

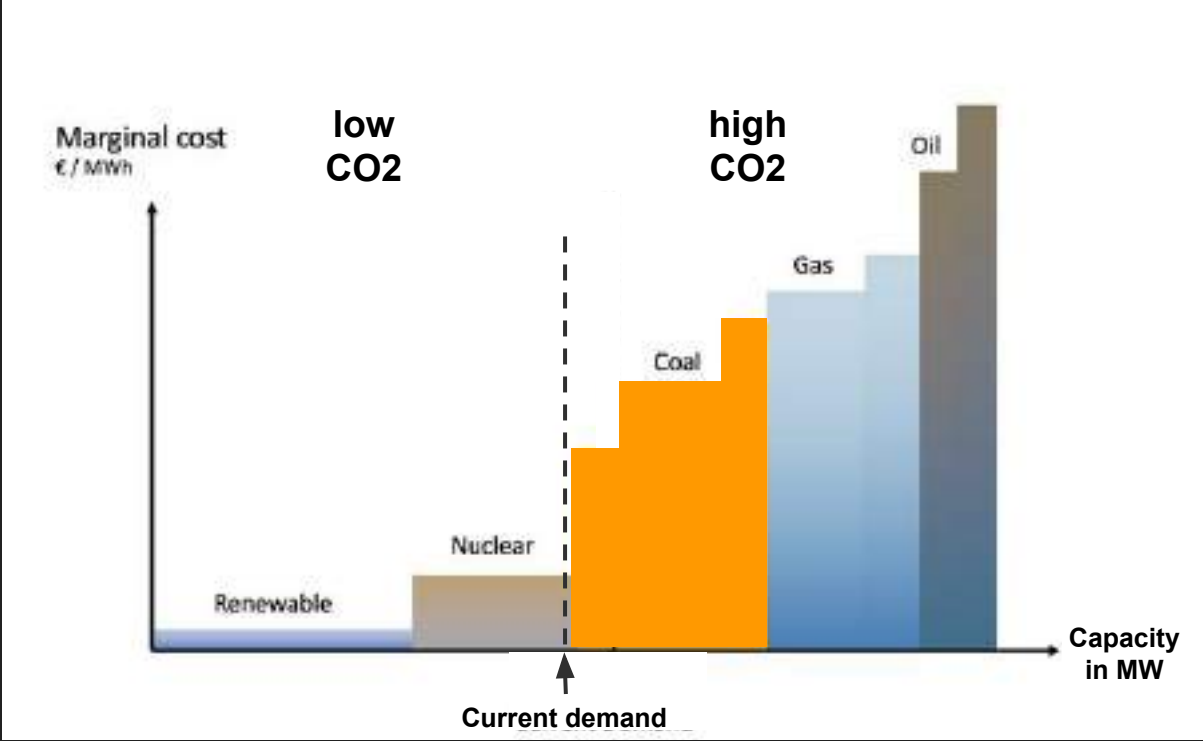
Electricity carbon intensity prediction

Predicting how clean or dirty electricity is

Bastian Kubsch

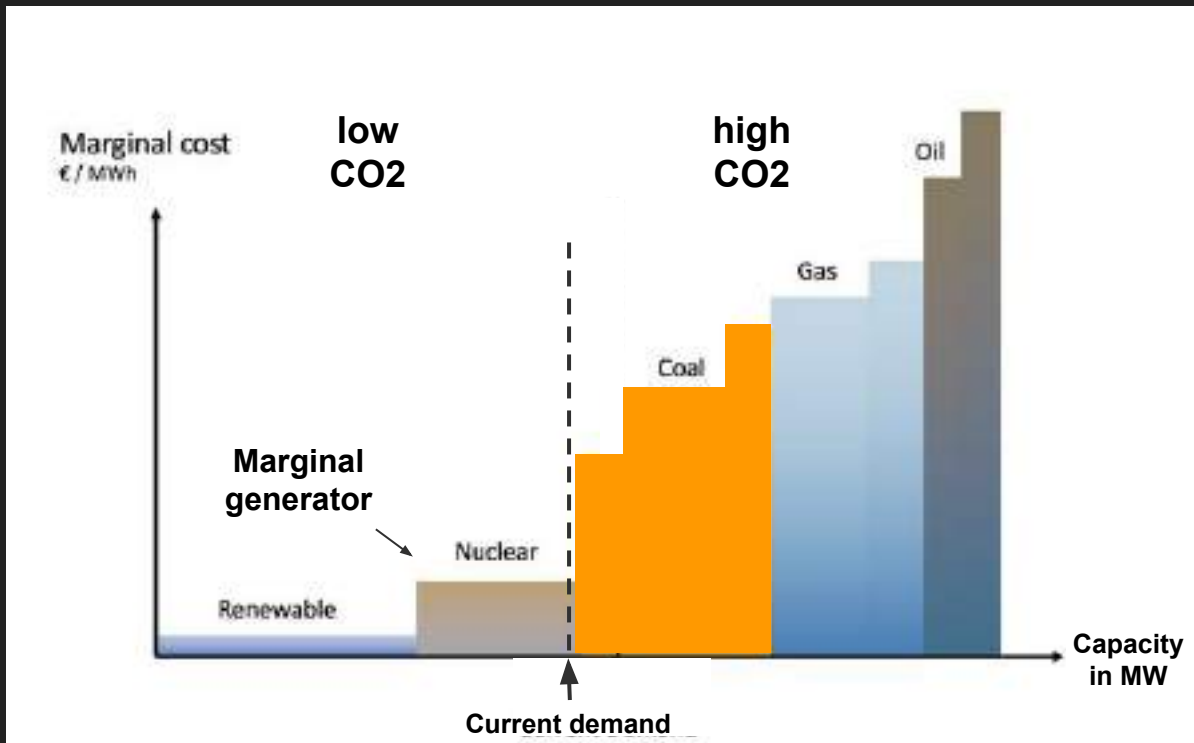
How much CO₂ emitted if consuming electricity at certain time?

How much CO2 emitted if consuming electricity at certain time?



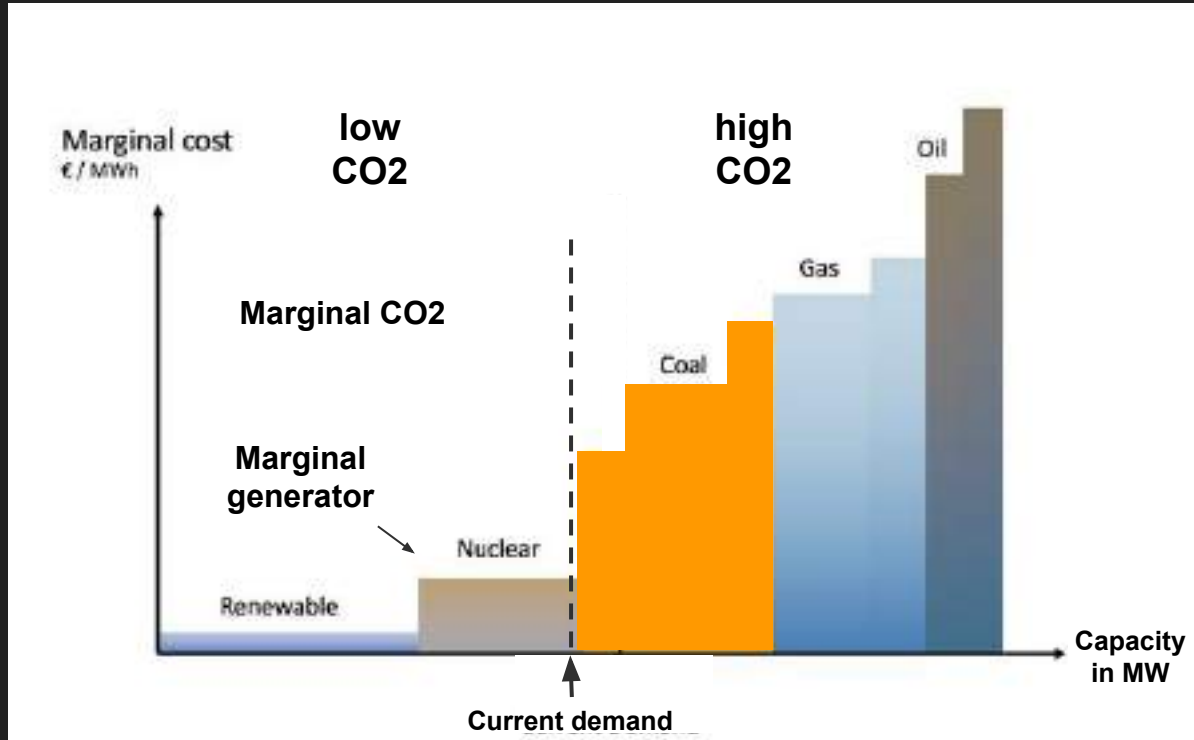
Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



