A new method for very fast simulation of blast wave propagation in complex built environments

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Abstract

The paper is concerned with the development of a fast, accurate, and versatile method of simulating the propagation of a blast wave within complex built environments. An ability to complete a simulation of the propagation of a blast wave within a few seconds or minutes is an essential tool for evaluating its impact on key structures and to find an optimal design for components such as blast barriers. Existing methods of modelling the propagation of a blast wave fail to satisfy all of the above requirements. They lack either the accuracy required to produce useful results, the versatility necessary to model problems with complex geometries, or the processing speed critical to generating results within an acceptable period of time. An alternative method proposed here is to use a simulation approach implemented within a coarse spatial and time framework, where the mesh elements and time steps are orders of magnitude larger than those used in conventional CFD simulations. Preliminary research suggests that the reduced computational load resulting from this method will allow simulations to be executed several orders of magnitude faster than conventional CFD methods, such that a simulation which would take a day to process could be completed within a few seconds. The paper describes the new approach in detail and provides some analysis of its likely performance in terms of processing speed.

*Keywords*: blast-wave propagation, coarse-grain simulation, CFD, very fast simulation

1 Introduction

This concept paper proposes a new approach to simulating the propagation of blast waves in a built-up environment that has the potential to be accurate, generate results rapidly (in a matter of seconds), and has the versatility to model complex building configurations. Such a tool is necessary to allow engineers to design new structures (including new buildings, retrofits of existing buildings, and protective structures such as blast walls) that perform effectively in terms of both blast-mitigation and cost-effectiveness. The need for rapid simulation is made more important by the many uncertainties that exist about the blast environment, such as the size and location of a bomb and the status of temporary obstacles to the blast wave (including whether blast doors are open or closed). Significant uncertainties require a simulation to be executed many times using, for example, Monte Carlo sampling to derive an accurate statistical assessment of the impact of the blast. Rapid simulation would also allow engineers to use immersive visualization techniques, such as virtual reality, to gain better insight into the behaviour of a blast wave and the way it interacts with the built environment.
Existing blast modelling tools are a trade-off between the complexity of the environment they can model and the time they take to generate results. Modelling tools that can produce results rapidly are direct mapping devices (see, for example, Remennikov (2003)), the best performing of which are the neural network models such as those described by Remennikov and Rose (2007) and Flood et al. (2009). Artificial neural networks (an introduction to which is provided by Flood & Kartam (1994)) are very versatile, and capable of considering many independent variables that have non-linear relationships with the dependent variables. The Remennikov and Rose (2007) models were trained using data from miniature bomb-barrier-building experiments (Chapman et al., 1995), while the Flood et al. (2009) models were trained using data synthesized from CFD (Computational Fluid Dynamic) simulations and other established modelling techniques. These neural network models can produce results in a fraction of a second, and can be very accurate. Figure 1, for example, demonstrates the performance of a neural network trained to predict the peak pressure (psi) on the face of a building where there is a blast barrier positioned between the bomb and the building, for the set of configurations illustrated in Figure 2. Each point in the figure represents 1 of 252 randomly selected test problems, plotting the neural networks predicted value against the actual value - if the model was perfect, all the points would fall on the diagonal line. The results gave a correlation between the model output and actual values of 0.9959, indicating excellent performance.

Unfortunately, empirically derived models (such as neural networks) cannot usually extrapolate to problems beyond those represented by the data set used to develop the model. Moreover, the size of the data set required to develop direct mapping empirical models (such as the above artificial neural networks) increases geometrically with the number of independent variables describing the problem. In practical terms, for blast wave modelling this limits the complexity of a problem to about five independent variables - this has constrained application to setups such as that shown in Figure 2 comprising a two-dimensional blast wave propagating over a blast barrier onto the face of a building, where the barrier and building are perpendicular to the plane of the blast wave.

