rf_week_ahead

July 23, 2023

1 Week-ahead Prediction Accuracy

In this notebook I hope to illustrate the differences between week-ahead prediction accuracies for Random Forest models trained in the same way on 2022-2023 data.

[ ]:
```
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
from tscv import GapRollForward
from tqdm.notebook import tqdm
from sklearn.ensemble import RandomForestRegressor
```

[ ]:
```
df = pd.read_csv('../data/merged_interpolated.csv')
df.datetime = df.datetime.astype('datetime64')
df.head()
```

[ ]:
```
              datetime  tempc  cloud8  windk   wdir  humid  rainmm  radkjm2  \
0 2018-03-06 09:30:00  20.75     2.5   14.5  135.0   44.5     0.0   1915.0
1 2018-03-06 10:00:00  21.50     1.0   16.0  140.0   40.0     0.0   2340.0
2 2018-03-06 10:30:00  22.25     1.5   15.5  145.0   37.0     0.0   2570.0
3 2018-03-06 11:00:00  23.00     2.0   15.0  150.0   34.0     0.0   2800.0
4 2018-03-06 11:30:00  23.55     2.0   13.0  145.0   32.0     0.0   2945.0

    pv_est  net_load  total_load
0  318.991      1288     1136.79
1  375.231      1237     1054.87
2  430.909      1189     1002.35
3  485.129      1150      971.54
4  523.989      1122      943.68
```

Expand datetime feature to its various component parts, plus day of week and week of year.

[ ]:
```
dt = df['datetime'].astype('datetime64[ns]').dt
df['year'] = dt.year
df['month'] = dt.month
df['day'] = dt.day
df['hour'] = dt.hour
```

```
df['minute'] = dt.minute
df['day_of_week'] = dt.day_of_week
df['week'] = dt.isocalendar().week
df.dtypes
```

```
[ ]: datetime       datetime64[ns]
     tempc                 float64
     cloud8                float64
     windk                 float64
     wdir                  float64
     humid                 float64
     rainmm                float64
     radkjm2               float64
     pv_est                float64
     net_load                int64
     total_load            float64
     year                    int64
     month                   int64
     day                     int64
     hour                    int64
     minute                  int64
     day_of_week             int64
     week                   UInt32
     dtype: object
```

Select training features and extract training matrix X and response y.

```
[ ]: X_inds = list(range(1, 8)) + list(range(11, 18))
     y_ind = 9
     X = df.iloc[:, X_inds].to_numpy()
     y = df.iloc[:, 9].to_numpy()

     print(X.shape, y.shape)
     df.columns[X_inds], df.columns[y_ind]
```

```
(87726, 14) (87726,)
```

```
[ ]: (Index(['tempc', 'cloud8', 'windk', 'wdir', 'humid', 'rainmm', 'radkjm2',
             'year', 'month', 'day', 'hour', 'minute', 'day_of_week', 'week'],
            dtype='object'),
      'net_load')
```

Cross-validation splits are done in an appropriate time-series fashion, with one observation-year (48 observations * 365 days) for each training set and test set. There should be a good number of splits with a roll size (gap between successive training set starting points) of 30 days.

```
[ ]: obs_year = 48*365
     obs_week = 48*7
     tscv = GapRollForward(min_train_size=obs_year, max_train_size=obs_year,
```

```
                         min_test_size=obs_week, max_test_size=obs_week,
                         roll_size=48)

df_2022 = df[df['year'] >= 2022]
n_splits = sum(1 for i in tscv.split(df_2022)) # get length of a generator

print('Number of models to be trained:', n_splits)
```

```
Number of models to be trained: 60
```

Training of each forest is parallelised to save time, but even so the full training takes a few minutes. No hyperparameters are selected or tuned. Models and their last training observation's timestamps are saved.

