Prediction of Explosive Spalling of Heated Steel Fiber Reinforced Concrete using Artificial Neural Networks

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Abstract

Explosive spalling is a severe threat to concrete at high temperature. The addition of steel fibers is believed to be useful to mitigate explosive spalling of concrete. But predicting explosive spalling of steel fiber reinforced concrete remains to be a challenging topic. This paper adopted a popular machine learning approach, i.e., artificial neural network (ANN), to predict explosive spalling of steel fiber reinforced concrete and furthermore study the effect of steel fibers on explosive spalling resistance of concrete. Two ANN models were developed, with ANN1 concrete mix-based and ANN2 concrete strength-based. Twenty groups of heating tests were conducted to validate the proposed ANN models. Both ANN models showed the prediction accuracy of 100%, which demonstrates that ANN is a powerful tool for assessing explosive spalling risk of steel fiber reinforced concrete. A parametric study was also conducted to investigate the effect of steel fibers on explosive spalling resistance of concrete using the well-validated ANN1.

1. Introduction

Considering increasing number of fire accidents in recent years, fire resistance of construction materials is gaining more attention. Concrete, as the most widely used construction material, is generally believed to perform well in fire. However, fire-induced concrete spalling has been a big concern of concrete as it can reduce fire resistance of concrete members significantly by reducing section size and raising temperature increase rate of rebar in concrete.

Fire-induced concrete spalling is a phenomenon that describes the dislodgement of concrete pieces from section at elevated temperature. Fire-induced concrete spalling can be grouped into two categories in terms of spalling behavior: violent spalling and non-violent spalling. It can be grouped into three categories in terms of spalling mechanism: thermo-hygral spalling, thermo-mechanical spalling and thermo-chemical spalling (Liu et al. 2018). Thermo-hygral spalling, often entitled “explosive spalling”, occurs in a violent manner; while thermo-mechanical spalling and thermo-chemical spalling typically occurs in a non-violent manner. Among the three types of thermal spalling, thermo-hygral spalling is the most dangerous. Not only because thermo-hygral spalling occurs in a violent manner, but also because it occurs at early stages of a fire. Therefore, it is very important to predict and prevent thermo-hygral spalling of concrete. For easy understanding, the most-widely term “explosive spalling” instead of thermo-hygral spalling is used in the rest of this paper.

Steel fiber is one popular type of fiber used in concrete to enhance mechanical behavior of concrete. The addition of steel fibers in concrete produces a positive effect on mechanical behavior of concrete at elevated temperature by improving toughness and controlling cracking (Kim et al. 2015). However, the extent to which explosive spalling of concrete can be mitigated by steel fibers is still not completely understood. Furthermore, the effect of diameter and length of steel fibers on explosive spalling has not been studied well. The most straightforward method to assess explosive spalling of concrete is conducting experimental tests. So far a number of experimental studies (Peng et al. 2006; Sanchayan and Foster 2016; Serrano et al. 2016; Czoboly et al. 2017; Yermak et al. 2017; Ahmad et al. 2019) were conducted to examine explosive spalling resistance of steel fiber reinforced concrete. However, the experimental tests are costly, time-consuming, and that works only for target concrete mixes. Therefore, it is necessary to find alternative methods for examining explosive spalling resistance of steel fiber reinforced concrete.

Finite difference method and finite element method (Gawin et al. 2006; Zeiml et al. 2006; Dwaikat and Kodur 2009; Davie et al. 2012; Zhao et al. 2014; Zhang et al. 2017; Liu and Zhang 2019) provide alternative methods for predicting explosive spalling of concrete. However, all of these numerical models did not consider the effect of steel fibers and were only used to validate plain concrete cases. Furthermore, these models need permeability of concrete as one important parameter, which is extremely difficult to measure. In the past, some permeability measurements were conducted on concrete at isothermal or residual state (Suhaendi and Horiguchi...
2006; Zeiml et al. 2008; Noumowe et al. 2009; Bošnjak et al. 2013). However, what the numerical models need is the permeability at a transient hot state. Therefore, it is not convincing to use these models to predict explosive spalling of many different steel fiber reinforced concrete mixes at the moment. As such, an alternative numerical method, besides FDM or FEM, to predict explosive spalling of heated steel fiber reinforced concrete is still desirable.

