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A Direction-Encoded Machine Learning Approach for Peak Overpressure Prediction in Urban Environments

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Keywords: AI/ML, Numerical Simulation, Effects on Humans

Abstract

The use of Machine Learning (ML) models in blast protection engineering has rapidly expanded in recent years, with various publications applying bespoke algorithms to blast wave propagation, fragmentation and structural response problems. The benefits of using this approach for predicting the effects of urban explosions is driven by the need to comprehensively quantify risk through analysing a significant number of unique threats with limited computational expense. However, due to the presence of complex wave coalescence effects, the current state-of-the-art for predicting blast loads in urban environments using ML, the Direction-encoded Neural Network (DeNN), is only able to predict in domains with a limited number of orthogonally placed rectangular obstacles. Therefore, this paper presents a series of developments to the DeNN that allow the tool to predict more complex domains featuring varied obstacle shapes and positions. This is achieved through novel feature engineering that trains the model to understand how the local environment surrounding a point of interest and the strength of the blast wave that is impacting the point influences the magnitude of the prediction. It is shown that peak overpressure can be predicted with an average error of 16.2 kPa for a randomly generated urban environment that emulates a typical city. Future developments will expand the new approach to predict other variables alongside implementing an improved ML architecture.

Introduction

A comprehensive understanding of the risk posed to an urban environment by an explosive detonation requires tens, or hundreds, of unique threats to be considered. Existing work achieves this with numerical simulations that take probabilistically determined inputs of key parameters related to the possible charge characteristics and locations [1]. However, Computational Fluid Dynamics (CFD) solvers requiring large computation times can prohibit the exploration of entire parameter ranges and in most cases, varied building geometries.

Recent experimental work that aims to improve the efficiency of analysing urban environments explores the use of small-scale explosive charges or detonators with TNT equivalency under 3 grams [2, 3]. Combining this with Hopkinson-Cranz scaling [4, 5] enables obstacles to be positioned on a table, or work surface, such that a large scale blast can be emulated with lower risk. However, again, this approach currently lacks the ability to explore the full range of threats in an efficient and cost-effective way.

As an emerging alternative to CFD and experiments, Machine Learning (ML) models are typically used to generalise the relationships between several parameters associated to complex phenomenon. This allows for predictions of specified outputs to be generated rapidly, with limited computational expense. They are therefore well suited to this problem, however, [6] discusses how many existing works focus on the creation of tools that are bespoke to specific geometries, lacking the ability to produce outputs when changes to the charge size or domain are required.

In an attempt to avert these issues, [7] introduced the Direction-encoded Neural Network (DeNN) as a means of predicting peak overpressure in obstacle filled environments. The study adopted a novel methodology for translating local geometrical information to the ML tool, but it was only capable of generating predictions in domains with rectangular obstacles at 0° or 90°. Also, predictions in channelled and shielded regions were largely inaccurate due to the inability of the approach to relate complex wave interaction processes to the required reductions and amplifications in the observed pressure.

This study therefore builds upon the DeNN through novel feature engineering that introduces 19 new inputs to the ML model. This allows more complex urban domains, featuring angled obstacles of varied shapes and sizes, to be analysed.

Overview of Machine Learning

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that involves pattern recognition and the representation of the relationships between variables [8]. To develop a ML tool, a training process is required so that the calculations being performed by the model capture the required complexities of the problem, resulting in acceptable levels of predictive accuracy.

Supervised Learning is one of the simplest approaches for developing a ML tool as it involves the use of a training dataset of known inputs and outputs. Batches of inputs are provided to the model so it can make a prediction of the outputs, then, comparisons between these predictions and the known outputs are used to evaluate performance. The errors are summed and used to update the model's calculation in an iterative process that continually aims to improve its accuracy [9].

A key aspect of developing ML tools is therefore related to how the training dataset, that consists of the input/output combinations, is developed. Often it is formed from numerical modelling data that can be expensive to collect even when algorithms to speed up batch computations, such as the branching algorithm [10, 11], are used. Similarly, the process of feature engineering that concerns the extraction, transformation, selection, analysis and evaluation of the raw data that is used as inputs for the chosen ML algorithm is a critical step in tool development [12].

