An Introduction to Fire Performance Monitoring for Buildings

By

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ABSTRACT

Performance gaps exist in all building disciplines. Whether the performance (gap) in a building area can be monitored indicates the degree of maturity of this engineering area. Compared to the relatively high measurability of performance (gap) in building energy efficiency and structural health, it is much harder to identify and measure the fire performance (gap) of buildings in use, indicating less maturity of the fire protection discipline. This dissertation documents a study on building fire performance monitoring. The key idea is that although a fire accident is an acute phenomenon that is rare and unpredictable and makes observing a building's fire performance very difficult, the evolution of underlying factors that could determine the building fire performance in a future fire accident is in fact a chronic phenomenon that is frequent, observable and predictable. A conceptual design of building fire performance monitoring (FPM) is proposed, which includes an input module, building fire performance gap (BFPG) checking module, and measure refining module. Due to the computational resource costs, CFD tools like FDS commonly used in performance-based fire protection design are inappropriate to be called frequently to estimate the dynamic fire performance of buildings in use. The development of substitute models is needed to check for BFPGs.

Building fire performance includes various aspects like life safety, property loss, business continuity, and environmental damage, etc. This dissertation only focuses on the life safety aspect described by the available safe egress time (ASET) and/or required safe egress time (RSET) as well as the ratio of ASET to RSET which is the egress safety ratio (ESR). To set the fire scenarios, a small three-story apartment building is employed which includes eight 100m^2 apartments in every story. A propane gas-burner fire is put close to the southeast corner of the southeast apartment at the first floor. There are two corridor doors set close to each end of the main corridor. In order to quickly calculate or estimate the building fire egress performance gap caused by changes in six input variables including peak heat release rate (HRR), the width of the apartment corridor door, the soot yield of the fuel, the width of the apartment window, the width of the apartment door, and the corridor smoke exhaust flow rate, three substitute methods are developed: sensitivity matrix method (SMM), response surface method (RSM), and artificial neural network (ANN). These methods are then applied and compared based on their applicability in terms of either model uncertainties including system bias and relative standard deviation (RSD), or percentages of model predictions falling in a preset acceptable error range.

Based on Taylor's linear approximation which only keeps the first order derivatives in Taylor's series expansion, two SMMs are proposed: SMM-Center which uses center difference, and SMM-B/F which uses a combination of forward difference and backward difference depending on the value of an input variable in relation to its baseline value. The application results show that the SMM-B/F has slightly higher applicability, but the SMM-Center is more convenient. A prototype of fire performance monitoring (FPM) is demonstrated by tracking the building fire egress performance calculated by SMM-Center in the small three-story apartment building. Unlike the linear SMM, both RSM and ANN are commonly used non-linear function fitting methods. Different from the traditional RSMs where the necessary cases increase exponentially with the number of input variables, the two RSMs, i.e., the RSM-1 and RSM-2, introduced in this dissertation are based on a novel two-phase power function fitting process where the necessary cases rise linearly with the number of input variables, thanks to the two assumptions adopted: the power function relationship between an output quantity and input variables, and the independence among input variables. RSM-1 is developed from a specially designed dataset, whereas the RSM-2 is developed from a random dataset. The results of applying both RSMs to the same dataset shows that RSM-1 has higher applicability and lower cost. While both SMM and RSM are to some extent physics-based methods, the development of an ANN does not rely on any physical knowledge about how a system responses to input changes: it only depends on the training/validation dataset. In this dissertation MATLAB's feedforward neural networks with error backpropagating algorithm is employed to approximate the FDS response. The optimizing process shows that a hidden layer size of 2 and training/validation dataset size of 80 are the best options as to the problem specified in this dissertation. The pros and cons of the three kinds of substitute methods are compared by applying them to the same group of data, which can be summarized as: the SMMs have the lowest cost and lowest applicability, whereas the RSMs and ANNs have comparable higher applicability; the ANNs work much better when the available safe egress time (ASET) is far away from the baseline ASET value, but fail to catch the changing directions of the ASET as in comparison to the other two methods. It is suggested from the comparative analysis of the methods that to better understand the BFPG dynamically it is a good choice to start with the SMMs and then move to RSMs and ANNs when enough cases are accumulated during the application of the SMMs. As an initial exploration in the area of FPM, this dissertation leaves many practical issues to be solved in the future such as: how to collect the data available in the current building management system and transform these data into what are directly adopted in the fire effect or egress models, how to integrate the fire frequency related factors into the process of FPM, and how to refine the current version of FPM tool.

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I thank God, my family, my advisors, and WPI mates

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Section 1

INTRODUCTION

INTRODUCTION

Building performance covers all the major functional aspects of a building system: energy consumption, lighting, thermal comfort, indoor air quality, visual comfort, acoustics, hygiene, serviceability, fire safety, structural health, security, etc. The building performance gap is defined as the difference between the designed performance and the real performance of operational buildings. It exists ubiquitously in each building discipline and is only partially recognized in some building disciplines like fire protection engineering. Research interests are not equally distributed in all the building disciplines, and some building performance have potential conflicts with others. In relatively well-developed building areas like energy efficiency and structural health, the performance is able to be obtained timely or monitored dynamically, whereas in developing building areas like fire protection engineering it is hard or costly to frequently obtain performance for multiple reasons: lack of active intentions to invest in fire protection systems, lack of explicit quantitative fire performance criteria set in the design stages, lack of confidence in the capability of fire simulation tools to predict the building fire performance, lack of quantitative tools to directly measure the actual fire performance of operational buildings, lack of methods to measure actual data needed to model fire performance in operational buildings, and lack of policies to dynamically update the actual fire performance, etc.

To monitor building fire performance, the physical difficulty focuses on the damaging and acute property of a fire accident which leaves few chances for engineers to measure the building fire performance during the fire process. Instead of monitoring directly the building fire performance during a real fire accident, which is impractical, our research relies on the monitoring of the underlying influencing factors which define the potential building fire performance when a fire occurs in the future. This approach however eases greatly the process of building fire performance monitoring. CFD tools like FDS are commonly used in the process of performance-based fire protection design, which can also be used to estimate the current fire performance of buildings in-use. However, the issue with these CFD tools is that they are usually computationally intensive which is inconsistent with the process of fire performance monitoring which requires dynamic and frequent estimation of performance. To overcome this difficulty, three substitute methods are introduced, which are sensitivity matrix method (SMM), response surface method (RSM), and artificial neural network (ANN).

Section 2 explicitly identifies the existence of the building fire performance gap by comparing with performance gaps in other building disciplines: building energy performance, structural health, etc., and proposes a conceptual design of a building fire performance monitoring process by comparing with the performance monitoring tools in other building disciplines: EnergyPlus, Structural Health Monitoring (SHM), etc.

In Section 3, based on first-order approximation of Taylor's series, SMMs are introduced to dynamically predict the change of building fire performance gap by monitoring the chronically changing factors that could affect the building fire performance. This process is demonstrated by a prototype of a building fire performance monitoring tool, FPM.

In Section 4, a novel two-phase power function based RSM is proposed and applied to various datasets as a substitute model of the time-consuming FDS simulations. Feedforward artificial neural networks (ANN) with error back propagating algorism in MATLAB’s neural network toolbox are also introduced. The applicability of RSMs, ANNs as well as SMMs is compared.

Section 5 describes conclusions and future work.

Section 2

CONCEPTUAL DESIGN OF A BUILDING FIRE PERFORMANCE MONITORING PROCESS

Conceptual Design of a Building Fire Performance Monitoring Process

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Abstract:

The building performance gap, defined as the gap between predicted or desired performance and actual performance of a building throughout its entire lifecycle, has been a topic of interest for decades. Understanding the gap is closely related to development of performance monitoring processes or tools. In the areas of building energy efficiency and structure health where the majority of loads are continuous and/or frequent, performance monitoring is well developed. In the area of building fire protection, however, such kinds of monitoring methods or tools are rare, mainly due to the acute or disruptive characteristics of fire accidents which make it hard, unreasonable, or unrealistic for stakeholders to measure the current fire performance of a building until a real severe fire accident occurs. The main purpose of this paper is to show the feasibility and potential of building fire performance monitoring. Following the Identify-Quantify-Close process, research about how to improve the actual performance or close the performance gap in the building areas of energy efficiency, structure health and fire protection are first reviewed, which then provides inspiration for a conceptual design for a fire performance monitoring process. The basic idea of fire performance monitoring is: although a fire accident is an acute phenomenon that is rare and unpredictable and cannot be relied on by us to demonstrate a building's fire performance, the evolution of influencing factors that could someday in the future cause a fire accident is in fact a chronic phenomenon that is either observable or predictable. Three main modules of fire performance monitoring are conceptually introduced:1) input module addressing the baseline/reference point, performance indicators, types of input variables influencing the performance indicators, and output variables directly or indirectly related to performance indicators; 2) building fire performance gap checking module addressing the methods to efficiently predict the building fire performance gap based on significant changes of input influencing variables; 3) refinement module addressing the methods to generate advice on how to improve the actual building fire performance or close the building fire performance gap.

Keywords: fire protection engineering**;** building fire performance gap; building performance simulation, Post-Occupancy Evaluation; FDS; ASET; RSET;

Abbreviations: AFP, Active Fire Protection; AHJ, Authority Having Jurisdiction; AI, artificial intelligence; ANN, Artificial Neural Network; ASET, Available Safe Egress Time; RSET, Required Safe Egress Time; BAS, Building Automation System; BPS, Building Performance Simulation; BEPG, Building Energy Performance Gap; BFPG, Building Fire Performance Gap; BIM ,Building information modeling; BMS, Building Management System; CFD, Computational Fluid Dynamics; DA, data acquisition; FEM, Finite Element Method; FFR, Firefighter Fire Response; FPE, Fire Protection Engineer; FPS, Fire Performance Simulation; FSCT, fire safety concept tree; FSE, Fire Safety Engineering; GHG ,Green House Gas; HRR, heat release rate; HRRPUA, Heat Release Rate Per Unit Area; IAQ, Indoor Air Quality; IBC, International Building Code; IQC, Identify-Quantify-Close; NFPA, National Fire Protection Association; PBD, Performance Based Design; PBFPD, Performance Based Fire Protection Design; PFP, Passive Fire Protection; PMV, Predicted Mean Vote; POE, Post-Occupancy Evaluation; OFR, Occupant Fire Response; RSM, Response Surface Method; SFPE, Society of Fire Protection Engineers; SMM, Sensitivity Matrices Method; SPG ,structural performance gap; UAV, Unmanned Aerial Vehicle

1. Introduction

Every 24 seconds, a fire department in the United States responds to a fire somewhere in the nation, more than one third of which are structural fires [1]. It is suggested in NFPA reports that although many fires do happen in buildings lacking sufficient designs, some buildings that were at least fully code-compliant at the time of handover also were involved in fire accidents with considerable losses [2 ~ 6]. So why have fires occurred and resulted in large losses in buildings with designs which have been considered as sufficient? The answer is that the predicted fire performance of building designs is not identical to the actual fire performance of buildings in-use.

The phenomenon that buildings do not perform as well as predicted has been termed previously as "the performance gap" [7 ~ 9], denoting deviations between a building's predicted/desired performance and actual performance [10]. Usually the predicted/desired performance is guided by a preset performance which after being agreed on by the stakeholders sets a minimum demand for predicted performance. The difficulties to measure the actual performance of operational buildings are different in various building disciplines.

In the area of fire protection, buildings may experience considerable changes over their lifetimes in the passive and active fire protection systems, fire load, and occupants' demography, etc. Admittedly, in order to address these changes, many fire codes and standards have already included requirements for fire safety management and evacuation plan, and Authorities Having Jurisdiction (AHJs) are expected to conduct fire safety inspections or audits at a frequency based on the occupancy risk classification of a building [11~13]. In reality, however, the implementation of this part of the fire codes and/or standards may be compromised [14]. The methods employed in the process of fire safety inspection/audit are largely qualitative: the method of safety checklist.

Since human behavior has a large influence on the actual building fire performance but is hard to address well during the design stage, the potential fire performance gap in an operational building can be quite large. On the other hand, due to the low frequency of fire accidents, it is usually very hard to obtain the actual fire safety level of an operational building before a severe fire happens. To improve the actual building fire performance or close the building fire performance gap (BFPG), the ability to quantitatively understand the actual fire performance level of a building in-use is necessary. However, currently few tools exist for engineers to conveniently and quickly understand the changing building fire performance gap accumulated due to chronically changing underlying influencing factors like: increase of fire loads, rearrangement of compartments, degradation of fire resistance in fire doors, fire walls and smoke barriers, etc..

In addition to the fire protection area, building performance gaps also exist in other building-related disciplines like: energy efficiency, structural health, thermal comfort, etc., although the magnitudes and the methods adopted to close these various gaps are quite different. Of which, the research on improving the actual building energy performance and structural performance are reviewed in this paper due to the existence of numerous available publications in both areas and the comparability of them to the research on improving actual building fire performance.

In the building energy efficiency area, there is extensive evidence to suggest that buildings usually do not perform as well as predicted or expected [15~ 18]. This is often attributed to the lack of feedback to designers after handover, which inhibits improvements both to existing buildings and future designs [18]. Due to the large uncertainties related to human behavior influencing the actual energy consumption, it is usually challenging to predict accurately the energy consumption during the design stage, leading to a considerable building energy performance gap [18]. Many studies have been conducted to improve the actual building energy performance, or in other words, to close the building energy performance gap (BEPG) [7,15~ 22]. The methods adopted include Post-Occupancy Evaluation (POE) and/or (online) energy performance monitoring tools like: Building Automation System (BAS), Building Management Systems (BMS) [23], and ObepME [24].

In the structural health area, although there is not much research focusing directly on the topic of the structural performance gap, publications on structural health monitoring are numerous. Structural health is the most significant aspect for buildings and structures as possible structural failure is serious [25]. Therefore, it is paramount to understand the current structural health status of an operational building, which is usually achieved by structural health monitoring (SHM) methods. Unlike the area of fire protection and energy efficiency, the structural health level of a building is much less affected by unpredictable human behavior, which could partly explain a relatively smaller number of publications directly centering on the structural performance gap (SPG) compared to that on the building energy performance gap . Additionally, widely applied SHM methods provide valuable information for designers, owners and managers in order to improve the structural performance of both existing and future new buildings [26~ 29,35].

Unlike the areas of energy efficiency and structural health, building fire performance monitoring (FPM) methods are currently absent in the fire protection area, but why? This paper is first prepared to answer this question by comparisons with state-of-the-art research about improving the actual building performance in the areas of energy efficiency and structural health (detailed in section 2). Then based on inspiration from these other two areas, a conceptual design of FPM for buildings is proposed, as shown in the following flowchart (Figure 1):

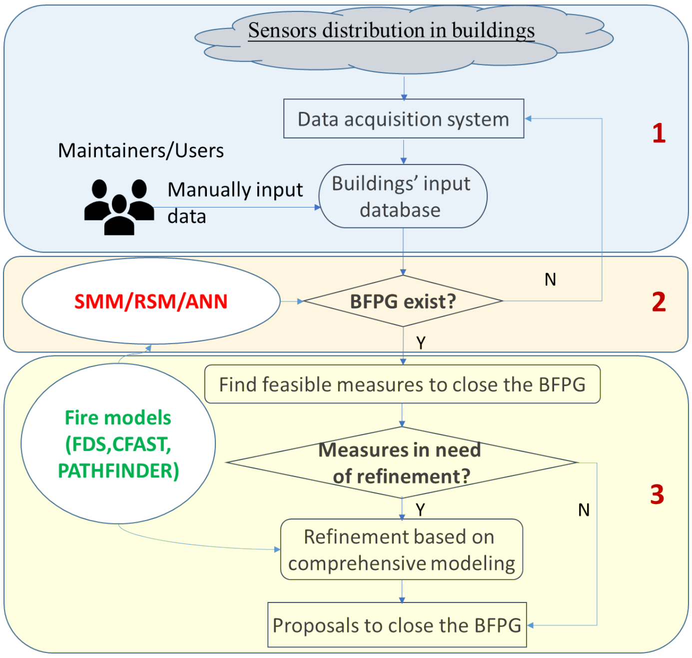

Figure 1 Flowchart of building fire performance monitoring (SMM: Sensitivity Matrix Method; RSM: Response Surface Method; ANN: Artificial Neural Network; 1: Input module; 2: BFPG-checking module; 3: refinement module)

The underlying basic idea of FPM is: although a fire accident is an acute phenomenon that is rare and unpredictable and cannot be relied on by us to demonstrate a building's fire performance, the evolution of factors that could someday in the future cause a fire accident is in fact a chronic phenomenon that is either observable or predictable. By monitoring or predicting the changes of these underlying influencing factors (e.g., fire growth rate or heat release rate (HRR), fire load, compartmentation, degradation of fire resistance of doors/walls/ceilings, number and characteristics of occupants, etc.), we may be able to know the current fire performance of buildings in-use by employing computational models like CFAST, FDS, FLUENT, PATHFINDER, etc. As shown in Figure 1, FPM basically includes three modules: 1) the data collection module, including automatic data acquisition (DA) system and manual input system; 2) the module to check if a BFPG exists, including the development of SMM/RSM/ANN and the checking process; 3) the module to advise and refine feasible measures to improve the actual building fire performance or close the BFPG. In section 3, the conceptual design of FPM for buildings will be explained in detail. Section 4 addresses major points of this paper.

2. Research status of performance gaps in building energy, structural health, and fire protection areas

2.1 Basic concepts of building performance and performance-based design/approach

Building performance is a term often used in the Architecture, Engineering and Construction (AEC) sector [30], typically in association with issues like the energy efficiency of buildings [31], indoor environmental quality [32,33], thermal comfort [34], structural health [35], fire safety [36,37], etc.. However, its meaning has been rarely defined in technical articles of research [30]. After reviewing seminal works on the topic of building performance, Pieter [38] defines building performance as "a concept that describes, in a quantifiable way, how well a building and its systems provide the tasks and functions expected of that building". This definition is taken in this paper.

Building codes can be either prescriptive-based where most requirements prescribe the solutions without explicitly stating their intent, or performance-based where desired objectives are presented and the designers are given the freedom to choose a solution that will meet the objectives [36]. The concept of performance-based design (PBD) focuses on "the practice of thinking and working in term of ends rather than means" [39], whereas the prescriptive-based design does the opposite. For example, "An acceptable level of protection against structural failure under extreme load will be provided" is a performance-based statement, its prescriptive-based counterpart could be "0.5 in. diameter bolts spaced no more than six feet on center shall anchor the wood sill of an exterior wall to the foundation" [40]. Although prescriptive codes and standards provide the designers with sufficient guidance, sometimes they may fail to meet the expectations of either building owners or code officials, especially for more complex buildings or processes or where the potential exists for extremely high property damage or life loss [37]. The translation from prescriptive-based codes to performance-based codes is currently the tendency around the world [41].

The performance approaches in buildings can be traced back thousands of years, but it is in the last century that formal performance concept methodology was developed and applied [42]. Contemporary performance-based terminology has coined two widely used terms, namely user needs, and performance requirements [39]. PBD mainly includes the identification of user needs, the transformation of user needs into performance requirements, and the assessment of design solutions based on performance criteria. In general, the transformation of user needs into a set of performance criteria, which are quantified performance requirements, is linked to the identification of threshold values for relevant physical factors, although these acceptable threshold values may not be fully satisfactory.

Performance-based approaches are widely applied in the areas of building energy efficiency and structural health, which serve as models in the derivation of fundamental principles of PBD. Both can thus be used as a basis for other performance attributes [39]. Due to various degrees of uncertainties of input parameters adopted during the design stage, some extent of building performance gaps present in different building disciplines are inevitable. Since the performance-based approaches are target-oriented, they allow stakeholders to improve the actual building performance or to close the building performance gap in a discipline by adopting various methods. The next subsections show the research status of improvement in actual building performance in the areas of energy efficiency, structural health, and fire protection, by generally following an overall Identify-Quantify-Close (IQC) process.

2.2 Common roadmap to research the performance gaps in various building disciplines

Performance gaps may exist in each building related area. A common IQC process can be followed to research the performance gap in each building discipline, as shown in the following figure:

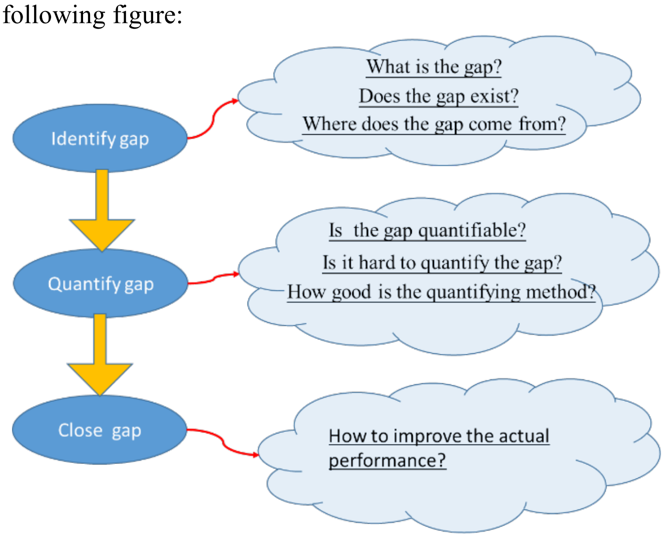

Figure 2 The Identify-Quantify-Close (IQC) process to research building performance gaps

In this figure, to identify a gap means to show the definition of the gap and the proof of the existence of the gap; to quantify a gap means to quantitatively describe and measure the gap; to close a gap means to seeking feasible measures to improve the actual performance gap.

2.3 Research status on the BEPG

2.3.1 Identification of the BEPG

The building sector is responsible for about 40% of the energy consumption and related CO2 emissions worldwide [23]. There is an increasing concern about a mismatch between the predicted building energy performance and the measured actual building energy performance, which is typically addressed as “the performance gap” [9]. It is reported that the measured energy use can be as much as 2.5 times the predicted energy use [18], indicating an unacceptable gap even with the related uncertainties being considered [9]. Therefore, energy performance improvement is the central theme of sustainable building design under the pressure of global energy and environmental issues [22].

It is relatively easy to recognize the BEPG due to the following facts:

1) There is a big driving force to recognize and close the BEPG, which is the considerable and immediate economic return. A new cladding system with good insulation will save the building owners/users money as soon as it is effectively installed [43,44].

2) The factors related to human behavior usually have high uncertainties, which sometimes leads to noticeable energy performance gap [18].

3) The criteria of (building) energy performance design is very clear: buildings should consume as little energy as possible [45,46].

4) Building energy performance simulation tools are well developed. The building energy community has high confidence in these tools if they believe the input parameters are good enough [47~ 50].

5) It is easy to measure the current energy performance, for example, by electricity bills [18,51,52].

6) The data related to energy consumption can be monitored easily [9,10,18,43~52]. The energy metering is prevalent and easy to implement. For example, gas meters are used to monitor the flow rate of natural gas being consumed; thermometers are used to monitor the indoor temperature, etc.

7) Currently it is possible to update the current building energy consumption hourly with the help of state-of-the-art monitoring systems like the automated meter reading technology [9,18,51].

The root causes for the BEPG are grouped in three main categories: factors that pertain to the design stage, factors rooted in the construction stage (including handover), and factors that relate to the operational stage, as shown in Figure 3[7,20,21,24,52].

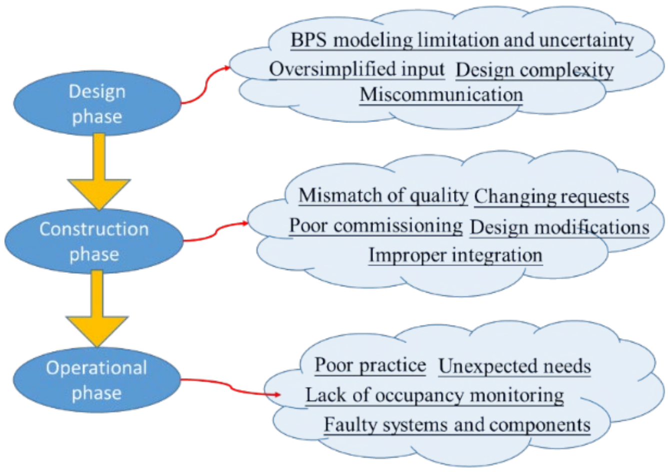

Figure 3 Root causes of the BEPG come from design phase, construction phase, and/or operational phase

Part of these root causes may somehow result in other building performance gaps. For example, except for energy performance, structural health and fire performance may also be affected by integrity problems of walls which stem from poor commissioning in the construction stage.

2.3.2 Quantification of the BEPG

Due to the fact that energy distribution and consumption are highly commercialized, it is convenient to monetarize the absolute volume of energy consumed. As to the BEPG, it can be either an absolute value (e.g., dollar), or a relative value (e.g., the percentage higher than the predicted energy consumption).

Since a building design is assumed to be able to satisfy the energy performance criteria set by related stakeholders, acquisition of the actual energy consumption of an operational building is needed to work out the size of the BEPG. The actual energy consumption can be obtained quantitatively by electricity bills and/or gas meters. Furthermore, more advanced and cheaper sensors recently developed can provide an increasingly high-resolution map of reality and higher performance predictions [53]. Dynamic and online monitoring tools have been developed to automatically monitor the building systems' energy performance and to identify possible performance discrepancies and deviations [53,54].

2.3.3 Close the gap: how to improve the actual building energy performance

Models and tools of building performance simulation (BPS) have been adopted to improve the actual energy performance of buildings for decades worldwide [42,55~57] by providing a means by which one can compare the measured performance versus the design intent, test systems for installation and operational faults, deduce effective control sequences [58], and dynamically manage passive planning [59,60]. However, current simulation tools still do not accurately model the impact of occupants and management on the energy performance of buildings due to their inability to represent realistic use and operation of buildings [61,62]. This major source of the performance gap can be considerably narrowed by the practice of post-occupancy evaluation (POE) which can provide actual measured or observed data related to in-use buildings as inputs to calibrate the building performance prediction models [18,54,63~66]. A well-calibrated model can then demonstrate the major contributors of the building energy performance gap by sensitivity analysis [66].

With the major sources of building energy performance gap being identified, the last step to close the gap is for the stakeholders to adopt feasible measures delivered by the calibrated BPS models or tools.

2.4 Research status on SPG

2.4.1 Identification of the SPG

A health problem of structure can be defined as deviation from "a sound condition" as result of damage and deterioration that would warrant repair, retrofit or strengthening of the structure [67]. The structural health provides the ability to a building structure to perform as promised [40]. Although various indices mainly related to "structural safety" are traditionally adopted to describe the health of a structure, such as safety factor, condition rating, load-capacity rating, sufficiency index, capacity-demand ratio, redundancy, etc., a broader definition of structural health involving limit states of serviceability and durability that assure functional performance of a structure seems to be more proper [40]. Therefore, the desired structural performance is achieved by not exceeding the limit states of safety, serviceability and durability during the lifecycle of a structural or structural component [35].

For an operational building, the SPG indicates the discrepancy between the structural health level it should be and the structural health level it actually is at the current operational time. Unexpected structural failures are signs of the presence of SPG. Structural deterioration or damage due to progressive and sudden damaging events may also indicate changes of structural performance. Here progressive deterioration may result from adverse environmental conditions such as high temperature, humidity and carbonation, chloride ingress, biodeterioration, etc., and sudden damaging events may include earthquakes, floods, snowstorm, etc. [68]. Due to the complexity of extreme loads caused by sudden damaging events, there have been continuous observations that significant damage can occur even when buildings are compliant with the building code, indicating a deficiency mainly focusing on life safety intent [69, 70]. Also, as revealed by the damage patterns in the Northridge earthquake (1994), buildings designed to resist the larger equivalent lateral forces required by more recent codes do not always perform better than older buildings [70].

The SPG develops due to building defects stemming from either the design stage, construction stage, or the operation/maintenance stage. Design problems include the areas of tension/compression reinforcement, software constraint used in design, extra loads (e.g., mobile crane) on the existing building not considered during the design process, effect of wind load not taken into consideration, wrong connections, ignorance of cyclic loading and/or vibration, etc. [35]. A poor design will definitely spread the design effects into the following construction and operation/maintenance stages. During the construction phase, the defects may come from low-quality materials, poor workmanship, and inadequately prepared subsurface impacting the foundation etc. [71]. Building maintenance has an important role to ensure the long-life span of the building [72]. Poor and improper building maintenance will definitely cause more damage and costly repair work if left unattended [73]. However, many building problems during the maintenance phase can be traced back to the design and/or construction defects [72].

2.4.2 Quantification of the SPG

Structural performance of either components or the whole building involves several aspects: safety, serviceability and durability, etc., each has various limit states or performance criteria (e.g., for safety, the limit states include excessive movements, settlements, geometry changes, material failure, fatigue, etc.; for serviceability and durability, the limit states include excessive displacements, deformations, drifts, deterioration, local damage, vibrations, etc.) [40,67]. Therefore, it is challenging to describe the structural performance with a single uniform unit. As a non-dimensional magnitude, component or system reliability index, β, can be considered as a performance index which relates in concept to the determination of "safety factors" or "load rating" most engineers use in practice [40,67, 74]. Different measures of reliability may be appropriate for different systems and for demands at different limit states and events [40]. In seismic structural design, the structural performance level is adopted to describe the performance under specific design earthquake levels. There are five seismic performance levels: operational (no damage for the structural and non-structural members), immediate occupancy (limited damage for the structural and non-structural members), damage control (considerable damage for the structural and non-structural members), life safety (significant damage to the structure has occurred), and collapse prevention (large permanent lateral deformation has occurred) [75]. In life-cycle analysis of structural performance, the structural (health) condition at a given time is measured in terms of the system's remaining life, which is defined in practice in terms of structural capacity (e.g., material resistance, displacement, inter-story drift, etc.) [76].

SPG can therefore be described by either a lack of reliability, a lower structural performance level, or an insufficient structural capacity, the amount of which can be determined thanks to the available methods to evaluate structural health conditions[77~ 80], including visual inspection and tap tests, records of the realistic performance of the structures during hurricanes, earthquakes, snowstorms, and floods, as well as the most import one: structural health monitoring (SHM).

2.4.3 Close the gap: how to improve the actual building structural performance

SHM, which has the potential to make structures safer by observing both long-term structural changes and immediate post-disaster damage, is a promising method with widespread applications in civil engineering over decades of continuous progress [26,29]. SHM is defined by Chang [81] as an "autonomous (system) for the continuous monitoring, inspection, and damage detection of (a structure) with minimum labor involvement." Buildings sometimes are exposed to aggressive environmental and operational conditions of extreme weather events and accidental damage, leading to potential unexpected structural changes [26]. Therefore, it is of great importance to quantitatively assess the performance and integrity of any structure, to identify the root causes of unexpected structural performance, and to propose feasible measures to enhance the actual building structural performance, which constitute the main objectives of SHM.

SHM can first help to identify the potential SPG of a building. Based on the collected real-time continuous data or intermittent data, various models of inverse strategies and/or statistical analysis [26] can be adopted by SHM to determine the current structural health and performance by evaluating the structural damage or abnormities (e.g., unanticipated movements and geometry changes, displacements, vibrations, distress and damage/deterioration to materials, elements and connections, etc. [67]).

After that, it can be implemented to understand the root causes of problems. In most cases, monitoring over an extended time may be a necessity for definitively identifying the root cause(s) and mechanisms leading to symptoms of deterioration or damage [67]. Sometimes the use of simulated response data from an analytical structural model based on an existing structure would allow for comparisons with data taken on the actual structure, which helps to identify the root causes of structural failures or damage since there may be many ways leading to same or similar appearances of structural health. Further, a monitoring system can help to avoid many unexpected failures that may lead to economic or personal injury [29].

With root causes being identified by means of SHM, the last step to improve the actual building structural performance would be to determine the most effective and compatible renewal/repair/retrofit technology for current or future use based on mitigating the root cause [67].

2.5 Research status on BFPG

2.5.1 Definition of BFPG

The BFPG is defined as the gap between the predicted/desired building fire performance during the design stage and the actual building fire performance during the operational stage.

According to the fire safety concept tree (FSCT), fire safety objectives can be achieved by measures of both preventing fire ignition and managing fire impact [82]. In this paper, only the component systems that help to manage fire impact are considered, which are further grouped into four categories: Passive Fire Protection (PFP) systems, Active Fire Protection (AFP) systems, Occupants' Fire Response (OFR), and Fire Fighters' Response (FFR). These four components work together to fulfill the performance requirements of life, property, business continuity and the natural environment [83,84]. PFP measures aim at containing the fire/smoke in a limited area for a given timespan by providing fire doors, fire walls, smoke barriers, etc., which have appropriate fire resistance functions: stability, insulation and integrity. AFP measures are designed to alarm, extinguish or control the fire, or maintain a specific smoke layer thickness within a given timespan. Both PFP and AFP measures may help to increase the Available Safe Egress Time (ASET) or decrease the Required Safe Egress Time (RSET). OFR options are crucial to evaluate the RSET, where FFR methods are responsible for rescuing persons who fail to self-egress, and extinguishing the fire to minimize property damage and business interruption. The four component performances may be quantified by time (RSET/ASET), fire/smoke damaged area, or peak HRR of the fire.

A framework is proposed in [85] to analyze the building fire performance based on a thought process that tracks functional component performance and integrates the micro behavior of individual components with the macro building performance. This framework incorporates active fire defenses, defined as "a device or action that must receive a stimulus to act in a real or a perceived fire condition", and passive fire defenses with the definition of "a building component that remains fixed in the building whether or not a fire emergency exists". Three categories we defined above, namely AFP, OFR and FFR, fall into the class of active fire defenses, whereas the PFP is almost identical to that of passive fire defenses.

Given a fire scenario, all four components of performance work together to achieve an acceptable overall fire performance level (if it exists) consistent with performance goals. Any gap in these four performance components indicates potential threats to the achievement of fire performance goals.

2.5.2 Identification of the BFPG: difficulties

Compared to the performance gaps existing in other building related disciplines, especially the energy area, the performance gap in fire protection engineering is much harder to identify due to the following reasons:

First, lack of active intentions to invest in fire protection systems. People are happy to insist on safety as long as others pay for it, so fire safety becomes a legislated solution rather than a designed solution [85]. Although building fires happen every day around the world, they are considered as statistically rare events with respect to a single building or single apartment [86,87], and most people do not think about fire design in buildings unless they have experienced one [85]. People tend to invest less in things like fire protection measures whose benefits are hidden, intangible, or not imperative [36] than in things like energy saving measures with quick and obvious returns, let alone paying attention to the fire performance gap. One of the lessons learned from The Grenfell Tower fire which occurred June 14, 2017 in London is the neglect of increased fire risk when refurbishing the building with aluminum façade [88]. It may seem to be surprising that other disasters like earthquakes, which are considered as rarer than fires, have been paid so much attention that the SPG are better covered during the design stage with "safety factors" (widely accepted, objective safety factors usually don't exist in the fire protection designs [89]). The reason for this may be that most earthquakes, if not all, occur due to forces of nature whereas most fires happen due to improper human behaviors and activities like smoking, cooking, use of candles and fireworks [90~ 94], etc.. People may think they can reduce the risk of fires by safer behaviors [95], but during an earthquake it is hard to do so. Evidence of the neglect of the BFPG is that the building fire performance has been rarely considered as one of the performance objectives for optimization during the building design process. In many cases the value of building fire protection designs lies in how to ease the process of code compliance [96]. In economics, diminishing marginal utility is a common rule which implies that at some point the benefit of any additional investment will become lower than the cost of additional investment itself, making an investment unreasonable. However, in fire protection engineering, the cost of an investment is much clearer than the benefit of it, making it hard to judge if an investment is reasonable. For example, different views on the values of human lives will make an investment either reasonable or unreasonable.

Second, lack of explicit, quantitative, and acceptable fire performance or fire risk level set in the design stages. The performance-based fire protection design (PBFPD) is still in an immature stage compared to other building related disciplines like structural stability and energy efficiency which are to a larger extent based on first principles. In practice, it is a common rule for a PBFPD to arrive at a fire performance level at least equal to that provided by corresponding prescriptive codes which is often implicitly assumed to be acceptable [95,97,98]. The fire performance levels provided by prescriptive codes, however, are hard to quantify, and the comparison of performance levels between a PBFPD and a prescriptive one is not a trivial exercise [135]. For example, as far as the building egress performance is concerned, codes specify good practices to help individuals leave a building safely in a fire emergency, but the level of risk is indeterminate, safety is not assured and alternatives cannot be compared [85,99]. Furthermore, this kind of "equivalent approach" causes several challenges, including lack of consistency (it is easy to find a prescribed design variant with higher risk than an alternative design), wrong analytical focus (more focus on finding an appropriate reference design than on assessing the safety of proposed design), and inability of handling novel designs (no applicable prescribed design rules) [100].

Third, lack of confidence in the capability of fire simulation tools to predict the fire performance of a building design due to considerable uncertainties embedded in input parameters and simulation models. Even if it is assumed that all stakeholders have clear ideas about what is the minimum fire performance level they can accept and have arrived at some kind of written agreements, there are still a lot of uncertainties lying in the input parameters and the simulation models themselves, which mean that the fire performance simulation tools may not be able to deliver predicted results with high confidence. Although the simulated results look "quantitative", they are often adopted qualitatively and find their value in comparative studies [41].

Fourth, lack of quantitative tools to directly measure the actual fire performance of operational buildings. If you don't know where you are, you can't decide where to go. When we look at the other end of the fire performance gap, we unfortunately find that there are currently no available quantitative tools to directly measure the actual fire performance of operational buildings, whereas such kinds of measuring tools exist in some other building-related disciplines like energy efficiency (energy bill-based method or monitoring based method) and structural health (visual observation or monitoring by sensors). Theoretically, the best way to measure a building's fire performance, taking egress performance for an example, is to set a fire in an occupied building, watch the real evacuating process of occupants and simultaneously record the real ASET and REST. Such kinds of real environment experiments are popular in other engineering fields but are obviously unrealistic in fire protection engineering due to the fire damage and ethical concerns [101]. We then can obtain the ASET and RSET separately, namely set a fire in a real scale building without occupants to get the ASET and spread low or non-poisonous artificial smoke in a real scale building with occupants to get the RSET. Sometimes even this is unrealistic due to time and cost limits. We then have to resort to employing fire performance simulation tools in occupied buildings as we did in the building design stage [102]: "Of practical significance is that direct measurement of the fire safety performance of a building or building system is not usually possible; therefore we must rely on the technical predictive ability of scientific tools such as existing fire models." Still there is an issue: can we to a large extent take the simulated fire performance of operational buildings as actual fire performance after we use more valid data as input parameters than those default or estimated or averaged data we adopted during the design stage?

Fifth, lack of methods to measure data needed to model actual fire performance in operational buildings. Even if we can trust the simulated fire performance of operational buildings, it is still a huge challenge to decide what level of precision is needed and what kind of actual data we need most as input for fire modeling tools and how can we obtain these actual data in a relatively precise, efficient, and cheap way. Uncertainty quantification can help us figure out the limit bands of both input and output variables, whereas sensitivity analysis can help us screen out the most important factors affecting the fire effects. Both Building Information Modeling (BIM) and Building Management System (BMS)/Building Automation System (BAS) can provide us data about operational buildings, some data may be directly adopted as input to fire modeling tools or as output to validate fire modeling tools, some other data may need further treatment before being used as input to fire modeling tools. The available data may still be insufficient for us to conduct detailed fire simulations, and therefore other data may be needed to be obtained by deploying new sensors.

Six, lack of policies to dynamically update the actual fire performance in a quantitative way. Even if we are able to measure the actual fire performance of existing buildings by simulation tools, we still need policies or rules to determine the frequency and triggering conditions of this kind of measurement including costly fire performance simulations or even costlier fire performance experiments. Operational buildings keep changing day by day, month by month, and year by year. Fire safety issues from some changes may be well identified, and that from other changes may not. For example, building stakeholders may decide to establish additional "chronic" objectives like increased security when the building is actually operating [103], whereas the increased RSET may be ignored. Therefore, the actual fire performance is always changing to some extent. Due to the cost of measuring actual fire performance, it is impossible to conduct the measurements based on every change in operational buildings. Most fire codes have already included requirements for fire safety and evacuation plans, and AHJs are expected to conduct fire safety inspections or audits at a frequency based on the occupancy risk classification of a building [11,12]. In reality, however, the implementation of this part of the fire codes may be compromised [14]. Also, the methods employed in the process of fire safety inspection/audit are largely qualitative: the method of safety checklist. Some appropriate policies or rules have to be developed to determine what conditional changes warrant a new quantitative building fire performance assessment. Thresholds for changes should include any significant changes of input influencing factors that could lead to a significant increase of fire risk predicted by either deterministic analysis or probabilistic analysis. These input factors may affect either the frequency of a fire scenario (e.g., occupants' cooking frequencies, the number of occupants who smoke indoor, etc.), or the consequence of a fire scenario (e.g., fire load, occupant load, HRR, etc.), or both (e.g., occupants' party frequency). However, it is not a trivial task to figure out the mechanism of how a specific input factor affects the fire risk.

