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Building Artificial-Intelligence Digital Fire (AID-Fire) System: A Real-scale Demonstration

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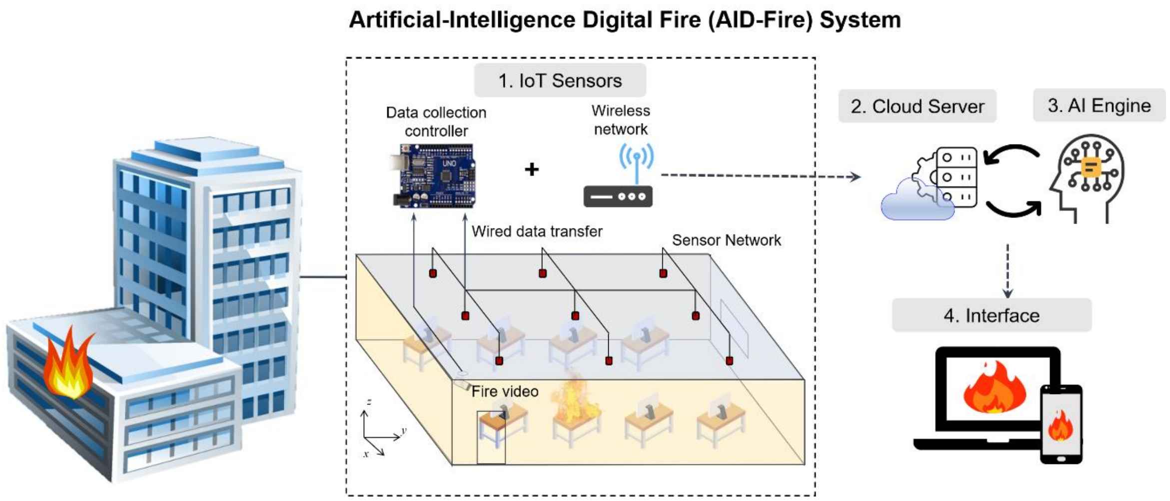
Abstract: The identification of building fire evolution in real-time is of great significance for firefighting, evacuation, and rescue. This work proposed a novel framework of Artificial-Intelligence Digital Fire (AID-Fire) that can identify complex building fire information in real-time. The smart system consists of four main parts, Internet of Things sensor network (data collection and transfer), cloud server (data storage and management), AI Engine (data processing), and User Interface (fire information display). A large numerical database, containing 533 fire scenarios with varying fire size, positions, and number of fire sources, is established to train a Convolutional Long-Short Term Memory (Conv-LSTM) neural network. The proposed fire digital twin is demonstrated and validated in a full-scale fire test room (26 m^2). Results show that the AI engine successfully identify the fire information by learning the spatial-temporal features of the temperature data with a relative error of less than 15% and a delay time of less than 1 s. Moreover, detailed fire development and spread can be accurately displayed in the digital-twin interface. This proposed AID-Fire system can provide valuable support for smart firefighting practices, thus paving the way for a fire-resilient smart city.

Keywords: *Digital Twin; Cyber-physics; IoT; Building fire; Deep learning; Smart firefighting*

Graphic Abstract



1. Introduction

Driven by the globalization and the fast urbanization, the vast growth of building density, building complexity, and population introduce great fire risks. Today, the mean cost of fire safety on society is estimated at 1% of global annual GDP, and it increases with the per capita GDP and human development index [1]. Besides the cost of fire protection and economic loss of fire incidents, fires also pose terrible casualties in both occupants and firefighting teams. The US statistics show that building fires during 2013 – 2017 resulted in more than 16,500 casualties and more than US$ 10 billion direct economic losses [2]. In China, the fire caused 1,987 deaths, 2,225 injuries, and around US$ 1 billion direct economic losses in 2021 [3].

Lack of fire information and the bad decision making are critical threats to firefighting and rescue operations. Outside the fire scene, it is hard for the fire commander to make an effective and correct firefighting decision without knowing the fire state. For example, the 2017 Grenfell Tower fire in London resulted in 72 fatalities (Fig. 1a) [4]. In 2007, nine firefighters died in a store fire in South Carolina due to the sudden flashover (Fig. 1b) [5]. The mini-storage fire that happened at Hong Kong, in 2016 (Fig. 1c), lasted for more than 100 hours and killed two firefighters [6], mainly because it was difficult to determine fire locations.

