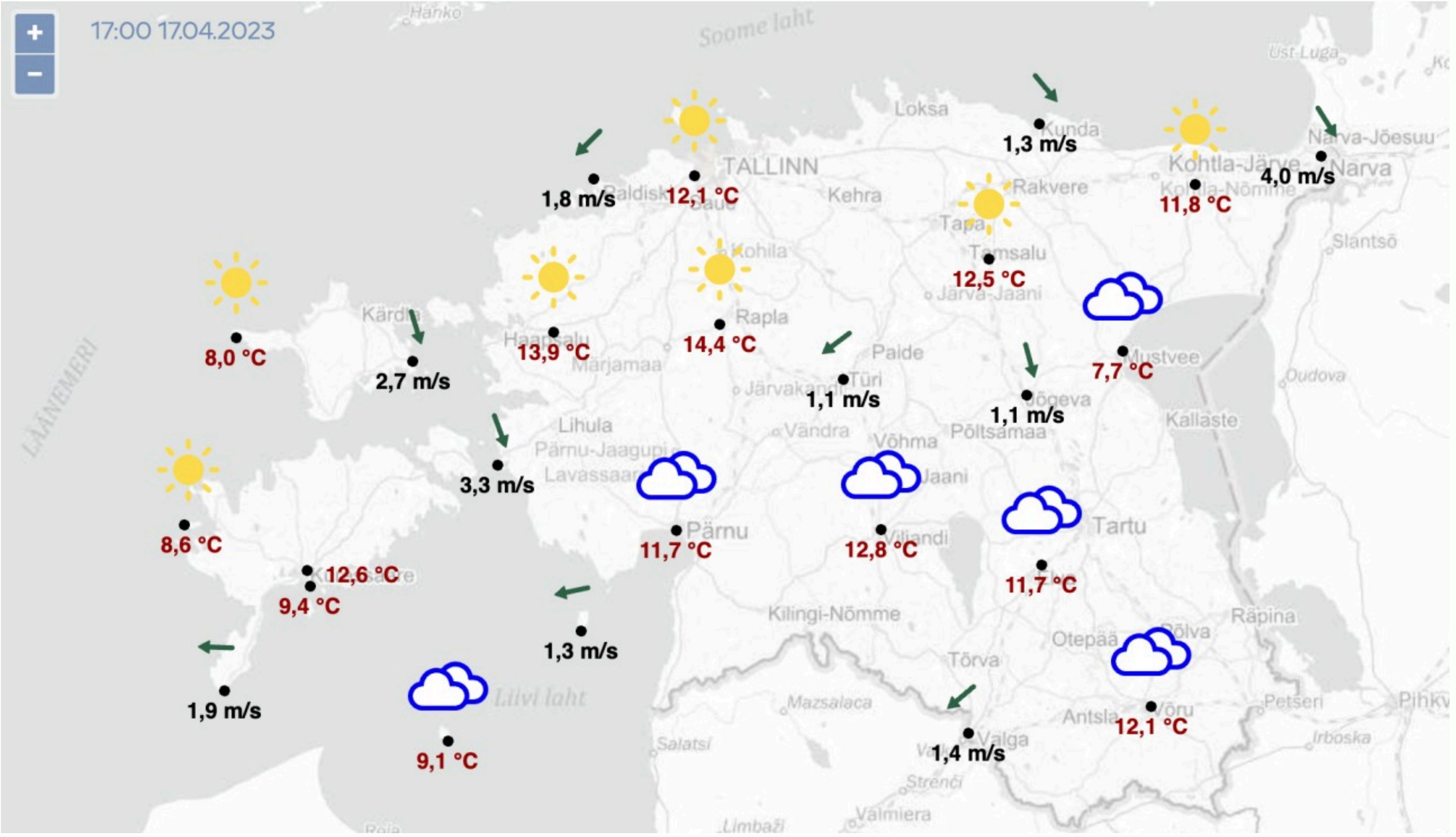
WHAT FEATURES CAN BE RELEVANT?

A shot list on possible features:

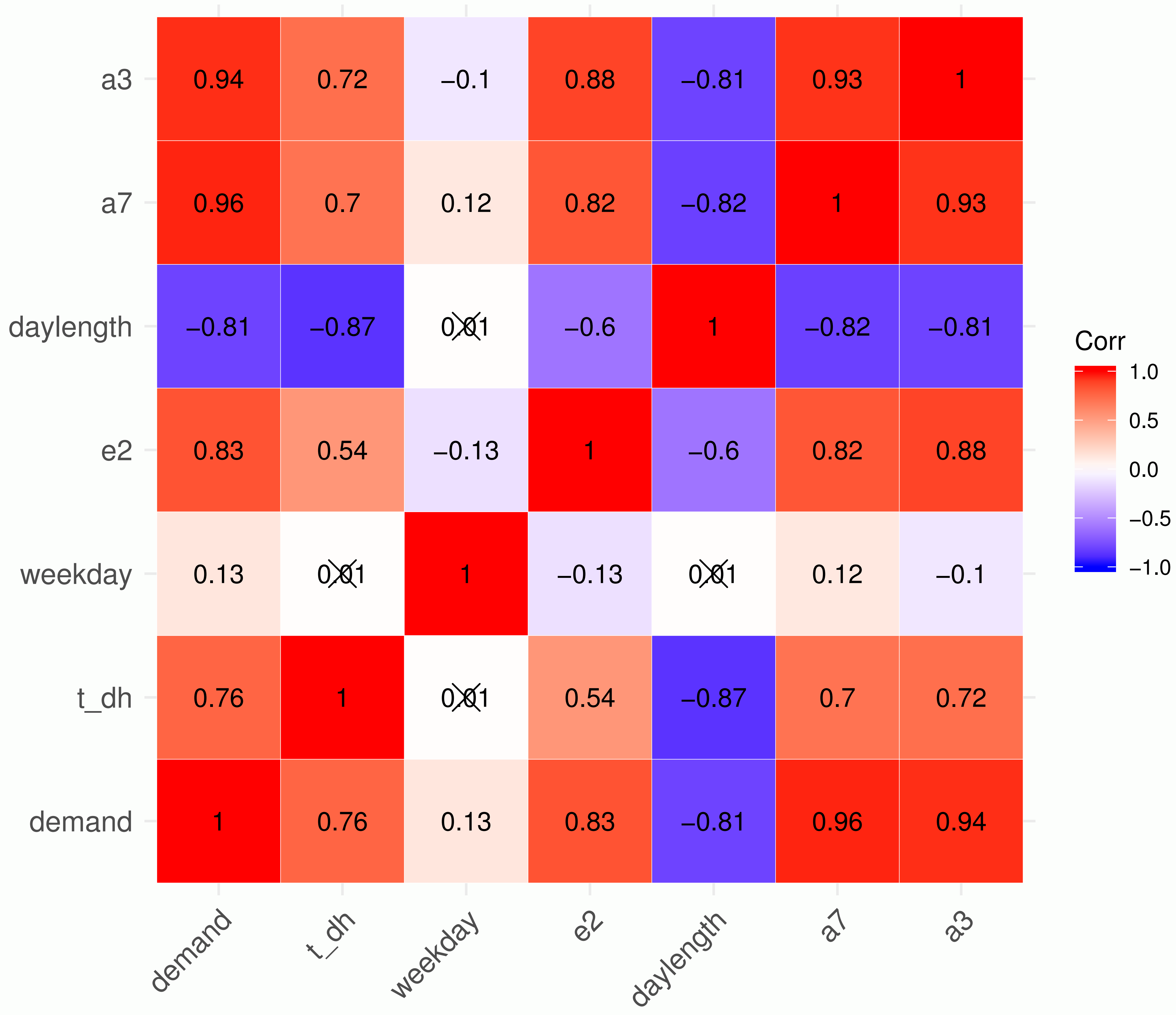
- Previous electricity consumption: a day, a week ago
- Weather: temperature, irradiation, wind direction/ speed, humidity
- Day length: sunset/sunrise
- Weekday
- Hour of the day
- Electricity price

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**



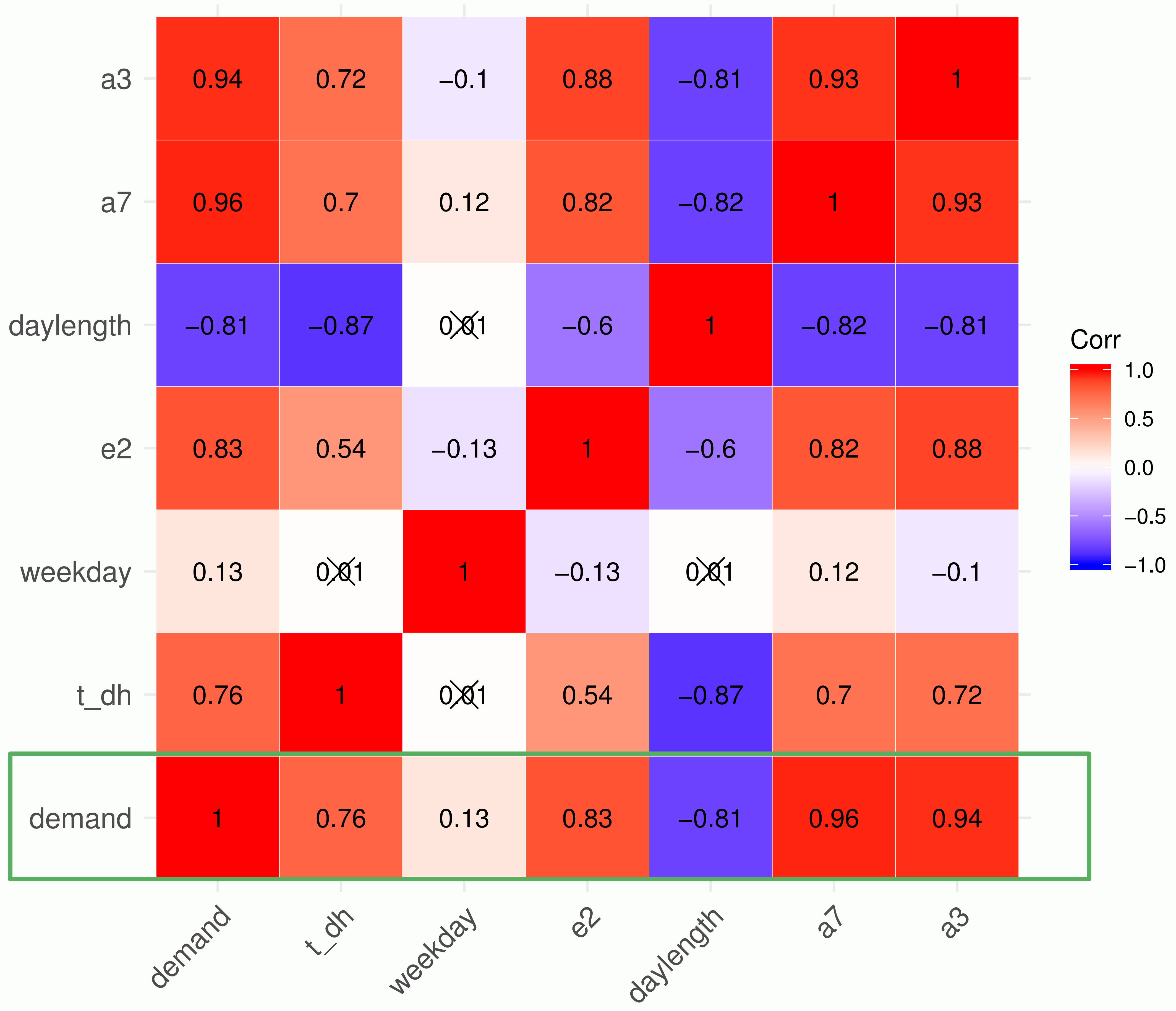
CHECK WHICH FEATURES ARE IMPORTANT



`a3`, `a7` are Alexela total consumption at the same hour 3 and 7 days ago
`e2` is the total Estonian consumption
`t_dh` is the degree-hour parameter
`weekday` is the day of the week

M. Spichakova, J. Belikov, K. Nõu, E. Petlenkov. Feature engineering for short-term forecast of energy consumption. *IEEE PES Innovative Smart Grid Technologies Europe: Bucharest, Romania*, 2019.
M. Sinimaa, M. Spichakova, J. Belikov, E. Petlenkov. Feature engineering of weather data for short-term energy consumption forecast. *IEEE Madrid PowerTech: Madrid, Spain*, 2021.

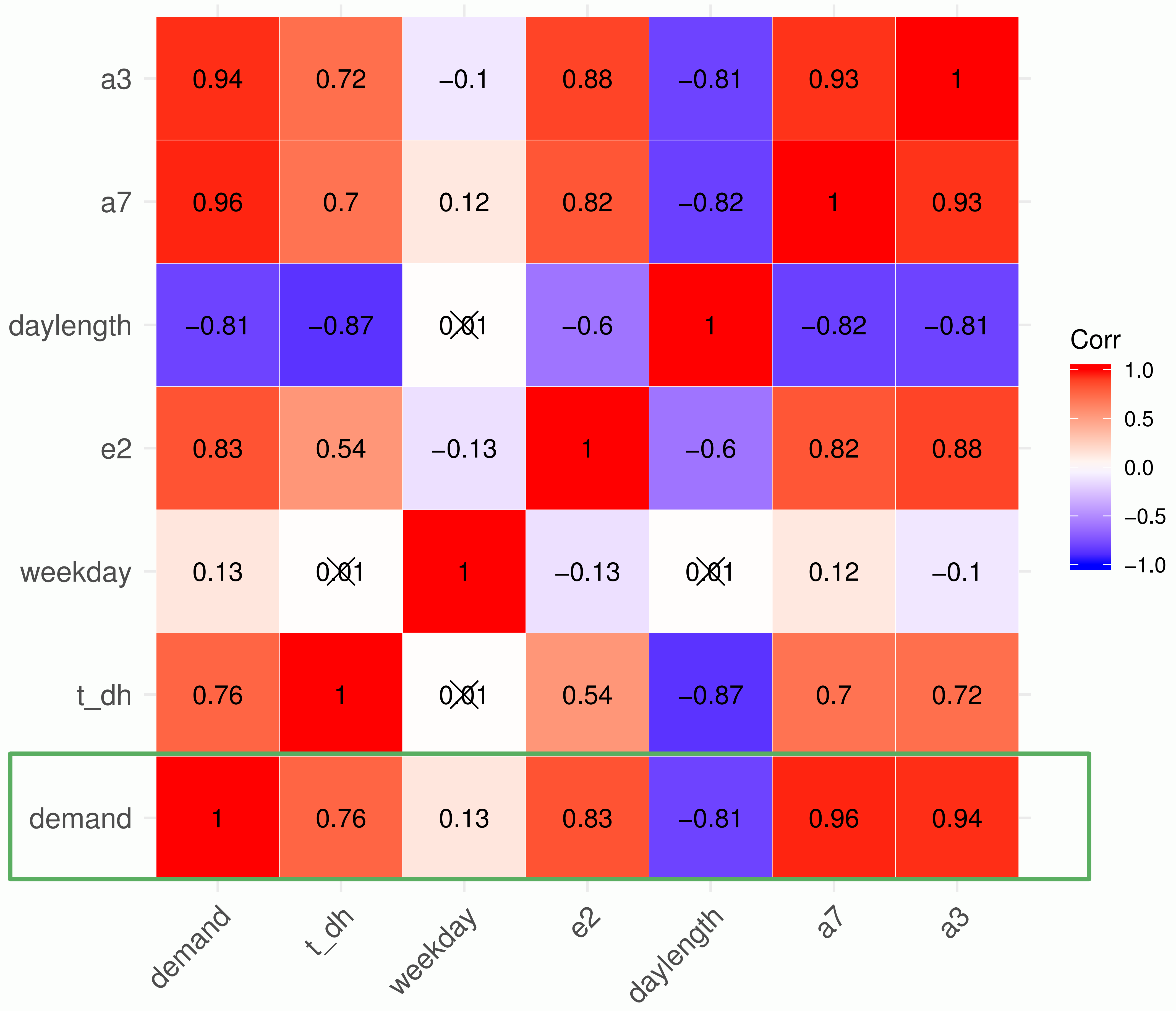
CHECK WHICH FEATURES ARE IMPORTANT

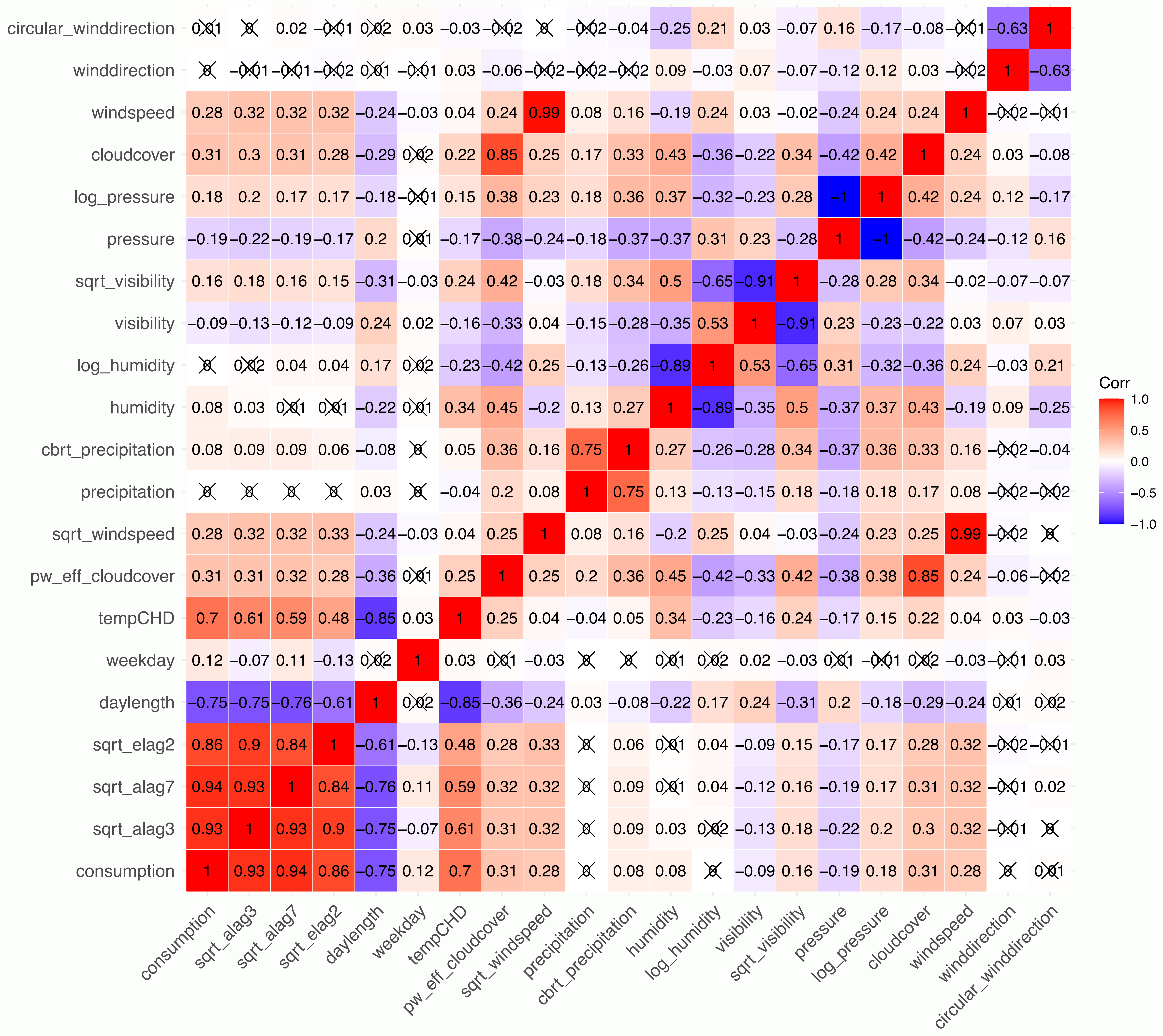


`a3`, `a7` are Alexela total consumption at the same hour 3 and 7 days ago
`e2` is the total Estonian consumption
`t_dh` is the degree-hour parameter
`weekday` is the day of the week

M. Spichakova, J. Belikov, K. Nõu, E. Petlenkov. Feature engineering for short-term forecast of energy consumption. *IEEE PES Innovative Smart Grid Technologies Europe: Bucharest, Romania*, 2019.
M. Sinimaa, M. Spichakova, J. Belikov, E. Petlenkov. Feature engineering of weather data for short-term energy consumption forecast. *IEEE Madrid PowerTech: Madrid, Spain*, 2021.

