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AIoT-powered building digital twin for smart firefighting and super real-time fire forecast

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ABSTRACT

Complex dynamics inherent of building fire poses big challenges to firefighting and rescue, especially with limited access to critical fire-hazard information. This work proposes the novel AIoT-integrated Digital Twin for the full-scale multi-floor building to manage the dynamics fire information. This system allows for super real-time mapping of actual building fires into accurate and concise digital fire scene at the cloud platform. By developing the ADLSTM-Fire model, we effectively transform discrete sensor-array data into high-dimensional spatiotemporal temperature fields in real-time, and furthermore, forecast future fire development and hazardous regions 60 s in advance. By comparing with benchmark numerical simulations, the Digital Twin system demonstrates the high reliability of super real-time fire-scene reconstruction and the capacity of fire-risk forecasting in supporting firefighting. The full-scale building fire experiment is employed to validate the generalisation capability of the proposed smart firefighting method. This work demonstrates the great potential and robustness of AIoT and digital twin in support smart firefighting and reducing fire casualties by information fusion.

1. Introduction

Today, the concept of smart cities has gained significant traction playing a pivotal role in enhancing urban information management [1]. Through creating a virtual replica of physical systems, the rising technology Digital Twin enables real-time monitoring the building lifecycle [2] and thereby improves the urban infrastructure operation and maintenance [3]. These emerging methods is widely used for smart operation of various types of infrastructures such as civil infrastructures [4], stormwater infrastructure systems [5] and hydro-steel structures [6]. Moreover, data computing technology featured by the multi-source data fusion allows for the in-depth discovery of critical information, which makes smart buildings resilient to unforeseen events especially in urban hazard management [7]. Data-driven approaches are widely used in urban disaster management [8–10].

Among the various hazards faced by urban environments, building fires remain a predominant threat, causing substantial damage and loss of life [11,12]. The catastrophic fires accidents, like the 2017 London Grenfell Tower Fire (Fig. 1a), happen frequently worldwide. The total cost of fire safety, emergency response, and fire losses are approximately 1–2 % of annual global GDP [11]. A large portion of casualties in urban fires resulted from insufficient information of fire scenes. Although

Abbreviations: AI, Artificial intelligence; ADLSTM, AutoDecoder Long short-term memory neural network; AIoT, Artificial intelligence of things; ANN, Artificial neural network; CNN, Convolutional neural networks; FBG, Fiber Bragg Grating; FASA, Fire and ambulance services academy; GAN, Generative adversarial network; GNN, Graph neural network; HRR, Heat release rate; IoT, Internet of things; LoRa, Long range; MSE, Mean square error; RNN, Recurrent neural network; SureFire, Smart Urban Resilience and Firefighting; UI, User interface.

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firefighters usually have good experiences and extra information from the commander, lack of fire information in complex built environment poses a high risk to firefighting operation and decision-making [13,14]. For example, in the 2016 Hong Kong mini-storage fire, two firefighters lost in contact after entering the smoky fire scene in two separated days, and eventually both lost their lives (Fig. 1b). In the firefighting operation of a recent battery energy storage station fire in Beijing, a sudden explosion killed two firefighters and one electrician (Fig. 1c).

There is an urgent demand for a method to provide building interior information in the event of fire. Several type of fire-scene information can be acquired and valuable for firefighting, evacuation, and rescue, such as temperature [15,16], heat flux, smoke colour and visibility [17,18], sound [19,20], images and videos of fire and smoke [21,22]. For example, the ceiling temperature distribution is a critical parameter for fire detection [23–25]. However, heat detectors are neither always available nor accessible, and eventually, they can be damaged by growing hot fire smoke. Moreover, most of fire detectors only provide binary information (Y/N) once reaching certain thresholds, rather than providing continuous readings about fire scene. Therefore, IoT sensor network has been employed to measure the time-evolution temperature data and enable automatic mitigation measures, such as alarms, sprinklers [26], smoke ventilation system [27], fire hose [28], and fire doors.

However, without building fire knowledge and model, information collected by IoT alone cannot contribute to the full understanding of fire spatiotemporal development. Currently, various methods are applied to the study of building fire patterns. Full-scale fire experiments are reliable methods for data collection, serving as benchmarks for empirical fire modelling [29–31]. Nonetheless, conducting many high-risk and costly building fire experiments is unrealistic. Even if large fire tests are available, limited spatiotemporal temperature data can be acquired [32]. Subsequently, massive and accurate fire simulations driven by Computational Fluid Dynamics (CFD) codes are more effective in understanding fire developments [33], but they are too time-consuming to predict fire in real-time and support smart firefighting [34]. Moreover, the demand for real time mapping of fire spatiotemporal information is growing to support future smart firefighting system. Therefore, Artificial Intelligence of Things (AIoT) has been proposed for smart building that can achieve real-time fire forecast through the functional convergence of Internet of Things (IoT), smart sensors and Artificial Intelligence (AI) algorithm [35]. Particularly, deep learning can explore hidden fire information and advance smart fire services systems by facilitating big data processing, complex system analysis and making decisions [36]. Recent studies have demonstrated AIoT systems in fire localization, evacuation route optimization, and planning firefighting strategy [8,37,38]. Despite these new technologies are not fully realized in complex-built environment, they provided better awareness of fire.

Digital twin is also proposed to enhance the intelligence and reliability of fire safety management and firefighting [22,39–42]. Serving as a data-fusion platform, Digital Twin contributes to sharing real-time information and resources regarding the on-scene situation. Recent advancements have demonstrated the potential of digital twin systems in building fire key parameters inference, such as fire location and intensity within the single room [41], or the dativization of human evacuation behaviour during building fires [40]. Although the advanced information computation is initially applied to enhance building fire safety [43,44], there is still limited research on real-time digitisation of the effects of fire on the overall environment of complex multi-room buildings. Therefore, the pursuit of high-dimensional information like dynamic of temperature fields over time is an important objective in this work for Digital Twin systems development. The digital models driven by the limited on-site information represents a promising avenue in supporting smart firefighting practices. Once equipped with information-generating capabilities, the smart firefighting can bridge the gap between the available on-site fire information and the comprehensive understanding of the temperature field, even obtaining super real-time information on fire dynamics.

To improve the urban safety and resilience, this study proposes the development of an AIoT-integrated Digital Twin system specifically designed for smart building management, with a focus on fire safety. The smart firefighting framework is proposed, tailored for a multi-floor firefighting training building. We have developed an ADLSTM-Fire model for real-time reconstruction and 60 s advance forecasting of temperature field by inputting low-dimensional sparse data from the IoT. Full-scale fire experiments are conducted to demonstrate the competitiveness and robustness of the proposed Digital Twin system for smart firefighting practices, including real-time inference of fire hazardous area, and the guidance of firefighting operation and evacuation process.

2. Methodology

2.1. Wireless thermometry in building IoT

The IoT systems that integrate various interconnected electronic and optical devices enables the environment sensing, so it is a prerequisite for building intelligence and disaster informatisation [1,45]. For the comprehensive insights into building fire dynamics, the thermometry array constructed from sensors need to be deployed to support real-time temperature monitoring. Although there are smoke/temperature sensors wired to fire alarm control panels in some new buildings, either many existing buildings are not equipped with these wired sensors or these sensor data are not accessible for firefighting operation. In addition, cons of wired sensor networks include cumbersome equipment upgrades, inflexible layout adjustments, and high labour cost [46].

Fig. 1. Major fire accident sites (a) Grenfell Building fire, London in 2017 (cc by: The Telegraph), (b) Ngau Tau Kok mini-storage fire, Hong Kong in 2016 (cc by: RTHK), and (c) Dahongmen fire in battery energy storage station, Beijing in 2021 (cc by: Sina).

Consequently, the wireless integration of IoT systems has emerged as an imperative requirement, offering a viable solution to overcome these challenges.

Temperature measurement encompasses a broad array of sensor options, primarily classified as contact or non-contact sensors. Table 1 demonstrates the characteristics comparison among common building temperature monitoring technologies [47,48]. Thermocouples are currently widely used for temperature measurement, relying on the thermoelectric effect of dissimilar metals at varying temperatures [49]. However, thermocouple needs a reference room temperature, so the accuracy of wireless thermocouple is questionable. Resistance temperature detector (RTD) works based on a strong linear relationship between resistance and temperature. But response speed and probe size also affect its competitiveness in wireless temperature measurement. Thermistors satisfy the requirements for fire temperature wireless sensing in buildings by virtue of their resistance-based thermometric principle [50]. For example, Negative Temperature Coefficient of Resistance is widely integrated into wireless sensing devices due to their affordability, compact size, high precision, and rapid response. Some optical-based temperature measurement methods such as fibre optics (FBG/DTS) and infrared (IR) cameras are also suitable for temperature measurement in the built environment. However, the integration into smart firefighting is still under-researched due to high overheads.

Advances in wireless technology eliminated the limitations of wired, allowing the widespread implementation of IoT. The integration of wireless networks and devices has garnered significant attention in various areas such as object detection, environment monitoring and disaster management [51]. There are already a variety of wireless sensing protocols have been adopted in industry, such as Zigbee, Wi-Fi, and Bluetooth [52]. Considering the low power consumption characteristics required for long-term operation of the device, LoRa (Long Range) is an alternative wireless IoT connectivity method. The feature of transmitting limited data over long distances in a short period of time makes LoRa increasingly popular in low-power battery-powered embedded systems [53]. However, the existing IoT communication is limited to simple feedback on monitored fire signals, while the potential for smart firefighting driven by wireless IoT data inputs remains largely unexplored.

2.2. Ai-driven smart firefighting

Currently, AI technology represented by deep learning is widely used in construction safety assessment and information management [54]. AI-driven fire forecast is primarily achieved by the multi-dimensional fitting via artificial neural networks (ANN). Database is constructed from large amounts of fire experiments and simulations to assist deep learning in characterizing building fires. Deep learning models can accelerate the solution process by establishing efficient mapping relationships [55]. Presently, various deep learning algorithms [55,56] have been developed and migrated to fulfil research on smart firefighting. It expedites access to fire-related information for decision-makers, encompassing aspects, such as fire source localization, heat release rate (HRR), and fire development stages [57–59]. Leveraging convolutional neural networks (CNN) for image processing, computer video techniques can be utilized to detect visual target in fire scenarios [60,61]. Advanced algorithms like recurrent neural networks (RNN), graph neural networks (GNNs), generative adversarial network (GAN), and Diffusion models can rapidly identify or advance forecast disaster escalations such as flashover and booms [62–65].