Predictions are made on a full ensuing year per model and merged into a single dataframe, with calculated residuals and absolute percentage error.

```
[ ]: models, train_ends = [], []
prdfs = []

for i, (train_ind, test_ind) in tqdm(enumerate(tscv.split(df_2022))):
    X_train, X_test = df_2022.iloc[train_ind, X_inds], df_2022.iloc[test_ind,␣
 ↪X_inds]
    y_train, y_test = df_2022.iloc[train_ind, y_ind], df_2022.iloc[test_ind,␣
 ↪y_ind]

    # train
    rf = RandomForestRegressor(n_jobs=8)
    rf.fit(X_train, y_train)
    models.append(rf)
    train_ends.append(df_2022.iloc[train_ind[-1], 0])

    # predict
    prd = rf.predict(X_test)
    prdf = pd.DataFrame({'datetime': df_2022.iloc[test_ind, 0],
                         'model': i,
                         'obs_ahead': np.arange(len(prd)) + 1,
                         'predicted': prd,
                         'net_load': df_2022.iloc[test_ind, 9]})
    prdfs.append(prdf)
predictions = pd.concat(prdfs)
predictions['residual'] = predictions['net_load'] - predictions['predicted']
predictions['ape'] = predictions['residual'].abs() / predictions['net_load']
predictions
```

```
0it [00:00, ?it/s]
```

```
[ ]:                  datetime  model  obs_ahead  predicted  net_load  residual  \
84557  2023-01-01 00:00:00      0          1    1602.96      1472   -130.96
```

```
84558 2023-01-01 00:30:00      0          2    1550.04       1456     -94.04
84559 2023-01-01 01:00:00      0          3    1536.32       1446     -90.32
84560 2023-01-01 01:30:00      0          4    1524.67       1402    -122.67
84561 2023-01-01 02:00:00      0          5    1363.20       1329     -34.20
…                    …    …        …        …        …        …
87720 2023-03-07 21:30:00     59        332    1510.31       1500     -10.31
87721 2023-03-07 22:00:00     59        333    1438.06       1464      25.94
87722 2023-03-07 22:30:00     59        334    1417.35       1406     -11.35
87723 2023-03-07 23:00:00     59        335    1382.15       1373      -9.15
87724 2023-03-07 23:30:00     59        336    1375.41       1364     -11.41

            ape
84557  0.088967
84558  0.064588
84559  0.062462
84560  0.087496
84561  0.025734
…           …
87720  0.006873
87721  0.017719
87722  0.008073
87723  0.006664
87724  0.008365

[20160 rows x 7 columns]
```

Demonstrate model prediction windows.

[ ]:
```python
for i in range(3):
    print(i)
    print(predictions.loc[predictions['model'] == i, 'datetime'].
 ↪describe()[['first', 'last']])
```

```
0
first    2023-01-01 00:00:00
last     2023-01-07 23:30:00
Name: datetime, dtype: object
1
first    2023-01-02 00:00:00
last     2023-01-08 23:30:00
Name: datetime, dtype: object
2
first    2023-01-03 00:00:00
last     2023-01-09 23:30:00
Name: datetime, dtype: object
```

