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PREDICTION OF BLAST LOADS USING MACHINE LEARNING APPROACHES

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Abstract: *The assessment of human injuries and structural damage following the detonation of a high explosive requires an understanding of blast load parameters. Use of physical experiments or physics-based numerical tools require large amounts of time and expertise, often restricting their use to deterministic analyses. Since explosive events are inherently unpredictable and key variables (e.g. charge size, mass, composition, location) may not be known a priori, there is a clear need for rapid analysis tools that can embrace this uncertainty in a probabilistic framework. Machine learning tools have been developed for this purpose, however, the features of the problem that are selected as model inputs can result in predictions being fixed to a single domain, thus requiring the tool to be re-trained for every new scenario. This paper details how the Direction-encoded Neural Network (DeNN), a novel Machine Learning method, takes inspiration from the operation of robot vacuum cleaners to prevent this issue by considering the surroundings of each prediction point. Through comparisons to a traditional Artificial Neural Network (ANN), provided with global domain inputs, it is shown that the DeNN's unique feature selection process allows for predictions in domains of variable sizes with movable obstacles, ultimately producing a tool that can be used in a range of studies without requiring additional task-specific training.*

Introduction

With the continual presence of terrorist attacks, conflict and industrial accidents occurring all over the world, understanding the risk associated to the detonation of explosive materials is vital for designing and developing protective structures and procedures that can reduce any detrimental impact on human life. A key component of this involves developing an understanding of how the blast wave that emanates from an explosive compound propagates and interacts with its surroundings.

Historically this was achieved using physical experiments in controlled test environments where the number of trials, extractable data points and variety of test scenarios is limited by cost, safety and expertise. However, the evolution of widely available computing power has meant that this approach is often replaced by validated numerical methods that can be evaluated without data limitations or health and safety risks.

Semi-empirical tools, such as the Kingery and Bulmash method (Kingery and Bulmash, 1984), have been derived from experimental trials that enable the relationships between variables to be defined by simplified equations and charts. The can therefore be implemented rapidly with a reduced number of inputs, yet, this also restricts their use to a limited range of modelling scenarios. Conversely, validated Computational Fluid Dynamics (CFD) or Finite Element (FE) numerical models, such as Viper::Blast (Stirling, 2023), and LS-DYNA (Livermore Software Technology Company, 2015), obey conservation laws in a discretisation of space and time using estimated material properties in an attempt to accurately model the physics of the detonation and the subsequent wave interaction effects. They are therefore well suited to evaluating diverse problems, however, computation times can last many hours or days depending on the complexity of the problem and the desired level of predictive accuracy.

At present, this computational analysis of explosive events is commonly performed using deterministic approaches, providing a single output to a well-defined problem. However, many researchers note that this ignores the variability of the explosion itself and the inherent uncertainty associated to the charge size, shape, location and material that is characteristic of the situations where explosions occur. Probabilistic approaches, such as the one shown in Figure 1, are therefore becoming more common so that the risk associated to a specific outcome can be

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evaluated. Here, various input variables are randomly sampled from independent probability distributions 100 times. Each unique input combination is evaluated using a deterministic model with the outputs forming probability distributions that enable the risk of specific occurrences to be understood and used in decision making processes.

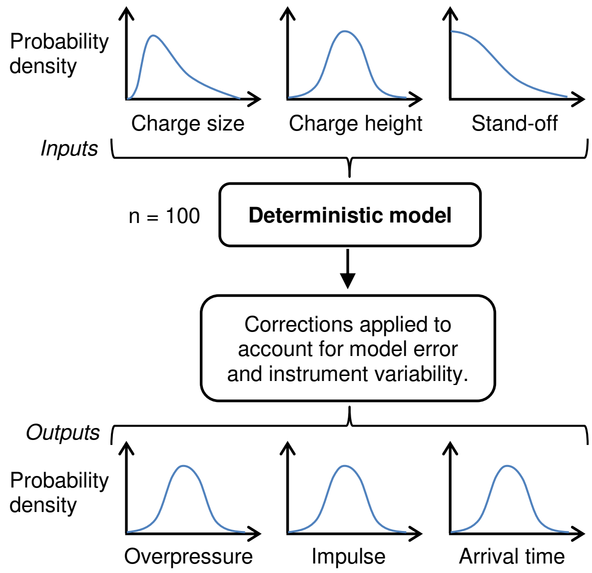

Figure 1. Example probabilistic framework.