The following figure summarizes the six barriers of identifying the BFPG:

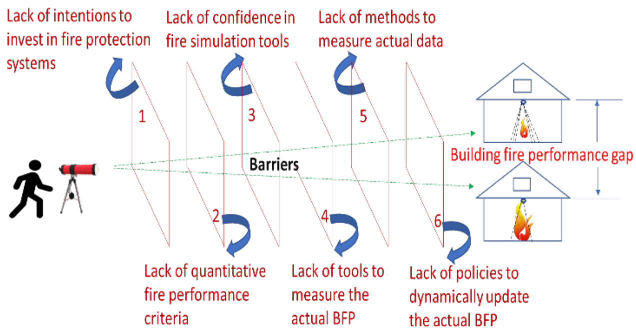

Figure 4 The six difficulties of identifying the BFPG

2.5.3 The sources of the BFPG

The sources of the BFPG can be investigated in two dimensions: the time dimension and the space dimension. In the time dimension, similar to the sources of the BEPG as shown in Figure 3, the BFPG may come from either the design stage, the construction stage, or the operational stage. In the space dimension, the BFPG may come from either the passive fire protection system (PFP), active fire protection system (AFP), the occupant fire response system (OFR), or firefighter response system (FFP). In this paper, the sources of the BFPG are discussed in the space dimension since the terms of PFP, AFP, OFP and FFP are widely adopted in the fire protection area.

PFP systems are designed to be effective in-place anytime during fire incidents. The performance gap of PFP systems has been explicitly identified. Defects in construction of PFP systems is a fire performance gap, or fire safety gap identified by Littlewood [104 ~ 107]. These defects include incorrect installation, missing, inappropriate or defective components that make up compartmentation and fire stopping, and workmanship errors. The result enables rapid smoke spread across compartments, preventing the safe evacuation of occupants by shortening the ASET. In addition to the defects of PFP systems due to construction quality, the lack of maintenance of PFP systems also undermines their fire performance. Investigation by FM Global [108,109] shows that on average 82% of fire doors operated properly, whereas the research done by CIGNA Property and Casualty Loss Control staff [108] shows that "41.1% of in-place fire doors had some type of physical or mechanical problem that would prevent them from operating properly during a fire event". Of 91,909 installed fire doors in several occupancies surveyed in [110], 13.4% were propped open. The problem was at its worst in institutional occupancies (39% of the doors were propped open) and at its best in assembly occupancies (only 5% of the doors were propped open). Scarff [111] reported that fire doors were blocked open or had kick-down stops in 18% of the 275 hotels surveyed from June 1992 to June 1993. Exit signs are important for people to egress in case of a fire. In some department stores, however, the exit signs are obstructed from people's view. The following photos taken by the first author show an example of a clothing department where the exit sign can only be seen by standing right in front of it.

a) view from side aisle b) view from front aisle

Figure 5 Example of an obstructed exit sign in a clothing department

AFP systems mainly include the fire detection and alarm, sprinkler and smoke evacuation systems. These mechanical systems may have very high reliability. However, what finally matters as far as their fire performance is concerned is their effectiveness. "Reliability" is defined as the probability that a product or system will operate under designated operating conditions for a designated period of time or number of cycles, whereas "effectiveness" refers to the ability of a system to achieve desired objectives [108]. First, sprinklers are designed not to respond to "small fires". This condition is not clearly announced in building codes, misleading the occupants to believe that they will work for all fires and overestimating the fire performance of buildings designed according to these building codes, although the losses due to "small fires" failing to activate a sprinkler are generally minimal. Second, although in fires big enough to activate these AFP systems, they may still fail to be effective after being activated due to other relevant issues like lack of water supply. For fire detectors and alarms, except the failure modes mentioned by Fitzgerald[85] including a high unwanted nuisance alarm rate and improper locations of installation, the biggest issue is that sometimes people just don't respond to them. Milke [112] states that occupants responded in only 36% of the fire incidents where an audible alarm was produced as a result of an operating smoke detector. Statistics show that smoke alarms operated in only 33% of multiple-fatality fires from 2009 to 2011 where smoke alarms were present [113]. Bryan has cited one study that found "the response to fire alarm bells and sounders tends to be less than optimum" [114]. If the fire safety design or the fire safety management plan assumes people will hear a fire alarm, recognize it as an alarm, and begin moving immediately to an exit, the RSET and exposure to untenable conditions could be significantly underestimated [115]. As a result, there may be a higher likelihood of injury than expected. For sprinklers, the dominant cause for ineffectiveness is the system being turned off [3]. The reported effectiveness of sprinklers differs from country to country, varying from 38% to 99.5%. The reasons leading to this huge range of reported effectiveness of sprinklers include the quality of statistics (for example the design of the incident report), different management of sprinkler systems (installation, inspection and maintenance) between countries, and the most important one : if the sample space includes "fires too small to activate the sprinklers" [116 ~ 121].This ineffectiveness of AFP systems is not well documented in both the prescriptive codes and the performance-based codes, resulting in overestimated fire performance of buildings during the design stages.

The performance gap of OFR has be addressed in [122,123]. By analyzing several fire accidents with fatalities, the authors stated that "the measures currently required by law do not always provide the support that people in burning buildings need". It is also shown that some principles and assumptions in current (Dutch) policy are not consistent with the recent knowledge (e.g., people's walking speed is assumed constant in the policy regardless of whether or not they are walking through smoke, which is inconsistent with the recent research showing much slower walking speed in smoke)[122,123], indicating that a building designed according to building codes may not be able to deliver some expected fire performance level after occupancy due to lack of consideration of realistic OFR.

The performance gap of FFR has been discussed by Starnes [124], Mills [125], and Barrett & Greene [126]. Starnes points out four critical issues affecting fire services across the United States in 2019, which are: securing funding and retention, ensuring firefighter safety, enhancing fire department communication, and coordinating agency resources. Mills groups the performance gap into the external performance gap and the internal performance gap. The external performance gap applies in those areas in which new services, additional services, or a more timely delivery of services is necessary for the community whereas no more, or even less volunteer fire service is available due to the increase of two-income households. The worse thing is that, as Barrett & Greene state [126], "Without enough volunteers to respond to emergencies, some fire departments are cutting services or even shutting down". The majority of smaller communities is served predominately by volunteer fire departments. Recent NFPA research shows that the rate of civilian fire deaths per million population in communities with less than 5,000 people is significantly worse than in larger communities [127]. Therefore, the stress on fire departments serving these smaller communities is higher, implying a wider gap of firefighting performance. The internal performance gap mainly stems from untimely training and newer equipment, which may not become readily apparent until the need for new or additional skills becomes evident through incident responses. Technology and equipment deficiencies often go hand-in-hand and are a regular source for change that impacts firefighting capabilities and personnel safety. Business activities may also lead to the performance gap of FFP by influencing the community's tax base which the local fire department's expense and capital budgets rely on [125].

Another source of the holistic BFPG comes from the potential competition in the building-occupant system between the "acute" fire safety objective and the other "chronic" objectives like security, natural lighting, energy efficiency, flexibility for future uses, and low life-cycle cost, etc., since fire is not a daily concern of building users but other objectives are [103]. When this competition occurs, the chance for the fire safety objective to survive at the expense of the other objectives are very low. Fire safety shouldn't be taken as a "bonus" but an essential part of the whole design task.

Fire incident reports like NFPA's annual reports about large-loss fires in the US also shed light on the sources of the BFPG. Of the 23 large-loss structure fires that happened in 2016 [4], seven structures had sprinklers installed but still underwent large losses. In the fire accidents that happened in Texas and California, both smoke detection systems and dry pipe sprinkler systems were present in both structures, but the fires still resulted in more than $10 million damage for each due to the ineffectiveness of the sprinkler system which had been shut down prior to the fire or been supplied with insufficient water. In Florida, one complete-coverage smoke detection system and one wet pipe sprinkler system present in a one-story 126,000-square-foot department store of unprotected ordinary construction operated and helped control the fire. The losses still arrived at $13 million, indicating a possible performance gap of AFP which may come from the misunderstanding of the performance expectation of AFP. Two fires that happened in Maryland and Oregon both had smoke alarms installed, operated, and the fire departments were notified, but still led to 6 fatalities (in Maryland) and large losses, implying a possible performance gap of FFR. In 2016, two catastrophic multiple death fires happened where smoke alarms operated but the victims did not escape, indicating a possible performance gap of OFR. Most large-loss fires from 2014 to 2016 happened in unprotected ordinary constructions, indicating a possible performance gap of PFP. Although the acceptable risk level of the society about these high loss-low frequency fires is not clear, it may seem to be unreasonable to agree that these large losses are acceptable according to the as-designed fire performance. If these huge losses are not expected, the fire performance gap must have been hidden in these buildings for a while before the fire incidents [4, 6, 128~130]. If an appropriate FPM tool were available, the BFPG could have been identified before the fire accidents and the huge losses could have been avoided.

2.5.4 Quantification of the BFPG: description of building fire performance

In general, building fire performance should be described by (the level of) fire risk or safety (safety is usually taken as an inverse measure of risk, albeit it may be beyond risk [131].). Fire risk is defined as the product of the probability of fire occurrence and the consequence or extent of damage to be expected on the occurrence of fire [132]., which can be mathematically expressed as

$$R = \sum R_i = \sum \left(L_i \cdot P_i \right) \qquad E(1)$$

Where R_i, L_i and P_i are the risk, loss/consequence and frequency of scenario i, respectively.

In ISO 23932 [13], quantitative fire risk analysis approaches include both probabilistic analysis and deterministic analysis. In probabilistic analysis, the full range of representative scenarios are identified, the occurrence probability of each scenario is evaluated, and therefore the uncertainty is directly addressed in the analysis. In this case, the holistic building fire performance can be represented by the overall fire risk (R). In the deterministic analysis, a set of worst case credible scenarios are evaluated and the uncertainty is partially addressed by assuming worse than average exposure. These deterministic analysis methods are sometimes characterized as consequence analyses. Since usually the occurrence frequencies of these worst credible scenarios are unavailable in deterministic analysis, the building fire performance can be represented by fire loss/consequence corresponding to some specific worst credible cases.

Although the use of the concept of risk is inevitable for the quantification of the building fire performance, the application of this concept is not simple due to lack of sufficient statistical data for large loss-low frequency fires [133] and lack of accurate reliability data about the fire protection systems [134], which is why the PBFPD aims more at the reduction of the magnitude of fire losses than that of the fire frequencies [135,136], or in other words people have more confidence in the prediction of fire losses/consequences under given fire scenarios than the prediction of fire scenarios' occurrence frequencies.

For given fire scenarios, the fire losses are usually categorized into direct fire losses which can be further divided into life losses and property losses, and indirect fire losses which can be further divided into business continuity loss and environmental impact/loss [84,137~139]. Due to the difficulty of assigning a monetary value to human life, life loss and non-life losses are usually separately assessed with different units [140]. Life safety is considered as one of the most essential requirements for fire safety implementation in a building [89], which is reflected in various building codes [136,141]. In building fire protection design, various untenable thresholds are set to protect people from being trapped, which mainly involve criteria of visibility, temperature/heat flux, and toxicity [36,142]. Research shows that the visibility limitation is usually first met due to the fast speed of smoke traveling inside buildings [142~145]. Therefore, visibility (of 5m in small buildings and 10m in large buildings) has been commonly taken as a rule to measure the ASET. Although not perfect, the analysis of ASET combined with the RSET, including safety ratio (ASET/RSET), safety margin (ASET-RSET), and probability of exceeding a limit stage (e.g., P(ASET-RSET<0) [131]) is a commonly used building fire performance indicator [89,142,146~149].

2.5.5 Various methods to estimate the BFPG

To understand the BFPG, we need to know the initial building fire performance agreed by the stakeholders when a building is delivered, and the actual fire performance of an operational building. The initial building fire performance is usually deemed to be good enough, which may not always be true in practice, in a prescriptive-base design if all the provisions are met. In a PBFPD, the initial building fire performance needs to be predicted by engineering methods based on many input parameters, some of which may be quite different from the operational stage, resulting in a significant BFPG. For an operational building, there are several methods to estimate the BFPG.

First, code-compliance validation. This method is straightforward for buildings designed from a prescriptive code. By checking an existing building with the prescriptive code, the fire performance gap can be found and expressed qualitatively by the degree of the existing building satisfying the code provisions. For buildings designed from a performance-based code, however, it is not easy to judge if an existing building satisfies the code. Usually, fire performance simulation tools like CFAST, FDS, PATHFINDER, etc., are involved to conduct this validation process. This method is treated as a static one in that the frequency of using this method is very low, maybe only once for a building design when it is submitted to the AHJs for approval.

Second, safety index method. This is a semi-quantitative or crude quantitative method based on index tables which include input parameters considered as key factors by a group of experts. One of these tools is the Fire Safety Evaluation System (FSES) in the 2013 edition of NFPA 101A [136], which is still considered a "valid tool" years after its first publication [150]. To some extent this method can also be treated as a static one since it is not used frequently. Other methods that can be grouped into this type include the Dow Fire and Explosion Index [151], the building fire safety evaluation method (BFSEM) [152], and the fire risk assessment method for engineering (FRAME) [153], just name a few.

Third, fire performance simulation (FPS) for quantitative analysis. FPS includes fire models, evacuation models, and sometimes cost-benefit models. Usually, fire models can be categorized into zone models, field models, network models, or combinations of them. Evacuation models can be categorized into hydraulic models or steering models (agent-based models). For example, CFAST is a popular zone model, FDS is a popular field model, and PATHFINDER integrates both hydraulic and steering models. Although these simulation tools are usually adopted during the design phase of an irregular building where prescriptive codes don't apply to make sure the expected performance levels are met, they can also be employed to tell if the fire performance gap exists in operational buildings through similar simulations with updated inputs from current conditions. Probabilistic software tools like: CUrisk [154, 155] and FIRECAM[156], can also be used as FPS tools [134]. An integrated risk assessment method developed in [157] can be deemed as an advanced FPS tool where event trees are used to set the frequency of each possible fire scenario and response surface methods (RSM) developed from deterministic fire sub-models are adopted to quickly determine the consequence of each scenario. FPS is deemed as a semi-dynamic method, which means the users can use it as a dynamic method by manually running the simulation tools whenever necessary. It cannot run by itself without significant involvement of the users.

Fourth, fire performance tests. This method includes real scale tests and small-scale tests. Compared to real scale tests, small-scale tests are much cheaper. The issue with small-scale tests is to what extent the result generated from small-scale tests can be scaled up without introducing considerable additional errors. Fire performance tests are commonly believed to be the most accurate method to investigate building fire performance, but most of the time it is unrealistic, especially for an occupied building, to conduct a real physical fire or evacuation test. This method can also be considered as a semi-dynamic method.

Fifth, fire performance monitoring. This method is based on the idea that the accuracy of fire performance simulation tools can be maximized by providing input data with maximum accuracy. By dynamically monitoring and updating the current status of input parameters, dynamic fire performance monitoring tools deliver a fire performance report of existing buildings by triggering fire performance simulation tools based on the extent of changes of monitored parameters. This is a new dynamic method (see section 3 for detail) which can be adopted to better understand the fire performance gap of an operational building.

In addition to the above five methods, Fitzgerald [85] has conceptually proposed a three-level probabilistic method to evaluate building fire performance, which may help to figure out the potential BFPG. A level 1 evaluation can be deemed as qualitative in that it provides a basic understanding of the building and a sense of proportion for performance expectations and risk characterizations. A level 2 evaluation can be thought of as quantitative since it considers details more carefully and calculation procedures more generally. A level 3 evaluation is an updated version based on the level 2 evaluation by providing an understanding of performance sensitivity.

Another work related to evaluate the actual building fire performance has been conducted by Park [101]. Based on the holistic understanding of the interactions of both "hard" characteristics (physical building systems and components, fire protection measures, etc.) and "soft" characteristics (building design features, occupant activities, and interactions among them, etc.), a quantification method commonly used in Analytic hierarchy process(AHP) was utilized to evaluate fire safety performance.

2.5.6 Close the gap: how to improve the actual building fire performance

In the last section, several methods, either qualitative or quantitative, are introduced which have the potential of identifying the BFPG. This process of determining the BFPG also generates information about the underlying reasons leading to the BFPG, which in turn can be generally adopted by stakeholders to decide and implement means and strategies related to both preventing fire ignition and managing fire impact [82] to improve the actual building fire performance.

Besides, a risk-informed, performance-based process has been proposed to improve the actual building fire performance by viewing fire as a disruptive or acute event within an holistic, chronic "building-occupant" system and shifting from a fire-centered paradigm to one in which building performance metrics are evaluated in the case of fire events [103]. Henrik [100] believes that buildings including infrastructure and activities associated with them are complex socio-technical systems constantly adapting to changes within themselves and the environment, and therefore should be "designed for change" so that the (building) systems are kept within a safe state by imposing safety constrains (e.g., a specified maximum number of people, maximum fire load, etc.) on the systems' behaviors.

Another interesting work related to improve the building fire performance has been conducted by the research team of Guillero Rein [158]. They developed the "Fire Navigator", which can forecast the spread of building fires on the basis of sensor data before the real fire/smoke arrives at a target during an ongoing fire. This time span gained by the tool can be used to inform the fire service in advance so that the fire fighters can be more prepared before or during their firefighting. Therefore, the primary usage of this tool is to help the firefighters to better fight the fire. Usually there are three stages in which people can do something to reduce the fire loss: before the fire, during the fire, and after the fire. Before the fire, the focus is on prevention and mitigation measures. During the fire, the focus is on controlling or extinguishing the fire as well as rescuing more occupants or valuable items, which mainly depends on the fire protection systems installed in the fire building and the response of fire fighters. After the fire, the focus is rehabilitation of building damage, business confidence and/or personal injuries, which depends on the recovery measures. FPM tools belong to the prevention measures before the fire by informing the stakeholders about valuable information related to the dynamically changing building fire performance. The Fire Navigator belongs to the controlling measures during an ongoing fire. The Fire Navigator is more time sensitive than FPM tools. For example, a half minute improvement in prediction is crucial to the Fire Navigator, whereas at least more than a half day of improvement in prediction may become significant to fire performance monitoring tools.

In addition to these aforementioned discussions explicitly centering on the improvement of fire performance gap, people have in fact worked to narrow the fire performance gap for centuries although they possibly didn't realize that they were dealing with the fire performance gap, or they just didn't use the term of BFPG. The evolving history of building codes has witnessed goodwill and efforts to make the buildings safer by modifying specific provisions in the building codes thought of as major reasons leading to fire incidents. One of the major reasons people change from prescriptive codes to performance-based codes is the underperformance of prescriptive code compliant buildings as compared to expectations.

3. Conceptual design of fire performance monitoring

3.1 Similarities and differences among the building disciplines of energy efficiency, structural health, and fire protection

Section 2 discusses the current state-of-the-art research in improvements of actual building performance in the areas of energy efficiency, structural health, and fire protection, respectively. There are several similarities existing among these three building disciplines:

1) Performance gaps all exist to some extent in these three areas;

2) In both energy efficiency and fire protection areas, the performance is highly affected by human behavior which is hard to predict and/or the corresponding uncertainties are insufficiently identified during the design stage. This leads to considerable building performance gaps in both areas.

3) Engineering measures in both structural health and fire protection focus not on how to generate positive economic benefits but on how to make the building safer and/or free from unexpected performance. Therefore, the economic return of a better structural or fire protection design is hard to perceive until a real accident (structural failure or large fire) occurs.

4) The risks of experiencing extreme loads in both structural health and fire protection areas can not be ignored.

5) In both energy efficiency and structural health areas; a) The majority of the loads: heating, cooking (for energy loads), wind, snow and, flood (for structural loads), are frequent or continuous; b) performance monitoring tools like BMS/BAS and SHM, exist and are widely implemented; and c) performance simulation tools (e.g., FEM tools in structural health, and EnergyPlus in energy efficiency) can be used to analyze the potential reasons leading to the performance gaps.

The following differences among these areas exist:

1) The BFPG is hard to quantify and is possibly large; the BEPG is considered large but easy to quantify; the building structural performance gap is also easy to quantify but possibly not as big as the BEPG due to: a) The design of load-bearing structures is a mature engineering area, in which the methods are related to underlying principles leading to risk control by including partial safety factors associated with loading combinations [39,41,159~162]; b) The extensive infrastructure of university education, practice guidelines, professional registration, continuing education criteria, and research has supported the assurance of structural safety in the phases of building design and construction [159]; and c) Unlike the area of building fire and energy performance, the design of structures doesn't involve uncertain inputs due to human factors.

2) Unlike the other two areas, few building fire performance monitoring tools exist. Although many methods can be adopted to evaluate the actual building fire performance, in reality they are not applied as frequently or continuously as what BMS/BAS or SHM does, which can be partly explained by: a) Unlike the other two areas where most of the cases the loads are either frequent or continuous, the meaningful fire loads (from established fires) are disruptive or acute (for example, in residential buildings, ignitions are very frequent, but fires big enough to trigger the sprinkler system are rare); b) For an operational building, the outcomes of extreme structural loads and fire loads (e.g., building collapse, building burn out) are usually much more severe than that of extreme energy loads (higher energy costs).

3) A SHM tool usually works by monitoring the signs or modal properties (e.g., natural frequencies, modal damping, and mode shapes, etc.[78,79]) of structures which in turn can be used to predict changes in structural performance. However,

energy performance simulation tools can either monitor the change of the energy performance directly (e.g., gas and electricity meters) or monitor the influencing factors of energy performance (e.g., humidity, temperature, wind speed, occupants' activities, windows'/doors' status, etc.)

3.2 Significances of FPM

After delivery of the building to the owner, theoretically there should be a thorough investigation of the building to make sure that the input parameters are the same or close enough to what were adopted during the design stage. Unfortunately, it is rarely the case. Official inspections are usually superficial and qualitative, only obviously abnormal conditions are able to be identified. The Post Occupancy Evaluation (POE) method has been selected to figure out the BEPG. Data from POE reports: cracks and leakage in walls, floors, windows and doors, etc., may also be useful to figure out the BFPG.

Building energy or structural performance gaps are able to be dynamically monitored because the changes of variables describing them are basically continuous/frequent, chronic and perceptible. For example, it is possible to obtain hourly energy consumption data. For the building fire performance, strictly speaking there is no way other than setting a fire or recording a fire accident to investigate the fire performance of operational buildings. Although fire incidents are occurring every day around the world, for a specific building they are rare events with return periods of many years [87] depending on the occupancy types and building areas. As complex socio-technical systems that continuously interact with and adapt to their environment [131], buildings usually accumulate significant changes in occupancy type, contents, interior finishes, and/or fire protection systems over these periods, deviating gradually from the design fire scenarios and trial designs developed in the design stages. However, the public generally lack a method to report the current fire performance of buildings in use. A building that passed the official inspection when it was delivered is sometimes deemed by the public to be safe enough "forever" until a disaster happens. Although most building codes require a periodic check of the fire safety state of operational buildings, the result of this implementation is sometimes far short of expectation [14].

Since the fire performance of a building is constantly changing as the system adapts to changes within itself and the environment [131], a building FPM tool should be appealing to the public. It is possible to move towards this objective currently based on the availability of cheaper, smaller and popular sensors. By monitoring or predicting the chronic changes of factors affecting the building fire performance, we may be able to know the current fire performance of buildings in-use with the help of computational models like CFAST, FDS, FLUENT, PATHFINDER, etc. This approach can be analogous to vibration-based damage identification methods, which are used for structure health/performance monitoring. The fundamental idea for vibration-based damage identification is that the damage-induced changes in the physical properties (mass, damping, and stiffness) will cause detectable dynamical changes in modal properties (natural frequencies, modal damping, and mode shapes)[77,78], which means the current structural health/performance status can be predicted by measuring these dynamic modal properties. The difference between a vibration-based damage identification method and our FPM method is that the former measures the modal properties of the unhealthy structure or the structural performance gap, whereas the latter measures the changing status of building factors (input parameters) that could lead to a BFPG in the future.

3.3 Dependent pyramid of building fire performance

Fire protection engineering design typically includes the determination of project scope, goals, objectives and performance criteria, design fire scenarios, and trial design strategies [163], the core task of which focuses on checking against performance criteria if proposed trial designs consist of different combinations of fire protection strategies that can survive design fire scenarios accepted by all stakeholders.

The SFPE Engineering Guide to Performance-Based Fire Protection groups the types of methods that might be used in trial designs into six subsystems: fire initiation and development, smoke control, fire detection and notification, fire suppression, occupant behavior and egress, and passive fire protection [164]. The results of how trial designs or fire protection strategies handle fire scenarios are indicated by component performance of PFP, AFP, OFR, and FFR, which in turn define the fire performance of a whole building. On the other hand, fire scenarios are defined by three kinds of characteristics related to the building, fire, and human occupants. By focusing on the fire dynamics and human behavior during the interaction process between fire scenarios and trial designs, direct factors influencing the fire scenarios and trial designs can be abstracted. These direct factors may include heat release rate per unit area (HRRPUA), soot yield, CO yield, etc. for fire scenarios, walking speed, specific flow rate, pre-movement time, etc. for egress systems, and exhausting flow rate of fans, activation or alarming time of sprinklers/detectors, etc. for active fire protection systems. Although these direct influencing factors usually present as input parameters in various fire or egress modeling tools, usually they cannot be conveniently or directly obtained by sensors deployed inside a building which can only provide fundamental visual or numerical data. Currently, our research focuses on the direct influencing factors, further detailed work is needed in the future to transform the fundamental data to direct influencing data. For example, a video camera set inside an apartment can provide pictures about the change of interior finishes and furniture (discussion about the privacy issues is out of the scope of this paper), but a changing HRRPUA cannot be directly worked out. Techniques of image recognition and statistical experimental data about what combustible materials can lead to what levels of HRR in what fire scenarios need to be involved.

The dependent relationship among the holistic building fire performance (HBFP), component performance, fire scenarios/trial designs, direct influencing factors, and fundamental influencing factors are shown in the following pyramid:

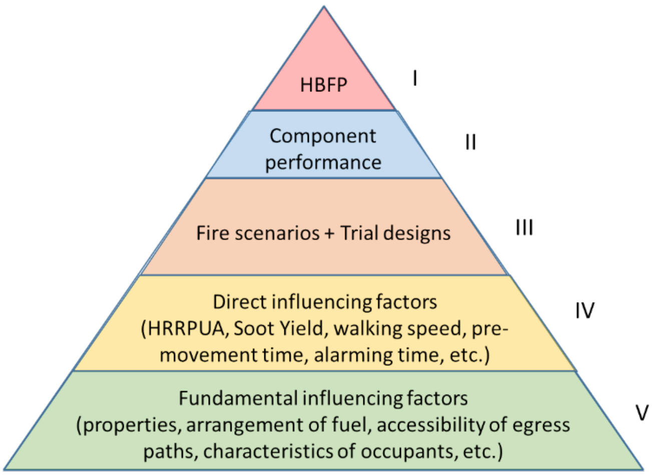

Figure 6 Dependent pyramid of building fire performance (HBFP=holistic building fire performance)

In an operational building whose fire protection strategies have been proven to be able to survive design fire scenarios, the BFPG comes from changes either in fire scenarios or in fire protection strategies/trial designs or both, assuming the initial approval of fire protection strategies is impeccable. The changes in fire scenarios include either unexpected new fire scenarios or changes of characteristics of the building, occupants and fire. The major source of changes in fire protection strategies is the diminished reliability of each strategy due to poor construction or installation quality or lack of appropriate maintenance. The interaction between changes in fire scenarios and changes in fire protection strategies leads to some kinds of component fire performance gaps and finally the holistic building fire performance gap.

3.4 Data collection: methods and significance

3.4.1 Classification of needed data

Before discussing the methods to collect different data, it is necessary to classify input data into: a) static/quasi static data which usually don't change a lot during quite a long period (if not life cycle) and can be deemed as almost constant, and b) dynamic/quasi dynamic data which on the other hand changes continuously or frequently and can be deemed as variable. For example, the building area, height, structural elements are static/quasi static data, whereas the interior finish material, contents, the number of occupants, and human behavior are dynamic or quasi dynamic data. Uncertainties from static/quasi static data usually can be well estimated, no online monitoring systems are needed. Dynamic/quasi dynamic data are much harder to be predicted during the design stage and may need online sensor/monitoring systems to acquire the ever-changing data. For example, the fire load may change when new tenants move in and move out, the weather changes every day which may influence people's activities and the frequency of fires. The operational status of other systems in the building like elevators, HVAC, fire alarm systems, etc., may influence the development of a fire and the evacuation of occupants.

3.4.2 Methods of data collection

Some data acquisition systems already installed in a building may share some useful information for FPM. A BIM can be introduced to acquire static/quasi static data during the design and construction stage (like: construction materials, wall thickness, etc.). Utilizing the BMS or BAS that already exists in a constructed building to control and monitor the building's mechanical and electrical equipment such as HVAC, lighting, power system, fire alarm system, and security systems, will help to acquire both static and dynamic data for buildings in-use (like: locations of heaters/coolers, ventilation networks, indoor/outdoor temperature/humidity, etc.). If a SHM system is also available in a building, it may be able to provide the actual structural stability and integrity which contribute to the fire resistance of structural elements.

Various video cameras can be used to monitor the evolving input parameters (factors). For example, given the output from common RGB cameras, it is possible to perceive the changes of fire load by recognition of different objects by using, for example, suitable machine leaning technologies [165,166]. Infrared thermal cameras can be adopted to quantify the air leakage through walls, floors, windows and doors [167], which also matter in case of fire. Thermal cameras may also be used to check if the sprinkler system is ready to activate because different water conditions inside the pipes will display different colors. If the status of some parameters is hard to be accessed automatically, they can at least be obtained manually.

A sensor package mounted on a small unmanned aerial vehicle (UAV) can be utilized to investigate/inspect dynamic data for buildings in-use that cannot be obtained by existing monitoring systems. For example, the 360° assessment of a building, which is crucial for firefighting performance, is not possible to be conducted by existing monitoring system. In this case, a small UAV carrying a sensor package may be an ideal choice.

3.4.3 Significance of data collection

Beyond preparing data for FPM, data collection may have other significance:

1) During the process of collecting static/quasi-static and dynamic/quasi-dynamic data, we may be able to identify some new fire scenarios that have not been addressed during the design stage since one fire scenario selected during the design stage may not be representative of a much larger and more varied collection of scenarios [135,168]

2) According to Heinrich's Triangle Theory of 300:29:1 [169], for one major injury accident there are 29 minor injury accidents and 300 near miss incidents. The process of collecting dynamic data continually may be able to find these "300 near miss incidents" before a major injury fire accident happens. In fire protection engineering, a basic concept is the "fire triangle" which includes fuel, heat, and oxygen. If all these elements of the triangle coexist, a major or minor fire accident will occur. However, if only two of the three elements coexist, it can be called a near miss fire incident. If we pay more attention to these near misses, we may be able to avoid the "major or minor injury accident". Experience of avoidance of fire accidents are also beneficial for improved future building designs.

3) In case of real fire accidents, the long-term data collection about the building structural integrity, the operational characteristics of building equipment, and the activity patterns of occupants will help fire forensics and fire damage assessments.

3.5 Modules involved in the conceptual design

3.5.1 Introduction to the conceptual design

From the discussions above, it becomes clear that building fire performance monitoring, which is absent in the area of fire protection engineering, will help to improve the actual building fire performance. A flow chart of FPM is shown in Figure 1. It is a prerequisite to identify important input parameters by sensitivity analysis, and then these chosen input parameters are measured continually by a data acquisition (DA) system or manually by building personnel. Once significant changes (e.g., 5%) of input parameters' values are recorded, a rough estimate of the fire performance (gap) can be immediately worked out by either a Sensitivity Matrices Method (SMM) or a Response Surface Method (RSM) or an Artificial Neural Network (ANN), which depends on the application stages and the amount of the sample data. If the estimated result is considerable (e.g., 10%), more detailed fire simulations will be conducted as well as solicitation of experts' judgements to confirm the estimated result. If the rechecked result is still considerable, the stakeholders will be informed and persuaded to do something to address the fire performance gap.

A FPM tool is expected to work in a way similar to a building energy performance monitoring tool or a SHM tool. Assuming the FPM tool is based on fire modeling tools like CFAST or FDS, we can maintain database files of inputs, outputs, and intermedia results from SMM, RSM or ANN. Based on these data, FPM will trigger CFAST or FDS simulations based on defined criteria. For example, a trigger can be defined as "A considerable fire performance gap (e.g. 10%) is estimated by SMM", which means that a CFAST or FDS simulation would be automatically triggered once this gap is detected/predicted by the SMM. Meanwhile, the analytical charts/figures/reports stemming from the fire modeling results will be updated accordingly.

In this tool, the trajectories of both evolving data changes and the building fire performance changes are recorded in a timely manner, providing support for designs of future buildings.

As shown in Figure 1, a FPM tool usually includes three modules: input module, BFPG-checking module, and refinement module, which are correspondingly discussed in the following three subsections.

3.5.2 Conceptual design of the input module

In the input module, the following information should be provided:

1) A baseline/reference point. FPM focuses on monitoring the real time fire performance of an operational building. However, to judge if the actual fire performance deviates too much from the desired fire performance, or in other words to calculate the BFPG, a baseline/reference point at which the

same building has an acceptable and desired fire performance should be set. For example, if we take the egress safety ratio (ESR), which is the ratio of ASET to RSET, as a fire performance indicator, then a baseline point can be the acceptable and desired ESR of the building when it was first occupied.

2) What are the performance indicators, input and output variables. A FPM tool should be told what performance indicators it should monitor. For different types of buildings and different research/application purposes, the performance indicators can be ASET, RSET, ESR, the fire/smoke damage area (percentage), the time before collapse due to fire effects, heat flux imposed on neighboring buildings, business hours/days lost due to a fire, the cost to restore the building's major functions, etc. Input variables in FPM can be defined as the ones that could significantly affect the values of performance indicators. Input variables can be chosen by either sensitivity analysis or expert judgements. For example, if ASET is chosen as a performance indicator, then input variables may include HRR, soot yield, exhausting flow rate, apartment door status, etc. Output variables in FPM can be defined as variables that can be directly or indirectly related to the performance indicators. For example, with ASET being chosen as a performance indicator, the visibility of smoke at exits at some height (e.g., 1.8m) can be taken as an output variable. Critical values may be needed to calculate the value of performance indicators. For the same example of ASET as a performance indicator and the visibility as an output variable, a critical value for visibility below which an untenable condition appears at exits needs to be set. This value can be, for example, 5m for small building or 10m for a large building.

3) How to generate data necessary for SMM/RSM/ANN. The development of SMM/RSM/ANN necessitates various levels of simulation/experiment data. For example, if FDS is chosen as the fire model to generate the simulation data, at least two simulation points for each input variable should be provided for SMM to build a sensitivity matrix, which means that at least two different FDS files for each input variable should be prepared/generated by FPM.

4) How to update the values for input variables. The input module should be able to handle either manual input data or automatic input data from a DA system, or a combination of them. If input data come from a DA system, the data logging frequency may be as high as once per second, which may generate a large volume of data records and make the input data file size unmanageable. The chronic input variables of FPM, however, usually change at a much lower frequency than the data logging frequency of a DA system (e.g., in the unit of once per day/week/month). To avoid storing lots of identical or similar data, a significance threshold (e.g., 5%) should be set so that only data beyond this threshold relative to the baseline/referencing data need to be registered in the FPM input data files. For the manual input data, the persons responsible for data input can be informed to update the data only when the changes are beyond the significance threshold. The assumption of setting a significance threshold is that in the worst case when the input variables vary within the threshold the building fire performance will not deviate substantially from the baseline/reference performance (e.g., 20%). Experts' or end users' experience can be adopted to set an initial value of the significance threshold which can be further adjusted later on when a SMM is available.

3.5.3 Conceptual design of the BFPG-checking module

The major work of the BFPG-checking module is to check if the BFPG exists when significant changes of input variables happen. Since the direct measures of the actual building fire performance or the BFPG are usually unavailable or unrealistic (for example, it is possible to set a fire in an occupied building to "measure" the ASET/RSET, but this method is not realistic), some methods are needed to infer the actual building fire performance or the BFPG. Real buildings are usually too complicated to apply experience/experiment-based equations obtained from single compartment or simple building fire tests to calculate the values of output variables related to performance criteria. This condition necessitates the use of fire models (e.g., CFAST, FDS, etc.) or human behavior models under fire condition (e.g., PATHFINDER), or combined models (e.g., EVAC+FDS).

FPM, or any monitoring system, demands quick response to varying situations. However, some of the CFD models are time consuming (for example, a FDS simulation in a small hotel building may need a couple of days to couple of weeks, depending on the number of cells and physical/numerical models involved), which makes it impossible to directly call these models in the FPM. On the other hand, although human behavior models require much less time (for example, a PATHFINDER simulation in a small hotel building may need only several minutes, depending on settings of the egress scenario), the direct calls of these tools may need more coding work to integrate the functions of these models into a FPM tool. In some cases, it is almost impossible to do so if the models are not open source. To handle these difficulties, some intermediate models based on simulation results from these CFD or human behavior models seem to be more promising, which include SMM, RSM, and ANN, just name a few. Once built, these intermediate models, whenever applicable, can be adopted to determine the actual building fire performance or the BFPG, which in turn serves as input to the refinement module if the BFPG is greater than the significance threshold (e.g., 20%).

Properties of SMM/RSM/ANN in the context of designing a FPM tool are briefly discussed below:

1) The basic idea of SMM comes from the Taylor Series approximation which states that a nonlinear problem can be locally linearized if the changes of input variables are small enough. In the area of mathematics, a sensitivity matrix only applies in conditions where the changes of the input parameters around the baseline points are so small (e.g. <1% of the base values) that the acceptable errors of this linear approximation, which are usually small (e.g. <1%), can be maintained. In engineering, however, the acceptable errors can be as large as 20% or even 50%, therefore the corresponding applicable range of the Taylor's first order approximation, namely the sensitivity matrices, may be possibly larger, but still quite limited. A SMM only needs simulation/experiment data of two points around the baseline point for each single input variable to build the model/sensitivity matrix. After that the model validation can be conducted by another several or dozens of data points involving combined changes from all the input variables. A new sensitivity matrix may become necessary over time when the present building conditions drift far away from the baseline point which voids the old sensitivity matrix. The establishment of new sensitivity matrices, however, provides a chance to add or drop some input/output variables, which makes the SMM quite flexible during on-going building fire performance monitoring.

2) RSM is a collection of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest and a number of associated control (or input) variables [170]. Although the functional relationship can be either linear or quadratic equations, the latter type is more common in publications [171~173]. In RSM, traditionally the number of physical or numerical experiments needed to develop a good model rises exponentially when the input variables grow, which means it will take a lot of time to develop a RSM in the fire protection engineering area due to the large number of potential input parameters as well as the time consuming property of fire effect simulations, which makes it quite inflexible to change the structure of the model equations. Therefore, some assumptions may be necessary to reduce the necessary data points. The applicable range of an RSM, which depends on the non-linear degree of the fitting functions adopted and the distribution of the data points chosen, is usually much larger than that of a SMM. The larger number of data points, however, indicate more resources needed than for a SMM.

3) Unlike the statistics/regression based RSM, ANN is a machine learning based method which can study and simplify the performance of any arbitrary, complex and non-linear process by simulating the neurological processing ability of the human brain with few prior assumptions being needed [171~173]. Although an ANN may perform better than the corresponding RSM, it needs more data points [174,175]. Other perceived disadvantage of an ANN compared to RSM is the lack of capability of getting insightful information on the system such as sensitivity analysis and/or any interactions between components [171].

4) The different characteristics of the SMM, RSM and ANN make it possible to involve them in the process of understanding the BFPG at various stages which differ in available time and data points. At the start of the process, a baseline case or scenario is available which fits a SMM well. The experience with the applications of the SMM will then provide more and more data points for the corresponding RSM and/or ANN. With the accumulation of the data points, at some time the establishment a RSM becomes possible, and the application of the RSM will in turn provide more data points to build a corresponding ANN which is supposed to be the most general of the three methods.

3.5.4 Conceptual design of the refinement module

Once a significant BFPG is predicted with the BFPG-checking module, the refinement module starts to work.

First, it works out feasible measures based on reverse application of SMM/RSM/ANN. Since usually there are many ways to develop a BFPG, conversely there should be many methods to improve the actual building fire performance or close the BFPG. For example, different combinations of fire initial locations, fire loads, and fire growth rates may result in the same flashover time; both exhausting fans and sprinklers can make sure that a minimum smoke layer depth is maintained; different combinations of human behaviors and egress designs may result in the same RSET. Potential methods to close the BFPG may or may not include input variables which have caused the current BFPG. For example, a BFPG of ASET caused by increased HRR doesn't have to be closed by decreasing the HRR, other alternatives may also work: installation of a sprinkler system, increase of the smoke exhaust flow rates, installation of self-closing door hinges, etc. Moreover, it is possible to seek an alternative fire protection measure when the present one stops working due to either accidents or planned activities, leading to a noticeable BFPG. For example, if the sprinkler system is out of commission due to a retrofit, alternative fire protection measures: reduction of the combustibles, installing of the temporary smoke barriers, etc., can be adopted to maintain the same building fire performance (e.g., the ASET) during the retrofitting period.

Second, these measures to close the BFPG obtained by corresponding application of SMM/RSM/ANN may need to be further refined and/or checked. The reasons for this kind of refinement and/or check include:

1) There are some degree of deviations between the simulation results of the CFD/fire behavior models and the SMM/RSM/ANN. If the measures proposed by SMM/RSM/ANN look insufficient, it's better to verify them by fire or human behavior models on which the SMM/RSM/ANN are based.

2) The measures to close the BFPG proposed by SMM/RSM/ANN, which are only mathematically feasible, may not be applicable in reality due to constraints of specific building settings.

3) The end users may have their own preferred measures different from that proposed by SMM/RSM/ANN and the effectiveness of their favorite methods needs to be validated.

Once the measures to improve the actual building fire performance or close the BFPG are refined and rechecked, the work of FPM completes. It is the end users' responsibility to implement detailed plans for these measures.

