A review of artificial intelligence techniques in blast field shockwave pressure testing

Liangquan Wang[1], Binwen Qian[2], Chunyan Zhang[3], Xin Zhang[4], Zhenghao Wu[5], Botian Zhang[6]
[1, 2, 4, 5, 6]Northwest Institute of Nuclear Technology, Shanxi, Xi'an, China
[3]Nanjing Institute of Technology, Jiangsu, Nanjing, China
[2, 3]Corresponding author
E-mail: [1]*2223263181@qq.com*, [2]*qianbingwen@nint.ac.cn*, [3]*zhangchunyan@njit.edu.cn*, [4]*zhangxin@nint.ac.cn*, [5]*wuzhenghao@nint.ac.cn*, [6]*17622789156@163.com*

Received 1 August 2024; accepted 11 December 2024; published online 11 May 2025
DOI https://doi.org/10.21595/jme.2024.24423

Check for updates

Abstract. Ammunition explosion shockwave pressure is an important war technology indicator to evaluate the explosive damage power of ammunition, and it is of great significance to accurately obtain the law of shockwave pressure distribution to evaluate and guide the design of ammunition. With the rapid development of artificial intelligence technology, researchers have applied artificial intelligence technologies such as neural networks, machine learning, deep learning, big data and large models to shock wave pressure testing, pressure field distribution reconstruction and explosion damage assessment, greatly improving the working bandwidth of the measurement system, the accuracy of calculation results and the efficiency of damage assessment under current test conditions. This study summarizes the application of the above methods in the explosion shock wave pressure measurement and the relevant achievements, discusses the shortcomings of the current research, puts forward the problems that should be analyzed in the follow-up research, and points out the direction of the follow-up research.

Keywords: shockwave, artificial intelligence techniques, pressure testing, pressure reconfiguration, damage assessment.

1. Introduction

When explosives explode in the air, the surrounding air medium is directly affected by the high temperature, high speed, high pressure explosion products. At the junction of explosives and air media, the explosion product to a very high speed to the surrounding spread, and strongly compressed adjacent air media, so that the pressure, density and temperature rise abruptly, the formation of the initial shock wave [1-4]. Initially, because it is driven like a piston in motion, constantly replenish the energy to the compressed air layer; late due to the pressure is too small, so that the inability to compress the surrounding air, when the explosion product expansion to a certain limit volume, the pressure drops to the surrounding medium is not perturbed when the initial pressure P0, but at this time the explosion product did not stop the movement, but in the role of inertia occurs in the over-expansion, until a certain maximum volume. Finally, the average pressure of the explosion product is lower than P0, which appeared in the "negative pressure zone". After the emergence of negative pressure zone, the surrounding medium will, in turn, the explosion of the product of the first compression, so that its pressure is increasing. Similarly, under the action of inertia to produce excessive compression, resulting in the explosion of the product pressure will be slightly greater than the initial pressure, and began the second expansion and compression pulsation process. After a number of collision compression pulsation, the explosion products eventually stop moving and reach equilibrium. Typical shock wave pressure time curve shown in Fig. 1 [5, 6].

However, the explosion field test environment is relatively special, there are generally high temperature, high pressure and strong electromagnetic interference, resulting in the output signal of the pressure sensor is accompanied by thermal parasitism and shock vibration parasitism effect response, and the test process of debris and flying stones will hit the sensor mounting plate and the sensor sensitive surface, resulting in high pressure pulses in the test signal [7-9]. These interfering signals are overlapped in the pressure signal, resulting in low signal-to-noise ratio of the test results, and it is difficult to directly extract the characterization parameters of shock wave pressure from the original measurement results, such as the peak pressure, the positive pressure time and the specific impulse, resulting in the reconstruction of the pressure field distribution using the measured data, which affects the reconstruction accuracy of the pressure field and the credibility of the reconstruction results is not high. In order to improve the accuracy of shock wave pressure testing, it is usually necessary to process the measurement results.

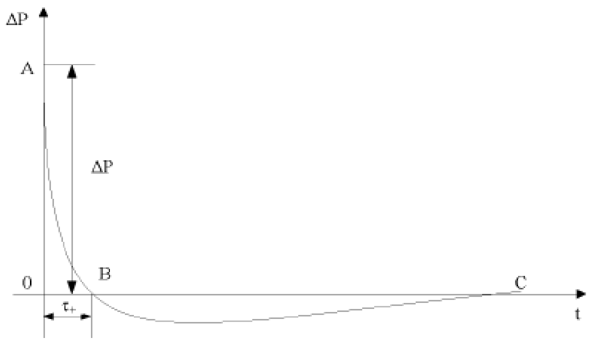


Fig. 1. Shock wave pressure curve [5]

According to the above analysis, the testing of shock wave pressure distribution in explosion fields is affected by many factors, resulting in poor signal-to-noise ratio of test results, high difficulty in data processing, low reliability of characteristic parameter extraction results, and difficulty in accurately compensating the shock wave pressure measurement system with conventional technical means. Data processing methods are also difficult to accurately identify and extract the characteristic parameters of pressure signals, leading to problems such as "inability to measure, inaccurate measurement, and unclear explanation" in the testing of shock wave pressure distribution in explosion fields. Artificial intelligence technology has significant advantages such as autonomous learning and adaptation ability, intelligent decision-making and reasoning ability, large-scale data processing ability, multimodal perception ability, and automated decision-making ability, which make up for the shortcomings of current stress testing and signal processing methods. Therefore, more and more researchers are using it as a scientific and effective tool to conduct research on various difficult problems, and have made significant progress. According to the analysis of existing literature, relevant researchers have conducted research on dynamic compensation of pressure measurement systems, reconstruction of pressure field distribution patterns, and evaluation of explosive damage using methods such as neural networks, machine learning, and deep learning, and have achieved outstanding results, highlighting the significant application value of artificial intelligence technology in ammunition / warhead explosive damage testing and evaluation.

2. Application of artificial intelligence technology in pressure measurement system

The pressure measurement system under ideal conditions needs to satisfy the correspondence between input and output as a linear system in order for the measurement results to have a high degree of confidence [10]. However, the actual measurement system consists of sensors, data collectors, signal conditioners and signal transmission cables, etc., and the measurement system is generally a nonlinear system. In testing, the measurement system is required to work in the linear region as much as possible, so the linear working range of the measurement system directly determines the working bandwidth of the measurement system. The commonly used method to increase the bandwidth of testing systems is mainly achieved by designing compensation circuits. Firstly, identify the transfer characteristics of the measurement system to obtain its transfer function. Then, compensate for the transfer function to increase its linear range. Finally, design a compensation circuit based on the designed dynamic compensation function and connect it to the measurement system to improve its dynamic characteristics. However, this method has significant errors in the system identification process, resulting in inaccurate identification of the system transfer function and unsatisfactory circuit compensation effect. Artificial intelligence technology has the ability of autonomous recognition and decision-making, which makes up for the shortcomings of numerical compensation technology. Therefore, in order to improve the working bandwidth of the measurement system, researchers have applied artificial intelligence technology to the dynamic correction of the shock wave pressure measurement system model in the explosion field, in order to correct the dynamic output characteristics of the sensor in the nonlinear working range and improve the accuracy of the measurement results.

At present, related scholars have carried out some research work on this aspect of the study, such as in 2008, Zhang [11] for the linear system theory of the test system to establish a model can not fully reflect the dynamic nonlinear characteristics of the sensor, there is a large modeling error, so that some of the dynamic error correction methods have great limitations. Based on the NARX (Nested Auto-Regressive Exponential) neural network, he established a relatively high accuracy nonlinear model for pressure sensors and high G-value acceleration sensors, and summarized the structure of the network model and the corresponding training algorithm that are suitable for modeling pressure sensors and high G-value acceleration sensors. The flowchart structure of NARX neural network algorithm is shown in Fig. 2. Based on this model, a mathematical model for the dynamic compensation and correction of sensors was established to correct measurement errors in the testing system and improve the accuracy of measurement results.

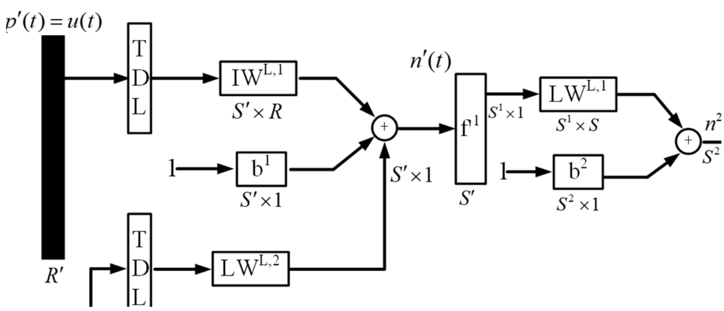


Fig. 2. NARX neural network algorithm structure diagram [11]

In 2012, Liu et al. [12] in order to solve the problem of violent oscillations of test data caused by the insufficient bandwidth of the sensor, a fuzzy neural network algorithm is used to inverse model the sensor and thus eliminate the dynamic error of the sensor. This method can accurately and quickly derive the weights and coefficients of the dynamic compensation device. The researchers also analyzed the time domain and frequency domain dynamic characteristics of the sensor before and after the compensation in detail, proving that the dynamic compensation device can reduce the dynamic error of the sensor and accurately obtain the peak overpressure after it is applied to the engineering. In 2017, Hao [13] carried out a study on the compensation of dynamic characteristics of the test system based on the principle of BP (Back Propagation) neural network system identification and system dynamic characteristics compensation. They excited the test system through the step pressure signal generated by the excitation tube to obtain the system time domain response data, and the BP neural network dynamic characteristic compensation model constructed by the system input and output data was trained offline. Aiming at the problem of insufficient training data for the compensation network, the method of generating a large number of training samples under the excitation of a cluster of step signals by the neural network identification system model is proposed to improve the generalization ability of the dynamic characteristic compensation network of the test system. The structure of the dual neural network dynamic compensation model of the test system is shown in Fig. 3.

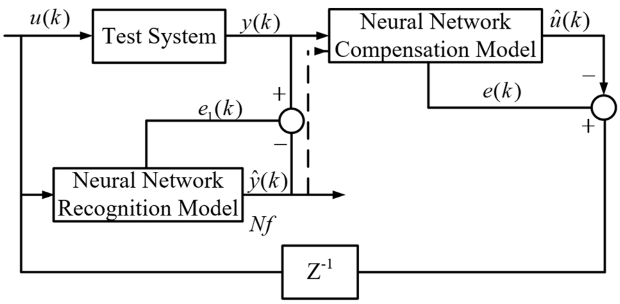


Fig. 3. Dynamic compensation structure of double neural network of test system [13]

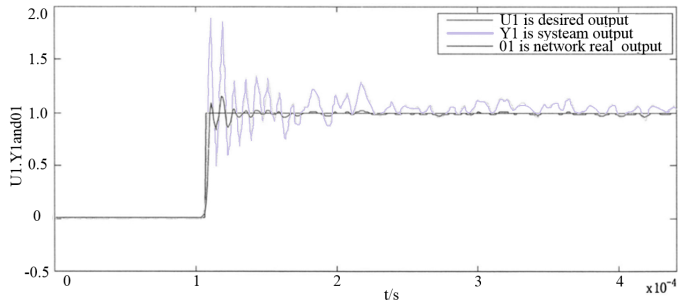


Fig. 4. Comparison of excitation signal, test system output signal and compensation network output signal [13]

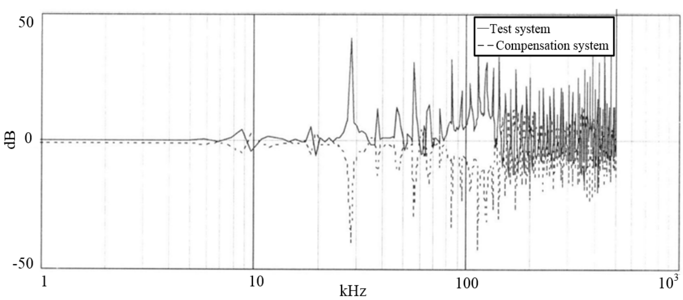


Fig. 5. Comparison of amplitude-frequency characteristics of the system with those of the compensated network model [13]

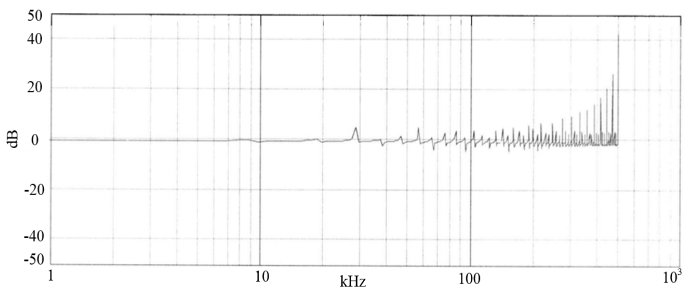


Fig. 6. System amplitude-frequency characteristic compensation effect [13]

The output data of the shock wave overpressure test system is used to train the model, and the training effect of the compensation model and the dynamic characteristics of the compensation system are shown in Figs. 4-6.

By comparing the error relationship between the measured shockwave data, the offline compensation data and the theoretical calculation data, the dynamic compensation of the measurement system has improved in the overshoot and amplitude stabilization time, which verifies the effectiveness of the compensation algorithm to improve the dynamic characteristics of the test system. In the same year, Yang et al. [14, 15] in order to study the dynamic characteristics of the shock wave pressure sensor component, based on the double membrane excitation tube on the shock wave pressure sensor component dynamic calibration, obtained the step response signal; using the differential method to obtain the dynamic characteristics of the sensor component nonparametric model; according to the non-parametric model of the dynamic characteristics of the shock wave pressure sensor component non-parametric model of the changing law, in the frequency domain of the reasonable segmentation, and based on the BP neural network segmentation modeling. According to the non-parametric model of the dynamic characteristics of the shock wave pressure sensor component, it is reasonably segmented in the frequency domain and the dynamic characteristic model of the sensor component is obtained based on the segmented modeling method of BP neural network. The segmentation modeling process based on BP neural network is shown in Fig. 7.

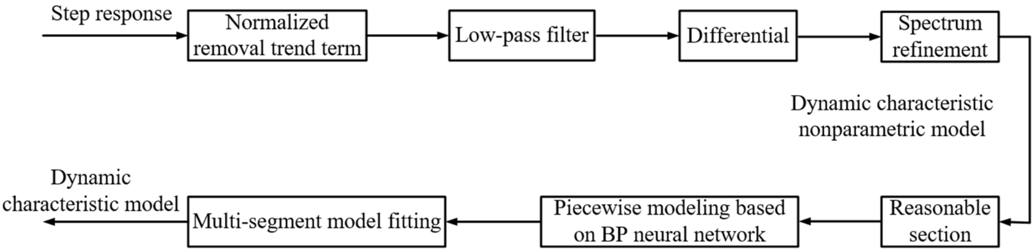


Fig. 7. Segmentation modeling method of BP neural network [14]

By comparing the dynamic output characteristics of the sensing system after nonparametric modeling and modeling based on BP neural network, it can be seen that the segmented modeling method based on BP neural network is more accurate for the identification of the first resonance peak, and it can realistically reproduce the change rule of the dynamic characteristics near the first resonance peak, whereas the model constructed by the non-segmented method is fuzzy, and it ignores the details of the dynamic characteristics in the frequency band, and the segmented method has a clear advantage in modeling effect. The segmented method has obvious advantages in modeling effect.

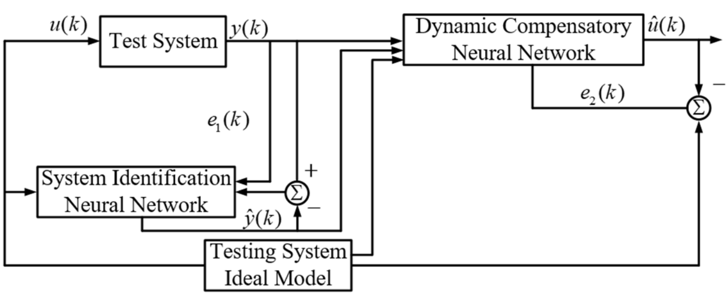


Fig. 8. Test system neural network dynamic compensation structure block diagram [16]

In 2018, Zhang et al. [16] found that the dynamic characteristics of the explosion field shock wave testing system composed of domestically produced sensors were not ideal, causing distortion of shock wave testing data. In order to improve the dynamic output characteristics of the testing system, BP neural network, testing system output, and testing system ideal model were used to construct system discrimination neural network simulation and dynamic compensation neural network models, respectively. After training and comparison, a testing system model with dynamic compensation characteristics was finally obtained, and the model structure is shown in Fig. 8.

