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Prediction Model using a Multi-Layer Perceptron Neural Network for Military Plastic Explosive PE4 Blast Performance in a Significant Effect of Tropicalisation

Mohd Sharil Salleh [1,2], Khalid Isa[1,*], Fakroul Ridzuan Hashim[3]

[1] Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Johor, Malaysia
[2] Centre for Research and Innovation Management, Universiti Pertahanan Nasional Malaysia, Kem Sungai Besi, 57000 Kuala Lumpur, Malaysia
[3] Faculty of Engineering, Universiti Pertahanan Nasional Malaysia, Kem Sungai Besi, 57000 Kuala Lumpur, Malaysia

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ABSTRACT

Over the years, plastic explosive PE4 has been imported from the United Kingdom and is fully utilised in military activities and drills. This study is to discover a ratio of the plastic explosive PE4 explosion performance in tropical conditions and develop a multilayer perceptron neural network model for the prediction of plastic explosive in Malaysia. Several environmental tests have been performed in Kem Kongkoi, Jelebu, Negeri Sembilan. Six parameters were considered, including environmental temperature, distance measurement, explosive material, variety of shapes, weight and ignition point. In this paper, the Bayesian Regularization, Levenberg-Marquardt algorithm and Scaled Conjugate Gradient model were developed. Every model was tested with 24 datasets to discover the root mean square error and regression performance. The Bayesian Regularization model provides the best prediction model as it has a mean square error of 0.0005 and a regression performance value that is close to 1 at 0.9992.

1. Introduction

Over the years, a significant number of scientists and researchers have utilised a diverse set of methodologies to explore the military plastic explosive's influence on the product's shelf life and stability. Experiments session which required a significant investment of the researcher's time, money and effort, were carried out in order to discover and accurately specify the features of each explosive material. These parameters included the detonation velocity, the detonation rate, and the detonation pressure. According to the definition provided from the previous study [1], due to the chemical reactivity of the components that make up some explosives, these substances can detonate when placed in certain conditions. Hence, before conducting an experiment using explosives, it is essential to understand the approximate range of parameters for each explosive substance. This is need to be measured in order to limit the risk that for an experiment with explosives.

* *Corresponding author.*
E-mail address: halid@uthm.edu.my

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1.1 Matter of Explosion

The high explosives used by the military are safe to handle and have a long shelf life, a high energy density, and a rapid detonation reaction [2]. Due to this quality standard, they are particularly well-suited for use in explosive weapons. The chemical makeup of a quantity of high explosive will determine how much energy is released and how much of a blast load is generated when that explosive is detonated. Consequently, these two variables are related to each other. This is going to be the case in every scenario, regardless of whether or not the bulk of the explosive was really detonated.

Primary and secondary high explosives are the two categories of high explosives that may be differentiated from one another based on the explosive grade and the explosive sensitivity to the quantity of energy input. Primary high explosives are typically used in military applications. Primary explosives are particularly sensitive to even minor amounts of energy that may be brought into the system by means of friction, shock, or static electricity [3]. These types of energy can cause the primary explosive to detonate prematurely. It just takes a small amount of energy to generate a shock wave, which then moves through the unreacted explosive as it moves through the system. Figure 1 shows the types and applications of explosives.

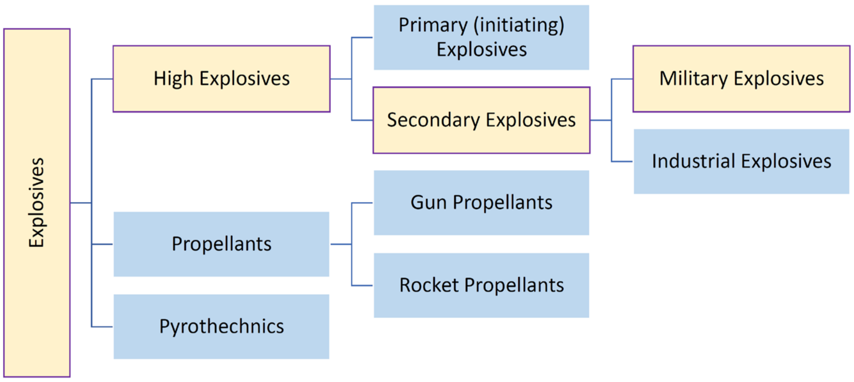

Fig. 1. Classification of explosive material for high explosives [1]

1.2 Plastic Explosive PE4

Military explosive is a type of high explosive with a detonation velocity of greater than 7000 meters per second (m/s). PE4 is a conventional plastic explosive, widely used for the production of improved energetic systems for defensive and offensive use. PE4 is RDX-based and is available in the cartridge and in bulk form. Previous research has defined the characteristics of PE4 and measured its great performance in blast experiments and explosion performance [4].

Currently, the well-known plastic explosive PE4, or called PE4, imported from Europe specifically from defence manufacturers from the United Kingdom, is broadly used by the Malaysian Armed Forces (MAF) in military training. As stated by the Malaysian Army, PE4 has been used in their routine for the past 20 years. Due to the widespread use of British PE4 in explosion, demolition, and blast testing activities according to the previous study [4-6], the authority has imposed Rules and Regulations specifically for PE4 usage and Standard Operation Procedures (SOP) in military drills. It is almost certain that plastic explosive PE4 product specifications in the military practical are referring to European standards.