As proved by [7], use of domain-specific knowledge in the feature engineering process can ensure that the model captures the relevant physical behaviour. In this example, the direction-encoded approach allowed for geometrical information to be translated to the model with no dependency on overall domain layout. Therefore, the tool could be applied to domains of varied geometries. This study builds upon this method with additional feature engineering to develop a new model that can provide predictions for more complex urban domains.

Input Features

The direction-encoded approach used to develop a new ML tool in this study is formed from multiple novel concepts that simplify blast parameter prediction. The first captures local geometric information around a point of interest (POI) through a series of directional 'lasers', or rays. This paradigm shift was first introduced by the author in [7] to centre predictions on the POI rather than the charge with the goal of removing the need to provide details of the entire domain geometry to the model with every prediction.

Figure 1 provides an example of how a series of 16 directional lasers are projected from the POI with angular spacing of 22.5°. Adapting the previously implemented approach, here the rosette of lasers is rotated such that direction 1 points towards the incoming wave. This aims to enable the POI to relate the proximity of the surrounding obstacles to the direction of the incoming blast.

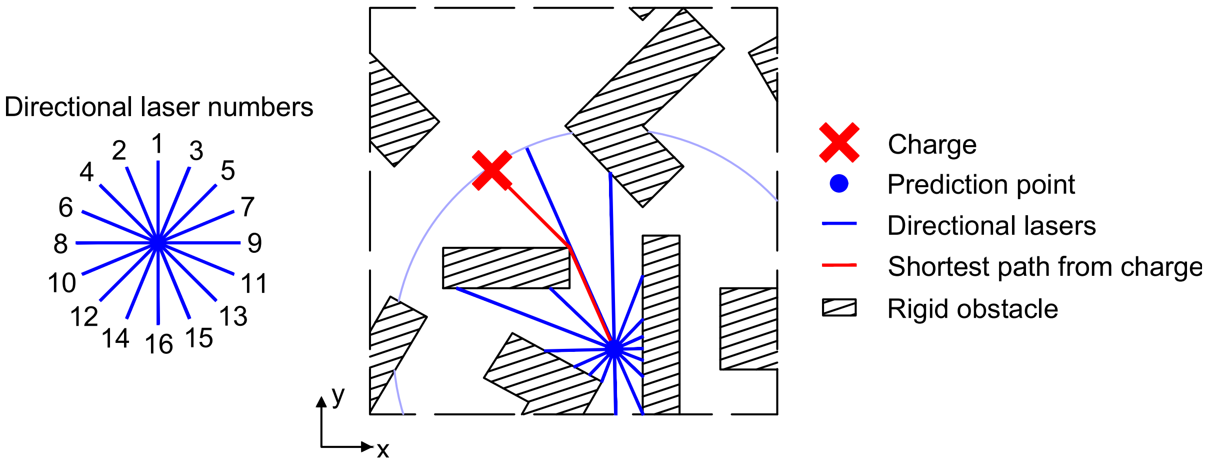

Figure 1. Summary of directional inputs to the Machine Learning model.

Each directional laser is used to identify an obstruction distance that is then processed using the wave reflection equation given below:

$$\text{Directional input} = \max(\text{Shortest path from charge} - \text{Obstruction distance}, 0) \qquad (1)$$

Use of this equation ensures that obstacles that are close to the POI provide large input values to the ML model, implying that the obstacle is having a large influence on the blast parameter being predicted. Conversely, an intersection that is further from the POI is translated to the ML model as a smaller number, suggesting that the effect of the obstacle is low.

The directional input value is limited to a maximum value equal to the shortest path distance from the charge. This is shown in an example given by Figure 2 which highlights an 'influence zone' around the prediction point where any obstacles outside of this region are deemed to be insignificant for generating a peak overpressure prediction. Lasers that do not intersect an obstacle provide an input of 0, indicating no effect. Another example is given in Figure 1 where the influence zone of the POI is shown by the thin blue line.

