ÉCOLE NATIONALE SUPÉRIEURE DE L'ÉNERGIE, L'EAU ET L'ENVIRONNEMENT

Smart Systems

Grafana Report

Electricity Consumption Estimation

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Table of Content

Smart Systems - Electricity Consumption Estimation based on Weather Conditions

1. Introduction

Due to increasing share of renewable energies in the electricity mix and resulting volatility of electricity generation demand prediction and demand response becomes more and more important. Electricity demand often correlates with weather conditions, e.g. the demand for indoor lighting increases when it is more clouded. At the same time solar panels are producing less electricity during this time. This requires prediction of the electricity demand to ensure grid stability and activate backup resources in time. Grid operators can then coordinate the required generation to meet the demand.
In this study we are analyzing the performance of a decision tree classifier to estimate the electricity consumption of a residential house near Grenoble based on weather data. The variables used are humidity, luminosity and temperature. Gas heating is installed in the house.
The goal of this study is to find the weather variables that are most suitable to be used for these kinds of predictions and find explanations for our results. However, the goal is not to achieve the most accurate results possible. To achieve a more accurate performance many more variables, e.g. previous energy consumption (one week ago, one day ago,..), must be included.

2. Methodology

We applied the decision tree algorithm to estimate the hourly electricity consumption. Decision trees are supervised machine learning algorithms. This means that the data is labeled. In our case the label data is the hourly electricity consumption.
We divided our data set into training and test data. The size of our training set is 80% and the test set 20%.
To measure and compare performances we used mean errors. We decided not to use accuracy in our study, because we did not discretize our label data. Meaning that each level of consumption is a single class. Hence it is very difficult to achieve exact predictions.

The data is downloaded from the Grafana website.[1] The observed label data in this project is the electricity consumption. The feature data are weather measurements, such as humidity, temperature and luminosity, that are observed by several sensors.

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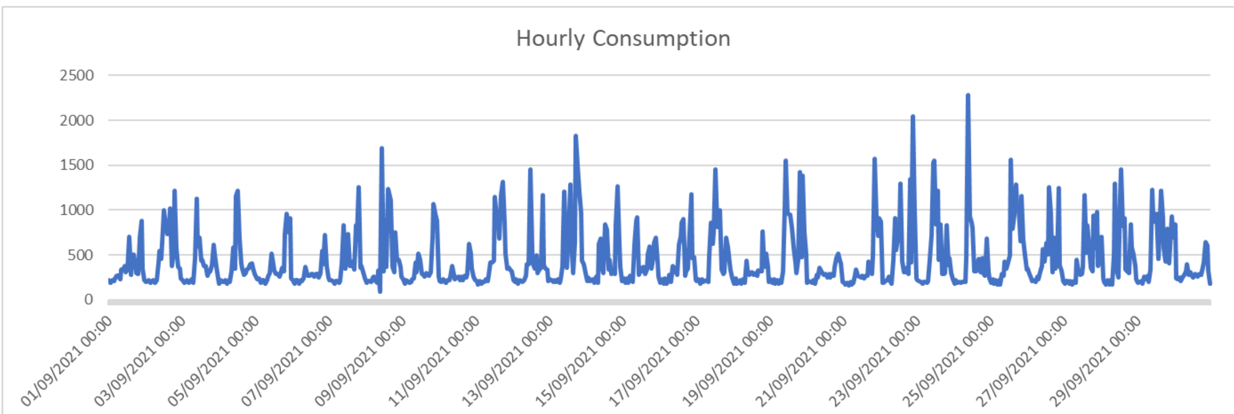
[1] Jerome Ferrari. Grafana data home. 2022. url: https://jarvis-oneforall.duckdns.org:
3000.

Before using the data we did some data cleaning for missing values. For missing temperature values, we assume that the reason was a failure of the sensor, therefore we used the data from 24 hours before. Missing luminosity values existed only during night time. Therefore, we replaced the blank cell by 0. Regarding humidity we faced the problem of multiple values for the same time. We solved this problem by using average values when we had multiple data for the same time.
The data was observed between 01.09.2021 and 31.09.2021.

