同濟大學 TONGJI UNIVERSITY | 土木工程学院 COLLEGE OF CIVIL ENGINEERING

Real-time Early Warning of Fire-Induced Collapse of Steel Building Structures: Theory and Test Validation

Guo-Qiang Li[1,2], Shaojun Zhu[2], Jinyu Li[2], Wei Ji[2], Yao Wang[2] and Honghui Qi[2]

1. State Key Laboratory of Disaster Reduction in Civil Engineering, Tongji University
2. College of Civil Engineering, Tongji University

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01 Background

Steel structures are widely used

Public buildings

Industrial buildings

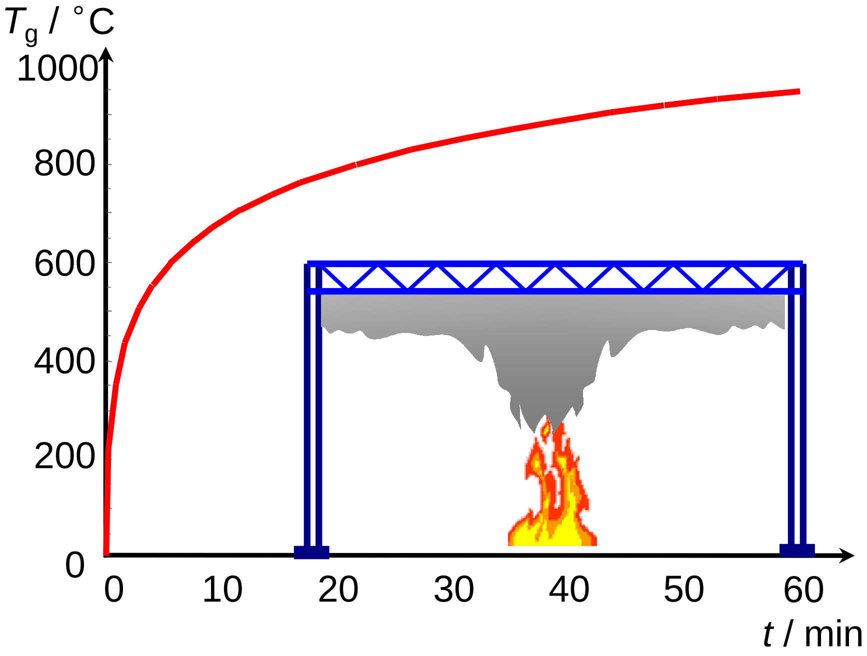
- **Advantages:** ***Good*** load-bearing capacity; ***Large*** internal space
- **Disadvantages:** ***Low*** in redundancy; ***Poor*** in fire resistance

Building collapse accidents under fire in China

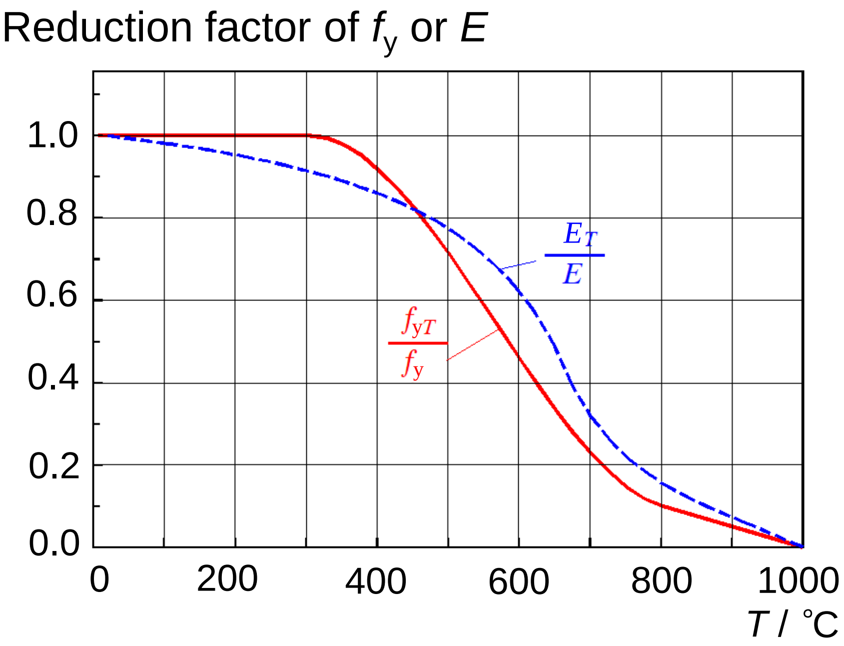
Statistic data of 2019

Type	Industrial	Public	Residential	Hospital & School	Office
Proportion (%)	55.6	22.2	11.1	7.4	3.7

01
Background



Rapid temperature development of building fires



Material property degradation of steel at elevated temperatures

01
Background


Brussels


Hong Kong


Tehran


Chonburi

01
Background

Lives of firefighters being
at risk under unexpected collapse *

* *if unable to evacuate timely*

Many cases of firefighter deaths caused by building collapse in fire

Building	Location	Time	Type	Situation	Casualties
Plasco Building	Tehran	2017	Steel	Total collapse	30 firefighters
Bowling alley	Taoyuan	2015	Steel	Roof collapse	6 firefighters
Factory building	Shanghai	2014	Steel	Total collapse	2 firefighters
Factory building	Wenzhou	2013	Steel	Total collapse	5 firefighters
Sofa super store	California	2007	Steel	Total collapse	9 firefighters

01 Background

Early warning fire-induced collapse of buildings is a ***critical demand*** for firefighters to make ***scientific decision*** in firefighting

Firefighting

Decision making

Collapse judging too early

Lifesaving time reduced

Scientifically warning collapse

Raise firefighting efficiency and safety

Collapse judging too late

Firefighters' life endangered

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02

Early-warning approach

Estimation

Aim

Serve ***structural design***

Characteristics

- Can be ***conducted offline***
- ***Conservative conditions***
  - *Fire scenario*
  - *Load condition*
  - *Material properties*

Early warning

Aim

Serve ***firefighting***

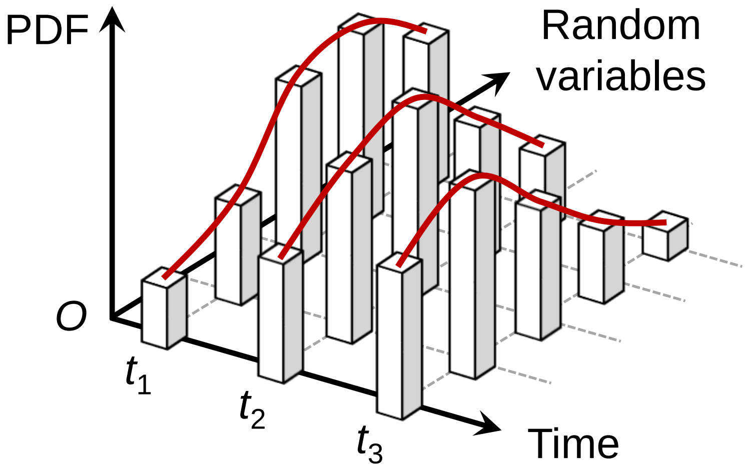
Characteristics

- Must be ***on-site conducted***
- ***Actual conditions***
  - *Uncertain at fire scenes*
  - *Influential to results*
  - *Hard to quantify*

Early warning of fire-induced collapse must consider ***uncertainties*** in ***real time***

