Fire induced Progressive Collapse Potential assessment of Steel Framed Buildings using machine learning

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Abstract In this paper, a new Machine Learning framework is developed for fast prediction of the failure patterns of simple steel framed buildings in fire and subsequent progressive collapse potential assessment. This pilot study provides a new tool of fire safety assessment for engineers in an efficient and effective way in the future. The concept of Critical Temperature Method is used to define the failure patterns for each structural member which is incorporated into a systematic methodology employing both Monte Carlo Simulation and Random Sampling to generate a robust and sufficient large dataset for training and testing, hence guarantees the accurate prediction. A comparative study for different machine learning classifiers is made. Three classifiers are chosen for failure patterns prediction of buildings under fire: Decision Tree, KNN and Neural Network using Google Keras with TensorFlow which is specially used for Google Brain Team. The Machine Learning framework is implemented using codes programmed by the author in VBA and Python language. A case study of a 2 story by 2 bay steel framed building was made. Two different fire scenarios were chosen. The procedure gives satisfactory prediction of the failure pattern and collapse potential of the building under fire.

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Keywords: Fire; Decision Tree; KNN; Neural Network; Critical Temperature Method; TensorFlow; Monte Carlo Simulation; Random Sampling

1. Introduction

The recent disaster in Grenfell tower [1] embarked the increasing interests in fire safety design for multi-story buildings. Across the world, large percentage of the tall buildings or multi-story buildings are steel structures, so fire safety is one of the key concerns in the design practice. The traditional design process of building under fire is time consuming and is limited by the ability of an engineer to fully understand the failure potential of the structure under fire loadings. This is primarily due to the complexity of this engineering problem. So far, there is no efficient way to tackle this problem in the construction industry. One of the possible ways to solve this problem is to use artificial intelligence.

Although construction research has considered machine learning (ML) for more than two decades, it had rarely been applied to fire safety design of buildings. Some research has been undertaken in the past by using the machine learning for certain construction problems. Adeli, H. et al. [2] made a comprehensive review on the neural networks in structural engineering. Paudel et al. [3] used Machine learning for the prediction of building energy demand. Zhang et al. [4] developed a machine learning framework for assessing post-earthquake structural safety. Shi et al. [5] set up an evaluation model to assess the intelligent development of 151 cities in China. The model is based on the analytic hierarchy process and back propagation neural network theory. Puri et al [6], set up the relationships between in-place density of soil using SPT N-value, compression index (Cc) using liquid limit (LL) and void ratio (e), and cohesion (c) and angle of internal friction (ϕ) using machine learning techniques. Tixier et al. [7] use random forest (RF) and stochastic gradient tree boosting (SGTB) method to predict the injury in the construction sites. The dataset is extracted from large pool of the construction injury report. It is found that, their models can predict injury type, energy type, and body part with high accuracy, outperforming the parametric models found in other literature. Chou [8] proposes a novel classification system integrating swarm and metaheuristic intelligence, with a least squares support vector machine (LSSVM). The system was applied to several geotechnical engineering problems that involved measuring the groutability of sandy silt soil, monitoring seismic hazards in coal mines, predicting post-earthquake soil liquefaction, and determining the propensity of slope collapse. Ozturan et al. [9] used the artificial neural network to predict the concrete strength. Lagaros [10] made Fragility assessment of steel frames using neural networks. De Lautour et al [11] made prediction of seismic-induced structural damage using artificial neural networks. Mangalathu, S., et al. [12] used artificial neural network to develop multi-dimensional fragility of skewed concrete bridge classes. Wang, Z. et al. [13] also made seismic fragility analysis with artificial neural networks for nuclear power plant equipment. Hozjan et al [14] developed an artificial neural network (ANN) in the material modelling of steel under fire.

From above literature review, it can be seen that little research has been done on using machine learning to predict failure mode and consequently the potential of the collapse under fire. Therefore, it is imperative a study on fire safety assessment using machine learning is timely. Therefore, in this paper, a new Machine Learning framework is developed which provides a new tool to assist engineers in fire safety assessment. The concept of Critical Temperature Method is used to define the failure patterns of each structural member, which is incorporated into a systematic methodology employing both Monte Carlo Simulation and Random Sampling to generate a robust and sufficient large dataset for training and testing, hence guarantees the accurate prediction. The Machine Learning framework is implemented using a code programmed by the author in VBA and Python language. Case studies of machine learning prediction were also made, the machine procedure gives satisfactory prediction of the failure pattern and collapse potential of the building under fire.

2. Framework of structural fire safety assessment and classifiers selections

2.1 Process of Fire Safety Assessment of Buildings through Machine Learning

The whole process of the fire safety assessment using machine learning can be demonstrated in Figure 1. The detailed procedure will be introduced in the following sections.