For many years, this phenomenon was surprisingly neglected by the researcher as well as the military personnel to the considerable risk that the explosion standard will vary owing to the tropical impacts in Malaysia, due to the PE4 being imported directly from the United Kingdom. This can be illustrated briefly by Figure 2, which shows the comparison data taken from the previous study [7] for both countries as the United Kingdom is the explosive manufacturer while Malaysia is the end user. To date, no Tropical Standards have been developed for PE4 explosives. One of the most obvious possibilities is that erroneous explosion tests have been performed as a result of tropical effects when compared to the Standard provided by the manufacturer. Furthermore, there are currently no research or guidelines that take into account tropical elements. Thus, there is a significant risk that an explosion will have a direct impact or cause injuries.

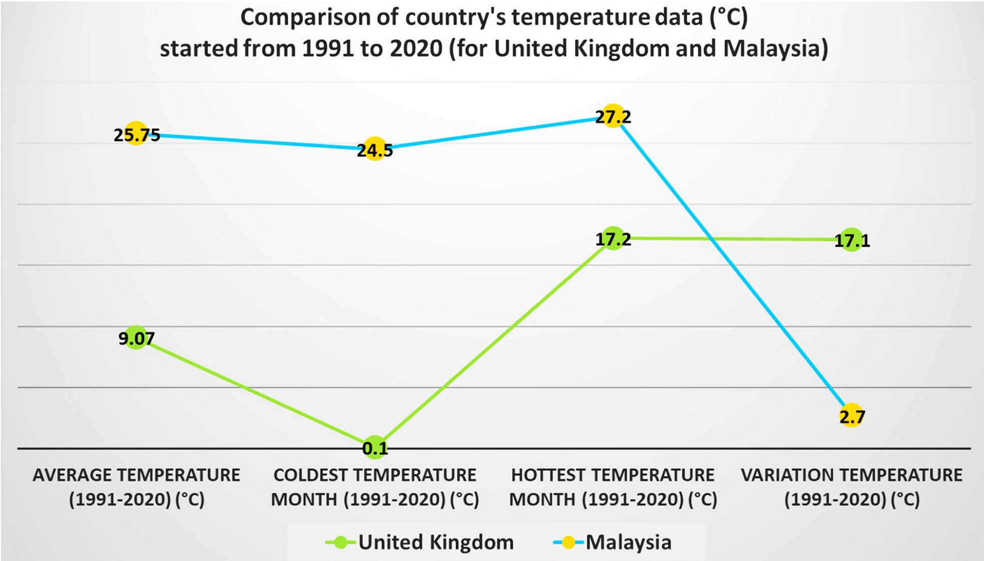

Fig. 2. Comparison of the country's temperature data

1.3 Predictive Models Deployment in an Explosion

Artificial Neural Networks (ANNs) are becoming more commonplace in the field of explosion. One use of this technology is the prediction of explosion, which is just one of its many applications. ANNs can be trained to perceive patterns and correlations within vast datasets, and after the training session has been completed, they can be used to make accurate predictions based on suitable input parameters. According to the previous study [8], this ability to learn comes from the fact that ANNs are capable of being taught to recognise patterns and correlations hidden within enormous datasets. Artificial neural networks (ANNs) have the ability to accurately anticipate a variety of explosions including Blast-Induced Ground Vibration (BIGV), Rock Burst Failure, Flyrock-Induced Explosions, and Boiling Liquid Expanding Vapour Explosion (BLEVE). ANNs are able to be trained by utilising data relevant to the qualities of the explosive material, the environment in which it is located, and numerous physical parameters such as detonation pressure, temperature, and vibrations.

Significant analysis has been postulated from the previous studies [9-15], on ANN can be trained using data concerning the characteristics of the explosive substance, the distance from the blast site to nearby structures, and the geological properties of the area that surrounds the blast site. All of these different aspects can be taken into account when making predictions regarding the likelihood of BIGV. It has been demonstrated that the ANN can make accurate predictions based on the input data, such as the predicted quantity of ground vibration and the likely damage to structures in the nearby area.

Several lines of evidence suggest that ANNs can also be trained on data related to the geological properties of the location, the stress level in the rock formations, as well as the type and frequency of previous rock burst failures. The prediction of rock burst failure is made possible as a result of these variables. Many recent studies [16,17], have shown that the ANN are able to generate predictions about the likelihood of future rock burst failures and the likely effects those failures could have on mining equipment and employees.

ANNs can be trained on data relating to the explosive material and blast design parameters, as well as the physical qualities of the surrounding environment, such as the distance to any other structures and the topography of the area, in order to anticipate the potential for flyrock-induced explosions. This will allow for more accurate predictions of the likelihood of explosions being caused by flyrock. According to previous study [18], the reason for doing this is to increase the accuracy with which the possibility of flyrock-induced explosions can be predicted.

