IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 5 February 2023, accepted 7 March 2023, date of publication 15 March 2023, date of current version 20 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3257345

RESEARCH ARTICLE

Prediction of Peak Pressure by Blast Wave Propagation Between Buildings Using a Conditional 3D Convolutional Neural Network

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This work was partly supported by Agency for Defense Development and Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.RS-2022-00155857, Artificial Intelligence Convergence Innovation Human Resources Development (Chungnam National University)).

ABSTRACT To predict the damage resulting from an explosion in the middle of a city, where buildings are concentrated, the peak pressure reaching the walls of the buildings or in between buildings should be accurately and rapidly calculated. However, predicting peak pressure between buildings is known to be very difficult because of the diffraction and reflection of blast waves, which have generally been analyzed by numerical analysis methods. However, numerical analysis is not suitable in a military operation environment which requires rapid analysis, because it takes considerable time and resources. This study proposes a deep neural network that quickly and accurately predicts the peak pressure caused by the propagation of blast waves, for the effective analysis of weapon effectiveness and damage in urban environments. The proposed deep learning model is based on a 3-dimensional convolutional neural network (3D CNN) model that processes the spatial information of explosion and measurement in the 3D spaces using 3D kernels. To predict the peak pressure between buildings separated by an arbitrary distance using a single model, we also propose using conditional convolution, which modulates the prediction output according to the building distance. The proposed models were trained with a dataset constructed through finite element analysis with various building distances, explosion locations, and explosive weights. The experiment with a fixed building distance showed that the relative error of the proposed 3D CNN is less than 7%, which is 2.5 times more accurate than a simple multi-layer perceptron (MLP) model. For unseen building layouts, the conditional 3D convolution showed 3.6 times lower error than the MLP model, demonstrating the effectiveness of the conditional convolution for prediction in arbitrary building layouts. Most importantly, the proposed deep learning models took less than one minute per prediction, which is significantly faster than finite element analysis, which takes 6 to 8 hours to analyze a single simulation case.

INDEX TERMS Blast wave propagation, blast response, damage assessment, CNN, deep learning, CFD, Ansys Autodyn.

I. INTRODUCTION

The task of weapon effectiveness analysis is to quantify the degree of damage that can be inflicted on a target by weapons. To accurately predict the damage inflicted in internal or external components such as buildings, personnel, and machines by an explosion, it is necessary to calculate the peak pressure at each target location, by analyzing the blast wave propagation generated by the explosion [1]. The propagation of blast waves varies greatly depending on the local environment. The theory of blast wave propagation in open areas and free spaces is well known, and physical quantities such as pressure, impulse, and duration of blast wave can be predicted with acceptable accuracy using models

The associate editor coordinating the review of this manuscript and approving it for publication was Jesus Felez.

such as Kingery-Bulmash model, which were developed using experimental data [2]. When an explosion occurs externally, blast damage to a single building and its internal and external components can be assessed by calculating the load caused by blast waves acting on the building structural members according to the Kingery-Bulmash model, and the methodology described in UFC-340-02 [3]. However, when several buildings are located closely together, and the gap between buildings is not large enough, it becomes impossible to apply the Kingery-Bulmash model and UFC 340-02 methodology. When the distance between buildings is less than the width or height of the building, it is very difficult to predict the peak pressure in the space between buildings due to the diffraction and reflection of the blast waves [4], [5], [6]. Until now, numerical simulations using finite element analysis tools ([7], [8], [9]) have been considered the most accurate method for predicting blast wave propagation. However, these models require considerable amounts of processing time to complete the simulation run, even with top-of-the-line computers. Therefore, numerical analysis is not suitable for military operational environments that require the rapid prediction of damage or weapon effectiveness.

While a few studies have improved prediction speed by using equations empirically generated based on the results of multiple finite element analysis [13], [14], they provide fair accuracy only in specific configurations assumed by the equations. In an effort to increase accuracy as well as the speed, recent studies introduced neural networks that can predict explosion pressures in complex environments [15], [16]. However, these studies utilized simple multi-layer perceptron (MLP) models, and they did not consider various interference effects produced by buildings in a city center.

In this study, we develop a method that can quickly predict damage when an explosion occurs in the middle of the city where buildings are concentrated. The proposed method utilizes artificial neural networks to overcome the significant computational cost required by numerical analysis based peak pressure estimation. The explosion scenarios in actual combat environment can be so diverse that a single deep learning model cannot cover them all with high prediction accuracy. Therefore, this study focuses on common scenarios in structured environments with buildings of the same size and shape placed in a straight line, which is generally assumed to be the case in urban combat situations by most weapon effectiveness analysis methods. In short, the purpose of this work is to predict the peak pressure at certain locations between buildings with arbitrary spacing, when variable weights of TNT (trinitrotoluene) explosives are exploded at diverse locations.

Among these diverse variables, the location of the explosion, the weight of TNT, and the peak pressure at each measurement location involve information in three-dimensional (3D) space. Therefore, instead of simply supplying their numerical values to the model, we propose constructing them as 3D features. To effectively learn and infer these 3D features, we design a model based on a 3D convolutional neural network (3D CNN) that performs the transformation between three-dimensional features.

As mentioned above, this work aims to predict the peak pressure between buildings when the buildings are spaced with arbitrary distances. Therefore, it is necessary to develop a method that can effectively perform inference at different distances using a single model, so that simulations of varying distances do not require additional data collection and model learning. To accomplish this, building layout information should also be provided to the model so that the model can consider the spatial relationship between the buildings and the explosion/measurement space. This information can be regarded as a condition variable that affects the CNN model's function between the input and output features. Accordingly, we apply the conditional convolution technique, which has been used to effectively supply condition variables for deep learning models. Specifically, the building distance information is supplied to the intermediate layer of the model using the feature-wise linear modulation technique, to effectively predict the peak pressure for various building placement environments.

