Testing for Knowledge

Maximising Information Obtained from Fire Tests by using Machine Learning Techniques

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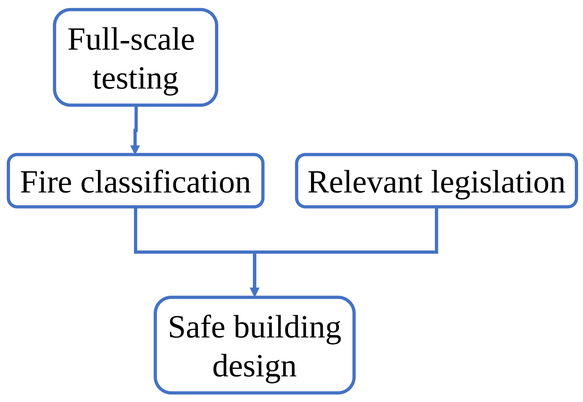
Full-scale testing

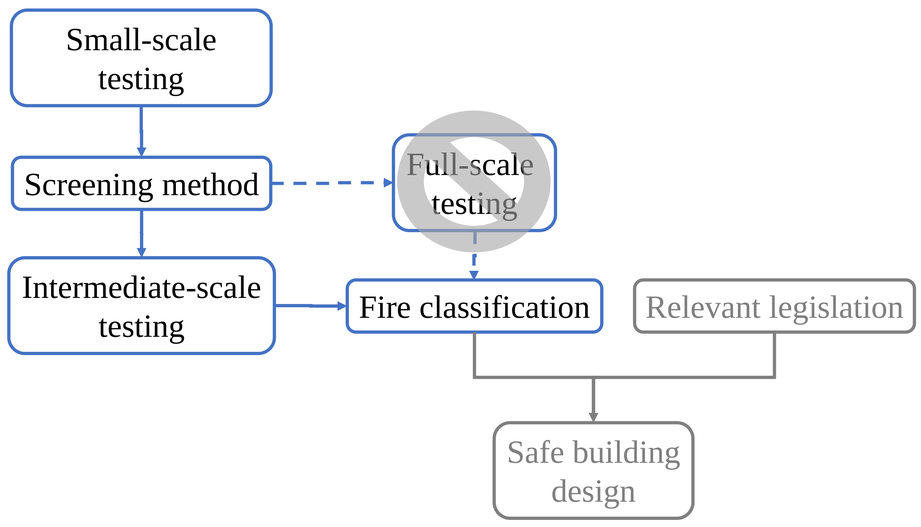


Safe building design is obtained through:

- Fire classification, and
- Relevant legislation

The classification of a product should in principle be deduced from its behaviour to fire in a scenario that represent **the end-use situation**, i.e., a full-scale test.

Current optimization of full-scale testing



Because large scale-tests are often costly and labour intensive, the follow strategies were developed to allow for efficient product development:

- **Screening methods** were designed to make a prediction about a materials full-scale fire behaviour, based on small-scale tests.
- **Intermediate-scale testing** can be used, in certain scenarios, to replace full-scale testing.

Optimization challenges

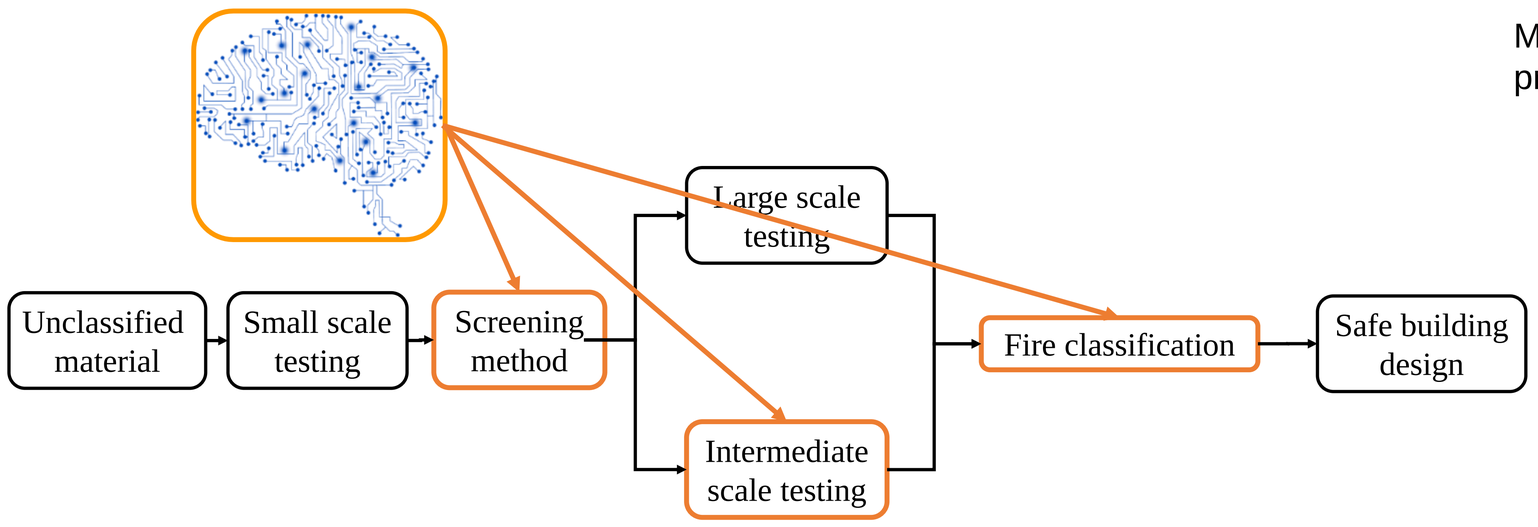
Challenges of current screening methods:

- The algorithms are **not accurate** enough to allow for efficient product development.
- The algorithms **cannot be adjusted** fast enough to cope with innovative materials and design solutions.