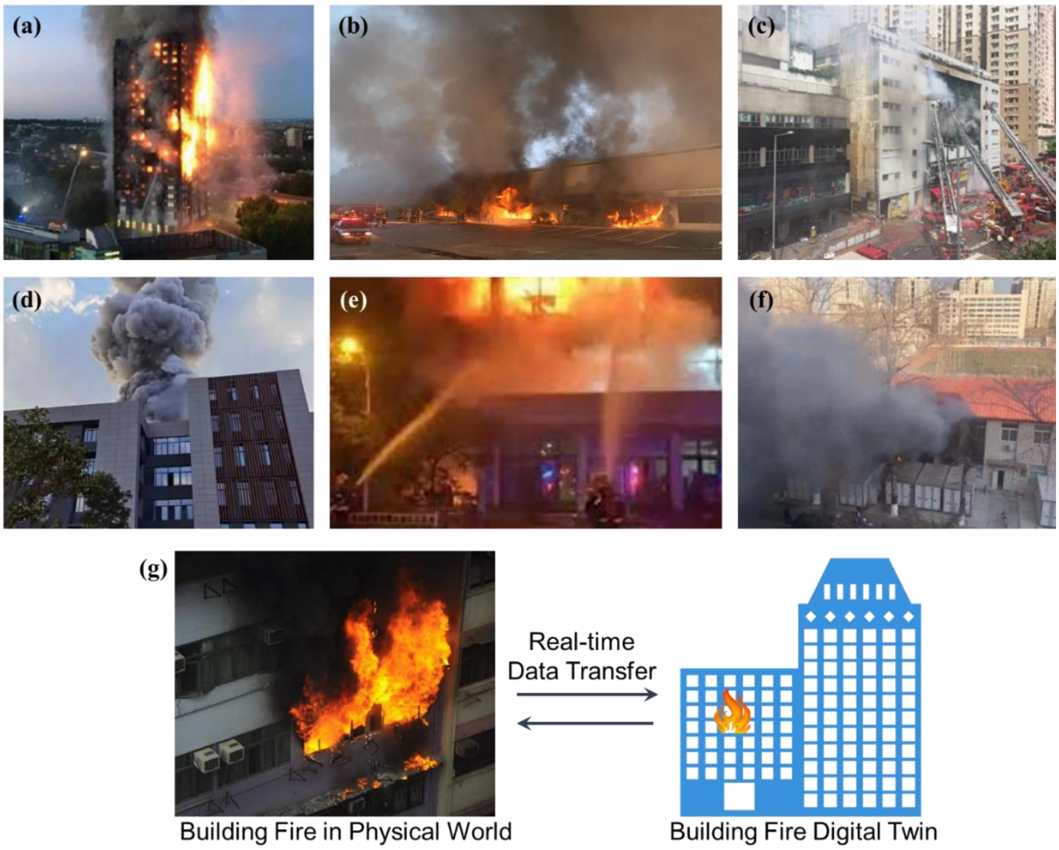


Fig. 1. Typical building fires (a) London Grenfell Tower Fire, 2017 (b) Charleston Sofa Super Store fire, 2007, (c) Ngau Tau Kok mini-storage fire, 2016, (d) Nanjing University of Aeronautics and Astronautics fire, 2021 (e) Nanjing University of Technology fire, 2019, (f) Beijing Jiaotong University fire, 2018, and (g) Demonstration of digital twin structure.

Recently, there are frequently reported fire disasters happened in university laboratories, e.g., Nanjing University of Aeronautics and Astronautics fire in 2021 (Fig. 1d), Nanjing University of Technology fire in 2019 (Fig. 1e), and Beijing Jiaotong University fire in 2018 (Fig. 1f), leading to massive casualties and negative public opinion. These fire cases highlight the need and significance of real-time fire identification and forecast in firefighting, evacuation, and rescue, especially in those facilities and infrastructures with high fire risks.

Many research efforts have been made to simulate and predict the fire growth in buildings [7–13]. Classical models include the standard fire temperature curve, the Kawagoe's law [7], the MQH correlation [8], and the numerical fire models [9]. Analytical models cannot predict transient fire development, while for numerical models, they take hours and even days to simulate fire scene [10]. Therefore, traditional fire modeling approaches cannot realize real-time fire identification and prediction in firefighting practice. Since the 2010s, the sensor-data-driven method was introduced to fast predict building fire growth [14,15]. For example, the FireGrid system collected real-time sensor data to predict the fire evolution based on a zone model that was demonstrated in the flat-scale fire test [14]. Different optimization algorithms [16–19] were adopted to simplify the fire model and increase the computational speed that cope with the rapid change of fire scenes.

Recently, artificial intelligence (AI) technologies were introduced in fire research and support the development of smart firefighting in various aspects [20–22]. For fire scenario identification, a hybrid artificial neural network (ANN) model was developed to evaluate the temperature distribution in a compartment fire [12,23]. Also, computer vision methods based on the convolutional neural network (CNN) are adopted to achieve the identification of fire heat release rate (HRR) by extracting the features of flame and smoke images [24,25] . For fire prediction, machine learning with zone model was proposed to recover the miss data in case sensors were destroyed in fires [26,27]. Long Short-Term Memory (LSTM) model has also been used to predict fire scenarios with a certain lead time, e.g., tunnel fires [28–30], and compartment fires [31]. Besides the application in firefighting, AI tools were also introduced to assist the fire engineering performance-based design in the atrium [32].

In practice, the AI model cannot be applied to assist firefighting without a mature system for data communication, computing, data visualization, and interaction. The digital twin is a key element of intelligent building and smart firefighting [22]. The concept of 'twin' was firstly proposed by NASA in the Apollo space program [33], in which two identical space vehicles were built so that the earth vehicle could simulate, mirror, and predict the conditions of the one in space. Since the 2000s, the term "digital twin" firstly appeared in an urban road network design program [34] and is formally defined as the "digital equivalent to a physical product". Then, similar concepts (i.e., cyber-physical world and metaverse) has been widely spread and adopted by scholars in various research fields and industrial applications, e.g., smart building [35,36], construction [37,38], and manufacturing [39].

Defined by Grieves et al. [40], a standard Digital Twin structure should have three parts: 1) The physical components, 2) The virtual models, and 3) The Data that connect them, as shown in Fig. 1g.

Based on this framework, the application of digital twin in building engineering is considered to start with building information modelling (BIM), which provides a semantically rich 3D cyber-model and allows for various applications [41]. The Internet of Things (IoT) technologies are introduced to fill the gap between the physical and virtual worlds [42]. Recently, data-driven models and artificial intelligence (AI) algorithms are widely applied to process the data obtained by the IoT sensors from the physical side and simulate the interaction in the virtual side [43]. So far, relatively mature framework, and theoretical system are established at the building design [44,45], construction [46,47] and operation [36,42] stages, marking the building engineering is embracing the digital age. However, to date, no related framework and demonstration of digital twin for building fire safety management and firefighting has ever been made, posing a big sci-tech gap.

This study proposes a framework for a novel building fire digital twin system, namely Artificial intelligence Digital Fire (AID-Fire). It includes four main components (IoT sensors, cloud server, AI model, and user interface) to transmit, manage, identify, and visualize the fire scenario in real-time. A convolutional long short-term memory neural network (Conv-LSTM) is selected to construct the correlation between the spatial-temporal temperature distribution and the number, size and location of fire sources. The identification performance of the fire digital twin is evaluated in terms of accuracy and timeliness and demonstrated in a full-scale fire test room (26 m^2). Moreover, the AID-Fire system also shows great potential for further development with more functions, such as real-time forecast of fire evaluation, onset of critical fire events, and evacuation guidance panel.

2. System framework

Today, the network of heat and smoke detectors have been widely adopted as part of the building fire service system. In case of a building fire, these sensors can detect the hot fire smoke that reaches and accumulates on the ceiling and then send alarms to occupants and local fire services. Afterwards, these sensor data are not further analyzed for fire evacuation and firefighting operations. The CCTV camera system can also monitor the fire scene, but it has a low coverage due to cost and privacy concerns. Moreover, the dense and heavy smoke can block the view of CCTV cameras in real fire scene that prevent a continuous monitoring. Comparatively, these pre-installed fire sensors continue providing vital fire information that can derive fire location, size, and development by spatial-temporal analysis.

Fig. 2 shows the framework of the Artificial intelligence Digital Fire (AID-Fire). To achieve the target of fire identification, heat detectors will first collect temperature data using an IoT sensor network that then transmit data to a cloud server. The server can manage and store the data following a pre-set and standard format, which is accessible by the AI engine. The AI engine can make use of the data to identify fire state and provide early warning on the potential fire risks to occupants and firefighters in real-time. Finally, a User Interface (UI) is developed to display the fire information (measured data and AI output) and allow cyber-physical interaction. A fire-test room with the dimensions of 7.5 (L) × 3.4 (W)× 5.4 (H) m^3 was selected as the target physical twin to demonstrate the fire digital twin. The four main sections are introduced in detail subsequently.

