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THE CORRECTION RATIO OF ENVIRONMENT EFFECT TO PE-4 AND EMULEX EXPLOSIVE IN TROPICAL REGION AND MODELED USING ARTIFICIAL INTELLIGENCE

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Abstract

Scientists have investigated the blast wave profile produced by an explosive detonation for decades. The blast wave propagation profile has been estimated under given parameters based on a large amount of experimental data. However, the explosion performance may be affected by environment or topical (topical region) effect and unable to plot actual results. The project tries to find the gap ratio between actual experiment been done and tabled by the manufacturer. The project also developed the weight correction ratio between PE-4 (experiment) and Emulex at the same performance. On top of that, a prediction model using a Multilayer Perceptron (MLP) network are developed. A total of 500 grams of PE-4 and Emulex were used in this experiment, which hang-up at the height of 1.2 meters above the ground. The device was detonated at distances of 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 meters. The best training technique for modelling Explosive Blast Prediction is the Bayesian Regularization (BR) training algorithm.

Keywords: Blast, Emulex, Explosive, Multilayer perceptron, PE-4.

1. Introduction

Explosives are highly reactive substances with a lot of energy that can cause light, heat, sound, and pressure explosions when released quickly. The number of explosives employed determines the force of each detonation. An explosive's rate of expansion can be used to characterize it. Explosive materials and defective materials are referred to as "high explosives" and "low explosives," respectively [1, 2]. Explosives are always classified according to their sensitivity. The second and third explosions are less romantic due to explosives' vulnerability to heat and pressure. The speed of an explosion can reach 1800 m/s. Because of its strength, which is characterized by high explosive rates and gas pressure, ammonium nitrate (AN) is classed as a strong explosive [3, 4]. The two types of AN are homogeneous and heterogeneous AN. Natural resources are used to make primary, secondary, and tertiary explosives, whereas a chemical mixture is used to make tertiary explosives.

For the time being, the global economy has had an impact on a number of countries, including Malaysia. This economic impact has had an impact on Malaysia's Ministry of Defence. Malaysia's Armed Forces (ATM) and government have been hard at work reorganising spending without jeopardising the country's defence readiness. Military supplies and equipment, as well as defence assets, must be made available. PE-4 explosives are used in ATMs for cutting charges, bridge demolition, and building damage, among other things, and were imported from Europe country for training purposes [5]. Working with PE-4 is an extremely expensive chemical. Malaysian companies, on the other hand, can manufacture commercial explosives. A good initial step is to develop local explosives that match PE-4's military training capacity. It also lowers the cost of importing PE-4 from other countries. The cost of commercial explosives is far higher than that of military explosives. This is related to the suitable proportion of the mixture's specific composition. Commercial explosives, on the other hand, are nearly identical to military explosives and can be used to achieve the same consequences as PE-4 [6-9]. Figures 1 and 2 show commercial and military explosives, respectively.

Fig. 1. Commercial explosive (Emulex) [10].

Fig. 2. Military explosive (PE-4) [10].

Two numerical prediction techniques that can be used to predict the explosion effect are the Support Vector Machine (SVM) and the Hidden Markov Model (HMM) [10, 11]. In terms of prediction and optimization, both statistical methodologies yielded positive outcomes. The prognosis was also made using artificial intelligence, namely a neural network [12]. Various studies have employed neural network approaches to predict the explosive effect [13]. The Multilayer Perceptron (MLP) network will be used in this study to forecast the peak pressure of commercial explosives. After preliminary tests, the MLP network will be taught to make predictions based on data from previous studies [14]. In order to acquire peak pressure measurements recorded throughout the explosion process, certain parameters are specified, such as the type of explosives supplied, the shape of the explosives supplied, and the reference point distance from the explosives.

The remaining content in the manuscript is formatted as follows. In part 2, the literature review on the explosion material is reviewed and MLP networks is discussed in Part 3. Part 5 offers the conclusion after Part 4 shows the results and addresses certain issues for discussion.