02
Early-warning approach

Uncertainties future evolution

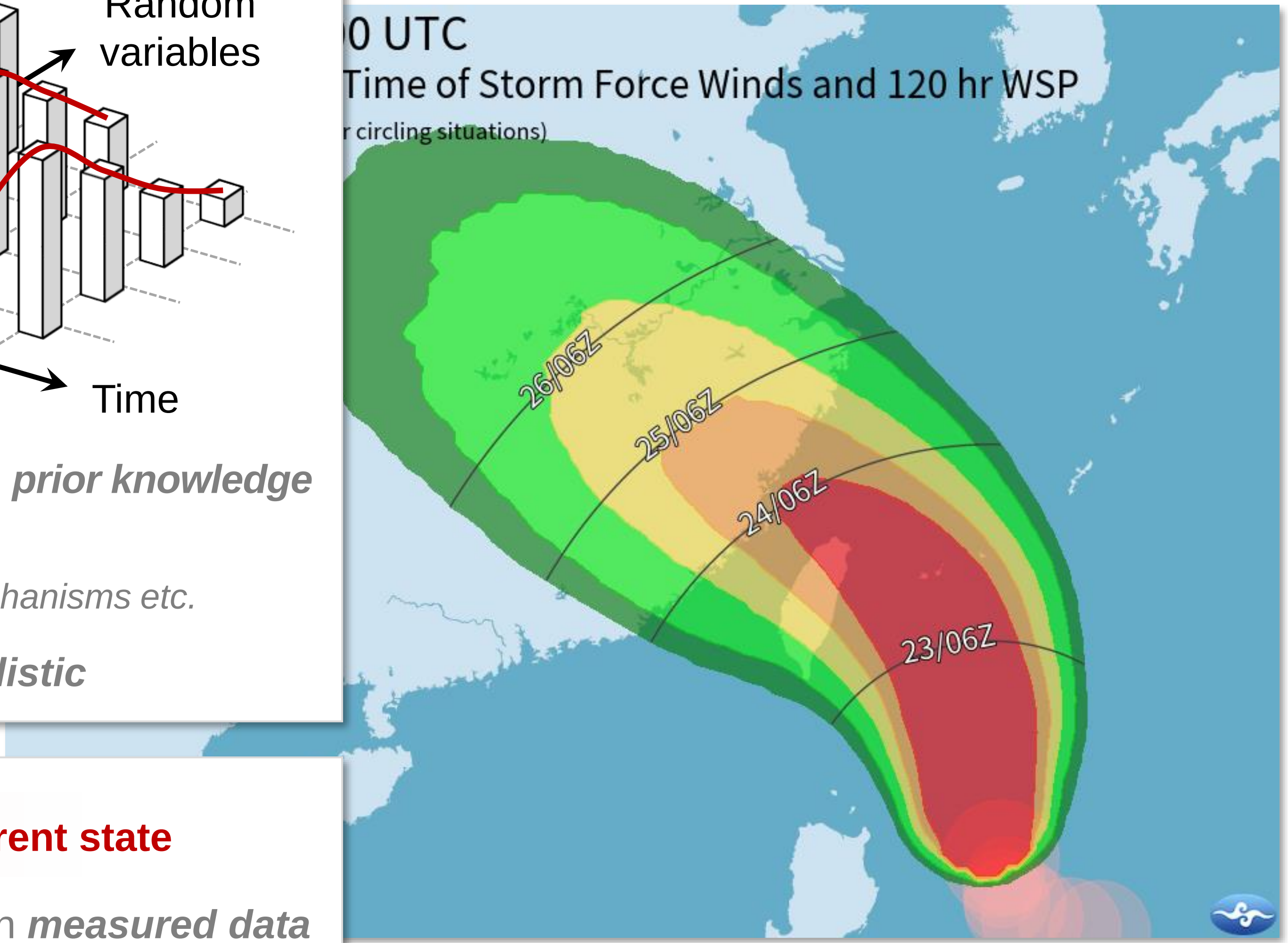


- Quantified based on ***prior knowledge***
  - *Physical laws*
  - *Summarized mechanisms etc.*
- Should be ***probabilistic***

Uncertainties at current state

- Quantified based on ***measured data***
- Can be ***deterministic***

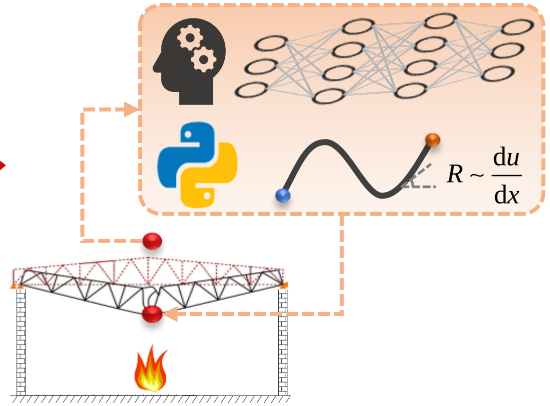
Inspiration from typhoon prediction



02 Early-warning approach

Real-time monitoring

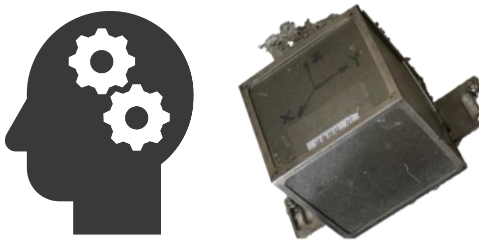
On-line analysis



Instant forecasting

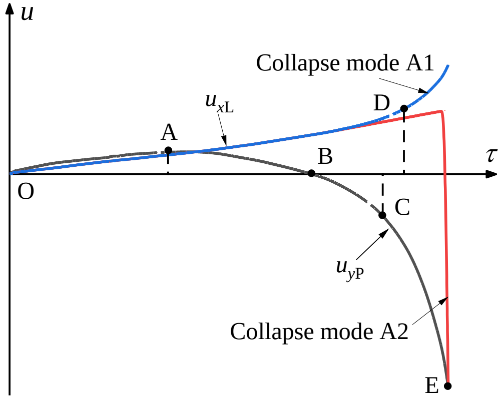
Current uncertainties

ML and new sensors as ***key techniques***



Uncertainty evolution

Physical law & theory as ***prior knowledge***



Scientific guidance

Rescue efficiency ↑
Casualties ↓

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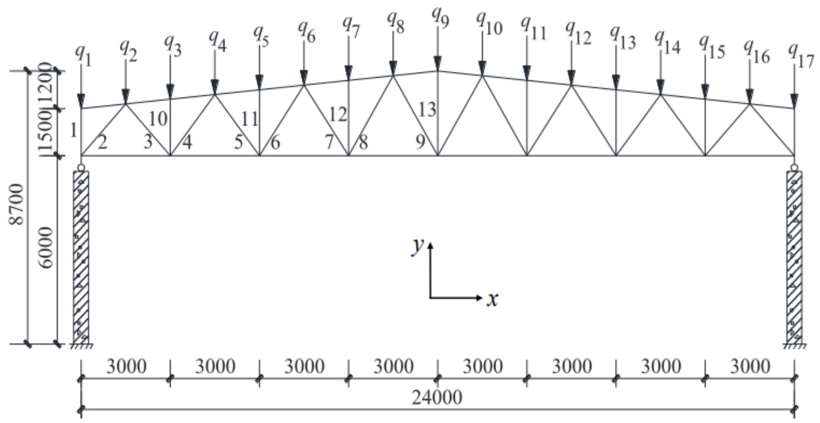
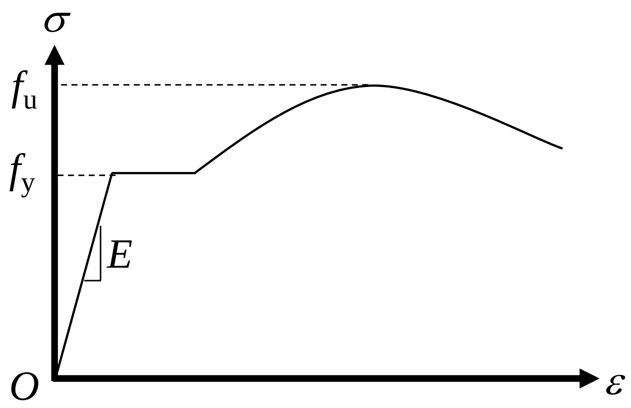
03
Early-warning theory

Analysis scheme

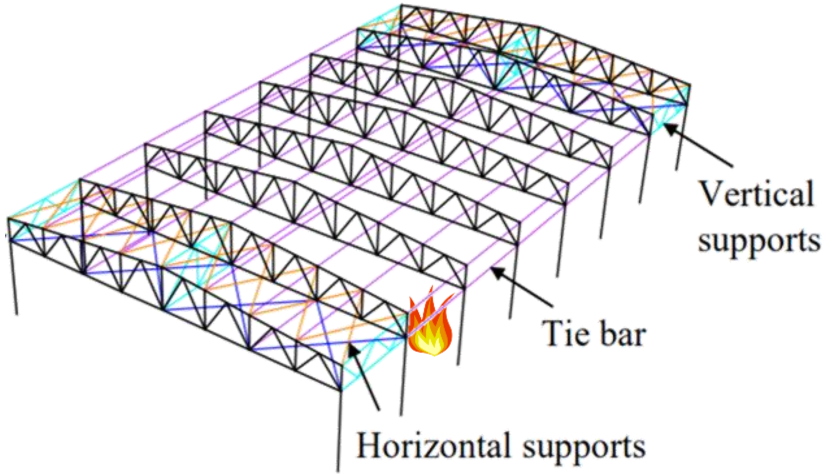
Systematic parametric analysis considering ***various uncertainties***



