AI-Based Material Parameter Prediction for Fire Propagation Analysis

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Introduction

This study aims to explore various AI-based methods for predicting material parameters, which play a crucial role in fire propagation. These parameters are essential for numerically modelling the dynamics of fire propagation, particularly heat transfer and pyrolysis. In general, the determination of these parameters is challenging. Material parameters are often obtained indirectly through experiments such as TGA (thermogravimetric analysis) and cone calorimeter tests, which record values like mass loss rate, local temperature, or ignition time. Further, material parameters can be estimated via techniques like inverse modelling [1], which is computationally expensive and time-consuming as the optimisation process needs to evaluate the fire model very often. Or, as presented in our previous work [2], with a random forest method for TGA data for up to three different pyrolysis reactions.

Employing trained and evaluated AI models for the prediction of pyrolysis parameters offers the advantage of fast predictions, typically taking only some seconds once provided with HRR curve values. However, a significant hurdle lies in the acquisition of appropriate training data, as experimental data for this purpose is often scarce and limited in availability.

Methodology

The first step involves creating an expanding database that includes experimental data and simulation data generated using FDS (Fire Dynamics Simulator) [3], both on the micro-scale (e.g. TGA, MCC, etc.) and the bench-scale (e.g. cone calorimeter). The evaluated AI models are trained on this data to predict material parameters. The validation of the AI models and calculation of uncertainty in the predictions are based on experimental data.

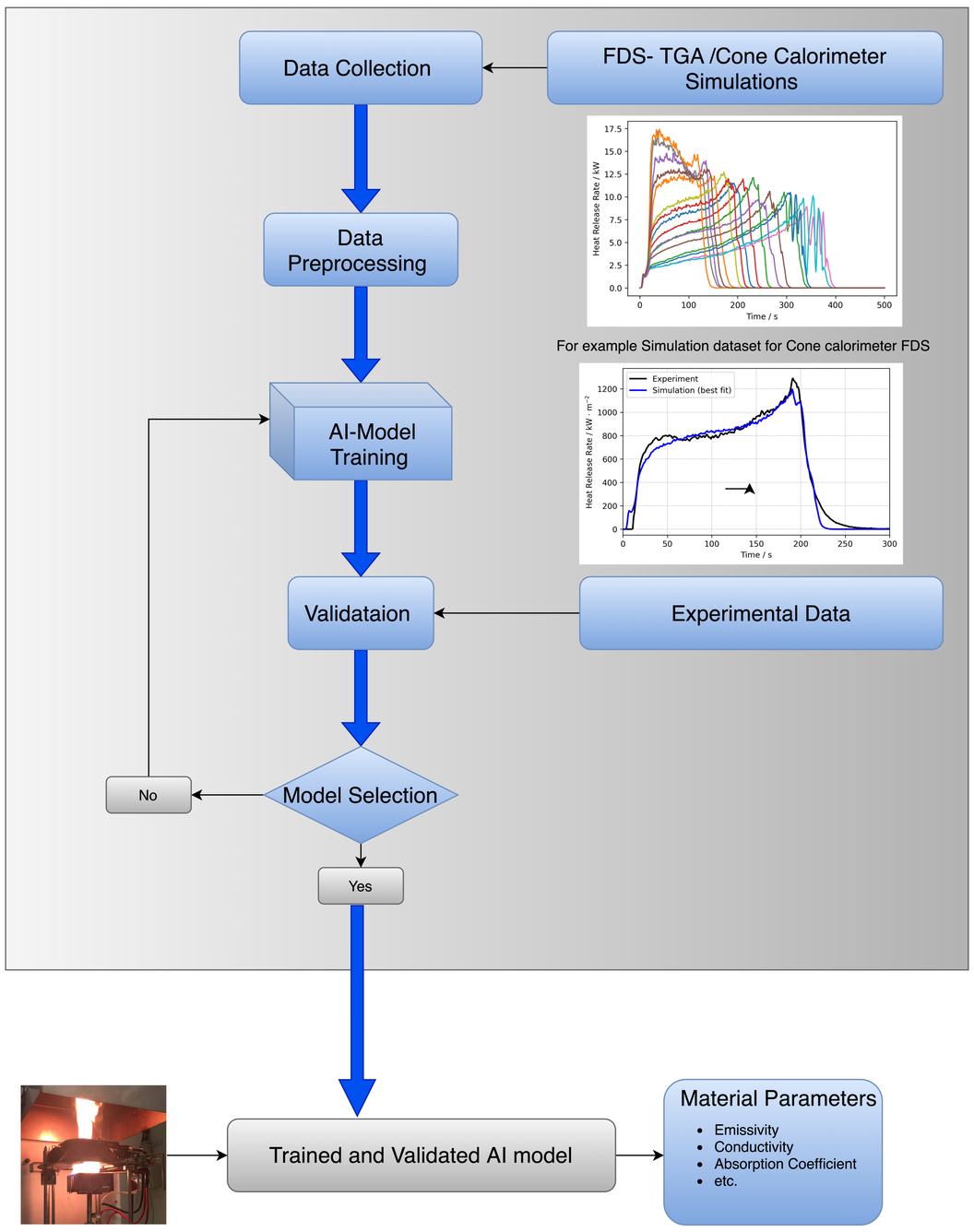


Figure 1: *General steps in material parameter predictions using AI models*

Sandbox for Model Testing: HRR Curve Imitation

A synthetic dataset is constructed by employing a mathematical equation governed by eight parameters to emulate the characteristic shape of the Heat Release Rate (HRR) curve obtained in cone calorimeter experiments .