CHECK WHICH FEATURES ARE IMPORTANT

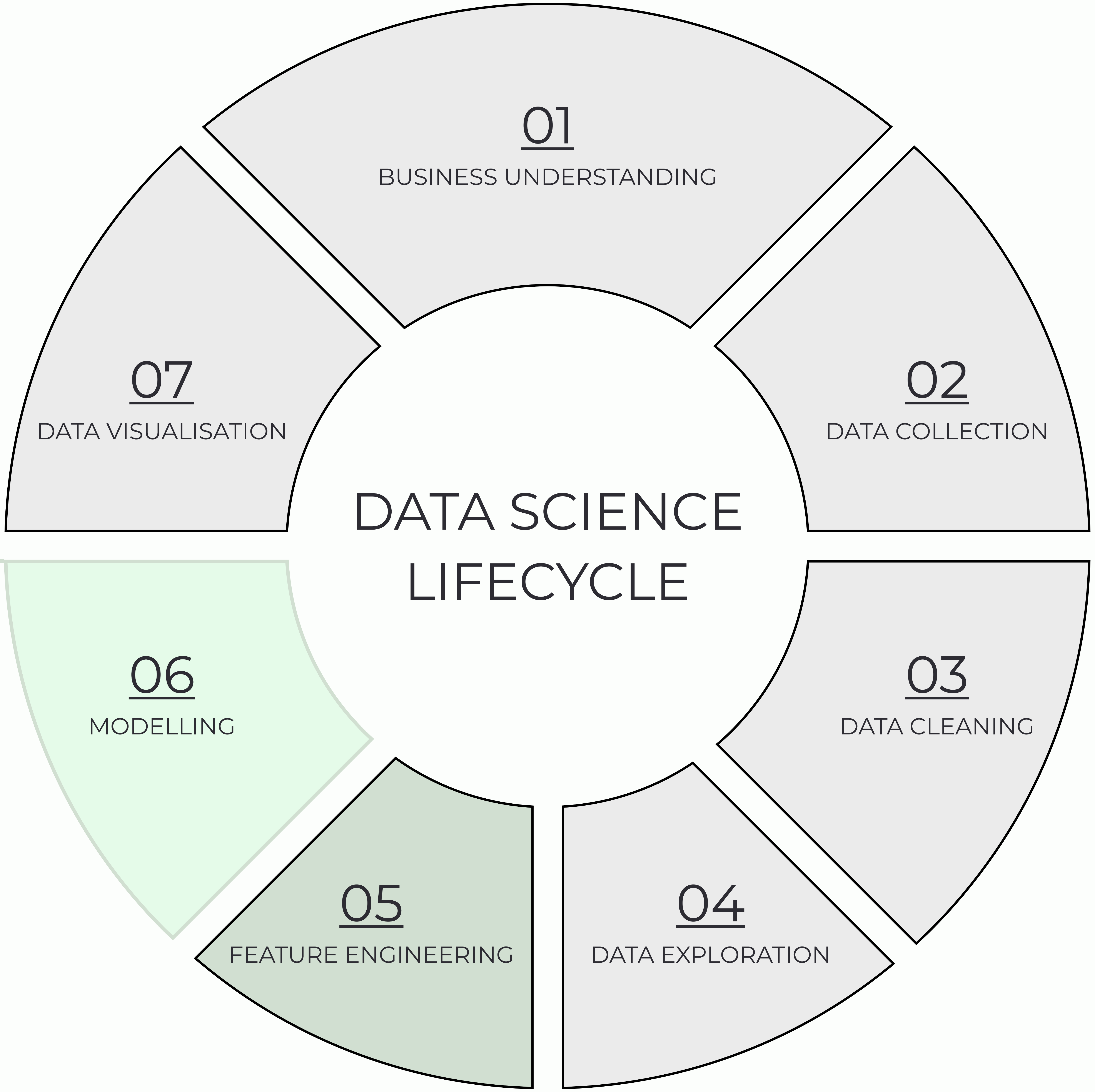




a3, a7 are Alexela total consumption at the same hour 3 and 7 days ago
e2 is the total Estonian consumption
t_dh is the degree-hour parameter
weekday is the day of the week

M. Spichakova, J. Belikov, K. Nõu, E. Petlenkov. Feature engineering for short-term forecast of energy consumption. *IEEE PES Innovative Smart Grid Technologies Europe: Bucharest, Romania*, 2019.
M. Sinimaa, M. Spichakova, J. Belikov, E. Petlenkov. Feature engineering of weather data for short-term energy consumption forecast. *IEEE Madrid PowerTech: Madrid, Spain*, 2021.

Train machine learning models, evaluate their performance, and use them to make predictions.



OVERVIEW OF THE MODELLING TECHNIQUES

Short-term load forecasting methods

- **Statistical methods**
  - Simple forecasting methods
  - Regression methods
  - Exponential smoothing
  - ARIMA family methods
  - Kalman filter
- **Machine learning and AI**
  - Artificial neural networks
  - Support vector machines
  - Fuzzy logic
  - Decision tree
  - Genetic algorithm
  - Knowledge-based expert systems
  - LSTM
- **Hybrid methods**
  - Combination of models
  - Decomposition into components

FORMAL PROBLEM STATEMENT

Input: $x^i \in \mathbb{R}^n, i = 1,\ldots,m$

Output: $y^i \in \mathbb{R}$

Model parameters: $\theta \in \mathbb{R}^k$

Predicted output: $\hat{y}^i \in \mathbb{R}$

We define a function that maps inputs to feature vectors:

$$\phi : \mathbb{R}^n \to \mathbb{R}^k$$

We are looking for a model that performs *well* on the given data:

$$\hat{y}^i \approx y^i, \forall i$$

The difference between a prediction and an actual output are measured using **loss function**:

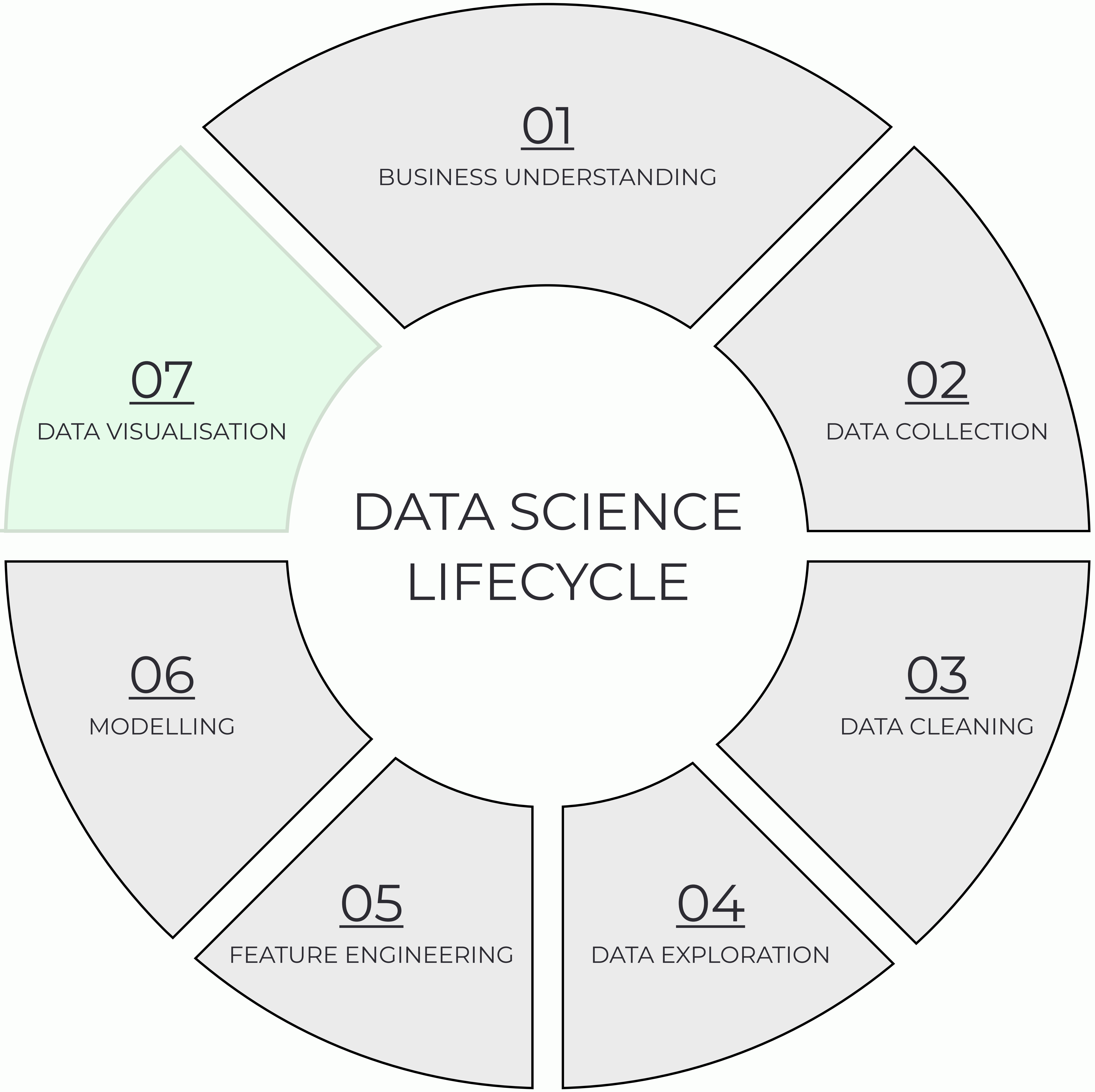
$$\ell : \mathbb{R} \times \mathbb{R} \to \mathbb{R}_+, \qquad \ell(\hat{y}, y) \in \mathbb{R}_+$$

We want to find model parameters that minimise sum of costs over all input/output pairs:

$$J(\theta) = \sum_{i=1}^{m} \ell(\hat{y}^i, y^i) = \sum_{i=1}^{m} (\theta^\mathsf{T}\phi(x^i) - y^i)^2$$

$$\text{minimize}_\theta J(\theta)$$

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



COMMUNICATE YOUR RESULTS

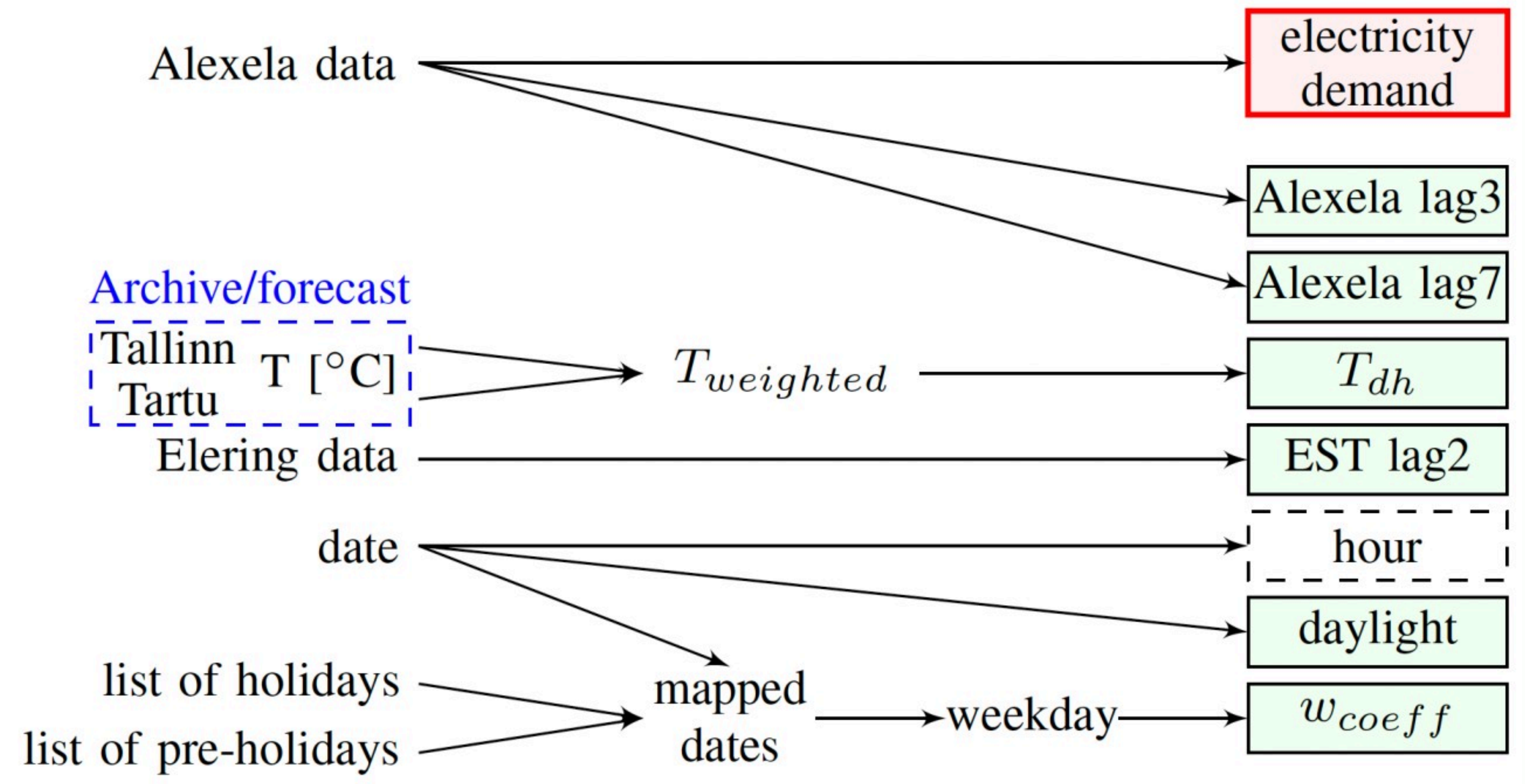


Fig. 5: Relations between different factors revealed by the feature analysis.

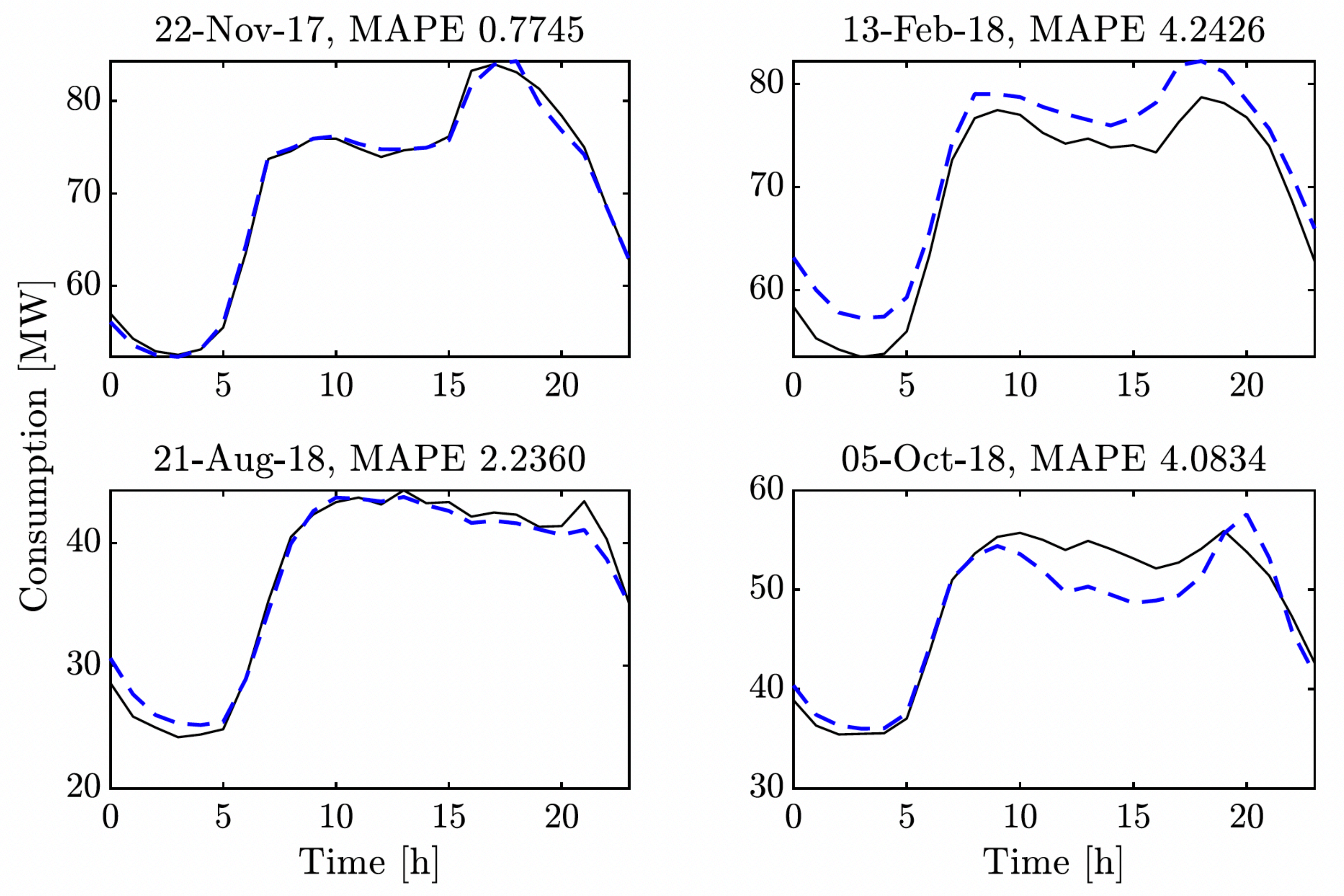


Fig. 8: Real ('—') and predicted ('- - -') electricity consumption for several representative days within the test set.

