PROCEEDINGS, Fire and Evacuation Modeling Technical Conference (FEMTC) 2024
Hybrid In-Person and Online Event, September 18-20, 2024

AI PREDICTION OF FDS FIRE SCENARIOS

Ruggero Poletto

CFD FEA SERVICE SRL
Via Borgo Grande 19
Cologna Veneta, VR – 37044 - ITALY
e-mail: ruggero.poletto@cfdfeaservice.it

ABSTRACT

This paper discusses the development of an AI model that can predict the results of Fire Dynamics Simulator (FDS) simulations. FDS is a widely used tool for fire safety engineering, but it can be computationally expensive. The AI model can greatly reduce the time and cost of running FDS simulations by providing fast and accurate predictions of key fire safety parameters such as smoke visibility, temperature, and heat release rate.

The paper details the development process of the AI model, including the generation of a database of FDS simulation results, the training of the model, and the evaluation of its performance. The model was tested on a variety of fire scenarios and shown to achieve high accuracy in predicting the results of FDS simulations.

The paper concludes that the AI model has the potential to significantly improve the efficiency and effectiveness of fire safety engineering. It can be used to rapidly assess the safety of buildings and other structures, helping to ensure that people are safe in the event of a fire.

INTRODUCTION

This presentation explores the potential of Artificial Intelligence (AI) to enhance and accelerate the process of fire safety design using Fire Dynamics Simulator (FDS) software. FDS, a widely recognized tool in fire safety engineering, provides valuable insights into fire behaviour, smoke spread, and temperature distribution within buildings. However, running complex FDS simulations can be computationally expensive and time-consuming, often requiring significant hardware resources and substantial processing time.
This presentation introduces a novel approach to overcome these limitations by leveraging AI to predict the outcomes of FDS simulations. By training an AI model on a comprehensive database of FDS simulation results, we aim to achieve faster and more cost-effective predictions of fire behaviour. This advancement has the potential to revolutionize the field of fire safety engineering by enabling quicker and more efficient design iterations.
The presentation will delve into the following aspects:

- The rationale behind using AI for FDS predictions: This section highlights the challenges posed by traditional FDS simulations and outlines the benefits of using AI to accelerate and streamline the design process.
- Methodology and training of the AI model: This section explains the data collection and preparation procedures, the chosen AI model, and the training process involved in developing the predictive AI system.
- Evaluation and validation of the AI model: This section assesses the accuracy and reliability of the AI model by comparing its predictions with actual FDS simulation results.
- Applications and limitations of AI in fire safety design: This section explores the potential applications of the AI model in various fire safety engineering scenarios, as well as identifies its limitations and areas for future improvement.

The ultimate goal of this project is to demonstrate the feasibility and advantages of incorporating AI into fire safety design workflows. By harnessing the power of AI, we aim to empower engineers with a more efficient and reliable tool for designing safer buildings and mitigating fire risks.

AI ACTIVITIES

This paper investigates the transient behaviour of localized fires based on limited data sources. Specifically, we focus on qualitative analysis of smoke and temperature readings in the context of localized fire events. Our aim is to explore the predictive potential of these data in characterizing the fire's evolution without relying on a comprehensive set of fire parameters.
Hypothesis: The patterns observed in smoke and temperature data can be qualitatively analysed to provide insights into the transient behaviour of localized fires.
Requirements:

- Data sets containing smoke and temperature readings from localized fire events.
- Methods for qualitative analysis of these data, including visualization techniques and pattern recognition.

Limitations:

- This study focuses on qualitative analysis, providing insights but not necessarily quantitative predictions.
- The data set is limited to smoke and temperature readings, potentially excluding important fire parameters.

Expected Outcomes:

- Identification of qualitative relationships between smoke and temperature data and the temporal evolution of localized fires.
- Assessment of the potential for qualitative analysis to contribute to understanding and predicting fire behaviour.

