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

22

23 **1. Introduction**

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

32 Although construction research has considered machine learning (ML) for more than two decades,
33 it had rarely been applied to fire safety design of buildings. Some research has been undertaken in
34 the past by using the machine learning for certain construction problems. Adeli, H. et al. [2] made
35 a comprehensive review on the neural networks in structural engineering. Paudel et al. [3] used
36 Machine learning for the prediction of building energy demand. Zhang et al. [4] developed a
37 machine learning framework for assessing post-earthquake structural safety. Shi et al. [5] set up
38 an evaluation model to assess the intelligent development of 151 cities in China. The model is
39 based on the analytic hierarchy process and back propagation neural network theory. Puri et al [6],
40 set up the relationships between in-place density of soil using SPT N-value, compression index
41 (Cc) using liquid limit (LL) and void ratio (e), and cohesion (c) and angle of internal friction (ϕ)

42 using machine learning techniques. Tixier et al. [7] use random forest (RF) and stochastic gradient
43 tree boosting (SGTB) method to predict the injury in the construction sites. The dataset is extracted
44 from large pool of the construction injury report. It is found that, their models can predict injury
45 type, energy type, and body part with high accuracy, outperforming the parametric models found
46 in other literature. Chou [8] proposes a novel classification system integrating swarm and
47 metaheuristic intelligence, with a least squares support vector machine (LSSVM). The system was
48 applied to several geotechnical engineering problems that involved measuring the groutability of
49 sandy silt soil, monitoring seismic hazards in coal mines, predicting post-earthquake soil
50 liquefaction, and determining the propensity of slope collapse. Ozturan et al. [9] used the artificial
51 neural network to predict the concrete strength. Lagaros [10] made Fragility assessment of steel
52 frames using neural networks. De Lautour et al [11] made prediction of seismic-induced structural
53 damage using artificial neural networks. Mangalathu, S., et al. [12] used artificial neural network
54 to develop multi-dimensional fragility of skewed concrete bridge classes. Wang, Z. et al. [13] also
55 made seismic fragility analysis with artificial neural networks for nuclear power plant equipment.
56 Hozjan et al [14] developed an artificial neural network (ANN) in the material modelling of steel
57 under fire.

58 From above literature review, it can be seen that little research has been done on using machine
59 learning to predict failure mode and consequently the potential of the collapse under fire. Therefore,
60 it is imperative a study on fire safety assessment using machine learning is timely. Therefore, in
61 this paper, a new Machine Learning framework is developed which provides a new tool to assist
62 engineers in fire safety assessment. The concept of Critical Temperature Method is used to define
63 the failure patterns of each structural member, which is incorporated into a systematic
64 methodology employing both Monte Carlo Simulation and Random Sampling to generate a robust

65 and sufficient large dataset for training and testing, hence guarantees the accurate prediction. The
66 Machine Learning framework is implemented using a code programmed by the author in VBA
67 and Python language. Case studies of machine learning prediction were also made, the machine
68 procedure gives satisfactory prediction of the failure pattern and collapse potential of the building
69 under fire.