Used shock tubes to dynamically calibrate and calibrate the testing system, and obtain the system identification neural network model and dynamic compensation neural network model of the testing system. Compared the measured results with the dynamic compensation results, as shown in Fig. 9.

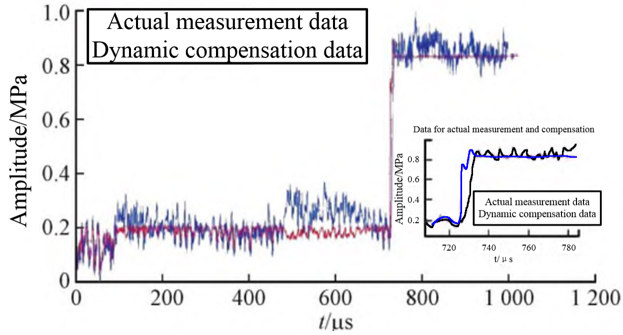


Fig. 9. Comparison between measured results and dynamic compensation results [16]

From the above comparison results, it can be seen that the testing system correction compensation model established using system identification method and dynamic compensation method improves the dynamic output characteristics of the testing system and enhances the measurement accuracy of the testing system.

In 2020, Lei et al. [17] addressed the problem of stress wave effect causing pressure sensors to generate erroneous signals, and used Hopkinson's pressure bar to study the relationship between the stress wave and the output characteristics of piezoelectric pressure sensors, utilized the research data to train the artificial neural network (ANN) and applied it to compensate for the error of the sensor's output signal due to the stress wave effect. The structure of the constructed model is shown in Fig. 10.

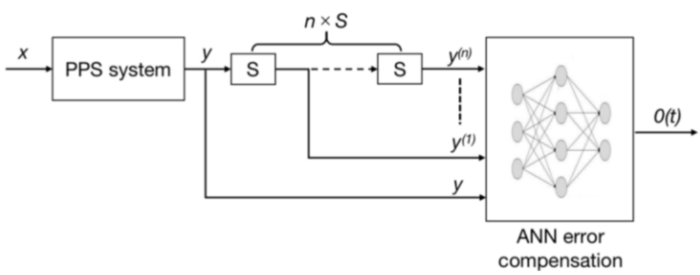


Fig. 10. Compensation principle and algorithm block diagram [17]

The test results show that the digital error compensation method based on ANN is better than the isolation method in terms of error elimination, but its prominent disadvantage is that it cannot protect the PPS from damage caused by stress waves, and it is difficult to be used online in embedded electronic instruments with limited hardware configuration. Physical isolation or digital compensation algorithms can be used to realize the attenuation of the stress wave effect according to the needs in the actual engineering test. In 2023, Yang et al. [18] designed a specialized buffer device for dynamic pressure sensors in response to the problem of impact vibration effects affecting the dynamic parameter test results during the test process. Based on the BP neural network, a mathematical model for the characterization of the pressure sensor with buffer device was constructed, and the method for realizing the dynamic compensation of the pressure sensor was studied. According to the dynamic calibration and compensation results of a typical pressure sensor with a cushioning device, the dynamic compensation method based on BP neural network can not only effectively broaden the operating bandwidth of piezoelectric dynamic pressure sensors, but also improve the accuracy of dynamic measurement.

3. Application of artificial intelligence techniques in pressure field distribution prediction

The shock wave pressure test is affected by various interference factors, resulting in significant differences in pressure measurement results under the same explosive environment. During the test, high-speed flying fragments, flying rocks, etc. directly hit the sensors and signal transmission cables, resulting in signal interruption and inability to effectively obtain the pressure variation law over time at the measuring point. Considering that a large amount of manpower and material resources are required during the experiment, it is not possible to conduct unlimited tests on the explosive destructive power of ammunition, and it is also impossible to deploy a large number of pressure sensors at different measuring points during the experiment. Therefore, the shock wave pressure data collected in the experiment is very limited. Using a small amount of measured data cannot accurately evaluate the explosive damage power of ammunition and guide ammunition design. Therefore, it is necessary to conduct research on the prediction of pressure distribution of shock waves in explosion fields, construct a pressure field prediction model under the influence of multiple factors, invert the pressure field distribution law under different experimental conditions, and make up for the problem of insufficient measured pressure data [19].

Aiming at the above existing problems, related scholars have carried out a lot of research on this. In the process of pressure field prediction/reconstruction, the different applied artificial intelligence techniques can be roughly divided into the following three categories, which are (1) CNN, DCNN, ANN, RNN network model in pressure field prediction; (2) Deep learning, machine learning in pressure field prediction; (3) BP neural network model in pressure field prediction.

3.1. Application of CNN, DCNN, ANN, RNN network models for pressure field prediction

In 2007, Alex M. R. et al. [20] used ANN (Artificial Neural Network) to predict the pressure distribution of blast shock wave behind buildings and structural elements, using wall height, distance behind wall, height from ground and distance from ground as training input data and using peak pressure and specific impulse as output data. The structure of the constructed neural network prediction model is shown in Fig. 11.

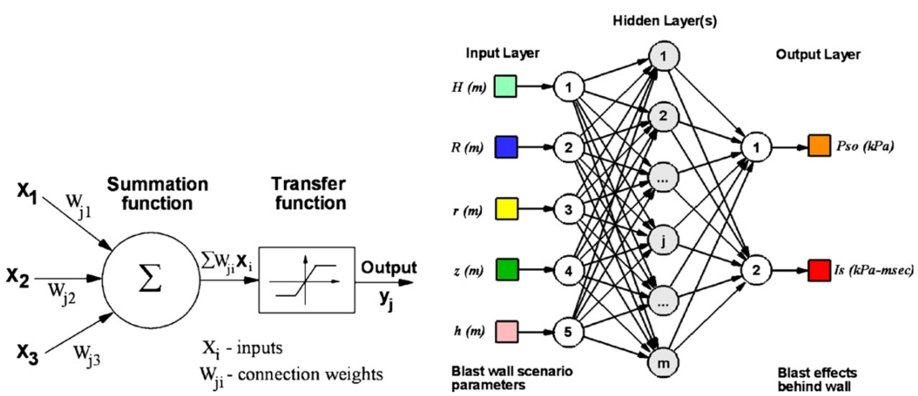


Fig. 11. Basic operations of artificial neurons and multilayer perceptual neural network models [20]

The model constructed above is used to predict the peak shock wave pressure in a specific environment. The comparison between the predicted results and the measured results is shown in Fig. 12.

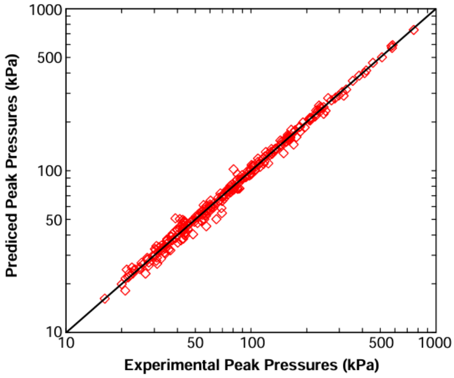


Fig. 12. Prediction of peak pressure by artificial neural networks vs. measurements [20]

The experimental results show that the prediction model developed in this study can predict the pressure distribution behind buildings and structural components with high accuracy, and compared with the traditional numerical CFD simulation method, the computation time can be shortened from hours to days to a few minutes, which substantially improves the computational efficiency.

In 2021, Adam A D et al. [21] addressed the particular explosion loads in confined exploders, where the distribution of such loads cannot be predicted using simple tools, but rather requires specialized computational software or actual testing, which is impractical for a wide range of input variables. An artificial neural network (DNN) was used to construct a prediction model for explosion loads in confined spaces under the influence of multiple input conditions. The structure of the prediction model is shown in Fig. 13.

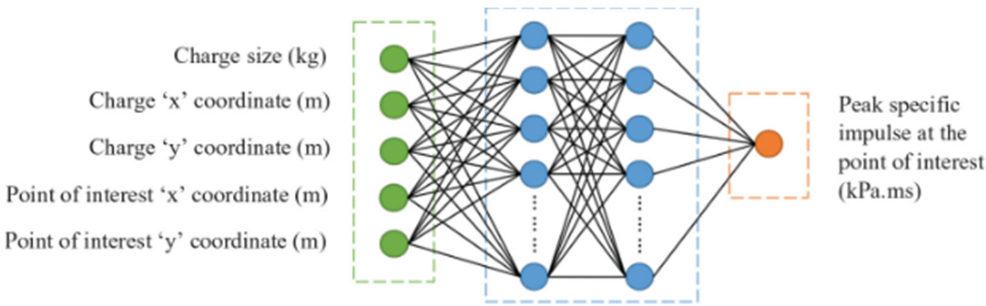


Fig. 13. Regression network model structure [21]

The artificial neural network was trained using validated simulation data and key parameters related to the training data and network structure were rigorously analyzed to maximize the predictive ability of the network. The results of the comparison between the training data and the predicted data are shown in Fig. 14.

The validation results show that the network model has a strong generalization ability in the region near the reflective surface and near the ambient outflow boundary region. Artificial neural networks are well suited for modeling blast loads in narrow interior spaces. If a robust and well distributed training dataset is used together with a network structure tailored to the problem being solved, the accuracy of model calculations can be significantly improved.

ISSN PRINT 2335-2124, ISSN ONLINE 2424-4635

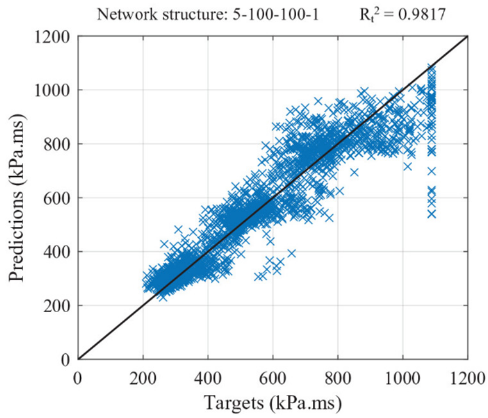


Fig. 14. Comparison between prediction results and training data [21]

In 2022, Sun et al. [22] introduced deep convolutional neural networks (DCNN) to capture local information and high-order features of shock wave signals, and introduced bidirectional long short-term memory networks (Bi LSTM) to capture temporal dependencies of shock wave overpressure data, thereby constructing a deep learning based explosion shock wave signal reconstruction model. Refactoring the model structure is shown in Fig. 15.

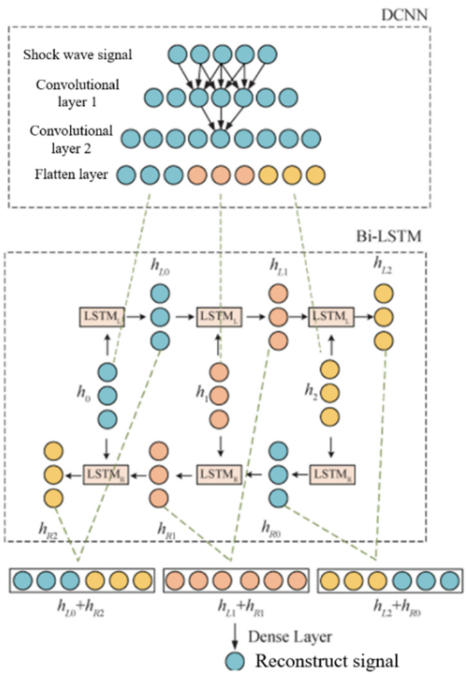


Fig. 15. Shock wave signal reconstruction model structure based on deep learning [22]

In the shock wave field pressure distribution reconstruction experiments based on limited measurement point data, the simulated and measured overpressure peak average error of 3.53 % and 13.71 %, respectively, the average error of the positive pressure action time of 7.35 % and 14.26 %, respectively, than the impulse of the average error of 4.02 % and 11.92 %; In the experiment of reconstructing the shock wave pressure curve based on incomplete data, the missing values of simulated and measured signal reconstruction are basically consistent with the original values, and the deviations are both around 0, which meets the requirements of the explosion shock wave pressure reconstruction index. The results of the study have important significance in guiding the reconstruction of the explosion shock wave signal. Dou et al. [23] for the reconstruction effect of the signal by the sparse matrix selection or design, the traditional compressed perception technology in the processing of shock wave signals require the signal to meet the sparse a priori in a certain transform domain. In order to avoid the problem that the sparse matrix is not easy to select, an algorithm based on the combination of deep convolutional network and compressed sensing technology is proposed. The flow structure of the algorithm is shown in Fig. 16.

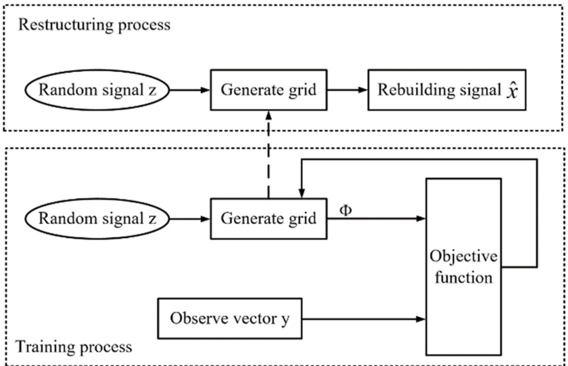
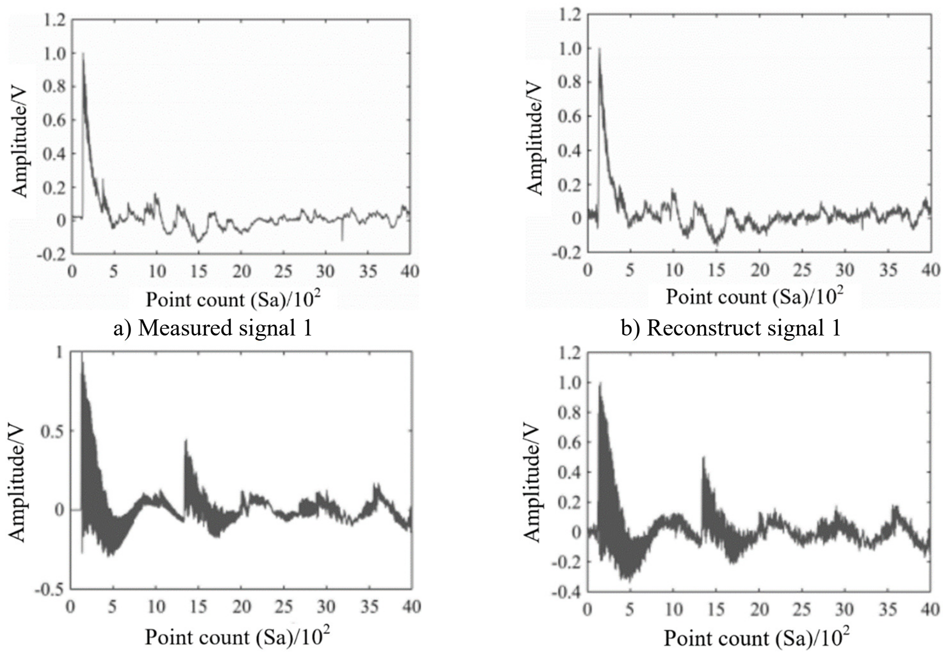


Fig. 16. DCGN-CS algorithm flow [23]

The algorithm takes the fixed random signal as the input value of the network, and the output result of the network is the reconstructed signal, optimizes the parameters in the network by using the designed loss function, realizes the end-to-end recovery of the signal, and verifies that the reconstruction error has been effectively reduced through simulation tests. The measured signal and the reconstructed signal are shown in Fig. 17.



a) Measured signal 1 b) Reconstruct signal 1

c) Measured signal 2 d) Reconstruct signal 2

Fig. 17. Comparison between measured signal and reconstructed signal [23]

From the reconstruction results, it can be seen that the shock wave signal compression sensing method of deep convolutional network proposed in this study can better reconstruct the pressure signal, and the reconstructed signal error is 0.5 times of the reconstructed signal error of the traditional compression sensing technique, which confirms the validity of the method. Kong et al. [24] proposed a multi-runner flow field prediction model based on the wall pressure sequences to realize the flow field prediction. The prediction model is mainly constructed using convolutional neural network. The distribution data of supersonic experimental data under different evolution laws in the isolator are utilized to construct the experimental dataset, and the flow field prediction model is trained and validated using independent experimental data. The structure of the constructed multipath flow field prediction CNN model is shown in Fig. 18.