Clearly, the move towards this approach still relies on a suitable deterministic model that can accurately represent the physics of the various scenarios being simulated. Moreover, the chosen model must be rapid in its execution of each unique scenario so that the time required to develop a comprehensive understanding of the threat is not unfeasible.

This paper discusses recent progress made in this field in terms of the development of Machine Learning (ML) tools for blast load predictions that provide accuracy and reduced computation times for a range of scenarios. It is shown how consideration of an additional variable, versatility, is also essential when developing fast running engineering models (FREMs) that can be useful in a range of probabilistic scenarios.

Machine Learning in Blast Engineering

Background and example applications

The requirement for rapid analysis tools to evaluate large batches of models in probabilistic frameworks with limited computational expense is highlighted by Figure 2. Here, a target zone is positioned such that the combination of rapid execution from the semi-empirical, quick running methods is met by the accuracy of the physics-based numerical models.

Machine Learning methods present a means of achieving this goal due to their simplified calculation approaches that have been shown to provide low percentage errors and high correlation coefficients between targets and predictions in a wide range of disciplines. In simple terms ML tools learn the relationships between a series of input variables during a training process that optimises various parameters to improve the predictive accuracy of the model. The setup of each tool is initially dictated by a range of bespoke hyperparameters that control the structure and training progress, however, these can be tuned during development. This enables ML based approaches to generalise highly complex, multi-parameter problems to generate predictions for unseen input combinations, provided that they fall within the bounds of the training variables (Dennis et al., 2021).

There are many instances of ML tools being used to solve problems related to Blast Engineering, including applications for near field loading, obstructed environments and behind blast walls. Table 1 provides a summary of a select range of studies to highlight the diversity in the way that problem-specific blast load predictions are generated.

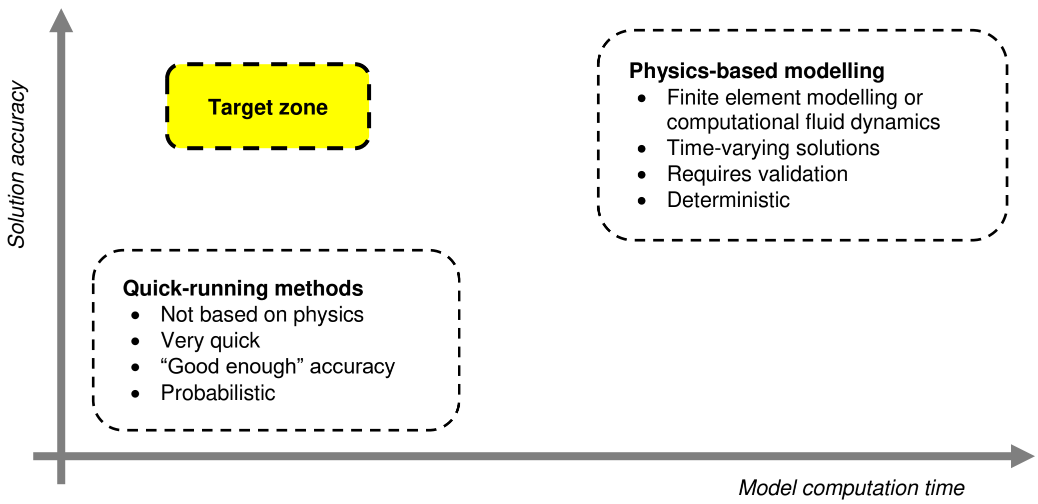

Figure 2. Comparison of model computation time and solution accuracy, showing the zone that is commonly considered to be a target for the development of fast running engineering models (FREMs).

