Hybrid Multilayer Perceptron Network for Explosion Blast Prediction

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Abstract. For decades, scientists have studied the blast wave profile produced by an explosive detonation. Based on a significant amount of experimental data, the blast wave propagation profile has been predicted under given parameters. However, most studies have only looked at the central point of initiation for spherical form explosives. The purpose of this research is to compare the blast pressure readings of shaped charges on the blast profiles of Emulex and PE-4, as well as to develop a prediction model using a Hybrid Multilayer Perceptron (HMLP) network. This experiment, which began at a distance of 1.2 meters from the ground, employed a total of 500 grams of military explosive and Emulex. At distances of 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 meters, the bomb was exploded. The Bayesian Regularization (BR) training algorithm is the best training strategy for modelling Explosive Blast Prediction.

INTRODUCTION

Explosives are highly reactive elements with a lot of energy that, when released rapidly, can generate explosions with light, heat, sound, and pressure. The power of each detonation is determined by the number of explosives used. The rate of expansion of an explosive can be used to classify it. The terms "high explosives" and "low explosives" refer to explosive materials and faulty materials, respectively (Cooper, 1996; Rahim et al., 2020). The sensitivity of the substance is always used to classify explosives. Due to the susceptibility of explosives to heat and pressure, the second and third explosions are less romantic. An explosion's speed can reach 1800 m/s. Ammonium nitrate (AN) is classified as a strong explosive because of its strength, which is characterised by high explosive rates and gas pressure (Yusof et al., 2021; Jelani et al., 2016). Homogeneous and heterogeneous AN are the two forms of AN. Primary, secondary, and tertiary explosives are made from natural materials, while tertiary explosives are made from a chemical mixture.

The global economy has had an impact on various countries, including Malaysia, for the time being. Malaysia's Ministry of Defense has been influenced by this economic impact. Malaysia's Armed Forces (ATM) and government have been working diligently to restructure spending without jeopardising the country's defence readiness. Military supplies and equipment must also be made available, as well as defence assets. PE-4 explosives, imported from the United Kingdom for training purposes, are being used in ATMs for cutting charges, bridge demolition, and building damage, among other things (Swisdak, 2010). PE-4 is a very expensive chemical to work with. Malaysian businesses, on the other hand, are capable of producing commercial explosives. Developing local explosives that match PE-4's military training capability is a solid first step. It also makes importing PE-4 from other countries less expensive. Commercial explosives are much more expensive than military explosives. This is due to the mixture's particular composition of the appropriate amount. On the other hand, commercial explosives are essentially identical to military explosives and can be employed to achieve the same results as PE-4 (Zdzislaw et al., 2014; Yusof et al., 2019; Isa et al., 2017; Jelani et al., 2014; Jelani et al., 2015). Commercial and military explosives are depicted in Figures 1 and 2, respectively.

FIGURE 1. Commercial Explosives (Emulex) (Azmi, 2018)

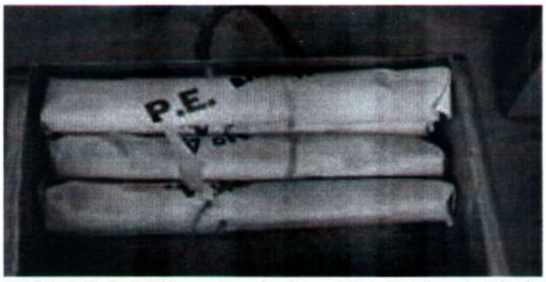

FIGURE 2. Military Explosives (PE-4) (Azmi, 2018)

The Support Vector Machine (SVM) and Hidden Markov Model (HMM) are two numerical prediction algorithms that can be used to predict the explosion effect (Derek et al., 2012). (Chatteriee et al., 2017). Both statistical strategies produced good results in terms of prediction and optimization. Artificial intelligence, specifically a neural network, was also used to create the forecast (Roy et al., 2011). Neural network techniques were used in various studies to predict the explosive effect (Zhongya & Xiaoguang, 2018). This study will use the Hybrid Multilayer Perceptron (HMLP) network to predict the peak pressure of commercial explosives. The HMLP network will be taught to provide predictions using data from prior experiments after preliminary tests are completed (Jamil et al., 2020). Certain criteria, such as the type of explosives, the shape of the explosives supplied, and the reference point distance from the explosives, are entered in order to receive peak pressure readings recorded throughout the explosion process.

METHODOLOGY

Artificial neural networks (ANN) are a type of artificial intelligence based on the way the brain functions. The artificial neural network is based on brain principles and is designed to imitate brain functions such as structure creation, learning procedures, and operating approaches (Etham, 2019; Ahmad et al., 2019). Figure 3 depicts the nonlinear neuron model.