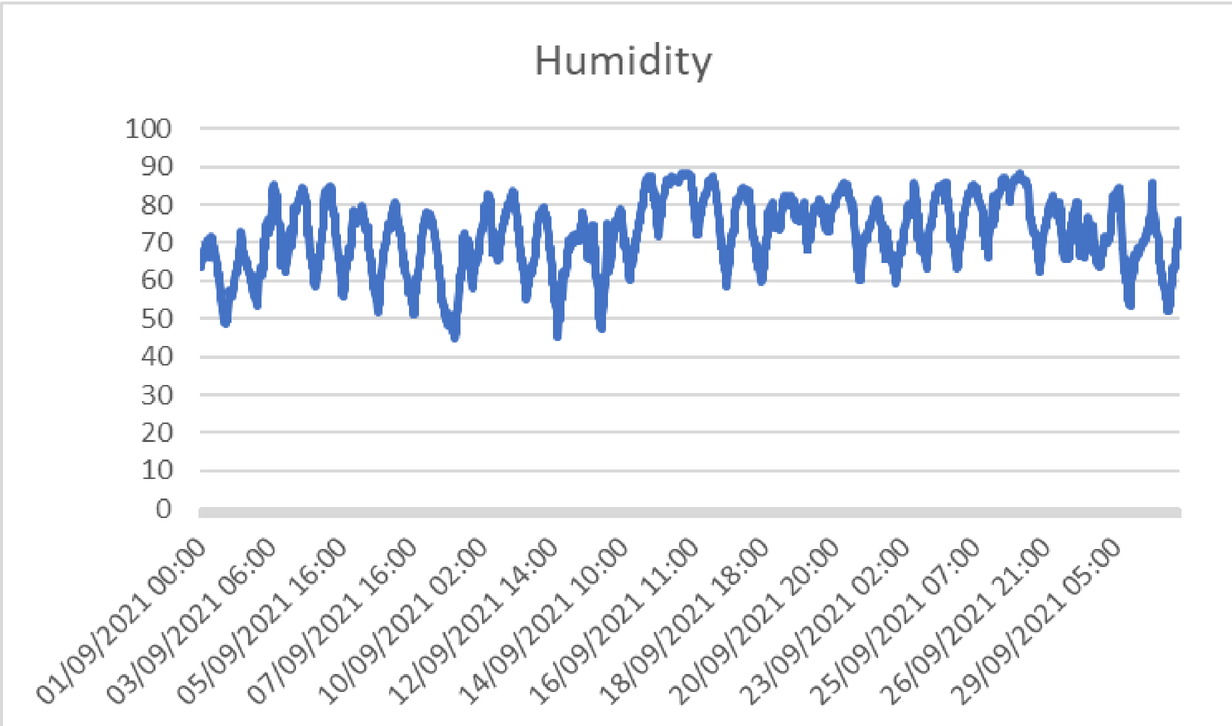
The electricity consumption, humidity, temperature and luminosity during this period can be observed in the following graphs.

1. Hourly Electricity Consumption



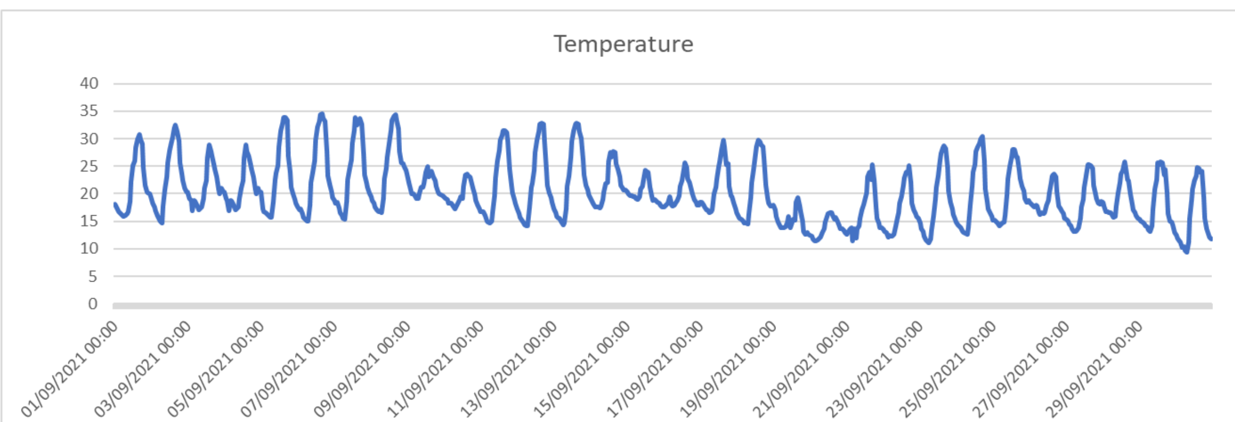
The hourly electricity consumption is measured in Wh.