Previous research has focused on extracting crucial insights from extensive field data such as the fire source important that is important for fire analysis and modelling. However, to support immediate firefighting decisions, generalized information such as temperature spatiotemporal distribution needs to be accurately access. In case of emergency, intuitive temperature field can provide comprehensive view of fire behaviour throughout the entire structure. Such fundamental information can be widely and effectively used in firefighting decisions such as hazardous area identification, structural damage assessment and rescue route planning. Many studies assumed the uniform ceiling temperature for a room based on zone models [15,64]. Some studies have quantified flame and smoke by parameter characteristics [66,67], but dissimilarities in fire scales and data types restrict the transferability of knowledge. Considering the scarcity of internal building data during fire incidents, unresolved challenges arise in reconstructing the 2D or 3D spatial distribution of the temperature field and forecasting temperature evolution in advance.

In this work, the hybrid deep learning model of AutoDecoder Long Short-term Memory Neural Network (ADLSTM-Fire) is proposed, which enable real-time high-dimensional spatiotemporal inference for building fires based on discrete sensor information. Mathematically speaking, ADLSTM-Fire model could forecast the 2D temperature field information Y after K-steps in advance when the previous sensor array historical data X is given. The X represents the temperature information of sensor array for J moments, which can be expressed as $X = [X_1, X_2, \ldots, X_J]$. Y represents the forecasted temperature distribution after K moments since the beginning of J moments. The mathematical expressions are as follows:

$$X = \begin{pmatrix} X_1^1 & \cdots & X_{S\_No}^1 \\ \vdots & \ddots & \vdots \\ X_1^J & \cdots & X_{S\_No}^J \end{pmatrix}, Y = \begin{pmatrix} Y_{1,1}^{J+K} & \cdots & Y_{1,n2}^{J+K} \\ \vdots & \ddots & \vdots \\ Y_{n1,1}^{J+K} & \cdots & Y_{n1,n2}^{J+K} \end{pmatrix} \tag{1}$$

where S_No represents the number of sensors. $(n1, n2)$ represents the slice consisting of any two dimensions within a three-dimensional space.

In the architecture of the proposed deep learning model, the integrated LSTM enables the model with the capability of advance forecast for temperature field based on the historical data. AutoDecoder can achieve the mapping from low-dimensional discrete temperature values to high-dimensional 2D temperature slices by fusing DNN and Decoder [68]. The information flow is shown as follows:

$$X_{S\_No}^{J+K} = LSTM^{w_1}(X_{S\_No}) \tag{2}$$

$$H = Dnn^{w_2}(X_1^{J+K}, X_2^{J+K}, \cdots X_{S\_No}^{J+K}) \tag{3}$$

$$Y = AutoDecoder^{w_3}(H) \tag{4}$$

where X_{S_NO} is the historical data of the sensor in J moments $X_{S\_NO} = [X^1,$

Table 1
Characteristics comparison of three types of temperature sensors.

Feathers	Thermocouple	Thermistor	RTD	Optical fibre	IR camera
Range (℃)	−270 ~ 2,300	−100 ~ 1,000	−200 ~ 850	0 ~ 320	−20 ~ 2000
Output signal	Voltage	Resistance	Resistance	Optical signal	Thermal Image
Linearity	Moderate	Poor	High	High	Moderate
Accuracy (±℃)	Low (0.05 ~ 5)	High (0.001 ~ 1)	High (0.001 ~ 1)	High (0.001 ~ 1)	Low (0.5 ~ 5)
Sensitivity	Low	High	Moderate	High	High
Probe size (mm)	0.5 ~ 8	0.4 ~ 3	3 ~ 7	0.2 ~ 8	N/A
Response (s)	0.1 ~ 10	0.1 ~ 10	1 ~ 50	0.01 ~ 60	0.001 ~ 0.05
Cost	Low	Moderate	High	Very High	Very High

X^2, …, X^J] $_{S\_NO}$. *LSTM*, *Dnn* and *AutoDecoder* is the different neural network. $w = [w1, w2, w3]$ are the corresponding hyperparameters inside different neural networks, which will be optimised during model training.

Moreover, the simple model used for temperature field real-time reconstruction can be developed by directly combining the two equations Eq. (3) and Eq. (4). The mathematical expression can be shown as follows:

$$X = (X_1, X_2, \cdots X_{S\_No}), Y = \begin{pmatrix} Y_{1,1} & \cdots & Y_{1,n2} \\ \vdots & \ddots & \vdots \\ Y_{n1,1} & \cdots & Y_{n1,n2} \end{pmatrix} \tag{5}$$

Compared to the thermometry system that can only get the data at limited locations in the building, the simplified model derived from ADLSTM-Fire could reconstruct the complete temperature field distribution at the current moment. Furthermore, the well-trained ADLSTM-Fire exhibits the capability to forecast the future temperature field evolution, allowing for sufficient decision-making time in AI-driven smart firefighting operations.

2.3. Digital Twin system

Digital Twin is initially defined for production lifecycle management by Grieves in 2002 [69], which is then re-contextualized by NASA during the Apollo space program as the digital equivalent of a physical product [70]. The maturity of data-driven system can be categorized into 6 levels, where Digital Twin signifies Level 4 [71]. By efficiently integrating the overall data-driven system, the real-time interaction and synchronization between the physical model and digital model is achieved. Furthermore, the Digital Twin becomes powerful to deal with complex target with the advancement of AIoT in real-time sensing and efficient data processing [72]. Gradually, AIoT-integrated Digital Twin is gaining traction in smart building and safety management [73].

Notably the concept of digital twins is still evolving in fire safety research, and researchers are actively exploring its new applications. Building fire Digital Twin not only takes care of the dynamic visualization of the real fire, but also assumes responsibility for data distillation and analysis for a faster emergency response. For example, Zhang et al. [35] constructed the AIoT-enabled Digital Twin system of tunnel to predict fire location, motion, power, fuel hazard, and evacuation risk in tunnel fire. A Digital Twin platform can also predict and monitor crowd evacuation and fire risk during emergency events based on the computer vision and deep learning [40,43,74]. Nevertheless, detailed approaches to generating the invisible high-dimensional physical fields have not yet been fully investigated. Therefore, it is necessary to develop the AIoT-integrated Digital Twin to demonstrate the application value of temperature field spatiotemporal forecast for building smart firefighting. By accessing sensor data in the fire scene, the system can provide firefighter commanders with spatio-temporal forecast of the temperature field through a user-friendly interface. Commanders can identify hazardous areas by setting temperature thresholds and develop specific strategies accordingly for frontline firefighters. This interaction enhances

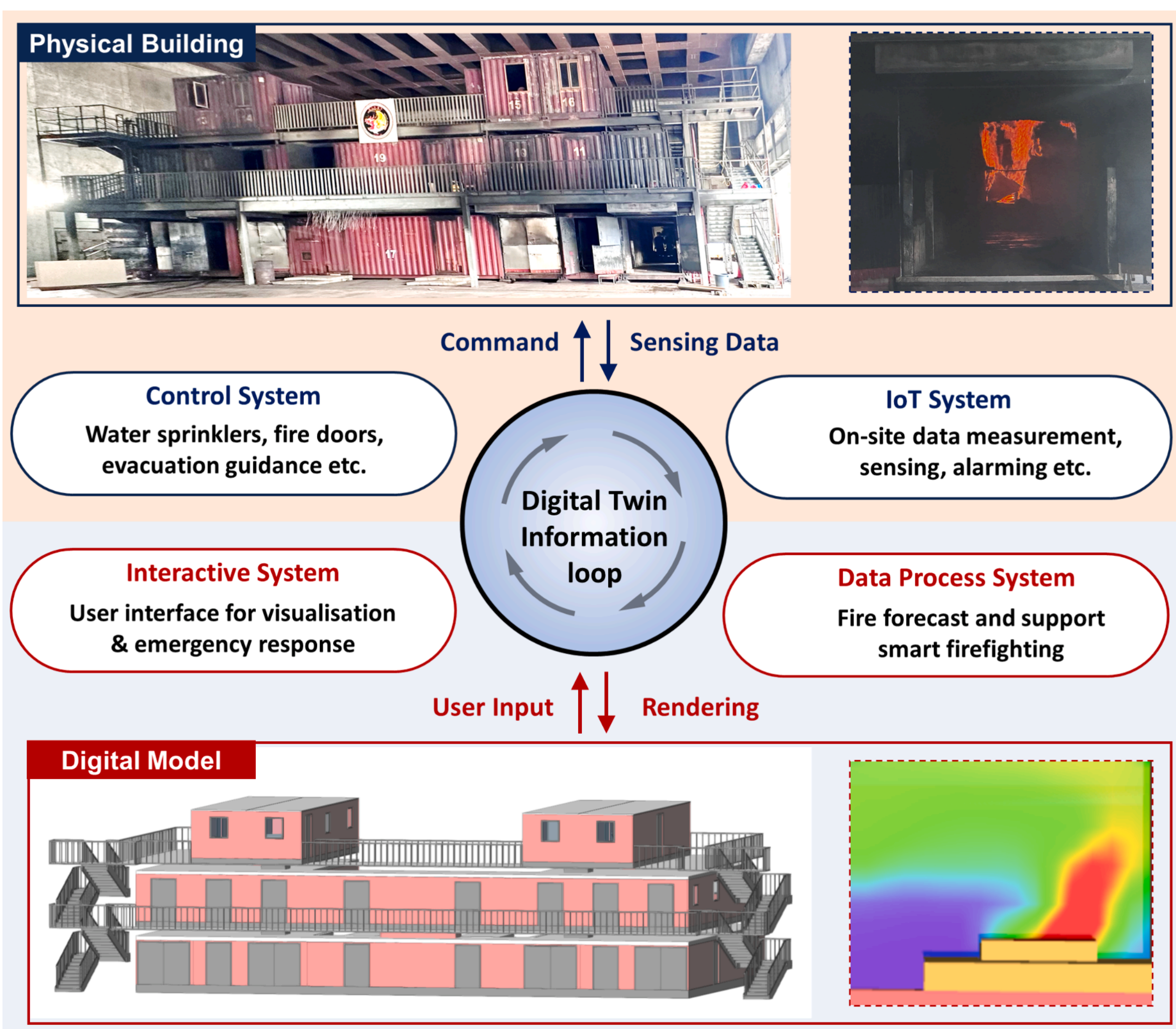

Fig. 2. AIoT-Powered Digital Twin framework for a full-scale three-storey firefighting training building.

situational awareness and coordination, ultimately improving the efficiency and safety of firefighting operations.