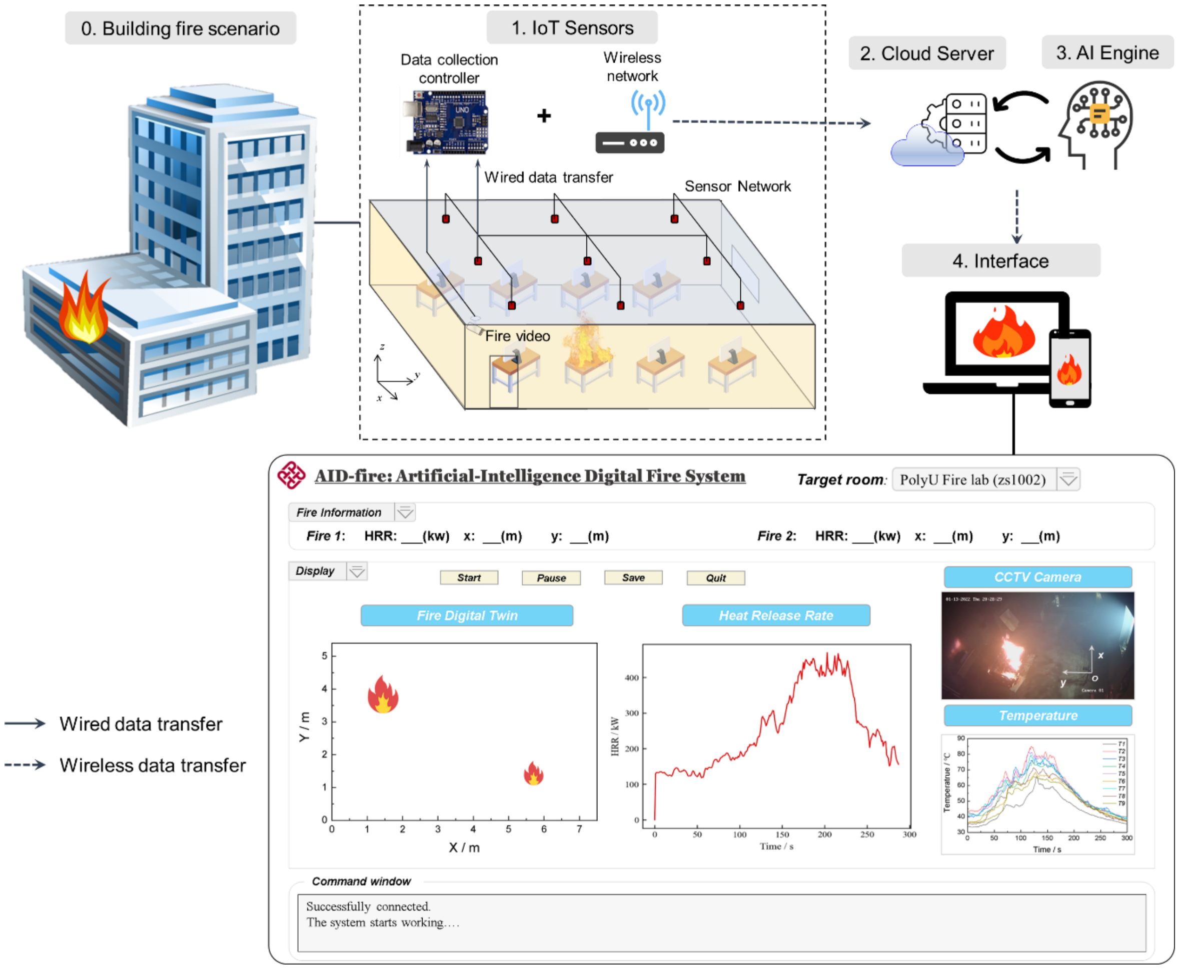


Fig. 2. The framework of the intelligent fire digital twin

2.1. IoT Sensor network

Many indicators (e.g., temperature, heat flux, gas concentration, etc.) can be used to analyze the fire intensity. Among them, the temperature is one of the most feasible indicators for many reasons (e.g., direct, convenient, and relatively reliable). Commercial temperature sensors (essentially thermocouples) are cheap, fire-resistant, and pre-installed. Therefore, the heat-detector network and temperature data are adopted as the data collected to identify the fire scenario in the AID-Fire system. Alternatively, a matrix of smoke detectors can also be used for building the sensor network and form a database of smoke visibility.

The temperature evolution is collected by a wired local data logger that is protected from the high temperature and irradiation from fire and smoke. The data collection controller is equipped with a Wi-Fi module to achieve the wireless data transmission to the cloud, as shown in Fig. 2. To extend the system lifetime, the data collecting frequency is set to be low (e.g., 1/60 Hz) in daily use [48,49] and can switch to the high-frequency mode (e.g., > 1 Hz), once any sensor temperature exceeds a pre-set threshold (e.g., 60 °C in this study) in a fire [30]. The layout of the IoT sensor network is shown in Fig. 3b. The network consists of nine wireless thermocouples, which installed 10 cm below the ceiling with 1.8 m interval along the x-axis direction and 1.4 m interval along the y-axis direction, to form a 3 × 3 matrix.

2.2. Cloud Server

To store, manage, and process the sensor data transferred from the fire field, a remote cloud database is built in a server. There are many advantages to adopt a cloud server in the AID-Fire system, such as global access and stability. The data in the database are stored as multiple sheets organized by MySQL. Currently, there is no universal standard to organize fire data. Therefore, the data structure refers to our previous tunnel fire database [30,50]. The database is formed by two sheets, namely, a) measurement sheet, which records the temperature data from each thermocouple in the associate column; b) forecast sheet, which stores the real-time prediction results by the AI model. The real-time video captured by the CCTV camera (for the validation purchase) is also stored in the server as video streaming. The data interaction uses the MySQL Connector [51].

2.3. AI Engine

The AI engine builds the correlation between the spatial-temporal temperature distribution and the fire information (fire HRR, location, etc.), so it is the core of the AID-Fire system. All raw temperature data in the database are pre-processed by a data-cleaning algorithm, which can avoid the influences of potential invalid data (e.g., “missing," “out of range," “burn out,” etc.) caused by broken sensors. For the temperature sensor, the most common issues are “sensors broken” and “package loss in data transfer”. For broken sensors, the associated invalid data types are “out of range” (short circuit) and “burn out” (open circuit). For package loss, the associated invalid data type is “missing”. Abnormal data will be replaced by the average value of the data from nearby thermocouples once detected. More details, including fire database, training process, and model structure, see Section 3.