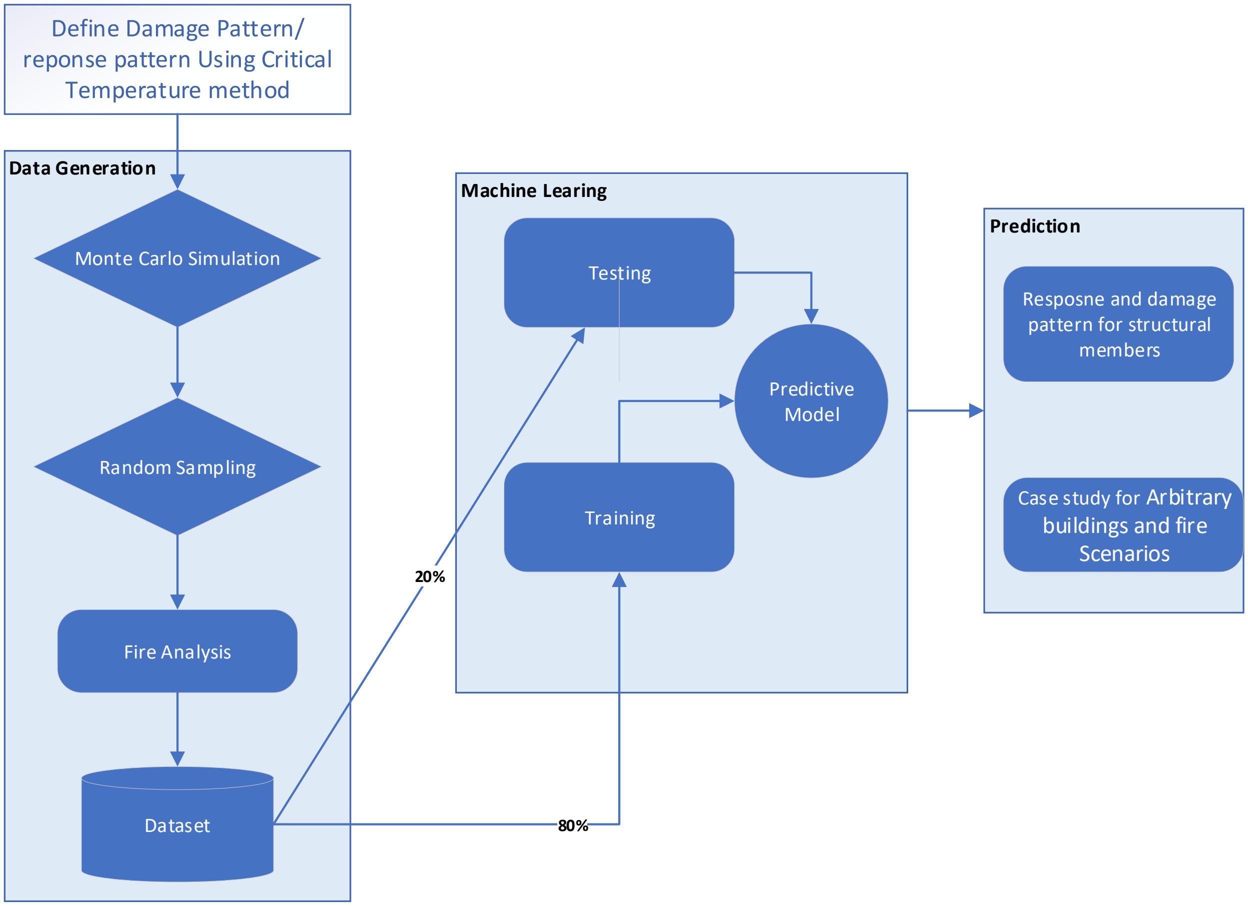


Figure 1 Fire Safety Assessment of Buildings through Machine Learning

2.2 Major classifiers in machine learning

2.2.1 Artificial Neural Network (ANN)

Artificial neural network is one of the major tools used in machine learning. It mimics the brain systems and intend to replicate the way humans learning. The neural network consists several simple processing units called neurons. Typically, the neurons are organized into layers: the input layer, hidden layers, and the output layer. There are various types of neural network, such as Singer-Layer Feed-forward Networks, Multilayer Feed-forward Networks, *Recurrent Neural Networks.* In deep learning neural networks, a multilayer network extract different features until it can recognize what it is looking for. Therefore, it can possess greater learning abilities and are widely used for complex tasks.

2.2.2 Decision Tree Learning

Decision tree is one of the predictive modelling approaches used in machine learning. It uses the tree model to make decision. In these tree structures, leaves represent class labels and branches represent conjunctions of features that lead to those class labels. If the target variable can take continuous values are called regression trees, where the target variable can take a discrete set of values are called classification trees.

2.2.3 KNN

KNN is one of the simplest classifiers s. It is a non-parametric method used for both classification and regression. The data points are separated into several classes to predict the classification of a new sample point. It is based on feature similarity. How closely out-of-sample features resemble training set determines how to classify a given data point.

2.3 Selection of suitable classifiers for fire safety assessment

Choosing a correct classifiers is essential for accurate machine prediction. Each learning classifiers has consist advantages and disadvantages due to their different features. Not a single machine learning classifiers works for every problem. The way to choose the right classifiers is often a process of trial and error, especially for this particular new problem of fire safety, no previous study has ever been made. However, the key characteristics of various classifiers s has been studied by several researchers.

Table 1 Characteristics of popular classification classifiers s [15]

Algorithm	Prediction Speed	Training Speed	Memory Usage	General Assessment
Logistic Regression (and Linear SVM)	Fast	Fast	Small	Good for small problems with linear decision boundaries
Decision Trees	Fast	Fast	Small	Good generalist, but prone to overfitting
(Nonlinear) SVM (and Logistic Regress	Slow	Slow	Medium	Good for many binary problems, and handles high-dimensional data well
Nearest Neighbor	Moderate	Minimal	Medium	Lower accuracy, but easy to use and interpret
Naïve Bayes	Fast	Fast	Medium	Widely used for text, including spam filtering
Neural Network	Moderate	Slow	Varies	High accuracy and good performance for small- to medium-sized datasets
Ensembles	Moderate	Slow	Medium to Larg	Popular for classification, compression, recognition, and forecasting

Based on Table 1 and aforementioned literature review, it can be seen that, compared to other classifiers , ANN has been frequently used for solving various construction problems. Therefore, ANN has been chosen as a learning classifiers for this particular fire safety problem. In addition, from Table 1, it can be seen that Decision Tree and KNN are easy to use and interpret, therefore, they are also chosen.

3. Define the failure patterns

The first step in machine learning is to define the failure patterns. There are several major failure modes of the structural members in fire, such as Beam Buckling, Column Buckling, Due to the complexity, they are difficult to be digitalized and quantified to make the machine understand. However, when assessing the fire induced collapse, the machine only needs to make judgement on whether a structural member will fail, regardless the way it fails. Therefore, one of the common design approaches to determine the failure of structural members under fire, critical temperature method, which is stipulated by Eurocode 3 [16], is used here to define the failure patterns of the structural members. This method has been adopted by several researchers [23] in fire safety assessment and by many design practioners for fire safety assessment of more complicated structures, such as tall buildingsThis method is simple and effective. The engineers only need to know the designed load at ambient temperature, when the temperature increased to the critical temperature under the design load, the structural member is deemed to fail. Therefore, it avoids sophisticate FE analysis, which is also proved to be sufficient accurate..