3. AIoT-integrated Digital Twin

Fig. 2 shows the concept of AIoT-integrated Digital Twin system for smart firefighting training and practices, which is part of our proposed SureFire (Smart Urban Resilience and Firefighting) system. The selected physical building is full-scale structure for the firefighter training, located at the Fire and Ambulance Services Academy (FASA) of Hong Kong Fire Services Department. This firefighter-training building has three floors (i.e., Ground Floor, First Floor, and Second Floor), which are

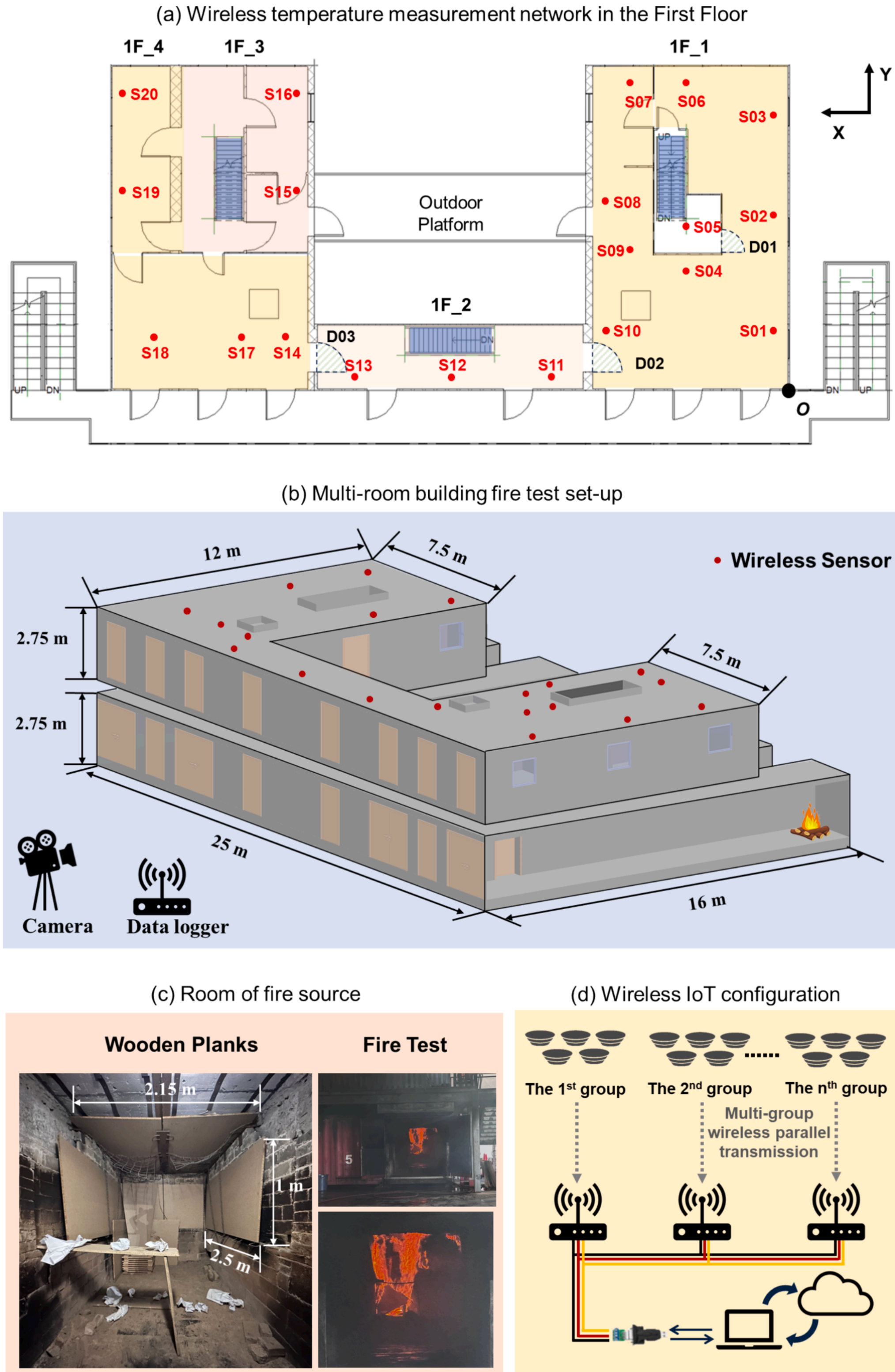

Fig. 3. Schematic of wireless thermometry system in full-scale building fire test, (a) Wireless temperature measurement network in the 1st Floor, (b) Fire test set-up with Ground Floor and 1st floor, (c) detailed of the room of fire source on the Ground floor, and (d) wireless IoT configuration.

connected by external and internal staircases. It is made of two 10-feet, three 30-feet, twelve 40-feet standard containers, and another four 52-feet customized containers. Containers can be easily connected or insulated by doors to create different training areas. Then, instructors can conduct various training tasks, e.g., observing flashover and roll-over, practicing fire hoses, and testing novel and advanced smart fire-fighting technologies.

The Digital Twin connects the functions of the systems in series through data loops. Thermometry arrays is deployed in buildings and responsible for collecting field data. The uploaded fire data triggers relevant mitigation measures within the control system, and simultaneously being fed into the data processing system. Equipped with deep learning models, the data processing system can analysis the input data and guide smart firefighting. As a specific case study, temperature field real-time reconstruction and advance 60 s forecast are presented to exemplify the function of smart firefighting in Digital Twin system. This is achieved based on AI architecture of ADLSTM-Fire and its simplified model. The models are hosted on the cloud server, which can generate reliable fire-related prediction and visualize to the user. The dynamic Digital Twin of temperature field can assist firefighters in making decisions and evaluating the effectiveness of mitigation measures.

3.1. Building fire test

Fig. 3 illustrates the configuration of wireless thermometry system in full-scale building fire test. The overall geometry dimensions of the building structure are approximately length = 25 m, width = 16 m, and height = 8.5 m, respectively. The typical fire case that hot smoke spreading to other floors is selected as the building fire experiment scenario, because it's common in building fires and will cause the disaster escalation[75]. The First Floor is utilised as the main experimental subject, where four rooms (or areas) are highlighted with different colours (Fig. 3a). To collect the real-time temperature data, thermometry arrays that integrated into IoT systems are strategically deployed on the ceiling of the First Floor. Fig. 3b shows the specific configuration of building fire test. The camera is setup for recording videos of the fire experiment. The router works as data acquisition unit to receive the temperature signal from the thermometry network. As shown in Fig. 3c, the room of fire source is located at the Ground Floor where wooden planks were fuel and placed in the innermost part of the room. The door open/ close is configurated to ensure that high-temperature gas will enter the First Floor through the stairwell in room 1F_1. Fig. 3d demonstrates the wireless IoT configuration on the First Floor. For stable signal transmission with multiple sensors, the wireless thermometry array divides sensors into serval groups and establish the star appropriate network topology.

The data acquisition unite can get the overall temperature information under the topology network by accessing the central nodes. The private cloud server and edge computing devices are both deployed within the same local area network (LAN) to support data transfer efficiency and privacy. The polling mechanism is adopted where the data acquisition unit periodically accesses each sensor. During the building fire test, the sampling frequency of edge computing devices are set 1/6 Hz (i.e., once every 6 s) to collect and process data into simplified temperature value to reduce the transmission burden. Edge computing devices will store data locally while uploading to ensure system reliability. This setting is to balance the requirements of real-time data collection, stable upload of signals in the building fires, and reduction of battery energy consumption. With continuous invasion of high-temperature gases into the First Floor, the sequential temperature data will be transmitted directly to a data logger approximately 50 m away via LoRa wireless protocol. Afterwards, the sensed data is further synchronised to the IoT for user access. The feasibility of wireless IoT-based fire monitoring in real-world scenarios is validated (see Video S1 for more details). Moreover, the experimental data will be further utilized in the following CFD accuracy validation and generalization investigation of the Digital Twin system for building fire.

3.2. Benchmark numerical dataset

Constrained by the high cost of building fire experiments and the impracticality of obtaining full-dimensional physical temperature field, benchmark numerical dataset is very important to understand the accident evolution process. Referring to the experimental configuration, different fire scenarios can be simulated by adjusting the fire source parameters. The resulting benchmark numerical dataset can fully reflect real-world fire dynamic, and the huge amount of data containing different scenarios will be the basis for training ADLSTM-Fire models. As an alternative of real-world sensor data, numerical datasets generated through widely-validated Computational Fluid Dynamics (CFD) meets the requirements of deep learning models with satisfactory accuracy [41]. As a representative CFD software for fire simulation, the Fire Dynamics Simulator (FDS) [76] is employed to simulate the building fire and establish the benchmark database. This work can be divided into two steps:(1) FDS accuracy validation based on fire experiments (2) Numerical benchmark dataset development.

Step 1: CFD model validation via fire experiments. A precondition for database construction using numerical simulation is the credibility of this method. According to the building fire test in FASA, the full-scale FDS simulation is conducted to reproduce the experiment and verify FDS accuracy. For avoiding the effect of the computational domain on the simulation results, the computational domain is set as 30 m × 20 m × 10 m and the boundary condition is set as Open. In this configuration, the high-temperature smoke overflowing the building can be accurately modelled, which can guarantee the correctness of the calculation convergence. Based on mesh sensitivity analysis, the grid size is determined as 0.2 m in all directions for the trade-off between computational accuracy and efficiency. To simulate the fire experiment, we use the recorded fire video and AI-image fire calorimetry method [60,77] to help estimate the evolution of HRR in the room of fire source (see Fig. 3c) as the boundary condition in the CFD model. As illustrated in Fig. 4(a), the fire is modelled to increase linearly until 500 kW at 1,400 s and then stabilise for another 1,000 s.