In the past decade, artificial neural network (ANN), a powerful tool of machine learning, has become very popular in the area of civil engineering. More specifically, in areas of structural materials, ANN has been widely used to predict fresh and hardened properties of various kinds of concrete (Ghafari et al. 2015; Chithra et al. 2016; Rafiei et al. 2016; Sonebi et al. 2016; Oh et al. 2017; Golafshani and Behnood 2018; Naser 2019). More recently, hybridized artificial neural network has also been used to predict hardened properties of different types of concretes and to improve the training and generalization capability of standard ANN (Behnood and Golafshani 2018; Golafshani et al. 2020). ANN is especially good at dealing with complex nonlinear problems with unclear mechanisms. Explosive spalling of concrete belongs to this type of problem, which involves coupled heat and moisture transfer in a heterogeneous porous microstructure. Therefore, it could offer a possible solution to predict thermal explosive spalling of steel fiber reinforced concrete at the moment. Recently, Seittlari and Naser (2019) developed an ANN model to predict fire spalling in reinforced concrete columns. In their model, compressive strength of concrete, width of RC column, applied axial load and eccentricity were selected as the input parameter. A good prediction result was achieved by their model. However, fire spalling in concrete columns may also include thermo-mechanical spalling; in addition, explosive spalling resistance is highly dependent on a number of factors, e.g., concrete mix proportions, ingredients, moisture content, and heating rate.

In this study, the authors developed two ANN models (ANN1 and ANN2) to predict thermal explosive spalling of steel fiber reinforced concrete. Fourteen and eight parameters were selected as the input parameters for ANN1 and ANN2, respectively. To validate the capability of ANN1 and ANN2 to predict explosive spalling of steel fiber reinforced concrete, 20 groups of heating tests were conducted on high performance concrete (HPC) and ultra-high performance concrete (UHPC) containing steel fibers. Both ANN models showed excellent prediction accuracy and can serve as a tool for assessing thermal explosive spalling risk of steel fiber reinforced concrete. The effects of quantity, diameter, and length of steel fibers on explosive spalling resistance of concrete were also studied by the validated ANN model.

2. Artificial Neural Network (ANN)

ANN is a nonlinear statistical data modeling tool for learning the relationship between input and output data. An ANN model is composed of a number of neurons, which are arranged in layers. The first layer is entitled the input layer, which receives the ANN input data, and the last layer is named as the output layer, which outputs the results of the ANN. The layer(s) in between the input layer and the output layer are named as hidden layer(s). Typically, the neurons in the adjacent layers are fully connected to each other; however, there is no interconnection between neurons in the same layer. A fundamental representation of an artificial neural network is shown in Fig. 1, which processes input data from previous layer and outputs the processed data to next layer. The mathematical equation of an artificial neuron can be expressed by:

\[ Y_k = f(\sum_{i=1}^{n} w_i X_i + b) \] (1)

where

- \( X_i \) is the input value from previous layer,
- \( w_i \) is the weight of neural input value,
- \( b \) is the neuron’s bias,
- \( f \) is an activation function and
- \( Y_k \) is the output.

Selection of activation functions varies from problem to problem and depends on the type of the problem. In this study, rectified linear unit (ReLU) activation function was chosen for the hidden layer and the sigmoid activation function for the output layer. The tanh activation function used to be the most popular for the hidden layer. Now, this role has been taken by the ReLU activation function, which produces better performance. For classification problems, the sigmoid activation function is the most popular for the output layer. Predicting whether a concrete mix is vulnerable to explosive spalling is a problem of binary classification. Therefore, sigmoid transfer function is used on the output layer.

2.1 Input and output parameters

The priority of developing an ANN model is to extract input and output parameters from target problem. The
target problem of this study is to predict whether explosive spalling will occur in steel fiber reinforced concrete at elevated temperature. Obviously, it is a binary classification problem. There are only two possible results for the output, namely, explosive spalling occurs or does not occur in steel fiber reinforced concrete. Since it is easy for ANN to handle numerical values, so the output is taken as 1 if explosive occurs or 0 if not.

