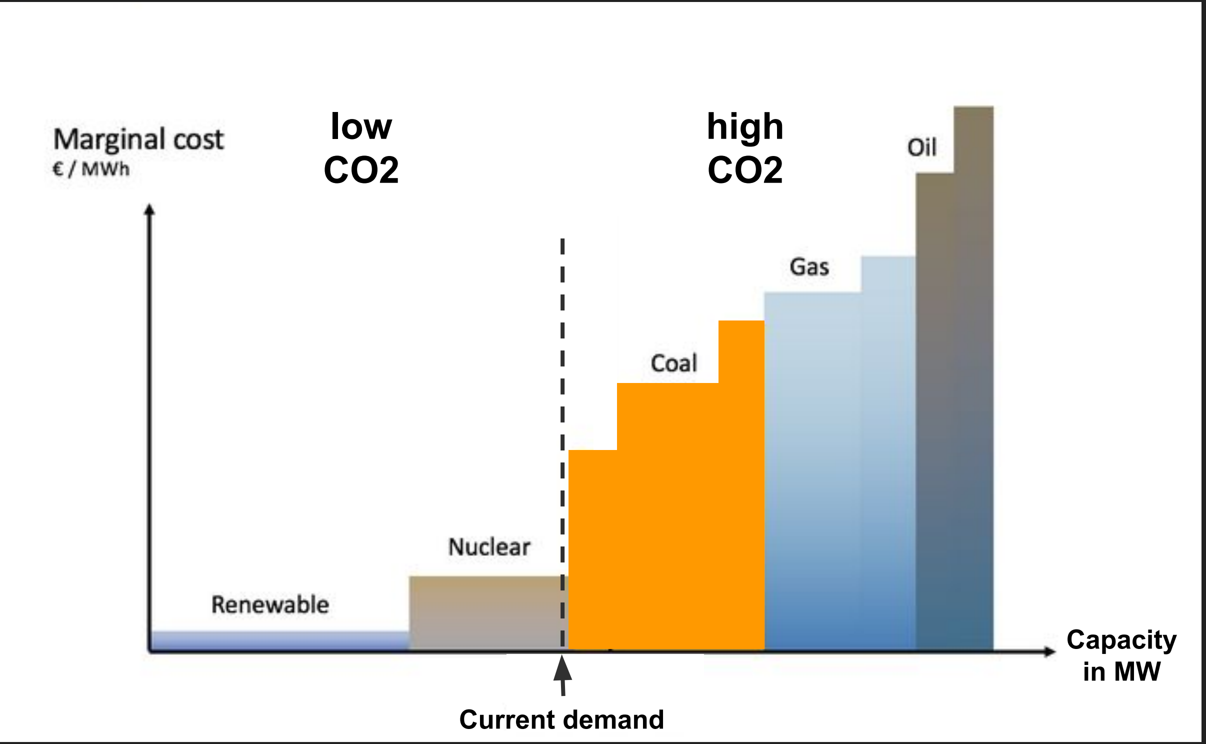
Electricity carbon intensity prediction

Predicting how clean or dirty electricity is

Bastian Kubsch

How much CO_2 emitted if consuming electricity at certain time?

How much CO2 emitted if consuming electricity at certain time?



Modified from Olivier Corradi

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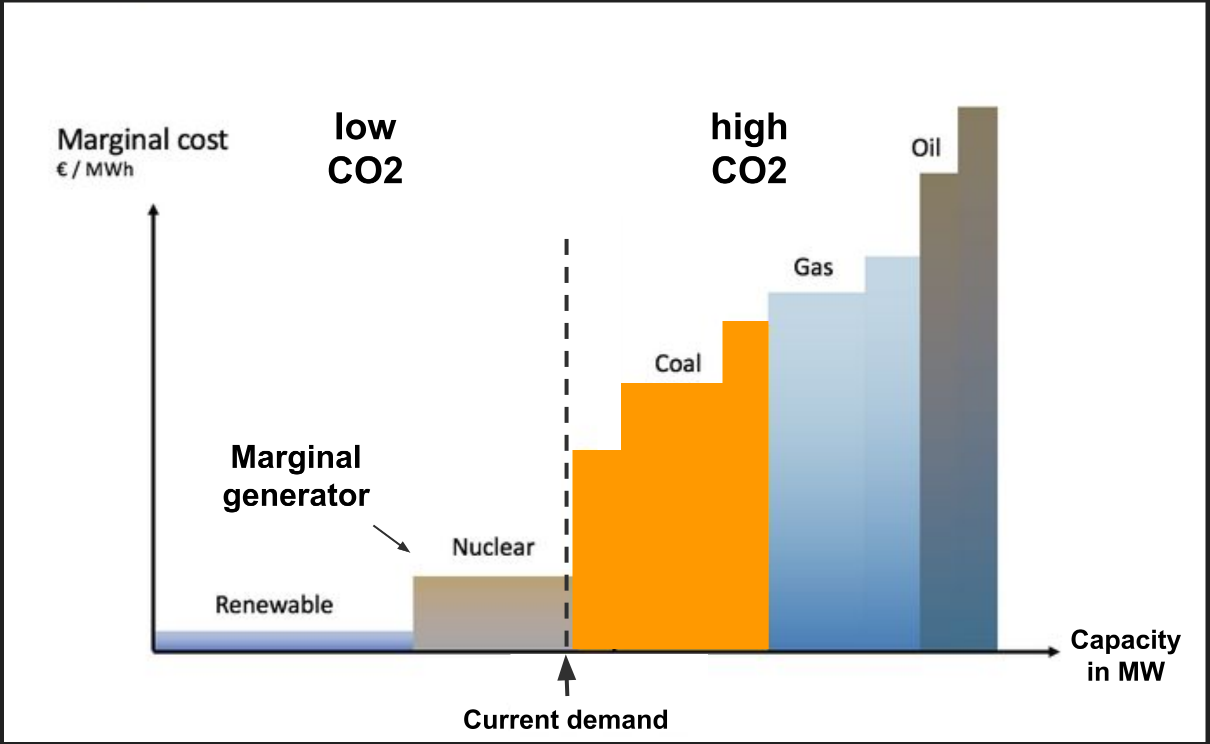

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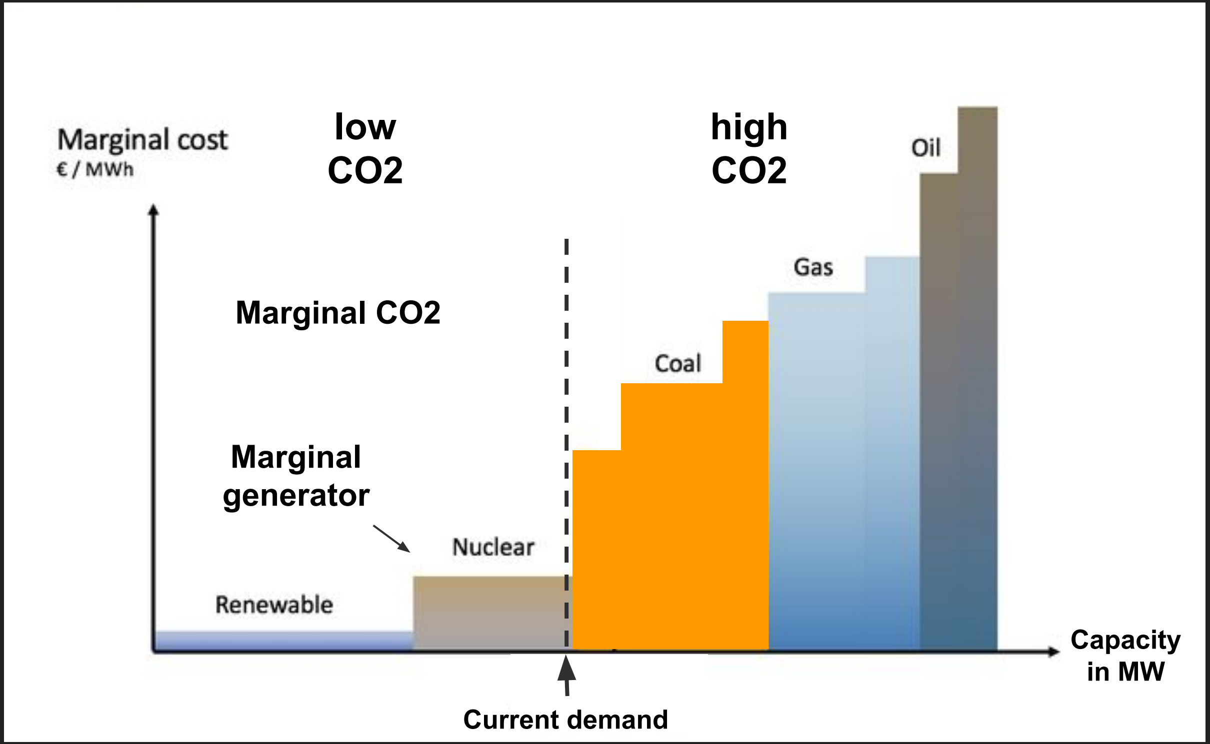

