A preliminary artificial intelligence model for predicting the risk from glass windows subject to airblast overpressure

H. S. Suisiswo*, T. Ngo, C. Duffield, and P. Mendis
(Dept. of Civil and Environmental Engineering, The University of Melbourne, Melbourne, Australia)

Abstract: Building façade is the first line defence of buildings, and glass window is particularly the weakest part as well as the major cause of injuries and blast events. Understanding the vulnerability of glass windows to blast loading is therefore important. As a result of limited understanding of the behaviour of glass and glass fragment in response to blast wave, predicting the potential hazard from failed glass under blast loading is highly difficult. The present paper investigates the efficacy of the artificial neural network in predicting the risk from glass window subject to airblast pressures. In addition, some important lessons from the recent Woomera full scale blast tests are also briefly presented. The information provide useful basis in assessing the conditional risk of glass windows subject to blast loads.

Keywords: risk, glass window; blast; hazard; neural network

1 Introduction

Building façades are particularly vulnerable as they are considered the first line of defence due to their closeness to the source of an external explosion. Further, the glass in windows is considered the weakest building component and flying glass fragment is often the major contributor of injuries in blast incidents. The behaviour and performance of glass windows subject to blast overpressure, unfortunately, are not fully understood by the structural engineering community.

Different types of glass have particular strength characteristics and behave differently under blast loadings. Common glass types used in buildings include annealed glass, heat-strengthened glass and toughened glass as monolithic glass or multi panes glass made of one type or combination of those materials for laminated glass or double glass for insulation. These different types of material and designs respond differently to blast pressure. Moreover, different types of glazing materials exhibit different failure modes.

Predicting the performance of glass window under airblast pressures is extremely difficult, as it requires a proper estimation of the behaviour of glass plate subject to dynamic blast loading, the strength and failure characteristics of glazing material as well as the behaviour of glass fragment upon failure. Some prediction tools have been developed based on the combination between the single degree of freedom (SDOF) and fragment flight model, such as HazL, WinGard and WinDas [1; 2]. Such tools are not widely accessible. Moreover, a proper model may be required to accurately predict the behaviour of glass and glass fragment in response to blast wave. Complex behaviour of glass fragment has been reported, include aerodynamic stabilisation and spinning, that may result in horizontal, vertical (flat), angular and accentual impact on objects inside the buildings [3].

This paper discusses the use of artificial intelligence to predict the risk of glass windows subject to airblast overpressure, following a brief description of available design guides and general risk identification from full scale blast trials. Neural network model is a potential method to predict the performance of glass windows accurately and efficiently.

2 Window design consideration

2.1 GSA Glass Performance Condition classification

In order to protect building occupants, the behaviour of glass upon failure should carefully be considered. The US General Services Administration (GSA) specifies six different Performance Conditions of glass under blast pressure to classify glazing protection level [4]. This classification was developed based on the expected impact location of glass fragments upon failure as a result of blast loadings, as described in Fig. 1, and is explained in Tab. 1.

* H. S. Suisiswo, Mr.
Correspondence to H. S. Suisiswo; E-mail: h.suisiswo@clenv.unimelb.edu.au.
GSA defines hazard levels based on potential impact of glass fragments on building occupants. Safe condition (Performance Condition 1 and 2) refers to the situation where no hazard is expected, whereas injuries to lower body part are likely from very low to medium level of hazard (Performance Condition 3 and 4). More serious injuries, especially to upper body part as well as fatalities are anticipated from the highest level of hazard (Performance Condition 5).