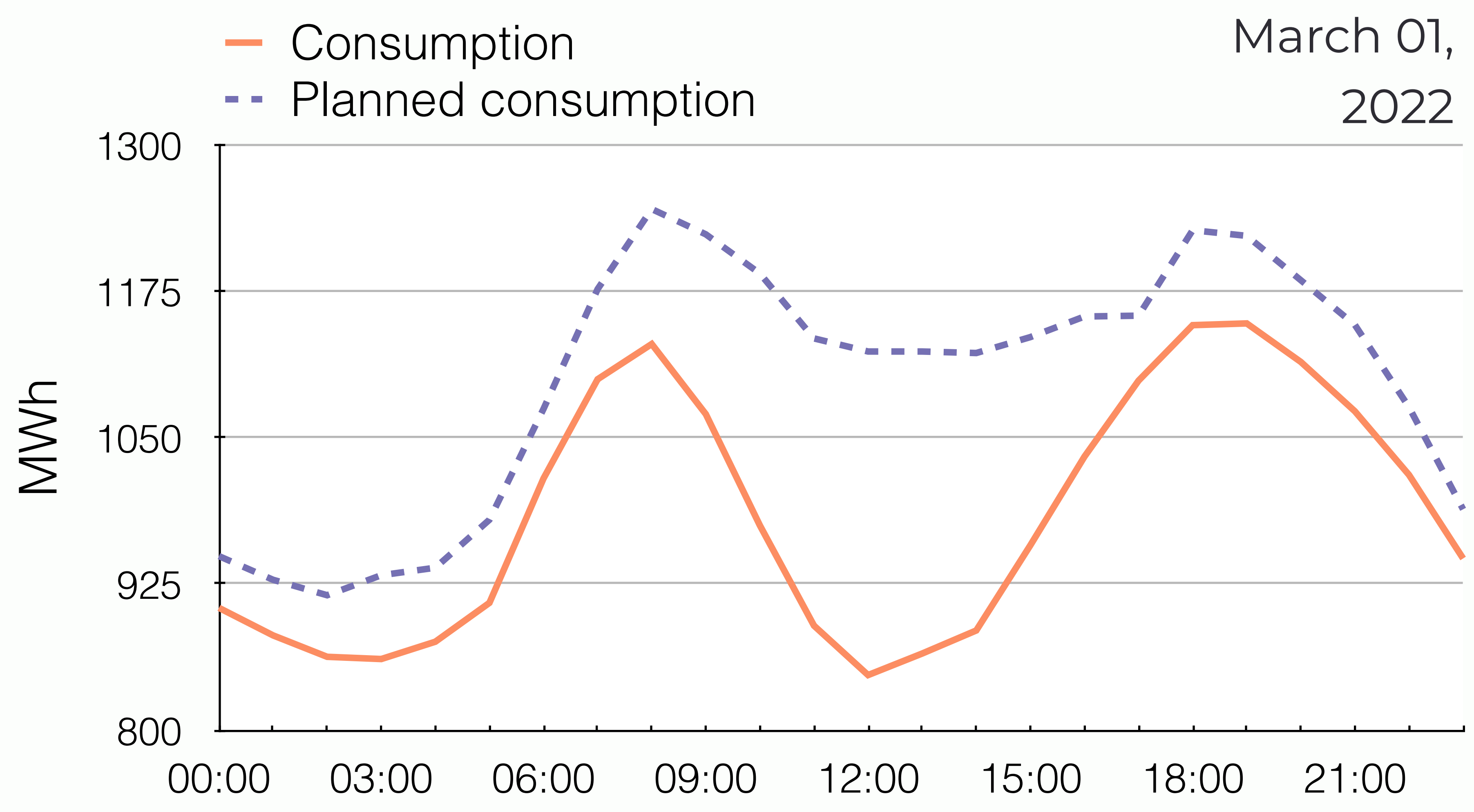
TABLE II: Validation Results: Monthly MAPE

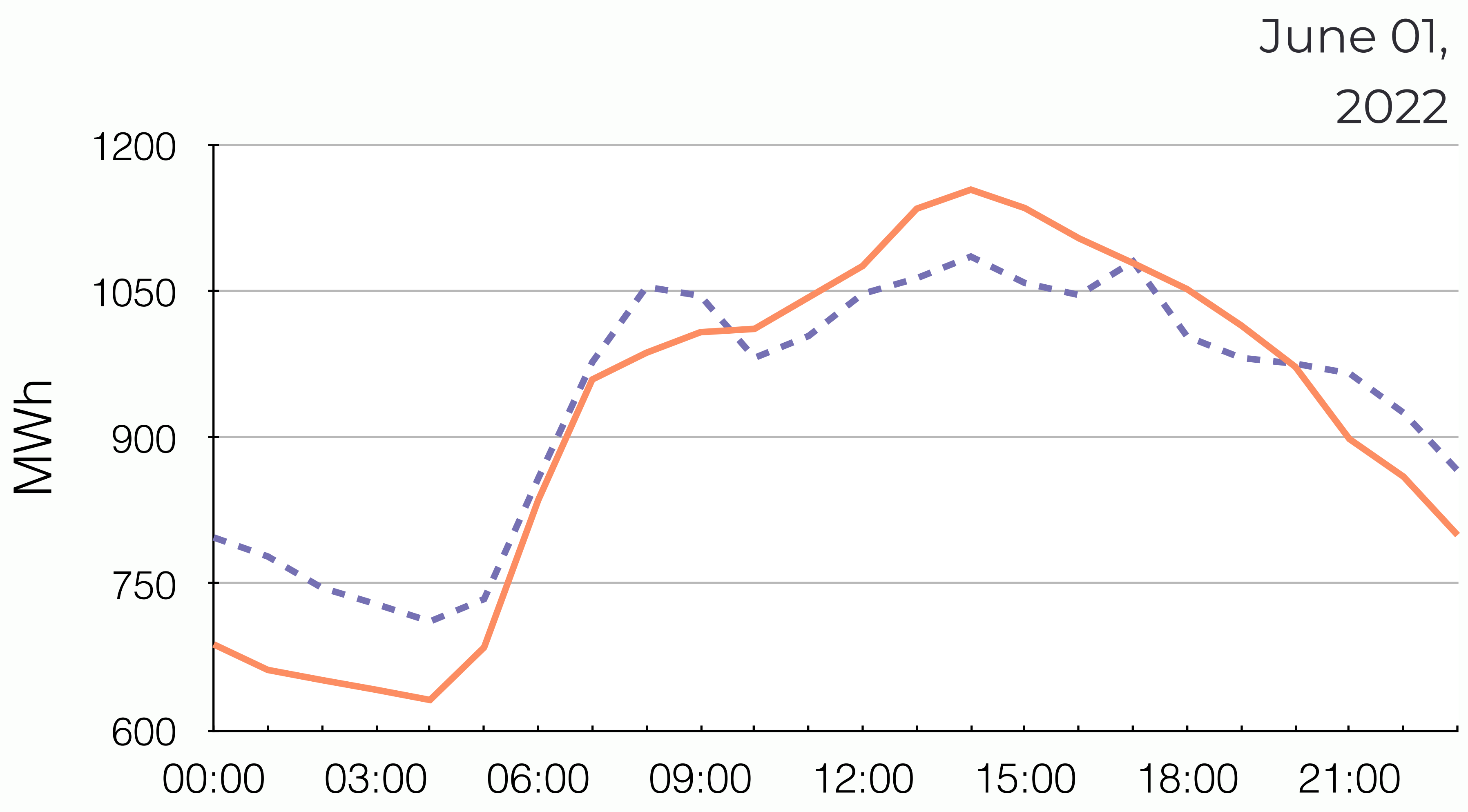
Year/Month		Proposed	Var1	Var2	Var3	Var4
2017	November	1.959	2.589	2.562	2.578	3.791
	December	2.358	3.39	3.104	3.39	4.009
2018	January	2.829	4.561	4.782	4.561	7.183
	February	4.412	4.654	4.444	4.654	5.808
	March	4.217	5.046	5.236	5.046	8.779
	April	2.73	3.823	3.725	3.951	8.563
	May	3.235	4.066	4.065	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		**3.339**	**4.099**	**4.19**	**4.222**	**5.626**

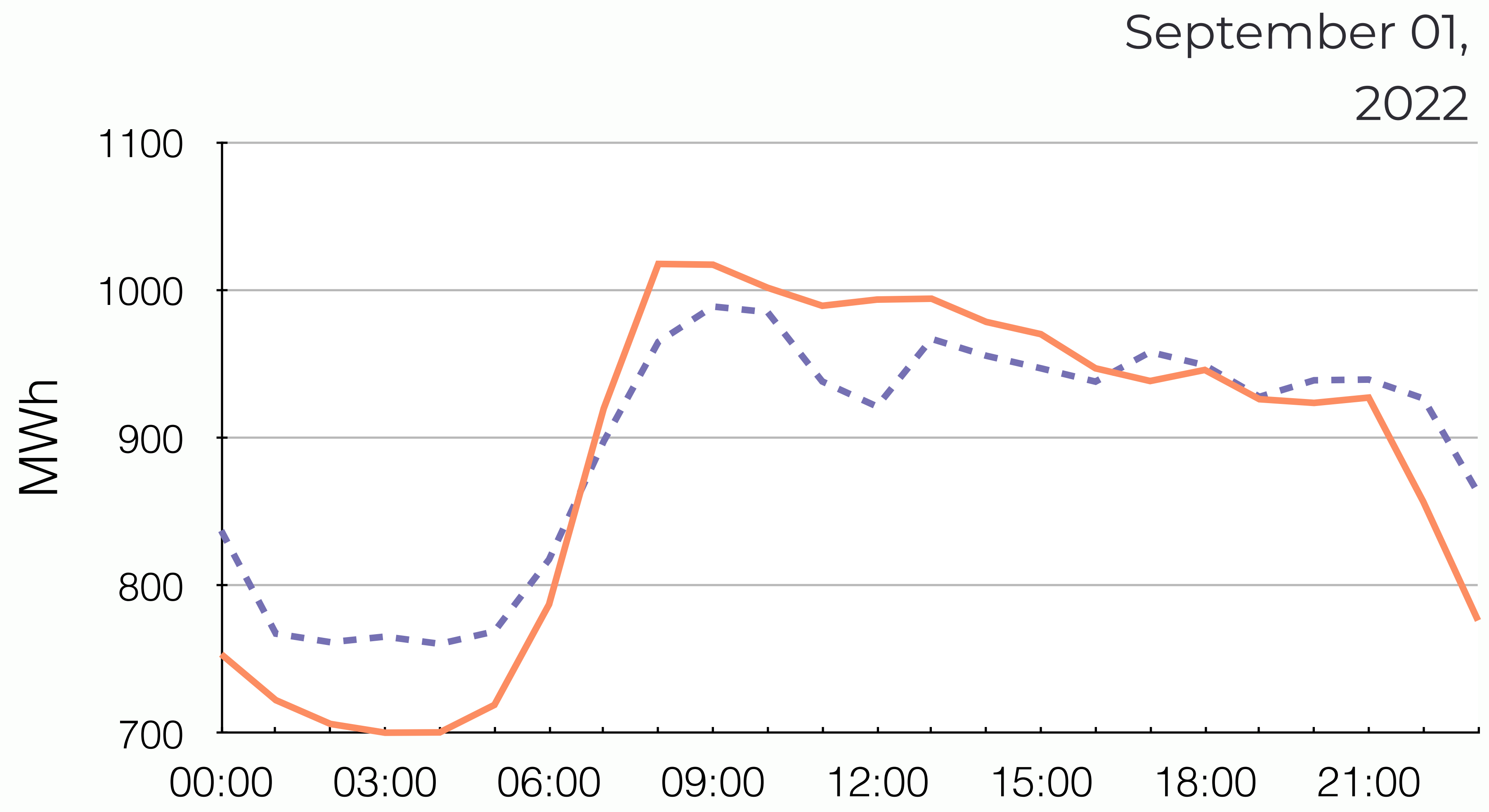
[a] Var1 has all 6 features, except $w_{tln} = w_{trt} = 0.5$ in T_{dh}.
[b] Var2 has 5 features: $a3$, $a7$, $e2$, T_{dh}, and daylight.
[c] Var3 has all 6 features, but T_{dh} is replaced by $(T_{tln} + T_{trt})/2$.
[d] Var4 has 2 features: $a7$ and T_{dh}.