Reference	Machine learning tool	Scenario	Inputs	Output(s)
Dennis et al. 2021	Multi-layer perceptron	Partially internal room	POI x and y coordinate. Charge x and y coordinate. Charge size	Peak Overpressure
Pannell, Rigby and Panoutsos, 2022a	Transfer neural network	Near field panel loading	Angle of incidence. Scaled distance. Length/diameter ratio.	Peak specific impulse
Pannell, Rigby and Panoutsos, 2022b	Physics guided neural network	Near field panel loading	Angle of incidence. Scaled distance.	Peak specific impulse
Remennikov and Rose, 2007	Multi-layer perceptron	Effectiveness of blast walls	Wall, charge and target height. Distance from wall to target. Distance from wall to charge. All scaled according to charge size.	Peak overpressure and specific impulse
Li et al., 2023	Transformer neural network	Free air	Tank failure pressure. Liquid fill ratio. Tank width, height and length. Explosive material height. Vapour and liquid temperature. Liquid status. Vapour height and stand-off distance.	Peak overpressure
Zahedi and Golchin, 2022	XGBoost	Protruded structure	Protrusion length and height, charge size and stand-off, POI x, y and z coordinates.	Peak overpressure and impulse

Table 1. Applications of Machine Learning tools in blast related literature. Some inputs refer to a POI – point of interest.

Each study presents notable developments related to how ML based tools could be created. For example, Pannell, Rigby and Panoutsos (2022) trained a neural network (NN) to predict the specific impulse from the detonation of cylindrical charges that incorporated a NN that was previously trained to predict the output from spherical charges. This transfer network ultimately enabled a reduction in prediction variability when compared to a new NN that had no integration with previous data. Furthermore, the gap in performance continued to increase as the training dataset reduced, showing the transfer learning can be used to supplement problems where data collection is challenging.

Similarly, Li et al. (2023) present a comparative study between a Gradient Boosted Decision Tree (GBDT), a multi-layer perceptron, an image recognition based Residual Network (ResNet), and a Transformer NN. Despite this type of network originally being developed to process sequential data (Vaswani et al., 2017), for the specific application, data processing approach and hyperparameter limitations applied in this study, the transformer was shown to provide the most accurate predictions for a regression based task. Li et al. (2023) therefore conclude that this approach provides the best performance, drawing attention to how many previous studies have defined the 'best' performing tool as the one with the lowest prediction errors, ignoring the requirements for training data, training time, and resulting tool versatility.

Model versatility

The idea of tool versatility is worth noting as ML models progress to deployment and use in industry based applications. In each example provided in Table 1 the input parameters are intrinsically linked to the scenario being modelled. In some cases this means that a change to the basic domain arrangement would require a new model to be developed. For example, in the study by Dennis et al. (2021), Cartesian coordinates are used to define where the point of interest (POI) and charge are positioned in a fixed domain. If a user required predictions in a domain of a different size or shape, the developed tool would not be able to provide reliable predictions, thus necessitating an entirely new training process with a new dataset.

It is common for training datasets to be formed through a data collection process that requires the simulation of tens, or hundreds, of physics-based numerical models that encompass the problem that the tool is being developed to model. In situations where the developed tool is only applicable to a select range of explosive scenarios, the computation time associated to its development can therefore become comparable to exclusively using numerical models in the analysis of a given problem. For some ML based applications that are thought of as being positioned around the target zone of Figure 2, the underlying cost of development is ignored despite this being a key factor in determining if a tool is useful in practice.