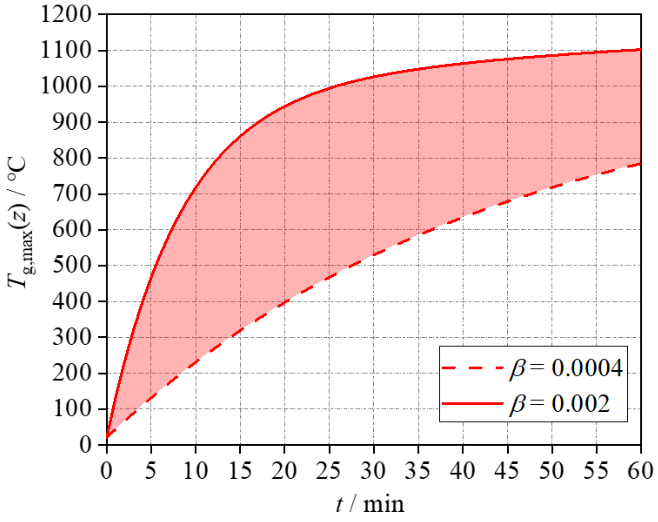
Random load and boundary conditions



Random material properties



Random fire locations



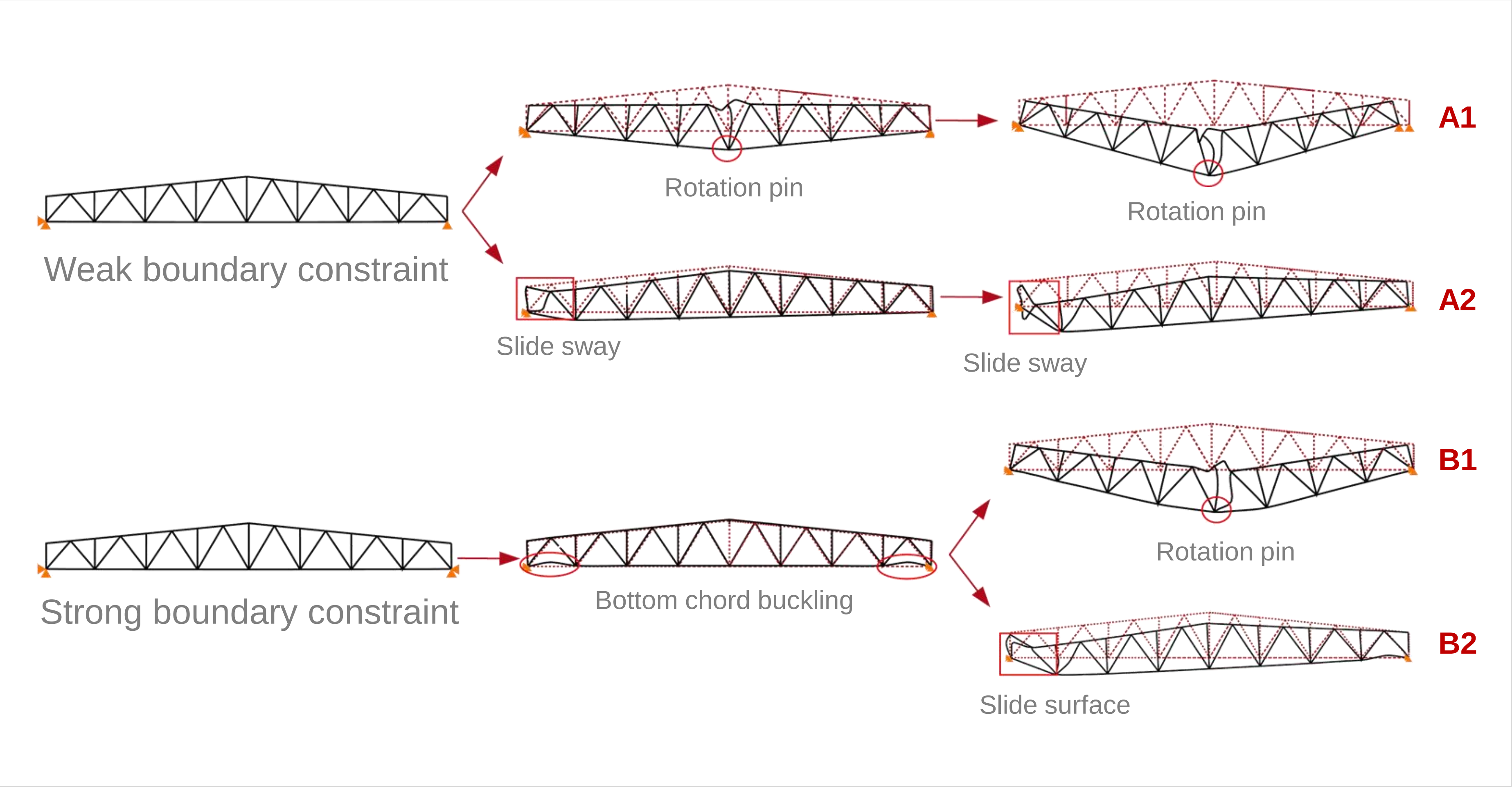
Random heat release rates

03

Early-warning theory

Limited potential collapse modes

Collapse modes are ***limited*** under random fire & structural conditions

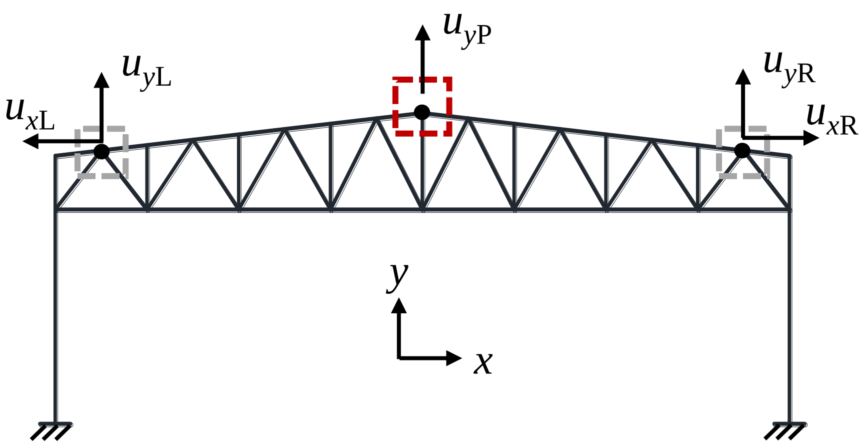


03 Early-warning theory

Key Physical Parameters (KPPs) and variation laws

Evolution of KPPs of steel trusses **up to collapse** exhibits ***unique laws***

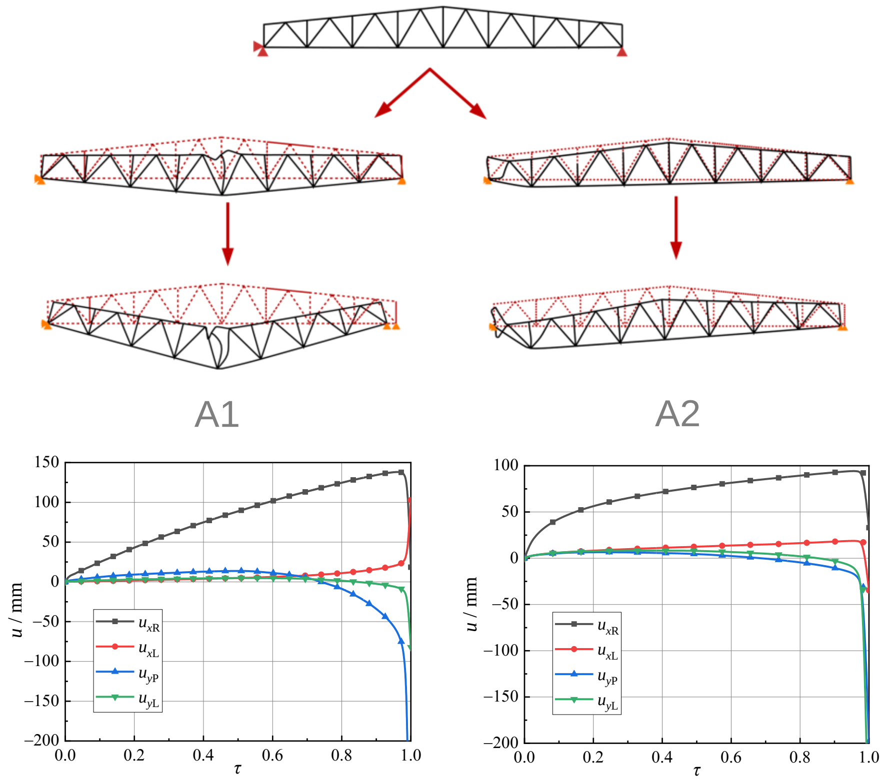
KPPs of steel trusses



Selection principle

- Reflect effects of ***uncertainties***