To train the deep learning model with high inference accuracy, we constructed a large quantity of relevant data through numerical analysis. The performances of the proposed models, a 3D CNN and a conditional 3D CNN with building layout conditions, were compared with a simple multi-layer perceptron (MLP) model as well as a finite element analysis technique. The experimental results showed that the average root mean square error (RMSE) of the peak pressure values predicted by the proposed model is within 7% of the peak pressure values from a finite element analysis technique, for an arbitrary explosive position and TNT weight in a trained building placement scenario. The 3D CNN showed 3.8 times and 2.5 times higher accuracy than the MLP model using 3D coordinate features or distance-angle features. In addition, the peak pressure prediction even in unseen building placement conditions exhibited relative error within 10%, which is 2.6$\sim$3.6 times less than the prediction from the MLP models. Most importantly, the proposed model took only about 40 msec to predict one scenario, significantly reducing prediction time compared to finite element analysis techniques, which take 6-8 hours.

The key contributions of this paper can be summarized as follows:

- This is the first study that utilizes an artificial neural network to predict peak pressure between buildings after a weapon explosion, as far as we know.
- This paper proposes an effective neural network architecture for predicting peak pressure in cases with diverse building layout by exploiting 3-dimensional convolution and conditional convolution.
- The proposed model achieved fair prediction performance (less than 10% relative error) compared to finite element analysis, with a significantly lower computing latency.

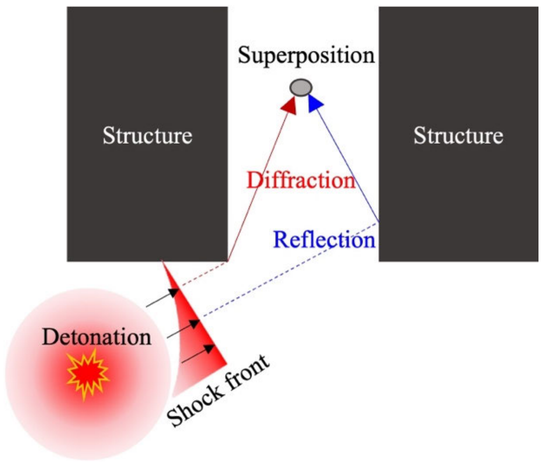

FIGURE 1. Diffraction and Superposition of blast waves between buildings.

The rest of this paper is organized as follows. Section II introduces related studies and the theoretical background of this study. Section III describes the construction of training/validation data. In Section IV, we propose three types of deep learning models, a simple multi-layer perceptron, 3D CNN, and conditional 3D CNN, for peak pressure prediction. Section V evaluates the proposed method against other approaches, and Section VI concludes our study.

II. RELATED STUDIES

To rapidly calculate the peak pressure of blast waves propagated by weapon explosions in open space, Kingery-Bulmash (K-B) charts [10] are commonly used. However, the K-B chart is more limited in a city with many buildings because it does not consider reflection and diffraction generated between buildings.

When blast waves are propagated in a narrow passage between buildings, reflected waves are generated from the outer walls and the ground of the building as shown in Figure 1. It is then diffracted by the corners of the building, and the intensity of the peak pressure is reduced. These reflected waves, diffraction waves, and waves with interference effects are overlapped at the point where the peak pressure is measured. To predict the peak pressure without using simulations, the waves and their interference effects have been theoretically calculated. The reflected wave can be calculated by applying the reflection coefficient to the peak incident pressure, as follows [11]:

$$P_r(t) = C_R \times P_{SO} \times \left[1 - \frac{(t - t_A)}{t_0}\right] \times e^{-\left(\frac{t - t_A}{\theta}\right)} \quad (1)$$

where $P_r(t)$ is the time-pressure history of the reflected wave (kPa), C_R is the reflection coefficient, P_{SO} is the peak incident pressure (kPa), t_A is an arrival time of the initial shock front (msec), t_0 is the positive pressure duration (msec), and θ is the shape constant of the pressure waveform.

Diffraction waves have been continuously studied to determine diffraction coefficients. Miller et al. noted that the diffraction coefficient of a rectangular structure is 0.35 [12]. When theoretically calculating the overlap of waves with this interference effect, it is impossible to calculate all waves reaching the pressure measurement position, so only a few waves with high pressure are added. While theoretical equations have been used when quickly considering interference effects such as reflection and diffraction, the accuracy was inevitably reduced by the many assumptions and limited theoretical predictions. Therefore, in an environment where reflection and diffraction occur a lot, peak pressure analysis is generally performed using a numerical analysis tool, which has been proven to be the most accurate compared to the actual experiments.

Using numerical analysis to predict blast propagation involves a considerable amount of computing time. However, in a military environment, much faster prediction methods are required than is possible with a numerical analysis program to provide rapid analysis of the damage or weapon effectiveness. Recently, studies have been conducted to improve prediction speed with high accuracy, by developing empirical prediction equations based on numerical analysis. For instance, Sung et al. proposed a simplified explosion prediction method acting on structures located at the rear of a single barrier [13]. In this technique, the peak pressure is predicted based on a wave propagation distance and a diffraction coefficient empirically generated by the finite element analysis results. In [14], a model was developed that predicted the magnitude of the pressure acting on the column by calculating an interpolation equation based on the results of a finite element analysis when the blast wave propagated. However, it still has poor predictive performance compared to finite element analysis and cannot be applied to various environments such as the space between two buildings.

In an effort to increase accuracy and the speed of calculation, research has also begun to predict peak pressure using neural networks. Remennikov et al. [15] and Bewick et al. [16] developed high-speed analysis models that can predict the effects of explosion pressure on structures above a barrier by applying neural networks. Zhou et al. proposed an approximate similarity analysis formula based on the optimal curve of numerical simulations [17]. Because neural network approaches are nonlinear and perform well on problems involving many independent variables, they are suitable for predicting explosion pressures in complex environments.