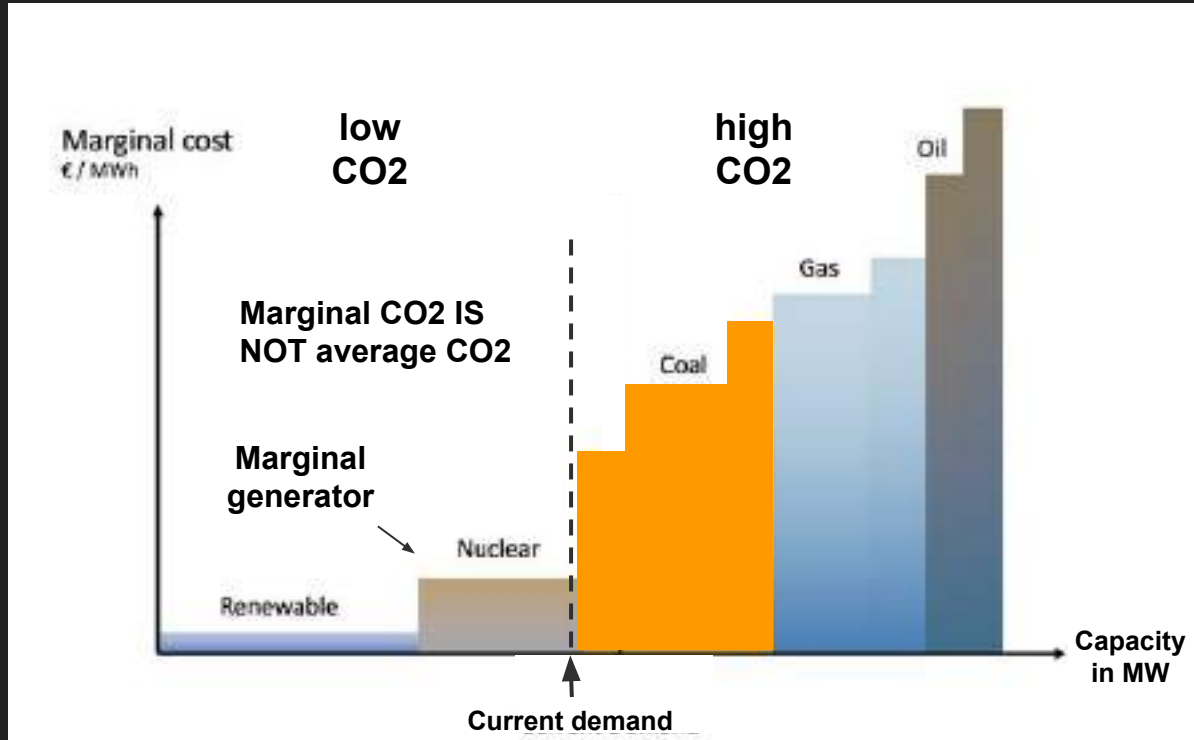
Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



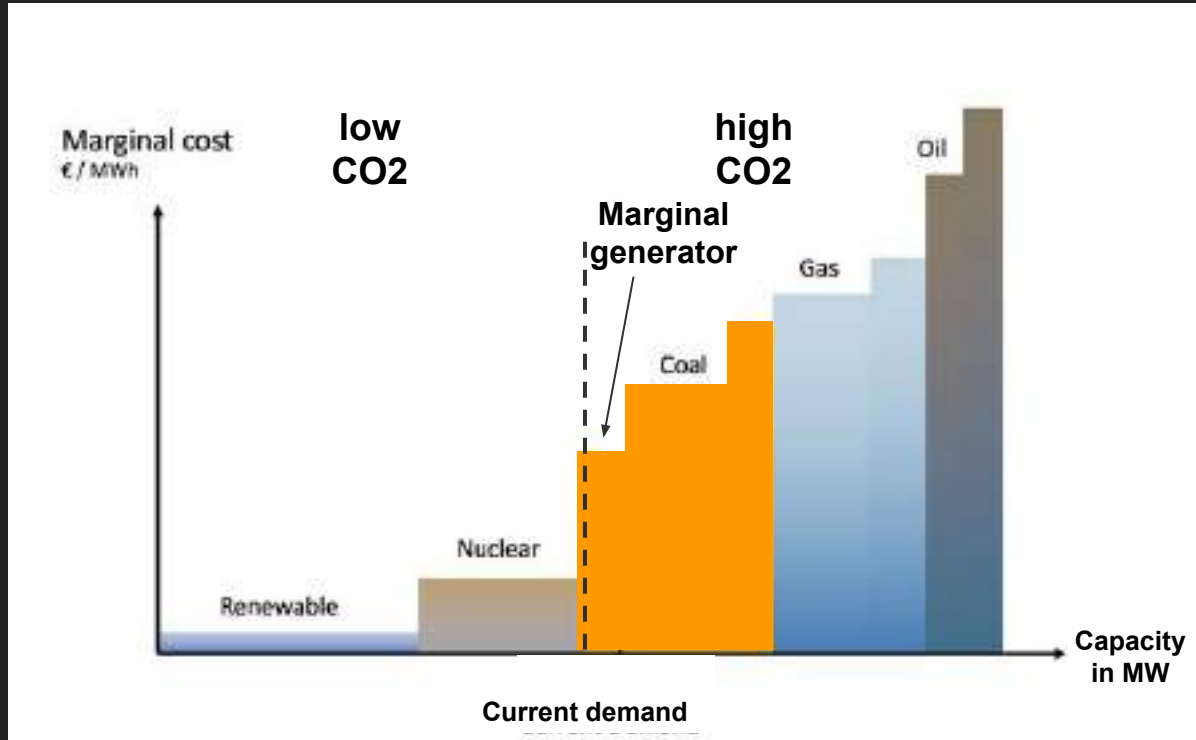
Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



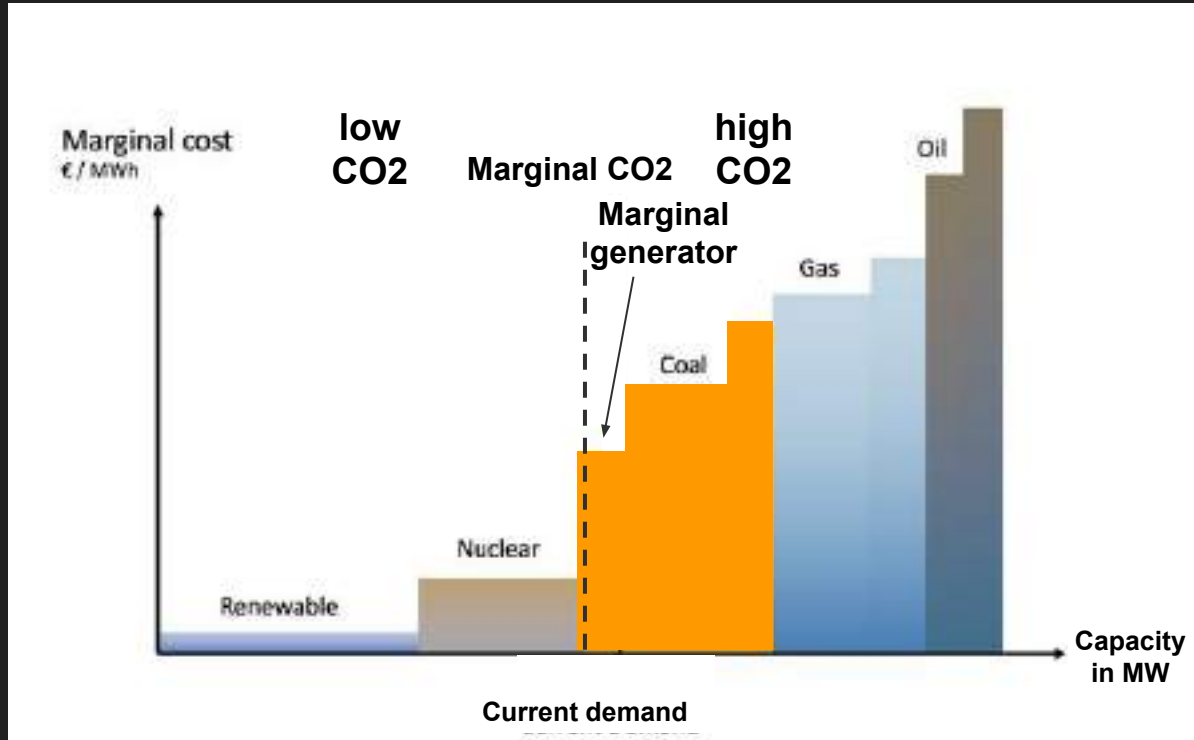
Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