![Diagram of GSA Glass Performance Condition]

**Fig. 1 GSA Glass Performance Condition**

<table>
<thead>
<tr>
<th>Class</th>
<th>Hazard Level</th>
<th>Window glazing response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance Condition 1</td>
<td>None</td>
<td>Glazing does not break. No visible damage to glazing or frame.</td>
</tr>
<tr>
<td>Performance Condition 2</td>
<td>None</td>
<td>Glazing cracks but it is retained by the frame. Dusting or very small fragments near sill or on floor acceptable.</td>
</tr>
<tr>
<td>Performance Condition 3a</td>
<td>Very Low</td>
<td>Glazing cracks. Fragments enter space and land on floor no further than 1 meter from the window.</td>
</tr>
<tr>
<td>Performance Condition 3b</td>
<td>Low</td>
<td>Glazing cracks. Fragments enter space and land on floor no further than 3 meter from the window.</td>
</tr>
<tr>
<td>Performance Condition 4</td>
<td>Medium</td>
<td>Glazing cracks. Fragments enter space and land on floor and impact a vertical witness panel at a distance of no more than 3 meter from the window at a height no greater than 0.6 meter above the floor.</td>
</tr>
<tr>
<td>Performance Condition 5</td>
<td>High</td>
<td>Glazing cracks and window system fails catastrophically. Fragments enter space impacting a vertical witness panel at a distance of no more than 3 meter from the window at a height greater than 0.6 meter above the floor.</td>
</tr>
</tbody>
</table>

Laminated glass is well known as a superior design for blast resistant window. GSA recommends the use of this particular type of glazing to provide building occupants a better protection from explosive threats. This laminated glass window can either be fabricated with annealed, heat strengthened or toughened glass. In addition, toughened glass with security film as well as blast curtain also recommended as appropriate design in response to blast overpressure. The use of monolithic toughened glass is acceptable provided that it is carefully considered based on design threat to achieve Performance Condition 1. The use of untreated monolithic annealed glass, heat strengthened or wired glass is unacceptable.

In order to determine the performance of a glass window subject to blast pressure based on the GSA rating, a standardised test according to the GSA test method [5] is required. Such tests are costly.

### 1.2 DoD UFC 4-010-01

To minimise the risk of mass casualties in the event of terrorism acts, the US Department of Defense (DoD) established a Minimum Antiterrorism Standards for Buildings, UFC 4-010-01 [6]. The Standard 10 of this document provides general requirements for windows, skylights and glazed doors, and consists of provisions to reduce hazards from flying glass fragment in the event of an explosion. This standard was later upgraded through the introduction of its addendum [7] that incorporates design considerations of the ASTM F2248-03, the Standard Practice for Specifying an Equivalent 3-Second Duration Design Loading for Blast Resistant Glazing Fabricated with Laminated Glass, in combination with application of the ASTM E 1300-04, Standard Practice for Determining Load Resistance of Glass in Buildings. As a minimum antiterrorism standard, the provisions in this document offer a very low level of protection.
for inhabited buildings. According to this DoD level of protection, glazing is expected to break and enter into building interior, but with reduced fragments. In this condition, potential serious injuries with limited number fatalities, between 10% and 25%, are still expected.

For windows panel, this standard recommends the use of minimum 6 mm nominal laminated glass to achieve the intended level of protection for building occupants. This nominal thickness is achieved by using two layers of 3mm glass bonded together using PVB interlayer. The difficulty of implementing this standard is associated to the determination of the level of threat for the given level of protection. The level of threat adopted in the standard, which represents the size of the explosive and corresponding standoff distance, is not available in public domain.

3 Woomera full scale blast test

3.1 General

As different sizes of explosive produce different blast wave characteristics, full scale trials are required to investigate the response of structure elements to blast overpressure. The recent full scale blast tests took place in the Woomera Prohibited Area, South Australia, in April and May 2006, and in March 2007, involving participants from various countries, including Australia, UK, USA and Singapore, and involving a large number of various materials and modules. The Advanced Protective Technology for Engineering Structures (APTES) of the University of Melbourne tested concrete panel, blast doors and various types of glass window on large single-storey concrete modules in order to obtain information for validating theoretical and analytical model in damage prediction of actual blast incidents. As an example, further discussion is focused on the results of the April 2006 trial.