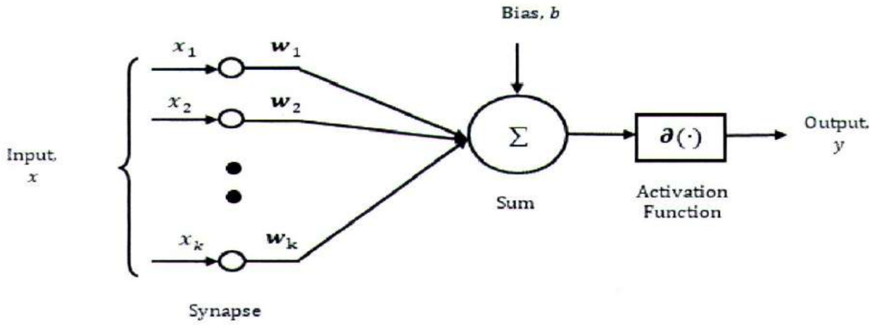

FIGURE 3. Nonlinear neuron model (Haykin, 2011)

A set of synapses or network connection, a sum, and an activation function are all important components of a neuron development, according to Figure 3. A weighted value is assigned to each neuron's synapse. Assuming that the neuron has *k* synapses, it has *k* input. $(x_1, x_2 .. x_k)$ represents the input at each synapse, whereas $[\mathbf{w}_1, \mathbf{w}_2 .. \mathbf{w}_k]$ represents the weight at each synapse, and $\boldsymbol{\partial}(\cdot)$ represents the model's activation function. The value of the jth synaptic weights $[\mathbf{w}_j]$ influences the weight value for the processing of the synapses to the neuron's output. Input x j at the input synapses connected to the neuron will be multiplied by the value of the j^{th} synapse weights $[\mathbf{w}_j]$. The output of a sum process is transmitted to the activation function, which sums all the multiplied signals or input and bias (b). The following two equations can be used to define the mathematical modelling of neurons based on Figure 3:

$$u = \sum_{j=1} \mathbf{W}_j x_j + b \tag{1}$$

and

$$y = \boldsymbol{\partial}(u) \tag{2}$$

In Equations (1) and (2), u is the summation output, x_j is the jth data or synapse input signal, $\mathbf{W}_j$ is the weights to the j^{th} neuron synapse, $\boldsymbol{\partial}(\cdot)$ is the activation function, and y is the output product. The fixed limiter function, piecewise linear function, Logsig function, and linear function are all examples of regularly used activation functions (Haykin, 2011).

One of numerous modified variants based on ordinary MLP networks is the inclusion of a linear connection directly from the input layer to the output layer to produce a new network known as the HMLP network. In terms of accuracy, Mashor (2000) found that HMLP networks beat standard MLP networks. The training methodologies used and the structure's design play a big role in ANNs' capacity to make correct predictions (Mashor, 1999). To improve the efficiency and generalisation of classic nonlinear neural networks, the HMLP network was built by adding a straight linear connection between the input and output layers (Etham, 2019; Haykin, 2011). They also pointed out that employing a nonlinear network like MLP to represent a linear system will not result in an accurate forecast. The HMLP network effectively copes with linear systems due to direct input to output connections, as indicated by the dotted line in Figure 4. The figure is made up of an input layer, a single hidden layer, and an output layer.

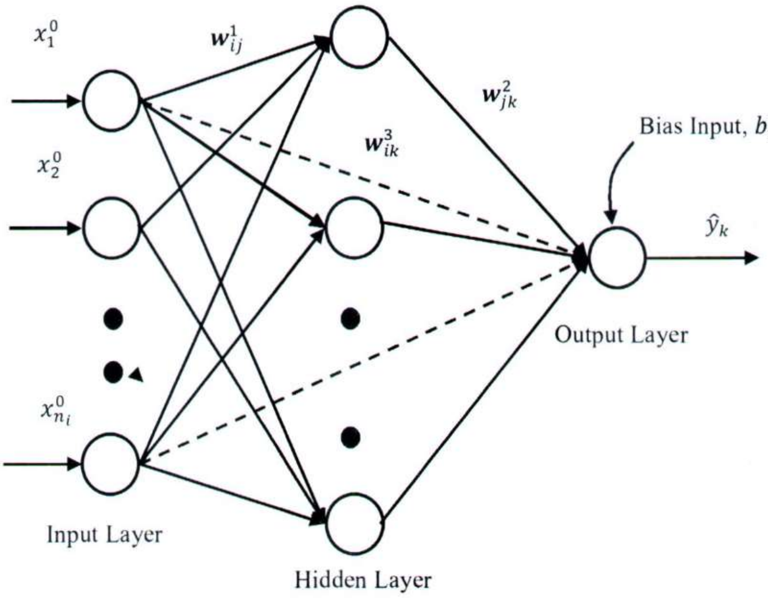

FIGURE 4. A schematic diagram of a HMLP network with one hidden layer

The output of the network is given by:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right) + \sum_{i=1}^{n_i} w_{ik}^3 x_i^0(t) \tag{3}$$