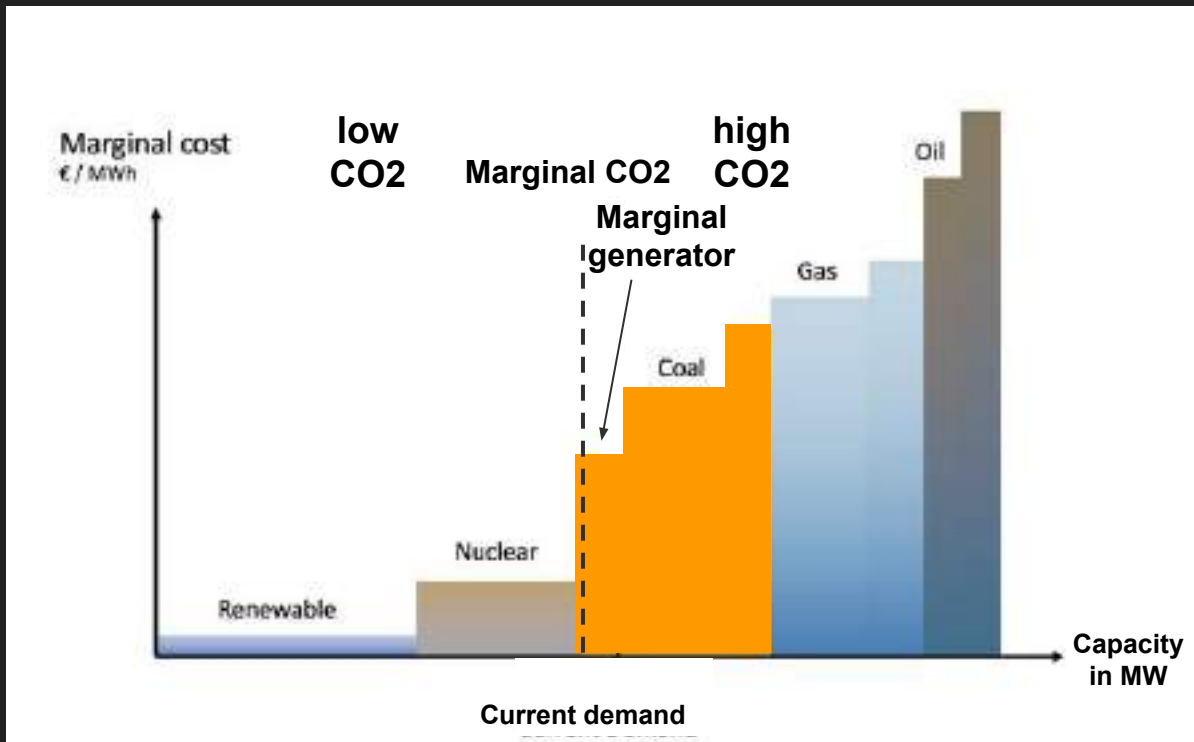
Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



Modified from Olivier Corradi

How much CO2 emitted if consuming electricity at certain time?



Modified from Olivier Corradi

- predictions about demand and marginal generator to reduce CO2 emissions

Approach to predict marginal CO2 emissions

t CO2-e / MWh

2019-08-01 03:55:00	0.380340
2019-08-01 03:50:00	0.456409
2019-08-01 03:45:00	0.573436
2019-08-01 03:40:00	0.573436
2019-08-01 03:35:00	0.573436

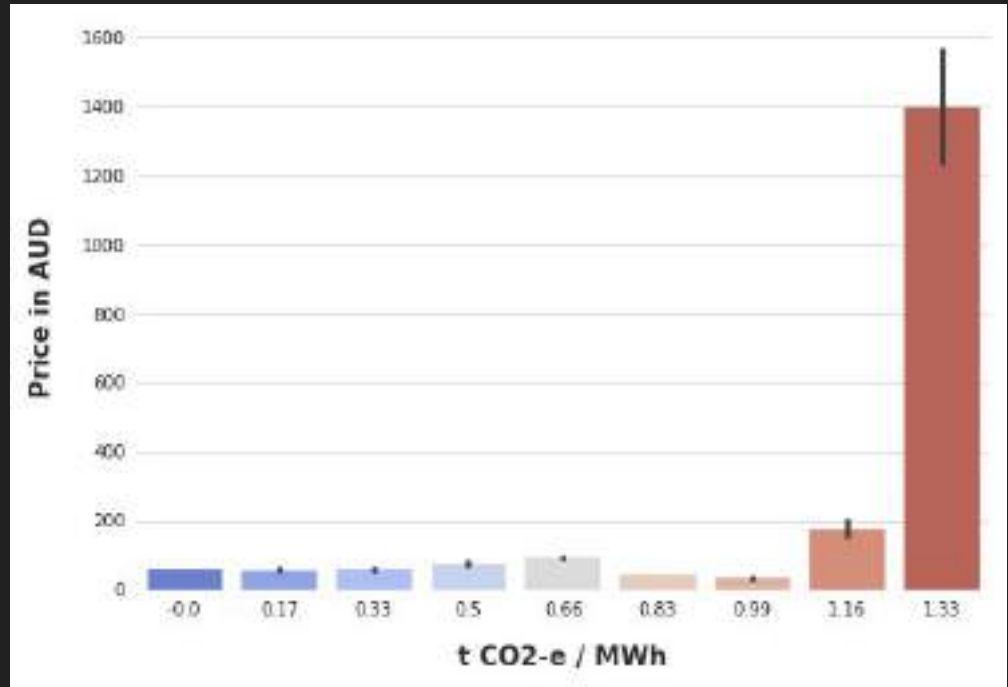
- marginal generator of South Australian electricity market
- dispatch of marginal generator at a 5 min frequency
- focus: exploration of time-dependent behaviour

Before we start: is clean or dirty energy more expensive?

	t CO2-e / MWh	Price
2019-08-01 03:55:00	0.380340	79.52391
2019-08-01 03:50:00	0.456409	79.17710
2019-08-01 03:45:00	0.573436	85.14416
2019-08-01 03:40:00	0.573436	84.78689
2019-08-01 03:35:00	0.573436	84.78346

Before we start: is clean or dirty energy more expensive?

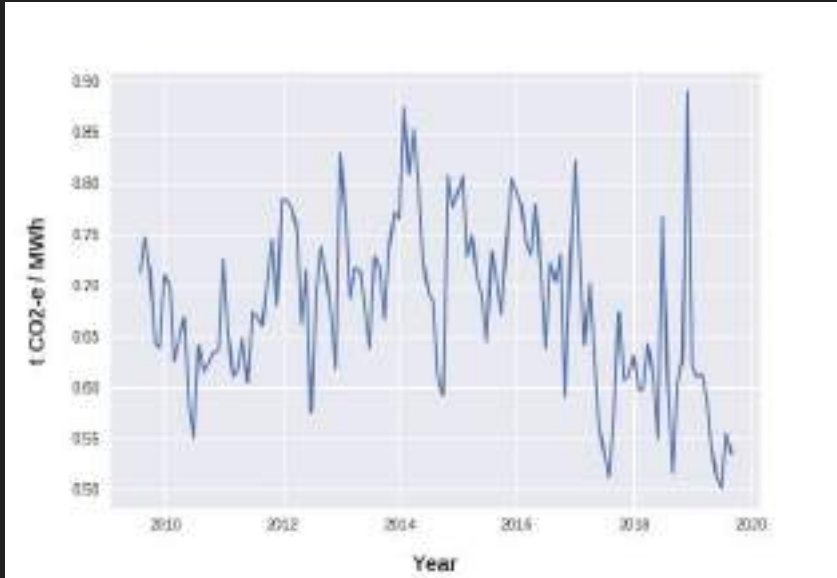
	t CO2-e / MWh	Price
2019-08-01 03:55:00	0.380340	79.52391
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2019-08-01 03:35:00	0.573436	84.78346



Dirty energy has been more expensive!

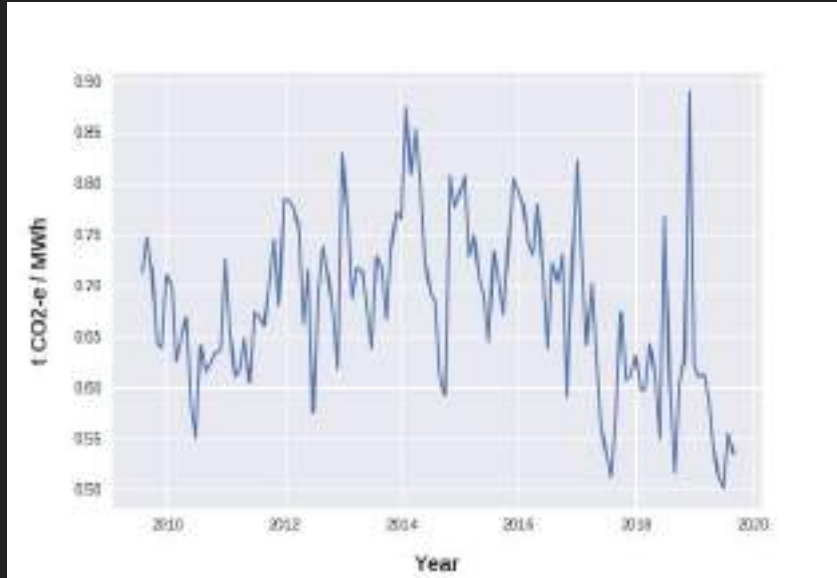
Let's start: marginal CO2 emissions over time