Next step is to determine the input parameters of ANN, or put it another way, factors that have possible influence on explosive spalling of steel fiber reinforced concrete at high temperature. Explosive spalling resistance is highly dependent on concrete mix. Some types of concrete are highly vulnerable to explosive spalling, e.g., ultra-high performance concrete (UHPC); while some are not, e.g., normal strength concrete (NSC). Therefore, mix proportions of concrete were selected as part of the input parameters. It should be noted that the input concrete mix was characterized by relative ratios of concrete ingredients instead of absolute quantities per unit volume as adopted in many other studies (Chithra et al. 2016; Getahun et al. 2018; Abbas et al. 2019), except for quantity of steel fibers. In modern concrete, supplementary cementitious materials like silica fume, ground granulated blast furnace slag (GGBS) and fly ash are frequently used for high performance and reducing carbon footprint (Sakai et al. 2009; Hashimoto and Torii 2013; Kanda et al. 2015). Therefore, the relative ratios of concrete ingredients were water/binder ratio, silica fume/binder ratio, GGBS/binder ratio, fly ash/binder ratio, fine aggregate/binder ratio and coarse aggregate/binder ratio. In addition to concrete mix, moisture content, maximum aggregate size, and specimen dimensions are also important parameters that influence explosive spalling of concrete (Majorana et al. 2010; Pan et al. 2012). To consider the influence of specimen dimensions in ANN models, characteristic length is introduced as one of input parameters. The characteristic length of a concrete specimen is defined as the distance of shortest escape path of steam from its centroid to its surface. For example, the characteristic length of a cylinder specimen is presented in Fig. 2. If the height of the cylinder is no less than its diameter, then its characteristic length is half of its diameter; otherwise, its characteristic length is half of its height. Regarding the heating load applied to concrete specimens, the heating rate and the maximum exposure temperature were chosen as the input parameters.

The authors also noted that compressive strength of concrete is one popular indicator to measure explosive spalling likelihood of concrete. However, it is a function of concrete mix and aggregate size. Therefore, two ANN models, i.e., ANN1 and ANN2, were developed in this study. The input parameters for ANN1 and ANN2 are summarized in Table 1.

### Table 1 Input parameters for ANN1 and ANN2.

| Parameters for ANN1                  | Parameters for ANN2                  |
|-------------------------------------|-------------------------------------|
| Water/binder ratio                  | Compressive strength                |
| Silica fume/binder ratio            | Moisture content                    |
| Fly ash/binder ratio                | Heating rate                        |
| GGBS/binder ratio                   | Maximum exposure temperature        |
| Fine aggregate/binder ratio         | Characteristic length               |
| Coarse aggregate/binder ratio       | Quantity of steel fibers            |
| Maximum aggregate size              | Diameter of steel fiber             |
| Moisture content                    | Length of steel fiber               |
| Heating rate                        |                                     |
| Maximum exposure temperature        |                                     |
| Characteristic length               |                                     |
| Quantity of steel fibers            |                                     |
| Diameter of steel fiber             |                                     |
| Length of steel fiber               |                                     |

Fig. 2 Characteristic length of cylinder specimens.

If $h \geq D$, then $L = D/2$; If $h < D$, then $L = h/2$

$D$: Diameter of cylinder

$h$: Height of cylinder

$L$: Characteristic length

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Ruano et al. 2018; Li et al. 2019), which contain complete information, were collected to train the ANN models. The following rules were established when collecting test data from the literature:

a) If concrete specimens were exposed to a multi-linear heating curve, e.g., a heating curve as shown in Fig. 3, then the heating rate was taken as the linear heating rate up to the maximum exposure temperature.

b) If concrete specimens were exposed to a standard fire curve, e.g., ISO 834 fire curve, then the maximum exposure temperature was taken as the temperature at 30 minutes of heating and the heating rate was taken as the linear heating rate up to the maximum exposure temperature.

c) The moisture content of concrete is weight loss percentage of concrete after drying at 105°C until constant weight. If only the weight loss percentage of concrete at 120°C was available, then the moisture content of concrete was taken as 80% of the weight loss percentage at 120°C.

d) As long as explosive spalling was observed in one specimen of a concrete mix, the concrete mix was classified as not resistant to explosive spalling.

In total, 377 data samples were collected for ANN1 and 375 data samples were collected for ANN2. Among 377 samples for ANN1, there are 157 samples containing silica fume, 99 samples containing GGBS, and 53 samples containing fly ash. Table 2 shows the statistical summary of 15 input data parameters for ANN1 and ANN2 extracted from the literature. Figure 4 shows the statistical correlation between the 15 individual input parameters and spalling result in literature. As expected, if the maximum exposure temperature is below a critical temperature or compressive strength of concrete is lower than a certain limit, explosive spalling hardly occurs in concrete as can be seen in Fig. 4. No other sound conclusions can be made from the figure regarding the effect of each input parameter on explosive spalling occurrence. For instance, in terms of heating rate, concrete under a low heating rate may explode under heating, while concrete under a high heating rate may not explode as can be seen in Fig. 4. For another instance, in terms of quantity of steel fibers, concrete containing more than 200 kg/m³ steel fibers may explode under heating, while concrete containing a smaller amount of steel fibers may not. It implies that thermal explosive spalling of concrete is not a function of one single parameter but rather a number of parameters. It also implies a large variety of the collected data, which is desirable for developing less-biased ANN models.