2. Literature review

In practically, explosives are things that can set off an explosion in a certain location. Due to the gas from explosives expanding, effectiveness explosions in closed spaces are significantly more common than in open places. The effects of the increasing temperature and air pressure cause the gas particles to expand more quickly. As a result of this activity, the atomic shift will happen more quickly, which will lead to combustion and an explosion [2]. The reaction velocity and the result of the attained explosion pressure are frequently used to distinguish between explosions. As a result, the pressure reached falls within the range of bars because the default reaction velocity is substantially slower than the speed of sound. The chemical reaction between the explosive and the air that occurs in explosives above the speed of sound is what causes the reaction rate for gas production [3]. In turn, a supersonic shock wave is produced. Before gas release begins, there is a shock wave. When compared to gas pressure, which is smaller but greater, shock energy has a larger peak pressure that is only momentary [3]. Low explosives are defined as materials that ignite easily and burn quickly as a result of gas release. In the case of black powder, reaction velocities are frequently between 600 and 1000 metres per second.

Explosives are highly energetic, reactive substances that, when rapidly released, can cause explosions, the majority of which are accompanied by pressure, light, heat, and sound. Each blast's intensity varies according to the amount of explosives utilised. The rate at which it expands can be used to describe an explosive. High explosives are materials that are explosive, and low explosives are materials that are faulty [1]. Explosives are always categorised according to how sensitive the substance is. Explosives are less sentimental for second and third explosions because of how sensitive they are to heat and pressure. The maximum speed of an explosion is 1800 metres per second. Ammonium nitrate (AN), a commercial substance, is categorised as a high explosive based on its strength by high explosive rates and gas pressure [5]. Additionally, AN might be homogenous or heterogeneous. While the tertiary explosives are created using a combination of chemicals, the primary, secondary, and third explosives are based on actual materials.

Malaysia is now influenced by the effects of the global economy, which are currently felt in many nations. The Ministry of Defence Malaysia has also been affected by this economic impact. Together with the Malaysia Armed Forces (ATM), the nation has been putting a lot of effort towards reorganising spending without compromising the nation's definition of preparedness. Defence assets must also be safeguarded and supplies of military supplies and equipment must be made available. At the moment, ATMs use PE-4 explosives purchased from the United Kingdom for training reasons such cutting charges, bridge demolition, building damage, and so forth [5]. The cost of using PE-4 is high. However, Malaysia is home to home-grown businesses that can manufacture commercial explosives. It is a wise strategy to create regional explosives with military training capabilities comparable to PE-4.

Explosives are highly reactive materials containing a lot of energy that, when swiftly released, can result in explosions of light, heat, sound, and pressure. The amount of explosives used will influence how powerful each explosion is. A characteristic of an explosive is its rate of growth. "High explosives" and "low explosives," respectively, are terms used to describe explosive and flawed materials [2]. Explosives are always categorised based on how sensitive they are. Due to explosives' susceptibility to heat and pressure, the second and third explosions are less romantic. An explosion has a maximum speed of 1800 metres per second. Ammonium nitrate (AN), which is characterised by its strength and high explosive rates and gas pressure, is categorised as a strong explosive [7, 8]. They are homogenous and heterogeneous, respectively. Tertiary explosives are made from a chemical mixture, whereas primary, and secondary explosives are made from natural resources.

3. Methods

Artificial neural networks (ANN) are a type of artificial intelligence that is inspired by how the brain operates. The artificial neural network is designed to mimic brain operations such as structure formation, learning procedures, and operating ways. It is based on brain principles [15-17]. The nonlinear neuron model is shown in Fig. 3.

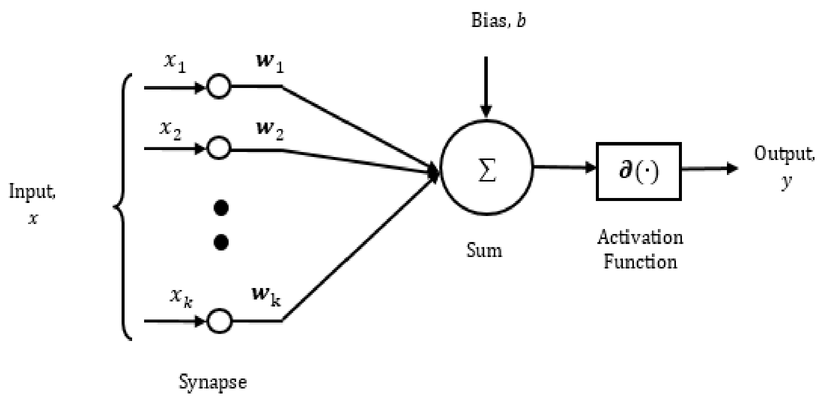

Fig. 3. Nonlinear neuron model [18].