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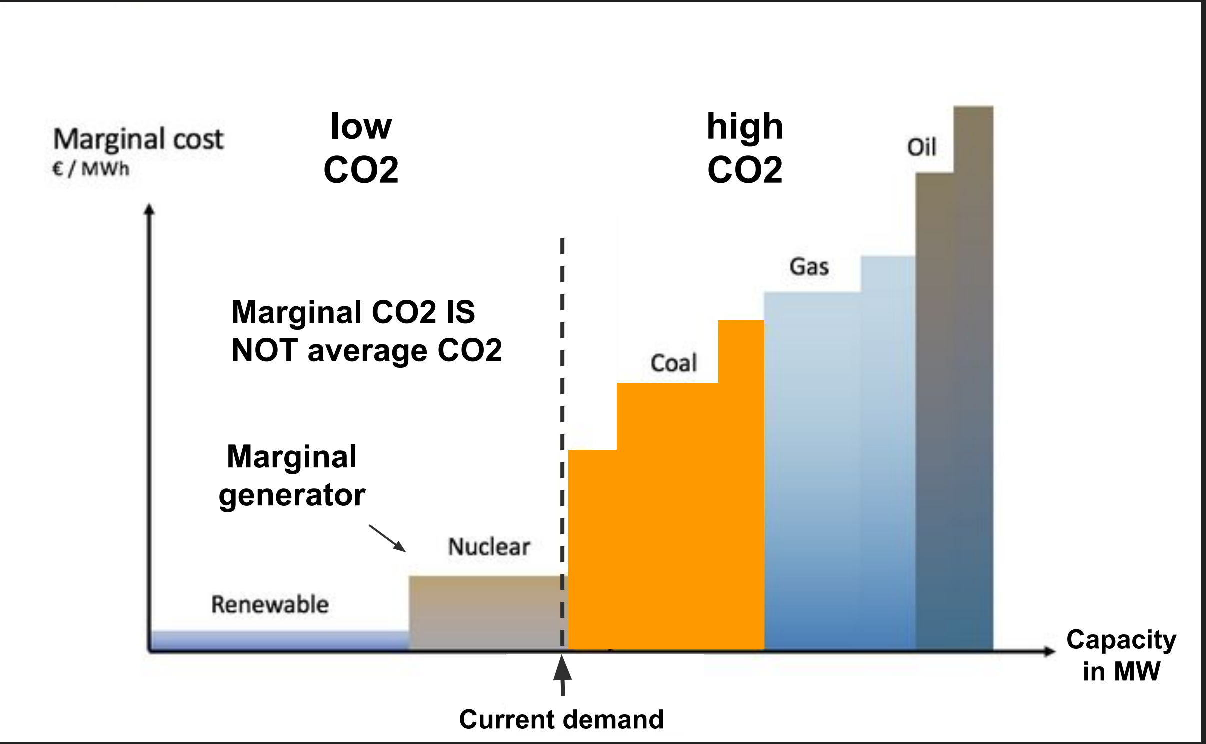

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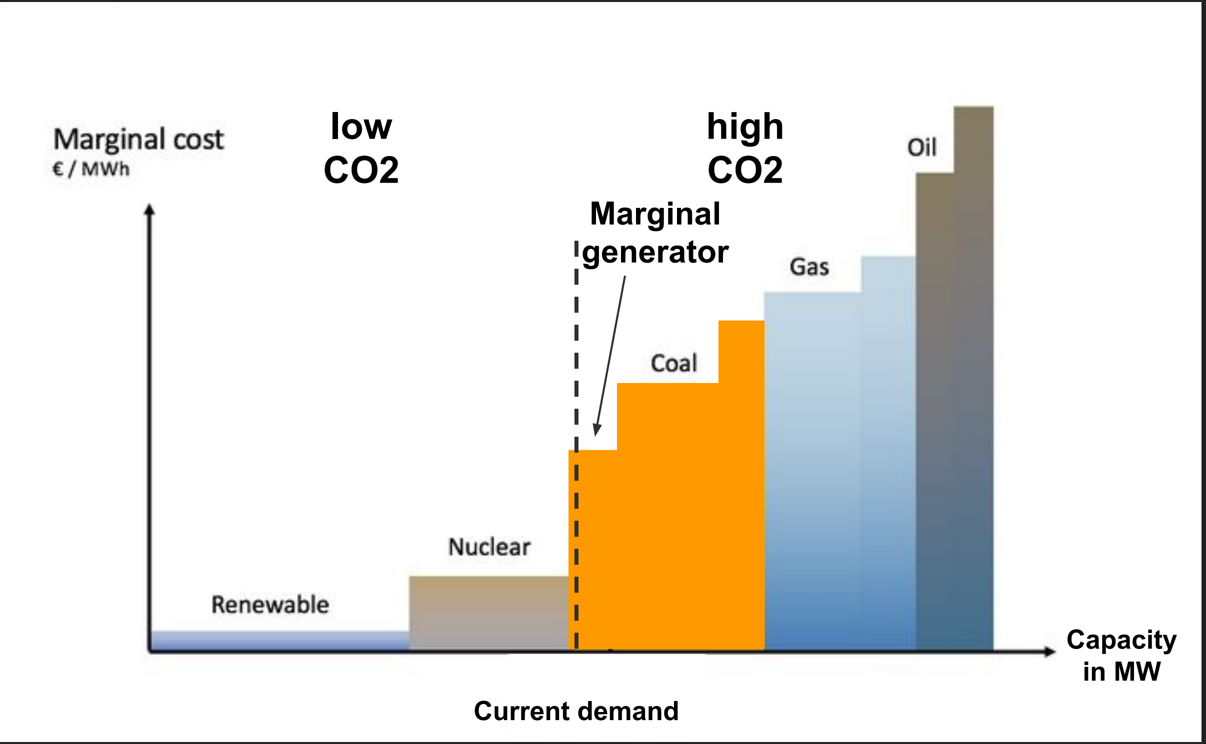

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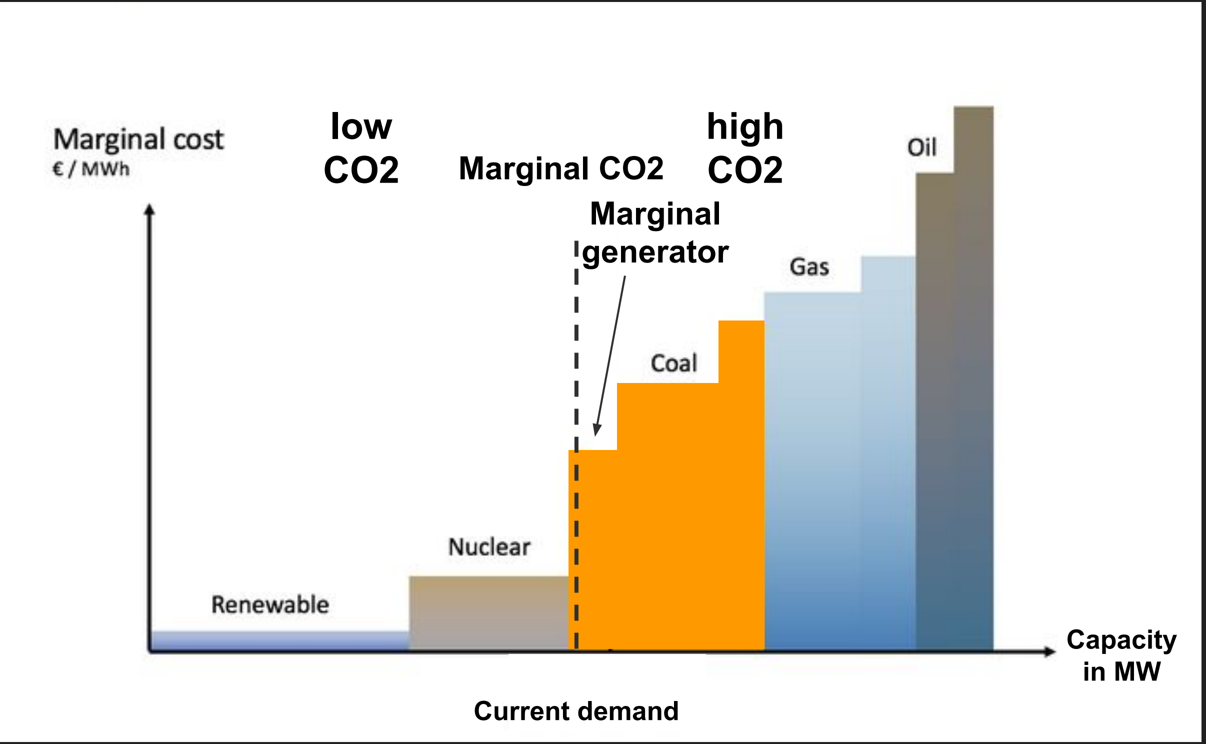

