

# Spatiotemporal Prediction of Fire-Hazard Parameters in Commercial Buildings Considering Active Fire Protection Systems

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## Research Article

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# **Spatiotemporal Prediction of Fire-Hazard Parameters in Commercial Buildings Considering Active Fire Protection Systems**

## **Abstract**

Sprinkler activation and mechanical smoke exhaust reshape thermal and smoke transport in commercial building fires, causing systematic bias in distributed optical-fiber temperature sensing (DTS) based temperature-to-smoke field mappings developed under uncontrolled conditions. This study proposes a temperature-correction and fire-hazard prediction framework for the critical evacuation plane under active fire protection. A PyroSim database covering sprinkler-only, smoke-exhaust-only, and combined sprinkler–smoke-exhaust scenarios was analyzed using nonparametric tests and generalized estimating equations. Artificial neural network, graph neural network (GNN), support vector regression, and random forest models were compared for temperature correction, after which the corrected temperatures were used to predict CO<sub>2</sub> and O<sub>2</sub> volume fractions, gas-mixture density, soot mass fraction, and visibility. Relative to uncontrolled fires, sprinkler-only, smoke-exhaust-only, and combined operation reduced the mean critical-plane temperature by 30.64, 10.52, and 59.47°C, respectively. Under combined operation, the corrected predictions achieved MAPE of 4.93%, 1.21%, and 0.65% for CO<sub>2</sub>, O<sub>2</sub>, and gas-mixture density, respectively; the MAE-to-mean ratio for soot mass fraction was 5.15%, and visibility MAPE decreased from 7.87% to 2.68%. Stable performance across independently simulated commercial spaces demonstrated cross-geometry generalizability. The proposed correction effectively limits error propagation and improves DTS-based multiphysics fire-hazard monitoring under active fire protection.

**Keywords:** Commercial building fires; Active fire protection systems; Distributed optical-fiber temperature sensing; Temperature correction; Cross-physics prediction; machine learning

## 1. Introduction

Rapid high-density urbanization and the expansion of retail-oriented public spaces have driven sustained growth in the number of commercial complexes, shopping malls, and large public commercial buildings, thereby increasing both fire exposure and the scale of potential losses [1,2]. Commercial buildings are typically characterized by large spatial volumes, mixed functions, high occupant mobility, dispersed fuel loads, and diverse interior finishing materials [2,3]. In the event of a fire, open structures such as atria, connecting corridors, and large enclosures can accelerate the vertical and horizontal spread of hot smoke, allowing hazardous conditions to affect extensive evacuation areas within a short period [4,5]. Combustion of fuels within these buildings also releases substantial heat, carbon dioxide, toxic gases, and soot particles, creating multiple hazards, including thermal exposure, oxygen depletion, toxic exposure, and reduced visibility [6,7].

Active fire protection systems are essential for controlling the thermal environment, limiting smoke-related hazards, and maintaining tenable evacuation conditions in commercial building fires [6,8]. The systems considered in this study primarily comprise automatic sprinkler systems and mechanical smoke exhaust systems. Following sprinkler activation, heat absorption through droplet evaporation, gas-phase cooling, smoke drag, and entrainment-induced flow disturbances alter the evolution of the fire plume, ceiling jet, and descending smoke layer [6,9]. Mechanical smoke exhaust systems affect pollutant concentrations, oxygen distribution, and visibility through smoke removal, induced makeup airflow, and flow-field reorganization [5,8]. Consequently, active fire protection systems do more than simply reduce temperature or remove smoke; they reshape the spatiotemporal distributions of both the thermal and smoke fields at the critical evacuation plane [8].

The early and pre-flashover stages constitute a critical window for occupant evacuation and firefighting intervention. Real-time characterization of temperature, gas concentrations, soot concentration, and visibility at evacuation height under active fire protection is therefore essential for fire situational awareness and emergency decision-

making [10,11]. Existing building fire-monitoring systems, however, rely primarily on point-type heat, smoke, and gas detectors and are designed mainly to identify fire occurrence. They are consequently unable to provide continuous, spatially dense, multiphysics information in dynamically evolving fire environments following sprinkler or smoke-exhaust activation [12,13]. Deploying large numbers of heterogeneous sensors to obtain comprehensive fire-field information would substantially increase system complexity, installation costs, and maintenance requirements [12]. Recent research on fire detection and monitoring has increasingly shifted from conventional alarm functions toward multisource sensing, dynamic hazard identification, and fire-field reconstruction. Nevertheless, acquiring continuous spatial information in commercial buildings under rapidly changing conditions induced by active fire protection systems remains a major challenge for existing sensing frameworks [12,13].

Distributed optical-fiber temperature sensing (DTS) provides an effective means of continuously monitoring fire-induced temperature variations under active fire protection [14]. DTS employs an optical fiber as the sensing medium and uses backscattered optical signals to measure and spatially locate temperature along the fiber. In Raman-based DTS systems, the temperature distribution is inferred from the intensity ratio between the Stokes and anti-Stokes components [15]. Compared with point-type temperature sensors, DTS offers continuous measurements, long transmission distances, immunity to electromagnetic interference, unobtrusive installation, and high spatial resolution. Optical fibers can be installed along ceilings, sidewalls, or other critical areas to form continuous temperature-sensing lines, thereby capturing temperature-field evolution during fire growth and after activation of fire protection systems [14–16]. The application of optical-fiber sensing to fire monitoring has also expanded from fire-source localization and threshold-based alarms to temperature-field reconstruction, dynamic temperature correction, and fire-growth prediction. These advances provide a foundation for developing temperature-correction models applicable to actively controlled fire environments [14,17,18].

Although DTS provides continuous temperature measurements, evacuation safety

is jointly governed by the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, soot mass fraction, gas-mixture density, and visibility [19]. From a fire-dynamics perspective, the thermal and smoke fields are intrinsically coupled. The heat release rate governs fire-plume development and smoke-layer descent, while combustion simultaneously consumes O<sub>2</sub> and generates CO<sub>2</sub> and soot. The soot mass fraction and gas-mixture density further influence visibility attenuation [6,19]. The temperature field can therefore serve as an important proxy for the combustion stage, smoke transport, and spatial distribution of fire-hazard parameters [19]. Multiphysics fire-prediction studies have increasingly recognized that temperature alone cannot fully characterize evacuation tenability and must be evaluated together with gas composition, soot concentration, and visibility [19]. Under sprinkler and smoke-exhaust operation, however, the responses of smoke-related hazard parameters to temperature variations may exhibit time lags, localized disturbances, and spatial heterogeneity. Consequently, temperature-to-smoke-field mappings developed under uncontrolled fire conditions may not be directly transferable to scenarios involving active fire protection systems [6,8,19].

In recent years, fire-prediction methods based on numerical simulation datasets and machine-learning algorithms have advanced rapidly, demonstrating considerable potential for fire-source identification, heat release rate prediction, smoke transport forecasting, and fire-risk assessment [20–22]. Previous studies have further established cross-physics mappings between DTS-derived temperature data and smoke-related hazard parameters, showing that temperature-related features extracted at the critical evacuation plane can be used to predict the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility [19]. However, most existing temperature-to-smoke-field prediction models have been developed for scenarios without active fire protection or under relatively stable boundary conditions. The effects of sprinkler and smoke-exhaust systems on temperature-mapping relationships and smoke-field distributions have therefore not been adequately addressed [19,20,22].

Following activation of active fire protection systems, the thermal relationships among the ceiling, sidewalls, and critical evacuation plane may be altered, introducing errors into the critical-plane temperatures inferred from DTS measurements [6,8,19].

Because these inferred temperatures serve as key inputs to subsequent smoke-hazard prediction, such errors can propagate to predictions of CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility, thereby reducing model applicability under active fire-control conditions in commercial buildings [19]. Incorporating the effects of active fire protection systems into the DTS-based temperature-to-smoke-field cross-physics prediction framework is therefore essential for improving its engineering reliability [6,8,19].

The principal contributions of this study are as follows: (1) the effects of active fire protection systems on the temporal evolution of the thermal field and smoke-related hazard parameters at the critical evacuation plane are quantitatively characterized; (2) a DTS-based temperature-correction method is developed for actively controlled fire scenarios, improving the accuracy with which ceiling- and sidewall-mounted DTS measurements are mapped to critical-plane temperatures; (3) the corrected critical-plane temperatures are coupled with a cross-physics prediction model, enhancing the predictive accuracy of CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility under active fire protection; and (4) numerical generalization tests are conducted in a small enclosed compartment, an atrium, and a large commercial space, providing a scalable framework for multiphysics fire-hazard monitoring in commercial buildings using a single DTS system.

## **2. Methods**

### **2.1 Research Framework**

This study developed a DTS-driven framework for predicting multiphysics fire-hazard parameters in commercial buildings under active fire protection. The framework builds on an established DTS-based temperature-to-smoke-field cross-physics model, in which temperature features at the critical evacuation plane are used to predict the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction; visibility is subsequently calculated from the predicted soot mass fraction and gas-mixture density [19]. The present study further accounts for changes in fire-field

boundary conditions induced by sprinkler and mechanical smoke-exhaust systems [6,8]. Specifically, a correction model was developed for temperatures at the critical evacuation plane under active fire protection. The corrected temperature features were then fed into the baseline smoke-field prediction module, yielding a fire-hazard prediction framework applicable to actively controlled fire scenarios.

The overall workflow is illustrated in Fig. 1. First, representative commercial-building fire scenarios were modeled using PyroSim to generate thermal- and smoke-field data for different enclosure heights, peak heat release rates, and fire protection configurations [23]. Virtual DTS sampling points, fire-hazard parameter monitoring points, and alarm-trigger sensors were then deployed within the computational domain to establish a fire-simulation database. Statistical analyses were subsequently conducted to quantify the effects of sprinkler operation, smoke-exhaust operation, enclosure height, and peak heat release rate on the temperature and fire-hazard parameters at the critical evacuation plane. Machine-learning algorithms were then employed to develop the critical-plane temperature-correction model, and the optimal algorithm and input-feature combination were selected using model-performance metrics. Finally, the corrected temperature-field information was supplied to the cross-physics smoke-field prediction module to estimate the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction at the critical evacuation plane, from which visibility was further calculated. Model generalizability was subsequently evaluated across commercial spaces of different scales.

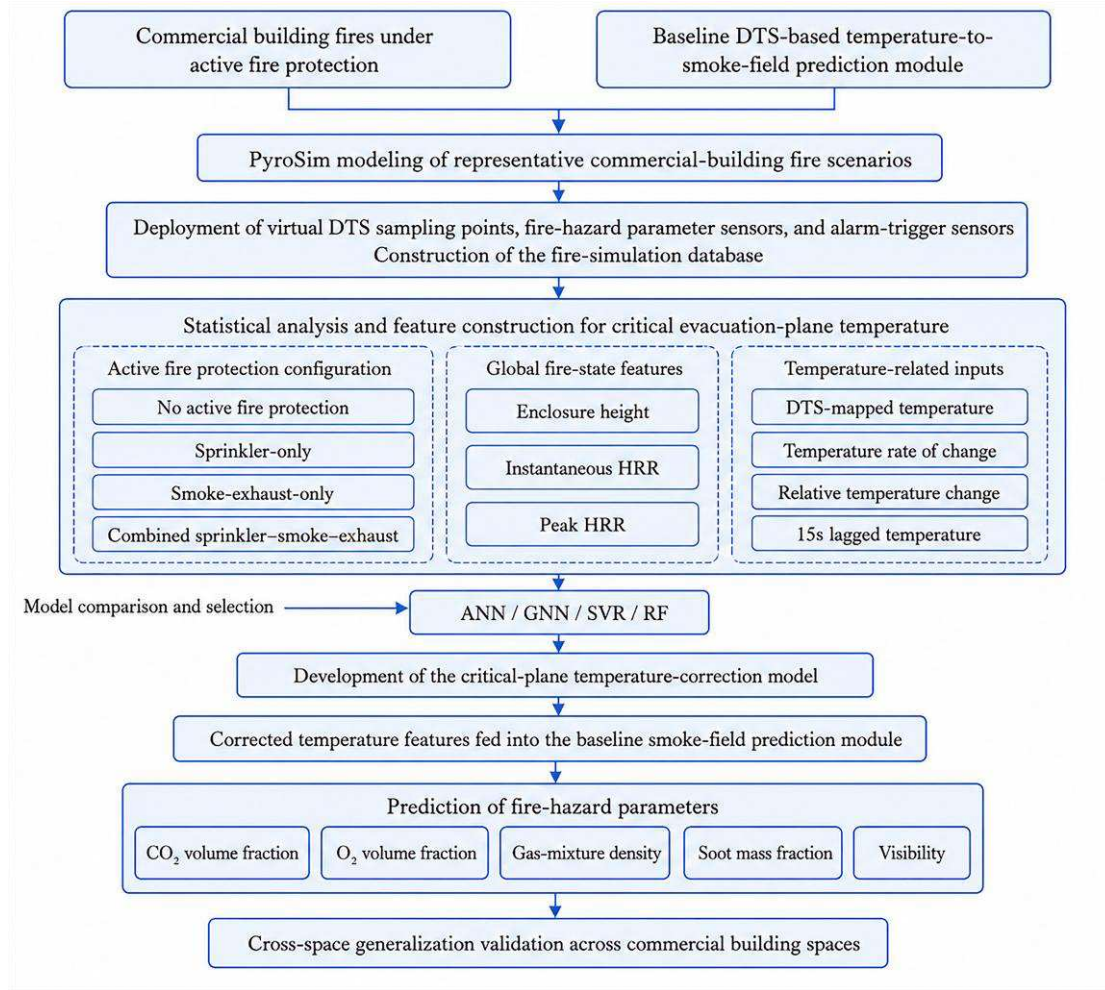


Fig. 1. Research framework

## 2.2 Critical Evacuation Plane and Fire-Hazard Assessment Parameters

The principal threats to occupant evacuation in fire environments include thermal exposure, oxygen depletion, exposure to toxic combustion products, and smoke-induced visibility reduction [24,25]. Following the general framework for assessing occupant tenability and smoke hazards in NFPA 92 and related studies, a horizontal plane 1.8m above the floor was adopted to evaluate smoke hazards at occupant breathing and visual-recognition height [25,26]. This plane is therefore defined as the critical evacuation plane and is used to characterize fire hazards at the evacuation level.