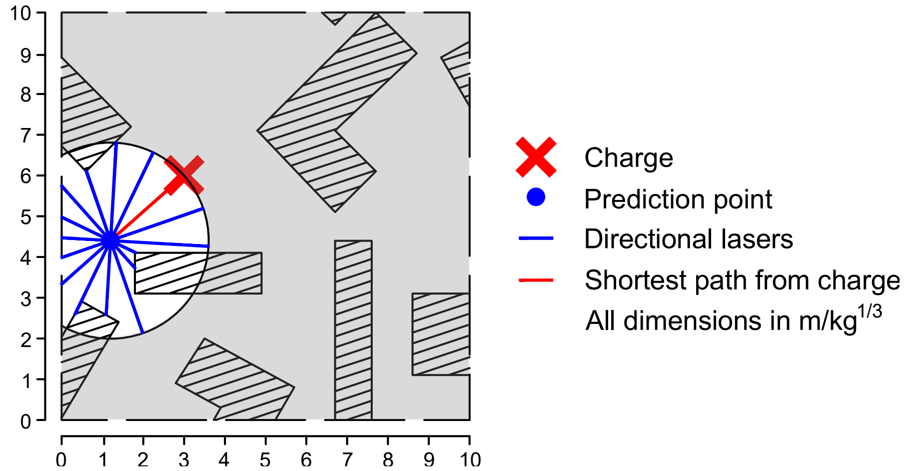

Figure 2. Zone of influence for a given prediction point. Drawn as a circle with radius equal to the shortest path distance from the charge.

Adapting the previous method further, this study introduces 16 new inputs to the ML model that correspond to intersection angles (between 0° and 90°) of each laser. They are calculated to assist the tool in learning the influence of the obstacle's orientation around each POI. Two examples are given in Figure 3 for the highlighted directional lasers. A lower intersection angle corresponds to a shallower interaction, and a larger angle implies a direct hit.

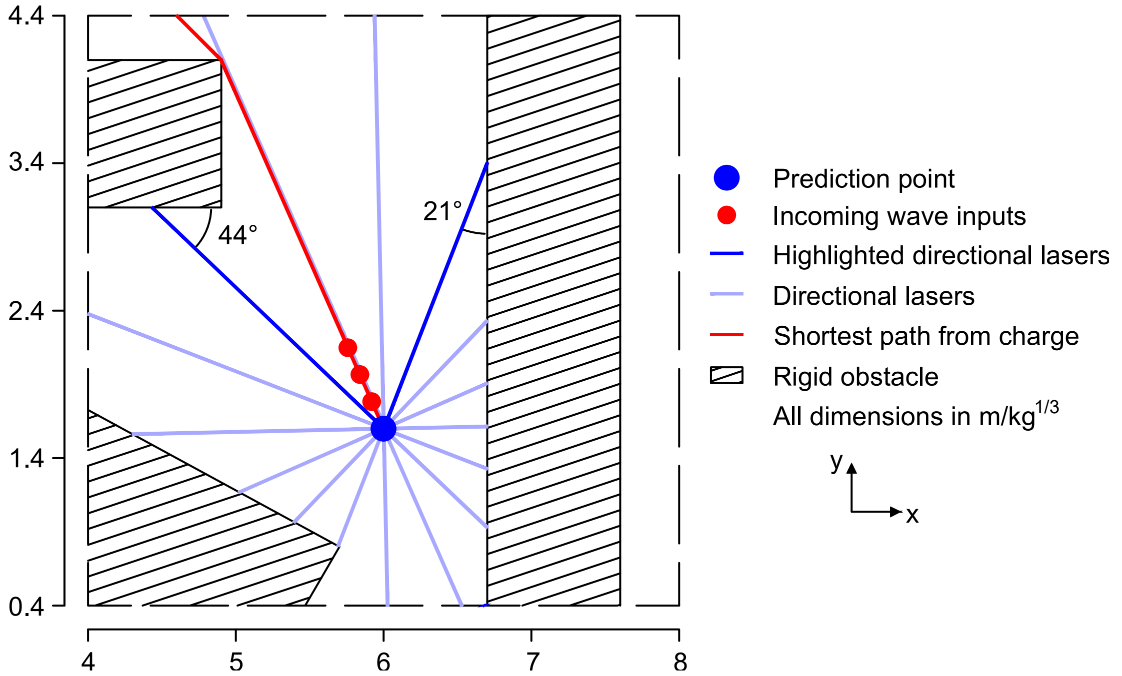

Figure 3. Example of the new input features allowing for predictions in more complex urban domains. Highlighted directional lasers correspond to angular inputs. Reduced domain and prediction point taken from Figure 1.

