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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 prediction performance of blast peak overpressure based on type of explosive, shape of explosive and point of detonation. 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 m from the ground, employed a total of 500 grams of military explosive and Emulex. At distances of 0.5 m, 1.0 m, 1.5 m, 2.0 m, 2.5 m, 3.0 m, 3.5 m and 4.0 m, the bomb was exploded. The Bayesian Regularization (BR) training algorithm is the best training algorithm for modelling Explosive Blast Prediction.

1. Introduction

Explosives are compounds that can set off an explosion in a specific location. Effective explosions in restricted spaces are far more often than in open spaces because of gas expansion from explosives. The petrol particles expand more quickly as a result of the higher temperature and air pressure impacts. This activity will speed up the atomic shift, which will afterwards lead to an explosion and combustion [1]. The reaction velocity and the outcome of the explosion pressure achieved frequently serve to distinguish an explosion. Since the default reaction speed is slower than the speed of sound, the pressure reached falls within the range of bars. The chemical reaction in the explosive with the air above the speed of sound in explosives is what causes the reaction rate for petrol formation [2]. A supersonic shock wave results from this. This shock wave travels before the gas discharge starts. In contrast to the gas pressure within the smaller but higher, the shock energy has a high peak pressure

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that is only temporary [3]. Low explosives include deflagration and materials that burn quickly as a result of gas release. Reaction velocities in black powder, for instance, are frequently between 600 and 1000 m/s [4].

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 [5]. 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 characterized by high explosive rates and gas pressure. 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 [1,3].

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 jeopardizing the country's defense readiness. Military supplies and equipment must also be made available, as well as defense 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 [6]. 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 [5,7,8]. Commercial and military explosives are depicted in Figure 1 and Figure 2, respectively.

Fig. 1. Commercial explosive (emulex) [9]

Fig. 2. Military explosive (PE-4) [9]

To solve this issue, a Blast Explosive Prediction system that can predict the peak overpressure of Emulex and/or PE-4 (type of explosive); spherical, cylindrical and/or hemisphere (shape charge); top, bottom and/or center (point of detonation); and distance of sensor form explosive (0.5m to 4.0 m). Explosive tests are actively carried out in order to gather data [3]. Several predicting methods are used to predict explosive activity, according to studies. Moreover, different parameters are used in accordance with the specifications provided by the user. Typically, statistically-based prediction algorithms offer accurate predictions [10,11]. However, the most recent method, which uses artificial intelligence, can produce better prediction outcomes. There are many forecasting systems available, however the accuracy of the predictions depends heavily on data enrichment during blast tests [12].

The Support Vector Machine (SVM) and Hidden Markov Model (HMM) are two numerical prediction algorithms that can be used to predict the explosion effect [13-15]. 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 [15-17]. Neural network techniques were used in various studies to predict the explosive effect. 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. Certain criteria, such as the type of explosives, the shape of the explosives supplied, and the reference point distance from the explosives, are entered to receive peak pressure readings recorded throughout the explosion process [2-3].

2. Methodology

Field blast test was conducted at the disclosed military camp in Malaysia. A wooden timber supporting the explosive was erected to hold the charge. All of the charge was placed at the height of 1.2 m from the ground in order to ensure that there is no reflection from the soil interfering the measured pressure. There are eight (8) pencil probes has been set on the site to record the pressure from the explosion which are 0.5 m, 1.0 m, 1.5 m, 2.0 m, 2.5 m, 3.0 m, 3.5 m and 4.0 m for all different types of explosives, shapes and also point of detonation. The field blast testing setup is shown in Figure 3. These explosives will be weighted and molded into spherical, hemisphere and/or cylindrical charge. The explosive was detonated using electric detonator at three different point of initiation as shown in Figure 4.

Fig. 3. Field blast test set up [3]

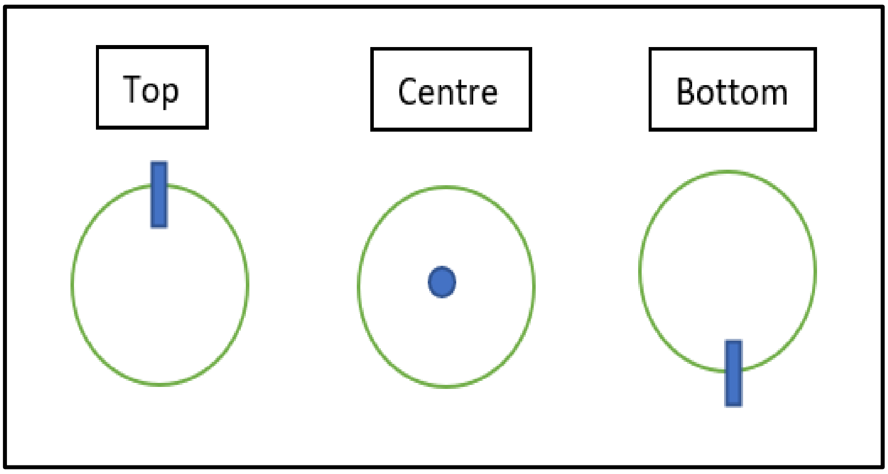

Fig. 4. Point of initiation

High speed data acquisition (DAQ) system includes software, a signal procedure, sensors, transducers, and cables that are connected to test specimens, PXI instrumentations, including a Tetra RPC PXI chassis from Logic Instruments, NI PXI-8110 embedded controller, and NI PXI-6133 multifunction DAQ device can be used to capture the data from the sensors. Meanwhile LabVIEW to program the system and display test results. The high-speed data acquisition system is shown in Figure 5.