Until now, there has not been much research using neural networks that predict blast propagation or blast pressure under the various interference effects produced by buildings in a city center. In addition, existing studies of neural network based peak pressure prediction have mainly utilized simple multi-layer perceptron (MLP) based models, and no study has used CNNs to predict the peak pressure of a blast wave. In this study, we propose using 3D CNN models to speed up the online prediction of peak pressure while maintaining a

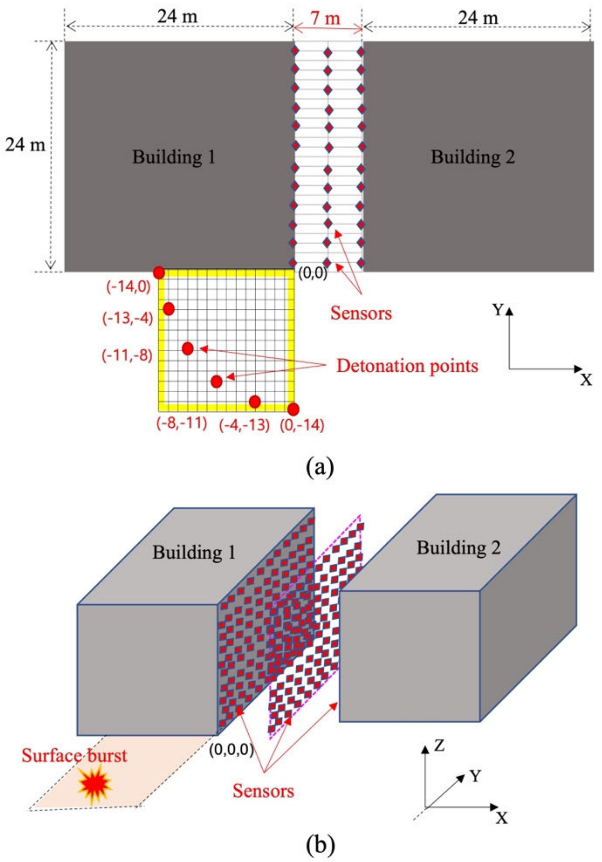

FIGURE 2. (a) Model for finite element analysis shown in top view and (b) shown in bird-eye view.

level of accuracy similar to that achieved by finite element analysis.

III. DATA CONSTRUCTION

To train and test the proposed neural network models that predict the peak pressure, we first constructed a dataset by performing the finite element analysis using a commercial software called AUTODYN [18]. An analysis was performed using commercial hydrocode under various scenarios, with the goal of establishing a database to develop a rapid-process model capable of analyzing a blast wave while also considering interference phenomena such as reflection and diffraction produced by buildings.

A. DESIGN OF FINITE ELEMENT ANALYSIS SCENARIOS

Figure 2 shows the environment for the blast wave propagation analysis considering the interaction between buildings. The buildings were assumed to be rigid, and the size of each building is 24 m (width) × 24 m (length) × 24 m (height). Since the distance between buildings in the city is generally about 7m, two buildings that are placed with an interval of 7 m on the X-axis, as illustrated in Figure 2. The variable environmental settings for AUTODYN analysis are shown in Table 1.

TABLE 1. Environmental variable value set for AUTODYN.

Parameter	Value
Equation of State	*Ideal Gas*
Reference density	*1.22500E-03 (g/cm3)*
Gamma	*1,40000E+00 (none)*
Reference Temperature	*2.88200E+02 (K)*
Specific Heat	*7.17600E+02 (J/kgK)*

TABLE 2. Detailed information on explosive set.

Parameter	Value
Equation of State	*JWL*
Reference density	*1.63000E+00 (g/cm3)*
Parameter A	*3.73770E+08 (kPa)*
Parameter B	*3.74710E+06 (kPa)*
Parameter R1	*4.15000E+00 (none)*
Parameter R2	*9.000004:40 (none)*
Parameter W	*3,50000E-01 (none)*
C-J Detonation velocity	*6.93000E+03 (m/s)*
C-J Energy / unit volume	*6,00000E+06 (kJ/m3)*
C-J Pressure	*2,10000E+07 (kPa)*
Auto-convert to Ideal Gas	*Yes*

It was assumed that the explosive is hemispherical TNT without a shell that explodes on the ground, and simulations of seven TNT weights (900 kg, 1000 kg, 1100 kg, 1200 kg, 1300 kg, 1500 kg, and 2000 kg) were performed, considering that typical weapons used to hit buildings are about 1 to 2 tons. The explosion occurs in an area 14 m (horizontal) x 14 m (vertical) forward of Building 1, as shown in Figure 2. To determine the explosion distance, we performed an initial simulation by changing the distance from a distance of 0 m (the lower right corner of Building 1) to a distance of 24 m, which is the horizontal length of Building 1. The case of the distance 14 m was determined to best represent the pressure difference between buildings, and the diffraction at the corner of Building 1.

We selected explosion locations at six points about 14 m distance from the origin. Figure 2 shows the explosion locations whose coordinates were (−14, 0), (−13, −4), (−11, −8), (−8, −11), (−4, −13), (0, −14), assuming the explosion takes place on the ground. A total of 42 scenarios were composed using a combination of seven TNT weights and six explosion locations. Detailed information about the explosives is provided in Table 2.

The locations of gauges (sensors) used to measure the peak pressure are shown in Figure 2, from a top view and a birds-eye view. When the distance between buildings is 7 m, three planes containing the gauges are located on the right wall of Building 1 (X = 0 m), the middle point between two buildings (X = 3.5 m), and the left wall of Building 2 (X = 7 m), respectively. Figure 3 shows the gauge locations in each plane. Twelve rows and columns of gauges were arranged at intervals of 2 m starting from a point 1 m from the origin on the Y and Z axes, respectively. In three planes (X=0 m, 3.5 m, 7 m), the positions of the gauges are the same. Therefore, the total number of gauges used for one analysis is 432, which is

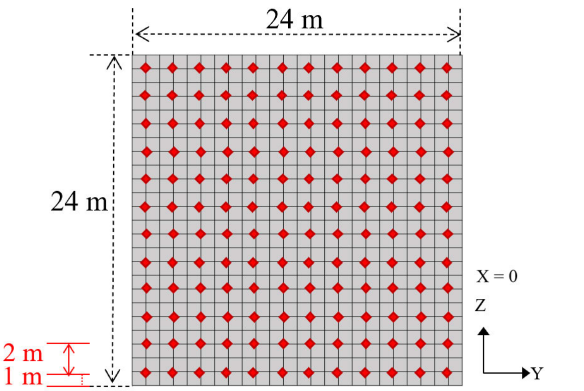

FIGURE 3. Position of gauges for the peak pressure measurement on the side wall of Building 1 (X=0).