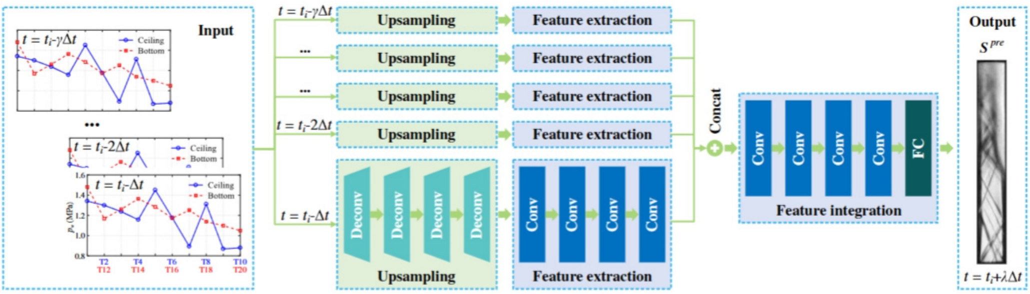


Fig. 18. Multi-runoff prediction CNN model structure [24]

Using the above constructed model to carry out the flow field prediction for a particular environment, the results of the flow field prediction at different moments are shown in Figs. 19-20.

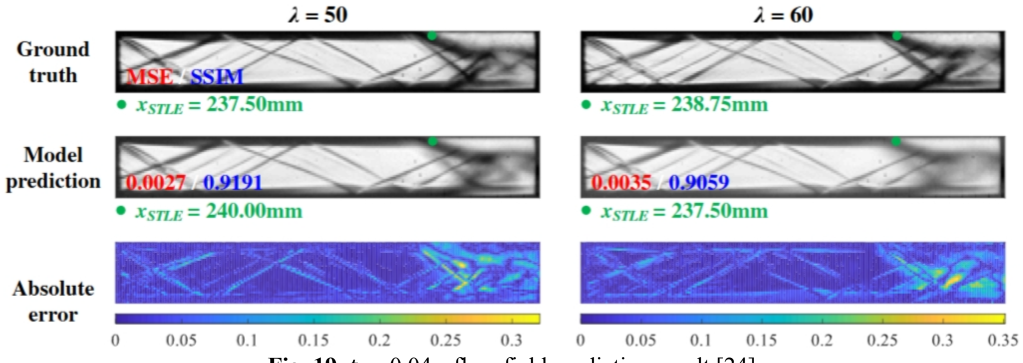


Fig. 19. $t = 0.04$ s flow field prediction result [24]

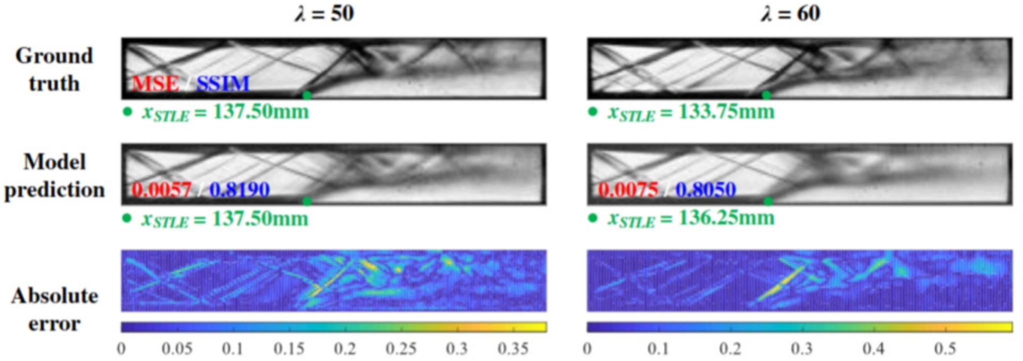


Fig. 20. $t = 0.6$ s flow field prediction result [24]

The test results show that the predicted flow field matches well with the ground reality, and even if the leading edge of the excitation wave will change intermittently, the structure of the background wave and the excitation wavefront will be basically restored. The model successfully captures the flow characteristics of the supersonic flow field, and predicts with high accuracy the future change rule of the flow field in the isolator. This study provides an effective method for the prediction of the supersonic flow field inside the isolator of the super-combustion ram engine, and the introduction of deep learning makes it possible to obtain the future flow field evolution law based on the wall pressure sequence. Bian et al. [25] aiming at the problem that the detonation wave surface consists of lead excitation and reaction front surface, which is difficult to make simultaneous measurements, they proposed a method for predicting the reaction front lead excitation to obtain a complete detonation wave surface reconstruction method. The reconstruction method is constructed based on the convolutional neural network (CNN) model, which has the advantages of feature extraction and data dimensionality reduction. The structure of the convolutional neural network (CNN) model is shown in Fig. 21.

The reconstructed shock wavefront and relative error results are shown in Fig. 22.

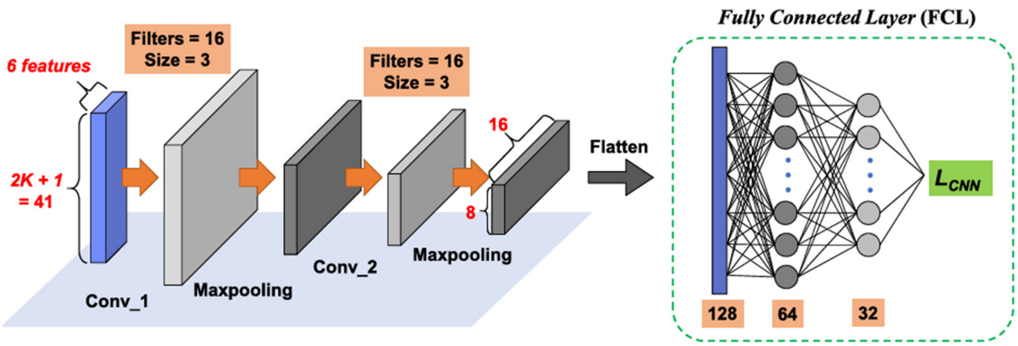
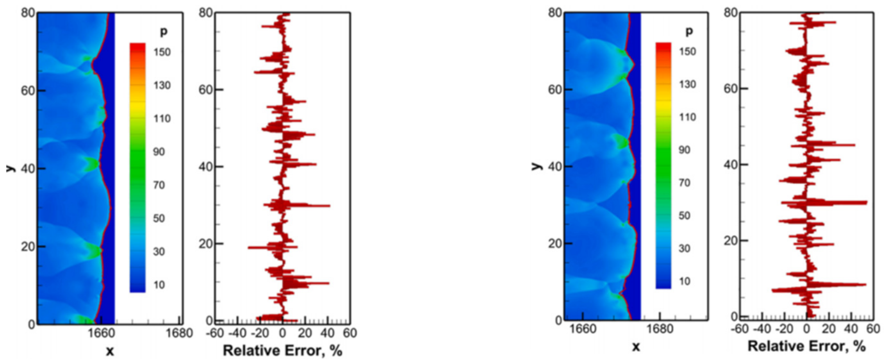


Fig. 21. CNN model structure [25]



a) Histogram of relative error frequency distribution b) Box plot

Fig. 22. The reconstructed shock wavefront and relative error results [25]

The reconstruction results show that the well-trained CNN model is able to reconstruct the leading excitation wavefront position with a low relative error. Hyperparameter discussion is also carried out for the number of input grids K. The results show that the method is robust to the selection of the hyperparameter K, which is more efficient and effective than the traditional MLP method. This is attributed to the principle advantage of the CNN model, which inputs the details of neighboring reactive fronts into the neural network instead of considering only the reactive fronts featured just before the lead shock. For a burst wave with two activation energy values, the CNN model-based approach reduces the reconstruction error by nearly 2 % compared to the results of the MLP approach. Meanwhile, the well-trained CNN model still has some generalization ability for the burst flow field with different activation energies, although the generalization performance improvement is very limited compared with that of the MLP method, it still has some guiding value for engineering tests.

In 2023, Sofos F. et al. [26] investigated deep learning methods in the framework of convolutional neural networks for reconstructing compressible turbulence fields. The aim was to develop methods capable of scaling coarse turbulence data into high-resolution images. The method is based on a parallel computational framework that accepts five image sets of different resolutions trained to correspond to the corresponding fine resolutions. The network architecture consists mainly of convolutional layers to construct an encoder/decoder network. Based on the U-Net scheme, three different implementations are proposed, including residual connections and skip connections. The structure of the encoder/decoder network and the residual connection and skip connection algorithms are shown in Figs. 23-24.

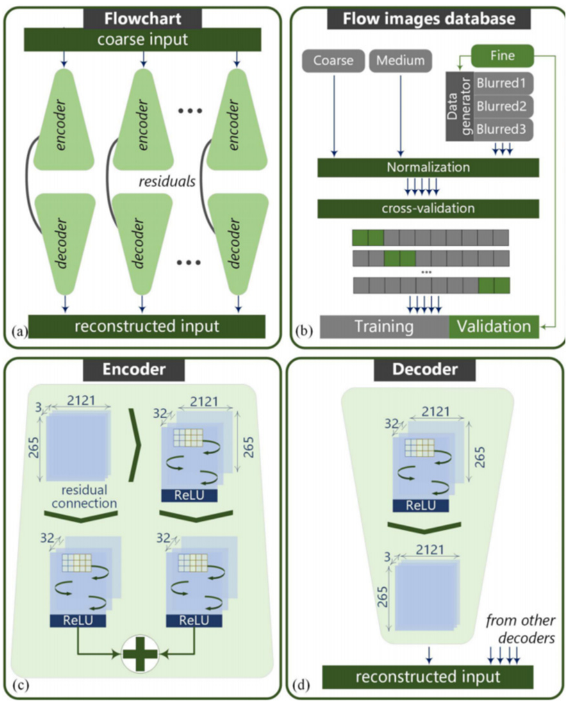


Fig. 23. Encoder/decoder parallel branch and residual connection EDR stream reconstructs the overall flow of the model [26]

a) Residual connections b) Skip connections

Fig. 24. Techniques for improving CNN accuracy in hierarchical networks [26]

The deep learning model is trained using real images and the prediction accuracy of the model is verified using the validation set of images and the validation results are shown in Fig. 25.

The reconstruction results show that the simple network performs better when trained on limited data, which is a practical and fast solution for dealing with turbulent data, whose computational burden is difficult to reduce in most cases. With this computational model, a coarse simulation grid can be upgraded to a fine grid.

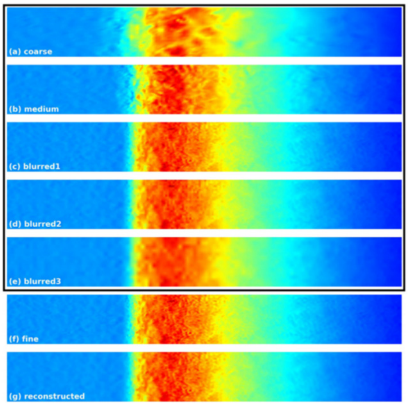


Fig. 25. Verify group data prediction results [26]

Xi et al. [27] used AUTODYN-2D to obtain the peak overpressure of a cylindrical charge explosion in air near the surface. Based on this, attempts were made to construct a multiple linear regression (MLR) and optimal error back-propagation artificial neural network (ANN) model with three geometrical parameters as inputs, which are linear scaling distance (SLSD), vertical scaling distance (VSD), and scaled height of burst (SHOB). The structure of the ANN model is shown in Fig. 26.

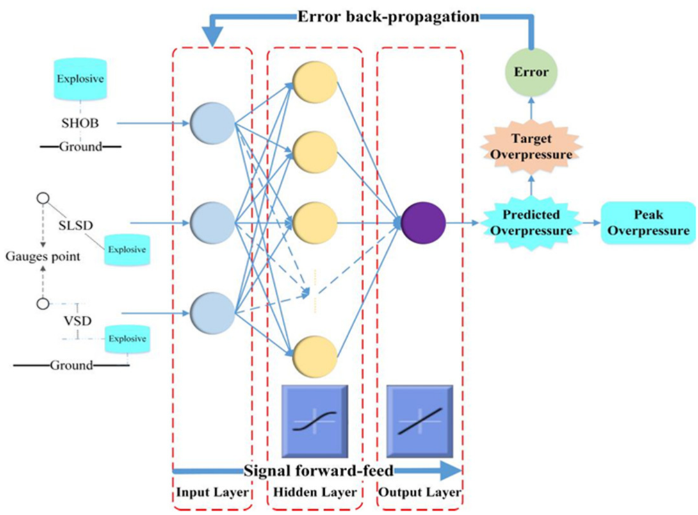


Fig. 26. Artificial neural network topology [27]

The prediction results of the MLR and ANN models were validated and compared on a test set. The results show that the ANN model with geometric parameters as inputs outperforms the MLR model in predicting the peak overpressure of an air blast. The former computes 1441 sets of inputs in less than 0.2 s, providing a fast reference for predicting spatial peak overpressure in large-scale shock waves of air blasts. Mat M.H. et al. [28] compared the accuracy of blast peak overpressure prediction based on the type of explosives, their shapes, and their locations. The study used a multilayer perceptron (MLP) network to create a prediction model and carried out explosion tests with 500 g of plastic explosive 4 (PE-4) and Emulex at different ranges (0.5 m to 4.0 m). The Lavenberg Marquardt (LM) training method outperformed the backpropagation (BP) algorithm when modeling the test results using the Tansig and Logsig training algorithms. The MSE and regression scores using the LM training algorithm were 1.1348 and 0.9512, respectively, with better model performance. Jordan J. P. et al. [29, 30] enhanced the generalization ability of neural networks by using migration learning and imposing monotonic loss constraints on the objective function, respectively, which provided an effective method for predicting the specific impulse load of the high explosives explosive shockwave pressure acting on a rigid target. Li et al. [31] proposed a flow field time series prediction framework-compressed convolutional gate recursion unit (CC-GRU) for predicting the flow parameters of future supersonic vane grids. CC-GRU embeds the convolutional method into a gate recursion unit (GRU) to deal with the complex spatio-temporal behavior of supersonic vane grids' flow field. The CC-GRU framework is shown in Fig. 27.

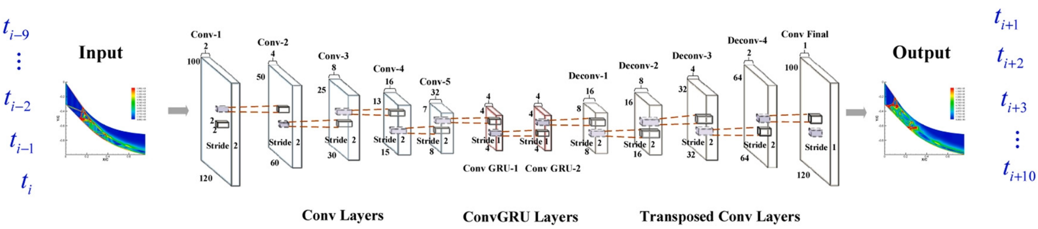


Fig. 27. CC-GRU framework [31]

The prediction results of the flow field pressure and density gradient by the CC-GRU model for Mach numbers of 2.4 and 2.7 are shown in Figs. 28-29.