Finally, artificial neural networks (ANNs) can be trained on vast data related to the properties of the liquid and vessel, such as the temperature and pressure of the liquid, as well as the design parameters of the vessel, in order to make a prediction about the possibility of a BLEVE explosion. This can be accomplished by feeding the ANNs information about the properties of the liquid and vessel. As noted from previous study [19], the ANN are able to predict the likelihood of a BLEVE explosion and the potential repercussions of such an explosion on nearby structures and human life.

In conclusion, artificial neural networks are a powerful tool that can be used to evaluate the risks associated with explosives and to forecast the performance of explosions. ANNs can be trained on large datasets and then used to make accurate predictions based on the input data linked to the qualities of the explosive material, the environment it is in, and the physical parameters.

1.4 Tropicalisation in Defence Area

The term "tropicalisation" is used in the context of defence and security to refer to the process of adapting military equipment, infrastructure, and procedures in order for them to be able to function effectively and sustain the unique challenges and climatic conditions that are prevalent in tropical countries. In Malaysia, which is located in a tropical zone, it is indispensable for the defence and security sector to measure to tropicalisation standards [20]. This proactive action is a must to ensure that military actions must be planned and carried out with the highest possible effectiveness.

Hence, some prospective knowledge contributions could make by academics and researchers on the topic of tropicalisation are environmental testing and simulation, material and equipment selection, infrastructure design and equipment adaptation as well as research and development (R&D) collaboration which is relevant to the country's defence and security concerns. In general, a multidisciplinary approach is required for Malaysia's knowledge contributions in the field of tropicalisation for the sake of defence and security. Furthermore, the Malaysian defence and security sector will be able to improve its operational readiness, lengthen the lifespan of its equipment, and raise the efficiency of military operations performed in tropical circumstances if it places a greater emphasis on tropicalisation.

2. Methodology

There has been significant development in the field of computer intelligence science in the form of a new subfield known as artificial neural networks since the 1980s. These advancements have been made at a rapid pace by researchers in artificial neural networks (ANN) [21]. At this point in time, ANN is considered to be one of the intelligent tools that can be utilised in order to gain a better understanding of difficult problems. The Artificial Neural Network (ANN) is gaining popularity as an effective tool that can assist researchers, designers, industry players and other professionals in accomplishing their work. Therefore, ANN is currently being applied successfully in various business contexts in addition to the arena of academic research. An artificial neural network (ANN), also known as a flexible mathematical model structure, is a technology that is used in information computing that imitates the structure, processing methods, as well as learning skills and capacities of the human brain [22-24].

In this paper, a research methodology will be composed of two stages which are plastic explosive field testing and computer modelling and simulation as summarised in Figure 3. The first methodology consists of a flow of activities on technical processes that must be taken in order to fulfil the objective of checkout the tropical effect on explosive PE4 performance. Also, the second methodology outlines the design techniques and the sequence of actions that must be performed in the Matlab programme for modelling plastic explosive performance based on previous experimental data. In addition, research methodologies offer a technical perspective that occurred in the process of investigating the tropical effects in an explosion situation for plastic explosives.

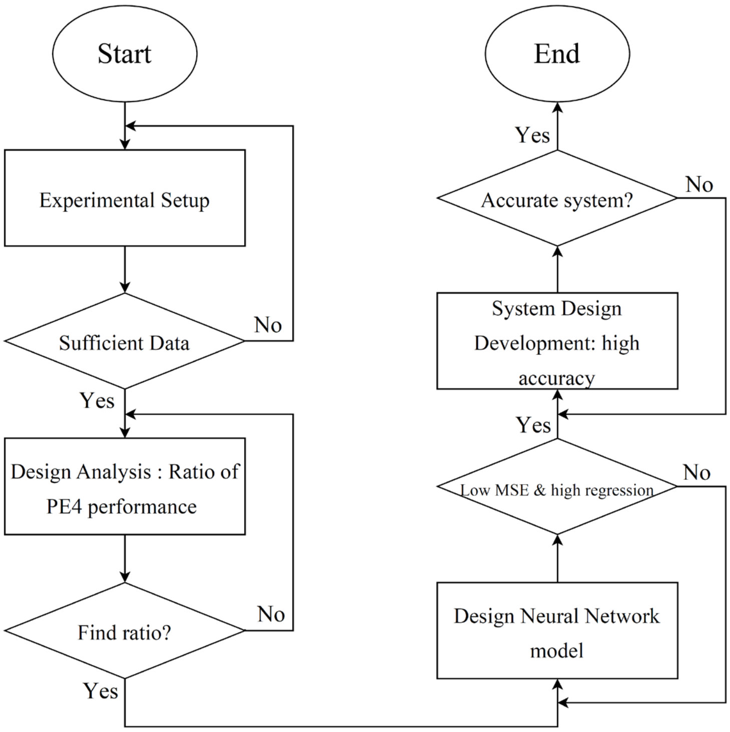

Fig. 3. Research activities flowchart

2.1 Experimental Setup and Data Collection

Field test operations have been carried out as part of a significant number of research projects in order to investigate the pattern of explosive effects in tropical environments. During the experiment, a series of investigations were performed to identify the volatile pattern of the PE4 subjected to air blast loading. This was done to ensure that the experiment was conducted correctly. The experimental works are carried out in the designated military camp in Peninsular Malaysia, which is located in Kem Kongkoi, Jelebu, Negeri Sembilan. The PE4 explosive is obtained from the Malaysian Armed Forces. This place was selected for the experiment because it has a long history of explosive activities, and is very accessible by military and researchers to coordinate the fieldwork.