- Represent actual ***collapse state***
- Can be obtained ***at fire scenes***

KPP evolution for modes A



Similar for collapse modes B1 & B2

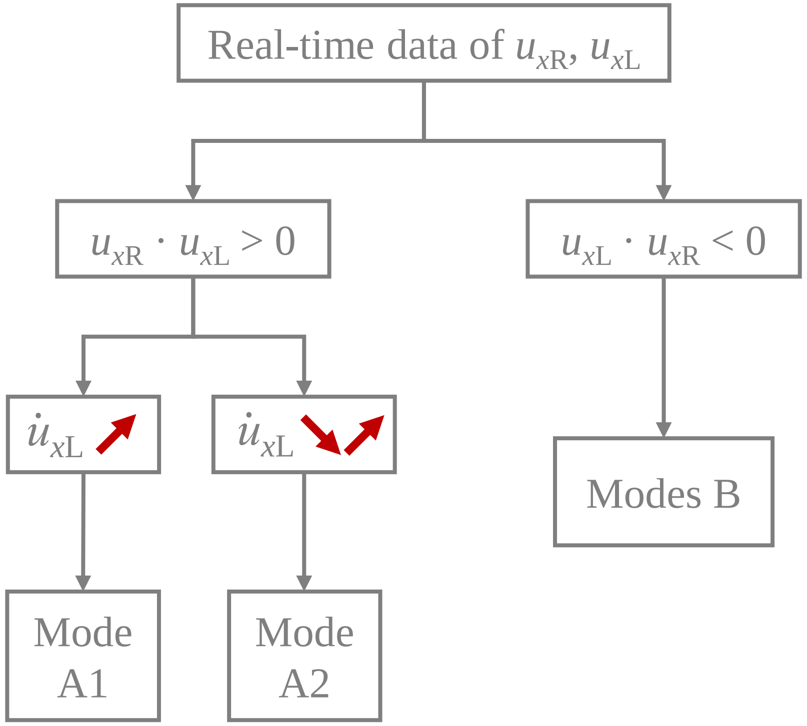
03

Early-warning theory

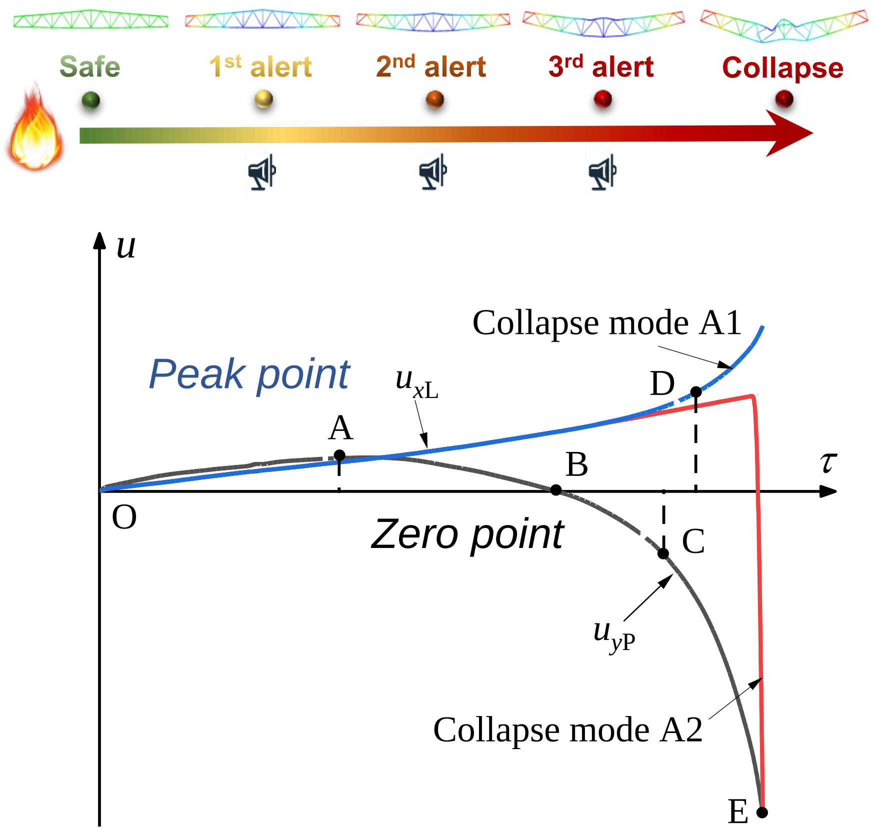
Key Physical Parameters (KPPs) and *variation laws*

Evolution of KPPs of steel trusses **up to collapse** exhibits ***unique laws***

Judging actual collapse mode



Judging actual collapse state



03

Early-warning theory

Key Physical Parameters (KPPs) and *variation laws*

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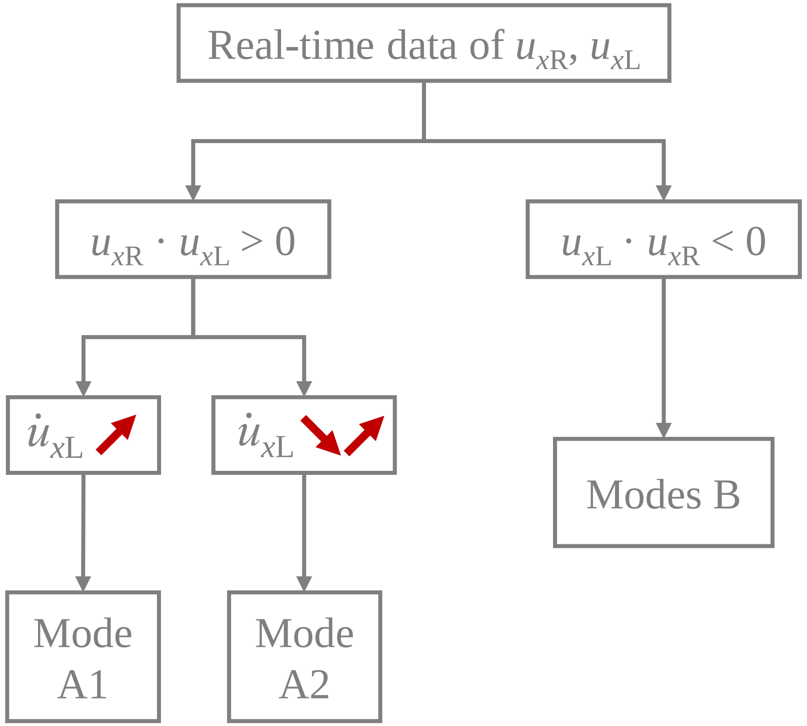
Judging actual collapse mode