According to Fig. 3, a neuron's development includes a collection of synapses or network connections, a sum, and an activation function. Each neuron's synapse is given a weighted value. The neuron has *k* input assuming it has k synapses. The input at each synapse is represented by $(x_1, x_2 .. x_k)$, the weight at each synapse is represented by $[w_1, w_2 .. w_k]$, and the model's activation function is represented by $\partial(\cdot)$. The weight value for the processing of the synapses to the neuron's output is influenced by the value of the j^{th} synaptic weights $[w_j]$. The value of the j^{th} synaptic weights $[w_j]$ will be multiplied by the input x_j at the input synapses connected to the neuron. The activation function receives the output of a sum process and sums all the multiplied signals or input and bias (b). Based on Fig. 3, the following two equations can be utilised to define the mathematical modelling of neurons:

$$u = \sum_{j=1} W_j x_j + b \tag{1}$$

and

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

where *u* is the summation output, x_j is the jth data or synapse input signal, W_j is the jth neuron synapse weights, $\partial(\cdot)$ is the activation function, and y is the output product in Eqs. (1) and (2). Regularly used activation functions include the fixed limiter function, piecewise linear function, Logsig function, and linear function [19-21]. As a schematic diagram of an MLP network, Fig. 4 shows an input layer, a single hidden layer, and an output layer.

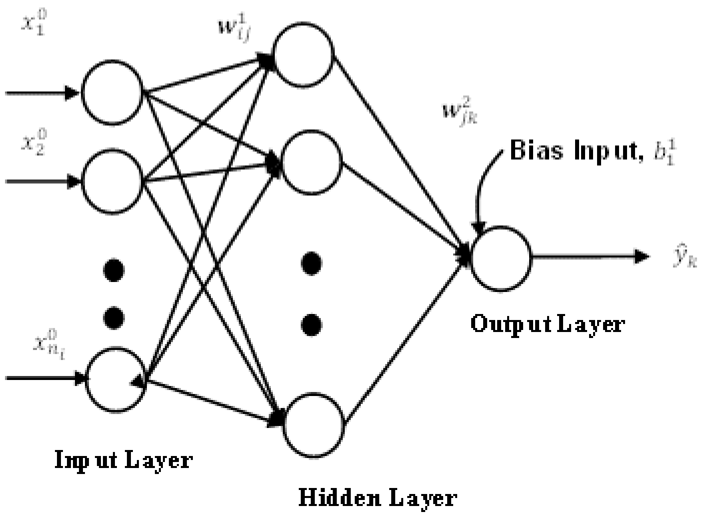

Fig. 4. A schematic diagram of a MLP network with one hidden layer.

The output of the network is given by:

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

for *1≤j≤n_h and 1≤k≤m*

where n_h represents the number of hidden nodes, while m represents the number of network outputs. $\partial(\cdot)$ is the activation function utilised to activate the MLP network in this case using the Logsig activation function. The unknown variables w_{ij}^1, w_{jk}^2, w_{ik}^3 and threshold b_j^1 must converge to optimum values in order to minimise the prediction error stated in Eq. (4).

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

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

The learning 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 typically used: supervised learning and unsupervised learning [22]. A neural network's learning time is crucial. The method assures that the neural network performs in accordance with its design parameters. Unsupervised learning and supervised learning are the two most often utilised learning paradigms [22]. Supervised learning can be used to create a global model that maps the intended output to the input. Unsupervised learning approaches, on the other hand, need that well-known training models be estimated. There is no output goal, which distinguishes the learning process from supervised learning. Unsupervised learning requires the collection of a set of input data, which is assumed to be made up of a set of random variables. On the basis of the datasets, a density model will be created, and unsupervised learning will be based on prior experience. To put it another way, learning is unguided and entirely dependent on prior experience. Data compression is aided by unsupervised learning. An experimental procedure was followed by a modelling procedure employing a neural network approach for the study. In addition to the target, a supplementary dataset is obtained. As a result, receiving guided teaching is the ideal option. The algorithm typically trains the network through the steepest descent technique.

