OPTIMIZATION *VIA* ARTIFICIAL INTELLIGENCE OF INTUMESCENT COATING FOR WOOD SUBSTRATES

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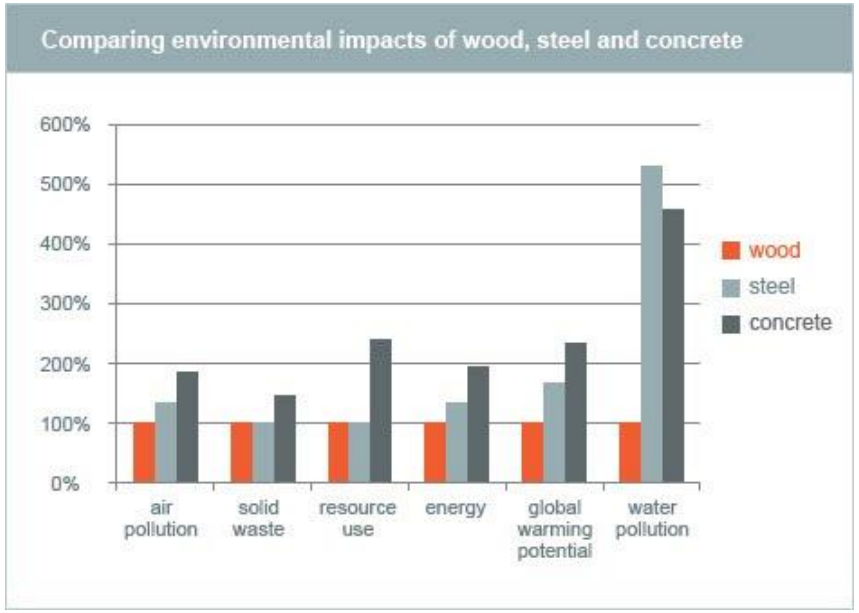
02/12/2022

Introduction

Wood is more and more used in building applications

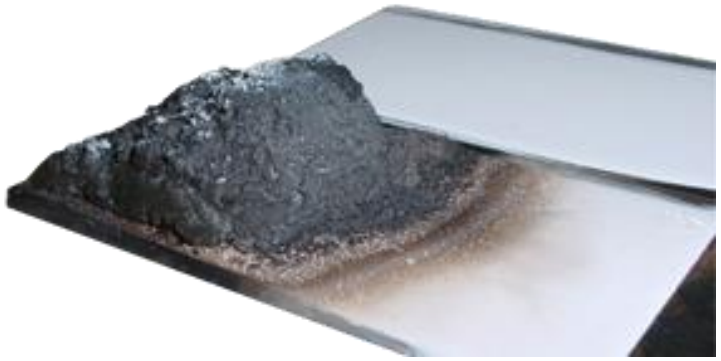
Low grey energy compared to traditional materials

How to protect efficiently wood against fire ?