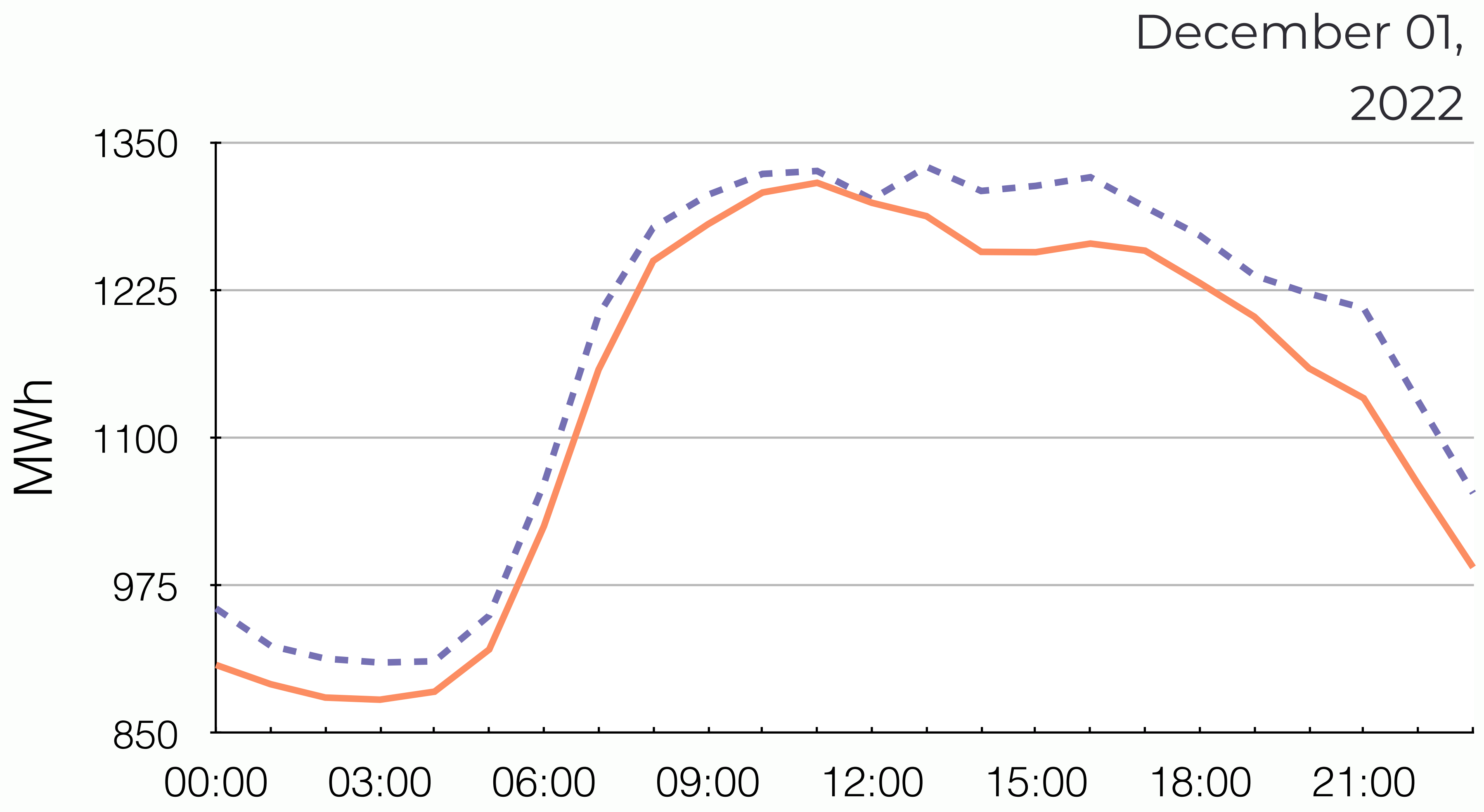
Performance Metrics: Regression

UNDERSTANDING ACCURACY

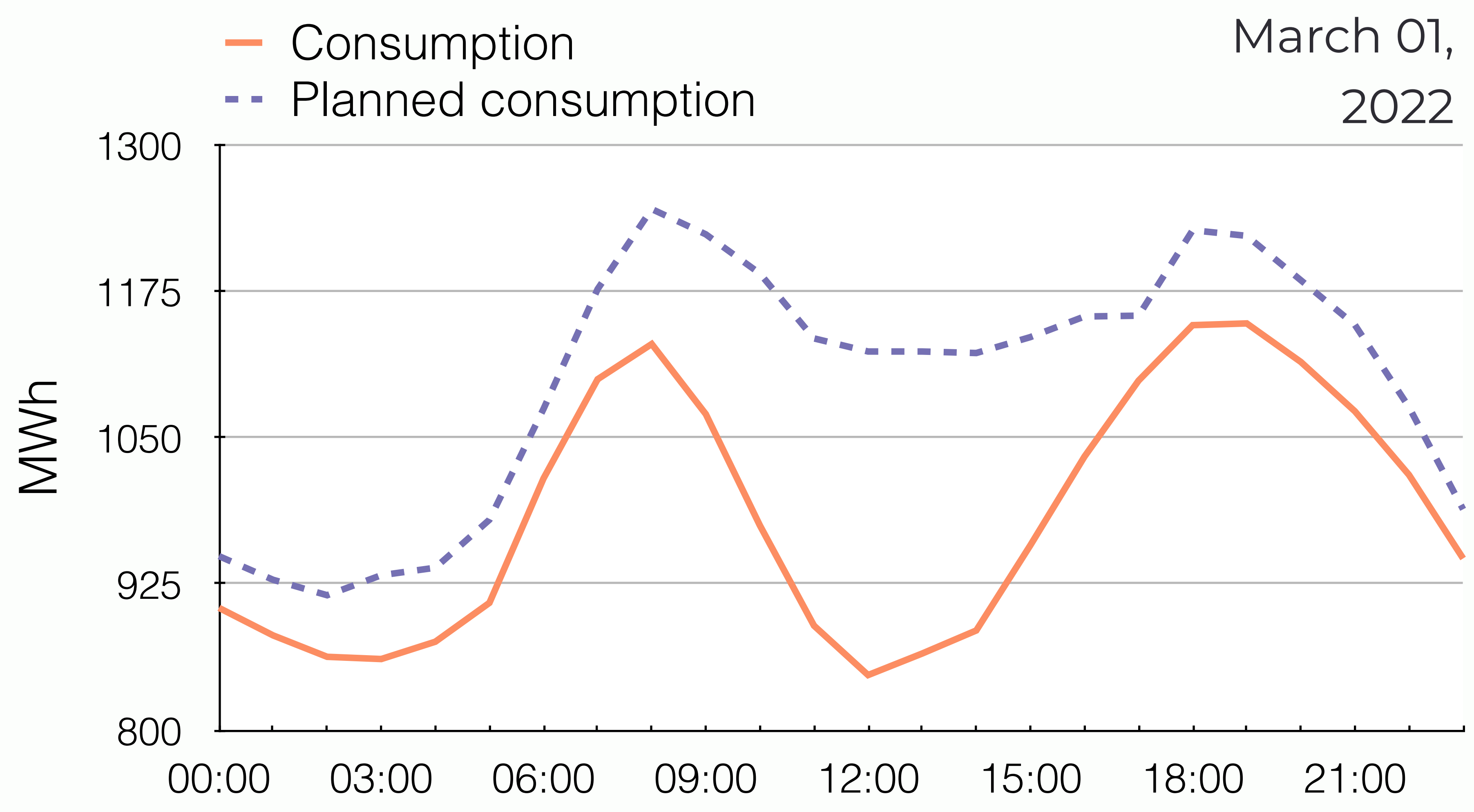


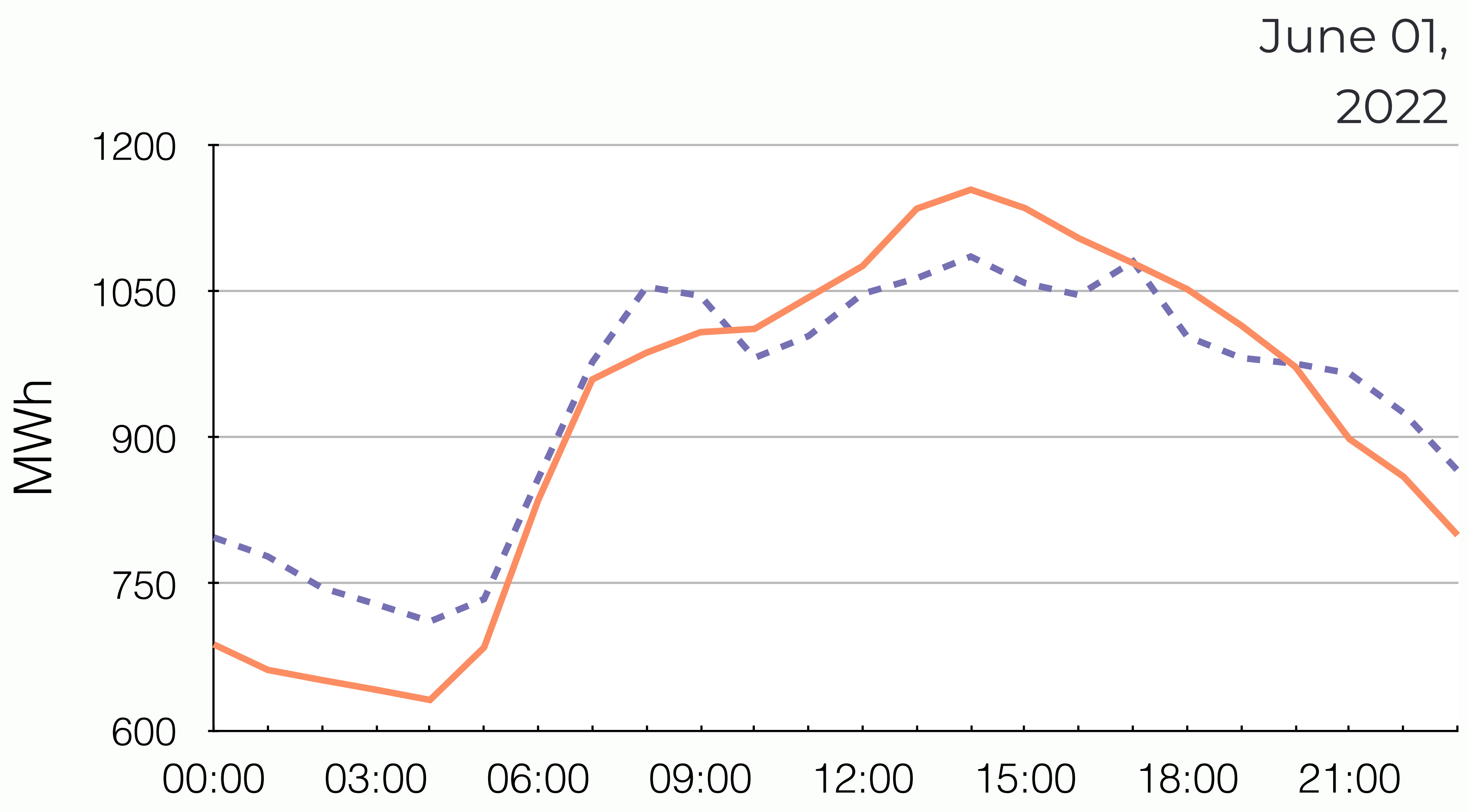




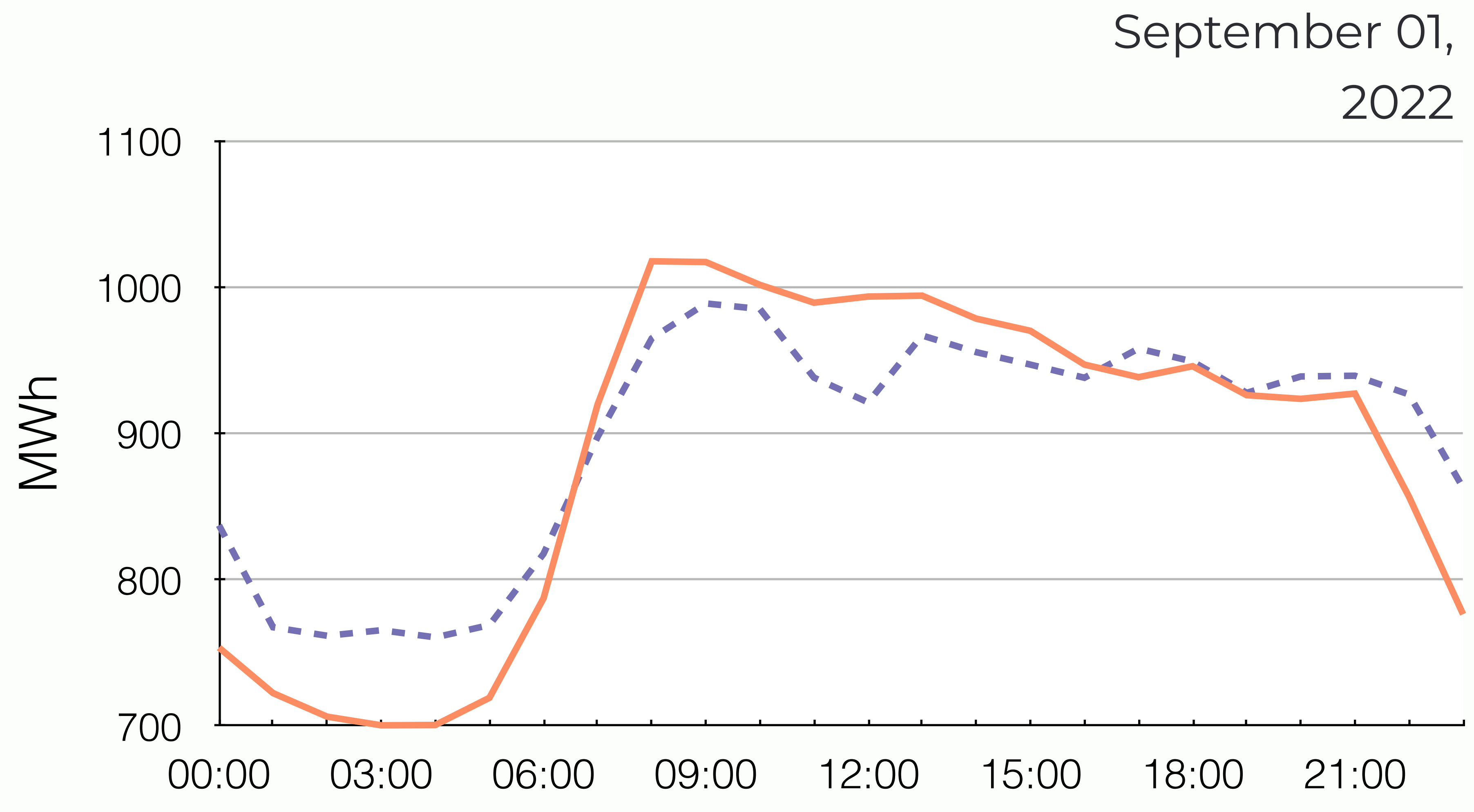


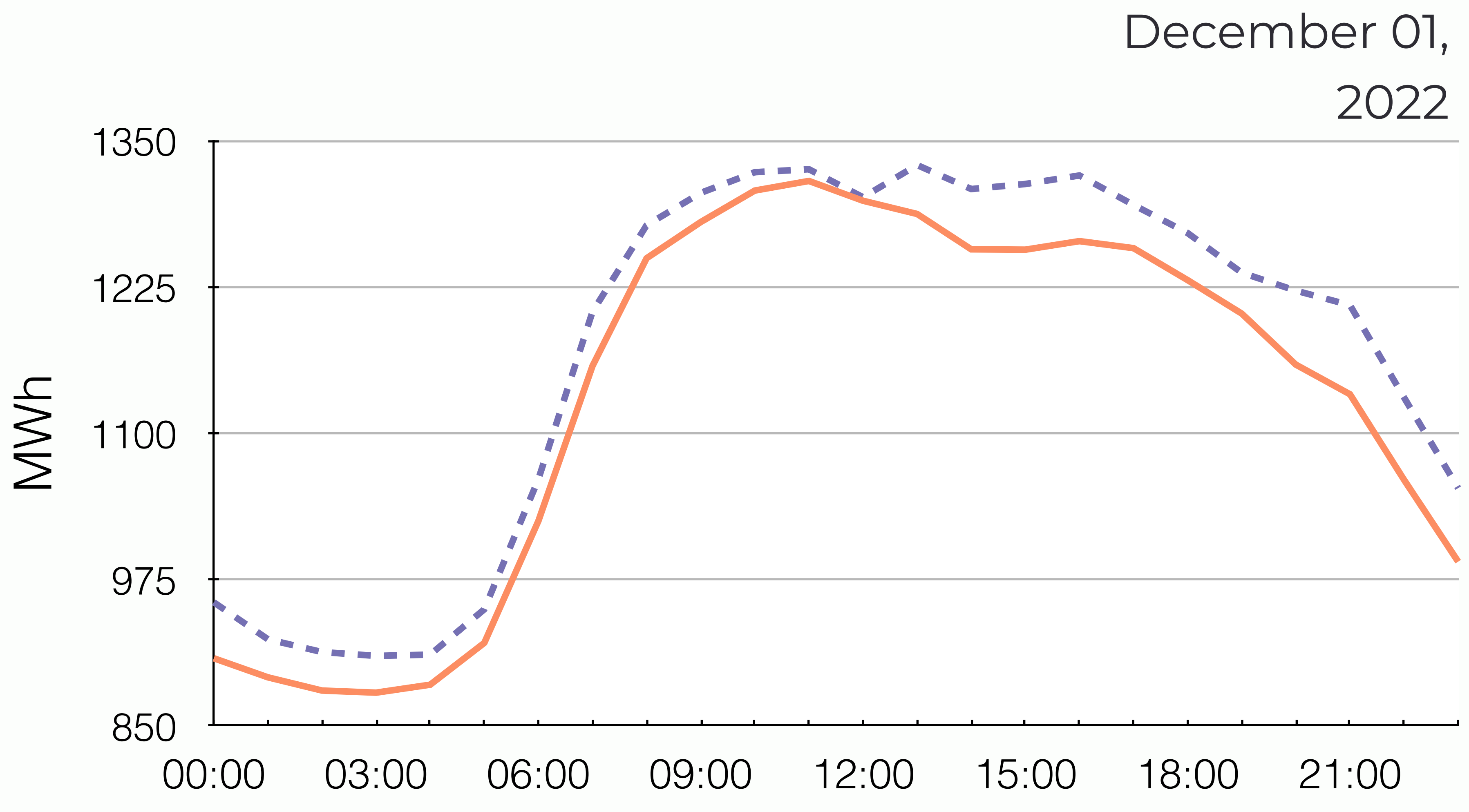
UNDERSTANDING ACCURACY





How to understand which prediction result is better?





COMMON METRICS

Metrics	Formula
R-squared	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i^{obs} - y_i^{pred})^2}{\sum_{i=1}^{n}(y_i^{obs} - \frac{1}{n}\sum_{j=1}^{n} y_j^{obs})^2}$
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)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert y_i^{obs} - y_i^{pred}\right\rvert$
Mean absolute percentage error (MAPE)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}}\right\rvert \times 100\,\%$

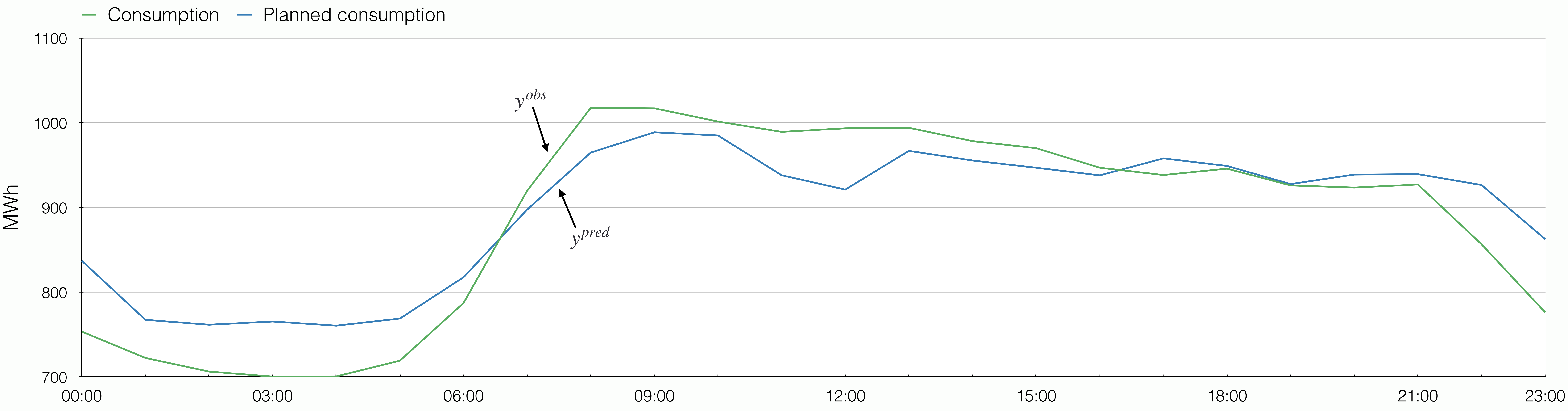
y_i^{obs} is the observed value

y_i^{pred} is the predicted value

i is the ith data point

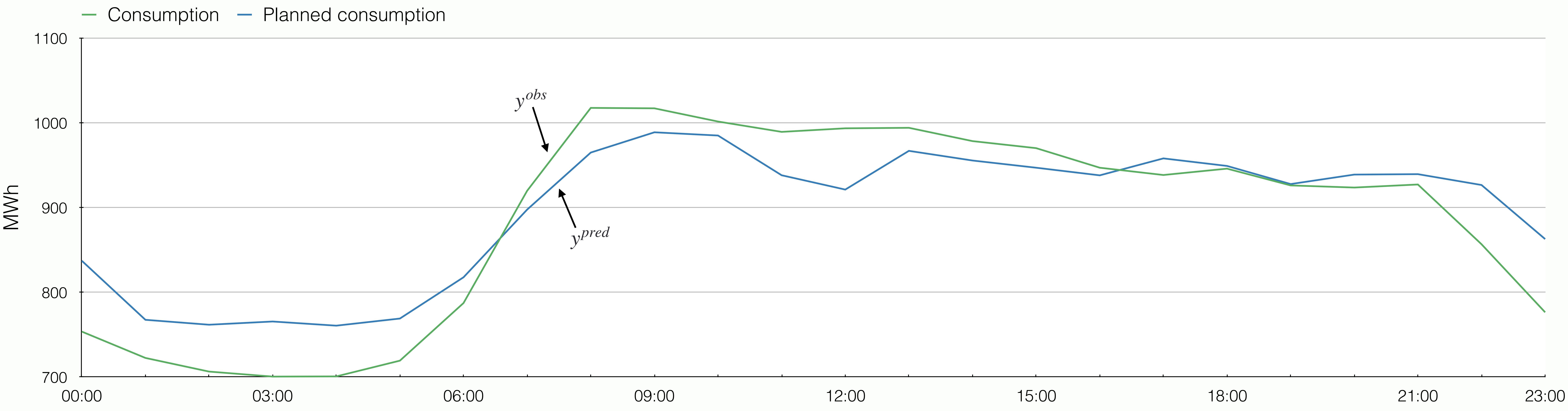
n is the total number of data points

ONE-DAY EXAMPLE (01.09.2022)



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

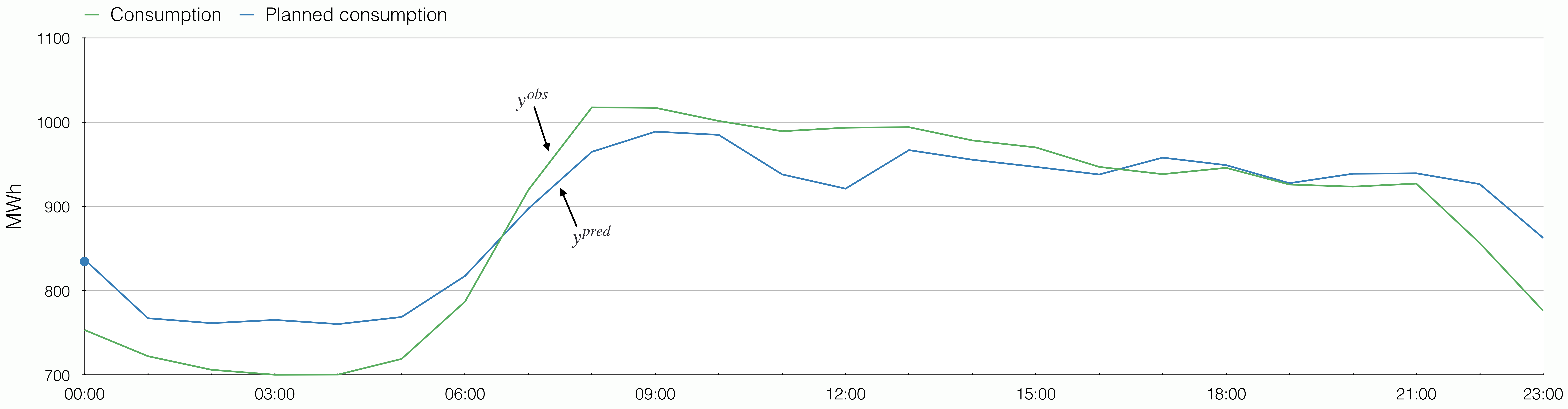
ONE-DAY EXAMPLE (01.09.2022)



i 1

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

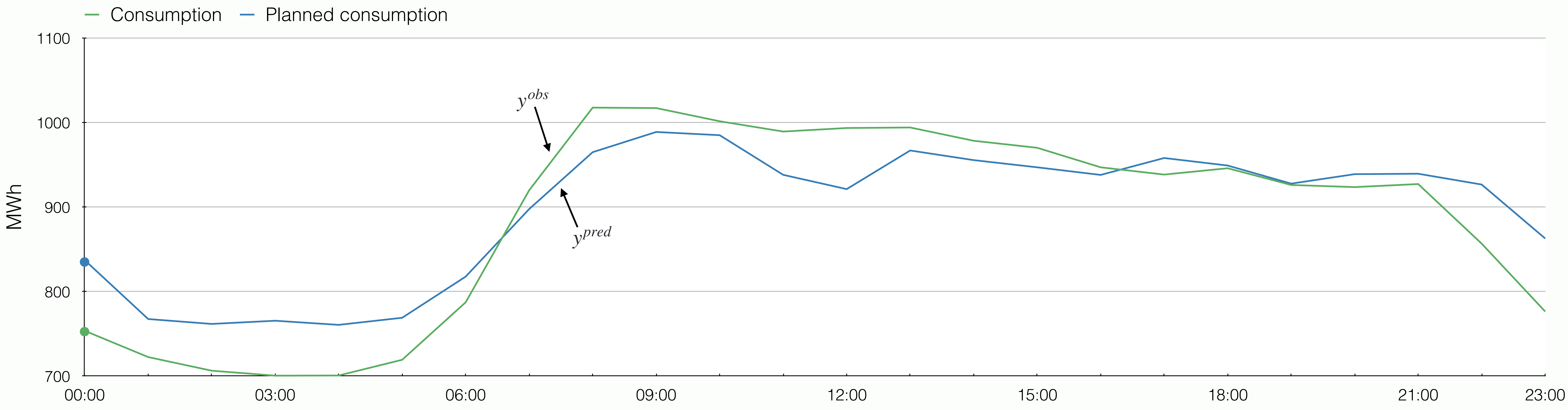
ONE-DAY EXAMPLE (01.09.2022)



i	1
y_i^{obs}	753.5

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

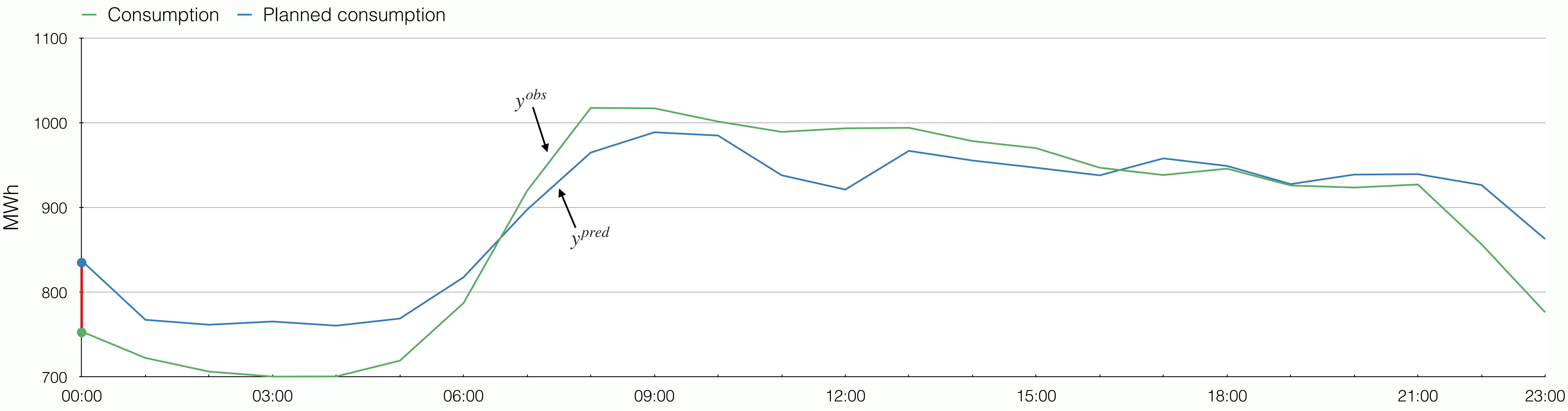
ONE-DAY EXAMPLE (01.09.2022)