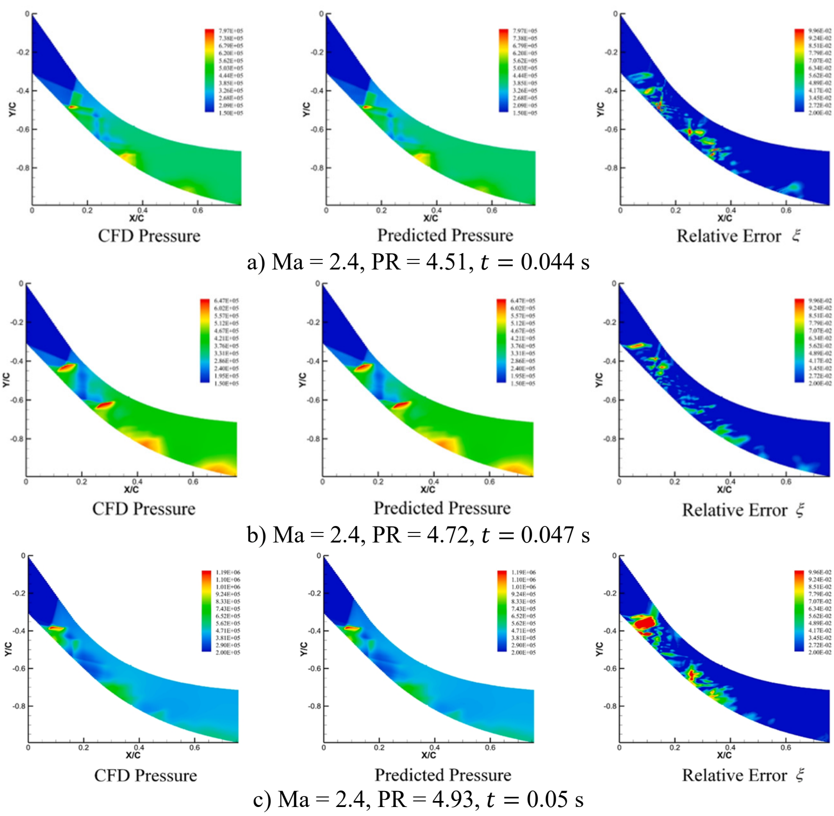
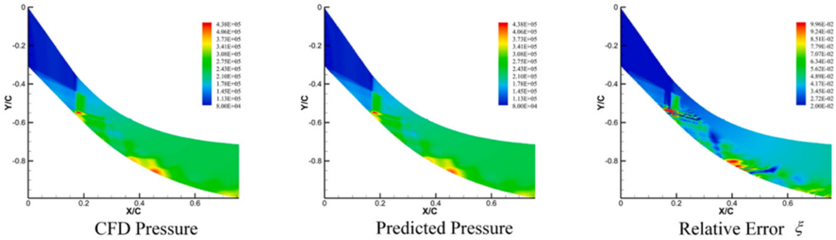
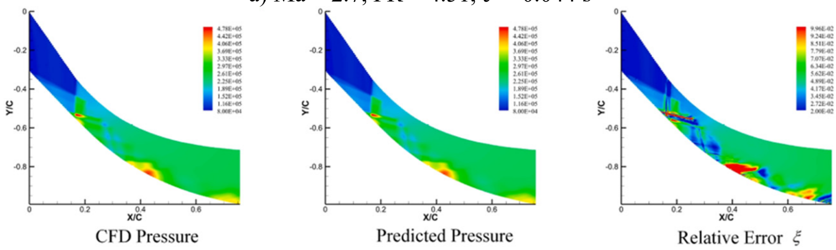


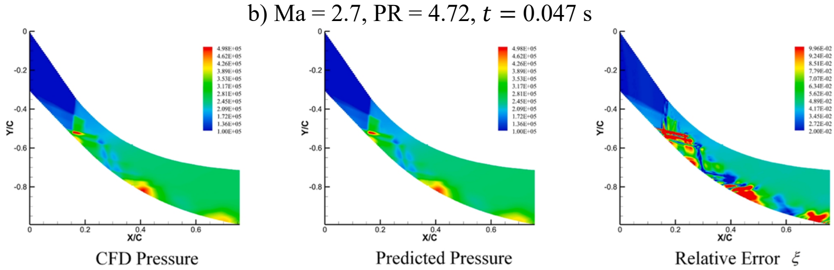
Fig. 28. The pressure flow field predicted by CC-GRU frame for Mach number of 2.4 is compared with the CFD result [31]



a) Ma = 2.7, PR = 4.51, t = 0.044 s



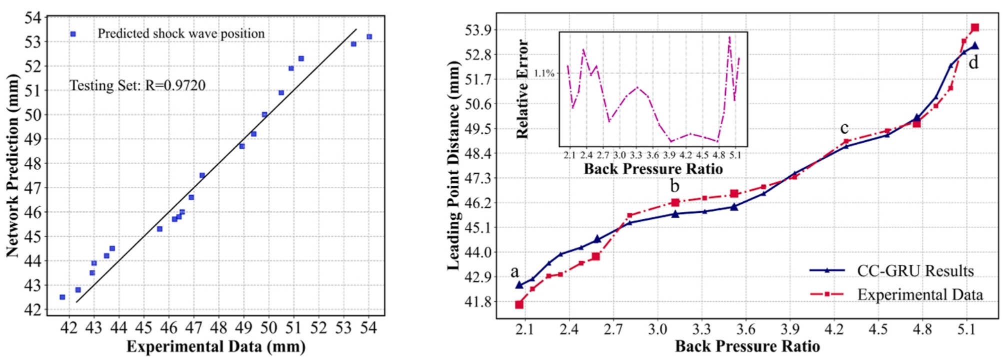
b) Ma = 2.7, PR = 4.72, t = 0.047 s



c) Ma = 2.7, PR = 4.93, t = 0.05 s

Fig. 29. The pressure flow field predicted by CC-GRU frame for Mach number of 2.7 is compared with the CFD result [31]

With Mach number of 2.4, the shock position timing prediction results of compressor cascade flow field based on CC-GRU model are shown in Fig. 30.



a) Correlation comparison b) Comparison of shock wave positions

Fig. 30. The shock position timing prediction results of compressor cascade flow field using CC-GRU model [31]

From the above validation results, it is shown that the framework can comprehensively predict the future high-backpressure flow field based on the low-backpressure flow field in the past period, which further verifies the effectiveness of the proposed time-series prediction model in the ground-based wind tunnel experiments. The CC-GRU model can accurately capture the fine surge structure and the flow separation region, and the relative error of the predicted pressure field is less than 10 %, which mainly concentrates on the inside of the surge structure. Therefore, the study provides a new research perspective and technical support for comprehensive and rapid state monitoring of supersonic vane-grid flow field.

In the same year, Liu et al. [32] proposed an adaptive gene expression program-ming (AGEP) optimized deep neural network (DNN) prediction model for the specific impulse of underwater polymerization charge in order to realize the intelligent prediction of the specific impulse of underwater polymerization charge. (The flow structure of AGEP-DNN algorithm is shown in Fig. 31.

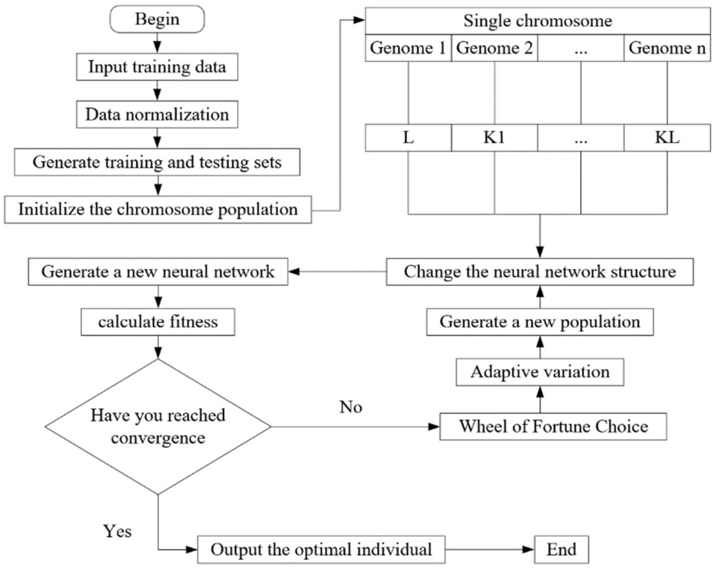


Fig. 31. Flowchart of the AGEP-DNN algorithm [32]

Based on the simulation and experimental data, the above constructed impulse prediction model is trained and tested for accuracy, and in the simulation experiments containing nine intelligent algorithms, the AGEP-DNN model has the minimum value in the four accuracy evaluation indexes of MAE, MSE, RMSE, and MAPE, which verifies the validity of the model, and illustrates that the use of the AGEP-DNN model in the prediction model of the impulse ratio of the underwater poly-energy charge reliability in the construction of the model, which helps to evaluate the destructive effect of the poly energy combatant in the underwater environment, and can be used in the field of military and explosives research.

3.2. Application of deep learning, machine learning in pressure field prediction

Pasini M. L. et al. [33] proposed a supervised deep learning (DL) method for adaptive partitioning of transient partial differential equations to simulate the propagation of a one-dimensional shock wave in a compressible medium. The neural network is trained on a dataset consisting of different static shock curves that are associated with corresponding adaptive grids computed using standard adaptive partitioning techniques. The experimental results show that the trained deep learning model can capture the presence of shock waves in the domain and generate an adaptive non-uniform grid at each time step, which relocates grid nodes to improve the accuracy of discretization between Lax Wendroff and fifth order weighted intrinsic non oscillatory (WENO5). The study also shows that the proxy DL model reduces the computational time to perform adaptive partitioning by at least a factor of 2 compared to standard techniques without compromising the accuracy of the reconstruction results for the physical quantities of interest. Poulinakis K. et al. [34] applied long short-term memory deep learning models to supersonic shock boundary layer interaction flows, aiming to demonstrate how to reconstruct near wall pressure fluctuations from a small (undersampled) dataset of pressure signals. The constructed deep learning model is shown in Fig. 32.

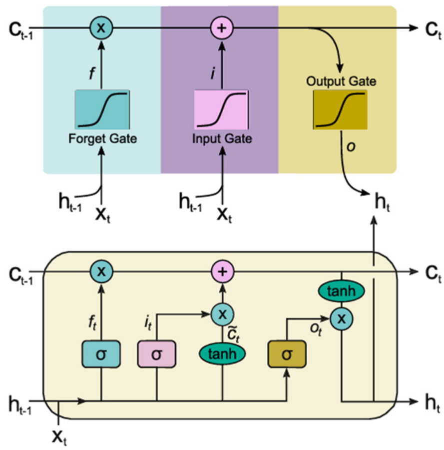
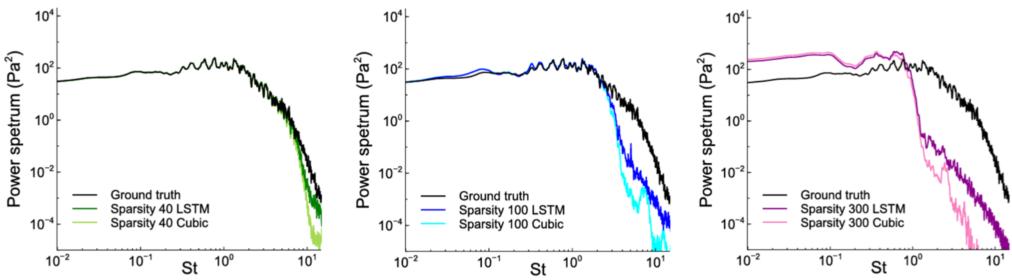


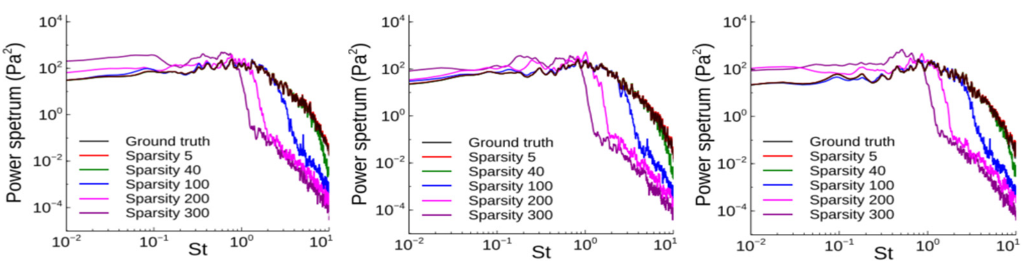
Fig. 32. Deep learning network model [34]

The training of the deep learning model is based on the results of direct numerical simulations of supersonic ramp flow, focusing on the region upstream of and around the region of surge-boundary layer interaction. In the preprocessing stage, the cubic spline function improves the fidelity of the sparse signal and feeds it back into the long-short memory model for accurate reconstruction. The reconstructed power spectra of the pressure signal by different reconstruction methods are shown in Figs. 33-35.



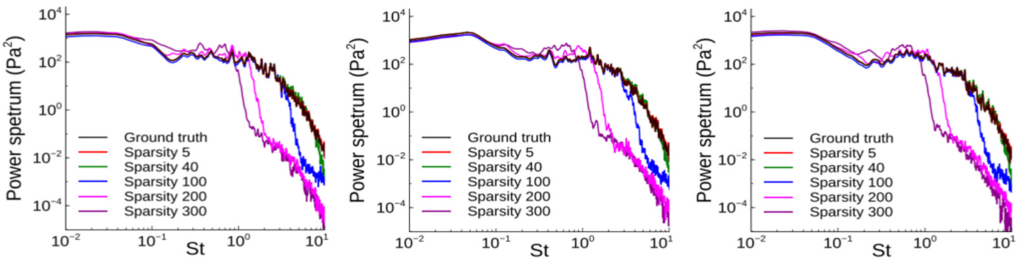
a) Sparsity 40 b) Sparsity 100 c) Sparsity 300

Fig. 33. The original (ground truth) power spectrum, LSTM prediction, and cubic spline interpolation pressure signal at probe 7 for sparsities 40,100, and 300 [34]



a) Probe 7 b) Probe 1 c) Probe 4

Fig. 34. The power spectrum of the raw (ground truth) and LSTM predicts the pressure signals of probes 7 (training), 1, and 4 [34]

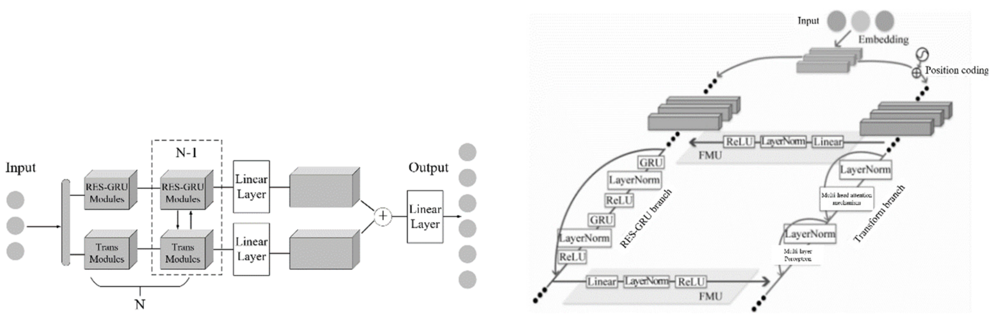


a) Probe 8 b) Probe 2 c) Probe 5

Fig. 35. Raw (ground truth) and LSTM power spectra predict pressure signals for probes 8 (training), 2, and 5 [34]

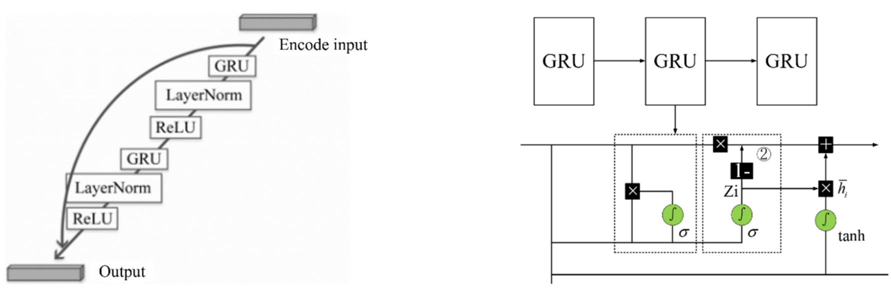
After qualitatively evaluating the accuracy of the model on the pressure signal and quantitatively evaluating the accuracy of the model using the root-mean-square error and the power spectrum, it can be obtained that deep learning has a high reconstruction accuracy, which is promising for the application in the field of pressure prediction and can be extended to the research field that includes other aerodynamic or aeroelastic parameters of interest.