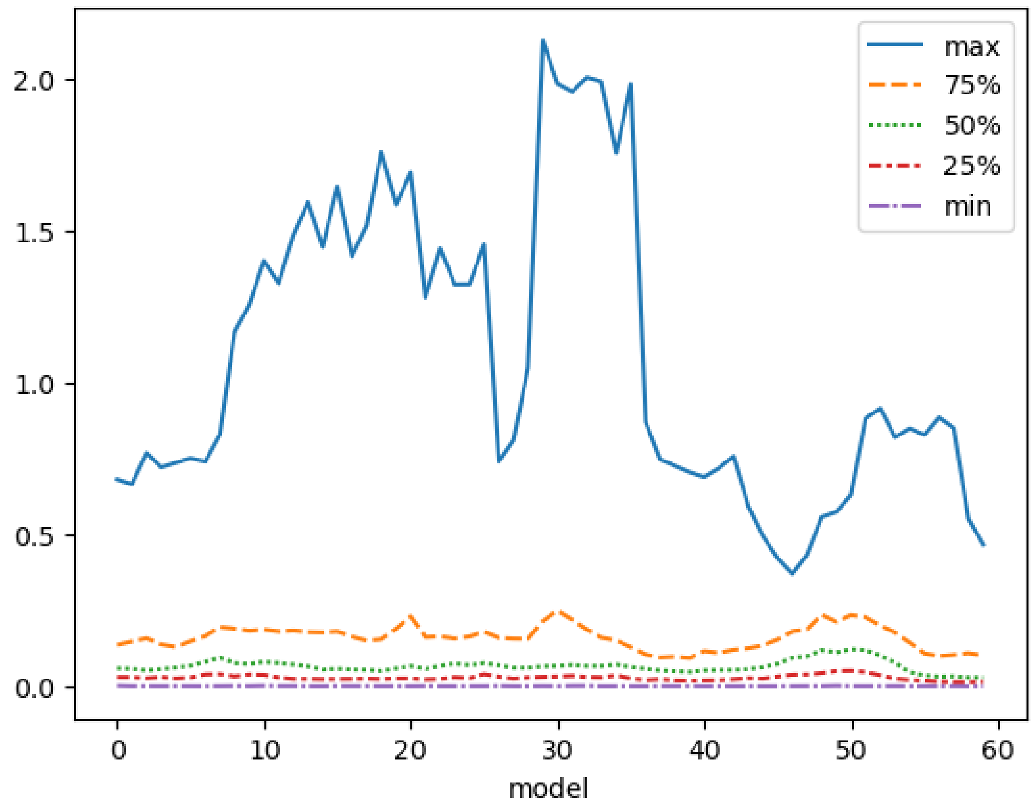
```
/var/folders/q1/x9cngnlj2pdglh47tvmrz2s40000gn/T/ipykernel_55752/408809817.py:3:
FutureWarning: Treating datetime data as categorical rather than numeric in
`.describe` is deprecated and will be removed in a future version of pandas.
```

```
Specify `datetime_is_numeric=True` to silence this warning and adopt the future
behavior now.
  print(predictions.loc[predictions['model'] == i,
'datetime'].describe()[['first', 'last']])
/var/folders/q1/x9cngnlj2pdglh47tvmrz2s40000gn/T/ipykernel_55752/408809817.py:3:
FutureWarning: Treating datetime data as categorical rather than numeric in
`.describe` is deprecated and will be removed in a future version of pandas.
Specify `datetime_is_numeric=True` to silence this warning and adopt the future
behavior now.
  print(predictions.loc[predictions['model'] == i,
'datetime'].describe()[['first', 'last']])
/var/folders/q1/x9cngnlj2pdglh47tvmrz2s40000gn/T/ipykernel_55752/408809817.py:3:
FutureWarning: Treating datetime data as categorical rather than numeric in
`.describe` is deprecated and will be removed in a future version of pandas.
Specify `datetime_is_numeric=True` to silence this warning and adopt the future
behavior now.
  print(predictions.loc[predictions['model'] == i,
'datetime'].describe()[['first', 'last']])
```

Plot absolute percentage error quartiles over time/models.

[ ]:
```
sns.lineplot(predictions.groupby('model').describe()['ape'][['max', '75%',
    '50%', '25%', 'min']])
```