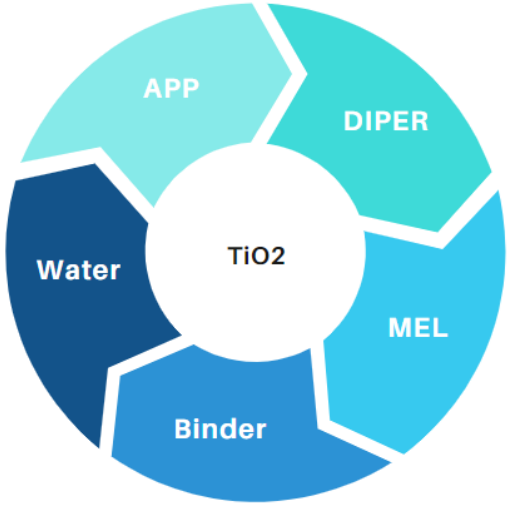


Our strategy

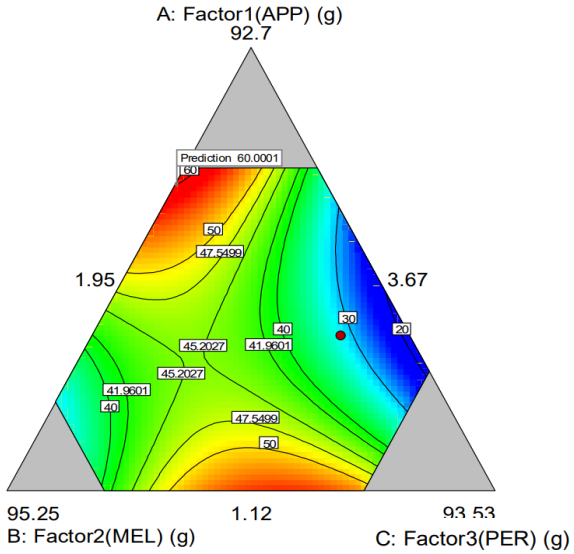
Intumescent system very efficient



Composition of the FR paint



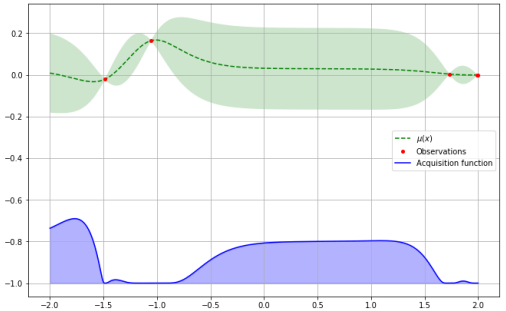
Design of experiment (DoE) : lot of test in high dimension



Dimension 6 in our case study

Machine learning

Optimisation of the chemical composition of an intumescent coating



Bayesian optimisation

Can we optimise better and faster with AI ?

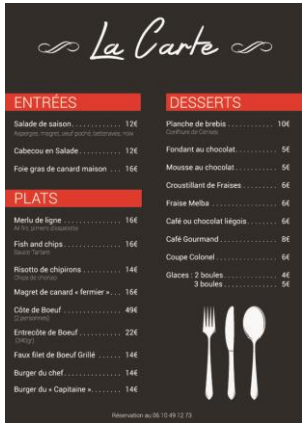
Weil, Edward D. "Fire-protective and flame-retardant coatings-A state-of-the-art review." Journal of fire sciences 29.3 (2011): 259-296.
Kotthoff, L., Wahab, H., & Johnson, P. (2021). Bayesian Optimization in Materials Science: A Survey. arXiv preprint arXiv:2108.00002.

What is machine learning?