2.4. User interface

The User Interface (UI) is developed to realize the function of information visualization and cyber-physical interaction, as shown in Fig. 2. The UI can connect to the target database on the remote server according to the IP address, username, and password input by the user. In the display area, the measured raw temperature data are plotted and fed to the AI engine. The AI predictions are rendered in the digital twin showing the number, size, and 2-D location of virtual fire. The historical and real-time fire HRRs are also plotted to give an overview of the fire development.

The CCTV video is also shown to verify the AI predictions before it is blocked by smoke, but in reality, it is usually not available inside the room for privacy reasons. On the bottom, a dialogue box presents the system operation status, e.g., successful actions, failed actions, and possible reasons. Moreover, the occurrence of the critical event, such as fire spread, flashover, backdraft, etc., will be shown in this dialogue box with a warning signal.

3. AI method and numerical validation

3.1. Database generation

A large and reliable database with reasonable data distribution is the first step to developing a well-performed AI model. The numerical fire simulation by CFD tools is high-efficiency and time-saving to generate a big database that is bounded by physics laws. The feasibility and accuracy of numerical fire data have been validated by previous studies [13,24,52]. In this work, Fire Dynamic Simulator (FDS) is adopted to generate the building fire scenarios, and this model is calibrated by experimental data. The numerical model is established with the same geometries as the physical chamber (7.5 × 3.4× 5.4 m^3), as shown in Fig. 3a.

The mesh size is set as 0.1 m in all directions according to a mesh independency study. The default Large Eddy Simulation (LES) turbulence model was employed, and a single-step and mixing-controlled combustion model was adopted. The material of the walls is set as concrete with a thickness of 0.2 m, and the door (2.1× 1.4 m^2) is set as "open." A rectangular liquid pool fire with the geometry of 1× 1 m^2 is adopted as the fire source, and the fuel type is set as "propanol." The simulation time is set as 300 s to ensure the fire can grow to a quasi-stable state. To capture the temperature distribution, nine thermocouples are arrayed to form a 3 × 3 matrix and installed 10 cm below the ceiling, as shown by T1 - T9 in Fig. 3b. The sampling frequency is set as 1 HZ, i.e., one data point per second.

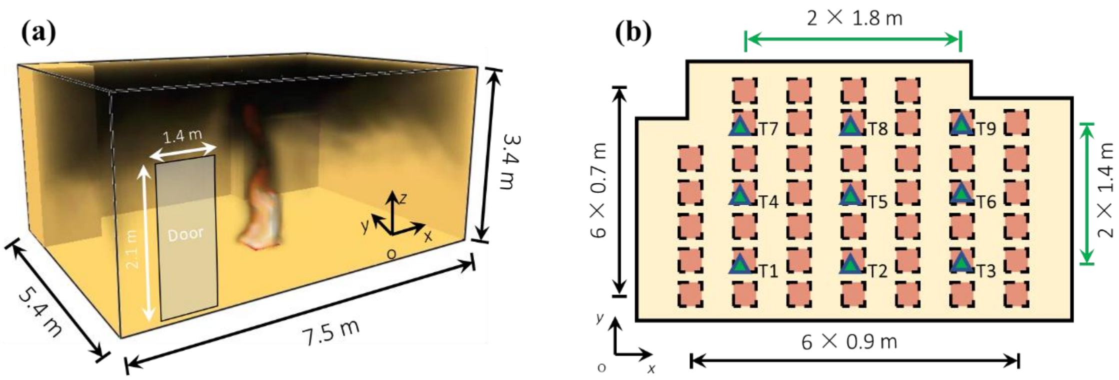


Fig. 3. Numerical model (a) model setup, and (b) layout of the thermocouples and the fire source location

Fire intensity (or HRR) and locations are critical indicators for building fire scenarios that can guide firefighting strategies. Meanwhile, fire scenes with multiple fire sources are also most dangerous for firefighters, and it can also provide evidence for arson. In this work, 45 pre-set fire locations, with 0.9 m interval along the x-axis and 0.7 m interval along the y-axis, are designed, as shown in Fig. 3b. We simulate the fire scenes with one or two fire sources, and the HRR for each fire source ranges from 50 - 500 kW. When two fire sources are close to each other, they can be regarded as a larger single fire case. Totally, 553 fire scenarios, including 225 single fire cases and 328 dual fire cases with various HRRs and fire locations, are contained in the database.

For each fire simulation, the captured data stored in the datasheet is a 300 (simulation time) × 9 (sensor number) matrix. The flow chart to process the raw data and generate the database is shown in Fig. 4. The datasheet is firstly cut into 100 data fragments with a 3-s temporal length along the time sequentially. The 100 data fragments multiplying 553 scenarios form a dataset of 55,300 samples. To train the AI model, all input data should be labeled with an expected output in the database [28]. In this study, the output is the fire HRR and coordinates, which can be expressed as the following vector:

$$[\mathrm{hrr}_1\,, x_1\,, y_1\,, \mathrm{hrr}_2\,, x_2\,, y_2] \tag{1}$$

where the subscript i = 1, 2 represents the number of the fire source; hrr, x, and y can be valued according to the simulation conditions. For a single fire case, the HRR and coordinates value for the second fire source are set as 0.

After labeling, these samples are normalized between 0 and 1 using "MinMaxScaler" to avoid the potential influence caused by the data scale [53,54]. Then, they are randomly shuffled and divided into the training and validation datasets with the ratios of 75% and 25%, respectively. To further test the generalization ability and demonstrate the smart fire digital twin, a set of real scale fire tests are conducted in the physical chamber. The experimental results (fire HRR and location) are adopted as the test dataset, which will be introduced in detail subsequently.