The BP algorithm is able to calculate the value of derivatives in performing efficient weight adjustments based on a parameter/protocol known as the learning phase [23]. The BP algorithm is a type of steepest descent method, and then it suffers slow convergence speed or rate. The searching for global minimum could be trapped in local minima. It is likewise sensitive to user selected parameters [23]. The Levenberg Marquardt (LM) training algorithm operates on a deterministic gradient of optimization. The LM algorithm is a better version of the BP algorithm. Upon training the MLP network, the profitability of the LM algorithm will be compared with the BP algorithm to provide a faster convergence rate than the BP algorithm. Still, relative stability is maintained [24]. Based on the quasi-Newton method, the LM training algorithm is designed to increase the second-order training speed. Thomas Bayes in his study introduced a training/learning algorithm known as the Bayesian Regularization (BR) [25]. The Bayes rule is suitable for obtaining posterior probability. Generally, the posterior probabilities obtained represent the entire distribution of possible values. which can be derived from the initial probability of a parameter, continuing with the likelihood of the data before the probability of data. This rule of thumb is then applied to MLP network and affects the probability distribution among the network weights.

The number of repetitions of training data will be determined by observing the performance and accuracy of the prediction mean square error (MSE) during the training and testing stages [26]. MSE is the error that occurred on each of the data each time iteration data is introduced. The smaller the MSE value acquired, the more accurate the predictions, and the smallest MSE value obtained when the MSE graph is horizontal. The current performance of neural networks is consistent and reliable. The maximum prediction accuracy with the lowest MSE value will be used to calculate the suitable amount of iteration data. The performance of the neural network, on the other hand, is focused on its performance during the testing phase. After that, the number of hidden nodes is determined in the same manner. The number of training data iterations is set to the best value found earlier in the process. To determine the accuracy of detection data, the amount of correctly classified data will be divided by the number of data in the class. One of the most basic models for forecasting outcomes or measuring data fitness is regression [27]. It models how the independent and dependent variables interact. In basic linear regression, there is only one independent variable and one dependent variable. Multiple Linear Regression, on the other hand, tries to fit a linear equation to observed data in the study experimental dataset to represent the relationship between two or more explanatory variables and a response variable.

There have been no studies that have employed neural network methodologies to predict the effects of explosions up to this point. Training in explosive testing is done on a regular basis. Simply based on prior experience, the useful impact is projected as in Fig. 5.

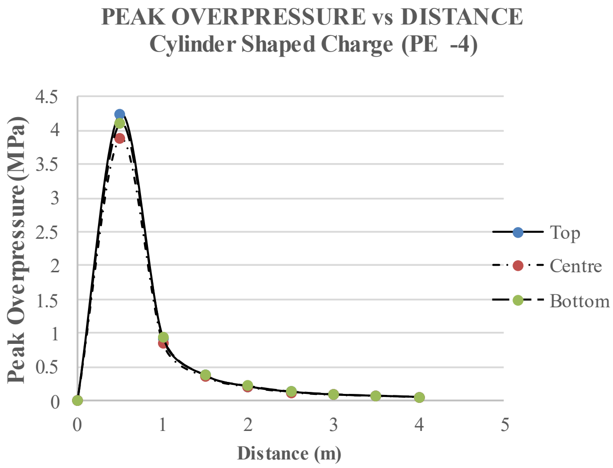

Fig. 5. The recorded data during the explosive testing.

A total of 500 grams of PE-4 and Emulex were used in this experiment, which began at the height of 1.2 meters above the ground know as free-space explosion. The device is detonated at distances of 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0 meters. Data Acquisition (DAQ) system is used to record explosive peak overpressure reading. The experiment has been carried-out in place restricted place in Malaysia. The type of shape of explosive (cylinder, sphere or hemisphere), the placement of explosive charge at the explosive (top, canter or bottom), the type of explosive (PE-4 or Emulex), and the distance of the sensor and explosive suggested as the input parameter of the neural network to document the explosive pressure readings at the output of the network. The experiment has been done since 2010 and the database have been increase from time to time. The total number of the dataset used in the modelling Explosive Blast Prediction is about 144 and 60% of that used to train the network while the rest for testing and validation.

4. Result and Discussion

Several studies were carried out to determine the impact of the tropics on PE-4. The weight of PE-4 is fixed at 500 grams. Table 1 shows the explosion pressure readings, which were compared to data provided by PE-4 manufacturer. Using Emulex, similar experiments were carried out to acquire explosive pressure measurements. The weight of Emulex is also 500 grams. Table 2 compares the impact of tropical weather on PE-4. Table 2 shows the Emulex explosion pressure measurements. The ability of the MLP neural network to predict explosive pressure must be shown in the simulation phase through prediction performance analysis. The analysis is divided into three steps in the MATLAB neural network tools (nntool): 60% training, 30% testing, and 10% validation.