Complete time period (monthly average)

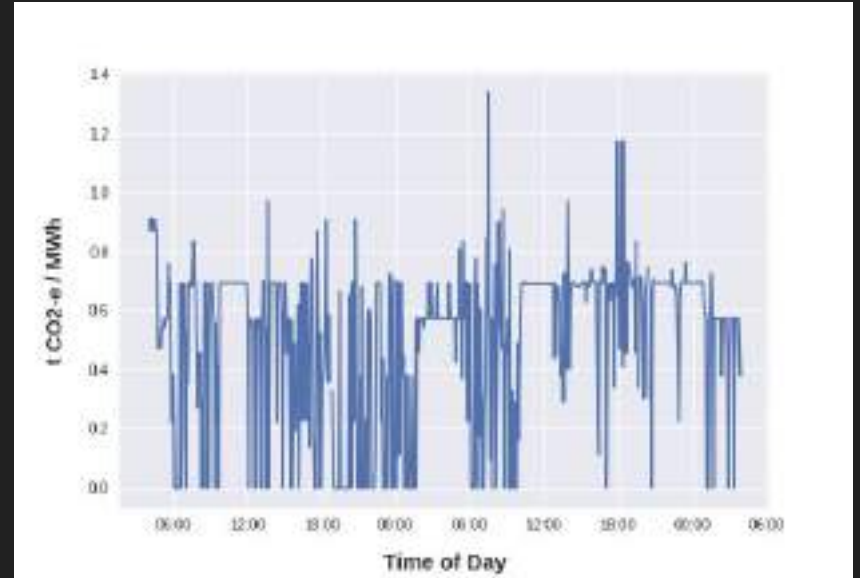


Let's start: marginal CO2 emissions over time

Complete time period (monthly average)



48h interval



Checking for random time behaviour

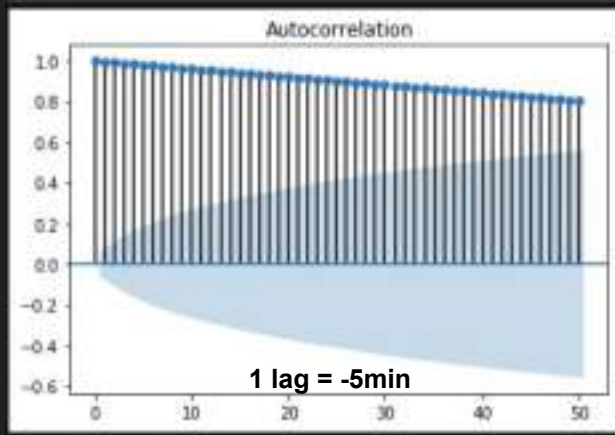
- **Random walk:**

- $CO2_{\text{now}} = CO2_{5 \text{ min}} + \text{stochastic error}$

- $CO2_{5 \text{ min}} = CO2_{10 \text{ min}} + \text{stochastic error}$

- etc.

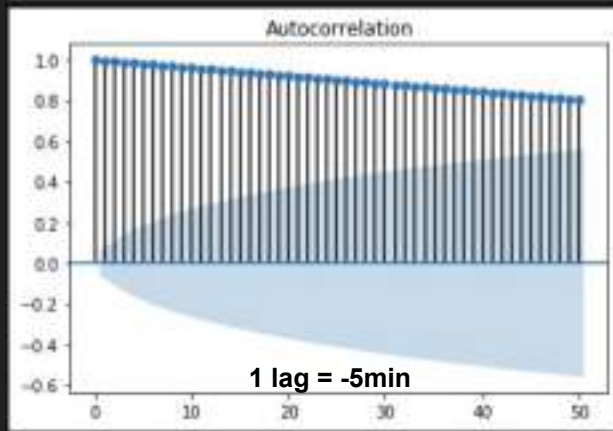
Checking for random time behaviour



- Random walk:

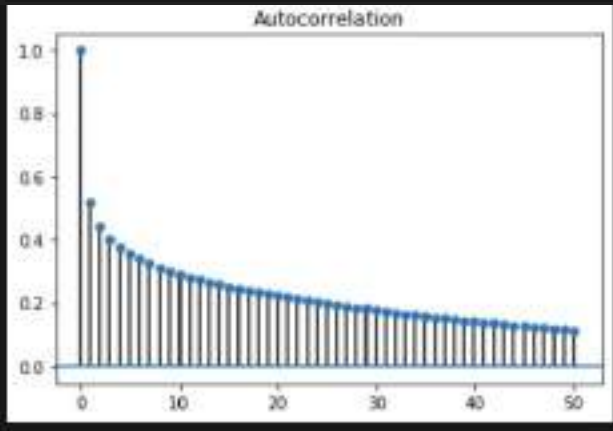
- $CO2_{\text{now}} = CO2_{5 \text{ min}} + \text{stochastic error}$
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- etc.

Checking for random time behaviour



- Random walk:

- $CO2_{\text{now}} = CO2_{5 \text{ min}} + \text{stochastic error}$
- $CO2_{5 \text{ min}} = CO2_{10 \text{ min}} + \text{stochastic error}$
- etc.

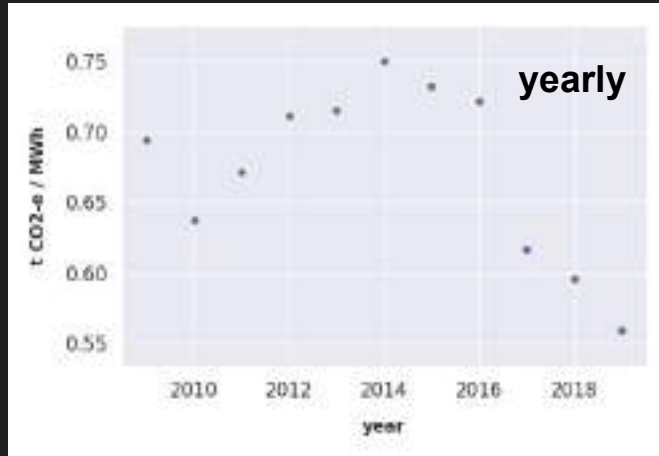


- Our dataset:

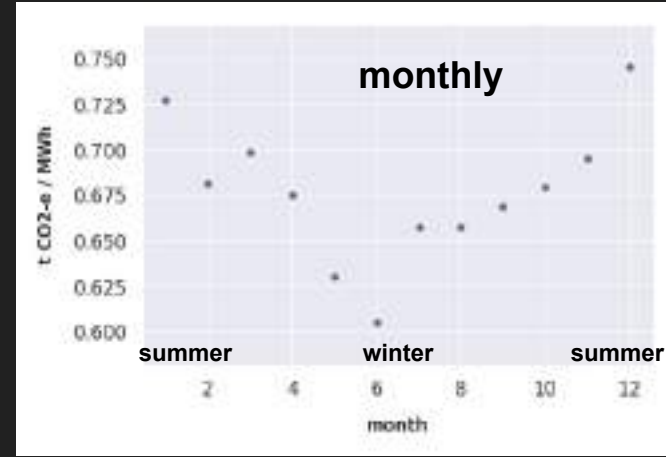
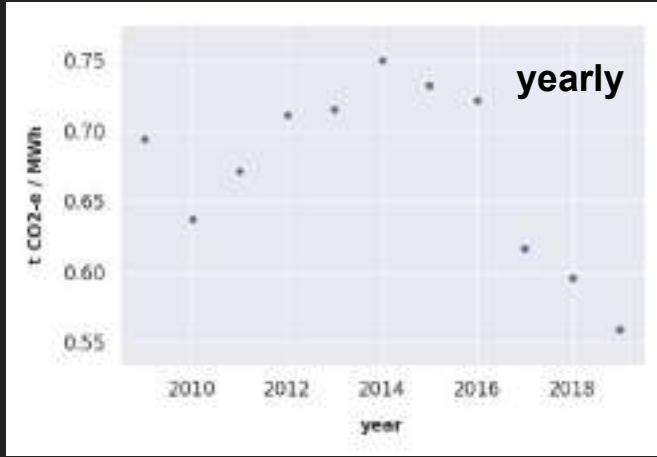
- not a random walk