Fig. 5. High speed DAQ system [3]

Back to the prediction method, a set of synapses or network connection, a sum, and an activation function are all important components of a neuron development, according to Figure 6. A weighted value is assigned to each neuron's synapse. Assuming that the neuron has k synapses, it has k input. $(\mathrm{x}_1, \mathrm{x}_2 \,..\, \mathrm{x}_\mathrm{k})$ represents the input at each synapse, whereas $[\mathbf{w}_1, \mathbf{w}_2 .. \mathbf{w}_\mathrm{k}]$ represents the weight at each synapse, and $\boldsymbol{\partial}(\cdot)$ represents the model's activation function. The value of the j[th] synaptic weight $[\mathbf{w_j}]$ influences the weight value for the processing of the synapses to the neuron's output. Input $\mathrm{x_j}$ 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, $\mathbf{b}$. The following two equations can be used to define the mathematical modelling of neurons based on Figure 6 [18-21]:

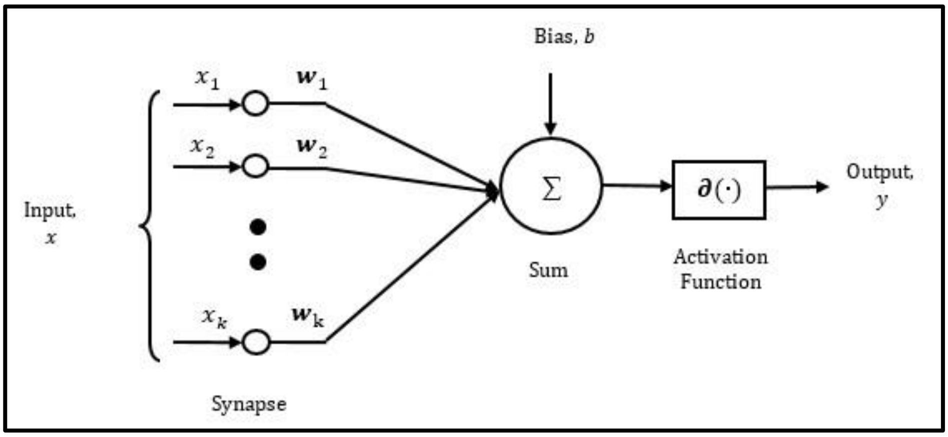

Fig. 6. Nonlinear neuron model (PE-4) [18]

$$\mathrm{u} = \sum \mathbf{W}_\mathrm{j}\mathrm{x}_\mathrm{j} + \mathbf{b} \tag{1}$$

and

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

In Eq. (1) and Eq. (2), u is the summation output, $\mathrm{x_j}$ is the jth data or synapse input signal, $\mathbf{W}_\mathrm{j}$ 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 [18].

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, Zorkafli *et al.,* [21] 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 [20]. To improve the efficiency and generalization of classic nonlinear neural networks, the HMLP network was built by adding a straight linear connection between the input and output layers [18,21]. 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 7. The figure is made up of an input layer, a single hidden layer, and an output layer. The output of the network given by;