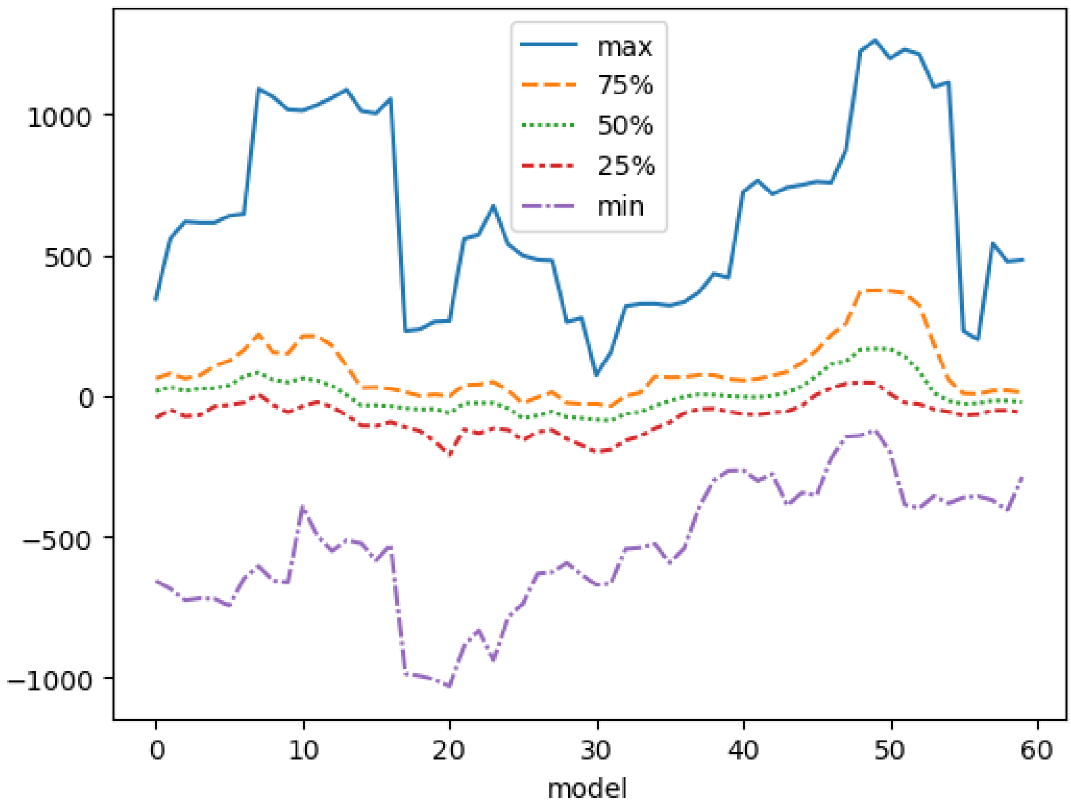
[ ]:
```
<Axes: xlabel='model'>
```



Plot residual quantiles over time/models.

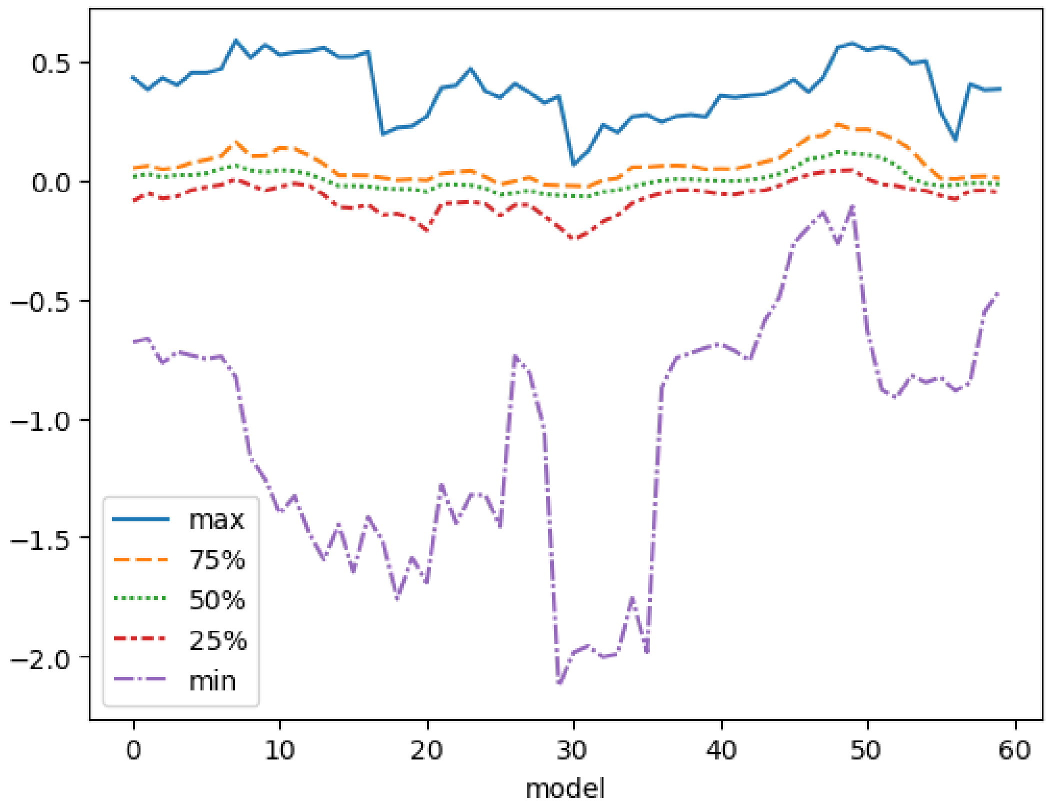
```
[ ]: sns.lineplot(predictions.groupby('model').describe()['residual'][['max', '75%',␣
     ↪'50%', '25%', 'min']])
```

```
[ ]: <Axes: xlabel='model'>
```