# Parameters for the Gaussian curve
A = Amplitude
mu = Mean
sigma = Standard deviation

# Parameters for the smooth top hat function
k1 = Steepness of the rising edge
k2 = Steepness of the falling edge
x0 = Center of the rising edge
x1 = Center of the falling edge
h= height

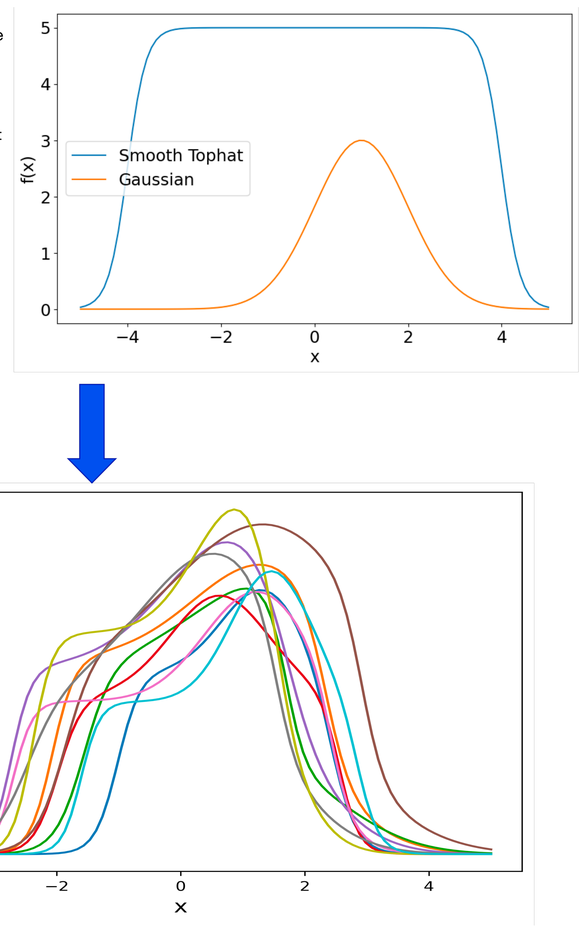
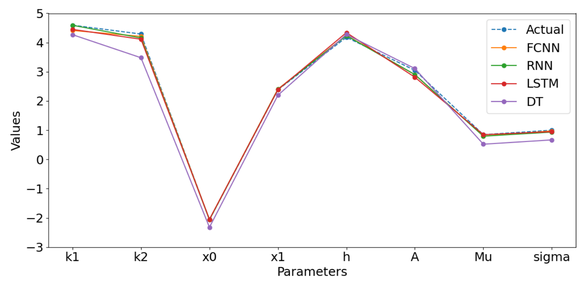
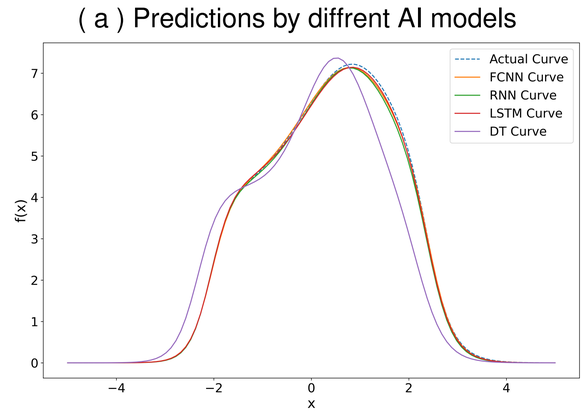


Figure 2: *Curve in shape of synthetic cone calorimeter HRR curve, created from mathematical equation*

Subsequently, this synthetic dataset is utilized as the training data for four distinct artificial intelligence (AI) models: Fully connected Neural Network, Decision Tree, Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) models. AI models like classic RNN and LSTM are well suited for time series data and capturing underlying relationships.The primary objective of training these models is to predict the eight parameters corresponding to each individual curve represented in the synthetic dataset.



(a) Predictions by diffrent AI models



(b) Curves from the predicted parameters

Figure 3: *Example of predicted parameters and curves generated by predicted parameters for different AI models*

Conclusion

The results obtained from the model testing presented above are promising, as they affirm that AI models, when tailored to our specific problem through fine-tuning, have the potential to provide accurate material parameter predictions. This method, which may be used in conjunction with or as an alternative to inverse modeling, presents a highly promising and efficient means of attaining precise material parameter predictions.

Reference

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[2] P. Lauer, L. Arnold, & F. Brännström. Inverse modelling of pyrolization kinetics with ensemble learning methods. Fire Safety Journal, 2023.DOI: https://doi.org/10.1016/j.firesaf.2023.103744
[3] K. McGrattan, S. Hostikka, J. Floyd, R. McDermott, & M. Vanella. Fire Dynamics Simulator User's Guide, DOI: http://dx.doi.org/10.6028/NIST.SP.1019, 05 2023.

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