MLP Network Prediction for Blast Explosive based Training Algorithm

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Abstract— For many years, researchers have been examining the profile of blast waves resulting from detonations and using experimentation to make predictions based on specific parameters. However, previous studies have mainly focused on the central point of initiation for spherical explosive shapes. The aim of this study is to compare the accuracy of predicting the blast peak overpressure based on various factors, including the type and shape of the explosive and the location of detonation. The experiment involved detonating 500 grams of PE-4 and Emulex at different distances (ranging from 0.5 to 4.0 meters) and creating a prediction model using a Multilayer Perceptron (MLP) network. Bayesian Regularization (BR) proved to be more effective than Backpropagation (BP) when modelling Explosive Blast Prediction.

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

I. INTRODUCTION

Explosives are capable of releasing a significant amount of energy in the form of light, heat, sound, and pressure. The strength of an explosion is determined by the quantity of explosives used, while its classification as a high or low explosive is based on the rate of expansion [1]. Explosives are also categorized based on their sensitivity to heat and pressure, as subsequent explosions can be less predictable due to their vulnerability to these factors [2, 3]. Explosions can propagate at a speed of up to 1800 meters per second. Ammonium nitrate (AN) is considered a powerful explosive due to its high explosive rates and gas pressure. It exists 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 affected various sectors in Malaysia, including the Ministry of Defense. The government and Armed Forces are working together to restructure their spending while maintaining the country's defense readiness. This involves ensuring that there is an adequate supply of military equipment and defense assets. However, using PE-4 explosives for training purposes is expensive, as they are imported from the UK. To reduce costs, it makes sense to develop local explosives that match PE-4's military training capability. This would eliminate the need to import PE-4 from other countries, thereby reducing expenses. Commercial explosives are typically more expensive than military explosives due to their specific composition [5, 6]. However, they can be used for various applications, such as cutting charges, bridge demolition, and building damage, achieving similar results to PE-4. Figure 1 and Figure 2 illustrate commercial and military explosives, respectively.

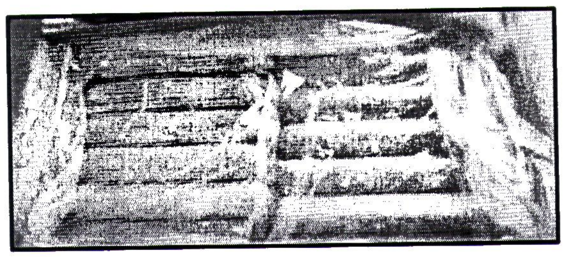

Figure 1. Commercial explosive (Emulex) [7].

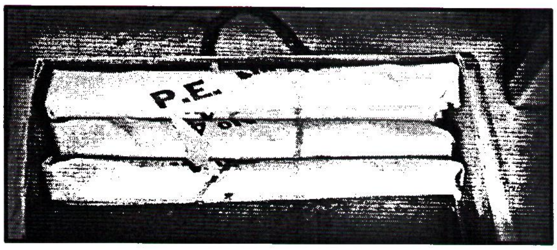

Figure 2. Military explosive (PE-4) [7].

To tackle this challenge, a Blast Explosive Prediction system has been developed to forecast the peak overpressure of different types of explosives, such as Emulex and PE-4. The system takes into account the 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, explosives tests are conducted actively. Various predicting methods have been employed, with different parameters based on the user's requirements. While statistically-based prediction algorithms have typically yielded accurate predictions, the latest method utilizing artificial intelligence has demonstrated better results. Several forecasting systems are available, but the precision of the predictions is highly dependent on data enrichment during blast tests.

In conclusion, various numerical algorithms such as SVM and HMM have been utilized to predict the effect of explosions [9-11]. Additionally, neural network techniques such as the MLP network have been used to forecast peak pressure of commercial explosives using data from prior experiments and specific criteria [12, 13]. The accuracy of these predictions is dependent on the enrichment of data during blast tests [14, 15].

II. Methodology

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

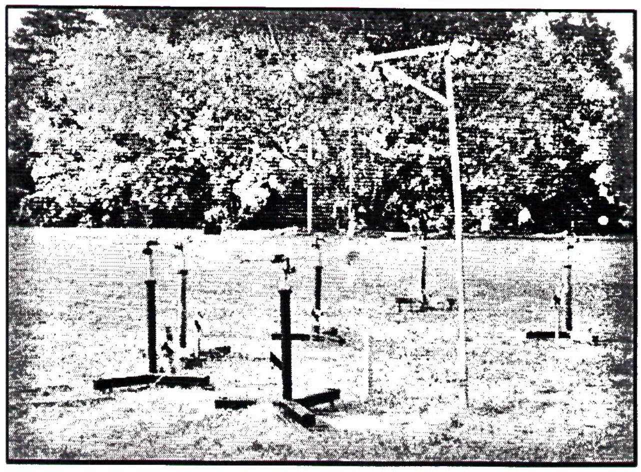

Figure 3. Field blast test set up [7].