3.1 The Critical temperature method to determine the failure pattern of steel members

The Critical temperature method is to determine a critical temperature (Eurocode 3[16]) based on the load utilization of a structural member. This is the simplest method of determining the fire resistance of a loaded member in fire conditions. The critical temperature is the temperature at which failure is expected to occur in a structural steel element with a uniform temperature distribution In Eurocode 3 [16]. Its value is determined from:

$$\theta_{cr} = 39.19 ln\left[\frac{1}{0.9674\mu_0^{3.833}} - 1\right] + 482$$

Where,

μ_0 Is the degree of load utilization

According to Eurocode 3[16], this equation can be used only for member types for which deformation criteria or stability considerations do not have to be taken into account (such as beams). Eurocode 3 [16] also provides the way to work out the critical temperature for compression members (such as columns) and unconstrained members, which can be tabulated in Table 2.

Table 2 Critical temperatures of steel compression members (partial adapted from Eurocode 3 [16])

	Critical Temperature (Cº) for Utilization Factor (load Ratio)					
λ\ Utilization Factor	0.7	0.6	0.5	0.4	0.3	0.2
0.4	485	526	562	598	646	694
0.6	470	518	554	590	637	686
0.8	451	510	546	583	627	678
1	434	505	541	577	619	672
1.2	422	502	538	573	614	668
1.4	415	500	536	572	611	666
1.6	411	500	535	571	610	665

3.1.1 Load ratio (degree of utilization)

Load Ratio is defined as applied load (primarily due to gravity load, such as dead load and live load) in fire conditions to resistance capacity of the member at room temperature condition (Eurocode3 [16]), it is defined using below formula:

$$\mu_0 = \frac{E_{fi,d}}{R_{fi,d,0}} \qquad \text{Equation 1}$$

Where:

$E_{fi,d}$ is the applied load under fire condition

$R_{fi,d,0}$ is the design moment of resistance of the member at ambient temperature

It is also known that in virtually every situation the critical temperature is dependent on the fraction of the ultimate load capacity that a member withstand in fire. When the load ratio is greater than 1, this indicates that the load applied on the structural member is greater than the resistance capacity of the structural member, so it will fail even at the ambient temperature purely due to mechanical failure.

3.2 Determine the failure pattern of the structural members in fire

Based on above introduction, it can be seen that, to be able to determine the failure of a structural member under fire, below factors need to be determined: the maximum atmosphere temperature

the maximum temperature of the steel members under fire, the load ratio, and the critical temperature of the steel member. Then the failure of a structural member under fire can be determined as follows:

1. ***If*** *maximum temperature of the steel member> critical steel temperature,* ***Then***

this member fails, (the failure is due to fire)

2. ***If*** *(maximum temperature of the steel member< critical steel temperature)* ***and*** *load ratio >1* ***Then*** *this member fails* (the failure is due to overloading)
3. ***Else***
   the member is safe

Therefore, one response pattern and two failure patterns can be identified. They are:

- safe
- failure due to fire
- failure due to mechanical rather than fire.

Based on above discussions, the structural fire analysis based on the Critical temperature method from the Eurocode is implemented in an Excel VBA software program.

3.3 Heat transferring and Thermal Response of Structural Members

The heat from fire transferred to the structural members are worked out using the formulae based on the Eurocode. The atmosphere fire temperature is first determined using Equation 2

$$\Theta_g = 20 + 1325(1 - 0.324e^{-0.2t^*} - 0.201e^{-1.7t^*} - 0.472e^{-19t^*}) \qquad \text{EQUATION 2}$$

Where:

Θ_g Is the gas temperature in the fire compartment

And $t^* = \Gamma t$

with

t time

$\Gamma = [O / b]^2 / [0.04 / 1160]^2$

O = opening factor, $O = A_v \cdot H_w^{\wedge 0.5} / A_t$

A_t = Total internal surface area of compartment [m^2]

A_v = Area of ventilation [m^2]

H_w = Height of openings [m]

b = Thermal diffusivity, 100 [b [2000 ($J/m^2\ s^{1/2}\ K$)

The maximum temperature Θ_{max} in the heating phase happens for $t^* = t^*_{max}$

$t^*_{max} = t_{max} \bullet \Gamma$

with $t_{max} = (0.2 \cdot 10^{-3} \bullet\ q_{t,d} / O)$ or t_{lim}.

$q_{t,d}$ is the design value of the fire load density related to the total surface area A_t of the enclosure, whereby $q_{t,d}$ = $q_{f,d} * A_f / A_t$ [MJ/m^2]. The following limits should be observed: 50 <$q_{t,d}$ <1 000 [MJ/m^2].

$q_{f,d}$ is the design value of the fire load density related to the surface area A_f of the floor [MJ/m2] taken from EN1991-1-2: Eurocode 1; Part 1.2 annex E.[18]

The Parametric temperature-time curves in the cooling phase given by EN1991-1-2: Eurocode 1; Part 1.2 [18] is

$\Theta_g = \Theta_{max} - 625\ (t_* - t_{*max} * x)$ for $t_{max} \leqslant 0,5$
$\Theta_g = \Theta_{max} - 250(3 * t_{*max})\ (t_* - t_{*max} * x)$ for $0,5 < t_{max} \leqslant 2$
$\Theta_g = \Theta_{max} - 250\ (t_* - t_{*max} * x)$ for $t_{max} \geqslant 2$

After the atmosphere temperature is determined, the thermal response of each structural member can be worked out. For Unprotected steel Section, the increase of temperature in small time intervals is given by BS EN 1993-1-2: Eurocode 3 [16] and BS EN 1994-1-2: Eurocode 4 [17]

as follows:

$$\Delta\boldsymbol{\Theta}_{a,t} = \boldsymbol{k}_{sh} \frac{A_m/_V}{c_a \rho_a} \boldsymbol{h}_{net} \Delta \boldsymbol{t} \qquad \textbf{EQUATION 3}$$

Where,

$\Delta\Theta_{a,t}$ is the increase of temperature

A_m/V is the section factor for unprotected steel member

c_a is the specific heat of steel

ρ_a is the density of the steel

h_{net} is the designed value of the net heat flux per unit area

Δt is the time interval

k_{sh} is the correction factor for shadow effect

Using this formula, the maximum temperature for the steel member under certain fire scenario can be worked out. Among these parameters, the section factor A_m/V is one of the dominant factors, which correlated to different member sizes. It can be checked in the steel design tables

Above formula were implemented in the Excel VBA code, therefore the fire temperature and the maximum fire temperature can be calculated.