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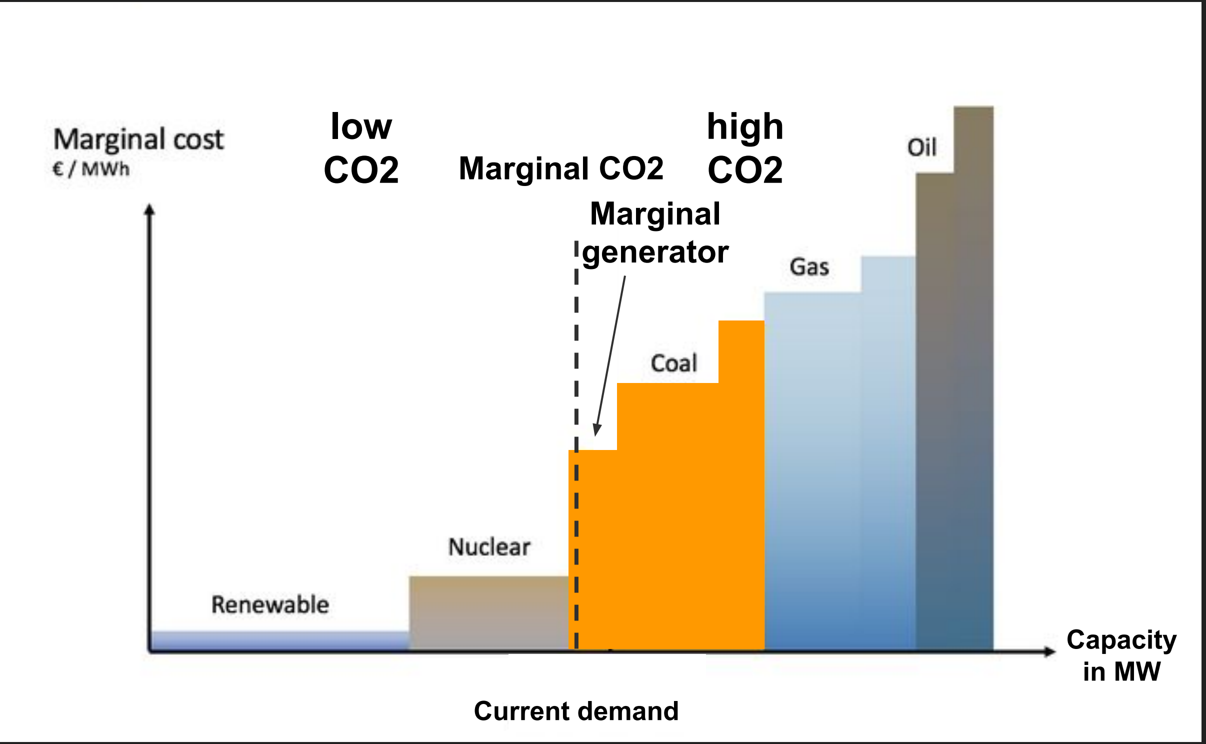

Modified from Olivier Corradi

- predictions about demand and marginal generator to reduce CO2 emissions

Approach to predict marginal CO_2 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

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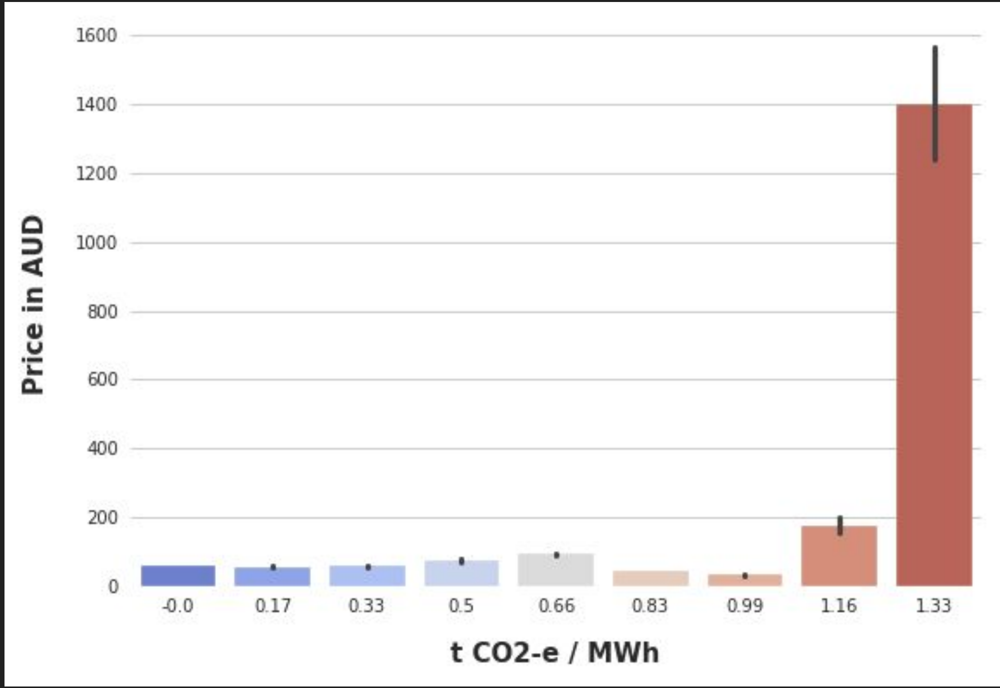
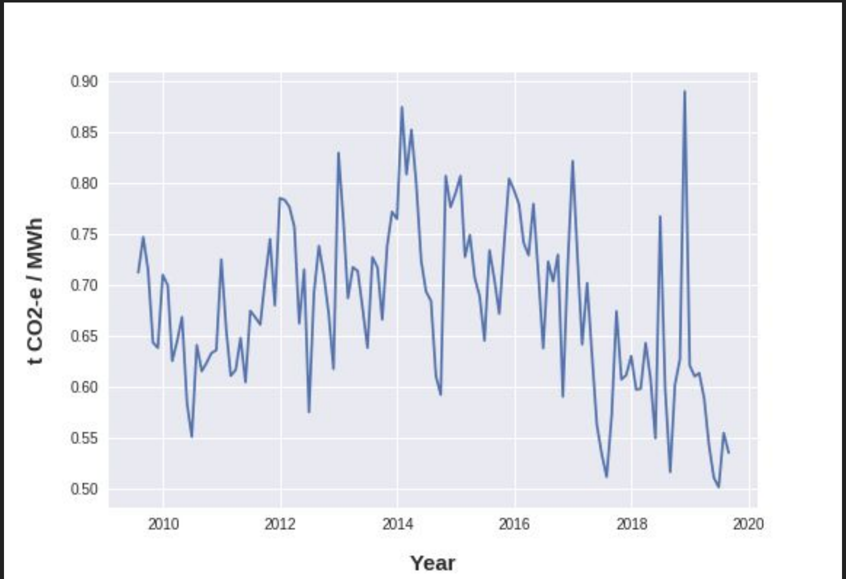


Dirty energy has been more expensive!