Machine learning = Data driven prediction

Unknwon picture

Machine learning algorithm



Unsupervised learning
-
Unlabeled data

MACHINE LEARNING

Supervised learning
-
Labeled data

Ex :Spam identification

Classification

Ex : trading prediction

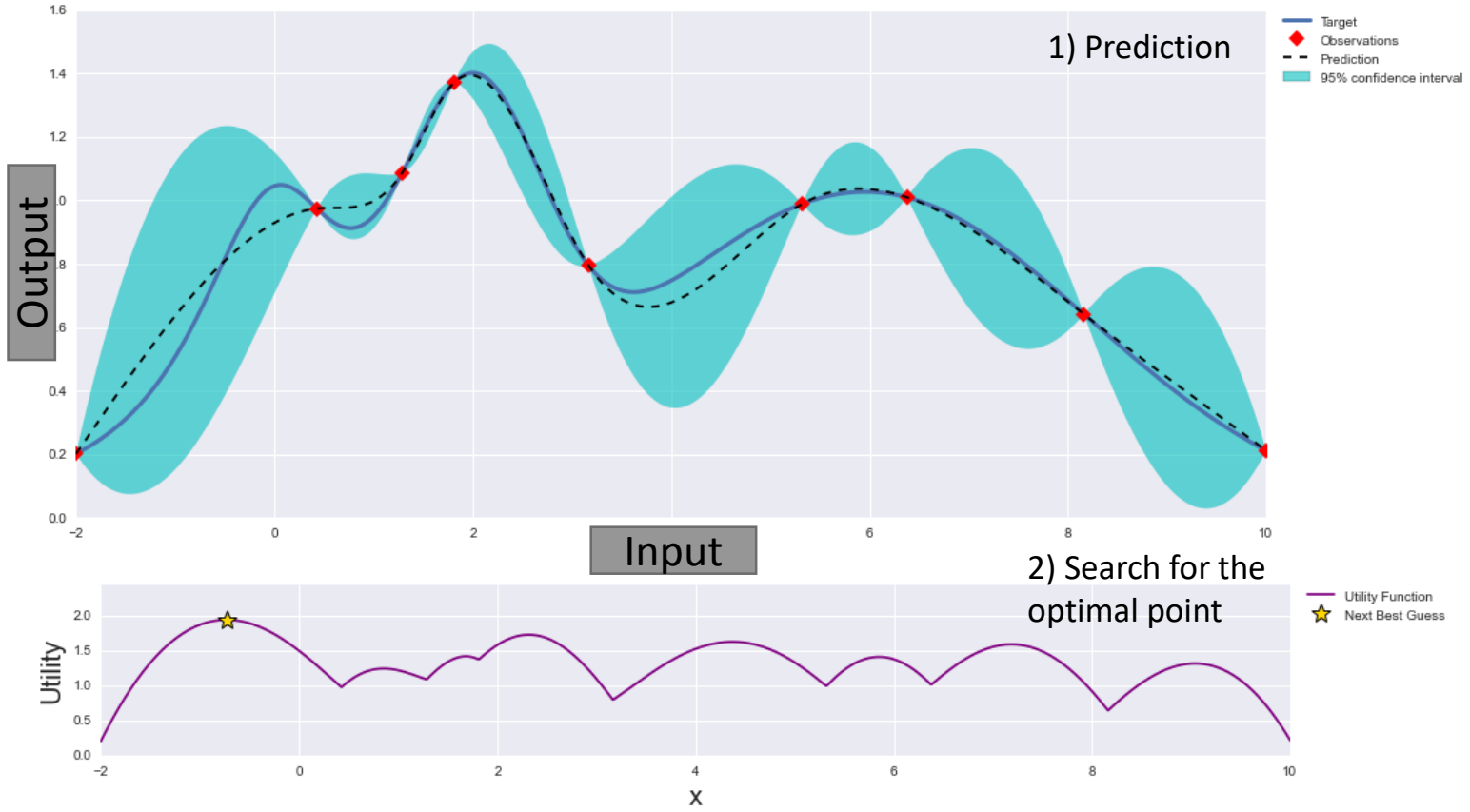
Regression

Reinforced learning

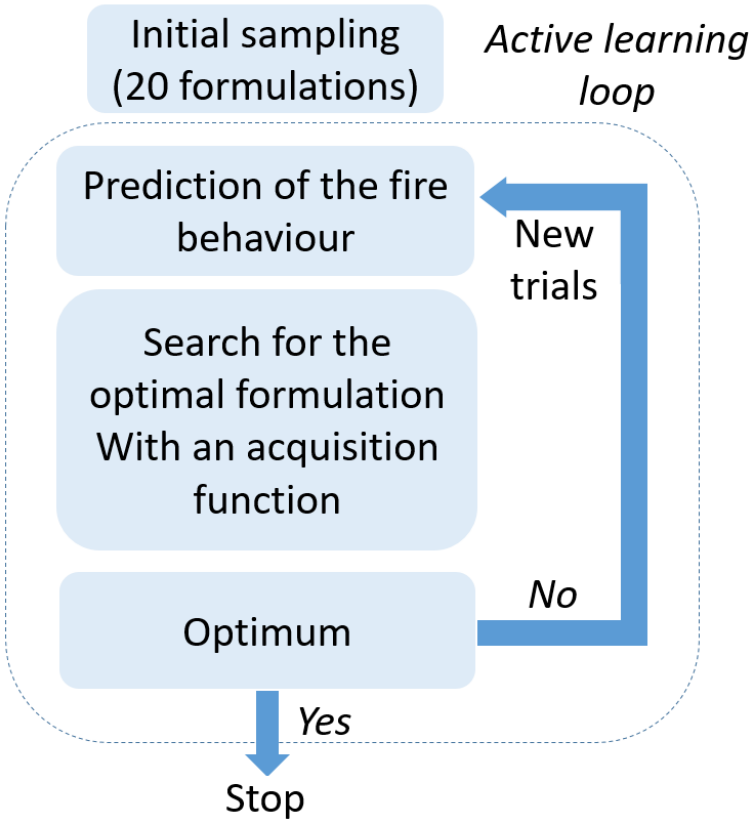
Learning from mistakes

Robotic

What is bayesian optimisation ?



Our pipeline



Why using Bayesain optimisation ?