Seasonal behaviour of marginal CO₂ emissions

Seasonal behaviour of marginal CO2 emissions

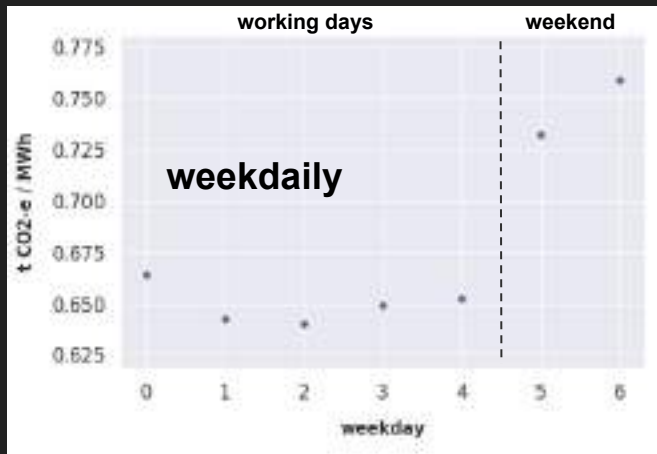
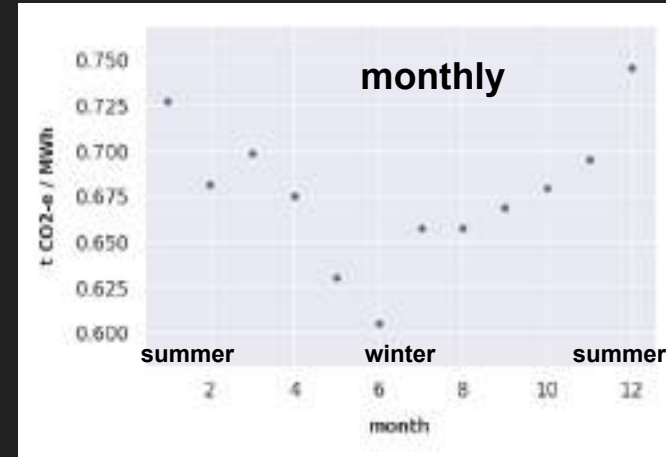
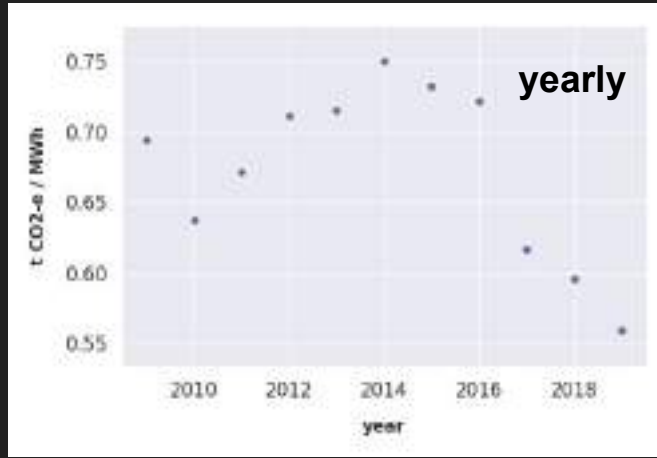


Seasonal behaviour of marginal CO2 emissions

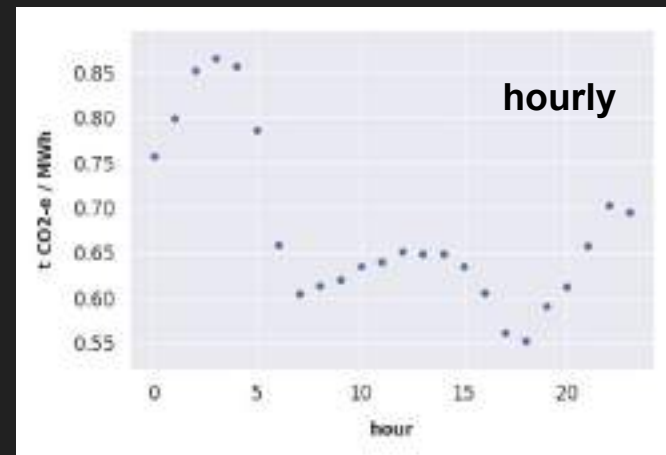
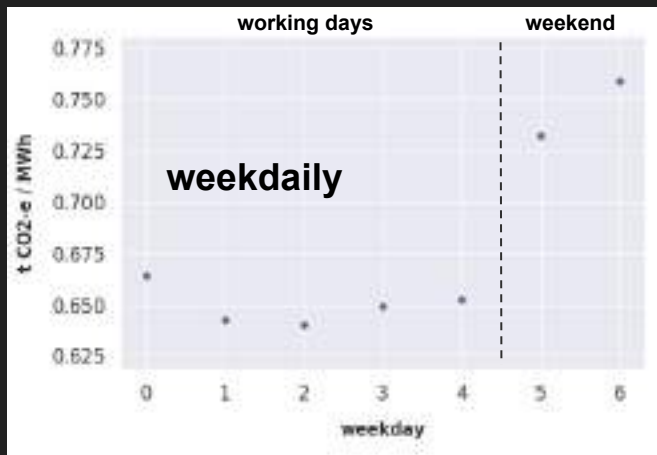
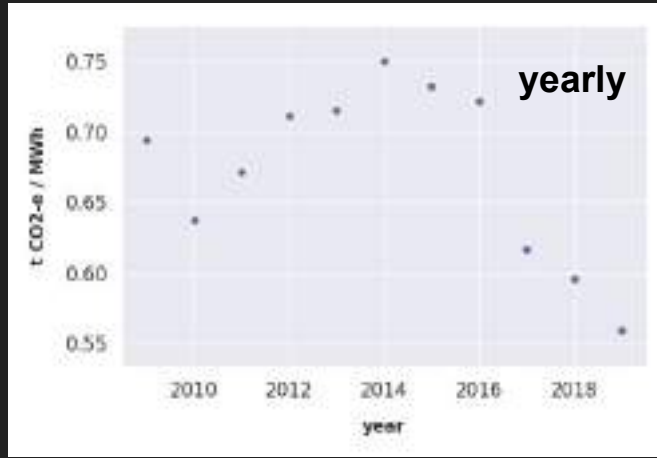