4. Learning Dataset generation using Monte Carlo simulation and Random sampling

To accurate predict the failure pattern, sufficiently large amount of training cases is important for the machine. However, it is hard to find the enough training cases in the construction industry due to lack of fire incidents database. To tackle this problem, a method based on Monte Carlo simulation and Random Sampling is developed to generate sufficient large dataset in this project. The key parameters which affects the failure patterns of a structural member under fire is generated using the Monte Carlo simulation, such as opening factors and fire load density (to determine atmosphere fire temperature), imposed load (to determine gravity load) and steel grades (to determine material properties) etc. After Monte Carlo simulation, these parameters are selected using Random Sampling techniques with equal opportunities for structural fire analysis based on the Eurocode and failure judgement by the machine. The whole process is also programed into the software program in the paper.

4.1 Monte Carlo simulation for different design parameters

Monte-Carlo simulation is to simulate a probability distribution for different variable. It is used here to generate leaning cases for the machine. Firstly, a probability distribution for each individual variable will be determined. It is also essential to determine the dependencies between simulation inputs based on their real quantities being modelled. In fire safety design, there are some key parameters which will affect the design values. For example, when determining atmosphere temperature, opening factor and fire load density are the two key parameters to affect its value, they are mutually independent. The probability distribution or the range of these parameters are readily known from design guidelines such as Eurocode [16,17,18] and research [19]. Therefore, using the available distributions and key statistic index obtained from Eurocodes (see table 3), the random value of opening factor and fire load density can be generated. Subsequently, the correspondent atmosphere temperature can be calculated based on design formula. As these values follow the specific distribution discovered in the design practice, which are determined from large-scale data analysis and tests. they are not arbitrary values. Therefore, it can represent the real quantities in the design practice.

When using Monte Carlo simulation to generate the learning data, a probability model with correspondent random variables or the range of the parameters should be used. They are listed in Table 3. These statistical parameters are selected based on the Eurocodes [16,17]. using these statistic variables and the range of the design parameters, the values of the parameters are generated using the Monte Carlo simulation implemented using Visual Basic code.

Table 3 Probabilistic variables and range of design parameters in Monte Carlo simulation

Variable	Distribution	Units	mean	Standard Deviation	Range	Source
opening factor	Normal	N/A	N/A	N/A	0.02-0.2	Eurocode 1; Part 1.2 [18]
fire load density	Gumbel	MJ/m^2	420	126		Eurocode 3 [16]
Imposed load	Extreme type I	KN/m^2			1-5	Eurocode 1; Part 1.2 [18]
Yield strength of steel	Log-normal	MPa	280	28	275-355	Eurocode 1; Part 1.2 [18]
Partial safety factors	Normal	-	-	-	1.5-2	Eurocode 1; Part 1.2 [18]

4.2 Random sampling

Random sampling is a simple way of collecting data from a total population, in which each sample has an equal probability of being chosen. It guarantees an unbiased representation of the total population. An unbiased random sample is important for fire safety design. For an example, when we took out the sample of 10 opening factors from a total population of 100 parameters generated through Monte Carlo simulation, there is always a possibility that 8 opening factors which is smaller than 0.1, even if the population consists of 50 opening factors which are greater than 0.1 and the other 50 which are smaller than 0.1. Hence, some variations when drawing results can come up, which is known as a sampling error. To minimize the sampling error, random sampling is a best tool. In this proposed machine learning framework, it can avoid the bias in the parameter selections when performing the structural fire analysis and failure judgement. Therefore, to enable accurate machine learning result, Random sampling is performed after Monte Carlo simulation.

4.3 Response and failure judgment of structural members

When all the design parameters for structural fire analysis are generated using Monte Carlo simulation method, Random Sampling technique is used to select parameters without bias. , Subsequently, the parameters such as load ratio can be determined and temperature of the structural member can be calculated based on the Eurocode [16.17] Finally, the failure pattern of the structural members under fire can be determined using the Critical Fire Temperature method.

4.4 Leaning dataset generation

The process of Monte Carlo simulation, Random sampling and response calculation are implemented using VBA code designed by the author and the training data is correspondently generated, as it shown in Table 3. It can be seen from Table 3 that , it primarily includes following key variable which is necessary for machine learning: Maximum fire temperature (column 1), Maximum steel member temperature (column 2), load ratios (column3), critical temperature (column 4), member size index (column 5,representing different member section sizes) and failure judgment(column 6). When judging the failure of the structural members, 1 means safe, 2 means failure due to over loading, 0 means failure due to fire.

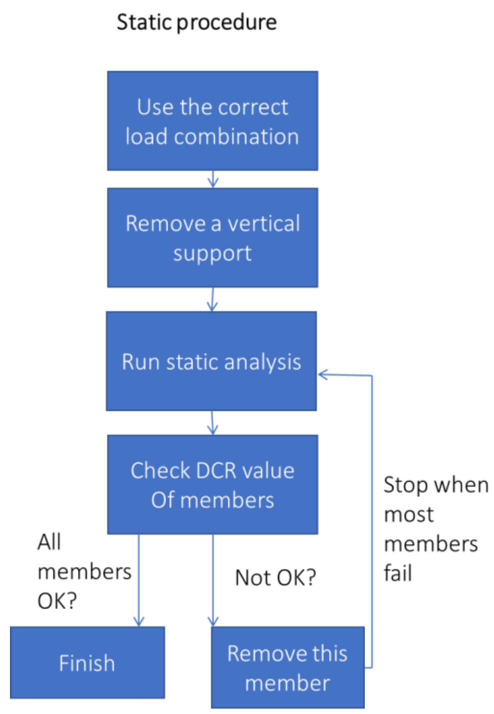
Table 4 Training dataset generated using the Monte Carlo Simulation and Random sampling technique