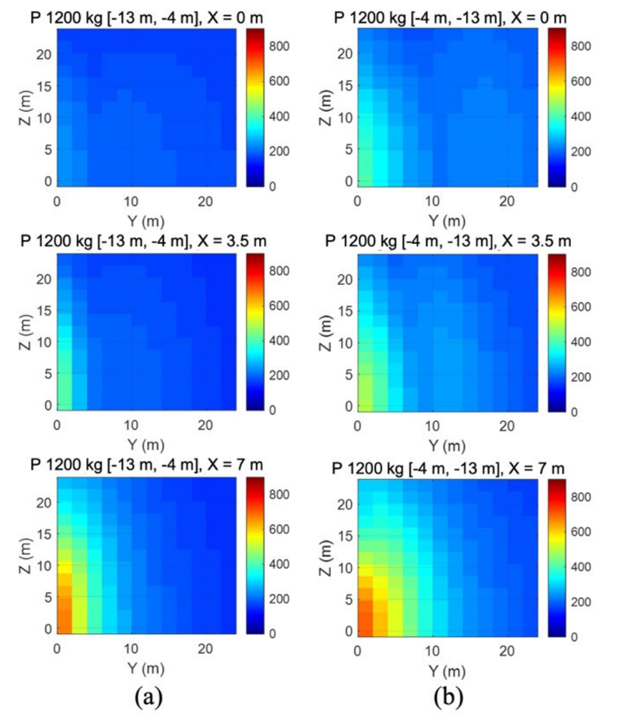

FIGURE 4. Results of AUTODYN analysis for the peak pressure (kPa) between buildings (X = 0 m (right wall in Building 1), X = 3.5 m (intermediate between Building 1 and Building 2), and X = 7 m (left wall in Building 2)).

the product of the number of gauges, 144, and the number of planes, 3.

In order to compare the predictive performance on an arbitrary building layout, the analysis model was additionally composed of cases with building distances other than 7m. That is, the spacing between buildings also included 3m, 5m, 9m, and 11m in addition to 7m. In these cases, one plane of gauges was located in the middle between two buildings, and other two planes were located on two walls of the buildings, as in the 7m distance case.

B. FINITE ELEMENT ANALYSIS RESULTS AND DATA CONSTRUCTION

Figure 4 compares the analysis result when the distance between buildings was 7m and the explosion location was at $(-13, -4)$ and $(-4, -13)$, with 1200 kg of TNT weight. The figure shows that the explosion pressure measured at X = 0 m is smaller than the pressure measured at X = 7 m, although the gauges at X=0 were closer to the explosion point. This is because the large diffraction angle of the blast wave at X = 0 resulted in a reduction in peak pressure. Figure 5 shows the pressure distribution of the gauges on the left wall of Building 2 when 1200 kg of TNT explodes at $(-13, -4)$ with varying spacing between buildings. It shows that the narrower gap between buildings leads to greater peak pressure, because of more reflection and overlapping of the blast waves.

IV. PROPOSED MODEL

The goal of this study is to predict the peak pressure at measurement positions when the explosion position, the weight of TNT, and measurement positions are given as input variables. Various forms of deep learning models can be designed to map these input/output variables to the input/output layers of the neural network model. In this section, we propose three types of deep learning models: (1) a multi-layer perceptron (MLP) model that predicts a peak pressure value corresponding to the input features such as explosion information and a measurement position. (2) a 3D CNN model where explosion information and measured peak pressures are treated as an input and output in 3D space, respectively. (3) a conditional 3D CNN model with building layout conditions that performs prediction in different building distance environments.

A. MLP MODEL

Assuming the distance between buildings is fixed, we can design an initial neural network model using a simple MLP structure. The input feature of the MLP model includes the measurement position along with other input variables, and the corresponding output is the maximum pressure at the input measurement position. The input features such as the explosion location, the spatial information of the buildings, and the measurement location can be supplied either as cartesian coordinates or as coordinates of the relative distance and angle values.

1) CARTESIAN COORDINATE-BASED FEATURES

The explosion and measurement locations can be represented as cartesian coordinates. The six input variables in the MLP model include two-dimensional explosion positions (Ex, Ey), TNT weight (W), and the three-dimensional coordinates (x, y, z) of the measurement position. The output of the model is the explosion pressure at the measurement position. With these input and output feature dimensions, we constructed an MLP model with three hidden layers, each having 100, 300, and 50 nodes.

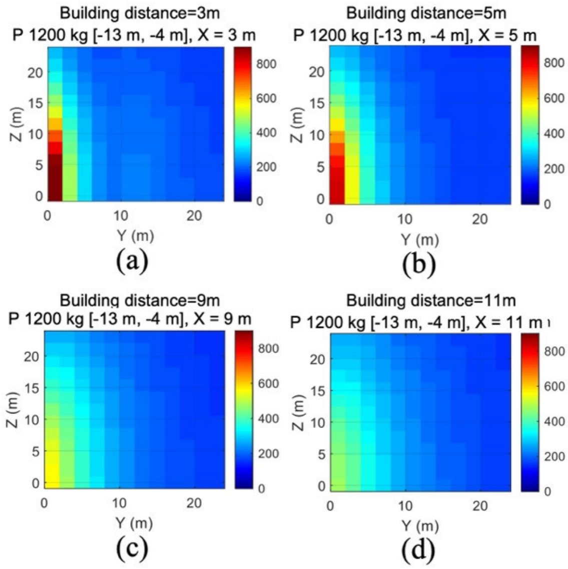

FIGURE 5. Results of AUTODYN analysis for the peak pressure (kPa) between buildings with different distances.