This research will contribute to a better understanding of fire dynamics using limited data sources, potentially informing future development of predictive models for fire behaviour.

Training

The foundation of our AI model relies on a comprehensive database of simulation results generated using the Fire Dynamics Simulator (FDS). This database serves as the training data for the AI, defining the operational boundaries within which it can generate accurate predictions. The more simulations included in the database, the wider the range of scenarios the AI can effectively analyse and the more precise its predictions will be.
The training process is computationally intensive, demanding significant hardware resources. Our current system requires approximately one hour of processing time for each simulation added to the database. This emphasizes the importance of efficient data management and optimized hardware utilization for maximizing training efficiency.

Prediction

Once trained, the AI model enables near-instantaneous predictions. To perform a prediction, users simply input an FDS input file (.fds) containing the specific scenario parameters. This file provides the AI with all the necessary information to generate a prediction regarding the fire behaviour, including smoke propagation, heat release, and potential hazards.
This approach offers a significant advancement in fire safety analysis. By leveraging the power of AI, we can bypass the time-consuming process of traditional simulations, allowing for rapid and efficient hazard assessments in real-time scenarios. Further research will focus on expanding the

database with diverse fire scenarios, improving training efficiency, and exploring the potential for real-time integration with existing fire safety systems.

VARIATIONS IN FDS ANALYSIS

Geometry and Ventilation:

A diverse selection of building geometries is considered, encompassing different functional areas and structural designs. Ventilation systems investigated include jet fans, supply/exhaust fans, and natural ventilation through grids, windows, and openings. The impact of ventilation strategies on fire growth, smoke movement, and temperature distribution within the building is evaluated.

Fire Source and Characteristics:

A prescribed single-point fire location is assumed, with the fire modelled as a heat surface situated within a specific area of the building. The fire is characterized by its Heat Release Rate (HRR) curve, which can be customized to represent various fire types and intensities. The study investigates the influence of different HRR curves, including variations in total HRR per unit area (HRRPUA), on fire behaviour.

Physical and Numerical Variations:

The study explores the impact of various physical and numerical parameters on fire simulation results. Physical variations include:

- Sprinkler systems: The presence and activation of sprinkler systems, their impact on fire suppression and smoke control.
- Fire propagation: The modelling of fire spread within the building, considering factors like flame impingement, thermal radiation, and fuel availability.
- Chemical reactions: The simulation of chemical reactions, including soot and carbon monoxide (CO) yield, which influence smoke toxicity and visibility.
- Dynamic geometry: The effects of changes in building geometry over time, such as door openings and closures, on fire spread and ventilation.

Numerical variations explored include:

- FDS versions: The impact of different Fire Dynamics Simulator (FDS) versions on simulation outcomes, considering advancements in model physics and numerical algorithms.
- Time steps: The influence of different time steps employed in the simulations on accuracy and computational efficiency.
- Turbulence model: The effects of different turbulence models used to simulate turbulent flow, which impacts smoke diffusion and fire behaviour.
- Wall representation: The impact of different methods for representing walls and building materials on heat transfer and fire spread.
- Mesh resolution: The influence of mesh size and density on the accuracy and computational cost of the simulations.

DEFINITION OF REFERENCE CASE

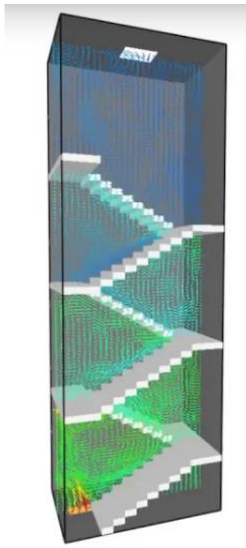

Figure 1: Representation of the chosen geometry as provided by FDS tutorials

Geometry and Discretization

The staircase geometry is modelled with a defined set of horizontal slices at 1.5, 1.7, 1.8 and 2.0 metres above the ground. Two vertical slices are further defined, positioned at the centre of the domain, perpendicular to the X and Y axes. This allows for detailed analysis of the fire behaviour in both horizontal and vertical planes.