Fire Temp °C	Max St,Temp °C	Load Ratio	Critical Steel Temp	Member Index	Failure Judgeme
1078.777112	1072.972258	1.906004337	0	1016305393	2
1044.847302	1035.86298	0.019668301	1073.456629	1528916	1
859.3743067	825.3909286	3.910972054	0	25410225	2
894.3031378	822.9862876	1.571725344	0	686254170	2
723.2403915	645.7673271	0.092510361	840.872358	457191106	1
1087.993266	1083.770738	0.262457208	684.0113434	20320352	0
1149.164052	1142.13558	0.878904533	467.7620262	53316575	0
1002.466858	998.6432318	0.264232525	682.9927543	1016305222	0
977.5063653	960.1034175	0.038337423	973.2000918	305305158	1
1067.616506	1055.234069	0.214171489	714.6740143	356368129	0
962.4113027	905.0539032	0.134932148	784.1599671	40614039	0
793.2113903	716.3826089	0.673155554	533.4029976	30516554	0
806.3825375	729.7198245	0.61671292	549.4579589	20320386	0
1016.843216	994.1335539	0.520444807	578.1684951	305305158	0
977.9954012	958.8996631	0.168472021	750.7889545	25410222	0
730.4020384	627.4183099	1.756390206	0	53316566	2
983.5084047	980.3737012	0.270432692	679.4871069	15215237	0
999.8262873	983.5010033	1.693384511	0	356406509	2
992.2768322	984.0502959	0.034727581	988.0552671	305305137	1
882.5428465	878.9754656	0.258628121	686.2314234	356368202	0
1017.646293	1006.125124	0.134142161	785.0424082	610229125	0

5. Collapse potential check a building under fire using machine learning

In structural fire analysis, one of the key tasks is to check the collapse potential of the overall buildings under fire. This becomes possible using machine learning. When the prediction of failure mode or response of each individual structural member is successful, the prediction of the collapse of a building can be based on the procedure stipulated by U.S. design code GSA [20] and DOD [21]. These two are the most recognized codes for progressive collapse design. The collapse potential check can be summarized into the framework flowchart as it shown in Note: **DCR is Demand capacity ratio**

Figure 2. This procedure is based on the response of each individual structural member. For these failed members, they will be removed from the structure, then a static progressive collapse check will be performed through static analysis following [20,21], which is to check the Demand capacity ratio (DCR) value of the remaining structural members, if the DCR value for all the remaining members are satisfactory, the building will not collapse. If the DCR value of any member is not satisfactory, this member will also be removed, and re-run the static analysis. If most members fail, say 40% of the members fail, this indicate that structure is deemed to collapse, therefore, the who procedure can be stopped.



Note: DCR is Demand capacity ratio

Figure 2 The flow chart of collapse potential check ([20],[21][22])

One of the difficulties for building progressive collapse check under fire load using machine learning is how to correctly represent the building information, such as the location of the structural members, type of the structural member (column or beam), member sizes, design load and other design parameters. To tackle this problem, as it is shown in Table 5, an Excel worksheet is designed for building information capture. a special naming system is invented here for denotating the structural members. The beams and columns are denoted as follows:

for an example,

- B-A-12-2 represents beam at grid A in between grid 1and 2, at level2.
- C-1-A-1 represents Column at the joints of grid 1 and A at level 1.

The spreadsheet can automatically make the judgment of whether it is a beam or column according to the name of the structural members. It can also check the properties such as the section factors and plastic modulus using the section tables included in the Excel file. It also allows the user to input the gravity load such as dead load and live load, the parameters for the calculation of the fire temperature such as opening factor, fire load density and other required parameters.

Based on the building information captured in this sheet, a VBA code is designed, which can read this information and work out the values for key input variables for each structural member, such as Fire Temperature, Maximum Steel Temperature, Load Ratio, Critical Temperature based on the Eurocode. It can also make a failure judgement of each individual member for the validation of the machine learning outcome.

Based on Figure 2, after the failure mode and response of each individual structural member are determined by the machine, a progressive collapse potential check will also be performed by the program.

6. Machine Learning (Training and Testing)

Before the machine can make an accurate prediction of the failure mode for each individual structural member, training and testing is essential. The training and testing are performed based on Python code developed by the author in Anaconda. In convention, 80% of the data is used for training, 20% of the date is used for testing for most data scientist and computer scientist . Therefore, it is also used here. Three classifiers Decision Tree, KNN and Neural Network are chosen for the machine learning. When sufficient accurate prediction is achieved, the machine can start to predict the failure patterns of the structural members for real projects.

6.1 Neural Network-TensorFlow

Python provides two numerical platforms for Deep Learning research and development. They are: Keras and TensorFlow. TensorFlow is developed by Google Brain team. It is an open-source software library for dataflow programming. It is a symbolic math library used for machine learning applications such as Neural Networks. Keras is an open source neural network library written in Python. It is capable of running on top of TensorFlow. It enables fast experimentation with deep neural networks.