i	1
y_i^{obs}	753.5
y_i^{pred}	837.1

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

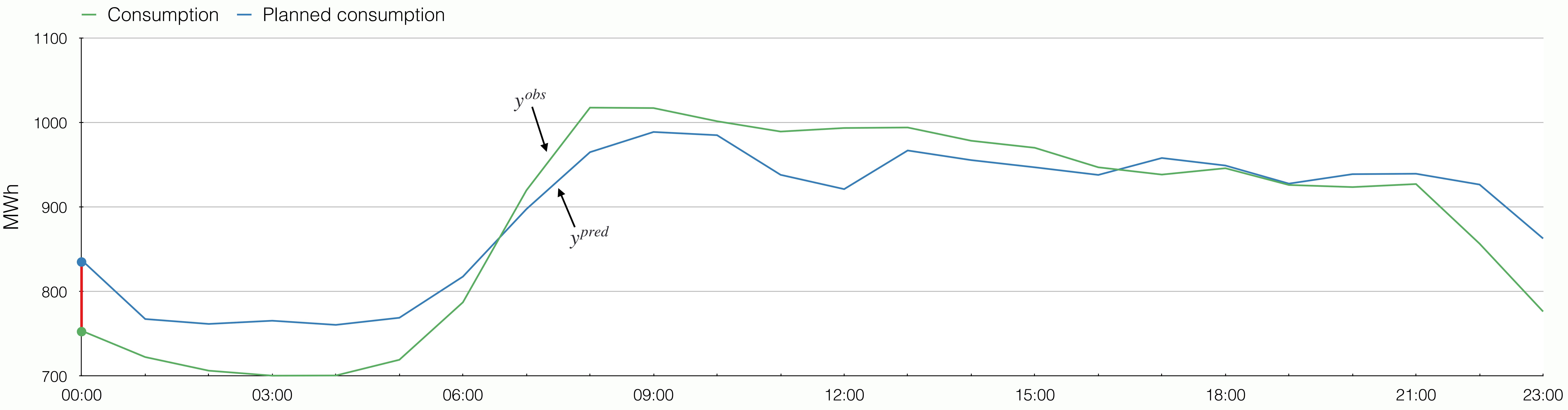
ONE-DAY EXAMPLE (01.09.2022)



i	1
y_i^{obs}	753.5
y_i^{pred}	837.1
$y_i^{obs} - y_i^{pred}$	-83.6

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

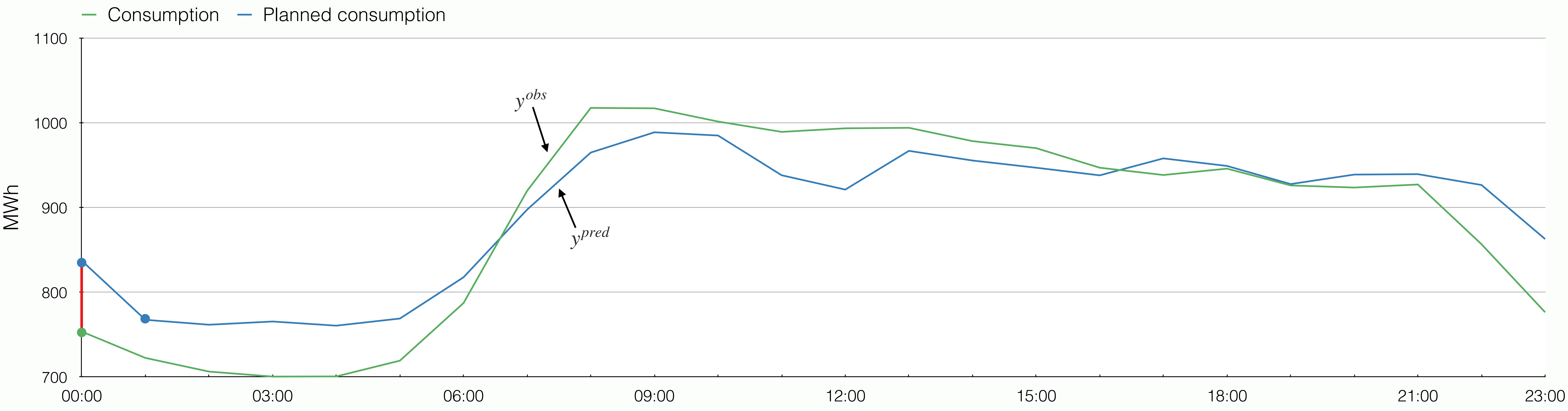
ONE-DAY EXAMPLE (01.09.2022)



i	1	2
y_i^{obs}	753.5	
y_i^{pred}	837.1	
$y_i^{obs} - y_i^{pred}$	-83.6	

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

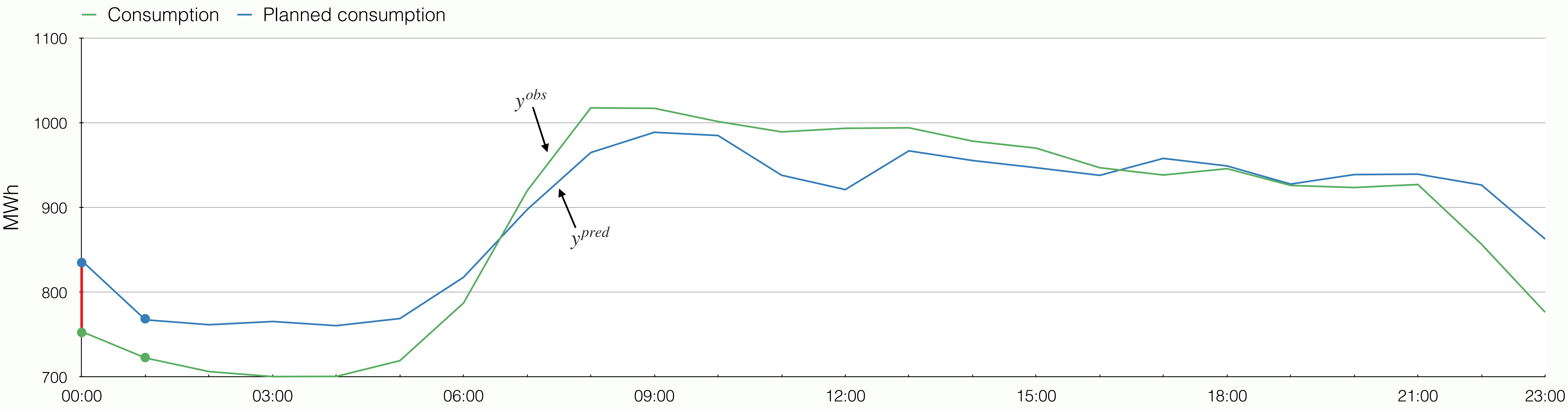
ONE-DAY EXAMPLE (01.09.2022)



i	1	2
y_i^{obs}	753.5	722.4
y_i^{pred}	837.1	
$y_i^{obs} - y_i^{pred}$	-83.6	

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

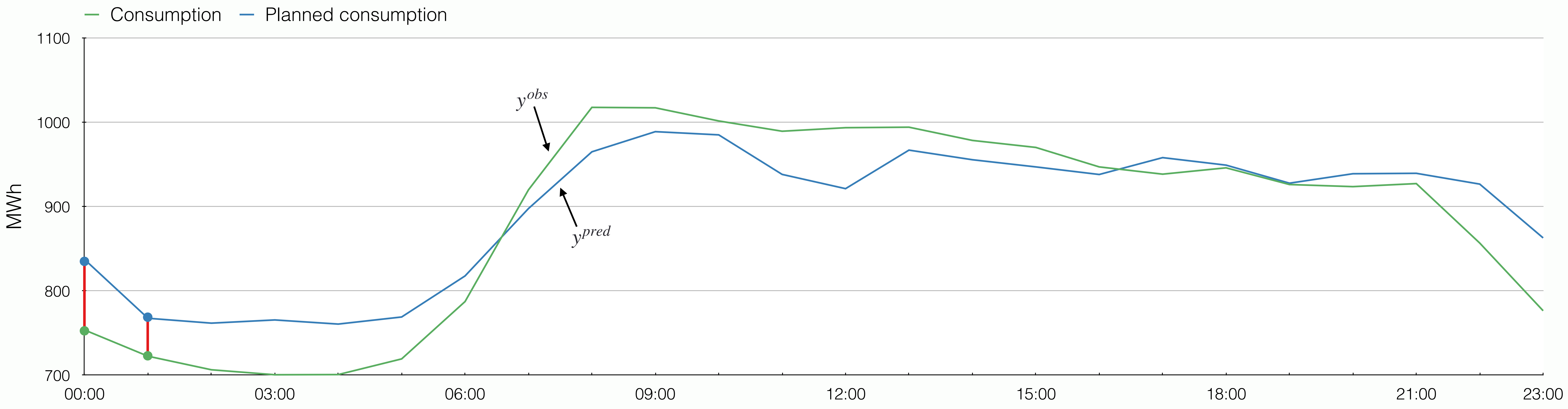
ONE-DAY EXAMPLE (01.09.2022)



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	

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

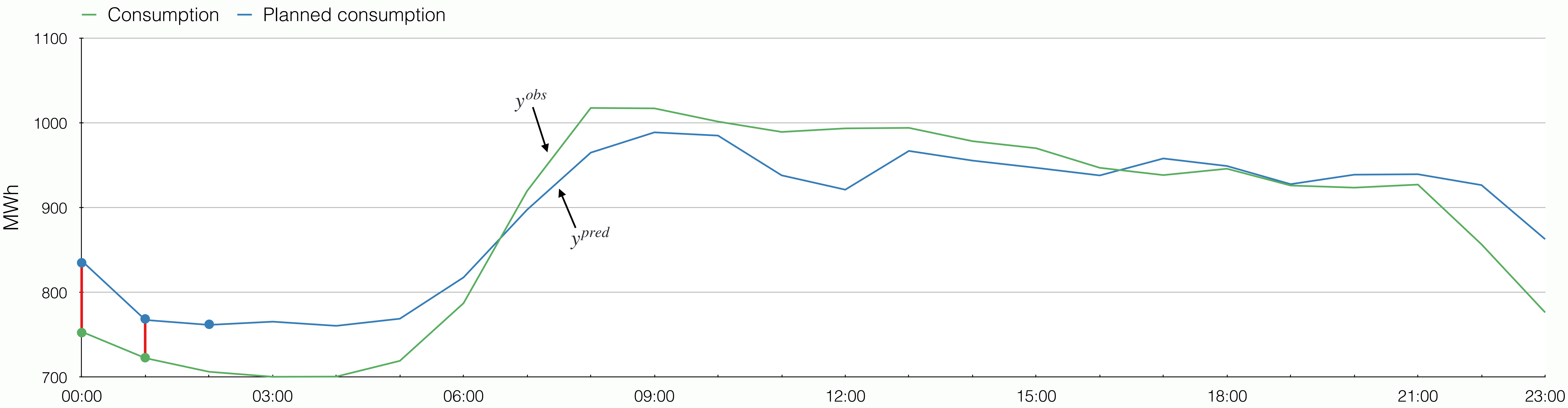
ONE-DAY EXAMPLE (01.09.2022)



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	-45

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

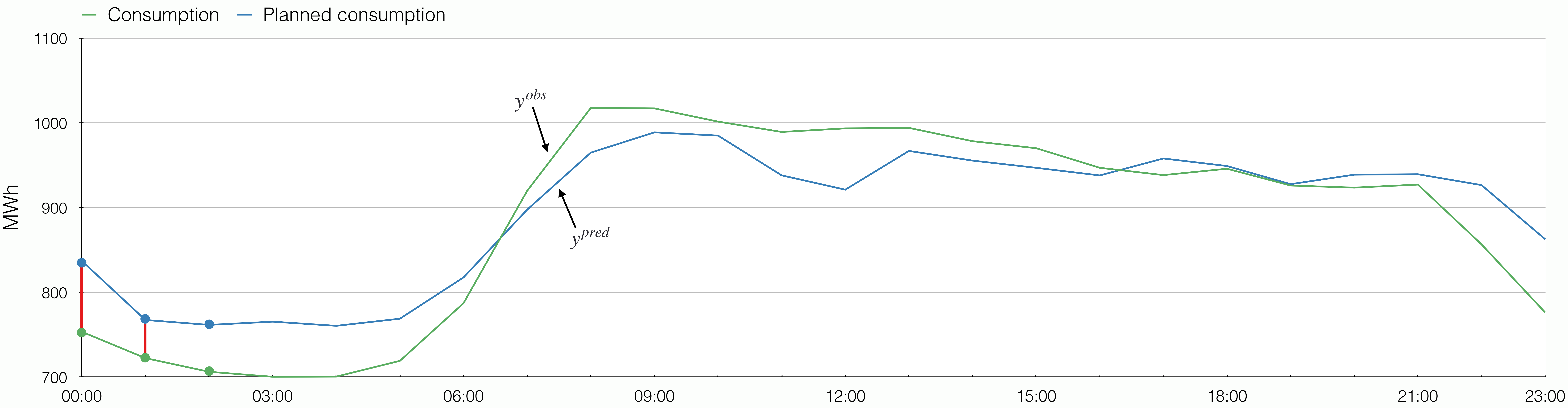
ONE-DAY EXAMPLE (01.09.2022)



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	

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

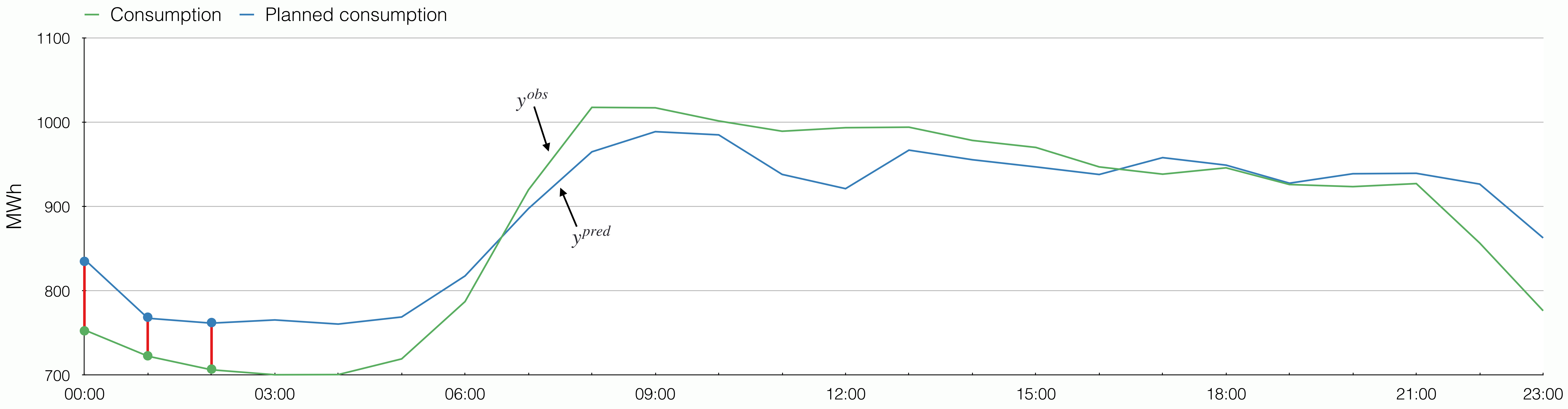
ONE-DAY EXAMPLE (01.09.2022)



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	

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

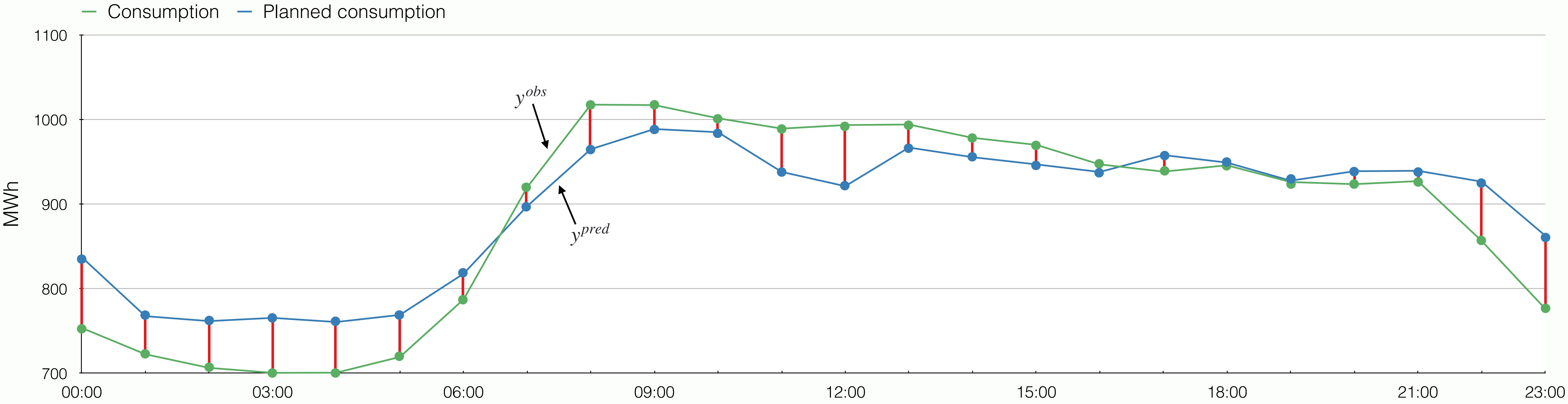
ONE-DAY EXAMPLE (01.09.2022)



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

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

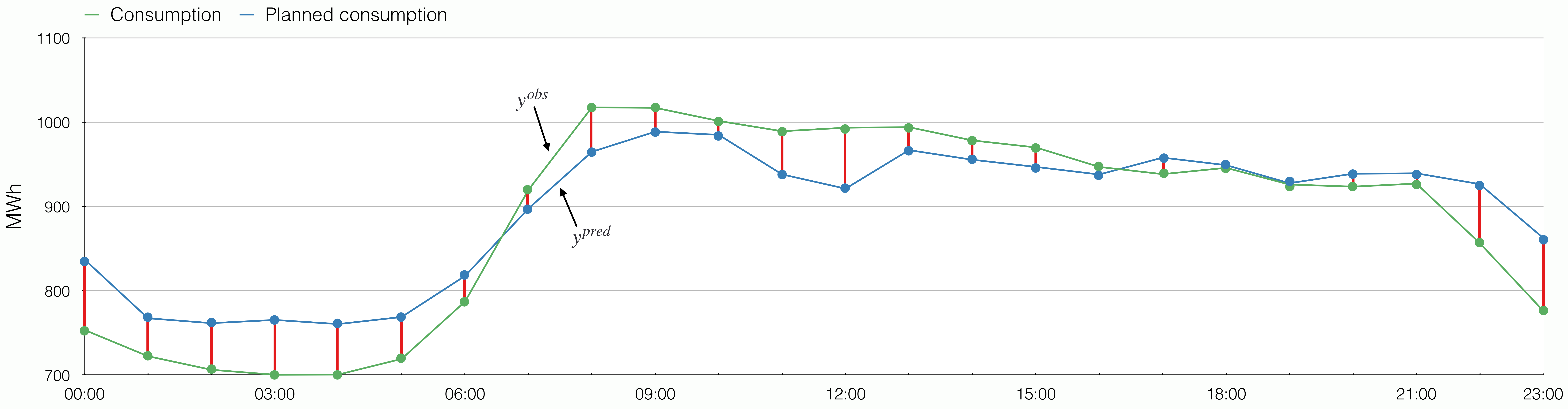
ONE-DAY EXAMPLE (01.09.2022)



i	1	2	3	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

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

ONE-DAY EXAMPLE (01.09.2022)

