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What fire modelling resolution is needed in AI training data for smart firefighting in tunnels?

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ABSTRACT

The adoption of smart firefighting in tunnels – intended here as fire modelling coupled with sensor data - requires a broad discussion into the suitability of different tools and approaches for decision support in case of emergency. In particular, Artificial Intelligence (AI) tools have shown great potential to support real-time emergency management, given their ability to simulate and predict the evolution of fire scenarios with low computational cost. AI tools for fire modelling predictions generally rely on a given simulation database for their training. Such databases can be developed through a variety of fire modelling approaches with different resolutions, e.g. hand-calculations, (multi-)zone modelling and computational fluid dynamics (CFD). This study proposes an approach to investigate the suitability of different modelling resolutions for generating AI training datasets for tunnel fire scenarios, considering heat release rate as the key variable to predict. Regression modelling allows estimating this key variable. Testing has been performed through a set of fire scenarios within and outside the training dataset fire intensity intervals. An experimental dataset from real-world repeated experiments was used to understand the prediction performance based on different modelling resolutions. The prediction performance was assessed through the error evaluation for the testing and experimental datasets. The error of the testing data shows how strongly the regression model correlates to the assumptions taken in the training scenarios. Here, the regression model based on CFD shows the best fit when predicting fire intensity within the range used for training. The regression model based on multi-zone modelling shows a better fit for larger fires. Finally, the comparison to experimental data shows that hand-calculations are not suitable for this type of applications while multi-zone and CFD modelling approaches can provide sufficient resolution to predict fire intensity when adopting them to train a regression model and using temperature sensor data.

KEYWORD: smart firefighting, tunnel fire modelling, modelling resolution, training database

NOMENCLATURE

Symbols

c_p	Specific heat of air at constant pressure (kJ/kgK)
ρ	Density (kg/m ³)
ΔT	Temperature difference (K)
e	Error (%)
g	Gravity constant (m/s ²)
H	Tunnel height (m)
h_t	Total heat transfer coefficient (kW/m ² K)
k	Ventilation ratio (-)
l_f	Fire characteristic length (m)
$\dot{m}_0$	Mass flow rate (kg/s)
$\dot{Q}$	Heat release rate (kW)

$\dot{Q}''$	Heat release rate per unit area (kW/m ²)
$\dot{Q}^*$	Dimensionless heat release rate (-)
RMSPE	Root mean square percentage error (%)
T	Temperature (K)
t	Time (s)
T ₀	Ambient temperature (K)
u ₀	Longitudinal ventilation flow (m/s)
V _c	Critical velocity (m/s)
V _c [*]	Dimensionless critical velocity (-)
w _p	Perimeter of the tunnel cross-section (m)
x	Fire position (m)

Subscripts

i	Training scenario
j	Testing scenario
m	Fire modelling approach
e	Experiment

1. INTRODUCTION

Emergency procedures in tunnels are critical for ensuring the safety of individuals during fire incidents. In these events, smart firefighting can help ensure decisions are taken promptly so that evacuation and rescue service operations are safely executed. First responders such as rescue services and tunnel operators are expected to control the traffic, facilitate the evacuation, monitor the fire development and road obstructions, and perform fire and rescue operations [1]. All these activities are associated with a key set of decisions which rely on information available and a dynamic risk assessment which identify their consequences. However, available technology (such as camera systems, fire detection systems, and supervisory control and data acquisition ventilation controllers) most often only provide information on current status rather than predicted consequences [2].

In tunnel fires, after the arrival of the rescue service outside the tunnel, it is required to determine the location of the fire to define the closest safety access to the fire, especially if it is not known in advance, such as when being notified by tunnel operators who perform surveillance of the tunnel. In that location, it might be assumed that the ventilation flow is as much as required to suppress the back layering upstream of the fire. Depending on the facility's emergency procedures, ventilation flow may be minimized to maintain smoke stratification during self-evacuation. However, without immediate guidance on the situation or expected ventilation changes, occupants may independently choose an evacuation route with the highest smoke concentration caused by longitudinal ventilation, potentially the least safe direction. These procedures present a high degree of complexity as they involve the tunnel controller, the incident commander, and the firefighters on-site evaluating the heat release rate and determining the requirement for higher ventilation flows to prevent backlayering in case of longitudinal ventilation. [3]

For this reason, smart firefighting concepts such as fire modelling coupled with sensor data can be a useful tool to inform decisions and optimise the emergency response, resources, and defining strategies. Smart firefighting, intended here as guided emergency response through sensor data, can offer enhanced situational awareness and critical decision-support information. This approach can enable a more efficient and safer emergency response by providing deeper insights into the dynamics of the situation. This includes the assessment of current and future conditions that can be estimated through the integration of sensor data with fire models.

The scientific literature includes different fire modelling approaches of varying resolution, reliability,

precision, and computational cost for tunnel fire safety design and assessment, such as one-dimensional hand calculations [4], multi-zone modelling [5], and computational fluid dynamics (CFD) [6], [7]. Regardless of the model in use, the goal is to predict the fire and smoke development (and associated tenability conditions) in relation to different scenarios. In this context, the trade-offs between computational costs of each modelling approach and accuracy is an open question. This is particularly important for data-driven modelling approaches which rely on sensor data, i.e. those attempting integrating real-time measurements into fire models to perform predictions [8]. In fact, recent research has used machine learning models for tunnel fire development predictions. For instance, these models have been used to predict temperature distributions in tunnel and compartment fires concluding that higher accuracy results require deep learning models including hidden layers to process massive amounts of data [9], [10].

The purpose of the study is to investigate the resolution in training databases required to perform data-driven prediction for emergency response in tunnel fire scenarios. By determining whether a model that is faster or more efficient to run can generate a training dataset of sufficient quality, the study aims to assess its potential as a valuable resource for further development of predictive models for tunnels. Such advancements could enhance the capability of smart firefighting systems, supporting more effective and informed emergency response strategies. This will be demonstrated through a case study of a 60 meters tunnel fire experimental facility located in Revinge, Sweden for which mass loss rates and temperature sensor data have been collected in a range of repeated experiments [11]. The case study assumes the fire intensity as the key variable to be predicted by models using available sensor data.