In this study, Keras with TensorFlow are used for training and testing. As it shown in Figure 3, one input layer which includes variables shown in Table 3, two hidden layers and one output layer (indicating failure judgement,1,2,0) were used for the prediction. Different activation functions were choosing for the testing, it is found that "sigmoid" gives the most satisfactory results, therefore, "sigmoid" was chosen as it shown in equation 4.

$$f(x) = 1/(1+e^{-x}) \qquad \text{EQUATION 4}$$

The data is also normalized before the training and testing. This is because the Activation function sigmoid is used, so the prediction values are between 0-1. After data processing (shown in the code), they are converted back to [1] or [0] or [2], which representing the failure patterns of the structural members

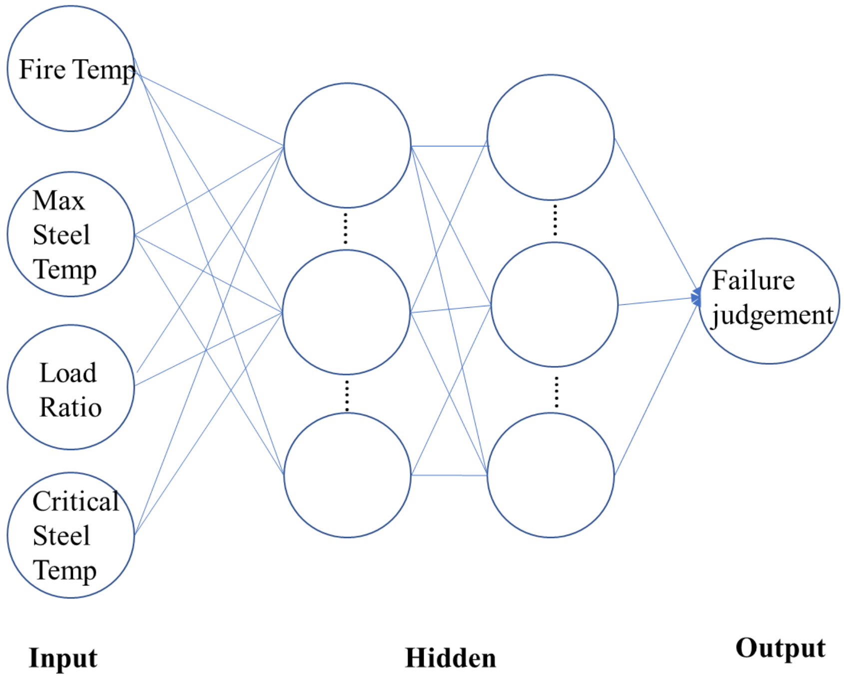


Figure 3 Hidden layer network with input and output layers

6.2 Prediction using Decision Tree Learning

Python provides Decision tree leaning classifiers. The representation of the tree model is a binary tree. A node represents a single input variable and a split point on that variable, assuming the variable is numeric. The leaf nodes of the tree contain an output variable used to make a prediction. Once created, a tree can be navigated with a new row of data following each branch with the splits until a final prediction is made.

Creating a binary decision tree is actually a process of dividing the input space. Different approach can be used. Splitting continues until nodes contain a minimum number of training examples or a maximum tree depth is reached.

6.3 KNN

Python provides KNN classifiers . The data points are separated into several classes to predict the classification of a new sample point.

For classification: the output is a class membership (predicts a class—a discrete value). An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours.

For regression: the output is the value for the object (predicts continuous values). This value is the average (or median) of the values of its k nearest neighbours.

7. Case study progressive collapse potential check using machine learning

7.1 The prototype building

After training and testing, as it shown in Figure 3, a two-story moment resisting steel frame building is used for progressive potential check using machine learning. . The normal design loads, dead load and live load, are chosen according to the Eurocode, so the load ratio of each member can be worked out. Design values of opening factor and fire density are 0.02 and 487 J/m^2 respectively. Two scenarios have been chosen:

- A fire was set at the ground level,
- A fire was set at the level 2

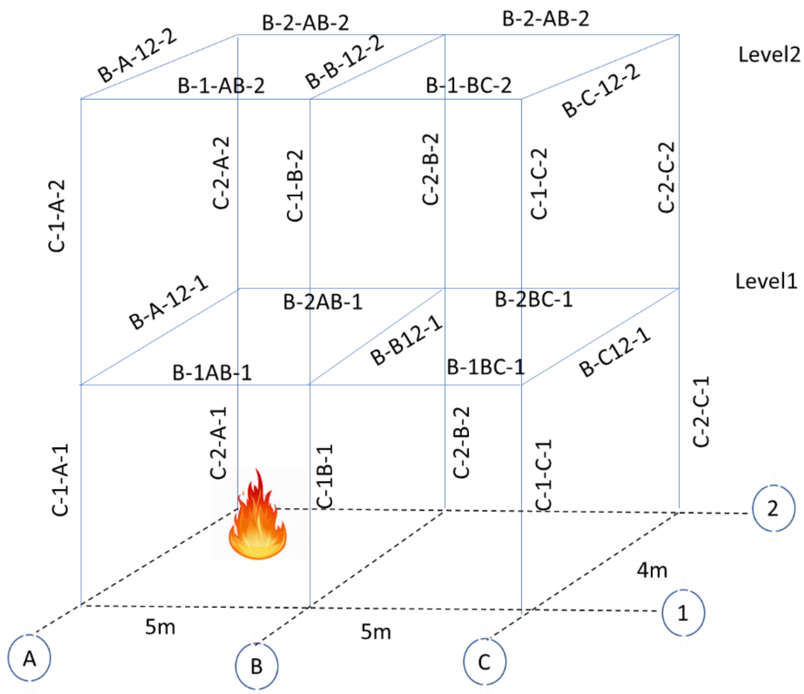


Figure 3 Schematic arrangement of the prototype building

The section sizes, section properties the spacing of the structural members, loadings of the building is shown in table 5