In 2024, Sun et al. [35] established the Res GRU branch to capture local temporal dependencies of shock wave overpressure signals in a serial manner; Establish Transformer branches to analyze the global latent features of signals in parallel; A feature fusion unit was established for high-order feature fusion, achieving layer by layer complementarity of information at different stages. Subsequently, a series parallel dual branch network (G-TNet) based on gated recurrent unit (GRU) and Transformer model was constructed to reconstruct the shock wave pressure curve of incomplete data. The G-TNet network structure and Res GRU model are shown in Figs. 36-37.



a) Network architecture diagram b) Dual branch structure and feature fusion unit

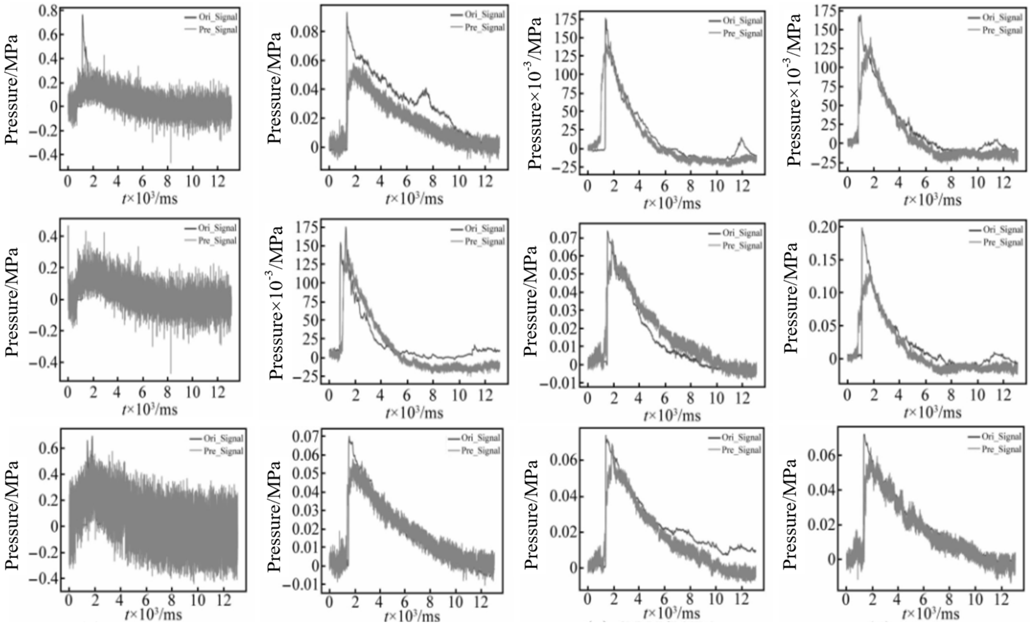
Fig. 36. G-TNet network structure [35]



a) Res-GRU structure b) GRU structure

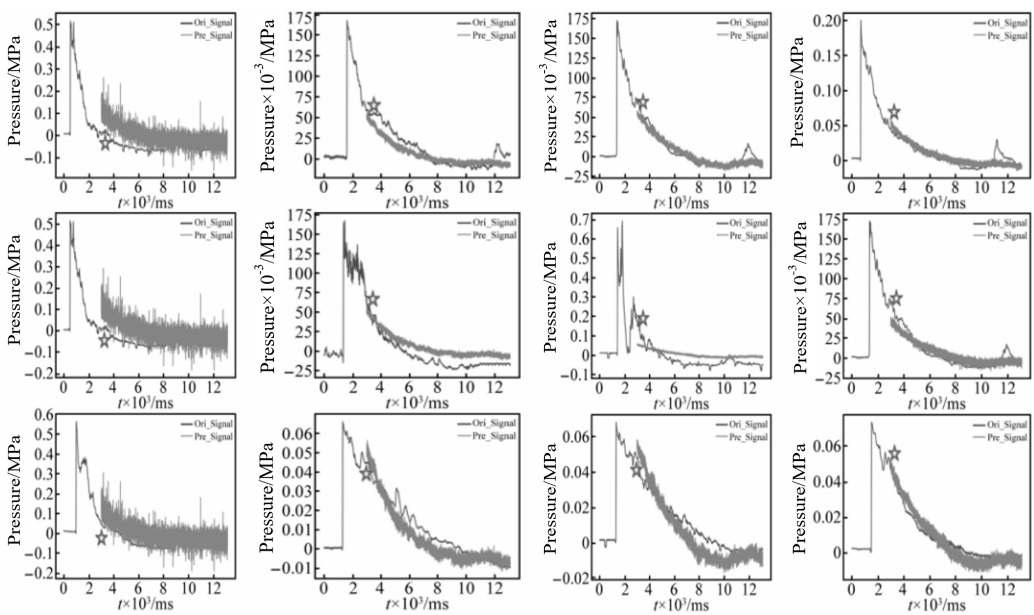
Fig. 37. Res-GRU model structure [35]

The above model is used to reconstruct the shock wave pressure signal of the limited measurement point data and the incomplete data, and the reconstruction results are displayed in Figs. 38-39.



a) GAN-GRU b) Bi-LSTM c) CNN-BiLSTM d) G-TNet

Fig. 38. Reconstruction results of shock wave pressure distribution from finite measuring point data [35]



a) GAN-GRU b) Bi-LSTM c) CNN-BiLSTM d) G-TNet

Fig. 39. Reconstruction results of shock wave pressure distribution with incomplete data [35]

From the reconstruction results, it can be seen that in the reconstruction test of shock wave field pressure distribution based on the limited measurement point data, the mean square error (MSE) between the reconstructed simulated and measured overpressure data and the original values are 5.0×10^{-6} and 1.2×10^{-3}, respectively, the average peak error is 0.49 % and 27.01 %, the average orthostatic action time error is 15.62 % and 15.91 %, respectively, and the average specific impulse error is 17.66 % and 19.33 %. The average specific impulse errors are 17.66 % and

19.33 %, respectively. In the reconstruction test of the shock wave pressure curve based on the residual data, the MSEs between the reconstructed analog signal, the missing value of the measured signal and the original value are 5.0×10^{-6} and 5.0×10^{-4}, respectively, and the average absolute errors (Mean Absolute Error (MAE)) are 0.0010 and 0.0171, respectively; it can be seen that the G-TNet reconstruction result is better than the current one. TNet reconstruction results are better than the current mainstream calculation methods, to meet the requirements of the explosion shock wave pressure reconstruction index.

In the same year, Peng et al. [36] constructed a two-dimensional explosion field sparse reconstruction model based on machine learning. The model utilizes sparse observation data to establish a mapping model of the entire flow field distribution. The model is constructed by a graph neural network (PIGN) based on physical principles, and the model structure is shown in Fig. 40.

The process of converting model grid data into graph data is displayed in Fig. 41.

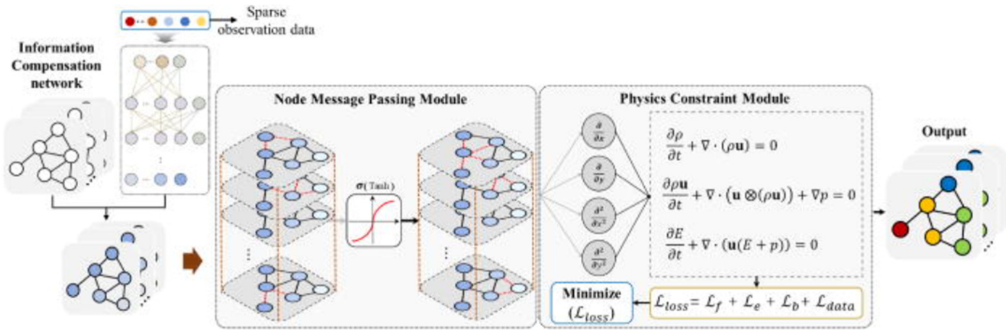


Fig. 40. PIGN model structure [36]

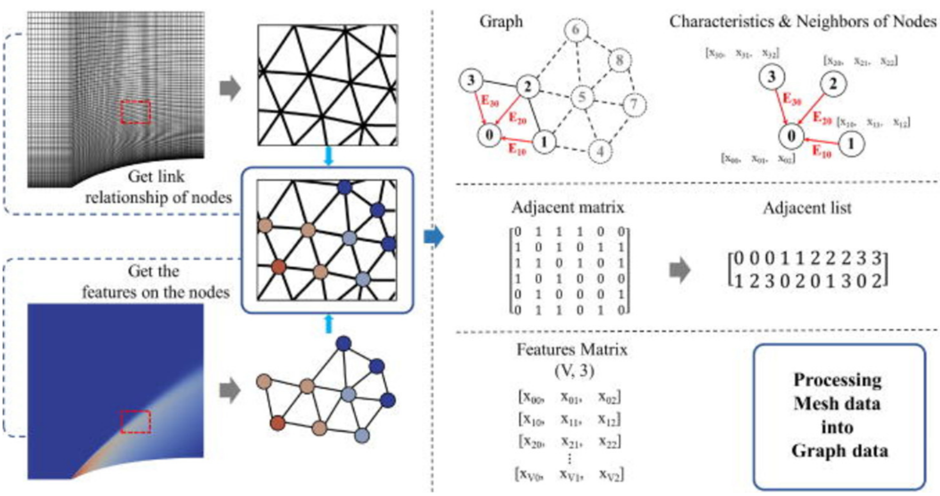


Fig. 41. Grid data is converted to graph data and represented [36]

The steady-state flow field of the supersonic projectile reconstructed by the PIGN model is shown in Fig. 42.

By comparing the results of the model with numerical simulations, the results show that the PIGN model can effectively reconstruct the explosion flow field distribution, and the average error of the reconstructed flow field is less than 4 %, which provides a novel method for realizing the fast and reasonable prediction of the explosion field or two-dimensional compressible flow field. Dimitris D et al. [37] used a long-short memory model to predict the flow field with turbulence, surge-boundary layer interaction and separation of the wall pressure fluctuations in physical states.

The sensitivity of the model to data inputs was checked using different input datasets. The RNN neural network model structure is shown in Fig. 43.

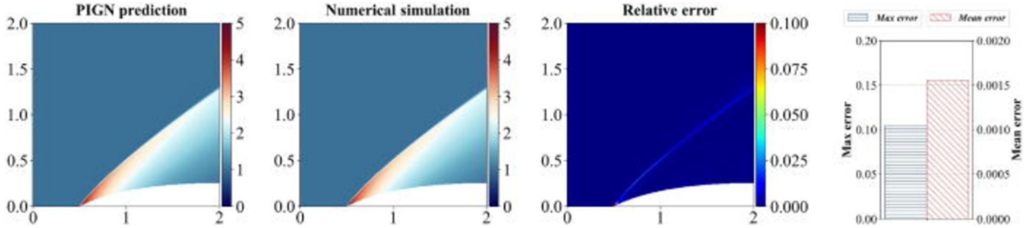


Fig. 42. The steady state flow field of supersonic projectile is reconstructed by PIGN model [36]

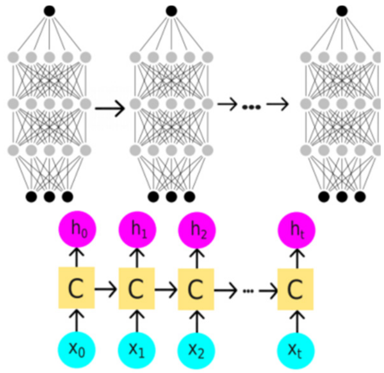


Fig. 43. RNN neural network model structure [37]

Different verification data were used to verify the prediction accuracy of the neural network model, and the verification results are illustrated in Figs. 44-46.

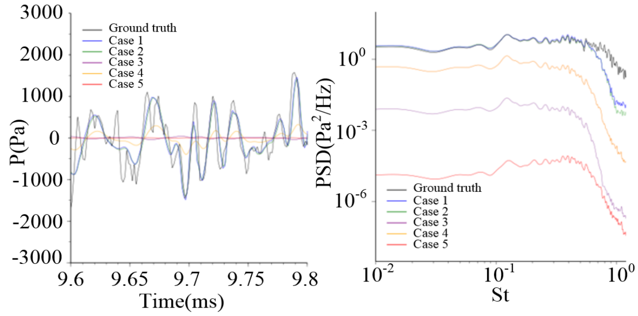


Fig. 44. Pressure fluctuation (P0) and corresponding power spectral density (PSD)-1 [37]

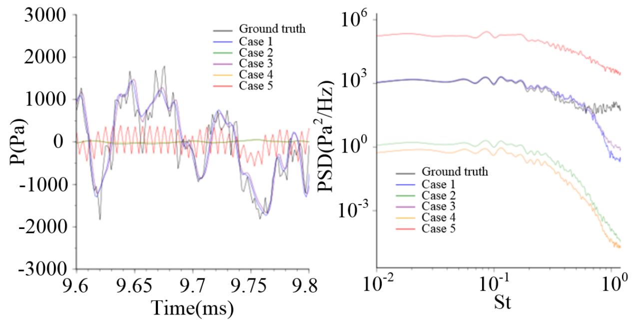


Fig. 45. Pressure fluctuation (P0) and corresponding power spectral density (PSD)-2 [37]

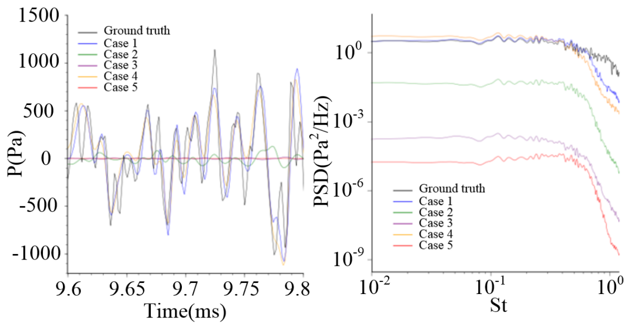


Fig. 46. Pressure fluctuation (P0) and corresponding power spectral density (PSD)-3 [37]

The validation results show that the data must be properly preprocessed prior to training in order to keep the deep learning model prediction results consistent. Removing the mean and using the signal normalized fluctuation components not only greatly improves the accuracy of the deep learning model prediction results, but more importantly, keeps the convergence of the results highly consistent as long as the signal sparsity stays within the inertia subrange of the turbulence energy spectrum cascade.

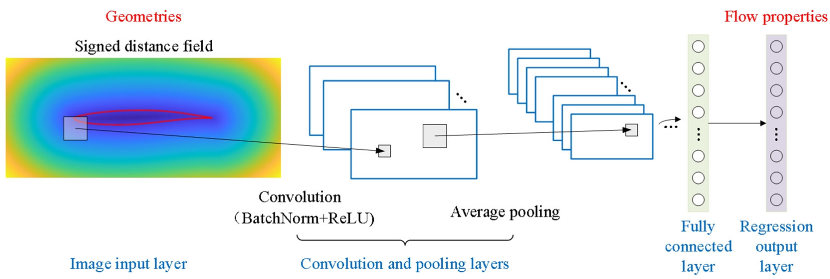


Fig. 47. Return to CNN architecture [38]

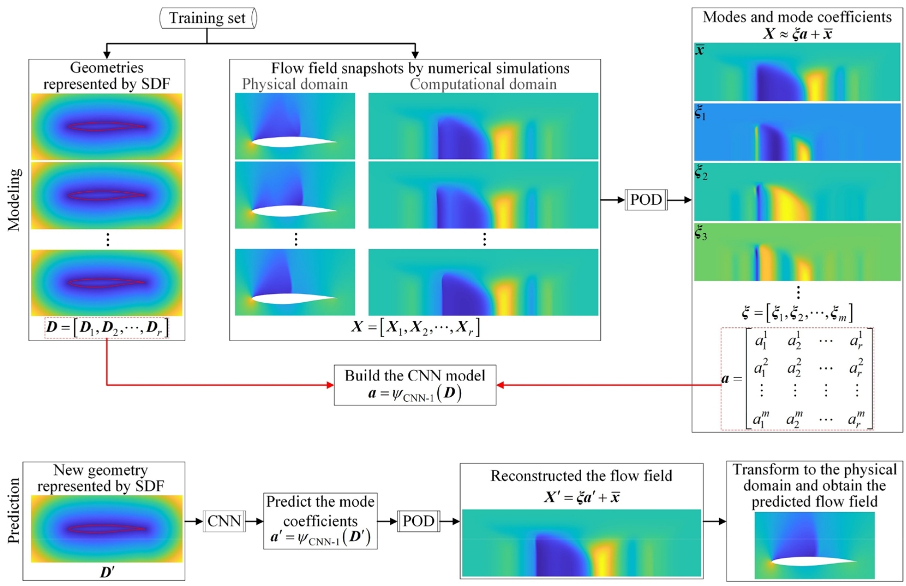
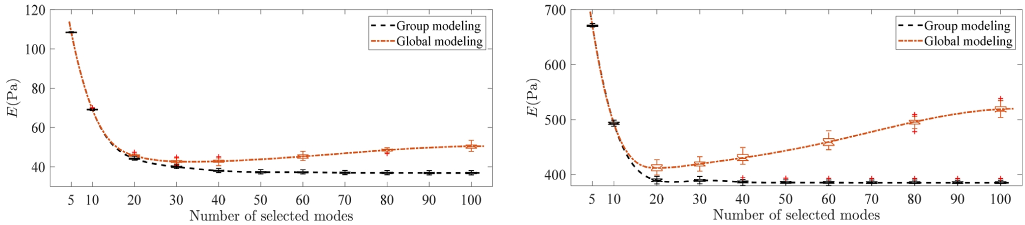


Fig. 48. The CNN-POD method is used to model and predict the flow field [38]

The power spectra of the surface pressure fluctuations indicate that the model provides a highly accurate reconstruction method for full turbulence at certain frequencies. Despite significant differences in turbulence characteristics in the training dataset, the consistency of the deep learning model can still be demonstrated by transferring between individual probe locations on the wall. The consistency and invariance of the model's prediction of the training locations of turbulence signals promises to apply the deep learning model to a variety of turbulence prediction applications. Jia et al. [38] developed an accuracy-enhanced flow prediction method that fuses deep learning and reduced-order modeling to achieve accurate flow field prediction for a variety of aerodynamic shapes. A convolutional neural network/orthogonal decomposition (CNN-POD) model was developed in this study for mapping geometric shapes to the entire flow field. Localized flow regions containing nonlinear flow structures are identified by POD reconstruction to construct an enhanced model. The constructed CNN neural network model framework and the prediction process are shown in Figs. 47-48.

The pressure prediction error results of CNN-POD method under different POD mode numbers are shown in Fig. 49.



a) Global flow field b) Local flow field with shock wave

Fig. 49. Pressure prediction error [38]

The prediction results show that the proposed accuracy-enhanced flow field prediction method is able to reduce the prediction errors of flow properties in the region of nonlinear flow structures by 13 % to 66.27 %. In addition, compared with the existing prediction methods, the proposed method exhibits better computational efficiency and robustness, and is able to solve the complex transonic flow prediction problem with multiple strong nonlinear structures.