Temperature, CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility were selected as the fire-hazard assessment parameters [19,24]. Temperature characterizes thermal hazards; the CO<sub>2</sub> and O<sub>2</sub> volume fractions indicate the accumulation of combustion products and the development of oxygen-deficient conditions, respectively; gas-mixture density and soot mass fraction

characterize smoke and particulate concentrations; and visibility represents occupants' ability to visually identify their surroundings during evacuation [19,24]. Visibility was calculated from the extinction coefficient, soot mass fraction, and gas-mixture density as follows [23,27,28]:

$$S = \frac{C}{K} \quad (1)$$

$$K = K_m \rho_s \quad (2)$$

$$\rho_s = W \rho \quad (3)$$

where  $S$  is the visibility (m);  $K$  is the extinction coefficient ( $\text{m}^{-1}$ );  $C$  is a dimensionless constant, set to 3 in this study [28];  $K_m$  is the mass-specific extinction coefficient of soot, set to  $7600 \text{ m}^2 \text{ kg}^{-1}$ ;  $\rho_s$  is the soot mass concentration ( $\text{kg m}^{-3}$ ) [27];  $W$  is the soot mass fraction ( $\text{kg kg}^{-1}$ , dimensionless); and  $\rho$  is the gas-mixture density ( $\text{kg m}^{-3}$ ). Visibility was not treated as a direct output of the machine-learning model; instead, it was derived from the predicted soot mass fraction and gas-mixture density using Eqs. (1) – (3) [19,23].

## 2.3 PyroSim Fire-Scenario Setup

### 2.3.1 Simulation Platform and Baseline Spatial Model

PyroSim was used for fire-scenario modeling and post-processing, with its integrated Fire Dynamics Simulator (FDS 6.7.6) serving as the computational solver [23,29]. PyroSim was employed to construct the geometry, assign material properties, define boundary conditions, specify fire sources, deploy virtual sensors, and extract simulation results [29].

This study primarily considered commercial spaces with large clear heights and partially open commercial spaces, which typically have floor areas of  $120\text{--}350\text{m}^2$ . A square commercial compartment measuring  $14 \text{ m} \times 14 \text{ m}$ , with a floor area of  $196\text{m}^2$ , was adopted as the baseline model. Previous studies have demonstrated pronounced vertical stratification in indoor fire-induced temperature fields, with enclosure height exerting a substantial influence on temperature distributions at the critical evacuation plane [30]. Cooling by sprinkler droplets, smoke drag, and mechanically induced

exhaust airflow further alter the thermal field and smoke transport [8]. To investigate the effects of enclosure height on the thermal field, smoke field, and temperature-correction model, the enclosure height was varied from 8 to 12m at 1m intervals. The material properties used in the PyroSim models are provided in Appendix A.

### 2.3.2 Operating Conditions and Fire-Source Settings

To establish a database for temperature correction and cross-physics smoke-field prediction under active fire protection, enclosure height, peak heat release rate, and fire protection system configuration were selected as the principal scenario variables.

Commercial buildings contain diverse combustible materials, including interior finishes, merchandise, furniture, and plastic products. Fire development is influenced by fuel type, spatial arrangement, separation distance, and fire load, resulting in strongly time-dependent heat release rates [31]. Accordingly, the commonly used  $t^2$  design-fire model was adopted to describe the fire-growth stage [25,32]:

$$\dot{Q}(t) = \alpha t^2, \dot{Q}(t) \leq \dot{Q}_{\max} \quad (4)$$

where  $\dot{Q}(t)$  is the instantaneous heat release rate (kW),  $\alpha$  is the fire-growth coefficient ( $\text{kW s}^{-2}$ ),  $t$  is time (s), and  $\dot{Q}_{\max}$  is the peak heat release rate (kW). Based on the  $t^2$  design-fire growth-rate classifications adopted in NFPA 92, a fast-growing fire was considered, with  $\alpha = 0.0469 \text{ kW s}^{-2}$  [25,32]. The fire source, with an area of  $3 \text{ m}^2$ , was positioned at the center of the enclosure to represent a localized combustible fuel package commonly encountered in commercial buildings.

Peak heat release rates of 3, 8, and 20MW were specified to represent, respectively, a moderate commercial fire, a large commercial fire, and a severe high-fire-load scenario [31,33,34]. According to Eq. (4), the three fires reached their prescribed peak heat release rates at approximately 253, 413, and 653s, respectively. Thereafter, the heat release rate was maintained at  $\dot{Q}_{\max}$ . The total simulation duration was 900s, allowing all three fires to reach their prescribed peak values and maintain peak-HRR plateaus for approximately 647, 487, and 247s, respectively.

Three active fire protection configurations were considered: sprinkler-only, smoke-exhaust-only, and combined sprinkler–smoke-exhaust operation. Combining five

enclosure heights, three peak heat release rates, and three fire protection configurations yielded 45 actively controlled fire scenarios. Corresponding uncontrolled reference scenarios with identical enclosure heights and peak heat release rates were also simulated to evaluate the effects of active fire protection systems on the temporal evolution of fire-field variables and the applicability of the original temperature-mapping model.

### **2.3.3 Active Fire Protection System Configuration and Activation Logic**

The sprinkler system was configured in accordance with the Code for Design of Sprinkler Systems (GB 50084–2017) and coordinated with the general requirements of the General Code for Fire Protection Facilities (GB 55036–2022) [35,36]. Considering the ambient operating conditions and spatial characteristics of commercial buildings, a wet-pipe system equipped with upright standard-coverage sprinklers was adopted. The design discharge density was set to  $15\text{L}/(\text{min}\cdot\text{m}^2)$ , with a sprinkler spacing of 2.5m [35]. The number of sprinklers and the discharge rate of each sprinkler were determined according to the enclosure dimensions and sprinkler layout to ensure that the prescribed average discharge density was achieved throughout the study area. The sprinkler-system parameters used for the baseline model and the external generalization-validation spaces are provided in Appendix B.

The smoke-exhaust system was configured with reference to the General Code for Fire Protection Facilities (GB 55036–2022) and the Technical Standard for Smoke Management Systems in Buildings (GB 51251–2017) [36,37]. Both natural openings and mechanical smoke-exhaust boundaries were incorporated into the numerical model. Permanently open natural vents measuring  $2\text{m} \times 2\text{m}$  were arranged on two opposing sides of the enclosure, with a total opening area equivalent to approximately 4% of the floor area. This opening ratio was adopted as a numerical boundary condition representing natural ventilation and makeup-air supply. Mechanical smoke-exhaust vents measuring  $1\text{m} \times 1\text{m}$  were installed on the sidewalls. Their elevation, number, and separation from other openings were determined according to the dimensions of each modeled space. For the baseline high-clearance commercial space, the mechanical exhaust flow rate was set to  $242,000\text{m}^3/\text{h}$  for scenarios without sprinkler operation

and 122,000m<sup>3</sup>/h for sprinkler-protected scenarios [37].

#### **2.3.4 Virtual DTS Sensors, Fire-Hazard Parameter Sensors, and Data Extraction**

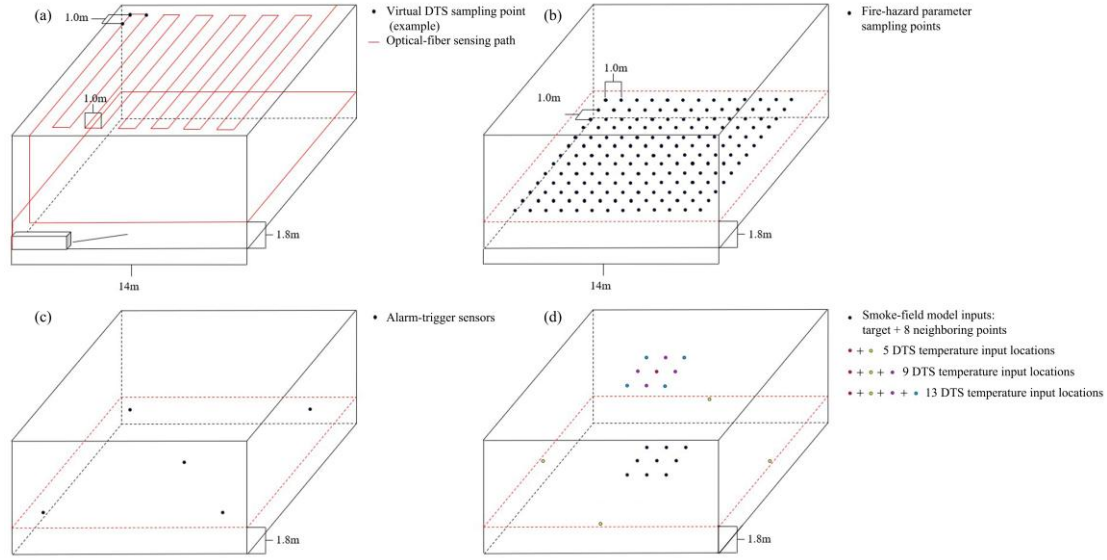
Three types of virtual sensors were deployed in the PyroSim models: DTS temperature sensors, fire-hazard parameter sensors, and fire-alarm sensors. To simulate temperature acquisition by a DTS system in a commercial building, thermocouple devices were used to represent discrete virtual DTS sampling points [29,38]. Their deployment paths corresponded to the proposed engineering layout of the optical fiber. One set of temperature sensors was installed along the perimeter sidewalls at the elevation of the critical evacuation plane (1.8m above the floor), while another set followed a serpentine path across the ceiling. Adjacent sensors were spaced at 1m intervals to discretize the fiber-optic sensing path and represent meter-scale spatial sampling [15]. This arrangement reproduced the continuous acquisition of temperature-field information from optical fibers installed along the ceiling and perimeter walls in practical applications [38].

Gas-phase devices were used as fire-hazard parameter sensors and were uniformly distributed across the critical evacuation plane at 1m intervals. Each device recorded the O<sub>2</sub> volume fraction, CO<sub>2</sub> volume fraction, soot mass fraction, and gas-mixture density.

To apply a consistent activation criterion across all fire protection configurations, five temperature-triggering sensors, represented by thermocouple devices, were uniformly distributed over the critical evacuation plane. When the temperature measured by any alarm sensor reached or exceeded 68°C, the sprinkler system, smoke-exhaust system, or combined sprinkler–smoke-exhaust system was activated, and the simulation entered the active fire-control stage.

For each scenario, ten target locations were selected on the critical evacuation plane. At each target location, fire-hazard data were extracted from the target sensor and its eight neighboring sensors, yielding nine fire-hazard parameter sampling points. Temperature data were simultaneously extracted from 13 virtual DTS sensors, comprising the ceiling sensor vertically aligned with the target location and its eight neighboring ceiling sensors, together with four corresponding sensors on the

surrounding sidewalls [19]. The 45 actively controlled fire scenarios therefore yielded 450 target-location sample units for developing the critical-plane temperature-correction model and the cross-physics smoke-field prediction model. Representative sensor layouts are shown in Fig. 2.



(a) virtual DTS temperature sensors; (b) fire-hazard parameter sampling points; (c) fire-alarm-trigger sensors; (d) sensors used to construct the model input features

Fig. 2. Representative spatial layouts of the sensors

### 2.3.5 Mesh-Independence Analysis

A mesh-independence analysis was conducted to ensure the reliability of the numerical simulations. In PyroSim, the relative mesh resolution of the fire source and plume can be preliminarily assessed using the ratio of the characteristic fire diameter to the mesh size,  $D^* / \delta x$  [39]. The characteristic fire diameter  $D^*$  was calculated as:

$$D^* = \left( \frac{\dot{Q}}{\rho_{\infty} c_p T_{\infty} \sqrt{g}} \right)^{2/5} \quad (5)$$

where  $D^*$  is the characteristic fire diameter (m);  $\dot{Q}$  is the heat release rate (kW);  $\rho_{\infty}$  is the ambient air density ( $\text{kg m}^{-3}$ );  $c_p$  is the specific heat capacity of air at constant pressure ( $\text{kJ kg}^{-1} \text{K}^{-1}$ );  $T_{\infty}$  is the ambient temperature (K); and  $g$  is the gravitational acceleration ( $\text{m s}^{-2}$ ). Taking the fire condition at which the temperature at the critical evacuation plane reached  $68^{\circ}\text{C}$  as representative, the mean characteristic fire diameter was calculated to be approximately 1.8m. Based on the commonly adopted preliminary

criterion of  $D^* / \delta x = 4\text{--}16$ , the corresponding acceptable mesh-size range was 0.113–0.45m [39,40].

Three uniform mesh sizes: 0.125, 0.25, and 0.45m were evaluated. Across the complete temperature time series, the results obtained using the 0.25m mesh exhibited MAEs of 0.81 and 2.42°C relative to those obtained using the 0.125 and 0.45m meshes, respectively, with corresponding MAPEs of 0.91% and 2.67%. Mesh convergence was further assessed using Richardson extrapolation [41]. The grid convergence indices for the 0.45/0.25m and 0.25/0.125m mesh pairs were 0.252371% and 0.031729%, respectively, and the convergence-test ratio was 1.00720526. Considering both computational accuracy and cost, a mesh size of 0.25m was adopted for all subsequent simulations.

## 2.4 Statistical Analysis

The effects of active fire protection systems on temperature and fire-hazard parameters at the critical evacuation plane were statistically evaluated. Normality of the temperature, CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction data were assessed using the Lilliefors-corrected Kolmogorov–Smirnov test [42]. For variables that did not follow a normal distribution, nonparametric tests were applied. Differences associated with sprinkler-only and smoke-exhaust-only operation were evaluated using the Wilcoxon signed-rank test, whereas the effects of enclosure height and peak heat release rate on temperature and the fire-hazard parameters were assessed using the Friedman test [43,44]. The significance level was set at 0.05, and very small  $p$ -values are reported uniformly as  $p < 0.001$ .

Because temperature observations recorded at the same sensor location within a given scenario constituted repeated measurements over time and were therefore not independent, generalized estimating equations (GEE) were further employed to quantify the population-averaged effects of fire protection configuration, enclosure height, and peak heat release rate on temperature at the critical evacuation plane [45,46]. As temperature was a continuous response variable, the GEE models assumed a Gaussian distribution with an identity link function. Regression coefficients,  $\beta$  and their corresponding 95% confidence intervals (CIs) were reported to characterize the

magnitude and uncertainty of the estimated marginal effects [45,46]. Uncontrolled-fire scenarios were specified as the reference category, while sprinkler-only, smoke-exhaust-only, and combined sprinkler–smoke-exhaust operation were included as categorical fire protection states. Enclosure height and peak heat release rate were incorporated as covariates. Each scenario–sensor combination was treated as a cluster. Robust covariance estimation was applied, and an exchangeable working correlation structure was used to account for temporal dependence among observations within each cluster [45].

To further compare the effects of the fire protection systems across combinations of enclosure height and peak heat release rate, stratified GEE models were fitted separately for each height–peak-HRR combination. In each stratified model, the uncontrolled-fire condition remained the reference category, and the marginal temperature differences associated with sprinkler-only, smoke-exhaust-only, and combined sprinkler–smoke-exhaust operation were estimated relative to the uncontrolled condition.