Level 1	Element Code	Section	Spacing	Span	Grade	Dead Load	Live Load	Type	Grid 1	Grid 2	Level	Profile Selection	Profile Column	Section Factor	Plastic Modulous	Load Applied
Beam	B-1-AB-1	762 x 267 x 197	5	4	275	10	5	Beam	1	AB	1	Profile 4 sides	8	102	7170	150
	B-2-AB-1	762 x 267 x 197	5	4	275	10	5	Beam	2	AB	1	Profile 4 sides	8	102	7170	150
	B-2-BC-1	762 x 267 x 197	5	4	275	10	5	Beam	2	BC	1	Profile 4 sides	8	102	7170	150
	B-1-BC-1	762 x 267 x 197	5	4	275	10	5	Beam	1	BC	1	Profile 4 sides	8	102	7170	150
	B-A-12-1	457 x 152 x 67	5	4	275	10	5	Beam	A	12	1	Profile 3 sides	7	157	1450	150
	B-B-12-1	457 x 152 x 67	5	4	275	10	5	Beam	B	12	1	Profile 4 sides	8	175	1450	150
	B-C-12-1	457 x 152 x 67	5	4	275	10	5	Beam	C	12	1	Profile 4 sides	8	175	1450	150
Column	C-1-A-1	356 x 406 x 235	5	4	275	10	5	Column	1	A	1	Profile 4 sides	8	76	4690	150
	C-2-A-1	203 x 203 x 86	5	4	275	10	5	Column	2	A	1	Profile 4 sides	8	113	977	150
	C-1-B-1	203 x 203 x 86	5	4	275	10	5	Column	1	B	1	Profile 4 sides	8	113	977	150
	C-2-B-2	152 x 152 x 44	5	4	275	10	5	Column	2	B	2	Profile 4 sides	8	165	372	150
	C-1-C-1	152 x 152 x 44	5	4	275	10	5	Column	1	C	1	Profile 4 sides	8	165	372	150
	C-2-C-1	152 x 152 x 30	15	4	275	10	5	Column	2	C	1	Profile 4 sides	8	235	248	450
Level 2																
Beam	B-1-AB-2	762 x 267 x 197	5	4	275	7.5	5	Beam	1	AB	2	Profile 4 sides	8	102	7170	125
	B-2-AB-2	762 x 267 x 197	5	4	275	7.5	5	Beam	2	AB	2	Profile 4 sides	8	102	7170	125
	B-2-BC-2	762 x 267 x 197	5	4	275	7.5	5	Beam	2	BC	2	Profile 4 sides	8	102	7170	125
	B-1-BC-2	762 x 267 x 197	5	4	275	7.5	5	Beam	1	BC	2	Profile 4 sides	8	102	7170	125
	B-A-12-2	457 x 152 x 67	5	4	275	7.5	5	Beam	A	12	2	Profile 4 sides	8	175	1450	125
	B-B-12-2	457 x 152 x 67	5	4	275	7.5	5	Beam	B	12	2	Profile 4 sides	8	175	1450	125
	B-C-12-2	457 x 152 x 67	5	4	275	7.5	5	Beam	C	12	2	Profile 4 sides	8	175	1450	125
Column	C-1-A-2	356 x 406 x 990	5	4	275	7.5	5	Column	1	A	2	Profile 4 sides	8	22	24300	125
	C-2-A-1	356 x 406 x 990	5	4	275	7.5	5	Column	2	A	1	Profile 4 sides	8	22	24300	125
	C-1-B-1	356 x 406 x 990	5	4	275	7.5	5	Column	1	B	1	Profile 4 sides	8	22	24300	125
	C-2-B-2	356 x 406 x 990	5	4	275	7.5	5	Column	2	B	2	Profile 4 sides	8	22	24300	125
	C-1-C-1	356 x 406 x 744	5	4	275	7.5	5	Column	1	C	1	Profile 4 sides	8	27	17200	125
	C-2-C-1	152 x 152 x 30	5	4	275	7.5	5	Column	2	C	1	Profile 4 sides	8	235	248	125

TABLE 5 EXCEL TABLE FOR BUILDING DESIGN INFORMATION INPUT

7.2 The process of progressive collapse potential check using Machine learning

The machine learning for progressive collapse potential check of a building check is divided into below stages:

a. The Maximum fire temperature, Maximum steel temperature, load ratios, critical steel temperature, member size index are input into the machine
b. failure and response predictions for each structural member.
c. based on the response of each individual members, using the design procedure from DOD (2009) and GSA (2003), the collapse potential of the whole building can be assessed.

7.3 Machine prediction and Performance evaluation of different classifiers

Table 6 shows the prediction results of each individual members using different classifiers . It can be seen that, sufficient large database is needed for accurate machine learning. When using 3000 entries training data, both KNN and decision tree give less accurate predictions.

When the data entries increase to 10000, both KNN and Neural network gives 100% accurate prediction for the dataset from real design calculation with 26 entries. However, decision tree only yields 80% accuracy.

It can be seen that, among the three classifiers , Neural Network yield accurate results, this may because, , Neural Network is a more advanced learning process, therefore, it yields accurate prediction results. KNN also yields accurate prediction. This may because it is based on the feature similarity, for this particular problem the feature similarity is evident. Therefore, they are two promising classifiers s for this particular engineering problem.

Level 1	Element Code	Fire Temp °C	Max SteelTemp	Load Ratio	Critical Steel Temp °C	Failure Judgement	KNN prediction (3200 data entries)	decision tree prediction (3000 data entries)	KNN prediction (10000 data entries)	decision tree prediction (10000 data entries)	Tensorflow (10000 data entries)
Beam	B-1-AB-1	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-2-AB-1	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-2-BC-1	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-1-BC-1	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-A-12-1	852.9173	850.3203	0.250784	690.8819	0	0	0	0	0	0
	B-B-12-1	852.9173	850.5966	0.250784	690.8819	0	0	0	0	0	0
	B-C-12-1	852.9173	850.5966	0.250784	690.8819	0	0	0	0	0	0
Column	C-1-A-1	852.9173	847.3149	0.077534	434	0	0	0	0	0	0
	C-2-A-1	852.9173	849.2547	0.372197	434	0	0	0	0	0	0
	C-1-B-1	852.9173	849.2547	0.372197	434	0	0	0	0	0	0
	C-2-B-2	852.9173	850.4508	0.977517	422	0	0	0	0	0	0
	C-1-C-1	852.9173	850.4508	0.977517	422	0	0	0	0	0	0
	C-2-C-1	852.9173	851.205	4.398827	0	2	2	2	2	2	2
Level 2											
Beam	B-1-AB-2	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-2-AB-2	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-2-BC-2	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-1-BC-2	852.9173	848.8358	0.050716	931.1663	1	0	0	1	1	1
	B-A-12-2	852.9173	850.5966	0.250784	690.8819	0	0	0	0	0	0
	B-B-12-2	852.9173	850.5966	0.250784	690.8819	0	0	0	0	0	0
	B-C-12-2	852.9173	850.5966	0.250784	690.8819	0	0	0	0	0	0
Column	C-1-A-2	852.9173	784.2671	0.014964	422	0	0	0	0	1	0
	C-2-A-1	852.9173	784.2671	0.014964	422	0	0	0	0	1	0
	C-1-B-1	852.9173	784.2671	0.014964	422	0	0	0	0	1	0
	C-2-B-2	852.9173	784.2671	0.014964	422	0	0	0	0	1	0
	C-1-C-1	852.9173	813.2911	0.021142	434	0	0	0	0	1	0
	C-2-C-1	852.9173	851.205	1.466276	0	2	2	2	2	2	2
					Accuracy of building data		0.69230769	0.69230769	1	0.807	1