The final three new model inputs are based on the idea that a blast wave propagating through space can be considered as information being passed sequentially to its surroundings. This is captured by CFD solvers; however, the computation complexity of the time stepped process is simplified here by providing three 'incoming values' as model inputs.

As shown in Figure 3, for a given POI, three points along the shortest travel path of the blast wave are identified with a predefined spacing. The peak overpressure at these locations is provided as inputs to the model when predicting the POI to establish the strength of the blast wave that is approaching. Pairing this with an understanding of the local geometry, translated to the model via the directional laser obstructions and angles, allows for the magnitude of the blast wave to be understood, and then adjusted based on the relevant surroundings.

Implementation of this novel addition is achieved by sequencing the ML tool to predict the peak overpressure on a grid of POIs through the domain in order of the shortest path distance from the charge. This ensures that the incoming values being used in input sets can be interpolated from an array of known values.

Training dataset

Training the ML tool requires a dataset of known input/output combinations. In this study, this is developed from 40 models that were simulated using walair++, a GPU based Computational Fluid Dynamics (CFD) solver produced and maintained by Thornton Tomasetti Defence Ltd.

Each model has a domain of 10x10x4 m/kg$^{1/3}$ with a 1 kg TNT hemispherical charge. The minimum z boundary is defined as reflective to replicate a rigid ground plane whereas all other boundaries are transmissive. All obstacles are 4 m tall to match the height of the domain.

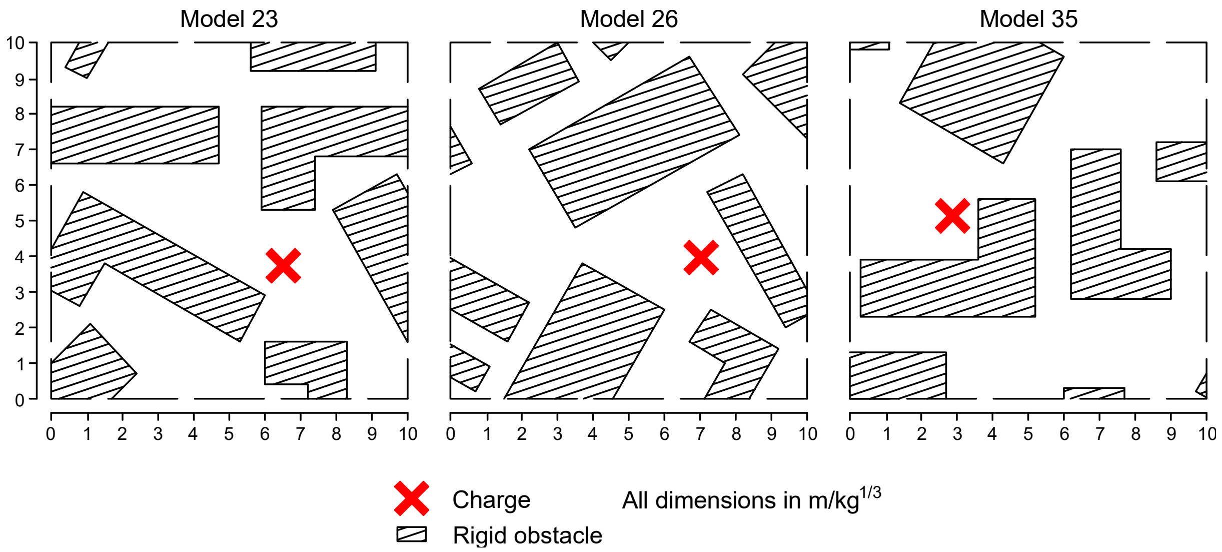

Figure 4. Three example domains used in the training dataset.