Let’s start: marginal CO2 emissions over time

Complete time period (monthly average)



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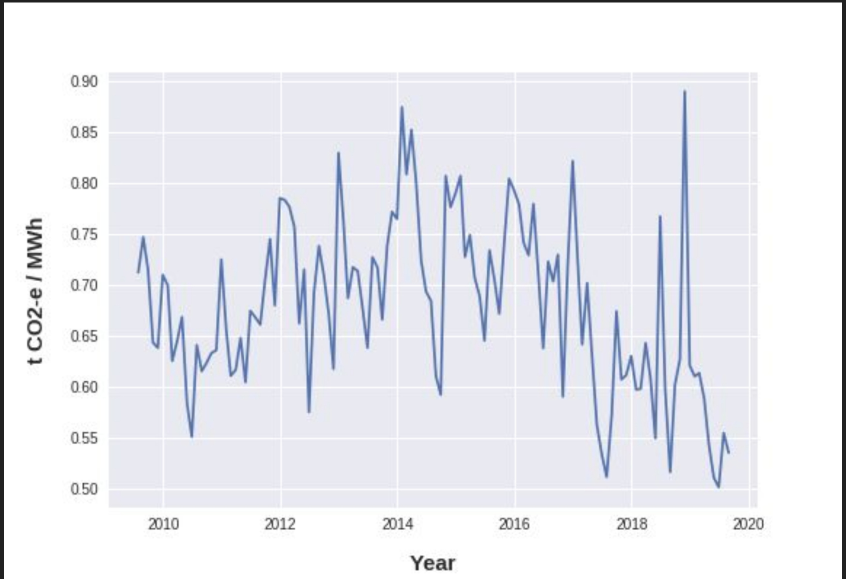
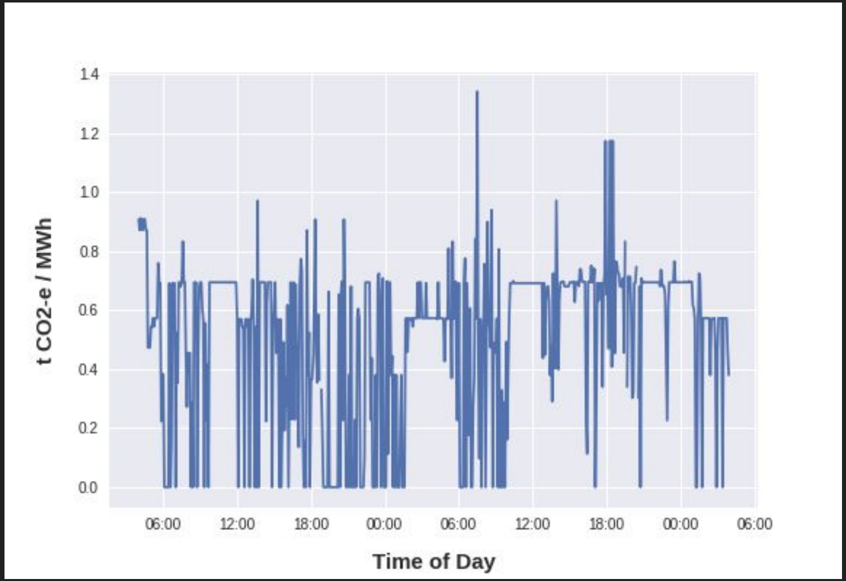


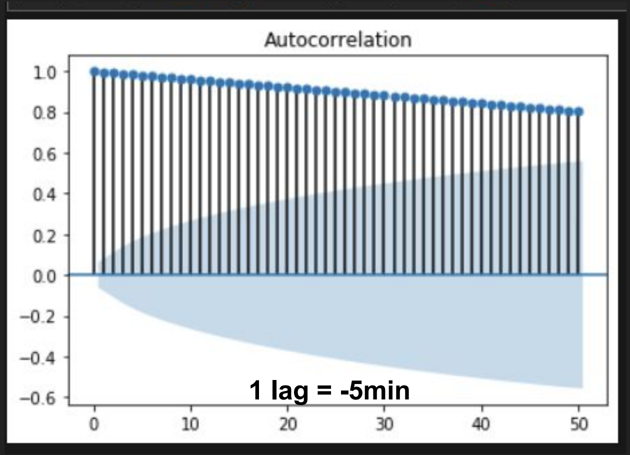
48h interval



Checking for random time behaviour

- **Random walk:**
  - $CO2_{now} = CO2_{5\ min}$ + stochastic error
  - $CO2_{5\ min} = CO2_{10\ min}$ + stochastic error
  - etc.

Checking for random time behaviour



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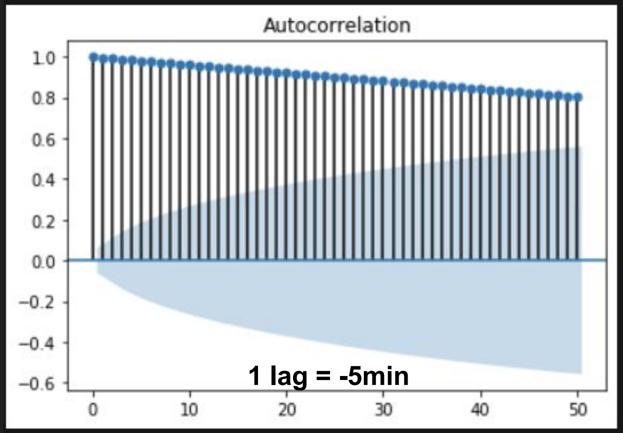

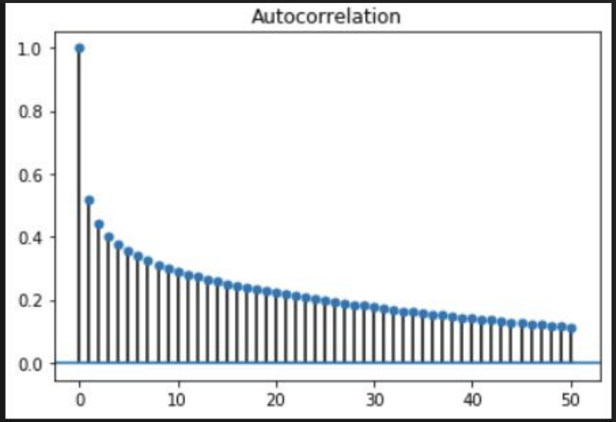

1 lag = -5min

- **Random walk:**
  - $CO2_{now}$ = $CO2_{5\ min}$ + stochastic error
  - $CO2_{5\ min}$ = $CO2_{10\ min}$ + stochastic error
  - etc.
- **Our dataset:**
  - not a random walk

Seasonal behaviour of marginal CO_2 emissions

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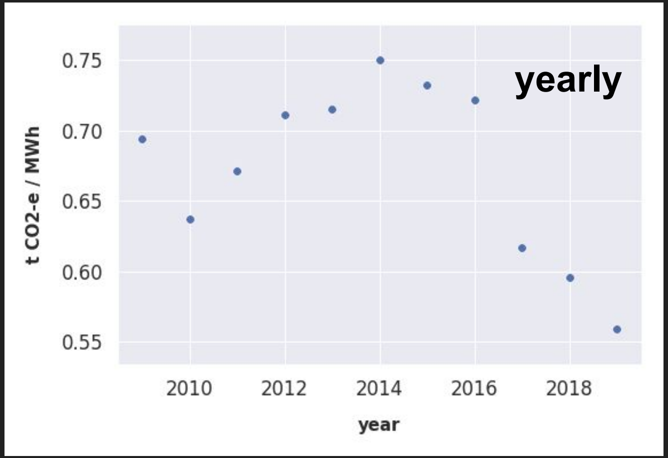
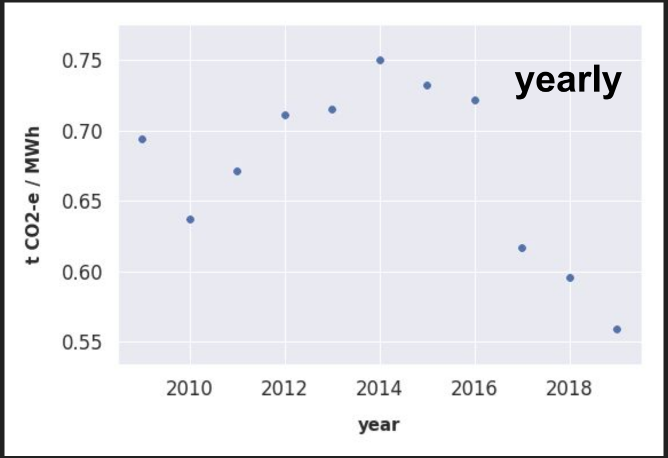
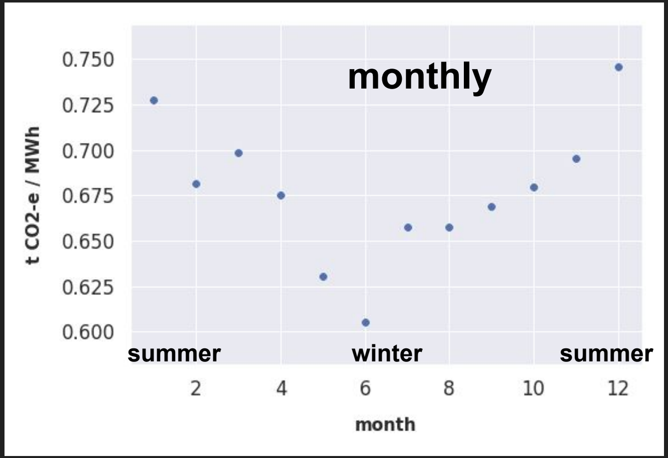