- Noisy data
- Small dataset
- Cost function evaluation

Experimental Design *via* Bayensian Optimisation (EDBO)

Parameter of the dataset

%wt

0,35 < water <0,45
0,10 < Binder <0,20
0,20 < APP <0,30
0,05 < DIPER < 0,15
0,05 < MEL < 0,15
0 < TiO_2 < 0,10

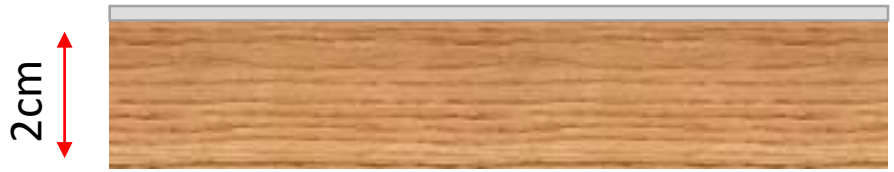
$$\sum_i x_i = 1$$

20 formulations randomly chosen

Conditioning

Before coating : 7 days at 30°C and 40%HR
After coating : 7 days at 30°C and 40%HR

Constant dry Coating : 230g/m²



White fir

Input

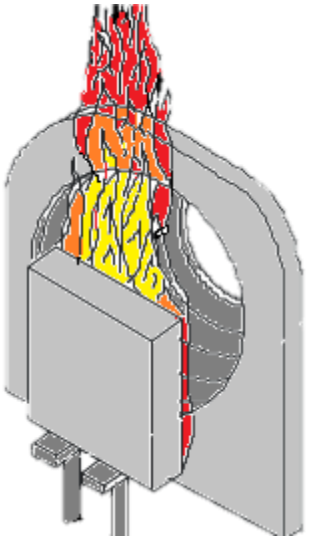
weight percentage of each component (*%wt*)