3.6 FPM as part of fire risk analysis

A FPM tool can work as a calculator of the BFPG under some specified fire scenarios. The application of FPM needs a baseline/reference point, which can be either one of the identified fire scenarios in probabilistic analysis or one in the set of worst credible case scenarios in deterministic analysis. Thus, the BFPG calculated by FPM is fire scenario sensitive. The overall BFPG should be the sum of each BFPG weighted by the probability of its corresponding fire scenario, as shown below:

$$G = \sum \left(G_i \cdot P_i \right) \qquad E(2)$$

Where G is the overall BFPG, G_i is the BFPG under fire scenario i, and P_i is the probability of fire scenario i (for probabilistic analysis) or weight of worst credible fire scenario i (for deterministic analysis).

3.7 Summary

As discussed throughout this paper, the difficulties of recognizing the BFPG is due to the lack of dynamic tools that can be used conveniently to track the changes in building fire performance. Similar tools do exist in other building areas like energy efficiency and structural health. Therefore, the comparison of methods to improve the actual performance of an operational building in the areas of energy efficiency, structural health, and fire protection provides valuable insights for us to develop a promising dynamic tool, namely the FPM, to improve the actual fire performance of an operational building. In this section, the conceptual design of FPM is introduced, which includes discussions of related data collection methods, three major modules (Input, BFPG-checking, and Refinement) as well as how to apply a FPM tool in fire risk analysis. The benefits of using a FPM tool include the potential of closing the BFPG by informing the stakeholders in a timely manner of changes to the fire performance of their buildings, as well as for them to conduct trade off analysis among alternative fire protection strategies.

4. Conclusions

Measurability characterizes the maturity of a discipline, as a maxim says: "if you can't measure it, you can't manage it" [176]. An extension of this maxim in any engineering area could be: "if you can't monitor the performance, you can't control the risk". Compared to the relatively high measurability of performance (gap) in building energy efficiency and structural health, it is much harder to identify and measure the performance (gap) of buildings in fire protection engineering, indicating less maturity of the fire protection discipline. The reasons for this are extensive, including fire protection engineering not being well represented in the building performance optimization process, performance-based fire protection design methods not yet being widely trusted in the fire protection community, fire accidents being rare events, and lack of any realistic tools to measure the current status of fire performance of operational buildings. Based on insights from building energy performance monitoring and structural health monitoring, a conceptual design of FPM is proposed to address the important issue of how to improve the actual building fire performance or close the BFPG, providing a way to increase the maturity of fire protection engineering.

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Reference

[1] Ben Evarts (2018), Fire loss in the United States during 2017, NFPA

[2] Marty Ahrens (2017), U.S. experience with Sprinklers, NFPA

[3] Hall, J. (2011), U.S. experience with sprinklers, NFPA, Quincy MA

[4] Stephen G. Badger (2017), Large-loss fires in the United States 2016, NFPA report

[5] Stephen G. Badger (2016), Large-loss fires in the United States 2015, NFPA report

[6] Stephen G. Badger (2015), Large-loss fires in the United States 2014, NFPA report

[7] Carbon Trust. (2012). Closing the gap – lesson learned on realising the potential of low carbon building design. London: The Carbon Trust

[8] Burman, E., Mumovic, D., and Kimpian, J. (2014). Towards measurement and verification of energy performance under the framework of the European directive for energy performance of buildings. Energy 77, 153–163. https://doi:10.1016/j. energy.2014.05.102

[9] De Wilde, P. (2014). The gap between predicted and measured energy performance of buildings: a framework for investigation. Autom. Constr. 41, 40–49.

[10] Beat Frei, Carina, Sagerschnig, Dimitrios Gyalistras (2017), Performance gaps in Swiss buildings: an analysis of conflicting objectives and mitigation strategies, CISBAT 2017 International Conference – Future Buildings & Districts – Energy Efficiency from Nano to Urban Scale, 6-8 September 2017, Lausanne, Switzerland

[11] NFPA 1 Fire Code (2018), National Fire Protection Association, Quincy, MA

[12] International Fire Code (2018), International Code Council (ICC)

[13] ISO 239321-1 (2018), Fire safety engineering — General principles — Part 1: General

[14] Thomas P. DiNapoli (2015), Fire Safety, 2015-MS-1, Stake of New York, Office of the State Comptroller, https://www.osc.state.ny.us/local-government/audits/city/2015/05/27/fire-safety-2015-ms-1 accessed 10 July 2019

[15] Demanuele C, Tweddell T, Davies M (2010). Bridging the gap between predicted and actual energy performance in schools. World renewable energy congress XI: 25–30, September, Abu Dhabi, UAE

[16] Bordass B, Cohen R, Field J (2004). Energy performance of non-domestic buildings – closing the credibility gap. In: International conference on improving energy efficiency in commercial buildings. Frankfurt, Germany

[17] Bordass B, Cohen R, Standeven M, Leaman A (2001). Assessing building performance in use 3: energy performance of probe buildings. Build Res Inform;29(2):114–28.

[18] Anna Carolina Menezes, Andrew Cripps, Dino Bouchlaghem , Richard Buswell (2012), Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap, Applied Energy 97: 355–364

[19] Burman, E., Mumovic, D., and Kimpian, J. (2014). Towards measurement and verification of energy performance under the framework of the European directive for energy performance of buildings. Energy 77, 153–163. https://doi:10.1016/j. energy.2014.05.102

[20] van Dronkelaar, M. Dowson, E. Burman, C. Spataru, D. Mumovic (2016), A review of the energy performance gap and its underlying causes in non-domestic buildings, Front Mech Eng, 1 , p. 17

[21] J.F. Robinson, T.J. Foxon, P.G. Taylor (2016), Performance gap analysis case study of a non-domestic building, Proc. Inst. Civil Eng. Eng. Sustainability 169: 31–38.

[22] Yuming Sun (2014), Closing the building energy performance gap by improving our predictions, PhD thesis of Georgia Institute of Technology

[23] Magdalena Hajdukiewicz, David Byrne, Marcus M. Keane, Jamie Goggins (2015), Real-time monitoring framework to investigate the environmental and structural performance of buildings, Building and Environment, 86:1-16

[24] M.Jradi, K.Arendt, F.C.Sangogboye, C.G.Mattera, E.Markoska, M.B.Kjærgaard, C.T.Veje, B.N.Jørgensen (2018), ObepME, An online building energy performance monitoring and evaluation tool to reduce energy performance gaps, Energy and Buildings, Volume 166, Pages 196-209

[25] Jianhui Hu, WujunChen, YegaoQu, DeqingYang (2020), Safety and serviceability of membrane buildings: A critical review on architectural, material and structural performance, Engineering Structures, Volume 210

[26] Christian Cremona, Joao Santos (2018), Structural Health Monitoring as a Big-Data Problem, Structural Engineering International Jr: 243-254

[27] Hyun-Hee Ryu, Jong Soo Kim, Eun Gyu Choi, Sang-hoon Lee (2007), Preliminary design of structural health monitoring for high-rise buildings, International Journal of High-Rise Buildings, 6(3): 279-284

[28] Jerome Peter (2007), An overview of wireless structural health monitoring for civil structures, Phil. Trans. R. Soc. A: 345–372

[29] E. A. Johnson, A.M.ASCE1 ; H. F. Lam2 ; L. S. Katafygiotis, A.M.ASCE3 ; and J. L. Beck, M.ASCE (2004), Phase I IASC-ASCE Structural Health Monitoring Benchmark Problem Using Simulated Data, JOURNAL OF ENGINEERING MECHANICS © ASCE

[30] Pieter de Wilde (2019), Ten questions concerning building performance analysis, Building and Environment, 153: 110-117

[31] Hensen, J.L.M. & Lamberts, R. (Eds.) (2011). Introduction to building performance simulation. Building performance simulation for design and operation, pp. 1-14. London: Spon Press.

[32] Hyeun Jun Moon, Jong-Ryeul Sohn & Taeyon Hwang (2016), Indoor Air Quality Performance of Ventilation Systems in Classrooms, Journal of Asian

Architecture and Building Engineering, 15:2, 343-348
[33] D. P. Wyon (2004), the effects of indoor air quality on performance and productivity, Indoor Air ; 14 (Suppl 7): 92–101
[34] Noel Djongyang, , Rene´ Tchinda,, Donatien Njomo (2010), Thermal comfort: A review paper, Renewable and Sustainable Energy Reviews, Volume 14, Issue 9, Pages 2626-2640
[35] M.Z. Yusof (2014), Building Investigation: Material or Structural Performance, MATEC Web of Conferences 10
[36] George V. Hadjisophocleous, Noureddine Benichou (1999), Performance criteria used in fire safety design, Automation in Construction 8: 489–501
[37] Brian J. Meacham, Richard L.P. Custer (1995), Performance-based fire safety engineering: an introduction of basic concepts, Journal of Fire Protection Engineering, 1995, 7(2): 35-54
[38] P. de Wilde (2017), The concept of building performance in building performance simulation: a critical review, 15th IBPSA Conf, 2017 San Francisco, USA
[39] Rachel Becker (2008), Fundamentals of performance-based building design, Build simulation 1(4):356-371
[40] Aktan, A. E., Ellingwood, B. R. et al. (2007). Performance-based engineering of constructed systems, Journal of Structural Engineering, ASCE 133(3): 311–323
[41] Brian J. Meacham (1999), International experience in the development and use of performance-based fire safety design methods: evolution, current situation and thoughts for the future, Fire safety science-proceedings of the sixth international symposium, pp 59-76
[42] Mondrup, T. F., Karlshøj, J., & Vestergaard, F. (2014). Building Performance Simulation tools for planning of energy efficiency retrofits. In J. Arfvidsson, L-E. Harderup, A. Kumlin, & B. Rosencrantz (Eds.), Proceedings of the 10th Nordic Symposium on Building Physics Lund University.
[43] Theodoros G.Theodosiou, Aikaterini G.Tsikaloudaki, Karolos J.Kontoleon, DimitriosK.Bikas (2015), Thermal bridging analysis on cladding systems for building facades, Energy and Buildings, 109(15): 377-384
[44] H. Radhi, S. Sharples (2014), "Assessing the environmental and economic impacts of cladding systems for green buildings" in Eco-efficient Construction and Building Materials, Pages 484-501
[45] Ralph Evins (2013), A review of computational optimisation methods applied to sustainable building design, Renewable and Sustainable Energy Reviews, Volume 22, Pages 230-245
[46] ARUP (2012), The Building performance gap – closing it through better measurement
[47] Hensen, J.L.M. (2004), Towards more effective use of building performance simulation in design, In: Van Leeuwen, J.P. and H.J.P. Timmermans (eds.) Developments in Design & Decision Support Systems in Architecture and Urban Planning, Eindhoven: Eindhoven University of Technology, ISBN 90-6814-155-4, p. 291-306
[48]Roya Rezaee, Godfried Augenbroe, and Jinsol Kim (2015), Assessment of uncertainty and confidence in building design exploration, Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 29, 429–441
[49] R. C. G. M. Loonen, M. L. de Klijn-Chevalerias & J. L. M. Hensen (2019), Opportunities and pitfalls of using building performance simulation in explorative R&D contexts, Journal of Building Performance Simulation, 12:3, 272-288, DOI: 10.1080/19401493.2018.1561754
[50] Niko Gentile, Jouri Kanters and Henrik Davidsson (2020), A method to introduce building performance simulation to beginners, Energies, 13, 1941; doi:10.3390/en13081941
[51] Hong, T., Feng, W., Lu, A., Xia, J., Yang, L., Shen, Q., Im, P., Bhandari, M. (2013), Building energy monitoring and analysis. Lawrence Berkeley National Laboratory, LBNL-xxxxx.
[52] Xing Shi, Binghui Si, Jiangshan Zhao, Zhichao Tian, Chao Wang, Xing Jin and Xin Zhou (2019), Magnitude, causes, and solutions of the performance gap of buildings: a review, 11, 937; doi:10.3390/su11030937
[53] A. Ahmed, N. Korres, J. Ploennings, H. Elhadi, K. Menzel (2011), Mining building performance data for energy-efficient operation, Adv. Eng. Inform. 25: 341–354.
[54] W.L. Lee, W.H. Yik, J. Burnett (2001), Simplifying energy performance assessment in Hong Kong environmental assessment method, Building Services Engineering Research and Technology 2: 113–132
[55] Jan LM Hensen (2011), Building performance simulation for sustainable building design and operation, Proceedings of the 60th anniversary Environmental Engineering Department, Prague, Czech Technical University, pp.8
[56] J.A. Clarke, J.L.M. Hensen (2015), Integrated building performance simulation: progress, prospects and requirements, Building and Environment 91:294-306
[57] Kristoffer Negendahl (2015), Building performance simulation in the early design stage: an introduction to integrated dynamic models, Automation in Construction 54:39–53
[58] Joe Clarke (2015), A vision for building performance simulation: a position paper prepared on behalf of the IBPSA Board, Journal of Building Performance Simulation, 8:2, 39-43, DOI: 10.1080/19401493.2015.1007699,
[59] Mauricio Nath Lopes, Gabriel Iwamoto, Humberto Leitao Riella, Roberto Lamberts and Lucila Maria Souza Campos (2011):. The building simulation as an alternative method in Brazilian energy efficiency labelling of commercial buildings. Proceedings of Building Simulation, 12th Conference of International Building Performance Simulation Association, Sydney, 2055 - 2062
[60] M. Nadarajan and V. Kirubakaran (2016), Simulation tools for residential buildings – a review on concepts and technologies, ARPN Journal of

Engineering and Applied Sciences, VOL. 11, NO. 5
[61] Shengwei Wang, Chengchu Yan, Fu Xiao (2012), Quantitative energy performance assessment methods for existing buildings, Energy and Buildings 55: 873–888
[62] W.L. Lee, F.W.H. Yik, J. Burnett (2003), A method to assess the energy performance of existing commercial complexes, Indoor and Built Environment 12 (5): 311–327
[63] Preiser, W.F.E., Rabinowitz, H.Z. and White, E.T. (1988) Post-Occupancy Evaluation. Van Mostrand Reinhold Co., New York
[64] Robert Cohen, Mark Standeven, Bill Bordass, Adrian Leaman (2001)), Assessing building performance in use 1: the Probe process, Building Research & Information 29 (2): 85–102
[65] A.J. Field, J. Soper, P. Jones,W. Bordass, P. Grigg (1997), Energy performance of occupied non-domestic buildings: Assessment by analysing end-use energy consumption, Building Services Engineering Research and Technology 18 (1): 39–46
[66] Zheng Yang, Burcin Becerik-Gerber (2015), A model calibration framework for simultaneous multi-level building energy simulation, Applied Energy, 149: 415-431
[67] Catbas, F. N (2009), Structural health monitoring: applications and data analysis, Woodhead Publishing Series in Civil and Structural Engineering, Pages 1-39
[68] M. SÁNCHEZ-SILVAJ. RIASCOS-OCHOA (2013), Seismic risk models for aging and deteriorating buildings and civil infrastructure, in "Handbook of Seismic Risk Analysis and Management of Civil Infrastructure Systems", Woodhead Publishing Series in Civil and Structural Engineering, Pages 387-409
[69] FEMA P-424 (2010), Design guide for improving school safety in earthquakes, floods, and high winds
[70] FEMA 454 (2006), Designing for Earthquakes
[71] Kicklighter Law (2019), https://kicklighterlaw.com/blog/4-types-of-construction-defects/, first accessed on July/29/2020.
[72] Sheelah Sivanathan, Jibril D. Jibril, Jivasangeeta, Puvaneswary Thanaraju, Yakubu Amin Dodo, Suleiman Aliyu Shika (2012), An overview of design deficiencies on building maintenance, OIDA International Journal of Sustainable Development
[73] Ahmad Suffian (2013), Some common maintenance problems and building defects: our experiences, The 2nd International Conference on Rehabilitation and Maintenance in Civil Engineering, Procedia Engineering 54: 101 – 108
[74] Ellingwood, B. and Harris, J.R. (1977), Reliability-based performance criteria for structures, Proceedings, 2nd Engrg Mech Specialty Conference, ASCE, pp. 124-127,
[75] N. X. Liu, X. Zhao, H. H. Sun, Y. M. Zheng, and J. M. Ding (2011), Structural performance assessment and control of super tall buildings during construction, The Twelfth East Asia-Pacific Conference on Structural Engineering and Construction, Procedia Engineering 14: 2503–2510
[76] Mauricio Sanchez-SilvaGeorgia-Ann KlutkeDavid V. Rosowsky (2011), Life-cycle performance of structures subject to multiple deterioration mechanisms, Structural Safety, Volume 33, Issue 3, Pages 206-217
[77] Wei Fan and Pizhong Qiao (2011), Vibration-based damage identification methods: a review and comparative study, Structure Health Monitoring, Vol 10(1): 83–29
[78] Peter C. Chang, Alison Flatau and S. C. Liu (2003), Review paper: health monitoring of civil infrastructure, Structural Health Monitoring, 2(3): 257-267
[79] Jan D.Achenbach (2009), Structural health monitoring – What is the prescription, Mechanics Research Communications 36(2): 137-142
[80] R. Unzu J.A. Nazabal, G. Vargas, R.J. Hernández, C. Fernández-Valdivielso, N. Urriza, M. Galarza, M. Lopez-Amo (2013), Fiber optic and KNX sensors network for remote monitoring a new building cladding system, Automation in Construction, Volume 30, Pages 9-14
[81] Chang, F.-K. (1999). Structural Health Monitoring 2000: Proc., 2nd Int. Workshop on Structural Health Monitoring, Stanford Univ., Technomic, Lancaster, Pa.
[82] NPFA 550 (2007) Guide to the fire safety concepts. National Fire Protection Association, Quincy, MA
[83] Ian Jutras, Brian J. Meacham (2016), Development of objective-criteria-scenario triplets and design fires for performance-based Fire Safety Design, Journal of Building Engineering, volume 8, 269-284
[84] Martin, D., Tomida, M. & Meacham, B (2016). Environmental impact of fire. Fire Sci Rev 5, 5. https://doi.org/10.1186/s40038-016-0014-1
[85] Robert W. Fitzgerald (2003), Building fire performance analysis, John Wiley & Sons Ltd, 1st Edition, John Wiley & Sons Ltd
[86] Katharina Fischer, Gianluca De Sanctis, Jochen Kohler, Michael H. Faber, Mario Fontana (2015), Combining engineering and data-driven approaches: calibration of a generic fire risk model with data, Fire Safety Journal, Volume 74, pp. 32-42
[87] Takeyoshi Tanaka (2011), Integration of fire risk concept into performance-based evacuation safety design of buildings, Fire Safety Science – Proceedings of the 10th International Symposium, pp. 3-22
[88] Emina Brulić, Sanin DŽIDIĆ (2018), Lessons learned from Grenfell tower fire, Scientific Conference, Planning, Design, Construction and Building Renewal, NOVI SAD
[89] Kong D, Lu S, Frantzich H, Lo SM (2013), A method for linking safety factor to the target probability of failure in fire safety engineering. Journal of Civil Engineering and Management,19:S212–S221.
[90] Marty Ahrens (2019), Home fires started by smoking, NFPA report
[91] Marty Ahrens (2018), Home structure fires, NFPA report

[92] Marty Ahrens (2016), High-rise building fires, NFPA report
[93] Richard Campbell (2013), U.S. Structure fires in office properties
[94] Wen-xia Ye (2016), Investigation and identification of fire caused by setting off fireworks, Procedia Engineering 135: 427 – 430
[95] Wolski, N. Dembsey, B.J. Meacham (2000), Accommodating perceptions of risk in performance-based building fire safety code development Fire Saf. J., 34, pp. 297-309
[96] Cristian Maluk, Michael Woodrow, Jose Luis Torero (2017), The potential of integrating fire safety in modern building design, Fire Safety Journal, vol 88, pp 104-112
[97] Brian Meacham, Robert Bowen , Jon Traw & Amanda Moore (2005), Performance-based building regulation: current situation and future needs, Building Research & Information, 33:2, 91-106
[98] He, Y. & Grubits, S. (2010). A risk-based equivalence approach to fire resistance design for buildings. Journal of Fire Protection Engineering, 20(1):5–26
[99] Bjelland, H., & Njå, O. (2012). Fourteen years of experience with performance-based fire safety engineering in Norway – lessons learned. Paper presented at the 9th International Conference on Performance-Based Code and Fire Safety Design Methods
[100] Henrik Bjelland (2013), Engineering safety with applications to fire safety design of buildings and road tunnels, PhD Thesis, University of Stavanger, Norway
[101] Park, H., Meacham, B.J., Dembsey, N.A. et al (2015). Conceptual model development for holistic building fire safety performance analysis. Fire Technol 51, 173–193 https://doi.org/10.1007/s10694-013-0374-1
[102] Kathy A. Notarianni (2000), The role of uncertainty in improving fire protection regulation, PhD thesis of Carnegie Mellon University
[103] Alvarez A (2012), An integrated framework for the next generation of risk-informed performance-based design approach used in fire safety engineering. WPI, Worcester
[104] Littlewood, J. R. Alam, M. Goodhew, S. Davies, G (2017), The 'Safety Gap' in buildings: perceptions of Welsh Fire Safety Professionals, Energy Procedia 134: 787–796
[105] Littlewood, J.R. Alam, M. Goodhew, S. (2017), A new methodology for the selective measurement of building performance and safety. Energy Procedia, Volume 111, Pages 338–346
[106] Littlewood, J.R. Smallwood. I. (2015), Testing building fabric performance and the impacts upon occupant safety, energy use and carbon inefficiencies in dwellings. Energy Procedia, Volume 83, Pages 454–463.
[107] Littlewood, J.R. Smallwood, I. (2017), In-construction tests show rapid smoke spread across dwellings. Journal of Engineering Sustainability, 170(2): 102-112
[108] James A. Milke (2014), Effectiveness and reliability of fire protection systems, , https://www.sfpe.org/page/2014_Q4_4/Effectiveness-and-Reliability-of-Fire-Protection-Systems.htm, accessed 19 September 2018
[109] Viera, D (1991), Can you count on your fire doors? Record, July/August: pp. 12-15
[110] Dusing, J., Buchanan, A. and Elms, D (1979). Fire spread analysis of multi-compartment buildings, Research Report 79112, Department of Civil Engineering, University of Canterbury, New Zealand
[111] Scarff, S. (1993), Field performance of fire protection systems, Balanced Design Concepts Workshop, Richard W. Bukowski, ed., NISTIR 5264, NIST, Gaithersburg, MD,
[112] Milke, J., Hanson, R., and Mizrack, D (2013). Comparison of the life safety performance of smoke detectors and sprinklers in commercial, industrial and education institution housing, Department of Fire Protection Engineering, University of Maryland, College Park, MD
[113] FEMA (2013), Multiple-fatality fires in residential buildings (2009-2011), Topical Fire Report Series, 14(6)
[114] Bryan, J.L. (1995), Behavioral response to fire and smoke, FPE Handbook of Fire Protection Engineering, 2nd ed., NFPA, Quincy, MA
[115] Brian J. Meacham, (1999) Integrating human behavior and response issues into fire safety management of facilities, Facilities, 17(9/10): .303-312,
[116] Nicholas A. Dembsey, Brian J. Meacham, Honggang Wang (2017), A literature review of sprinkler trade-offs, report of NASFM fire research and education foundation
[117] Kevin Frank, Neil Gravestock, Michael Spearpoint and Charles Fleischmann (2013), A review of sprinkler system effectiveness studies, Fire Science Reviews, 2 (6): 1-19
[118] R. W. Bukowski, E. K. Budnick and C. F. Schemel (1999), Estimates of the operational reliability of fire protection systems, International Conference on Fire Research and Engineering (ICFRE3), 3rd Proc.: 97-98
[119] Leong Poon (2013), Assessing the reliance of sprinklers for active protection of structures, The 9th Asia-Oceania Symposium on Fire Science and Technology, Procedia Engineering, 62: 618–628
[120] John R. Hall, Jr. (2013), U.S. Experience with sprinklers, NFPA
[121] Daniel Malm and Ann-Ida Petterson (2008), Reliability of automatic sprinkler systems: an analysis of available statistics, Lund University, Stockholm, Sweden
[122] Margrethe Kobes, Ira Helsloot, Bauke de Vries, Jos G. Post (2010), Building safety and human behavior in fire: a literature review, Fire Safety Journal 45: 1–11.
[123] Kobes, M., I. Helsloot, B. de Vries, N. Oberijé, N. Rosmuller (2007). Fire response performance in a hotel - Behavioral research. In: Conference proceedings Interflam 2007. 11th international fire science and engineering conference. Vol. 2, pp. 1429-1434
[124] Andy Starnes (2019), Four Critical Issues Facing Fire Services Today,

https://insights.samsung.com/2019/06/17/four-critical-issues-facing-fire-services-today/, accessed 30 June 2020

[125]Steven Mills (2005), Managing change, Fire Engineering, https://www.fireengineering.com/articles/print/volume-159/issue-8/features/managing-change.html, accessed 19 September 2018

[126] Katherine Barrett & Richard Greene (2019), Shortage of volunteer firefighters threatens fire departments' existence, https://www.governing.com/topics/public-justice-safety/gov-volunteer-firefighters-department.html, accessed 30 June 2020

[127] Hylton J.G. Haynes (2017), Fire loss in the United States during 2016, NFPA research

[128] Stephen G. Badger (2015), Catastrophic multiple-death fires in 2014, NFPA report

[129] Stephen G. Badger (2016), Catastrophic multiple-death fires in 2015, NFPA report, September

[130] Stephen G. Badger (2017), Catastrophic multiple-death fires in 2016, NFPA report

[131] Henrik Bjelland, Ove Nja, Atle William Heskestad, Geir Sverre Braut (2015), The concepts of safety level and safety margin: framework for fire safety design of novel buildings, Fire Technology, 51, 409–441

[132] J.M. Watts, J.R. Hall (2015), Introduction to fire risk analysis, SFPE Handbook for Fire Protection Engineering (Fifth ed.), NFPA, Quincy, MA

[133] M. Fontana, J.P. Favre, C. Fetz (1999), A survey of 40,000 building fires in Switzerland, Fire Safety Journal. 32: 137 – 158

[134] George V. Hadjisophocleous, Noureddine Benichou and Amal S. Tamim (1998), Literature review of performance-based fire codes and design environment, Journal of Fire Protection Engineering, 9(1), pp 12-40.

[135] A Alvarez, BJ Meacham and NA Dembsey (2013), Twenty years of performance-based fire protection design: challenges faced and a look ahead, Journal of Fire Protection Engineering, 249-276

[136] NFPA Technical Committees (2009). NFPA 101 Life Safety Code. Quincy, MA: National Fire Protection Association,

[137] B.J. Meacham (2001), Addressing risk and uncertainty in performance-based fire protection engineering, Fire Protection Engineering, Vol. 10, pp. 16-25

[138] Jun Zhuang, Vineet M. Payyappalli, Adam Behrendt, and Kathryn Lukasiewicz (2017), Total cost of fire in the United States, NFPA Fire Protection Research Foundation report

[139] Morgan J. Hurley (2013), Achieving the right balance – safety and the cost of safety, https://www.sfpe.org/page/2013_Q2_5, accessed 10 June 2019

[140] G.V. Hadjisophocleous and Z. Fu (2004), Literature review of fire risk assessment methodologies, International Journal on Engineering Performance-Based Fire Codes, Volume 6, Number 1, p.28-45

[141] International Code Council (ICC) (2018), Chapter 9 Fire protection and life safety systems, International Building Code

[142] Daniel Rosberg, Andrew Purchase and Karl Fridolf (2018), Acceptance criteria in fire safety engineering: a review and case study, Fire and Evacuation Modeling Technical Conference (FEMTC)

[143] K. Kang (2007), Prediction of smoke visibility during an underground rail station fire, International Association for Fire Safety Science

[144] Peacock, R.; Jones, W.; Bukowski, R. (1993). Verification of a model of fire and smoke transport, Fire Safety Journal 21(2): 89–129.

[145] Henrik Bjelland, Audun Borg (2013), On the use of scenario analysis in combination with prescriptive fire safety design requirements, Environ Syst Decis, 33:33–42

[146] David Purser (2003), ASET and RSET: addressing some issues in relation to occupant behavior and tenability, International Association for Fire Safety Science

[147] W.K. Chow (2011), Six points to note in applying timeline analysis in performance-based design for fire safety provisions in the far east, International Journal on Engineering Performance-Based Fire Codes, 10(1), p.1-5

[148] S.L. Poon (2014), A dynamic approach to ASET/RSET assessment in performance based design, Procedia Engineering 71: 173 – 181

[149] CFPA-E Guideline No 19:2009 F (2009), Fire safety engineering concerning evacuation from buildings, CFPEEUROPE

[150] Michael Crowley, Dick Bukowski, Carl Baldassarra (2014), Validation of the fire safety evaluation system (FSES) in the 2013 Edition of NFPA 101A, NFPA's Fire Research Foundation

[151] Dow (1987). Dow's fire and explosion index hazard classification guide, 6th ed. Midland

[152] Fitzgerald R (1993) Building fire safety evaluation method. Worcester Polytechnic Institute, Worcester

[153] Danzi, E., Fiorentini, L. & Marmo, L. (2020), FLAME: A Parametric Fire Risk Assessment Method Supporting Performance Based Approaches. Fire Technol

[154] Xiao Li (2015), Modeling of Barrier Failure and Fire Spread in CUrisk, PhD thesis, Carleton University

[155]Hadjisophocleous, G., Fu, Z., and Li, X.(2011), Technical report on CU risk – fire risk analysis model, Department of Civil and Environmental Engineering, Carleton University Ottawa, Ontario

[156]Yung, D., Hadjisophocleous, G.V., and Proulx, G., (1997), Modelling concepts for the risk-cost assessment model 'Firecam' and its application to a Canadian government office building, Fire Safety Science 5: 619-630. DOI:10.3801/IAFSS.FSS.5-619

[157] Bart Van Weyenberge, Xavier Deckers, Robby Caspeele, and Bart Merci (2019), Development of an integrated risk assessment method to quantify the

life safety risk in buildings in case of fire, Fire Technology, 55:1211–1242

[158] Nahom Daniel and Dr. Guillermo Rein (2016), The fire navigator: forecasting the spread of building fires on the basis of sensor data, Fire Protection Engineering, Extra Issue 3

[159] Matthew A. Johann, Leonard D. Albano, Robert W. Fitzgerald, and Brian J. Meacham (2006), Performance-based structural fire safety, Journal of performance of constructed facilities, 20(1): 45-53

[160] Ellingwood, B. (1978), Reliability basis of load and resistance factors for reinforced concrete design. NBS Building Science Series 110, NBS

[161] Johan Lundin (2005), Safety in case of fire – the effect of changing regulations, PhD thesis, Lund University

[162] Denis H Camilleri (2003), An overview of the structural Eurocodes in the construction industry, The Structural Engineer, July 15, 14-17

[163] Morgan J. Hurley, Eric R. Rosenbaum (2015), Performance-based fire safety design, CRC Press, Taylor & Francis Group, LLC

[164] SFPE (2007), SFPE engineering guide to performance-based fire protection, National Fire Protection Association, Quincy, MA

[165] A. Bwalya, G. Lougheed, A. Kashef, H. Saber (2011), Survey results of combustible contents and floor areas in Canadian multi-family dwellings, Fire Technol. 47:1121-1140

[166] Sikkink, Pamela G.; Lutes, Duncan C.; Keane, Robert E (2009), Field guide for identifying fuel loading models. Gen. Tech. Rep. RMRS-GTR-225. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 33 p

[167] Balaras C., Argiriou A. (2002), Infrared thermography for building diagnostics. Energy Build. 34: 171–183.

[168] Hall JR Jr and Watts J Jr. (2008), Fire risk analysis. The Fire Protection Handbook. Vol. 1, 20th ed. Section 3 (Cote AE, ed.), Quincy, MA: NFPA

[169] Heinrich, H. W. Industrial accident prevention: a scientific approach, New York: McGraw-Hill, 1st edition, 1931; 2nd edition, 1941; 3rd edition, 1950; 4th edition, 1959

[170] Andre I. Khuri, Siuli Mukhopadhyay (2010), Response surface methodology, Advanced Review, Volume 2, March/April 2010

[171] Kiran M. Desai, Shrikant A. Survase, Parag S. Saudagar, S.S. Lele, Rekha S. Singhal (2008), Comparison of artificial neural network (ANN) and response surface methodology (RSM) in fermentation media optimization: case study of fermentative production of scleroglucan, Biochemical Engineering Journal 41: 266–273

[172] J. Prakash Maran, B. Priya (2015), Comparison of response surface methodology and artificial neural network approach towards efficient ultrasound-assisted biodiesel production from muskmelon oil, Ultrasonics Sonochemistry Volume 23, Pages 192-200

[173] Shafiul Haque, Saif Khan, Mohd Wahid, Sajad A. Dar, Nipunjot Soni, Raju K. Mandal, Vineeta Singh, Dileep Tiwari, Mohtashim Lohani, Mohammed Y. Areeshi, Thavendran Govender, Hendrik G. Kruger and Arshad Jawed (2016), Artificial intelligence vs. statistical modeling and optimization of continuous bead milling process for bacterial cell lysis, Microbiol

[174] Ebrahimpour A, Abd Rahman RN, Ean Ch'ng DH, Basri M, Salleh AB. (2008), A modeling study by response surface methodology and artificial neural network on culture parameters optimization for thermostable lipase production from a newly isolated thermophilic geobacillus sp. strain ARM. BMC Biotechnol, 23;8:96. doi: 10.1186/1472-6750-8-96. PMID: 19105837; PMCID: PMC2637859.

[175] Mahiran Basri, Raja Noor Zaliha Raja Abd Rahman, Afshin Ebrahimpour, Abu Bakar Salleh, Erin Ryantin Gunawan, and Mohd Basyaruddin Abd Rahman (2007), Comparison of estimation capabilities of response surface methodology (RSM) with artificial neural network (ANN) in lipase-catalyzed synthesis of palm-based wax ester, BMC Biotechnol: 7: 53

[176] Lucas Coffeen (2009), "If You Can't Measure it, You Can't Manage it", MARKETCULTURE BLOG, http://blog.marketculture.com/2009/03/20/if-you-cant-measure-it-you-cantmanage-it-peter-drucker/, archived at http://perma.cc/3VVC-SGHT, accessed 10 May 2020

Section 3

A SENSITIVITY MATRIX METHOD TO UNDERSTAND THE BUILDING FIRE PERFORMANCE GAP

A Sensitivity Matrix Method to Understand the Building Fire Egress Performance Gap

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Abstract:

A building performance gap, defined as the gap between predicted or desired performance and actual performance of a building throughout its entire lifecycle, may exist in each building area, but the treatment of it differs from discipline to discipline. While performance monitoring tools are available and widely applied in energy efficiency and structural health, there are currently no available performance monitoring tools in the area of fire safety. Although a fire accident is an acute phenomenon that is rare and unpredictable and makes observing a building's fire performance very difficult, the evolution of underlying factors that could determine the building fire performance in a future fire accident is in fact a chronic phenomenon that is observable and predictable. This article proposes a sensitivity matrix method (SMM) based on Taylor series expansion to better understand the building fire egress performance gap by analyzing changes in chronic influencing factors. Uncertainty of this method is investigated against FDS simulations in an exemplar 3-story apartment building and described by two parameters: the system bias and the relative standard deviation. As to the 25 selected cases, the system bias of the SMM is about 12% less than one, showing that this model tends to underpredict the available safe egress time (ASET). The relative standard deviation is about 18%. The applicability of SMM expressed by the percentage of predictions within a 20% error range is 76%. Combining ASET with the required safe egress time (RSET), the resulting Egress Safety Ratio (ESR) is chosen as the key building fire egress performance indicator in case studies, and a prototype fire performance monitoring tool based on the SMM is developed, indicating its potential of closing and tracking the building fire egress performance gap.

Keywords: Structural health monitoring, Building fire egress performance gap, FDS, sensitivity matrix method, ASET, RSET, Egress safety ratio, Fire Performance Monitoring, model uncertainty, applicability

Nomenclature

S	Sensitivity (matrix)
Y	Response vector
X	Input vector
R	Fire protection performance
a	Design parameters (vector)
Δa	Change of design parameters (vector)
G	Fire performance gap
E	Relative error

1. Introduction

As used in this paper, the performance gap is defined as the gap between the predicted/desired performance and the actual performance in buildings. The performance gap exists in energy efficiency, structural health, thermal comfort, indoor air quality, fire protection, and other building performance areas [1]. How it is treated, however, differs across engineering disciplines. The degree to which performance is measurable in a widely agreed manner indicates to a large extent the degree of maturity in the study of the specific building area. For example, building energy performance and structural health performance are deemed as well developed partly due to the wide application of energy and structural health monitoring systems [2 ~ 8], whereas fire protection engineering is deemed as still in its developmental stage since currently the concept of building fire performance monitoring is not well developed.

The building fire performance gap (BFPG) is defined as the gap between the predicted building fire performance during the design stage and the actual building fire performance during the operation stage [9]. A component performance assessment identifies the intended fire performance of an individual building system or component, such as a fire door, structural framing, or a smoke detection system. There are four types of component performance: Passive Fire Protection (PFP) system performance, Active Fire Protection (AFP) system performance, Occupants' Fire Response (OFR) performance, and Fire Fighters' Response (FFR) performance, which work together to fulfill the performance criteria related to life safety, property protection, business continuity and the natural environment. Factors that could affect each of the four component performances stem from three sets of characteristics [10]: building characteristics, occupant characteristics, and fire characteristics. Building characteristics describe the physical features, contents, and ambient environment within the building. They can affect the evacuation of occupants, growth and spread of fire, movement of combustion products, and firefighting response. Occupant characteristics determine the ability of building occupants to respond and evacuate during a fire emergency. Fire characteristics describe the history of a fire scenario, including first item ignition, fire growth, flashover, full development, decay and extinction. Although a fire accident is an acute phenomenon that is rare and unpredictable and makes observing a building's fire performance very difficult, the evolution of these factors that could someday in the future determine the building fire performance in a fire accident is in fact a chronic phenomenon that is frequent, observable and predictable [9]. For example, the degradation of fire resistance capacities of building elements does not happen suddenly, or the changes of the walking speed of occupants due to the aging process of the occupants. The changes of apartment finishes and furniture, which influence the fire load, flame spread rate, and the heat release rate, may be faster when new occupants move in, but may still be predictable or observable.

With the increasing of complexity of problems to be solved, it becomes challenging or even impossible to work out analytical solutions for these problems. Numerical methods with different needs of computational resource have to be introduced. It is not easy to understand the response of output variables under given changes of input parameters until specific numerical methods are employed. However, the sensitivity matrix of some complicated problems may be easier to obtain because it needs to consider only the change of one input parameter at a time. The application of a sensitivity matrix provides a first order approximate estimation of the response of output variables under given variations of input parameters, which is convenient, fast, effective, and thus meets the needs of dynamically updating the building fire performance in a timely fashion.

Based on the theory of Taylor series expansion, a Sensitivity Matric Method (SMM) [11,12] is proposed in section 2 to evaluate the changes of building fire performance based on the chronic changes of input parameters. In other words, the SMM makes it possible to dynamically monitor the potential building fire performance (gap). Following Figure 1 adjusted from [9] shows the schematic diagram of a fire performance monitoring tool (FPM):

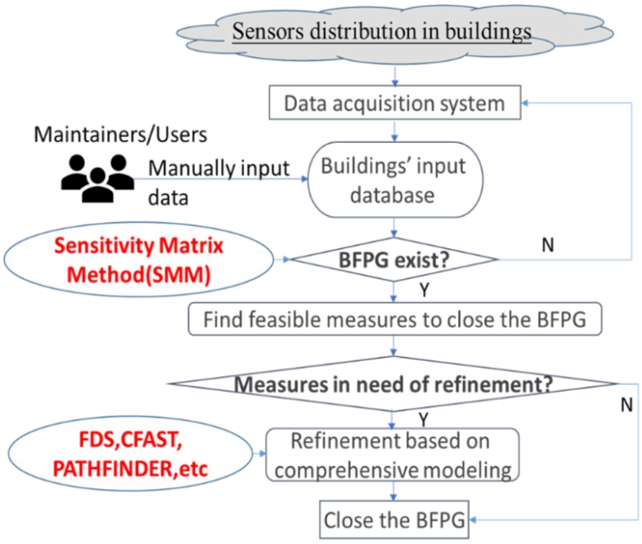

Figure 1 Schematic view of a dynamic building fire performance (gap) monitoring tool: FPM

In this figure, input parameters are first screened by sensitivity analysis to determine the ones of importance, and then they are measured continually. Once significant changes (e.g. 5%) of input parameters' values are recorded, an estimate of the fire performance (gap) can be immediately worked out by a SMM. If the estimated result changes considerably (e.g., exceeding 10%), more detailed fire simulations will be conducted to confirm the estimated result. If the rechecked result is still considerable, the stakeholders will be informed and persuaded to do something to close the fire performance gap.

In section 3 an available safety egress time (ASET) analysis in an exemplar 3-story apartment building is described in terms of applying the SMM, followed in section 4 by a combined application of the SMM in closing and tracking the building fire performance gap related to egress safety ratio (ESR) which is the ratio of ASET to required safe egress time or RSET. Conclusions and potential work are discussed in the section 5.

2. Development of the Sensitivity Matric Method (SMM) in building fire performance analysis

2.1 Sensitivity analysis (SA) method in component fire performance gap analysis

2.1.1 Introduction to SA

Sensitivity analysis is an important way to address the uncertainties in issues related to building fire safety. Saltelli et al[13] define sensitivity analysis as: "The study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input". Ideally, uncertainty and sensitivity analyses should be run in tandem, with the former focusing on the possible varying range of both input parameters and output variables of models, and the latter focusing on how output variables are affected by input parameters.