for 1≤j≤n_h and 1≤k≤m

The weight of the additional linear connection between the input and output layers is w_{ik}^3, the number of hidden nodes is n_h, and the number of network outputs is m. In this scenario, with the Logsig activation function, $\boldsymbol{\partial}(\cdot)$ is the activation function used to activate the HMLP network. In order to minimise the prediction error defined as in Equation (4), w_{ij}^1, w_{jk}^2, w_{ik}^3, and threshold b_j^1 , the unknown variables w_{ij}^1, w_{jk}^2, w_{ik}^3, and threshold b_j^1 must converge to optimum values.

$$e_k(t) = y_k(t) - \hat{y}_k(t) \tag{4}$$

with $y_k(t)$ being the actual output from the system while $\hat{y}_k(t)$ is the predicted output.

In a neural network, the learning period is a crucial step. The procedure assures that the neural network can perform to its design specifications. supervised learning and unsupervised learning are two types of learning paradigms that are commonly used (Thirunavukkarasu et al., 2018). The learning period of a neural network is critical. The technique ensures that the neural network will perform according to its design parameters. There are two types of learning paradigms that are commonly used: unsupervised learning and supervised learning (Thirunavukkarasu et al., 2018). Supervised learning can be used to develop a global model that maps the input to the desired output. Unsupervised learning methods, on the other hand, necessitate estimate using well-known training models. The learning process varies from supervised learning in that there is no output aim. Unsupervised learning necessitates the gathering of a set of input data, which is thought to consist of a set of random variables. A density model will be built based on the datasets, and unsupervised learning will be based on prior experience. To put it another way, the learning process is undirected and completely reliant on prior experience. Unsupervised learning aids data compression. For the study, an experimental process was carried out first, followed by a modelling process using the neural network approach. The supplementary dataset is acquired in addition to the goal. As a result, it is best to receive supervised instruction. The Blast Pressure Prediction system uses supervised training methods such as backpropagation (BP) (Dar and Winzer, 2016), Lavenberg Marquardt (LM) (Bari et al., 2019; Multazam et al., 2017), and Bayesian Regularization (BR) (Handayani et al., 2018).

Observing the performance and accuracy of the prediction mean square error (MSE) in the training and testing phases will determine the number of repetitions of training data (Dekking et al., 2005). Each time iteration data is added, MSE is the error that occurred on each of the data. The more accurate the predictions, the smaller the MSE value received, and the smallest MSE value obtained when the MSE graph is horizontal. The performance of neural networks is currently steady and stable. The appropriate number of iteration data will be determined by the maximum prediction accuracy with the lowest MSE value. The focus of the neural network's performance, on the other hand, is on its performance during the test phase. The number of hidden nodes is then calculated using the same way. The number of training data iterations is set to the optimum value achieved earlier at this point. The amount of correctly classified data will be divided by the number of data in the class to determine the accuracy of detection data. Regression is one of the most basic models for predicting outcomes or determining data fitness (Montgomery et al., 2012). It simulates the interaction between the independent and dependent variables. One independent variable and one dependent variable are involved in simple linear regression. Multiple Linear Regression, on the other hand, aims to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data in the research experimental dataset.

There have been no studies to date that have used neural network approaches to anticipate the impacts of explosions. Explosive testing training is conducted on a regular basis. The explosive impact is predicted simply on the basis of previous experience. As a result, the neural networks used in this study can provide an automatic forecast. Previously, explosive pressure readings were documented by defining the types and shapes of explosives. The Data Acquisition (DAQ) technology is used to record explosive pressure data depending on distances defined before. As a result, the HMLP network's input parameters are the kind and shape of explosives, as well as the reading sites, while the HMLP network's output parameter is the explosive pressure. Once the input parameters are set, the explosion pressure may be projected at the end of the project. Figure 6 depicts the recorded data from the prior explosive experiment.