The charge position, number of obstacles, obstacle shapes and obstacle positions are all randomised with consideration of their typical size in an urban blast event when applying Hopkinson-Cranz scaling [4, 5]. For example, the 1 kg hemispherical charge in the 10x10 m/kg$^{1/3}$ domain corresponds to a 1000 kg hemispherical charge and a domain of 100x100 m. A building length of 20 m could therefore be represented as 2 m in the scaled training models. Three examples of the training models are given in Figure 4.

Details of the Ideal Gas, walair++ simulations are provided in Table 1. In each case, 1D to 3D mapping was used when the blast wave had propagated 0.5 m/kg$^{1/3}$ from the charge centre. The chosen termination time was found to allow the wave to fully propagate through the domain with any reflections becoming sufficiently small that they no longer influence the peak overpressure values at each gauge.

In each training model gauges were placed with 0.1 m/kg$^{1/3}$ grid spacing in x and y to provide an average of 7464 POIs per domain. Then, as discussed by [7], each POIs directional lasers can be mirrored to double the amount of physically valid input-output training combinations. This ensures that the trained models are consistent for predictions where obstacles are on either side of the POI.

Table 1. walair++ simulation inputs.

Parameter	Value	Unit
CFL 1D	0.5	-
CFL 3D	0.4	-
Termination time	0.075	s
Cell size 1D	0.001	m
Cell size 3D	0.02	m
Spherical charge mass	1.8	kg
Charge density	1600	kg/m^3
Charge initial energy	4.52e6	J/kg

Network Architecture and Training

The ML tool being developed in this study comprises of four individual Multi-Layer Perceptrons (MLPs) with the architecture and hyperparameters given by Table 2.

Table 2. Network parameters and architecture.

Parameter	Value
Inputs	- Shortest path distance (m/kg$^{1/3}$), - 16 directional laser obstructions (m/kg$^{1/3}$), - 16 directional laser angle interactions (°), - 3 peak overpressures at ground level, one from each incoming value position (kPa) [Networks 2, 3 and 4 only]
Output	Peak overpressure at ground level (kPa)
Layers and neuron counts	512 / 512 / 512 / 512 / 512 / 512
Activation function	ReLU
Optimiser	Adagrad
Learning rate	0.02
Dropout	0.03
Batch size	32
Training steps	Maximum 500, early stopping when validation dataset loss does not improve for 10 steps.
Loss function	Mean squared error with added penalty for predictions below 0 kPa.
Weight initialiser	Glorot normal
Bias initialiser	Zeros
Regularisation	L2

Inputs for each network are normalised using the following Z-score equation to rescale the data so that each feature has zero mean and a variance of one. This is a common approach for improving the speed and quality of training [13].

$$Z = \frac{x - \mu}{\sigma} \tag{1}$$

Where Z is the scaled input feature value, x is the original input feature value, μ is the mean of the training samples for this feature, and σ is the standard deviation of the training samples for this feature.

The use of four networks leverages how blast waves decay with distance from the charge, allowing reduced ranges of peak overpressure to be provided to each network during training. This removes the need for a single network to learn the entire parameter space. The choice of network separation given in Table 3's shortest path distance requirement column means that generally N1 predicts values above 1500 kPa, N2 predicts between 200 and 1500 kPa, N3 between 100 and 200 kPa, and N4 between 0 and 100 kPa.

Table 3. Training dataset variables for each network.

Network number	Shortest path distance (s) requirement	Data augmentation approach	Number of datapoints
1	$s \leq 1.5$	-	44904
2	$1.5 < s \leq 4$	Gaussian noise added to incoming values, 10% and 15%.	594864
3	$4 < s \leq 6$		566154
4	$6 < s$		495594

Table 2 showed that N1 does not use any incoming values in its input, instead all predictions for this network rely on the directional lasers and shortest path distance. This allows the tool, comprising of all four networks, to generate initial predictions without any other data from empirical or numerical sources. The results from N1 are used to calculate the incoming values of the first points being predicted by N2 as the wave expands beyond 1.5 m/kg$^{1/3}$. This continues with the final values from N2 initiating N3, and N3 initiating N4.

