Approach using VAR

In [18]:

```
import os
import numpy as np
import pandas as pd
import pandas_profiling
import matplotlib.pyplot as plt
import datetime as dt

import seaborn as sns

from statsmodels.tsa.vector_ar.vecm import coint_johansen
from statsmodels.tsa.vector_ar.var_model import VAR
```

In [ ]:

```

```

Load Data and Set Index

In [19]:

```
# Paths
cwd = os.getcwd()
path_to_challenge1 = os.path.dirname(os.path.dirname(cwd))
path_to_all_data = os.path.join(path_to_challenge1, 'data', 'dataset_500.csv')
path_to_test_data = os.path.join(path_to_challenge1, 'data', 'test_dataset_500.csv'
path_to_train_data = os.path.join(path_to_challenge1, 'data', 'training_dataset_500
```

In [20]:

```
# All Data
df = pd.read_csv(path_to_all_data)
df_test = pd.read_csv(path_to_test_data)
df_train = pd.read_csv(path_to_train_data)
```

In [21]:

```
df.head()
```

Out[21]:

	ID	Label	House	Year	Month	Temperature	Daylight	EnergyProduction
0	0	0	1	2011	7	26.2	178.9	740
1	1	1	1	2011	8	25.8	169.7	731
2	2	2	1	2011	9	22.8	170.2	694
3	3	3	1	2011	10	16.4	169.1	688
4	4	4	1	2011	11	11.4	169.1	650

In [22]:

```
# Keeping only main features (avoiding highly correlated or useless columns)
key_cols = ['House', 'Temperature', 'Daylight', 'EnergyProduction']
ts_cols = ['Temperature', 'Daylight', 'EnergyProduction']

# Set Index Method
def get_datetime_index(input_df, key_cols):
    input_df['DateTime'] = pd.to_datetime(input_df.Year.map(str) + input_df.Month.ma
    input_df.set_index(['DateTime'], inplace=True)
    return input_df[key_cols]

# Get Index
df = get_datetime_index(df, key_cols)
df_test = get_datetime_index(df_test, key_cols)
df_train = get_datetime_index(df_train, key_cols)
```

In [23]:

```
df.head()
```

Out[23]:

DateTime	House	Temperature	Daylight	EnergyProduction
2011-07-01	1	26.2	178.9	740
2011-08-01	1	25.8	169.7	731
2011-09-01	1	22.8	170.2	694
2011-10-01	1	16.4	169.1	688
2011-11-01	1	11.4	169.1	650

Model TimeSeries

It is important to notice that the dataset include multiple samplingpoints (Houses). In the present work, each house will treated indepedently and model fit/parameters will be independently obtained for each.

In [24]:

```
def get_VAR_prediction(df_train, df_test, house, ts_cols, maxlagsint, ic, trend):

    #creating the train and validation set
    train = df_train[ df_train['House'] == house ][ts_cols].asfreq('MS')

    # Checking Stationarity
    # Similar to the Augmented Dickey-Fuller test for univariate series, we have Joh
    # stationarity of any multivariate time series data. For a series to be stationa
    # be less than 1 in modulus.
    eigen = coint_johansen(train,-1,1).eig
    if all(i < 1.0 for i in eigen):
        pass
        #print('All eigen values are ok')
    else:
        print('Problem with Eigen Value', eigen)

    # Fit the model
    # Parameters
    # - maxlagsint: Maximum number of lags to check for order selection, defaults to
    #   see select_order function
    # - method{'ols'}: Estimation method to use
    # - ic{'aic', 'fpe', 'hqic', 'bic', None}: Information criterion to use for VAR
    # aic : Akaike fpe : Final prediction error hqic : Hannan-Quinn bic : Bayesian a
    # - trend: str {"c", "ct", "ctt", "nc"}: "c" - add constant "ct" - constant and
    # linear and quadratic trend "nc" - co constant, no trend Note that these are pr
    # of the dataset.
    model = VAR(endog=train)
    if maxlagsint:
        model_fit = model.fit(maxlags=maxlagsint, ic=ic, trend=trend)
    else:
        model_fit = model.fit(ic=ic, trend=trend)

    # make prediction on validation
    prediction = model_fit.forecast(model_fit.y, steps=1)

    # Focus on Extracting "EnergyProduction"
    energy_pred = prediction.tolist()[0][-1]
    energy_value = df_test['EnergyProduction'].tolist()[0]
    error = abs(energy_value - energy_pred)/energy_value

    return energy_pred #, energy_value, error
```