70 **2. Framework of structural fire safety assessment and classifiers**

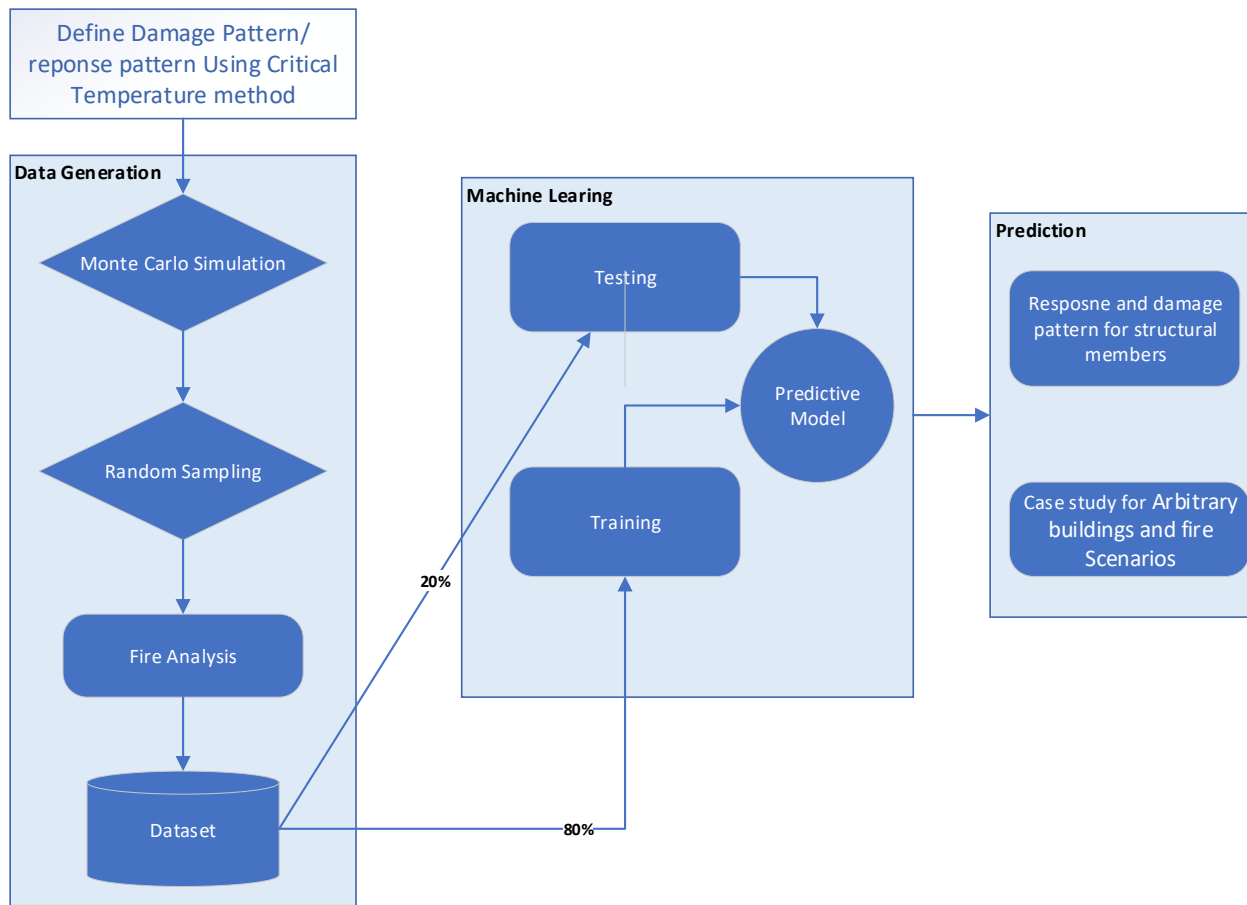
71 **selections**

72 *2.1 Process of Fire Safety Assessment of Buildings through Machine Learning*

73

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

76



77

78

79

Figure 1 Fire Safety Assessment of Buildings through Machine Learning

80

2.2 Major classifiers in machine learning

81

2.2.1 Artificial Neural Network (ANN)

82

Artificial neural network is one of the major tools used in machine learning. It mimics the brain

83

systems and intend to replicate the way humans learning. The neural network consists several

84

simple processing units called neurons. Typically, the neurons are organized into layers: the input

85

layer, hidden layers, and the output layer. There are various types of neural network, such as Singer-

86

Layer Feed-forward Networks, Multilayer Feed-forward Networks, *Recurrent Neural Networks*.

87

In deep learning neural networks, a multilayer network extract different features until it can

88 recognize what it is looking for. Therefore, it can possess greater learning abilities and are widely
89 used for complex tasks.

90 2.2.2 *Decision Tree Learning*

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

96 2.2.3 *KNN*

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

101 ***2.3 Selection of suitable classifiers for fire safety assessment***

102

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

109

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
Naive 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 Large	Popular for classification, compression, recognition, and forecasting

110

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

116 **3. Define the failure patterns**

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

130 **3.1 The Critical temperature method to determine the failure pattern of steel members**

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

136

$$137 \theta_{cr} = 39.19 \ln \left[\frac{1}{0.9674 \mu_0^{3.833}} - 1 \right] + 482$$

138 Where,

139 μ_0 Is the degree of load utilization

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

144 **Table 2 Critical temperatures of steel compression members (partial adapted from Eurocode 3**
 145 **[16])**

	Critical Temperature (C°) for Utilization Factor (load Ratio)					
$\lambda \backslash$ 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

146 *3.1.1 Load ratio (degree of utilization)*

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

150
$$\mu_0 = \frac{E_{fi,d}}{R_{fi,d,0}}$$

151 Equation 1

152 Where:

153 $E_{fi,d}$ is the applied load under fire condition

154 $R_{fi,d,0}$ is the design moment of resistance of the member at ambient temperature