Fig. 4(b) compares the temperature evolution at four positions in the building. The selection contrasting locations represents the sensors from different rooms in Fig. 3a (S02, S06, S13 and S18). Nicely the comparison of the curves shows the satisfactory fitting of the simulation results with the experimental data in terms of slopes and durations. The comparative results explain that numerical simulation can robustly predict overall temperature change for the fire scenarios, thereby enabling the database construction for the subsequent development of deep learning models.

Step 2: Numerical benchmark dataset development. Based on the verified availability, the FDS is employed to generate the building fire numerical benchmark dataset. A total of 75 building fire scenarios were simulated by considering 3 fire locations in the combustion chamber, 5 HRRs (300, 500, 1000, 1500, 2000 kW) and 5 duration times (1000, 1300, 1500, 1800, 2000 s). Referring to the sampling frequency of the sensors (1/6 Hz) in the experiment, 10 consecutive temperature data (within 1 min) is extracted as a dataset and collectively constructs the 1,644 sets of dataset D = [$X^{10\times20}$, $Y^{150\times100}$]. The constructed dataset D will be further used for ADLSTM-Fire model construction where X is the input data and Y is the label. $X^{10\times20}$ represents the 10 temperature values collected by each of the 20 sensors over a 1-minute period. $Y^{150\times100}$ represents horizontal temperature slice 2.7 m above the ground, which is depends on the sensor installation height. The size of the slice is 150 × 100 (length × width), which contains 150 × 100 temperature values. Among the datasets, 80 % samples are designed as the train dataset D_{train} for the training and validation during the model construction. The remaining 20 % serves as test dataset D_{test} to evaluate the generalisation ability of the well-trained model.

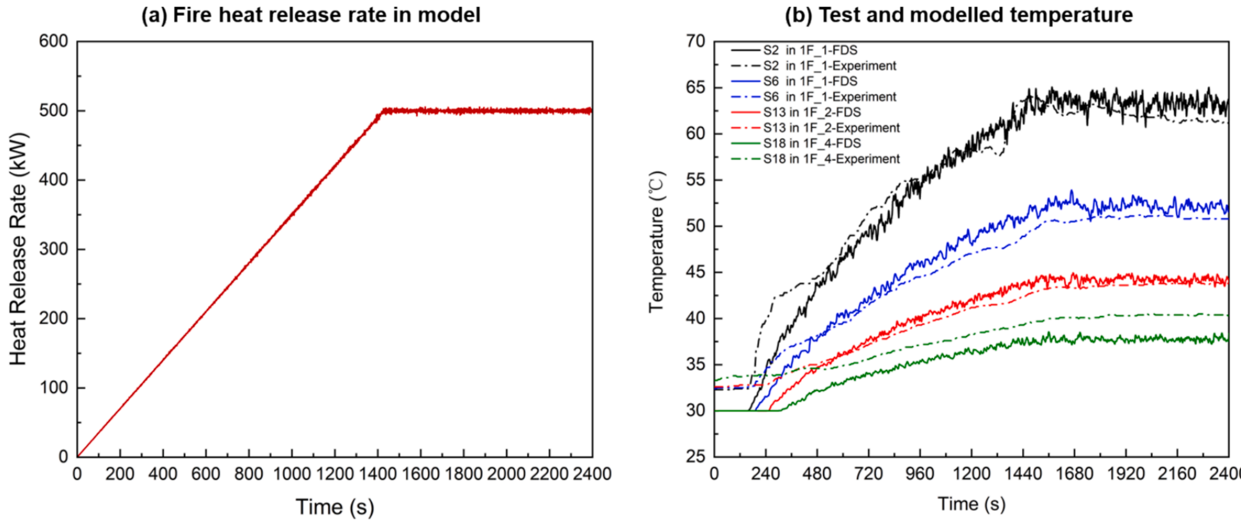

Fig. 4. Numerical model validation, (a) heat release rate curves for fire sources set in the model, and (b) Data comparison between experiments and numerical simulations.

3.3. ADLISTM-Fire development

The utilization of deep learning for smart firefighting is a key feature of the proposed AIoT-integrated Digital Twin System. Given the significance of temperature in guiding firefighting, the approach of temperature fields spatiotemporal prediction is proposed to showcase the feasibility of digital system for smart firefighting.

This work aims to (1) reconstruct the current temperature field in real time and (2) forecast the future temperature distribution 60 s in advance, based on the temperature history data from the sensors. This requires temporal advance forecasting based on time-series data and spatial feature inference of the 2D temperature field based on discrete data. To address these challenges, the deep learning model of ADLSTM-Fire is developed to handle complex spatiotemporal relationships.

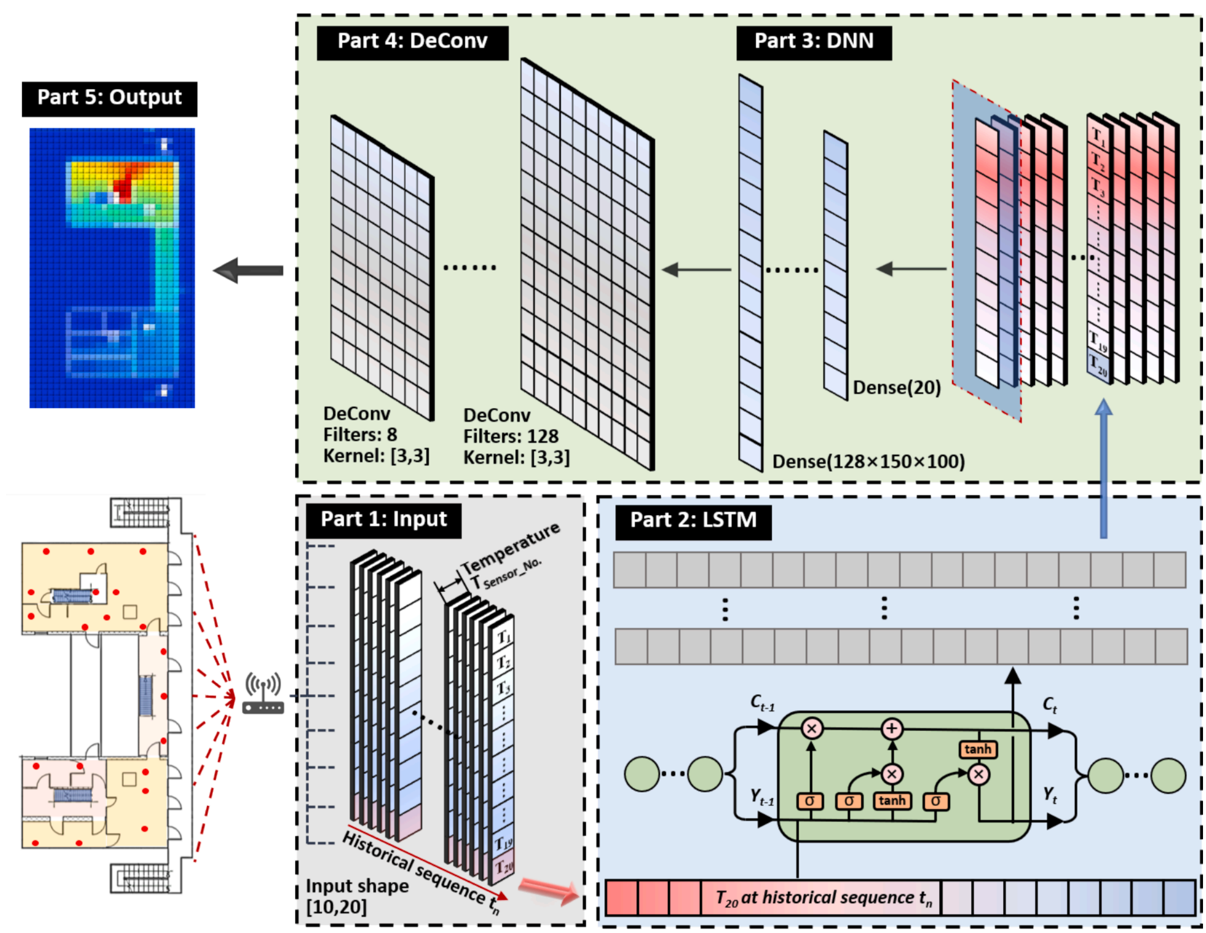

Fig. 5. Architecture of ADLSTM-Fire.

As shown in Fig. 5, proposed ADLSTM-Fire model can advance forecast the temperature field based on sensor data with the hybrid algorithm. The target function is implemented in two steps that can investigate the spatio-temporal pattern of temperature evolution using LSTM and DeConv.

The First Step is to forecast temperature value 1 min in advance based on current collected sensor data, which is achieved by Part 1 and Part 2. Part 1 represents the input layer where the data format is data values obtained from 20 sensors for 10 sampling. Subsequently, Part 2 should handle temporal correlation of the data collected by each sensor. Traditional RNNs (recurrent neural network) for temporal correlation prediction often suffer from vanishing gradient during model training. The architecture of LSTM is selected because its cell state and gating mechanisms allows it to retain relevant information over extended time periods. Therefore, this capability enables that the ADLSTM-Fire model can learn from historical data and forecast the temperature value in advance for each sensor location.

The Second Step is the upscaling of the discrete temperature forecasted values to a 2-D temperature slice, which is achieved by Part 3 and Part 4. Part 3 indicates the DNN model that is responsible for connecting the sequence of forecasted temperature values from Part 2 to the fully connected neural network. Information expansion is achieved through the increasing number of neurons in each layer along with the superposition of the fully connected layers. Part 4 employs DeConv, the reverse of the convolution operation, to discover the spatial distribution of temperature features embedded in the data. Generally, the convolution operation for a 2-D matrix is to extract the key information and reduce it to 1-D data. In this work, DeConv can reverse output the 2-D space by multiplying two 1-D matrices, the data from Part3 and model hyperparametric filter. This upscaling transformation enables the ADLSTM-Fire model to effectively capture the spatial distribution characteristics of the temperature field based on information from the previous part. Finally, the spatial distribution of temperatures $Y^{150\times100}$ is obtained as output (Part 5) through multiple transpose-convolution.