In [25]:

```
houses = df['House'].unique()
prediction_list = []

for house in houses:
    # As the dataset is small, parameter optimisation will be performed with a grid
    # own optimal prediction
    actual_value = df_test.loc[df_test['House'] == house, 'EnergyProduction'].iloc[(
    predicted = []
    for trend in ['c', 'nc', 'ct', 'ctt']:
        for ic in ['aic', 'fpe', 'hqic', 'bic', None]:
            for maxlagsint in [1, 2, 3, 4]:
                value_predicted = get_VAR_prediction(df_train, df_test, house, ts_co
                predicted.append(
                    {'trend': trend,
                     'ic': ic,
                     'maxlags': maxlagsint,
                     'prediction': value_predicted,
                     'error': abs(actual_value - value_predicted)
                    })
    # Select Best
    bestPrediction = min(predicted, key=lambda x:x['error'])
    d = {
        'House' : house,
        'ModelParamters_trend' : bestPrediction['trend'],
        'ModelParamters_ic' : bestPrediction['ic'],
        'ModelParamters_maxlags' : bestPrediction['maxlags'],
        'Error': bestPrediction['error'],
        'Prediction' : bestPrediction['prediction']
    }
    prediction_list.append(d)

df_prediction = pd.DataFrame(prediction_list)
```

In [26]:

```
# Results
df_prediction.head()
```

Out[26]:

	Error	House	ModelParamters_ic	ModelParamters_maxlags	ModelParamters_trend	Prec
0	19.019555	1	aic	3	ct	797.0
1	19.753771	2	aic	4	ctt	646.7
2	29.339770	3	aic	4	ct	764.3
3	65.865639	4	None	3	c	598.8
4	65.865639	5	None	3	c	598.8

In [27]:

```
# Print File with Predicted Values
df_prediction_print = df_prediction[['House', 'Prediction']]
df_prediction_print.to_csv('predicted_energy_production.csv', index=False)
```

In [28]:

```
# Combine DF
df_all = df_test.merge(df_prediction, left_on='House', right_on='House')
df_all.head()
```

Out[28]:

	House	Temperature	Daylight	EnergyProduction	Error	ModelParamters_ic	ModelParamt
0	1	22.0	125.5	778	19.019555	aic	
1	2	21.1	123.1	627	19.753771	aic	
2	3	21.9	126.8	735	29.339770	aic	
3	4	20.2	125.2	533	65.865639	None	
4	5	20.2	125.2	533	65.865639	None	

In [31]:

```
# Error
MAPE = np.mean(np.abs((df_all['EnergyProduction'] - df_all['Prediction']) / df_all[
MAPE
```

Out[31]:

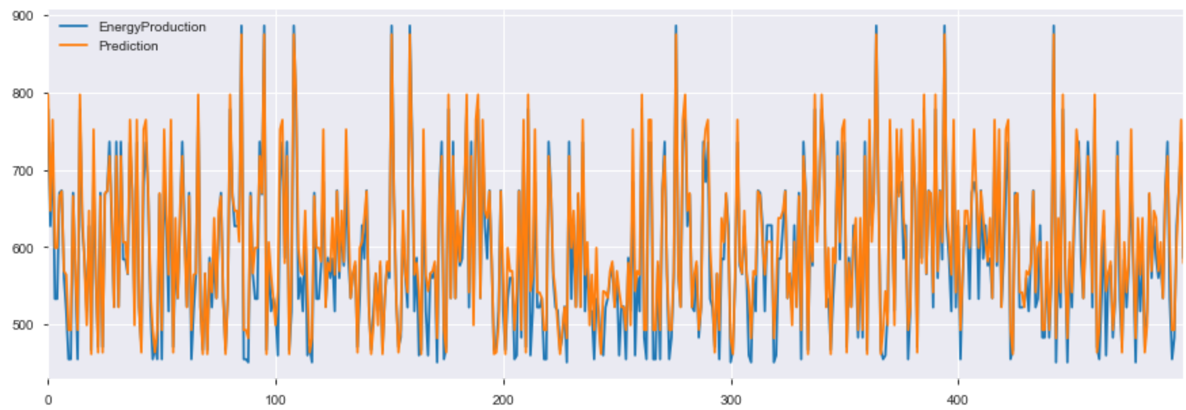
4.023386014469117

In [30]:

```
# Prediction
df_all[['EnergyProduction', 'Prediction']].plot(figsize=(15,5))
```

Out[30]:

<matplotlib.axes._subplots.AxesSubplot at 0x12624fa58>



Clearly the main problem of the present appoach regarding parameter optimisisation is related to Overfitting. This could be addressed by grouping houses by type (which seems possible as based on the Data Exploration) and then identify the best hyperparameters for such "House Type".

In [ ]: