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A Physics-Guided Machine Learning Approach to Understanding Loading Distributions from Explosive Events

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1 Project objectives and goals

Over recent years, the use of explosives for malicious attacks has become increasingly more common. The scale of these attacks varies: from larger scale attacks such as in Oslo (2011) and Oklahoma City (1995) to smaller scale, more targeted attacks such as at the Manchester arena (2017) and the 7/7 bombings in 2005. Explosions from terrorist attacks are killing people, and as engineers we have a duty to design and build resilient structures that can provide adequate security against a threat to life.

To do this, it is crucial we have a good understanding of the pressure load following a high explosive detonation. We currently have physics-based solvers (computational fluid dynamics codes) that can provide highly accurate solutions but will take several hours to days to complete. We also have very simplistic methods that allow us to do risk-based design approaches, but these are not accurate and can only give very vague approximations – not the level of confidence required in the context of saving human lives.

This project proposes a data-driven modelling approach of explosive events through novel machine learning techniques. Setting out to answer the question: can we find a way to match the accuracy of physics-based models but in a way that runs as quickly as these approximate methods, such that we can perform risk-based engineering with far more accurate information?

2 Description of method and results

This research has a focus on explosive events that have smaller distances between charge and target as this is where the more complex (and more damaging) loading occurs. It is also a region where current literature falls short in approximating the loading to a sufficient level of accuracy.

Through novel machine learning techniques, we have been able to train a model based on highly complex data such that in the future we can bypass the expensive step of solving the physics and instead jump straight to the answer.

Initially a mathematical model was found that can be fitted to the spatial distribution of the maximum impulse on a target (see Figure 1). Impulse is the integral of pressure at a given point over a certain time domain. By taking the maximum of this impulse-time history at each location on a target of interest, we can understand how the loading is distributed along the span of a target (where target is a column, wall, etc.). The maximum impulse itself provides the information about the loading that we as engineers are interested in designing against.

By performing optimisation of the mathematical model and fitting this to experimental data, we can develop a model that accurately “mimics” this loading distribution. Through repeating this optimisation procedure for a vast range of explosive scenarios and storing these optimum model parameter values, we can build a picture of how the parameters of a model vary with the fundamental parameters of an explosive scenario (charge mass, charge type, distance from explosive to target).

Initial results have been incredibly promising (Pannell et al. 2019) proving that this is a viable approach to generate reliable, meaningful data.

3 Potential for application of results

There are several interesting applications of the results of this work:

- Through studying the sensitivity of the model on the number of experimental samples it is trained on we can direct physical experiments in a more meaningful way (only performing the amount required to build a reliable “picture” of the physics, which would improve the cost efficiency of experimental work).

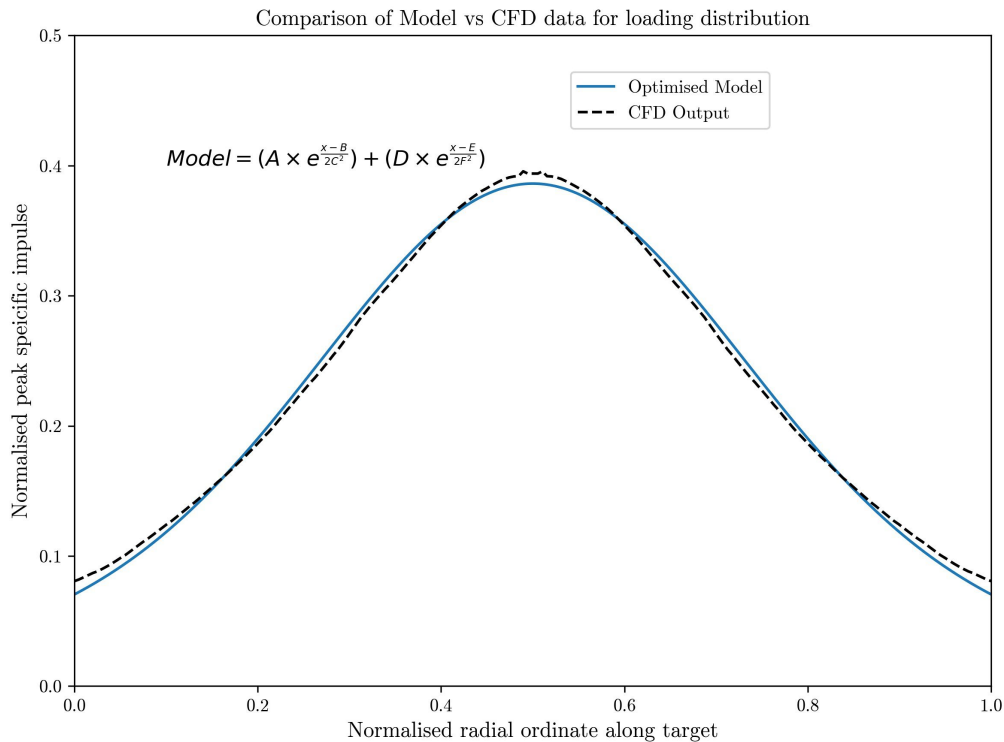


Figure 1: Example scenario of model approximating a loading distribution

- There is also the opportunity to link the predictive tool to structural response algorithms, such as those in Rigby et al. (2019), to directly form a relationship between input charge parameters and structural responses themselves. This would vastly increase the number of situations that can be studied in a survivability assessment. These survivability assessments are used in a wide manner of applications, from structural design, security and resilience studies, to actuarial studies in the insurance industry.
- It could be useful in forensic events, by studying the deflections of structural materials after an event, can we work backwards to infer what the loading must have been and where this could have occurred?
- Most importantly, however, the application of this work must be focused on improving the structural resilience of public infrastructure through the development of a quick running loading tool to be used in survivability analyses. This tool will approximate loading from several parameters fundamental to an explosive event (charge type, charge mass, distance between explosive and target). This will facilitate the analysis of individual structural components to certain blasts as knowledge of the loading will be known. Ultimately, modelling the loading in a more accurate way will lead to more resilient designs and better protection for civilians, potentially saving lives.

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