2.3 Artificial neural network architecture

So far there are no existing theoretic principles for selecting an artificial neural network architecture for a certain problem. Therefore, a number of ANN architectures were built and evaluated based stratified 10-fold cross-validation method. Cross-validation is a statistical technique for measuring the performance of an ANN model on test data sets. The basic idea, behind cross-validation technique, consists of dividing the data into two sets: (a) the training set used for training the model and (b) the testing set used for testing the model. In case of 10-fold cross-validation, the data set is divided into 10 subsets randomly. Out of the 10 subsets, one subset is taken as test data to measure the performance of the model, and the remaining 9 subsets are held as training data to train the model. The process is repeated.

Table 2 Statistical summary of input parameters of experimental data.

| Input parameters          | Minimum | Maximum | Average | Standard deviation |
|---------------------------|---------|---------|---------|--------------------|
| Water/binder ratio        | 0.115   | 0.64    | 0.33    | 0.13               |
| Silica fume/binder ratio  | 0.0     | 0.232   | 0.045   | 0.091              |
| GGBS/binder ratio         | 0.0     | 0.458   | 0.070   | 0.131              |
| Fly ash/binder ratio      | 0.0     | 0.7     | 0.041   | 0.131              |
| Fine aggregate/binder ratio | 0.345  | 3.38    | 1.50    | 0.64               |
| Coarse aggregate/binder ratio | 0.0   | 3.952   | 1.43    | 1.12               |
| Maximum aggregate size (mm) | 0.12  | 32.0    | 10.3    | 7.8                |
| Moisture content          | 0.0     | 0.073   | 0.022   | 0.020              |
| Heating rate (°C/min)     | 0.25    | 240.0   | 23.3    | 37.4               |
| Maximum exposure temperature (°C) | 100.0 | 1200.0 | 561.0   | 248.2              |
| Characteristic length (mm) | 20.0   | 200.0   | 55.0    | 35.8               |
| Quantity of steel fibers (kg/m³) | 0.0  | 243     | 52.9    | 77.4               |
| Diameter of steel fibers (mm) | 0.0  | 1.0     | 0.12    | 0.21               |
| Length of steel fibers, mm | 0.0   | 60.0    | 6.1     | 10.9               |
| Compressive strength (MPa) | 15.6   | 170.4   | 92.1    | 46.9               |

Fig. 3 Determination of equivalent linear heating rate for a two-stage heating curve.
10 times, until each of the 10 subsets has served as the test set. The average of the 10 recorded evaluation results is used as performance metric for the model. The benefit of using this cross-validation technique is that we make use of all samples of data and hence the performance metric is less biased.

The number of layers, number of neurons, number of epochs, and batch size are important parameters of an ANN model. Past studies showed that three-layer ANN performed well generally in concrete material problems. Considering the limited number of data for training, in this study the number of layers was determined to be three for both ANN1 and ANN2, i.e., one input layer, one hidden layer, and one output layer. In this case, the number of neurons simply means the number of neurons in the hidden layer. It should be noted that too few neurons in the hidden layer may lead to poor training performance of an ANN model, while too many neurons may lead to overfitting of an ANN model. The number of epochs is defined as the number of passes through the entire training data set. The batch size is defined as the number of data samples processed before updating the weights of the model. Usually bad choices of these parameters lead to a low prediction accuracy of an ANN model on new test data.

| Number of neurons | Batch size | Number of epochs |
|-------------------|------------|-----------------|
| 10                | 1          | 100             |
| 20                | 5          | 200             |
| 30                | 10         | 300             |
| 40                | 15         | 400             |
| 50                | 20         | 500             |

There is no universal law for selecting these parameters of an ANN model. In this paper, a number of ANN models were built and evaluated in order to find a competent set of parameters. Table 3 lists the parameter values used in the ANN models. As shown in the table, five values were chosen for number of neurons, number of epochs, and batch size, respectively. So there are 125 (= 5 × 5 × 5) ANN models for ANN1 and ANN2, respectively. All these ANN models were evaluated by the 10-fold cross-validation technique to find the most competent model. The optimal set of parameter values for the two ANN models is shown in Table 4. The most competent model for ANN1 has 50 neurons in the hidden layer, a batch size of 20, and training epochs of 400. The most competent model for ANN2 has 50 neurons in the hidden layer, a batch size of 1, and training epochs of 400. Figure 5 shows the adopted architectures for ANN1 and ANN2.