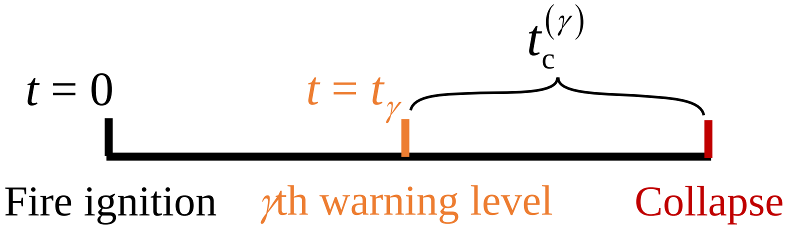
Judging actual collapse state

Level	Criteria	Remarks
Safe	No points	/
1st	Point A	A: $\dot{u}_{yP} = 0$
2nd	Point B	B: $u_{yP} = 0$
3rd	Point C or D	C: $\dot{u}_{yP} = 2\times\dot{u}_{yP}^{A}$ D: $\dot{u}_{xL} = 2\times\dot{u}_{xL}^{A}$

03 Early-warning theory

Prediction of remaining time to collapse (RTC)

Problem description



Dimensionless time ratio

$$\tau_w^{(\gamma)} = \frac{t_\gamma}{t_\gamma + t_c^{(\gamma)}} \qquad \tau_R^{(\gamma)} = \frac{t_c^{(\gamma)}}{t_\gamma} = \frac{1}{\tau_W^{(\gamma)}} - 1$$

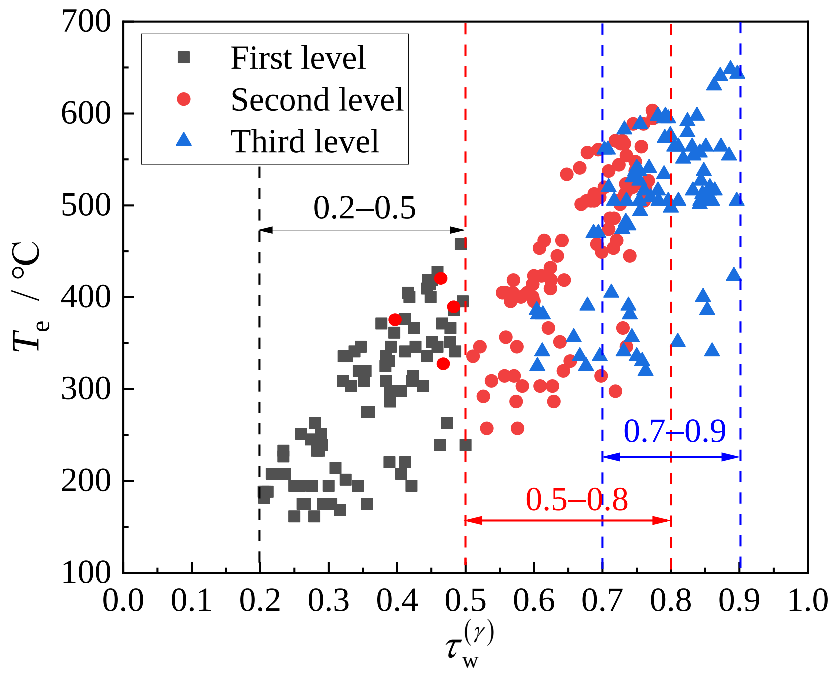
RTC/early-warning time ratios

less affected by actual fire exposure time

RTC $t_c^{(\gamma)} = \tau_R^{(\gamma)} \cdot t_\gamma$ **Fire exposure time**

Determined ***at fire scene***

Pre-determination of time ratios



Discrete distribution of time ratios due to uncertainties

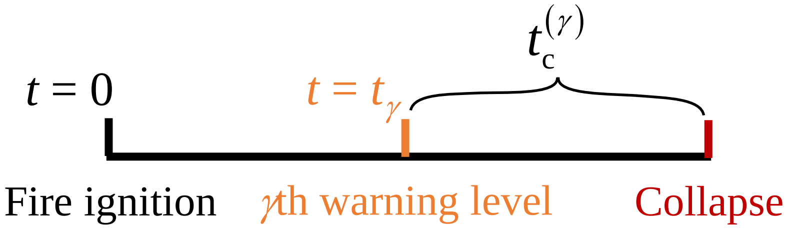
Values with confidence levels can be pre-determined

03 Early-warning theory

Prediction of remaining time to collapse (RTC)

The RTC can be forecast based on the ***reliability theory***

Problem description



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$$\tau_W^{(\gamma)} = \frac{t_\gamma}{t_\gamma + t_c^{(\gamma)}} \qquad \tau_R^{(\gamma)} = \frac{t_c^{(\gamma)}}{t_\gamma} = \frac{1}{\tau_W^{(\gamma)}} - 1$$

RTC/early-warning time ratios

less affected by actual fire exposure time

RTC $t_c^{(\gamma)} = \tau_R^{(\gamma)} \cdot t_\gamma$ **Fire exposure time**

Determined ***at fire scene***

Pre-determination of time ratios

α	$\tau_W^{(1)}$	$\tau_R^{(1)}$	$\tau_W^{(2)}$	$\tau_R^{(2)}$	$\tau_W^{(3)}$	$\tau_R^{(3)}$
30%	0.33	2.03	0.54	0.85	0.83	0.20
40%	0.36	1.78	0.57	0.75	0.85	0.18
50%	0.39	1.56	0.65	0.54	0.86	0.16
60%	0.45	1.22	0.70	0.43	0.89	0.12
70%	0.47	1.13	0.74	0.35	0.90	0.11
80%	0.52	0.92	0.75	0.33	0.91	0.10
90%	0.58	0.72	0.78	0.28	0.93	0.08

Discrete distribution of time ratios due to uncertainties

Values with confidence levels can be pre-determined

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04
Early-warning techniques

Some KPPs are hard to measure directly at fire scenes

Traditional contact measurement

Devices are ***prone to be destroyed in fire***

Optical non-contact measurement

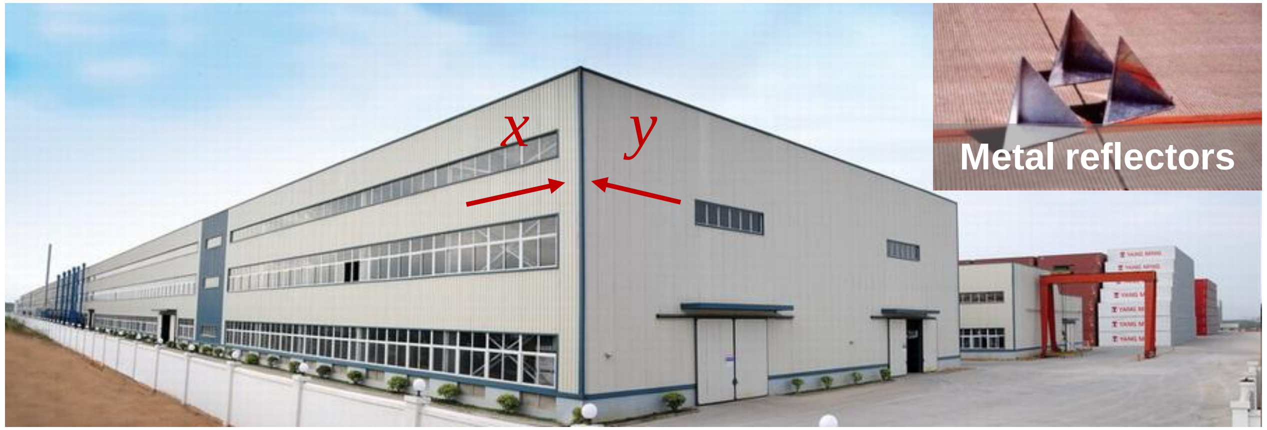
Technique is highly ***sensitive to smoke***

04
Early-warning techniques

Advantages of microwave radars

Conclusion:

Microwave radars are able to measure KPPs in fire



Microwave radar to measure KPPs at fire scene

Accuracy: 0.1–0.01 mm

Working distance: ≥ 100 m

***Workable** at dense smoke and high-temperature scenes*

04 Early-warning techniques

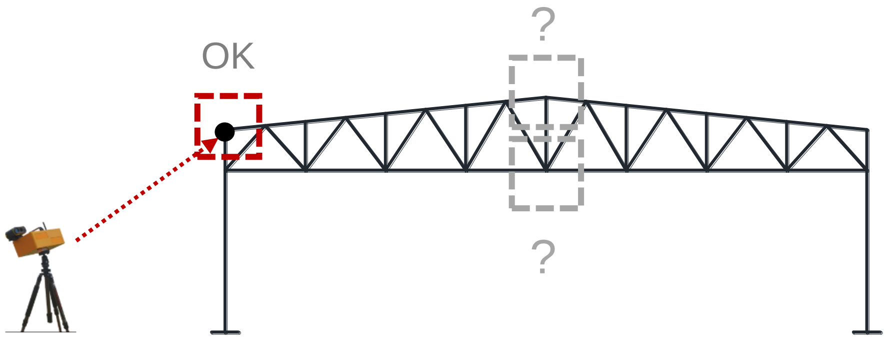
Limits of microwave radar

Conclusion:

Microwave radars alone are unable to acquire complete set of KPPs in fire

Microwave radars need to “see” the position for measurement

* *Requiring high platform*



What about the ***top or interior joints*** of the building?