The statistical analyses served two purposes: first, to verify the significant effects of sprinkler and smoke-exhaust systems on fire-environment variables at the critical evacuation plane; and second, to provide a statistical basis for retaining enclosure height, instantaneous heat release rate, and peak heat release rate as input features in the subsequent temperature-correction model.

## **2.5 Machine-Learning Model Development, Training, and Evaluation**

### **2.5.1 Prediction Tasks and Modeling Workflow**

The machine-learning framework in this study comprised two sequential tasks: (1) correction of the temperature at the critical evacuation plane under active fire protection and (2) cross-physics smoke-field prediction based on the corrected temperatures. For the smoke-field prediction task, this study builds on the DTS-based temperature-to-smoke-field cross-physics prediction method developed and validated in our previous work [19]. The input-feature construction scheme, optimal algorithm type, and main model hyperparameters from that method were retained. Using the actively controlled fire-scenario database established in the present study, data preprocessing, model

training, and performance evaluation were then repeated following the same modeling workflow, thereby forming a smoke-hazard parameter prediction module applicable to fire scenarios involving active fire protection systems.

On this basis, the present study focused on the development and algorithm selection of the temperature-correction model for the critical evacuation plane. The corrected temperature features were then fed into the retrained smoke-field prediction module to estimate the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility. Therefore, the input-feature dimensionality and algorithm selection for the smoke-field prediction module are not discussed again in this paper. Instead, the analysis focuses on correcting temperature-mapping deviations induced by active fire protection systems and evaluating their influence on the accuracy of cross-physics smoke-field prediction.

### 2.5.2 Input-Feature Construction

In addition to instantaneous temperature, the temperature rate of change and relative temperature change were used to characterize the temporal evolution of the fire-induced temperature field [30]. For a temperature sensor  $I$ , these two features were defined as:

$$R_i(t) = \frac{T_i(t) - T_i(t - \Delta t)}{\Delta t} \quad (6)$$

$$P_i(t) = \frac{T_i(t) - T_i(t - \Delta t)}{T_i(t - \Delta t)} \quad (7)$$

where  $T_i(t)$  is the temperature measured at sensor  $I$  at time  $t$ (°C);  $\Delta t$  is the data-output interval (s);  $R_i(t)$  is the temperature rate of change (°C/s); and  $P_i(t)$  is the dimensionless relative temperature change.

The baseline smoke-field prediction module used the temperature at the target location on the critical evacuation plane and those at its eight neighboring locations as spatial inputs [19]. For each of the nine input locations, three temperature-related features—instantaneous temperature, temperature rate of change, and relative temperature change—were extracted, yielding 27 temperature-related features. Enclosure height, instantaneous heat release rate, and peak heat release rate were additionally included as three fire-scenario descriptors, resulting in a total of 30 input

features [19].

The temperature-correction model used virtual DTS temperature measurements as its primary inputs. The input variables included the DTS-mapped temperature, temperature rate of change, relative temperature change, temperature recorded 15s earlier, enclosure height, instantaneous heat release rate, and peak heat release rate. Historical temperature information provides temporal-dependence features that enable machine-learning models to identify temperature-evolution trends [47]. Accordingly, the temperature recorded 15s earlier was introduced as a short-term lag feature to characterize the transient temperature response at the critical evacuation plane following sprinkler and smoke-exhaust activation.

Three temperature-correction datasets containing 5, 9, and 13 temperature input locations were constructed to evaluate whether incorporating broader local spatial information improved model performance [30]. These datasets contained 23, 39, and 55 input features, respectively. Of these, 15, 27, and 39 were derived from instantaneous fiber-optic temperature measurements; 5, 9, and 13 were lagged-temperature features; and the remaining three were global fire-state features. Representative sensor locations are shown in Fig. 2(d).

### **2.5.3 Machine-Learning Model Configuration**

The cross-physics smoke-field prediction module employed the previously validated optimal ANN configuration [19]. The present study focused on developing and selecting the temperature-correction model for actively controlled fires. Four regression algorithms—a fully connected artificial neural network (ANN), graph neural network (GNN), support vector regression (SVR), and random forest (RF)—were trained and compared using input sets containing 23, 39, and 55 features. The ANN and GNN were used to establish, respectively, a fully connected nonlinear mapping and a model that explicitly encoded the graph topology among sensing locations [48–50]. SVR and RF represented kernel-based regression and randomized decision-tree ensemble approaches, respectively [51,52].

The fully connected feedforward neural network, hereafter referred to as ANN, is a nonlinear function-approximation model suitable for capturing complex relationships

between multisource input features and continuous response variables [48]. The ANN can approximate the nonlinear relationship between the input features and critical-plane temperature under active fire protection. However, a conventional fully connected architecture organizes all inputs into a fixed-length vector and therefore does not explicitly represent spatial adjacency among temperature-sensing locations [48,50].

Graph neural networks perform representation learning on graph-structured data. Temperature-sensing locations can be represented as nodes, while their spatial adjacency can be represented as edges, thereby preserving the topology of the sensor network [49,50]. A GNN performs message passing through neighborhood aggregation and node-state updating, which can be generally expressed as [49,50]:

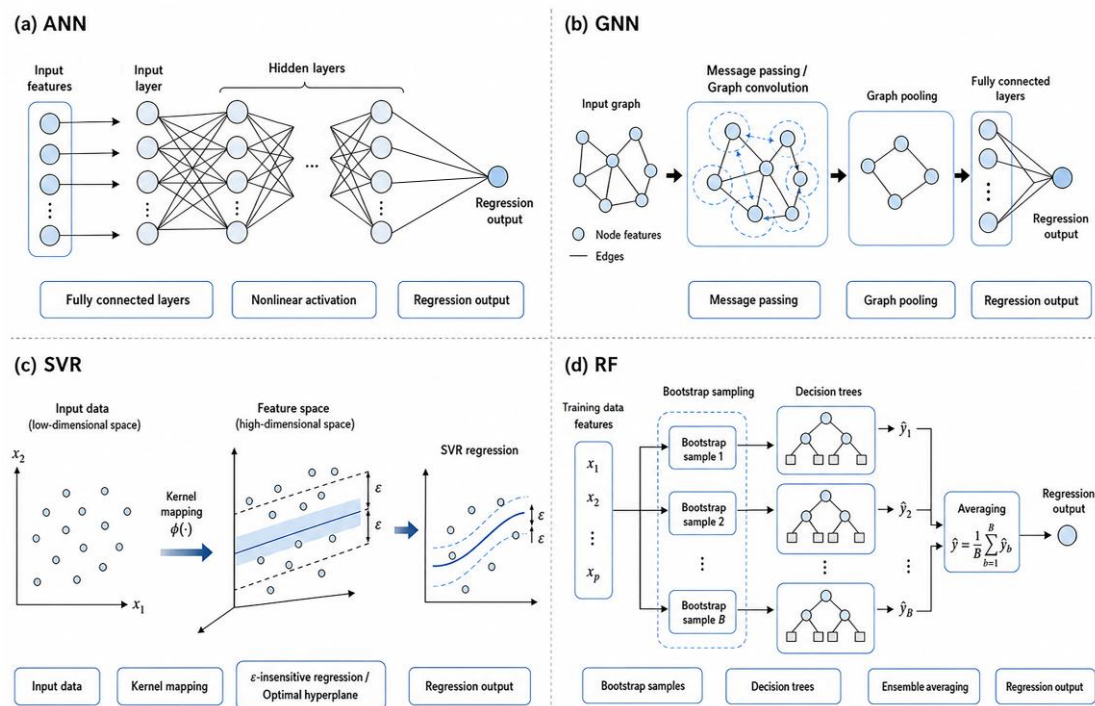
$$\mathbf{h}_i^{(l+1)} = \phi^{(l)} \left( \mathbf{h}_i^{(l)}, \sum_{j \in N(i)} \psi^{(l)} \left( \mathbf{h}_i^{(l)}, \mathbf{h}_j^{(l)} \right) \right) \quad (8)$$

where  $\mathbf{h}_i^{(l)}$  is the feature representation of node  $i$  at layer  $l$ ;  $N(i)$  is the set of neighboring nodes of node  $i$ ;  $\psi^{(l)}(\cdot)$  is the neighborhood-message function; and  $\phi^{(l)}(\cdot)$  is the node-update function. Graph convolutional networks have previously been applied to fire-induced temperature-field prediction by integrating temperature dependencies among adjacent regions through graph structures [53]. Accordingly, the GNN was included as a candidate model to determine whether explicitly incorporating the spatial relationships between the target and neighboring sensing locations could better characterize localized temperature disturbances induced by sprinkler cooling, exhaust-driven airflow, and smoke drag.

Support vector regression (SVR) is a nonlinear regression method grounded in statistical learning theory and is well suited to robust prediction with small-to-medium datasets and high-dimensional features [51]. SVR maps the input features into a high-dimensional feature space through a kernel function and constructs a regression function within an  $\varepsilon$ -insensitive error tube while maximizing model flatness, thereby enhancing generalization performance [51]. In this study, SVR was adopted as a non-neural-network candidate to evaluate the performance of kernel-based regression for temperature correction.

Random forest (RF) is an ensemble-learning method composed of multiple

regression trees [52]. It generates multiple training subsets through bootstrap sampling and averages the predictions of the individual trees, thereby reducing prediction variance and the risk of overfitting relative to a single decision tree [52]. RF also exhibits a degree of robustness to noise and outliers and was therefore used as the tree-based benchmark for the temperature-correction task [52]. Schematic representations of the four machine-learning architectures are presented in Fig. 3.



(a) ANN; (b) GNN; (c) SVR; (d) RF

Fig. 3. Candidate machine-learning architectures for correcting temperature at the critical evacuation plane

## 2.5.4 Data Preprocessing and Dataset Partitioning

Before model training, all input features were min-max normalized to reduce the influence of differences in physical units and numerical scales. To prevent data leakage, normalization parameters in the five-fold cross-validation were calculated exclusively from the training subset of each fold. For final model training, the parameters were recalculated using all training scenarios and then applied to the test and generalization datasets [54]. Isolated anomalous samples arising under active fire protection were identified and removed using the local outlier factor method [55].

The 45 actively controlled fire scenarios were partitioned at the scenario level into

40 training scenarios and five test scenarios. All sensor measurements and time-series observations from the same scenario were retained within a single subset. Grouped five-fold cross-validation, with scenarios used as the grouping units, was performed within the training set for hyperparameter optimization and model selection. The test scenarios were reserved exclusively for final performance evaluation [54,56].

For generalization assessment, four independently simulated and previously unseen spaces—an  $8\text{m} \times 8\text{m}$  small retail compartment, a  $20\text{m} \times 20\text{m}$  atrium, a  $30\text{m} \times 20\text{m}$  atrium, and a  $50\text{m} \times 40\text{m}$  large commercial space—were used as external validation datasets. These datasets were excluded from model training, preprocessing-parameter estimation, and hyperparameter selection and were used solely to evaluate the cross-space generalizability of the corrected model across commercial-building environments [57].

### **2.5.5 Hyperparameter Settings and Training Strategy**

To ensure consistent comparisons among the algorithms and enhance experimental reproducibility, all four temperature-correction models used the same scenario-level data partitioning, within-fold preprocessing, and performance-evaluation procedures [54]. A fixed random seed of 42 was used for dataset partitioning, ANN and GNN parameter initialization, training-batch generation, RF bootstrap sampling, and randomized hyperparameter search. Localized anomalous samples arising under active fire protection were identified using the local outlier factor method [55], with the number of neighbors set to 20 and the contamination parameter set to 0.02.

Both the ANN and GNN treated temperature at the critical evacuation plane as a continuous response variable. Mean squared error was used as the data-fitting loss, and model parameters were updated using the Adam optimizer [58]. To mitigate overfitting, an  $L_2$  penalty was added to the mean squared error loss, with the regularization coefficient set to  $1 \times 10^{-4}$  [59].

The ANN adopted a fully connected feedforward architecture [48] comprising three hidden layers with 128, 64, and 32 neurons, respectively. The rectified linear unit (ReLU) activation function was applied to the hidden layers [60], while a linear activation function was used in the output layer. The learning rate was set to 0.001, and

the batch size was 64.

The GNN explicitly represented the spatial adjacency among temperature-sensing locations [49,50]. Each sensing location was defined as a graph node with four node features: instantaneous temperature, temperature rate of change, relative temperature change, and temperature recorded 15s earlier. Spatial proximity between sensing locations was represented by graph edges. The edge set comprised horizontal and vertical adjacency connections; an undirected edge was established between two sensors when they satisfied the predefined spatial-adjacency criterion, with all edge weights set to unity. Enclosure height, instantaneous heat release rate, and peak heat release rate were treated as graph-level global features and concatenated with the graph representation after graph-level pooling.

The GNN comprised two graph message-passing layers, each with a hidden dimension of 64. After updating the node representations, global mean pooling was applied to obtain a graph-level embedding. This embedding was concatenated with the three global fire-scenario features and passed through a fully connected regression head containing 64 and 32 neurons. The output was the corrected temperature at the critical evacuation plane. The learning rate and batch size were set to 0.0005 and 32, respectively.

SVR employed a radial basis function kernel to construct a nonlinear temperature-regression model [51]. Following min–max normalization of the input features, the penalty parameter  $C$  was set to 100, the kernel coefficient  $\gamma$  was set to scale, and the  $\varepsilon$ -insensitive loss parameter was set to 0.5 °C. Here,  $C$  controls the trade-off between model complexity and training error,  $\gamma$  determines the effective range of the radial basis function kernel, and  $\varepsilon$  defines the temperature-error tolerance within which deviations are not penalized [51].

RF was used as the tree-based ensemble benchmark [52]. The number of regression trees was set to 500, the maximum tree depth to 20, the minimum number of samples per leaf to 2, the minimum number of samples required to split an internal node to 4, and the maximum fraction of features considered at each split to 0.7. Multiple regression trees were trained on bootstrap samples, and their predictions were averaged

to reduce prediction variance relative to that of an individual decision tree [52].

### 2.5.6 Evaluation Metrics

Model performance was evaluated using the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient of determination ( $R^2$ ) [61]:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (12)$$

where  $y_i$  is the simulated value,  $\hat{y}_i$  is the model-predicted value,  $\bar{y}$  is the mean of the simulated values, and  $n$  is the number of samples.