### Experimental verification

#### 3.1 Validation tests

To check the applicability and generality of the ANN1 and ANN2 developed in Section 2 for assessing explosive spalling risk of steel fiber reinforced concrete, twenty groups of heating tests were designed and conducted. For each group, three Φ100 mm × 200 mm cylinder speci-
mens were prepared. The mix proportions of concrete, curing conditions, and heating schemes used for the heating tests are described in Sections 3.1.1 to 3.1.3.

### 3.1.1 Mix proportions of concrete

Five concrete mixes were used in the validation tests, which included three steel fiber reinforced high performance concrete (HPC) mixes and two steel fiber reinforced ultra-high performance concrete (UHPC) mixes. Hooked-end steel fibers were used in HPC and straight steel fibers were used in UHPC as shown in Table 5, which follows common practice. It should be noted that although hooked-end steel fibers improve fracture energy of concrete slightly compared to straight steel fibers,

| Geometry of steel fibers | Type I | Type II |
|-------------------------|--------|---------|
| Diameter (mm)           | 0.54   | 0.16    |
| Length (mm)             | 35     | 13      |

#### Table 5 Geometry of two steel fibers.

![Fig. 5 Architectures of ANN1 and ANN2.](image-url)
this increased fracture energy is negligible compared to the thermal energy accumulated in water vapor that triggers explosive spalling. Therefore, contribution of hooked end effect of steel fibers to resisting explosive spalling is minimal. The mix proportions of three HPCs and two UHPCs are presented in Table 6. Three $\Phi 100 \text{mm} \times 200 \text{mm}$ cylinder specimens were prepared for compression tests for each concrete mix. The compressive strength of each concrete mix in Table 6 was the average value of three specimens.

### 3.1.2 Curing conditions

Moisture content of concrete is closely related to the environment where the concrete specimens are cured. Two types of curing methods were used for each concrete mix in order to observe the possible effect of moisture content on explosive spalling. For each mix (SHPC1, SHPC2, SHPC3, SUHPC1, and SUHPC2) in Table 6, one group of cylinder specimens were cured in air until testing; the other group of cylinder specimens were cured in air initially and then stored in water for 3 to 4 weeks until testing. Accompanied with the cylinder specimens, three cube specimens with an edge length of 50.8 mm were prepared for each concrete mix to determine moisture content of concrete. For each concrete mix under each curing condition, three cube specimens were prepared. These cube specimens were also divided into two groups and stored in the two conditions as those of the concrete cylinder specimens. The moisture content of a cube specimen is calculated as the weight loss percentage of the specimen before and after drying to constant weight at $105^\circ \text{C}$. The moisture content of each concrete mix under each curing condition was taken as the average value of three readings from three cube specimens.

### 3.1.3 Heating schemes

Two types of heating schemes were used for each concrete mix under each curing condition in order to observe the possible effect of heating rate on explosive spalling. A heating rate of $5^\circ \text{C}/\text{min}$ and $15^\circ \text{C}/\text{min}$ was adopted for the two heating schemes, respectively. The maximum exposure temperature for the both heating schemes was $600^\circ \text{C}$ and it was kept steady for one hour before shutting down the power.

### 3.1.4 Summary of heating tests

To sum up, there were in total five steel fiber-reinforced concrete mixes, which included two UHPC mixes (SUHPC1 and SUHPC2) and three HPC mixes (SHPC1, SHPC2, and SHPC3). Specimens of each concrete mix were cured in two conditions. Specimens of each concrete mix under each curing condition are subjected to two heating schemes. Therefore, there were $20 (= 5 \times 2 \times 2)$ cases to be tested in total. Table 7 presents detailed information of all the 20 testing cases. Considering stochastic nature of explosive spalling, three $\Phi 100 \text{mm} \times 200 \text{mm}$ cylinder specimens were prepared for each case. So in total, 60 cylinder specimens were prepared for the heating tests.