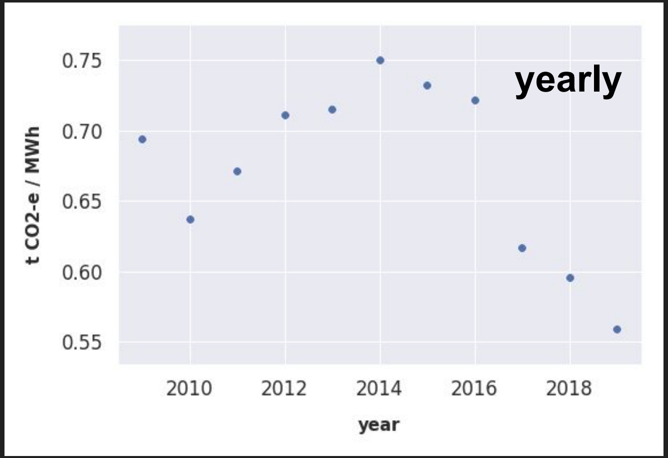
Seasonal behaviour of marginal CO2 emissions

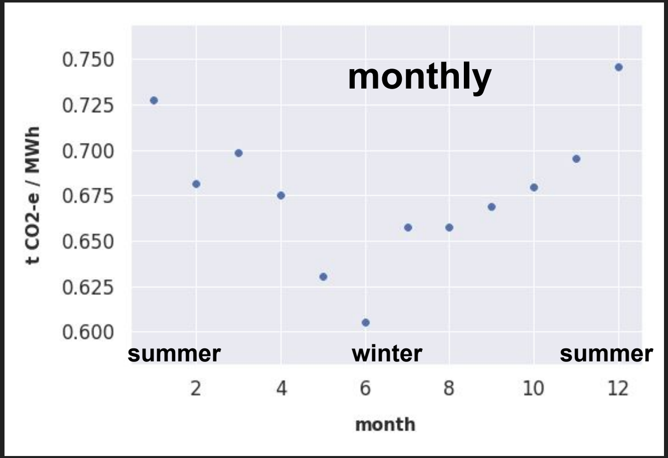


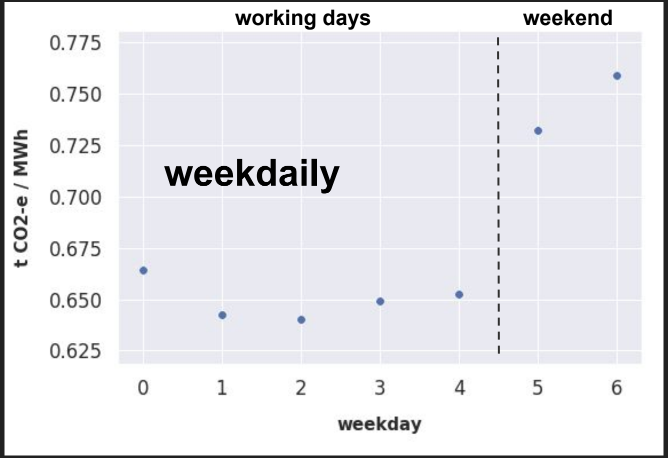


hourly

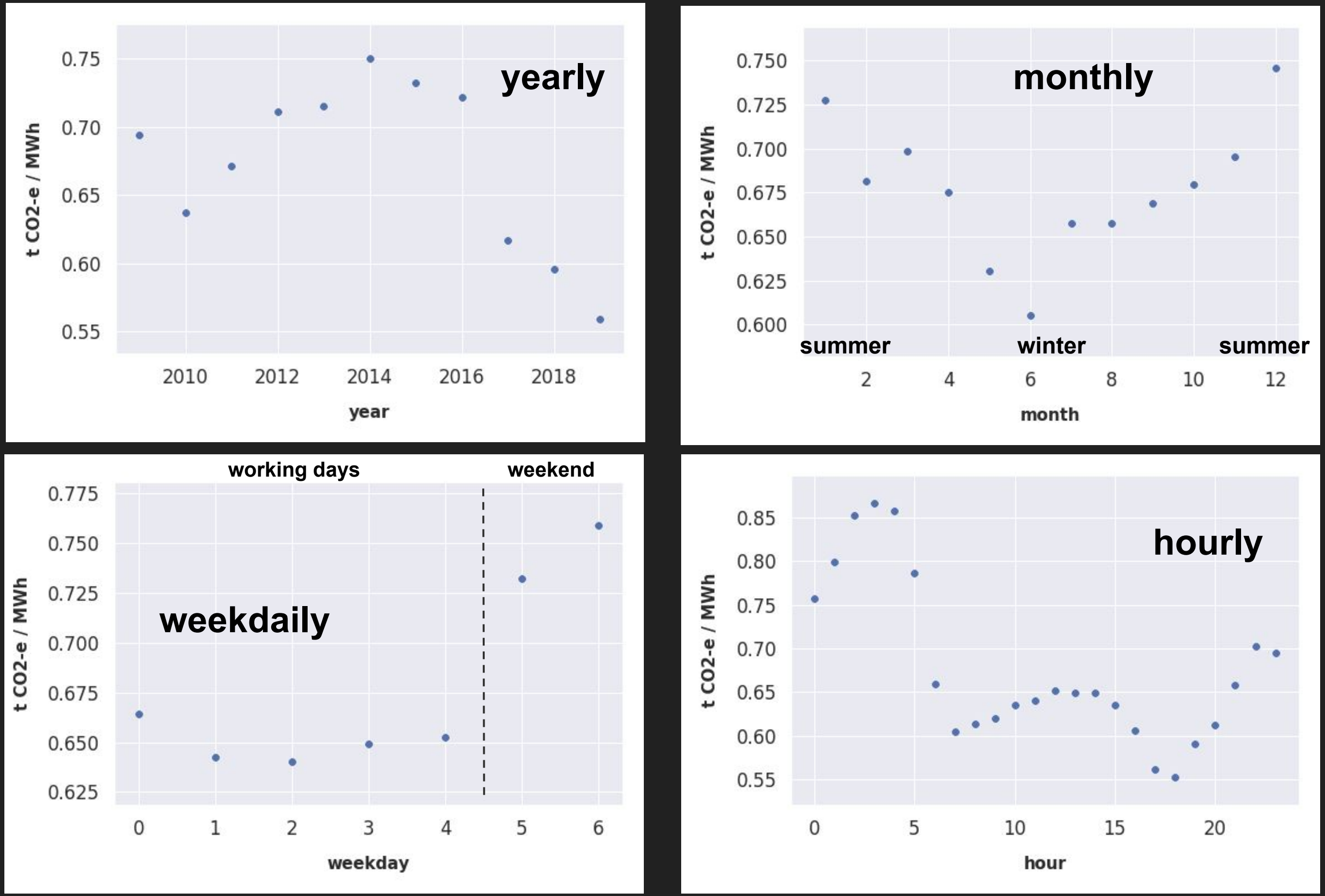
Seasonal behaviour of marginal CO2 emissions







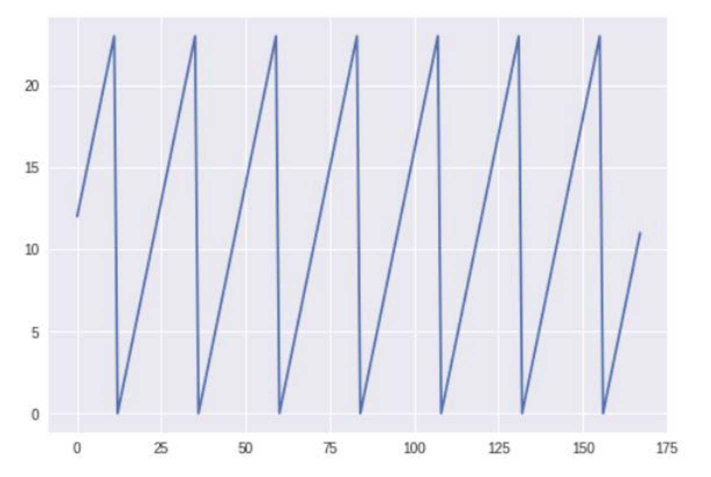
Seasonal behaviour of marginal CO2 emissions