2. METHODOLOGY

Figure 1 presents the overall methodology of this work. For the given case study, a set of 27 training design scenarios are defined varying the fire intensity (Q_i), fire position (x_i), and longitudinal ventilation flow (u_i). The training dataset is used to develop a prediction model based on a linear regression analysis. This method analyses the simulated temperature values (T) at certain positions in the tunnel. The temperature values are estimated through 3 different approaches: hand calculations [4], multi-zone modelling [5], and CFD through the Fire Dynamics Simulator (FDS) [7]. Then, the prediction model is tested by a set of 5 scenarios that are within and outside the range of fire intensity in the training scenarios. Finally, the performance of the prediction model is evaluated through a set of experimental heat release rate ($\dot{Q}_e$) and temperature (T_e) values.

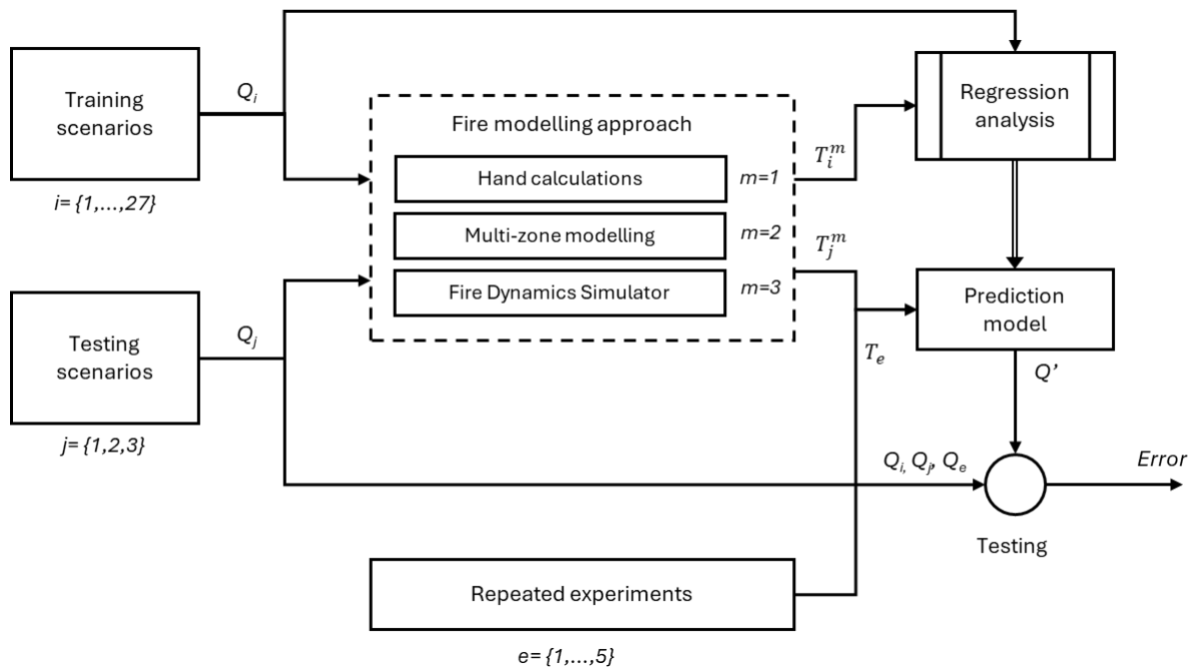


Figure 1 Research methodology flowchart for a 'blind' prediction method over three fire modelling

approaches (m) including testing and experimental benchmarking for a number of (j) scenarios. Q = heat release rate, T = temperature.

2.1. Regression analysis

The method used to determine the correlation between the heat release rate (HRR) and other variables (e.g., temperature) is the same for all fire modelling techniques adopted here. To ensure transparency and explainability, a simple and established statistical approach, specifically multiple linear regression analysis, is applied. It should be noted that more sophisticated approaches (e.g., based on artificial intelligence, AI) could have been used as an alternative to the simple method used here. Linear regression is indeed often used as baseline against AI approaches.

Linear regression is a statistical method used to model the relationship between a dependent variable such as HRR (Q) and one or more independent variables such as the longitudinal velocity (u_0) and temperature (T). The linear regression is used to predict the value of $\dot{Q}$ based on the values of u_0 and T to understand the relationship between them [12], [13]. A statistical package can be used to perform the linear regression, and it provides various statistics that can be used to analyze the result of the regression analysis. The coefficient of determination (R^2) gives a measure of the proportion of the variance in the dependent variable that is explained by the independent variables in the regression expression. The overall significance gives a p -value for that at least one of the variable coefficients is not equal to zero, i.e., there is at least one useful linear relationship. The significance of the individual coefficients is presented with the so-called p -value of coefficients, which indicated if the associated coefficient is significantly different from zero [12]. In this work the Microsoft Excel Analysis ToolPak is used to perform the regression analysis and to calculate the associated statistical parameters.

2.2. Error Analysis

As shown in Figure 1, an error analysis is performed to evaluate the performance of the regression analysis through the prediction ($\dot{Q}$) of the testing ($\dot{Q}_t$), and experimental cases ($\dot{Q}_e$). This is done through the Root Mean Square Percentage Error (equation 1) for a population of scenarios such as the training dataset, and through the Percentage Error (equation 2) to evaluate the error between expected and real values such as testing dataset or experimental data. The lower the score, the better the predictive performance of the model.

$$RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^n (e_i)^2} \quad (1)$$

$$e = \frac{Q' - Q_{i,j,e}}{Q_{i,j,e}} \times 100\% \quad (2)$$

3. TUNNEL FIRE SCENARIOS

The design of the scenarios under consideration is meant to represent a simplified version of a tunnel fire. As shown in Figure 2, this design setup represents a real-world tunnel facility in Revings, Sweden, where repeated experiments were conducted as detailed in [11]. The tunnel case study assumes a rectangular cross-section, constant longitudinal flow, and unobstructed fire on a fixed position.



Figure 2 Experimental tunnel located at the Swedish Contingency Agency training facility in Revvinge, Sweden.

A schematic representation of the tunnel layout is shown in Figure 3, including the dimensions of the tunnel cross-section, the position of the thermocouples and the fire source (x_i), the fire characteristic length (l_i), and the longitudinal ventilation flow (u_i).