### 3.2 Test results and model verification

All the heating tests for the 20 cases as shown in Table 8 were conducted at a concrete age of at least three months. After the heating tests, pictures were taken to record the status of the concrete specimens. The states of concrete samples after exposure to high temperature for the 20 cases are presented in Appendix 1. As shown in Appendix 1, all the steel fiber reinforced HPC (SHPC1, SHPC2, and SHPC3) specimens did not spall under heating, regardless of heating rate and moisture content, and all the steel fiber reinforced UHPC (SUHPC1 and SUHPC2) specimens experienced severe spalling, regardless of heating rate and moisture content. It is noted that although the quantity of steel fibers used in HPC specimens was the same as that in UHPC specimens, HPC and UHPC specimens exhibited opposed explosive spalling resistance. Therefore, steel fibers are more effective in mitigating explosive spalling in HPC than UHPC. Furthermore, the supplementary cementitious material did not seem to influence explosive spalling resistance in the case of steel fiber reinforced HPC. Silica fume, GGBS, and fly ash were used respectively in SHPC1, SHPC2, and SHPC3, yet all the specimens remained integral after heating.

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| Mix   | SHPC1 | SHPC2 | SHPC3 | SUHPC1 | SUHPC2 |
|-------|-------|-------|-------|--------|--------|
| Cement | 1     | 1     | 1     | 1      | 1      |
| Silica fume | 0.18  | 0.18  | 0.18  | 0.2    | 0.2    |
| GGBS   | 0     | 0.36  | 0     | 0      | 0      |
| Fly ash | 0     | 0     | 0.36  | 0      | 0      |
| Water  | 0.378 | 0.493 | 0.493 | 0.288  | 0.288  |
| Fine aggregate (0 - 4 mm) | 1.2 | 1.2 | 1.2 | 0.6 | 0 |
| Silica sand (120 mesh) | 0 | 0 | 0 | 0.6 | 0.6 |
| Coarse aggregate (4 - 10 mm) | 1.5 | 1.5 | 1.5 | 0 | 0 |
| Superplasticizer | 0.014 | 0.013 | 0.012 | 0.049 | 0.049 |
| Steel fibers, type I (kg/m$^3$) | 50 | 50 | 50 | 0 | 0 |
| Steel fibers, type II (kg/m$^3$) | 0 | 0 | 0 | 50 | 50 |
| Compressive strength at testing day (MPa) | 93.2 | 95.8 | 91.4 | 112.2 | 127.7 |
Table 8 summarizes the input parameters of the 20 cases for ANN1 and ANN2. The 20 sets of parameter values were input into ANN1 and ANN2 to make predictions, respectively.

Table 9 summarizes the test results and predicted results of ANN1 and ANN2 for the 20 cases on whether explosive spalling occurred in steel fiber reinforced or not. As shown in Table 9, both predictions made by ANN1 and ANN2 for the 20 cases matched perfectly with the test results, i.e., the prediction accuracies of ANN1 and ANN are both 100%.

The different behaviors of HPC and UHPC specimens under heating were likely due to difference in their mix proportions. To be specific, larger water/binder ratios was used in HPC mixes than in UHPC mixes. Besides, the compressive strength of concrete.
coarse aggregates were used in HPC mixes, while not in UHPC mixes. Both water/binder ratio and maximum aggregate size are input parameters of ANN1. Therefore, ANN1 can take the influence of these two factors into account and make correct predictions. For ANN2, these two factors are not considered explicitly, however, compressive strength of concrete is relevant to them. This might be the reason that ANN2 also showed a very good prediction performance. The major difference between UHPC1 and UHPC2 was the size of fine aggregates. The maximum size of aggregate used for UHPC1 was 4 mm, while for UHPC2 was 0.12 mm. Yet both UHPC mixes suffered from explosive spalling regardless of the aggregate size. It indicated that when the size of aggregate was small enough, its influence on explosive spalling resistance of UHPC was marginal. Specifically in this case under investigation, what is certain is that when the maximum size of fine aggregate was no larger than 4 mm, all the UHPC specimens tended to suffer from explosive spalling. This phenomenon was again well captured by model ANN1.

It should be noted that although the developed two ANN models were trained on a limited number of data from different sources, an excellent prediction performance were observed in both ANN1 and ANN2. This indicates that ANN technique is tolerant of random errors and systematic errors in the test data from different sources.