2) DISTANCE-ANGLE BASED FEATURES

As blast waves propagate, the magnitude of the explosion is greatly influenced by the distance and diffraction angle from the explosion location. Therefore, if each location and structure information can be entered as relative distances and angles rather than cartesian coordinates, the effects can affect the model learning and inference more explicitly. For this conversion, it is necessary to interpret the locations of the explosion and sensors geometrically in a 3D space, as illustrated in Figure 6, and the distance and angle to be used as input feature are calculated as

$$L_1' = \sqrt{Ex^2 + Ey^2},\ L_2' = \sqrt{X^2 + Y^2},\ Z' = Z \times \frac{L_1'}{L_1' + L_2'}$$
$$L_1 = \sqrt{{L_1'}^2 + {Z'}^2},\ L_2 = \sqrt{L_2'^2 + (Z - Z')^2}$$
$$\theta_1 = cos^{-1}\left(\frac{L_1'}{L_1}\right),\ \theta_2 = cos^{-1}\left(\frac{L_2'}{L_2}\right). \tag{2}$$

Five variables, including TNT weight (W), the distance from the explosion to the diffraction position (L_1), the distance from the diffraction position to the measurement position (L_2), the angle from the explosion to the diffraction position (θ_1), and the angle from the diffraction position to the measurement position (θ_2) form the input features, and the model is configured to output the explosion pressure at the corresponding measurement position. We used the MLP model structure with three hidden layers of 100, 300, and 50 nodes.

B. 3D CNN

Since the MLP structure described above quantifies all spatial information for its input and output features, it is limited to directly learning the relationships of the explosion and measurements in the 3D space. More effective learning of

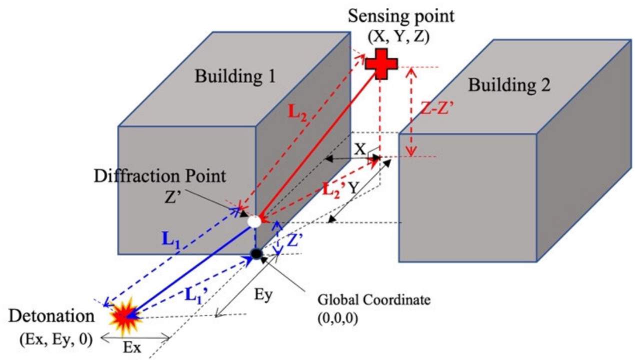

FIGURE 6. MLP model based the distance-angle features.

the spatial information requires the use of CNN models, which have been widely used in various spatial vision tasks such as image classification, object detection, video understanding. In 2D CNNs, convolutions are applied to the 2D features to compute 2D spatial dimensions. To effectively process 3D information, a number of studies have used 3D CNNs that convolve a 3D kernel to the cube formed by stacking multiple channels of the feature maps [19]. 3D CNNs are known to be very effective at analyzing volumetric data, because the feature maps in the 3D convolution can be connected to multiple channels [19], [22]. With the advantage of processing an additional dimension, several studies have utilized 3D CNNs for a variety of applications. An early study applied a 3D CNN in video-based human action recognition [19], and another study proposed learning spatiotemporal features in videos using 3D CNNs [20]. Recent studies have also exploited 3D CNNs for object recognition [21] and medical imaging applications [22].

We propose adopting a 3D CNN to effectively process the spatial information in the explosion space and to generate a peak pressure value in the 3D measurement space through convolution operations. In the proposed CNN model, the input feature is structured as a 2D matrix including the location and degree of explosion, as shown in Figure 7(a). The pixel values of the places where the explosion does not occur are all 0, and the pixel values of the explosion locations have a normalized explosion intensity where the maximum explosion intensity (2000 kg) is represented as 1. Similarly, the output of the proposed 3D CNN model is structured as a 3-dimensional matrix, as shown in Figure 7(b), where each pixel value is interpreted as a detonation pressure predicted at a corresponding position.

The model structure consists of a combination of convolution layers and pooling layers that extract information from features and reduce dimensions, as well as a transposed convolution layer that restores the dimensions of features. The proposed 3D CNN model consists of three pairs of convolution layers and transposed convolution layers, and the strides and paddings of each layer are appropriately adjusted to match the dimensions of the input/output feature, as shown in Figure 8.

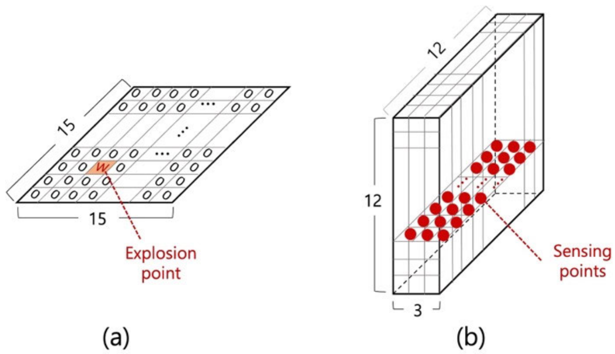

FIGURE 7. (a) input feature and (b) output feature for the CNN model.