Feature engineering: periodicity

Linear time representation

hour of day

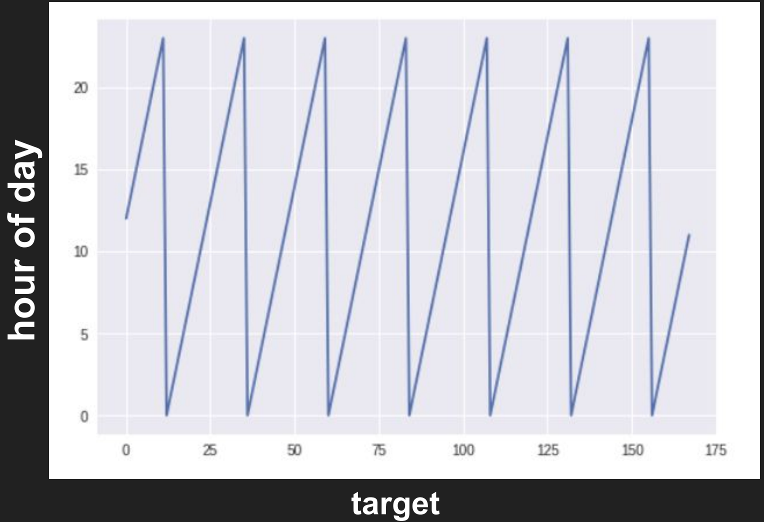


target

24 columns, i.e. features

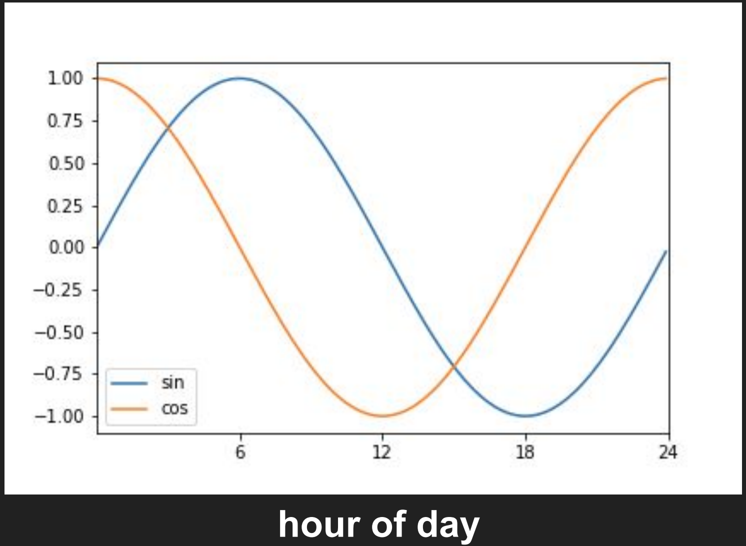
Feature engineering: periodicity

Linear time representation



Sine / cosine trafo

Cyclical time representation



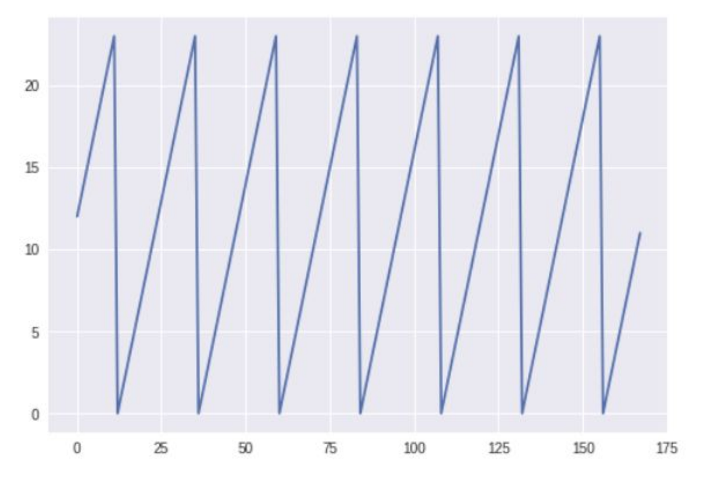
24 columns, i.e. features

2 columns, i.e. features

Feature engineering: periodicity

Linear time representation

hour of day



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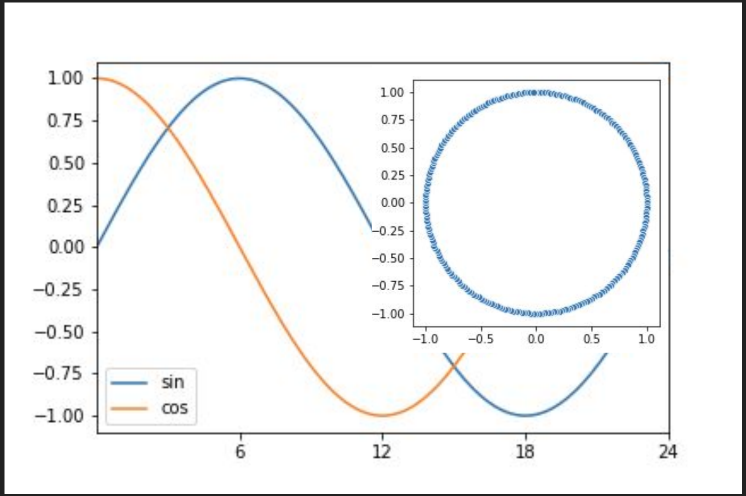

hour of day

24 columns, i.e. features

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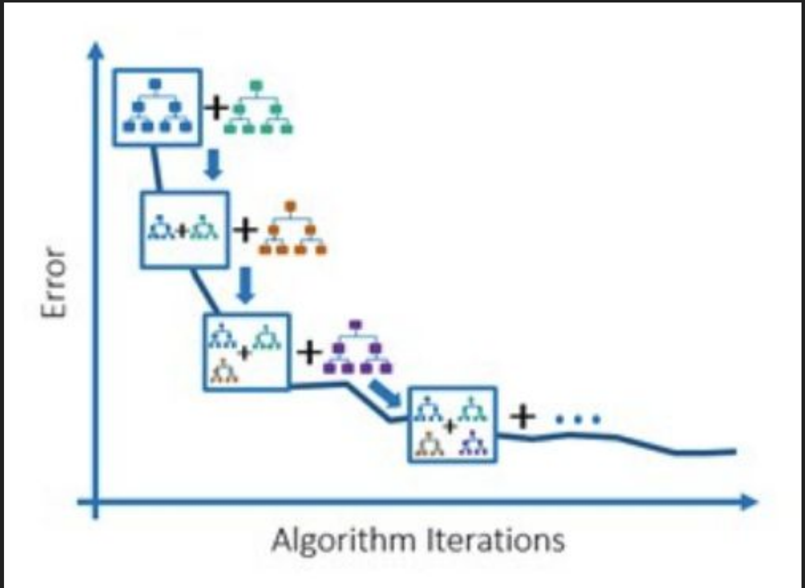
Fitting the data: Gradient boosting

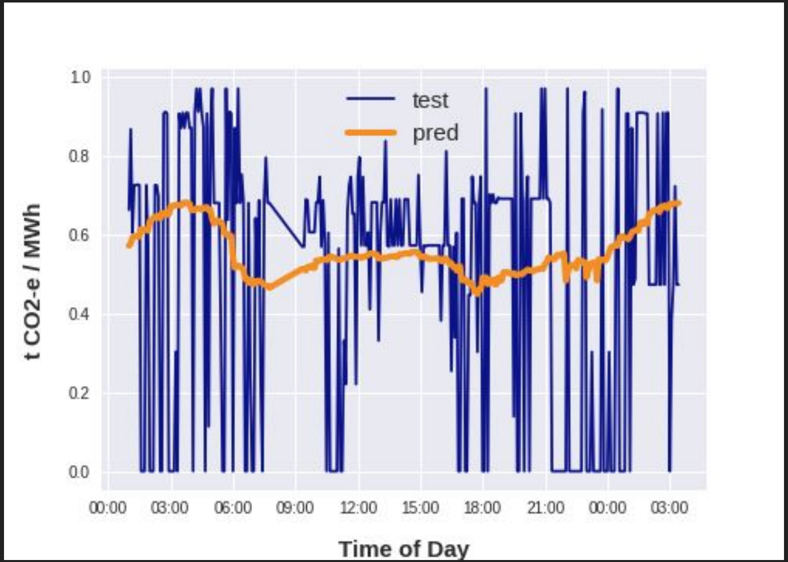


Richard Johansson

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

Fit with seasonal time features

Initial prediction (48h period shown)