Multiple readings have been taken to determine the cumulative temperature of the surrounding environment as well as to validate the exploration of the tropical elements in research. It is a measurement that is taken of the temperature at different heights within the atmosphere of the Earth. Temperature is used as a measurement for the quantity of energy that is absorbed by the earth from the sun. This energy comes in the form of heat. It is contingent on a broad variety of elements, such as height and humidity, among others. In addition, during the data collection process, various recording equipment has been set up as depicted in Figure 4 such as a hygrometer, a high-speed camera, a high-speed data acquisition system, and a free field pencil probe, were utilised. The experimental parameters measured are detailed in Table 1.

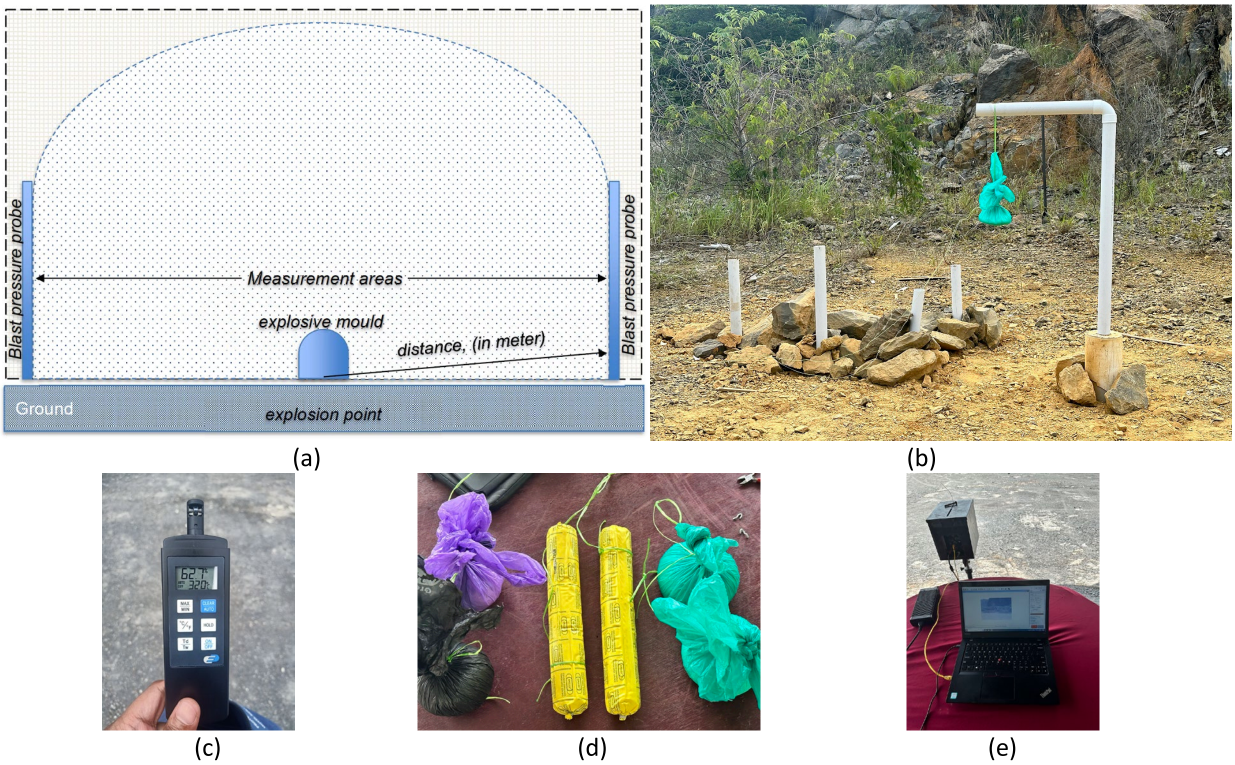

Fig. 4. Illustration of material preparation and equipment setting for plastic explosive PE4 explosion testing a) illustration of explosion test b) the blast test setup c) hygrometer for temperature measurement d) shapes of explosive material e) high-speed camera

Table 1
Experiment parameters

Parameter(s)	Scale or Type
Explosive Material	Plastic explosive PE4
Shape Mould	Spherical, Hemispherical, Cylinder
Distance	0.5 – 4.0 meter
Ignition Point	Top
Explosion performance	MPa
Environment temperature	29.0 – 32.3 (°C)
Weight	500 grams

Hopkinson-Cranz, also called "cube-root" scaling, is the type of blast scaling used most frequently. Researchers who have a comprehensive understanding of blast technology may be able to use these principles to anticipate the features of blast waves from large-scale explosions based on studies conducted on a much smaller scale. This is possible because scaling the properties of blast waves from explosive sources has its own approach, and researchers who have this understanding may be able to use it. Throughout history, this has typically been examined by comparing the findings of smaller-scale experiments to the conclusions of larger-scale testing.

$$Z = \frac{R}{W^{1/3}} \tag{1}$$

where R is the distance from the charge to the surface of a structure, W is a charge weight as TNT equivalent, and Z is scaled ground distance. To obtain the absolute values of the blast wave parameters, multiply the scaled values by a factor of $W^{1/3}$.