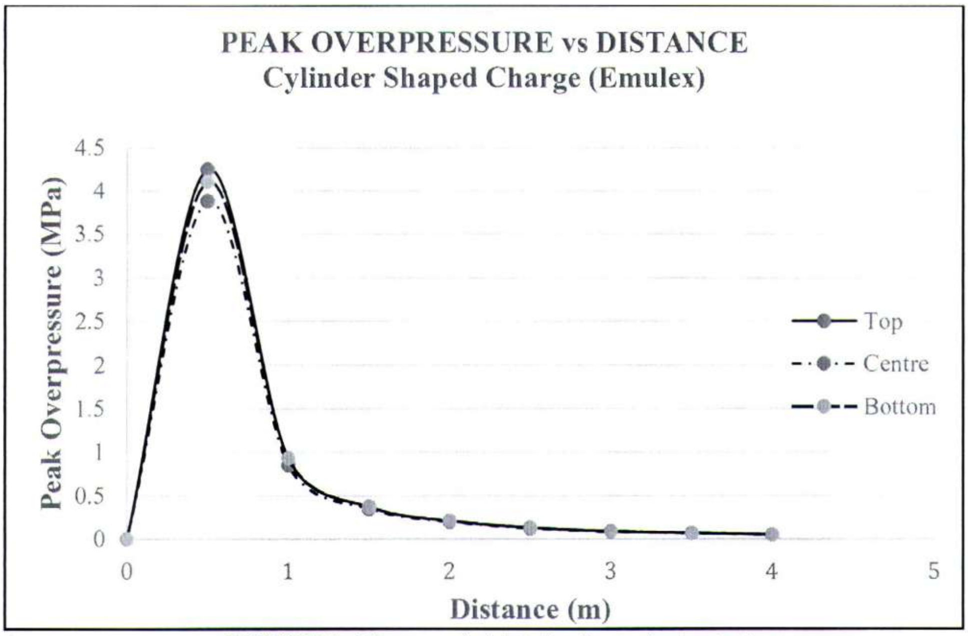

FIGURE 6. The recorded data by the explosive testing

RESULTS AND DISCUSSIONS

The HMLP neural network's ability to forecast explosion pressure must be demonstrated through prediction performance analysis. In the MATLAB neural network tools (nntool), the analysis goes through three stages: 60 percent training, 30 percent testing, and 10% validation. The examination of MSE for mistakes and regression for best fitting are two examples. The lowest MSE and highest regression performance are used to evaluate the training algorithm's performance. The lowest MSE indicates that the relative error during the prediction phase should be as low as possible. When compared to regression performance, the worst-case scenario occurs when the measurement is closest to 0, and the highest performance occurs when the measurement is closest to 1. The MSE and regression values for the difference training technique were calculated using the neural network tool in MATLAB. The performance of the HMLP network with three distinct training procedures and three activation functions is shown in Table 1, which is organised by lowest MSE performance highest sequences.

TABLE 1. MSE Performance of HMLP network

Training Algorithm	MSE Performance Analysis	Number of Epoch
BR	0.0079	958
LM	0.0157	21
BP	0.3376	13

TABLE 2. Regression Performance of HMLP network

Training Algorithm	Regression Performance Analysis	Number of Epoch
BR	0.9901	958
LM	0.9789	21
BP	0.3035	13

The BR training method, with an MSE of 0.0079 for the HMLP network, is shown in Table 1 as having the best MSE performance. The HMLP network trained using LM had the second best performance, with an MSE of 0.0157. The training process is then followed by the BP training algorithm, which has a performance of 0.3376 MSE. The BR training technique, as shown in Table 2, is capable of producing the highest regression reading of 0.9998. HMLP networks trained with the BR training algorithm outperform those trained using the LM and BP training algorithms. The regression performance of the HMLP network with the LM training procedure is marginally worse than that of the BP with 0.9789. The HMLP network with the BP training strategy may get a regression performance of 0.3035.

Tables 1 and 2 show a clear difference in performance when it comes to training algorithm models, with BR using a stochastic model and BP using a deterministic model. A stochastic model is a collection of random variables, whereas a deterministic model is by far the most researched when looking for a familiar method. As a result of the results, most BP-based algorithms are unable to function adequately since they become stuck in local minima throughout the training process. However, since some modifications have been made to release from local minima, the training algorithm is capable of performing better. The LM training process is based on the BP model, as seen in both tables. However, adding an extra Gauss-Newton algorithm to the method, as well as gradient descent via BP, enabled the network to seek for global minima. Unfortunately, the BR method takes a long time to converge with 958 (activated by the Tansig activation function), but it does so with good accuracy compared to other combinations. The BP training method, on the other hand, was able to converge in a short period of time with only 13 epochs, but it was unable to provide good accuracy performance.

CONCLUSION

The HMLP network prediction results demonstrate the network's aptitude and capability in predicting the explosive dataset. According to the results, the accuracy demonstrated by the BR training algorithm is the best, with the smallest MSE and highest regression performances. As a result, while the BP training approach has a short processing time and only requires a few epochs, it can only provide higher MSE and worse regression results. Although the LM outperforms the BP, it falls short of the BR training algorithm's ability. The type of explosive, the distance of explosive effect, and the shape of explosive are all perfect inputs to the HMLP network. The research's major goal is to determine the optimal algorithm to use as the brain of the 'Blast Prediction' model.

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