$SMAPE_{train}$ = 17.67 %
$SMAPE_{test}$ = 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

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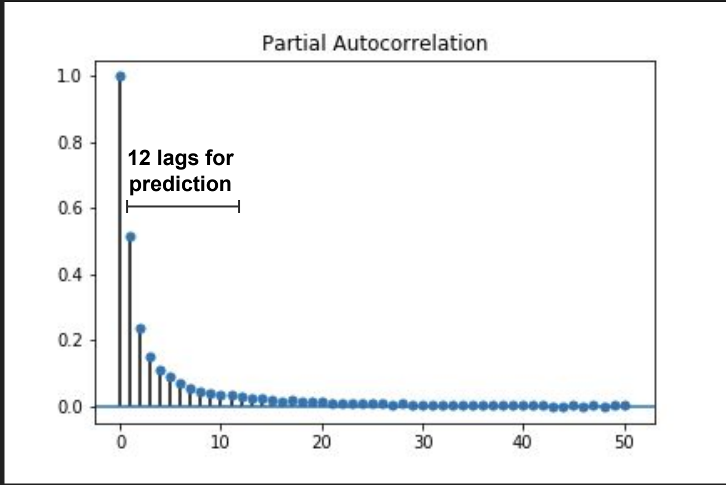

Next fit: seasonal and lag time features (and beyond)

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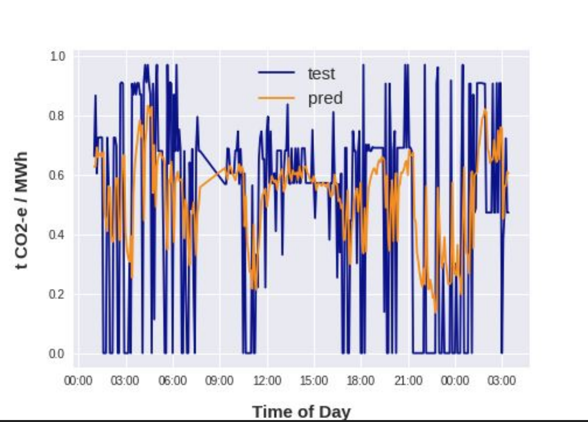
Time features (48h period shown)



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

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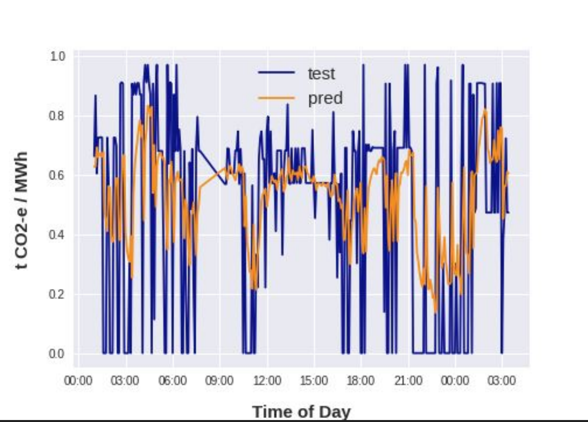

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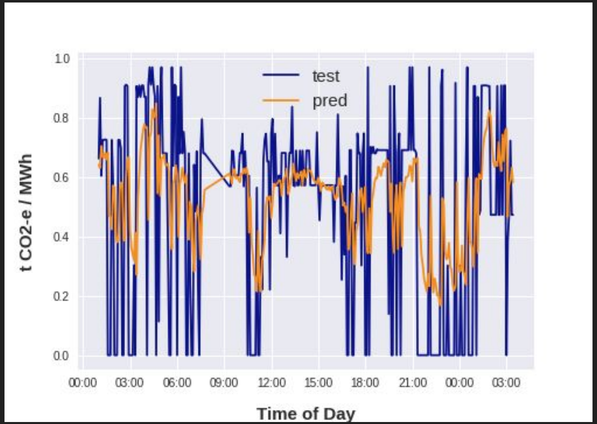
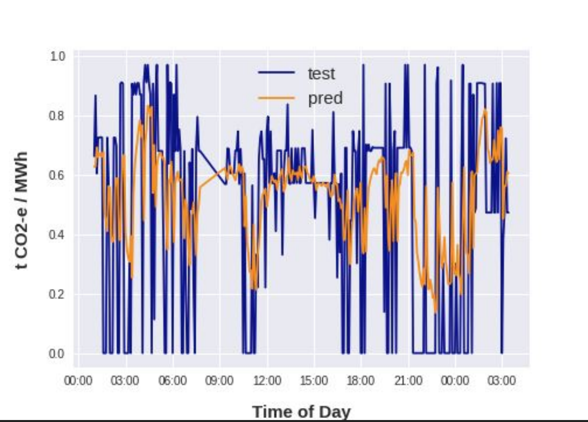
Time features +
electricity demand (48h period shown)



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

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

Time features (48h period shown)



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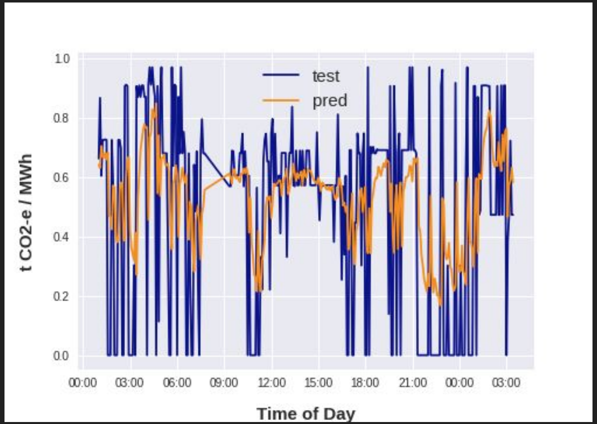

$SMAPE_{train}$: 13.88
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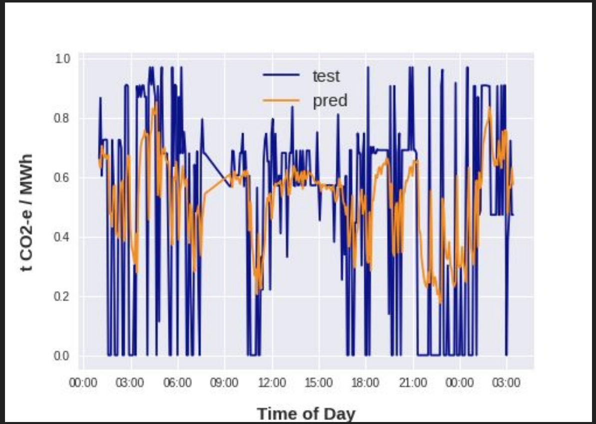
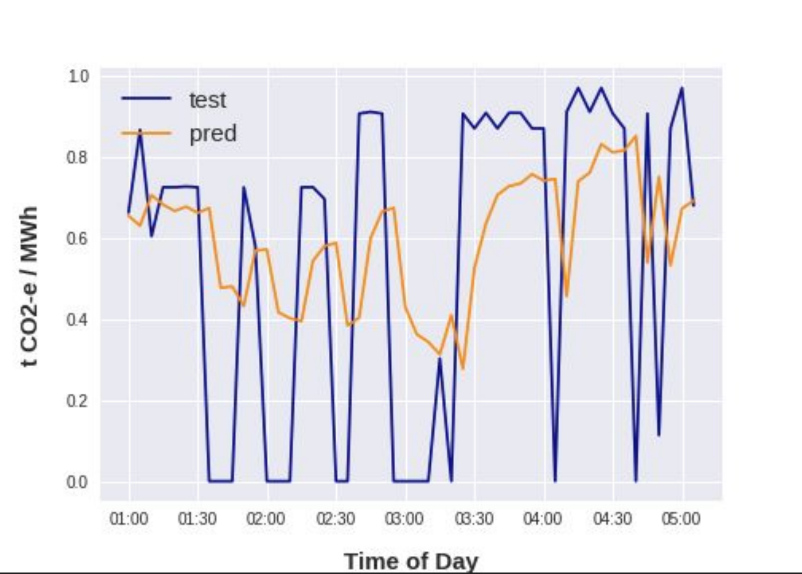
Time features + electricity demand + electricity import (48h period shown)