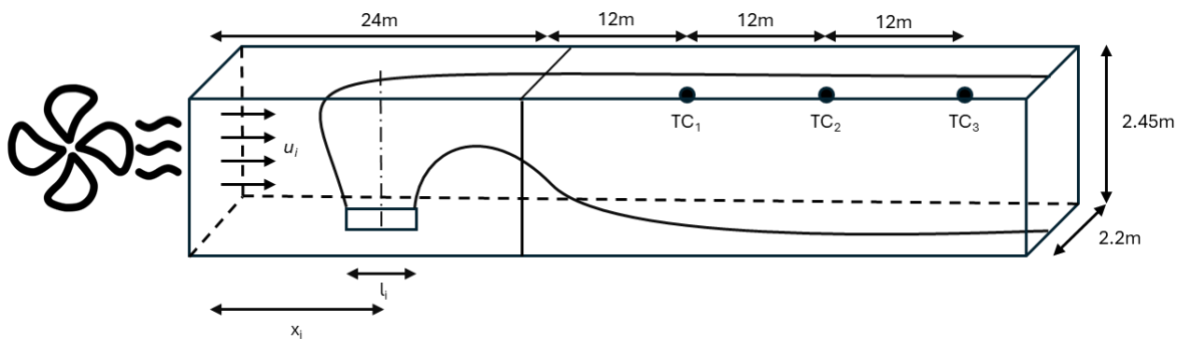


Figure 3 Schematic representation of the tunnel case study. The tunnel layout is not in scale. TC=thermocouples, u = longitudinal ventilation flow, x = fire position, l = fire characteristic length.

The fuel in the fire scenarios is represented with a heptane pool. The general assumptions taken for the case study are steady ventilation flow and no wind effect on the tunnel portals. Assuming well-ventilated fires where there is no significant heat feedback to the fuel and there is no increment of oxygen concentrations, the designed fires were simplified by decoupling the combustion process, setting up a constant value of heat release rate per unit area (HRRPUA) of 2000 kW/m².

The resulting fire scenarios are characterized by as per the document [14] for small, medium, and large pool fires, where the fire size is expressed in terms of the ratio between the length of the fire in the direction of the airflow, and the tunnel width.

The training data consists of 27 tunnel fire scenarios intended to represent a range of fire intensity, flow velocity, and fire position. For the testing a set of HRR values were defined, namely 80 kW, 1100 kW, 1500 kW, and 2200 kW. Those values are deliberately chosen outside and inside (650 kW) the HRR interval adopted in the training data. The fire characterisation for the training and testing sets is presented in

Table 1. The fire of the training set was placed at three different fire positions (x_i): 5 m, 10 m, and 15 m relative to the ventilation inlet at the tunnel portal (see Figure 3).

Table 1 Characteristics of the prescribed HRR or the training and testing datasets.

Dataset	HRR (kW)	Fire width (m)	Fire characteristic length (m)	Fire ratio	Fire size	Q*
Training	320	0.4	0.4	0.18	small	0.03
	500	0.5	0.5	0.23	small	0.05
	980	0.7	0.7	0.32	small	0.09
Testing	80	0.2	0.2	0.09	small	0.01
	650	0.5	0.65	0.30	small	0.06
	1100	0.5	1.1	0.50	medium	0.11
	1500	0.5	1.5	0.68	medium	0.14
	2200	0.5	2.20	1.00	large	0.21

The training and testing sets can be characterised through the dimensionless critical velocity (V_c^*) and the dimensionless heat release rate ($\dot{Q}^*$). Li et al. [15] developed an experimental and theoretical analysis to define the V_c^* for a tunnel without blockage as shown in Equation (3). Where the dimensionless variables of heat release rate and critical velocity are defined by Equation (4) and (5), respectively.

$$V_c^* = \begin{cases} 0.81Q^*, & \dot{Q}^* \leq 0.15 \\ 0.43, & \dot{Q}^* > 0.15 \end{cases} \quad (3)$$

$$Q^* = \frac{Q}{\rho_0 C_p T_0 g^{1/2} H^{5/2}} \quad (4)$$

$$V_c^* = \frac{V_c}{\sqrt{gH}} \quad (5)$$

The prescribed ventilation rates are 1.1 m/s, 2 m/s, and 4 m/s, which are intended to significantly impact the temperature values. Each scenario has been evaluated through the ratio of the design ventilation rate (u_0) and the respective critical velocity (V_c) leading to scenarios of longitudinal flows under and over the respective critical velocity. The characteristics of the ventilation flow for the training and testing sets are shown in Table 2.

Table 2 Characteristics of the prescribed ventilation for the training and testing datasets.

Dataset	$\dot{Q}^*$	V_c^*	V_c (m/s)	u_0 (m/s)	V_c/u_0	Ventilation type
Training	0.03	0.25	1.24	1.1	0.88	Under critical velocity
	0.05	0.29	1.44	1.1	0.76	Under critical velocity
	0.09	0.37	1.81	1.1	0.61	Under critical velocity
	0.03	0.25	1.24	2.0	1.61	Above critical velocity
	0.05	0.29	1.44	2.0	1.38	Above critical velocity
	0.09	0.37	1.81	2.0	1.11	Above critical velocity
	0.03	0.25	1.24	4.0	3.21	Above critical velocity
	0.05	0.29	1.44	4.0	2.77	Above critical velocity
	0.09	0.37	1.81	4.0	2.21	Above critical velocity
Testing	0.01	0.16	0.78	2.0	2.55	Above critical velocity
	0.06	0.32	1.58	2.0	1.27	Above critical velocity
	0.11	0.38	1.88	2.0	1.06	Above critical velocity
	0.14	0.42	2.08	2.0	0.96	Under critical velocity
	0.21	0.48	2.37	2.0	0.84	Under critical velocity

The arrangement of HRR, ventilation rates and positions result in a total training set of 27 scenarios. In contrast, the testing set was limited to one outbound position of 20 m from the inlet portal to evaluate the dependency of the position in the regression models. All scenarios were simulated with different fire modelling approaches estimating data points of temperature values. The data points are used to train the regression model. The temperature values taken for the training sets are consistently taken after 900 seconds of simulation. This choice was because corresponding experimental measurements from the real-world tunnel are available.

3.1. Hand calculation method

The analytical model used in this paper has been presented by Ingason [4]. The models are valid for tunnel fires with longitudinal ventilation, that is such that the flow can be assumed one-dimensional. The methods are based on simple mass and energy balance. The average gas temperature at x (m) downstream of the fire source at time t (s) can be estimated with equation 6.

$$\Delta T_{avg}(x, t) = \Delta T_{avg}(0, \tau) e^{-\frac{h_t w_p}{\dot{m}_0 c_p} x} \quad (6)$$

Where ΔT_{avg} is the average temperature increase over the whole cross-section, h_t is the total heat transfer coefficient ($\text{kW/m}^2\text{K}$), w_p is the perimeter of the whole tunnel cross-section, and $\dot{m}_0$ is the mass flow rate in the tunnel (kg/s). The time τ accounts for the transport time of the heat from the fire to the position x . For short distances $\tau = t - x/u_0$, where u_0 is the gas velocity, can be used. The average temperature increase at the fire source can be estimated with equation 7. It can be noted that the first term in equation 7 is a constant value, whereas the second term is a variable value depending on the fire scenario characteristics.

$$\Delta T_{avg}(0, \tau) = \frac{2}{3c_p} \frac{Q(\tau)}{\dot{m}_0} \quad (7)$$

Ingason [4] points out that the method can describe the average gas temperature downstream of the fire reasonably well for one-dimensional flows, however when the velocity is too low the one-dimensional model will not be applicable.