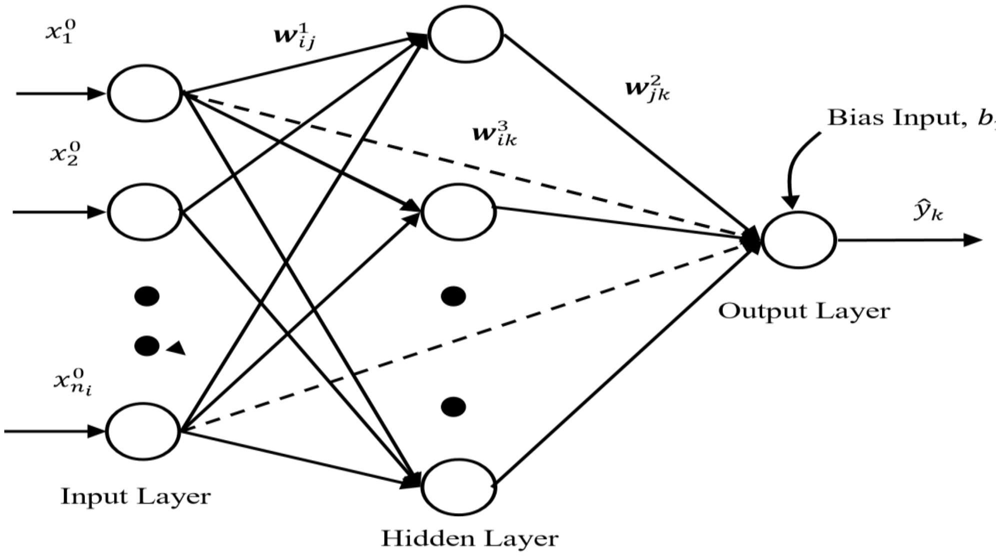

Fig. 7. A schematic diagram of a HMLP network with one hidden layer

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

for $1 \leq j \leq n_h$ and $1 \leq k \leq m$

The weight of the additional linear connection between the input and output layers is $\mathbf{w_{ik}^3}$, 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 minimize the prediction error defined as in Eq. 4, $\mathbf{w_{ij}^1}$, $\mathbf{w_{jk}^2}$, $\mathbf{w_{ik}^3}$ and threshold b_j^1. The unknown variables $\mathbf{w_{ij}^1}$, $\mathbf{w_{jk}^2}$, $\mathbf{w_{ik}^3}$ 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 [22,23]. 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 [22]. 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 [24]. 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), Lavenberg Marquardt (LM), and Bayesian Regularization (BR) [25-27].

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 [28]. 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 [29]. 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 some 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. DAQ system is used to record explosive pressure data depending on distances defined before and point of detonation. 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 8 depicts the recorded data from the prior explosive experiment.

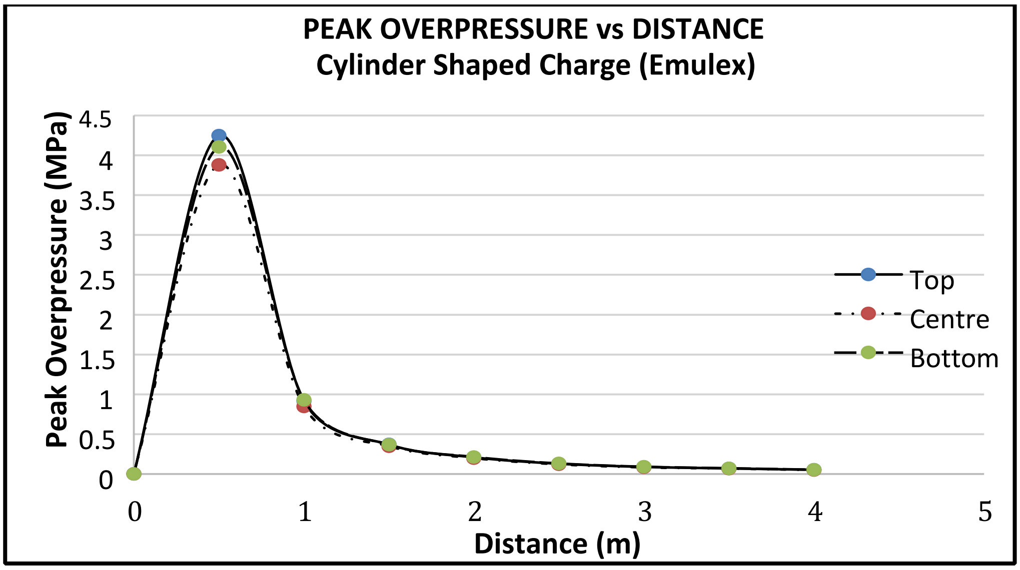

Fig. 8. The recorded data by the explosive testing [12]

3. Results

The HMLP neural network's ability to forecast explosion pressure must be demonstrated through prediction performance analysis. In the MATLAB neural network tools, the analysis goes through three stages: 70% for training and 30% for testing, with 144 blast test dataset. The performance of MSE's error 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 different training algorithm which activated by Sigmoid activation function is shown in Table 1, which is organised by lowest MSE performance highest sequences.

The BR training method, with an MSE of 0.9280 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 1.3213. The training process is then followed by the BP training algorithm, which has a performance of 2.5236 MSE. The BR training technique, as shown in Table 2, is capable of producing the highest regression reading of 0.9658. 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 0.9232. The HMLP network with the BP training strategy may get a regression performance of 0.7245.

Table 1 and Table 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 452 (activated by the Sigmoid 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 21 epochs, but it was unable to provide good accuracy performance.

Table 1
MSE performance of HMLP network

Training Algorithm	MSE Performance Analysis	Number of Epoch
BR	0.9280	452
LM	1.3213	23
BP	2.5236	21

Table 2
Regression performance of HMLP network

Training Algorithm	MSE Performance Analysis	Number of Epoch
BR	0.9658	452
LM	0.9232	23
BP	0.7245	21

4. Conclusions

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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