Adam A. D. et al. [39] proposed the use of machine learning to construct a new method for calculating the explosion load in the obstacle environment, the model construction mainly uses the DeNN model can predict the peak overpressure of any shape or size of invisible complex region, DeNN model structure is shown in Fig. 50.

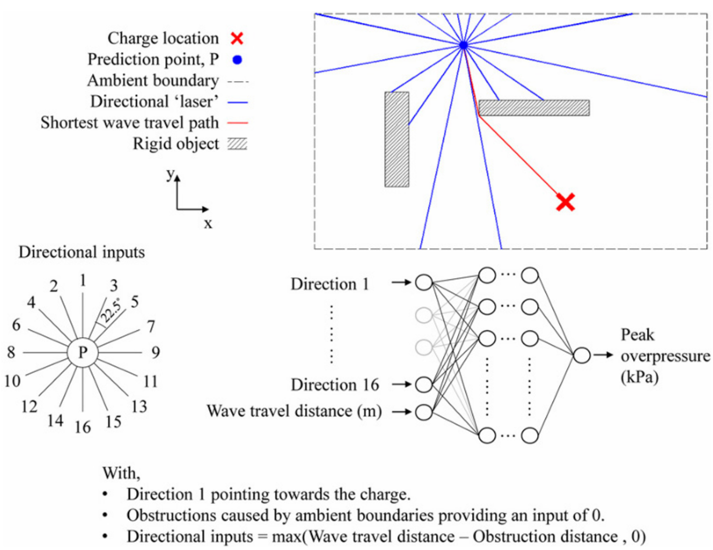
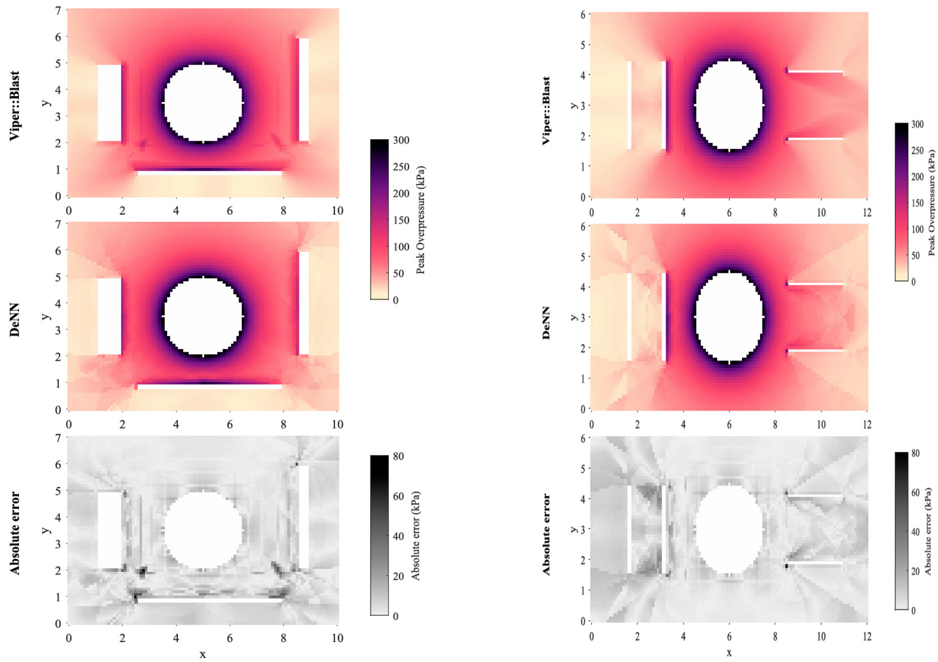


Fig. 50. DeNN neural network model structure [39]

The model was utilized to reconstruct the shock wave pressure distribution for both obstacle conditions and the reconstruction results are shown in Fig. 51.

From the reconstruction results of different models, it can be seen that the model is able to accurately predict the pressure distribution around the obstacle, with the absolute error of the peak pressure prediction being less than 5 kPa and the correlation coefficient being greater than 0.993, which demonstrates the significant application value of machine learning in this research area.



a) First obstacle situation b) Second obstacle situation

Fig. 51. Comparison of reconstruction results [39]

3.3. Application of BP neural network model in pressure field prediction

Liu et al. [40] conducted 52 sets of on-site blasting tests on the surface load mechanism using underground public tunnels as the experimental target. Surface load data samples were obtained, and the key influencing parameters of reflected explosion loads were obtained through dimensional analysis. Based on the test data, a backpropagation neural network model was constructed, and the Levenberg Marquardt algorithm was used to train and optimize the neural network. The accuracy of the prediction results was evaluated by comparing and evaluating the neural network, empirical formula, and nonlinear regression analysis (NRA) method. The constructed BP neural network model includes 4 input layers, 15 hidden layers and 1 output layer. The neural network model structure and training results are shown in Figs. 52-53.

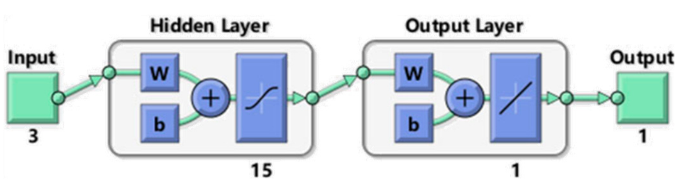


Fig. 52. BP neural network model structure [40]

The load distributions calculated by the neural network for typical working conditions show that the combined variable input parameters can further improve the neural network prediction accuracy compared to a single physical variable input parameter. The neural network model with combined variable input parameters provided the most accurate prediction compared with the empirical formula method and the NRA method. Li et al. [41] trained the neural network product state equations using a BP neural network and strong explosion product state data, and implanted the obtained state equations into a self-programmed one-dimensional spherically symmetric numerical simulation program to compute the strong explosion shock wave parameters. The structure of the constructed BP neural network model is shown in Fig. 54.

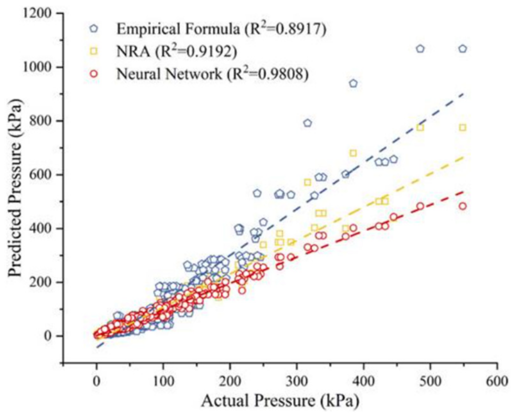


Fig. 53. The comparison between the predicted result and the target result [40]

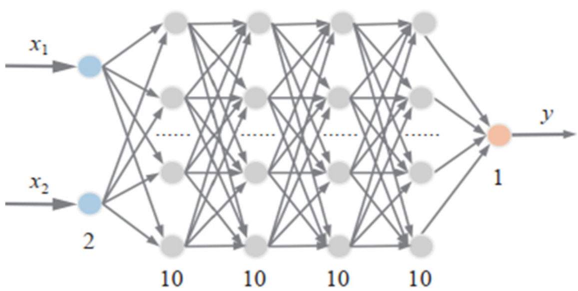


Fig. 54. BP neural network model structure [41]

The accuracy check of the model prediction results shows that the calculated peak shock wave overpressure, shock wave arrival time, and positive pressure action time are in good agreement with the standard values, which proves that the neural network equation of state is feasible to be applied to the numerical simulation of strong explosion shock wave.

In order to improve the accuracy and stability of the prediction of the explosion shock wave parameters of the underwater polymer charge, Liu et al. [42] proposed a dynamic adaptive ant colony algorithm (DACO) to optimize the BP neural network prediction model of the peak overpressure of the underwater polymer charge. The Mason rotation algorithm is used to randomly sort the data to improve the model's ability to generalize to different data distributions. The MT algorithm data random swap process is shown in Fig. 55.

The global optimal solution obtained by DACO algorithm is mapped to the weights and thresholds of the BP neural network model to improve the accuracy and stability of the prediction results of the BP neural network model. The experimental results show that the dynamic adaptive ant colony optimization BP neural network prediction model of peak overpressure of underwater poly energy charge has good effectiveness, stability and credibility. Li et al. [43] constructed a peak pressure prediction model for the explosion shock wave of underwater dual explosive sources based on BP neural network. The total mass of the explosive source and the straight-line distance from the center of the explosive source as the input parameters, the establishment of the BP neural network model shown in Fig. 56.

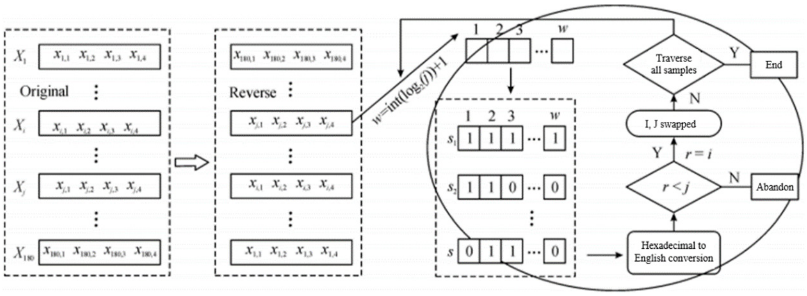


Fig. 55. Random data exchange process [42]

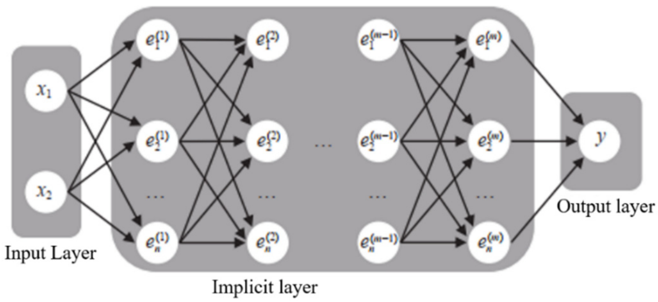


Fig. 56. Neural network model structure [43]

The peak pressure calculated by the BP neural network model was compared with the theoretical formula calculation results, and the average relative error between the formula calculated value and the actual value was 1.08 %, and the average relative error between the BP neural network predicted value and the actual value was 0.52 %. Compared with the formula calculation results, the BP neural network is able to achieve higher accuracy prediction with less data sample capacity.

4. Application of artificial intelligence techniques in blast damage assessment

The testing of damage parameters such as shock waves, fragments, fireballs, and electromagnetic radiation generated by ammunition explosions is to comprehensively and reliably evaluate the accurate destructive power of ammunition explosions. Before the widespread application of artificial intelligence technology, the evaluation of the explosive damage power of ammunition usually used a numerical weighting method to calculate the damage level of targets caused by the joint action of multiple parameters. However, there are generally some problems, such as the non-standard proportion factors set for each damage parameter in the calculation process, inconsistent evaluation results by researchers with different experimental results, and significant interference from human factors in the evaluation results. In order to solve these problems in the current research, the researchers combined the advantages of artificial intelligence technology such as neural network, deep learning and machine learning, and introduced artificial intelligence technology into the research of explosive damage test and evaluation technology, to carry out multi-parameter comprehensive consideration of the target's destructive power assessment.

At present, relevant scholars have carried out some research on this, such as, in 2021, Zhang et al. [44] proposed a damage assessment method based on improved GA-BP neural network for the problems of general timeliness and strong subjectivity in the assessment of target damage effect after the incident. This method takes the aircraft system as an example, analyzes the target characteristics of the system, and constructs a target damage tree and divides the damage levels according to the structural order of the target system layer, functional damage layer, and physical damage layer; Introducing genetic algorithm to improve its selection operator, crossover and mutation probabilities, in order to obtain the optimal weight values of BP neural network, enhances the diversity and generalization ability of the genetic algorithm population, and improves the accuracy of the network model. The improved GA-BP neural network model structure is shown in Fig. 57.

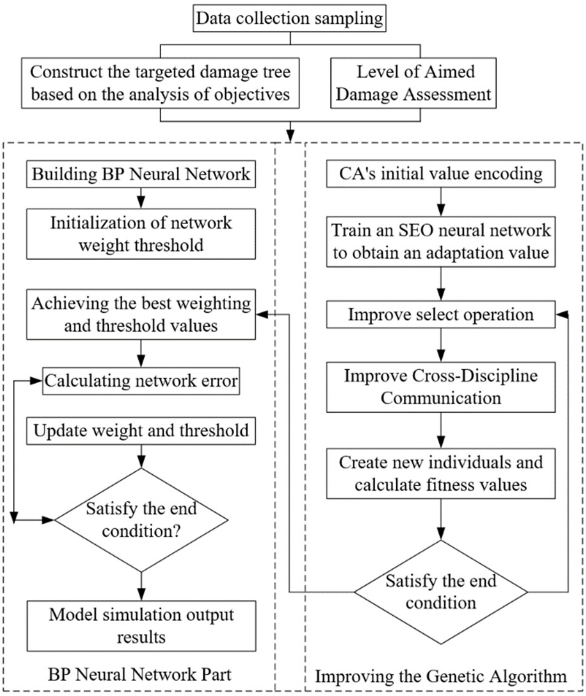


Fig. 57. Improved GA-BP neural network model flow chart [44]

Three models were used to evaluate the measured data, and the comparison results are displayed in Fig. 58.

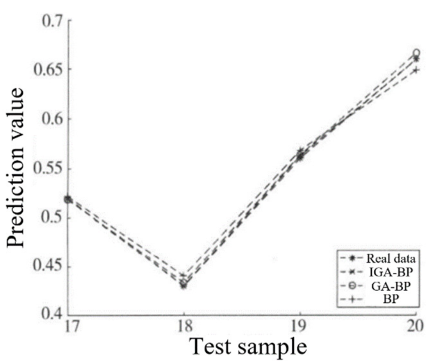


Fig. 58. Comparison chart of evaluation results [44]

From the validation results, it can be seen that the IGA-BP model is closer to the actual value curve. Both the traditional BP algorithm and GA-BP algorithm are lower than the improved GA-

BP neural network model in terms of accuracy. The model can provide certain auxiliary decision support for the assessment of target destruction effect and battlefield damage assessment for both offense and defense in exercise drills, and has certain inspiration and reference significance for the development of artificial intelligence for target destruction effect assessment. Zou et al. [45] established a damage degree assessment method based on target detection and identification of component failure modes. A quantitative structural damage level assessment method was developed based on the damage type and degree of the component. Multiple categories of damage (fine cracks, wide cracks, concrete spalling, exposed reinforcement and flexural reinforcement) were detected using You Only Look Once v4 (YOLOv4) network. Depth separable convolution was introduced in YOLOv4 to reduce the computational cost without decreasing the accuracy. The structure of the YOLOv4 network is shown in Fig. 59.

Different network models were used to identify and analyze the validation data set, and the recognition results are displayed in Fig. 60.

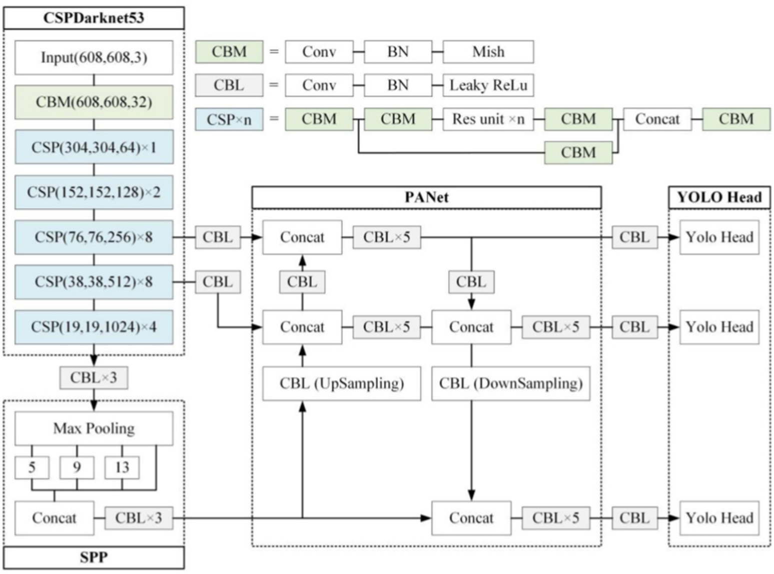


Fig. 59. YOLOv4 Network architecture [45]

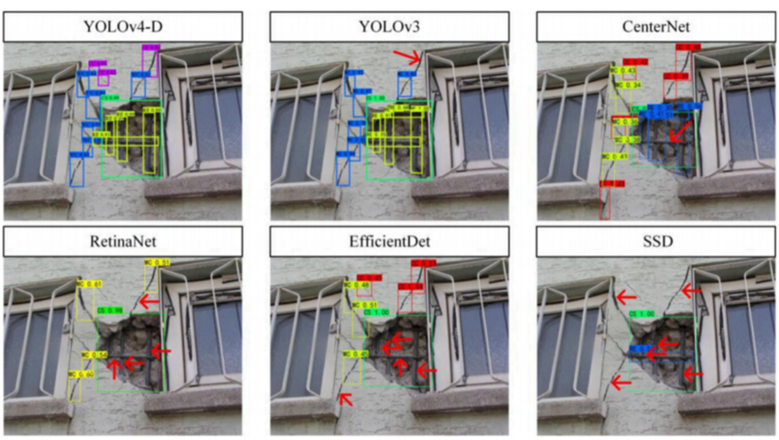


Fig. 60. Identification result [45]

The test results show that the improved target network can yield accurate detection results, and the preliminary safety assessment method can determine the extent of damage and failure modes.

