Kitchen Energy Optimisation

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1 Introduction

In a world where energy consumption and energy sobriety is more and more advocated, energy optimisation is more and more interesting. Some houses are already equipped by a lot of sensors, keeping a close watch on energy consumption. An inhabited house had been equipped by sensors in 2018, and data are available. This project called Expe-Smart House has been installed especially by G2Elab.
To optimise energy consumption of the house, kitchen energy use will be optimised. Indeed, heating of most of kitchen devices could be used to warm the room. So we will study the impact of the oven, dishes washer, washing machine and induction plates on the kitchen temperature.

2 Extraction of Data

First, to interpret data, we should extract it. So data had been download from Grafana to a Excel file. To do that, we launched a Python code to extract data with the ID of the studying sensor. It automatically saves it as a CSV file, than it can be opened in Excel. Data chosen at this moment had been extract from :

- Oven sensor,
- Washing machine sensor,
- Dishes washer sensor,
- Global energy consumption,
- Induction plates sensor

All this data had been extract with time memory. It means all the sensor data can be plotted in function of time.
Here comes the first issue : sensors do not save data at the same moment. For example, global energy sensor collect data every five or six minutes. In comparison, oven sensor collect data only if the oven consumption is different from zero, and with a different time step. So we manage to average out all the data in one hour. This had two main benefits. First, we can compare all the data with each other in Excel file. Secondly, it had reduced the number of line in Excel file, decreasing the complexity of the problem. Indeed, we extract data from 05/08/2022 to 05/23/2022. So, we had in the first times about 200.000 lines from global energy consumption. After this average in one hour, only about 400 values.
Estimating kitchen temperature in function of kitchen devices could see the influance of the different elements on kitchen temperature. This could be useful in winter, saving energy due to heating, in the kitchen.

3 Machine Learning

In this section, kitchen temperature will be estimated by machine learning. This learning had been coded with a decision tree algorithm.
First, we extract data from csv file to a .txt document. Then algorithm is trained with $N = 316$ values extract in different data set except global consumption. Result are shown in Figure 1. To know how this model is accurate, we introduced two indicators : average error (noted A_v) and accuracy (noted A_c). With this first attempt we found $A_v \simeq 1.36$ and $A_c \simeq 0.22$.

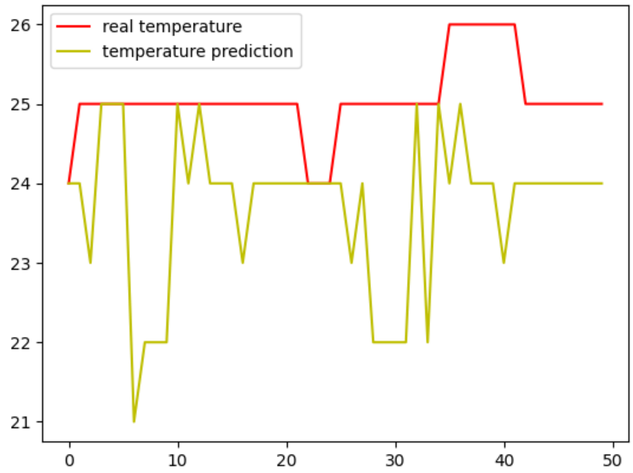

Figure 1: Estimation and real temperature in the room

As we can see in the Figure 1, our model is very inaccurate. We should make it better. To improve our model, maximum depth of the tree must be found. Due to a high depth of the tree, the algorithm over fit it results of training. Also, a smaller tree will be easier to analyse and to understand.

To know the best width of the tree, we plotted the accuracy and average error in function of the depth of the decision tree. Figure 2 is found. We can see that the optimal depth is 4. Even if maximum accuracy is for $width = 6$, it is stable, on contrary to error whose minimum is for $width = 4$ and quite high for $width = 6$. Later, width for decision tree will be 4.