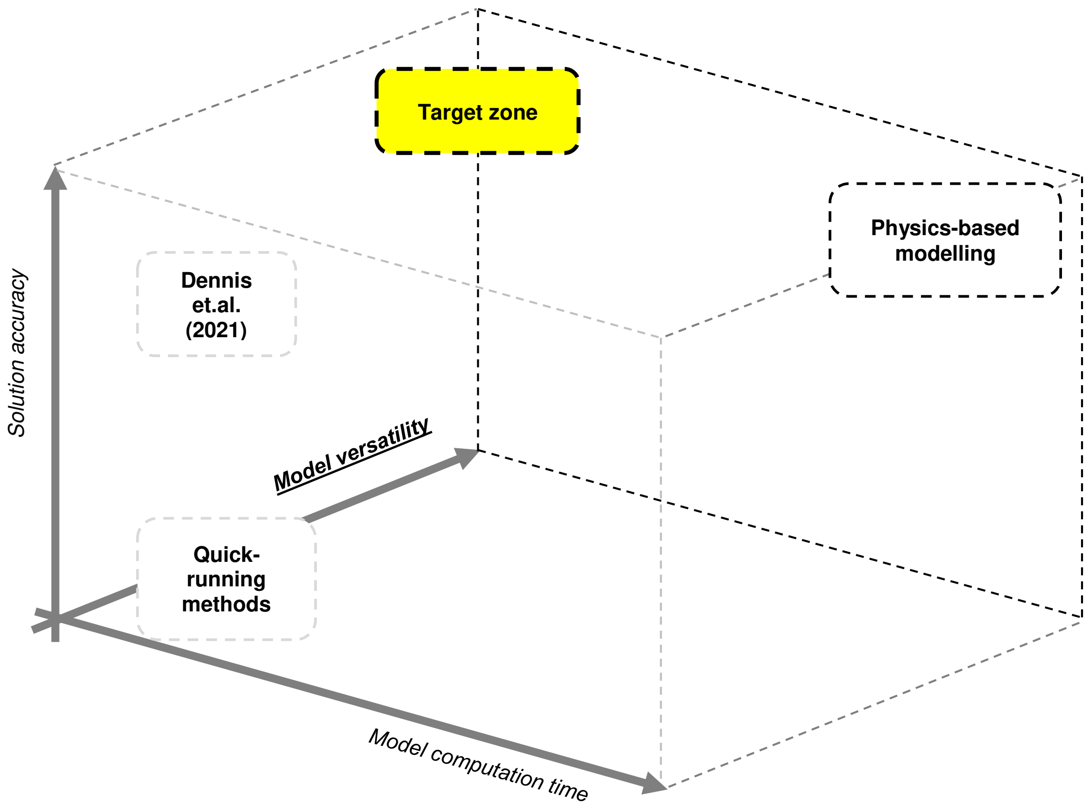

Figure 3. The proposed target zone for FREM development, incorporating the versatility of the tool being produced.

Consequently, Figure 3 provides an updated view of the target zone for FREM development considering a new set of axes that includes model versatility. This provides a distinction between ML tools that are developed with limited scope for reuse in alternative studies and tools that are able to be applied more generally to blast loading based problems. It is shown that the resulting network from the study by Dennis et al. (2021) may achieve suitable computation time and accuracy, but it's limitations associated to varying domain arrangements restricts its versatility and use in probabilistic studies where obstacles and alternative domain shapes may need to be evaluated.

The Direction-encoded Neural Network

Introduction

An example of a ML tool that aims to provide versatility in its application is the Direction-encoded neural network (DeNN) introduced by Dennis and Rigby (2023) and used to analyse a batch of models by Dennis, Stirling and Rigby (2023). Through a novel feature engineering process, the inputs to the multi-layer perceptron neural network are related to the surroundings of each prediction POI instead of any global domain properties. Predictions of peak overpressure can therefore be generated for points in obstructed environments of any shape and size, with movable obstacles and charge positions.

Inspired by how autonomous robot vacuum cleaners use ultrasonic or infrared sensors to navigate their surroundings (Chiu, Yeh and Lin, 2009; Kang et al., 2014), Figure 3 shows how the inputs to the DeNN are formed with 16 directional 'lasers' that are projected from the POI. As with robot vacuum cleaners, each laser is used to calculate an obstruction distance to a surface. However, in this application, if no rigid surface is met, the corresponding directional input equals 0. Conversely, identification of a rigid surface means that the directional input is evaluated using the following equation:

$$\text{Directional input} = \max(\text{Wave travel distance} - \text{Obstruction distance}, 0) \qquad (1)$$

Where the wave travel distance is calculated as the shortest path between the charge centre and each POI on a 2D plane.

The wave travel distance is also used as an input to the DeNN to complete the set of 17 values that are used to form predictions at each individual point in a given domain. As shown in Figure 3, directional input 1 must point towards the charge centre, removing symmetrical prediction issues by allowing the rosette of lasers to rotate relative to the position of the charge.