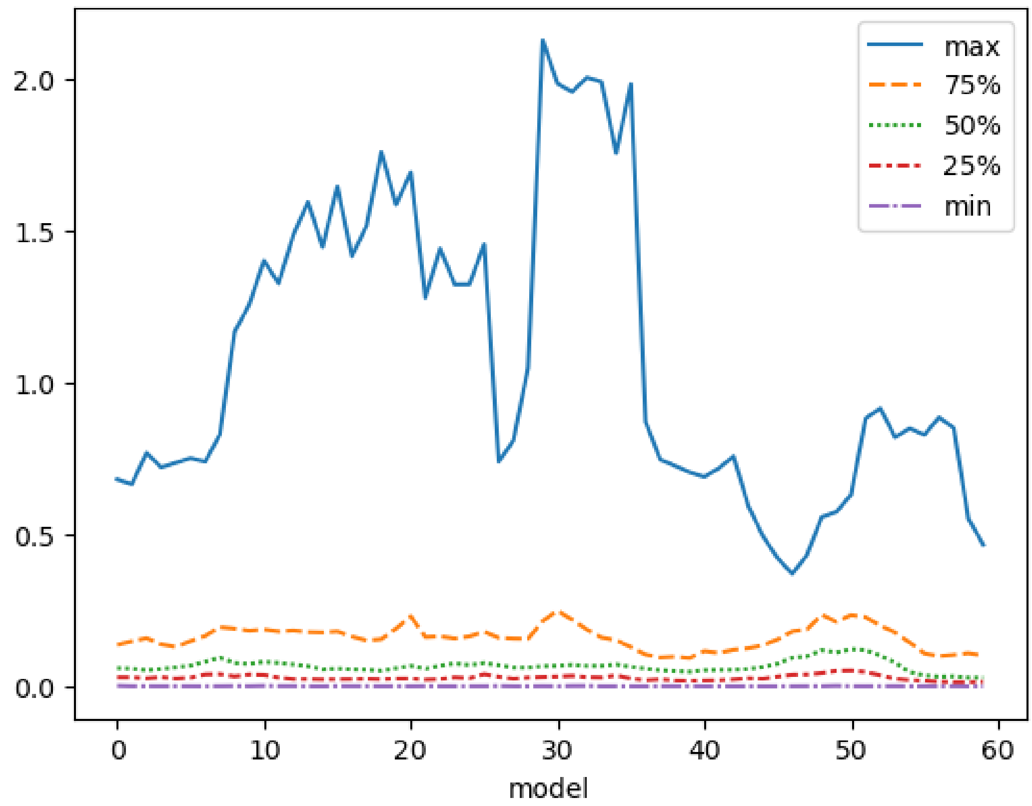

```
[ ]: predictions['pe'] = predictions['residual'] / predictions['net_load']
     sns.lineplot(predictions.groupby('model').describe()['pe'][['max', '75%',␣
      ↪'50%', '25%', 'min']])
```

```
[ ]: <Axes: xlabel='model'>
```