04
Early-warning techniques

Solution

Conclusion:

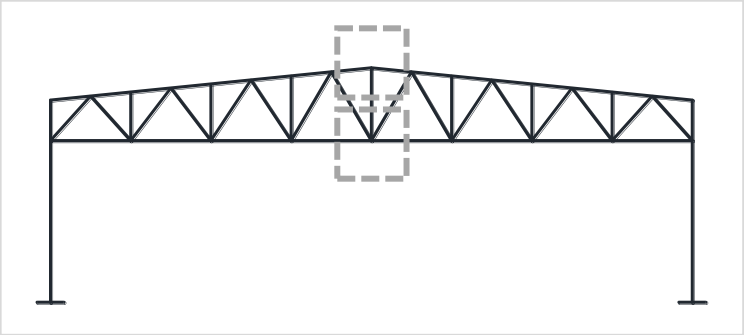
Pre-embedded thermocouples and inclinometers to acquire complete sets of KPPs

Concept

Rotation   Temperature

Easy-to-measure parameters

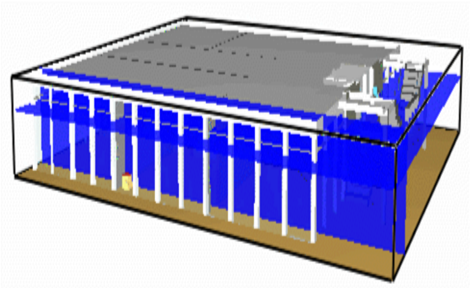
DL



Joint displacement

Hard-to-measure KPPs

Challenge



Temperature fields of large-space buildings

Fire tests

Excellently accurate
Extremely expensive

Parametric model

Least accurate
Least expensive

Coarse training dataset

Coarse DL model

Transfer learning

Field simulation

Relatively accurate
Relatively expensive

Precise training dataset

Well-trained DL model

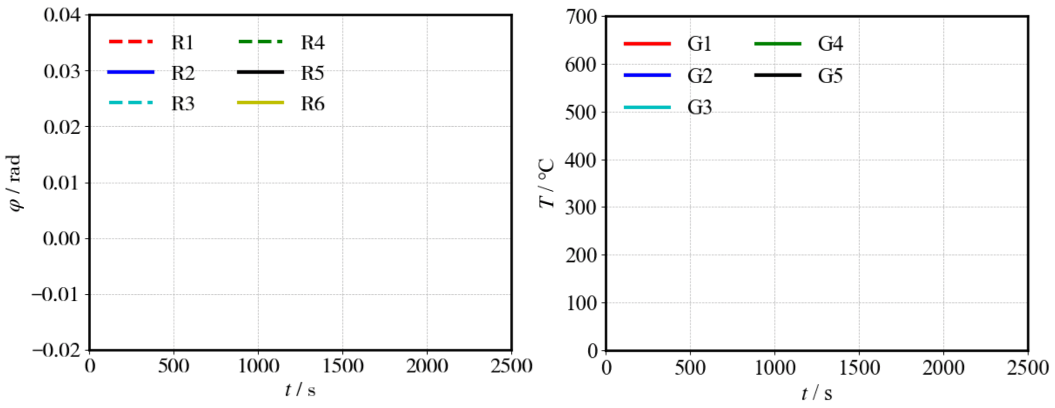
04
Early-warning techniques

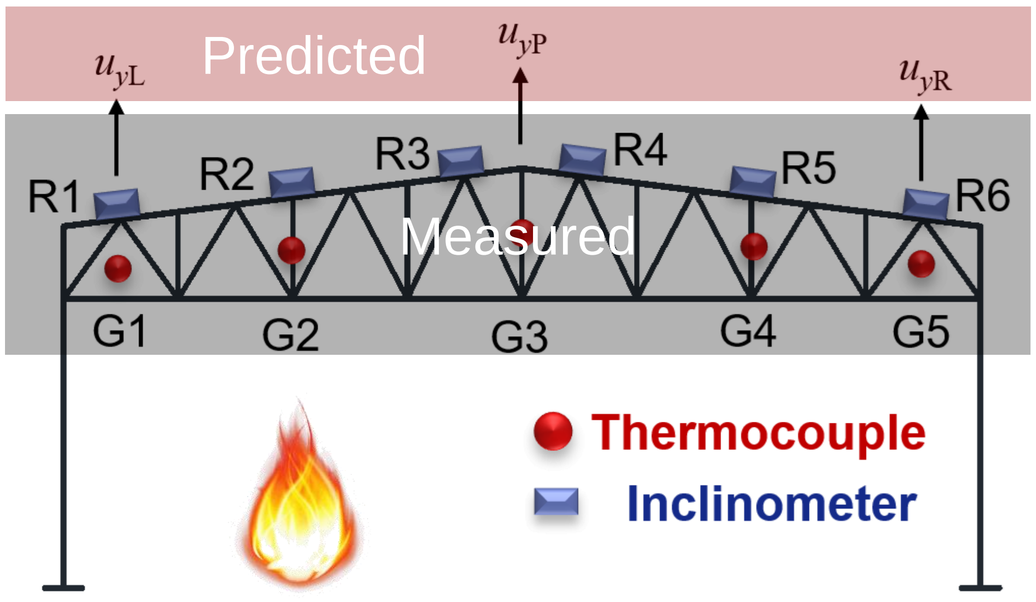
DL Method Results

Conclusion:

Real-time, accurate prediction of KPPs

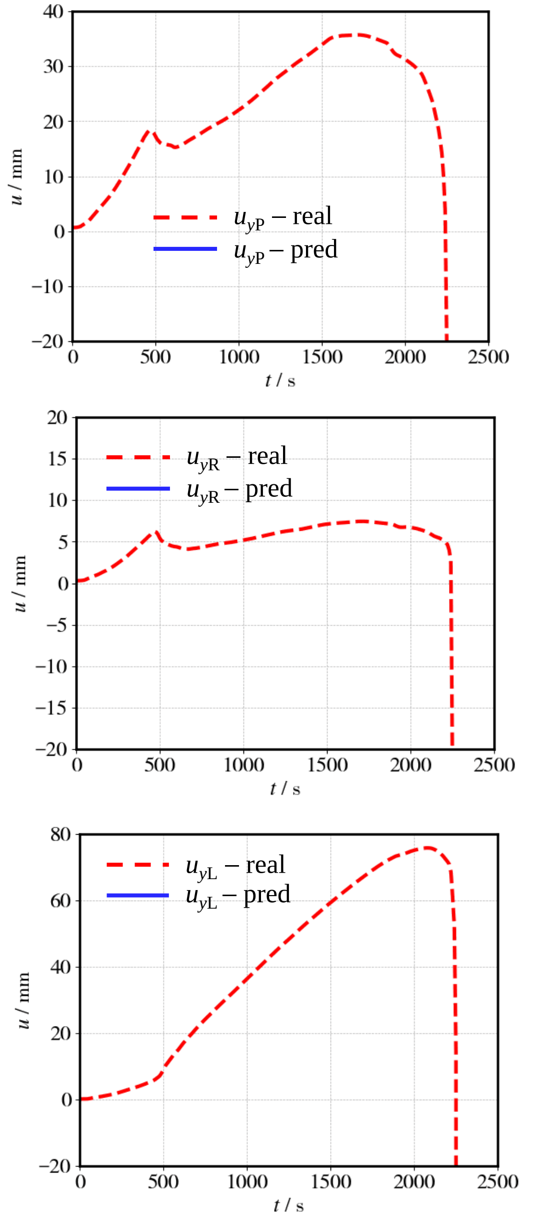
Measured





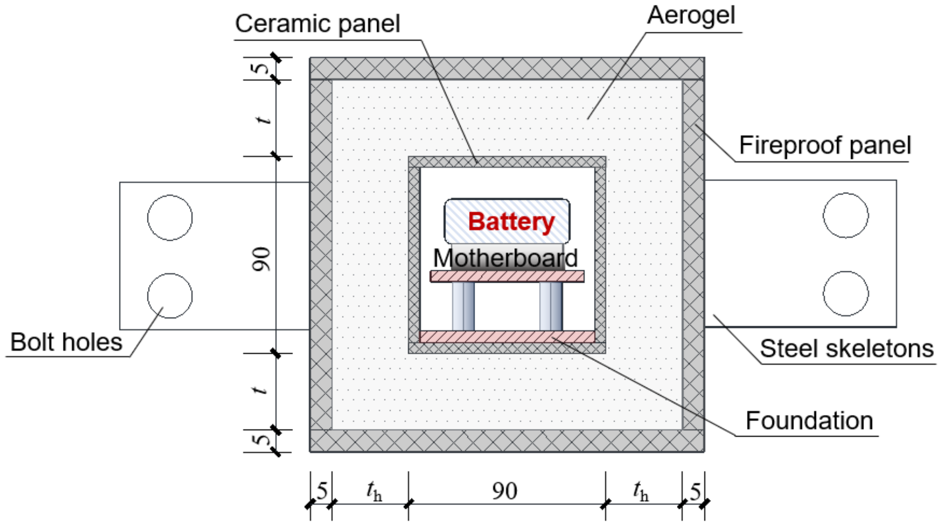
On-line validation of an unknown scenario

Predicted

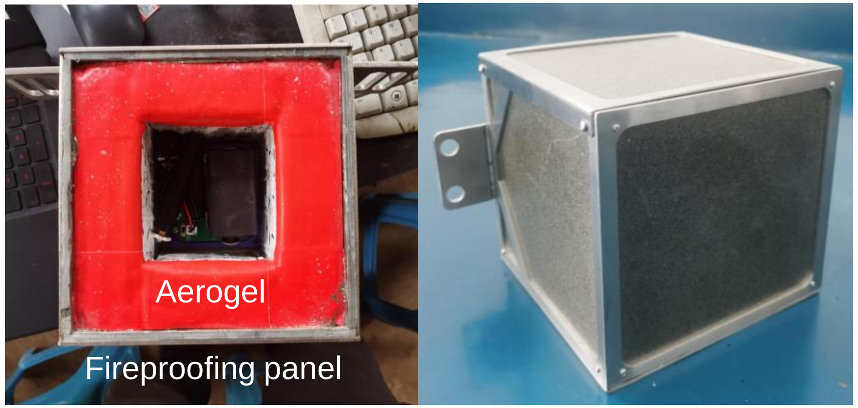


04 Early-warning techniques

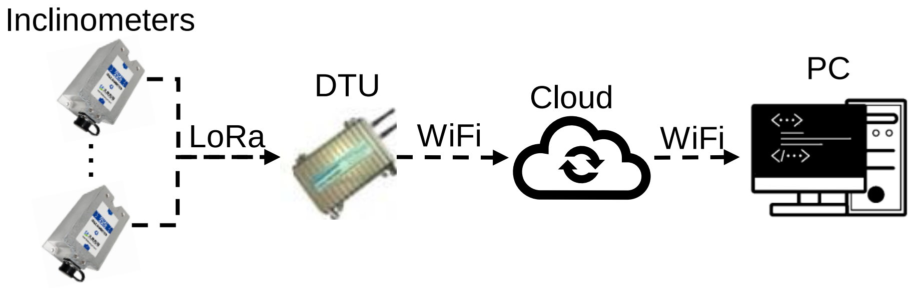
Development of fire resistant inclinometers



Configuration



Developed product



Wireless data communication

LoRa: long range radio
(low power consumption and high penetration)

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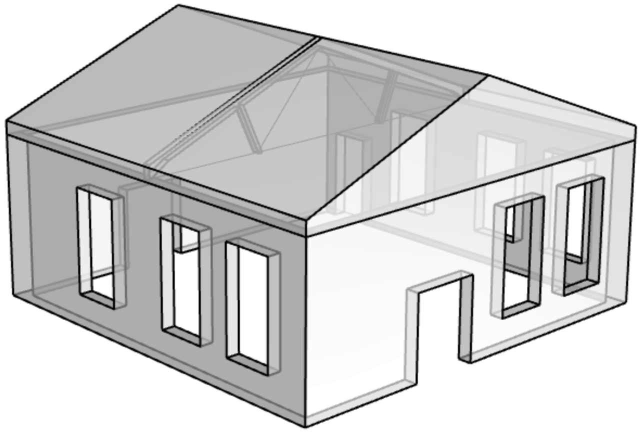
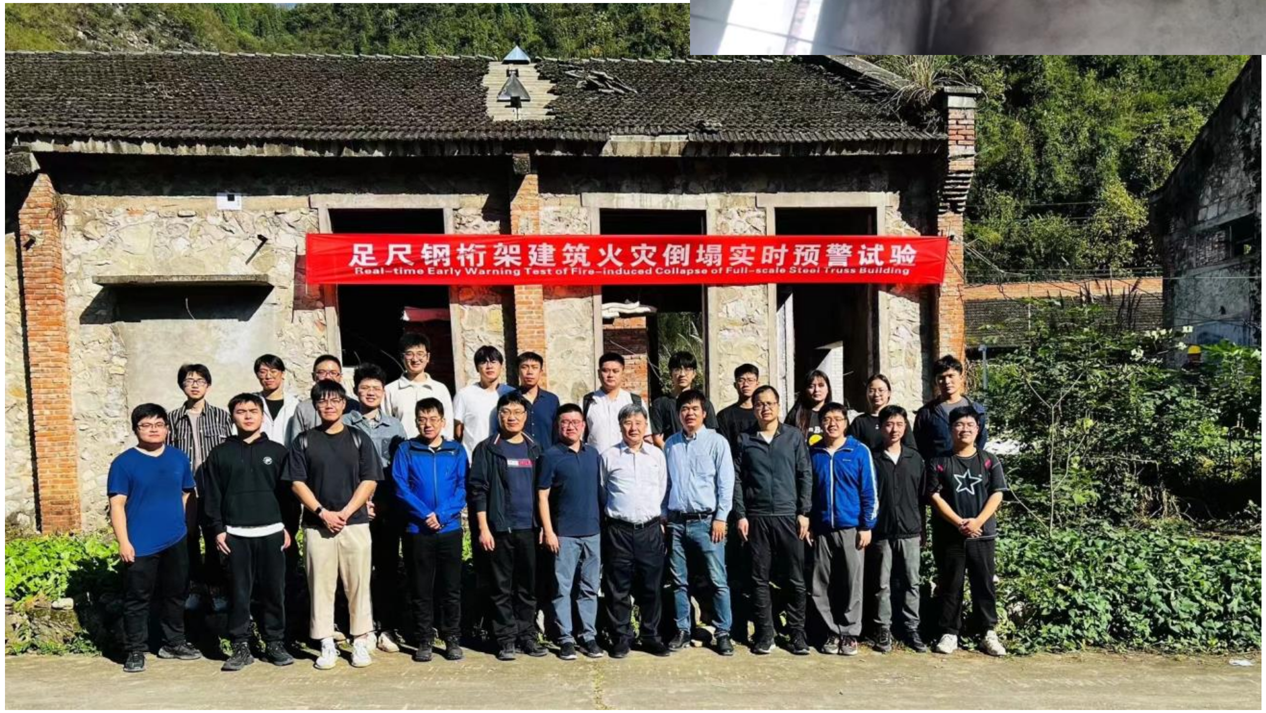
05 Experimental validation