More specifically, an input feature with dimensions of $15 \times 15 \times 1$ as in Figure 8 is first 2D-convolved with 24-channel 7×7 kernels and appropriate zero-padding, to generate feature dimensions of $13 \times 13 \times 24$. Then, the feature is downscaled in every dimension by 3D max pooling, which makes the feature dimensions $7 \times 7 \times 12$. By considering the channel depth (twelve here) as the z-axis dimension of the 3D shape, we can perform 3D convolution of the feature. With successive 3D convolution and pooling operations, a $3 \times 3 \times 3$ latent vector with 128 channels is generated. The reconstruction of the output feature ($3 \times 12 \times 12$) is performed by the transposed convolution using proper stride values. That is, to upscale the second and third axes by four, the stride of 2 is set twice for each axis in three transposed convolution layers. The number of intermediate layers and the number of hidden nodes by layer were designed considering prediction accuracy and computational complexity. In Section V-C, we compare the performance of the CNN structure of Figure 8 with various other structures.

C. CONDITIONAL 3D CNN WITH BUILDING LAYOUT CONDITION

In the 3D CNN model of Figure 8, the output is determined only by the input feature which represents the explosion information. However, in actual explosion scenarios, the location and the distance between buildings affect the propagation of the blast wave. Therefore, the conditions of the building layout (distance between buildings) should be properly supplied to the model. One of the ways of modulating output features according to the condition is to use a conditional convolution.

Conditional convolutions aim to control the behavior of convolution operations by modulating intermediate features or kernels using a condition input, as opposed to the conventional static convolutional kernels. One of the initial approaches included a dynamic filter network that adaptively generates sample-specific filter parameters conditioned on the network's input [23]. Another early work presented CondConv that conditionally parameterizes convolutional kernels as a function of the input [24].

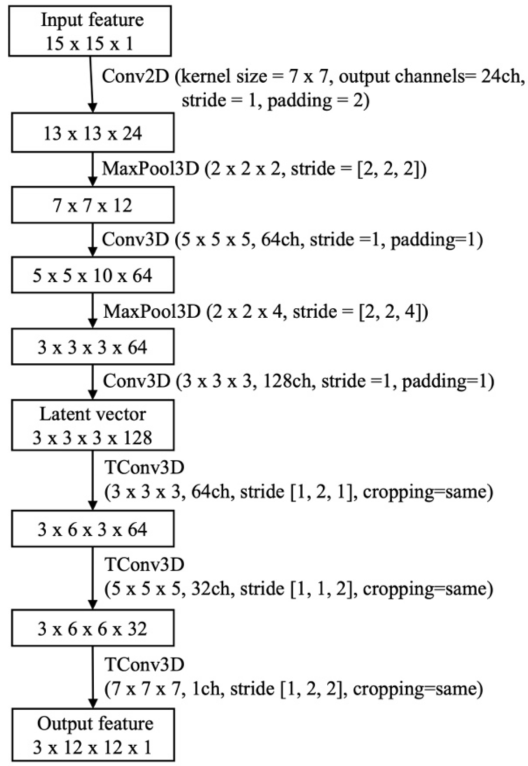

FIGURE 8. The structure of a CNN model.

More recently, Feature-wise Linear Modulation (FiLM) [25] adaptively influences the neural network output by applying an affine transformation to the intermediate features based on some input. Specifically, FiLM generates two features $\gamma_{i,c}$ and $\beta_{i,c}$ using functions f and h, which can be arbitrary functions such as a multi-layer perceptron or an identity function:

$$\gamma_{i,c} = f_c(x_i) \quad \beta_{i,c} = h_c(x_i), \tag{3}$$

where x_i refers to the input and the subscripts i and c refer to the input and channel number, respectively. Then, $\gamma_{i,c}$ and $\beta_{i,c}$ modulate the model's intermediate feature $F_{i,c}$ via a feature wise affine transformation:

$$FiLM\left(F_{i,c} \,|\, \gamma_{i,c}, \beta_{i,c}\right) = \gamma_{i,c}F_{i,c} + \beta_{i,c}. \tag{4}$$

The FiLM layers are known to manipulate the feature maps of a target, by scaling, negating, shutting off, selectively thresholding them, and more. With the ability to effectively control the neural network output, the feature modulation technique has been widely adopted in various areas, including for image synthesis [26], transfer learning [27], and image compression [28].

In this work, we propose adopting conditional convolution to modulate the CNN according to the building layout information. Specifically, the scalar value of the building distance is processed through a two-layer MLP with 128 hidden nodes, generating a condition feature with the same channel size as the target feature to be modulated. The condition feature is

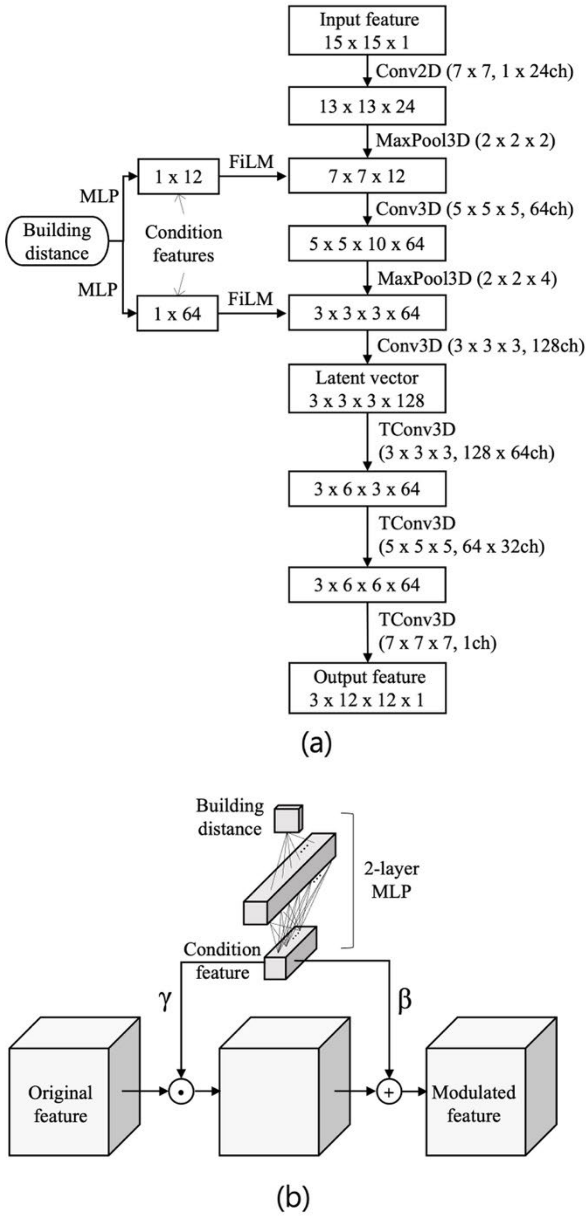

FIGURE 9. (a) A conditional 3D CNN model and (b) conditional convolution using FiLM.