Because the soot mass fraction may approach or equal zero at certain time steps, direct calculation of MAPE can produce numerically unstable or misleading results [62]. Therefore, the ratio of MAE to the sample mean was used as the relative-error metric for soot mass fraction:

$$MAE/Mean = \frac{MAE}{\bar{y}} \times 100\% \quad (13)$$

Visibility was calculated from the predicted soot mass fraction and gas-mixture density and compared with the corresponding simulated visibility. Because extremely high and extremely low visibility values may disproportionately affect aggregate error metrics, visibility performance was assessed using both the overall prediction error and the error within the evacuation-relevant visibility range of 1–30 m.

## 3. Results and Discussion

### 3.1 Effects of Active Fire Protection Systems on Fire-Environment Variables at the

## Critical Evacuation Plane

To examine the effects of active fire protection systems on the spatiotemporal distributions of fire-hazard parameters in commercial buildings, the temporal variations in fire-environment variables at the critical evacuation plane were first compared between the uncontrolled-fire and combined sprinkler–smoke-exhaust scenarios. A representative case involving a  $14\text{m} \times 14\text{m}$  commercial space with an enclosure height of 9m and a peak heat release rate of 8MW was selected. Temperature,  $\text{CO}_2$  volume fraction,  $\text{O}_2$  volume fraction, gas-mixture density, and soot mass fraction were compared at the same monitoring location on the critical evacuation plane. This case was used to illustrate typical fire-field evolution under active fire protection, whereas the subsequent temperature-correction and cross-physics prediction models were developed using the complete set of actively controlled fire scenarios.

As shown in Fig. 4(a), without active fire protection, the temperature at the critical evacuation plane increased continuously as the fire developed and remained elevated during the middle and late stages of the simulation. Following activation of the combined sprinkler–smoke-exhaust system, the temperature curve exhibited a pronounced transition at approximately 350–400s, after which the temperature decreased and stabilized at a substantially lower level. This behavior indicates that sprinkler-induced cooling, exhaust-driven airflow, and the coupled makeup-air and smoke-removal processes collectively altered the thermal environment at the critical evacuation plane.

The  $\text{CO}_2$  volume fraction and soot mass fraction were also markedly affected by active fire protection. As shown in Fig. 4(b) and 4(e), both variables increased continuously as the uncontrolled fire developed. Following activation of the combined sprinkler–smoke-exhaust system, their rates of increase were suppressed, and both gradually stabilized at lower levels.

The temporal trends in  $\text{O}_2$  volume fraction and gas-mixture density were consistent with these observations. Fig. 4(c) shows that the  $\text{O}_2$  volume fraction decreased continuously during uncontrolled fire growth, whereas activation of the combined system mitigated oxygen depletion. As shown in Fig. 4(d), the gas-mixture density

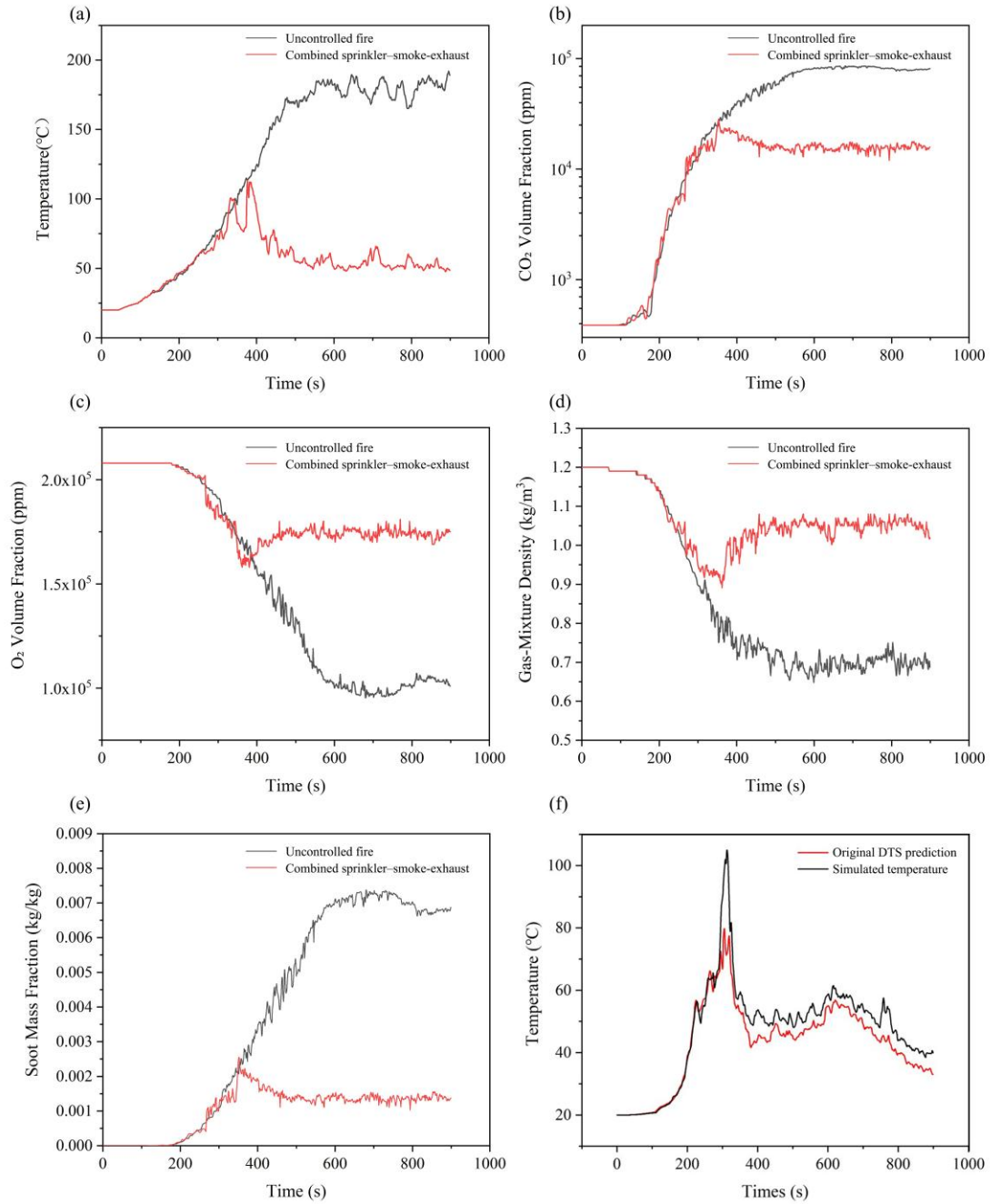
recovered or stabilized after system activation, indicating substantial changes in gas composition and smoke transport at the critical evacuation plane.

Overall, temperature, CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction all exhibited pronounced transitions following activation of the fire protection systems. These results demonstrate that sprinkler and smoke-exhaust operation altered not only the thermal field but also the smoke environment and evacuation-related hazards at the critical evacuation plane. Consequently, the DTS-based temperature-to-smoke-field cross-physics mapping established under uncontrolled fire conditions may become systematically biased after activation of active fire protection systems.

To determine whether the effects of sprinkler and smoke-exhaust systems on the fire-environment variables were statistically significant, Lilliefors-corrected Kolmogorov–Smirnov normality tests were conducted for temperature, CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction. None of the variables followed a normal distribution; therefore, Wilcoxon signed-rank tests were used to compare each parameter between scenarios with and without active fire protection. As reported in Appendix C, sprinkler-only operation produced significant differences in temperature, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction across all enclosure heights from 8 to 12m. For CO<sub>2</sub> volume fraction, the difference was significant at  $p = 0.041$  for the 10m enclosure and at  $p < 0.001$  for all other enclosure heights. Under smoke-exhaust-only operation, all five variables differed significantly from their uncontrolled-fire counterparts at every enclosure height ( $p < 0.001$ ). These results confirm that both sprinkler and smoke-exhaust systems significantly alter the thermal environment and smoke-related hazard distributions at the critical evacuation plane.

Friedman tests were further performed to evaluate the effects of enclosure height and peak heat release rate under active fire protection. As shown in Appendix D, both factors significantly affected temperature and all four smoke-related hazard parameters. Thus, even after sprinkler or smoke-exhaust activation, enclosure height and peak heat release rate remained important determinants of fire-hazard distributions at the critical

evacuation plane. These variables were therefore retained as input features in the subsequent temperature-correction and cross-physics prediction models.



(a) Temperature; (b) CO<sub>2</sub> volume fraction; (c) O<sub>2</sub> volume fraction; (d) gas-mixture density; (e) soot mass fraction; (f) predictions of the original DTS temperature-mapping model versus simulated values

Fig. 4. Effects of the combined sprinkler-smoke-exhaust system on the temporal evolution of fire-environment parameters at the critical evacuation plane and on the original DTS temperature mapping for the representative scenario

Building on the nonparametric analyses, a GEE model with a Gaussian distribution and identity link function was used to quantify the population-averaged effects of fire protection configuration, enclosure height, and peak heat release rate on temperature at the critical evacuation plane. The results are presented in Table 1. The uncontrolled-fire condition was used as the reference category; thus,  $\beta < 0$  indicates a lower temperature than that under the uncontrolled condition.

Table 1. Full-sample GEE estimates of the effects of fire protection configuration, enclosure height, and peak heat release rate on temperature at the critical evacuation plane

| Explanatory variable                    | $\beta$   | Robust standard error (SE) | p-value |
|-----------------------------------------|-----------|----------------------------|---------|
| Intercept                               | 135.70°C  | 4.72                       | < 0.001 |
| Sprinkler-only system                   | −30.64°C  | 1.18                       | < 0.001 |
| Smoke-exhaust-only system               | −10.52°C  | 0.92                       | < 0.001 |
| Combined sprinkler–smoke-exhaust system | −59.47°C  | 2.64                       | < 0.001 |
| Enclosure height                        | −4.06°C/m | 0.29                       | < 0.001 |
| Peak heat release rate                  | 3.16°C/MW | 0.13                       | < 0.001 |

Note: Because enclosure height and peak heat release rate were not mean-centered, the intercept was retained primarily for model fitting and was not assigned a direct engineering interpretation.

As shown in Table 1, all three fire protection configurations significantly reduced the temperature at the critical evacuation plane after adjustment for enclosure height and peak heat release rate. The estimated coefficients were −30.64°C for sprinkler-only operation, −10.52°C for smoke-exhaust-only operation, and −59.47°C for combined sprinkler–smoke-exhaust operation. These results indicate that sprinkler activation exerted a more direct cooling effect at the critical evacuation plane, whereas mechanical smoke exhaust alone produced a comparatively smaller temperature reduction. Under combined operation, droplet-induced cooling, smoke removal, and makeup-air-driven flow collectively modified the thermal environment, resulting in the largest temperature reduction.

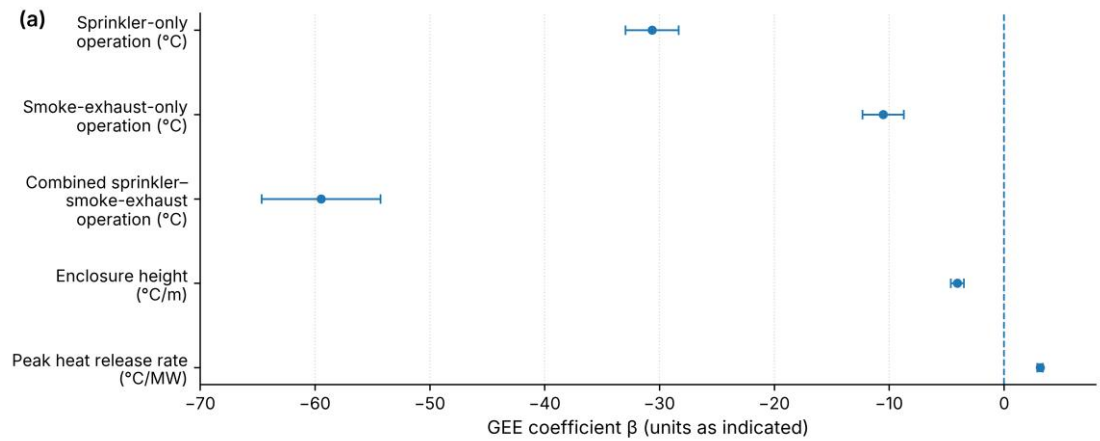
The coefficient for enclosure height was −4.06°C/m, indicating that, for a given fire protection configuration and peak heat release rate, each 1m increase in enclosure

height was associated with an average decrease of approximately 4.06°C at the critical evacuation plane. A greater enclosure height provides a larger volume for the vertical spread and accumulation of hot smoke, thereby delaying its influence on the critical evacuation plane at 1.8m. The coefficient for peak heat release rate was 3.16°C/MW, indicating that each 1MW increase in fire-source intensity was associated with an average temperature increase of approximately 3.16°C. Thus, enclosure height and fire-source intensity remained important determinants of the critical-plane thermal field even under active fire protection.

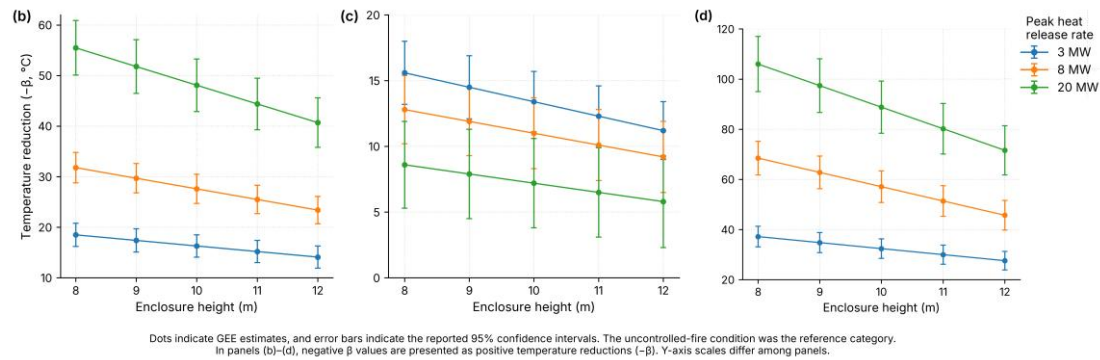
To further compare the effects of active fire protection systems across different combinations of enclosure height and peak heat release rate, stratified GEE models were fitted separately for each height–fire-intensity combination; the detailed results are provided in Appendix E. Across enclosure heights of 8–12m and peak heat release rates of 3–20MW, all three fire protection configurations produced significant temperature reductions relative to the uncontrolled-fire condition. Sprinkler-only operation reduced the mean temperature at the critical evacuation plane by 14.1–55.5°C, smoke-exhaust-only operation by 5.8–15.6°C, and combined sprinkler–smoke-exhaust operation by 27.6–106.0°C. For the representative 9m, 8MW scenario, the coefficient for the combined system was –62.8°C, consistent with the substantially lower post-activation temperatures observed in Fig. 4(a) relative to the uncontrolled-fire condition. The GEE coefficient  $\beta$  represents the population-averaged marginal temperature difference estimated from repeated observations across the complete time series and multiple sensor locations, rather than the maximum instantaneous temperature difference at a particular time.