Random gaussian noise is added to the incoming value inputs to networks 2, 3 and 4. This aims to improve the robustness of the predictions being made by these models when they are provided with incoming values that rely on previous ML predictions that could have some error. A similar technique is used with recurrent or graph neural networks that can be used to predict time series data [14]. Here, the magnitude of the noise for each value is calculated from profiles with standard deviations of 10% and 15% of the value itself. The triples the size of the dataset that extracted from the 40 training models to give the datapoint counts listed in Table 3.

Performance Evaluation

Performance of the trained tool is evaluated by generating predictions for a domain that was not used in the training process. This challenges the networks with unseen sets of inputs whilst also testing the tool's ability to use incoming values that are derived from its own predictions rather than known CFD points.

Figure 5 shows the randomly generated domain. Based on the obstacle positions, there are regions that require predictions of free air propagation, clearing, channelling and shielding.

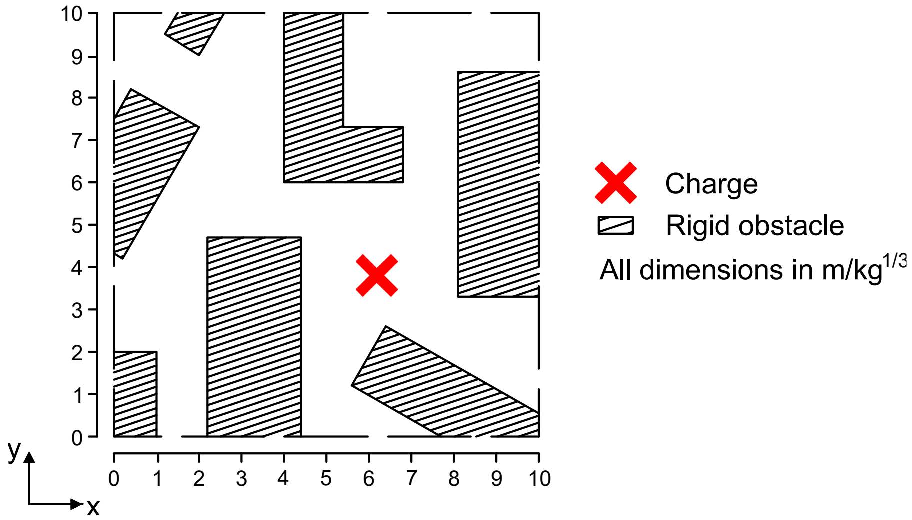

Figure 5. New domain that was not used in the training dataset. Used as a use case test of the developed ML tool.

A comparison of the ML tool's predictions to an equivalent walair++ simulation is shown in Figure 6, where values are capped at 600 kPa to enhance the clarity of the domain beyond the near-field region. It shows that agreement between the methods is very good, particularly in areas of intense pressure build up on the surface of the obstacles.