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

160 *3.2 Determine the failure pattern of the structural members in fire*

161 Based on above introduction, it can be seen that, to be able to determine the failure of a structural
162 member under fire, below factors need to be determined: the maximum atmosphere temperature
163 the maximum temperature of the steel members under fire, the load ratio, and the critical
164 temperature of the steel member. Then the failure of a structural member under fire can be
165 determined as follows:

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

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

168 2. **If** (*maximum temperature of the steel member < critical steel temperature*) **and** *load*

169 *ratio > 1* **Then** *this member fails* (the failure is due to overloading)

170 3. **Else**

171 *the member is safe*

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

- 173 • safe
- 174 • failure due to fire
- 175 • failure due to mechanical rather than fire.

176 Based on above discussions, the structural fire analysis based on the Critical temperature method

177 from the Eurocode is implemented in an Excel VBA software program.

178 ***3.3 Heat transferring and Thermal Response of Structural Members***

179

180 The heat from fire transferred to the structural members are worked out using the formulae based

181 on the Eurocode. The atmosphere fire temperature is first determined using Equation 2

182 $\Theta_g = 20 + 1325(1 - 0.324e^{-0.2t^*} - 0.201e^{-1.7t^*} - 0.472e^{-19t^*})$ EQUATION 2

183 Where:

184 Θ_g Is the gas temperature in the fire compartment

185 And $t^* = \Gamma t$

186 with

187 t time

188 $\Gamma = [O / b]^2 / [0.04 / 1160]^2$

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

190 A_t = Total internal surface area of compartment [m²]

191 A_v = Area of ventilation [m²]

192 H_w = Height of openings [m]

193 b = Thermal diffusivity, 100 [b [2000 (J/m² s^{1/2} K)

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

195
$$t^*_{max} = t_{max} \cdot \Gamma$$

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

197 $q_{t,d}$ is the design value of the fire load density related to the total surface area A_t of the enclosure, whereby $q_{t,d} =$
198 $q_{f,d} \cdot A_f / A_t$ [MJ/m²]. The following limits should be observed: $50 < q_{t,d} < 1\ 000$ [MJ/m²].

199 $q_{f,d}$ is the design value of the fire load density related to the surface area A_f of the floor [MJ/m²] taken from
200 EN1991-1-2: Eurocode 1; Part 1.2 annex E.[18]

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

203 $\Theta_g = \Theta_{max} - 625 (t^* - t^*_{max} \cdot X)$ for $t_{max} \leq 0,5$

204 $\Theta_g = \Theta_{max} - 250(3 \cdot t^*_{max} \cdot X)$ for $0,5 < t_{max} \leq 2$

205 $\Theta_g = \Theta_{max} - 250 (t^* - t^*_{max} \cdot X)$ for $t_{max} \geq 2$

206 After the atmosphere temperature is determined, the thermal response of each structural member can be worked
207 out. For Unprotected steel Section, the increase of temperature in small time intervals is given by BS EN 1993-
208 1-2: Eurocode 3 [16] and BS EN 1994-1-2: Eurocode 4 [17]

209 as follows:

210
$$\Delta\Theta_{a,t} = k_{sh} \frac{A_m/V}{c_a \rho_a} h_{net} \Delta t \quad \text{EQUATION 3}$$

211 Where,

212 $\Delta\Theta_{a,t}$ is the increase of temperature

213 A_m/V is the section factor for unprotected steel member

214 c_a is the specific heat of steel

215 ρ_a is the density of the steel

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

217 Δt is the time interval

218 k_{sh} is the correction factor for shadow effect

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

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

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

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

234 the Eurocode and failure judgement by the machine. The whole process is also programed into the
235 software program in the paper.

236 *4.1 Monte Carlo simulation for different design parameters*

237 Monte-Carlo simulation is to simulate a probability distribution for different variable. It is used
238 here to generate leaning cases for the machine. Firstly, a probability distribution for each
239 individual variable will be determined. It is also essential to determine the dependencies between
240 simulation inputs based on their real quantities being modelled. In fire safety design, there are
241 some key parameters which will affect the design values. For example, when determining
242 atmosphere temperature, opening factor and fire load density are the two key parameters to affect
243 its value, they are mutually independent. The probability distribution or the range of these
244 parameters are readily known from design guidelines such as Eurocode [16,17,18] and research
245 [19]. Therefore, using the available distributions and key statistic index obtained from Eurocodes
246 (see table 3), the random value of opening factor and fire load density can be generated.
247 Subsequently, the correspondent atmosphere temperature can be calculated based on design
248 formula. As these values follow the specific distribution discovered in the design practice, which
249 are determined from large-scale data analysis and tests. they are not arbitrary values. Therefore, it
250 can represent the real quantities in the design practice.