2. Humidity



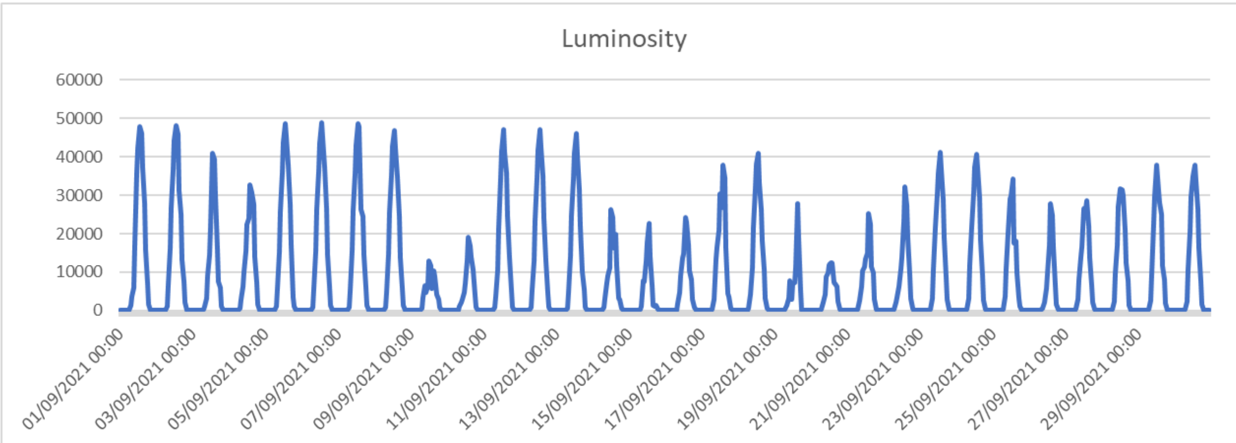
The humidity is measured in %.

3. Temperature



The outdoor temperature is measured in °C.

4. Luminosity

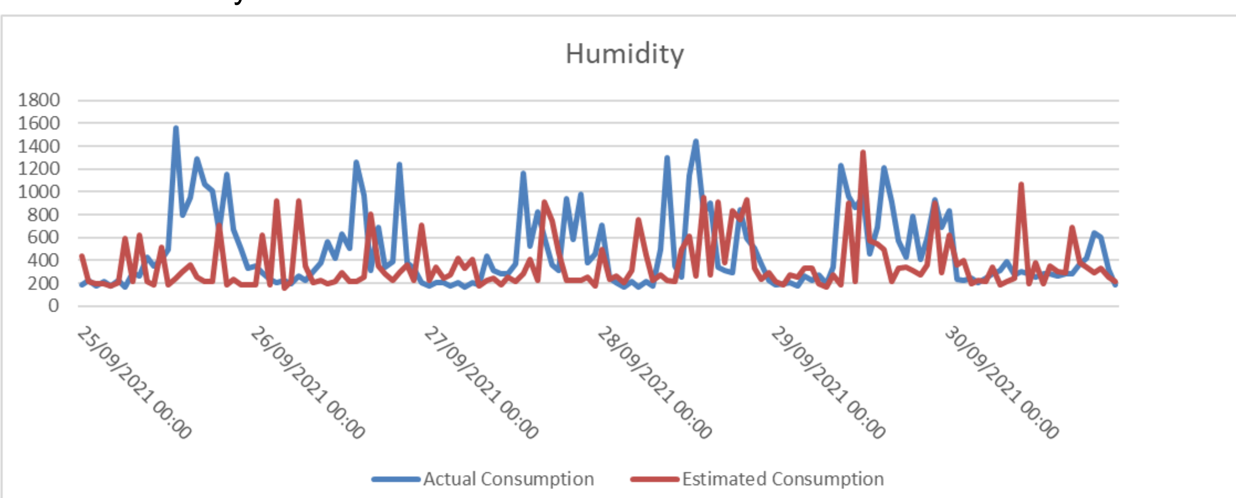


The luminosity is measured in lumen.

3. Results

The results of the predictions by the decision tree classifier are presented as follows. We used the three feature data humidity, luminosity and temperature and all possible combinations of them to predict the label “hourly electricity consumption”. The results show the actual and the estimated consumption between 25.09.21 and 30.09.21.