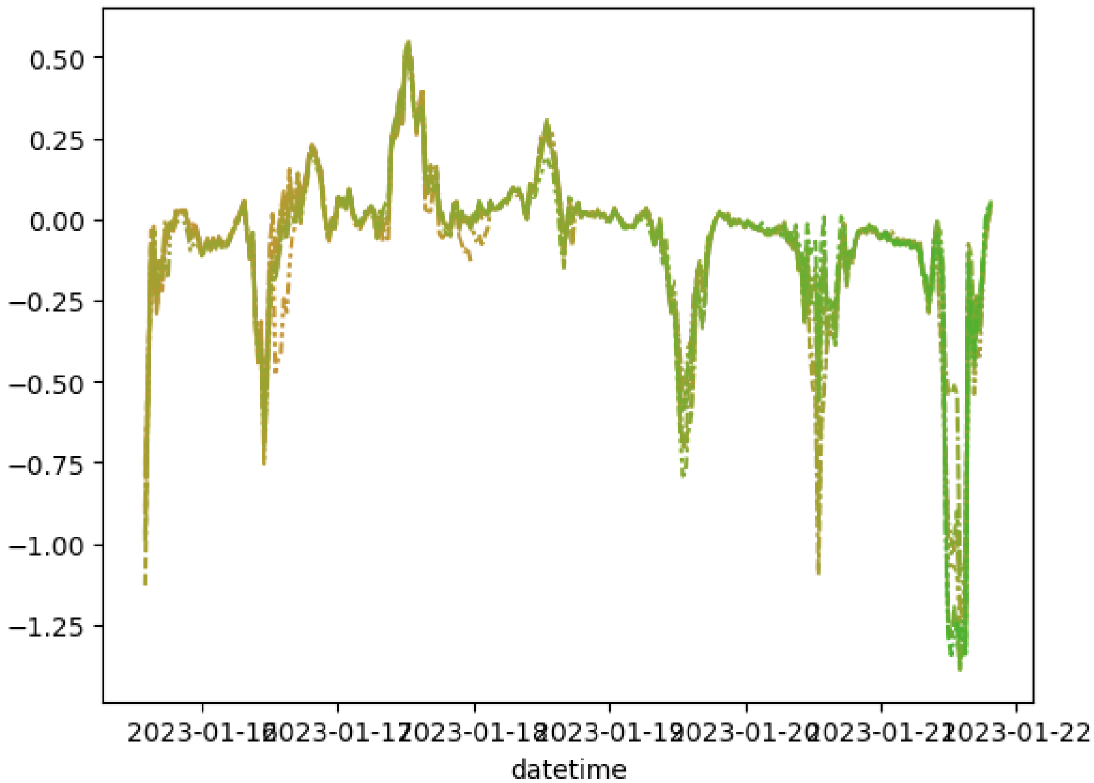
[ ]:
```
sns.lineplot(predictions.groupby('model').describe()['ape'][['max', '75%',
    '50%', '25%', 'min']])
```

[ ]: <Axes: xlabel='model'>




```
[ ]: per_model_pe = predictions.pivot(index='datetime', columns='model', values='pe')
     sns.lineplot(per_model_pe.iloc[700:1000,], legend=False)
```

```
[ ]: <Axes: xlabel='datetime'>
```