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

256

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]

257

4.2 Random sampling

258

Random sampling is a simple way of collecting data from a total population, in which each sample

259

has an equal probability of being chosen. It guarantees an unbiased representation of the total

260

population. **An unbiased random sample is important for fire safety design. For an example, when**

261

we took out the sample of 10 opening factors from a total population of 100 parameters generated

262

through Monte Carlo simulation, there is always a possibility that 8 opening factors which is

263

smaller than 0.1, even if the population consists of 50 opening factors which are greater than 0.1

264

and the other 50 which are smaller than 0.1. Hence, some variations when drawing results can

265

come up, which is known as a sampling error. To minimize the sampling error, random sampling

266

is a best tool. In this proposed machine learning framework, it can avoid the bias in the parameter

267

selections when performing the structural fire analysis and failure judgement. Therefore, to enable

268

accurate machine learning result, Random sampling is performed after Monte Carlo simulation.

269 ***4.3 Response and failure judgment of structural members***

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

275 ***4.4 Learning dataset generation***

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

284
285

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

286

287

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

288

In structural fire analysis, one of the key tasks is to check the collapse potential of the overall

289

buildings under fire. This becomes possible using machine learning. When the prediction of failure

290

mode or response of each individual structural member is successful, the prediction of the collapse

291

of a building can be based on the procedure stipulated by U.S. design code GSA [20] and DOD

292

[21]. These two are the most recognized codes for progressive collapse design. The collapse

293

potential check can be summarized into the framework flowchart as it shown in Note: **DCR is**

294

Demand capacity ratio

295

Figure 2. This procedure is based on the response of each individual structural member. For these

296

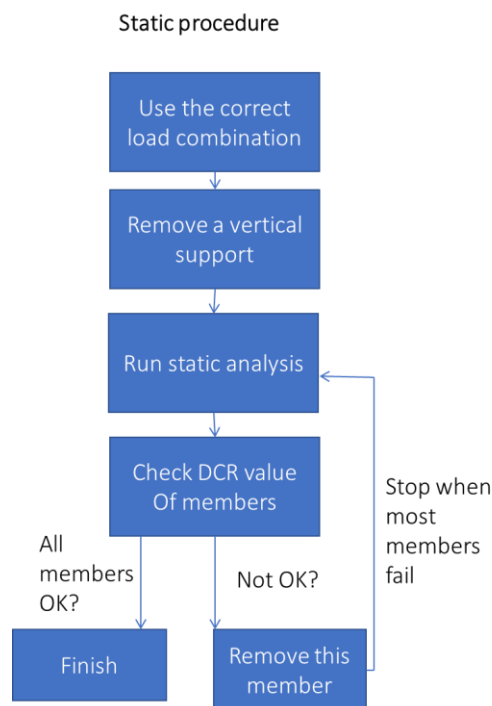
failed members, they will be removed from the structure, then a static progressive collapse check

297

will be performed through static analysis following [20,21], which is to check the Demand capacity

298 ratio (DCR) value of the remaining structural members, if the DCR value for all the remaining
299 members are satisfactory, the building will not collapse. If the DCR value of any member is not
300 satisfactory, this member will also be removed, and re-run the static analysis. If most members
301 fail, say 40% of the members fail, this indicate that structure is deemed to collapse, therefore, the
302 who procedure can be stopped.

303



304

305

Note: DCR is Demand capacity ratio

306

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

307 One of the difficulties for building progressive collapse check under fire load using machine
308 learning is how to correctly represent the building information, such as the location of the structural
309 members, type of the structural member (column or beam), member sizes, design load and other

310 design parameters. To tackle this problem, as it is shown in Table 5, an Excel worksheet is designed
311 for building information capture. a special naming system is invented here for denotating the
312 structural members. The beams and columns are denoted as follows:

313 for an example,

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

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

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

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

329 **6. Machine Learning (Training and Testing)**

330 Before the machine can make an accurate prediction of the failure mode for each individual
331 structural member, training and testing is essential. The training and testing are performed based

332 on Python code developed by the author in Anaconda. In convention, 80% of the data is used for
333 training, 20% of the date is used for testing for most data scientist and computer scientist .
334 Therefore, it is also used here. Three classifiers Decision Tree, KNN and Neural Network are
335 chosen for the machine learning. When sufficient accurate prediction is achieved, the machine can
336 start to predict the failure patterns of the structural members for real projects.