Generally there are three kinds of sensitivity analysis methods, namely the derivative-based local sensitivity analysis (LSA) method [12,13] the Morris one-at-a-time (OAT) method [14], and the variance based global sensitivity analysis (GSA) method [13,15]. In LSA, the local sensitivity index is defined as the scaled partial derivative of output variable y_j with respect to input parameter x_i. It is computed by changing each parameter by a small increment Δx_i from the reference parameter values x_i^0 and computing the difference in y_j. The Morris one-at-a-time (OAT) method can be considered as an extension of the LSA method, where each parameter range is scaled to the unit interval [0, 1] and partitioned into (p−1) equally sized intervals. The reference value of each parameter is selected randomly from the set {0, 1/(p−1), 2/(p−1), …, 1−Δ}. The fixed increment Δ=p/{2(p−1)} is added to each parameter in random order to compute the elementary effect (EE) of x_i on output y_j. While the LSA and OAT methods are difference-based, the Sobol′ /Saltelli's GLA method is variance-based. The random variable vector $Y=\{y_j\}$ and the random vector $X=\{x_i\}$ are defined for the system response and the parameters, respectively. The sampled response and parameters are y_j and x_i. The first-order sensitivity index is defined by $S_i = V\left[E\left[Y \mid X_i\right]\right]/V\left[Y\right]$, where E[•] and V[•] represent mean and variance, respectively. S_i quantifies the first-order effect, i.e., the relative contribution of x_i to the uncertainty of Y excluding the interaction effect with other parameters. In addition, the total sensitivity index of x_i is defined by $S_{ti} = 1 - V\left[E\left[Y \mid X_{\sim i}\right]\right]/V\left[Y\right]$, where $E\left[Y \mid X_{\sim i}\right]$ represents the mean of Y conditioned on all the parameters but x_i. S_{ti} accounts for the total effect of x_i including interactional effects, and is used to identify parameters with negligible effects and parameters that can be fixed.

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2.1.2 Theoretical basis of SMM

In fire protection engineering, deterministic fire models are widely applied in performance-based design (PBD) [16,17,18]. To analyze the uncertainties and sensitivity of input parameters in PBD, the derivative-based LSA method is more suitable than GSA method and simpler than Morris' OAT method. First, the LSA method needs a reference or base line, which readily exists in PBD: either the corresponding prescriptive-based design or a trial design can work as a baseline. Second, the physical meaning of LSA is straightforward. In PBD, the fire protection performance R_j can be deemed as a function of design parameters a_i, thus the derivative $\partial R_j / \partial a_i$ can be thought of as fire performance gap ΔR_j caused by changes of a single design parameters Δa_i.

It is the interaction between fire scenario and trial designs, which is simulated by appropriate fire models, that results in component fire performance. Any change in parameters defining a fire scenario or trial designs may lead to changes in component fire performance represented by a series of time variables or m output responses of an adopted fire model. In vector notation, the m responses are represented as the column vector $R = \left(R_1, ..., R_m\right)^T$, of which each R_j is a function of the parameters vector $a = \left(a_1, ..., a_k\right)^T$:

$$R_j = R_j\left(a_1,...,a_k\right) = R_j\left(a_1^0+\Delta a_1,...,a_k^0+\Delta a_k\right) \quad E(1)$$

Where $a=\left(a_1,...,a_k\right)^T$ is the input parameter of an operational building, $a^0=\left(a_1^0,...,a_k^0\right)^T$ is the input parameter vector of the same building at design stage (baseline). $\Delta a=\left(\Delta a_1,...,\Delta a_k\right)^T$ is the change vector of input parameters between the design stage and the operational stage, namely

$$\Delta a_i = \left(a_i - a_i^0\right) \quad E(2)$$

. Expanding $R_j\left(a_1^0+\Delta a_1,...,a_k^0+\Delta a_k\right)$ in a Taylor series around the design values $a^0=\left(a_1^0,...,a_k^0\right)^T$ and retaining only the terms up to the n^{th} order in the variations around a_i^0 gives:

$$\begin{aligned} R_j &= R_j\left(a_1,...,a_k\right) = R_j\left(a_1^0+\Delta a_1,...,a_k^0+\Delta a_k\right) \\ &= R_j\left(a^0\right)+\sum_{i_1=1}^{k}\left(\frac{\partial R_j}{\partial a_{i_1}}\right)_{a^0}\Delta a_{i_1} \\ &\quad +\frac{1}{2}\sum_{i_1,i_2=1}^{k}\left(\frac{\partial^2 R_j}{\partial a_{i_1}\partial a_{i_2}}\right)_{a^0}\Delta a_{i_1}\Delta a_{i_2} \\ &\quad +\frac{1}{3!}\sum_{i_1,i_2,i_3=1}^{k}\left(\frac{\partial^3 R_j}{\partial a_{i_1}\partial a_{i_2}\partial a_{i_3}}\right)_{a^0}\Delta a_{i_1}\Delta a_{i_2}\Delta a_{i3}+... \\ &\quad +\frac{1}{n!}\sum_{i_1,i_2,...i_n=1}^{k}\left(\frac{\partial^n R_j}{\partial a_{i_1}\partial a_{i_2}...\partial a_{i_n}}\right)_{a^0}\Delta a_{i_1}...\Delta a_{i_n} \end{aligned} \quad E(3)$$

For large complex systems with many parameters like fire models, it is impractical to consider the nonlinear terms. As a first-order approximation neglecting the nonlinear terms, the response $R_j\left(a_1,...,a_k\right)$ becomes a linear function of the parameters $a=\left(a_1,...,a_k\right)^T$ of the form

$$\begin{aligned} R_j\left(a_1,...,a_k\right) &\approx R_j\left(a_1{}^0,...,a_k{}^0\right)+\sum_{i=1}^{k}\left(\frac{\partial R_j}{\partial a_i}\right)_{a_i^0}\Delta a_i \\ &= R_j{}^0+\sum_{i=1}^{k}S_{ji}\Delta a_i \end{aligned} \quad E(4)$$

Where $R_j\left(a_1{}^0,...,a_k{}^0\right)=R_j{}^0$ is the baseline output and $S_{ji}=\frac{\partial R_j}{\partial a_i}$ is the sensitivity of the response $R_j\left(a_1,...,a_k\right)$ to the input parameter a_i . All the S_{ji} form a rectangular sensitivity matrix S of order $m\times k$.

Equation (4) can be rewritten in terms of the fire performance gap as:

$$\begin{aligned} G_j\left(\Delta a_1,...,\Delta a_k\right) &= R_j\left(a_1,...,a_k\right)-R_j{}^0 \\ &\approx \sum_{i=1}^{k}S_{ji}\Delta a_i \end{aligned} \quad E(5)$$

Which means that when input parameters have small changes around their baseline or reference values, the total fire performance gap due to simultaneous small changes of each input parameter equals the sum of each fire performance gap caused by the change of each single input parameter. Note that the input parameters are not necessarily independent, but the application of the first order approximation results in small and thus neglectable interactions between input parameters which are the coupled derivatives of the input variables

Physically, most input parameters of fire models can be categorized into some kinds of initial/boundary conditions or source terms in a fire involved flow field controlled by ordinary differential equations (ODEs) (for zone models) or partial differential equations (PDEs) (for field models). Therefore, equation (5) means that the influences of small changes in initial/boundary conditions or source terms of a fire involved flow field are linearly additive. As a matter of fact, if the PDEs controlling a flow field is linear or quasi-linear or could be linearized in part of the resolution space around some baseline points, this superposition characteristic always exists [19] to a degree depending on how linear the PDEs are locally.

Although mathematically equations (4) or (5) only exist for small changes of input parameters due to the very small acceptable error employed in mathematics, it can be used in engineering to estimate the possible total fire performance gap due to significant changes of input parameters given that the acceptable error in engineering can be larger (e.g., 20%). The effectiveness of this estimation partly depends on the linear degree of the problem to be resolved.

2.1.3 Numerical methods to calculate the sensitivity matrix

For a complicated problem lacking analytical functions to map the inputs to the outputs, it is hard to compute the partial derivatives of outputs to inputs, which forms the sensitivity matrix in equations (4) and (5). Therefore, numerical methods are introduced to estimate the sensitivity matrix around some baseline point.

There are three difference methods available to calculate the numerical values of the sensitivity matrix: center difference, backward difference, and forward difference. At a baseline point, the numerical calculation equations are:

(1) For center difference

$$S_{ji}=\frac{\partial R_j}{\partial a_i}=\frac{R_j\left(a_1^{\,0},\ldots,a_i^{\,0}+\Delta a_i,\ldots,a_k^{\,0}\right)-R_j\left(a_1^{\,0},\ldots,a_i^{\,0}-\Delta a_i,\ldots,a_k^{\,0}\right)}{2\Delta a_i} \qquad E\,(6)$$

(2) For forward difference

$$S_{ji}=\frac{\partial R_j}{\partial a_i}=\frac{R_j\left(a_1^{\,0},\ldots,a_i^{\,0}+\Delta a_i,\ldots,a_k^{\,0}\right)-R_j^{\,0}}{\Delta a_i} \qquad E\,(7)$$

(3) For backward difference

$$S_{ji}=\frac{\partial R_j}{\partial a_i}=\frac{R_j^{\,0}-R_j\left(a_1^{\,0},\ldots,a_i^{\,0}-\Delta a_i,\ldots,a_k^{\,0}\right)}{\Delta a_i} \qquad E\,(8)$$

Center difference can be deemed an average of forward difference and backward difference. With second order error ($O\left(h^2\right)$), center difference is a better approximation of the derivative at a baseline point than either forward or backward difference which has only first order error ($O\left(h\right)$). However, when applying these approximations in prediction, the combination of sensitivities developed from both forward and backward difference, which employs the sensitivity from forward difference if an input variable is greater than its baseline value or the sensitivity from backward difference if an input variable is less than its baseline value, may have higher accuracy than the central difference (see APPENDIX I for proof). The comparison of applications between center difference and combination of forward and backward differences is shown in next section.

Usually different input variables have different capacities to affect the outputs. The normalized sensitivity [20] can be used to rank the importance of each parameter by removing the effects of units, which is defined as:

$$\phi_{ji}=\frac{\partial R_j / R_j^0}{\partial a_i / a_i^{\,0}}=S_{ji}\frac{a_i^{\,0}}{R_j^0} \qquad E\,(9)$$

Where ϕ_{ji} is the normalized sensitivity, S_{ji} is the sensitivity defined by E(6) to E(8), $a_i^{\,0}$ and R_j^0 are baseline point input i and baseline point output j, respectively.

The normalized sensitivity can be expressed as "percentages of output change due to unit percentage of input change".

2.1.4 Method to calculate uncertainty of the SMM

The overall uncertainty of a model prediction is a combination of the uncertainty of the input parameters and the uncertainty of the model assumptions. The former is referred to as parameter uncertainty; the latter model uncertainty [21]. A method is described in [21, 22] to estimate the model uncertainty using comparisons of model predictions with experimental measurements whose uncertainty has been quantified. This method reports the model uncertainty in terms of only two metrics, a system bias factor, $\bar{\delta}$, and a relative standard deviation (RSD), $\bar{\omega}$, which can be calculated by:

$$\bar{\delta}=\exp\left(\frac{1}{n}\sum_i^n\ln\left(\frac{M_i}{E_i}\right)+\frac{s^2-\omega_E^2}{2}\right) \qquad E\,(10)$$

and

$$\bar{\omega}=\exp\left(\frac{1}{n}\sum_i^n\ln\left(\frac{M_i}{E_i}\right)+\frac{s^2-\omega_E^2}{2}\right)\cdot\sqrt{s^2-\omega_E^2} \qquad E\,(11)$$

Where M_i and E_i are the model output and experimental measurement at sample point i, respectively; n is the number of sample points; s and ω_E are sample variance and relative experimental uncertainty, respectively, which can be calculated by

$$s^2=\frac{1}{n-1}\sum_i^n\left[\ln\left(\frac{M_i}{E_i}\right)-\frac{1}{n}\sum_i^n\ln\left(\frac{M_i}{E_i}\right)\right]^2 \qquad E\,(12)$$

$$\omega_E^2=\omega_0^2+\sum_i p_i^2 w_i^2 \qquad E\,(13)$$

The relative experimental uncertainty, ω_E, includes both the uncertainty of the experimental device (ω_0) that measures the quantity the model is trying to predict, and the uncertainty of the device (w_i) that measures the various input parameters that the model requires. The factors, p_i , represent the power dependences of the individual input parameters

In this paper, our purpose is to investigate the "model uncertainty" of the SMM, and FDS simulations are considered here as "numerical experiments". Unlike the physical experiments where the relative experimental uncertainty, ω_E , can be calculated according to the method provided in [23], for numerical experiments in our case it is difficult to accurately calculate the ω_E due to lack of knowledge about the ω_0 , p_i and w_i of the FDS software as a numerical experimental device. From equation (10) and (11), it is clear that an overestimate of ω_E^2 will result in underestimate of model uncertainty. Since it doesn't make sense for a relative experimental uncertainty to be greater than the computed model uncertainty, the reasonable range of ω_E should be [0, s^2] (In equation (11), if $\omega_E^2 = s^2$, then $\bar{\omega}=0$) , which results in reasonable range of $\bar{\delta}$ and $\bar{\omega}$ as below:

$$\bar{\delta} \in \left[\exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) \right), \exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) + \frac{s^2}{2} \right) \right] \quad E\ (14)$$

$$\bar{\omega} \in \left[0, \exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) + \frac{s^2}{2} \right) \times s \right] \quad E\ (15)$$

2.2 Output responses and input parameters

Fire safety problems usually include many output variables and more input parameters. Theoretically all of them can be analyzed by the SMM.

As exemplar tools, the zone model CFAST [24] and the field model FDS [25] as well as egress model PATHFINDER [26] can be applied to specific buildings. Most of the outputs in these tools, with time as the unit, can be related to one of the four component performance classes; PFP, AFP, OFR and FFR, as shown in Table 1.

Table 1 Output responses of component fire performances

performance components	output response (performance indicator)
PFP	Time to flashover in fire initial room Time to contain the fire in fire initial room Time to contain the smoke in fire initial room Time to contain the fire in fire initial story Time to contain the smoke in fire initial story Time to contain the fire in fire initial building Available safety egress time (ASET)
AFP	Time to activate the first sprinkler Time to alarm Time to activate smoke control system Time to contain a fire in the original object Time to maintain a pre-set smoke layer height
OFR	Required safety egress time (RSET)
FFR	Time to arrive fire spot Time to control the fire Time to put out the fire

With these output responses, direct fire loss including life/injury loss and property loss can be worked out. For example, life/injury loss can be related to the egress safety ratio (ESR), which is the ratio of ASET to RSET. The property loss can be calculated by fire/smoke damaged area. NFPA fire loss reports [27, 28] relate indirect fire loss including business interruption to direct fire loss by a factor of 10%. For more accurate estimation, more non-fire related information is needed to estimate the business interruption loss and environment impacts.

In reality, only a very limited number of output variables working as performance indicators will be deeply studied due to the time or resource constrains of specific projects. As commonly used performance indicators of life safety in fire, the ASET, RSET and ESR, are the key elements to be discussed in the following sections. Accordingly, the idea of BFPG is mainly represented by the gap of ASET and/or ESR.

The input parameters of interests come from two groups, one related to characteristics of the building, fire, and occupants that define fire scenarios and the other related to fire protection strategies that define trial designs. Common input parameters are listed in

Table 6 in APPENDIX II.

3 ASET analysis using the SMM: case study

3.1 Introduction to the physical model

3.1.1 Common tools to calculate fire dynamics effects on buildings

Usually there are three kinds of tools to simulate the building fire effects [29]: hand-calculation, zone model, and field model. Hand-calculation tools like McCaffrey-Quintiere-Harkleroad (MQH) method [30] are simple theories where the parameters are determined by comparison to experimental data, thus are fastest when the input ranges of a compartment fire are within the ranges of these background experiments. The accuracy of extrapolating these algebra equations are much less determined than that of interpolation.

Zone models like CFAST [31] usually adopt a series of ordinary differential equations (ODEs) derived from mass, momentum, energy and species conservation, describing changes of output variables in each zone with time. Some typical output variables are gas temperatures in the hot layer and cool layer, smoke layer height, etc. Within each zone, the output variables only change with time and don't change with location. Since the output variables usually exist in each ODE and are coupled together, they are often determined numerically, implicitly, and simultaneously. Like hand-calculations, the major applications of zone models are in single room fires although applications of them in multi-apartment and even multi-story buildings have been reported.

Field models can be deemed as an extension of zone models in the space dimension. In other words, field models usually separate the computational domain into thousands of tiny "zones" or "cells". Instead of ODEs used in zone models, partial differential equations (PDEs) derived from the same four conservation laws are applied in field models by discretizing these PDEs for each tiny cell and solving them from one cell to another. Since field models address both temporal and spatial changes of output variables, they are believed as the most accurate method. However, a large number of equations to solve means field models usually need much more computational resources than zone models and hand-calculations, limiting their applications to cases where zone models and hand-calculation are incapable of delivering reliable results.

The SMM can be adopted to investigate the combined effects of small changes of input parameters on output variables. Due to the lower computational demands of zone models and hand-calculation methods, the application of SMM, which is only a first-order approximation of the targeted problems, has very limited significance in problems where hand calculation and zone models are competent. However, zone models and hand-calculation methods are not suitable for simulating real world building geometries. For complicated problems necessitating field models like FDS [32] which are usually computational-intensive, the application of a SMM is reasonable and efficient by eliminating the need for time consuming model runs.

3.1.2 Untenability criteria

Comparison between ASET and RSET, or the ESR, has been the key index of performance-based fire design for life safety in buildings for a long time. By using an exemplar 3-story apartment building as a physical built environment, this section illustrates an application of the SMM in ASET analysis by using FDS.

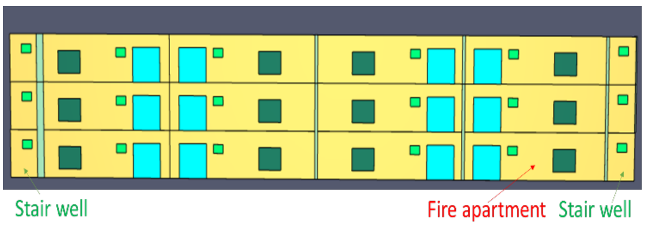
To decide the ASET, the following tenability criteria and associated limits are commonly considered during the fire modeling process[33]:

a) Air temperature: 76°C (169°F) (20 minutes' exposure)
b) Radiant heat flux: 2.5 kW/m^2 (maximum)
c) Smoke obscuration (soot visibility): 10 m (32.8ft) visibility (minimum) in large enclosure and 5 m (16.4ft) in small enclosure
d) Carbon monoxide concentration: 1,400 ppm (20 minutes' exposure)
e) Hydrogen cyanide concentration: 100 ppm (20 minutes' exposure)

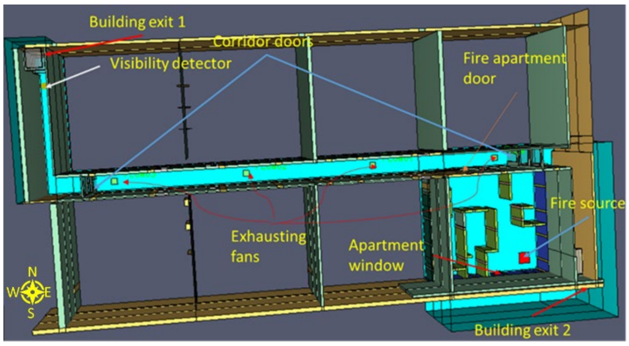
However, visibility distance is typically the first hazard parameter to reach an untenable condition [33]. Therefore, in this paper the visibility criterion is adopted.

3.1.3 Problem description

Figure 2 shows an exemplar 3 story residential building with an area of about 1000m^2 for each floor. This building would be designated as 'R-2' by the International Building Code (IBC) in the USA [34]. There are eight 100m^2 apartments in every story. The corridor is 2m wide, floors are connected by two staircases at the west and east ends of the building. A propane gas-burner fire is located close to the southeast corner of the southeast apartment on the first floor. There are two corridor doors located close to each end of the main corridor. All the apartment doors are closed except the fire apartment, the entry doors of the building (the exits) are kept open during the simulations.



a) elevation view



b) plan view

Figure 2 Room fire scenario in a 3-story R-2 building (generated by Pyrosim)

Six input variables are considered:

(1) peak Heat Release Rate (HRR) of the fire, $HRR(KW)$.

As the driving force of a fire, the HRR is the most important factor affecting the building fire performance. The changing patterns of HRR are very diverse, including changes of fire growth rate, peak HRR, burn duration, etc. For example, the replacement of the inner finishes and furniture may result in changes in each aspect. In this case study, we use the change of peak HRRPUA (HRR per unit area) to consider changes in both the peak HRR and the fire growth rate, with the burn duration constant. For example, if we increase peak HRRPUA from 1MW/m^2 to 2/MW/m^2 and at the same time keep the ramp time (the time needed for the fire to reach the specified value of HRRPUA) constant, it equals doubling both the peak HRR and the fire growth rate.

(2) width of the west corridor door, $W_c(m)$.

Corridor doors are key points which the smoke has to pass by before it arrives at the exits. Therefore, the opening widths of them directly affect the smoke spread rate and thus the ASET of the apartment building. When a fire occurs, most of the time a corridor door is either open or closed. Sometimes it can also be partly opened purposely by somebody. When this occurs the opening width can be random. To analyze the influence of the opening width of a corridor door, in this case it is assumed that a corridor door can be opened to any width. Note that the east corridor door is always open for each FDS simulation.

(3) soot yield of the fuel, Y_s

When other factors are kept constant, the increase of the soot yield can reduce the ASET by reducing the visibility. Both the ventilation condition and the material properties could affect the soot yield of a fuel. In this case, to investigate the impact of soot yield on the ASET, it is assumed that the soot yield can be chronically changed without further illustration about the underlying reasons.

(4) width of fire apartment window $W_w(m)$

The window is in the exterior wall of the fire apartment, whose opening width determines the amount of smoke flowing out of the apartment through it. Although in reality it will also affect the process of fire growth, this influence is not considered in this case. Furthermore, we assume that the window is opened to a random width when a fire occurs because people have various demands on it.

(5) width of the fire apartment door $W_d(m)$.

The apartment door connects to the corridor. In a fire scenario, the apartment door is paramount in that: 1) It is the major path for fresh air to come into the apartment and support the burning, and for the hot smoke to flow out of the apartment and fill the whole building. 2) the quality and state of the apartment door to a large extent determines whether flashover or self-extinction will happen. Before the occurrence of the fire, it is highly possible that the apartment door is closed. When a fire happens and the occupants leave the apartment, however, the apartment door can be left either open or closed by the occupants. If it is left open, the width of door opened can be deemed as random.

(6) flow rate of exhaust fans, $E_f(m^3/s)$

In an apartment fire, exhaust fans are expected to remove the hot smoke accumulated beneath the ceiling. In our case, four exhausting fans are set in the ceiling of the corridor. Exhaust fans usually have various working conditions providing a range of flow rates. Here it is assumed that the flow rate of exhaust fans can be chronically changed.

Only ASET, A_t ,which is measured by a visibility detector close to Exit 1 (west) with a threshold of 5m (since the apartment building we employ is relatively small), is considered as the output variable. It is assumed in this case that all the six input factors change chronically. Therefore, the SMM is suitable to rapidly estimate the building fire performance, or the ASET in this case.

3.1.4 Mesh resolution

For a large volume, different meshes with different resolutions can be set so that the FDS simulation time can be considerably reduced and at the same time the flow field accuracy will not be compromised. A rule of thumb is to set higher resolution in areas close to the fire source and coarser resolution in areas far away from the fire source. In our case, the fire apartment in the first floor is meshed as 6.25cm by 6.25cm by 25cm (x by y by z), the corridor having the corridor doors in the first floor is meshed as 6.25cm by 25cm by 25cm (x by y by z), the left corridors in the first floor as well as all the volume in the second and third floors are meshed as 25cm by 25cm by 25cm. This results in a total cell number of 634,568.

For simulations involving buoyant plumes, a measure of how well the flow field is resolved is given by the non-dimensional expression $D^* / \delta x$, where D^* is a characteristic fire diameter and δx is the nominal size of a mesh cell [25]. As to the mesh resolution in our case, this non-dimensional quantity has a range of about 4 to 30 (see APPENDIX III for details of calculation), which is comparable to the quantity values for similar corridor fire simulation listed in table 3.35 of reference [22].

3.1.5 Some notes about Fire Dynamic Simulator (FDS)

As an open source fire modelling software, FDS is widely adopted worldwide, especially in the area of building performance-based design. Compared to CFAST, FDS as a field model introduces and adopts some new aspects that make its simulation results more consistent with reality. This, however, also causes new issues related to repeatability, stability and convenience.

a) FDS initializes the flow field with a very small amount of "noise" to prevent the development of a perfectly symmetric flow when the boundary and initial conditions are perfectly symmetric [35], which partly contributes to the small discrepancy of some output variables between repeated simulations with identical FDS input files. This small amount of "noise" has only a very limited effect on some output variables of interest like HRR, temperature, velocity, species concentration, and visibility. However, this "noise" may have considerable effect on the sensitivity matrix generated from small change of input factors.

b) The resolution of FDS, which is controlled by the grid size, may have significant influence on the sensitivities of geometry-based input variables like width/height of a hole/vent/wall. To make a difference, the change of such kind of variables should cover at least one cell size, and the more cells that are covered, the more accurate the simulation results are. The curves of outputs with response to inputs are smoother and more monotonic within some promising and reasonable input intervals if the grid cell is smaller. However, this will increase exponentially the computational time.

c) FDS allows different meshes to run on different computer cores, which speeds the simulation process. However, this also partly causes a repeatability issue: different simulation results for an identical input file run repeatedly. Deployment of all the jobs on one computer core may remove this part of the repeatability issue but will inevitably result in longer simulation time.

d) Due to the inherent turbulence of the smoke flow field driven by a fire, visibility change with time at some points (in our case at Building Exit 1 in Figure 2) is not smooth and monotonic, resulting in the time for the visibility to first pass through the preset threshold of 5m, or ASET, to change nonlinearly with the input parameters, as shown in the figure below:

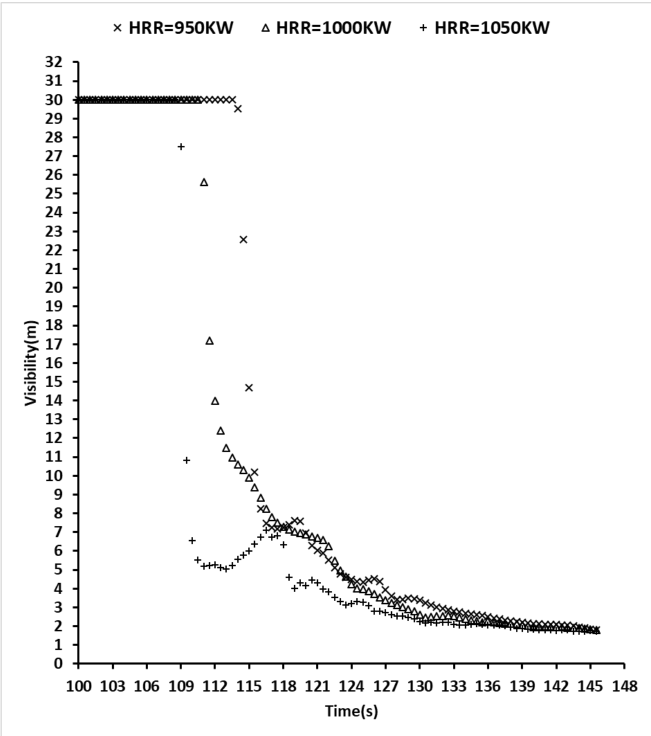


Figure 3 Visibility changes with time for different fire powers at Building Exit 1 in Figure 2

We can see from Figure 3 that for the curve of HRR=1050kW, once the visibility is very close to 5m at 113s (5.03m), we cannot take 113s as the ASET because our criteria of deciding ASET is "visibility drops below the 5m line". After some fluctuations it does drop below the 5m line at about 118.4s. The ASET gap between the visibility being first very close to the 5m line and dropping below the 5m line is only 5.4s, which is not greatly significant as compared to the ASET values. However, when it comes to the sensitivity of ASET to HRR, it makes a lot of difference. The ASET for HRR=1000kW is 123s, and that for HRR=950kW is 122.6s. ASET is expected to decrease as the HRR increases monotonically. In this case, however, it is clear that the change of ASET with HRR is not monotonic since 123s is not between 118.4s and 122.6s. One would have been wondering why we do not replace the current criterion of deciding the ASET with other more flexible ones, like "close to 5m". The issue with this flexible criterion is how to define "close". Another seemingly promising method is the introduction of a moving average. The issue with this method is how to define the range of the average. If the range is too narrow, the fluctuations still exist. If it is too wide, part of the import physical information will be removed and the sensitivity matrix becomes less meaningful. Since each alternative method of deciding the ASET has its own limitations especially in the context of our case study, the current criterion seems reasonable. Nevertheless, in average it is pretty fair to each fire scenario once a fixed criterion is set. Below we will discuss some methods of rearranging the FDS simulation data instead of replacing the current ASET method, which is more promising.

e) It should be borne in mind that there are inevitable differences between model and experiment due to limitations or errors in the numerical solution and/or physical sub-models [22]. Our simulations of the exemplar residential building fire can be deemed as a combination of enclosure fire development (in the initial fire apartment) and a smoke filling process in the corridor. Although the prediction of ASET by FDS has been rarely validated by experiments in geometries similar to our building, many FDS validation work have been done in various geometries regarding to the quantities of plume temperature and vertical/radial velocity, ceiling jet temperature and velocity, hot gas layer (HGL) temperature and height, smoke concentration, smoke obstruction, etc. [22,23]. Limited validations of smoke concentration predicted by FDS against experiments show that the predicted concentrations are about 50% higher than the measured in the open-door tests, which can be explained in terms of uncertainty in the measurement and the specified smoke yield. However, in the close-door tests, the predicted concentrations are as much as six times the measured concentrations, which is unreasonable, partly due to the existence of an oxygen-starved condition or the changes of optical properties of the smoke leading to a misleading measurement of the smoke mass per unit volume [23].

Other smoke related quantities include O_2/CO_2/CO concentration and smoke obscuration. ASET at Building Exit 1in the exemplar building we adopt here depends also on the process of smoke filling in the corridor, which in turn is dominated by the smoke velocity and temperature. These quantities have been validated, as shown in the following table which is extracted from table 16.1 in [22]:

Table 2 Validation results of other smoke related quantities

Quantity	**RSD($\bar{\omega}$)**	**Bias($\bar{\delta}$)**
O2 Concentration	0.17	0.98
CO2 Concentration	0.15	1.01
CO Concentration	0.41	0.97
Smoke Obscuration	0.10	1.10
Velocity	0.27	1.00
Ceiling Jet Temperature	0.12	1.03

In general, the FDS predictions of near-field and/or in the early stages of a fire are more prone to error than far-field and/or in the later stages of a fire [22,36]. Although there are uncertainties, FDS has been adopted as a benchmark model to validate other simpler algebra and/or zone models [37~39].

In this paper, as a realistic field model case, the following measures are taken in FDS simulations of fire scenarios in the exemplar residential building as shown in Figure 2: 1) the "noise" mentioned above is activated (since the default value in FDS is TRUE there is no need to explicitly set it to TRUE); 2) in the input files all the meshes are deployed on multi computers and cores; 3) and grid cells as large as 6.25cm are used so that the minimum 10% change level of geometry-related input factor, namely the width of the corridor door with a baseline value of 75cm, can at least cover one cell.

3.2 ASET analysis with the Sensitivity Matrix Method (SMM)

3.2.1 Calculation of the sensitivity matrix

In this case, grid cells are 6.25cm. To at least cover one cell, here a 20% changing rate is adopted to generate the sensitivity matrix based on central difference (since the baseline corridor door width is 75cm and there should be at least one cell on each side of the baseline point) , and a 10% changing rate is adopted to generate the sensitivity matrix based on forward/backward difference. The characteristics of the two methods are compared in the following analysis by applying the sensitivity matrices to changes of input variables beyond the changing rates used to develop the sensitivity matrices.

To generate a more accurate sensitivity matrix, at least two tests with distinct results for each changing rate should be conducted to work out a series of averaged ASETs that are more stable and reasonable. sensitivity matrices thus calculated are shown below:

(1) Inputs/outputs and baseline scenario

In the following sensitivity matrices developed from different methods of difference, the one output and six input variables mentioned in section 3.1.3 are:

$$y_1 = A_t$$

$$x_1 = HRR, x_2 = W_c, x_3 = Y_s,$$
$$x_4 = W_d, x_5 = W_w, x_6 = E_f$$

The baseline values for the output and inputs are:

$$y_1 = 194.5s, x_1 = 3000KW, x_2 = 0.75m,$$
$$x_3 = 0.052, x_4 = 0.8m, x_5 = 1m, x_6 = 1m^3 / s$$

Based on the realistic practices (see APPENDIX IV for validation of the baseline scenario settings), the baseline scenario is selected so that the values of inputs are around the middle of the changing ranges of the inputs so that SMM is suitable.

In the following calculation of sensitivity matrices, the ASETs are obtained by FDS simulations.

(2) For center difference

$$S_{1i} = \frac{\partial y_1}{\partial x_i} \approx \frac{\Delta y_1}{\Delta x_i} = \frac{y_1\big|_{x=x_i^0+0.1x_i^0} - y_1\big|_{x=x_i^0-0.1x_i^0}}{\left(x_i^0 + 0.1x_i^0\right) - \left(x_i^0 - 0.1x_i^0\right)}$$
$$= \begin{pmatrix} \frac{190.30-201.33}{3300-2700} \\ \frac{192.87-198.13}{0.825-0.675} \\ \frac{193.8-196.8}{0.0572-0.0468} \\ \frac{187.90-197.40}{0.88-0.72} \\ \frac{195.82-193.09}{1.1-0.9} \\ \frac{198.15-190.10}{1.1-0.9} \end{pmatrix} = \begin{pmatrix} -0.0183s / KW \\ -35.11s / m \\ -286.06s \\ -59.375s / m \\ 13.64s / m \\ 40.275s^2 / m^3 \end{pmatrix} \quad E(16)$$

According to E(9), the corresponding normalized sensitivity matrix is:

$$\phi_{1i} = \begin{pmatrix} -0.28226 \\ -0.13539 \\ -0.07648 \\ -0.24422 \\ 0.07013 \\ 0.20707 \end{pmatrix} \quad E(17)$$

(3) For forward difference

$$S_{1i} = \frac{\partial y_1}{\partial x_i} \approx \frac{\Delta y_1}{\Delta x_i} = \frac{y_1\big|_{x=x_i^0+0.1x_i^0} - y_1\big|_{x=x_i^0}}{\left(x_i^0 + 0.1x_i^0\right) - \left(x_i^0\right)}$$
$$= \begin{pmatrix} \frac{190.30-194.5}{3300-3000} \\ \frac{192.87-194.5}{0.825-0.75} \\ \frac{193.8-194.5}{0.0572-0.052} \\ \frac{187.90-194.5}{0.88-0.8} \\ \frac{195.82-194.5}{1.1-1.0} \\ \frac{198.15-194.5}{1.1-1.0} \end{pmatrix} = \begin{pmatrix} -0.0140s / KW \\ -21.78s / m \\ -129.81s \\ -82.5s / m \\ 13.22s / m \\ 36.55s^2 / m^3 \end{pmatrix} \quad E(18)$$

According to E(9), the corresponding normalized sensitivity matrix is:

$$\phi_{1i} = \begin{pmatrix} -0.21594 \\ -0.08398 \\ -0.03470 \\ -0.33933 \\ 0.06797 \\ 0.18692 \end{pmatrix} \quad E(19)$$

(4) For backward difference

$$S_{1i} = \frac{\partial y_1}{\partial x_i} \approx \frac{\Delta y_1}{\Delta x_i} = \frac{y_1\big|_{x=x_i^0} - y_1\big|_{x=x_i^0-0.1x_i^0}}{\left(x_i^0\right) - \left(x_i^0 - 0.1x_i^0\right)}$$
$$= \begin{pmatrix} \frac{194.5-201.33}{3000-2700} \\ \frac{194.5-198.13}{0.75-0.675} \\ \frac{194.5-196.8}{0.052-0.0468} \\ \frac{194.5-197.40}{0.8-0.72} \\ \frac{194.5-193.09}{1.0-0.9} \\ \frac{194.5-190.10}{1.0-0.9} \end{pmatrix} = \begin{pmatrix} -0.0228s / KW \\ -48.44s / m \\ -442.31s \\ -36.25s / m \\ 14.06s / m \\ 44s^2 / m^3 \end{pmatrix} \quad E(20)$$

According to E(9), the corresponding normalized sensitivity matrix is:

$$\phi_{1i} = \begin{pmatrix} -0.35167 \\ -0.18679 \\ -0.11825 \\ -0.1491 \\ 0.07229 \\ 0.22622 \end{pmatrix} \qquad E(21)$$

The normalized sensitivities calculated above show that heat release rate (HRR), apartment door width (W_d), and the exhausting flow rate (E_f) are the most important input variables, seconded by the corridor door width (W_c). The soot yield (Y_s) and window width (W_w) are the least important input parameters. However, the rankings of inputs' importance are not identical in these three normalized sensitivities, suggesting possible difference of inputs' importance in different ranges of input variables.

3.2.2 Application of the SMM

As a method with first order approximation, the SMM can only be applied under input domains in which an output changes monotonically (although non-linearly) with each single input variable.

If an output depends only on single input variable, it is straightforward to define the applicable input range given a specific acceptable error or accuracy. However, if an output depends on multi independent input variables, things become complicated since the combinations of input variables that could lead to one output value can be infinite. The applicable ranges of SMMs are dataset sensitive: how the dataset is designed or selected affects the applicable ranges. Currently the methods to predict the applicable range of a SMM before its application in specific cases are absent. Qualitatively and generally, the farer the points are from the baseline point, the less accurate is the prediction, as suggested by Taylor's linear approximation. Instead of calculating quantitatively the applicable input ranges of a method, which is very hard in our case of a multi-variable system, the applicability of a method can be expressed by model uncertainties (system bias and RSD) and/or the percentage of predictions within preset error ranges which are allowable or acceptable in the related engineering area. To explore the applicability of a SMM, 25 tests are adopted, as shown in Table 3, where the range of the input variables are:

HRR : 1400~5200 (kW), W_c : 0.20~1.20(m), Y_s : 0.0208~0.0832, W_d : 0.32~1.28(m), W_w : 0.3~1.5(m), E_f : 0.4~1.6(m^3/s).

Table 3 Input data and results from FDS simulation, SMM of center difference, and SMM of combined backward/forward difference. For the first three cases, the HRR, corridor door width, apartment door width, and the soot yield change at same rate, whereas the window width and the exhausting flow rate change at same rate. For the remaining 23 cases, the red input variables in a row change at a same rate, the other input variables are randomly given.

Case#	Input						ASET(s) predicted by		
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS	SMM-center	SMM-B/F
1	4800	1.20	1.28	0.40	0.40	0.0832	134.3	76.0	69.3
2	4500	1.13	1.20	0.50	0.50	0.0780	138.8	95.7	90.2
3	3900	0.98	1.04	0.70	0.70	0.0675	152.0	135.3	132.0
4	5200	0.98	1.04	1.30	1.30	0.0676	160.3	143.8	151.9
5	4800	0.90	0.96	1.20	1.20	0.0624	161.8	154.6	161.4
6	4400	0.83	0.88	1.10	1.10	0.0572	168.2	165.4	171.0
7	3000	1.13	1.20	1.50	1.50	0.0780	171.8	177.1	174.8
8	4200	0.79	0.84	1.05	1.05	0.0546	172.1	170.8	175.7
9	3600	0.90	0.96	1.20	1.20	0.0624	173.0	176.6	178.2
10	2600	0.98	1.04	1.30	1.30	0.0676	177.2	191.4	191.8
11	3500	1.10	0.50	0.50	0.80	0.0280	189.5	182.9	185.5
12	3200	0.60	0.64	0.80	0.80	0.0416	196.9	197.8	197.8
13	2400	0.90	0.96	1.20	1.20	0.0624	200.0	198.5	200.3
14	3800	0.30	1.00	1.30	1.60	0.0800	203.0	204.0	210.9
15	2500	1.10	0.40	0.40	0.80	0.0400	210.0	202.3	200.9
16	2800	0.53	0.56	0.70	0.70	0.0364	210.2	208.6	208.2
17	3500	0.20	1.10	1.40	1.20	0.0700	214.0	195.2	199.7
18	2200	0.83	0.88	1.10	1.10	0.0572	216.0	205.7	208.8
19	2500	0.20	1.10	1.40	1.20	0.0700	238.0	213.5	218.1
20	1800	0.68	0.72	0.90	0.90	0.0468	243.0	219.9	224.9
21	1600	0.60	0.64	0.80	0.80	0.0416	269.0	227.1	232.5
22	2000	0.38	0.40	0.50	0.50	0.0260	295.7	230.2	232.4
23	1400	0.53	0.56	0.70	0.70	0.0364	349.5	234.2	240.1
24	2200	0.38	0.40	0.30	1.40	0.0300	430.0	258.9	259.9
25	1600	0.30	0.32	0.40	0.40	0.0208	457.9	241.0	249.1

The values in the column of FDS are ASET stemming from FDS simulations. The values in the column of SMM-center are calculated based on the corresponding input data and the sensitivity matrix based on center difference (as shown in E(16)). For example, in case number 4, the ASET predicted in SMM-center column is calculated by:

$$194.5 + \begin{pmatrix} \left(-0.0183(s/KW)\times(5200-3000)(KW)\right) \\ +\left(-35.11(s/m)\times(0.98-0.75)(m)\right) \\ +\left(-286.06(s)\times(0.0676-0.052)\right) \\ +\left(-59.375(s/m)\times(1.04-0.8)(m)\right) \\ +\left(13.64(s/m)\times(1.30-1)(m)\right) \\ +\left(40.275(s^2/m^3)\times(1.30-1)(m^3/s)\right) \end{pmatrix}$$

$$=194.5-50.7=143.8s$$

The values in the column of SMM-B/F are calculated based on the sensitivity matrices of forward and backward difference in E(18) and E(20), depending on whether the value of each variable is greater than the baseline value. For example, in case number 13, the ASET predicted in SMM-

B/F column is calculated by:

$$194.5+\begin{pmatrix}\left(-0.0228(s/KW)\times(2400-3000)(KW)\right)\\+\left(-21.78(s/m)\times(0.90-0.75)(m)\right)\\+\left(-129.81(s)\times(0.0624-0.052)\right)\\+\left(-82.5(s/m)\times(0.96-0.8)(m)\right)\\+\left(14.06(s/m)\times(1.20-1)(m)\right)\\+\left(36.55(s^2/m^3)\times(1.20-1)(m^3/s)\right)\end{pmatrix}$$

$$=194.5+5.8=200.3s$$

Where the sensitivities used for input variable HRR comes from backward difference as shown in E(20), and that used for the other five input variables come from forward difference as shown in E (18).

