Explosive Blast Prediction using MLP Network based Training Algorithm

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Abstract—Peoples have been studying the blast wave profile resulting from detonations for many years. Through extensive experimentation, they have been able to predict the propagation profile of blast waves given certain parameters. However, previous studies have primarily focused on the central point of initiation for spherical explosive shapes. The purpose of this research is to compare the predictive performance of blast peak overpressure based on the type and shape of the explosive, as well as the point of detonation. To achieve this, the experiment involved detonating 500 grams of PE-4 and Emulex at various distances (ranging from 0.5 m to 4.0 m) and developing a prediction model using a Multilayer Perceptron (MLP) network. Lavenberg Marquardt (LM) training algorithm perform better than Backpropagation (BP) for modelling the Explosive Blast Prediction using Tansig and Logsig training algorithm.

Keywords- MLP; Explosion; Blast Prediction; PE-4; Emulex.

I. Introduction

Explosives contain a large amount of energy that can produce light, heat, sound, and pressure when released rapidly. The strength of an explosion is dependent on the number of explosives used, while the rate of expansion of the explosive is used to classify it as either a high or low explosive [1]. The sensitivity of the substance is also used to classify explosives. Due to their vulnerability to heat and pressure, subsequent explosions are less predictable [2, 3]. Explosions can travel at a speed of up to 1800 m/s. Ammonium nitrate (AN) is considered a strong explosive due to its high explosive rates and gas pressure. AN can be found in two forms: homogeneous and heterogeneous. Primary, secondary, and tertiary explosives are derived from natural materials, while tertiary explosives are produced through a chemical mixture [4].

The global economy has had an impact on Malaysia, including the Ministry of Defense. Malaysia's Armed Forces and government are working hard to restructure spending without compromising the country's defense readiness. This includes ensuring that military supplies and equipment are available, as well as defense assets. However, using PE-4 explosives, imported from the UK for training purposes, is very expensive. Therefore, the development of local explosives that match PE-4's military training capability is a logical first step. This would make importing PE-4 from other countries less costly. Commercial explosives are more expensive than military explosives due to their specific composition. However, they can be used to achieve the same results as PE-4 in terms of cutting charges, bridge demolition, building damage, and other applications [5, 6]. Figure 1 and Figure 2 depict commercial and military explosives, respectively.

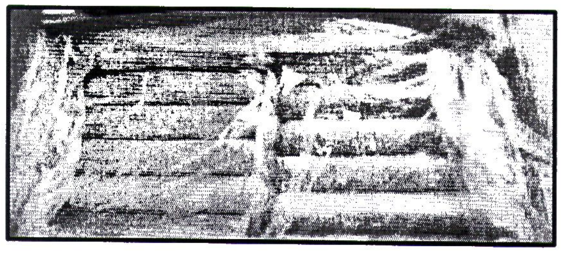

Figure 1. Commercial explosive (Emulex) [7].

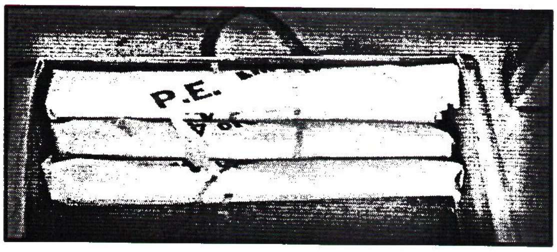

Figure 2. Military explosive (PE-4) [7].

To address this issue, a Blast Explosive Prediction system has been developed to predict the peak overpressure of different types of explosives such as Emulex and PE-4, based on their shape charge (spherical, cylindrical, or hemisphere), point of detonation (top, bottom, or center), and sensor distance from the explosive (0.5m to 4.0m) [7, 8]. To gather data, explosive tests are actively conducted. Various predicting methods have been used to predict explosive activity, with different parameters based on the user's specifications. While statistically-based prediction algorithms typically offer accurate predictions, the most recent method utilizing artificial intelligence has shown to produce better results. Several forecasting systems are available, but the accuracy of the predictions is highly dependent on data enrichment during blast tests.