![Fig. 2 Front elevation of test typical module](image)

![Fig. 3 (a) Test Module 1, and (b) Test Module 2 of the April 2006 test](image)

The April 2006 test was conducted using 500 kg ANFO (Ammonium Nitrate Fuel/Oil), which is approximately equivalent to 400 kg TNT. Two test modules, namely Module 1 and Module 2 were tested subject to corresponding blast pressure from abovementioned charge. Both modules were set back 30 m from the source of the blast. The elevation of the modules is as shown in Fig. 2.

Test Module 1, shown in Fig. 3(a) consisted of:
- Opening 1A for trial on blast door featuring laminated glass specimens,
- Opening 1B for trial on filmed annealed glass window,
- Opening 1C for trial on blast resistant laminated glass window,
- Opening 1D for trial on blast resistant door,
- Energy absorbing tiles and aluminium foam composite front wall.
Test Module 2, shown in Fig. 3(b) consisted of:
- Opening 2A and 2B for trials on energy absorbing tiles and corrugated steel composite,
- Opening 2C for trial on blast resistant laminated glass window,
- Opening 2D for trial on blast door featuring laminated glass and polycarbonate specimens,
- Energy absorbing tiles and aluminium foam composite front wall, similar to those of Module 1.

### 3.2 General risk identification

The risk of injury to building occupants from an explosion can generally be categorised into primary, secondary and tertiary injuries. Primary injuries refer to the direct consequences of blast overpressure to human body, such as lung collapse and eardrum rupture. Secondary injuries are the consequences from failed building elements impacting human body, such as traumas from glass fragments. Tertiary injuries attributes to the consequences of human body impacting other object, such as falling down as the result of blast wave.

The full scale test results showed that the annealed glass window with film application of Opening 1B completely failed in the test. Moreover, a significant amount of fragments were captured on the witness cards indicated potential hazardous material resulted from this window for the given blast event. In these circumstances, primary, secondary and tertiary may threat building occupants. This particular outcome emphasizes the great danger of annealed glass even though treated with security film.

The test also showed that the glazing of the laminated glass in Opening 2C severely cracked but remained in its frame. The whole window system, however, dislodged from the opening. All types of injury are also likely under this situation. While the risk of skin laceration due to flying glass fragment is less threatening, this particular situation increases the risk of building occupant being hit by the whole window unit. This case highlights the importance of balance design for the whole glass window system.

In general, the other openings performed satisfactorily under this test, as their damage was not substantial. For example, laminated glass of Opening 1C cracked but still retained by its frame, demonstrates a safe failure mode. The top laminated glass of the blast door of Opening 1A did not shatter but partly pulled out the frame edge capture, underlines the significance of frame design. The overall risk, however, decreased in this case.

### 4 Neural Network modelling

#### 4.1 General

Artificial neural network is a computational model that consists of parallel elements and is developed based on the inspiration from biological nervous systems. The network function is determined largely by the connection between elements, as illustrated by a basic diagram in Fig. 4 (a). The input layer and the output layer are connected by a network through the hidden layer. The number of hidden layer may be more than one, depend on the particular case and complexity of the problem.

Basically, a neural network needs to be adjusted in the training process, so that a particular input leads to a specific target output. In the training process, the network is adjusted based on a comparison between the output and the target, until the network output matches the target. Once the output closely matches the target, the network is considered established. From this point, the network is able to perform the appropriate function to estimate the output from different sets of input. The basic concept of the development of neural network model is illustrated in Fig. 4 (b).

The advantage of neural network simulation in predicting blast pressures on buildings of different heights separated by a long street of various widths has been investigated. The efficacy of neural network simulation was found accurate for street configuration within the boundaries of network data training [8].

![Neural Network](attachment:neural_network.png)

Fig. 4 Neural Network, (a) Simple model concept model, and (b) general modelling principle
4.2 Glass performance prediction model

The distribution of the data of different glass windows performance subject to various threat levels are summarised in Tab. 2. Tab. 2 shows that the data are unevenly distributed for each performance class, i.e., only small portion of data represents the lowest and the highest levels of hazard. In this model development, the overall test data were initially separated randomly, 75% for training and 25% for testing the model.