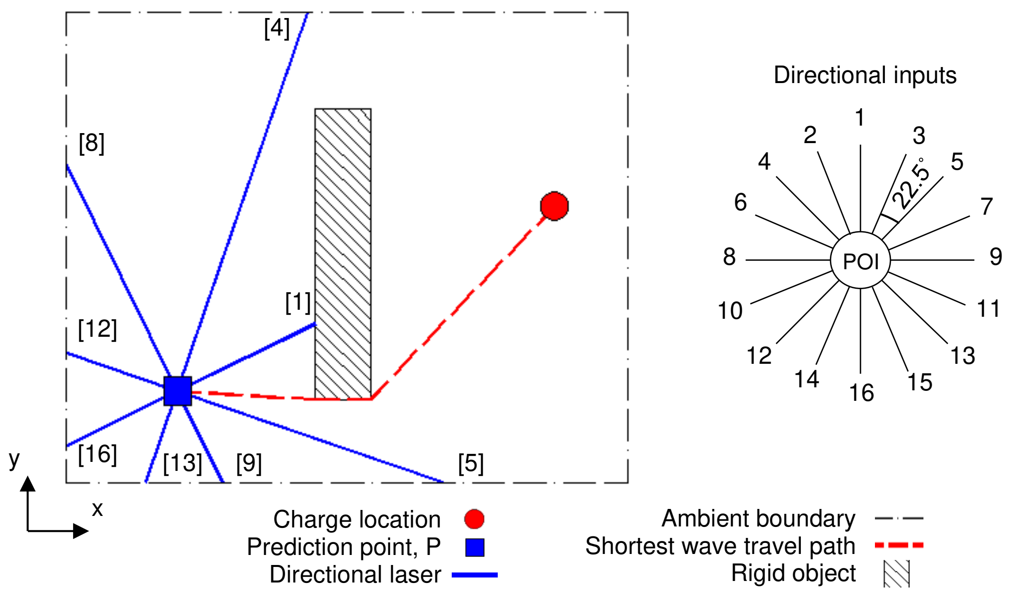

Figure 4. Example application of the DeNN directional inputs. Only 8 directions shown on the domain plot for brevity. Note that direction 1 points towards the charge.

Performance overview

In the introductory study for this approach by Dennis and Rigby (2023), the authors trained the DeNN using 25 domains that featured randomised object counts, object sizes and domain sizes. The developed tool can therefore be applied to any domain provided that the inputs associated to a new problem fall within the bounds of the original training dataset. This includes a requirement for all POIs to have an elevation, and minimum clear distance from the charge, of 1.5m.

Figure 5 provides a comparison of two models that conform to these requirements when modelled using the numerical solver Viper::Blast and the DeNN.