Fire test

Evaluation of the coating at lab scale

Horizontal cone calorimeter

Vertical cone calorimeter



1. Total heat release
2. Peak of heat release
3. Time of ignition

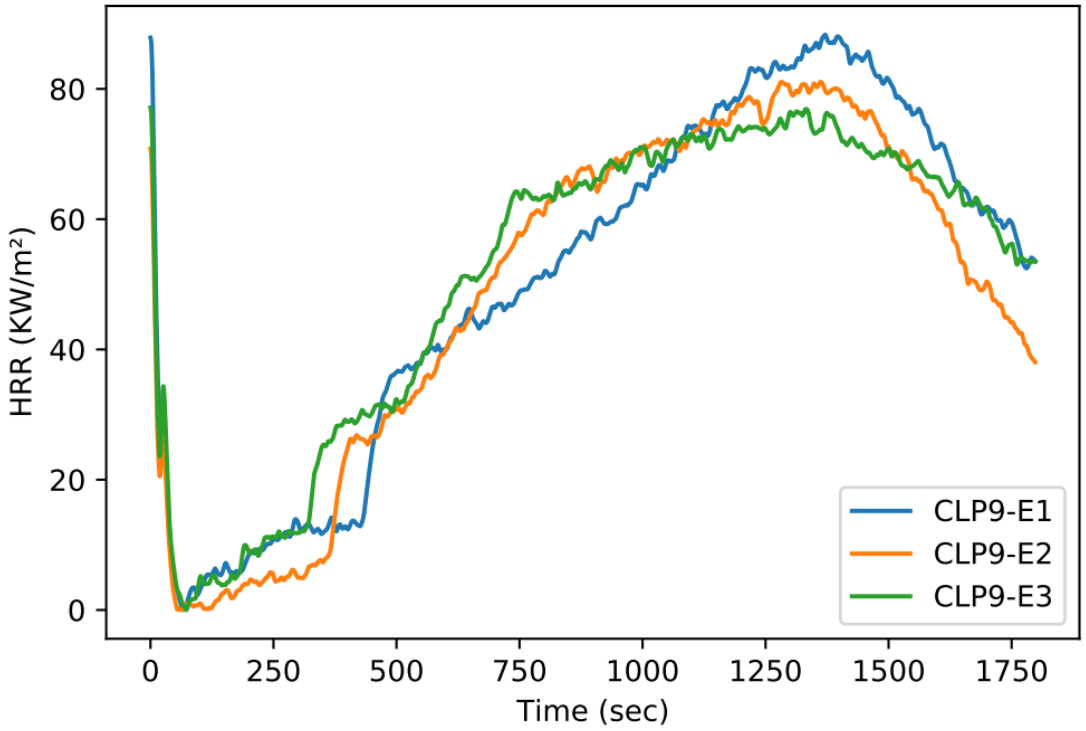
4. Time of ignition
5. Mass loss rate

Dewaghe, C., Lew, C. Y., Claes, M., Belgium, S. A., & Dubois, P. (2011). Fire-retardant applications of polymer–carbon nanotubes composites: Improved barrier effect and synergism. In *Polymer–carbon nanotube composites* (pp. 718-745). Woodhead Publishing.

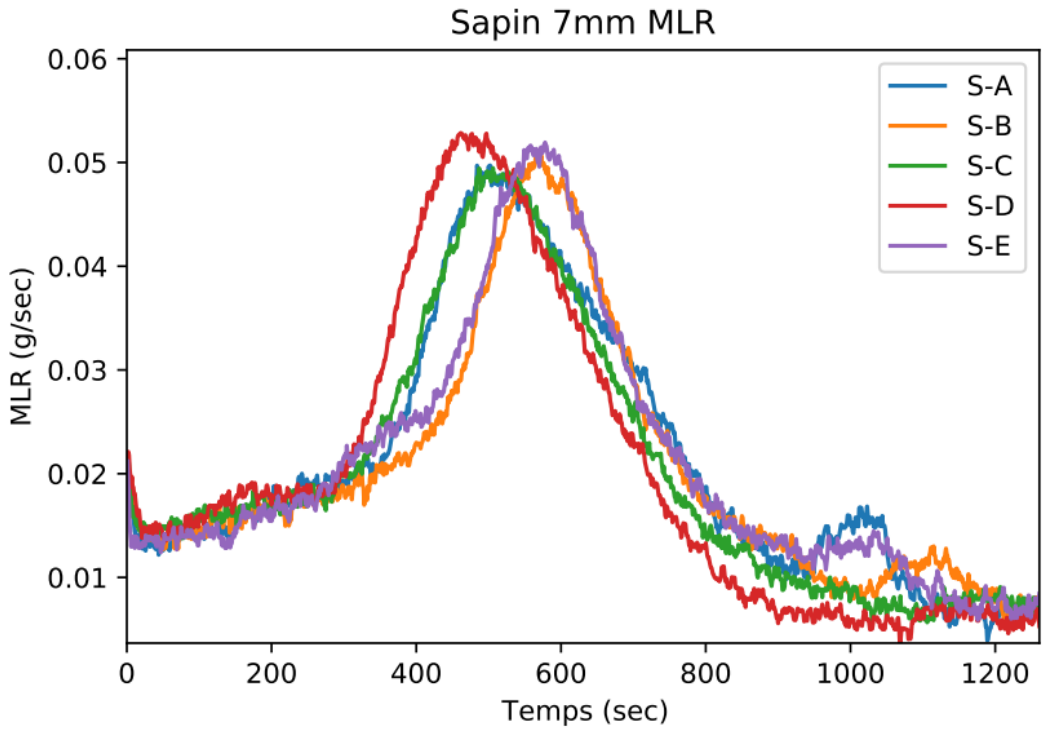
Cone calorimeter testing

Horizontal MLC

- Heat flux : 50 kW/m²
- Test time : 30 min
- Mesurement of the heat released : Thermopile