3.2. Multi-zone modelling

The general multi-zone (MZ) concept has been described in previous work [16]. In a multi-zone model the enclosure is divided into several regions (horizontal) and zones (vertical). This means that the entire enclosure is made up of several smaller computational volumes. The conservation mass and energy are applied for each volume. The calculated properties (like temperature or soot concentration) are uniform in each zone, and the model extends into a three-dimensional volume. An empirical plume model is used to calculate the plume entrainment. The MZ fire model used in this paper has been adapted to tunnel fires and it has been tested against experimental data on large-scale tunnel fires [5].

3.3. Computational fluid dynamics model

The CFD model used is the Fire Dynamics Simulator (FDS). It is an established tool for fire safety analysis. FDS is developed by the National Institute of Standards and Technology [17], and it is a large-eddy simulation (LES) code for low-speed flows. The software solves the Navier–Stokes equations numerically, emphasising heat and smoke transport. The FDS validation guide [18] includes a large amount of validation and testing examples and independent research teams have done significant validation work of the model. FDS is tested and frequently used for tunnel fire scenarios [19].

The pressure considerations for the tunnel scenarios with medium and large fire size (see Table 1) were varied from default values to avoid numerical instabilities. These scenarios were configured to have a maximum of 30 pressure iterations and a reduced pressure tolerance of up to half the default value.

3.4. Experimental data

Experimental data were retrieved from repeated experiments of an experimental campaign conducted at the tunnel facility in Revinge (see Figure 2) and are summarised in Table 3. Thermocouple trees were positioned at different distances from the fire along the tunnel; however, in this study, information from only three thermocouples - assumed to represent temperature sensors underneath the ceiling - are used (see Figure 3). The fire source was a heptane pool fire with an area of 0.25 m² and the mass of the fuel was measured during the experimental tests. A longitudinal ventilation velocity was generated with a positive pressure fan; the ventilation flow velocity was measured with an anemometer prior to all tests. A full description of the experimental setup has been presented in a previous publication [11].

The HRR and temperature values in Table 3 are estimated during the main burning period, approximately for a period of 600s, when the mass loss was stable. The HRR is calculated based on the load cell data, effective heat of combustion of 41.2 kJ/g for heptane (C₇H₁₆), as suggested in Table A.40 in [20].

Table 3 *Experimental data collected in the tunnel facility*

Experiment	Q (kW)	u _o (m/s)	x (m)	ΔT _{24m}	ΔT _{36m}	ΔT _{48m}
1	659	2	6	88.0	74.7	64.1
2	667	2	6	116.9	96.0	82.1
3	663	2	6	106.6	88.1	77.2
4	737	2	6	66.4	57.7	51.0
5	651	2	6	65.0	55.9	49.4

4. RESULTS

This section presents the results of this study. First, it describes the temperature estimations obtained through the three fire modelling techniques adopted and an overview of the predicted HRR for the training scenarios. Then, the result of the multiple linear regression is presented for each fire model correlating the prescribed (in training) and predicted HRR. Finally, it presents the error evaluation for the testing and experimental datasets against the prediction method for the three fire modelling resolutions.

4.1. Training modelling results

The 27 training scenarios were simulated through Hand calculations (HC), Multi-Zone (MZ), and FDS. Each fire model estimated the temperature values for 900s at the three relative positions of 24m, 36m, and 48m from the tunnel portal. The temperature increment (ΔT) and HRR ($\dot{Q}$) values were averaged over the last 30s of the simulation time.

As described in Equation 7, the second term is the ratio between the HRR ($\dot{Q}$) and the mass flow rate ($\dot{m}_0$). Therefore, when correlating ΔT with $\dot{Q}/\dot{m}_0$ it is expected to have a linear slope, as Figure 7 shows the temperature increments (ΔT) at 24 meters. This figure shows that each fire model presents a different temperature trendline. As expected, the results from the hand calculations matches the trendline since it is based on Equation 7. In contrast, FDS and MZ present higher distributions at higher ratios.

4.2. Results of regression analysis

Figure 7 presents an overview of the predicted heat release rates. As the figure shows, the predicted values follow the prescribed HRR trendlines for each modelling approach. The following sub-sections present the linear regression equations shown in Figure 7 for the different fire modelling resolutions.

4.2.1. Hand calculation method

The training dataset generated from the hand-calculation method results in the following regression expression:

$$\widehat{HRR} = 22.03 + 1174.03 \cdot \Delta T_{24m} - 2861.27 \cdot \Delta T_{36m} + 1763.40 \cdot \Delta T_{48m} - 5.52 \cdot u_0 \quad (8)$$

The R^2 values is 0.98 and the overall significance is much less than 0.05. The individual p-values of the coefficients are less than 0.05 for ΔT_{24m} , ΔT_{36m} and ΔT_{48m} while it is > 0.05 for the constant and u_0 . Even though the p-values for the temperature measurements are < 0.05 , an additional regression analysis is performed where ΔT_{36m} is excluded, and that analysis results in the following expression:

$$\widehat{HRR} = -149.71 - 24.56 \cdot \Delta T_{24m} + 62.28 \cdot \Delta T_{48m} + 77.08 \cdot u_0 \quad (9)$$

For this second expression the R^2 value decreased to 0.95 and the overall significance level is well below 0.05. The individual p-values for all the coefficients are below 0.05. Figure 4 illustrates the correspondence between the training set data and the model predictions. Additionally, it includes the test data and its corresponding predictions.