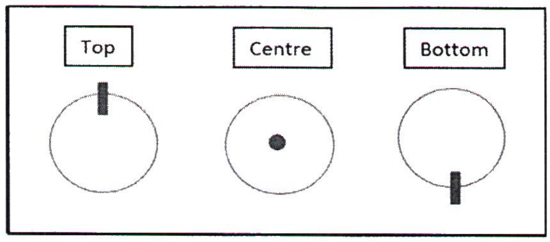

Figure 4. Point of initiation [7].

The equation shown defines the weighted sum of the inputs to a neuron, as illustrated in Figure 5.

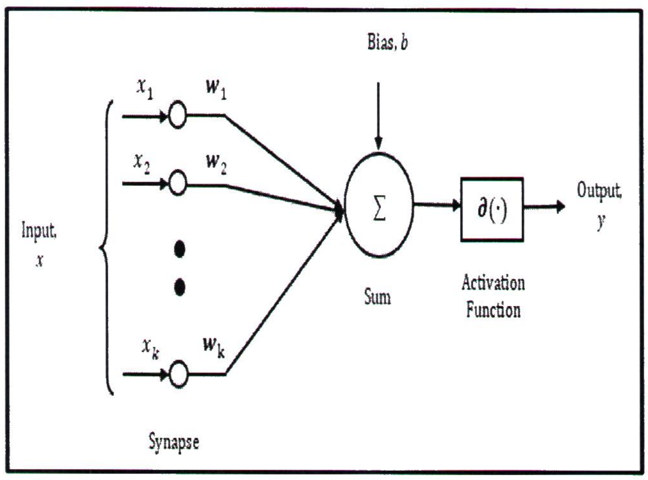

Figure 5. Nonlinear neuron model [16, 17].

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

The first equation represents the calculation of the weighted sum of inputs received by a neuron, as illustrated in Figure 5. The output of the weighted sum is represented by the variable u, where x_j refers to the input signal received by the j^{th} synapse and $\mathbf{W}_j$ is the weight assigned to that synapse. The second equation defines the output of the neuron after the weighted sum has been processed by an activation function.

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

The activation function is a key element in neural networks, as it introduces nonlinearity and allows the model to learn complex patterns in the data. The choice of activation function depends on the task at hand and the characteristics of the data. The sigmoid function, also known as the logistic function, is commonly used for binary classification problems because it maps the output to a probability between 0 and 1 [18, 19]. The ReLU (Rectified Linear Unit) function, on the other hand, is commonly used for regression problems because it is fast to compute and can handle large datasets. Other activation functions include the hyperbolic tangent (tanh) function, the softmax function, and the leaky ReLU function.

Equations 1 and 2 describe the process by which the neuron produces an output by summing the inputs received from its synapses, multiplying them by their respective weights, and passing the result through an activation function. The specific activation function used can vary depending on the problem being solved, with different options such as the fixed limiter, piecewise linear, Logsig, and linear functions commonly employed in neural networks [18].

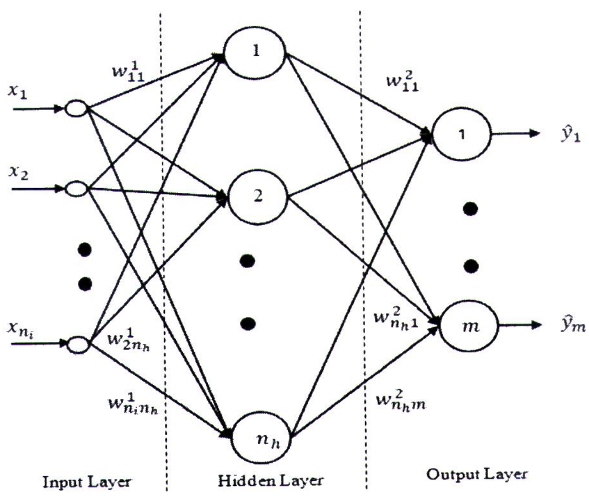

Figure 6. MLP structure [20].

The accuracy of artificial neural networks in making precise predictions relies heavily on the training techniques and the design of the network structure [18]. To enhance the performance and generalization of nonlinear networks, the MLP network was developed by including a linear connection between the input and output layers. It has been observed that using a nonlinear network such as MLP to model a linear system may not produce reliable predictions. The MLP network consists of an input layer, a single hidden layer, and an output layer. The output of the network is determined 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 commonly used to activate the MLP network, and the objective is to minimize the prediction error, as defined in Equation 4, by determining the 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 ensuring the performance of neural networks. Two types of learning paradigms are commonly used, namely supervised and unsupervised learning [21, 22]. Supervised learning is used to develop a model that maps input to output. In contrast, unsupervised learning involves estimating using known training models and does not have an output goal. Unsupervised learning relies on prior experience and is useful for data compression [23]. For the study, an experimental process was carried out, followed by a modelling process using neural network approach. As the supplementary dataset was acquired in addition to the goal, supervised training methods such as backpropagation (BP) [24], Levenberg-Marquardt (LM) [25], and Bayesian Regularization (BR) [26] were used in the Blast Pressure Prediction system.