![252 Test Patterns Performance](image)

Figure 1, Typical performance results for an artificial neural network model developed to predict peak pressure on the surface of a building
Blast waves propagating through more complex environments, and acting in three spatial dimensions, can usually only be considered using CFD techniques (such as ANSYS (2008)). Unfortunately, three dimensional CFD models of blast wave propagation, even when limited to a single barrier and building configuration and run on a supercomputer, can take several days or more to complete a single simulation run (Flood et al, 2009).

One approach for simplifying the difficulty in blast load predictions is to use ray tracing. This uses an algorithm that identifies the most significant paths (the shortest) that a blast wave can follow from the point of detonation to specific target points, taking into account reflection and diffraction. The time-based forms of the waves arriving along each path are determined using the semi-empirical TNT Standard Methodology and are then superimposed using the LAMB Shock Addition rules (Needham & Crepeau, 1981). Enhancements to the approach have been used by Frank et al. (2007a, 2007b) to predict behaviour in environments with complex geometries. The approach certainly provides a highly versatile method of modelling complex internal geometries, and it is claimed that the results are of reasonable accuracy and that the model runs fast. However, a comprehensive set of case studies is required to determine more precisely the accuracy and processing speed relative to established approaches to the problem. The algorithm required to determine all significant paths for the blast wave appears to be too complex to allow results to be generated in a matter of seconds for all target points across all relevant surfaces of the environment that would be required for the applications proposed in this paper.

An alternative approach to these issues, considered by Löhner et al. (2004), was to test the sensitivity of processing time and accuracy on the coarseness of the modelling mesh for three dimensional CFD simulations of blast wave propagation through complex building geometries. In an example study of a concert hall, consideration was given to a range of resolutions ranging from main element sizes of 0.3 m to 1.2 m in length. It was found that moving to the coarser mesh reduced
processing time from 18 hours to 7 minutes, although the predictions of the coarse mesh model were about 50% off compared to the fine mesh model. While the speed of processing of the coarse mesh approach makes it accessible to users of desk-top computers, the authors of this paper believe greater accuracy in the predictions of the model is needed.

2 Coarse-grain based simulation

This paper proposes a coarse-grain approach to achieving a modelling system that is fast, accurate, and versatile. It differs fundamentally from the coarse-grain approach of Löhner et al. (2004) discussed above in that it uses empirical rather than theoretically derived functions to drive a simulation. In Löhner’s study, the coarseness of a model was achieved by simply increasing the size of the spatial elements comprising a model, while using the same discretized driving equations used in the fine-grain models. Increasing the size of the elements reduces dramatically the number required for any given situation and thus similarly reduces the computational load of a simulation, hence the significant reduction in processing time. However, the driving equations used assume an infinitesimally small element size, and so become less accurate the larger the size of those elements – this is also true of the size of the time step during the execution of a simulation. Consequently, the accuracy of the simulations reduces very quickly with model coarseness. In this study, it is proposed to compensate for this in the following two ways:

1. Artificial neural networks will be used to learn a more accurate form for the driving equations operating in a coarse-grain modeling environment. These neural networks will be trained based on data gathered from a comprehensive set of CFD simulations of building element geometries.
2. Each coarse-grain element will include an additional set of independent variables sampling the state of the element historically (in the time domain) to compensate for the loss of information by the low resolution in the spatial domain.

This approach, developing a set of discretized driving equations tailored to a coarse-grain modelling environment, has been demonstrated to be very effective in an earlier series of studies modelling dynamic heat transfer in complex building configurations (Flood et al. (2004)). For transient heat transfer, it was found that a system could be decomposed into very coarse elements while maintaining accuracy in predicted performance. Indeed, each wall, ceiling, floor, or open space could be represented by a single element, as shown in Figure 3. Two primary element types were considered, those representing open spaces (such as rooms and attic spaces) and those representing boundaries between spaces (such as walls, floors/ceilings, and roof membranes). The simulation advances in a manner very similar to CFD techniques, by predicting the temperature at each element at the next point in time based on its current and historic temperatures and those of its neighbouring elements – the difference being that the equations used to make these predictions are empirically derived compensating for the large distances between adjacent points and between points in time by using many historical sampling points. In a case study of a simple house, simulated for a one-year heating and cooling cycle with a 15 minute time-step, the model was found to end within 0.25 oF of the actual value. The results also indicated that a three-dimensional coarse-grain simulation of the house could be performed several thousand times faster than a conventional CFD model.
3 Coarse-grain modelling applied to blast wave propagation