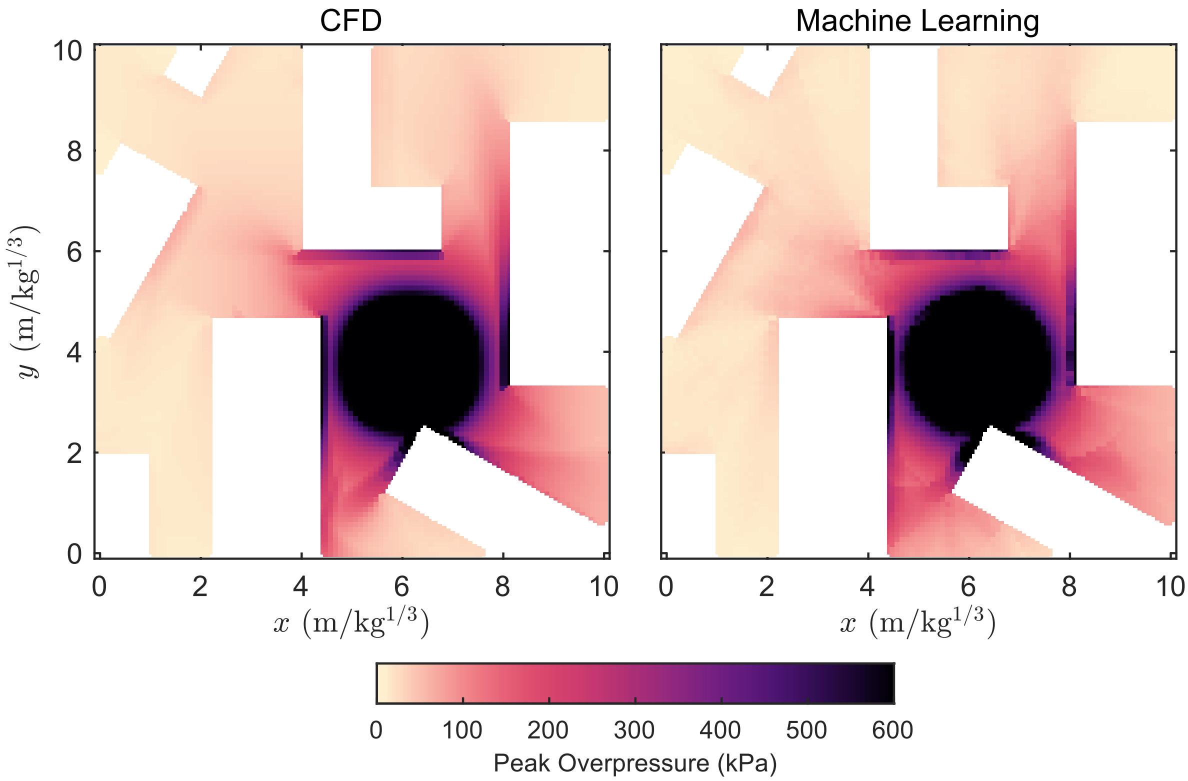

Figure 6. Comparison of the ML predictions and a CFD simulation of the same domain.

Unlike previous rapid analysis tools for urban environments, this approach is also shown to capture channelling and some shielding with good qualitative agreement, particularly around (3, 6), (2, 2) and (9, 2) [x, y]. The addition of interaction angles and incoming values is proved to be effective in expanding the capability of the ML models to understand the relationship between the magnitude of the blast wave and the local surroundings of the POI. However, larger inaccuracies are still observed in shielded regions such as at (7,0.5) [x, y].

Quantitatively assessing the results, Table 4 provides the mean absolute error and percentage error for each network as well as the overall domain performance when compared to CFD. As discussed in [7], solely assessing the percentage error can ignore the success of the ML tool due to the relative magnitudes of the errors being calculated. For example, a 36.5% error for N4 corresponds to a mean absolute error of under 4 kPa. The high percentage error is therefore due to how most points being predicted by this network are under 20 kPa, in highly shielded regions of the domain.

Table 4. Use model performance metrics.

Network number	Mean absolute error (kPa)	Percentage error (%)
1	62.2	4.8
2	19.6	17.2
3	5.9	22.2
4	3.9	36.5
Overall	16.2	22.4

The calculated MAE values are excellent considering the ranges of values being predicted by each network, however, performance of the networks deteriorated as the predictions progressed away from the charge. This is due to incoming values being used as inputs with larger errors than expected for the networks that are responsible for predictions at larger distances from the charge (N3 and N4). Adding more noise to the training inputs to further expand the training process may help to reduce this effect.

Conclusions

This paper has introduced a novel Machine Learning (ML) tool that builds upon work previously published by the author to predict the peak overpressure in urban areas following the detonation of an explosive. This is achieved by training ML models with intersection angles and distances from 16 directional 'lasers' that are projected from point of interest, and three peak overpressure values that indicate the strength of the approaching blast wave. This combines an understanding of the local geometry with an appreciation for how the blast wave has propagated through space in a sequential and expansive manner.