This research has high potential in estimating the earthquake damage state of reinforced concrete structures.

In 2023, Wei et al. [46] proposed a combination of Convolutional Neural Network (CNN) and Random Forest (RF) for the problem that the traditional method of destructive effect estimation could not distinguish between the target features and the background features, which led to inaccurate evaluation results. It is labeled as CNN-F algorithm. The Convolutional Neural Network (CNN) and Random Forest (RF) are used to process the image, extract the image features, and then use the RF to replace some of the fully connected layers in the CNN and use the Softmax classifier to categorize the damage results of the target. The flow of the CNN-F algorithm and the flow of the damage effect evaluation are shown in Figs. 61-62.

To verify the evaluation accuracy of the model, the damage effects of the three tests were evaluated, and the performance of the model is listed in Table 1.

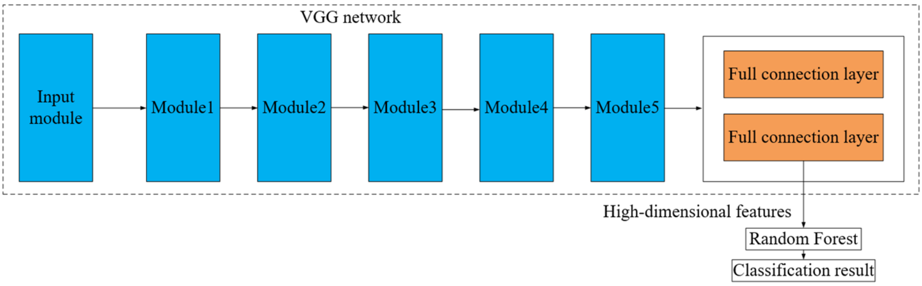


Fig. 61. CNN-F algorithm flow [46]

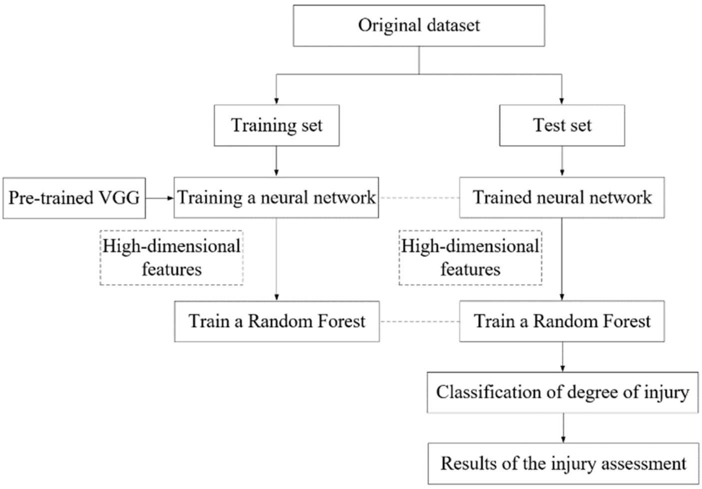


Fig. 62. Evaluation process of damage effect based on CNN-F [46]

Table 1. Experimental result [46]

Experiment number	Experimental method	Accuracy rate / %	Accuracy rate / %	Recall rate / %	F1 value / %
1	Texture segmentation	62.000	62.265	62.000	61.829
2	VGG16	80.050	80.454	80.050	80.146
3	CNN-F	83.050	83.585	83.050	82.945

Through three comparative experiments, it can be seen that Experiment 2 has improved accuracy by about 18.05 %, accuracy by about 18.189 %, recall by about 18.05 %, and F1 value by about 18.317 % compared to Experiment 1. This indicates that convolutional neural networks can effectively distinguish target features from background features when processing images, and also demonstrates that the work of distinguishing target features from background features is meaningful in evaluating damage effects. Compared with Experiment 2, Experiment 3 showed significant improvements in accuracy, precision, recall, and F1 score, reaching 83.050 %, 83.585 %, 83.050 %, and 82.945 %, respectively. This indicates that using a random forest instead of the last fully connected layer of VGG16 and using a softmax classifier have good results. Wang [47] analyzed the main factors affecting the damage effect based on a projectile penetration model, including incident angle, incident velocity, target plate thickness, and target plate material. They analyzed the impact of these factors on the target plate damage diameter and residual velocity of the projectile, established simulation datasets for projectile damage effect under different working conditions, and studied the genetic algorithm based BP neural network algorithm (GA-BP). The initial weights and thresholds of the BP network were optimized, and a projectile damage effect prediction model was constructed based on this. The calculation process of GA-BP prediction model is shown in Fig. 63.

The accuracy of the prediction model was verified by the test data, and the errors between the predicted results of the model and the actual measured values are listed in Table 2.

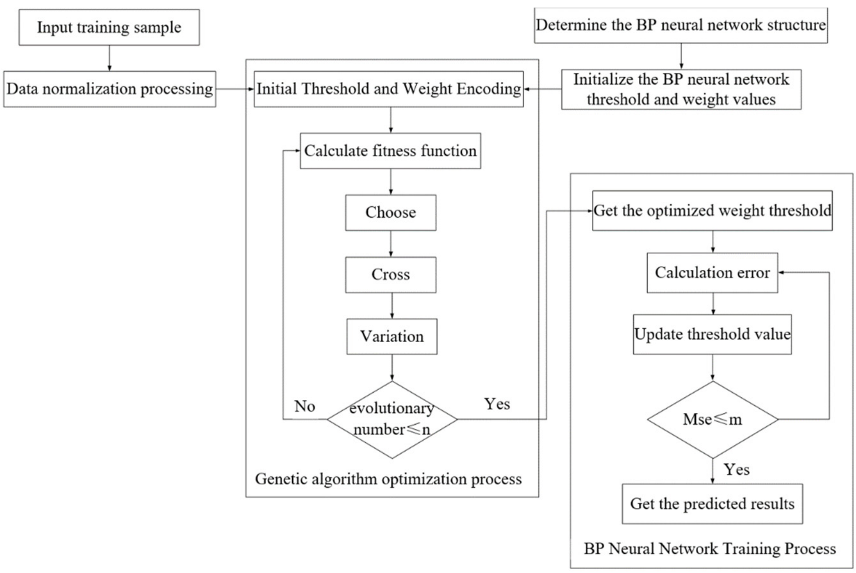


Fig. 63. BP neural network algorithm flow based on genetic algorithm [47]

Table 2. The relative error between the predicted result and the actual result [47]

Actual results (m/s)	Predicted result (m/s)	Error (%)
2925.09	2928.51	0.12
3022.38	3021.03	0.04
3118.77	3117.27	0.05
3215.49	3217.36	0.06
3312.35	3316.13	0.11
3415.28	3413.65	0.05
3516.82	3510.05	0.05
3612.95	3605.85	0.03
3710.78	3710.37	0.2
3806.44	3796.54	0.26
3903.45	3890.82	0.32

The experimental results show that the BP neural network prediction model optimized based on genetic algorithm ensures the accuracy of the prediction results under the premise of effectively guaranteeing a good global optimal solution. This method provides an efficient and feasible approach for achieving rapid prediction and analysis of destructive effects.

Sun [48] realized a humanoid target equivalent damage sensing system on the basis of constructing a target equivalent damage model. Combined with the AI intelligent algorithm to achieve the humanoid target targeting positioning perception, and at the same time using artificial intelligence optimization algorithms to construct a humanoid target damage assessment model, truly realizing the integration of intelligent "perception-reasoning-judgment" of the target range training. The overall scheme of humanoid target damage assessment is shown in Fig. 64.

The structural process of the ASO-DNN humanoid target damage assessment model established is shown in Fig. 65.

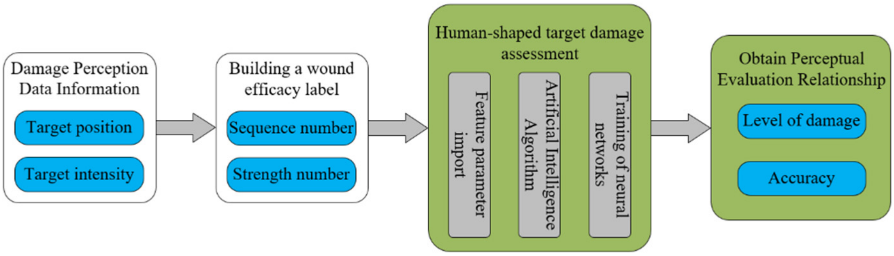


Fig. 64. Overall protocol for humanoid target damage assessment [48]

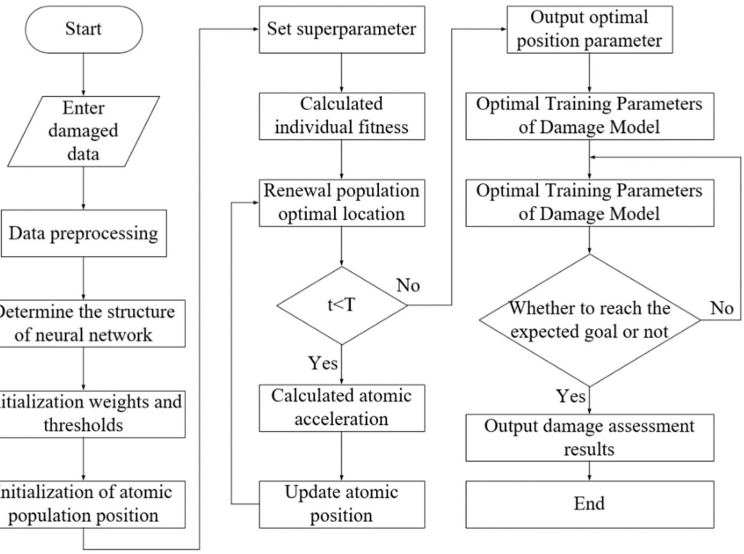


Fig. 65. Humanoid target damage assessment model based on SSA-DNN neural network [48]

The experimental results show that the improved ASO-DNN damage assessment model has a MAE of 5.535 % and a damage accuracy of 98.70 %, which is significantly improved compared to other models. The accuracy of the model evaluation results is high.

Xu et al. [49] proposed a method for identifying and assessing the damage of ground moving targets by cruise missiles based on multi-source information fusion, targeting the task scenario of using multiple cruise missiles to strike high defense ground moving targets. Implementing multi-source information fusion of infrared and visible light images based on IoU determination; Propose a two-stage tightly coupled patrol missile damage assessment method for ground moving targets based on YOLO VGGNet, utilizing the advantages of deep semantic information extraction using convolutional neural networks and introducing infrared damage information to achieve online real-time damage assessment of ground moving targets. The damage assessment process

ISSN PRINT 2335-2124, ISSN ONLINE 2424-4635

and the classification of the assessment level are shown in Figs. 66-67.

The damage effect of a target after an ammunition explosion was evaluated and analyzed. The evaluation effect of YOLO-VGG Net is displayed in Fig. 68.

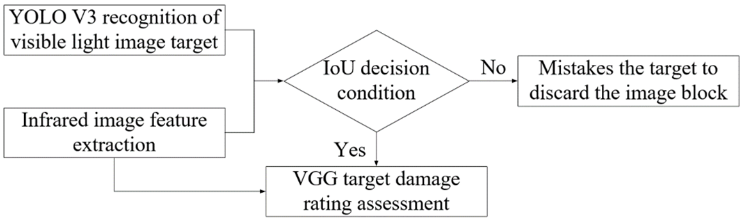


Fig. 66. Flow chart of ground target identification and damage assessment of bomb cluster nodes [49]

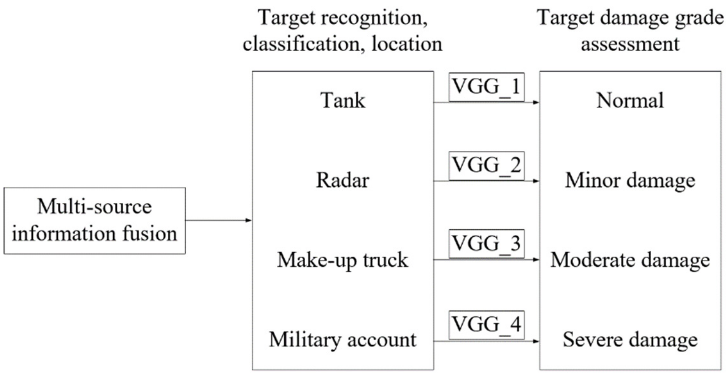


Fig. 67. VGG damage level assessment [49]

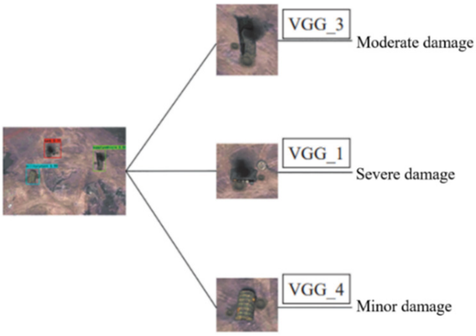


Fig. 68. YOLO-VGGNet evaluates the effect [49]

The experimental results show that the two-stage patrol missile damage assessment method based on YOLO VGGNet meets the online real-time combat requirements of missile swarm missions, and can fully utilize the advantages of CNN in extracting target semantic information. It can not only reduce the adverse effects of thick smoke and craters around the target, but also effectively utilize the limited damage infrared radiation and avoid the evaluation network from confusing the damage characteristics of the same type of target with different types of targets. Compared with the traditional PCA-k-means method based on image change detection and the two-stage evaluation method based on Mask-RCNN, it has significant advantages, with evaluation accuracy increased by 19 % and 10.25 % respectively.

5. Current research issues

According to the above analysis, it can be seen that the current application of artificial intelligence technology in the shockwave pressure test of the blast field mainly focuses on the use of neural networks, machine learning and deep learning to dynamically compensate the model of the pressure measurement system and improve the working bandwidth of the measurement system; the construction of the pressure and density field prediction model under the influence of multiple covariates and the reconstruction of the shockwave pressure field distribution law in specific conditions; the consideration of factors affecting the damage efficacy of targets and the construction of a multiple information fusion damage effect assessment model to realize the comprehensive damage assessment and analysis of the target. Considering the factors affecting the damage effectiveness of the target, we construct the damage effect assessment model with multiple information fusion to realize the comprehensive damage assessment and analysis of the target. The current research has achieved significant research results, but there are still some problems, such as:

(1) The applicability of artificial intelligence technology is insufficient. At present, artificial intelligence technology is mainly used to predict the distribution of shockwave pressure in the blast field, training data and verification data are derived from the actual experimental tests in the manual interpretation of the results, the accuracy of the interpretation results directly affect the model training accuracy and prediction accuracy. Therefore, to ensure the accuracy of the model training data and prediction data for the model is particularly important. Existing literature has not yet found the application of artificial intelligence technology in the processing of shockwave pressure data, signal denoising, high-pressure pulse removal and trend term removal, etc. In order to strengthen existing research, it is necessary to combine commonly used shock wave pressure data processing methods with artificial intelligence technology, deepen the application of artificial intelligence technology, standardize data processing procedures, and reduce the volatility of data processing results.

(2) The generalization of the model needs to be verified. Due to limited actual experimental data, the constructed model is only trained based on data obtained from a certain experiment or a few experiments. The model fails to extract feature parameters well from a large amount of experimental data, resulting in high accuracy of the trained model's prediction results under the same experimental conditions. When the experimental conditions change significantly, the predicted results have a large error compared to the actual measurement results.

(3) Accurate prediction, unclear explanation. The overall structure of the constructed model is basically a black box, which clarifies the input and output, but is not clear about the intermediate calculation process. Although it is possible to extract the weight matrix and bias matrix of the trained model, researchers have not yet focused on and explained the physical meanings represented by different data. Focusing too much on adjusting the parameters of the model to improve prediction accuracy without studying the intermediate calculation process is not conducive to fundamentally adjusting the structure of the model.