To sum up, the outcomes of the two ANN models are inspiring, indicating that ANN technique can serve as a cost-effective and reliable method to assess explosive spalling of steel fiber reinforced concrete at elevated temperature.

4. Discussion

4.1 Comparison with an analytical method
Mugume and Horiguchi (2014) developed a simplified method to judge explosive spalling likelihood of fiber reinforced concrete (FRC) at elevated temperature. Their method uses an index, relative predicted maximum pressure, to make the judgment. The relative predicted maximum pressure of fiber reinforced concrete is calculated using Eq. (2):

\[
P_{r,p} = 0.0113 f'_c - 0.057 f'_t - 0.001 I_f - 0.0021 S_{pf} - 0.0015 S_{sf}
\]

where \(P_{r,p}\) represents the relative predicted maximum pressure of FRC, \(f'_c\) is compressive strength of FRC, \(T_f\) is a constant regarding type of polymer fiber with values of 0.2 and 1 for PVA and PP fiber respectively, \(I_f\) is the length of polymer fibers, \(S_{pf}\) is the cumulative surface area of polymer fibers, and \(S_{sf}\) is the cumulative surface area of steel fibers.

If the relative predicted relative maximum pressure of FRC exceeds 0.183, thermal explosive spalling will occur in FRC; conversely, it will not occur if the relative maximum pressure is lower. Following this rule, the predictions made by the simplified method (Mugume and Horiguchi 2014) for the 20 cases are listed in Table 10. As shown in the table, explosive spalling was predicted to occur in all the 20 cases. However, the truth was that only the steel fiber reinforced UHPC cases (Cases 4 and 5, Cases 9 and 10, Cases 14 and 15, Cases 19 and 20) showed explosive spalling, all the rest fiber reinforced HPC cases (Cases 1 to 3, Cases 6 to 8, Cases 11 to 13, Cases 16 to 18) did not show any spalling. Compared to 100% accuracy by ANN1 and ANN2, the simplified method only achieved an accuracy of 40%. Although the simplified method did not make wrong predictions on the
cases that spalled at high temperature, it is too conserva-
tive and can lead to uneconomical design when used in
performance based fire safety design of concrete struc-
tures. The uncompetitive prediction performance of this
simplified method could be that it only considers the
effect of a few factors, namely, compressive strength,
polymer and steel fibers, while explosive spalling of con-
crete is also influenced by other factors, e.g., mois-
ture content, heating rate, and specimen size, etc.
Moreover, the prediction performance of ANN models
can keep improving as more data is available, while the
simplified model cannot. Therefore, the ANN method is
a more promising method than traditional simplified
method in terms of predicting explosive spalling of steel
fiber reinforced concrete. It would add more value if a
comparison between ANN models and numerical models
on explosive spalling is made. However, instantaneous
hot permeability of these concrete mixes under different
curing conditions is not available, and in fact, extremely
difficult to measure.

4.2 Effect of steel fibers
To study the effect of steel fibers on explosive spalling
resistance of concrete, the well-validated cost-effective
ANN1 developed in Section 2.3 was used instead of
cost-intensive experimental tests. ANN1 was used as the
numerical tool to conduct the parametric studies instead
of ANN2 was because ANN2 requires compressive
strength of concrete to be one of the input parameters,
which needs to be measured experimentally. In contrast,
all the input parameters required by ANN1 are known
variables.
The five concrete mixes in Table 6 (SHPC1, SHPC2,
SHPC3, SUHPC1, and SUHPC2) were used as control
mixes and their moisture contents were taken as those
cured in air. The control heating rate was taken as
15°C/min and the control maximum exposure tempera-
ture was 600°C. Three parameters, i.e., quantity, diam-
ter, and length of steel fibers, were investigated in the
parametric study.
Six values were chosen for quantity, diameter, and,
length of steel fibers, respectively. For SHPC1, SHPC2,
and SHPC3 specimens, the values for quantity of steel
fibers were 30, 40, 50, 60, 70, and 80 kg/m³; For
SUHPC1 and SUHPC2 specimens, the values were 50,
100, 150, 200, 250, and 300 kg/m³. Then the well-validated ANN1 model was used to predict explosive
tendency of these steel fiber reinforced concrete mixes. Figure 6(a) shows the effect of quantity of steel
fibers on explosive spalling resistance of concrete accor-
ding to ANN1. As shown in the figure, for SHPC
(SHPC1, SHPC2, and SHPC3) specimens, 30 kg/m³ steel
fibers were enough to prevent explosive spalling. In
contrast, much larger quantities of steel fibers were
needed to prevent explosive spalling of SUHPC
(SUHPC1 and SUHPC2) specimens, with 250 kg/m³ for
SUHPC1 and 300 kg/m³ for SUHPC2. The minor dif-
fERENCE between SUHPC1 and SUHPC2 was reasonable,
as SUHPC2 had smaller aggregate, larger compressive
strength and hence dense microstructure. It is widely
acknowledged that concrete with denser microstructure
is more likely to explode at high temperature.
The six values for diameter of steel fibers for SHPC1,
SHPC2, and SHPC3 specimens were 0.18, 0.36, 0.54,
0.72, 0.9, and 1.08 mm; For SUHPC1 and SUHPC2
specimens, the values were 0.16, 0.2, 0.24, 0.28, 0.32,
and 0.36 mm. All the diameters were chosen so that they
were within the reasonable range that adopted in practice.
Figure 6(b) shows the effect of diameter of steel fibers
on explosive spalling resistance of concrete based on