Vertical MLC

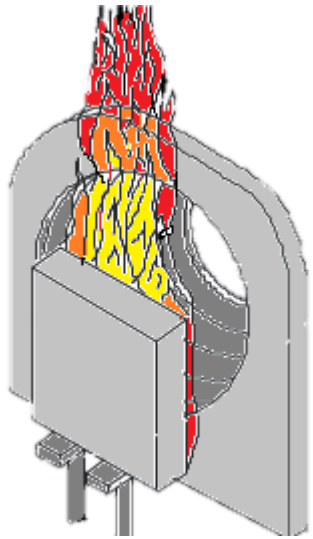


Fire test

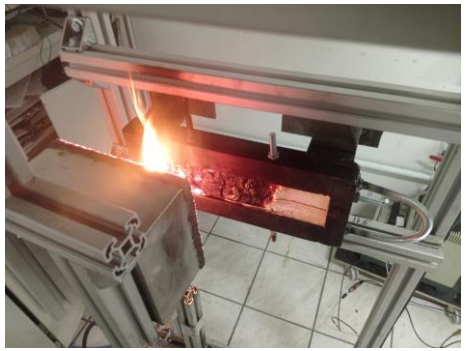
Evaluation of the coating at lab scale

Horizontal cone calorimeter

Vertical cone calorimeter



CFE scale 1/3



1. Total heat release
2. Peak of heat release
3. Time of ignition

4. Time of ignition
5. Mass loss rate

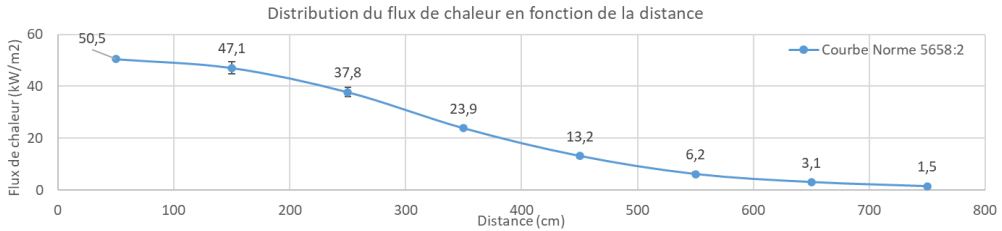
6. Preserved area
7. Flux of charbonisation

Multi criteria performance

Output : performance index = Σ of 3 fire tests
Multi criteria optimization

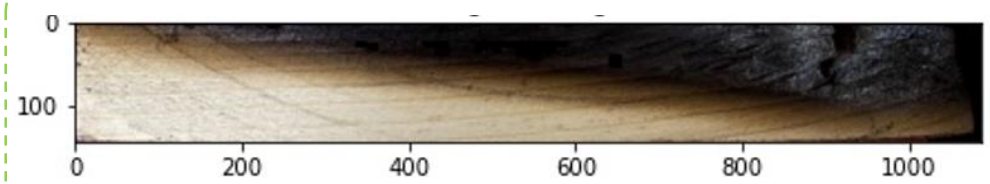
Dewaghe, C., Lew, C. Y., Claes, M., Belgium, S. A., & Dubois, P. (2011). Fire-retardant applications of polymer–carbon nanotubes composites: Improved barrier effect and synergism. In *Polymer–carbon nanotube composites* (pp. 718-745). Woodhead Publishing.

Critical heat flux at extinguishment (CFE)



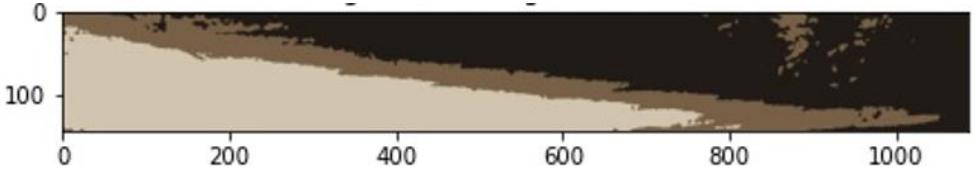
Machine learning algorithm = Image segmentation