The stratified GEE results further showed that enclosure height and peak heat release rate moderated the marginal effects of the fire protection systems. As enclosure height increased, the absolute magnitudes of the coefficients for all three configurations generally decreased. This finding suggests that greater enclosure height delayed smoke-layer descent to the critical evacuation plane, thereby reducing the marginal cooling effect of the systems at an elevation of 1.8m. As peak heat release rate increased, the absolute coefficients for sprinkler-only and combined sprinkler–smoke-exhaust

operation increased, whereas that for smoke-exhaust-only operation decreased. Under higher-intensity fire conditions, sprinkler cooling therefore became more pronounced, while the relative capacity of mechanical smoke exhaust alone diminished as hot-smoke production increased rapidly. These findings demonstrate that the effects of active fire protection systems on critical-plane temperature depend not only on system configuration but also on the combined influence of enclosure height and fire intensity. The GEE results are summarized in Fig. 5.



(a) Full-sample GEE coefficients and 95% confidence intervals;



(b) sprinkler-only system; (c) smoke-exhaust-only system; (d) combined sprinkler-smoke-exhaust system

Fig. 5. Full-sample and stratified GEE analyses of the effects of active fire protection systems on temperature at the critical evacuation plane

Overall, sprinkler-only, smoke-exhaust-only, and combined operation significantly altered both the thermal field and the distributions of smoke-related hazard parameters at the critical evacuation plane. The reductions in temperature were accompanied by decreases in CO<sub>2</sub> volume fraction and soot mass fraction and an increase in O<sub>2</sub> volume

fraction, demonstrating pronounced multiphysics coupling in the response of the evacuation environment to active fire protection. These statistical findings indicate that activation of fire protection systems can shift both the original DTS temperature-mapping relationship and the temperature-to-smoke-field cross-physics mapping. A temperature-correction model that explicitly accounts for active fire protection is therefore required.

### **3.2 Reduced Applicability of the Original DTS Temperature-Mapping Model under Active Fire Protection**

The cross-physics smoke-field prediction model uses temperature at the critical evacuation plane as a primary input; therefore, temperature-input accuracy directly affects the predicted CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility. To evaluate the applicability of the original DTS temperature-mapping model under active fire protection, the previously developed model was used to predict the temperature at a target location on the critical evacuation plane in the representative scenario, and the predictions were compared with the corresponding PyroSim-simulated values.

As shown in Fig. 4(f), the original DTS temperature-mapping model captured the overall temperature trend but exhibited substantial deviations from the simulated temperatures following activation of the combined sprinkler–smoke-exhaust system. Under this condition, the original model yielded a MAPE of 10.80% and an MAE of 6.45°C. These errors were markedly higher than the temperature-mapping error of approximately 2% obtained previously under uncontrolled-fire conditions, indicating that sprinkler and smoke-exhaust operation altered the relationship between ceiling- and sidewall-mounted DTS measurements and temperature at the critical evacuation plane.

Without active fire protection, the relationship between DTS temperatures measured at the ceiling and sidewalls and those at the critical evacuation plane is governed primarily by fire-plume rise, ceiling-jet propagation, and smoke-layer descent and is therefore relatively stable [14]. Following sprinkler and smoke-exhaust activation, however, droplet-induced cooling, smoke drag, mechanical extraction,

makeup-air entrainment, and localized mixing jointly modify the fire-induced temperature distribution, rendering the original DTS temperature-mapping model insufficiently transferable. Because errors in the mapped temperature subsequently propagate into predictions of CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility, the critical-plane temperature must first be corrected before smoke-field prediction is performed under active fire protection.

### 3.3 Selection of the Temperature-Correction Model under Active Fire Protection

To correct temperature-mapping deviations at the critical evacuation plane under sprinkler and smoke-exhaust operation, the performance of four machine-learning algorithms—ANN, GNN, SVR, and RF—was compared using different numbers of input features. The results are presented in Table 2 and Appendix F.

Table 2. Performance comparison of temperature-correction models under active fire protection

| Number of<br>input features | Algorithm | MAPE  | MAE (°C) | RMSE (°C) | R <sup>2</sup> |
|-----------------------------|-----------|-------|----------|-----------|----------------|
| 23                          | ANN       | 4.65% | 2.38     | 5.75      | 0.924          |
|                             | GNN       | 4.98% | 2.66     | 6.50      | 0.915          |
|                             | SVR       | 5.54% | 2.87     | 6.33      | 0.870          |
|                             | RF        | 2.27% | 1.53     | 3.69      | 0.978          |
| 39                          | ANN       | 2.43% | 1.50     | 3.58      | 0.964          |
|                             | GNN       | 2.21% | 1.48     | 3.51      | 0.974          |
|                             | SVR       | 3.27% | 2.01     | 4.86      | 0.965          |
|                             | RF        | 5.02% | 2.65     | 6.27      | 0.933          |
| 55                          | ANN       | 1.99% | 1.34     | 3.30      | 0.970          |
|                             | GNN       | 1.87% | 1.29     | 3.26      | 0.979          |
|                             | SVR       | 2.09% | 1.39     | 3.42      | 0.975          |
|                             | RF        | 6.26% | 3.62     | 7.85      | 0.886          |

As shown in Table 2, except for RF, the ANN, GNN, and SVR models demonstrated strong temperature-correction performance when using 39 or 55 input

features. The GNN with 55 input features achieved the best overall performance, with a MAPE of 1.87%, an MAE of 1.29°C, an RMSE of 3.26°C, and an  $R^2$  of 0.979. The ANN with 55 input features also achieved high accuracy, yielding a MAPE of 1.99% and an MAE of 1.34°C. These results indicate that incorporating temperature information from additional neighboring sensing locations improves the model's ability to capture localized thermal variations induced by sprinkler and smoke-exhaust operation. Accordingly, the 55-feature GNN was selected as the final temperature-correction model for the critical evacuation plane under active fire protection.

Fig. 6 illustrates the correction performance of the selected model for the representative scenario. The corrected temperature curve agreed substantially better with the PyroSim-simulated curve. In particular, during the post-activation cooling stage of the combined sprinkler–smoke-exhaust system, the correction model effectively reduced the systematic bias produced by the original temperature-mapping model.

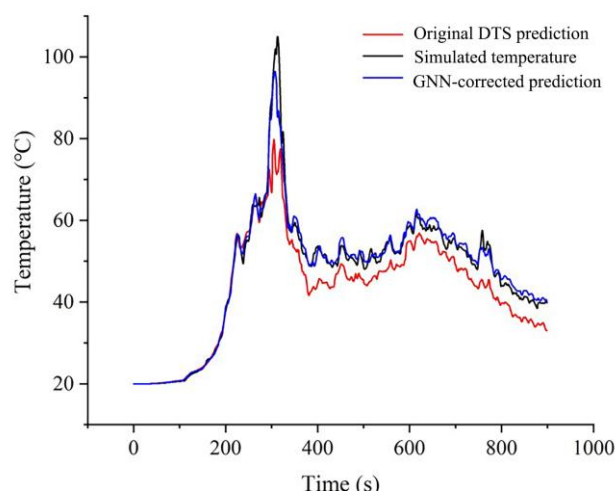


Fig. 6. Temperature-correction performance of the 55-feature GNN at the critical evacuation plane for the representative scenario

### 3.4 Improvement in Cross-Physics Smoke-Field Prediction through Temperature Correction

To evaluate the influence of critical-evacuation-plane temperature correction on the accuracy of cross-physics smoke-field prediction, the 55-feature GNN temperature-correction model selected in Section 3.3 was incorporated into the ANN-based smoke-hazard parameter prediction module retrained as described in Section 2.5.1. This

integration formed a cascaded “temperature correction–smoke-hazard parameter prediction” model for fire scenarios involving active fire protection systems. Specifically, the GNN model was first used to correct the deviations arising when DTS measurements under sprinkler and smoke-exhaust operation were mapped to temperatures at the critical evacuation plane. The corrected temperature features were then fed into the ANN-based smoke-field prediction module to estimate the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction, from which visibility was further calculated.

To evaluate the improvement in cross-physics smoke-field prediction achieved by temperature correction, the uncorrected and corrected temperatures at the critical evacuation plane were separately supplied to the smoke-field prediction model. The prediction performance for CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, and soot mass fraction was then compared. A 14m × 14m , 9m-high commercial space equipped with both sprinkler and smoke-exhaust systems was selected as the representative case. The prediction results are summarized in Table 3.

Table 3. Cross-physics prediction performance for fire-hazard parameters before and after temperature correction in the representative scenario

| Predicted parameter                          | Model state | MAE/Mean | MAPE   | MAE      | RMSE     | R <sup>2</sup> |
|----------------------------------------------|-------------|----------|--------|----------|----------|----------------|
| CO <sub>2</sub> volume fraction<br>(ppm)     | Uncorrected | —        | 13.96% | 2148 ppm | 4339 ppm | 0.980          |
|                                              | Corrected   | —        | 4.93%  | 956 ppm  | 2525 ppm | 0.980          |
| O <sub>2</sub> volume fraction (ppm)         | Uncorrected | —        | 1.30%  | 2036 ppm | 4750 ppm | 0.979          |
|                                              | Corrected   | —        | 1.21%  | 1995 ppm | 4517 ppm | 0.983          |
| Gas-mixture density<br>(kg m <sup>-3</sup> ) | Uncorrected | —        | 0.80%  | 0.00668  | 0.01233  | 0.980          |
|                                              | Corrected   | —        | 0.65%  | 0.00607  | 0.01027  | 0.985          |
| Soot mass fraction<br>(kg kg <sup>-1</sup> ) | Uncorrected | 11.73%   | —      | 0.000197 | 0.000469 | 0.962          |
|                                              | Corrected   | 5.15%    | —      | 0.000084 | 0.000208 | 0.978          |
| Visibility (m)                               | Uncorrected | —        | 7.87%  | —        | —        | —              |
|                                              | Corrected   | —        | 2.68%  | —        | —        | —              |

As shown in Table 3, temperature correction substantially improved cross-physics smoke-field prediction under active fire protection. For CO<sub>2</sub> volume fraction, MAPE decreased from 13.96% to 4.93%, corresponding to a relative error reduction of approximately 64.7%. For soot mass fraction, MAE/Mean decreased from 11.73% to 5.15%, representing a relative reduction of approximately 56.1%. These results indicate that temperature-input errors induced by sprinkler and smoke-exhaust operation can propagate substantially into predictions of combustion products and soot-related parameters, whereas temperature correction effectively suppresses this error propagation.

Although the uncorrected models already provided high predictive accuracy for O<sub>2</sub> volume fraction and gas-mixture density, further improvements were achieved after temperature correction. For O<sub>2</sub> volume fraction, MAPE decreased from 1.30% to 1.21%, while  $R^2$  increased from 0.979 to 0.983. For gas-mixture density, MAPE decreased from 0.80% to 0.65%, and  $R^2$  increased from 0.980 to 0.985. Thus, temperature correction not only improved predictions of the more strongly varying CO<sub>2</sub> volume fraction and soot mass fraction but also enhanced the overall stability of the smoke-field prediction framework.

Visibility was calculated from the predicted soot mass fraction and gas-mixture density before and after temperature correction. Its MAPE decreased from 7.87% to 2.68%. This finding further demonstrates that correcting the temperature at the critical evacuation plane improves not only the directly predicted parameters but also the accuracy of visibility derived indirectly from soot mass fraction and gas-mixture density.

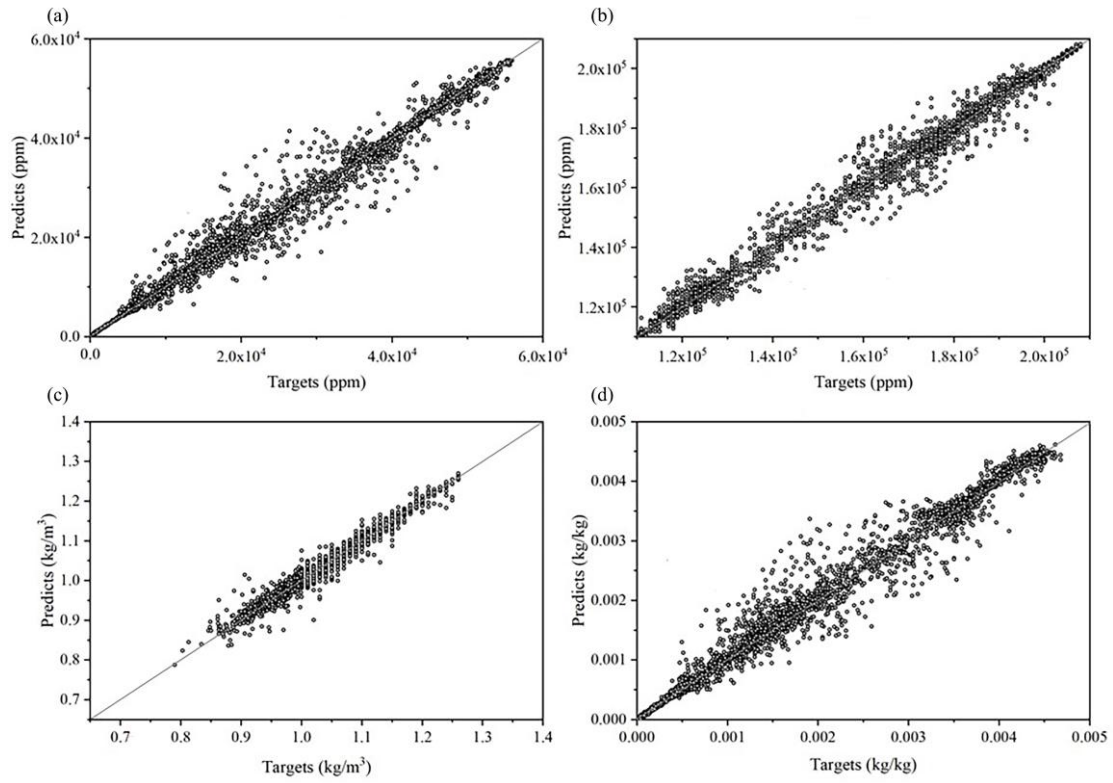


Fig. 7. Fire-hazard parameter predictions without temperature correction for the representative scenario