The training algorithm's performance is assessed using the lowest MSE and highest regression performance. The lowest MSE suggests that throughout the prediction phase, the relative error should be as low as possible. The worst-case situation occurs when the measurement is closest to 0, and the best-case scenario occurs when the value is closest to 1. Neural network in MATLAB is tool to perform prediction and generated the MSE and regression values for the difference training algorithm. Table 3 shows the performance of the MLP network with three different training techniques and three different activation functions, organised by lowest MSE performance highest sequences.

Table 1. PE-4 equivalence ratio between experiment to database (in MPa).

Distance (m)	PE-4 Database	PE-4 Experiment	PE-4 database to experiment correction ratio
0.5	4.254	3.703	1.15
1.0	0.892	0.734	1.22
1.5	0.348	0.296	1.18
2.0	0.167	0.139	1.20
2.5	0.217	0.105	1.21
3.0	0.082	0.069	1.19
3.5	0.062	0.053	1.17
4.0	0.054	0.045	1.18

Table 2. Emulex equivalence ratio of PE-4 to Emulex (in MPa).

Distance (m)	PE-4 Experiment	Emulex Experiment	PE-4 -Emulex correction ratio
0.5	3.703	2.756	1.34
1.0	0.734	0.557	1.32
1.5	0.296	0.222	1.33
2.0	0.139	0.106	1.31
2.5	0.105	0.074	1.42
3.0	0.069	0.052	1.33
3.5	0.053	0.041	1.28
4.0	0.045	0.036	1.32

The findings of explosive tests conducted in the tropics are shown in Table 1. In comparison to the manufacturer's data, the acquired results clearly illustrate that the tropic action reduces the pressure of PE-4 immediately. The correction ratio to be divided by the manufacturer's data readings, according to Table 1, was in the range of 1.15 to 1.22. The results of this mathematical process can provide a more accurate estimate of the explosion pressure than data provided by the manufacturer that was calculated without taking the effect of tropic into consideration. The Emulex explosion values for a particular number of distances are recorded in Table 2. The impact of the tropics and locally produced explosives are taken into account in these findings. Table 2 compares the explosions produced by PE-4 to those produced by Emulex. When the PE-4-Emulex ratio was calculated, it was shown that PE-4 had a larger explosive effect than Emulex, ranging from 1.28 to 1.42. To get an explosive strength equal to the explosive intensity of PE-4, the weight of the Emulex must be multiplied by the stated range.

Table 3. MSE and Regression Performance of MLP network.

Training Algorithm	MSE Performance Analysis	Regression Performance Analysis	Number of Epoch
BR	0.079	0.990	958
LM	0.157	0.979	21
BP	0.338	0.304	13

Table 3 shows that the BR training approach has the best MSE performance for the MLP network, with an MSE of 0.0079. With an MSE of 0.0157, the MLP network trained with LM obtained the second best performance. The BP training algorithm, which has a performance of 0.3376 of MSE, is then used to complete the training process. As demonstrated in Table 3, the BR training strategy is capable of giving the highest regression reading of 0.9991. The BR training algorithm outperforms the LM and BP training algorithms when it comes to MLP networks. The MLP network's regression performance with the LM training process is somewhat worse than the BP's (0.9789). With the BP training technique, the MLP network could achieve a regression performance of 0.3035.

5. Conclusions

Since the explosive tests are being conducted in a tropical environment, the PE-4 adjustment ratio must be used. Furthermore, the PE-4 – Emulex ratio was devised in order to compute the exact weight of Emulex required to equal PE-4 during an explosive test. The MLP network's capacity to forecast the explosive dataset is then demonstrated by the network's prediction results. The accuracy displayed by the BR training algorithm is the best, with the minimum MSE and the best regression performances, according to the data. As a result, even though the BP training method has a fast processing time and only takes a few epochs, it can only produce larger MSE and inferior regression outcomes. The MLP network accepts the type of explosive, the distance of the explosive effect, and the shape of the explosion as perfect inputs. The main purpose of the study is to find the best algorithm to use as the brain of the 'Blast Prediction' model.

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