Table 6 The prediction results for different classifiers

7.4 Progressive collapse potential check

Base on the prediction of each single members, the collapse potential of the building can be further checked by the machine. It can be seen that, for the first scenario, where fire was set at level 1, all columns in level 1 fail. According GSA [20] and DOD [22], the collapse is not avoidable. For the second scenario, failure also happen to all the columns, though they are located in level 2, and level 1 is intact (no fire), from the design codes it can also make a judgement that collapse will be triggered.

8. Conclusion

In this paper, a machine learning framework for fire safety assessment of multi-story buildings was developed, the following conclusions can be made:

1. Different classifiers were assessed in this study, KNN and Neural Network are two promising classifiers for this particular engineering problem. Decision Tree yield less promising result.
2. Accurate prediction requires large training dataset for this particular problem, therefore if computational power allows, more training data should be used..
3. The dataset generated using Monte Carlo Simulation can be effectively used for producing sufficient large dataset for machine learning.
4. The framework developed in this project provided a new tool for design engineers in structural fire design in the future.

Reference

[1]. Fu, F. (2017), Grenfell Tower disaster: how did the fire spread so quickly? BBC Australia.

[2]. Adeli, H., Seon Park, H. (1995). Counterpropagation neural networks in structural engineering. ASCE, Journal of Structural Engineering, 121(8), 1205-1212.

[3]. Paudel, S., Nguyen, P. H., Kling, Wil L., Elmitri, M., Lacarri`ere B.. (2015) Support Vector Machine in Prediction of Building Energy Demand Using Pseudo Dynamic Approach. Proceedings of ECOS, The 28th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, Pau, France.

[4]. Zhang, Y., Burton, H. V., Sun H, Shokrabadi, M. (2018), A machine learning framework for assessing post-earthquake structural safety, Structural Safety Volume 72,Pages 1-16

[5]. Shi, H.B., Tsai, S.B., Lin, X.W. and Zhang T.Y. (2018), How to Evaluate Smart Cities' Construction? A Comparison of Chinese Smart City Evaluation Methods Based on PSF, Sustainability, 10(1), 37

[6]. Puri, N., Prasad, H.D., Jain, A. (2018), Prediction of Geotechnical Parameters Using Machine Learning Techniques. Procedia Computer Science, Volume 125, Pages 509-517

[7]. Tixier, A.J.P., Hallowell, M.R., Rajagopalan, B., Bowman, D (2016), Application of machine learning to construction injury prediction, Automation in Construction Vol 69 pp102–114

[8]. Chou, J.S., Thedja, J.P.P., (2016) Metaheuristic optimization within machine learning-based classification system for early warnings related to geotechnical problems, Automation in Construction 68 pp65–80
[9]. Özturan M., Kutlu, B., Özturancomparison, T (2018), Comparison of concrete strength prediction techniques with artificial neural network approach. Building Research Journal 56.
[10]. Lagaros, N. D., Fragiadakis, M. (2007). Fragility assessment of steel frames using neural networks. Earthquake Spectra, 23(4), 735-752.
[11]. De Lautour, O. R., Omenzetter, P. (2009). Prediction of seismic-induced structural damage using artificial neural networks. Engineering Structures, 31(2), 600-606.
[12]. Mangalathu, S., Heo, G., Jeon, J. S. (2018). Artificial neural network based multi-dimensional fragility development of skewed concrete bridge classes. Engineering Structures, 162, 166-176.
[13]. Wang, Z., Pedroni, N., Zentner, I., Zio, E. (2018). Seismic fragility analysis with artificial neural networks: Application to nuclear power plant equipment. Engineering Structures, 162, 213-225.
[14]. Hozjan T., Turka G., Srpcic S., (2007) Fire analysis of steel frames with the use of artificial neural networks,Journal of Constructional Steel Research 63 pp1396–1403
[15]. MATLAB MathWorks, last accessed 2018
[16]. BS EN 1993-1-2 (2005a), Eurocode 3. Design of steel structures, Part 1-2; general rules. Structural fire design. Commission of the European Communities.
[17]. BS EN 1994-1-2 (2005b) Eurocode 4. Design of composite steel and concrete structures, Part 1-2: general rules. Structural fire design. Commission of the European communities.
[18]. BS EN 1991-1-2: Eurocode 1 (2002), Actions on Structures-Part 1-2: General actions – Actions on structures exposed to fire. Commission of the European communities
[19]. Elhewy A. H, Mesbahi E, Pu Y, (2006) Reliability analysis of structures using neural network method, Probabilistic Engineering Mechanics 21 44–53
[20]. GSA (2003). Progressive collapse analysis and design guidelines for new federal office buildings and major modernization projects. The U.S. General Services Administration, 2003.
[21]. Unified Facilities Criteria, Department of Défense (2009), UFC 4-023-03, Design of Buildings to Resist Progressive Collapse 14 July 2009 with Change 2
[22]. Fu, F. (2018b). Design and Analysis of Tall and Complex Structures. Butterworth-Heinemann, ELSEVIER, ISBN 978-0-08-101121-8.
[23]. Gernay T, Khorasani N E, Garlock M, Fire fragility functions for steel frame buildings: sensitivity analysis and reliability framework, Fire Technology, Vol 55,pp1175-1210