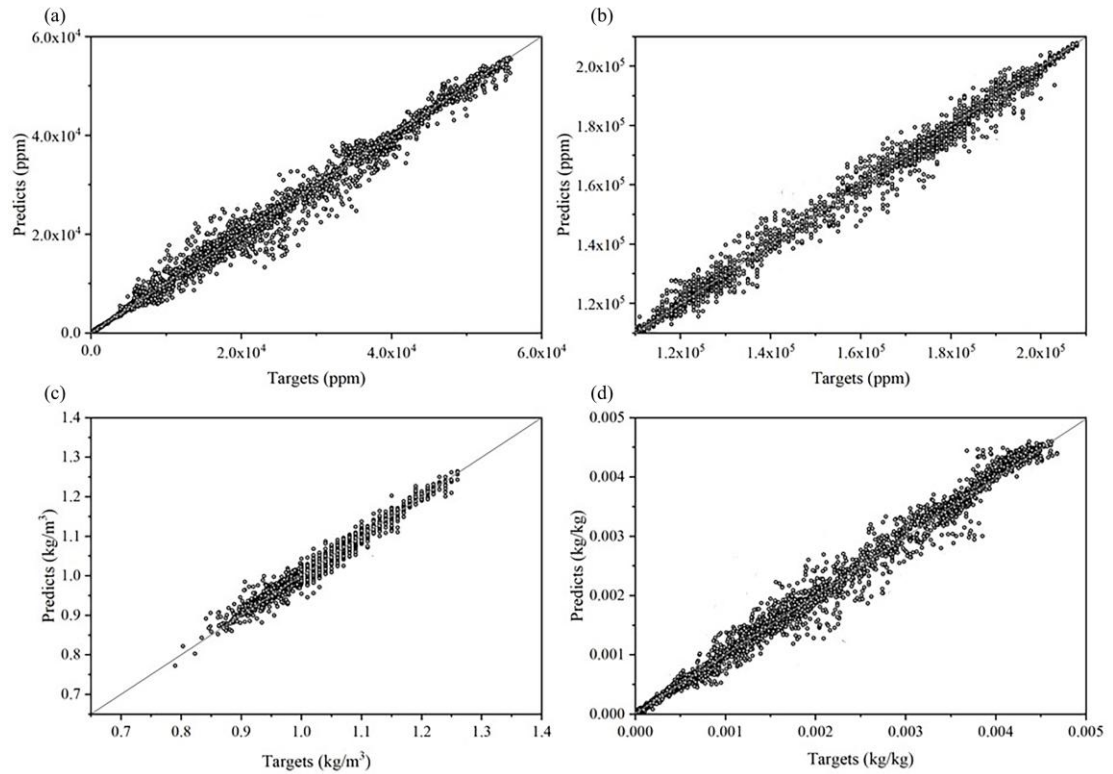


Fig. 8. Fire-hazard parameter predictions after temperature correction for the representative scenario

Fig. 7 and 8 compare the fire-hazard parameter predictions before and after temperature correction. Overall, active fire protection altered the temporal evolution of fire-hazard parameters at the critical evacuation plane, thereby reducing the accuracy of the temperature inputs supplied to the original temperature-to-smoke-field mapping model. By incorporating the proposed temperature-correction model, input errors in the cross-physics prediction framework were effectively controlled, and the predictive accuracy of the fire-hazard parameters was restored to a level comparable to that achieved under uncontrolled-fire conditions. These results demonstrate that the proposed correction method substantially improves the applicability of DTS-based cross-physics prediction to commercial-building fires involving active fire protection systems.

### 3.5 Cross-Space Generalization Validation in Commercial Buildings

To evaluate the applicability of the corrected cross-physics prediction model to different commercial-building environments, external validation was conducted using representative spaces of different scales and functional types: a 64m<sup>2</sup> small retail compartment, two atria with floor areas of 400 and 600m<sup>2</sup>, and a 2000m<sup>2</sup> large commercial space. These cases differed from the baseline space used to develop the temperature-correction model in terms of floor area, enclosure height, and functional type, thereby enabling assessment of predictive stability in previously unseen spatial configurations. The results are presented in Table 4.

Table 4. Generalization performance of the corrected cross-physics prediction model across commercial spaces of different scales

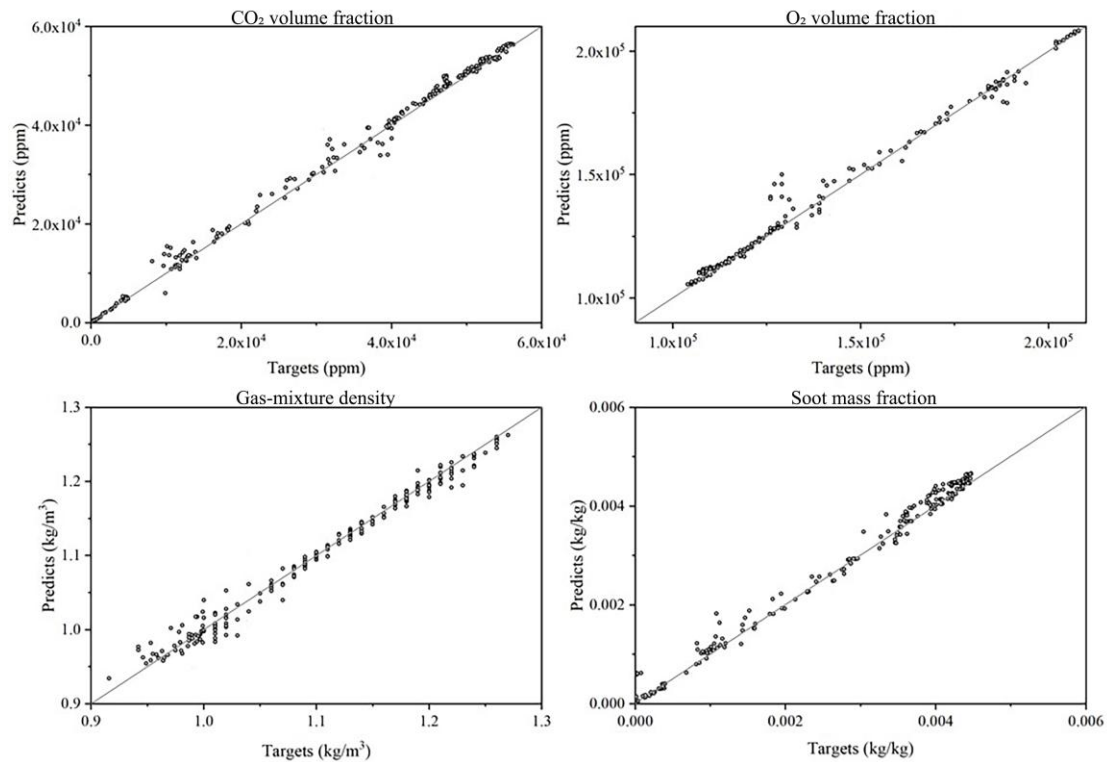
| Case                       | Fire-hazard parameter                 | MAE/Mean | MAPE  | MAE     | RMSE    | R <sup>2</sup> |
|----------------------------|---------------------------------------|----------|-------|---------|---------|----------------|
| 64m <sup>2</sup> , 4m high | CO <sub>2</sub> volume fraction (ppm) | —        | 4.88% | 1289    | 2171    | 0.994          |
|                            | O <sub>2</sub> volume fraction (ppm)  | —        | 2.75% | 3284    | 5583    | 0.989          |
|                            | Gas-mixture density                   | —        | 1.22% | 0.01345 | 0.01983 | 0.967          |

| Case                            | Fire-hazard parameter                | MAE/Mean | MAPE  | MAE      | RMSE     | R <sup>2</sup> |
|---------------------------------|--------------------------------------|----------|-------|----------|----------|----------------|
| 400m <sup>2</sup> , 15m<br>high | (kg m <sup>-3</sup> )                |          |       |          |          |                |
|                                 | Soot mass fraction                   | 5.48%    | —     | 0.000149 | 0.000211 | 0.988          |
|                                 | (kg kg <sup>-1</sup> )               |          |       |          |          |                |
|                                 | CO <sub>2</sub> volume fraction      | —        | 5.31% | 1001     | 1760     | 0.992          |
|                                 | (ppm)                                |          |       |          |          |                |
|                                 | O <sub>2</sub> volume fraction (ppm) | —        | 2.03% | 2186     | 3576     | 0.987          |
|                                 | Gas-mixture density                  | —        | 1.05% | 0.00942  | 0.01463  | 0.984          |
|                                 | (kg m <sup>-3</sup> )                |          |       |          |          |                |
|                                 | Soot mass fraction                   | 4.96%    | —     | 0.000063 | 0.000091 | 0.989          |
|                                 | (kg kg <sup>-1</sup> )               |          |       |          |          |                |
|                                 | CO <sub>2</sub> volume fraction      | —        | 5.08% | 591      | 1063     | 0.991          |
|                                 | (ppm)                                |          |       |          |          |                |
| 600m <sup>2</sup> , 20m<br>high | O <sub>2</sub> volume fraction (ppm) | —        | 1.67% | 2080     | 3231     | 0.989          |
|                                 | Gas-mixture density                  | —        | 0.91% | 0.00836  | 0.01237  | 0.990          |
|                                 | (kg m <sup>-3</sup> )                |          |       |          |          |                |
|                                 | Soot mass fraction                   | 5.62%    | —     | 0.000054 | 0.000073 | 0.989          |
|                                 | (kg kg <sup>-1</sup> )               |          |       |          |          |                |
|                                 | CO <sub>2</sub> volume fraction      | —        | 5.69% | 744      | 1268     | 0.990          |
| 2000m <sup>2</sup> , 6m<br>high | (ppm)                                |          |       |          |          |                |
|                                 | O <sub>2</sub> volume fraction (ppm) | —        | 2.01% | 1859     | 2996     | 0.993          |
|                                 | Gas-mixture density                  | —        | 0.88% | 0.00689  | 0.00991  | 0.990          |
|                                 | (kg m <sup>-3</sup> )                |          |       |          |          |                |
|                                 | Soot mass fraction                   | 5.80%    | —     | 0.000065 | 0.000098 | 0.987          |
|                                 | (kg kg <sup>-1</sup> )               |          |       |          |          |                |

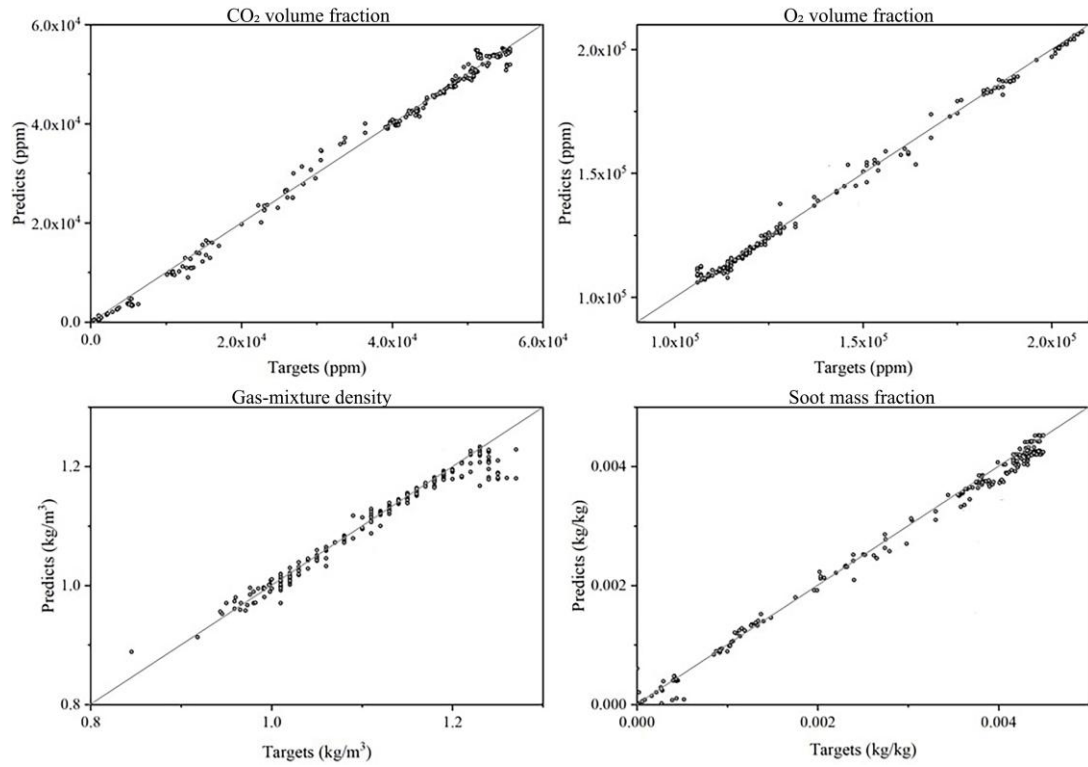
As shown in Table 4, the corrected model maintained stable predictive performance across the small retail compartment, atria, and large commercial space. The MAPE

ranged from 4.88% to 5.69% for CO<sub>2</sub> volume fraction, from 1.67% to 2.75% for O<sub>2</sub> volume fraction, and from 0.88% to 1.22% for gas-mixture density. The MAE/Mean for soot mass fraction ranged from 4.96% to 5.80%. High  $R^2$  values were retained for all fire-hazard parameters across all validation cases, indicating that the corrected model remained effective under active fire protection in commercial spaces with substantially different dimensions and configurations.