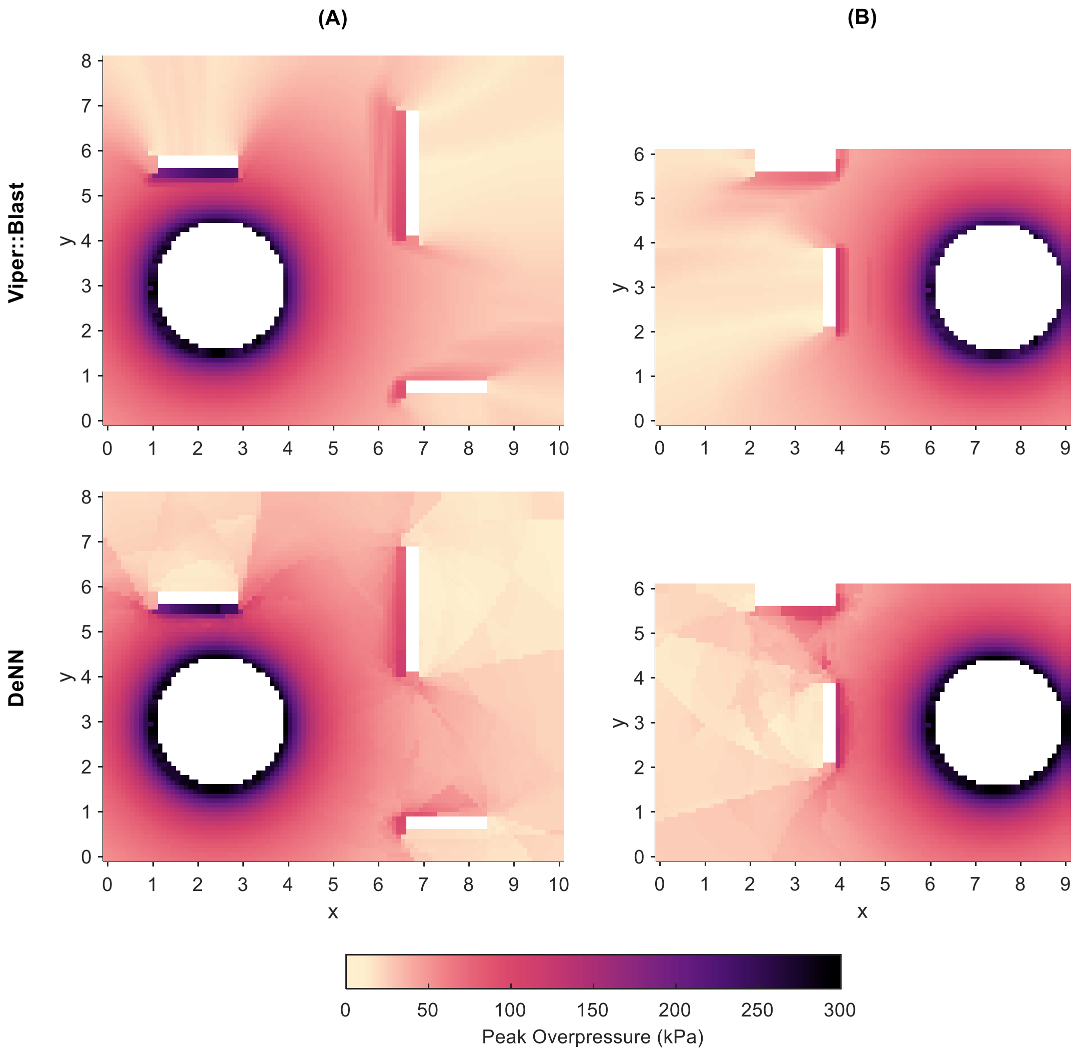

Figure 5. Peak overpressure comparison between the DeNN and Viper::Blast. White regions indicate points without a prediction due to being within a rigid obstacle, or the 1.5m exclusion zone around the charge.

Domain	MAE (kPa)	Young's correlation, R_t^2	Average percentage error (%)
A	3.05	0.9970	9.4
B	3.76	0.9965	13.4

Table 2. DeNN performance statistics following a comparison with Viper::Blast.

It is shown that the DeNN is able to qualitatively, and quantitatively, capture the distribution of peak overpressure for two unseen domains with sizes and obstacle locations that were not included in the development of the tool. The performance statistics shown in Table 2 prove that this approach is capable of providing useful results in analyses the evaluation of large batches of domains with relative errors below 15%.