Challenges with scaling-down strategies:

- A **knowledge gap** persists on the interaction of fire growth and combustible linings in an enclosure, which could lead to misclassification of (innovative) materials.
- Intermediate-scale testing is **still too cumbersome** to allow for efficient product development.

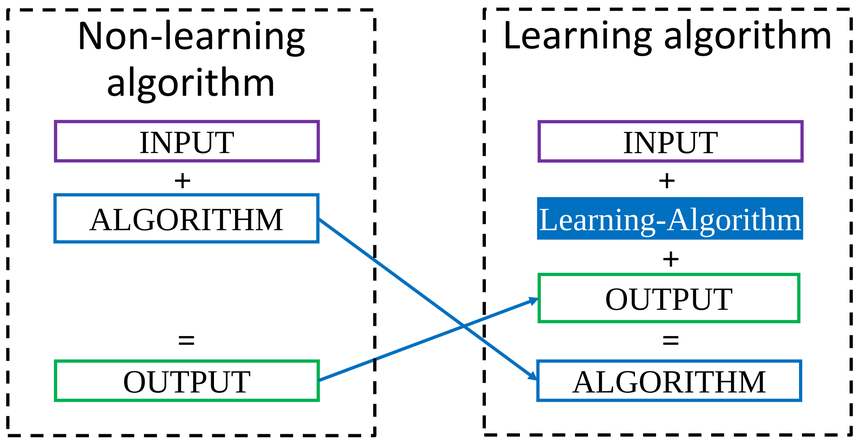
Can machine learning contribute?



Machine learning could provide a possible solution for the problem at hand in a variety of ways:

- **a new screening method** with higher accuracy so that full-scale testing only has to be done once, or ideally, not anymore.
- machine learning can aid with devising **a new intermediate-scale test** for innovative linings and design solutions.
- machine learning can be used to devise **a new classification system** that would allow to accurately rate the fire performance of materials.

A new screening method

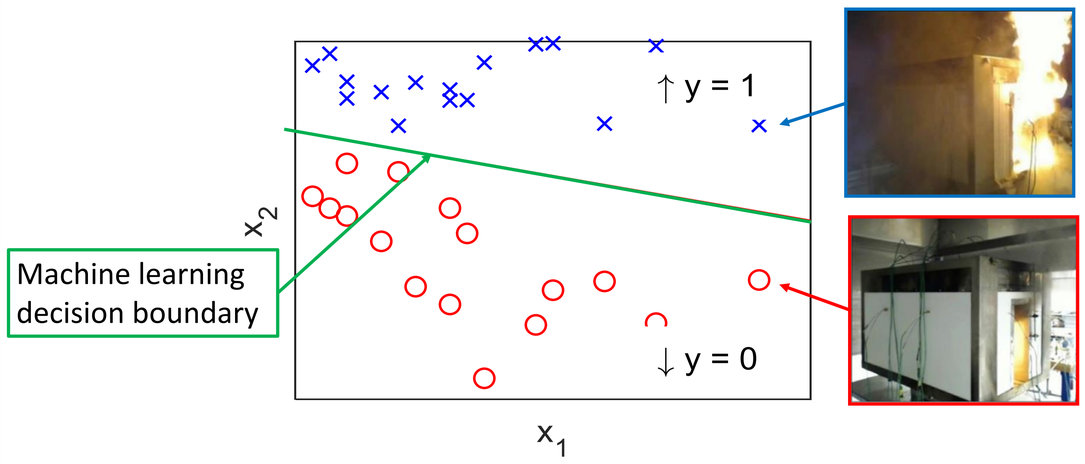


The non-learning algorithm takes the input – or data – it is given, does with it what it was programmed for and spits out the result. Machine learning turns this around, the input and output are given to the learning-algorithm, and the result is the algorithm that turns one into the other. In short, Learning-algorithms are algorithms that make other algorithms.

It is foreseen that, machine learning will proof to be a viable alternative to current screening methods for the following reasons:

- Machine learning possesses the **capability to learn by way of observation and experience,** rather than by using rigid prescribed equations.
- The learning-algorithm itself can be **surprisingly simple** but can easily prompt different programs that are magnitudes more complex for varying inputs and without the interference of the machine learning expert.

A new intermediate scale test



At Interflam 2019, a learning algorithm was proposed which could:

- **identify new test conditions** that would result in the greatest knowledge benefit
- **pinpoint the experimental parameters** which were relevant for the outcome

A new classification system

Machine learning could provide a **probabilistic performance parameter**, which would allow the user to make an informed decision between materials that are currently grouped within the same Euroclass.

Conclusion

The flexibility of ML algorithms is unmatched in current models. As such, it might proof to be the way forward for an ever-changing application of innovative materials and design solutions. Furthermore, it is foreseen that when enough data becomes available the machine learning algorithm will be able to produce more accurate results than contemporary models.