Ventilation and Mesh

For this initial study, the ventilation within the staircase is not considered. The domain is discretized using a mesh with 8 cells per dimension, resulting in a total of 8,000 cells.

```
&MESH ID='Mesh 01', IJK=14, 8, 72, XB=  0,2.1,0,1.2,0,6.12/
&MESH ID='Mesh 02', IJK=14, 8, 72, XB=2.1,4.2,0,1.2,0,6.12/

&MESH ID='Mesh 03', IJK=14, 8, 72, XB=  0,2.1,1.2,2.4,0,6.12/
&MESH ID='Mesh 04', IJK=14, 8, 72, XB=2.1,4.2,1.2,2.4,0,6.12/

&MESH ID='Mesh 05', IJK=14, 8, 72, XB=  0,2.1,0,1.2,6.12,12.24/
&MESH ID='Mesh 06', IJK=14, 8, 72, XB=2.1,4.2,0,1.2,6.12,12.24/

&MESH ID='Mesh 07', IJK=14, 8, 72, XB=  0,2.1,1.2,2.4,6.12,12.24/
&MESH ID='Mesh 08', IJK=14, 8, 72, XB=2.1,4.2,1.2,2.4,6.12,12.24/
```

Figure 2: The mesh is made of 8 meshes each of which approximately generates 8000 cells. The simulations have been performed on FDS 6.8.0 using 8 cores for each analysis.

Simulation Parameters

The simulation was run for a total duration of 1800 seconds (T_END = 1800s). Data was extracted and analysed at 300s intervals, covering the time points 300s, 600s, 900s, 1200s, 1500s and 1800s.

Data Processing

VTK data conversion was utilized to facilitate the analysis of simulation results. This allows for the visualization and further processing of the generated data, providing insights into the fire's progression and impact on the staircase environment.

Variations considered

For this first AI trained model based on FDS, the decision was to limit the possible variations that can be considered into a FDS analysis. In particular only fire locations and area variation is considered, as well as the HRR time variation. The fire location variations are reported in Figure 3 and they provide a mix between different fire locations and area where the fire is actually generated.

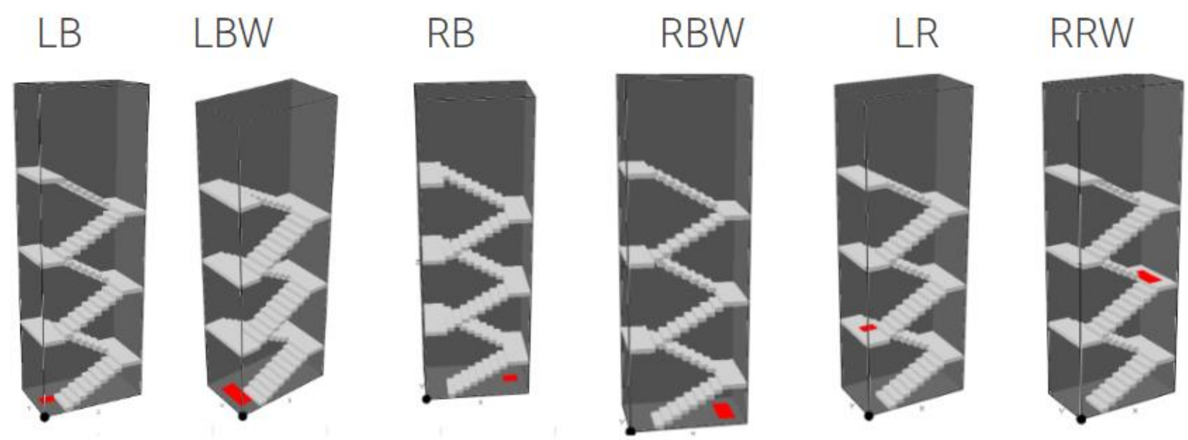

Figure 3: Variations of fire locations and dimensions withing the staircases. Six different variations have been defined by placing fire either at the bottom of the staircase or to the first level.