hourly

Seasonal behaviour of marginal CO2 emissions

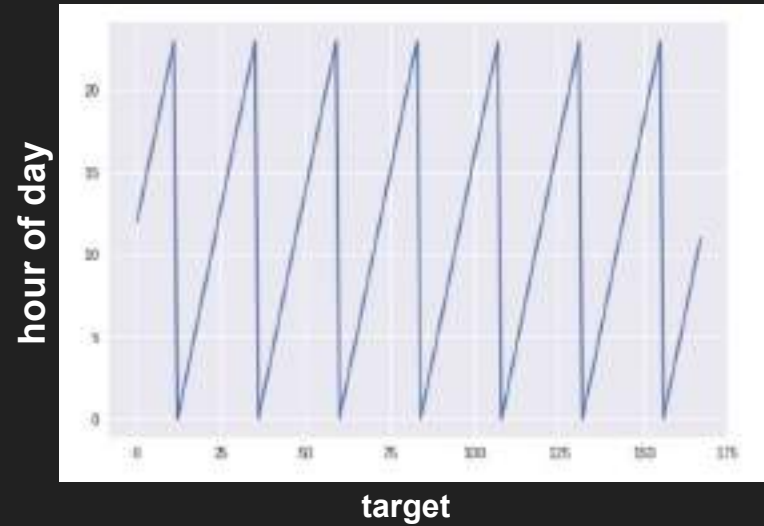


Seasonal behaviour of marginal CO2 emissions



Feature engineering: periodicity

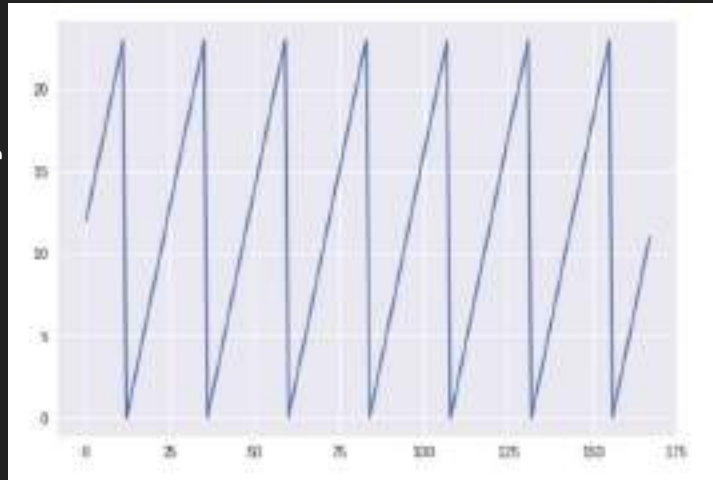
Linear time representation



24 columns, i.e. features

Feature engineering: periodicity

Linear time representation



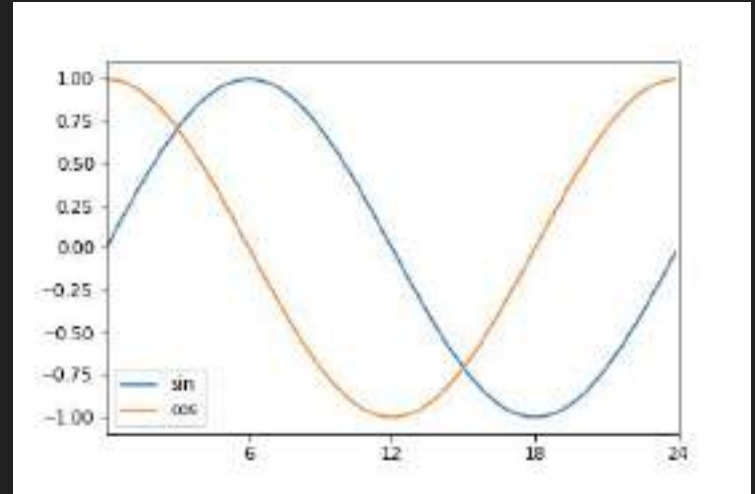
target

24 columns, i.e. features

Sine / cosine
trafo



Cyclical time representation

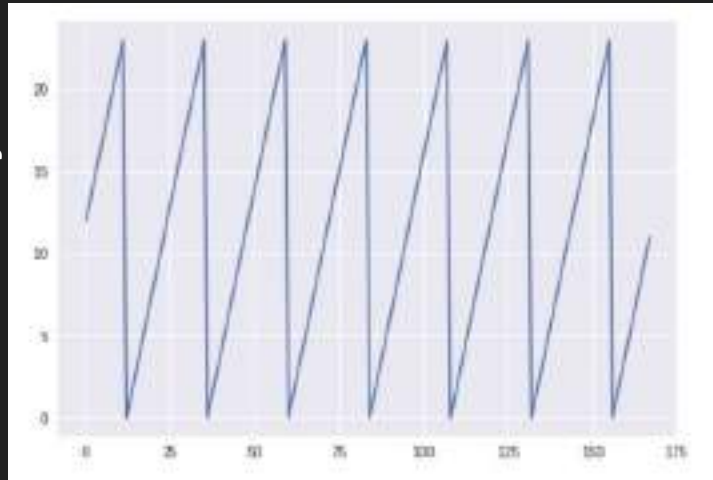


hour of day

2 columns, i.e. features

Feature engineering: periodicity

Linear time representation



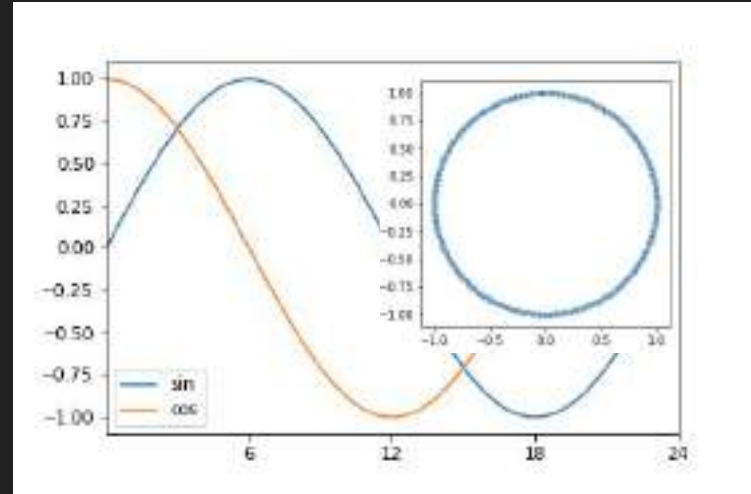
target

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Sine / cosine
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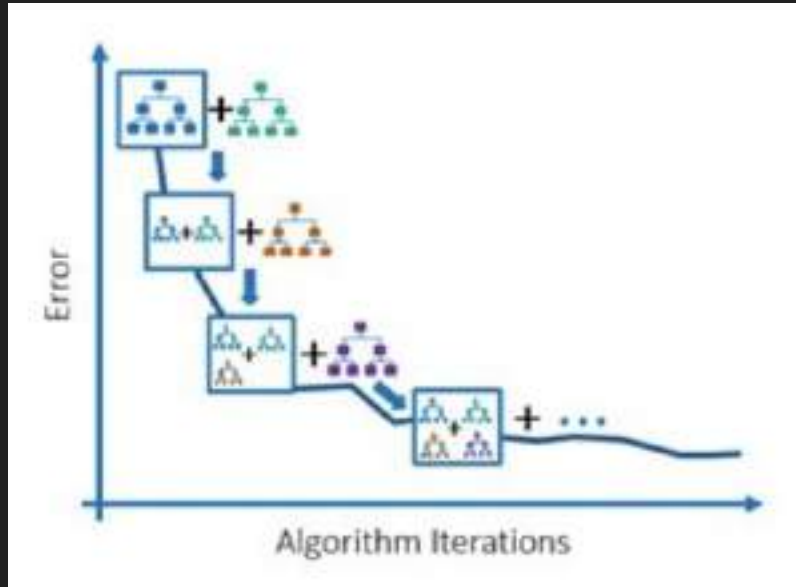
Cyclical time representation



hour of day

2 columns, i.e. features

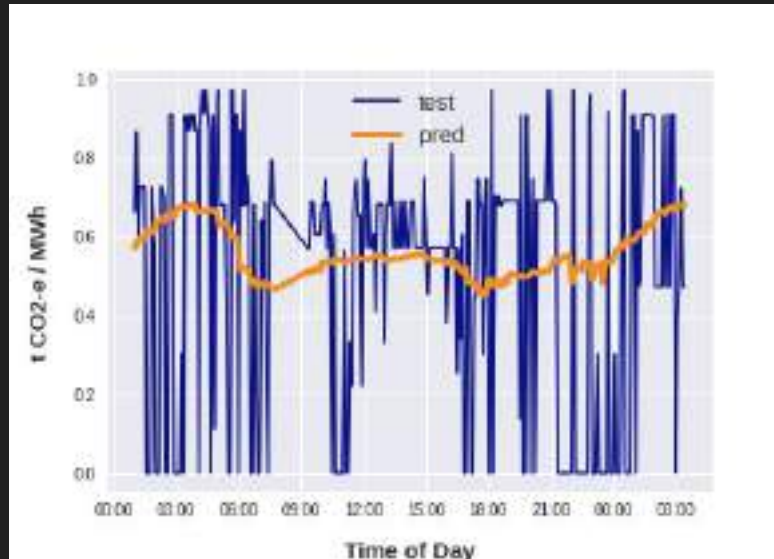
Fitting the data: Gradient boosting



- Ensemble learning using base learners, here: decision trees
- sequential minimisation of loss function gradient

Fit with seasonal time features

Initial prediction (48h period shown)



$$\text{SMAPE}_{\text{train}} = 17.67 \%$$
$$\text{SMAPE}_{\text{test}} = 22.86 \%$$

➔ predominantly catches the trend

Some more time feature engineering

x numbers of lags



t CO2-e / MWh	
2019-08-01 02:20:00	0.573436
2019-08-01 02:25:00	0.380340
2019-08-01 02:30:00	0.570054
2019-08-01 02:35:00	0.570054
2019-08-01 02:40:00	0.573436
2019-08-01 02:45:00	0.573436
2019-08-01 02:50:00	0.459168
2019-08-01 02:55:00	0.000000
2019-08-01 03:00:00	0.456409
2019-08-01 03:05:00	0.573436
2019-08-01 03:10:00	0.573436
2019-08-01 03:15:00	0.573436
2019-08-01 03:20:00	0.573436
2019-08-01 03:25:00	0.000000

target value
of interest

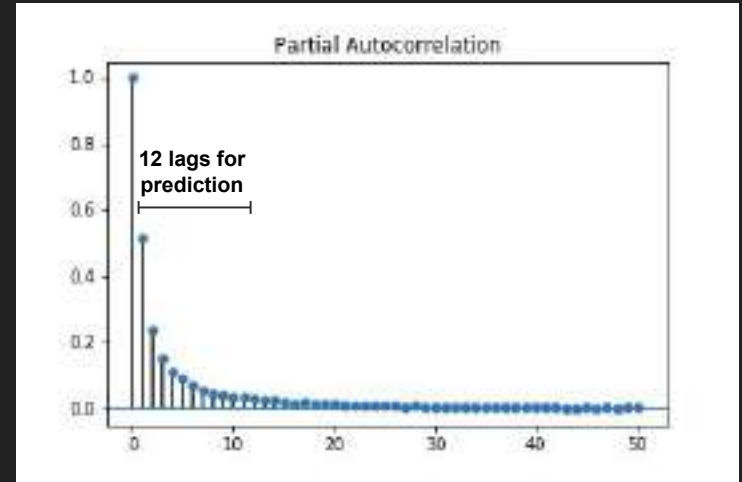


Some more time feature engineering

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2019-08-01 02:45:00	0.573436
2019-08-01 02:50:00	0.459168
2019-08-01 02:55:00	0.000000
2019-08-01 03:00:00	0.456409
2019-08-01 03:05:00	0.573436
2019-08-01 03:10:00	0.573436
2019-08-01 03:15:00	0.573436
2019-08-01 03:20:00	0.573436
2019-08-01 03:25:00	0.000000