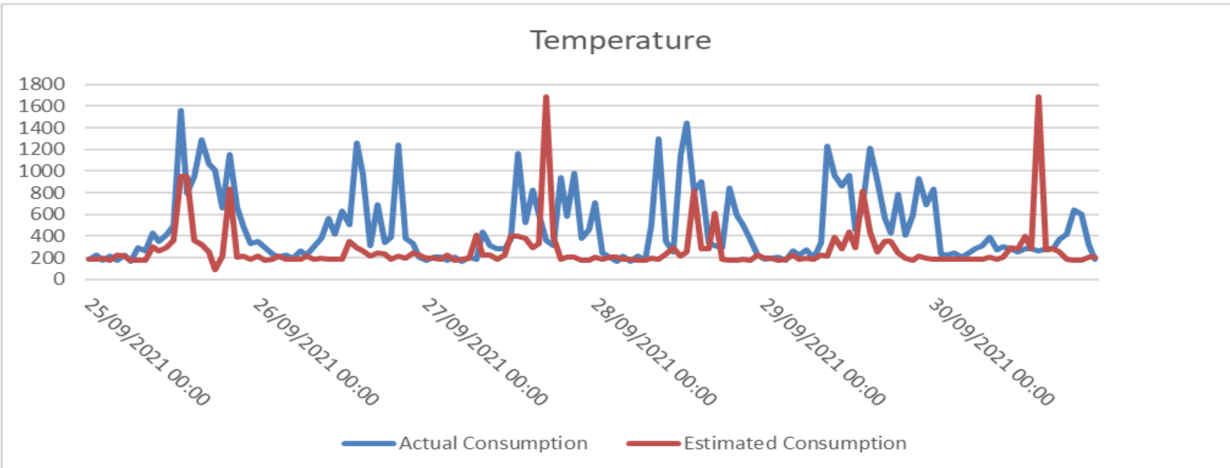
Feature: Humidity




```
Mean error is:  276.7083333333333
```

Humidity cannot really explain the electricity consumption very well. It is also not possible to identify any approximation of the estimated consumption to actual consumption.

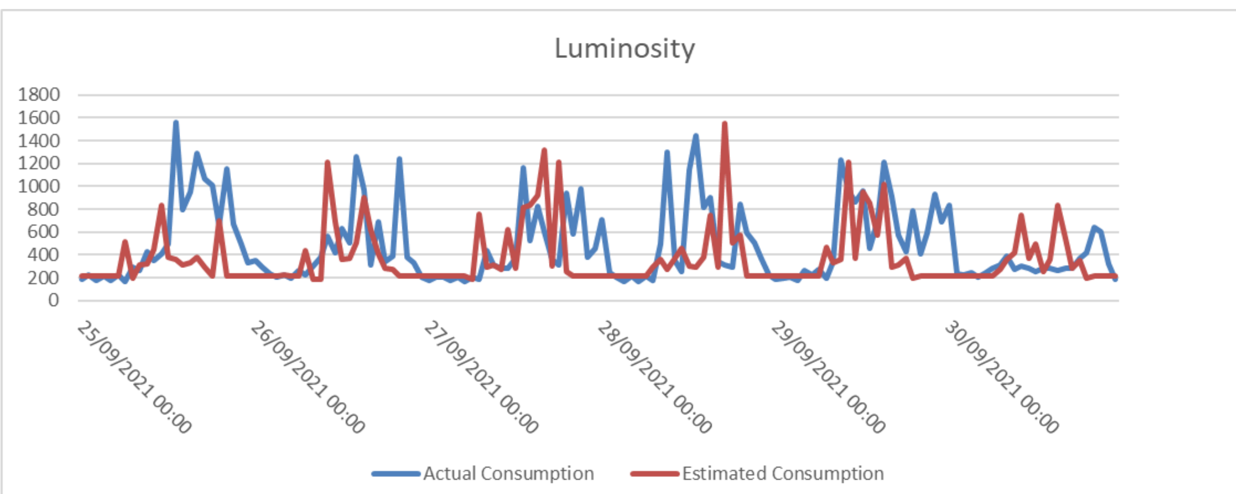
Feature: Temperature




```
Mean error is:  261.4236111111111
```

For temperature a trend of approximation can be identified. However, there are still strong deviating estimations.