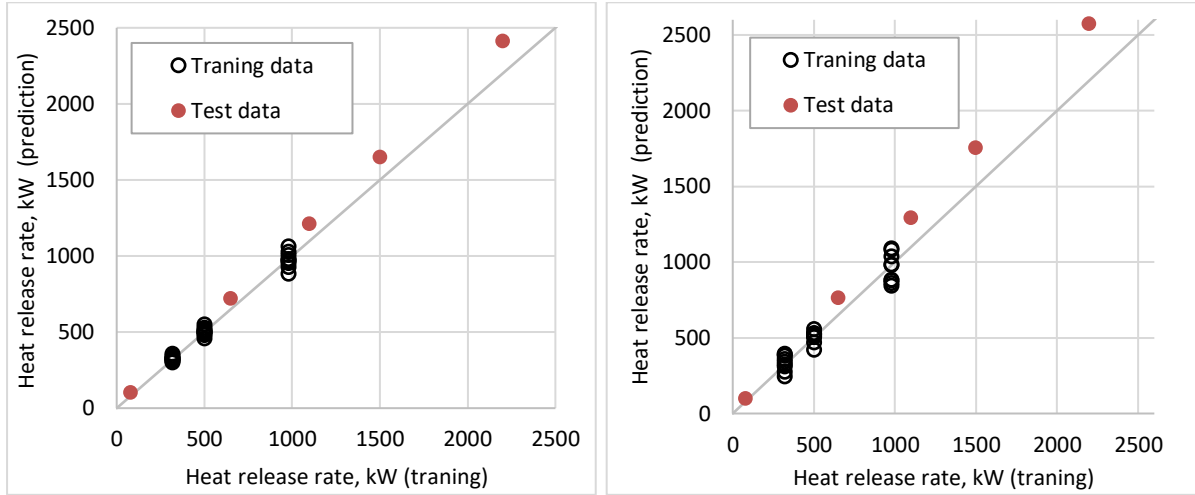


Figure 4 Prediction vs. training dataset of HRR for the hand-calculation method. To the left is the four-variable model and to the right the three-variable model.

4.2.2. Multi-zone modelling

The training dataset generated from the multi-zone model results in the following regression expression:

$$\widehat{HRR} = -276.26 - 9.07 \cdot \Delta T_{24m} + 23.17 \cdot \Delta T_{36m} - 4.11 \cdot \Delta T_{48m} + 72.99 \cdot u_0 \quad (10)$$

The R^2 value is 0.97, indicating a strong fit of the model to the data, and the overall significance level is well below 0.05. The individual p-values for the coefficients β_0 and u_0 are also below 0.05, suggesting they are statistically significant. However, the p-values for ΔT_{24m} , ΔT_{36m} and ΔT_{48m} are 0.08, 0.14, and 0.73, respectively, indicating that these coefficients are not significantly different from zero. To explore this further, a new regression analysis will be conducted, omitting ΔT_{36m} . This analysis results in the following expression:

$$\widehat{HRR} = -197.05 - 1.82 \cdot \Delta T_{24m} + 13.46 \cdot \Delta T_{48m} + 58.8 \cdot u_0 \quad (11)$$

The coefficient of determination decreased slightly to 0.94, which still indicates a strong fit of the model to the data, and the overall significance level is still well below 0.05. The individual p-values for the coefficients β_0 , ΔT_{48m} and u_0 are below 0.05; however, the p-value of ΔT_{24m} , is now 0.10. If the ΔT_{24m}

as a variable in the regression analysis as a variable, the R^2 value is reduced to 0.93. In Figure 5 it is shown how the prediction corresponds to the training set and test data for the four and three variable cases.

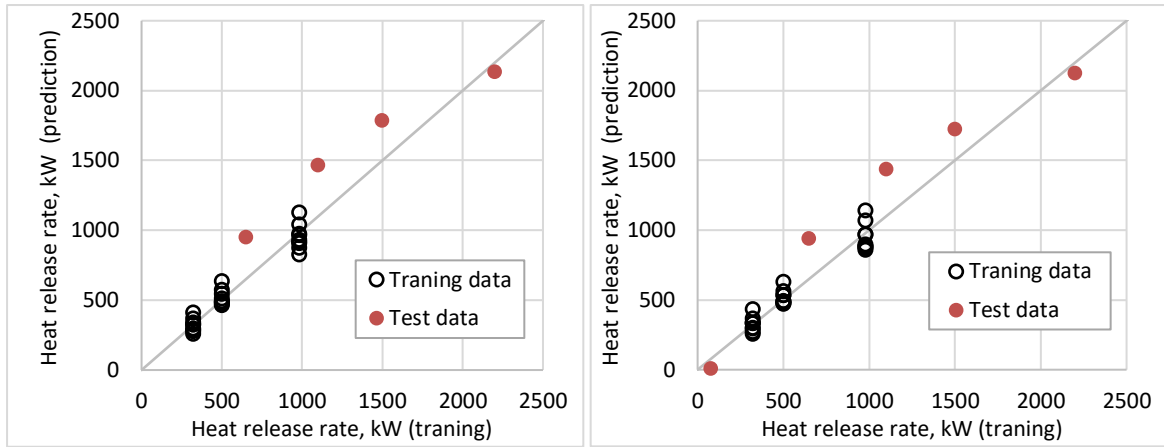


Figure 5 Prediction vs. training dataset of HRR for the zone modelling. To the left is the four variable model and to the right the three-variable model.

4.2.3. FDS modelling

The training dataset generated from the FDS model results in the following regression expression:

$$\widehat{HRR} = -252.0 + 60.63 \cdot \Delta T_{24m} - 67.78 \cdot \Delta T_{36m} + 45.70 \cdot \Delta T_{48m} + 144.03 \cdot u_0 \quad (12)$$

The coefficient of determination is 0.86, and the overall significance level is less than 10^{-8} . The individual p-values for the constant and coefficients for ΔT_{24m} and u_0 are also below 0.05, suggesting they are statistically significant. However, the p-values for ΔT_{36m} and ΔT_{48m} are 0.10 and 0.16 respectively, indicating that these coefficients are not significantly different from zero. To explore this further, a new regression analysis was conducted, omitting ΔT_{36m} . This analysis results in the following expression:

$$\widehat{HRR} = -311.40 + 13.24 \cdot \Delta T_{24m} - 5.98 \cdot \Delta T_{48m} + 163.73 \cdot u_0 \quad (13)$$

The R^2 value is 0.85, and the overall significance level is still well below 0.05. The individual p-values for the constant and the coefficients for ΔT_{24m} and u_0 are below 0.05; however, the p-value of ΔT_{48m} , is now 0.44. If the number of variables is further reduced, e.g., by removing ΔT_{48m} as a variable the coefficient of determination is reduced to 0.84. Figure 6 shows the correspondence between training data and prediction for the four and three-variable regression expression. It should be noted that the four-variable prediction fails to represent the fire phenomena in test five leading to a negative HRR prediction value which does not have a physical meaning.