In summary, various numerical prediction algorithms, including the Support Vector Machine (SVM) and Hidden Markov Model (HMM), have been used to predict the explosion effect [9-11]. Additionally, artificial intelligence, specifically neural network techniques such as the Multilayer Perceptron (MLP) network, has been used to forecast the peak pressure of commercial explosives [12, 13]. These techniques are trained using data from prior experiments and specific criteria, such as the type of explosives, shape, and distance from the reference point. The accuracy of the predictions depends heavily on data enrichment during blast tests [14, 15].

II. Methodology

The field blast test was conducted with various types of explosives in different shapes and points of detonation. The explosive charge was placed on a wooden timber at a height of 1.2 meters to avoid any interference from soil reflections. Eight pencil probes were placed at different distances from the explosive charge, ranging from 0.5 meters to 4.0 meters, to record the pressure generated by the explosion. The explosive charges were molded into spherical, hemisphere, and/or cylindrical shapes, and detonated using electric detonators at three different points of initiation. The setup for the field blast testing is shown in Figure 3, while Figure 4 shows the three different points of initiation. The data collected from this field test will be used to train the MLP network for predicting the peak pressure of commercial explosives.

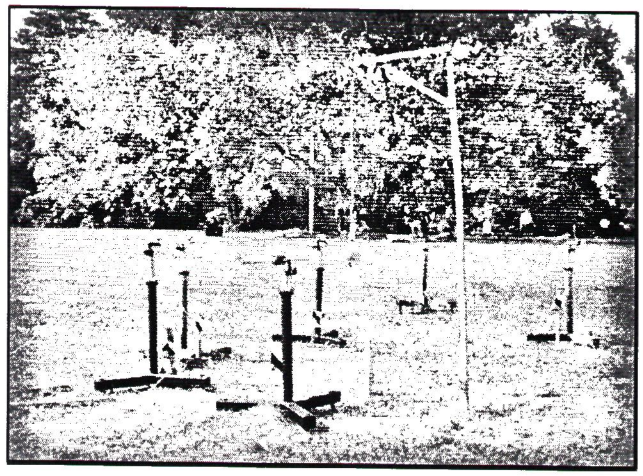

Figure 3. Field blast test set up [7].

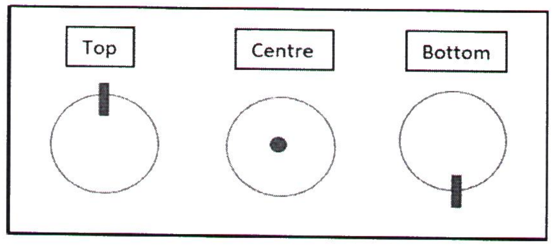

Figure 4. Point of initiation [7].

The first equation defines the weighted sum of inputs to the neuron as shown in Figure 5:

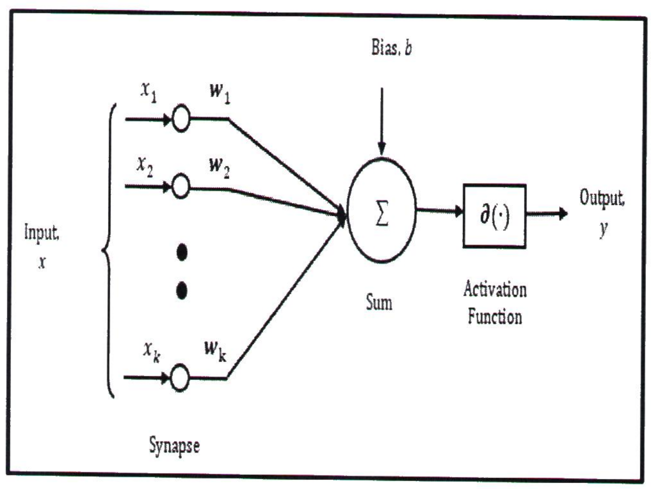

Figure 5. Nonlinear neuron model [16, 17].

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

where u is the weighted sum output, x_j is the input signal to the jth synapse, and $\mathbf{W}_j$ is the weight assigned to the j^{th} synapse. The second equation defines the output of the neuron after passing the weighted sum through an activation function:

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

where y is the output of the neuron, $\partial(u)$ is the activation function, u is the weighted sum of inputs, and **b** is the bias term added to the sum process. The activation function determines whether the neuron will be activated or not based on the weighted sum. Different types of activation functions can be used depending on the problem being solved [18, 19]. For example, the sigmoid function is commonly used for binary classification problems, while the ReLU function is commonly used for regression problems.