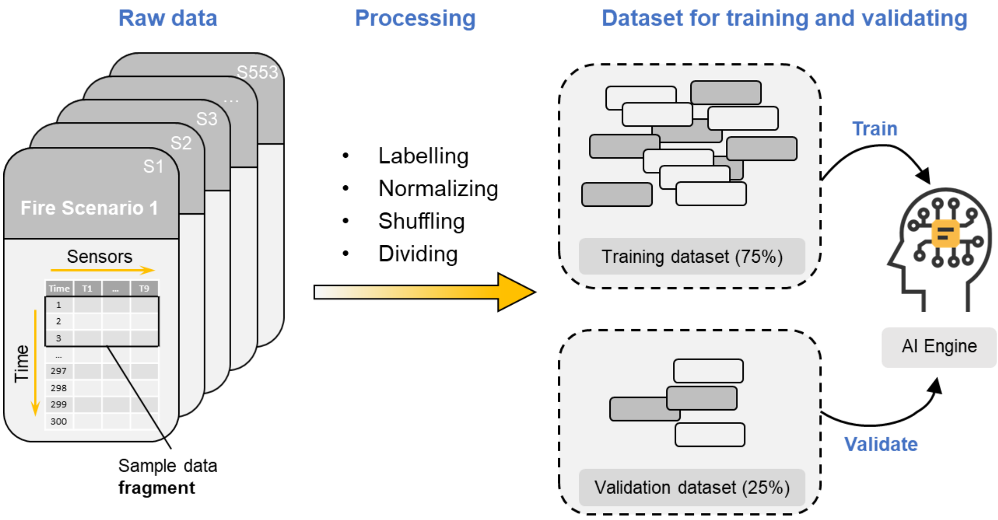


Fig. 4. Flow chart of dataset generation.

3.2. The framework of the Deep Learning algorithm

This work aims to identify the fire HRR and fire location based on the historical temperature information with time series. Note that the targeted information includes both the temporal parameter (HRR) and spatial parameter (fire location). Therefore, we use the Convolutional Long Short Term Memory (ConvLSTM) neural network [55,56], which is designed for the feature extraction of spatial-temporal data, to facilitate the fire information identification. The ConvLSTM network is built with TensorFlow Core v2.2.0.

The architecture of the network is illustrated in Fig. 5. The input data are firstly resized as a tensor with a dimension of 3 × 3 (thermocouple array) × 3 (sample interval) to fit the structure of the network. The proposed model consists of two ConvLSTM2D layers with a 2 × 2 convolutional kernel, a flatten layer, and two fully-connected layers with 64 and 36 units, respectively. The output layer of the model has six units to associate with the dimension of the output vector, i.e., Eq. (1). An initial dropout rate of 0.2 is set for each LSTM layer to avoid overfitting [57]. 'ReLU' activation function is selected for all hidden layers.

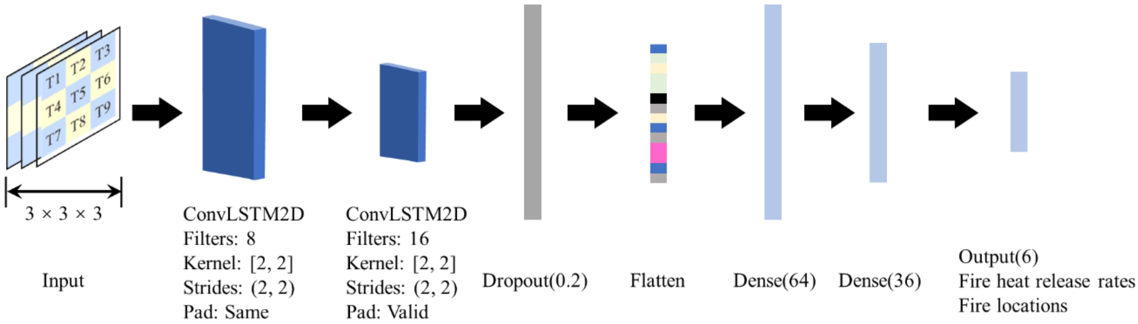


Fig. 5. Structure of the ConvLSTM2D network.

The fire identification results are continuously distributed values, i.e., HRR and x, y coordinate values. Therefore, the issue is treated as a regression problem. Mean squared error (MSE) and coefficient of determination (R^2) are adopted as the loss function and metrics to evaluate their performance on the regression problems. The initial learning rate and training epochs are set as 0.001 and 200 according to preliminary trials. The spatiotemporal temperature distribution of the fire scene is analyzed by the ConvLSTM network at each time step. Moreover, the relationship between the fire source information and the sensor data is stored by the parameters of each neural unit of the network and can be applied to identify fire information for unknown fire scenarios. The proposed AI engine can achieve a super-fast response with a calculation time of ~0.1 s.

3.3. Performance of AI model on numerical test data

Fig. 6 presents the model performance evaluated by R^2 and MSE on the training dataset (75% data) and validation dataset (25% data). It can be seen that the training efficiency is high at the beginning stage, while no significant improvement (the decay of MSE and growth of R^2) can be observed after 150 epochs, indicating that the model has almost converged, and the pre-set training epoch number of 200 is a sufficient choice. Finally, the R^2 converges to around 0.91, indicating the model has well learned the correlation between the input data and the label. The MSE converges to around 0.01, which means the overall identification error distributes in the range of ±10%. The slight fluctuations in the training dataset and the relatively drastic fluctuations in the validation dataset are common phenomena when training machine learning algorithms [58].

Figs. 6b shows the calculated R^2 of different fire parameters (fire source location and HRR) on the training and validation dataset during the training process. Compared to fire location, R^2 of HRR (presented by the blue curves) increases faster with the training epochs and the convergent value of HRR (around 0.92 for the training dataset and around 0.89 for the validation dataset) is higher than that of location (around 0.86 for both the training dataset and validation dataset, presented by the red curves), which indicates that it is easier to correlate the ceiling temperature distribution with HRR than the fire location.

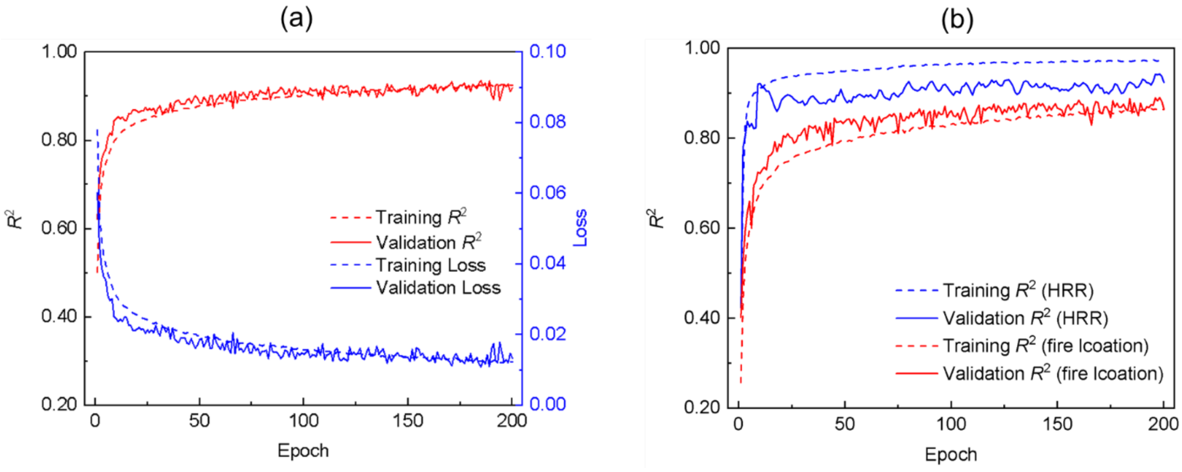


Fig. 6. The model performance (a) overall loss and R^2 curve, and (b) R^2 of fire HRR and location during the training process.