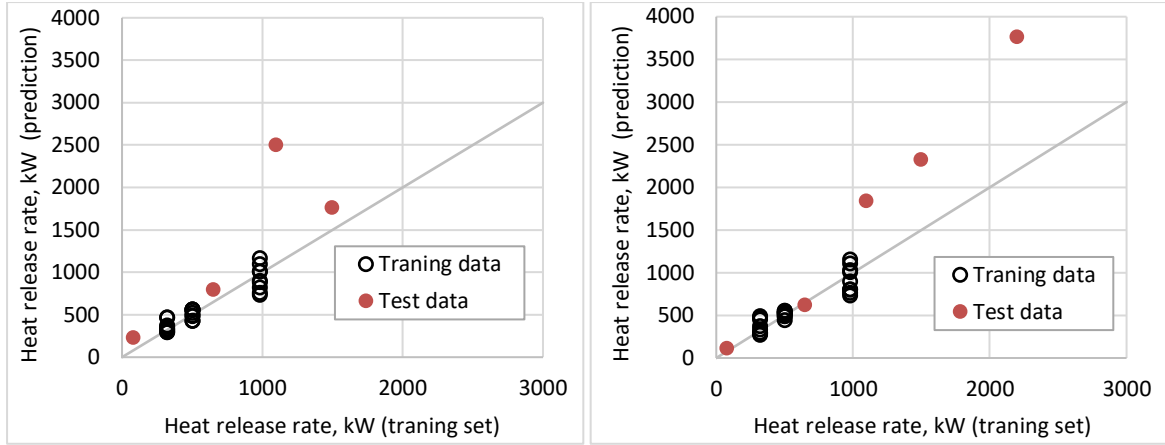


Figure 6 Prediction vs. training data set of HRR for the FDS modelling. To the left is the four variable model and to the right the three-variable model.

4.3. Prediction errors in testing

This comparison has been done considering the Root Mean Squared Percentage Error (RMSPE) of the testing data against the predicted HRR with the three-variable regression models (Equations 9, 11 and 13). Table 5 shows that the hand calculations have a strong dependence on the temperature values to estimate the heat release rate, and from Figure 7 it is clear that the error increases linearly with increasing HRR.

In contrast, the FDS simulations show the best fit when predicting the second test case (HRR= 650 kW). The multi-zone model shows a better fit for larger fires. It should be noted that those results consider a position of the fire of 20 m which is outside the range of fire position that was used in the training data. This means that those results should not be considered as providing a definitive assessment of the errors for the testing datasets, but rather providing approximate estimates of errors.

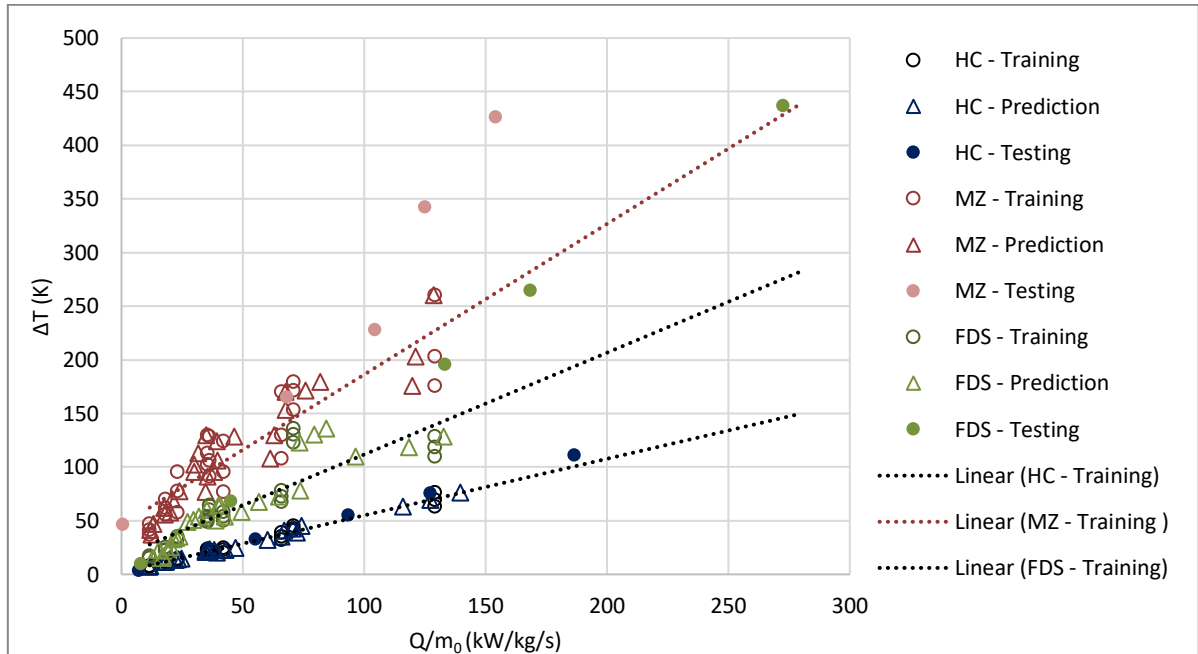


Figure 7 Temperature increment of the 27 scenarios modelled through hand calculations (HC), multi-zone modelling (MZ), and the Fire Dynamics Simulator (FDS) at training, predicted, and testing HRR values.

Table 4 Percentage errors of the testing datasets

Test	Q (kW)	Fire size	HC (%e)	MZ (%e)	FDS (%e)
1	80	small	22%	89%	36%
2	650	small	17%	45%	5%
3	1100	medium	17%	31%	67%
4	1500	medium	17%	15%	55%
5	2200	large	17%	3%	71%

4.4. Prediction errors in real experiments

The three-variable regression models (Equations 9, 11 and 13) together with experimental temperature measurements at 24 and 48 meters from the inlet tunnel portal are used to predict the experimental HRRs. As shown in Figure 8, the multi-zone and the FDS regression models provide predictions that are closer to the experimental HRRs. This is confirmed by the percentage error presented in Table 5 for the five repeated tests. It is observed that the average HRR value of the training dataset (650 kW) is in the range of the experimental HRR values. This is the error between the predicted and expected values from the three fire modelling resolutions. On average, the multi-zone approach presents a lower percentage error (21%) than FDS (32%) and the hand calculations (177%) regression model predictions.