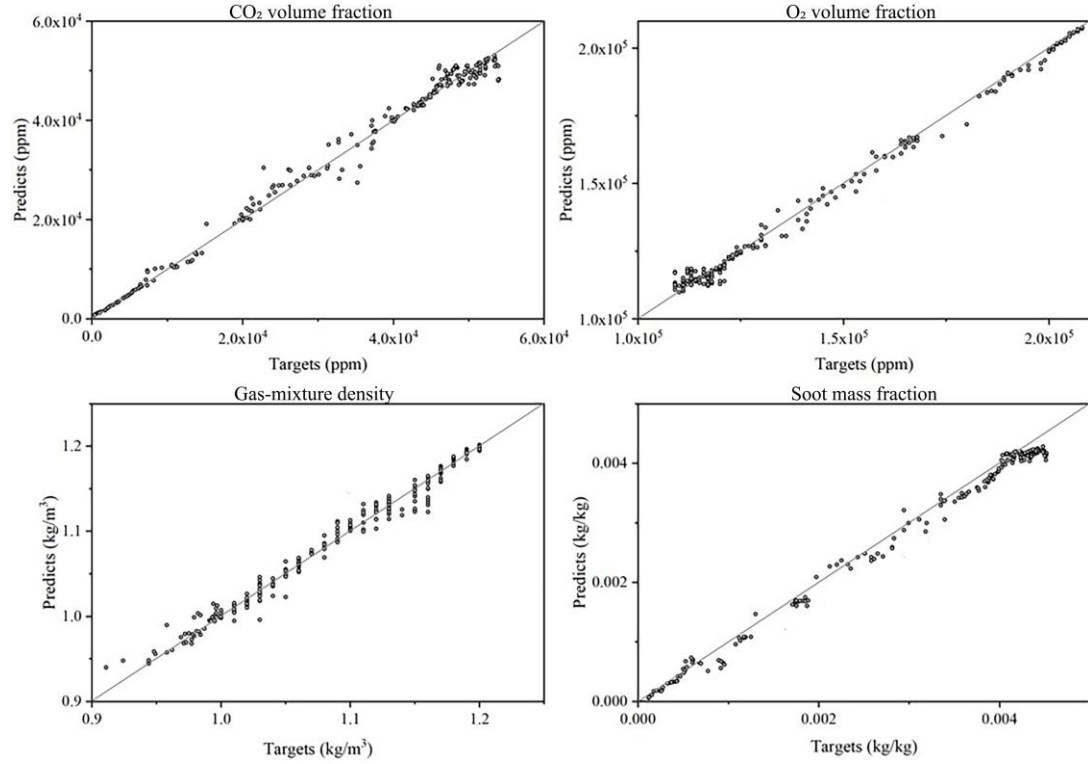
Generalization performance varied among the predicted parameters. O<sub>2</sub> volume fraction and gas-mixture density exhibited comparatively low errors, suggesting relatively stable mappings between these parameters and the corrected temperature features. CO<sub>2</sub> volume fraction and soot mass fraction showed moderately higher errors, indicating that the distributions of combustion products and soot particles were more sensitive to spatial scale, airflow organization, smoke-exhaust boundary conditions, and sprinkler-induced disturbances. Nevertheless, the corrected model maintained error levels comparable to those obtained for the baseline scenarios across all external validation cases, demonstrating satisfactory generalizability within the range of simulated commercial-building spaces. Fig. 9 presents the external validation results for the different spatial configurations.



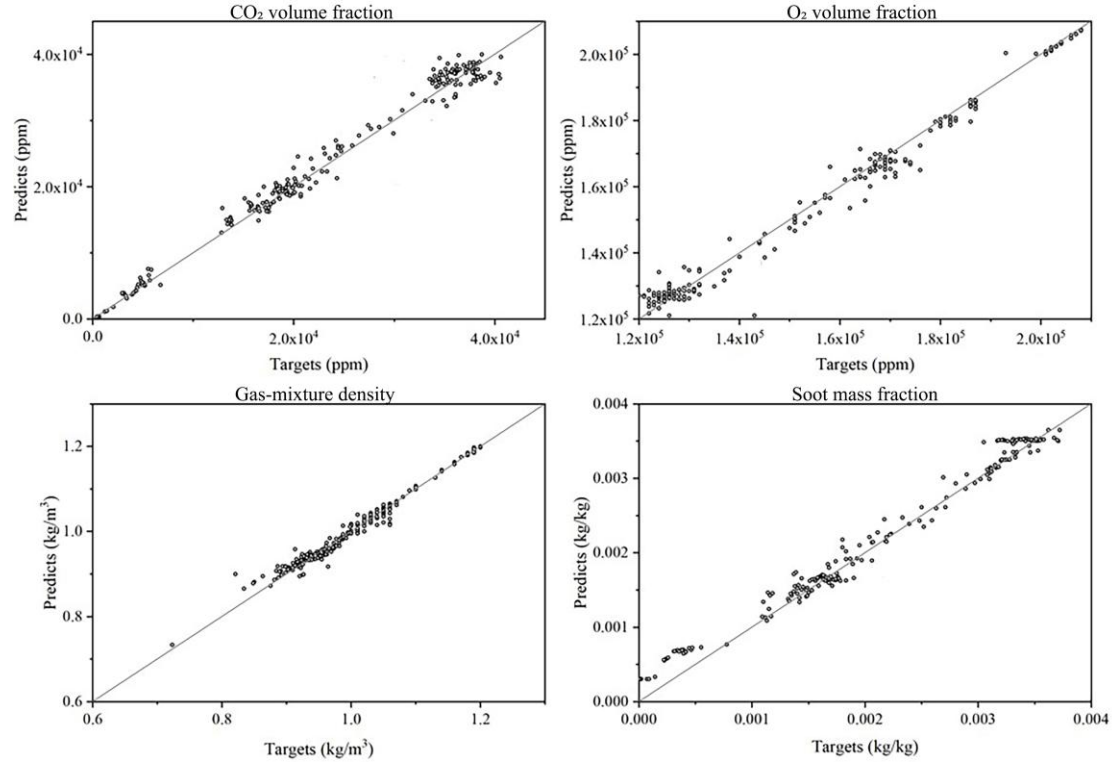
(a) 64m<sup>2</sup>, 4m high small retail compartment



(b) 400m<sup>2</sup>, 15m high atrium



(c) 600m<sup>2</sup>, 20m high atrium

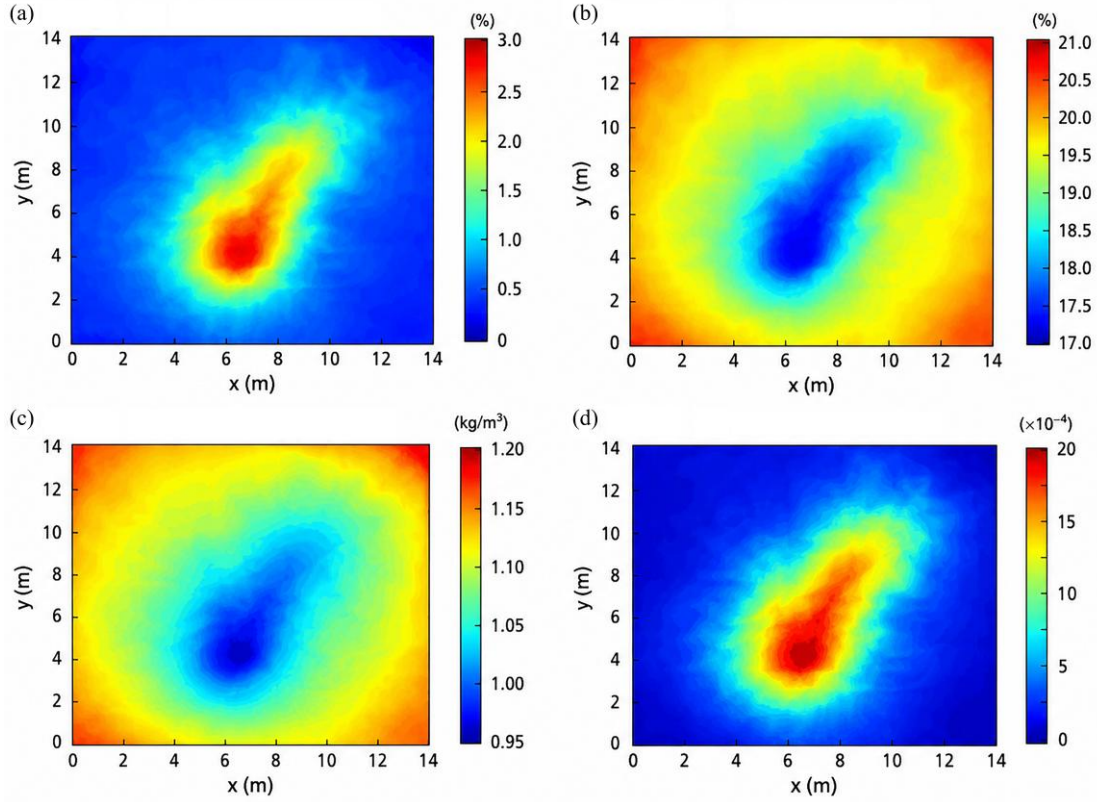


(d) 2000m<sup>2</sup>, 6m high large commercial space

Fig. 9. External generalization performance of the corrected cross-physics prediction model across commercial spaces of different scales

### 3.6 Engineering Applications and Limitations

The corrected cross-physics prediction model can be implemented through a workflow comprising “DTS temperature acquisition–critical-plane temperature correction–multi-hazard parameter prediction–threshold-based assessment and risk zoning.” Using DTS temperature measurements from the ceiling and sidewalls together with information on enclosure height, fire protection system status, and heat release rate, the framework predicts the CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility at the critical evacuation plane. By applying evacuation-tenability thresholds, hazardous zones characterized by low visibility, oxygen deficiency, elevated CO<sub>2</sub> concentrations, or high soot levels can then be identified. The resulting fire-hazard distribution maps can be overlaid with building layouts, evacuation routes, and emergency-exit information, as illustrated in Fig. 10, thereby supporting fire-hazard identification, evacuation-route optimization, and firefighting deployment.



(a) CO<sub>2</sub> volume fraction; (b) O<sub>2</sub> volume fraction; (c) gas-mixture density; (d) soot mass fraction

Fig. 10. Spatial distributions of fire-hazard parameters at the critical evacuation plane predicted by the corrected cross-physics model for the representative scenario

From an engineering perspective, the proposed framework offers three potential advantages. First, it generates multiphysics hazard information at the critical evacuation plane from DTS temperature data, potentially reducing the need for large-scale deployment of multiple types of point-based gas sensors. Second, the predicted spatial distributions of fire-hazard parameters can support the identification of low-visibility, high-soot, and oxygen-deficient zones, providing a basis for dynamic evacuation-route adjustment. Third, the framework can serve as a numerical decision-support tool for comparing fire protection system designs in commercial buildings by evaluating changes in critical-plane fire-hazard distributions under different sprinkler and smoke-exhaust configurations.

Several limitations should nevertheless be acknowledged. The present model was developed for a limited range of enclosure dimensions and peak heat release rates and employed a fixed alarm-triggering logic. In actual fires, fuel type and makeup-air

conditions may also affect predictive performance. Future research should therefore expand the range of fire scenarios and estimate the instantaneous heat release rate using DTS-based temperature inversion, fire-growth models, or data-assimilation methods. The effects of heat release rate uncertainty on smoke-field predictions should also be systematically investigated.

#### **4. Conclusions**

This study proposed a method for correcting temperature at the critical evacuation plane and predicting fire-hazard parameters in commercial buildings while accounting for the effects of sprinkler and smoke-exhaust systems on DTS-based temperature-to-smoke-field cross-physics prediction. Using a PyroSim-generated numerical database, the effects of active fire protection systems on temperature and smoke-related hazard parameters at the critical evacuation plane were quantified. A temperature-correction model was then developed, and the corrected temperatures were supplied to the cross-physics prediction module to estimate CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, gas-mixture density, soot mass fraction, and visibility. The principal conclusions are as follows.

(1) Sprinkler and smoke-exhaust systems significantly altered the thermal field and smoke-related hazard distributions at the critical evacuation plane, shifting the DTS-based temperature-to-smoke-field mapping established under uncontrolled-fire conditions. The GEE analysis showed that, relative to the uncontrolled condition, sprinkler-only, smoke-exhaust-only, and combined sprinkler–smoke-exhaust operation reduced the mean temperature at the critical evacuation plane by 30.64, 10.52, and 59.47°C, respectively. Each 1m increase in enclosure height was associated with an average temperature reduction of 4.06°C, whereas each 1MW increase in peak heat release rate increased the temperature by an average of 3.16°C. These findings demonstrate that active fire protection modifies the coupling between the thermal and smoke fields; consequently, DTS-based mappings developed for uncontrolled fires cannot be directly transferred to actively controlled scenarios.

(2) Active fire protection reduced the predictive accuracy of the original DTS

temperature-mapping model. In the representative combined sprinkler–smoke-exhaust scenario, the original model yielded a MAPE of 10.80% and an MAE of 6.45°C, substantially exceeding the errors obtained under uncontrolled-fire conditions. Among the ANN, GNN, SVR, and RF models evaluated, the GNN with 55 input features achieved the best performance. After correction, the temperature predictions attained a MAPE of 1.87%, an MAE of 1.29°C, an RMSE of 3.26°C, and an  $R^2$  of 0.979, demonstrating that the model effectively corrected temperature-mapping deviations induced by active fire protection systems.

(3) Temperature correction substantially improved the cross-physics prediction accuracy of smoke-related hazard parameters. Under combined sprinkler–smoke-exhaust operation, the corrected predictions yielded MAPEs of 4.93%, 1.21%, and 0.65% for CO<sub>2</sub> volume fraction, O<sub>2</sub> volume fraction, and gas-mixture density, respectively, and an MAE/Mean of 5.15% for soot mass fraction. Specifically, the MAPE for CO<sub>2</sub> volume fraction decreased from 13.96% to 4.93%, the MAE/Mean for soot mass fraction decreased from 11.73% to 5.15%, and the MAPE for visibility decreased from 7.87% to 2.68%. These results demonstrate that temperature correction effectively limits the propagation of input errors into downstream fire-hazard predictions.

(4) The corrected model maintained stable generalization performance across simulated commercial-building spaces of different scales. Validation in a 64 m<sup>2</sup> small retail compartment, 400 and 600 m<sup>2</sup> atria, and a 2000 m<sup>2</sup> large commercial space yielded MAPEs of 4.88%–5.69% for CO<sub>2</sub> volume fraction, 1.67%–2.75% for O<sub>2</sub> volume fraction, and 0.88%–1.22% for gas-mixture density. The MAE/Mean for soot mass fraction ranged from 4.96% to 5.80%. These findings indicate that the proposed method provides a feasible modeling framework for DTS-based multiphysics fire-hazard monitoring in commercial buildings.

Future research will incorporate full-scale experiments and field DTS measurements, expand the range of fire-source locations, fuel types, and fire-control strategies, and further investigate real-time heat release rate estimation and the effects of its uncertainty on prediction performance.