In equations 1 and 2, the output u is the sum of the synapse inputs x_j multiplied by their corresponding weights $\mathbf{W}_j$ and passed through an activation function $\partial(u)$ to produce the output y. Various activation functions are commonly used in neural networks, including the fixed limiter function, piecewise linear function, Logsig function, and linear function [18].

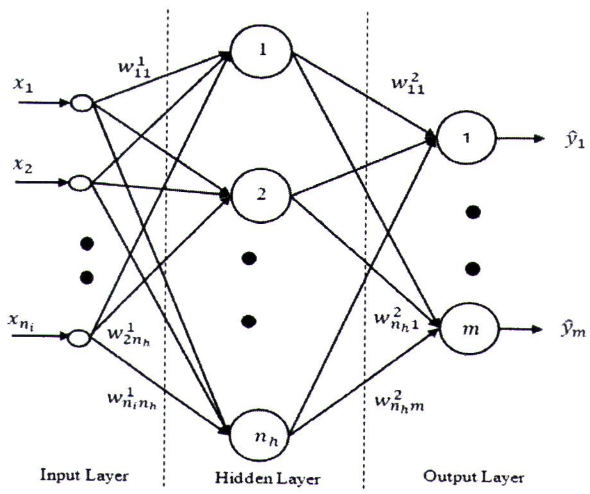

Figure 6. MLP structure [20].

The effectiveness of artificial neural networks in making accurate predictions depends on the training methodologies used and the network structure design [18]. To improve the performance and generalization of nonlinear neural networks, the MLP network was developed by adding a linear connection between the input and output layers. It was observed that using a nonlinear network like MLP to represent a linear system may not yield accurate predictions. The figure comprises an input layer, a single hidden layer, and an output layer. The output of the network is given by:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 \, \partial\left(\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + w_{k0}^1 x_0^1\right) \tag{3}$$

[21] $for\ 1 \leq j \leq n_h$ and $1 \leq k \leq m$

The Logsig activation function is typically used to activate the MLP network, and the goal is to minimize the prediction error defined in Equation 4 by finding optimal values for the unknown variables $\mathbf{w}_{ij}^1$, $\mathbf{w}_{jk}^2$ and threshold b_j^1.

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

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

The learning phase is a crucial step in neural networks as it ensures that the network performs as intended. There are two types of learning paradigms commonly used: supervised and unsupervised learning [21, 22]. Supervised learning is used to develop a global model that maps input to output. In contrast, unsupervised learning involves estimating using known training models. The learning process in unsupervised learning is different from supervised learning in that there is no output goal. Unsupervised learning requires gathering a set of input data, building a density model based on the data sets, and relying on prior experience. The learning process is undirected and entirely dependent on previous experience. Unsupervised learning is helpful for data compression [23]. For the study, an experimental process was first carried out, followed by a modelling process using the neural network approach. The supplementary dataset is acquired in addition to the goal, so it is best to receive supervised instruction. The Blast Pressure Prediction system uses supervised training methods such as backpropagation (BP) [24], Lavenberg Marquardt (LM) [25], and Bayesian Regularization (BR) [26].

The number of repetitions of training is determined by observing the performance and accuracy of the mean square error (MSE) prediction during the training and testing phases [27, 28]. The accuracy of the predictions is determined by the smallest MSE value received. Regression is used to predict outcomes or determine data fitness, with simple linear regression involving one independent variable and one dependent variable, while multiple linear regression involves two or more explanatory variables and a response variable. Some studies have used neural networks to predict the effects of explosions based on previous experience. The MLP network's input parameters are the kind and shape of explosives and reading sites, while the output parameter is the explosive pressure. Figure 7 shows the data recorded from previous explosive experiments.