3.2.3 Applicability of the SMM

Using E (14) and E (15), and taking FDS simulation results as numerical experiments, the uncertainties of the SMM based on center difference and the combined backward/forward difference can be calculated as:

(1) For SMM based on center difference

$$\bar{\delta}\in[0.8692,0.8868]$$
$$\left|1-\bar{\delta}\right|\in[0.1132,0.1308] \qquad E\ (22)$$

$$\bar{\omega}\in[0,0.1776] \qquad E\ (23)$$

(2) For SMM based on combined backward/forward difference

$$\bar{\delta}\in[0.8764,0.8965]$$
$$\left|1-\bar{\delta}\right|\in[0.1035,0.1236] \qquad E\ (24)$$

$$\bar{\omega}\in[0,0.1907] \qquad E\ (25)$$

Therefore, for the two SMMs, the applicability expressed by model uncertainties is very close: the SMM based on center difference has lower RSD but higher system bias gap (which is the distance of the system bias from the non-bias value of one) than the SMM based on combined backward/forward difference.

Assuming that the acceptable error is 20%, the following figure obtained from Table 3 shows that there are 6 points for each SMM falling outside the acceptable error scope, which means that as far as this specific dataset is concerned the applicability of both SMMs expressed by the percentage of predictions within the acceptable error range is 76%, as shown in the blue oval.

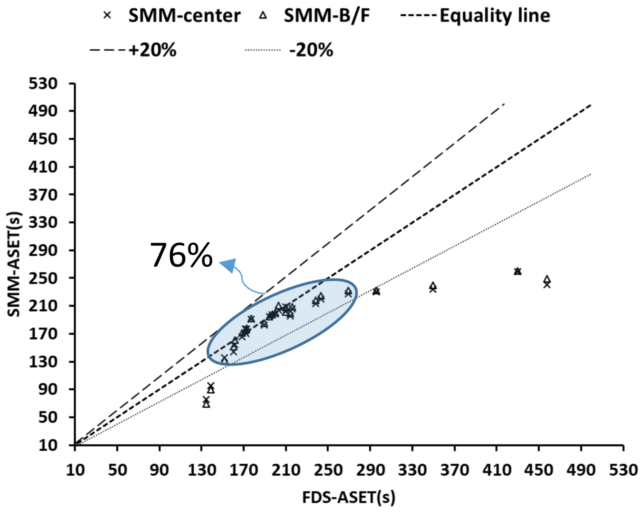


Figure 4 Comparison of ASET between FDS simulation and SMMs

The above analysis shows that:

a) In general the varying tendencies between the FDS simulation results (ASET numerical experiments) and predicted results by the SMM based on center difference and combined backward/forward difference are same, which can be seen in Table 3.

b) Although the two SMMs have close model uncertainties, in most cases (16 out of 25, or 64%), the predicted results from the SMM based on combined backward/forward difference are closer to the FDS simulation results.

c) There is a considerable mismatch when ASET from FDS simulations are "long" (for case number 22 to 24) or "short" (for case number 1 and 2) compared to the baseline ASET of 194.5s, which is consistent with the Taylor's linear approximation requiring small changes of input variables. Small changes of input variables will definitely result in small change of outputs, but small changes of outputs may be caused by large changes of input variables due to the cancellation effects among input variables. However, larger changes of outputs will be most likely caused by large changes of input variables, with exceptions where each input variable changes a little bit that affects the outputs in a same direction.

d) As far as the 25 data cases shown in Table 3 are concerned, the SMMs tend to underestimate ASET (the biases are less than one), which is on the safe side.

e) As shown in Figure 4, when the real (FDS simulated) ASET is far away from the baseline ASET (194.5s), the prediction accuracies of SMMs drop quickly, which suggests that new baseline points and corresponding sensitivity matrices may be necessary when the input values move far away from the original baseline point.

3.3 Summary

This section shows a case study of ASET by applying the SMM based on center difference and combined backward/forward difference. In this case we take the simulation results from FDS as the numerical experiment solution of the complicated practical problem which has one output (ASET) and six inputs (HRR, width of corridor door, soot yield, width of apartment door, width of window, and exhausting flow rate). Then we compare this numerical experiment solution with that obtained from the SMMs. It is found that in our case study the SMMs of both kinds of differences tends to underpredict the ASET by 10~13% with relative standard deviation around 17~19%. The good thing is that even at points where the SMM predictions have larger error, the results are on the safe side: they are lower than the numerical experiment results. Mathematically, if a straight line is tangent to a curve, the curve can be either above or below the straight line except for the tangent point. In our case, the predictions of SMMs can be analogous to the straight line, and the monotonical non-linear curve to the FDS simulation results. Note that the model uncertainties of SMMs are case sensitive: different cases may result in different uncertainties when applying the SMM.

Although it is possible for the SMM of combined backward/forward difference to work better than that of center difference due to its flexibility of dealing with various points with different sensitivities depending on the position of a point relative to the baseline point (see APPENDIX I for the proof of this), our case study shows that the advantages of adopting this SMM are very limited in these specific cases. Drawbacks of the SMM of combined backward/forward difference include: 1) the need of maintaining two sensitivity matrices; 2) the need of a highly accurate baseline point ASET since this ASET is involved in the calculation of the two sensitivity matrices. Considering the uncertainties related to the FDS simulations mentioned in subsection 3.1.3, this may necessitate more repeated simulations at the baseline point. On the other hand, the calculation of the SMM of center difference does not need the baseline point ASET. However, the baseline point ASET is needed when checking the reasonability of a sensitivity matrix. In other words, for SMM-center difference, the accuracy of baseline ASET is not so important only that it is within the two ASETs at two points around the baseline point (this possibility is very high). However, for SMM-B/F, the ASET of the baseline needs to be much more accurate since small differences in the value will result in considerable change of the sensitivity matrix. Therefore, in the analysis of next section, only the SMM of center difference is adopted

4 Understanding the BFPG related to life safety: maintaining egress safety ratio

4.1 Sensitivity matrix for the Egress Safety Ratio (ESR)

The last section presented the application of the SMMs in the prediction of ASET. As a common rule, keeping ASET greater than RSET, or equally the ratio of ASET to RSET, namely the ESR, greater than one, is a minimum requirement in building fire performance design. To leave some degree of safety margin, the required ESR should be greater than one. This required ratio varies in different building codes around the world. Here our concentration is not on what is the appropriate value for this ratio, but on how to close the BFPG related to life safety by maintaining this required value once it is properly set based on the appropriate considerations.

Factors that affect the ESR can be classified into two categories: ones influencing ASET and ones influencing RSET. Figure 5 shows possible factors that could affect the ESR through the ASET and RSET:

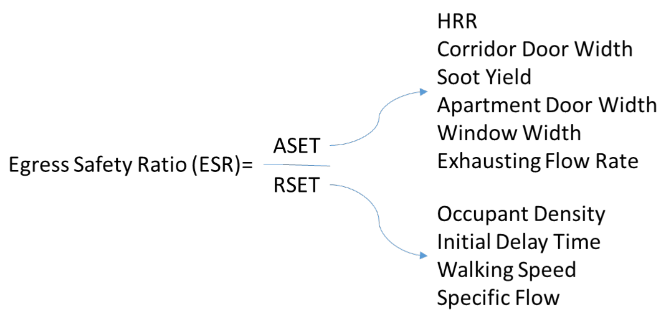


Figure 5 Factors influencing the egress safety ratio (ESR)

Sensitivity elements for ESR due to ASET change can be calculated by:

$$S\_ESR_{j1} = \frac{\partial Y_1}{\partial x_j} = \frac{\partial\left(\frac{y_1}{RSET^0}\right)}{\partial x_j} = \frac{1}{RSET^0}\frac{\partial y_1}{\partial x_j} \qquad E\,(26)$$

Where Y_1 is the final output variable, the ESR,

y_1 is the intermediate output variable, the ASET,

x_j are the input variables related to the ASET.

$RSET^0$ is the baseline value of the RSET.

Due to the fact that usually egress results can be generated quickly and directly for use in a SMM, to simplify the discussion we only focus on the factors that could affect the ESR through the ASET and take a constant baseline RSET of 194.5s which corresponds to the egress scenario in the same exemplar building of:

Occupant Density = 20/m^2, Initial delay time = 100s, Walking Speed =0.89m/s, Specific Flow = $1/(s\cdot m)$.

Since the baseline of $ASET$ is equal to $RSET^0$, the baseline of ESR, which is delegated by Y_1 in the following equation, is one.

Then the following sensitivity matrix/scalar for ESR can be worked out based on central difference equation 16:

$$S\_ESR_{j1} = \frac{\partial Y_1}{\partial x_j} = \begin{pmatrix} -0.00009(KW^{-1}) \\ -0.18051(m^{-1}) \\ -1.47075(s^{-1}) \\ -0.30527(m^{-1}) \\ 0.07013(m^{-1}) \\ 0.20707(s/m^3) \end{pmatrix} \qquad E(27)$$

4.2 A case study to understand the gap

4.2.1 Understanding the current gap

It is assumed that when the building was first delivered to the end users, all stakeholders agreed that the ESR of the building was to be 1.20 consistent with that used for small buildings. Here we are focusing not on a specific value of ESR, but on explaining our method. After several years since building delivery, the current ESR is found to be only 1.00 which corresponds to our baseline case. New building features related to new tenants or retrofitting such as removal of compartmentation and increased use of plastic based contents which tend to contribute to rapid smoke and fire spread [40], can lead to shorter ESR. The process of decrease in ESR from 1.20 to 1.00 could have been monitored if each of the six input variables listed previously had been tracked and a sensitivity matrix/scalar had been worked out when the building was delivered. Since the SMM is case sensitive, different sensitivity matrices may be necessary for different typical design fire scenarios, for example, as proposed in NFPA 101A [41]. Similar fire scenarios, like the change of fire source within the same apartment or even in the neighboring apartment, will not affect the ASET too much since the ASET is measured in locations far away from the fire source. Unfortunately, this hadn't been done due to lack of this new Fire Performance Monitoring (FPM) tool at that time. Now we can adopt this tool to see if it can help us to close the gap already existing now as well as to track the change of building fire performance in the future if stakeholders decide not to take immediate actions at this stage.

Since the ESR gap we need to close is 1.20-1.00=0.20, the following matrix can be calculated which indicates approximately the changes needed in each single input variable to close the BFPC related to life safety (the value within the brackets are baseline values of these input variables for the R2 building):

$$E_j = M_j = \frac{0.20}{\frac{\partial Y_1}{\partial x_j}} = \begin{pmatrix} \Delta HRR = -2025.68KW < 3000KW > \\ \Delta W_c = -1.11m < 0.75m > \\ \Delta Y_s = -0.14 < 0.052 > \\ \Delta W_d = -0.66m < 0.8m > \\ \Delta W_w = 2.85m < 1m > \\ \Delta E_f = 0.97m^3/s < 1m^3/s > \end{pmatrix} \qquad E(28)$$

The next step is to compare this matrix with the realistic intervals of each of the input variables and propose feasible measures that have the potential of closing the BFPG as denoted by ESR. In this case, the HRR would need to be lowered by about 2000 kW (for example, the designed HRR when the building was delivered could be 1000kW as a result of cellulose based contents, while the current baseline HRR of 3000kW may be the result of plastic based contents), which is possible by installing a sprinkler system (the consideration of cost of installing a sprinkler system is out of the scope of this paper). The advised changes for corridor door width (W_c) and soot yield (Y_s) are unrealistic because the needed decreases are greater than the baseline values. For the apartment door width (W_d), since its baseline width is 0.8m, it is possible to decrease it by about 0.66m: this can be done by simply setting a self-closing device to the apartment door. For the window width (W_w), it is unrealistic to raise it from the baseline width of 1m to 3.85m. For the exhaust flow rate (E_f), it is possible to increase the flow rate by 0.97m^3/s if the exhaust system has enough capacity. As a result, the most feasible single measures are 1) installing a sprinkler system; 2) doubling the exhausting flow rate; 3) setting a self-closing device on the apartment door. These actions are commonly heard when people are discussing the improvement of fire performance of operational buildings.

The above measures only take into account the changes of single input variables. In fact, different combinations of various changes constitute a solution space in which more refined analysis could be performed based on various realistic constrains like geometry, lighting, energy efficiency, thermal comfort, and cost, etc. Once some promising measures are worked out, the stakeholders can decide if it is necessary to refine these measures by further comprehensive fire modelling work. Also note that the three measures being verified as feasible are worked out by only using the linear SMMs. If other knowledge, for example the experts' experiences, are involved, other feasible measures may be confirmed. For example, the closure of the corridor door and the considerable drop of the soot yield will significantly increase the ASET.

4.2.2 Track the change of fire performance of buildings in-use

The same exemplar building is employed in this subsection. If the stakeholders think that the current BFPG of ESR 0.20 is not of concern, they may decide that no measures are currently necessary. However, since the current ESR is one, monitoring changes in the ESR to see if it drops further are warranted. Based on the data from either a data acquisition system or building users, FPM is able to track the change of ESR dynamically.

Since the purpose of this paper is to illustrate how the FPM tool works, here synthetic input data are adopted. As shown in Table 4, assume that the inputs uncertainty analysis (not mentioned in this paper) provides us information about the possible range of each of the six input factors as indicated by the columns of "lower range" and "upper range" The baseline column shows the baseline values of the input variables, and the S_ESR column shows the sensitivity value of ESR to each of the input variables. The baseline, minimum, and maximum values of ESR calculated based on the SMM are 1.00, 0.81 and 1.16, respectively.

Table 4 Varying range of inputs and output

Input variables	S_ESR	Lower range	Upper range	Baseline
HRR(kW)	-0.0001	2100	4500	3000
Corridor door width(m)	-0.1770	0.6	1.1	0.75
Soot Yield	-1.4640	0.035	0.078	0.052
Apartment Door Width(m)	-0.3039	0.6	1	0.8
Window width(m)	0.0698	0.7	1.5	1
Exhausting Flow Rate(m)	0.2061	0.7	1.5	1

One month's synthetic input data are randomly generated based on the following equation:

$$R_v = L_v + \left(U_v - L_v\right) \times R_n \qquad E\,(29)$$

Where R_v is random value of input variables, L_v and U_v are lower range value and upper range value as shown in the columns in Table 4, R_n is the random number between 0 and 1.

The one month's changes of input data are shown in Table 5, whereas the corresponding random numbers are attached in Table 7 of APPENDIX V.

Table 5 Randomly generated one month's synthetic data

Date	HRR(KW)	W_c(m)	Y_s	W_d(m)	W_w(m)	E_f(m3/s)
10/15	3000	0.75	0.0520	0.80	1.00	1.00
10/16	4370	0.76	0.0493	0.73	1.19	1.16
10/17	4283	0.91	0.0669	0.99	1.23	1.27
10/18	4099	0.62	0.0555	0.88	1.15	1.36
10/19	2118	0.81	0.0656	0.90	1.10	0.75
10/20	3187	0.73	0.0770	0.70	1.23	0.95
10/21	3115	1.09	0.0518	0.78	0.99	0.86
10/22	3882	0.93	0.0764	0.79	0.98	1.00
10/23	3712	0.87	0.0562	0.84	1.08	1.28
10/24	3004	0.74	0.0474	0.83	1.12	1.37
10/25	2647	0.73	0.0356	0.91	1.01	1.08
10/26	4190	0.93	0.0360	0.72	0.86	1.20
10/27	4195	0.88	0.0365	0.70	1.24	1.34
10/28	3120	0.75	0.0395	0.71	1.26	1.26
10/29	2773	0.70	0.0555	0.81	0.70	1.06
10/30	2598	0.80	0.0615	1.00	1.43	0.99
10/31	2218	0.78	0.0690	0.77	1.16	1.40
11/1	2528	0.63	0.0609	0.88	0.82	0.99
11/2	2249	0.75	0.0596	0.82	1.03	0.78
11/3	3527	0.83	0.0393	0.70	0.98	1.16
11/4	3824	1.06	0.0749	0.80	1.27	1.48
11/5	3511	0.92	0.0671	0.90	0.72	1.39
11/6	3683	1.03	0.0358	0.89	0.73	0.72
11/7	2493	0.68	0.0546	0.64	1.50	1.10
11/8	3562	0.97	0.0602	0.69	0.75	1.48
11/9	4363	0.79	0.0643	0.79	0.92	1.07
11/10	3047	0.97	0.0674	0.62	0.77	0.79
11/11	3322	1.03	0.0749	0.69	0.91	0.79
11/12	4298	0.71	0.0536	0.90	1.13	1.19
11/13	2823	1.04	0.0417	0.69	1.40	1.03
11/14	4379	0.76	0.0517	0.98	1.33	1.19

Under this change of input data, the change of output is shown in Figure 6:

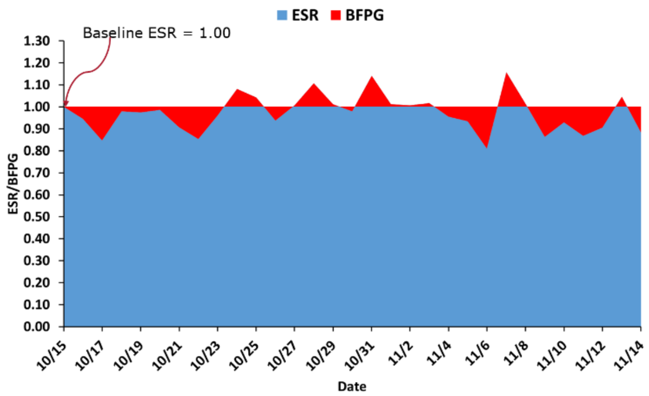


Figure 6 One month's change of output ESR and the BFPG expressed by ESR. The red area is the BFPG, that part of the red area underneath the of baseline ESR 1.0 indicates poorer fire performance and that area above the baseline indicates better fire performance.

In Figure 6, the red area shows the BFPG calculated by:

$$BFPG = SMM\ predicted\ ESR - Baseline\ ESR \qquad E\,(30)$$

A positive BFPG (the red part above the baseline) indicates that the dynamic ESR is greater than 1.00 meaning that the building is becoming safer, whereas the negative BFPG (the red part underneath the baseline) indicates that the dynamic ESR is less than 1.00 meaning that the building is unsafe and attention should be paid to this change.

4.3 Summary

In this section we present a case study of closing the potential BFPG and tracking the changing of fire performance (represented by the ESR) of the exemplar building discussed in Section 3 by using the sensitivity matrix of ESR.

The results show that this simple tool is able to deliver feasible fire protection measures to close the fire performance gap of existing buildings, although the effectiveness of these measures may need more verification by further fire effect simulations which is up to the stakeholders. One months' data produced randomly from the possible bands of uncertainties of input factors are used to feed the FPM tool to produce the corresponding changes of the outputs (ESR and BFPG expressed by ESR).

5 Conclusion and future work

5.1 Conclusion

One of major obstacles preventing people from addressing the issue of the BFPG is that currently there are few ways to dynamically measure the fire performance of buildings in-use, which is different from the areas of building energy performance (where either a electricity/gas bill or meter can be used as measuring tools) and structural health performance (where structural health monitoring tools are employed).

Identifying the acute nature of fire accidents differing from the chronic nature of energy consumption, a prototype tool, FPM, which is expected to be able to dynamically monitor the BFPG expressed by the ESR, is proposed by recording the chronic changes of key input factors that may cause an acute fire accident in the future. A sensitivity matrix method (SMM) based on both center difference and combined backward/forward difference is introduced into the FPM to translate the chronic changes of input parameters into a quantified measure of the BFPG.

An exemplar 3-story apartment building is adopted as the built environment to prototype the SMM-based FPM, showing the potential of this simple tool to work out possible fire protection measures to close a BFPG as well as to track the dynamic BFPG based on the changes of input data. The advantages of the SMM-based FPM include: 1) only 2 points are necessary for each input parameter to develop the sensitivity matrix/scalar of either center difference, backward difference or forward difference; 2) the SMM is open: an input parameter or output quantity can be deleted or added in whenever necessary; 3) the SMM is a “field model” method in that theoretically each output field quantity (e.g., pressure, temperature, incident heat flux, velocity, concentrations of combustion products, visibility, etc.) at each location (e.g., a cell in FDS simulations) can be monitored by tracking the changes of a same set of input variables. The disadvantages of SMM mainly focus on the limited applicability, the difficulty to predict the applicable input range before its application, and the demands of repeat FDS simulations if the predictions look unreasonable.

5.2 Future work

(1) Relating the fundamental influencing factors to the direct influencing factors

There are two levels of factors that finally could affect the holistic building fire performance: direct influencing factors and fundamental influencing factors. While direct influencing factors are usually input parameters of fire effect and egress simulation tools like FDS and Pathfinder, in reality they need to be determined based on the fundamental influencing factors which can be dynamically monitored by either visual or digital sensors. For example, advanced algorithms like artificial intelligence or machine learning may become necessary to translate the changes of photos taken by the IP cameras set in a building to related changes in peak HRR which is needed as an input variable for FDS simulations. In this paper we focus on the direct influencing factors and assume these factors could change chronically. Our future work will focus on how to calculate the values of the direct influencing factors based on the dynamically monitored data of the fundamental influencing factors.

(2) Developing a response surface method (RSM) or an artificial neural network (ANN) method

As to the limited applicability of the SMMs, an RSM or ANN can be developed, which is expected to have better applicability since its development is based on simulation data from many more points than the SMMs. Although the development of an RSM or ANN is time consuming, the experience with the SMMs may be able to ease this process by providing many data at various points.

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APPENDIX I

Theoretical proof that combination of forward difference and backward difference may outperformance center difference in prediction

From Taylor's Theorem [42,43], we have

$$f(x+h) = f(x) + hf^{'}(x) + \frac{h^2}{2} f^{"}(c_h)$$

Where c is some (unknown) number between x and x+h (h>0). Solving for $f^{'}(x)$ leads to

$$f^{'}(x) = \frac{f(x+h) - f(x)}{h} - \frac{h}{2} f^{"}(c)$$

Where $\frac{f(x+h) - f(x)}{h}$ is the forward difference approximation of $f^{'}(x)$ with reminder error of $-\frac{h}{2} f^{"}(c)$ which is $O(h)$

In the same way, we have

$$f(x-h) = f(x) - hf^{'}(x) + \frac{h^2}{2} f^{"}(c_h) \Rightarrow$$
$$f^{'}(x) = \frac{f(x) - f(x-h)}{h} + \frac{h}{2} f^{"}(c)$$

Where $\frac{f(x) - f(x-h)}{h}$ is the backward difference approximation of $f^{'}(x)$ with reminder error of $\frac{h}{2} f^{"}(c)$ which is also $O(h)$.

For the central difference, the error can be found from the third-degree Taylor polynomials with remainder:

$$\left.\begin{aligned} f(x+h) &= f(x) + hf'(x) + \frac{h^2}{2} f''(x) + \frac{h^3}{3!} f'''(c_1) \\ f(x-h) &= f(x) - hf'(x) + \frac{h^2}{2} f''(x) - \frac{h^3}{3!} f'''(c_2) \end{aligned}\right\} \Rightarrow$$

$$f'(x) = \frac{f(x+h) - f(x-h)}{2h} - \frac{h^3}{3!} \frac{f'''(c_1) + f'''(c_2)}{2}$$

Where $x \le c_1 \le x+h, x-h \le c_2 \le x$, and $\dfrac{f(x+h) - f(x-h)}{2h}$ is the central difference approximation of $f'(x)$ with remainder error of $-\dfrac{h^3}{3!} \dfrac{f'''(c_1) + f'''(c_2)}{2}$ which is $O(h^2)$.

Use again the Taylor's theorem at point (x+a), we have

$$f(x+a) = f(x) + af'(x) + \frac{a^2}{2} f''(c_a)$$

Replacing $f'(x)$ with its center difference form, we have:

$$f(x+a) = f(x) + af'(x) + \frac{a^2}{2} f''(c_a) \Rightarrow$$

$$f(x+a) = f(x) + a\left(\frac{f(x+h) - f(x-h)}{2h} - \frac{h^3}{3!} \frac{f'''(c_1) + f'''(c_2)}{2} \right) + \frac{a^2}{2} f''(c_a) \Rightarrow$$

$$f(x+a) - \left(f(x) + a \frac{f(x+h) - f(x-h)}{2h} \right) = \frac{a^2}{2} f''(c_a) - \frac{ah^3}{3!} \frac{f'''(c_1) + f'''(c_2)}{2}$$

Where

$$E_C = \frac{a^2}{2} f''(c_a) - \frac{ah^3}{3!} \frac{f'''(c_1) + f'''(c_2)}{2}$$

is the error of using center difference approximation of $f'(x)$ to predict $f(x+a)$.

Replacing $f'(x)$ with its forward difference form, we have:

$$f(x+a) = f(x) + af'(x) + \frac{a^2}{2} f''(c_a) \Rightarrow$$

$$f(x+a) = f(x) + a\left(\frac{f(x+h) - f(x)}{h} - \frac{h}{2} f''(c) \right) + \frac{a^2}{2} f''(c_a) \Rightarrow$$

$$f(x+a) - \left(f(x) + a \frac{f(x+h) - f(x)}{h} \right) = \frac{a^2}{2} f''(c_a) - \frac{ah}{2} f''(c)$$

Where

$$E_F = \frac{a^2}{2} f^{"}(c_a) - \frac{ah}{2} f^{"}(c)$$

is the error of using forward difference approximation of $f^{'}(x)$ to predict $f(x+a)$. Similarly we can prove that the error of using backward difference approximation of $f^{'}(x)$ to predict $f(x+a)$ is:

$$E_B = \frac{a^2}{2} f^{"}(c_a) + \frac{ah}{2} f^{"}(c)$$

When a>0:

If $f^{"}(c_a) \bullet f^{"}(c_h) > 0$ then $|E_F| < |E_B|$, which means forward difference is better than backward difference. Further given $f^{"}(c_a) > 0, f^{"}(c_h) > 0$ and $0 < \frac{ah^3}{3!} \frac{f^{'''}(c_1) + f^{'''}(c_2)}{2} < \frac{ah}{2} f^{"}(c_h) < \frac{a^2}{2} f^{"}(c_a)$, then

$$|E_F| < |E_C| < |E_B|$$

Which means accuracy of center difference is between that of forward difference and backward difference.

Now we prove that under these conditions the forward difference has higher accuracy than center difference. In the same way, we can prove that under some specific conditions the backward difference has higher accuracy than the center difference. Therefore, if we know the value of input variables, the combination of forward difference and backward difference may outperformance the center difference.

APPENDIX II

Table 6 Input parameters for component fire performance

parameter type	input parameter name
building characteristics	fire location (defined as the distance for smoke to travel to the main egress exit) compartment width, depth, height door height, width window height, width ceiling vent width, length ceiling vent location (defined as the horizontal distance to the fire plume center) diameter of duct exhaust fan flow rate stories corridor effective width, height maximum travel distance exit usability inside temperature and pressure outside temperature and pressure inside relative humidity distance to other building flammability/flame spread/conductivity/heat capacity/density/thickness of surface material
Fire characteristics	fire load density Fire area minimum distance to walls the height of fire source HRR per unit area fire growth rate radiative fraction species yields for Carbon(C), Carbon monoxide (CO)
Occupant characteristics	percentage of adult adult walking speed non-adult walking speed occupant density premovement time

fire protection strategies	RTI of sprinklers RTI of heat detectors temperature to activate heat detectors temperature to activate sprinklers specific extinction coefficient to activate smoke detector spray water density flow rate of smoke exhaust fan delay time to activate smoke control system air leakage area of fire doors thickness of GWB

APPENDIX III

The non-dimensional expression being used to measure how well the flow filed is resolved is calculated by:

$$\left(D^{*}/\delta x\right)_{\min} \approx 4, \left(D^{*}/\delta x\right)_{\max} \approx 30$$

$$Given$$

$$\delta x = 0.0625 \sim 0.25m$$

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

$$where$$

$$\rho_{\infty} = 1.2kg/m^{3}, c_{p} = 1kJ/(kg\cdot K), T_{\infty} = 293K, g = 9.81m/s^{2}$$

$$\dot{Q} = 1000 \sim 5000kW,$$

δx is the nominal cell size, D^{*} is the characteristic fire diameter, ρ_{∞} is the air density, c_p is the specific heat capacity of air, T_{∞} is the environmental temperature, g is the acceleration of gravity, and $\dot{Q}$ is the total heat release rate of fire.

APPENDIX IV

Validation of the baseline fire scenario

In the baseline scenario, the fire apartment includes two openings: the apartment door with a width of 0.8m and the floor window with a width of 1m (both have a height of 2m). The maximum possible HRR that could develop in this fire apartment can be calculated by the following equation [44]:

$$HRR_{\max} = 1500V_f = 1500A_v\sqrt{H_v}$$

Where V_f is the ventilation factor, A_v is the area of opening, and H_v is the height of the opening.

Therefore, the finally calculated maximum possible HRR is

$$HRR_{\max} = 1500 \times ((0.8+1) \times 2) \times \sqrt{2} = 7636kW$$

Which is larger than our baseline HRR of 3000kW, indicating that our baseline HRR is achievable in real fires. HRRs of about 3000kW are also reported in articles for room fires [45].

As to the soot yield [44], for common combustible gases, it ranges from 0.013 to 0.125; for common liquids, it ranges from 0.008 to 0.232; for synthetic solid materials, it ranges from 0.011 to 0.164; for foams, it ranges from 0.002 (Phenolic foams) to 0.227 (GM23); for woods, it ranges from 0.008 to 0.015. the materials used in the finishes and furniture of apartments are combination or mixture of woods, synthetic solid materials, and forms. The baseline soot yield of 0.052 allows for either a considerable reduction or a increase of the soot yield.

APPENDIX V

Table 7 Random numbers used to generate one month's synthetic data

Date	Random_HRR	Random_W_c	Random_Y_s	Random_W_d	Random_W_w	Random_E_f
10/15	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10/16	0.9459	0.3151	0.3317	0.3298	0.6113	0.5744
10/17	0.9096	0.6259	0.7418	0.9795	0.6656	0.7121
10/18	0.8331	0.0339	0.4767	0.7033	0.5645	0.8260
10/19	0.0073	0.4107	0.7116	0.7493	0.5017	0.0644
10/20	0.4530	0.2680	0.9764	0.2453	0.6654	0.3099
10/21	0.4230	0.9741	0.3898	0.4414	0.3662	0.1972
10/22	0.7426	0.6547	0.9633	0.4870	0.3473	0.3717
10/23	0.6717	0.5398	0.4935	0.5938	0.4724	0.7222
10/24	0.3767	0.2786	0.2887	0.5851	0.5269	0.8358
10/25	0.2280	0.2552	0.0143	0.7811	0.3837	0.4743
10/26	0.8708	0.6694	0.0236	0.3032	0.1985	0.6217
10/27	0.8729	0.5558	0.0349	0.2605	0.6705	0.7943
10/28	0.4251	0.3080	0.1036	0.2675	0.6949	0.7053
10/29	0.2804	0.2030	0.4763	0.5192	0.0032	0.4457
10/30	0.2076	0.4091	0.6169	0.9965	0.9105	0.3579
10/31	0.0493	0.3654	0.7915	0.4312	0.5723	0.8793
11/1	0.1783	0.0558	0.6014	0.7000	0.1521	0.3637
11/2	0.0620	0.3067	0.5713	0.5415	0.4079	0.1009
11/3	0.5945	0.4674	0.0998	0.2619	0.3465	0.5801
11/4	0.7185	0.9197	0.9286	0.4918	0.7132	0.9754
11/5	0.5878	0.6424	0.7469	0.7438	0.0278	0.8681
11/6	0.6597	0.8668	0.0184	0.7177	0.0397	0.0276
11/7	0.1639	0.1675	0.4551	0.0932	0.9952	0.4999
11/8	0.6090	0.7386	0.5858	0.2207	0.0594	0.9721
11/9	0.9428	0.3875	0.6817	0.4737	0.2734	0.4637
11/10	0.3946	0.7367	0.7543	0.0441	0.0905	0.1085
11/11	0.5094	0.8672	0.9282	0.2364	0.2608	0.1066
11/12	0.9156	0.2285	0.4329	0.7437	0.5413	0.6072
11/13	0.3012	0.8894	0.1548	0.2305	0.8811	0.4100
11/14	0.9496	0.3214	0.3874	0.9418	0.7928	0.6067

Reference

[1] Pieter de Wilde (2019), Ten questions concerning building performance analysis, Building and Environment, 153: 110-117

[2] Magdalena Hajdukiewicz, David Byrne, Marcus M. Keane, Jamie Goggins (2015), Real-time monitoring framework to investigate the environmental and structural performance of buildings, Building and Environment, 86:1-16

[3] M.Jradi, K.Arendt, F.C.Sangogboye, C.G.Mattera, E.Markoska, M.B.Kjærgaard, C.T.Veje, B.N.Jørgensen (2018), ObepME, An online building energy performance monitoring and evaluation tool to reduce energy performance gaps, Energy and Buildings, Volume 166, Pages 196-209

[4] Chang, F.-K. (1999). Structural Health Monitoring 2000: Proc., 2nd Int. Workshop on Structural Health Monitoring, Stanford Univ., Technomic, Lancaster, Pa.

[5]Christian Cremona, Joao Santos (2018), Structural Health Monitoring as a Big-Data Problem, Structural Engineering International Jr: 243-254

[6] Hyun-Hee Ryu, Jong Soo Kim, Eun Gyu Choi, Sang-hoon Lee (2007), Preliminary design of structural health monitoring for high-rise buildings, International Journal of High-Rise Buildings, 6(3): 279-284

[7] Jerome Peter (2007), An overview of wireless structural health monitoring for civil structures, Phil. Trans. R. Soc. A: 345–372

[8] E. A. Johnson, A.M.ASCE1 ; H. F. Lam2 ; L. S. Katafygiotis, A.M.ASCE3 ; and J. L. Beck, M.ASCE (2004), Phase I IASC-ASCE Structural Health Monitoring Benchmark Problem Using Simulated Data, JOURNAL OF ENGINEERING MECHANICS © ASCE

[9] Honggang Wang, Nicholas A. Dembsey, Brian J. Meacham, Shichao Liu, Simeoni Albert, Conceptual Design of a Building Fire Performance Monitoring Process, submitted to Fire Technology

[10] Morgan J. Hurley, Eric R. Rosenbaum (2015), Performance-based fire safety design, CRC Press, Taylor & Francis Group, LLC

[11] David J. Murray-Smith (2012), chapter 5 - Methods and applications of parameter sensitivity analysis, in: Modelling and Simulation of Integrated Systems in Engineering, Woodhead Publishing Limited

[12] D.G. Cacuci (2003), Sensitivity and Uncertainty Analysis, Vol. 1: Theory, Chapman and Hall/CRC Press, Boca Raton, FL

[13] Andrea Saltelli, Marco Ratto, Terry Andres, Francesca Campolongo, Jessica Cariboni, Debora Gatelli, Michaela Saisana and Stefano Tarantola (2008), Global Sensitivity Analysis. The Primer, John Wiley & Sons Ltd, The Atrium, Southern Gate, Chichester, West Sussex PO19 8SQ, England

[14] M.D. Morris (1991), Factorial sampling plans for preliminary computational experiments Technometrics, 33 (2) , pp. 161-174

[15] I.M. Sobol (2001), Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Mathematics and Computers in Simulation, 55(1–3), pp. 271-280

[16] ISO 239321-1, Fire safety engineering — General principles — Part 1: General

[17] Wolski, N. Dembsey, B.J. Meacham (2000), Accommodating perceptions of risk in performance-based building fire safety code development Fire Saf. J., 34, pp. 297-309

[18] Bart Van Weyenberge, Xavier Deckers, Robby Caspeele, and Bart Merci (2019), Development of an integrated risk assessment method to quantify the life safety risk in buildings in case of fire, Fire Technology, 55:1211–1242

[19] Wang H.-G., Zhang J.-R., Wu F.-L., Lin H.-F., Chang X.-T (2009)., Numerical calculation of flow field by application of superposition theory of partial differential equation, 2009 International Conference on Engineering Computation, ICEC 2009, pp. 55-58.

[20] D. M. Hamby (1994), A review of techniques for parameter sensitivity analysis of environmental models, Environmental Monitoring and Assessment 32: 135-154

[21] K. McGrattan and B. Toman (2011). Quantifying the predictive uncertainty of complex numerical models. Metrologia, 48:173–180,

[22] Kevin McGrattan Simo Hostikka Jason Floyd Randall McDermott Marcos Vanella (2020), FDS Technical Reference Guide Volume 3: Validation, NIST

[23] Verification and Validation of Selected Fire Models for Nuclear Power Plant Applications, Volume 2: Experimental Uncertainty, U.S. Nuclear Regulatory Commission, Office of Nuclear Regulatory Research (RES), Rockville, MD, 2007, and Electric Power Research Institute (EPRI), Palo Alto, CA, NUREG-1824 and EPRI 1011999.

[24] Richard D. Peacock Paul A. Reneke Glenn P. Forney (2020), CFAST – Consolidated Model of Fire Growth and Smoke Transport (Version 7) Volume 2: User's Guide, NIST Technical Note 1889v2

[25] Kevin McGrattan, Simo Hostikka, Jason Floyd, Randall McDermott, Marcos Vanella (2020), Fire Dynamics SimulatorUser's Guide, NIST Special Publication 1019Sixth Edition

[26] Thunderhead (2014), PATHFINDER User Manual

[27] Stephen G. Badger (2017), Large-Loss Fires in the United States 2016, NFPA report

[28] Stephen G. Badger (2016), Large-Loss Fires in the United States 2015, NFPA report November 2016

[29] Piotr Tofił, Wojciech Węgrzyński (2016), Hand calculations, zone models and CFD – areas of disagreement and limits of application in practical fire protection engineering, SFPE 11th Conference on Performance-Based Codes and Fire Safety Design Methods, At: Warsaw, Poland, May 2016

6

[30] McCaffrey, B. J., Quintiere, J. G. and Harkleroad, M. F (1981). "Estimating Room Temperatures and the Likelihood of Flashover Using Fire Test Data Correlations," Fire Technology, 17(2), pp. 98–119

[31] Peacock, R., Forney, G. and Reneke, P. A. (2013), "CFAST – Consolidated Model of Fire Growth and Smoke Transport (Version 6) Technical Reference Guide", Special Publication 1026r1, National Institute of Standards and Technology, Gaithersburg, MD, USA,. DOI: 10.6028/NIST.SP.1026r1

[32] Jason E. Floyd, Comparison of CFAST and FDS for Fire Simulation with the HDR T51 and T52 Tests (2002), NISTIR 6866, National Institute of Standards and Technology

[33] PERFORMANCE-BASED LIFE SAFETY ASSESSMENT OF THE FAST GARAGE, KOFFEL ASSOCIATES, INC, April 1, 2016

[34] International Code Council (ICC) (2018), Chapter 3 Occupancy Classification and Use, International Building Code

[35] Kevin McGrattan, Simo Hostikka, Randall McDermott, Jason Floyd, Marcos Vanella, Craig Weinschenk, Kristopher Overholt (2017), FDS User's Guide (six edition), NIST, November, 2017

[36] Wen Jiann Bong (2011), Limitations of Zone Models and CFD Models for Natural Smoke Filling in Large Spaces, Master Thesis in Department of Civil and Natural Resources Engineering, University of Canterbury

[37] Kashef, A.; Bénichou, N.; Lougheed, G. D.; Mccartney, C. J (2002), A Computational and experimental study of fire growth and smoke movement in large spaces, NRCC-45201, National Research Council Canada(NRC)

[38] Tosolini E., Grimaz S. Pecile L.C. and Salzano E. (2012), People evacuation: simplified evaluation of available safe egress time in enclosures, Chemical Engineering Transactions, 26, 501-506 DOI: 10.3303/CET1226084

[39] Tosolini E., Grimaz S. and Salzano E. (2013), A sensitivity analysis of available safe egress time correlation, Chemical Engineering Transactions, 31, 223-228 DOI: 10.3303/CET1331038

[40] Stephen Kerber (2011), Analysis of Changing Residential Fire Dynamics and Its Implications on Firefighter Operational Timeframes, Fire Technology, 48, 865–891

[41] NFPA Technical Committees (2009). NFPA 101 Life Safety Code. Quincy, MA: National Fire Protection Association,

[42] https://www.whitman.edu/mathematics/calculus_online/section11.11.html , first accessed on 11/20/2020

[43] http://www.ohiouniversityfaculty.com/youngt/IntNumMeth/lecture27.pdf, first accessed on 11/20/2020

[44] J.M. Watts, J.R. Hall (2015), Introduction to fire risk analysis, SFPE Handbook for Fire Protection Engineering (Fifth ed.), NFPA, Quincy, MA

[45] W. K. Chow, Fuel Load and Peak Heat Release Rate Correlations in Post-Flashover Room Fires, Heat Transfer Engineering, 31:3, 2010lgh

Section 4

COMPARISON OF SENSITIVITY MATIRX METHOD, POWER FUNCTION-BASED RESPONSE SURFACE METHOD, AND ARTIFICIAL NEURAL NETWORK IN THE ANALYSIS OF BUILDING FIRE EGRESS PERFORMANCE

Comparison of sensitivity matrix method, power function-based response surface method, and artificial neural network in the analysis of building fire egress performance

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Abstract:

Unlike the areas of building energy and structural health, performance monitoring tools are currently absent in the area of building fire protection. Computational Fluid Dynamics (CFD) models like Fire Dynamics Simulator (FDS) are widely applied in building fire performance design, which can be equally used to predict changes of building fire performance. However, due to its time-consuming nature, it is not realistic to apply FDS frequently. The sensitivity matrix method (SMM) has been discussed as a quick method to predict changes of building fire egress performance. However, this approach can have significant uncertainties when being applied to datasets with many input parameters due to its inherent incapability of predicting accurately system responses if input data are considerably far away from the baseline points around which a SMM is developed. Response surface methods (RSM) are commonly used to characterize the relationships between input variables and output quantities for complicated problems. Different from conventional RSMs, a novel two phase power function fitting process is proposed to develop substitute algebraic models of the available safe egress time (ASET) from FDS numerical experiments based on a theorem which states that an output variable is proportional to the product of input parameters to their respective powers if the output variable is proportional to each input parameter to some power and the input parameters are independent of each other. An artificial neural network (ANN) is a universal method to approximate any arbitrary complicated, nonlinear system response with limited number of discontinuities without deep understanding of how the system works. This paper employs MATLAB's feedforward neural networks with error backpropagating algorithm to approximate the FDS response. Applicability in terms of uncertainties including system bias and relative standard deviation (RSD) or percentage of predictions falling in a preset acceptable error range are compared among RSMs developed from various datasets, ANNs with various hidden layer sizes and dataset sizes, and SMMs which have been previously published by using the same fire scenarios in a small three-story apartment building. The result shows that it is possible for ANNs to have lowest model uncertainties and highest percentage of predictions within the preset 20% error scope as far as the specific fire egress safety problem discussed in this paper is concerned, but the cost of developing a SMM, namely the number of data cases, is the lowest. Due to the different aspects of RSMs, ANNs, and SMMs, to better understand the building fire performance gap continuously, a hybrid strategy of starting with SMMs followed by RSMs and/or ANNs is recommended.