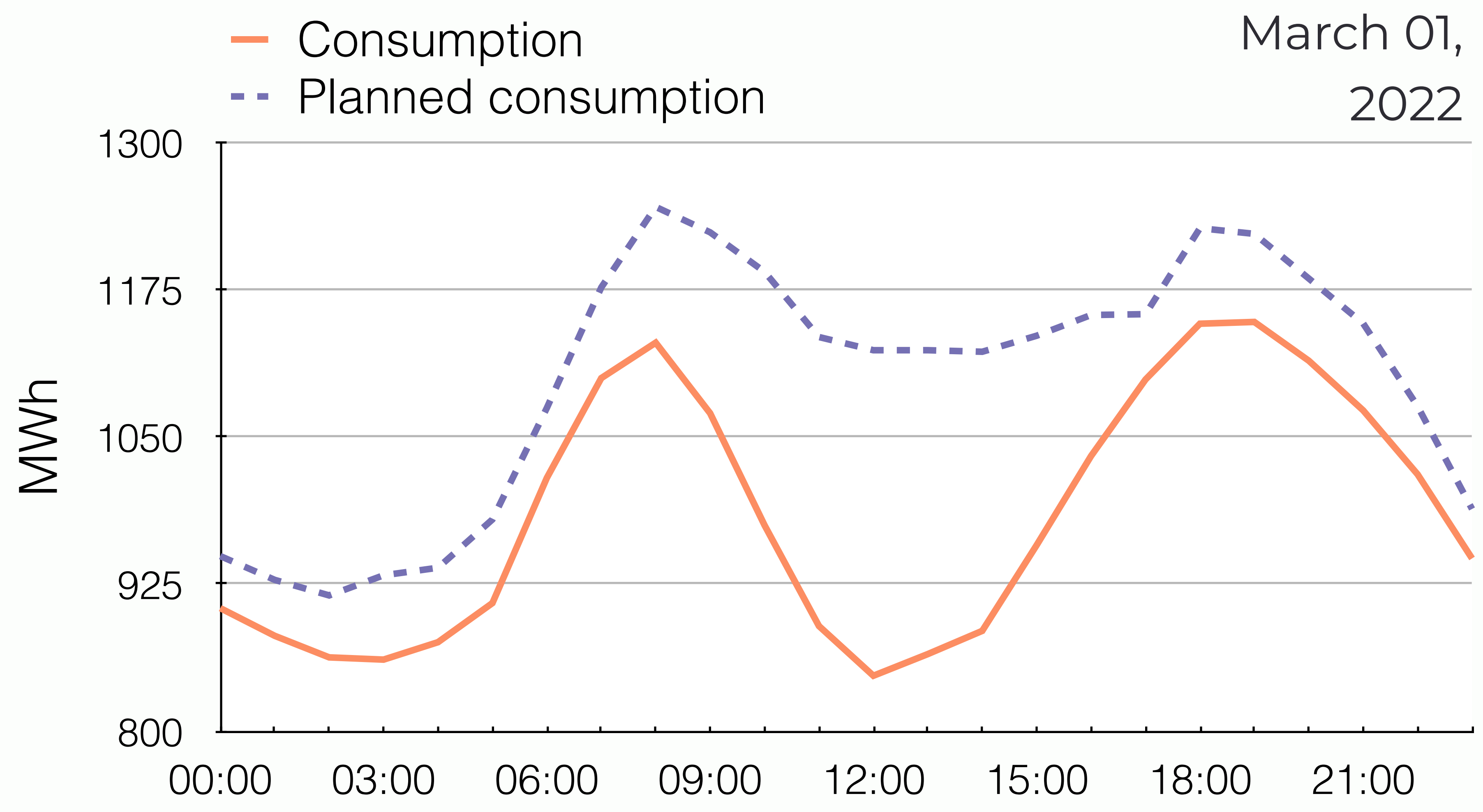


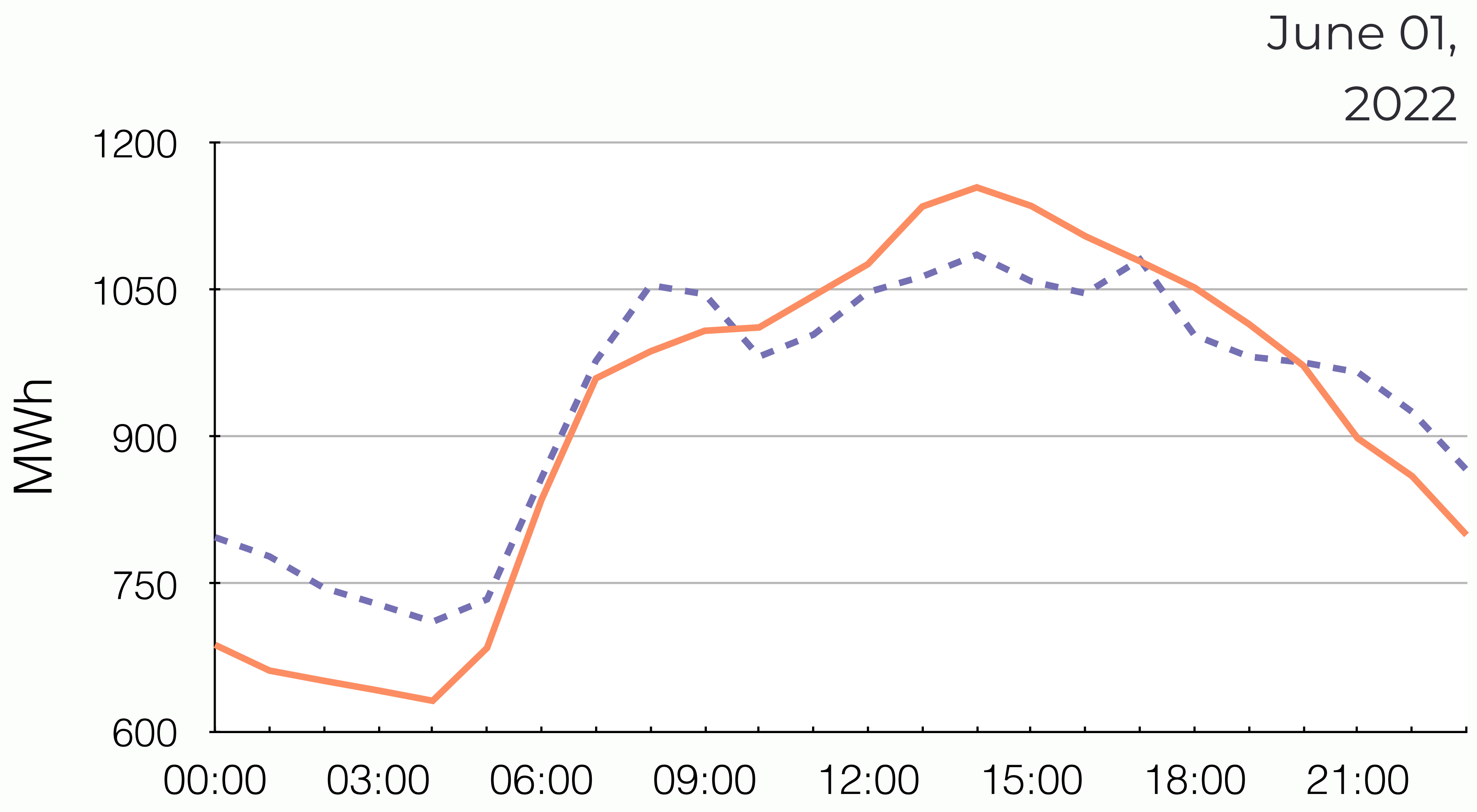
i	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
y_i^{obs}	753.5	722.4	706.3	700.4	700.6	719.2	787.2	919.7	1017.5	1017	1001.4	989.2	993.4	994	978.3	970	946.9	938.3	945.8	926	923.5	927.1	856.6	776.3
y_i^{pred}	837.1	767.4	761.6	765.4	760.5	768.9	817.6	897.5	964.8	988.7	984.9	938	921.1	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

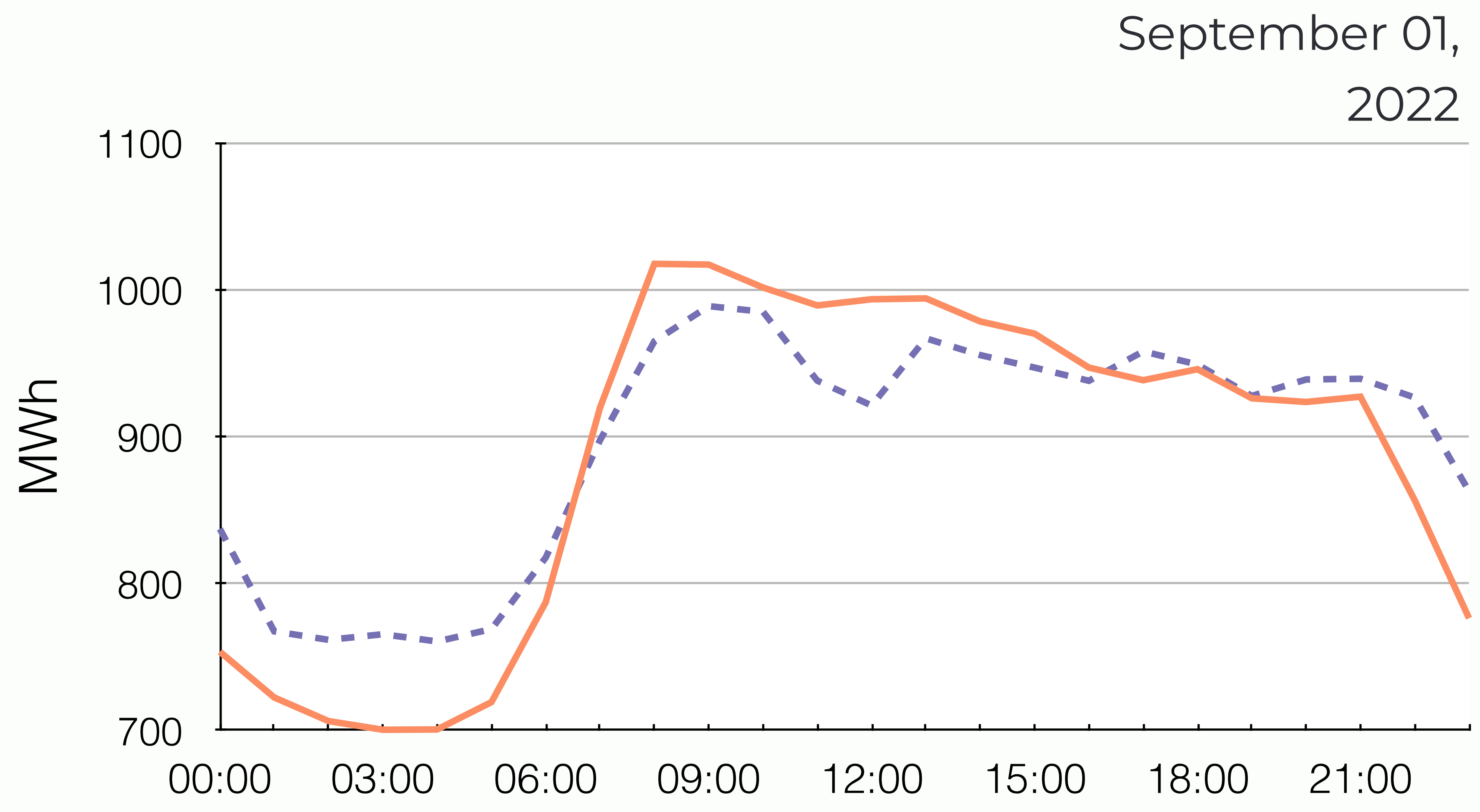
$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i^{obs} - y_i^{pred}}{y_i^{obs}}\right| \times 100\,\% \xrightarrow{n\,=\,24} \text{MAPE} = \frac{1}{24}\left(\frac{83.6}{753.5} + \frac{45}{722.4} + \frac{55.3}{706.3} + \cdots + \frac{12.2}{927.1} + \frac{69.9}{856.6} + \frac{86.4}{776.3}\right) \times 100\,\%$$

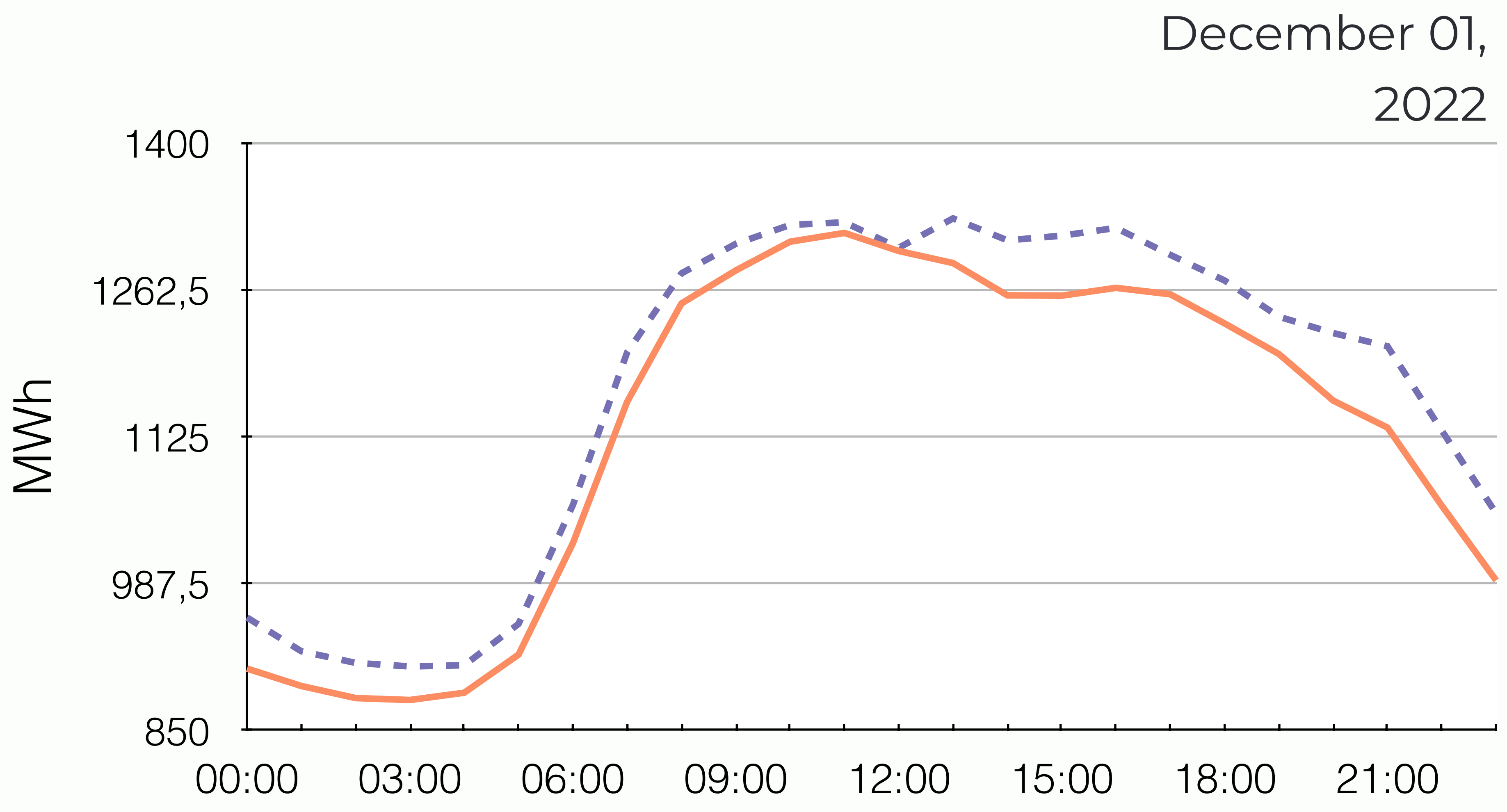
$$= \frac{1}{24}\left(11.09\% + 6.22\% + 7.83\% + \cdots + 1.32\% + 8.16\% + 11.13\,\%\right)$$

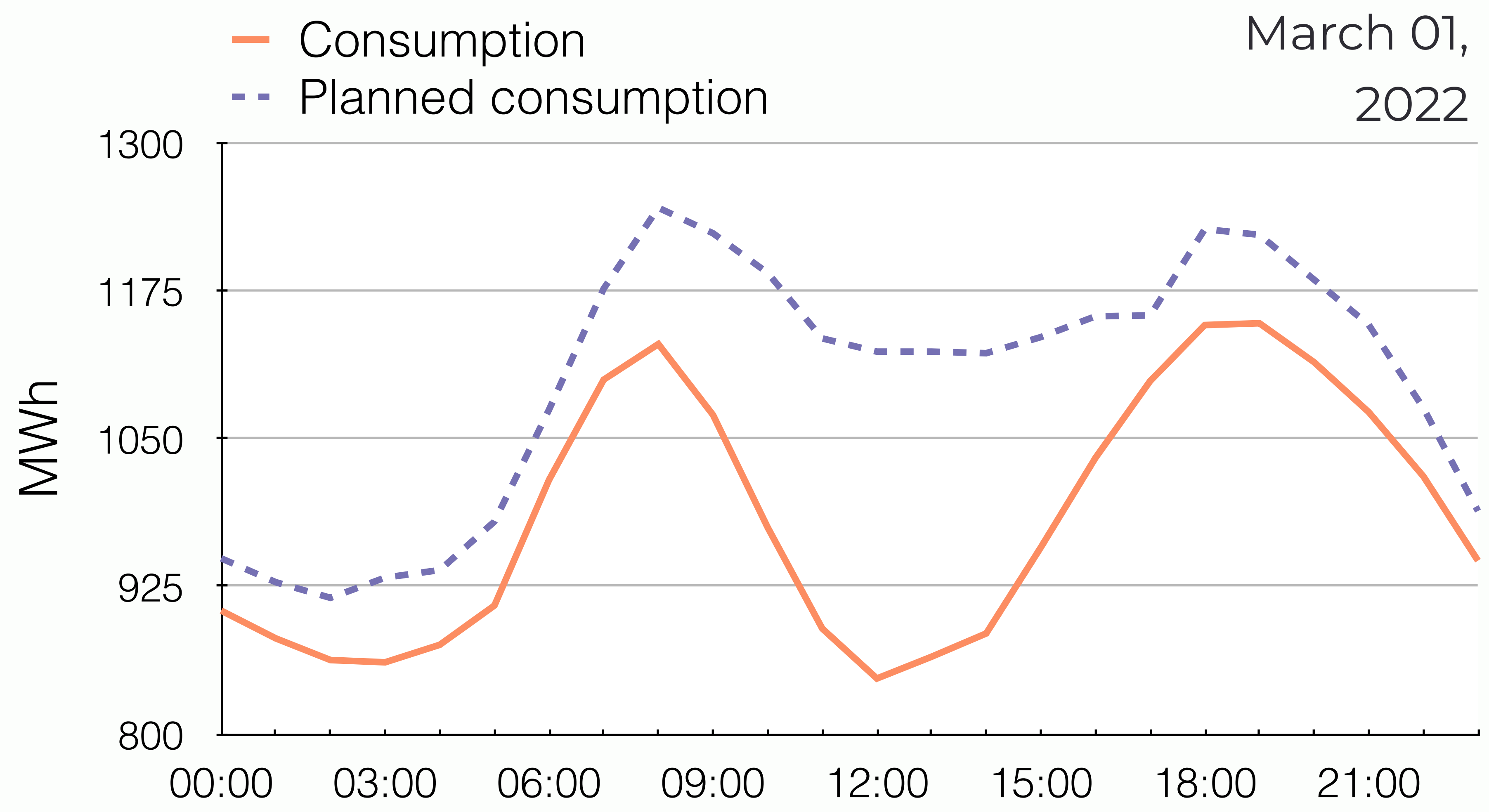
$$\approx 4.65\,\%$$


Consumption
Planned consumption
March 01, 2022
MWh
1300
1175
1050
925
800
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00


June 01, 2022
MWh
1200
1050
900
750
600
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00