During the training and testing phases, the performance and accuracy of the mean square error (MSE) prediction are closely monitored to determine the number of training repetitions necessary [27-28]. The aim is to achieve the smallest MSE value, indicating higher accuracy in predicting outcomes or determining data fitness using regression. Regression involves using one or more independent variables to predict the response variable. For example, simple linear regression involves one independent variable and one dependent variable, while multiple linear regression involves two or more explanatory variables and a response variable. Previous studies have utilized neural networks to predict the effects of explosions based on past experience, where the MLP network takes the kind and shape of explosives and the reading sites as input parameters and the explosive pressure as the output parameter. Figure 7 displays the data recorded from previous explosive experiments.

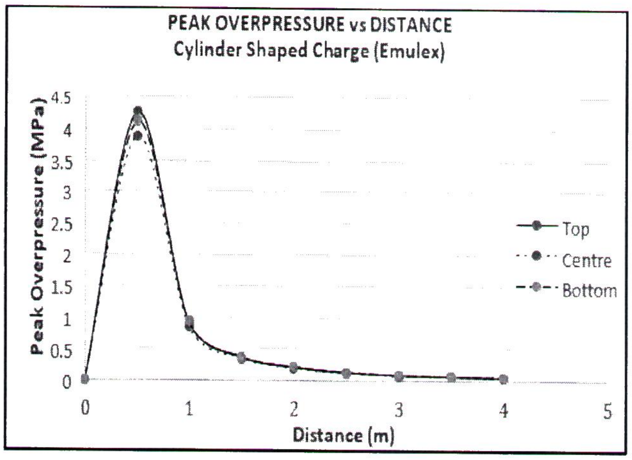

Figure 7. Recorded data by the explosive testing [12].

III. Results and Discussion

The MLP neural network's ability to predict explosion pressure can be demonstrated by evaluating its performance through prediction analysis, which can be carried out using MATLAB neural network tools. The evaluation involves three stages, with 70% of the data used for training, 30% for testing, and 144 blast test datasets used. Two examples of performance evaluation include the MSE error and regression for best fitting. The performance of the training algorithm is assessed based on the lowest MSE and highest regression performance, with lower MSE indicating better prediction ability with low relative error during the prediction phase. 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. Using the neural network tool in MATLAB, the MSE and regression values for different training techniques were calculated. Table 1 ranks the performance of the MLP network, using three different training algorithms activated by the Logsig and Purelin activation function, based on the lowest MSE performance and highest regression values.

TABLE I. MSE and Regression performance of MLP network

Training Algorithm	MSE Performance Analysis	Regression Performance Analysis	Number of Epoch
BR with Logsig	0.9280	0.9658	452
BR with Purelin	1.5242	0.8922	512
BP with Logsig	2.5236	0.7245	21
BP with Purelin	3.2578	0.6782	32

Table I displays the results of evaluating the performance of the MLP network using three different training algorithms and two activation functions, based on the MSE and regression values. The results show that the BR training algorithm with Logsig activation function had the best MSE performance of 0.9280, while the BP training algorithm with Purelin activation function had the worst performance with an MSE of 3.2578. The BR training algorithm with Logsig activation function also produced the highest regression reading of 0.9658, indicating a better fit of the predicted explosion pressure to the actual data. The MLP networks trained using the BR algorithm had higher regression performance than those trained using the BP methods, with regression performance of 0.7245 and 0.6782 for Logsig and Purelin activation function, respectively. These results suggest that the BR algorithm with Logsig activation function is the most effective method for training the MLP network to predict explosion pressure.

The results presented in Table I clearly demonstrate a significant difference in performance between the training algorithm models used. The BR algorithm, which employs a stochastic model, outperformed the BP algorithm, which uses a deterministic model. A stochastic model involves random variables, while deterministic models have been extensively researched and are more commonly used. Due to the nature of BP-based algorithms, they often get stuck in local minima during the training process, leading to suboptimal performance. However, modifications have been made to help the algorithm escape local minima and find global minima, which has improved its performance. The BP algorithm is capable of quickly finding the optimum structure, but its accuracy is lower compared to the BR algorithm. Conversely, the BR algorithm takes a longer time to converge, with 452 and 512 epochs required when using Logsig and Purelin activation functions, respectively. However, it provides a higher level of accuracy compared to other combinations.

IV. Conclusion

The results of the MLP network's prediction demonstrate its capability to accurately forecast explosive data. The BR training algorithm exhibited the best performance with the smallest MSE and highest regression values, while the BP training approach had a shorter processing time and required fewer epochs, but produced higher MSE and worse regression results. The MLP network is able to take inputs such as explosive type, explosive effect distance, and explosive shape, making it suitable for blast prediction modeling. The ultimate goal of this study is to determine the optimal algorithm to serve as the foundation of the Blast Prediction model.

Acknowledgment

This research is fully supported by FRGS grant, FGRS/1/2020/TK0/UPNM/02/1. The authors fully acknowledged the Ministry of Higher Education (MOHE) and National Defence University of Malaysia (UPNM) for

the approved fund, making this important research viable and effective.

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