There is a critical difference between modelling heat transfer and blast wave propagation that invalidates the coarse grain approach described in Section 2. Fundamentally, the problem arises from the fact that the temperature distribution within a structure changes very gradually in the spatial domain relative to the distance between the modelling elements, whereas a blast wave has a very short wavelength compared to the distance between coarse grain elements. Consequently, as illustrated in Figure 4, an advancing blast wave may be lost within the mesh, perhaps never intercepting more than one coarse grain element at a time, and for much of its existence not intercepting any coarse grain elements. This means that there would never be enough information about the state of the blast wave to be able to make predictions about its state at a succeeding point in time. The coarse grain approach described above for modelling transient heat transfer clearly needs to be modified to make it applicable to modelling the propagation of blast waves.

Figure 4. Illustration of the fact that an advancing blast wave will intercept very few coarse grain elements at any point in time

The basis of the proposed solution to this problem is to identify the state of the blast wave by all coarse-grain elements adjacent to it, not just those intercepted by it, and to advance the simulation at each step by jumping to the time at which the blast wave intercepts the next coarse grain element. The key properties of the wave to be captured at any point in time during this process are its location, corresponding peak pressure, trough pressure, and wave length, as indicated in Figure 5.
The specific steps in the proposed simulation can be understood by referring to Figure 6. Here, the advancing blast wave is represented by the gray line, moving south west, and is registered at all adjacent coarse grain elements shown as colour-shaded active nodes. The blue nodes are trailing the blast wave, the yellow one is currently intercepted by the wave, and the red nodes are leading the wave. Each of these nodes registers the following: the time until (or since) the peak pressure of the blast wave reaches (or reached) that node; the peak and trough pressures that will occur (or occurred) at that node; and the velocity of the propagating wave (presented in rectangular vector components so that information on the direction of travel of the wave is also implied). To advance the simulation to the next point in time, the following steps (similar to those used in next-event based discrete-event simulation) must be implemented:

**STEP 1:** Find the leading active node (red in this figure) that has the shortest time until arrival of the blast wave.
**STEP 2:** Advance the simulation to this point in time by increasing by a corresponding amount the time since arrival at the trailing active nodes, and reducing the time before arrival of the leading active nodes.
**STEP 3:** Remove any nodes from the active list that are no longer adjacent to the blast wave.
**STEP 4:** Add all nodes to the active list that are now adjacent to the blast wave. These nodes will be leading the blast wave.
**STEP 5:** For each leading node that has just been added to the active list in STEP 4, predict the time until arrival of the blast wave, the peak and trough pressures on its arrival, and the velocity the blast wave will have on arrival at that node (in rectangular vector coordinates). These predictions must be based on the state of the blast wave registered at its neighboring nodes. In Figure 6 for example, the green arrows point to a leading node that has just become active, and emanate from the nodes that will be used to calculate its blast wave attributes. In the proposed approach, these predictions will be made by artificial neural network modules trained using data from specific localized CFD experiments.
Estimate of performance of proposed coarse grain modelling approach

The next stage in the project will be concerned with implementing the proposed method and evaluating its performance in terms of processing speed and accuracy. However, based on past experiences with neural network modelling and coarse grain modelling it is possible to make a rough estimate of likely processing speed performance. This will be completed with reference to the 2 dimensional coarse grain model shown in Figure 7, that includes a 7 m square grid with coarse grain elements located at 1 m spacings, an obstruction on the top-left side, and a charge placed at the bottom-left corner. The performance of this model will be compared to that of a conventional CFD model (that uses the Finite Difference Method – FDM) that places elements on a 2 cm mesh (the largest spacing found in previous experiments to provide an acceptable level of accuracy).