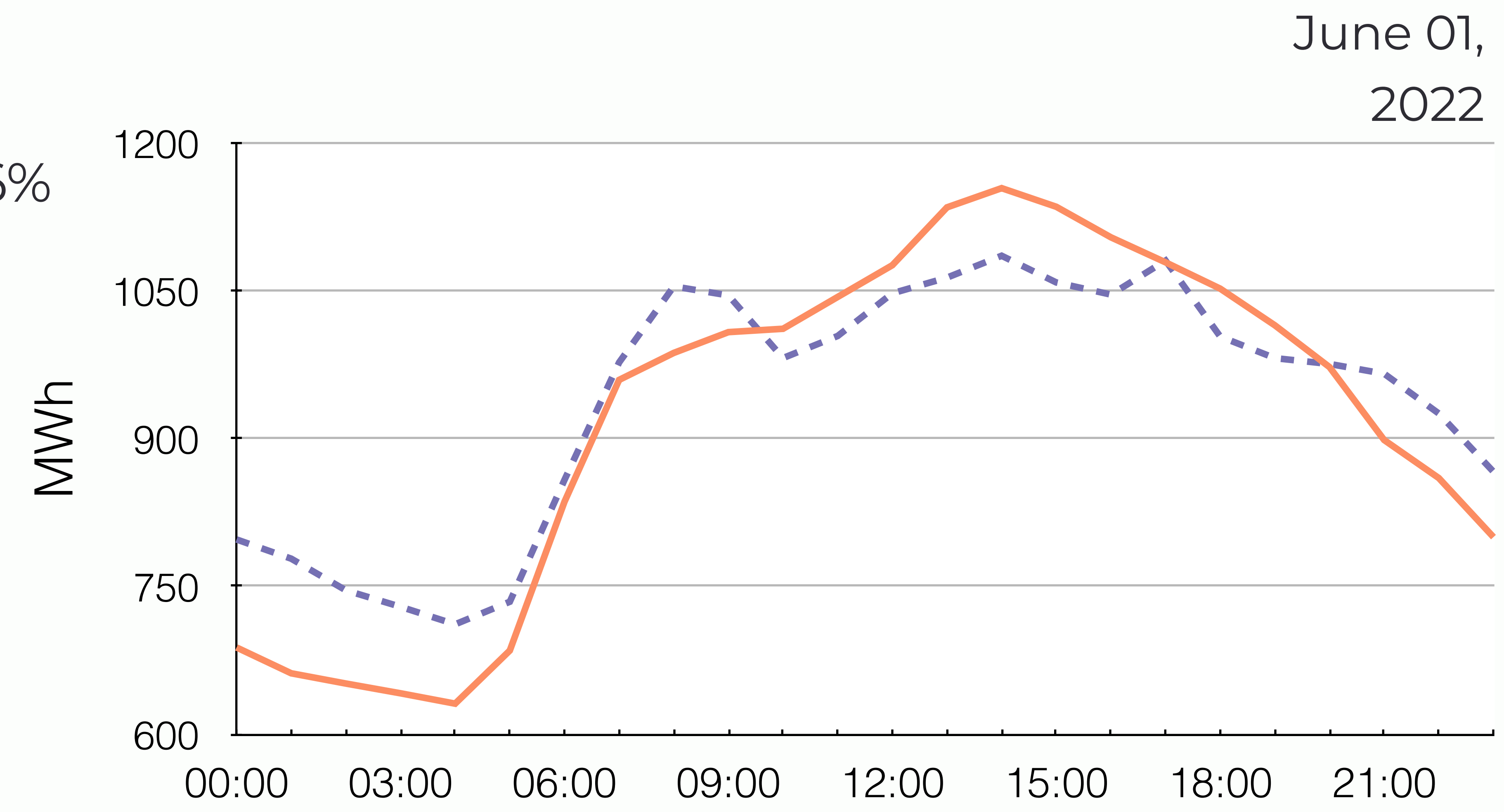

September 01, 2022
MWh
1100
1000
900
800
700
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00

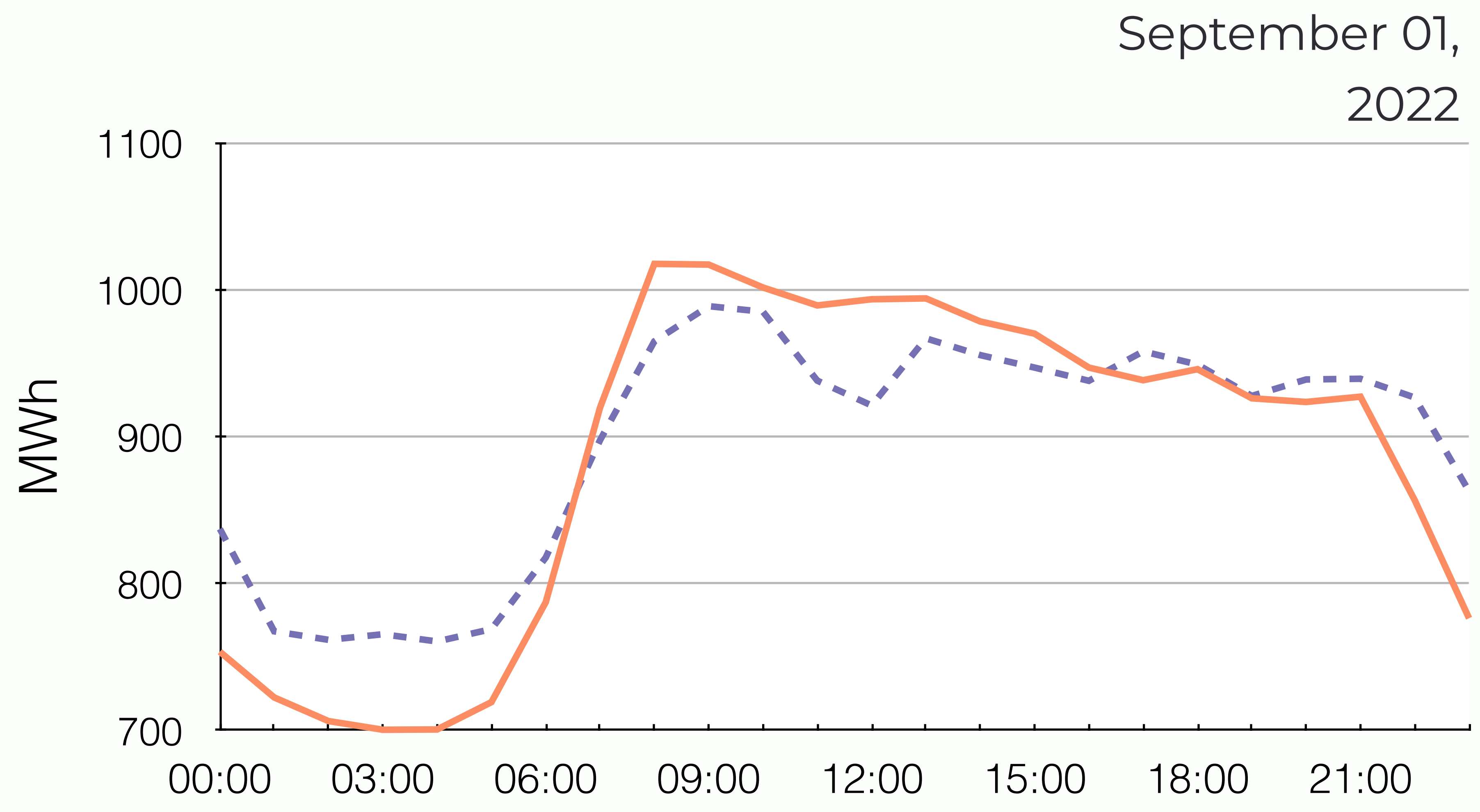

December 01, 2022
MWh
1400
1262,5
1125
987,5
850
00:00
03:00
06:00
09:00
12:00
15:00
18:00
21:00