Based on fire dynamics theory, the ceiling temperature should be positively associated with the fire HRR, i.e., higher fire HRR tends to cause higher temperature value and vice versa. However, the smoke temperature is almost evenly distributed below the ceiling in the quasi-stable stage (i.e. a hot smoke zone) [8]. Therefore, it is hard for the AI model to identify the fire location only bases on the tiny difference of each temperature value. Meanwhile, the uncertainty of the building fire system will also disturb the AI model to extract the real temperature distribution characteristics in the dataset.

4. Demonstration of Digital Twin for real-scale fire tests

To demonstrate and test the performance of this smart fire digital twin (AID-Fire system), three groups of real-scale fire tests are conducted in the PolyU fire lab (7.5 × 3.4× 5.4 m^3).

1) Moving-fire test, to test the AID-Fire system's capacity and delay time of tracking a moving 2-propanol ($CH_3CHOHCH_3$) pool fire;
2) Dual-fire test, to validate the fire digital twin's ability to identify fire scenarios with multiple pool-fire sources; and
3) Sofa-fire test, to examine the digital twin's performance of identifying more realistic building fires.

In the fire test room, the ceiling temperature is measured by a 3 × 3 thermocouple matrix, and their distribution is the same as the numerical model in Fig. 3. The experiment data are transferred to a local server and input into the AI engine (trained by the numerical database) to identify the fire information that is displayed in the user interface. The CCTV camera is installed in the ceiling corner of the room to verify AI's prediction of fire location. The scale is used to measure the fuel burning mass-loss rate and verify AI's prediction of fire HRR.

4.1. Moving-fire test

The test procedure and the associated AI identification results are shown in Video S1. Initially, a pool fire of 45-cm diameter is ignited (Phase I). When the fire becomes stable, we manually move it via a trolley along the x-axis (Phase II), and then ignite another pool fire. The fire movement and the new ignition aim to mimic the fire develop and spread inside the building. Afterwards, the fire decays as the fuel gradually burns out.

The CCTV camera proves that the movement of the fire source between 20 s to 40 s is well captured by the proposed AI model, and the response time of digital twin to the fire motion is less than 1 s. Moreover, the AI model can automatically identify two adjacent fires as a single larger fire. The rapid increase of fire HRR, right after igniting the second fire source, can also be timely captured by the two-dimensional fire digital twin. The time delay of digital twin (~ 1 s) is caused by many reasons, e.g., sensor response, data communication, AI model calculation, refresh of the user interface, and so on. Such a system time delay cannot be avoided, but the current AID-Fire system is sufficiently fast for firefighting applications.

Fig. 7a shows AI's prediction of fire HRR, where the reference HRR values of steady-state burning pool (97 ± 20 kW for a single pool fire and 297 ± 70 kW for two neighboring fires in Appendix). Overall, the predicted HRR evolution by AI is close to reference steady-state values. Note that the actual fire is never steady-state but fluctuating during moving and growing processes. Fig. 7b further visualizes AI's identification of the 2-D fire position at different moments after two fires merges. The prediction shows a group of discrete distributed points around the location of fuel rather than a fixed point. This is because the fire plume will swing and incline under the effects of local airflow, as observed in the Video S1, revealing the fact that the flame zone is wider than the fuel bed. Overall, the prediction is excellent, where 97% of AI-predicted fire locations fall into the observed flame zone in the camera, and the largest predicted error is less than 0.5 m (Fig. 7c).

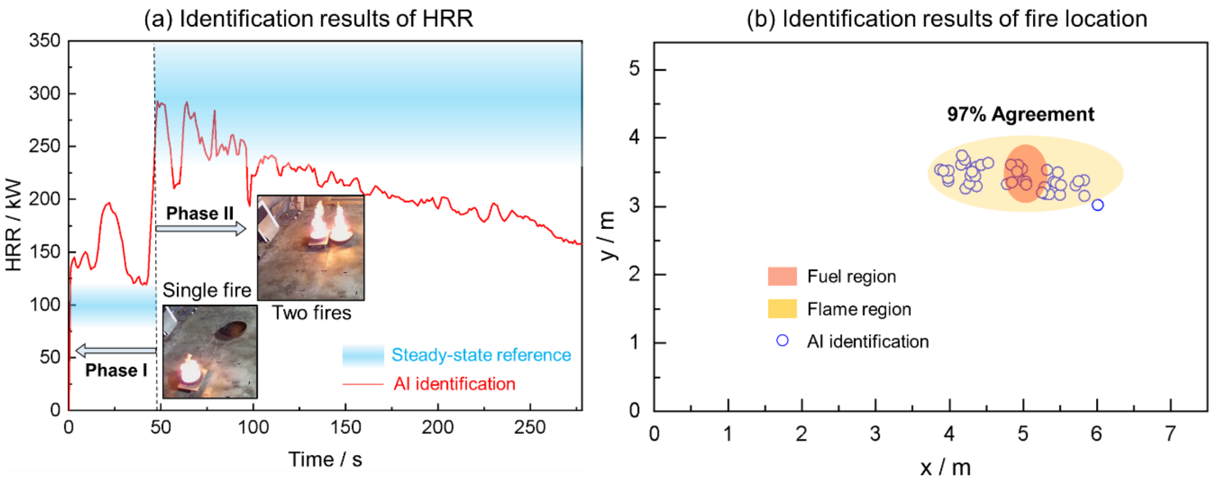


Fig. 7. AI identification results of the traveling fire case (a) fire heat release rate, and (b) fire location

4.2. Dual-fire test

In this experiment, two pool fire sources are set at a certain distance from each other and ignited individually. The burning process and associated real-time identification of the fire scene is shown in Videos S2. As observed, both fire sources are well identified by the AI model and displayed in the two-dimensional fire digital twin. Meanwhile, a relatively strong flame swing can be observed for both the two pool fires. Such flame swings with time are presented by the fluctuation of the identification of the fire HRR and location in Fig. 8.