then applied to perform a feature-wise affine transformation, as in FiLM [25], using a Hadamard product and addition as Figure 9(b) shows. Note that we use the condition feature generated by one MLP for both the Hadamard product (γ) and addition (β), as this reduces complexity with performance similar to the original FiLM structure, which uses separate MLPs for γ and β. By modulating the feature using the spatial condition information, it is possible to predict the progress of the explosion more effectively when the building distance varies. Figure 9 shows the structure of the proposed 3D conditional CNN model. With the same baseline architecture as the regular 3D CNN presented in Section IV-B, FiLM layers are added with the building distance as a condition variable.

V. RESULTS

A. EXPERIMENTAL SETTINGS

As described in Section IV-A, the data constructed through finite element analysis includes five building layouts with different distances between two buildings, 42 explosion scenarios by the combination of six TNT weights and seven explosion locations per building layout, and peak pressure values from 432 measurement locations per scenario. As a result, we constructed a total of 90,720 data points from 5 $\times$ 42 $\times$ 432.

The performance of each technique is evaluated by the root mean square error (RMSE) and the relative error (%). RMSE is computed as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_{pred,i} - P_{ref,i})^2}{n}}, \tag{5}$$

where P_{pred} and P_{ref} are the peak pressure values predicted by DNN models and the reference peak pressure values from numerical analysis tools, respectively, and n is the number of measurement sensors. Relative error indicates how large the RMSE error value is compared to the average of the reference peak pressure values, and it is calculated as

$$Relativeerror = \frac{RMSE}{\sum_{i=1}^{n}(P_{ref,i}/n)}. \tag{6}$$

The deep learning toolbox of MATLAB R2022a was used to process the data and to design and train deep learning models. For the training loss, we used the root mean square error (RMSE). The maximum training epochs were set to 300 and 200 epochs for the MLPs and CNNs, respectively. We used the Adam optimizer and reduced learning rate with a factor of 0.7 every 10 epochs.

B. ACCURACY AND COMPLEXITY ANALYSIS

The performance of the 3D CNN models proposed in this paper was compared with other DNN structures and finite element analysis methods. The analysis was conducted with two experiments. The first experiment was to test the prediction performance for explosion scenarios different from the trained ones when the distance between buildings was fixed. The second experiment was to evaluate the prediction performance with a building layout not included in the training.

1) PREDICTION PERFORMANCE FOR A FIXED BUILDING LAYOUT

First, to compare and analyze the prediction performance for a fixed building layout, 42 scenarios (18,144 data points) in an environment with a distance of 7 m between buildings were randomly divided into 33, 3, and 6 scenarios (14,256, 1,296, 2,592 data points) at a ratio of 11:1:2, for model training, validation, and evaluation. The validation set was used to tune the hyperparameters and to decide early stopping during training. We tried a minibatch size of $\{2^1, 2^2, \ldots, 2^7\}$ and the size 4 was chosen for the best performance. The initial

TABLE 3. Prediction performance in a fixed building layout.

	Coordinate based MLP	Distance/angle based MLP	3D CNN
RMSE	62.5	40.2	16.2
Relative error (%)	26.2	16.8	6.8

learning rate was determined to be 1E-3 among 1E-2, 1E-3, and 1E-4. Please note that this experiment used a 3D CNN without a conditional convolution, since the building distance is fixed.

Table 3 represents the prediction accuracy of the two types of MLP and the proposed 3D CNN. The table shows that, for MLP, using distance-angle information as an input feature was about 1.6 times more accurate than using cartesian coordinates.

This indicates that using relative information between the explosion and measurement positions can be more effective than cartesian coordinate values. However, it can be seen that the proposed 3D CNN structure provided prediction results closer to the finite element analysis than the MLP structures. Specifically, with an RMSE value of 16.2, the proposed model achieved 2.5∼3.8 times improvement in accuracy compared to the RMSE value range of 40.2∼62.5 when using MLP. This indicates that it is more effective to perform operations in 3D space using a 3D CNN rather than supplying spatial information as coordinate values in MLP.

2) PREDICTION PERFORMANCE IN UNSEEN BUILDING LAYOUTS

In actual weapon-effect analysis applications, accurate explosion predictions should be performed for any arbitrary building layout, not always on a learned building layout. To compare and analyze the performance in this approach, four cases out of a total of five different building-to-building distances were used for training, and the accuracy of the model was evaluated with the remaining one building-to-building distance layout data. We set model hyperparameters such as the minibatch size and the learning rate to the same values determined in the previous subsection.

Since a 3D CNN cannot reflect the distance information between buildings on the 3D matrix representing the peak pressures measured in the space between buildings, the 3D CNN cannot be used in this situation. Instead, we applied a conditional 3D CNN where the building distance information is given as a condition feature. Table 4 compares the prediction performance of peak pressure for unseen building layouts. Like the results with the fixed layout in Table 3, the MLP with distance-angle information achieved more accurate results than using the coordinate information.

However, the prediction using the conditional 3D CNN structure achieved results closer to the finite element analysis. On average, with an RMSE value of 22.7, the conditional 3D CNN showed an accuracy improvement of 2.6 to 3.6 times compared to the MLP models. It outperformed other models in all training/test combinations, with less than 10% errors from the ground-truth peak pressure values. These results confirm that it is more effective to perform spatial feature operations through 3D conditional convolutions even on arbitrary building arrangements.