It was shown that for an unseen domain, with peak overpressures ranging from 1 over 5000 kPa, predictions can be generated with a mean absolute error of 16.2 kPa when compared to a CFD simulation. This provides good quantitative agreement alongside an excellent qualitative representation of the threat posed to the environment in under 30 seconds.

Future work will explore how the performance of the approach can be improved through adjusting the input features further, before tuning neural network hyperparameters and altering the network structure. The tool will then be expanded to predict other blast parameters, ultimately allowing for rapid risk-based assessments of threats to urban environments. With this, users will be able to understand specific threat scenarios of interest, where existing CFD solvers such as walair++ can be used for detailed analysis.

Acknowledgements

The author would like to thank Nick Misselbrook, Daniel Clark, Fraser Mackay and Claus Halford from Thronton Tomasetti Defence Ltd for providing access to the walair++ software for use in generating the training dataset used in this study.

References

[1] N. A. Marks, M. G. Stewart, M. D. Netherton, and C. G. Stirling, "Airblast variability and fatality risks from a VBIED in a complex urban environment," *Reliab. Eng. Syst. Saf.*, vol. 209, no. June 2020, p. 107459, 2021, doi: 10.1016/j.ress.2021.107459.

[2] D. Farrimond *et al.*, "Microblast - A benchmarking study of gramme-scale explosive trials," in *26th International Symposium on Military Aspects of Blast and Shock*, Australia: MABS26, 2023.

[3] C. Fouchier, D. Laboureur, L. Youinou, E. Lapebie, and J. M. Buchlin, "Experimental investigation of blast wave propagation in an urban environment," *J. Loss Prev. Process Ind.*, vol. 49, pp. 248–265, 2017, doi: 10.1016/j.jlp.2017.06.021.

[4] B. Hopkinson, "British Ordnance Board Minutes, 13565," 1915, *British Ordnance*.

[5] C. Cranz, *Lehr der Ballistik*. Berlin, Germany: Verlag von Julius Springer, 1926.

[6] A. Dennis and S. Rigby, "Prediction of Blast Loads using Machine Learning Approaches," in *SECED 2023 Conference, Earthquake Engineering & Dynamics for a Sustainable Future, 14-15th September 2023*, Cambridge, UK, 2023.

[7] A. A. Dennis and S. E. Rigby, "The Direction-encoded Neural Network: A machine learning approach to rapidly predict blast loading in obstructed environments," *Int. J. Prot. Struct.*, vol. 15, no. 3, pp. 455–483, Sep. 2024, doi: 10.1177/20414196231177364.

[8] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of Machine Learning*, Second Edi. MIT Press, 2018.

[9] A. A. Dennis, J. J. Pannell, D. J. Smyl, and S. E. Rigby, "Prediction of blast loading in an internal environment using artificial neural networks," *Int. J. Prot. Struct.*, vol. 12, no. 3, pp. 287–314, 2021, doi: 10.1177/2041419620970570.

[10] A. A. Dennis, D. J. Smyl, C. G. Stirling, and S. E. Rigby, "A branching algorithm to reduce computational time of batch models: Application for blast analyses," *Int. J. Prot. Struct.*, vol. 14, no. 2, pp. 135–167, Jun. 2023, doi: 10.1177/20414196221085720.

[11] A. A. Dennis, C. G. Stirling, and S. E. Rigby, "Towards the development of Machine Learning tools for blast load prediction," in *6th International Conference on Protective Structures (ICPS6)*, 14--17th May, Auburn, AL, 2023.

[12] G. Dong and H. Liu, *Feature Engineering for Machine Learning and Data Analytics*, 1st ed. Boca Raton, Florida: CRC Press, 2018. doi: 10.1201/9781315181080.

[13] D. Singh and B. Singh, "Investigating the impact of data normalization on classification performance," *Appl. Soft Comput.*, vol. 97, p. 105524, 2020, doi: 10.1016/j.asoc.2019.105524.

[14] Q. Li, Y. Wang, W. Chen, L. Li, and H. Hao, "Machine learning prediction of BLEVE loading with graph neural networks," *Reliab. Eng. Syst. Saf.*, vol. 241, p. 109639, 2024.