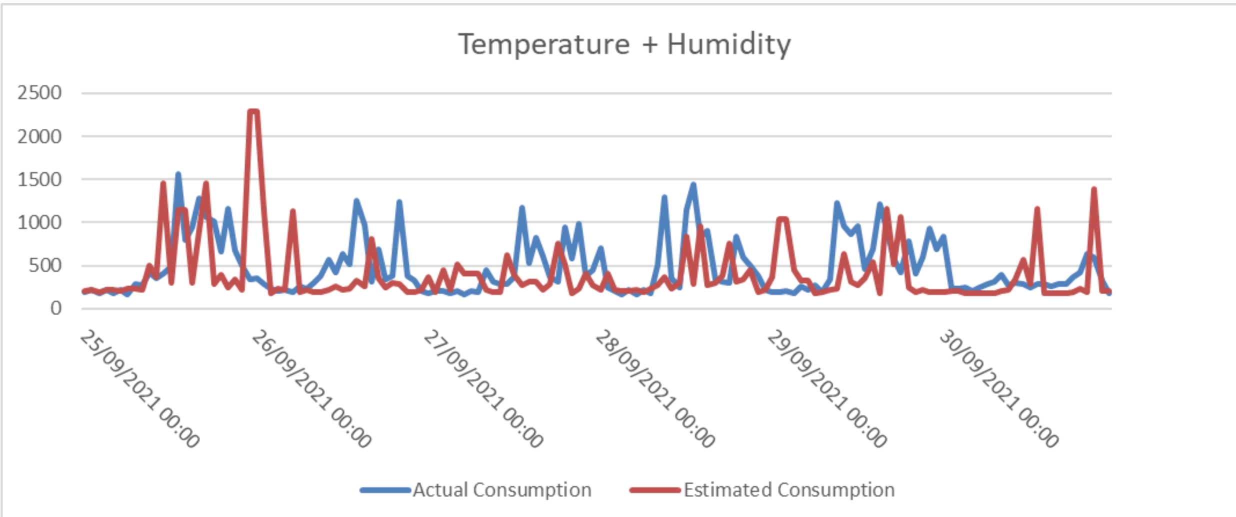
Feature: Luminosity




```
Mean error is:  252.11111111111111
```

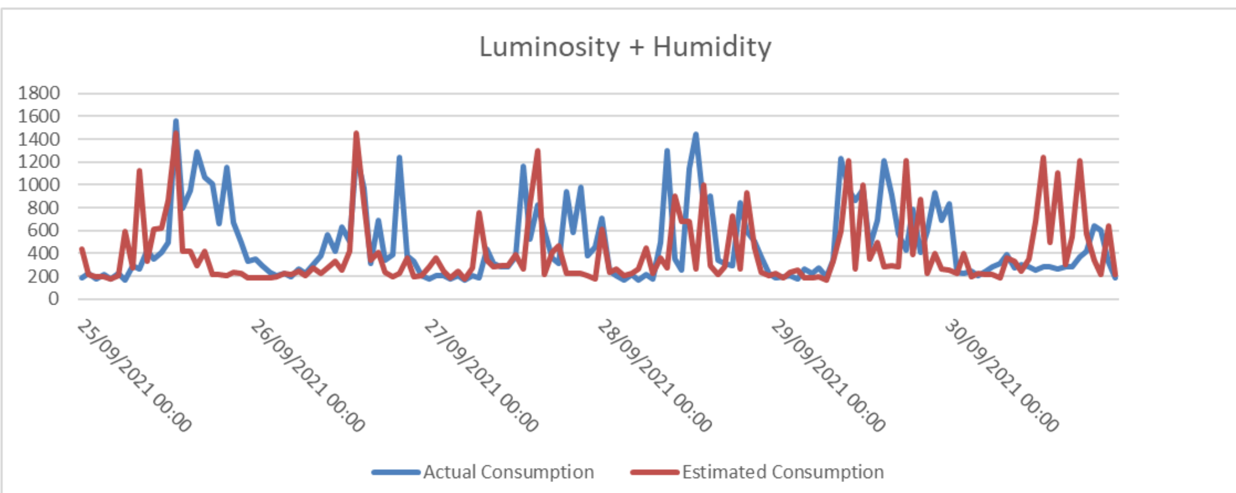
Luminosity can explain the electricity consumption quite well and an approximation of the estimated consumption to the actual consumption can be clearly identified.