Keywords: Response surface method; Artificial neural network; Sensitivity matrix method; Building fire performance gap; Performance-based design, ASET, RSET

Nomenclature

Y Response/output vector

X Input vector

K Size coefficient

C Coefficient covering the effects from all the constant parameters not selected as input variables

P Dependent factor

D_d Dependent factor

A_t ASET

R_t RSET

$\bar{\delta}$ System bias

$\bar{\omega}$ Relative standard deviation

M_i Model output at sample point i

E_i Experimental measurement at sample point i

n Number of sample points

s Sample variance

ω_E Relative experimental uncertainty

ω_0 Uncertainty of the experimental device

w_i Uncertainty of the device

p_i Power dependences of the individual input parameters

δ_j Error signals at the node j in a neural network

b_j Bias of the node j in a neural network

w_{ij} Connection weights between node i and j in a neural network

1. Introduction

The building fire performance gap (BFPG) is defined as the gap between predicted building fire performance during the design stage and the actual building fire performance during the operation stage [1]. Considering the difficulties for analytical solutions to describe increasingly complicated problems related to fires, a prototype of a fire performance monitoring tool based on a sensitivity matrix method (SMM) has been proposed in [2] to track the change of the BFPG based on egress safety ratio which is the ratio of the available safe egress time (ASET) to the required safe egress time (RSET).

Although the SMM is a good starting point to handle the BFPG due to its lower computational cost, its applicability in terms of either model uncertainties including system bias and relative standard deviation (RSD) or percentage of predictions falling into a preset acceptable error scope is low when wide ranging input datasets are employed. On the other hand, the fact that algebraic equations (e.g., the MQH method [3]) with a much wider applicable range obtained from extensive fire experiments are widely adopted for calculations involving selected scenarios indicates a promising potential for this kind of simple algebraic equation. Similar algebraic equations that include geometry and physical factors exist for engineers to determine the view factors in radiation heat transfer and fire resistance of structural members [4], and to calculate important parameters like peak discharge and the time to peak discharge in dam failure analysis [5,6]. Response Surface Methods (RSMs), which are a collection of mathematical and statistical techniques used in the development of an adequate functional relationship between a response of interest and a number of associated control (or input) variables[7], was originally developed to model experimental response [8~10] and then migrated into the modelling of numerical experiments [11,12]. Since ASET is a commonly used key index of building fire performance-based design, this paper focuses on the derivation and application of simple substitute algebraic equations for numerical/physical experiments, which relate ASET to some influencing input variables by using RSMs. Similar substitute algebraic models can be developed in the same way when different building characteristics are involved. Since these simple algebraic equations are obtained from sophisticated numerical experiments and/or physical experiments and can be easily understood by generally knowledgeable fire protection engineers, they may also be used to assist prescriptive code-based design by providing a more scientific basis. In a traditional RSM, the number of physical or numerical experiments needed to develop a good model rises exponentially when the input variables grow. For example, the easiest first order design in the traditional RSM needs 2^k experiments where k is the number of input variables. The novel power-function-based RSM developed in this paper needs much smaller number of experiments since the total number of experiments increases with the number of input variables linearly instead of exponentially. Moreover, if the SMM has been employed initially as a starting point, it could have generated some sampling points which can be adopted to build the RSM.

Alternatively, artificial Neural Networks (ANNs) are also a commonly used method to represent a complicated system response, especially when the detail mechanism between system inputs and system outputs/responses is unclear. By considering the system as a black box, an ANN method uses part of the input (and output for supervised ANNs) data to train the network, and then part of the data to validate the network. With increasing number of training data, an ANN method tends to describe the system more accurately until an optimum point is reached. Once a neural network is successfully trained, it can be used to process new input data and predict the system response. In this paper, MATLAB's feedforward neural networks with error backpropagating algorithms are adopted to approximate the FDS response. The same dataset is adopted to compare applicability of RSMs, ANNs, and SMMs in terms of model uncertainties and percentages of predictions within a preset acceptable error range.

As shown in the conceptual design flowchart of a building fire performance monitoring tool (see Figure 1) [1], the purpose of introducing SMM, RSM, ANN centers on dynamical calculation or tracking of the BFPG which is hard to do by employing common CFD models like FDS due to their time and computational resource costs. Instead of showing how the RSM and ANN could help to track the BFPG, which is similar to how the SMM works to track the BFPG discussed in reference [2], in this paper the focus is on the development of a novel RSM, application of an ANN, and comparison of applicability among SMM, RSM, and ANN in terms of model uncertainties (i.e., system bias and relative standard deviation (RSD)) and percentage of predictions within a preset error range.

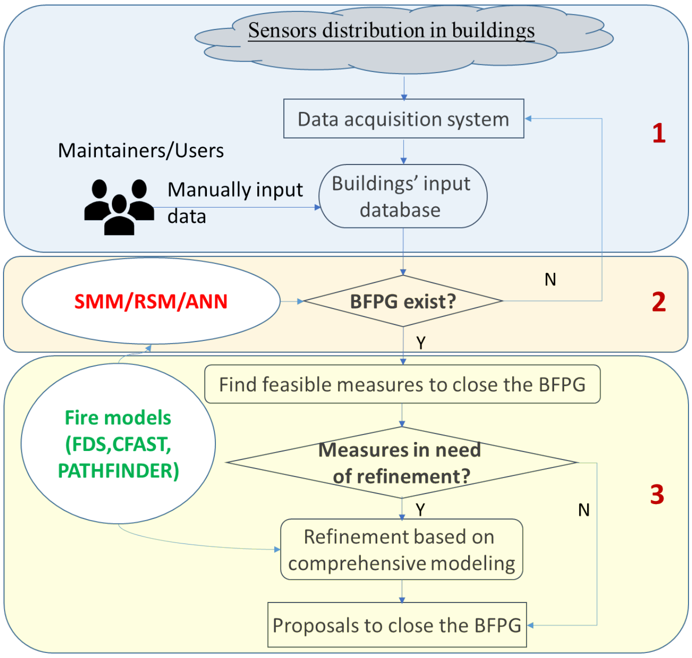


Figure 1 Flowchart of building fire performance monitoring (SMM: Sensitivity Matrix Method; RSM: Response Surface Method; ANN: Artificial Neural Network; 1: Input module; 2: BFPG-checking module; 3: measure-refining module)

In section 2, the theoretical basis of a novel two phase power function fitting RSM is illustrated, and a case study of this method is conducted with numerical experiments as the source data. The same narrative order is followed in section 3 for the application of ANNs. In section 4, the applicability is compared among two RSM models (RSM-1 and RSM-2), ANNs with dataset size of 80 and hidden layer size of 2, and two SMM models (SMM-center and SMM-B/F). Section 5 discusses the limitations of model developments and characteristics of RSM, ANN, and SMM, and summarizes the major conclusions of this paper.

2 Development and application of power function-based RSMs

2.1 Theoretical basis of power function-based RSM

2.1.1 Theorem I

Theorem I is similar to the equation of joint probability distribution for independent random variables.

Statement: For a complicated system without analytical solutions, if the output responses are proportional to each independent input parameter to its' specific power in a subset of input parameters, then the output responses are proportional to the product of these independent input parameters to their corresponding powers in the same subset.

Mathematical expression of Theorem I is:

Given a problem with an output vector $Y=\left(y_1,y_2,\ldots,y_i,\ldots y_M\right)$ and an input vector $X=\left(x_1,x_2,\ldots,x_j,\ldots x_N\right)$, if the following equations exist,

$$y_i \propto x_j^{k_{ij}}, x_j \in X_s \subseteq X_T, for\ \forall x_{l,l\neq j} \qquad E.\ 1$$

Meaning that y_i is proportional to $x_j^{k_{ij}}$ no matter what the values of the other input parameters are. In other words, the input factors are independent of each other: the change of any one of the input factors has no way to alter any of the other factors.

Then

$$y_i \propto \prod_{j=1}^{N} x_j^{k_{ij}}, x_j \in X_s \subseteq X_T \qquad E.\ 2$$

where X_T is the set consisting of all elements in the input vector $X_T=\left(x_1,x_2,\ldots,x_j,\ldots x_t\right)$ and X_s is a subset of X_T

Proof:

The proof of "if E.1 is correct, then E.2 exists" is equal to the proof "if E.2 doesn't exist, then E.1 is not correct".

E.2 doesn't exist means that for any input factor $x_j \in X_s \subseteq X_T$ within its domain, y_i is not proportional to $\prod_{j=1}^{N} x_j^{k_{ij}}$. Let's assume that any input factor except x_p is constant. Since each input factor is independent of the other factors, the values of input factors other than x_p won't affect the domain of x_p. Because "E.2 doesn't exit", now we take y_i is not proportional to $x_p^{k_{ip}}$, which is opposite to E.1. Therefore, Theorem I is proved.

2.1.2 Development of substitute models by two-phase power function fitting

Power function fitting is to fit a given set of data into a power function. Based on Theorem I, a substitute algebraic model with the form of the product of input factors to their specific powers can be worked out from a target problem by either physical experiments or numerical simulations. Here we propose an RSM with two-phase power function fitting to build the substitute algebraic model.

In the first phase of power function fitting, numerical simulations/experiments and/or physical experiments are performed to plot each output quantity/variable against the changes of each single input parameter, which is further fitted into a power function as shown in equation (1). Then by using theorem I with the assumption that each input parameter is independent of the others, equation (2) can be developed showing the relationship between the output variable and the product of each input variable of interest to its own power. The first phase can be deemed as a prediction process.

In the second phase of power function fitting, numerical simulations/experiments and/or physical experiments where all the six input parameters change simultaneously are conducted to verify or calibrate the relationship between the output variable (the left side of equation (2)) and the collection of the input parameters raised to some specific powers (the right side of equation (2)). In other words, the output is related to all the input parameters of interest. Remember that in the first phase it is assumed that the input parameters are independent of each other. In reality, however, some extent of interaction between input parameters are inevitable. Therefore, when calibrating equation (2), a lumped power is introduced which applies to the right side of the equation (2). The final equation will have the formation of:

$$y_i = C \bullet \left(\prod_{j=1}^{N} x_j^{k_{ij}} \right)^P \qquad E.\ 3$$

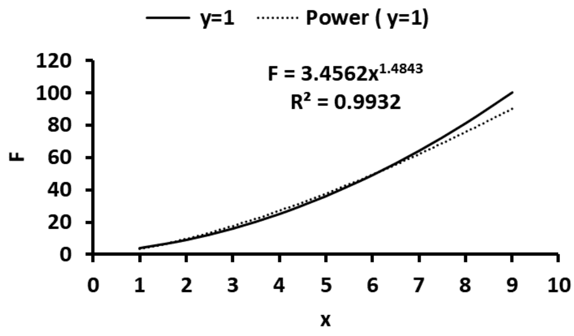
Where C is the coefficient covering the effects from all the constant parameters not selected as input variables, and the power P is the dependence factor indicating the coupling degree among input variables. A unity value of P indicates that all the input parameters are independent of each other. The bigger the gap between P and unity, the greater is the coupling among input variables. If P is negative, which is rare, if not impossible, it means that the interactional effects of these input factors are totally in the opposite direction of the effect of each single input. In this paper only positive P is addressed. If P is greater than one, it means the interactional effects among input factors are positive: they promote each other when they work together. On the other hand, if P is less than one (but greater than zero), it means the interactional effects among them are negative: they cancel each other when they work together. This explanation should be taken carefully when only part of the important influencing factors are considered, with the effects of the other influencing factors lumped together as a constant. The second phase can be deemed as a correction process. Together, the two-phase power function fitting is a predictor-corrector process.

2.1.3 Potential errors in the method of two-phase power function regression

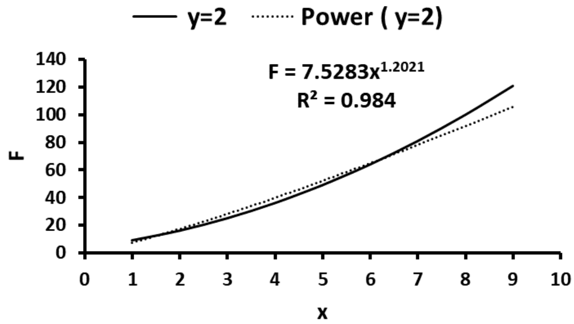
The substitute algebraic equations developed based on the two-phase power function fitting could deviate from its target model (the numerical/physical experiments it is approximating) due to two reasons:

First, the substitute algebraic equations are derived from approximate curve-fits (e.g., the process of comparing equation 2 with the results of numerical/physical experiments to get equation 3), the errors could be augmented when different single correlations are multiplied together.

Second, the existence of Theorem I is based on the assumption that power function correlation works when each parameter varies freely within its selected defined domain, which is expressed mathematically as $y_i \propto x_j^{k_{ij}}, x_j \in X_s \subseteq X_T, for\ \forall x_{l,l \neq j}$. This is a simplification. It is hard to check if this correlation exists even for very limited defined domains of small sets of input parameters due to the explosively growing number of combined scenarios. Instead, during the application processes of Theorem I, as shown in the next section, we only show that power function correlations do exist under only one scenario within the selected definition domains of input parameters, which is the default scenario. When the substitute algebraic equations are worked out based on this simplification, we hope that they are also applicable for any scenarios of input entries within their selected defined domains. Therefore, some considerable errors may be inevitable. For example, look at the following two functions: 1) $F = (x+y)^2$ and 2) $F = x^2 y^2$. If we only investigate the positive correlation between F and x under one scenario, for example, y=1, we can obtain by curve fitting that for function 1) $F \propto x^{1.4843}$. When y=2, however, by the same method of curve fitting we can obtain for function 1) $F \propto x^{1.2021}$, as shown in the following figures:



a) y=1



b) y=2

Figure 2 A case showing interaction between input parameters for

$$F = \left(x + y\right)^2$$

For function 2) it is obvious that no matter what value y is, $F \propto x^2$ always exists.

2.1.4 Method to calculate model uncertainty

The overall uncertainty of a model prediction is a combination of the uncertainty of the input parameters and the uncertainty of the model assumptions. The former is referred to as parameter uncertainty; the latter model uncertainty [13]. A method is described in [13,14] to estimate the model uncertainty using comparisons of model predictions with experimental measurements whose uncertainty has been quantified. This method reports the model uncertainty in terms of only two metrics, a system bias factor, $\bar{\delta}$, and a relative standard deviation, $\bar{\omega}$, which can be calculated by:

$$\bar{\delta} = \exp\left(\frac{1}{n}\sum_{i}^{n}\ln\left(\frac{M_i}{E_i}\right) + \frac{s^2 - \omega_E^2}{2}\right) \qquad E.\ 4$$

and

$$\bar{\omega} = \exp\left(\frac{1}{n}\sum_{i}^{n}\ln\left(\frac{M_i}{E_i}\right) + \frac{s^2 - \omega_E^2}{2}\right) \cdot \sqrt{s^2 - \omega_E^2} \qquad E.\ 5$$

Where M_i and E_i are the model output and experimental measurement at sample point i, respectively; n is the number of sample points; s and ω_E are sample variance and relative experimental uncertainty, respectively, which can be calculated by

$$s^2 = \frac{1}{n-1}\sum_{i}^{n}\left[\ln\left(\frac{M_i}{E_i}\right) - \frac{1}{n}\sum_{i}^{n}\ln\left(\frac{M_i}{E_i}\right)\right]^2 \qquad E.\ 6$$

$$\omega_E^2 = \omega_0^2 + \sum_i p_i^2 w_i^2 \qquad E.\ 7$$

The relative experimental uncertainty, ω_E, includes both the uncertainty of the experimental device (ω_0) that measures the quantity the model is trying to predict, and the uncertainty of the device (w_i) that measures the various input parameters that the model requires. The factors, p_i, represent the power dependences of the individual input parameters

In this paper, our purpose is to investigate the model uncertainty of the RSM, and the FDS simulations are considered “numerical experiments”. Unlike the physical experiments where the relative experimental uncertainty, ω_E, can be calculated according to the method provided in [15], for numerical experiments in our case it is difficult to accurately calculate the ω_E due to lack of knowledge about the ω_0, p_i and w_i of the FDS software as a numerical experimental device. From equation (4) and (5), it is clear that an overestimate of ω_E^2 will result in underestimate of model uncertainty. Since it doesn’t make sense for a relative experimental uncertainty to be greater than the computed model uncertainty, the reasonable range of ω_E should be [0,

s^2] (In equation (5), if $\omega_E^2 = s^2$, then $\bar{\omega}$ =0) , which results in reasonable range of $\bar{\delta}$ and $\bar{\omega}$ as:

$$\bar{\delta} \in \left[\exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) \right), \exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) + \frac{s^2}{2} \right) \right] \quad E.\ 8$$

$$\bar{\omega} \in \left[0, \exp\left(\frac{1}{n} \sum_i^n \ln\left(\frac{M_i}{E_i} \right) + \frac{s^2}{2} \right) \cdot s \right] \quad E.\ 9$$

2.2 Response surface methods from numerical experiments

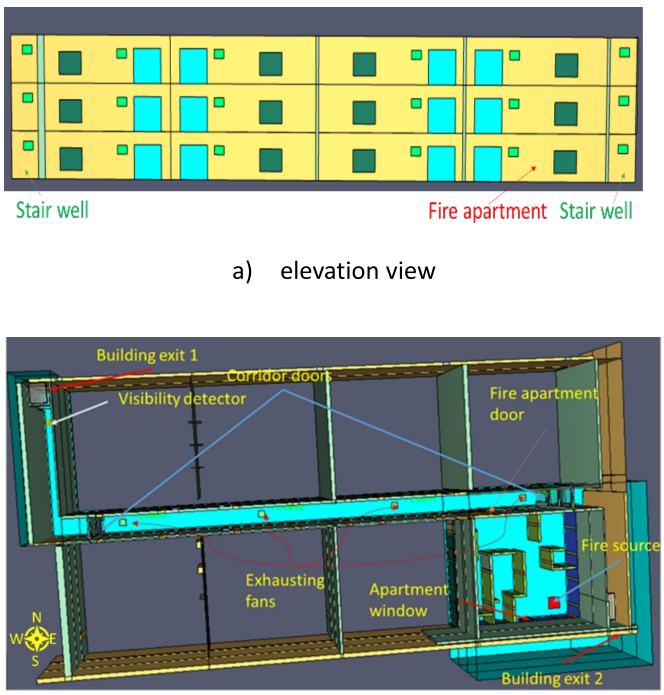
2.2.1 Problem description

The purpose of this section is to develop RSMs based on numerical experimental cases from FDS. Figure 3 shows an exemplar 3 story residential building with floor area of about 1000m^2. This building would be designated as 'R-2' by the International Building Code (IBC) in the USA [16]. There are eight 100m^2 apartments in every story. The corridor is 2m wide, floors are connected by two staircases at the west and east ends of the building. A propane gas-burner fire is put close to the southeast corner of the southeast apartment of the residential building. There are two corridor doors set close to each end of the main corridor. All the apartment doors are closed except the fire apartment, the entry doors of the building are kept open during the simulations. Six input factors are considered: the width of the west corridor door, $W_c(m)$, the Heat Release Rate (HRR) of fire, $HRR(kW)$, the soot yield of the fuel (in this case it is propane), Y_s, the width of a window which is in the exterior wall of the fire apartment, $W_w(m)$, the width of the apartment door which connects to the corridor, $W_d(m)$, and the total flow rate of the four exhausting fans set in the ceiling of the corridor, $E_f(m^3/s)$. Only ASET, A_t, is considered as an output variable: measured by a visibility detector close to exit 1, at a height of 1.8m above the floor, and with a threshold of 5m. The reference/baseline case is defined as:

$$W_c = 0.75m, HRR = 3000kW, Y_s = 0.052, W_w = 1m,$$
$$W_d = 0.8m, E_f = 1m^3/s, ASET = 194.5s$$

Where the ASET is obtained by FDS simulation with the baseline values of the six input variables.

These six input factors can be grouped into geometric variables, which include the corridor door width, apartment door width and the window width, and physical variables which include the HRR, the soot yield of propane, and the total flow rate of the exhausting fans. The status of these three geometric variables when a fire occurs depends on the design values as well as how people use and maintain them. For example, a door closer is designed to automatically close the door when people come across it. In reality, however, it is not uncommon to find a door with a closer being manually propped open [17]. Therefore, it is helpful during the design stage to investigate the influence of different values of these geometric variables on building fire performance. As to the three physical variables, both the HRR and the soot yield are important design parameters of a fire source, and the exhausting flow rate is key to smoke control design of buildings exposed to fire. During the building design stage, potential designs are evaluated and optimized based on merits like: structural stability, thermal comfort, energy efficiency, sustainability, security, and building fire performance. To arrive at an optimal building design, it is necessary to address the combined effects of these geometric and physical influencing factors on the building fire performance (e.g., ASET) when they vary to a reasonable extent.



a) elevation view

a) plan view

Figure 3 Room fire scenario in a 3-story residential building

2.2.2 First phase of power function regression using FDS simulation data

In the area of fire science, quite a few outputs respond to input factors in a non-linear power pattern, as shown in the hand-calculation equations of compartment fire issues [18]. Therefore, in this section we explore the possibility of achieving a sound non-linear power fitting curve of FDS's simulation data. By changing our six input parameters one by one from a changing rate of -0.7 to +0.7 (decrease 70% to increase 70%) with respect to the reference/baseline case defined in section 2.2.1, the following non-linear power fitting curves of FDS's simulation data are worked out:

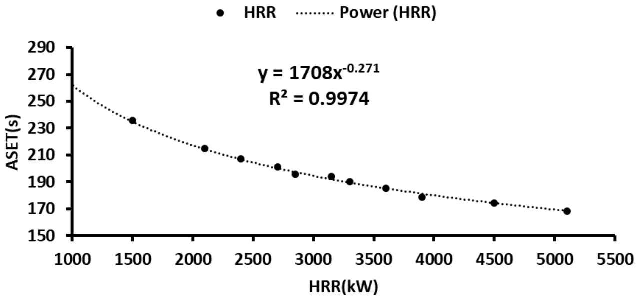


Figure 4 Power fitting of ASET changes with HRR

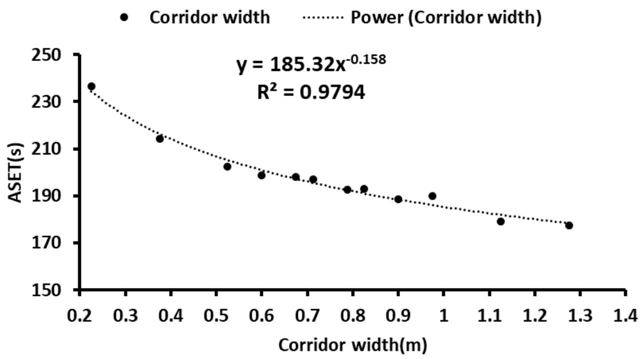


Figure 5 Power fitting of ASET changes with corridor width

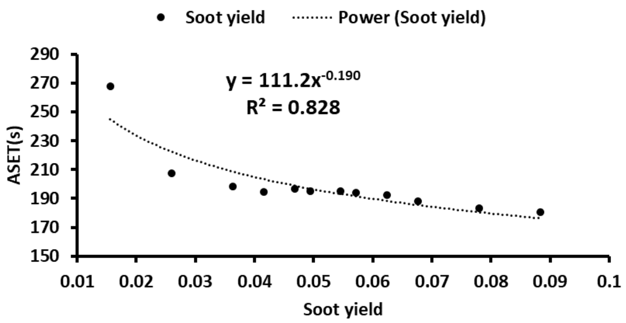


Figure 6 Power fitting of ASET changes with soot yield

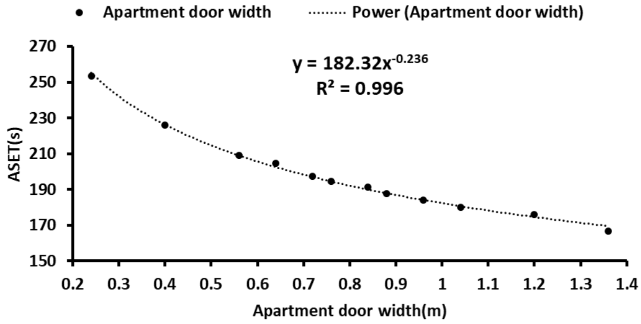


Figure 7 Power fitting of ASET changes with door width

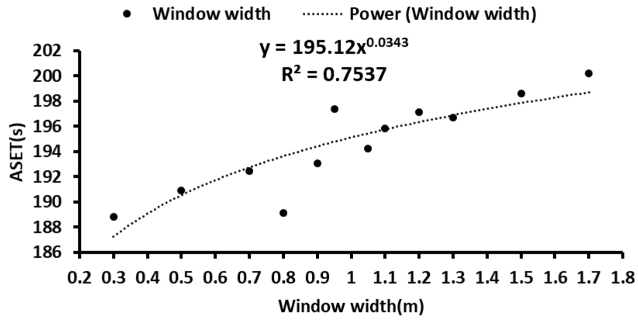


Figure 8 Power fitting of ASET changes with window width

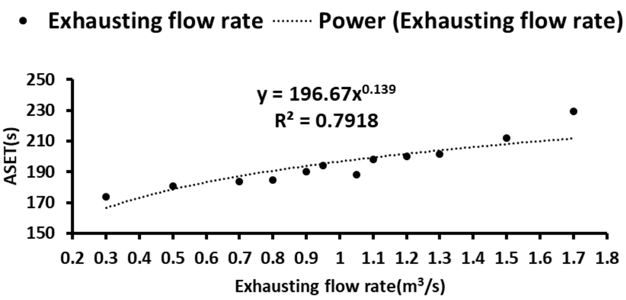


Figure 9 Power fitting of ASET changes with exhausting flow rate

In these figures, R^2 is the square of the correlation coefficient indicating how well the data fits the regression model. It is calculated based on the following equation:

$$R^2 = \left(\frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left(n\sum x^2 - \left(\sum x\right)^2\right)\left(n\sum y^2 - \left(\sum y\right)^2\right)}} \right)^2 \quad \textit{E. 10}$$

where x and y are the training data (FDS simulations) and the fitting model data, respectively.

From the above six figures, we have:

$$A_t \propto W_c^{-0.158}, A_t \propto HRR^{-0.271}, A_t \propto Y_s^{-0.19},$$
$$A_t \propto W_d^{-0.236}, A_t \propto W_w^{0.0343}, A_t \propto E_f^{0.1388} \quad \text{E. 11}$$

In theorem I it is said that if the input parameters are independent of each other, then the output parameters will be proportional to the product of all the input parameters to their powers provided the output parameters are proportional to each single input parameter to its power. Therefore, from equation (11), a potential substitute algebra model should be able to satisfy:

$$A_t \propto \begin{pmatrix} W_c^{-0.158} \cdot HRR^{-0.271} \cdot Y_s^{-0.19} \cdot \\ W_d^{-0.236} \cdot W_w^{0.0343} \cdot E_f^{0.1388} \end{pmatrix} \quad \text{E. 12}$$

2.2.3 Second phase of power function regression using FDS simulation data

(1) Development of RSM-1 from designed input data

The above equation (12) is only a proportional relationship. The combination scenarios of the right side of equation (12) are unlimited. To work out an expression between the left side and right side of this equation with some extent of accuracy, quite a large number of FDS simulations should be conducted, each of which includes a set of selected values for the input variables. However, in our case, it is assumed that all the input factors are independent of each other, which means, to generate an expression, it doesn't matter whether each input factor changes randomly or at the same rates. In order to obtain an accurate expression with a relatively small number of simulations, we design a series of input combinations (which can be further categorized into three groups), for each of which the six input variables change at the same absolute changing rate corresponding to a baseline point and the ASET is simulated by FDS, as shown below (Table 1):

Table 1 Development of RSM-1 from designed input data

Case#	Input						ASET	
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS(s)	RSM-1(s)
Baseline	3000	0.75	0.80	1.00	1.00	0.0520	194.5	204.0
1	2100	0.53	0.56	1.30	1.30	0.0364	271.7	312.3
2	2400	0.60	0.64	1.20	1.20	0.0416	236.2	267.3
3	2700	0.67	0.72	1.10	1.10	0.0468	211.6	232.3
4	2850	0.64	0.76	1.05	1.05	0.0494	202.3	222.1
5	3150	0.60	0.84	0.95	0.95	0.0546	177.2	202.2
6	3300	0.83	0.88	0.90	0.90	0.0572	176.7	180.8
7	3600	0.90	0.96	0.80	0.80	0.0624	160.8	161.1
8	3900	0.98	1.04	0.70	0.70	0.0675	152.0	144.2
9	4500	1.13	1.20	0.50	0.50	0.0780	138.8	115.7
10	4800	1.20	1.28	0.40	0.40	0.0832	134.3	103.3
11	1200	0.30	0.32	0.40	0.40	0.0208	517.0	436.0
12	1350	0.34	0.36	0.45	0.45	0.0234	446.6	395.4
13	1500	0.38	0.40	0.50	0.50	0.0260	396.8	362.4
14	1650	0.41	0.44	0.55	0.55	0.0286	348.9	334.9
15	1800	0.45	0.48	0.60	0.60	0.0312	296.1	311.6
16	2100	0.53	0.56	0.70	0.70	0.0364	228.0	274.2
17	2400	0.60	0.64	0.80	0.80	0.0416	216.6	245.5
18	2700	0.68	0.72	0.90	0.90	0.0468	200.2	222.7
19	2850	0.71	0.76	0.95	0.95	0.0494	199.4	212.9
20	3150	0.79	0.84	1.05	1.05	0.0546	189.8	196.0
21	3300	0.83	0.88	1.10	1.10	0.0572	185.5	188.5
22	3600	0.90	0.96	1.20	1.20	0.0624	175.2	175.4
23	3900	0.98	1.04	1.30	1.30	0.0676	171.4	164.2
24	4500	1.13	1.20	1.50	1.50	0.0780	158.8	145.8
25	4800	1.20	1.28	1.60	1.60	0.0832	158.2	138.2

Group One includes case numbers 1 to 4, where for each case the input variables change at an absolute rate that will increase ASET relative to the baseline case. For example, in case number 1, the HRR of 2100 kW is a 30% decrease from the baseline HRR of 3000 kW, this will increase the ASET according to Figure 4. At the same time, the exhausting flowrate (E_f) of 1.3 m^3/s is a 30% increase from its baseline value of 1 m^3/s, this will also increase the ASET according to Figure 9. The other variables change based on the same rule.

Opposite to cases in Group One, Group Two includes case numbers 5 to 10, where for each case the input variables change at an absolute rate that will decrease the ASET relative to the baseline case. For example, in case number 5, the HRR of 3150 kW is a 5% increase from the baseline HRR of 3000 kW, this will decrease the ASET according to Figure 4. At the same time, the exhausting flowrate (E_f) of 0.95 m^3/s is a 5% decrease from its baseline value of 1 m^3/s, this will also decrease the ASET according to Figure 9. The other variables change based on the same rule.

Group Three includes case numbers 11 to 25, where for each case the input variables change at the same rate regardless of the decrease or increase of the ASET. For example, in case number 11, each input variable decreases 60%, some will increase the ASET, some will decrease it.

The reason for designing the three groups of cases is to disperse the limited data points as widely as possible so that these data can work as good representatives of the underlying unlimited combinations.

By comparing the FDS simulations with the right side of equation (12), we get the following substitute algebra model:

$$A_t = 1278 \cdot \left(\begin{matrix} W_c^{-0.158} \cdot HRR^{-0.271} \cdot Y_s^{-0.19} \cdot \\ W_d^{-0.236} \cdot W_w^{0.0343} \cdot E_f^{0.1388} \end{matrix} \right)^{1.215} \quad E\ 13$$

The power of 1.215 in the above equation (13), being presented by P, indicates a degree of dependence among input parameters.

The ASETs from equation (13) are listed in Table 1 as the last column. The following figure shows the fitting results of Equation (13) in comparison to the FDS simulation:

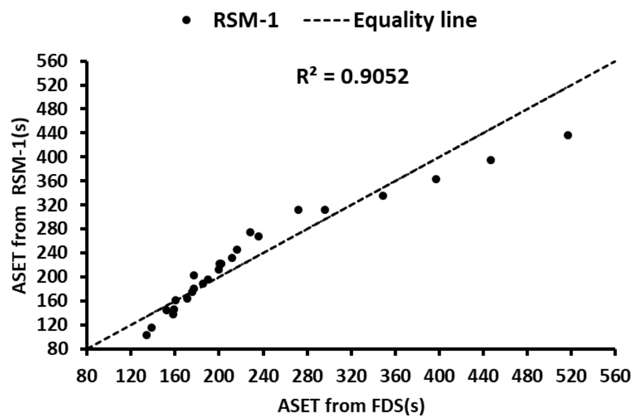


Figure 10 Power fitting of ASET from RSM-1(equation (13)) into FDS simulated ASET

The next step is to evaluate the accuracy of RSM-1 as shown in equation (13). We choose cases with random values of the input variables and compare the FDS simulation results with that predicted by equation (13):

Table 2 Comparison between FDS simulated ASET and RSM-1 predicted ASET based on random input data

Case#	input						ASET	
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS(s)	RSM-1(s)
1	2391	0.90	1.20	0.80	0.88	0.1400	173.1	145.8
2	3406	0.90	1.60	0.50	1.84	0.0800	173.9	151.0
3	4085	0.50	0.70	0.30	1.20	0.1100	174.8	170.8
4	1180	0.30	0.50	0.80	0.36	0.2000	217.6	231.3
5	3838	0.50	0.90	1.40	0.72	0.1400	162.3	150.1
6	2657	0.80	1.00	0.40	1.16	0.1300	176.4	157.2
7	1925	1.30	0.30	0.40	1.28	0.2000	254.9	207.0
8	4239	1.10	0.60	0.30	0.72	0.1900	155.7	122.6
9	3190	0.30	1.20	0.90	1.04	0.1500	175.8	166.6
10	3415	0.50	0.70	1.10	1.40	0.1300	209.1	188.9
11	3516	0.30	0.30	0.90	1.72	0.2000	277.9	244.5
12	1149	0.30	0.20	0.70	2.00	0.1500	500.0	430.7
13	4351	1.10	0.30	0.50	1.88	0.0900	277.3	211.6
14	4154	1.00	0.50	0.60	0.72	0.0600	177.5	177.9
15	1977	1.10	1.50	0.60	0.80	0.1400	172.5	136.2
16	3595	1.20	0.20	1.40	0.32	0.0900	203.2	192.7
17	3703	0.90	0.50	1.10	0.76	0.0800	179.2	182.5
18	3687	1.30	0.90	1.70	0.32	0.0200	182.8	174.4
19	1189	0.40	0.30	0.60	1.40	0.1300	451.5	346.9
20	4962	0.30	0.20	1.60	1.12	0.1200	250.0	262.9
21	4226	1.30	1.30	0.60	1.20	0.0800	145.2	130.4
22	4666	0.60	0.60	0.90	1.24	0.1500	178.9	161.7
23	4542	0.50	1.40	0.70	0.24	0.0600	141.9	122.8
24	1422	0.40	0.70	0.30	0.36	0.1800	200.2	183.8
25	3066	1.10	1.50	0.90	1.76	0.0500	177.7	173.7
26	1416	0.70	1.40	1.20	0.68	0.1200	188.7	175.5
27	1059	0.80	1.60	0.80	1.12	0.0700	222.7	219.5
28	1714	0.30	0.20	1.00	0.64	0.1200	297.5	332.9
29	2524	0.70	0.60	1.50	0.88	0.0600	218.6	228.9
30	2233	0.70	1.10	1.50	1.68	0.0800	225.4	209.0
31	4542	1.10	1.20	1.50	1.84	0.0800	182.6	150.2
32	1800	0.53	0.56	1.30	1.30	0.0364	289.9	328.6
33	1511	0.30	0.20	1.00	0.64	0.1200	304.8	347.0
34	3333	0.30	0.30	0.90	1.20	0.0500	296.6	322.6
35	4444	0.30	0.30	0.90	1.72	0.0220	385.7	376.8
36	5000	0.30	0.30	0.90	1.60	0.0400	266.9	311.9
37	2345	0.30	0.20	1.00	0.80	0.0800	328.0	342.4
38	2789	0.40	0.30	0.60	2.00	0.0700	386.0	321.0
39	2735	0.90	1.20	0.80	1.00	0.0520	178.7	179.1
40	3588	0.90	1.60	0.50	1.33	0.1798	151.7	116.5
41	2275	0.50	0.70	0.30	0.61	0.1454	183.0	173.2
42	3174	0.30	0.50	0.80	1.81	0.1540	251.2	232.8
43	2616	0.50	0.90	1.40	0.53	0.1110	176.8	170.3
44	1742	0.80	1.00	0.40	0.86	0.0401	203.1	225.1
45	2703	1.30	0.30	0.40	0.38	0.1351	193.2	165.1
46	3742	1.10	0.60	0.30	0.71	0.0789	167.4	156.2
47	4321	0.30	1.20	0.90	1.36	0.1887	168.2	149.6
48	2189	0.50	0.70	1.10	1.65	0.0597	291.3	269.0
49	2675	0.30	0.30	0.90	0.55	0.1317	230.2	242.7
50	2879	0.30	0.20	0.70	1.60	0.1774	323.9	294.9
51	3349	1.10	0.30	0.50	0.81	0.1349	197.1	182.1
52	3033	1.00	0.50	0.60	1.07	0.1244	181.2	178.2
53	3179	1.10	1.50	0.60	1.75	0.1857	161.5	124.5
54	4334	1.20	0.20	1.40	0.98	0.1297	216.0	201.3
55	2923	0.90	0.50	1.10	1.52	0.1852	225.0	182.7
56	3190	1.30	0.90	1.70	1.70	0.0337	203.5	214.9
57	3694	0.40	0.30	0.60	1.88	0.1981	261.9	227.7
58	3517	0.30	0.20	1.60	0.76	0.0768	274.5	305.8
59	2565	1.30	1.30	0.60	1.88	0.1236	183.5	150.0
60	1300	0.60	0.60	0.90	1.19	0.1808	253.7	234.1
61	2287	0.50	1.40	0.70	0.80	0.1384	169.5	155.4
62	4081	0.40	0.70	0.30	0.62	0.0491	183.8	192.3
63	1622	1.10	1.50	0.90	0.88	0.1599	179.8	145.6
64	2455	0.70	1.40	1.20	1.23	0.1974	171.4	144.3
65	3017	0.80	1.60	0.80	1.67	0.1620	173.2	137.0
66	4294	0.30	0.20	1.00	0.54	0.1981	206.8	213.2
67	3942	0.70	0.60	1.50	0.67	0.0483	188.6	198.3
68	4763	0.70	1.10	1.50	1.26	0.0587	212.4	166.7
69	4446	1.10	1.20	1.50	1.95	0.0949	169.5	146.8
70	4515	1.10	1.20	1.50	0.24	0.1749	145.0	89.2
71	4371	0.90	1.20	0.80	1.75	0.1285	162.0	136.9
72	2829	0.30	0.50	0.80	1.57	0.0282	298.0	349.6
73	2319	0.50	0.90	1.40	0.34	0.0826	188.2	176.0
74	2986	0.80	1.00	0.40	0.76	0.0896	165.6	153.6
75	4156	1.30	0.30	0.40	1.47	0.1495	215.4	175.9
76	3936	1.10	0.60	0.30	1.43	0.1037	185.0	162.2
77	1267	0.30	1.20	0.90	0.82	0.0851	222.0	247.3
78	4364	0.50	0.70	1.10	1.33	0.1425	181.8	169.0
79	1866	0.30	0.30	0.90	1.11	0.1839	345.3	285.1
80	4568	0.30	0.20	0.70	1.99	0.0354	305.7	381.3
81	4293	1.10	0.30	0.50	0.59	0.1344	166.9	159.5
82	3208	1.00	0.50	0.60	0.55	0.0825	175.6	172.2
83	1710	1.10	1.50	0.60	0.70	0.0436	186.0	182.9
84	1773	1.20	0.20	1.40	1.23	0.1925	318.0	256.1
85	2928	0.90	0.50	1.10	0.57	0.0905	183.7	182.6
86	3021	1.30	0.90	1.70	1.98	0.1528	219.2	158.4

In Table 2, two random mechanisms are investigated: the input data are randomly generated for the first 31 cases and the last 48 cases, and the input data for the remaining cases are randomly selected and manually input by the author. The boundaries of these six input variables are:

HRR : 1000~5000 (kW), W_c : 0.2~1.3(m), W_d : 0.2~1.6(m), W_w : 0.3~1.7(m), E_f : 0.2~2(m^3/s), Y_s : 0.02~0.2.