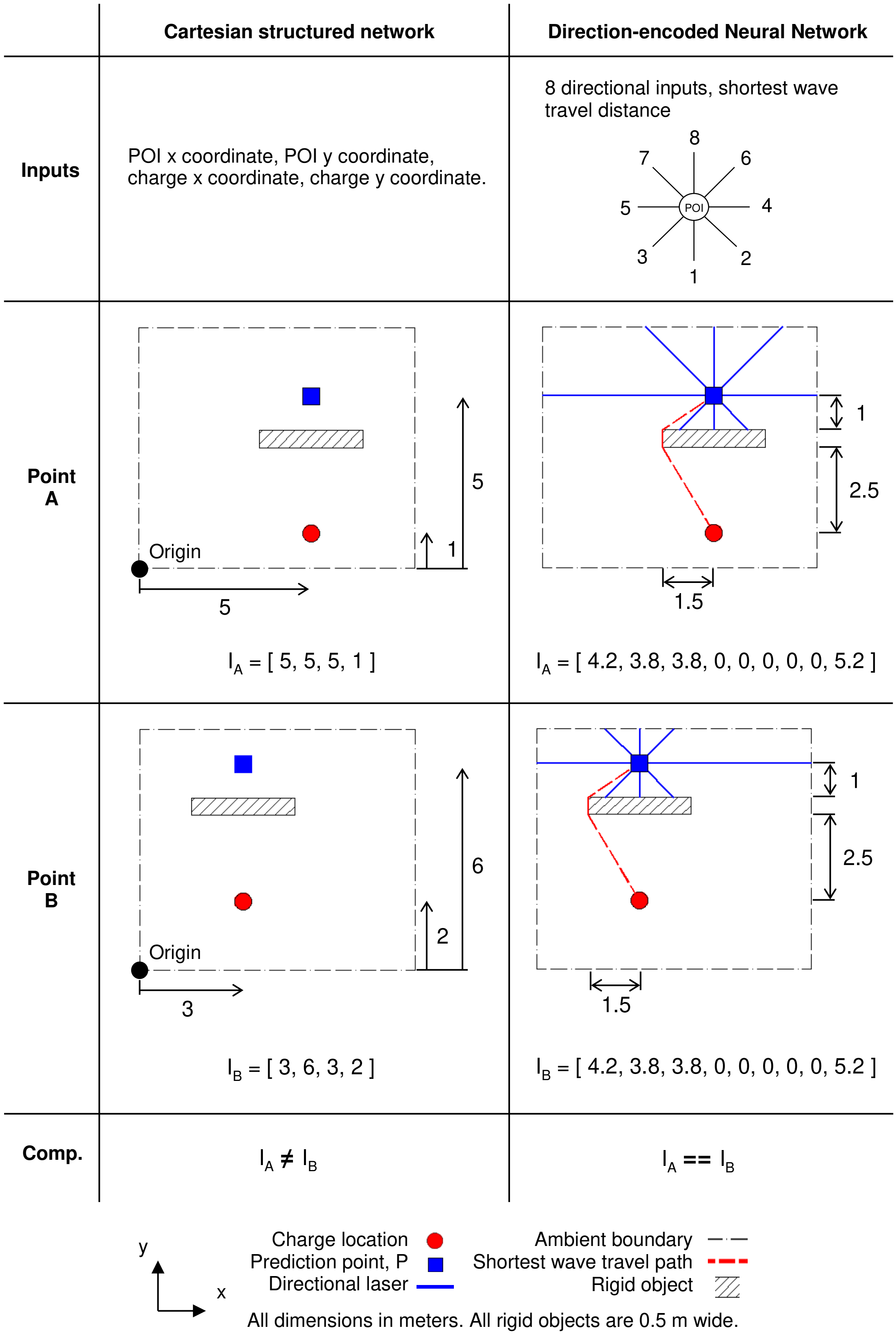

Figure 6. Comparison between how the input pattern is formed for two nominally identical points for a Cartesian structured NN versus the DeNN.

Comparison with previous approach

As mentioned previously, use of Cartesian coordinates for inputs to a ML tool that aims to model an obstructed/internal environment limits is application to scenarios that respect the same user-defined origin. The understanding of the relationship between the charge and POI positions is dependent on this fixed location and so obstacles must also remain in the same positions relative to this point. The DeNN averts these issues by receiving inputs that are relative to the POI itself, meaning the surroundings can change without preventing the tool from being applied.

Figure 6 provides a simple example of this to highlight the robust nature of the feature set used by the DeNN, where two POIs should be predicted with equal overpressures. Considering how points A and B are translated to the respective ML models, it is shown that use of Cartesian coordinates produces differing input patterns whereas the DeNN (with 8 directional inputs shown for clarity) provides consistent inputs to ensure equal predictions.