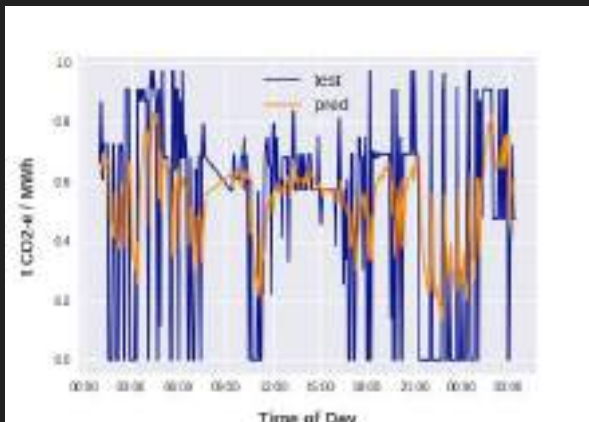
target value
of interest



Next fit: seasonal and lag time features (and beyond)

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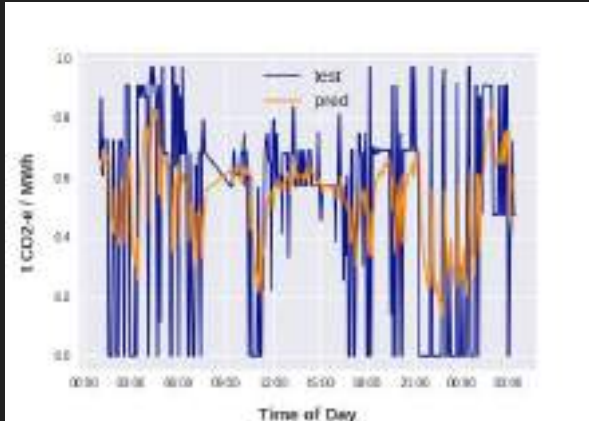
Time features (48h period shown)



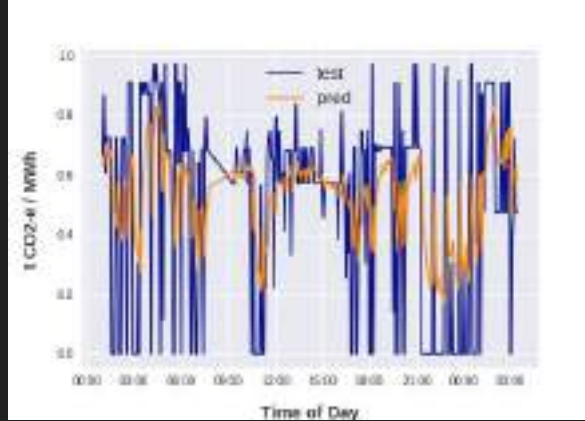
$\text{SMAPE}_{\text{train}}$: 13.89
 $\text{SMAPE}_{\text{test}}$: 19.04

Next fit: seasonal and lag time features (and beyond)

Time features (48h period shown)



Time features +
electricity demand (48h period shown)

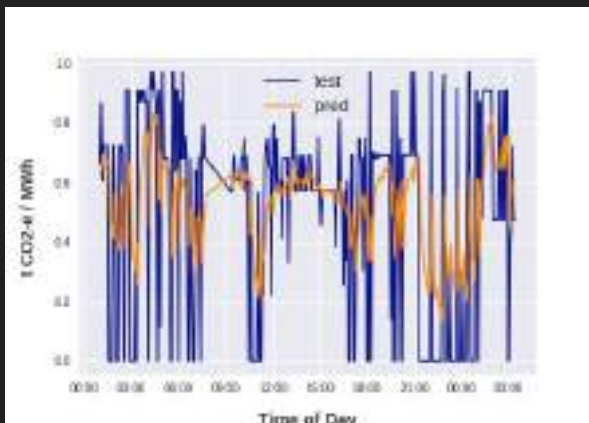


$\text{SMAPE}_{\text{train}}$: 13.89
 $\text{SMAPE}_{\text{test}}$: 19.04

$\text{SMAPE}_{\text{train}}$: 13.88
 $\text{SMAPE}_{\text{test}}$: 19.13

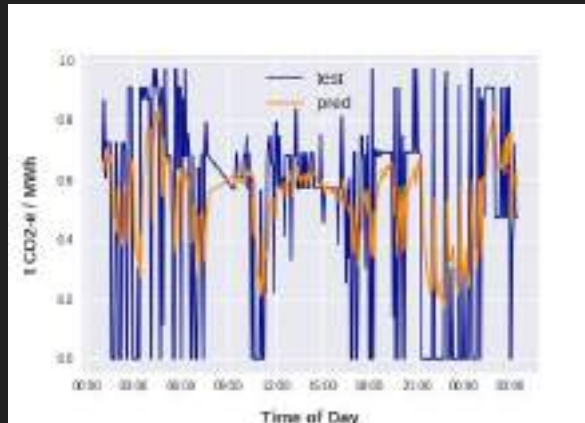
Next fit: seasonal and lag time features (and beyond)

Time features (48h period shown)



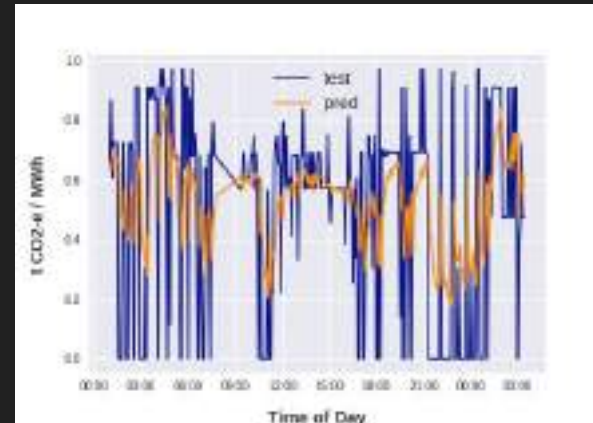
SMAPE_{train}: 13.89
SMAPE_{test}: 19.04

Time features +
electricity demand (48h period shown)



SMAPE_{train}: 13.88
SMAPE_{test}: 19.13

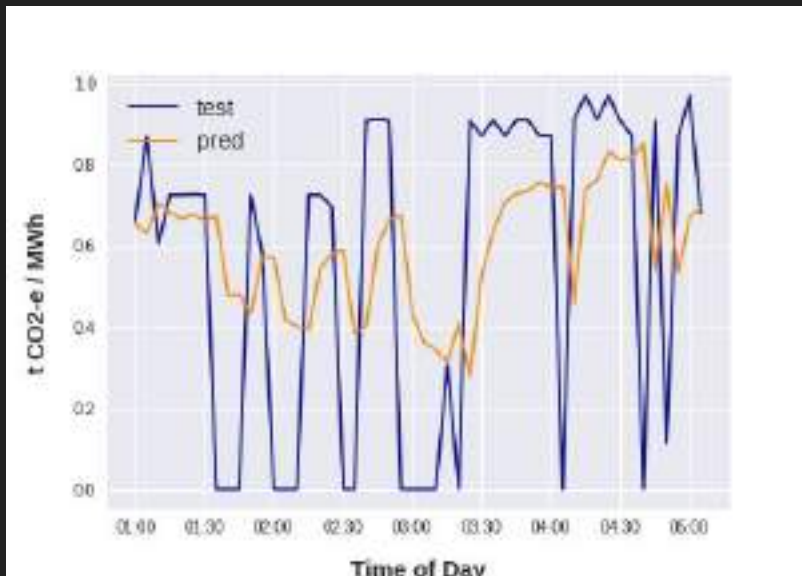
Time features +
electricity demand +
electricity import (48h period shown)



SMAPE_{train}: 13.87
SMAPE_{test}: 19.30

Next fit: seasonal and lag time features (and beyond)

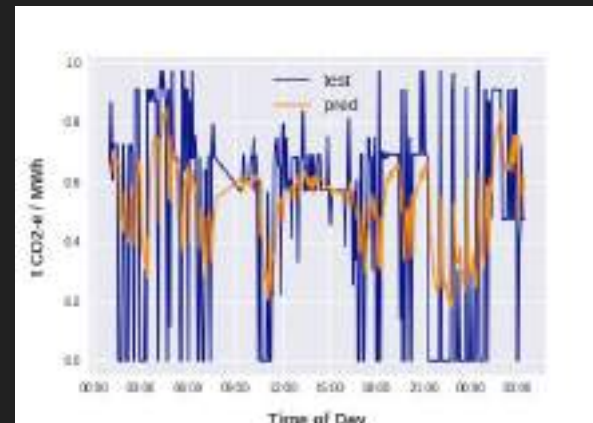
Time features +
electricity demand +
electricity import (5h period shown)