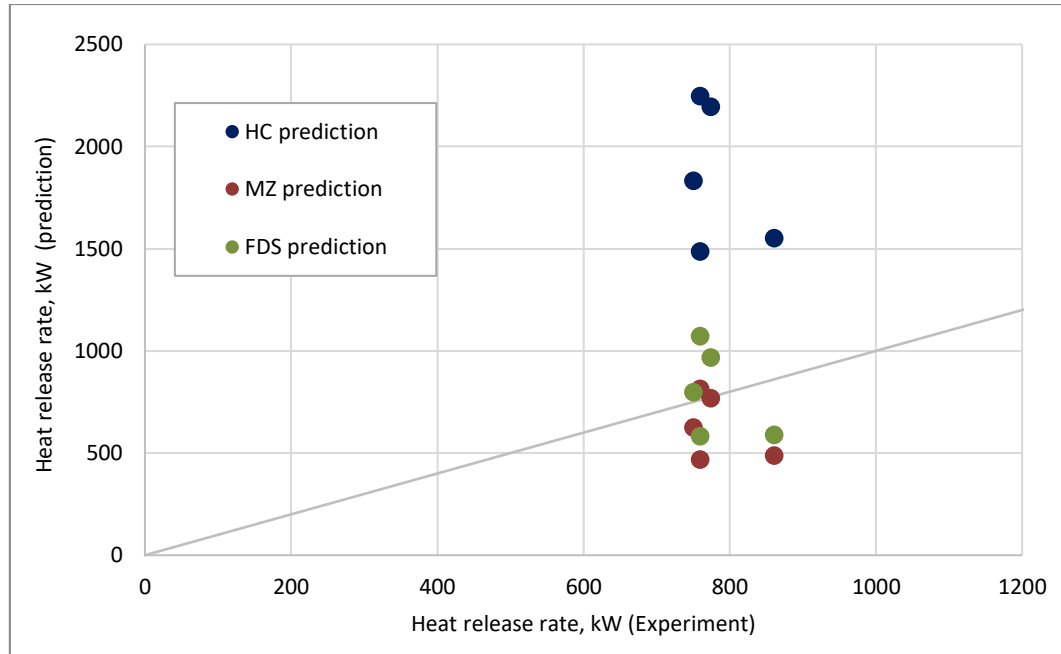


Figure 8 Prediction with the three models (three- variable) vs. data of HRR from five real experiments in a 60 m tunnel

Table 5 Percentage error of the predicted HRR for the repeated experiments

Experiment	Q (kW)	HC (%e)	MZ (%e)	FDS (%e)
1	659	178%	6%	21%
2	667	236%	22%	61%
3	663	231%	16%	46%
4	737	110%	34%	20%
5	651	128%	28%	11%
Mean	676	177%	21%	32%
Standard deviation	35	58%	11%	21%

5. DISCUSSION

The regression analysis results for the case study under consideration show a sufficient performance with a linear model, as the training dataset shows in Figure 4 - 6. The regression modelling shows an overfitting performance when correlating 4 variables. When considering 3 variables, including 2 temperature measurements and the ventilation velocity, it gives a more model that is sufficiently acceptable. It should however be stressed that multiple linear regression analysis assumes that the independent variables are uncorrelated. However, the temperature measurements are correlated with each other (mutual correlation). Additionally, temperature and velocity are correlated asymmetrically that is, temperature correlates with velocity but not vice versa.

As the analysis of testing data shows in Table 5, the regression model remains valid when the assumptions made in the training scenarios (such as the combustion process) are consistent with the specific scenario setup and its boundary conditions. Future research should investigate the suitability of different modelling resolutions in case of different scenarios and assumptions.

As mentioned in Section 3, the HRRPUA simplifies the combustion process. Therefore, the effect of ventilation on the heat release rate might not be accurately represented in the fire models, as the literature suggests in [14], [21], [22]. This issue should be considered when analysing the regression models.

Additionally, the predictions made for the repeated experiments are temperature sensor-dependent, where ventilation flow velocity was measured with an anemometer adding uncertainty to the estimated velocity value. The error analysis shows significant mean percentage errors on both models, multi-zone (21%) and FDS (32%), as shown in Table 5 and Table 6.

The results from the regression model based on hand-calculations (Equation 9) deviates from the experimental data. This is because the hand-calculation model gives the average cross section temperature and not the temperature underneath the ceiling. So, hand-calculations are not suitable if point sensor data should be used.

In Section 3, it was also mentioned that the characterization of the pool fire sizes is based on the ratio of the fire characteristic length and the tunnel width. Furthermore, the prediction errors in testing the FDS prediction model show higher errors at fuel geometries that are out of the training scenarios. However, since also the fire position was changed in the training dataset it is hard to separate which one of the two variables that had largest influence on the error. This highlights the importance that this type of predictive models needs to be based on a training dataset that covers all relevant scenario that can occur. It should not be expected that predictions can be done outside the boundaries of the training dataset.

Results demonstrate that CFD and MZ are promising approaches to use for the training of tools for smart firefighting. Nevertheless, more research is needed to explore other types of statistical and machine learning techniques that could be trained with those approaches. In addition, future work could focus on using other types of sensor data (i.e. not only temperature) to train this type of models, e.g. data from cameras [23], [24], [25]. However, temperature sensors are simple and robust and could together with a well-developed AI-based fire modelling tool be very efficient. In practice, smart firefighting requires a network to communicate real-world measurements to the model adopted, meaning that several practical issues need to be solved to ensure a functional and reliable smart firefighting approach which relies on coupling fire simulations with sensor data.

Furthermore, recent studies [24], [25] suggest that fire models should consider the position of obstructions in the airflow, as it reduces the longitudinal ventilation flow. This consideration should be included in a smart firefighting application.

Finally, multi-zone modelling [5] has shown to be promising in order to train a prediction model. This is an important finding since multi-zone modelling allows large computational savings compared to Computational Fluid Dynamics.

6. CONCLUSIONS

The present study demonstrates that multi-zone modelling and FDS are promising tools for the training of models for smart firefighting that rely on temperature sensor data and fire modelling. This implies that hand-calculations are not deemed suitable if point sensor data should be used. Multi-zone modelling has proven to be effective for training prediction models, and given its computational cost, it represents a valid option for this type of applications.

To avoid overfitting regression models, independent variables shall be included aiming to represent the assumptions (such as obstructions features and characteristic fuel length) and boundary conditions (such as tunnel geometry, obstructions, wall lining, and wind characteristics at the portals) for the training set of scenarios.

In this study, a simple linear regression approach was used. This simple statistical tool is a useful starting point for the analysis of needed modelling resolutions. Further studies can then explore the use of more complex machine learning approaches and test their ability to approximate physical fire phenomena. It is also important to highlight that regardless of the modelling approach in use, this study demonstrated how important it is to carefully select range of values in training datasets, so that they can allow representative predictions across all credible fire scenarios.