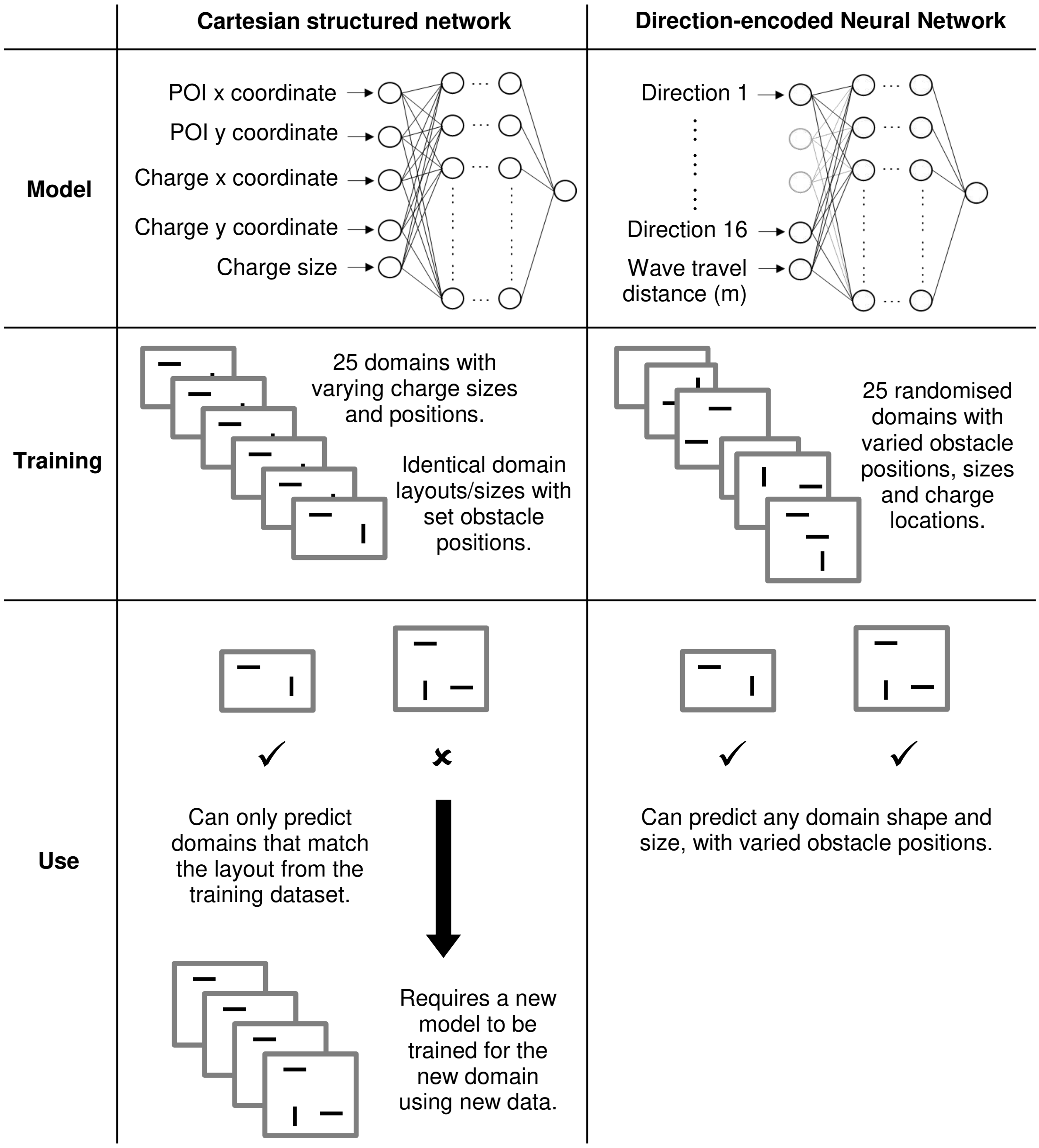

Figure 7. Comparison between an ANN that uses Cartesian inputs and the Direction-encoded Neural Network, using inputs that are relative to the POI and the charge.

In many studies where a similar dependency is present between the POI and some fixed point, the relationship between the charge and the POI is dependent on the network's understanding of the overall topology of the output value, instead of the mechanics of the blast wave and the interaction effects that will alter its magnitude.

Considering the benefit of the DeNN in terms of the development of FREMs, Figure 7 presents a comparison of the workflows that would be required when using an approach similar to the one explored by Dennis et al. (2021) and the DeNN. Using the former approach, a new dataset would have to be developed for each new application of the ML tool, while the generalised approach taken with the DeNN enables its use in a wider range of studies.

Conclusion

To conclude, it is well established that Machine Learning (ML) tools are capable of understanding the effects caused by the detonation of various explosive materials in a range of scenarios. Many studies that focus on this topic produce models with very good accuracy and low computation times, yet the versatility of the tool is rarely discussed.

For predictions in obstructed/internal environments, previous work has relied on globally referenced inputs that prevent the developed model from being used if the domain layout is required to change. The models are required to understand how the topology of the parameter space changes relative to fixed global parameters, as opposed to learning about the blast wave and its interactions directly. It was shown that a change to the prediction domain would require an entirely new model to be developed, necessitating the collection of more training data that is often costly in terms of computation time.

The Direction-encoded Neural Network (DeNN) therefore predicts peak overpressure based on the path that the blast wave has to take to reach the POI, in addition to the surrounding rigid reflecting surfaces that create coalescence effects (Dennis and Rigby, 2023). This results in the development of a robust model that can evaluate domains of any shape and size, with movable obstacles and charges. The approach acts as an example of how novel feature engineering can improve the versatility of ML tools that can ultimately be used in probabilistic studies where various domain parameters are required to change during the assessment of any given threat.

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