Use all models to predict the final week of observations.

```
[ ]: test_cutoff = df['datetime'].max() - pd.DateOffset(weeks=1)

     final_week = df[df['datetime'] >= test_cutoff]

     prdfs = []
     for i, rf in enumerate(models):
         prd = rf.predict(final_week.iloc[:, X_inds])
         prdf = pd.DataFrame({'datetime': final_week['datetime'],
                              'model': i,
                              'ahead': final_week['datetime'] - train_ends[i],
                              'predicted': prd,
                              'net_load': final_week['net_load']})
         prdfs.append(prdf)

     final_week_prds = pd.concat(prdfs)
     final_week_prds['residual'] = final_week_prds['net_load'] -␣
      ↪final_week_prds['predicted']
     final_week_prds['ape'] = final_week_prds['residual'].abs() /␣
      ↪final_week_prds['net_load']
     final_week_prds
```

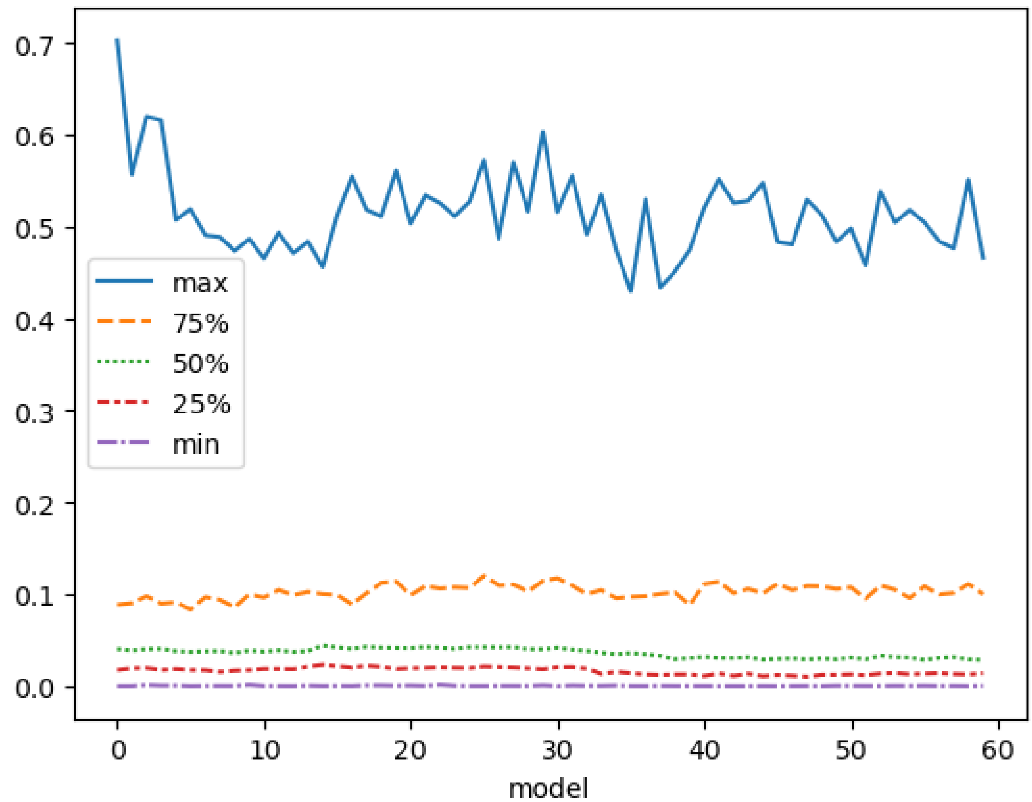
```
[ ]:                   datetime  model             ahead  predicted  net_load  \
     87389 2023-03-01 00:00:00      0 59 days 00:30:00    1492.03      1402
     87390 2023-03-01 00:30:00      0 59 days 01:00:00    1486.56      1401
     87391 2023-03-01 01:00:00      0 59 days 01:30:00    1471.78      1412
     87392 2023-03-01 01:30:00      0 59 days 02:00:00    1429.95      1374
     87393 2023-03-01 02:00:00      0 59 days 02:30:00    1362.12      1315
     …                     …    …                 …         …         …
     87721 2023-03-07 22:00:00     59  6 days 22:30:00    1438.06      1464
     87722 2023-03-07 22:30:00     59  6 days 23:00:00    1417.35      1406
     87723 2023-03-07 23:00:00     59  6 days 23:30:00    1382.15      1373
     87724 2023-03-07 23:30:00     59  7 days 00:00:00    1375.41      1364
     87725 2023-03-08 00:00:00     59  7 days 00:30:00    1474.01      1454

            residual       ape
     87389    -90.03  0.064215
     87390    -85.56  0.061071
     87391    -59.78  0.042337
     87392    -55.95  0.040721
     87393    -47.12  0.035833
     …           …         …
     87721     25.94  0.017719
     87722    -11.35  0.008073
     87723     -9.15  0.006664
     87724    -11.41  0.008365
     87725    -20.01  0.013762

     [20220 rows x 7 columns]
```