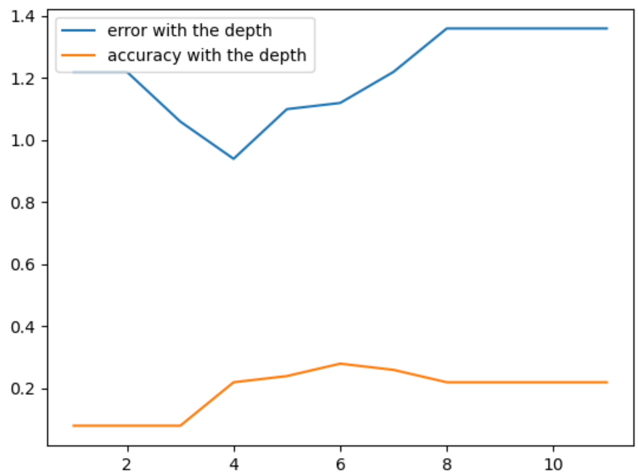

Figure 2: Average Error and Accuracy of our Decision Tree in Function of Depth

When the new estimation and real temperature are plotted, we found 3. Now $A_c = 0.22$ and $A_v = 0.94$. We can also see and analyse how the algorithm works. In Figure 4, it is shown the decision tree created during training phase. Most of the decision in Decision Tree are made with Washing Machine Consumption, it must be an essential feature. Moreover, decisions made with this feature have a lower entropy than others. So It is very effective way to estimate kitchen temperature, in about 20% of the cases.

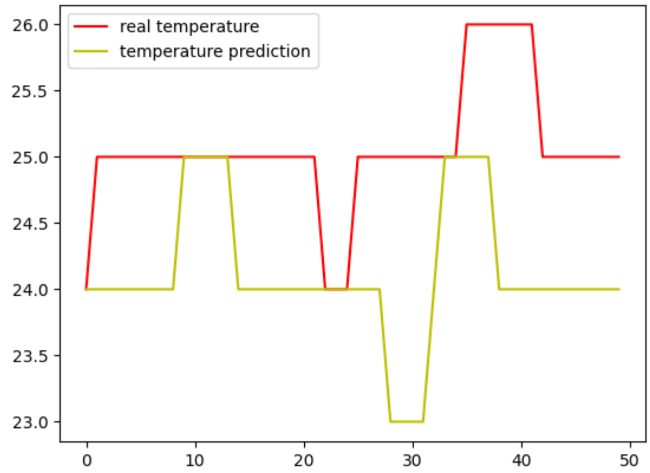

Figure 3: Estimation and real temperature of the kitchen for $width = 4$

4 Conclusion

This results are not sufficient. At least with the data used. There is two ways to explain why. First one, the algorithm must be trained with more data. Second one, the temperature could be estimated with difficulty because it does not have a big link with the different features. A way to choose the best explication is to increase the data for training.
Another elements which could be modified to improve the results is to take data during winter period. So we could compare heating from heating system and from different devices of the kitchen. It could actually be a big way to improve the results : the aim of this study is optimise kitchen heating. The only think we can conclude with this study is this system is ineffective from spring to autumn.

5 Appendix

5.1 Appendix 1 : Decision Tree

In this Figure 4, we have :

Feature	Meaning
X[0]	Hour
X[1]	Oven
X[2]	Dish Washer
X[3]	Induction Plates
X[4]	Washing Machine

Table 1: Features and Meaning of Figure 4

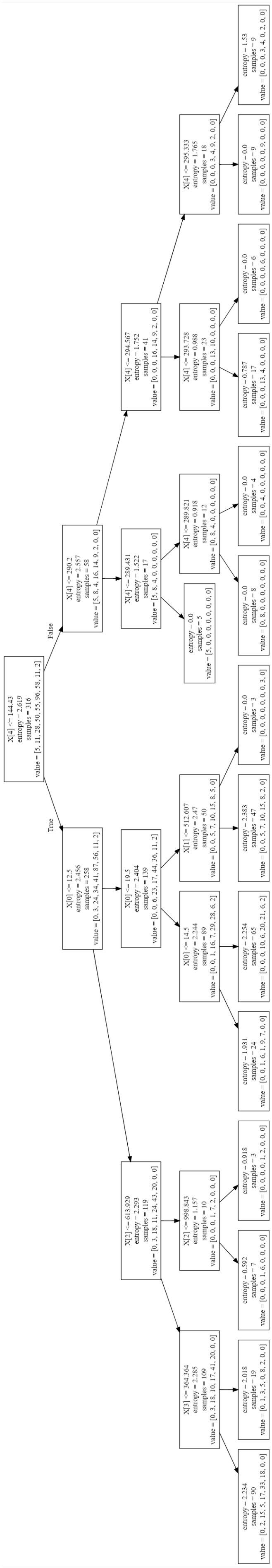

Figure 4: Decision Tree