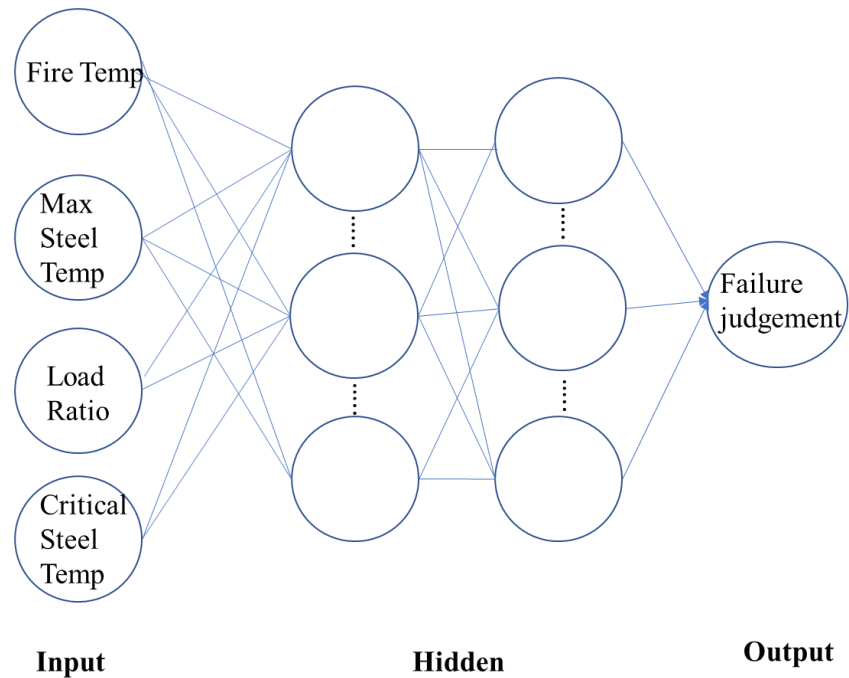
337 ***6.1 Neural Network-TensorFlow***

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

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

$$349 \quad f(x) = 1/(1 + e^{-x}) \quad \text{EQUATION 4}$$

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



354

Figure 3 Hidden layer network with input and output layers

355

6.2 Prediction using Decision Tree Learning

356

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

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

6.3 KNN

365

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

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

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

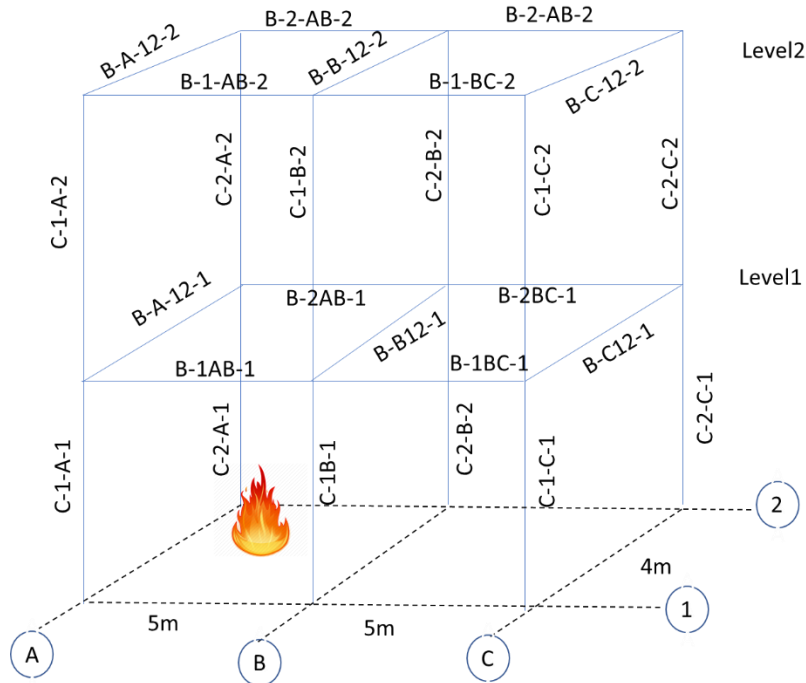
373

374 **7. Case study progressive collapse potential check using machine learning**

