Feasibility Analysis of Coupling FDS Modeling with Machine Learning for Situational Awareness in Aircraft Hangars

Alison Davis, Jim Milke, and Arnaud Trouve

SUPDET Conference
September 15, 2022
Motivation

• Inefficient and unsafe to survey building during the fire
• Situational awareness for incident commanders
  • “Understanding the current environment and being able to accurately anticipate future problems and enable effective action”
  • One of the leading factors in near-miss reports
• Aircraft hangars store expensive equipment
Scope of Work

• Phase 1: Perform Fire Dynamic Simulator (FDS) simulations for data acquisition

• Phase 2: Analyze parameters using machine learning techniques to determine:
  • Where is the fire located?
  • What is the magnitude of the fire?
  • What is burning?

• Overall approach is guided by the combination of sensors and modeling
Hangar Configuration

- 26 m x 26 m x 12 m
- 24 m x 7m door opening
- Outdoor area to account for entrainment effects
Instrumentation Devices and Spacing

• Sensors are chosen based on reconstruction goals
  • Smoke detector
  • Temperature sensor
  • CO detector
  • CO₂ detector

• Eight by eight grid located at the ceiling
  • High density of sensors
Grid Size

• Well-resolved region: plume and ceiling jet: $\Delta x = 0.1$ m
  • Determined by 1 m$^2$ burner
  • Plume = 7 m x 7 m x 11 m
  • Ceiling jet = 26 m x 26 m x 1m

• Other regions: $\Delta x = 0.5$ m
Fuels of Interest

- Douglas Fir - 2150 kW
- Polyethylene - 55 kW
- Large Box of Paper - 436 kW
- JP-8 - 2200 kW
- Propane - 2200 kW
- Polyurethane Foam GM21-2000 kW (Not used for training; only testing)
Differing Conditions

- “Wall of wind” approach
  \[ u = u_0 \left( \frac{z}{z_o} \right)^p \]
- W16x31 beams are added at the ceiling to determine impact on smoke movement
Location Identification Methodology

- Sensors numbered 0 to 63
- Fire locations labeled A through F
- Preprocessing required
  - Extract temperature data from FDS
  - Take a 20-point running average
- Use temperature to determine location
Temperatures of a single fuel
Ambient temperature range
(64,982) matrix
Maximum temperature range
Maximum temperature range

T - 0.15T
T + 0.15T
Maximum temperature range

Store index
Get closest location
Get/store sensor range
Identify and store the maximum value

(64,1)
(1,982)

DISTRIBUTION STATEMENT A. Approved for public release: distribution unlimited.
AFCEC-20220019, 12 April 2022
Location Results

• Correctly identified 45 out of 56 fire locations
• 100 % of JP-8 fires correctly identified
Heat Release Rate and Temperature Algorithm

• Average temperature across sensors of interest was taken
• Neural network needs to map temperatures to known HRRs to train
• 20-point running average of the HRRs was taken
• Scale input and output data from 0 to 1
Heat Release Rate and Temperature Algorithm

Input layer = temperature  
Hidden layers  
Output layer = HRR
Steps to Train Neural Network

1. Provide model inputs
2. Provide model targets that are to be mapped
3. Do a forward pass and make predictions
4. Compute the loss function
5. Update the model
6. Run through another epoch
Combining Fuels into Single Feed Forward Neural Network

• Training and testing set were manually created
• 40 fires in training set
  • 8 of each fuel package
• 16 fires in testing set
  • 8 Douglas fir
  • 2 of each of the remaining fuel packages
HRR Model Results

JP-8, Location F
(Red box)

JP-8, Location E, with wind
(Green box)
Fuel Discrimination Model

- Relationship between temperature and smoke obscuration
  - Time dependent quantities that scale according to HRR
Support Vector Machine (SVM) Visualization

• Used linear SVM for multi-class classification
• Maximize the distance between hyperplanes for classification
Overall HRR Model Results

- Category 1: 0-250 kW
- Category 2: 251-500 kW
- Category 3: 501-1000 kW
- Category 4: > 1000 kW

- Model could correctly identify 85% of categories except:
  - Douglas fir with wind
  - Douglas fir with 0.25xHRR
  - Polyethylene with 4xHRR
  - Paper with 0.5xHRR
All Fuel Discrimination Results

• 62% test accuracy
• 88% of JP-8 fires correctly classified
• Issue with misclassifying Douglas fir as polyethylene
Binary Classification Results

• 91% test accuracy
• 87.1% of JP-8 fires correctly identified
• Greater deviation between JP-8 from the other fuels at the start of the simulation
Conclusion

- Took in FDS sensor data to develop machine learning models
- Data of interest is temperature and smoke obscuration
- Location model is used to simplify the amount of data needed for HRR and fuel discrimination algorithms
- Indicates that a machine learning approach is feasible in a hangar space

- Location
  - 80% accuracy
  - Reduces time taken to survey the scene of the fire

- HRR
  - 85% accuracy
  - Allows to be better prepared for approach needed

- Fuel type
  - 62% all fuel
  - 91% binary
  - Determines suppression agent
Future Work

• Define the HRR a different way
  • Wind reduces HRR
  • Allow for fire to spread

• Increase size of training set
  • Experimentally
  • Increased simulations
    • Explore entrainment effects when fires are in the corner or by the wall
Thank You!

M.S. Thesis by Alison Davis: https://drum.lib.umd.edu/handle/1903/28859

Jim Milke
milke@umd.edu
fpe.umd.edu