Therefore, the hybrid ADLSTM-Fire model is proposed for building fire spatio-temporal prediction by integrating the advantages of LSTM in time-sequence processing and the DeConv in multidimensional information generation. Table 2 shows the specific configurations of ADLSTM-Fire model. Moreover, the advance forecast of sensor data is an important part of model development that makes the ADLSTM-Fire work more interpretable. Therefore, the LSTM in Part 2 requires pre-training to ensure the accurate advance forecast of temperature value in sensor location. In the pre-training, the model input is the temperature values collected by 20 sensors for 10 sampling $X^{10\times20}$. The output is the forecasted temperature value of these 20 sensors after 1 min X^{20}. Once the pre-training is completed, the neuron parameters of the LSTM are frozen [68] to avoid adjustment of this Part during subsequent ADLSTM-Fire model training. This manipulation ensures that the advance forecast sensor temperatures are taken as inputs to Part 3, thus guaranteeing accurate inference of ADLSTM-Fire model in the temporal dimension.

Table 2
Configuration of ADLSTM-Fire, where ↓ represents the layer connected to neural network below, and ↗ represents the layer connected to neural network of the next Part.

Part 1: Input + Part 2: LSTM	Part 3: DNN	Part 4: DeConv + Part5: Output
200 Dense ↓, ReLU	20 Dense ↓, ReLU32 Dense ↓, ReLU	3 × 3 128 DeConv2D ↓, ReLU 3 × 3 64 DeConv2D ↓, ReLU
100 LSTM ↓, Tanh	64 Dense ↓, ReLU128 Dense ↓, ReLU	3 × 3 32 DeConv2D ↓, ReLU 3 × 3 8 DeConv2D ↓, ReLU
20 LSTM ↗, Tanh	128 × 150 × 100 Dense↗, ReLU	3 × 3 1 DeConv2D, None

The forecast of the fire temperature field is a supervised regression issue. To govern the training process, the mean square error (MSE) is employed as a loss function. Meanwhile, the determination coefficient (R^2) is adopted to assess the regression performance of the model. During the model training process, the initial learning rate and the number of training epoch were set to 0.001 and 500. By training the neuron parameters, the model establishes the mapping relationship between sensor history information and future temperature field distribution. The deep learning-based model is allowed to obtain the target information directly without suffering the iterative computation of dynamical equations.

Regarding the real-time reconstruction of the temperature field, the framework of the deep learning model can be simplified as the DNN & DeConv in Fig. 5. The configuration of this simplified model can be referred to as Parts 3 & 4 in Table 2. The LSTM is abandoned since there is no requirement about the forecast the future scenarios. Then, the real-time data from the sensor array X^{20} will be employed as input. The temperature data is generalised to capture representative information for the entire temperature distribution based on multi-layer fully connected neural network. Subsequently, the 1D information will be deconvolved into 2D data and the temperature slice $Y^{150\times100}$ will be finally output. Therefore, 1,644 sets of dataset $D = [X^{20}, Y^{150\times100}]$ can be extracted for the development of temperature field real-time inversion model.

Fig. 6 demonstrates the training process of (a) the simplified real-time reconstruction model and (b) the ADLSTM-Fire advance forecast model. R^2 and MSE are used to measure the prediction accuracy of train dataset D_{train} and test dataset D_{test}. The dashed line represents the predictive performance of the model training based on train dataset D_{train}. The model performance keeps improving with the increase in the number of epochs, as evident form the growth in R^2 and decay in MSE. As expected, the training process of real-time reconstruction model initially exhibits a dramatic decrease in MSE to below 0.01 before epoch 70, and R^2 eventually stabilises above 95 %. Moreover, the ADLSTM-Fire advance forecast model shows the similar pattern with the R^2 ends up at around 94 %.

The solid line represents the validation of the prediction against the test dataset D_{test}. The validation curve exhibits that the proposed models still perform satisfactorily for scenarios. And there is no overfitting during the model training. R^2 for the ADLSTM-Fire model is about 92 %, which is slightly lower than that of 93 % for the simplified real time reconstruction model. Since omitting the prediction of temperature development, real-time reconstruction model tends to perform better. To predict the evolution of the temperature field, advance forecast model that integrates the LSTM models sacrifices accuracy partially. Noteworthy is the fact that the proposed models both present competitive R^2, indicating that the well-trained model can capture the relationship between the discrete data form thermometry array and the high-dimensional temperature field.

3.4. Information interactions for digital twins

Fig. 7 illustrates the information interaction of the AIoT-integrated Digital Twin system, designed to facilitate smart firefighting and integrate with existing smart building technologies. The system incorporates distinct types of data within different functional layers, including the Physical sensing layer, the Virtual data layer and the User application layer. The Network layer responsible for communication between different modules.

The Physical Sensing Layer constitutes the sensing and control system, so it is part of the interface for collecting real-world target objects and parameter data. In this implementation, the wireless sensors are the primary hardware component within this layer and required to acquire temperature data and synchronise it to IoT in real time. Data uploading relies on the network layer containing different communication protocols. The sensed data is wirelessly transmitted via LoRa within 433

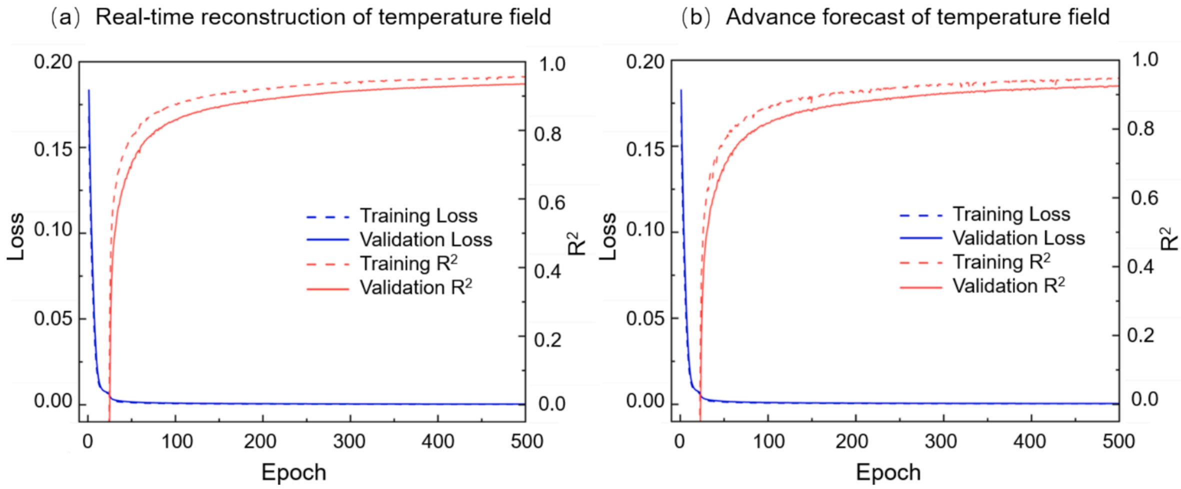

Fig. 6. The evaluation for temperature field by data-driven AI methods: (a) real-time reconstruction and (b) forecast with a lead time of 60 s.

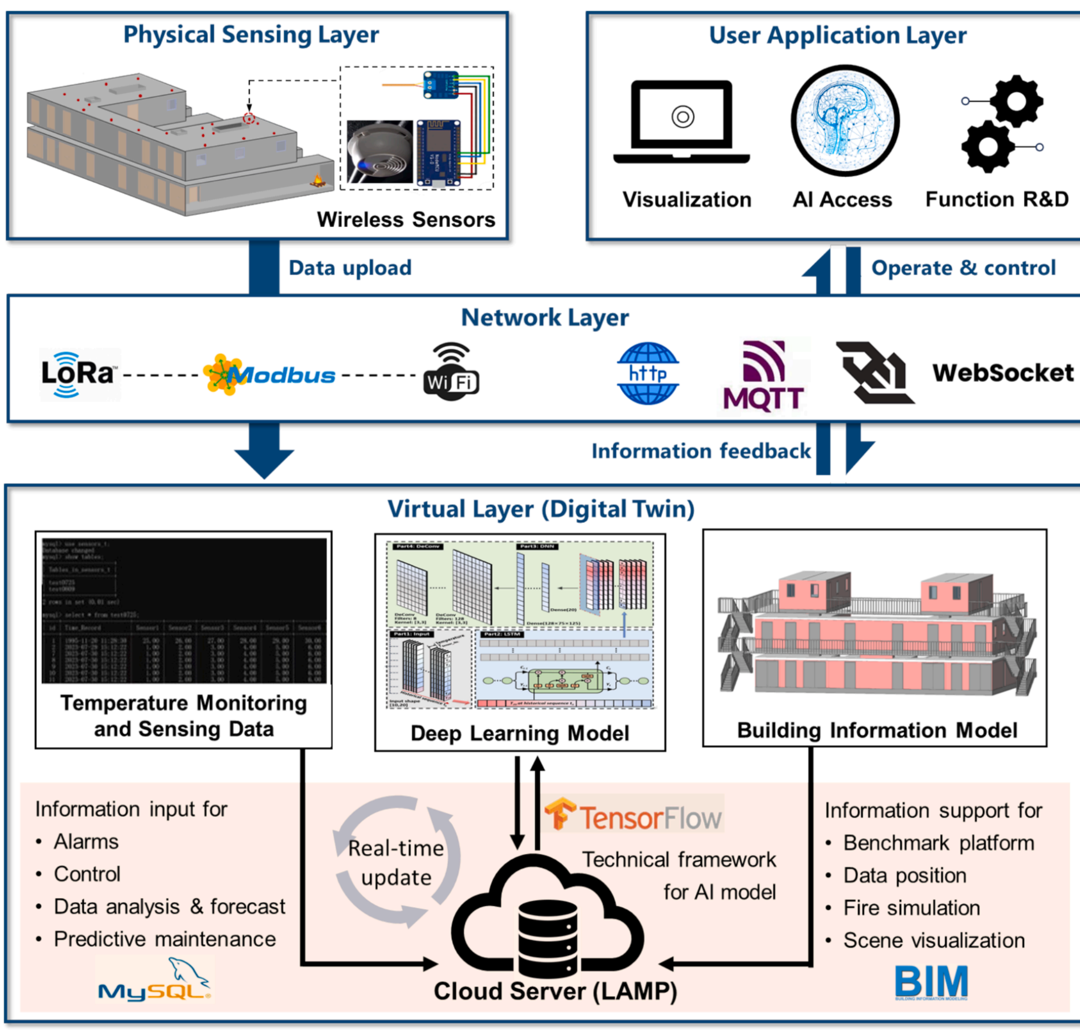

Fig. 7. Information interaction framework within the AIoT-integrated Digital Twin system.