A summary of the processing load for both the coarse grain and CFD models of this scenario are shown in Table 1. At each step in the coarse grain simulation only one element on average will be recalculated, whereas the CFD model will have approximately 122,500 elements to recalculate (see column 2 in Table 1). In addition, whereas the coarse grain model will require just 71 time steps to advance the blast wave from the bomb to the top right element (remembering there will be additional time steps resulting from the fact that the wave will be reflected off the obstruction), experience indicates that the CFD simulation will require around 7,425 time steps to make the same advancement. However, a disadvantage for the coarse grain approach is that the processing load to update one element at any time step may be around 600 times greater than the CFD model. This is because the CFD model uses a very simple discretized function whereas the coarse grain model requires the use of an artificial neural network – the value of 600 is based on earlier experiments with neural networks to model the state transition function for a coarse grain simulation. The net result of all these factors is a processing speed advantage of about 21,351 for the coarse grain approach. In other words, if the CFD simulation took 1 day to process, the coarse grain model would take about 4 seconds. This advantage would be expected to increase for a three dimensional model. For example, using the same 2 cm mesh size for the example shown in Figure 7, the CFD model would require 50 layers of elements for every meter depth whereas the coarse grain model would require just one layer. This would increase the processing advantage by a factor of 50 so that a CFD simulation that took 1 year to process could be completed by the coarse grain model in just 30 seconds (see the last column in Table 1).
Table 1. Processing speed comparison of conventional CFD model (Finite Difference Method – FDM) and proposed coarse grain method

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Number Elements/Time Step</th>
<th>Time Steps (to far corner)</th>
<th>Processing Load Per Calculation (normalized)</th>
<th>CFD Equivalent Calculations</th>
<th>Processing Speed Ratio</th>
<th>Example Processing Time</th>
<th>Extrapolate to 3D model Processing</th>
<th>Extrapolate to 3D model 1 year processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFD (2cm mesh)</td>
<td>122,500</td>
<td>7,425</td>
<td>1</td>
<td>909,562,500</td>
<td>1</td>
<td>1 day</td>
<td>1</td>
<td>1 year</td>
</tr>
<tr>
<td>Coarse Grain</td>
<td>1</td>
<td>71</td>
<td>600 (6x100)</td>
<td>42,600</td>
<td>21,351</td>
<td>4 seconds</td>
<td>1,067,550 (2D x 50)</td>
<td>30 seconds</td>
</tr>
</tbody>
</table>

Such an increase in performance would certainly make three dimensional simulation of blast wave propagation in a complex built environment accessible. However, the other question to be answered is the accuracy of the predictions. This is a more difficult question to address than that of processing speed without actually performing a comprehensive set of customized experiments. Such a set of experiments is proposed for the next stage of this study.

5 Discussion

Empirical methods of modelling the effects of bomb blast waves on buildings are fast and often accurate, but lack the flexibility to consider anything other than the simplest of built environment geometries. On the other hand, the CFD models, while potentially very versatile, can take several days to process a three dimensional model. As a consequence, CFD models cannot be used for interactive design, do not allow engineers to consider more than a few alternative setups, and prohibit consideration of stochastic effects (such as uncertainty about the size and location of the bomb, the open/closed status of blast doors, etc.) since this would require multiple simulation executions using techniques such as Monte Carlo sampling.

In response, this paper has proposed a new method of modelling based on simulating with a coarse-grained modelling mesh. Normally coarse meshes result in significant reductions in the accuracy of predictions; the intent here, however, is to compensate for the loss of spatial information by developing custom functions for coarse grain analysis that also sample in the time domain. Previous studies in the field of transient heat transfer have shown this to be
viable if artificial neural networks are used to learn the functions that drive the simulation. The approach has the potential to increase processing speed by several orders of magnitude compared to conventional CFD simulations. The next step in this project is to implement the new method and validate it for a comprehensive range of complex building environments.

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References