Fig. 8a shows that the AI identified HRR also matches the steady-state reference quantitatively. Moreover, the fluctuating HRR predicted by AI agrees well with the transient mass loss rate data in Fig. A1. In other words, different characteristics, including the fire growth, oscillation, and decay of the dual-fire system can be well captured and identified by the AI engine, as presented by the red solid line in. Therefore, the real-time identification of the AID-fire system, which presents the fire variation with time, is more realistic than the fixed stead-state reference value and can provide more dynamic information to support firefighting.

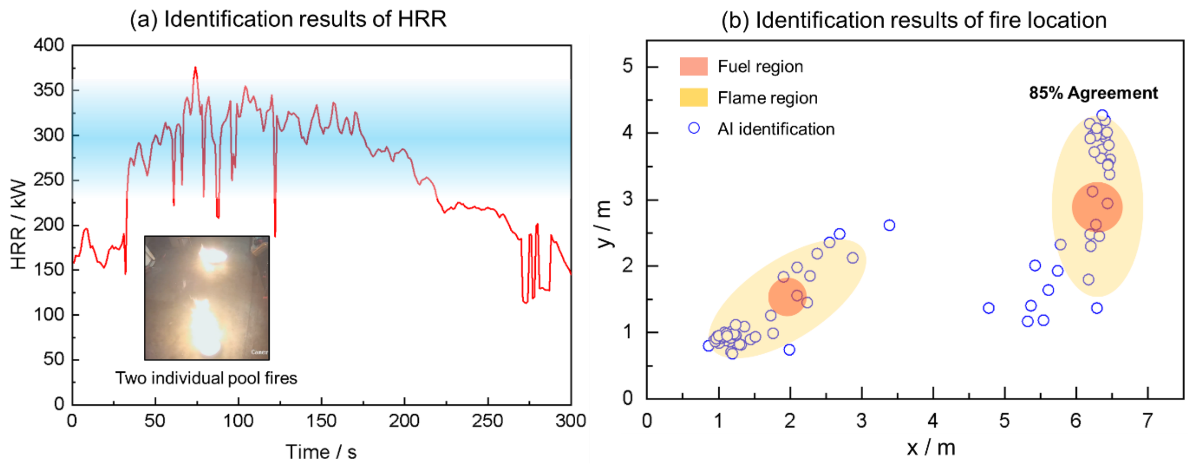


Fig. 8. AI identification results of the double fire case (a) fire heat release rate, and (b) fire location

For the dual-fire locations, the AI model predicts two groups of discrete distributed points around both fuel beds, as shown in Fig. 8b. The overall prediction accuracy is 85%, which is slightly lower than the moving-fire test. It is because the fire location is difficult to be identified based only on the ceiling temperature information, as discussed in section 3.3. On the other hand, the increase of the fire source number will increase the complexity of fire environment, so it is challenging to capture the spatial features accurately for each individual fire source. Therefore, we found both the accuracy and limitation of the proposed AID-fire system for multiple fire sources.

4.3. Sofa burning test

To examine the performance of the proposed AID-fire system in a realistic fire environment, a sofa fire is tested. The experimental procedure and the associated identification results are presented in Videos S3 and Fig. 9. A small amount of propanol (around 30 ml) is used to fast ignite the sofa at the beginning of the test. During the test, a small fire hose is used to suppress the fire when the fire becomes too large for safety concerns.

Fig. 9a shows a good overall agreement between AI's identification and the observed fire evolution phenomenologically. The predicted fire HRR increases at the development stages (the light-yellow regions) and decreases when the fire is discontinuously suppressed by a fire hose (the blue regions). Before the sofa fire is suppressed by a fire hose, the AI engine predicted a peak HRR of 470 kW at around 220 s, where half of the sofa is burning. Such a value is roughly 1/2 of the peak HRR of 992 kW found in previous literature [59] so that the AI's identification is reasonable.

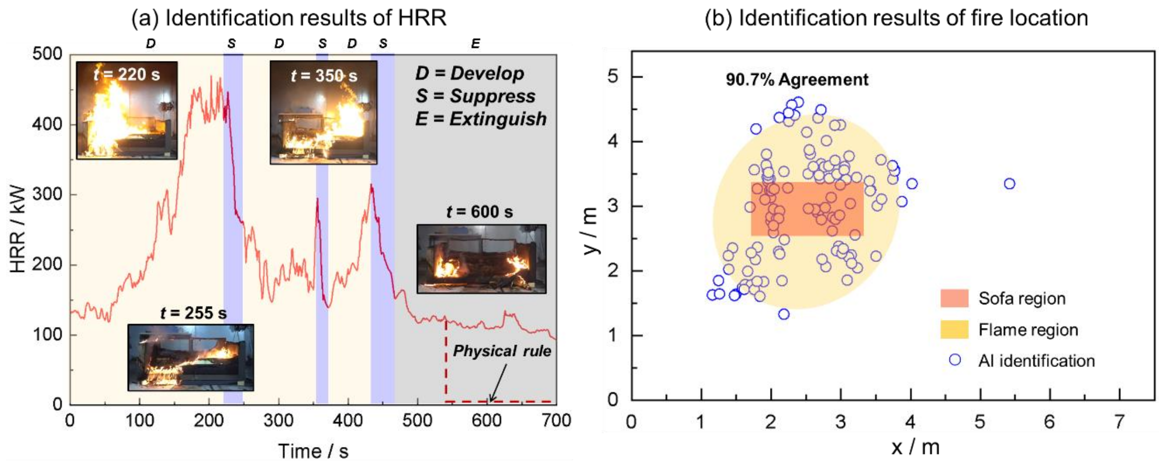


Fig. 9. AI identification results of the sofa burning test (a) fire heat release rate, and (b) fire location.

The fire position can also be accurately identified to locate at around thermocouple No. 3 at the beginning stage when the fire develops. However, when the fire hose suppresses the fire at around 220 s, the AI model predicts two fire sources with a large one in the correct place and a smaller one far away from the fire source, as shown in Videos S3. Similar abnormalities can be observed when the fire is suppressed again in the period from 450 s to 460 s.