Zooming in



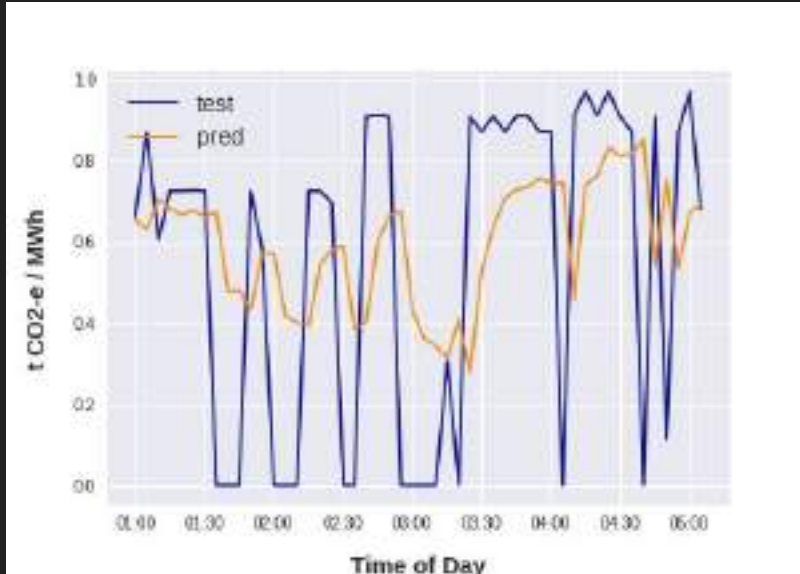
Time features +
electricity demand +
electricity import (48h period shown)



SMape_{train}: 13.87
SMape_{test}: 19.30

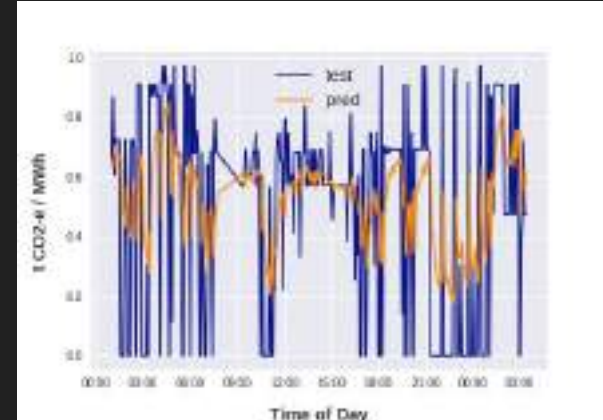
Next fit: seasonal and lag time features (and beyond)

Time features +
electricity demand +
electricity import (5h period shown)



Zooming in
←

Time features +
electricity demand +
electricity import (48h period shown)

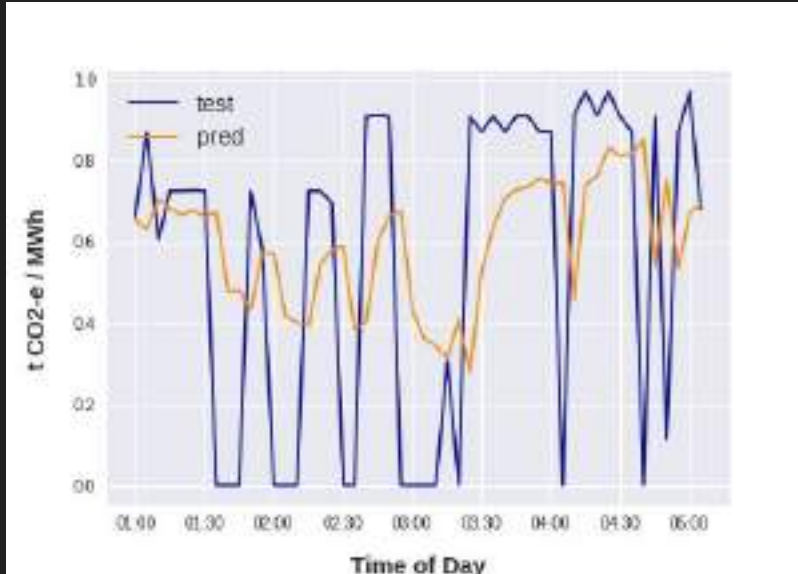


SMape_{train}: 13.87
SMape_{test}: 19.30

Is this a forecast?

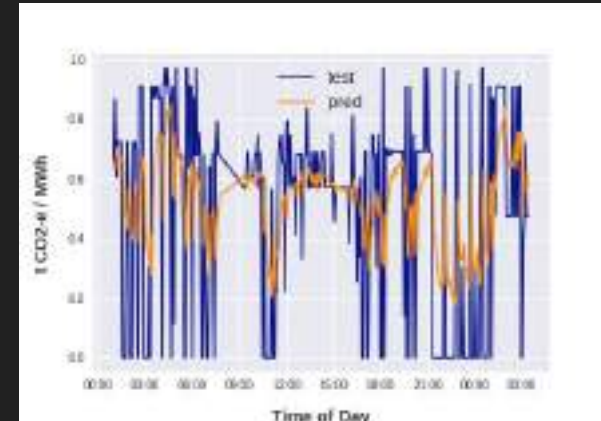
Next fit: seasonal and lag time features (and beyond)

Time features +
electricity demand +
electricity import (5h period shown)



Zooming in
←

Time features +
electricity demand +
electricity import (48h period shown)

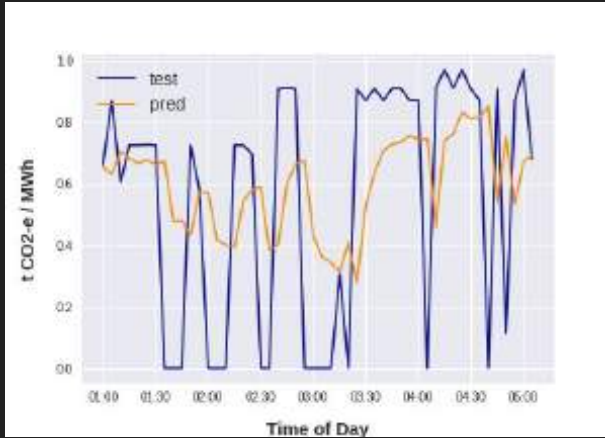


SMape_{train}: 13.87
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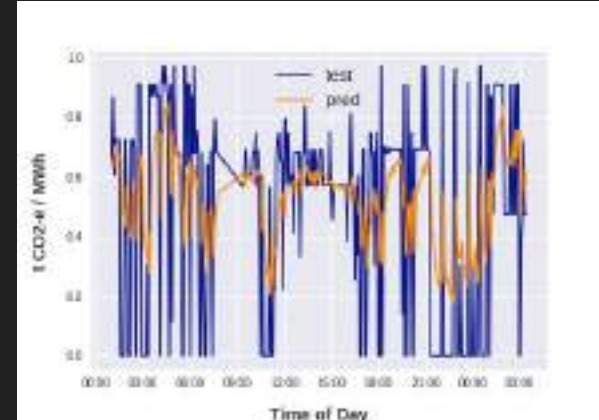
Is this a forecast? No!

Next fit: seasonal and lag time features (and beyond)

Time features +
electricity demand +
electricity import
(5h period shown)



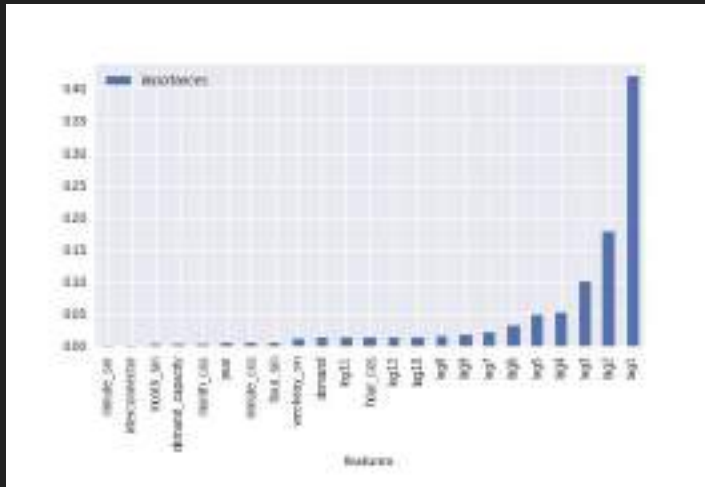
Time features +
electricity demand +
electricity import (48h period shown)



Zooming in



Feature importances



SMape_{train}: 13.87
SMape_{test}: 19.30

Conclusions:

- **be critical!**
- gradient boosting mimics time series trajectory, not forecasting it
- remains unknown if marginal CO₂ emissions can be predicted

Conclusions:

- **be critical!**
- gradient boosting mimics time series trajectory, not forecasting it
- remains unknown if marginal CO2 emissions can be predicted

Outlook:

- tweaking of current model and use of other models
- **more features**

Name: Bastian Kubsch

Linkedin: <https://www.linkedin.com/in/bastian-kubsch-phd-063419158/>

Github: <https://github.com/bkubsch/marginal-carbon>