## Appendix

Appendix A. Material properties used in the spatial models

| Property                                                     | Ceiling: gypsum | Walls: C30 concrete |
|--------------------------------------------------------------|-----------------|---------------------|
| Density ( $\text{kg m}^{-3}$ )                               | 930             | 2425                |
| Specific heat capacity ( $\text{kJ kg}^{-1} \text{K}^{-1}$ ) | 1.09            | 0.97                |
| Thermal conductivity ( $\text{W m}^{-1} \text{K}^{-1}$ )     | 0.8             | 0.8                 |

Appendix B. Number of sprinklers and discharge rate per sprinkler for spaces of different floor areas

| Floor area ( $\text{m}^2$ ) | Number of sprinklers | Discharge rate per sprinkler ( $\text{L min}^{-1}$ ) |
|-----------------------------|----------------------|------------------------------------------------------|
| 64                          | 16                   | 60                                                   |
| 200                         | 36                   | 85                                                   |
| 400                         | 64                   | 95                                                   |
| 600                         | 100                  | 90                                                   |
| 2000                        | 324                  | 95                                                   |

Appendix C1. Wilcoxon signed-rank test results for fire-environment variables with and without sprinkler operation at different enclosure heights

| Enclosure height (m) | Temperature | CO <sub>2</sub> volume fraction | O <sub>2</sub> volume fraction | Gas-mixture density | Soot mass fraction |
|----------------------|-------------|---------------------------------|--------------------------------|---------------------|--------------------|
| 8                    | < 0.001     | < 0.001                         | < 0.001                        | < 0.001             | < 0.001            |
| 9                    | < 0.001     | < 0.001                         | < 0.001                        | < 0.001             | < 0.001            |
| 10                   | < 0.001     | 0.041                           | < 0.001                        | < 0.001             | < 0.001            |
| 11                   | < 0.001     | < 0.001                         | < 0.001                        | < 0.001             | < 0.001            |
| 12                   | < 0.001     | < 0.001                         | < 0.001                        | < 0.001             | < 0.001            |

Note: All entries are p-values.

Appendix C2. Wilcoxon signed-rank test results for fire-environment variables with and without smoke-exhaust operation at different enclosure heights

| Enclosure height (m) | Temperature | CO <sub>2</sub> volume fraction | O <sub>2</sub> volume fraction | Gas-mixture density | Soot mass fraction |
|----------------------|-------------|---------------------------------|--------------------------------|---------------------|--------------------|
| 8                    | < 0.001     | < 0.001                         | < 0.001                        | < 0.001             | < 0.001            |

| Enclosure height<br>(m) | Temperature | CO <sub>2</sub> volume<br>fraction | O <sub>2</sub> volume<br>fraction | Gas-mixture<br>density | Soot mass<br>fraction |
|-------------------------|-------------|------------------------------------|-----------------------------------|------------------------|-----------------------|
| 9                       | < 0.001     | < 0.001                            | < 0.001                           | < 0.001                | < 0.001               |
| 10                      | < 0.001     | < 0.001                            | < 0.001                           | < 0.001                | < 0.001               |
| 11                      | < 0.001     | < 0.001                            | < 0.001                           | < 0.001                | < 0.001               |
| 12                      | < 0.001     | < 0.001                            | < 0.001                           | < 0.001                | < 0.001               |

Note: All entries are p-values.

Appendix D. Friedman test results for the effects of enclosure height and peak heat release rate on fire-environment variables, stratified by fire protection configuration

| Fire protection<br>configuration | Factor                       | Temperature | CO <sub>2</sub><br>volume<br>fraction | O <sub>2</sub><br>volume<br>fraction | Gas-mixture<br>density | Soot<br>mass<br>fraction |
|----------------------------------|------------------------------|-------------|---------------------------------------|--------------------------------------|------------------------|--------------------------|
| Sprinkler-only                   | Enclosure<br>height          | < 0.001     | < 0.001                               | < 0.001                              | < 0.001                | 0.002                    |
|                                  | Peak heat<br>release<br>rate | < 0.001     | < 0.001                               | 0.002                                | 0.011                  | < 0.001                  |
| Smoke-exhaust-only               | Enclosure<br>height          | < 0.001     | < 0.001                               | 0.002                                | < 0.001                | 0.011                    |
|                                  | Peak heat<br>release<br>rate | < 0.001     | 0.005                                 | 0.002                                | 0.002                  | < 0.001                  |

Note: All entries are p-values.

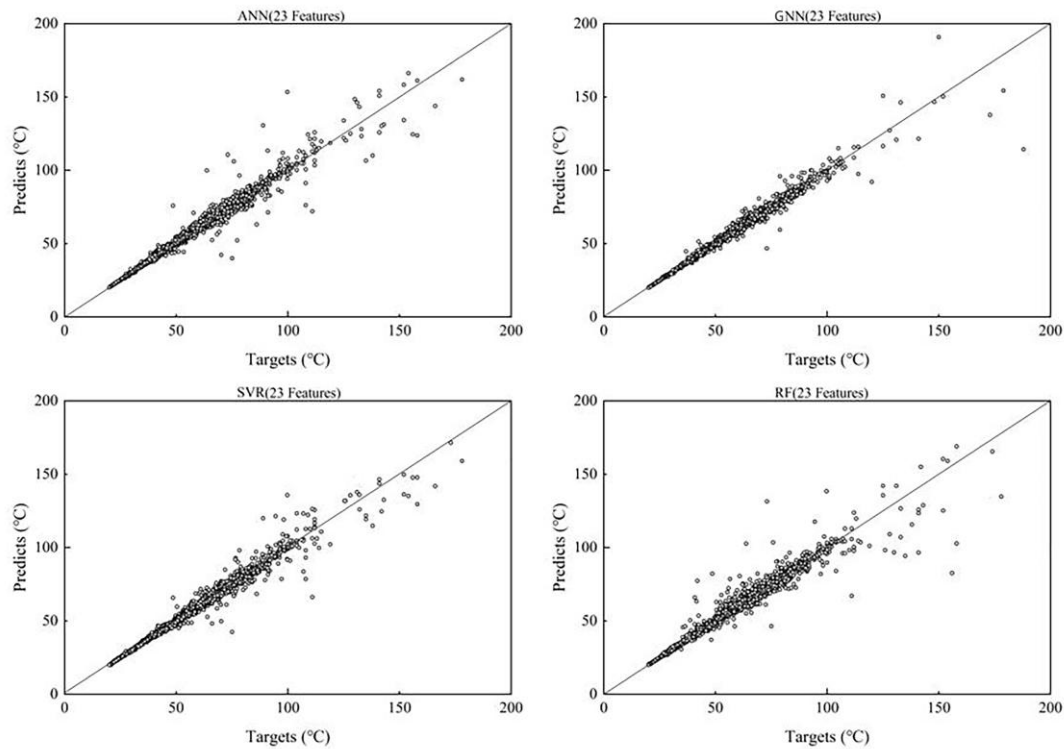
Appendix E. Stratified GEE estimates of the effects of active fire protection systems on temperature at the critical evacuation plane for different combinations of enclosure height and peak heat release rate

| Enclosure<br>height (m) | Peak<br>HRR<br>(MW) | Sprinkler-only, $\beta$<br>(SE), p | Smoke-exhaust-only, $\beta$<br>(SE), p | Combined sprinkler–smoke-<br>exhaust, $\beta$ (SE), p |
|-------------------------|---------------------|------------------------------------|----------------------------------------|-------------------------------------------------------|
| 8                       | 3                   | −18.5 (1.18), <<br>0.001           | −15.6 (1.22), < 0.001                  | −37.2 (2.10), < 0.001                                 |
| 8                       | 8                   | −31.8 (1.55), <<br>0.001           | −12.8 (1.32), < 0.001                  | −68.5 (3.40), < 0.001                                 |
| 8                       | 20                  | −55.5 (2.75), <<br>0.001           | −8.6 (1.70), < 0.001                   | −106.0 (5.60), < 0.001                                |
| 9                       | 3                   | −17.4 (1.16), <<br>0.001           | −14.5 (1.20), < 0.001                  | −34.8 (2.05), < 0.001                                 |
| 9                       | 8                   | −29.7 (1.50), <<br>0.001           | −11.9 (1.34), < 0.001                  | −62.8 (3.30), < 0.001                                 |
| 9                       | 20                  | −51.8 (2.70), <<br>0.001           | −7.9 (1.72), < 0.001                   | −97.4 (5.45), < 0.001                                 |
| 10                      | 3                   | −16.3 (1.14), <<br>0.001           | −13.4 (1.18), < 0.001                  | −32.4 (2.00), < 0.001                                 |
| 10                      | 8                   | −27.6 (1.46), <<br>0.001           | −11.0 (1.36), < 0.001                  | −57.1 (3.20), < 0.001                                 |
| 10                      | 20                  | −48.1 (2.64), <<br>0.001           | −7.2 (1.74), < 0.001                   | −88.8 (5.30), < 0.001                                 |
| 11                      | 3                   | −15.2 (1.12), <<br>0.001           | −12.3 (1.16), < 0.001                  | −30.0 (1.95), < 0.001                                 |
| 11                      | 8                   | −25.5 (1.42), <<br>0.001           | −10.1 (1.38), < 0.001                  | −51.4 (3.10), < 0.001                                 |
| 11                      | 20                  | −44.4 (2.58), <<br>0.001           | −6.5 (1.76), < 0.001                   | −80.2 (5.15), < 0.001                                 |

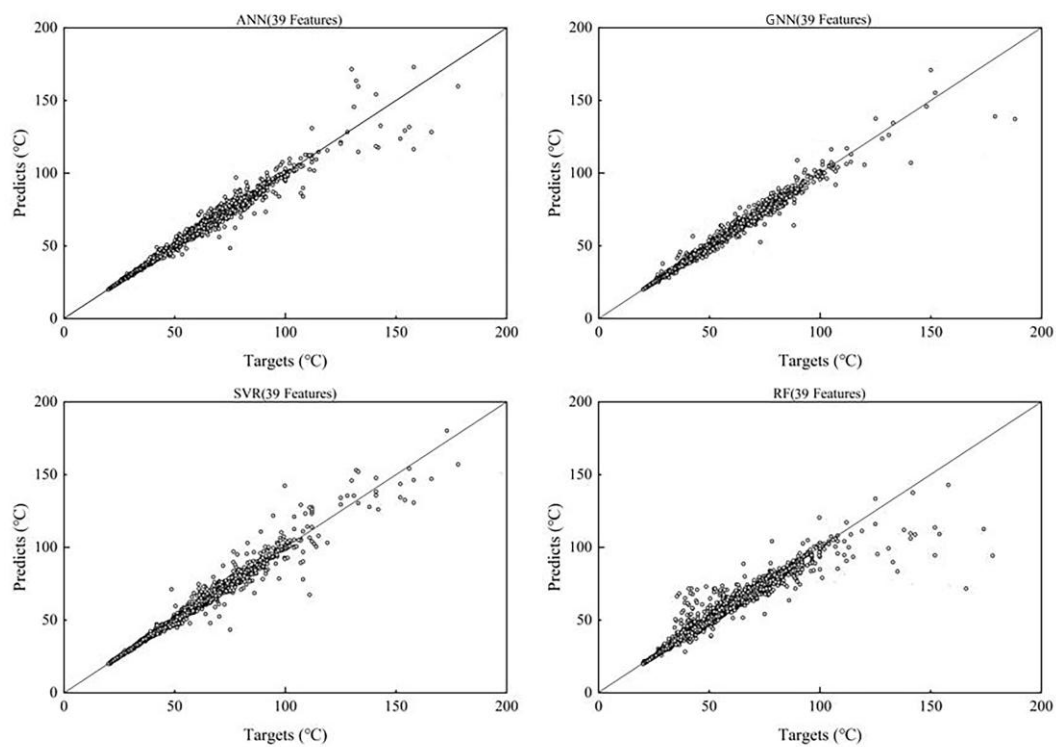
| Enclosure height (m) | Peak HRR (MW) | Sprinkler-only, $\beta$ (SE), p | Smoke-exhaust-only, $\beta$ (SE), p | Combined sprinkler–smoke-exhaust, $\beta$ (SE), p |
|----------------------|---------------|---------------------------------|-------------------------------------|---------------------------------------------------|
| 12                   | 3             | −14.1 (1.10), < 0.001           | −11.2 (1.14), < 0.001               | −27.6 (1.90), < 0.001                             |
| 12                   | 8             | −23.4 (1.38), < 0.001           | −9.2 (1.40), < 0.001                | −45.7 (3.00), < 0.001                             |
| 12                   | 20            | −40.7 (2.52), < 0.001           | −5.8 (1.78), 0.001                  | −71.6 (5.00), < 0.001                             |

Note: The uncontrolled-fire condition was used as the reference category. Negative  $\beta$  values indicate lower temperatures than those under the uncontrolled condition. Coefficients and standard errors are reported in °C.

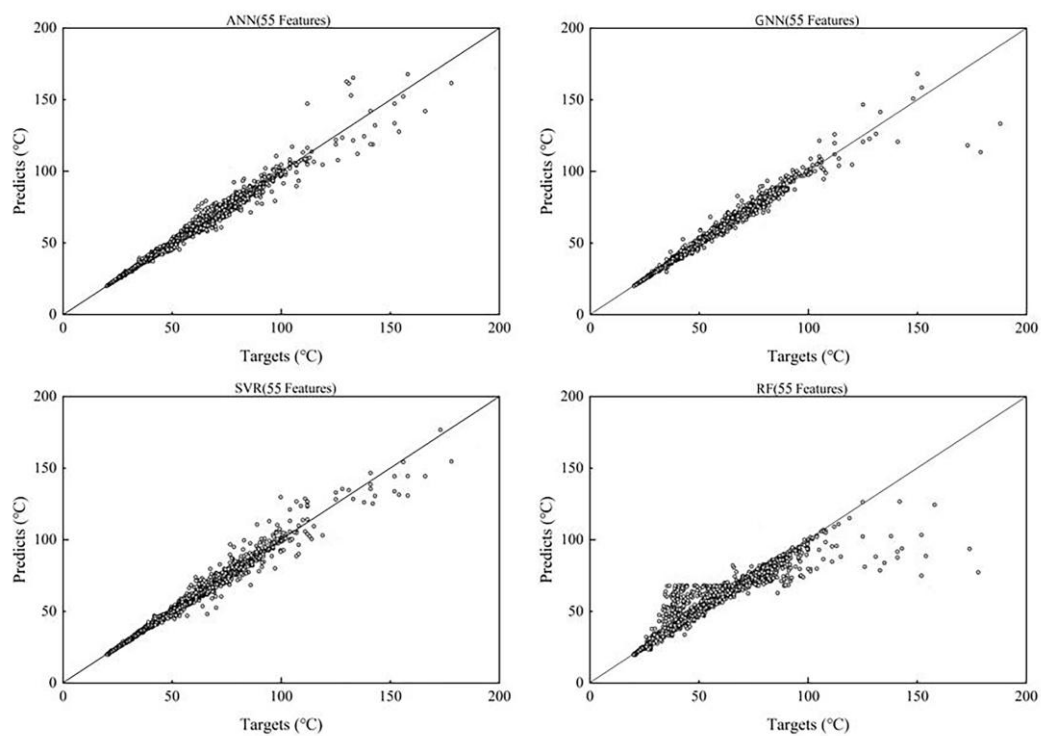
#### Appendix F. Predictions of the temperature-correction models using different numbers of input features



(a) 23 input features



(b) 39 input features



(c) 55 input features

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