2.2 Computer Model Setup and Configuration

This research was conducted to determine whether or not it is possible to predict the military explosion performance by using relevant parameters such as the explosive material, the blast design, and the explosion distance. At this point in time, it is difficult to ascertain all of the pertinent parameters that influence the prediction of the military explosion performance in a climate classified as tropical. Nevertheless, there is a strong correlation between the factors that play a role in the process. As a result of this, utilising each and every potential variable as an input parameter in the model was not required to be done. In light of prior discussion and the objectives of the current investigation, the neural network was designed to make accurate predictions regarding the explosion performance findings due to tropicalisation.

In this paper, three types of neural networks were developed to predict plastic explosive PE4 explosion performance which are the Levenberg-Marquardt algorithm, Bayesian Regularization and Scaled Conjugate Gradient model. The three methods are selected to apply a neural network fitting tool in MATLAB application. Each model was tested with 24 datasets to discover the root mean square error and regression performance. While developing and designing the model, the dataset was divided into 15 training sets (60%), 7 testing sets (30%) and 2 validation sets (10%), in a reasonably haphazard method. This was done in order to facilitate the development process. The dataset was utilised and optimised, initially for training the network, testing process and then, accordingly, to validate the selected network capabilities, as shown in Table 2. Based on the output, the least mean square error (LMSE) from both design and learning methods has been accepted as the most accurate artificial neural network model to predict detonation performance for the plastic explosive PE4 in the tropical settings of Malaysia.

Table 2
Details of the ANN algorithms

Model Information	Levenberg–Marquardt (LM)	Bayesian Regularization (BR)	Scaled Conjugate Gradient (SCG)
Network structure	6 x 8 x 1	6 x 8 x 1	6 x 8 x 1
Training	trainlm	trainbr	trainscg
Training dataset (%)	15 dataset (60%)	15 dataset (60%)	15 dataset (60%)
Testing dataset (%)	7 dataset (30%)	7 dataset (30%)	7 dataset (30%)
Validation dataset (%)	2 (10%)	2 (10%)	2 (10%)
Epochs set to	1000	1000	1000
Transfer function in the hidden layer	Log-sigmoid (log-sig)	Log-sigmoid (log-sig)	Log-sigmoid (log-sig)
Transfer function in the output layer	Linear (purelin)	Linear (purelin)	Linear (purelin)

2.3 Input Features

The research focused on predicting military PE4 explosion performance using relevant parameters such as explosive material, blast design, and explosion distance. In constructing the artificial neural network (ANN), input features played a crucial role in capturing the complexity of the explosive performance prediction. The network architecture involved an input layer, hidden layer(s), and an output layer. The input neurons comprised six parameters which are the PE4 as explosive material, 500 grams weight of the explosion substance, three different shape moulds such as spherical, hemispherical and cylinder, a range of distance from the explosion point starting from 0.5 meter to 4.0 meter, top ignition point at every moulds, and the suuroundING temperature for a range of 29.0 °C to 36.5°C. These features aimed to encapsulate the diverse aspects of the PE4 explosion performance and their interaction with the tropical environment.

2.4 Evaluation Metrics

Following is a list of assessment metrics that were utilized in order to measure the efficiency of the model's performance.

2.4.1 Mean Square Error

Mean Square Error formulation is derived Eq. (2). It has been found to be especially useful in detecting outlier within a predicted range.

$$\mathrm{MSE} = \frac{1}{n}\sum_{j}^{n}\left(Y_j - f(X)_j\right)^2 \quad (2)$$

2.4.2 Regression

R^2 or R-squared is given as follows. The numerator and denominator are respectively the total sum of squares and the residual sum of squares.

$$R^2 = 1 - \frac{\sum_j \left(Y_j - f(X)_j\right)^2}{\sum_j (Y_j - Mean_{out})^2} \quad (3)$$

2.5 Multi-Layer Perceptron

A Multilayer Perceptron network, also known as an MLP network, is a specific kind of artificial neural network that can be identified by numerous layers of neurons that are connected with one another. This is a type of feedforward neural network; hence the data starts at the input layer and continues all the way through the network until it reaches the output layer [25]. This shows that the data cannot go through the network simultaneously in both directions because the network cannot handle it. The MLP comprises three unique levels, as represented by the network structure in Figure 5. These are the input layer, one or more hidden layers and the output layer. The input layer is the lowest level. The input layer is the one that the user is actually looking at. Neurons can be found in each layer, and the neurons in each layer are connected to the neighbour's layer which is close to them. It is possible to have one or more neurons in each layer.

A multi-layer perceptron (MLP) is a type of artificial neural network in which every neuron in the network's input layer is connected to every neuron in the first hidden layer of the network. In a similar manner, each neuron in the first hidden layer is connected to each neuron in the second hidden layer, and so on and so forth, right up until the output layer is reached. It is conceivable that the hidden layer could contain traditional hidden units which would serve as inputs to gate units and memory cells if they were present [26]. It is widely believed that every unit in every layer is connected to every other unit through direct connections that act as inputs except gate units [27]. Hence, these connections go from one unit to the next layer.