TABLE 4. Prediction performance in untrained building layouts.

Trained building distance	Tested building distance	RMSE (Relative error)		
		Coordinate based MLP	Distance /angle based MLP	3D conditional CNN
5/7/9/11m	3m	92.0 (35.7%)	73.2 (28.4%)	25.3 (9.8%)
3/7/9/11m	5m	82.7 (33.4%)	58.4 (23.6%)	23.0 (9.3%)
3/5/9/11m	7m	76.7 (32.1%)	49.7 (20.9%)	21.7 (9.1%)
3/5/7/11m	9m	77.7 (33.6%)	54.4 (23.5%)	21.8 (9.4%)
3/5/7/9m	11m	81.4 (36.2%)	63.4 (28.2%)	21.8 (9.7%)
Average		82.1 (34.2%)	59.8 (24.9%)	22.7 (9.5%)

TABLE 5. Complexity and running time analysis.

Model	Complexity		Latency
	MFLOPs	# Params	
MLP	0.046	46.2 K	0.13 ms
3D conditional CNN	123.1	521.4 K	40 ms
FE	-	-	6 – 8 hours

TABLE 6. Ablation study for model structure.

# Layers	Layer structure (#channels(kernel size))	Complexity		RMSE
		MFLOPs	# Params	
4	24(7)-32(5)-16(5)-1(7)	43.2	36.2 K	23.9
	24(7)-64(5)-32(5)-1(7)	91.1	82.1 K	19.8
6	24(7)-32(5)-64(3)-32(3)-16(5)-1(7)	58.3	180.2 K	17.9
	24(7)-64(5)-128(3)-64(3)-32(5)-1(7)	115.8	514.1 K	16.2
8	24(7)-32(5)-64(3)-128(3)-64(3)-32(3)-16-1	187.0	1,135 K	16.0
	24(7)-64(5)-128(3)-256(3)-128(3)-64(3)-32(5)-1(7)	515.4	3,584 K	15.7

3) MODEL COMPLEXITY AND RUNNING TIME

While accuracy is the most critical requirement for weapon effectiveness analysis in a battlefield environment, the analysis time should also be short to allow for rapid damage calculation and response. To this end, this section compares and analyzes the complexity and execution time of each model and the finite element analysis technique.

The complexity of the artificial intelligence model is expressed in terms of parameter size (#Params) and number of operations (FLOPs) required to perform inference for one scenario, and execution time is expressed as inference latency for a single scenario. All the experiments were performed with a computer equipped with an NVIDIA RTX 3060 GPU. The finite element analysis is difficult to quantify by parameter size or computation amount, so it is expressed by inference time, on an 8-core CPU workstation. As shown in Table 5, the CNN model had a somewhat larger computation amount and model size compared to the MLP, and thus took more execution time. However, as discussed in the previous section, the 3D CNN enables a much more accurate inference compared to MLP, so this increase in complexity can be justified. More importantly, even when a conditional convolution technique was applied, it resulted in only a very slight increase in the complexity of model inference. In particular, the finite element analysis required six to eight hours, while inference using the CNN required less than one second, even in lighter computing environments. This confirms that it can be effectively used in battlefield environments that require rapid weapon effect analysis.

C. ABLATION STUDY

The 3D CNN model proposed in this study consists of 6 hidden layers and 32 to 128 channels per layer. As the deep learning model structure greatly affects training inference performance, complexity, and execution time, we analyzed complexity and accuracy on six different structures. From the 3D CNN model with six convolutional layers shown in Figure 8, we constructed a 4-convolutional-layered model by removing the two convolutional layers in the middle, and an 8-convolutional-layered model by adding two layers. For each model, we also created a variant by changing the number of channels in each layer, resulting in a total of six models, as shown in Table 6. We analyzed complexity by the parameter size and computation amount of the models.

As shown in Table 6, as the number of layers and nodes increased, the inference accuracy generally became higher. If the number of layers was increased to 8 and the number of nodes increased, the error was reduced accordingly. However, the error was not significantly reduced compared to the proposed model structure with 6 layers. Meanwhile, expanding the structure of the model in this way greatly increases the required amount of computation and memory capacity. Therefore, considering the results in this study, the combination of six layers and the number of nodes 24-64-128-64-32-1 seems to be appropriate for use.

VI. CONCLUSION

In this paper, we proposed a deep learning model that can quickly and accurately predict peak pressure when a blast wave propagates in urban environments. We designed a conditional 3D CNN model for learning the peak pressure data from various scenarios constructed through finite element analysis. We demonstrated that the prediction performance of the model was comparable to results from finite element analysis. The proposed conditional 3D CNN model had a relative error of less than 7% and the execution time was about one million times shorter than the finite element analysis. Importantly, conditional convolution enables flexible prediction for various building spacings, using just a single model.

However, it should be mentioned that the proposed neural network model is not immediately applicable to peak pressure prediction in all urban areas. The data used in developing this model should not be applied to environments different from those built here. The environment assumed in this paper was developed to predict the peak pressure between two identical buildings when an explosion occurs in front of one of the buildings. This study is meaningful for predicting peak pressure with high accuracy and fast analysis, similar to finite element analysis in a limited environment where data is built.

Nonetheless, we have demonstrated that deep learning-based algorithms can be applied to predict the interference effect between buildings at high speed. If it is not a ground explosion but an aerial explosion, or the prediction of blast propagation is pursued with a different building layout, we can create a model by constructing training data with finite element analysis.

The model developed through this study can be used to determine where weapons should be aimed to inflict maximum damage on the enemy in the military field. Also, in the urban construction design field, it can be used to optimize the design of buildings that can mitigate damage from deployment and explosions. It should also be noted that the proposed model can be used for various kinds of explosives other than TNT, as long as the explosion weight is represented as equivalent TNT in the input feature to the model. In the future, research will continue to be conducted to create a generally available model for various scenarios with more variables applied.

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