Using equation (8) and (9), as well as defining the bias gap as the distance from unity, and taking FDS simulations as numerical experiments, the model uncertainties of RSM-1 can be calculated:

$$\bar{\delta} \in [0.9255, 0.9327] \qquad \text{E. 14}$$
$$\left|1-\bar{\delta}\right| \in [0.0673, 0.0745]$$

$$\bar{\omega} \in [0, 0.1164] \qquad \text{E. 15}$$

For fire scenarios listed in Table 2, the above analysis shows that:

a) RSM-1 developed from limited design data can generally predict the tendency of ASET
b) RSM-1 generally underpredicts the ASET by about 7% with an uncertainty of less than 12%.

(2) Development of RSM-2 from random input data

In the last two subsections, RSM-1 is developed based on limited design data where in each combination the input variables vary at a same absolute rate with respect to a baseline point. Since Theorem I indicates that the changes of each input parameter don't have to be random, using the carefully designed data will reduce the number of cases needed from FDS simulations to develop an RSM. It is expected that an RSM developed from a larger number of cases where the input values are randomly obtained should work better as long as these random cases could form a good representation of the system response. However, it is challenging to define this critical number of random cases since it depends on the characteristics of a specific system's response. In order to verify if RSM-1 has reasonable accuracy, in this subsection RSM-2 is developed based on the 86 random cases from Table 2 and then applied to the 25 design input combination cases from Table 1, see Table 3 and Table 4.

Table 3 Development of RSM-2 from random input data

Case#	Input						ASET	
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS(s)	RSM-2(s)
Baseline	3000	0.75	0.80	1.00	1.00	0.0520	194.5	218.1
1	2391	0.90	1.20	0.80	0.88	0.1400	173.1	158.1
2	3406	0.90	1.60	0.50	1.84	0.0800	173.9	163.5
3	4085	0.50	0.70	0.30	1.20	0.1100	174.8	183.9
4	1180	0.30	0.50	0.80	0.36	0.2000	217.6	245.9
5	3838	0.50	0.90	1.40	0.72	0.1400	162.3	162.5
6	2657	0.80	1.00	0.40	1.16	0.1300	176.4	169.9
7	1925	1.30	0.30	0.40	1.28	0.2000	254.9	221.1
8	4239	1.10	0.60	0.30	0.72	0.1900	155.7	133.9
9	3190	0.30	1.20	0.90	1.04	0.1500	175.8	179.6
10	3415	0.50	0.70	1.10	1.40	0.1300	209.1	202.5
11	3516	0.30	0.30	0.90	1.72	0.2000	277.9	259.3
12	1149	0.30	0.20	0.70	2.00	0.1500	500.0	445.7
13	4351	1.10	0.30	0.50	1.88	0.0900	277.3	225.8
14	4154	1.00	0.50	0.60	0.72	0.0600	177.5	191.2
15	1977	1.10	1.50	0.60	0.80	0.1400	172.5	148.1
16	3595	1.20	0.20	1.40	0.32	0.0900	203.2	206.5
17	3703	0.90	0.50	1.10	0.76	0.0800	179.2	196.0
18	3687	1.30	0.90	1.70	0.32	0.0200	182.8	187.7
19	1189	0.40	0.30	0.60	1.40	0.1300	451.5	362.4
20	4962	0.30	0.20	1.60	1.12	0.1200	250.0	277.9
21	4226	1.30	1.30	0.60	1.20	0.0800	145.2	142.1
22	4666	0.60	0.60	0.90	1.24	0.1500	178.9	174.5
23	4542	0.50	1.40	0.70	0.24	0.0600	141.9	134.1
24	1422	0.40	0.70	0.30	0.36	0.1800	200.2	197.3
25	3066	1.10	1.50	0.90	1.76	0.0500	177.7	186.9
26	1416	0.70	1.40	1.20	0.68	0.1200	188.7	188.8
27	1059	0.80	1.60	0.80	1.12	0.0700	222.7	233.8
28	1714	0.30	0.20	1.00	0.64	0.1200	297.5	348.4
29	2524	0.70	0.60	1.50	0.88	0.0600	218.6	243.4
30	2233	0.70	1.10	1.50	1.68	0.0800	225.4	223.2
31	4542	1.10	1.20	1.50	1.84	0.0800	182.6	162.7
32	1800	0.53	0.56	1.30	1.30	0.0364	289.9	344.1
33	1511	0.30	0.20	1.00	0.64	0.1200	304.8	362.5
34	3333	0.30	0.30	0.90	1.20	0.0500	296.6	338.0
35	4444	0.30	0.30	0.90	1.72	0.0220	385.7	392.3
36	5000	0.30	0.30	0.90	1.60	0.0400	266.9	327.3
37	2345	0.30	0.20	1.00	0.80	0.0800	328.0	357.8
38	2789	0.40	0.30	0.60	2.00	0.0700	386.0	336.4
39	2735	0.90	1.20	0.80	1.00	0.0520	178.7	195.2
40	3588	0.90	1.60	0.50	1.33	0.1798	151.7	131.9
41	2275	0.50	0.70	0.30	0.61	0.1454	183.0	189.3
42	3174	0.30	0.50	0.80	1.81	0.1540	251.2	247.8
43	2616	0.50	0.90	1.40	0.53	0.1110	176.8	186.4
44	1742	0.80	1.00	0.40	0.86	0.0401	203.1	240.3
45	2703	1.30	0.30	0.40	0.38	0.1351	193.2	181.2
46	3742	1.10	0.60	0.30	0.71	0.0789	167.4	172.3
47	4321	0.30	1.20	0.90	1.36	0.1887	168.2	165.7
48	2189	0.50	0.70	1.10	1.65	0.0597	291.3	282.6
49	2675	0.30	0.30	0.90	0.55	0.1317	230.2	257.4
50	2879	0.30	0.20	0.70	1.60	0.1774	323.9	307.3
51	3349	1.10	0.30	0.50	0.81	0.1349	197.1	198.1
52	3033	1.00	0.50	0.60	1.07	0.1244	181.2	194.3
53	3179	1.10	1.50	0.60	1.75	0.1857	161.5	140.1
54	4334	1.20	0.20	1.40	0.98	0.1297	216.0	217.0
55	2923	0.90	0.50	1.10	1.52	0.1852	225.0	198.7
56	3190	1.30	0.90	1.70	1.70	0.0337	203.5	230.4
57	3694	0.40	0.30	0.60	1.88	0.1981	261.9	242.8
58	3517	0.30	0.20	1.60	0.76	0.0768	274.5	317.6
59	2565	1.30	1.30	0.60	1.88	0.1236	183.5	166.0
60	1300	0.60	0.60	0.90	1.19	0.1808	253.7	249.0
61	2287	0.50	1.40	0.70	0.80	0.1384	169.5	171.5
62	4081	0.40	0.70	0.30	0.62	0.0491	183.8	208.2
63	1622	1.10	1.50	0.90	0.88	0.1599	179.8	161.6
64	2455	0.70	1.40	1.20	1.23	0.1974	171.4	160.3
65	3017	0.80	1.60	0.80	1.67	0.1620	173.2	152.9
66	4294	0.30	0.20	1.00	0.54	0.1981	206.8	228.7
67	3942	0.70	0.60	1.50	0.67	0.0483	188.6	214.1
68	4763	0.70	1.10	1.50	1.26	0.0587	212.4	182.8
69	4446	1.10	1.20	1.50	1.95	0.0949	169.5	162.8
70	4515	1.10	1.20	1.50	0.24	0.1749	145.0	103.4
71	4371	0.90	1.20	0.80	1.75	0.1285	162.0	152.8
72	2829	0.30	0.50	0.80	1.57	0.0282	298.0	358.8
73	2319	0.50	0.90	1.40	0.34	0.0826	188.2	192.0
74	2986	0.80	1.00	0.40	0.76	0.0896	165.6	169.7
75	4156	1.30	0.30	0.40	1.47	0.1495	215.4	191.9
76	3936	1.10	0.60	0.30	1.43	0.1037	185.0	178.3
77	1267	0.30	1.20	0.90	0.82	0.0851	222.0	261.7
78	4364	0.50	0.70	1.10	1.33	0.1425	181.8	185.1
79	1866	0.30	0.30	0.90	1.11	0.1839	345.3	297.9
80	4568	0.30	0.20	0.70	1.99	0.0354	305.7	388.3
81	4293	1.10	0.30	0.50	0.59	0.1344	166.9	175.6
82	3208	1.00	0.50	0.60	0.55	0.0825	175.6	188.2
83	1710	1.10	1.50	0.60	0.70	0.0436	186.0	198.9
84	1773	1.20	0.20	1.40	1.23	0.1925	318.0	270.2
85	2928	0.90	0.50	1.10	0.57	0.0905	183.7	198.6
86	3021	1.30	0.90	1.70	1.98	0.1528	219.2	174.5

By comparing the FDS simulations with the right side of equation (12), we get the following substitute algebra model:

$$A_t = 1168 \cdot \left(\frac{W_c^{-0.158} \cdot HRR^{-0.271} \cdot Y_s^{-0.19}}{W_d^{-0.236} \cdot W_w^{0.0343} \cdot E_f^{0.1388}} \right)^{1.106} \qquad \text{E. 16}$$

The ASETs from equation (16) are listed in Table 3 as the last column. Figure 11 shows the fitting results of Equation (16) in comparison to the FDS simulations:

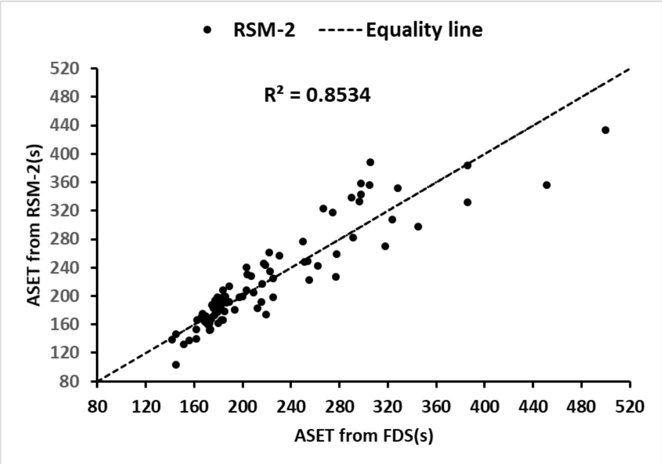


Figure 11 Power fitting of ASET from RSM-2(equation (16)) into FDS simulated ASET

The power of 1.106 in equation (16) indicates a degree of dependence among input parameters, which is lower than the power of 1.215 in equation (13).

The next step is to evaluate the accuracy of RSM-2 as shown in equation (16). We choose the cases with designed values of input variables and compare the FDS simulation results with that predicted by equation (16):

Table 4 Comparison between FDS simulated ASET and RSM-2 predicted ASET based on designed input data

Case#	Input						ASET	
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS(s)	RSM-2(s)
1	2100	0.53	0.56	1.30	1.30	0.0364	271.7	323.8
2	2400	0.60	0.64	1.20	1.20	0.0416	236.2	281.0
3	2700	0.67	0.72	1.10	1.10	0.0468	211.6	247.2
4	2850	0.64	0.76	1.05	1.05	0.0494	202.3	237.4
5	3150	0.60	0.84	0.95	0.95	0.0546	177.2	217.9
6	3300	0.83	0.88	0.90	0.90	0.0572	176.7	196.8
7	3600	0.90	0.96	0.80	0.80	0.0624	160.8	177.2
8	3900	0.98	1.04	0.70	0.70	0.0675	152.0	160.2
9	4500	1.13	1.20	0.50	0.50	0.0780	138.8	131.1
10	4800	1.20	1.28	0.40	0.40	0.0832	134.3	118.2
11	1200	0.30	0.32	0.40	0.40	0.0208	517.0	438.6
12	1350	0.34	0.36	0.45	0.45	0.0234	446.6	401.3
13	1500	0.38	0.40	0.50	0.50	0.0260	396.8	370.7
14	1650	0.41	0.44	0.55	0.55	0.0286	348.9	345.0
15	1800	0.45	0.48	0.60	0.60	0.0312	296.1	323.0
16	2100	0.53	0.56	0.70	0.70	0.0364	228.0	287.6
17	2400	0.60	0.64	0.80	0.80	0.0416	216.6	260.0
18	2700	0.68	0.72	0.90	0.90	0.0468	200.2	237.9
19	2850	0.71	0.76	0.95	0.95	0.0494	199.4	228.4
20	3150	0.79	0.84	1.05	1.05	0.0546	189.8	211.8
21	3300	0.83	0.88	1.10	1.10	0.0572	185.5	204.5
22	3600	0.90	0.96	1.20	1.20	0.0624	175.2	191.5
23	3900	0.98	1.04	1.30	1.30	0.0676	171.4	180.3
24	4500	1.13	1.20	1.50	1.50	0.0780	158.8	161.8
25	4800	1.20	1.28	1.60	1.60	0.0832	158.2	154.1

Using equation (8) and (9), as well as defining the bias gap as the distance from unity, and taking FDS simulations as numerical experiments, the model uncertainties of RSM-2 can be calculated:

$$\bar{\delta} \in [1.0722, 1.0788]$$
$$\left|1 - \bar{\delta}\right| \in [0.0722, 0.0788] \qquad \text{E. 17}$$

$$\bar{\omega} \in [0, 0.1195] \qquad \text{E. 18}$$

The above analysis shows that:

a) RSM-2 developed from randomly generated data can generally predict the tendency of random changes of ASET.
b) RSM-2 generally over predicts the ASET by about 7.5% with an uncertainty of less than 12%.

(3) Applying both RSM-1 and RSM-2 in hybrid cases

Theoretically RSM-2 should be better than the RSM-1 when the number of random cases is appropriately large so that these cases can be a good representation of the underlying system response. In our case, although the number of random cases of 86 is much larger than that of the designed cases of 25, the similar performance of RSM-1 and RSM-2 (the bias gaps and RSDs of RSM-1 and RSM-2 are similar) may imply that the set of random cases is not a better representation of the underlying system response.

In the above subsections, for RSM-1 and RSM-2, one is verified by the cases used to develop the other. In this subsection we use hybrid data cases to evaluate the two models, as shown in Table 5. Here "hybrid" means some cases are specially designed (e.g., case 1 to 3 are drawn from Table 4), some cases are randomly given (e.g., cases 11, 14, 15, 17, 19), the others include both specially designed input values and randomly given values (i.e., the red cells in a row change at a same rate, the other cells in a row are randomly given).

Table 5 Comparison between FDS simulated ASET, RSM-1 predicted ASET and RSM-2 predicted ASET based on hybrid input data. For the first three cases, the HRR, corridor door width, apartment door width, and the soot yield change at same rate, whereas the window width and the exhausting flow rate change at same rate. For the remaining 22 cases, the red input variables in a row change at a same rate, the other input variables are randomly given

Case#	Input						ASET(s) predicted by		
	HRR(kW)	W_c(m)	W_d(m)	W_w(m)	E_f(m3/s)	Y_s	FDS	RSM-1	RSM-2
Baseline	3000	0.75	0.80	1.00	1.00	0.0520	194.5	204.0	218.1
1	4800	1.20	1.28	0.40	0.40	0.0832	134.3	103.3	118.2
2	4500	1.13	1.20	0.50	0.50	0.0780	138.8	115.7	131.1
3	3900	0.98	1.04	0.70	0.70	0.0675	152.0	144.2	160.2
4	5200	0.98	1.04	1.30	1.30	0.0676	160.3	149.3	161.8
5	4800	0.90	0.96	1.20	1.20	0.0624	161.8	159.6	172.4
6	4400	0.83	0.88	1.10	1.10	0.0572	168.2	171.5	184.7
7	3000	1.13	1.20	1.50	1.50	0.0780	171.8	166.6	179.7
8	4200	0.79	0.84	1.05	1.05	0.0546	172.1	178.2	191.6
9	3600	0.90	0.96	1.20	1.20	0.0624	173.0	175.4	188.7
10	2600	0.98	1.04	1.30	1.30	0.0676	177.2	187.6	201.2
11	3500	1.10	0.50	0.50	0.80	0.0280	189.5	209.7	223.8
12	3200	0.60	0.64	0.80	0.80	0.0416	196.9	223.3	237.7
13	2400	0.90	0.96	1.20	1.20	0.0624	200.0	200.5	214.4
14	3800	0.30	1.00	1.30	1.60	0.0800	203.0	203.7	217.8
15	2500	1.10	0.40	0.40	0.80	0.0400	210.0	221.5	235.9
16	2800	0.53	0.56	0.70	0.70	0.0364	210.2	249.4	264.3
17	3500	0.20	1.10	1.40	1.20	0.0700	214.0	227.2	241.7
18	2200	0.83	0.88	1.10	1.10	0.0572	216.0	215.5	229.8
19	2500	0.20	1.10	1.40	1.20	0.0700	238.0	253.8	268.7
20	1800	0.68	0.72	0.90	0.90	0.0468	243.0	254.5	269.4
21	1600	0.60	0.64	0.80	0.80	0.0416	269.0	280.6	295.8
22	2000	0.38	0.40	0.50	0.50	0.0260	295.7	329.6	345.1
23	1400	0.53	0.56	0.70	0.70	0.0364	349.5	313.4	328.8
24	2200	0.38	0.40	0.30	1.40	0.0300	430.0	296.0	311.3
25	1600	0.30	0.32	0.40	0.40	0.0208	457.9	396.6	411.9

Using equation (8) and (9), as well as defining the bias gap as the distance from unity, and taking FDS simulations as numerical experiments, the model uncertainties of RSM-1 and RSM-2 can be calculated:

For RSM-1:

$$\bar{\delta} \in [0.9866, 0.9942]$$
$$\left|1-\bar{\delta}\right| \in [0.0058, 0.0134] \qquad E.\ 19$$

$$\bar{\omega} \in [0, 0.1227] \qquad E.\ 20$$

For RSM-2:

$$\bar{\delta} \in [1.0611, 1.0689]$$
$$\left|1-\bar{\delta}\right| \in [0.0611, 0.0689] \qquad E.\ 21$$

$$\bar{\omega} \in [0, 0.1293] \qquad E.\ 22$$

Assuming that an acceptable error is 20%, the following figure obtained from Table 5 shows that there are two points for both RSM-1 and RSM-2 falling outside the acceptable error scope, which means that as far as this specific dataset is concerned the applicability (expressed as the percentage of predictions within the acceptable error range) of both RSMs is 92%.

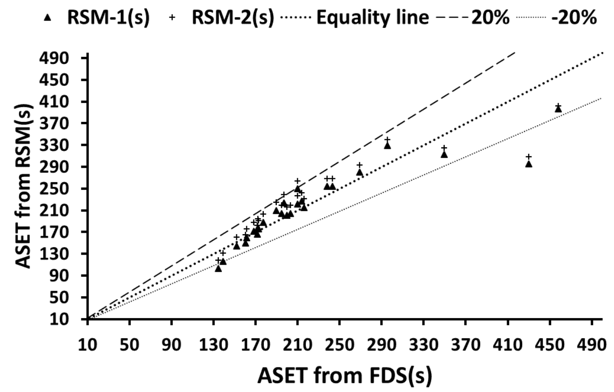


Figure 12 Comparison of ASET between FDS simulation and RSMs

The above analysis shows that, with respect to the test data as shown in Table 5, the model uncertainties of RSM-1 is smaller than that of RSM-2, which indicates that the model developed from limited design data cases is better than that developed from 3.5 times more random data cases. Therefore, what matters is not how many data are adopted but how well a dataset can represent real world conditions.

2.3 Summary

In this section, Theorem I is first derived as the theoretical basis of substitute models. Based on this theorem, a method of two-phase power function fitting is proposed to build algebraic substitute models. The reasons causing the deviation of the substitute models from its target problem are explained, and a method to evaluate the uncertainties of substitute models is proposed. Then as an application of Theorem I, this section adopts the two-phase power function-based method to develop substitute response surface models relating six input parameters to one output (ASET) by using

FDS simulation results in an exemplar 3-story apartment building. The results show that both the two models, RSM-1 and RSM-2, can capture the variation in ASET but RSM-1 is better than RSM-2 as far as the model uncertainties are concerned. Different from the assumption of Theorem I that all input parameters are independent to each other, the substitute model we developed shows dependency to an extent denoted by the dependence factor P.

3 Using ANNs to predict ASET

3.1 Application basis of ANN

3.1.1 Background

Motivated by a desire to try both to understand the human brain as well as to emulate some of its strengths [19], ANNs were originally introduced as very simplified computational models of brain function consisting of processing elements (neurons) and connections between them with coefficients (weights) bound to connections [20,21]. From an application perspective, ANNs can be described as a collection of mathematical techniques [22] (non-linear, multi-layered, parallel regression) that can be used for signal processing, forecasting and clustering.

An ANN usually includes an input layer, one or more hidden layers, and one output layer. Input data are fed to the neural network to train the weights of network connections. Once a network is successfully trained, it can be used to predict the system response from new data other than what are used as the training/validation data. The training or learning algorithms are currently classified into three groups: 1) supervised learning where output data are provided to supervise the learning process; 2) unsupervised learning where no output data are provided for supervision; 3) reinforcement learning where the connection weights of the network are adjusted by reward penalty learning [21]. Of these three learning algorithms, the supervised learning is widely used to learn highly complex functions. It is said that ANNs have a high capability in approximating input-output mappings that are complex and nonlinear to an arbitrary degree of precision [23]. Since the purpose of this paper is to seek a substitute model for the time consuming FDS numerical simulations which are highly nonlinear and can provide simulated outcomes, the supervised learning algorithm is adopted.

3.1.2 Training process of an ANN

.A common multi-layer ANN is shown in the following figure:

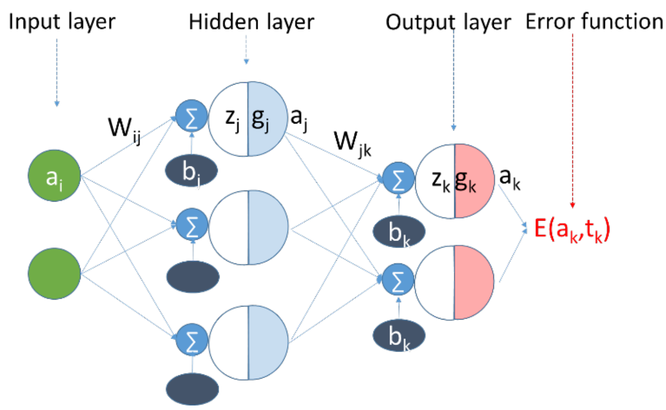


Figure 13 Forward-propagate input data in a multilayer ANN (updated from [24])

Where W_{ij} is the weight of the connection between input a_i and hidden layer neutron j; z_j is the input of hidden layer neutron j, a_j is the output of hidden layer neutron j, and g_j is the transfer or activation function between z_j and a_j; W_{jk} is the weight of the connection between hidden layer neutron j and output k, z_k is the input of output k, a_k is the prediction of output k, and g_k is the transfer or activation function between z_k and a_k; t_k is the target output k, $E(a_k,t_k)$ is some kind of error function calculating the error between the ANN output a_k and the real target output t_k.

Exemplar data are usually divided into three groups: training data, validation data, and test data. The training data are used to seek an appropriate network architecture, the validation data are used to control the training process by checking the performance of the network in training, and the test data are used to test the performance of the trained network and have no effects on the network architecture. The training process of an ANN includes two parts: forward-propagate input signal and back-propagate error signal

(1) Forward-propagate input signal

In Figure 13, $\sum$ means summation, g_j and g_k are transfer or activation functions of the hidden layer and the output layer, respectively. If a mean squared error (MSE) is employed, then

$$E(a_k,t_k)=\frac{1}{N}\sum_{1}^{N}\left(a_k-t_k\right)^2 \qquad E.\ 23$$

Where N is the output layer size.

The forward-propagating process can be described by the following equation:

$$\left.\begin{aligned} a_k &= g_k\left(z_k\right), a_j = g_j\left(z_j\right) \\ z_k &= b_k+\sum\nolimits_j a_j w_{jk} \\ z_j &= b_j+\sum\nolimits_j a_i w_{ij} \end{aligned}\right\} \Rightarrow \qquad E.\ 24$$

$$a_k = g_k\left(b_k+\sum\nolimits_j g_j\left(b_j+\sum\nolimits_j a_i w_{ij}\right) w_{jk}\right)$$

(2) Back-propagate error signal

In Figure 14, the red arrows indicate the back propagating process of errors; δ_k and δ_j are error signals at the output layer and hidden layer, respectively. The initial connection weights (w_{ij} and w_{jk}) and biases (b_k and b_j) are updated after some training data are processed (this number is named "batch size") according to the following equation:

$$w_{ij}^{new}=w_{ij}-\eta\left(\frac{\partial E}{\partial w_{ij}}\right), w_{jk}^{new}=w_{jk}-\eta\left(\frac{\partial E}{\partial w_{jk}}\right) \qquad E.\ 25$$

$$b_k^{new}=b_k-\eta\left(\frac{\partial E}{\partial b_k}\right), b_j^{new}=b_j-\eta\left(\frac{\partial E}{\partial b_j}\right) \qquad E.\ 26$$

Where

$$\frac{\partial E}{\partial w_{ij}}=a_i\delta_j, \frac{\partial E}{\partial w_{jk}}=a_j\delta_k, \frac{\partial E}{\partial b_j}=\delta_j, \frac{\partial E}{\partial b_k}=\delta_k \qquad E.\ 27$$

and

η =learning rate

Error signals δ_k and δ_j are at the output layer and the input layer, respectively, and can be calculated by:

$$\delta_k=g_k'\left(z_k\right)E'\left(a_k,t_k\right), \delta_j=g_j'\left(z_j\right)\sum_k \delta_k w_{jk} \qquad E.\ 28$$

By using the "chain rule" of derivatives, the whole deductive process of the gradients in equation (27) is shown in APPENDIX I (summarized from [25]).

When all the training data have been processed, the validation data are employed to check the error performance $E(a_k,t_k)$ of the so far trained network, this is called an epoch. If the training process stops improving the performance (lowering $E(a_k,t_k)$) for some epochs, the training process will be stopped earlier before the designed epochs are conducted, this mechanism is called "early stopping" which helps to avoid the overfitting of the network into the training data.

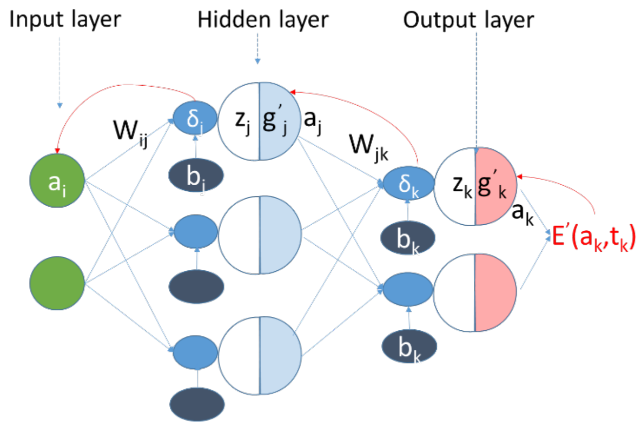


Figure 14 Back-propagate error signal in a multilayer ANN (updated from [24])

If the performance of a trained network is poor when applied to some test data, retrains of the network are necessary due to the following uncertainties associated with the ANN method:

(1) A network may have high performance in the validation data but low performance in the test data;

(2) A network may have high performance in both the validation data and the test data, but still may have poor performance when applied to other new test data

As shown in the case study of the next section, it is not always true that the better neural network has the lower error performance. Instead, a lower error performance secures only a higher accuracy when the neural network is applied in the data used to train/validate/test the network. If a network is overfitted into these data, it may lack accuracy when applied to other new data. An obviously high error performance will not work for any test data. Therefore, for specific applications, it is key to find a wide range of performance test data from various sources.

3.1.3 Selection of neural network tools in MATLAB

MATLAB includes ANN tools for both static (has no feedback or delays) and dynamic (with feedback or delays) networks dealing with both concurrent and sequential inputs by either batch training (update the weights and biases of a network based on entire set/batch of input vectors) or incremental training (update the weights and biases of a network as needed after presentation of each individual input vector). It is said that a multilayer feedforward network including a hidden layer with nonlinear transfer/activation function and an output layer with linear transfer/activation function can approximate any function with a finite number of discontinuities [26]. There are several different training algorithms for feedforward networks, all of which use the gradient of the error performance function to determine how to adjust the weights to improve performance. The Levenberg-Marquardt algorithm (trainlm) [26] appears to be the fastest method for training moderated-sized feedforward neural networks (up to several hundred weights), which is the default option in MATLAB.

For scenarios described in section 2.2.1, the input vectors are concurrent and an output vector only depends on the current input vector. Therefore, the type of neural networks we select to approximate the FDS simulations is a static feedforward network with error-backpropagation mechanism. The performance function is MSE, the training function is "trainlm", namely the Levenberg-Marquardt algorithm which uses batch training. Since the problem we are dealing with is in relatively small scale (only six inputs and one output), one hidden layer with limited number of neutrons is sufficient. During the training and validation process, an early stopping mechanism is adopted by setting the maximum failure epochs (which is the "max_fail" property of a neural network in MATLAB's ANN toolbox), which means the training process will stop when the error performance for validation data fails to enhance for "max_fail" epochs. Due to the random mechanisms adopted when initializing the weights and/or biases as well as when dividing the training dataset and validation dataset (even if the same percentages of training and validation datasets are set, the examples are randomly allocated into training and validation datasets to increase the chance of obtaining a better neural network), it is very common to get neural networks with different error performance for repeated trainings. In our study, the neural networks with error performance higher than 1000 are discarded since the possibility for these low performance neural networks to have a high accuracy when predicting new datasets are low. The next subsections will discuss more details about the training process.

3.2 Building neural networks from numerical experiments

3.2.1 Selection of training/validation/test data

The dataset used to train and validate potential neural networks is shown in Table 6:

Table 6 Dataset used for training and validating neural networks

Case#	Input						Target
	HRR(kW)	WC(m)	Wd(m)	WW(m)	Ef(m3/s)	YS	FDS(s)
1	2391	0.90	1.20	0.80	0.88	0.1400	173.1
2	3406	0.90	1.60	0.50	1.84	0.0800	173.9
3	4085	0.50	0.70	0.30	1.20	0.1100	174.8
4	1180	0.30	0.50	0.80	0.36	0.2000	217.6
5	3838	0.50	0.90	1.40	0.72	0.1400	162.3
6	2657	0.80	1.00	0.40	1.16	0.1300	176.4
7	1925	1.30	0.30	0.40	1.28	0.2000	254.9
8	4239	1.10	0.60	0.30	0.72	0.1900	155.7
9	3190	0.30	1.20	0.90	1.04	0.1500	175.8
10	3415	0.50	0.70	1.10	1.40	0.1300	209.1
11	3516	0.30	0.30	0.90	1.72	0.2000	277.9
12	1149	0.30	0.20	0.70	2.00	0.1500	500.0
13	4351	1.10	0.30	0.50	1.88	0.0900	277.3
14	4154	1.00	0.50	0.60	0.72	0.0600	177.5
15	1977	1.10	1.50	0.60	0.80	0.1400	172.5
16	3595	1.20	0.20	1.40	0.32	0.0900	203.2
17	3703	0.90	0.50	1.10	0.76	0.0800	179.2
18	3687	1.30	0.90	1.70	0.32	0.0200	182.8
19	1189	0.40	0.30	0.60	1.40	0.1300	451.5
20	4962	0.30	0.20	1.60	1.12	0.1200	250.0
21	4226	1.30	1.30	0.60	1.20	0.0800	145.2
22	4666	0.60	0.60	0.90	1.24	0.1500	178.9
23	4542	0.50	1.40	0.70	0.24	0.0600	141.9
24	1422	0.40	0.70	0.30	0.36	0.1800	200.2
25	3066	1.10	1.50	0.90	1.76	0.0500	177.7
26	1416	0.70	1.40	1.20	0.68	0.1200	188.7
27	1059	0.80	1.60	0.80	1.12	0.0700	222.7
28	1714	0.30	0.20	1.00	0.64	0.1200	297.5
29	2524	0.70	0.60	1.50	0.88	0.0600	218.6
30	2233	0.70	1.10	1.50	1.68	0.0800	225.4
31	4542	1.10	1.20	1.50	1.84	0.0800	182.6
32	1800	0.53	0.56	1.30	1.30	0.0364	289.9
33	1511	0.30	0.20	1.00	0.64	0.1200	304.8
34	3333	0.30	0.30	0.90	1.20	0.0500	296.6
35	4444	0.30	0.30	0.90	1.72	0.0220	385.7
36	5000	0.30	0.30	0.90	1.60	0.0400	266.9
37	2345	0.30	0.20	1.00	0.80	0.0800	328.0
38	2789	0.40	0.30	0.60	2.00	0.0700	386.0
39	3000	0.75	0.80	1.00	1.00	0.0520	194.5
40	2100	0.53	0.56	1.30	1.30	0.0364	271.7
41	2400	0.60	0.64	1.20	1.20	0.0416	236.2
42	2700	0.67	0.72	1.10	1.10	0.0468	211.6
43	2850	0.64	0.76	1.05	1.05	0.0494	202.3
44	3150	0.60	0.84	0.95	0.95	0.0546	177.2
45	3300	0.83	0.88	0.90	0.90	0.0572	176.7
46	3600	0.90	0.96	0.80	0.80	0.0624	160.8
47	3900	0.98	1.04	0.70	0.70	0.0675	152.0
48	4500	1.13	1.20	0.50	0.50	0.0780	138.8
49	4800	1.20	1.28	0.40	0.40	0.0832	134.3
50	1200	0.30	0.32	0.40	0.40	0.0208	517.0
51	1350	0.34	0.36	0.45	0.45	0.0234	446.6
52	1500	0.38	0.40	0.50	0.50	0.0260	396.8
53	1650	0.41	0.44	0.55	0.55	0.0286	348.9
54	1800	0.45	0.48	0.60	0.60	0.0312	296.1
55	2100	0.53	0.56	0.70	0.70	0.0364	228.0
56	2400	0.60	0.64	0.80	0.80	0.0416	216.6
57	2700	0.68	0.72	0.90	0.90	0.0468	200.2
58	2850	0.71	0.76	0.95	0.95	0.0494	199.4
59	3150	0.79	0.84	1.05	1.05	0.0546	189.8
60	3300	0.83	0.88	1.10	1.10	0.0572	185.5
61	3600	0.90	0.96	1.20	1.20	0.0624	175.2
62	3900	0.98	1.04	1.30	1.30	0.0676	171.4
63	4500	1.13	1.20	1.50	1.50	0.0780	158.8
64	4800	1.20	1.28	1.60	1.60	0.0832	158.2
65	2735	0.90	1.20	0.80	0.25	0.0520	178.7
66	3588	0.90	1.60	0.50	0.33	0.1798	151.7
67	2275	0.50	0.70	0.30	0.15	0.1454	183.0
68	3174	0.30	0.50	0.80	0.45	0.1540	251.2
69	2616	0.50	0.90	1.40	0.13	0.1110	176.8
70	1742	0.80	1.00	0.40	0.21	0.0401	203.1
71	2703	1.30	0.30	0.40	0.10	0.1351	193.2
72	3742	1.10	0.60	0.30	0.18	0.0789	167.4
73	4321	0.30	1.20	0.90	0.34	0.1887	168.2
74	2189	0.50	0.70	1.10	0.41	0.0597	291.3
75	2675	0.30	0.30	0.90	0.14	0.1317	230.2
76	2879	0.30	0.20	0.70	0.40	0.1774	323.9
77	3349	1.10	0.30	0.50	0.20	0.1349	197.1
78	3033	1.00	0.50	0.60	0.27	0.1244	181.2
79	3179	1.10	1.50	0.60	0.44	0.1857	161.5
80	4334	1.20	0.20	1.40	0.25	0.1297	216.0
81	2923	0.90	0.50	1.10	1.52	0.1852	225.0
82	3190	1.30	0.90	1.70	1.70	0.0337	203.5
83	3694	0.40	0.30	0.60	1.88	0.1981	261.9
84	3517	0.30	0.20	1.60	0.76	0.0768	274.5
85	2565	1.30	1.30	0.60	1.88	0.1236	183.5
86	1300	0.60	0.60	0.90	1.19	0.1808	253.7
87	2287	0.50	1.40	0.70	0.80	0.1384	169.5
88	4081	0.40	0.70	0.30	0.62	0.0491	183.8
89	1622	1.10	1.50	0.90	0.88	0.1599	179.8
90	2455	0.70	1.40	1.20	1.23	0.1974	171.4
91	3017	0.80	1.60	0.80	1.67	0.1620	173.2
92	4294	0.30	0.20	1.00	0.54	0.1981	206.8
93	3942	0.70	0.60	1.50	0.67	0.0483	188.6
94	4763	0.70	1.10	1.50	1.26	0.0587	212.4
95	4446	1.10	1.20	1.50	1.95	0.0949	169.5
96	4515	1.10	1.20	1.50	0.24	0.1749	145.0
97	4371	0.90	1.20	0.80	1.75	0.1285	162.0
98	2829	0.30	0.50	0.80	1.57	0.0282	298.0
99	2319	0.50	0.90	1.40	0.34	0.0826	188.2
100	2986	0.80	1.00	0.40	0.76	0.0896	165.6
101	4156	1.30	0.30	0.40	1.47	0.1495	215.4
102	3936	1.10	0.60	0.30	1.43	0.1037	185.0
103	1267	0.30	1.20	0.90	0.82	0.0851	222.0
104	4364	0.50	0.70	1.10	1.33	0.1425	181.8
105	1866	0.30	0.30	0.90	1.11	0.1839	345.3
106	4568	0.30	0.20	0.70	1.99	0.0354	305.7
107	4293	1.10	0.30	0.50	0.59	0.1344	166.9
108	3208	1.00	0.50	0.60	0.55	0.0825	175.6
109	1710	1.10	1.50	0.60	0.70	0.0436	186.0
110	1773	1.20	0.20	1.40	1.23	0.1925	318.0
111	2928	0.90	0.50	1.10	0.57	0.0905	183.7
112	3021	1.30	0.90	1.70	1.98	0.1528	219.2

Table 6 Dataset used for training and validating neural networks

In this table, the input training/validation data are grouped into the following classes:

(1) Green group

This group includes cases from number 1 to 31 and from number 65 to 96. The input data in this group are random.

(2) Blue group

This group includes cases from number 32 to 38. The input data in this group are randomly selected and manually input by the authors. The boundaries of these six input variables in both the blue group and the green group are:

HRR : 1000~5000 (kW), W_c : 0.2~1.3(m), W_d : 0.2~1.6(m), W_w : 0.3~1.7(m), E_f : 0.2~2(m^3/s), Y_s : 0.02~0.2

(3) Red group

This group only includes case number 39 which is the reference/baseline scenario.

(4) Gold group

This group includes cases from number 40 to 43. For each case in this group, the input variables change at an absolute rate that will increase the ASET.

(5) Orange group

The orange group includes case number 44 to 49. For each case in this group the input variables change at an absolute rate that will decrease the ASET.

(6) Yellow group

The yellow group includes case number 50 to 64, where for each case the input variables change at the same rate regardless of the decrease or increase of the ASET.

The reason for designing the green and blue groups is to present different random mechanisms. The reason for designing the gold, orange and yellow groups is to disperse the limited data points as widely as possible.

The last column in the above table is the target output from FDS simulations, which will be employed to supervise the training process for potential neural networks.

A subset of the data in Table 6 is adopted to train and validate a potential neural network. 75% percent of the chosen subset data are enrolled for training, and the remaining 25% are for validating.

After a neural network is trained and validated, its model uncertainties can be investigated by considering new test data. In Table 5, case 4 to 25 are new data, which are used below to evaluate the model uncertainties of a trained neural network when optimizing the hidden layer size (HLS) and the appropriate training/validation dataset size.