MHz band RF to the router. The local workstation can access the router utilizing the Modbus protocol, and upload the processed data into Virtual data layer in real time. Due to the requirements of smart fire-fighting, the real-time sensor data are eventually uploaded to a cloud server via WiFi or other methods for ready access to the components of the Digital Twin system.

The User application layer encompasses a range of functionalities such as user interface (UI). Its primary role involves presenting valuable data in a user-friendly manner, tailored to specific functional requirements. Also, it is the issuers of executive commands to make physical adjustments. To establish a connection between the User application layer and the Virtual data layer, a network layer is required for data transmission and communication. The network layer, situated within the computer network architecture, assumes the responsibility of delivering data packets between different hosts. To support diverse communication requirements and application scenarios, a variety of communication protocols such as HTTP, MQTT, and WebSocket can be deployed within this process.

As the core of the AIoT-integrated Digital Twin, the Virtual data layer is the data-fusion platform that integrates diverse information sources. On the one hand, it serves as a recipient of real-time data from the Physical sensing layer and handles access requests from the User application layer. On the other hand, it acts as a data processing carrier to fulfil the system-defined tasks. Through TensorFlow framework, the deep learning-driven models are deployed with the Digital Twin platform to implement specific smart functions. Throughout the loop iterations, the output keeps updating in real time by continuously feeding the latest data from the Physical sensing layer. A dynamic Building Information Modelling (BIM) [78] provides a benchmark information for establishing the building fires digital twin. Meanwhile, new data can be efficiently integrated into the BIM model by positioning technology; Moreover, the Digital Twin platform is deployed on cloud servers by using the LAMP stack, which is recognized as the open-source software for web servers development and applications [35]. Comprising four components, the LAMP stack encompasses the Linux operating system as the foundation, Apache as the web server, MySQL as the database management system, and programming languages such as PHP for application development.

4. Result and discussion

4.1. Ai-driven fire spatiotemporal inference

Numerical simulation results are taken as the benchmark to investigate the performance of the proposed models. Fig. 8 illustrated the spatiotemporal evolution comparison regarding the fire temperature field among the different models at four typical moments (see Video S2 for more details), where the peak HRR is set to 2,000 kW. The temperature evolution shown in the left column are benchmark data, which is obtained by CFD. Due to the heat loss during gas dispersion, the resulting temperature gradient can be used to infer the gas propagation path. About 220 s after fire ignition, high-temperature gas enters 1F_1 from the stairwell and heats up the area dramatically. The remainder gas keeps pouring into the First Floor through door D01. By the time 580 s elapse, the temperature of the whole floor continues to rise and there is obvious temperature gradient distribution within the building. Since heating stops at 800 s, there is a significant decrease in the area where temperature exceeds 50 °C after 60 s. For some areas that have been heated to 30 °C, the temperature decrease is not as drastic as in the high temperature areas. By 1,150 s, the original high-temperature areas have been reduced to 65 °C or even lower, while the slightly heated areas remain relatively stable.

The images in middle column are the temperature field inferenced by the real-time reconstruction model. The right column displays the 60 s advance forecast of temperature field by the proposed ADLSTM-Fire. It shows that both advance forecast model and the real-time reconstruction model successfully predict the similar distribution characteristics to

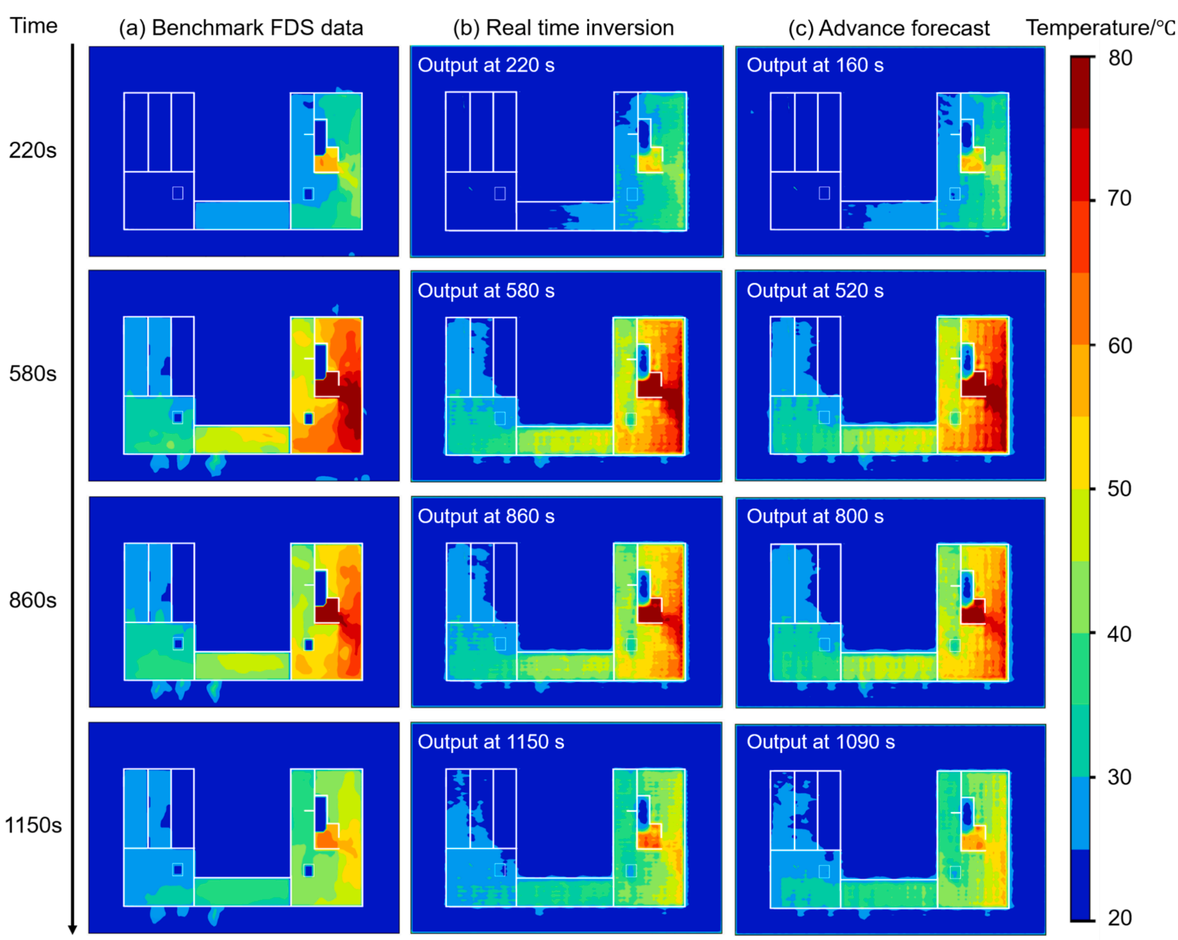

Fig. 8. Temperature field spatiotemporal evolution predicted by different AI model (a) baseline by CFD, (b) simplified real-time reconstruction result, and (c) forecast 60 s in advance. Please see Video S2 for more details.

the benchmark data. The relative locations of temperature regions and gradients are accurately predicted. Meanwhile, the characterization of isothermal development over time is also accurately presented by the proposed deep learning models. This demonstrates the accuracy and efficiency of deep learning-based numerical engines in predicting the building fire development. It should be recognized that there are still some differences in the specific outputs of these two deep learning models. Therefore, the systematic comparisons between models are performed by temperature change at specific location.

Fig. 9 illustrates the temperature evolution curve predicted by the different models. The output from the deep learning model is clearly consistent with the variation pattern of the numerical simulation represented by the black curve. Compare to the blue curve output by advance forecast model, the red curve inferred by the real-time reconstruction model closely resembles the black baseline curve. In addition, the simplified model shows high robustness in stable variation trend. On the contrary, the advance forecast curve clearly fluctuates around the baseline curve. Nevertheless, the similar trends to baseline data shows that the forecast bias will be corrected in time with the continuous data update. Therefore, this hybrid model demonstrates satisfactory capability and resilient in credible spatiotemporal forecasts.

Data-driven deep learning models are well validated to fire information monitoring and forecast based on temperature sensor array information. With inference time less than 0.3 s, the real-time reconstruction model can expand the spatial dimensionality of discrete sensor information in real time. Compared with single-point information, more comprehensive temperature field allows decision-makers to visualize the building damage in a fully manner. Moreover, the ADLSTM-Fire model is demonstrated to forecast the distribution characteristics of the future temperature field effectively within 0.5 s. The one-minute-advanced forecast from ADLSTM-Fire model demonstrates the capabilities of temporal dimension expansion based on the historical data. Such super real-time capability is crucial in firefighting scenarios characterized by urgency. With the integration of the proposed deep learning models, the developed smart firefighting Digital Twin system empowers decision-makers to foresee dynamic development of building fire, formulate firefighting strategies in advance, and avoid potentially hazardous areas in a timely manner.

4.2. Generalisation validation

The development of smart firefighting driven by deep learning is rooted in an extensive collection of numerical simulation data. In further consideration of the realistic suitability of the proposed methodology, full-scale building fire experiments are performed to showcase the generalisation capabilities of the AIoT-integrated Digital Twin system.