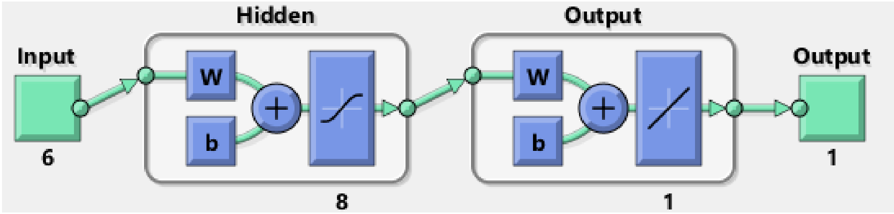

Fig. 5. Network structure for MLP Neural Network

2.6 Bayesian Regularization (BR) Algorithm

Utilising Bayesian Regularization Artificial Neural Network (BRANN) in explosion-related studies has proven effective across various contexts, including explosion risk analysis, blast-induced ground vibration, rock burst failure, fly rock induction, and Boiling Liquid Expanding Vapor Explosion (BLEVE) from the previous studies. Each application underscores the versatility and precision of BRANN in modelling and predicting complex phenomena associated with explosions.

The application of the Bayesian Regularization Artificial Neural Network across these explosion-related studies underscores its adaptability and effectiveness in handling diverse scenarios. BRANN's advantages include preventing overfitting, improving accuracy, and addressing imbalanced data issues, making it a valuable tool for predicting and understanding complex explosion phenomena.

3. Results

3.1 Plastic Explosive (PE4) Experimental Results

The findings from the field test and computer modelling and simulation are presented, along with a beneficial commentary with research findings that were produced. Based on Figure 6, Figure 7 and Figure 8, data collection illustrates a trend of explosion performance for the top point of initiation for both spherical, hemispherical and cylindrical-shaped charges of explosive. As a result, the data pattern has linearity for comparison to the standard set forth by a manufacturer. At the present time, the "standard" has been established and is been referenced by the manufacturer PE4, which was a pioneer in the manufacturing of explosives in the United Kingdom some decades ago. According to the graph in Figure 6, the highest pressure 4.216 MPa was measured at a distance of 0.5 meters, and the graph also shows that the wave quickly gradually decreases when it reaches a far distance from the explosion point at 4.0 meter.

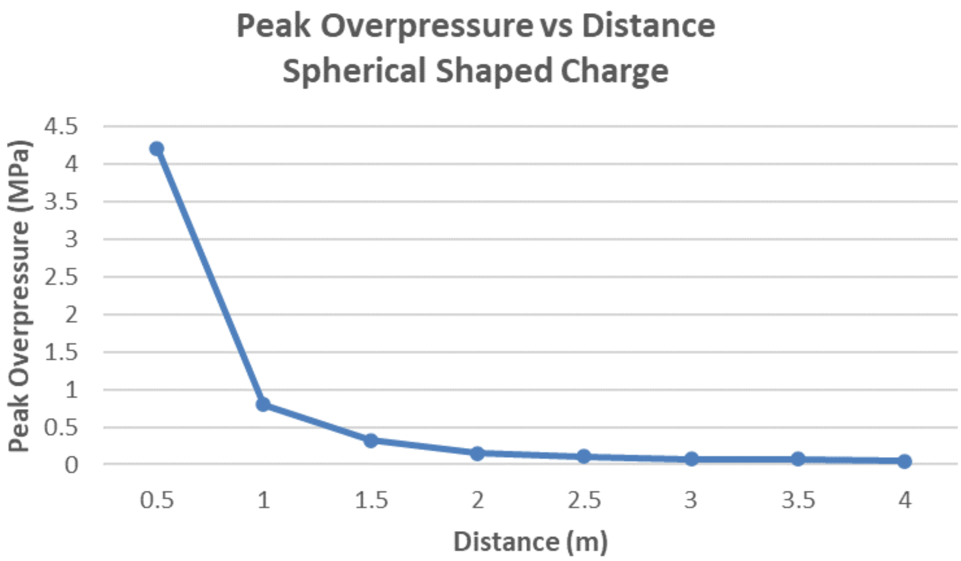

Fig. 6. Graph for spherical shaped charge

According to the graph in Figure 7, the highest pressure 5.209 MPa was measured at a distance of 0.5 meters, and the graph also shows that the wave quickly gradually decreases when it reaches a far distance from the explosion point at 4.0 meter. Based on Figure 8, the highest pressure 5.571 MPa was measured at a distance of 0.5 meters, and the graph also shows that the wave quickly gradually decreases when it reaches a far distance from the explosion point at 4.0 meter. The difference between the highest point and the lowest point is most pronounced between a distance of 0.5 meter and 4.0 meter, which is also the range in which the reading abruptly close to zero. The high point and the lowest point are separated by this distance, which reflects the greatest significant difference between the two points. After analysis of these three distinct types of shape charges, we discovered that the cylinder shape recorded the highest pressure at 0.5 meter distance.