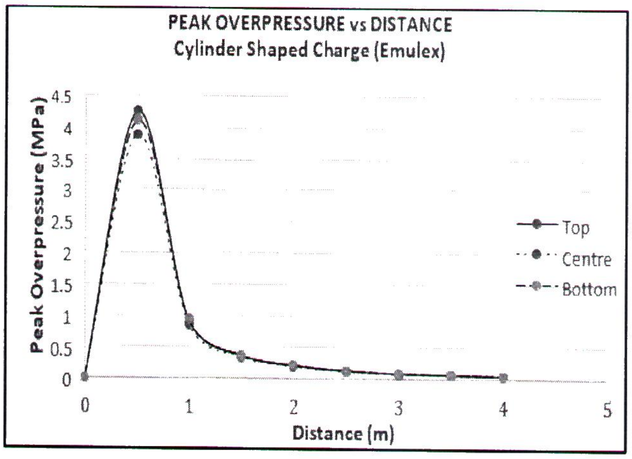

Figure 7. Recorded data by the explosive testing [12].

III. Results and Discussion

To demonstrate the MLP neural network's ability to predict explosion pressure, its performance must be evaluated through prediction analysis. This analysis is carried out in three stages using the MATLAB neural network tools: 70% of the data is used for training, 30% for testing, and 144 blast test datasets are used. Two examples of performance evaluation are the MSE error and regression for best fitting. The training algorithm's performance is assessed based on the lowest MSE and highest regression performance. The lower the MSE, the better the network's ability to predict the explosion pressure with low relative error during the prediction phase. On the other hand, the network's regression performance is measured by how close the measurement is to 1, with higher performance being closer to 1 and worse performance being closer to 0. The MSE and regression values for the different training techniques were calculated using the neural network tool in MATLAB. Table 1 shows the performance of the MLP network using LM and BP training algorithms activated by the Tansig and Logsig activation functions, ranked by lowest MSE performance and highest sequences.

TABLE I. MSE and Regression performance of MLP network

Training Algorithm	MSE Performance Analysis	Regression Performance Analysis	Number of Epoch
LM with Tansig	1.1348	0.9512	18
LM with Logsig	1.3213	0.9232	23
BP with Tansig	1.9832	0.8156	16
BP with Logsig	2.5236	0.7245	21

Table I indicates that the LM training algorithm with Tansig activation function had the best MSE performance, with an MSE of 1.1348 for the MLP network. The second-best performance was achieved by the MLP network trained using the LM and activated by Logsig activation function, with an MSE of 1.3213. The BP training algorithm with Tansig activation function given third best performance, while had the worst performance given by BP training algorithm with Logsig activation function, with MSE of 1.9832 and 2.5236, respectively. On the other hand, Table I shows that the LM training algorithm with Tansig activation function produced the highest regression reading of 0.9512. The LM training algorithm with Logsig activation function produced the second highest regression reading of 0.9232. The MLP networks trained using the LM algorithm outperformed those trained using the BP methods. The MLP network with the BP training algorithm had a regression performance of 0.8156 and 0.7245, respectively for Tansig and Logsig activation function.

Table I clearly demonstrate the difference in performance between the stochastic and deterministic models used in training algorithms. A stochastic model is based on random variables, while a deterministic model is a more commonly used and familiar method. The results show that most BP-based algorithms fail to function well because they get trapped in local minima during the training process. However, some modifications have been made to help these algorithms escape from local minima, which has improved their performance. The LM training process is based on the BP model. By adding a Gauss-Newton algorithm and gradient descent via BP, the network can search for global minima. Although the LM training algorithm takes longer to converge than BP, it achieves good accuracy compared to other combinations. On the other hand, the BP training method can converge in a short period but, its accuracy performance is not as good.

IV. Conclusion

The prediction results of the MLP network demonstrate its ability to accurately forecast the explosive dataset. The BR training algorithm exhibits the best performance, with the smallest MSE and highest regression values. In contrast, the BP training approach has a shorter processing time and fewer required epochs but produces higher MSE and worse regression results. The LM outperforms the BP, and Tansig activation function give better performance than Logsig. The MLP network accepts inputs such as explosive type, explosive effect distance, and explosive shape, making it suitable for blast prediction modeling. The primary objective of this research is to identify the best algorithm to use as the brain of the Blast Prediction model.

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