(4) The model lacks innovation. At present, the research that has been carried out is based on relatively mature models that directly adjust parameters to construct models with prediction results that meet the requirements. Although this method is fast and efficient, from a research perspective, it is necessary to develop proprietary prediction models that conform to the distribution law of damage elements as much as possible, starting from the generation mechanism and change law of damage parameters, surpassing the parameter adjustment in existing models, in order to achieve more accurate and universal predictions.

6. Conclusions

The application of artificial intelligence technology in explosion shock wave pressure testing is of great significance for improving the accuracy of shock wave pressure calculation and accurately evaluating the explosive damage power of ammunition. The current research has been widely applied in the dynamic compensation of shock wave pressure sensing systems, pressure field distribution prediction, and explosion damage assessment, and has achieved outstanding results, proving the application value of artificial intelligence technology in ammunition/warhead explosion shock wave damage testing and assessment. In subsequent research, the application of artificial intelligence technology in data processing can be further explored, efficient and automated data processing models can be developed, data processing processes and methods can be standardized, and the credibility of data processing results can be improved. Accumulate raw measurement results under different experimental conditions, develop proprietary prediction models that conform to the distribution law of explosive field damage elements, focus on the model calculation process, not just the results, achieve accurate prediction and clear explanation of the model, and have a clear understanding of the essence of the model from the source, which helps to independently develop relevant artificial intelligence prediction models.

Acknowledgements

The authors have not disclosed any funding.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contributions

Liangquan Wang: Data Curation, Formal Analysis, Methodology, Software, Writing – Original Draft Preparation, Writing – Review and Editing. Binwen Qian: Formal Analysis, Methodology, Project Administration, Writing – Review and Editing. Chunyan Zhang: Writing – review and editing; Xin Zhang: Writing – review and editing; Resources; Zhenghao Wu: Writing – review and editing; Botian Zhang: Writing – review and editing.

Conflict of interest

The authors declare that they have no conflict of interest.

References

[1] Y. H. Yu et al., “Overpressure characteristics of shock waves generated by underwater two-point explosion from aluminized explosives,” (in Chinese), *Journal of Underwater Unmanned Systems*, Vol. 30, No. 3, pp. 300–307, 2022, https://doi.org/10.11993/j.issn.2096-3920.2022.03.004

[2] Z. Sun, X. Miao, and C. Jagadeesh, “Experimental investigation of the transonic shock-wave/boundary-layer interaction over a shock-generation bump,” *Physics of Fluids*, Vol. 32, No. 10, p. 10610, Oct. 2020, https://doi.org/10.1063/5.0018763

[3] L. Q. Wang et al., “Numerical simulation experimental study on damage capability of high energy explosive,” (in Chinese), *Journal of Testing Technology*, Vol. 35, No. 1, pp. 6–11, 2021, https://doi.org/10.3969/j.issn.1671-7449.2021.01.002

[4] L. Chen, Z. Li, R. Chen, and F. Lu, “Propagation characteristics of blast shock waves in low-pressure environment,” *Shock Waves*, Vol. 33, No. 1, pp. 61–74, Feb. 2023, https://doi.org/10.1007/s00193-022-01116-z

[5] L. Wang, D. Kong, and F. Shang, “Mapping relationship between surface-reflection pressure and free-field pressure of explosion field shock waves,” *Pramana*, Vol. 97, No. 3, p. 89, Jun. 2023, https://doi.org/10.1007/s12043-023-02555-8

[6] L. M. Chen et al., “An experimental study on propagation characteristics of blast waves under plateau environment,” (in Chinese), *Explosion and Shock*, Vol. 42, No. 5, pp. 114–124, 2022, https://doi.org/10.11883/bzycj-2021-0279

[7] S. E. Rigby, A. Tyas, T. Bennett, S. D. Clarke, and S. D. Fay, “The negative phase of the blast load,” *International Journal of Protective Structures*, Vol. 5, No. 1, pp. 1–19, Mar. 2014, https://doi.org/10.1260/2041-4196.5.1.1

[8] L. Q. Wang, D. R. Kong, and F. Shang, "Mapping function model representing the relationship between explosion shock wave pressure and wavefront temperature," *AIP Advances*, Vol. 13, No. 6, p. 06501, Jun. 2023, https://doi.org/10.1063/5.0155382

[9] Y. Liu, X. Li, and C. S. Cui, "A joint processing method of removing high frequency noise from shock wave signal," (in Chinese), *Journal of Detection and Control*, Vol. 45, No. 2, pp. 61–66, 2023.

[10] Z. Y. Liang, D. X. Xiong, and D. X. Pei, "Noise reduction of blast wave signal," (in Chinese), *Fire Control and Command Control*, Vol. 47, No. 8, pp. 79–84, 2012.

[11] G. L. Zhang, "Research on nonlinear modeling method of neural network in Test system and its application," (in Chinese), Master's thesis, North University of China, 2008.

[12] Y. J. Liu et al., "A sensors dynamic compensation device in shock wave test system," (in Chinese), *Chinese Journal of Sensing and Technology*, Vol. 25, No. 11, pp. 1516–1521, 2012, https://doi.org/10.3969/j.issn.1004-1699.2012.011.010

[13] H. Liu, "Research on shock wave test system and dynamic characteristic compensation," (in Chinese), Master's thesis, North University of China, 2017.

[14] F. Yang et al., "Piecework modeling of dynamic characteristics of shock wave pressure sensor assembly based on BP neural Network," (in Chinese), *Journal of Vibration and Shock*, Vol. 36, No. 16, pp. 155–158, 2017, https://doi.org/10.13465/j.cnki.jvs.2017.16.024

[15] F. Yang et al., "Dynamic characteristics of shock wave pressure sensor based on shock tube calibration," (in Chinese), *Journal of Nanjing University of Science and Technology*, Vol. 41, No. 3, pp. 330–336, 2017, https://doi.org/10.14177/j.cnki.32-1397n.2017.41.03.009

[16] X. G. Zhang, B. You, and H. Liu, "Application of BP network in dynamic characteristic correction of shock wave measurement system," (in Chinese), *Journal of Projectiles, Rockets, Missiles and Guidance*, Vol. 38, No. 1, pp. 93–96, Jan. 2018, https://doi.org/15892/j.cnki.djzdxb.2018.01.022

[17] L. Feng and T. Ma, "Experimental study comparing the effectiveness of physical isolation and ANN digital compensation methodologies at eliminating the stress wave effect error on piezoelectric pressure sensor," *Sensors*, Vol. 20, No. 8, p. 2397, Apr. 2020, https://doi.org/10.3390/s20082397

[18] F. Yang, C. Zhao, H. Zhu, and D. Kong, "Study on mathematical model and dynamic compensation of oil down-hole pressure sensor based on BP neural network," in *Lecture Notes in Electrical Engineering*, Vol. 1060, pp. 374–379, Aug. 2023, https://doi.org/10.1007/978-981-99-4334-0_46

[19] I. Flood, B. T. Bewick, R. J. Dinan, and H. A. Salim, "Modeling blast wave propagation using artificial neural network methods," *Advanced Engineering Informatics*, Vol. 23, No. 4, pp. 418–423, Oct. 2009, https://doi.org/10.1016/j.aei.2009.06.005

[20] A. M. Remennikov and T. A. Rose, "Predicting the effectiveness of blast wall barriers using neural networks," *International Journal of Impact Engineering*, Vol. 34, No. 12, pp. 1907–1923, Dec. 2007, https://doi.org/10.1016/j.ijimpeng.2006.11.003

[21] 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," *International Journal of Protective Structures*, Vol. 12, No. 3, pp. 287–314, Nov. 2020, https://doi.org/10.1177/2041419620970570

[22] C. M. Sun et al., "Reconstruction model of explosion shock wave signal based on deep learning," (in Chinese), *Measurement Technology*, Vol. 42, No. 2, pp. 57–67, 2022, https://doi.org/10.11823/j.issn.1674-5795.2022.02.07

[23] J. M. Dou, Y. Wang, and Y. Wang, "Shock wave compression sensing method based on deep Convolutional generation network," (in Chinese), *Journal of Changchun University of Science and Technology (Natural Science Edition)*, Vol. 45, No. 1, pp. 72–78, 2022, https://doi.org/10.3969/j.issn.1672-9870.2022.01.011

[24] C. Kong, C. Zhang, Z. Wang, Y. Li, and J. Chang, "Efficient prediction of supersonic flowfield in an isolator based on pressure sequence," *AIAA Journal*, Vol. 60, No. 5, pp. 2826–2835, May 2022, https://doi.org/10.2514/1.j061375

[25] J. Bian, L. Zhou, P. Yang, H. Teng, and H. D. Ng, "A reconstruction method of detonation wave surface based on convolutional neural network," *Fuel*, Vol. 315, p. 123068, May 2022, https://doi.org/10.1016/j.fuel.2021.123068

[26] F. Sofos, D. Drikakis, I. W. Kokkinakis, and S. M. Spottswood, "Convolutional neural networks for compressible turbulent flow reconstruction," *Physics of Fluids*, Vol. 35, No. 11, Nov. 2023, https://doi.org/10.1063/5.0177654

[27] H. Z. Xi, D. R. Kong, Y. Q. Peng, S. M. Zhang, Q. Shi, and G. G. Le, "Prediction of spatial peak overpressure profile of air blast shocks using multiple linear regression and artificial neural network," *Journal of Physics: Conference Series*, Vol. 2478, No. 7, p. 072036, Jun. 2023, https://doi.org/10.1088/1742-6596/2478/7/072036

[28] M. H. Mat, P. Nagappan, S. H.-F. S. A. Jamil, F. R. Hashim, K. A. Ahmad, and K. Kamal, "Explosive blast prediction using MLP network based training algorithm," in *IEEE 13th International Conference on Control System, Computing and Engineering (ICCSCE)*, pp. 12–16, Aug. 2023, https://doi.org/10.1109/iccsce58721.2023.10237166

[29] J. J. Pannell, S. E. Rigby, and G. Panoutsos, "Application of transfer learning for the prediction of blast impulse," *International Journal of Protective Structures*, Vol. 14, No. 2, pp. 242–262, May 2022, https://doi.org/10.1177/20414196221096699

[30] J. J. Pannell, S. E. Rigby, and G. Panoutsos, "Physics-informed regularisation procedure in neural networks: An application in blast protection engineering," *International Journal of Protective Structures*, Vol. 13, No. 3, pp. 555–578, Apr. 2022, https://doi.org/10.1177/20414196211073501

[31] Y. Li and J. Chang, "Research on time sequence prediction of supersonic cascade flow field based on compressed sensing artificial neural network," *Aerospace Science and Technology*, Vol. 142, p. 108684, Nov. 2023, https://doi.org/10.1016/j.ast.2023.108684

[32] F. Liu et al., "Prediction model of specific impulse of underwater shaped charge based on AGEP-DNN," *Journal of Shenyang Ligong University*, Vol. 43, No. 2, pp. 15–21, 2024, https://doi.org/10.3969/j.issn.1003-1251.2024.02.003

[33] M. A. Panza, M. Pota, and M. Esposito, "Anomaly detection methods for industrial applications: a comparative study," *Electronics*, Vol. 12, No. 18, p. 3971, Sep. 2023, https://doi.org/10.3390/electronics12183971

[34] K. Poulinakis, D. Drikakis, I. W. Kokkinakis, and S. M. Spottswood, "Deep learning reconstruction of pressure fluctuations in supersonic shock-boundary layer interaction," *Physics of Fluids*, Vol. 35, No. 7, Jul. 2023, https://doi.org/10.1063/5.0156444

[35] C. M. Sun et al., "Shockwave signal reconstruction method based on a serial-parallel double branch network," (in Chinese), *Journal of Vibration and Shock*, Vol. 43, No. 6, pp. 38–49, 2024, https://doi.org/10.13465/j.cnki.jvs.2024.06.005

[36] J.-Z. Peng et al., "Rapid and sparse reconstruction of high-speed steady-state and transient compressible flow fields using physics-informed graph neural networks," *Physics of Fluids*, Vol. 36, No. 4, p. 04611, Apr. 2024, https://doi.org/10.1063/5.0202789

[37] D. Drikakis, I. W. Kokkinakis, P. Tirchas, and S. M. Spottswood, "Physical consistency and invariance in machine learning of turbulent signals," *Physics of Fluids*, Vol. 36, No. 1, p. 01613, Jan. 2024, https://doi.org/10.1063/5.0187089

[38] X. Y. Jia, C. Gong, and W. Ji, "An accuracy-enhanced transonic flow prediction method fusing deep learning and reduced-order model," *arXiv:2307.07702*, 2023.

[39] A. A. Dennis and S. E. Rigby, "The Direction-encoded Neural Network: A machine learning approach to rapidly predict blast loading in obstructed environments," *International Journal of Protective Structures*, Vol. 15, No. 3, pp. 455–483, Jun. 2023, https://doi.org/10.1177/20414196231177364

[40] F. Liu et al., "Prediction method of blast load on underground structure surface based on neural network," *AIP Advances*, Vol. 13, No. 4, Apr. 2023, https://doi.org/10.1063/5.0134126

[41] Q. C. Li et al., "Application of the neural network equation of state in numerical simulation of intense blast wave," (in Chinese), *Explosion and Shock Waves*, Vol. 43, No. 4, pp. 102–112, 2023, https://doi.org/10.11883/bzycj-2022-0222

[42] F. Liu et al., "Prediction of peak overpressure of underwater shaped charge based on DACO-BP," (in Chinese), *Journal of Ordnance Equipment Engineering*, Vol. 44, No. 6, pp. 17–24, 2023, https://doi.org/10.11809/bqzbgcxb2023.06.003

[43] T. B. Ma, J. W. Long, and Y. Liu, "Research on Prediction model of peak pressure of Explosion shock wave from double explosive source in water based on BP neural network," (in Chinese), *Journal of Beijing Institute of Technology*, Vol. 44, No. 3, pp. 260–269, 2024, https://doi.org/10.15918/j.tbit1001-0645.2023.097

[44] Z. T. Zhang et al., "Target damage evaluation based on improved GA-BP neural network," (in Chinese), *Fire Control and Command Control*, Vol. 46, No. 11, pp. 43–48, 2021, https://doi.org/10.3969/j.issn.1002-0640.2021.11.006

[45] D. Zou et al., "Multicategory damage detection and safety assessment of post-earthquake reinforced concrete structures using deep learning," *Computer-Aided Civil and Infrastructure Engineering*, Vol. 37, No. 9, pp. 1188–1204, Jan. 2022, https://doi.org/10.1111/mice.12815

[46] X. Wei, X. Li, and S. H. Zhao, "Damage effect evaluation method based on convolutional neural network and random forest," (in Chinese), *Fire Control and Command Control*, Vol. 48, No. 3, pp. 185–190, Mar. 2023, https://doi.org/1002-0640(2023)03-0185-06

[47] Y. S. Wang, "Prediction and analysis of damage effect of rigid-body projectile penetrating target," Master's thesis, Harbin Institute of Technology, 2023.

[48] C. Sun, "Humanoid target equivalent damage perception and evaluation based on Artificial intelligence," Xi'an University of Technology, 2023.

[49] Y. B. Xu et al., "Ground target recognition and damage evaluation of missile patrol based on multi-source information fusion," (in Chinese), *Journal of System Simulation*, Vol. 36, No. 2, pp. 511–521, 2019, https://doi.org/10.16182/j.issn1004731x.joss.22-1130

Liangquan Wang obtained his engineering Doctoral degree from Nanjing University of Science and Technology. His research direction is the research of blast field damage parameter testing and evaluation technology, including shock wave pressure test, fragment velocity and scattering characteristics research, and explosion field fireball surface temperature test and analysis.

Binwen Qian received the Ph.D. degree from Tsinghua University. He is currently working at the Northwest Institute of Nuclear Technology with the title of Researcher. His main research interests include munitions and combatant design, damage power field testing and evaluation.

Chunyan Zhang received a Ph.D. degree with Control Science and Engineering, Nanjing University of Science and Technology, 2020. She is currently a lecturer at Nanjing Institute of Technology. Her current research interests include target tracking, measurement and control technology.

Xin Zhang received the Ph.D. degree from Rocket Force University of Engineering. His main research interest is explosive field damage parameter testing and evaluation.

Zhenghao Wu received a master's degree from Southwest Jiaotong University. His main research interest is explosive field thermal damage parametric testing technology.

Botian Zhang received a bachelor's degree from Nanjing University of Science and Technology. He is currently pursuing his master's degree at Northwest Institute of Nuclear Technology. His main research interest is optical testing techniques for explosive field damage parameters.

ISSN PRINT 2335-2124, ISSN ONLINE 2424-4635