The fire forecast for smart firefighting is realized by the configured deep learning model, whose generalisation capability is significant for extending the model to different fire scenarios. The actual experimental case that was not involved in the model construction is employed to test the system's generalization ability for real-world scenarios. Compared with the numerical dataset in the previous section, the building fire experiments exhibit a considerably longer burning period more than one hour. In addition, the intensity of the fire source is controlled for safety reasons. In this configuration, the experimental temperature peaks were relatively low, and the curve dynamics are smoother. Therefore, the experimental scenario significantly differs from the database, which is suitable to test the generalization ability of the proposed AIoT-

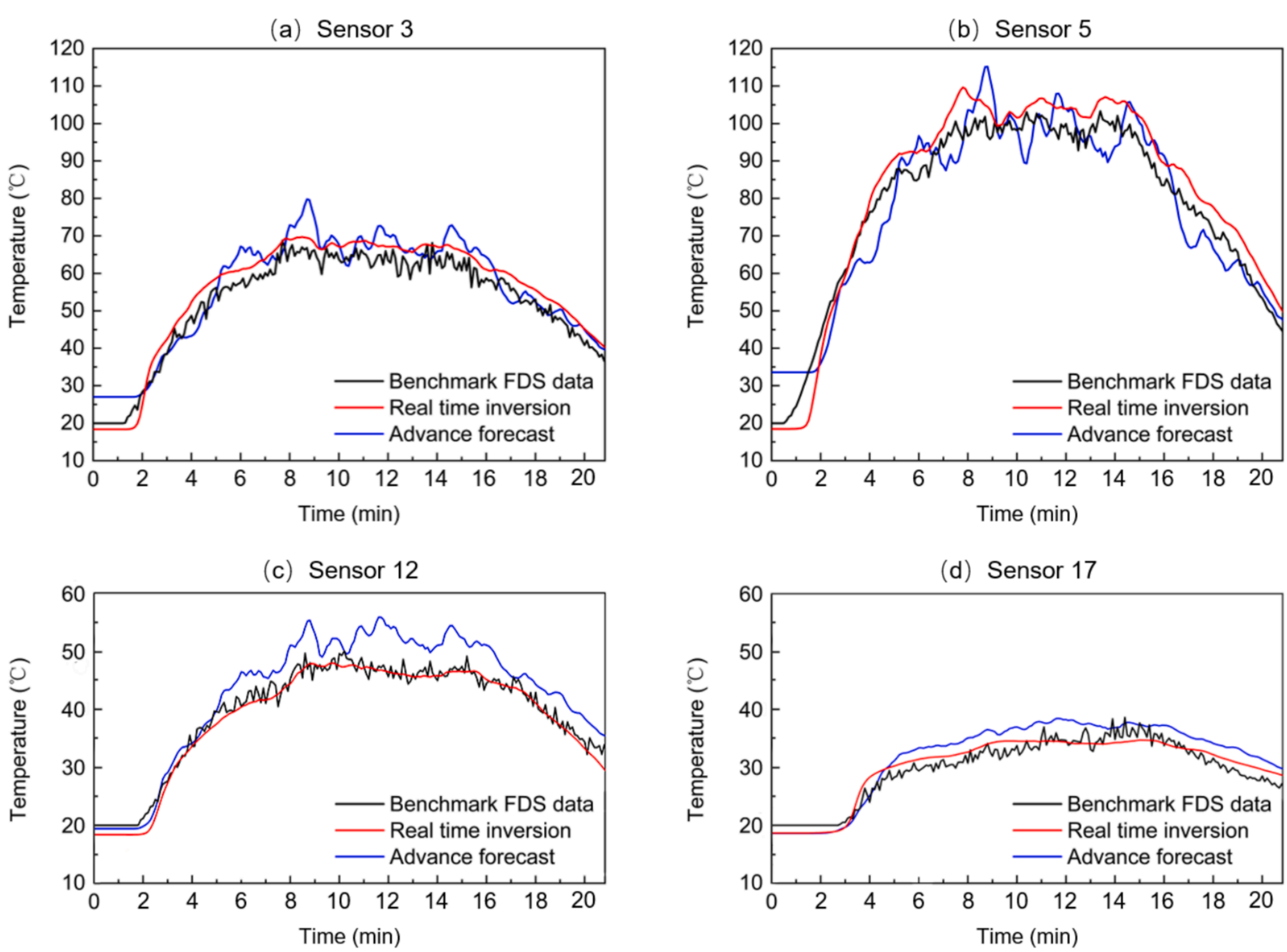

Fig. 9. Single-point temperature comparison in real-time inversion and forecast 60 s in advance (see detailed evolution in Video S1).

integrated Digital Twin system.

Fig. 10 illustrated the comparison among the experimental temperature values (black curve), real-time reconstruction values (red curve) and advance forecast values (blue curve). For temperature sensors S03 (Fig. 10a) and S12 (Fig. 10c), the deep learning model exhibit a great similarity to the experimental data, in terms of variation slope and stabilization time, where the error is less than 5 °C. The difference in initial temperatures between experiments and simulations poses the challenge to model fitting. The dramatic increase in the deep learning model prediction curve can be seen in the first 120 s. This indicates that the well-established model posse certain toughness to approximate the real situation by continuously iterating the input data.

For the other scenario like Fig. 10b, there are some biases in ADLSTM-Fire's advance forecasts for the temperature change with a maximum error of 18 %. As a supplement, the simplified model focusing on real-time inference achieve 7.2 % error, which shows more promising competitiveness in prediction accuracy. This indicates that the simplified model accurately captures the relationship between the input data and the spatial location of the sensors, good resilience allows for quick adjustment to ideal values.

Furthermore, this study expands its analysis by examining 2D slices for visual comparison of the overall outputs from different models. Fig. 11 shows the temperature field at various moments, with the real-time reconstructed image on the left and an advance forecast image on the right. By importing real-time temperature data from the experiment site, the models exhibit similar evolutions of the temperature field. At 300 s, the overall building temperature distribution is disturbed. There is a high-temperature area in the 1F_1 stairwell, and the wall facing the exit of the stairwell is also significantly heat up. At 900 s, the region above 25 °C expanded noticeably and a clear temperature gradient is observed from the stairwell to the far end. The overall building temperature reaches the maximum at around 1,500 s and

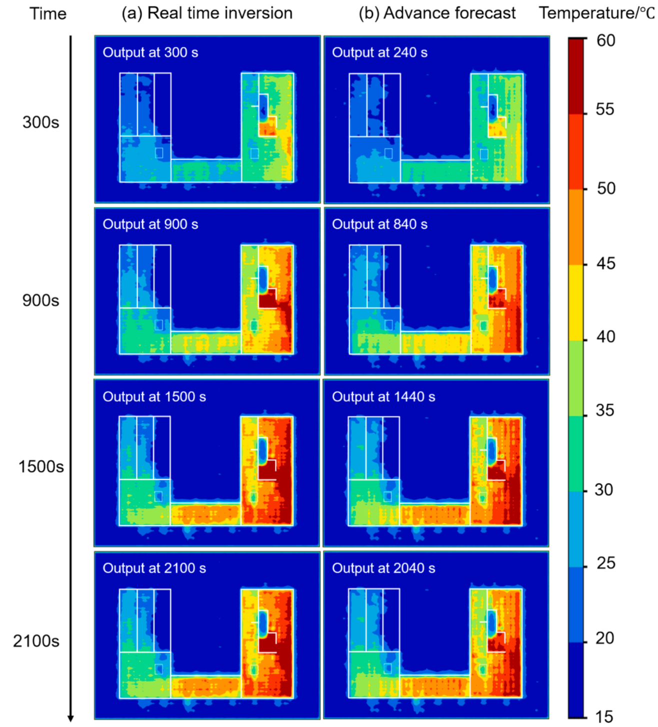

Fig. 11. Deep learning-driven temperature field inference based on experiment data input (a) simplified real-time reconstruction result, and (b) forecast 60 s in advance.

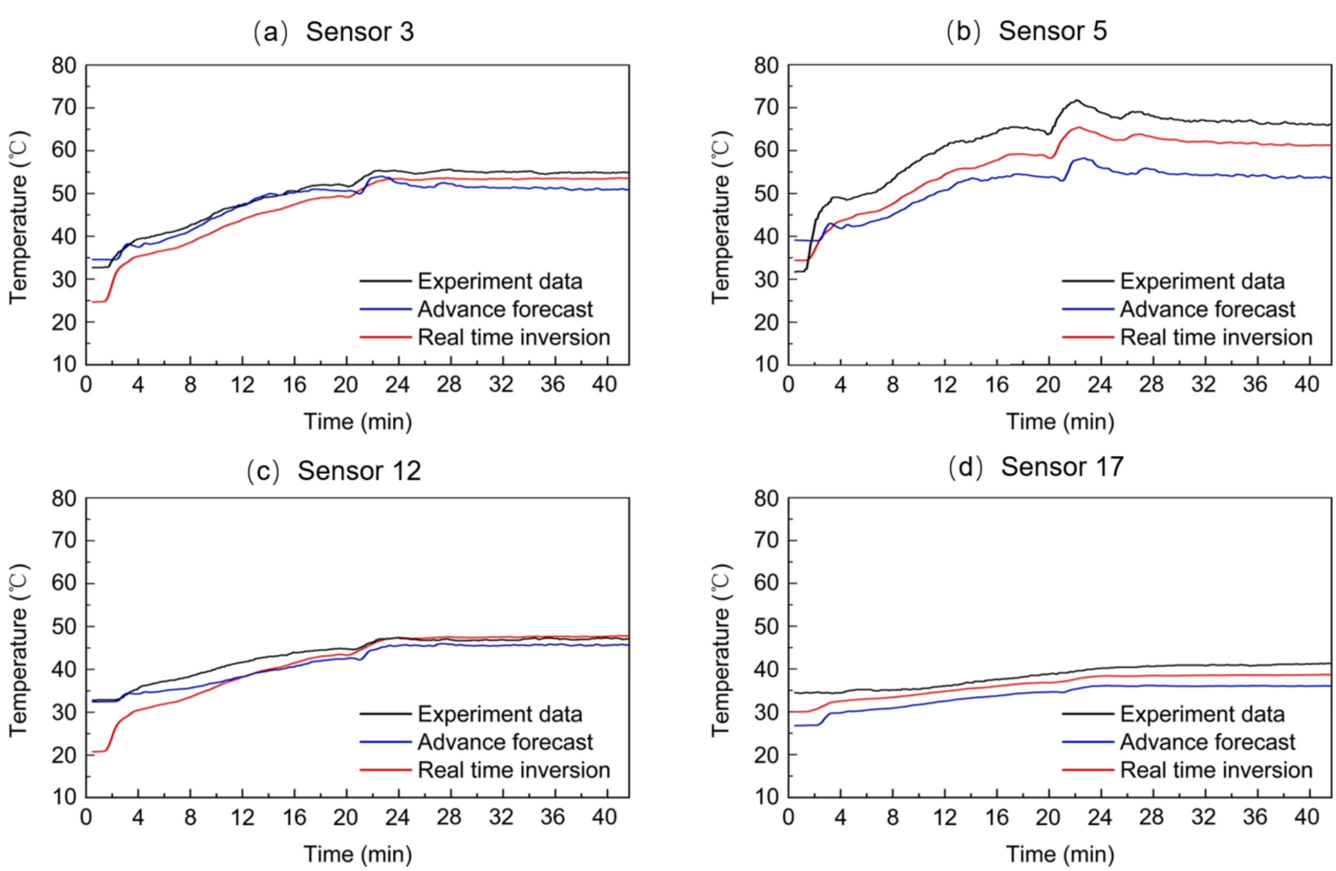

Fig. 10. Comparison of model generalisation capabilities based on experimental data, where the forecast is 60 s in advance (see Video S1 for more details).

remains stable thereafter, resulting in similar temperature slices at 2,100 s.