<table>
<thead>
<tr>
<th>Failure Class</th>
<th>Untreated Glass (%)</th>
<th>Annealed Glass With Film (%)</th>
<th>Laminated Glass (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failure Condition 1</td>
<td>8.9</td>
<td>2.9</td>
<td>5.7</td>
</tr>
<tr>
<td>Failure Condition 2</td>
<td>10.1</td>
<td>30.0</td>
<td>55.2</td>
</tr>
<tr>
<td>Failure Condition 3</td>
<td>15.2</td>
<td>34.3</td>
<td>22.0</td>
</tr>
<tr>
<td>Failure Condition 4</td>
<td>63.3</td>
<td>32.3</td>
<td>17.1</td>
</tr>
<tr>
<td>Failure Condition 5</td>
<td>2.5</td>
<td>0.5</td>
<td>0.0</td>
</tr>
</tbody>
</table>

The radial basis neural network is selected in the development of model to predict the performance of glass windows subject to airblast overpressures. In this case, glass window failure condition was identified based on five variables representing the characteristics of the window and the magnitude of blast loading. The characteristics of glass windows are represented by their dimension (width, height and thickness) and the relevant treatment characteristics. The level of threat is expressed by the maximum positive blast pressure and loading duration of the idealised triangle blast loading.

The basic concept of neural network modelling illustrated in Fig. 4 (a) is still applicable with several specific modifications. The neural network model is realised using Matlab [9]. The model consists of two hidden layers that represent a function that correlates the input layer and the output layer. The first layer measures how close a set input is to the sets of data that are used in the training process. The second layer is a competitive layer that selects the maximum probability of being appropriate class for the corresponding input set.

Neural network model can be developed in typical way for each type of window. The major difference is in the number of input element as the consequence of representing particular type of window, as the input data of glass with additional treatment will include information on the characteristics of the treatment. Further discussion is focused on the model of predicting the risk from untreated annealed glass subject to blast overpressure.

5 Result and discussion

5.1 Data of glass performance

In order to obtain an effective network, a well distributed training data is required. Tab. 2 shows that the data of the performance of glass from experiments are poorly distributed. Consequently, the network produced through the process of training using this set of data may constitute some potential deficiencies. As an artificial neural network model generally depend heavily on the reliability of data, the low number of certain class may decrease the efficacy of the model.

Glass is a very weak material that normally fails even under very low blast pressures. Therefore, surviving glass window is more probably found either in the case of very low explosion or if the glass was very thick. There is also a probability that a glass has very high strength so may not fail in a blast, thus a few data of surviving glass even subjected to relatively high blast pressure is reasonable. This typical phenomenon may result in difficulty in obtaining a set of data that is distributed evenly among different failure classes.

Tab. 2 also shows that the number of experiment data that represents the highest level of hazard is extremely low for all types of glazing design. For this reason, the effectiveness of the network to predict the occurrence of this hazard level is expected low.

5.2 Model accuracy

Based on the initial random selection, the total accuracy of the glass performance prediction was 87.1%, which includes 95% accuracy for predicting the performance of glass in training data and 68.4% accuracy for predicting the performance of glass in testing data. Data exchange selection method [10] was applied in order to increase the accuracy of the network. After step-by-step data exchange the total accuracy of the prediction was improved to 93.7%, which consists of 95% accuracy for estimating failure condition of glass in training data and 89.5% accuracy for those are in testing data.