Features: Temperature + Humidity



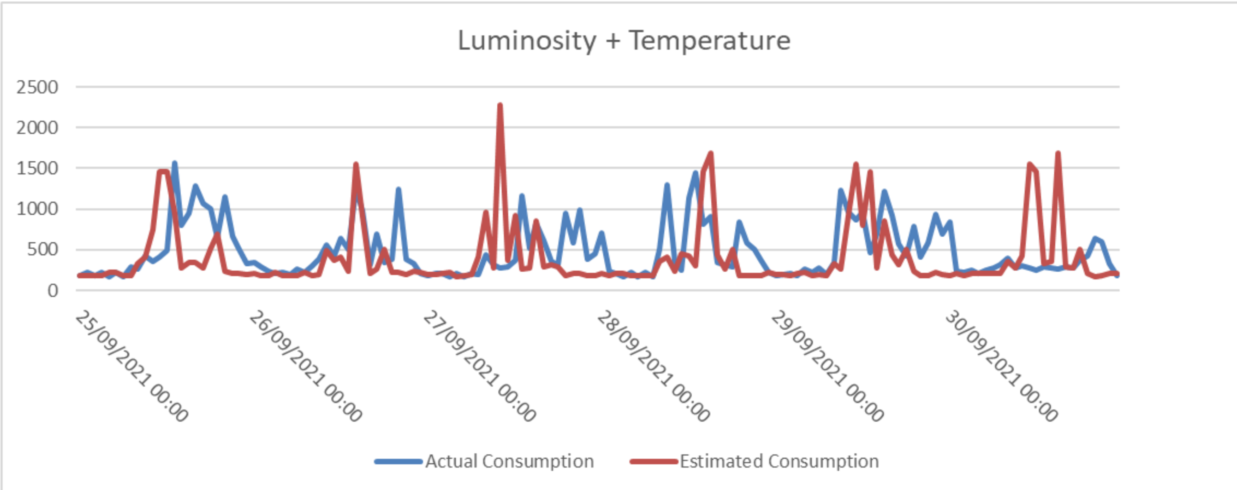

```
Mean error is:  308.55555555555554
```

Features: Luminosity + Humidity



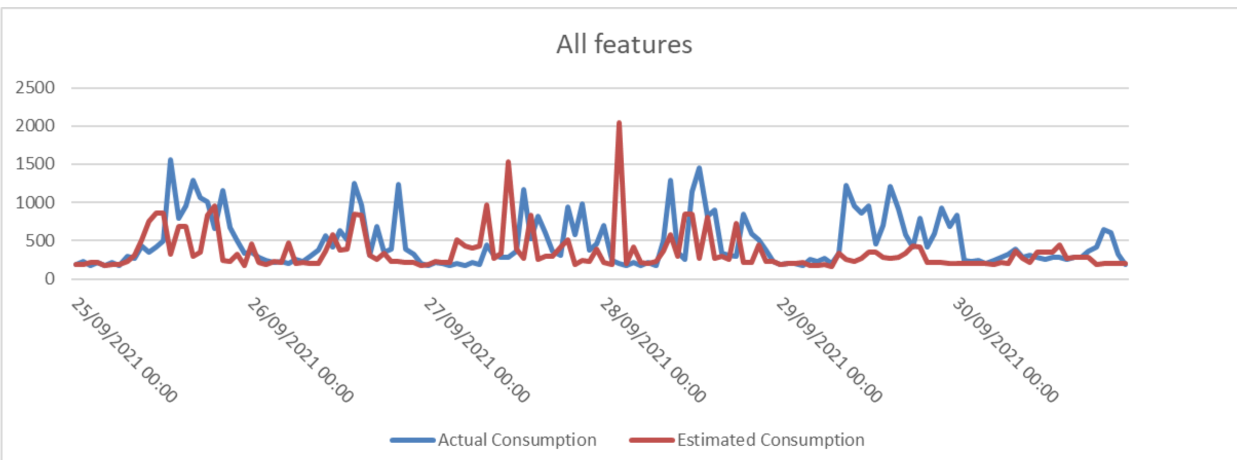

```
Mean error is:  259.75694444444446
```

Features: Luminosity + Temperature




```
Mean error is:  283.88194444444446
```

Features: Luminosity + Temperature + Humidity




```
Mean error is:  255.95138888888889
```

4. Conclusion

To summarize our results, we can conclude that luminosity gives us the best results and should be considered when doing electricity consumption prediction. This could be useful when coordinating demand and supply in a smart grid.

Temperature and humidity did not give very accurate results. We also tested different combinations of which luminosity and humidity performed best, but could not outperform luminosity alone. Surprisingly the combination of temperature and luminosity did not perform that well. We expect that strong intercorrelation between these two variables exists, that reduces the performance.

We must consider that the observed house is heated by gas. Which explains the relatively low influence of the outdoor temperature on the electricity demand. However, the heating system of many other buildings in France is based on electricity. And in the future the share of electricity based heating systems is expected to increase further due to a higher share of heat pumps. This will increase the influence of the temperature on the electricity demand a lot and we expect that temperature will then become the most important feature.