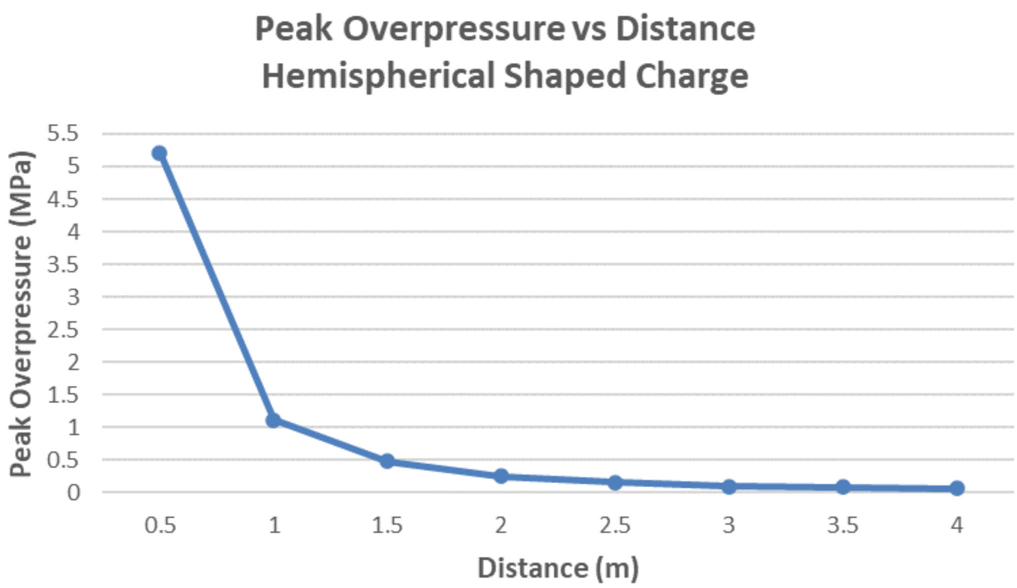

Fig. 7. Graph for hemispherical shaped charge

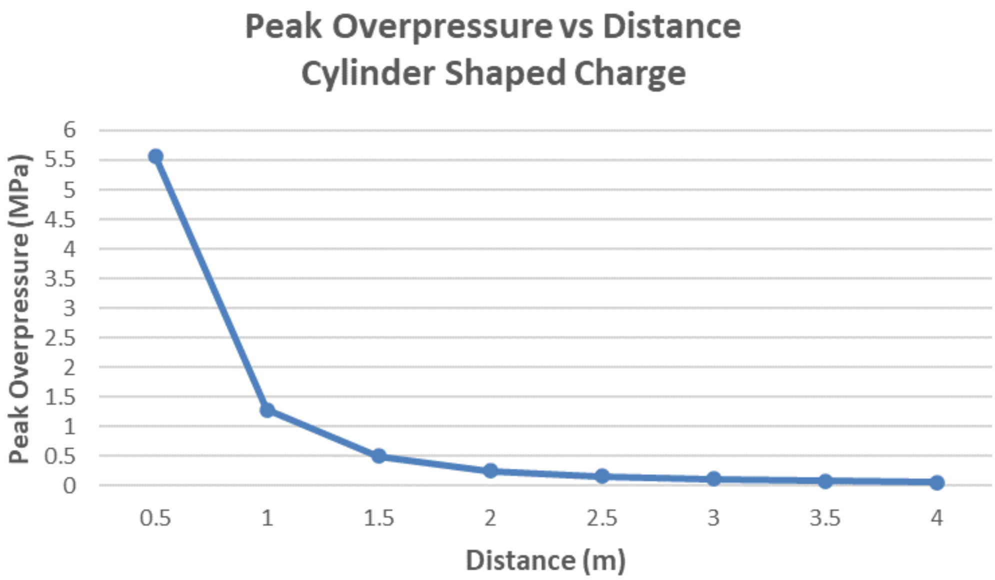

Fig. 8. Graph for cylinder shaped charge

The ratio of the PE4 field test measurement to the Standard from the manufacturer has been computed, assessed, and determined based on the peak overpressure value for each number of tests in order to fulfil the research objective. The fact that the PE4 product documentation is controlled by the authority, the standard measurement reading from the manufacturer cannot be divulged. As a result, the data tabulation is shown in Table 3 to illustrate the ratio based on the data results because this is the safest way to convey the information. According to the findings, the most achievable description of the blast pressure produced by an emulsion explosive reacting to the tropicalisation effect was obtained by using the PE4 ratio in the range of 1: (1.31 to 1.45).