To identify the fire position, the AI model analyzes the input temperature data and conducts non-linear interpolation by searching the temperature patterns with high similarity and correlation. However, when using the fire hose to suppress the fire, a large amount of vapor will be rapidly generated. Such a vapor plume disturbs buoyancy-driven smoke layer and changes the ceiling temperature distribution. Thus, the AI model tends to predict multiple fire sources in the suppressing stage, but such an abnormality quickly disappears after stopping suppressing. This issue could be addressed by adding more fire scenarios with different fire suppressions to the database. The overall accuracy of fire location identification is 91% (excluding suppressing stages), as shown in Fig. 9b.

Another interesting phenomenon is found after the fire is extinguished, where the AI model still predicts a fire with a certain HRR after 540 s. This is expected, because the upper layer gas can still maintain a relatively high temperature after the fire burns out. In fact, the AI's prediction is not just reasonable but also much safer. That is, although the flame is extinguished, the fire hazard (e.g., smoke and high temperature) still remains. Nevertheless, if a perfect fire identification is required, some physical rules can be applied to the outputs of AI model. For example, we can set the output HRR to be 0 when the ceiling temperature data meet the two conditions: a) the temperature keeps decaying in 10 seconds, and b) the average temperature is lower than 40 ℃. Then, overall prediction becomes more reasonable, as shown by the dashed line in Fig. 9a.

Determining the location of fire is a key feature of fire digital twin, and it is more difficult than determining the fire HRR. Identifying the 2D fire location in a building floor is more challenging than locate the fire in a 1D tunnel fire scenario [30]. The location of a fire and the spread of smoke layer in a tunnel is essentially limited by 1-D structure. The tunnel is very long, and there is a monotonical temperature decay along the tunnel. Therefore, it is easier for the AI model to identify the high-temperature region close to fire the low-temperature region far from fire.

However, in a typical building fire scenario, the space is relatively confined, and the smoke flow is restricted by the walls. Therefore, the smoke generated from the fire will accumulate and form a relatively stable smoke layer below the ceiling, that is less dependent on the fire location. As the smoke further accumulates and becomes thicker, the spatial gradient of the smoke temperature becomes small, so it is more difficult to identify the fire source location. We expect that the proposed AID-fire system should perform better in a large and less-confined space, e.g., tunnel, parking lot structure, and large-open office. It is because there is enough space for smoke to spread, and different fire will show a unique spatial distribution of smoke layer.

Compared with traditional fire alarming system, which can only identify if there is a fire or not, the proposed AID-fire system can provide more detailed information, e.g., temperature profile, fire location, fire size, etc., which is important to make effective firefighting decisions. What's more, the proposed system itself is a platform, which shows great potential for further development with more useful functions. For instance, the temperature data and video signals can be applied to forecast fire evolution, critical fire events based on deep learning models proposed in our previous studies [24,31]. The real-time identifications and predictions can also be accessed by people trapped in the fire building and guide them to evacuate along the safe path.

5. Conclusions

In this work, the framework of Artificial intelligence Digital Fire (AID-Fire) is proposed and demonstrated with a set of large-scale fire tests. Driven by the AI engine, which is constructed with Convolutional Long-Short Term Memory (Conv-LSTM) neural network and trained by a large numerical fire database, the proposed building fire digital twin can well identify different fire scenarios with more than 85% accuracy, a calculation time of ~0.1 s and a delay time around 1 s. Results show that compared with the fire location, the fire heat release rate is easier to be identified accurately. Meanwhile, critical fire events, including fire development, fire spread, fire movement, and firefighting actions, can also be accurately identified and displayed in the proposed AID-fire system. The introduction of physical rules can help achieve more reasonable identifications.

Compared with traditional fire alarming system, the novel AID-fire system can provide more detailed information to support firefighting. Meanwhile, it shows great potential for further development with more functions, such as real-time forecast of fire evaluation, onset of critical fire events, evacuation guidance panel, and robotic firefighting control panel.

To identify more complicated building fires, the future database will include more fire scenarios with different fuel types, loads, ventilation conditions, and suppression strategies to enhance AI's capability. Meanwhile, a professional rendering virtual reality engine combined with 3D BIM, will be applied to extend the AID-fire system from a room to a floor and the whole building.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Figure. A1 presents the moss loss rate of the liquid pool fire with different diameters. As shown, the mass loss rates for the 45 cm-diameter and 62-cm diameter pool fires are valued as 2.9 ± 0.6 g/s and 6.0 ± 1.5 g/s, respectively. By adopting the combustion heat of propanol as 33.4 MJ/kg and assuming the combustion efficiency to be 95-100%. The stable HRRs for the two pool fires are calculated as 96.9 ± 20.0 kW and 200.4 ± 50.1 kW as reference values, respectively.

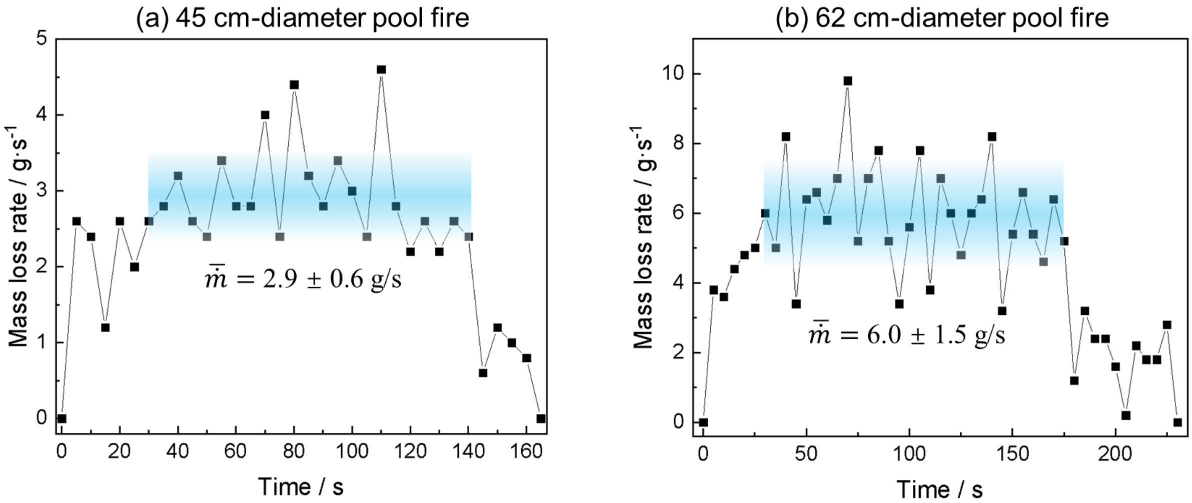

Fig. A1. Mass loss rate of (a) 45 cm-diameter pool fire, (b) 62 cm -diameter pool fire.