Fig. 6 Effect of steel fibers on explosive spalling resistance of concrete.
Predictions of ANN1. The diameter of steel fibers had negligible influence on explosive spalling of concrete. All the SHPC specimens did not show any spalling regardless of diameters of steel fibers; likewise, all the SUHPC specimens showed explosive spalling regardless of diameters of steel fibers.

The six values for length of steel fibers for SHPC1, SHPC2, and SHPC3 specimens were 20, 25, 30, 35, 40, and 45 mm; for SUHPC1 and SUHPC2 specimens, the values were 7, 10, 13, 16, 19, and 22 mm. All the lengths were chosen so that they were within the reasonable range that adopted in practice. Figure 6(c) shows the effect of lengths of steel fibers on explosive spalling resistance of concrete based on predictions of ANN1. Similar to diameter of steel fibers, the length of steel fibers had negligible influence on explosive spalling of concrete. All the SHPC specimens did not show any spalling regardless of lengths of steel fibers; likewise, all the SUHPC specimens showed explosive spalling regardless of lengths of steel fibers.

5. Conclusions

Predicting explosive spalling of steel fiber reinforced concrete via traditional numerical method is challenging and difficult. This paper developed two ANN models, i.e., ANN1 and ANN2, to predict explosive spalling of steel fiber reinforced concrete. ANN1 was developed based on concrete mix proportions, and ANN2 was based on compressive strength of concrete. The conclusions from this study are listed as follows:

(1) Both ANN models showed an excellent performance in predicting explosive spalling of steel fiber reinforced concrete, though they were developed based on limited test data from different sources. The excellent performance of the two ANN models indicates the ANN method is tolerant of random errors and systematic errors in the test data.

(2) ANN models performed better than traditional simplified method in predicting explosive spalling of steel fiber reinforced concrete. In addition, ANN models have more potential than traditional simplified method due to unique learning ability of ANN models. In general, ANN is a very promising method to assess explosive spalling risk of steel fiber reinforced concrete.

(3) A small quantity of steel fibers is enough to prevent explosive spalling of high performance concrete. In contrast, a much larger quantity is needed in order to prevent explosive spalling of ultra-high performance concrete. The diameter and length of steel fibers have a negligible influence on explosive spalling resistance of both high performance concrete and ultra-high performance concrete.

(4) Though ANN1 and ANN2 both had a prediction accuracy of 100%, ANN1 has more potential application fields than ANN2. Concrete mix is a known quantity without conducting tests, while compressive strength of a concrete mix is known until tests are conducted. Like in the case of parametric studies, ANN1 was able to provide an insight into effect of steel fibers on explosive spalling of concrete without any further tests, but ANN2 was not able to.

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APPENDIX 1 State of steel fiber reinforced concrete samples after exposure to heating.

(1) Case 1  (2) Case 2  (3) Case 3  (4) Case 4
(5) Case 5  (6) Case 6  (7) Case 7  (8) Case 8
(9) Case 9  (10) Case 10  (11) Case 11  (12) Case 12
(13) Case 13  (14) Case 14  (15) Case 15  (16) Case 16
(17) Case 17  (18) Case 18  (19) Case 19  (20) Case 20