Finally, it is important to emphasize that further research is needed to translate the findings and concepts presented in this paper into practical methods applicable to real facilities. Efforts should also be made to ensure that the results from this type of smart-firefighting tools are accessible and usable for fire services, enabling them to improve decision-making in emergency situations.

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REFERENCES

- [1] R. Carvel and A. Beard, *The Handbook of Tunnel Fire Safety*. 2005.
- [2] W. Jahn, “Sensor and Modelling Driven Real-Time Fire Forecast,” in *Intelligent Building Fire Safety and Smart Firefighting*, X. Huang and W. C. Tam, Eds., Cham: Springer Nature Switzerland, 2024, pp. 281–303. doi: 10.1007/978-3-031-48161-1_12.
- [3] “Fire and rescue operations oin tunnel fires: a discussion of some practical issues,” in *The Handbook of Tunnel Fire Safety*, 2005.
- [4] H. Ingason, Y. Z. Li, and A. Lönnemark, *Tunnel Fire Dynamics*. New York, NY: Springer New York, 2015. doi: 10.1007/978-1-4939-2199-7.
- [5] N. Johansson, E. Ronchi, R. Scozzari, and M. Fronterre, “The use of multi-zone modelling for tunnel fires,” *Tunn. Undergr. Space Technol.*, vol. 134, p. 104996, Apr. 2023, doi: 10.1016/j.tust.2023.104996.
- [6] H. K. Versteeg and W. Malalasekera, *An Introduction to Computational Fluid Dynamics: The Finite Volume Method*. Pearson Education Limited, 2007. [Online]. Available: <https://books.google.se/books?id=RvBZ-UMpGzIC>
- [7] K. B. McGrattan and G. P. Forney, “Fire dynamics simulator (version 4) : user’s guide,” National

- Institute of Standards and Technology, Gaithersburg, MD, NIST SP 1019, 2004. doi: 10.6028/NIST.SP.1019.
- [8] S.-H. Koo, J. Fraser-Mitchell, and S. Welch, "Sensor-steered fire simulation," *Fire Saf. J.*, vol. 45, no. 3, pp. 193–205, Apr. 2010, doi: 10.1016/j.firesaf.2010.02.003.
 - [9] X. Zhang *et al.*, "Perspectives of big experimental database and artificial intelligence in tunnel fire research," *Tunn. Undergr. Space Technol.*, vol. 108, p. 103691, Feb. 2021, doi: 10.1016/j.tust.2020.103691.
 - [10] X. Wu, X. Zhang, X. Huang, F. Xiao, and A. Usmani, "A real-time forecast of tunnel fire based on numerical database and artificial intelligence," *Build. Simul.*, vol. 15, no. 4, pp. 511–524, Apr. 2022, doi: 10.1007/s12273-021-0775-x.
 - [11] J. A. Morales Mere, D. Madsen, N. Johansson, and E. Ronchi, "Repeatability Assessment in Tunnel Fire Experiments".
 - [12] "Real World Research, 3rd Edition | Wiley," Wiley.com. Accessed: Dec. 04, 2024. [Online]. Available: <https://www.wiley.com/en-gb/Real+World+Research%2C+3rd+Edition-p-9781119959205>
 - [13] J. O. Rawlings, S. G. Pantula, and D. A. Dickey, Eds., *Applied Regression Analysis*. in Springer Texts in Statistics. New York: Springer-Verlag, 1998. doi: 10.1007/b98890.
 - [14] "The influence of tunnel ventilation on fire behaviour," in *The Handbook of Tunnel Fire Safety*, 2005, pp. 217–234.
 - [15] Y. Z. Li, B. Lei, and H. Ingason, "Study of critical velocity and backlayering length in longitudinally ventilated tunnel fires," *Fire Saf. J.*, vol. 45, no. 6, pp. 361–370, Nov. 2010, doi: 10.1016/j.firesaf.2010.07.003.
 - [16] N. Johansson, "Evaluation of a zone model for fire safety engineering in large spaces," *Fire Saf. J.*, vol. 120, p. 103122, Mar. 2021, doi: 10.1016/j.firesaf.2020.103122.
 - [17] K. McGrattan, R. McDermott, M. Vanella, S. Hostikka, and J. Floyd, "Fire Dynamics Simulator User's Guide," National Institute of Standards and Technology, Gaithersburg, Maryland, USA, NIST Special Publication 1019 revision FDS6.7.9, 2022.
 - [18] Kevin McGrattan, Randall McDermott, Marcos Vanella, and Eric Mueller, "Fire Dynamics Simulator Technical Reference Guide Volume 3: Validation," National Institute of Standards and Technology, Gaithersburg, MD, NIST SP 1018, 2024. doi: 10.6028/NIST.SP.1018.
 - [19] K. McGrattan and M. Bilson, "Modeling longitudinal ventilation in tunnels using fire dynamics simulator," *Fire Saf. J.*, vol. 141, p. 103982, Dec. 2023, doi: 10.1016/j.firesaf.2023.103982.
 - [20] M. J. Hurley *et al.*, Eds., *SFPE Handbook of Fire Protection Engineering*. in SpringerLink Bücher. New York, NY: Springer, 2016. doi: 10.1007/978-1-4939-2565-0.
 - [21] R. O. Carvel, A. N. Beard, P. W. Jowitt, and D. D. Drysdale, "Variation of heat release rate with forced longitudinal ventilation for vehicle fires in tunnels," *Fire Saf. J.*, vol. 36, no. 6, pp. 569–596, Sep. 2001, doi: 10.1016/S0379-7112(01)00010-8.
 - [22] Y. Z. Li and H. Ingason, "The maximum ceiling gas temperature in a large tunnel fire," *Fire Saf. J.*, vol. 48, pp. 38–48, Feb. 2012, doi: 10.1016/j.firesaf.2011.12.011.
 - [23] "Performance assessment of video-based fire detection system in tunnel environment - ScienceDirect." Accessed: Dec. 13, 2024. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0886779813001314>
 - [24] W. U. Rojas Alva, G. Jomaas, and A. S. Dederichs, "The influence of vehicular obstacles on longitudinal ventilation control in tunnel fires," *Fire Saf. J.*, vol. 87, pp. 25–36, Jan. 2017, doi: 10.1016/j.firesaf.2016.11.001.
 - [25] Y. Z. Li, B. Lei, and H. Ingason, "Study of critical velocity and backlayering length in longitudinally ventilated tunnel fires," *Fire Saf. J.*, vol. 45, no. 6–8, pp. 361–370, 2010, doi: 10.1016/j.firesaf.2010.07.003.