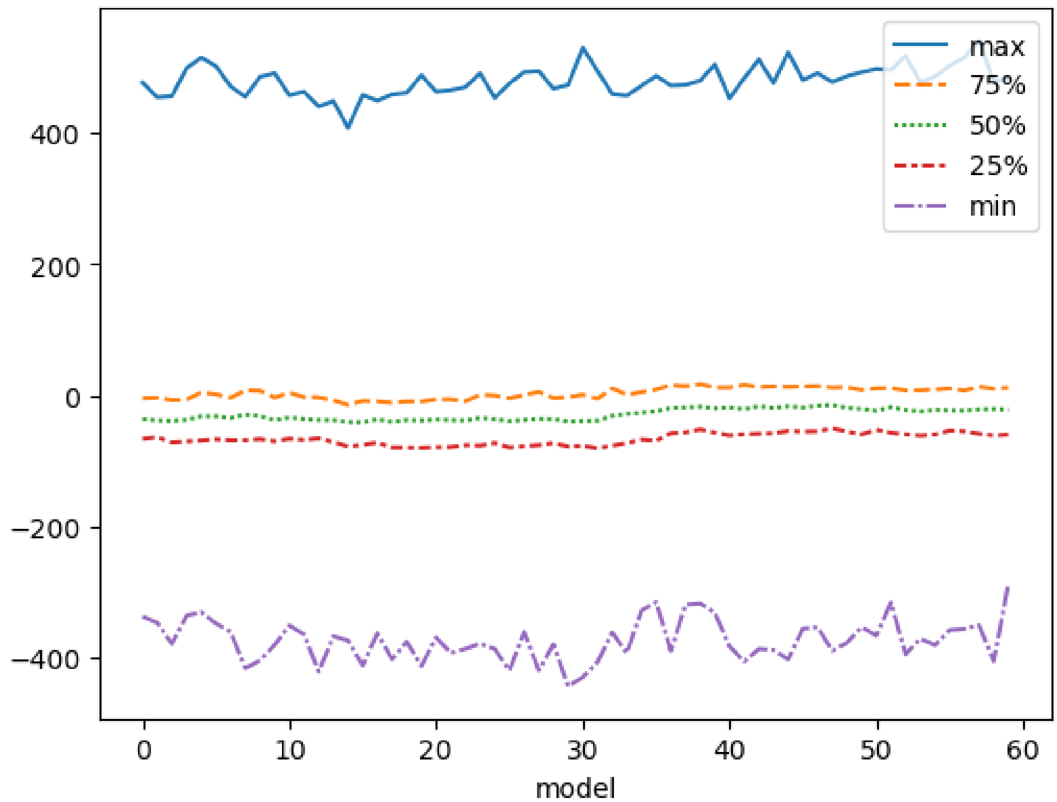
```
[ ]: sns.lineplot(final_week_prds.groupby('model').describe()['ape'][['max', '75%',
     '50%', '25%', 'min']])
```

```
[ ]: <Axes: xlabel='model'>
```



[ ]:
```
sns.lineplot(final_week_prds.groupby('model').describe()['residual'][['max',␣
↪'75%', '50%', '25%', 'min']])
```

[ ]: <Axes: xlabel='model'>


max
75%
50%
25%
min
400
200
0
−200
−400
0
10
20
30
40
50
60
model