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

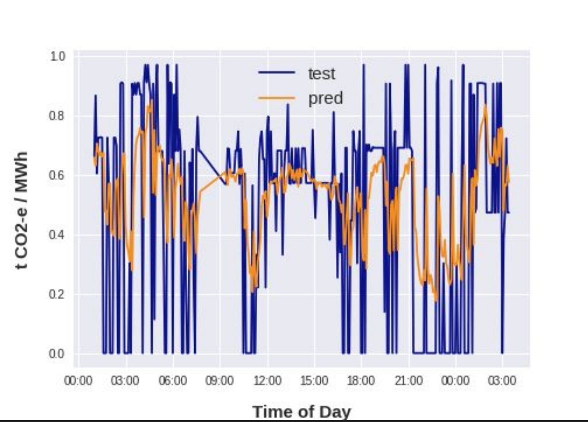
Next fit: seasonal and lag time features (and beyond)

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



Zooming in

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



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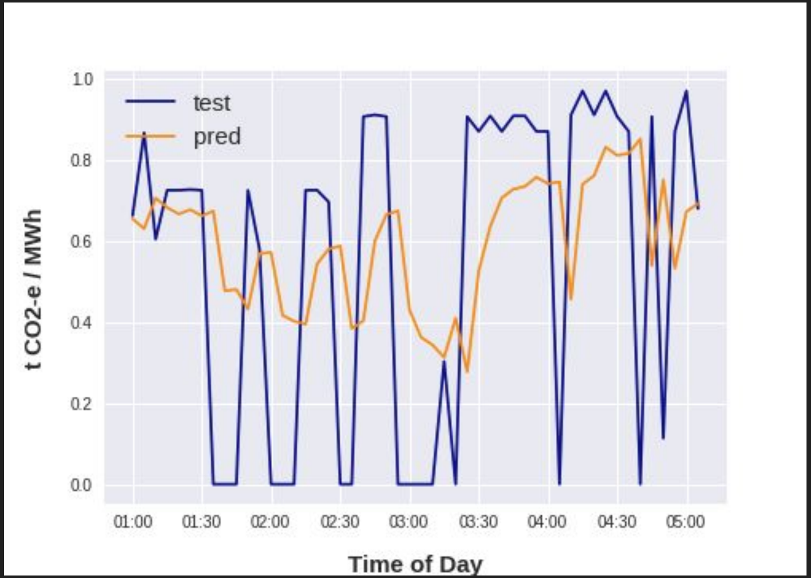

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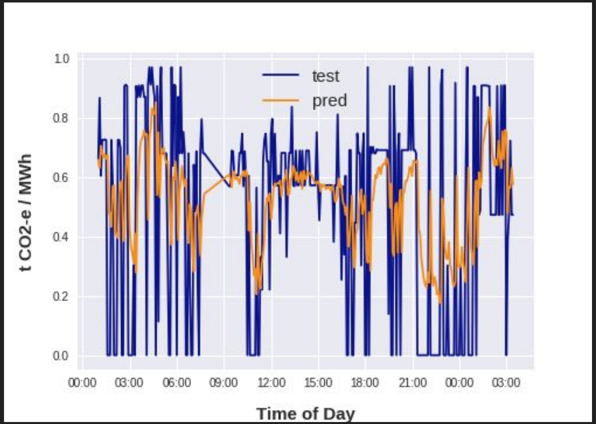

$SMAPE_{train}$: 13.87
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Is this a forecast?

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

Time features +
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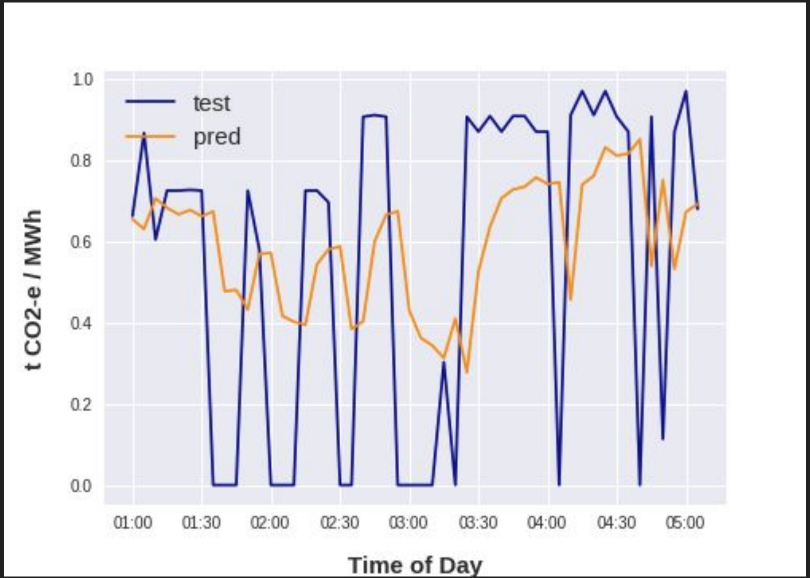

Zooming in

Time features +
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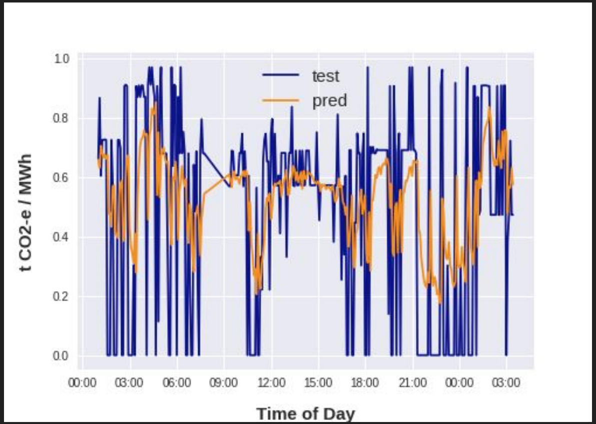
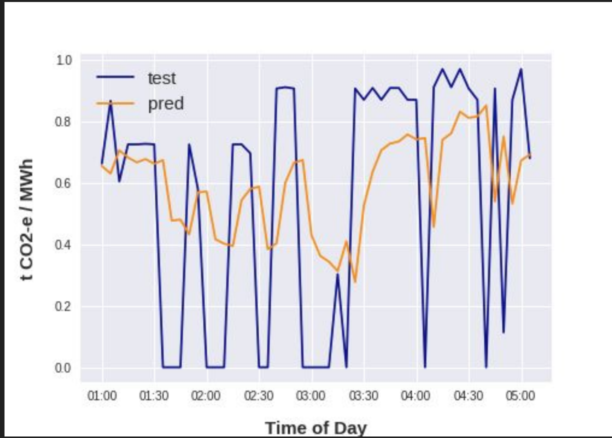


$\text{SMAPE}_{\text{train}}$: 13.87
$\text{SMAPE}_{\text{test}}$: 19.30

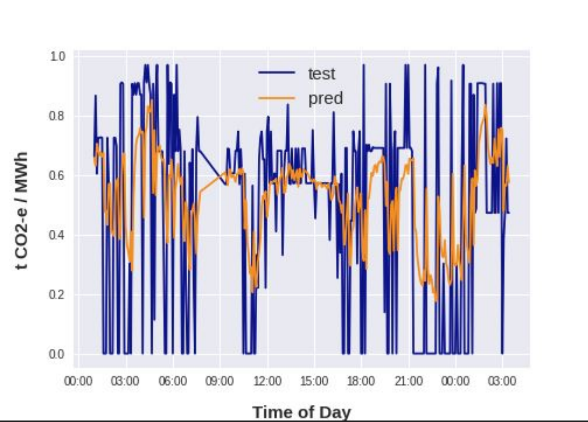
Is this a forecast? No!

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

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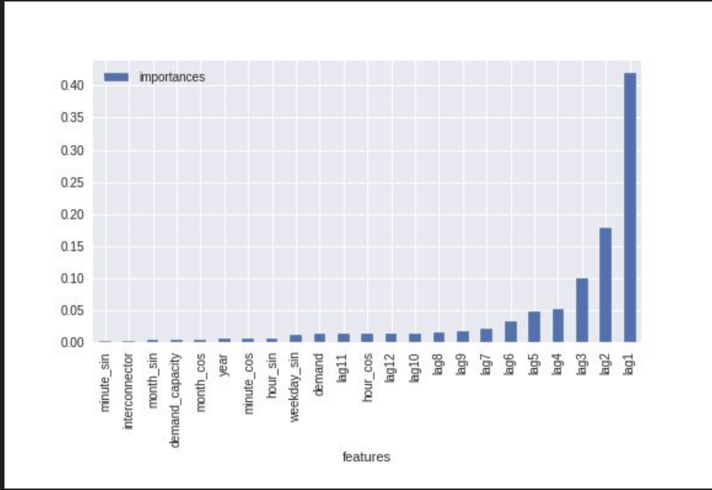
Feature importances



Conclusions:

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

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Outlook:

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

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