3.2.2 Optimization of hidden layer size

The number of neutrons in the hidden layer (as shown in Figure 13), or the HLS, could affect the performance of a neural network to an extent related to specific applications. In our case, a small network should be appropriate since we only have six inputs and one output. With the input training/validation dataset being selected as case 1 to case 64 in Table 6, neural networks with various HLSs (starting with two) are investigated to seek an optimum neutron number. For each HLS, nine training runs with error performance less than 1000 are recorded, as shown in the following table:

Table 7 Error performance and model uncertainties of neural networks with various HLSs

HLS	Perf	Bias	RSD	RMSD(BG)	AVG(RSD)
2	673.90	0.99141	0.11775	0.02643	0.11845
	577.42	0.99185	0.12381		
	417.03	0.99006	0.11676		
	436.82	1.04120	0.13052		
	434.76	1.01489	0.06469		
	282.54	1.03176	0.10876		
	346.97	1.04851	0.13754		
	726.24	1.02050	0.11173		
	481.57	1.01862	0.15453		
3	285.17	1.01139	0.10727	0.03947	0.11329
	244.19	1.06554	0.12894		
	655.20	0.99704	0.10464		
	304.44	0.99392	0.08639		
	303.71	1.05856	0.17768		
	695.27	0.97375	0.08635		
	619.89	1.02781	0.09988		
	372.54	1.04233	0.12573		
	127.89	0.94647	0.10273		
4	313.21	0.99737	0.09904	0.04547	0.14430
	689.92	0.96646	0.11134		
	197.07	1.04352	0.17947		
	807.37	1.10171	0.24702		
	375.96	1.03815	0.16909		
	335.42	1.03295	0.08565		
	433.39	0.98555	0.14749		
	470.29	1.04183	0.12223		
	300.36	1.02705	0.13737		

Table 7 Error performance and model uncertainties of neural networks with various HLSs

HLS	Perf	Bias	RSD	RMSD(BG)	AVG(RSD)
5	313.28	1.03015	0.10282	0.04472	0.14508
	396.41	0.94633	0.06980		
	443.48	0.97120	0.10307		
	497.68	1.05038	0.16283		
	335.66	1.02549	0.13634		
	394.15	1.02600	0.12157		
	569.94	0.99432	0.18950		
	710.39	1.06480	0.25004		
	542.54	1.07268	0.16978		
6	355.05	1.02818	0.16362	0.05054	0.15210
	830.91	0.89948	0.14032		
	70.85	0.99765	0.19634		
	172.12	1.03300	0.19343		
	376.43	1.02114	0.06447		
	211.71	0.97986	0.15661		
	522.76	1.07447	0.20223		
	319.07	1.04303	0.10295		
	521.09	1.05238	0.14895		
7	407.07	0.98875	0.14290	0.03081	0.14403
	297.96	1.05058	0.17426		
	591.31	1.02317	0.13452		
	457.75	1.02041	0.08216		
	166.04	1.02307	0.10064		
	511.89	1.03271	0.12876		
	801.22	0.96141	0.23729		
	949.42	1.04258	0.19660		
	207.12	0.99915	0.09914		

Table 7 Error performance and model uncertainties of neural networks with various HLSs

HLS	Perf	Bias	RSD	RMSD(BG)	AVG(RSD)
8	174.39	1.01826	0.25868	0.04280	0.12815
	577.16	1.05136	0.08992		
	367.40	1.00752	0.08154		
	335.88	1.03950	0.08254		
	289.47	1.05374	0.11451		
	215.90	1.08931	0.15852		
	364.76	1.01001	0.15141		
	377.80	0.99493	0.08547		
	574.34	1.03017	0.13073		
10	201.82	1.05999	0.12346	0.03893	0.18142
	422.52	0.94405	0.21774		
	593.35	1.02233	0.13669		
	566.97	1.00749	0.09241		
	81.30	1.02888	0.29674		
	186.71	1.05015	0.17379		
	54.25	1.05374	0.27788		
	302.36	0.99623	0.12376		
	716.52	1.01034	0.19034		
12	313.13	1.01564	0.10161	0.06763	0.18314
	493.19	1.02378	0.11888		
	132.99	1.07488	0.25105		
	438.96	1.15747	0.26969		
	723.45	1.03227	0.12491		
	676.87	1.01071	0.15857		
	673.58	1.08947	0.20226		
	674.37	0.99292	0.25737		
	417.19	1.02713	0.16390		

In Table 7, HLS is hidden layer size; Perf is error performance of a trained neural network (within the training and validation dataset); Bias indicates the upper or lower limit of the bias range in equation 8 corresponding to the maximum bias gap; RSD indicates the upper limit of relative standard deviation in equation 9; RMSD(BG) is the root mean squared deviation of the bias gap, which is calculated by:

$$RMSD(BG) = \sqrt{\frac{1}{9}\sum_{k=1}^{9}\left(Bias_k - 1\right)^2} \qquad \text{E. 29}$$

Where "1" means no bias gap. RMSD(BG) indicates a statistical property of the system bias of a network architecture (usually repeated trainings of the same network architecture lead to different weights and thus different performance). AVG(RSD) is the average of the relative standard deviation. By using equations 8 and 9, the "Bias" and "RSD" are calculated based on the comparisons between FDS simulations and trained neural networks' outputs (see Table 9).

Table 7 shows that neural networks with hidden layer size of 2 have close performance (RMSD(BG) and AVG(RSD)) to that with hidden layer size of 3: the RMSD(BG) is smallest for hidden layer size of 2 whereas the AVG(RSD) is smallest for hidden layer size of 3. Neural networks with other hidden layer sizes are less accurate. In the next subsection hidden layer size of 2 is adopted.

An interesting finding from Table 7 is that neural networks with better performance (lower value of error Perf) do not always lead to lower model uncertainties when they are applied to new test data. For example, the trained neural network with lowest Perf of 282.54 in the group HLS of 2 does not have the lowest system bias and RSD in the group. This can also be seen in Table 8.

3.2.3 Influence of training dataset size on the uncertainties of neural networks

It is obvious that neural networks trained and validated by an insufficiently large dataset will result in poor performance when they are applied to new test data, possibly because the chosen model overfits the training set or the training set is not sufficiently representative of the problem. On the other hand, an overly large data set will result in good but slightly lower than ideal test accuracy, perhaps because the chosen model does not have the capacity to learn the nuances of such a large training dataset, or the dataset is over-representative of the problem [27]. Therefore, an optimum training dataset size may exist for a specific problem. To find an appropriate input dataset size, in our case we use various subsets from Table 6 to train and validate neural networks, and use the data of case 3 to case 25 in Table 5 to evaluate the model uncertainties (Bias and RSD) of trained neural networks. The following table shows the results:

Table 8 Error performance and model uncertainties of neural networks with various input dataset sizes

Dataset size	Subset	Perf	Bias	RSD	RMSD(BG)	AVG(RSD)
		33.97	1.11041	0.13248		
	case1:case16	79.32	0.90099	0.21789		
		537.02	0.88830	0.45410		
		35.67	1.01844	0.16678		
16	case47:case62	21.87	1.28995	0.58173	0.14686	0.31898
		68.21	1.16938	0.54267		
		277.21	1.15237	0.29682		
	case37:case52	1.51	0.87464	0.26542		
		473.73	0.91282	0.21293		
		277.62	0.95178	0.16523		
	case1:case32	402.77	0.95406	0.12871		
		360.12	0.96514	0.14840		
		217.43	0.96742	0.20453		
32	case33:case64	643.09	0.91873	0.11336	0.06911	0.15489
		139.41	0.89136	0.19746		
		748.28	1.06043	0.12802		
	case17:case48	443.26	0.92650	0.13550		
		504.90	0.90613	0.17279		
		470.20	0.94409	0.11609		
	case 1 to 48	623.94	0.91022	0.14670		
		489.17	1.04390	0.09363		
		462.02	1.00167	0.08686		
48	case 17 to 64	461.51	1.02654	0.16244	0.05523	0.13058
		903.49	1.04948	0.25329		
		258.40	0.98228	0.06841		
	case 9 to 56	378.46	1.06537	0.12054		
		569.82	0.91876	0.12728		
		673.90	0.99141	0.11775		
		577.42	0.99185	0.12381		
		417.03	0.99006	0.11676		
		436.82	1.04120	0.13052		
64	case 1 to 64	434.76	1.01489	0.06469	0.02643	0.11845
		282.54	1.03176	0.10876		
		346.97	1.04851	0.13754		
		726.24	1.02050	0.11173		
		481.57	1.01862	0.15453		
		474.80	1.00858	0.12769		
		200.90	0.98568	0.10013		
		203.26	0.96463	0.08235		
		706.77	1.04192	0.11830		
80	case 1 to 80	628.67	0.97659	0.12734	0.02547	0.11417
		279.30	1.02830	0.11845		
		539.79	0.98904	0.12429		
		289.21	1.02797	0.09741		
		329.89	1.01729	0.13153		
		723.01	0.96843	0.12907		
		531.71	1.00916	0.11696		
		491.65	1.06403	0.13493		
		427.04	0.99644	0.08630		
96	case 1 to 96	470.73	1.00743	0.12098	0.03436	0.11462
		227.31	0.99266	0.10933		
		241.39	1.02602	0.10415		
		669.00	1.06522	0.10854		
		422.27	1.01986	0.12131		
		755.33	0.97315	0.11418		
		305.39	1.04564	0.11669		
		402.86	1.04057	0.11895		
112	case 1 to 112	593.69	1.01575	0.11016	0.03185	0.11240
		345.58	1.03133	0.11298		
		294.45	0.99592	0.08621		
		447.11	0.98708	0.10367		
		632.31	1.00458	0.11590		
		983.02	0.94303	0.13288		

In this table, nine neural networks are trained and validated for each dataset size. For dataset sizes of 16, 32 and 48, three data sources are defined for each and each data source serves for three neural network training runs. The model uncertainties of neural networks for the various dataset sizes are indicated by Bias and RSD. The definitions of Perf, RMSD(BG) and AVG(RSD) are same as those given for Table 7. The statistical model uncertainties of neural networks with various dataset sizes are shown in Figure 15.

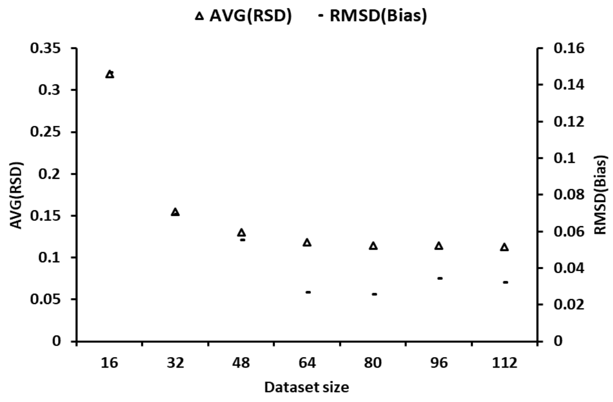


Figure 15 Model uncertainties changing with dataset size

From Figure 15, model uncertainties tend to first decrease with the increase of the dataset size and finally arrive at a relatively stable level. The statistically lowest model uncertainties are observed at dataset size of 80,

3.2.4 Using the optimized network architecture

In this subsection, the dataset shown in Table 5, the same dataset used to evaluate the applicability of SMMs[2] and RSMs, is fed to the optimized network architecture with HLS of 2 and training/validation dataset size of 80, the results are shown in Table 9.

Table 9 Comparison between FDS simulated ASET and ANNs predicted ASET. T1 to T9 are the ASETs predicted by the nine ANNs training runs of the network architecture with HLS of 2 and training/validation dataset size of 80. The values in the bias row are calculated from equation 8 corresponding to the maximum bias gap.

Case#	ASET(s) by	ASET(s) predicted by ANNs with HLS=2 and training dataset size of 80								
	FDS	T1	T2	T3	T4	T5	T6	T7	T8	T9
1	134.3	157.2	157.8	159.5	160.2	159.0	133.5	138.7	136.7	157.1
2	138.8	158.2	159.5	159.9	161.3	160.2	135.8	141.8	139.8	158.2
3	152.0	162.5	165.6	162.9	165.7	165.3	146.5	152.6	151.3	162.4
4	160.3	159.3	160.7	168.0	165.6	166.0	182.6	158.1	158.6	159.5
5	161.8	161.6	164.2	170.6	168.2	169.8	183.3	161.2	162.8	162.1
6	168.2	165.6	169.6	173.9	172.4	175.0	181.8	165.2	168.2	166.4
7	171.8	164.1	180.3	180.3	168.5	169.7	183.8	206.3	192.6	193.3
8	172.1	168.6	173.3	176.0	175.4	178.4	179.6	167.7	171.5	169.5
9	173.0	168.4	171.0	178.9	174.1	176.3	189.3	181.0	179.7	172.7
10	177.2	174.2	190.3	187.6	177.6	179.1	190.9	207.0	197.3	196.6
11	189.5	174.9	230.7	197.3	192.5	212.2	217.5	176.4	207.2	212.1
12	196.9	202.2	210.6	194.9	207.7	206.8	199.4	194.9	202.7	203.8
13	200.0	183.0	182.6	192.2	185.4	186.2	197.5	208.4	200.8	200.6
14	203.0	209.0	188.3	201.6	194.5	189.3	196.9	204.8	213.4	193.6
15	210.0	191.5	294.5	256.0	223.4	250.0	286.0	201.2	265.8	262.9
16	210.2	231.6	240.4	214.4	233.6	226.1	238.5	221.2	229.4	233.7
17	214.0	208.5	183.8	181.1	186.3	176.7	190.1	198.8	203.4	179.5
18	216.0	195.8	194.4	198.1	196.4	196.0	206.2	211.4	205.7	207.3
19	238.0	251.2	191.2	192.6	203.4	184.7	196.2	231.1	221.3	202.9
20	243.0	239.8	233.7	219.7	232.8	240.8	226.4	228.1	225.1	235.7
21	269.0	274.6	265.1	243.4	260.2	304.1	251.7	247.7	244.4	262.3
22	295.7	339.3	347.7	337.7	316.6	335.3	365.1	348.7	345.5	349.2
23	349.5	320.0	307.5	287.1	293.9	387.8	296.8	282.3	276.0	301.5
24	430.0	468.2	459.4	459.5	427.1	404.3	472.7	495.4	454.6	452.0
25	457.9	419.9	434.8	461.2	369.6	464.5	437.1	482.0	457.1	445.4
Bias	=	1.0069	1.0329	1.0147	0.9938	1.0298	1.0347	1.0131	1.0203	1.0291
Bias gap	=	0.0069	0.0329	0.0147	0.0062	0.0298	0.0347	0.0131	0.0203	0.0291
RSD	=	0.0766	0.1280	0.1076	0.0969	0.1085	0.1192	0.0889	0.0939	0.1045
RMSD(BG)	=					0.0233				
AVG(RSD)	=					0.1027				

The above table shows that the network architecture has an RMSD(BG) of 0.0233 and an average RSD of 0.1027. Of the nine trained ANNs, the T1 has lowest RSD and the T4 has the lowest bias gap, as shown in the blue and yellow ovals, respectively. However, T1 has the second lowest bias gap and T4 has the fourth lowest RSD, which suggests that overall T1 is better than T4.

Assuming that the acceptable error is 20%, Figure 16shows that overall 96% of the predictions of this network architecture are within the acceptable error range of 20%, whereas in the best cases all the predictions of T1 and T4 are within this error range, and in the worst cases 92% of the predictions of both T2 and T6 fall into the acceptable error range of 20%,

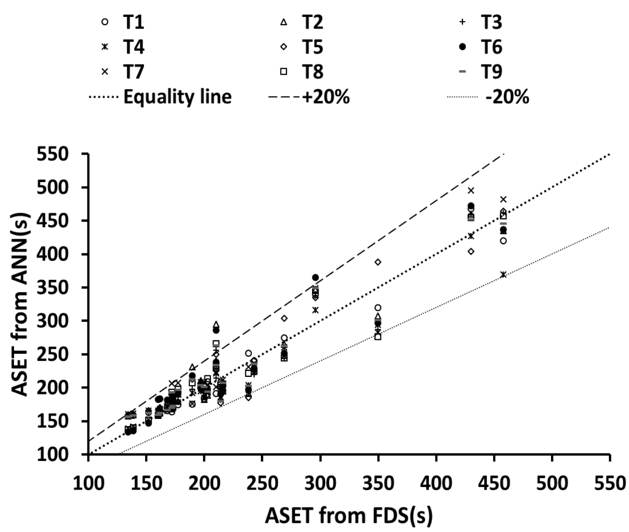


Figure 16 Comparison of ASET between FDS simulation and 9 trained ANNs with same network architecture

3.3 summary

Based on the theoretic knowledge of ANN, this section illustrates a case study of applying feedforward neural networks with the purpose of seeking appropriate neural networks to estimate the time-consuming FDS simulations. The results show that a hidden layer size of 2 is enough for our scenario of mapping a functional relationship between the six fire related inputs and the only output: ASET. Also, the dataset size used for training and validation an ANN is about 80. To compare the applicability of SMMs, RSMs and ANNS, the same dataset as shown in Table 5, which is an extension of the dataset used to optimize the HLS and the training/validation dataset size, is fed to the network architecture (HLS=2 and training/validating dataset size=80), showing an RMSD of bias of 0.0233, an average of RSD of 0.1027, and a ratio of 96% of the predictions within 20% error range.

4 Comparison of SMMs, RSMs, and ANNs models

Two SMM models are introduced in [2]: SMM-center and SMM-B/F. The SMM-center model predicts the ASET by using a sensitivity matrix developed from central difference around the baseline point (row 39 in above Table 6), whereas the SMM-B/F predicts the ASET by using a combination of sensitivity matrices from both backward difference and forward difference. In section 2 of this paper, two RSM models, RSM-1 and RSM-2, are developed by two-phase power function fitting. In section 3 of this paper, the application of the optimized network architecture results in a model based on HLS of 2 and training/validating dataset size of 80. Table 10 shows comparison of benefits indicated by model uncertainties and costs indicated by the data cases needed to develop the corresponding models among two SMMs, two RSMs and two ANNs (one is the best, the other is the worst of the nine trained ANNs as shown in Table 9):

Table 10 Comparison of benefit (applicability) and cost among the two SMMs two RSMs, and two ANNs. The benefit or applicability is represented by either the model uncertainties (bias, bias gap, and RSD) or the percentage of predictions falling in the 20% acceptable error range. The cost focuses on the data cases (fire scenarios in FDS) needed to develop each model. The last column shows the limitations/assumptions existing in each method.

Model	Bias	Bias gap	RSD	Percentage within 20% error	Cases used	limitations
SMM-center	0.8692	0.1308	0.1776	76	12	Linear approximation
SMM-B/F	0.8764	0.1236	0.1907	76	12	
RSM-1	0.9866	0.0134	0.1227	92	109	Power function and independence assumptions
RSM-2	1.0689	0.0689	0.1293	92	170	
ANN-T1	1.0069	0.0069	0.0766	100	112	No physical basis
ANN-T2	1.0329	0.0329	0.1280	92	112	

Figure 17 shows comparison of predictions by select models from the three methods:

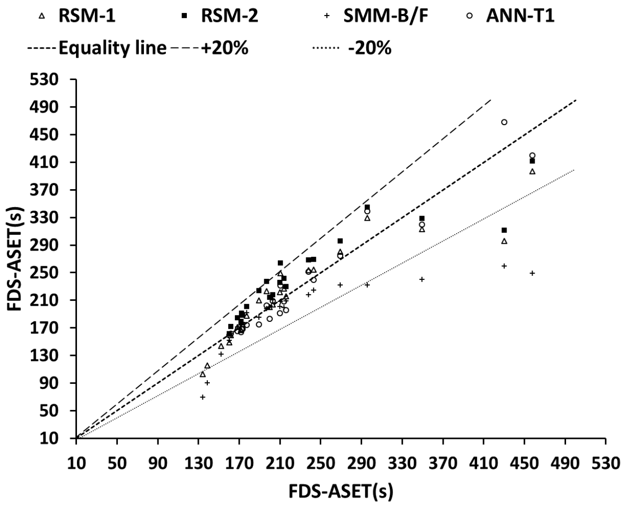


Figure 17 Predictions of ASET by select models from each of the three methods

Table 10 and Figure 17 show that:

a) As far as the model uncertainties are concerned, each method can be ranked from best to worst:

$$ANN-T1 > RSM-1 > ANN-T2 > RSM-2 > SMM-B/F > SMM-center \quad E.\ 30$$

b) The percentages of predictions by each model falling into the 20% acceptable error range can be ranked from best to worst:

$$ANN-T1 > RSM-1 = ANN-T2 = RSM-2 > SMM-B/F = SMM-center \quad E.\ 31$$

c) The costs of developing each method can be ranked from greatest to least:

$$RSM-2 > ANN-T1 = ANN-T2 > RSM-1 > SMM-B/F = SMM-center \quad E.\ 32$$

d) Each method has its' own limitations. SMM is a first order or linear method, which limits its applicability to small changes of both input variables and output quantities. RSM has higher applicability which depends on to what extent the underlying assumptions of power function relationship between output quantities and input variables as well as independence among input variables stand. Although it is possible for a trained ANN to outperform the other two kinds of methods, it is hard to understand the mechanism by which an input variable affects an output quantity since the development of an ANN does not rely on any physical knowledge. Compared to SMMs and RSMs, although a trained ANN can have better predictions when the ASETs are far away from the baseline point, there are less consistence of changing tendency between the predictions and the FDS simulated results. For example, when the fire scenario changes from case number 24 to 25 (see Table 9), the FDS simulated ASET increases from 430.0s to 457.9s. This increase is predicted precisely by both RSM-1 and RSM-2 models, but not by six of the nine trained neural networks

e) Although having better applicability than the SMMs, an ANN or RSM usually need more data points, indicating more time/resource demands. Since the continual experience with SMM is capable of generating more and more data points which can be adopted by an RSM and/or SMM, starting with a SMM followed by an RSM/SMM is a reasonable strategy.

5 Discussion and conclusion

5.1 Discussion

Building fire performance monitoring needs fast acting substitute models in place of time consuming FDS simulations. A linear substitute method, SMM, has been introduced in [2]. This paper discusses two additional methods: RSM and ANN, and compares them to SMM with respect to their applicability in terms of model uncertainties including system bias, RSD and percentages of predictions falling into a preset acceptable error range. This subsection addresses limitations and characteristics of these three methods.

(1) Limitations to the testing dataset

Although the same dataset as shown in Table 5 is employed to compare the three methods, 3 of the 25 cases in the dataset, or 12% of the data, are also used to develop RSM-1 and ANNs. In practical applications, it is possible for RSMs and ANNs to predict cases very close to the ones having been adopted to develop them. Compared to totally new cases, a dataset that includes some cases known to a model may lead to a seemingly better performance of the model. The extent of this kind of noise varies among different models. In our case study, compared to the use of the 22 totally new cases in Table 5, the use of 25 cases has very limited influence on RSM-1: the bias gap reduces to 0.0134 from 0.0137 (or 2.2%) and the RSD increases from 0.1136 to 0.1227 (or 8.0%). The influence of this on ANNs is slightly bigger: the bias gap reduces to 0.0233 from 0.0255 (or 8.6%) and the RSD reduces to 0.1027 from 0.1142 (or 10.1%). The calculation of bias gap and RSD based on the 22 cases is not shown in this paper. Unlike RSM-1 and the ANNs, the datasets used to develop SMMs and RSM-2 do not include the first 3 cases in Table 5, which means the comparative process tends to slightly undermine the performance of SMMs and RSM-2. Since the difference in model uncertainties of SMMS and RSM-2 as compared to RSM-1 and ANNs is larger than the change in uncertainties for RSM-1 and ANNs for 25 cases versus 22 cases, the influence caused by the small number of data known to part of the models on the comparison of performances of SMMs, RSMs and ANNs can be deemed as negligible.

(2) Limitations from fire scenarios

All three methods, SMM, RSM and ANN, are not only geometry dependent, but also fire scenario dependent. Although some factors about the fire scenario are involved in the substitute models like: HRR and soot yield, other fire scenario factors, especially the location of the fire, are not included. Although it is reasonable to conclude that the ASET will change little when the fire starts from apartments adjacent to the one we use in this paper, it is possible that the ASET will change a lot when the fire starts from locations farther removed. Therefore, it is recommended that new substitute equations be developed for each distinct fire scenario selected during the design stage. For example, NFPA 101A [28] suggests eight distinct design fires for a specific building. If the arrangements of the interior space within one class of buildings are similar, then one substitute model addressing the factors related to building size (e.g., stories, volume) should be developed based on the fire effects simulation results under each design fires.

(3) Characteristics of SMMs

As introduced in [2], SMM is a first-order or linear approximation of the underlying system response around a baseline point. Although it is hard to define quantitatively the applicable input ranges, SMMs are not designed to apply in cases where the input variables and output quantities will experience considerable changes compared to the baseline fire scenario. However, SMMs are usually economical in that smaller number of FDS simulations are needed to develop SMMs as compared to RSMs and ANNs.

(4) Characteristics of RSMs

The traditional RSM usually needs a large number of numerical and/or physical experiments which are time/resource consuming. This paper proposes a novel two-phase power function fitting RSM to generate substitute algebraic models which need a smaller number of experiments. The first phase is based on Theorem I with the assumption of independent input factors. However, in real world applications, the interaction between input factors are very common. Therefore, in the second phase, the concept of a dependence factor is proposed which partly explains the degree of coupling between input factors in a given case study. This two-phase power function fitting process is thus a predictor-corrector process.

In this paper, RSM-1 and RSM-2 are developed which only differ in the second phase power function fitting. The experience with these models shows that the models generated from a larger number of random cases (RSM-2) are not necessarily better than the one from a smaller number of designed cases, suggesting that what matters is not the number but the quality of cases (how good a dataset represents the underlying system response).

(5) Characteristics of ANNs

Due to the internal random mechanisms related to the initialization of weights and biases as well as the division of training and validation datasets, repeated trainings of neural networks with same model parameters/architecture (e.g., training methods, epochs, max failures, hidden layer sizes, etc..) and training/validation datasets generally produce different network weights which lead to different model performance and uncertainties. Therefore, nine training runs are conducted for each hidden layer size and/or training/validation dataset size, and statistical quantities of system biases (RMSD(BG))) and relative standard deviations (AVG(RSD)) are introduced to evaluate the expected model uncertainties of trained neural networks.

Compared to the RSM, not only the applicability of the best ANN (ANN-T1) is higher than that of the best RSM (RSM-1), but also the ANNs tend to have better fittings when the ASETs are far away from the baseline point. However, as a result of the inherent limitation of ANNs, which is its incapability of reflecting the physical mechanism of the system being approximated, varying tendencies or directions of ASET when the input variables change are badly predicted. Another feature of developing appropriate ANNs is the involvement of tuning of model parameters like: number of layers (not addressed in this paper) and/or neutrons, input training/validation dataset sizes, etc. Also, one has to remember that a higher performance obtained in the training/validation dataset does not always suggest a better neural network when dealing with new test datasets

5.2 Conclusion

The principal contribution of this paper is to provide alternative substitute methods (RSMs and ANNs) for time consuming FDS simulations which can be used to track the dynamic fire performance of an operational building.

Different from the linear SMMs, RSMs and ANNs are both commonly used non-linear methods to generate substitute models of numerical and/or physical experiments. Similar to the SMMs, the model uncertainties of RSMs and ANNs are evaluated by the system bias and relative standard deviation, and the model applicability can be expressed by either the model uncertainties or the percentages of predictions falling into a preset acceptable error range. A 3-story resident building is adopted for the fire scenarios. A commonly used building fire performance indicator, ASET, is selected as the only output variable. Six important factors are selected as input variables, which are HRR, corridor door opening width, apartment door opening width, window opening width, exhausting flow rate, and soot yield.

Based on Theorem I derived in this paper, a novel two phase power function fitting method is proposed to develop RSM-1 from specially designed cases and RSM-2 from random cases. The application of these models with various datasets shows that the RSM-1 is better than RSM-2. Different from RSM, ANN is a universal function fitting method. In the paper, MATLAB'S feedforward neural networks with backpropagation algorithm are employed to approximate the FDS model. Various hidden layer sizes and training/validation datasets are investigated in order to seek the optimum hidden layer size and the training/validation dataset size fitting our specific problem of building fire egress safety. The results show that a hidden layer size of 2 and a dataset size of 80 are enough to deliver neural networks with low model uncertainties.

As shown in equation 30 and 31, ANN-T1 has the highest applicability in terms of model uncertainties and/or percentages of predictions within 20% error range, followed by RSM-1, and the SMMs have the lowest applicability. However, in ANNs the details about how various input variables influence the output variables are hard to explain by even well-trained neural networks, whereas RSMs and SMMs are good at this kind of analysis. On the other hand, as far as the cost is concerned (see equation 32), which in our study mainly means the number of fire scenarios to be numerically simulated by FDS, the SMM has obvious advantage. Considering all the pros and cons of these three methods, it would be an attractive plan to first introduce the SMM and then adjust to the RSM and ANN after an increasing number of case data are produced by the application of the SMM for BFPG analysis.

Acknowledgements

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APPENDIX I

$$\frac{\partial E}{\partial w_{jk}} = E'\left(a_k, t_k\right)\frac{\partial a_k}{\partial w_{jk}} = E'\left(a_k, t_k\right)\frac{\partial g_k\left(z_k\right)}{\partial w_{jk}} = E'\left(a_k, t_k\right)g_k'\left(z_k\right)\frac{\partial\left(z_k\right)}{\partial w_{jk}} = E'\left(a_k, t_k\right)g_k'\left(z_k\right)\frac{\partial\left(b_k + \sum_j a_j w_{jk}\right)}{\partial w_{jk}}$$

$$= a_j E'\left(a_k, t_k\right)g_k'\left(z_k\right) = a_j\delta_k$$

$$\frac{\partial E}{\partial b_k} = E'\left(a_k, t_k\right)g_k'\left(z_k\right)\frac{\partial\left(b_k + \sum_j a_j w_{jk}\right)}{\partial b_k} = E'\left(a_k, t_k\right)g_k'\left(z_k\right)(1) = E'\left(a_k, t_k\right)g_k'\left(z_k\right)$$

$$\frac{\partial E}{\partial w_{ij}} = \sum_k\left(E'\left(a_k, t_k\right)\frac{\partial a_k}{\partial w_{ij}}\right) = \sum_k\left(E'\left(a_k, t_k\right)\frac{\partial g_k\left(z_k\right)}{\partial w_{ij}}\right) = \sum_k\left(E'\left(a_k, t_k\right)g_k'\left(z_k\right)\frac{\partial z_k}{\partial w_{ij}}\right) = \sum_k\left(\delta_k\frac{\partial z_k}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}}\right)$$

$$= \sum_k\left(\delta_k\frac{\partial\left(b_k + \sum_j a_j w_{jk}\right)}{\partial a_j}\frac{\partial a_j}{\partial w_{ij}}\right) = \sum_k\left(\delta_k w_{jk}\frac{\partial a_j}{\partial w_{ij}}\right) = \sum_k\left(\delta_k w_{jk}\frac{\partial g_j\left(z_j\right)}{\partial w_{ij}}\right) = \sum_k\left(\delta_k w_{jk} g_j'\left(z_j\right)\frac{\partial z_j}{\partial w_{ij}}\right)$$

$$= \sum_k\left(\delta_k w_{jk} g_j'\left(z_j\right)\frac{\partial\left(b_j + \sum_i a_i w_{ij}\right)}{\partial w_{ij}}\right) = \sum_k\left(\delta_k w_{jk} g_j'\left(z_j\right)a_i\right) = a_i g_j'\left(z_j\right)\sum_k\left(\delta_k w_{jk}\right) = a_i\delta_j$$

$$\frac{\partial E}{\partial b_j} = \sum_k\left(\delta_k w_{jk} g_j'\left(z_j\right)\frac{\partial\left(b_j + \sum_i a_i w_{ij}\right)}{\partial b_j}\right) = g_j'\left(z_j\right)\sum_k\left(\delta_k w_{jk}\right) = \delta_j$$

Reference

[1] Honggang Wang, Nicholas A. Dembsey, Brian J. Meacham, Shichao Liu, Simeoni Albert, Conceptual Design of a Building Fire Performance Monitoring Process, submitted to Fire Technology.

[2] Honggang Wang, Nicholas A. Dembsey, Brian J. Meacham, Shichao Liu, Simeoni Albert, A Sensitivity Matrix Method to Understand the Building Fire Performance Gap, **will be submitted to Fire Technology**.

[3] McCaffrey, B. J., Quintiere, J. G. and Harkleroad, M. F. (1981), "Estimating Room Temperatures and the Likelihood of Flashover Using Fire Test Data Correlations," Fire Technology, 17(2), pp. 98–119

[4] James A. Milke, Analysis Methods for Determining Fire Resistance of Steel Members (2016), SFPE, 5th, chapter 53, page 1909

[5] Robin Neupane, Huayong Chen & Chunran Cao (2019), Review of moraine dam failure mechanism, Geomatics, Natural Hazards and Risk, 10:1, 1948-1966, DOI: 10.1080/19475705.2019.1652210

[6] Omid Saberi (2016), Embankment dam failure outflow hydrograph development, Graz University of Technology, PhD thesis, 2016

[7] Andre I. Khuri, Siuli Mukhopadhyay (2010), Response surface methodology, Advanced Review, Volume 2, March/April 2010

[8] Box, G. E. P., & Wilson, K. B. (1951). On the experimental attainment of optimum conditions. Journal of the Royal Statistical Society, Series B, 13, 1–45

[9] Box, G. E. P., & Hunter, J. S. (1957). Multi-factor experimental designs for exploring response surfaces. Annals of Mathematical Statistics, 28, 195–241

[10] Angela Dean, Daniel Voss, Danel Draguljić (2017), Design and Analysis of Experiments, second edition, Springer International Publishing, 2017, p565

[11] K. Velmanirajan, A. Syed Abu Thaheer, R. Narayanasamy, C. Ahamed Basha (2012), Numerical modelling of aluminium sheets formability using responsesurface methodology, Materials and Design 41: 239-254

[12] I.M. Yusri, , A.P.P. Abdul Majeed, R. Mamat, M.F. Ghazali , Omar I. Awad , W.H. Azmi (2018), A review on the application of response surface method and artificial neural network in engine performance and exhaust emissions characteristics in alternative fuel, Renewable and Sustainable Energy Reviews, 90: 665-686

[13] K. McGrattan and B. Toman (2011). Quantifying the predictive uncertainty of complex numerical models. Metrologia, 48:173–180

[14] Kevin McGrattan, Simo Hostikka, Jason Floyd, Randall McDermott, Marcos Vanella (2020), FDS Technical Reference Guide Volume 3: Validation, NIST

[15] Verification and Validation of Selected Fire Models for Nuclear Power Plant Applications, Volume 2: Experimental Uncertainty, U.S. Nuclear Regulatory Commission, Office of Nuclear Regulatory Research (RES), Rockville, MD, 2007, and Electric Power Research Institute (EPRI), Palo Alto, CA, NUREG-1824 and EPRI 1011999.

[16] International Code Council (ICC) (2018), Chapter 3 Occupancy Classification and Use, International Building Code

[17] Dusing, J., Buchanan, A. and Elms, D. (1979), Fire Spread Analysis of Multi-compartment Buildings, Research Report 79112, Department of Civil Engineering, University of Canterbury, New Zealand

[18] Johansson, N. (2016). The pre-flashover compartment fire and fire safety engineering – a review of hand-calculation methods. In Proceedings 11th Conference on Performance-based Codes and Fire Safety Design Methods (pp. 84-95). Society of Fire Protection Engineers.

[19] ALI KATTAN, ROSNI ABDULLAH, ZONG WOO GEEM (2011), ARTIFICIAL NEURAL NETWORK TRAINING AND SOFTWARE IMPLEMENTATION TECHNIQUES, Nova Science Publishers, Incorporated

[20] Coryn A.L. Bailer-Jones, Ranjan Gupta, Harinder P. Singh (2011), An introduction to artificial neural network, Automated Data Analysis in Astronomy, Narosa Publishing House, New Delhi, India, pp. 51-68

[21] Subana Shanmuganathan, Sandhya Samarasinghe (2016), Artificial Neural Network Modelling, Springer International Publishing Switzerland

[22] T. Kohonene, G. Deboeck,Visual (1998), Explorations in Finance with Self-organizing Maps (Springer, London, 1998)

[23] S. Samarasinghe (2006), Neural Networks for Applied Sciences and Engineering: From Fundamentals to Complex Pattern Recognition (Auerbach, Boca Raton, 2006)

[24] https://dustinstansbury.github.io/theclevermachine//a-gentle-introduction-to-neural-networks, first accessed on 10/25/2020

[25] https://dustinstansbury.github.io/theclevermachine/derivation-backpropagation, first accessed on 10/25/2020

[26] Howard Demuth, Mark Beale (2004), Neural Network Toolbox For Use with MATLAB – User's Guide (version 4), The MathWorks

[27] https://machinelearningmastery.com/impact-of-dataset-size-on-deep-learning-model-skill-and-performance-estimates, first accessed on 10/30/2020

[28] NFPA Technical Committees (2009). NFPA 101 Life Safety Code. Quincy, MA: National Fire Protection Association, 2009

Section 5

CONCLUSION AND FUTURE WORK

CONCLUSIONS

Building fire performance monitoring is a relative new concept which is important in that if you cannot monitor or track the performance of a system, you cannot control the risk of the system. The purpose of this dissertation is to explore new methods to monitor fire performance of buildings in use. Three sections are composed to introduce the concept, prototype, and critical techniques of building fire performance monitoring. The main conclusions are summarized below:

Section 2: Conceptual Design of a Building Fire Performance Monitoring Process

(1) Difficulties of recognizing the building fire performance gap (BFPG) are identified, of which the most important one is the lack of methods to observe or measure a building's response or performance under fire conditions since fire accidents are rare and destructive

(2) It is possible to monitor the change of building fire performance by tracking the changes of the underlying chronic factors that could someday in the future affect the building fire performance.

(3) Due to the time and resource costs, CFD tools like FDS and physical fire tests are inappropriate to monitor the building fire performance which needs frequent or dynamic measurement or estimation of the building fire performance.

(4) Sensitivity matrix method (SMM), response surface method (RSM), and artificial neural network (ANN) have the potential to quickly estimate the changes of building fire performance when the underlying influencing factors change.

(5) The conceptual design of fire performance monitoring (FPM) proposed in this section has the potential of handling the important issue of how to improve the actual building fire performance or close the BFPG, providing a way to increase the maturity of fire protection engineering.

Section 3: A Sensitivity Matrix Method (SMM) to Understand the Building Fire Performance Gap

(1) Derived from Taylor's series, SMM is a first order or linear approximation method which can work as a substitute model of FDS around the baseline point.

(2) It is possibly for the SMM-B/F which uses the combination of backward difference and forward difference to outperform the SMM-center which uses the center difference, but the SMM-center is more convenient.

(3) The prototype of a FPM tool, which is based on using SMM-center, is able to track the change of building fire performance given changes of input variables related to a fire scenario in a small 3 story apartment building.

Section 4: Comparison of applicability among sensitivity matrix method, power function-based response surface method (RSM), and artificial neural network (ANN) in the analysis of building fire egress performance

(1) Thanks to the assumption of a power function relationship between outputs and inputs, and the assumption of independence among input variables, a novel two-phase power function based RSM is developed in this section which requires much less case data than traditional RSMs.
(2) RSM-1 developed with a small number of specially designed data is better than RSM-2 developed with much more random data, showing that what matters is not the number but the quality of the data.
(3) As to the application of ANNs, an optimum hidden layer size and dataset size exist for a specific problem. In our case of fire egress in a small 3 story apartment building, the hidden layer size of 2 and dataset size of 80 are found to be the optimum.
(4) Major differences among SMMs, RSMs, and ANNs include: SMMs and RSMs are physics-based models, whereas ANNs only depend on the training/validation data; SMMs are linear models, whereas RSMs and ANNs are non-linear models; ANNs and RSMs have higher applicability than SMMs, whereas the development of a SMM needs much less case data; ANNs have higher accuracy than SMMs and RSMs when the ASETs are far away from the baseline point, but they are unable to predict the changing tendencies of ASETs with changes in fire scenario characteristics.
(5) It may be a good strategy to start with SMMs and move to RSMs and ANNs when more case data are accumulated during the application of SMMs in building fire performance monitoring.

FUTURE WORK

This dissertation provides an introduction to a relatively new research area: building fire performance monitoring (FPM). Although the basic idea, concept and prototype of FPM are discussed, there are many practical tasks needed to be completed in the future before an FPM tool can be successfully applied in realistic fire risk management of buildings, a few of which are listed here:

1. Investigate the methods to translate the data or information that could be directly measured or obtained in a building into values of input and/or output variables of the FDS simulations. Since our FPM method depends on the tracking of changes of input variables, how to collect these data becomes paramount. In our current research, it is assumed that all the input variables for use in FDS can be observed and monitored, which is simplification for our prototype of an FPM tool. In reality, however, data/sensor fusion may be needed to prepare data used in FDS simulations.
2. Consider the factors influencing the frequency of fire accidents in a building. The factors that could affect the fire risk can be grouped into two categories: that affecting the frequency of fire accidents and that affecting the consequence of fire accidents. Currently in our research,

only the factors affecting the consequence of fire accidents are considered, therefore, the building fire performance is represented by a “fire loss”. Since fire risk is a produce of fire loss and fire frequency, we need to incorporate frequency factors like occupants’ activity in their apartments if we want to use fire risk to describe building fire performance.

3. Refine the FPM tool. In the conceptual design of the FPM tool; SMM, RSM, and ANN are proposed as low-cost substitute models of FDS. The current first version of the FPM tool only focuses on the core algorithm of generating sensitivity matrices and coefficients of RSM. ANN methods have not been involved yet. Also the input data are synthetic data generated manually. In the future, a friendly interface for users to prepare the input data for FDS simulations is expected.