Figure 4 instead illustrates the 4 different HRR curve which have been used to generate various scenario. All these curves have a parabolic start with different value of T_{alpha}.

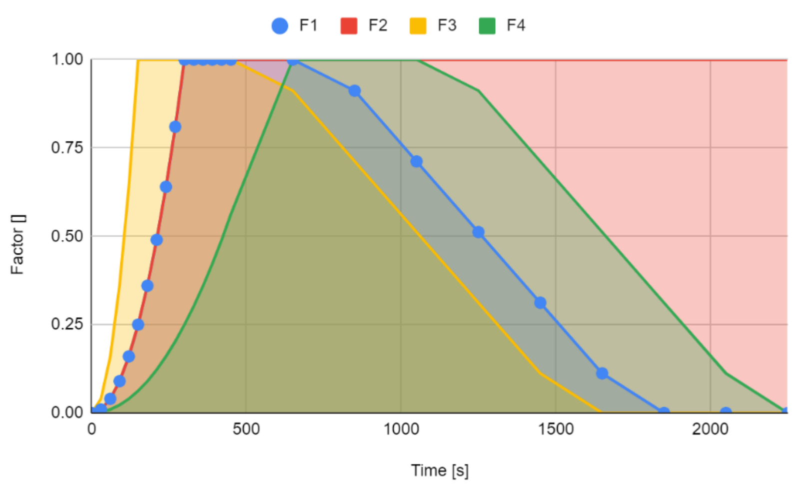

Figure 4: Four different time dependent HRR curve have been defined. These curves represent the time variation of the parameter HRRPUA (Heat release rate per unit of area) specified for each of the fire surfaces.

Figure 5: Out of the 24 variations generated, 22 have actually been used to train the AI, out of these 4 were used for testing the training. 2 extra analysis have not been provided to the AI and are used to validate the AI predictions against real FDS simulations results.

PREDICTIONS

The predictions for the current AI structure are defined all over the fluid domain and are able to generate a proper result set in VTK to open and visualize in Paraview. The following chapter shows some of the comparison between predictions and the actual FDS analysis, comparing them from a qualitative point of view.

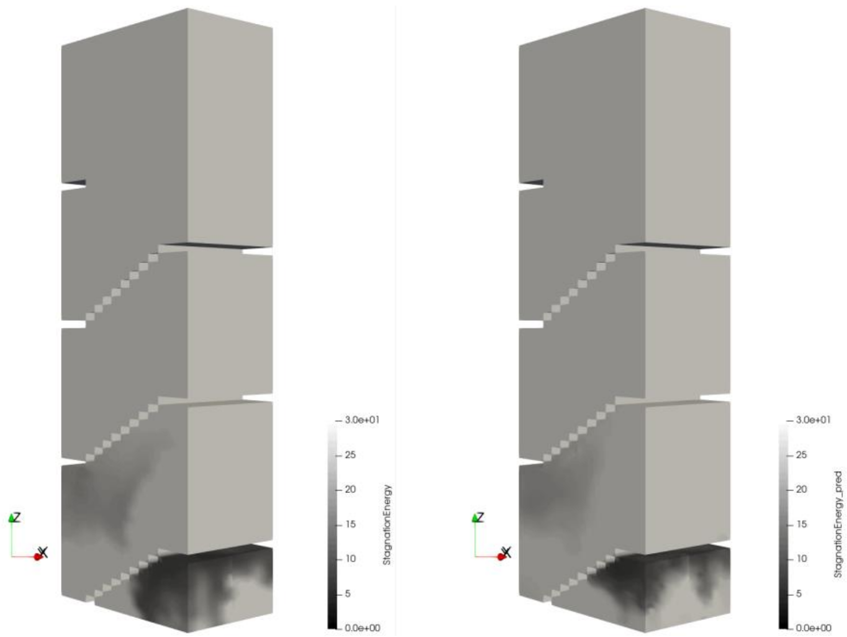

Figure 6: Smoke view transient prediction (right) compared against FDS analysis results (left). AI was able to correctly capture the main feature of the simulation as well as the transient characteristics of the predictions allow a qualitatively good approximation of the results of the FDS analysis.