The comparison between the actual performance obtained from full scale blast test and the predicted performance of untreated annealed glass from the model is shown in Fig. 5. Noticeably, the model can generally predict the performance of glass windows subject to airblast overpressure with high accuracy. The figure, however, only indicates the number of output data for each class, and does not show the extent of inaccurate prediction.
In order to closely evaluate the result of the prediction compared to the actual test data, a confusion matrix is developed as shown in Tab. 3. The matrix shows that the model is able to predict the performance of glass subject to airblast pressure satisfactorily, as a great deal of predicted performance falls into the same class with the actual test data. Besides the fact that only small fractions of predicted performance do not match the actual test data, Tab. 3 also shows that they were misplaced only to the nearest neighbouring classes, which highlights the accuracy of the model.

![Fig. 5 Comparison between actual and predicted failure class of annealed glass](image)

**Tab. 3 Comparison between test and model output for each failure class**

<table>
<thead>
<tr>
<th>Test Data</th>
<th>Class 1 (%)</th>
<th>Class 2 (%)</th>
<th>Class 3 (%)</th>
<th>Class 4 (%)</th>
<th>Class 5 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>71.4</td>
<td>28.6</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Class 2</td>
<td>-</td>
<td>75.0</td>
<td>25.0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Class 3</td>
<td>-</td>
<td>-</td>
<td>91.7</td>
<td>8.3</td>
<td>-</td>
</tr>
<tr>
<td>Class 4</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>100.0</td>
<td>-</td>
</tr>
<tr>
<td>Class 5</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>100.0</td>
</tr>
</tbody>
</table>

5.3 Simulation for risk prediction

Once a neural network is established, it is containing an approximate function that can be used to estimate different output from a different set of input. Fig. 6 shows the randomised simulation result of a 6mm annealed glass window of 0.8 x 1.5 m2 in size under various blast threat levels. Considering the range of blast pressure in the available experimental data, the peak pressures in the simulation were set in the range of 10 to 100 kPa, whereas the impulses were selected between 20 and 1000 kPa ms.

Generally, higher combinations of peak pressure and impulse impose higher levels of hazard. The model, however, exhibits some inconsistencies, as indicated by slight inconsistent increase of hazard level due to the raise of peak pressure or impulse. These inconsistencies are mainly attributed to the nature of the problem that involves high uncertainty. The most important factor is the variability of experimental result due to the uncertainty of glass failure modes in response to blast pressure. The uncertainty includes the inherent high variability of glass strength, the deficiency of the overall window system, and the complex behaviour of glass fragment in response to various characteristics of blast wave. Additionally, the uncertainty of glass failure is also complicated by the potential uncertainty and deviation of glass thickness to its nominal value [11].

The continuous line in the diagram in Fig. 6 represents the line of “breaksafe” of the window as resulted by window fragment hazard level analysis tool at 750 of 1000 probability of failure. For evaluating existing glass windows on buildings, the probability of failure 750 of 1000 is recommended [2]. Fig. 6 shows a close prediction between the window fragment hazard analysis tool and the neural network model.

Even though the model demonstrates a high accuracy in the model testing, Fig. 6 also shows the deficiency of the model. As previously predicted based on the distribution of failure class data from experiment, the model is not capable to recognise the highest level of hazard (failure class 5). This deficiency is due mainly to the lack of experimental data that represent the aforementioned level of hazard.

Beside the deficiencies in this particular risk prediction, the model also inherits common limitation of the artificial neural network model. The model is only capable to provide approximation of the risk of glass failure subject to blast pressure, and does not explain the behaviour of glass panel or glass fragment in response to blast wave. In this matter, structural engineering will have a significant role to provide analysis on the behaviour of glass subject to dynamic blast loadings. Finally, this model is also highly dependant on the characteristics of data, and is only effective to predict the output of a set of input that are in the range of input data, thus is not reliable for extrapolation.
6 Closing remarks

The artificial neural network is a potential effective and efficient model to predict the risk of glass window subject to blast overpressure. The limitation of available test data is the most important factor that may limit the efficacy of the model. So, additional supporting test data may improve the effectiveness of the model. The application of the model in assessing the risk of building façade to external explosion is an area of research requires further studies.

References

[1] Conrath, E. J. *Multi-hazard window (glazing) design [unpublished]*, [no date].