Basic information



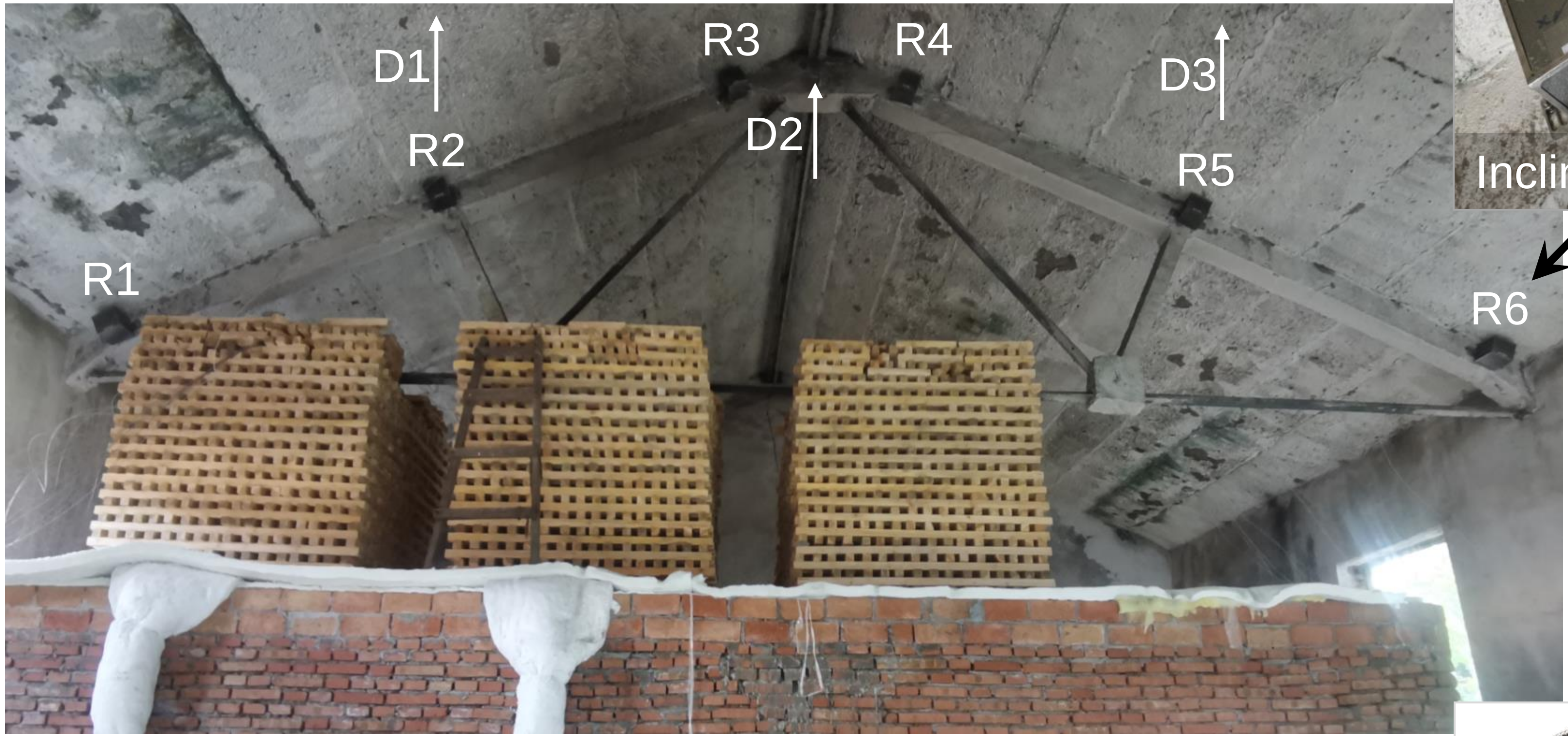


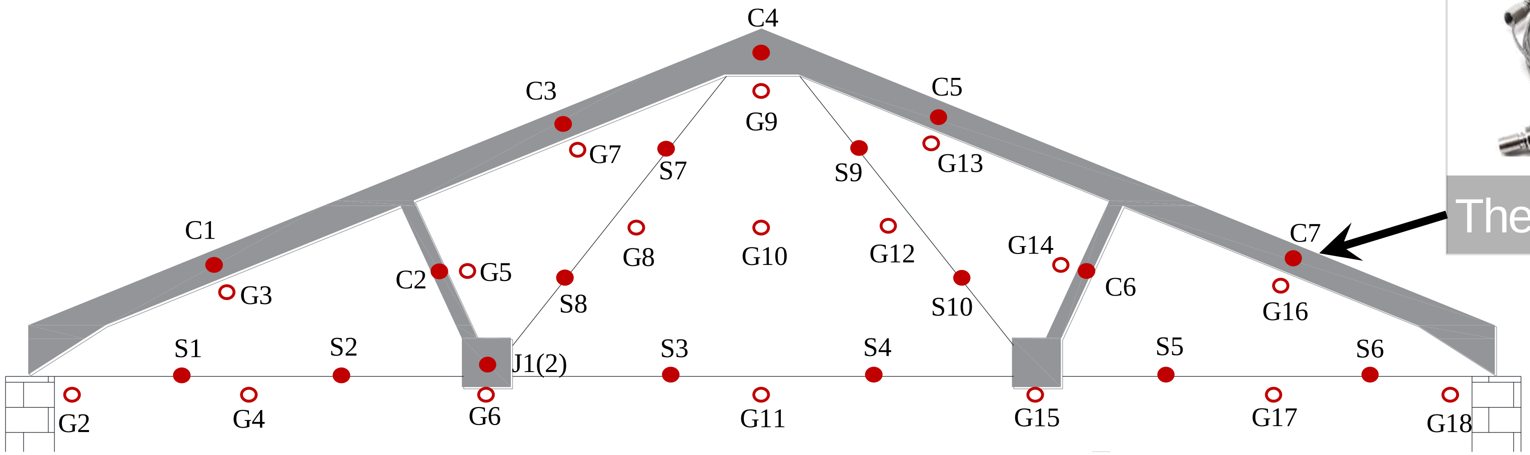
Fire test on a real building with steel truss roof

Real loads and material properties cannot be determined accurately before test

05 Experimental validation

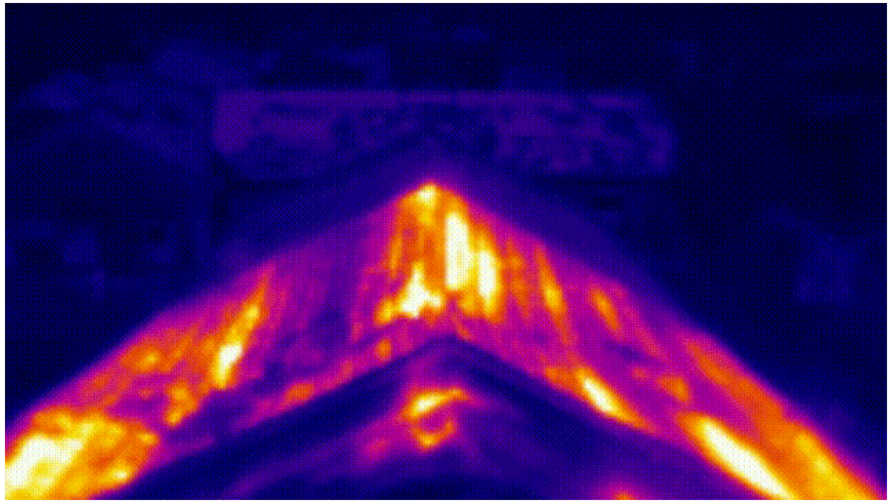
Measurement devices





05 Experimental validation

Collapse moment



05 Experimental validation

Real-time early-warning results

Time	Relative time / s	Incident	Predicted RTC / s	Real RTC / s
10:07:06	0	Open system	/	/
10:09:16	130	Ignition	/	/
10:17:48	642	1^{st} warning	≥ 1972	3621
10:22:54	948	2^{nd} warning	≥ 1327	3315
11:05:30	3504	3^{rd} warning	≥ 596	759

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06 Conclusions

- ***An early-warning system for fire-induced collapse of steel structures*** featuring ***"real-time data acquisition, on-line analysis and instant forecasting"*** has been developed and validated through a real fire test.

- Steel trusses exposed to fire have ***limited collapse modes***. Displacements of key joints, denoted as KPPs, exhibit ***unique evolution laws*** for a specific collapse mode.

- ***Three-level early-warning alerts*** can be issued for fire-induced collapse, based on the occurrence of ***feature points*** of ***KPP-time curves***.

- ***Hard-to-measure KPPs*** can be obtained in real time using easy-to-measure parameters via ***DL models.***

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Thank you for your guidance!

zhushaojun@tongji.edu.cn; zhushaojuntj@gmail.com