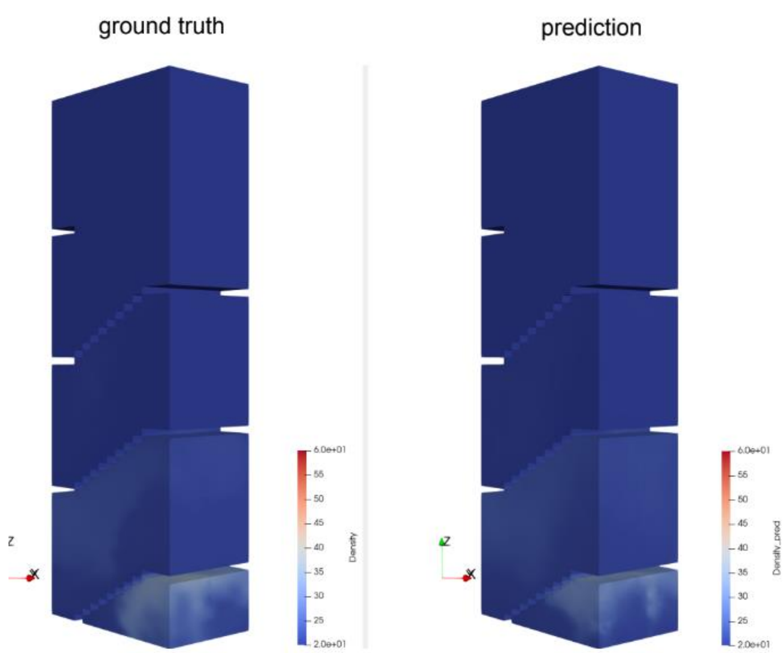

Figure 6: Another variable considered is the temperature that is actually correctly generated by the AI (right) when compared to the FDS results (left).