Table 3
Ratio of PE4 standard from manufacturer versus experimental session in tropical condition

Shape	Distance, meter	Temperature, ^{0}C	Pressure, MPa	Conversion MPa to kg (manufacturer standard)	Ratio, Standard: Experiment
Spherical, Hemi-spherical, Cylinder	0.5	30.1 to 31.4	4.216, 5.209 and 5.571	0.344, 0.362 and 0.378	1: 1.32 to 1.45
	1.0	29.3 to 30.1	0.802, 1.119 and 1.289	0.362, 0.370 and 0.378	1: 1.32 to 1.38
	1.5	30.3 to 31.2	0.232, 0.475 and 0.496	0.359, 0.362 and 0.378	1: 1.32 to 1.39
	2.0	29.3 to 29.7	0.150, 0.247 and 0.247	0.362, 0.376 and 0.378	1: 1.32 to 1.38
	2.5	30.1 to 31.3	0.108, 0.159 and 0.161	0.362, 0.369 and 0.380	1: 1.32 to 1.38
	3.0	30.2 to 32.0	0.074, 0.098 and 0.111	0.373, 0.379 and 0.380	1: 1.32 to 1.34
	3.5	31.3 to 32.3	0.070, 0.080 and 0.085	0.376, 0.380 and 0.381	1: 1.31 to 1.33
	4.0	31.4 to 32.0	0.044, 0.062 and 0.064	0.379, 0.382 and 0.385	1: 1.30 to 1.32

3.2 Neural Network Model Performance

An evaluation of the neural networks model's ability to predict plastic explosive PE4 explosion pressure was accomplished by carrying out a performance analysis with the help of the neural network tools provided by MATLAB (*nftool*). The process to analyse performance on the development of neural networks models consisted of a training phase, which made use of sixty percent of the data, a testing phase, which made use of thirty percent of the data, and a validation phase, which made use of ten percent of the data. The study consisted of selecting the regression that produced the greatest fit, as well as calculating the mean square error (MSE), in order to identify errors that may have occurred.

The analysis consisted of determining the regression that provided the best fitting as well as evaluating the mean square error (MSE) for every models. For the best prediction model, an MSE that is low suggests that there will be a minimum relative error, while a regression value that is higher implies that the performance will be at its finest. The mean square error (MSE) and regression values for three distinct models were analysed through the neural network fitting tools using the MATLAB program. Table 4 presents the results of the performance evaluation of the MLP network, with the three training techniques arranged in a descending order of the MSE performance they achieved.

Table 4
MSE Performance of MLP network

Training Algorithm	MSE Performance Analysis	Number of Epoch
Bayesian Regularization, (BR)	0.0005	826
Scaled Conjugate Gradient, (SCG)	0.0006	31
Levenberg-Marquadt, (LM)	0.0017	11

Table 4 presents the mean square error (MSE) performance of the MLP networks. It shows BR training technique is able to deliver the lowest MSE performance with 0.0005 for the MLP network when the Tansig activation function is utilised. This algorithm is able to do so because it uses the Tansig activation function. However, with an MSE performance of 0.0006, the MLP network that was trained and activated by SCG and Tansig produced the second best result for overall. The LM training algorithm, triggered by the Tansig activation function, is utilised in the training process since it performs at 0.0017 MSE.

Table 5 presents the Regression Performance of the MLP network. It shows the BR training procedure that was triggered into action by the Tansig activation function. This algorithm has the capability of producing the highest possible reading for regression, which is 0.9992. The MLP network that was trained using the BR training strategy and activated using the Logsig activation function generated the greatest results, outperforming the SCG with a regression performance of 0.9878. Both of these training techniques were carried out using the Logsig activation function. With a regression performance score of 0.9233, the MLP network that utilised the LM training technique and the Tansig activation function finished in third place, just behind the SCG neural network.

Table 5
Regression Performance of MLP network

Training Algorithm	Regression Performance Analysis	Number of Epoch
Bayesian Regularization, (BR)	0.9992	826
Scaled Conjugate Gradient, (SCG)	0.9878	31
Levenberg-Marquadt, (LM)	0.9233	11

Table 4 and Table 5 reveal that the number of epochs used for the Bayesian model is too high due to the unique qualities that distinguish them from other models. Bayesian is more accurate in dealing with limited data and the level of uncertainty estimation. The BR analysis was based on probabilistic inference and treating model parameters as a probability distribution.

Despite achieving the lowest mean square error (MSE) at 0.0005, the Bayesian model raises concerns about potential overfitting due to an extensive 826 epochs. To address overfitting, a technique inspired by prior research [28], involves early stopping in Bayesian optimization, with its probabilistic inference, which effectively handles limited data and uncertainty. Bayesian Regularization proves effective in preventing overfitting, addressing model uncertainty, and enhancing predictive performance in data-limited scenarios for PE4 explosion performance.

4. Conclusions

The purpose of this study is to analyse the tropical impact on the explosion performance of PE4, as well as to develop an artificial neural network model that would aid in the estimation of the detonation pressure of PE4. Specific parameters such as shape, distance and blast design were set during the experiment. The ratio of PE4 has been successfully measured to be between 1 :(1.31 to 1.45), which is based on manufacturer standards to the Malaysian tropical effect. The artificial neural network model has been shown to be reliable in estimating the detonation pressure of a plastic explosive PE4. This was demonstrated through extensive testing.

The accuracy, reliability and efficiency of the model were known using metrics mean-square error and regression analysis. The way that it is accomplished is by contrasting the target values with the model's output values. In conclusion, the Bayesian Regularization model provide a close estimation of detonation pressure values to actual values that are reached through experimentation because the model has an MSE that is close to 0 at 0.0005 and an R-values that are close to 1 at 0.9992. It is recommended that in future work, further experimental sessions must be performed in order to look for a continuous stability trend in an explosion. The continuous stability trend is important for another knowledge exploration in an explosion.

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