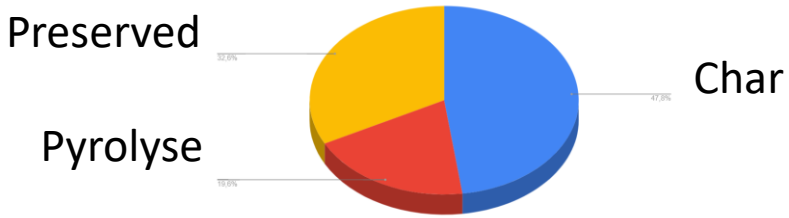
Input



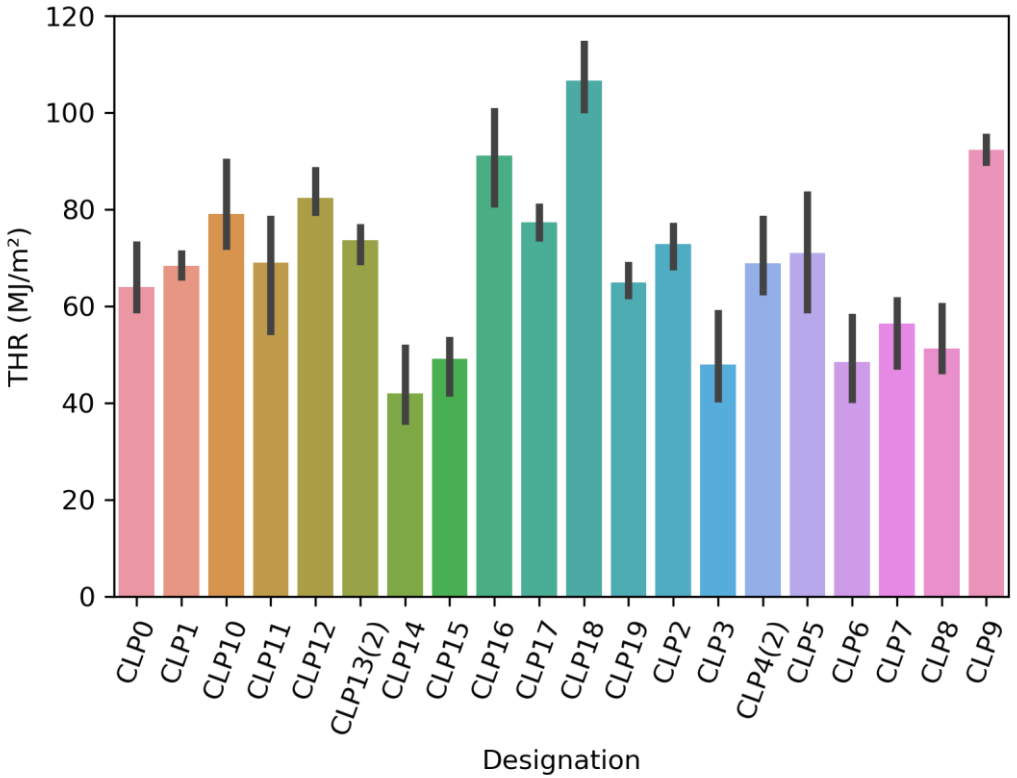
Output

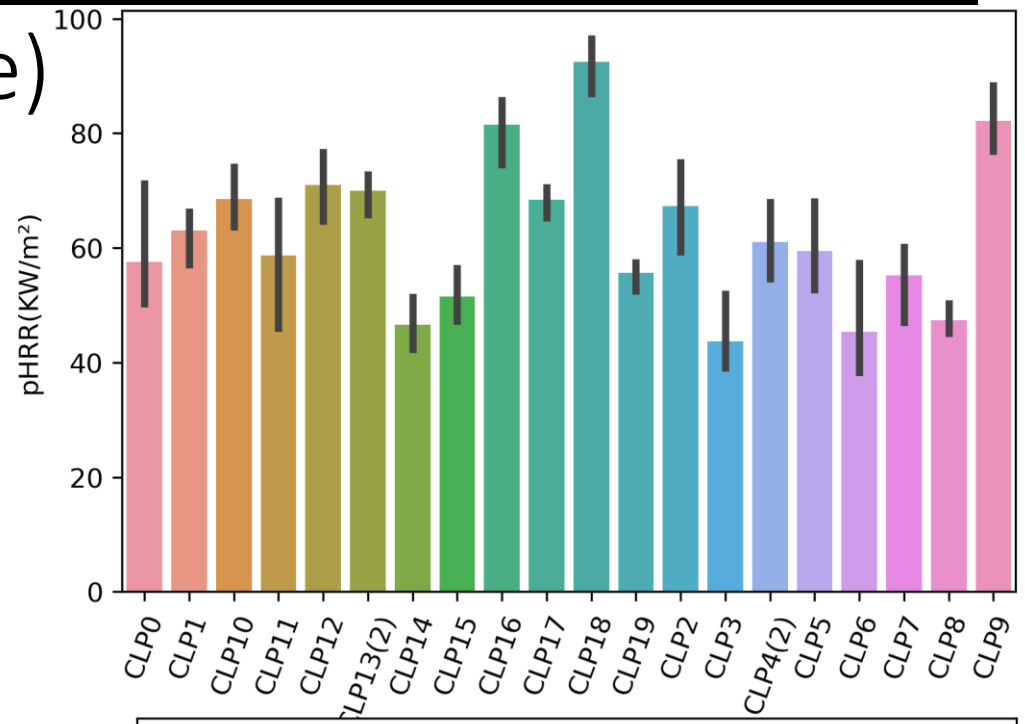
Identification of the preserved area

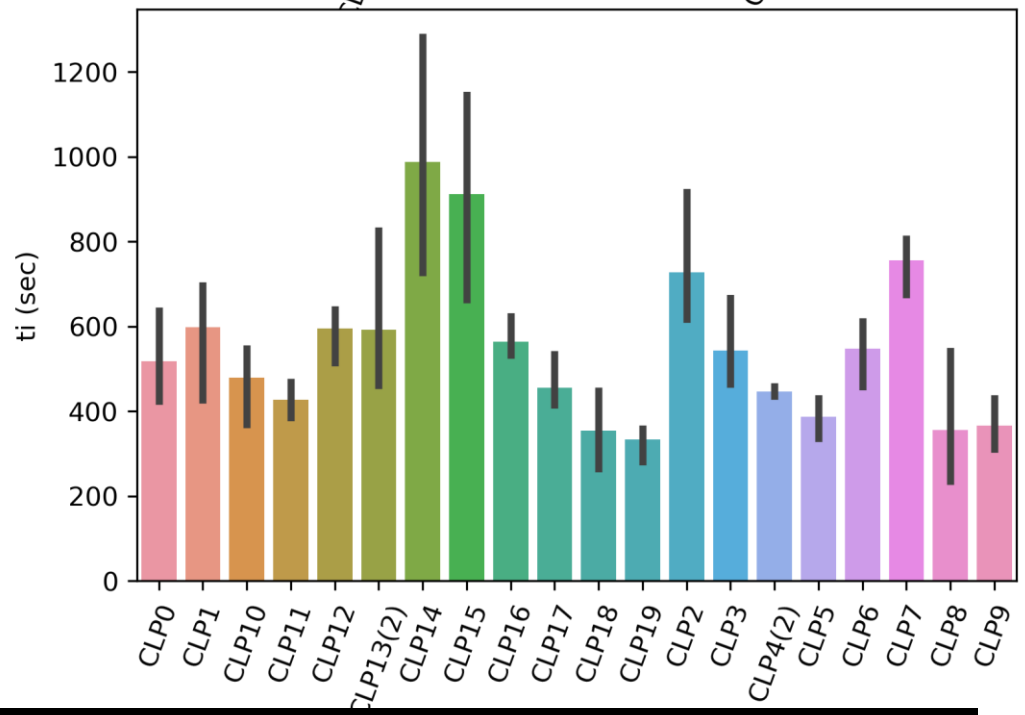




First results (Horizontal cone)







High variance for the time of ignition

Conclusion

- Simple intumescent coating as case study
- The performance of the coating is evaluate by 3 fire tests giving 8 parameters of performance and finally a Performance Index (work in progress)
- Experimental design via Bayesian optimization (EDBO) has been chosen to find the optimum configuration of the paint and minimize the number of samples

Outlooks

- Comparison of the Gaussian process with traditional machine learning method
- Comparison of the experimental design via Bayesian optimisation with design of experiment (DoE)

GitHub

Futur of AI and fire

ELSEVIER

Chemical Engineering Journal

Available online 23 November 2022, 140547

In Press, Corrected Proof

Machine learning-guided design of organic phosphorus-containing flame retardants to improve the limiting oxygen index of epoxy resins

Zhongwei Chen [a, b], Boran Yang [a], Nannan Song [a], Tingting Chen [a], Qingwu Zhang [a], Changxin Li [a], Juncheng Jiang [a], Tao Chen [b], Yuan Yu [a] ✉, Lian X. Liu [b] ✉

AI for fire retarded materials

- Data guided design
- First iteration of creation of a dataset for fire retarded materials

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Fire Safety Journal

Volume 130, June 2022, 103591

Machine learning-based surrogate model for calibrating fire source properties in FDS models of façade fire tests

Hoang T. Nguyen [a], Yousef Abu-Zidan [a, b] ✉, Guomin Zhang [a], Kate T.Q. Nguyen [a]

Numerical simulation

- Calibration of numerical models
- Fast development of numerical model
- Surrogate model for cost functions

Thank you for your attention !