Meanwhile, there are also distinctions in performance between the two developed deep learning models. One the one hand, the real-time reconstruction model shows more robustness in in face of drastic changes in data. In the initial 300 s, the prediction of real-time model is more aggressive than that of advance forecast model. It implies that the simplified model responds more sensitively to data variation. At the 900th second, the temperature gradient obtained from real-time reconstruction model is more obvious. Considering the previous comparison with the experimental benchmark data in Fig. 10, the temperature distribution predicted by the real-time reconstruction model aligns more closely with the actual working conditions with time goes by. One the other hand, the advance forecast model output the prediction that are similar but less precise than those from the real-time reconstruction model. Although the future temperature field cannot be flawlessly

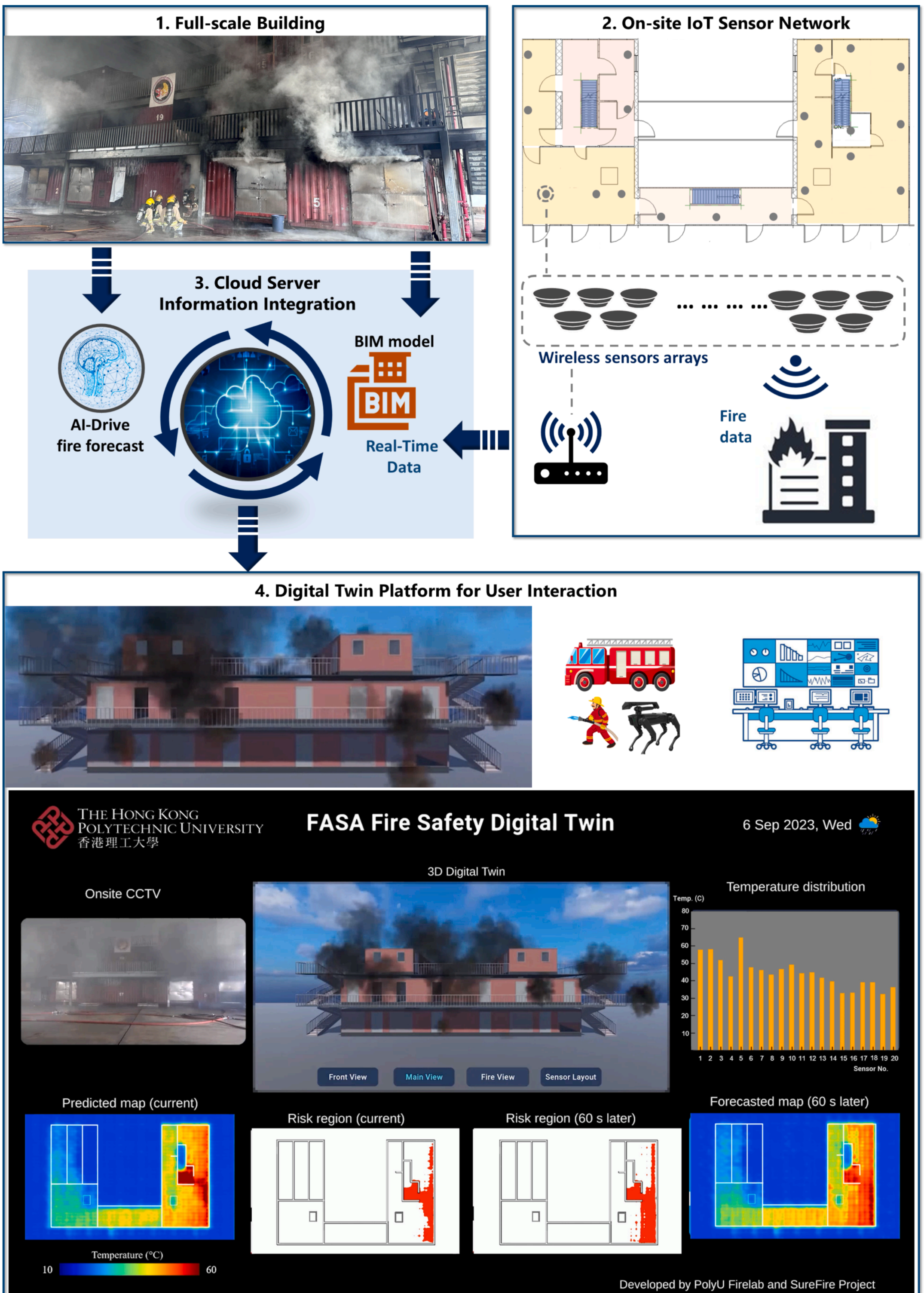

Fig. 12. Demonstration of the developed Digital Twin platform for smart building fire monitoring and forecast (see Video S3).

reproduced, advance forecasting makes more instructive for emergency decision-making.

Verification of the generalisation capability ensures that the constructed building fire Digital Twin system can effectively fulfil its smart firefighting function in different fire scenarios. Each deep learning model assumes distinct roles in smart firefighting. Without the information inference in temporal dimension, the simplified model shows higher confidence in inference of the temperature field in various scenarios. Meanwhile, the generalisation capability of ADLSTM-Fire model is partially affected by the complex model structure and demanding task requirements. Instead of the precise data generation, advance forecast from ADLSTM-Fire model remain satisfactorily competitive in forecasting development of building fires. Therefore, the proposed Digital Twin system is suitable for variable building fire scenarios. The generated reliable information allows firefighters to make proactive decisions based on the fire evolution, thereby enhancing their ability to respond effectively.

4.3. AIoT-integrated digital twin system for smart firefighting

The AIoT-integrated digital twin for SureFire system is constructed based on the above-mentioned technological framework. As shown in Fig. 12, the interactive Digital Twin necessitates the integration of multiple data types. Based on real full-scale buildings, separate processes are carried out including BIM construction, on-site sensing system deployment and AI model development. The cloud server assumes the responsibility of data interaction and Unity game engine is utilised as development engine and visualization platform. The system interface of FASA Fire Safety Digital Twin is demonstrated in Video S3. Users can access and operate the system through the cloud-based user interface (UI) by entering the IP address, username, and password. The main interface of the system comprises five functional modules, namely *On-site CCTV*, *Temperature distribution*, *3D digital twin*, *Temperature field inference*, and *Hazard risk region*.

In the event of building fires, data form sensors will be shown on *Temperature distribution* module as bar chart and synchronised to the cloud server by the IoT system. The AI-integrated system allows for the fire *Temperature field inference*, include real-time reconstruction and 60-second-advanced forecasting. By setting target information (like temperature above 50 °C), *Hazard risk region* module will display the valuable regional information to support fire evacuation and rescue planning. In addition, on-site CCTV enables direct monitoring of the actual environment as the realistic basis for smart fighting system. The 3D Digital Twin is designed to visualise the virtual scene of the building fire by rendering flame and smoke data.

5. Conclusions

For smart firefighting in buildings, this work proposes an information fusion framework for AIoT-integrated digital twin. ADLSTM-Fire model is developed to achieve the physical field spatiotemporal inference based the limited on-site data. Moreover, the generalization capability of the proposed approach is demonstrated through the full-scale building fire experiments. The main conclusions are:

(1) An AIoT-integrated Digital Twin system is proposed as the data fusion platform, overcoming the issues of data cross-domain collaboration during building fires. The system maps the complete building temperature field distribution in virtual space based on the collected discrete environmental data. Digitisation and visualisation of high-dimensional generic information can help decision-makers to fully understand the details of building fire and guide subsequent firefighting measures.
(2) The simplified model can reconstruct the complete 2D temperature field by discrete sensor data (Accuracy = 93 %), and its high robustness is well verified by benchmark numerical data. Moreover, ADLSTM-Fire model is developed leveraging the parameter initialization method based on model pre-training. ADLSTM-Fire model could forecast the temperature field distribution 60 s in advance based on the historical data (Accuracy = 92 %). Such super-real-time fire physical field information is available for building safety enhancement by fire prognosis and escalation prevention.
(3) Without involvement in the system construction, the full-scale building fire experiment is employed to demonstrate the generalisation capability of the Digital Twin model. The validation showcases that the constructed system can generates trustworthy predictions with the realistic fire dynamic pattern. Therefore, the proposed AIoT-integrated Digital Twin system could be extended to different fire scenarios and served as the information foundation for the development of smart firefighting features.

Future research of SureFire will further accommodate the challenges posed by scenario changes in real building fires. The ADLSTM-Fire model will be further refined for smart firefighting in unfamiliar buildings. With the building layout acting as an additional input parameter, a comprehensive multi-modal framework integrating ADLSTM-Fire will be developed to regulate the 2D data generation process of temperature field. Similarly, the dataset will be further enhanced by simulating more different factors in building fire scenarios such as structural type, room arrangement and wind environment. Rich datasets can enhance the comprehension of multi-factor coupled scenarios by AI models. Moreover, future research will be devoted to sensor layout optimisation to achieve a trade-off between system accuracy and cost. Case studies of various building types should be involved to establish sensor deployment guidelines.

CRediT authorship contribution statement

Weikang Xie: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Yanfu Zeng:** Software, Investigation, Data curation. **Xiaoning Zhang:** Visualization, Software, Investigation, Data curation. **Ho Yin Wong:** Resources, Investigation. **Tianhang Zhang:** Software, Investigation. **Zilong Wang:** Visualization, Investigation. **Xiqiang Wu:** Resources, Investigation. **Jihao Shi:** Supervision, Methodology. **Xinyan Huang:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Fu Xiao:** Supervision, Resources. **Asif Usmani:** Supervision, Project administration, Funding acquisition.

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 A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aei.2025.103117.

Data availability

Data will be made available on request.

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