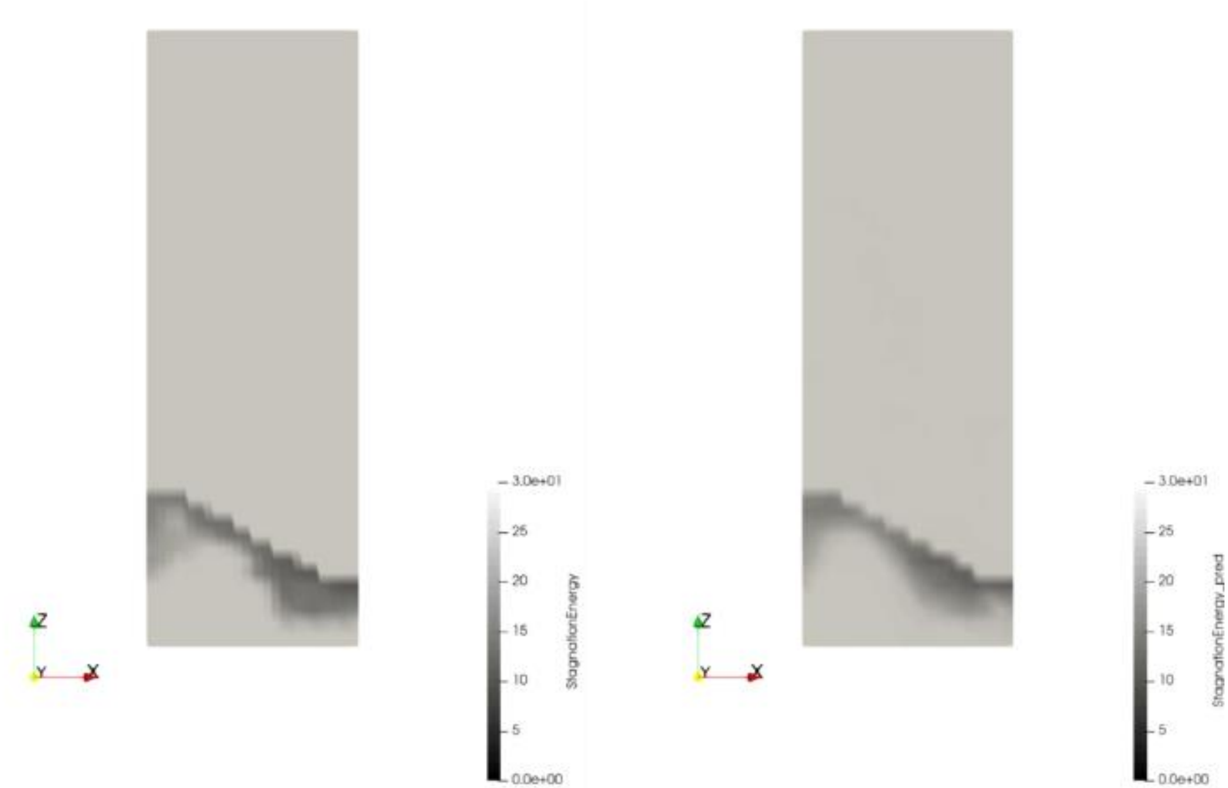

Figure 7: Results can be generated also on specific slices of the domain like this image displays. To the right it is possible to see the AI prediction while on the left the proper results generated by FDS.

The results showed the capability of the AI algorithm to actually correctly detect the main features of the simulation, even if some local details may be incorrect. In fact, the time required by the smoke to fill completely the staircase has been correctly predicted while it may happen than locally AI did not capture vortex or smoke diffusion which made the predictions differ from the results of the analysis.

CONCLUSIONS

This study demonstrates the potential of artificial intelligence (AI) to accurately predict key features of Fire Dynamics Simulator (FDS) simulations. The ability to generate a comprehensive database of simulations is crucial for training AI models to achieve reliable predictions. Once AI models are capable of accurately predicting FDS outcomes, they can be readily expanded to generate guidelines for selecting worst-case scenarios. This has significant implications for fire safety design and analysis, offering a powerful tool for optimizing fire safety strategies and minimizing risks.

FUTURE WORK

- **Handling Large Mesh Sizes**: The framework addresses the computational challenges of simulating fire behaviour in models with a large number of cells. Methods for optimizing mesh generation and reducing computational load for high cell counts are discussed.

- **Incorporating Geometric Variations**: The framework allows for the inclusion of various geometric variations in the model, such as different building shapes and internal layouts. This feature enables a more accurate representation of real-world scenarios.
- **Exploring Ventilation Variations**: The framework enables the simulation of different ventilation conditions, such as open windows, doors, and smoke exhaust systems. This feature allows for the analysis of how ventilation affects fire spread and smoke movement.
- **Accuracy and Output Definition**: A clear definition of accuracy measures and output parameters is crucial for evaluating the effectiveness of the simulation. The paper will outline the specific metrics used to assess the accuracy of the model and the data generated.
- **Optimized Data Output**: The output data from the simulation is tailored for efficient analysis. The framework focuses on providing only relevant slices of data, reducing the overall volume of output while preserving critical information.
    - **VTK Format**: While offering interactive visualization capabilities, the VTK format requires specialized software like ParaView or maybe Pyrosim for analysis.
    - **JPG Format**: JPG provides flexibility in image processing and sharing, but lacks the interactive features of VTK.