MAPE1 = 12%

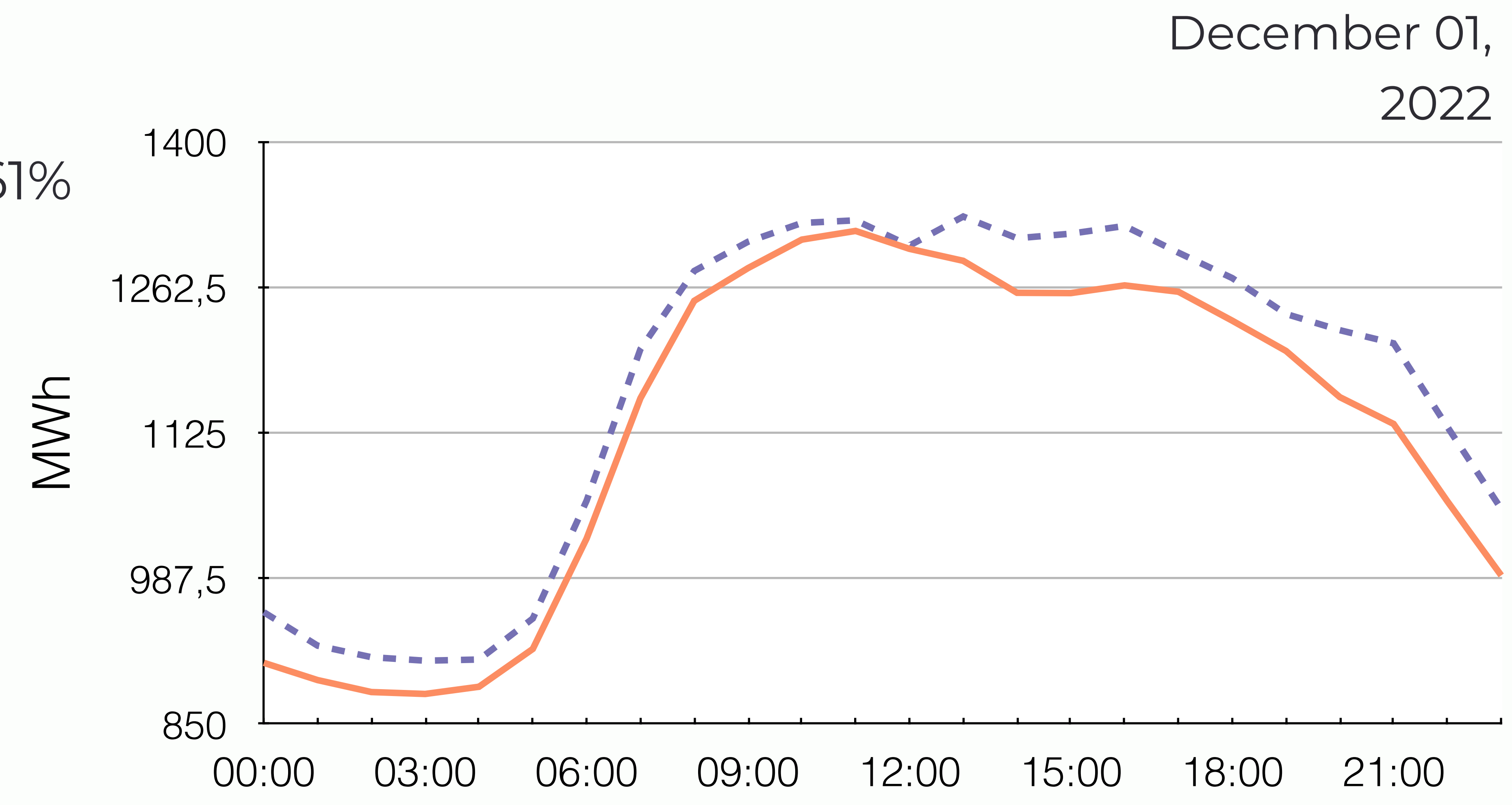
MAPE2 = 6.76%

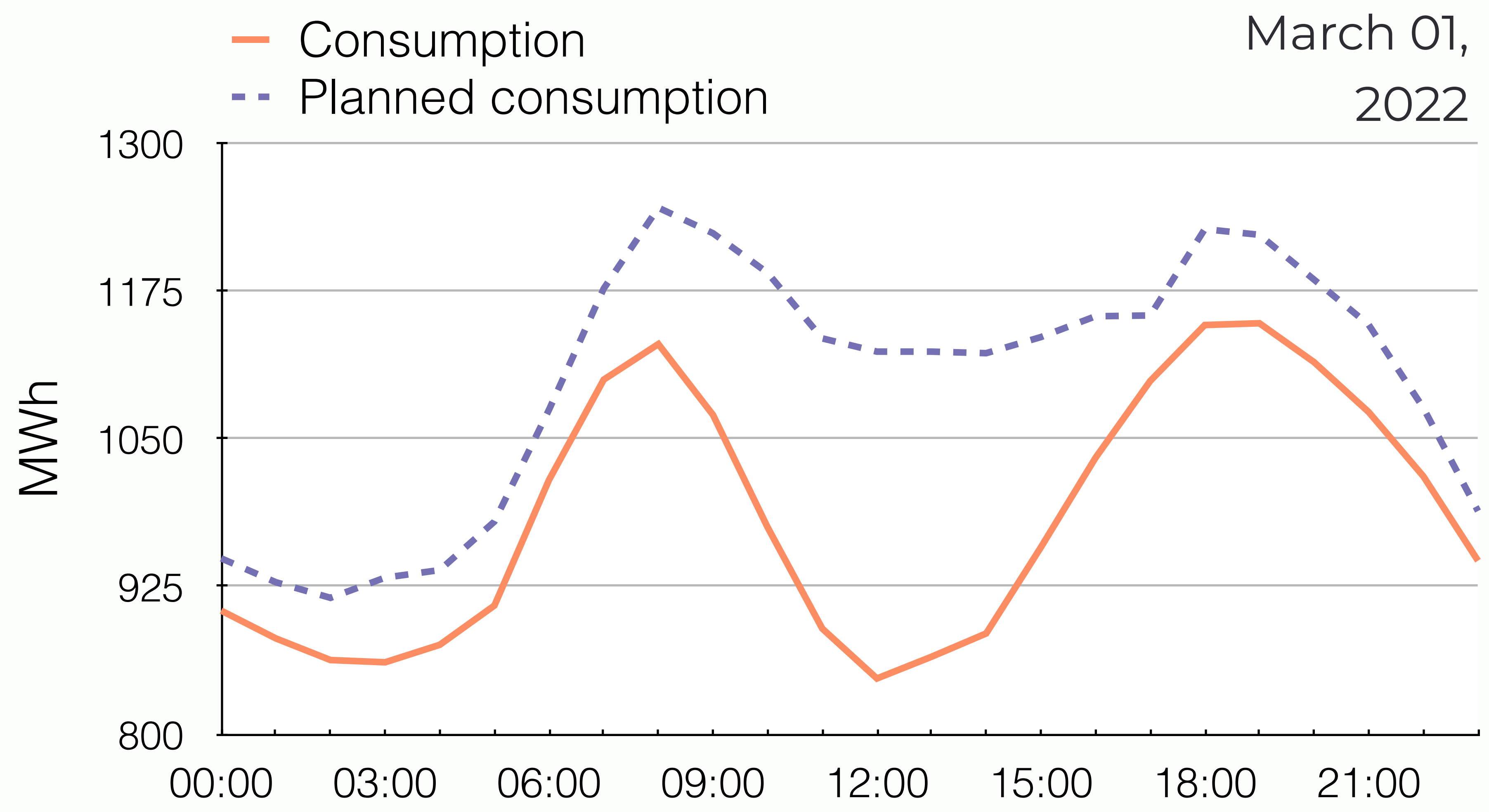




MAPE3 = 4.65%

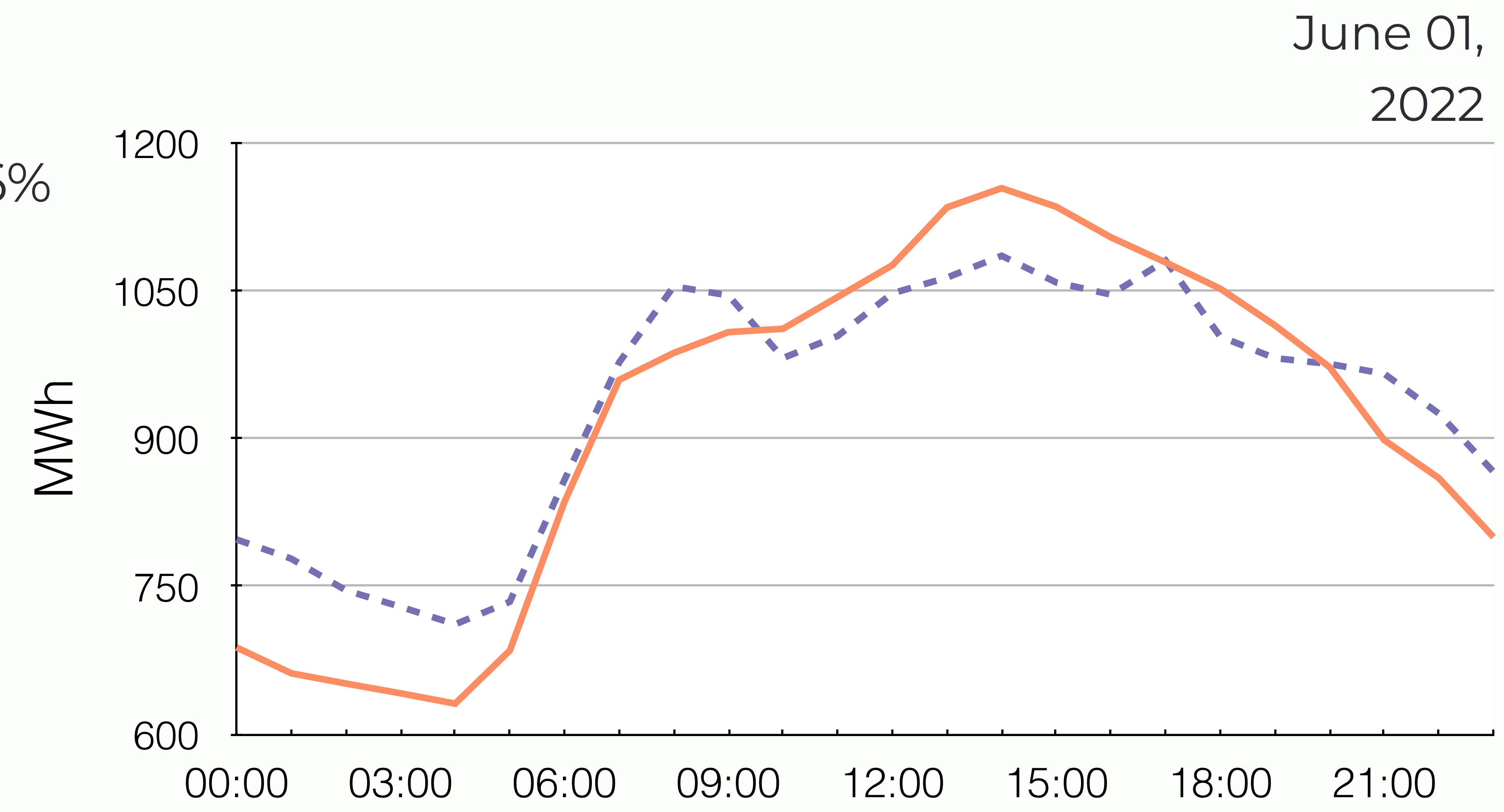
MAPE4 = 3.61%



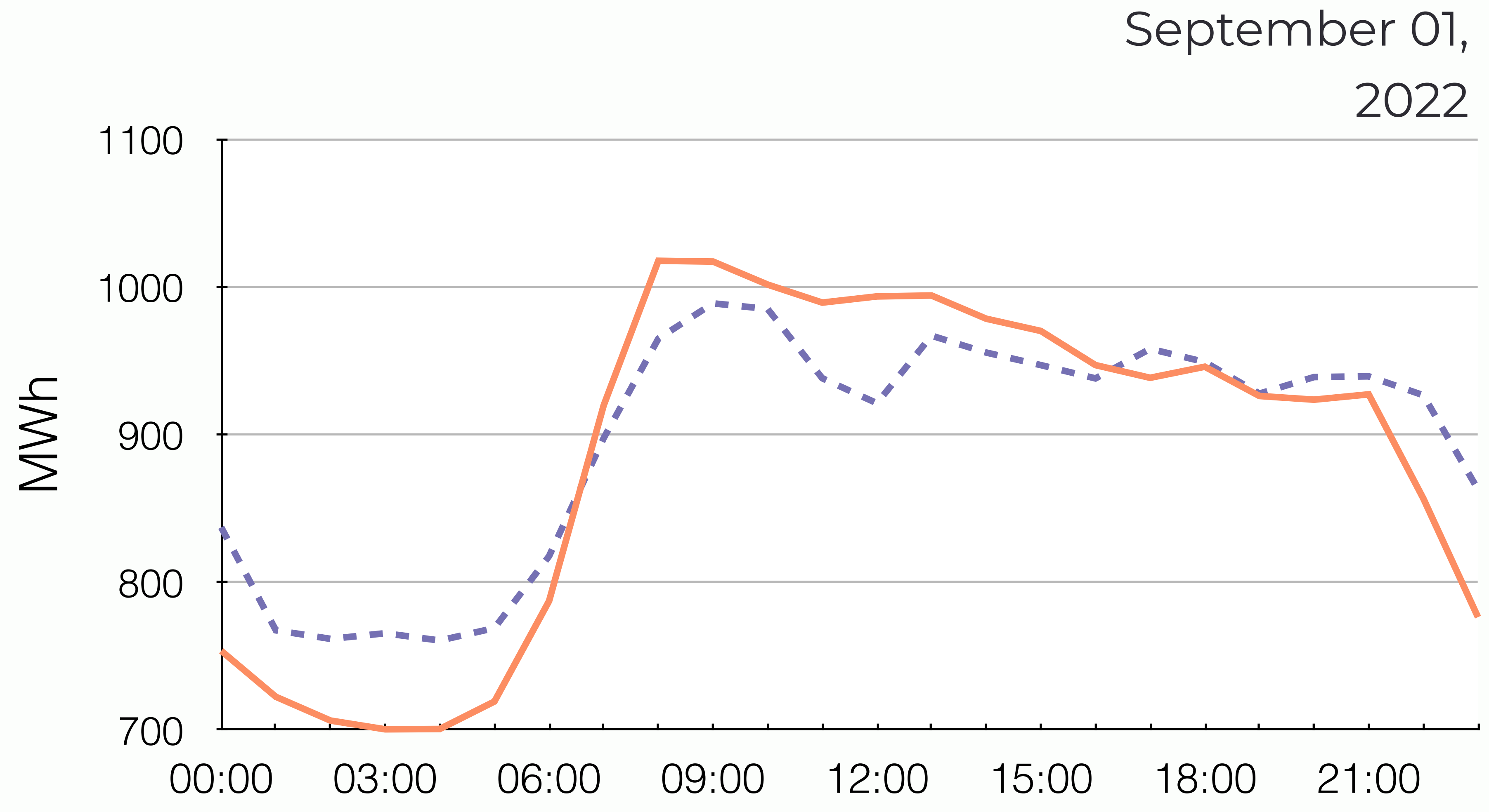


MAPE1 = 12%

MAPE2 = 6.76%

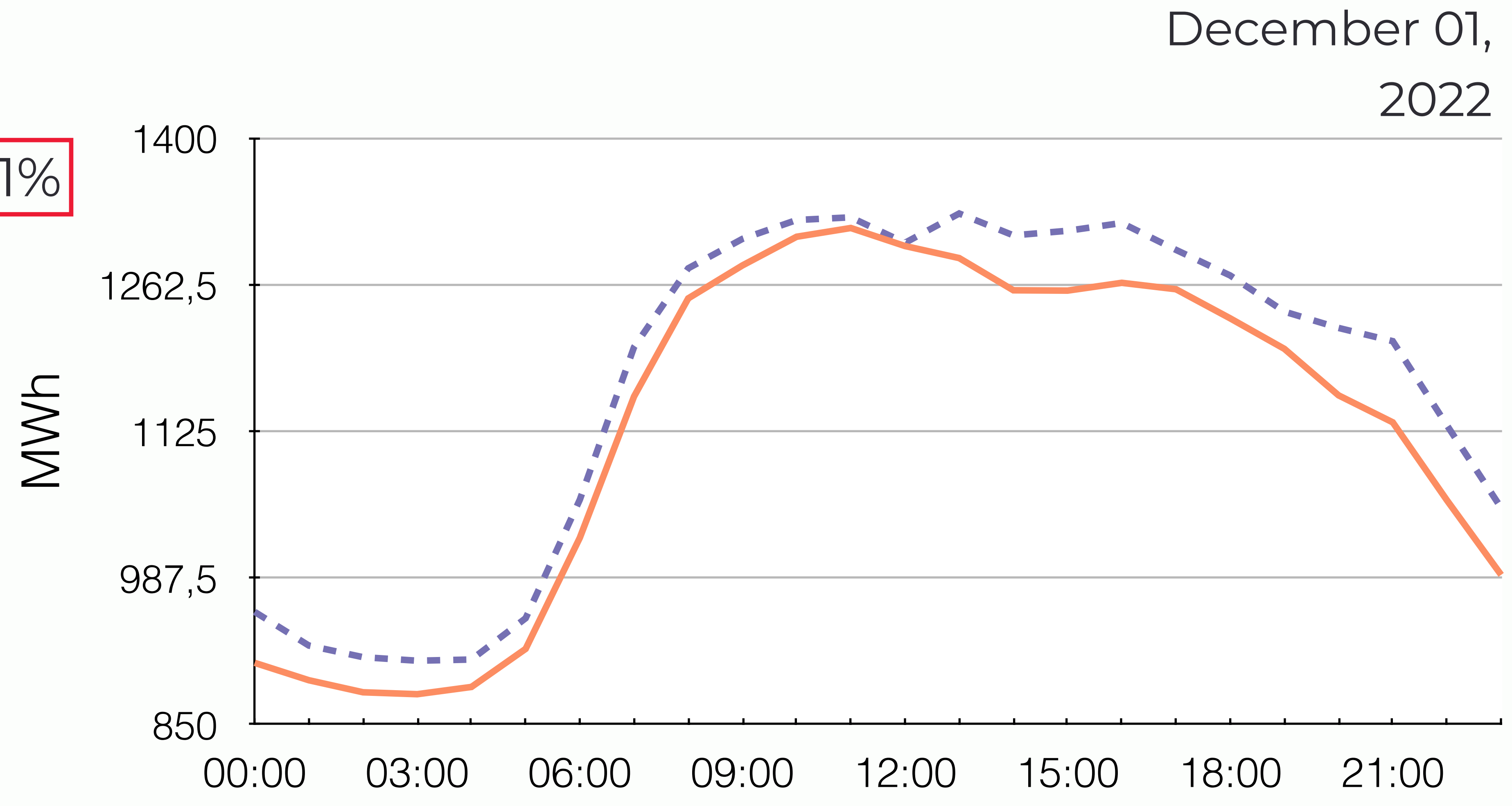


We have a clear winner - MAPE4

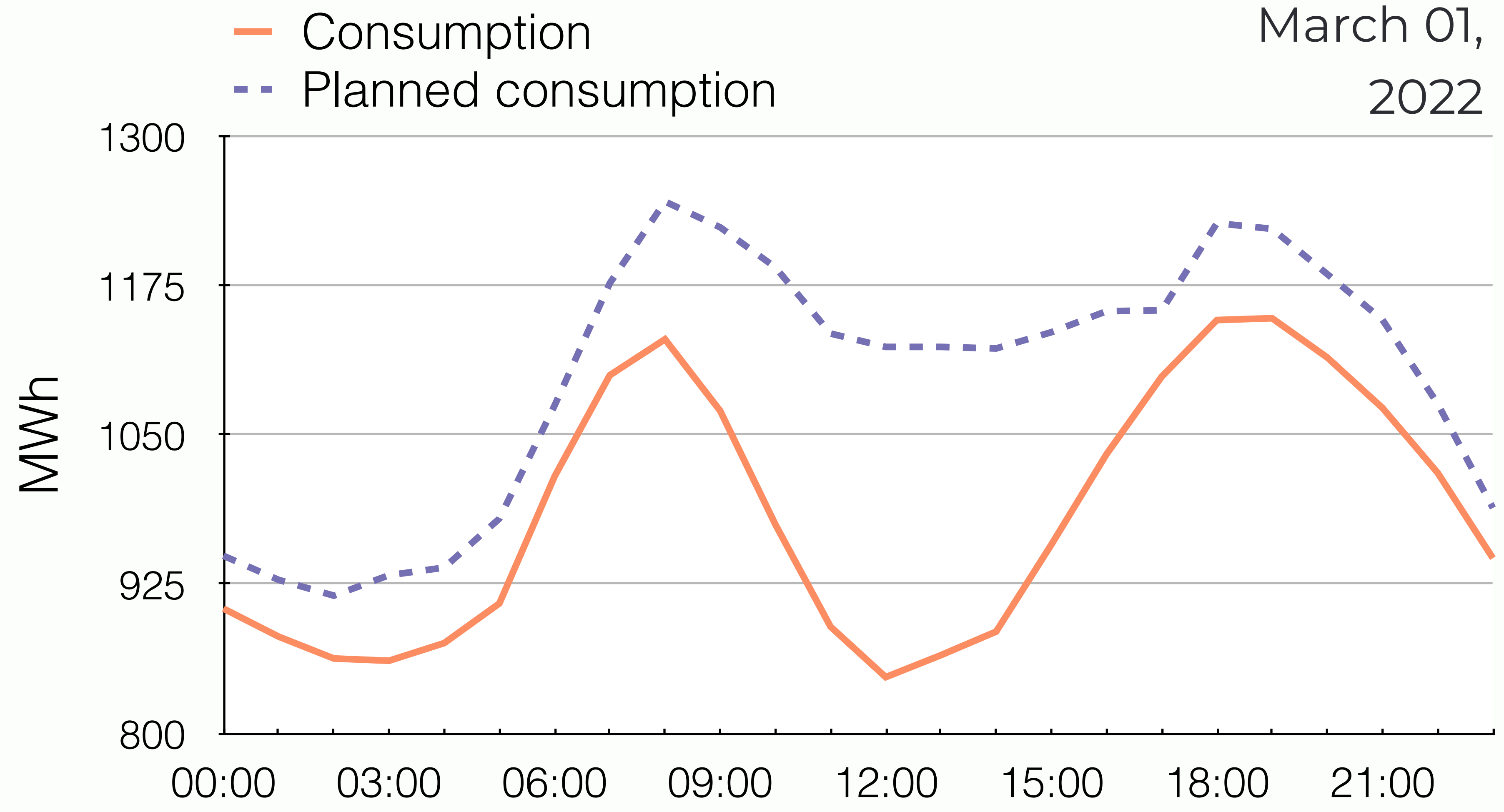


MAPE3 = 4.65%

$\boxed{\text{MAPE4 = 3.61\%}}$



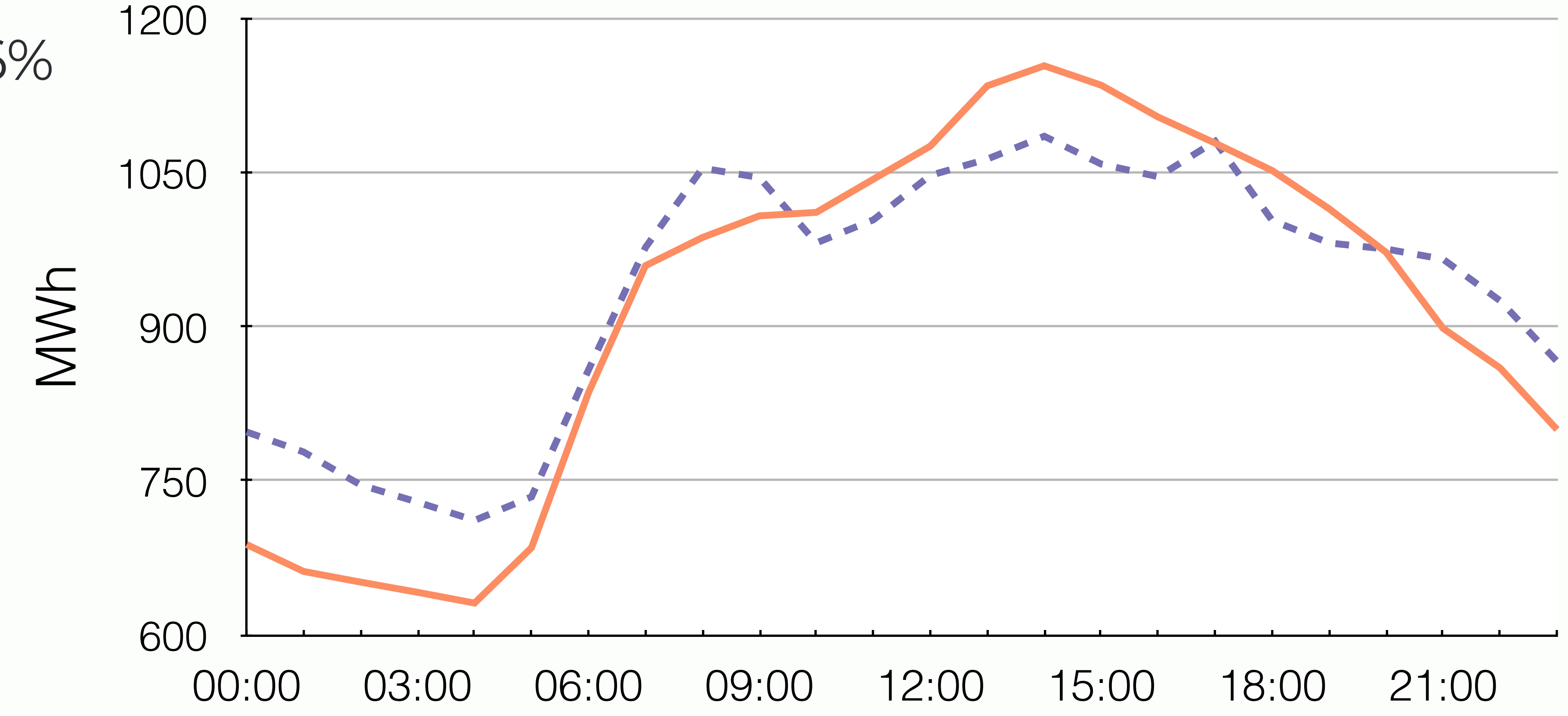
March 01, 2022



MAPE1 = 12%

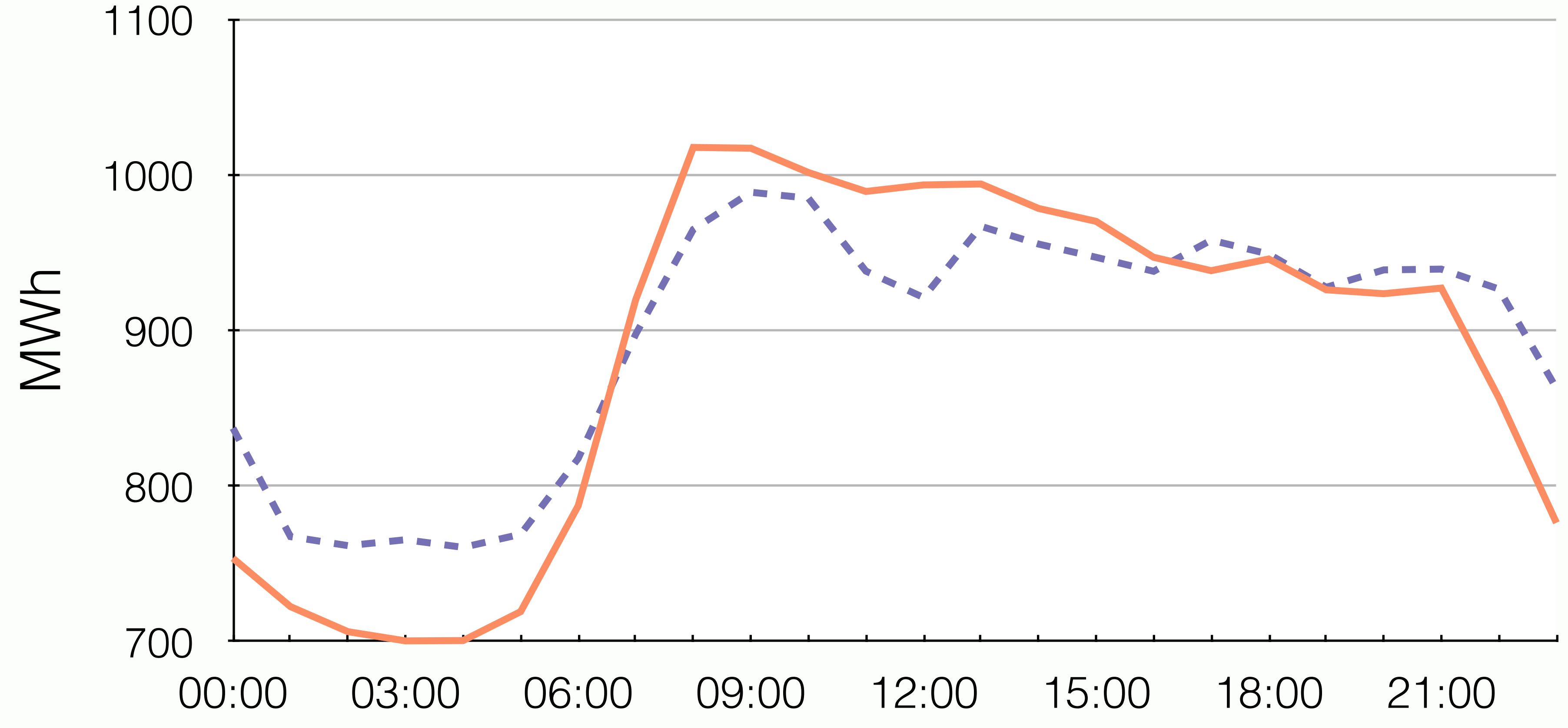
MAPE2 = 6.76%

June 01, 2022



We have a clear winner - MAPE4

September 01, 2022

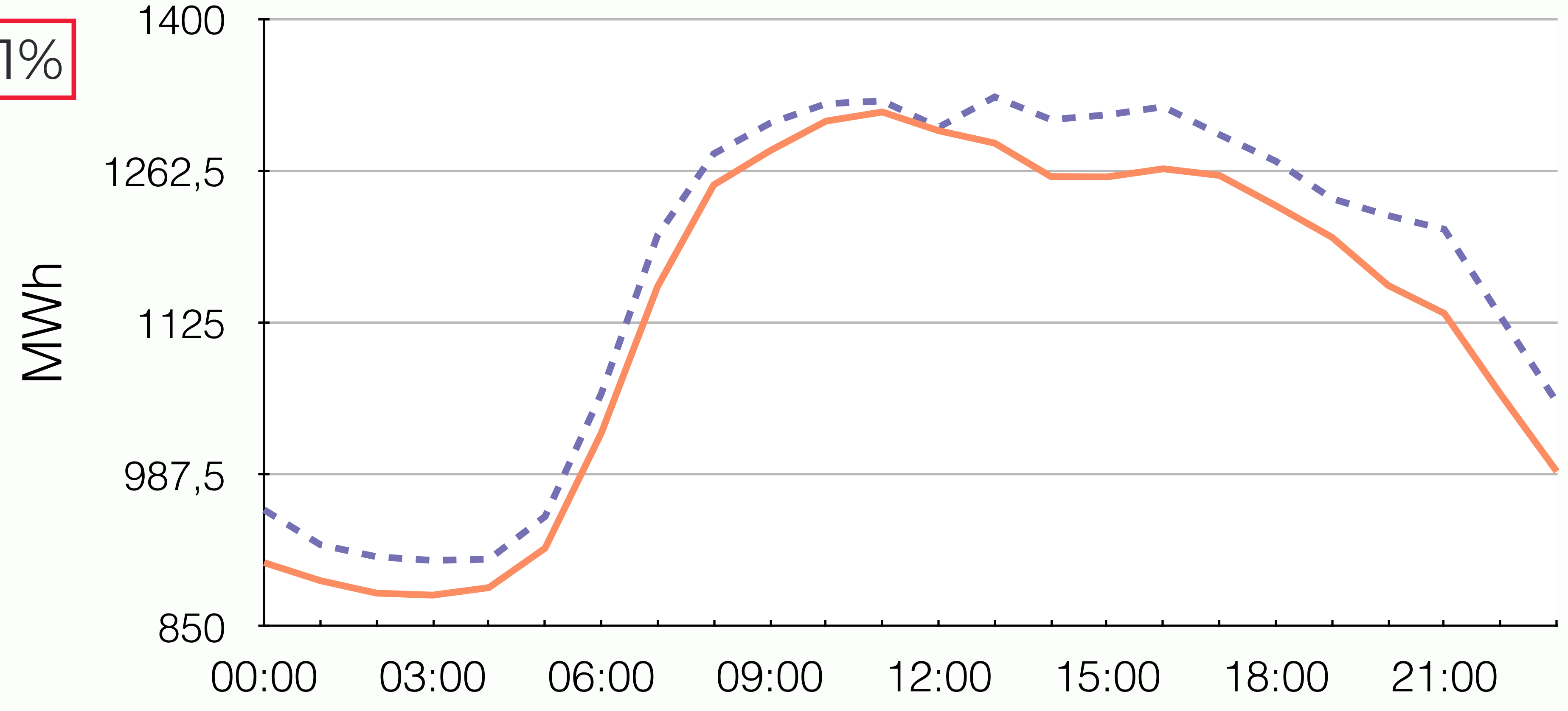


MAPE3 = 4.65%

MAPE4 = 3.61%

How about others?

December 01, 2022



Thank you!
Questions?