375 ***7.1 The prototype building***

376 After training and testing, as it shown in Figure 3, a two-story moment resisting steel frame
377 building is used for progressive potential check using machine learning. . The normal design loads,
378 dead load and live load, are chosen according to the Eurocode, so the load ratio of each member
379 can be worked out. Design values of opening factor and fire density are 0.02 and 487 J/m²
380 respectively. Two scenarios have been chosen:

- 381 • A fire was set at the ground level,
- 382 • A fire was set at the level 2



383

384

Figure 3 Schematic arrangement of the prototype building

385

The section sizes, section properties the spacing of the structural members, loadings of the building

386

is shown in table 5

Level	Element Code	Section	Spacing	Span	Grade	Dead Load	Live Load	Type	Grid 1	Grid 2	Level	Profile Selection	Profile Column	Section Factor	Plastic Modulus	Load Applied	
Level 1	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
		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																	
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
		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	

387

388 **TABLE 5 EXCEL TABLE FOR BUILDING DESIGN INFORMATION INPUT**

389

390 ***7.2 The process of progressive collapse potential check using Machine learning***

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

- 393 a. The Maximum fire temperature, Maximum steel temperature, load ratios, critical steel
394 temperature, member size index are input into the machine
- 395 b. failure and response predictions for each structural member.
- 396 c. based on the response of each individual members, using the design procedure from DOD
397 (2009) and GSA (2003), the collapse potential of the whole building can be assessed.

398

399 ***7.3 Machine prediction and Performance evaluation of different classifiers***

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

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

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

Level 1	Element Code	Fire Temp °C	Max SteelTemp p	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	1	1	1
	B-2-AB-1	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-2-BC-1	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-1-BC-1	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-A-12-1	852.9173	850.3203	0.250784	690.8819		0	0	0	0	0
	B-B-12-1	852.9173	850.5966	0.250784	690.8819		0	0	0	0	0
	B-C-12-1	852.9173	850.5966	0.250784	690.8819		0	0	0	0	0
Column	C-1-A-1	852.9173	847.3149	0.077534	434		0	0	0	0	0
	C-2-A-1	852.9173	849.2547	0.372197	434		0	0	0	0	0
	C-1-B-1	852.9173	849.2547	0.372197	434		0	0	0	0	0
	C-2-B-2	852.9173	850.4508	0.977517	422		0	0	0	0	0
	C-1-C-1	852.9173	850.4508	0.977517	422		0	0	0	0	0
	C-2-C-1	852.9173	851.205	4.398827	0		2	2	2	2	2
Level 2											
Beam	B-1-AB-2	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-2-AB-2	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-2-BC-2	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-1-BC-2	852.9173	848.8358	0.050716	931.1663		1	0	1	1	1
	B-A-12-2	852.9173	850.5966	0.250784	690.8819		0	0	0	0	0
	B-B-12-2	852.9173	850.5966	0.250784	690.8819		0	0	0	0	0
	B-C-12-2	852.9173	850.5966	0.250784	690.8819		0	0	0	0	0
Column	C-1-A-2	852.9173	784.2671	0.014964	422		0	0	0	1	0
	C-2-A-1	852.9173	784.2671	0.014964	422		0	0	0	1	0
	C-1-B-1	852.9173	784.2671	0.014964	422		0	0	0	1	0
	C-2-B-2	852.9173	784.2671	0.014964	422		0	0	0	1	0
	C-1-C-1	852.9173	813.2911	0.021142	434		0	0	0	1	0
	C-2-C-1	852.9173	851.205	1.466276	0		2	2	2	2	2
						Accuracy of building data	0.69230769	0.69230769	1	0.807	

411

412

Table 6 The prediction results for different classifiers

413

7.4 Progressive collapse potential check

414

Base on the prediction of each single members, the collapse potential of the building can be further

415

checked by the machine. It can be seen that, for the first scenario, where fire was set at level 1, all

416

columns in level 1 fail. According GSA [20] and DOD [22], the collapse is not avoidable. For the

417

second scenario, failure also happen to all the columns, though they are located in level 2, and

418

level 1 is intact (no fire), from the design codes it can also make a judgement that collapse will be

419

triggered.

420

8. Conclusion

421

In this paper, a machine learning framework for fire safety assessment of multi-story buildings

422

was developed, the following conclusions can be made:

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

432

433

434

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