Prediction of blast-induced ground vibrations with the use of artificial neural networks. A case study in Greece.

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Abstract. Creating models, capable of making accurate predictions of the Peak Particle Velocity (PPV) after a blast, is always one of the researchers’ most important goals. The use of such prediction can assist in assessing the intensity of the blast vibrations and more importantly in designing the whole blasting phase so as to mitigate potential problems to nearby structures. Main aim of this paper is to demonstrate the capabilities of artificial intelligence applications in geotechnology and more specifically to assess PPV and the characteristics of the blast wave attenuation in an underground construction case study in Greece, using multilayer feed forward artificial neural networks (ANNs). The results showed that the forecasting ability of the developed ANNs was, in almost every case, more accurate than the ones given by the use of traditional empirical formulas, as benchmarked using Root Mean Squared Error (RMSE) and coefficient correlation (R). In this manner, the ANNs proved to be a reliable and accurate method to assess PPV from underground blasting and once trained they become an efficient off-the-shelf tool to assist engineers both in the blast design and in the mitigation of blast wave induced problems.

1. Introduction

The use of explosives for the disintegration and fragmentation of the rock structure is one of the most dominant methods used in mining as well as in civil engineering applications. Especially in the excavation process of hard rocks, this particular option can perhaps be the only available alternative. Even though the drill-and-blast method is characterized by its flexibility, simplicity and effectiveness, one of its main problems is the adverse effect of the ground vibrations that propagate through the ground medium and can have adverse effects on both the construction itself and on the neighboring surface buildings [1]. The ill effects of blasting, the ground vibrations as well as the air blast, flyrocks, nuisance, etc. are inevitable and cannot be completely eliminated but can be certainly minimized to permissible levels so as to avoid damage to the surrounding environment [2, 3]. Thus, establishing the golden mean between the effective rock breakage and the minimization of vibrations is the main pursue of the blast professionals in each and every blasting campaign [4].

Ground vibration is directly related to the quantity of the explosives used, the distance between the blast front and the point of interest and the geological and geotechnical conditions. The two latter factors cannot be altered. On the other hand, the weight of the explosives per delay and the general blasting characteristics can be adjusted accordingly. Thus, this is finally translated to setting up a blasting pattern which can limit the ground motion below an allowable peak particle velocity (PPV) threshold. This limit is set with respect to the attained frequency of the blast wave and to the importance of the structures under threat. In doing so, the use of empirical formulae using the scaled
distance concept is selected, decoding not only the blast and distance data but the specific characteristics of the ground medium at the site of analysis [5]. The methodology of establishing the ground vibration attenuation law and thus the PPV value is well documented and can yield fairly safely recommendations and actual results. However, the complexity of the phenomenon cannot be easily calibrated and fit into empirical predictors, especially in extreme cases where the margin of error can either threaten heritage structures or the feasibility of the basting operations [6, 7, 8, 9].

The paper presents the modeling of the blast wave attenuation through the use of artificial intelligence method and more specifically through the use of Artificial Neural Networks (ANN). The main aim is to develop models that can predict the PPV values more accurately, through the assimilation of the inherent characteristics of the area under investigation and the blast design parameters. The ANN can identify hidden patterns and complex relations between the input parameters and compile them altogether, establishing and calibrating the model to reflect the precise conditions of the area.

The ANN development is made for the case of the Lavrion Technological and Cultural Park (LTCP) where the construction of an underground hazardous waste repository took place in the vicinity of buildings, characterized as heritage monuments with special protection status. The most intriguing issue at the site was the close existence, sometimes at distances less than 50m, of unique heritage buildings, characterized as protected and preserved monuments of industrial architecture. Consequently, the accurate assessment of a blast design is of critical importance to the success of the development works.

2. PPV assessment using conventional scaling law predictors

Many researchers over the world have studied ground vibrations originating from blasting and theoretical empirical analyses have been developed to explain the measured data [2, 5, 6]. The scaled distance (SD) model for vibration analysis is currently the most widely accepted method to predict as well as to control the amplitude of vibrations with consideration of the combined effect of charge weight and distance [10, 11]. It provides a normalized comparative figure of the explosion’s intensity taking into account the prevailing ground conditions and the fact that the vibration velocity is directly proportional to the weight of explosives detonated while at the same time being inversely proportional to the distance from the blasting point [12].

It can be used to describe the vibration’s attenuation law, an empirical ground motion predictor, which is usually used to determine PPV levels, as expressed by the following commonly used formula:

$$PPV = K \frac{D^\alpha}{W^{\beta}}$$  \hspace{1cm} (1)

where, $PPV$ is the vibration velocity (mm/s), $W$ is the weight charge of the explosive charge (kg), $D$ is the distance from the source (m) and finally $K$, $\alpha$, $\beta$ are factors depending on the shot and the geological site conditions.

Namely, two types of scaled distance are used; the first is the square-root ($SD = D/W^{1/2}$), usually employed for surface blasting [1, 5, 13] while the second is the cube-root ($SD = D/W^{1/3}$) which is usually used in large scale underground explosions or spherical charge blasting [6]. With respect to these scaled distance types, eq. (1) can be transformed to:

$$PPV = K \left( \frac{D}{\sqrt{W}} \right)^m$$  \hspace{1cm} (2) \hspace{1cm} or \hspace{1cm} $$PPV = K \left( \frac{D}{\sqrt[3]{W}} \right)^m$$  \hspace{1cm} (3)

where, $m$ is a site depended attenuation slope

Assessing the $K$ and $m$ parameters is something requiring an extensive blasting program and data measurement campaign to make the correlation between the actual and predicted values, usually employing a least squares regression analysis, which is applied to blast vibration data pairs, namely the PPV and the scaled distance (SD).
3. Artificial Neural Networks - ANNs

The development of Artificial Neural Networks (ANNs) began as an attempt to understand the human brain capabilities and imitate them, for example its ability to make decisions when there is insufficiency of data, uncertainty, unforeseen factors and to overcome situations that are completely unknown to it. Actually, the artificial neural network method is an information processing system that simulates the structures and the functions of the human brain [14].

An ANN can be defined as a data processing system consisting of a large number of simple but highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain. These processing elements are usually organized into a sequence of layers or slabs with full or random connections between the layers. The input layer is a buffer that presents data to the network. The following layer(s) is called the hidden layer(s) because it usually has no connection to the outside world. The output layer is the following layer in the network, which presents the output response to a given input. A typical neural network is “fully connected”, which means that there is a connection between each of the neurons in any given layer with each of the neurons in the next layer [15].

Feed-forward back propagation neural networks are reported to be suitable for problems based on pattern matching and pattern prediction. Pattern matching is basically an input/output – mapping problem. The closer the mapping, the better will the performance of the network be. Based on the input patterns, the network performs feed-forward computations to calculate the output patterns. In the end the output pattern is compared to the corresponding target patterns and the summation of the mean squared error (MSE) is calculated. The error is then back propagated through the network using the gradient descent rule to modify the weights and minimize the summed mean squared error. Thus, a good mapping between input patterns and target patterns can be achieved, resulting in a network capable of predicting the target pattern for a given input pattern [15].

Back-propagation networks are considered the most popular, effective and easy-to-learn models for complex, multi-layered networks of the supervised learning techniques. The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically one or two hidden layers are enough for complex problems. Each layer is fully connected to the succeeding layer, as shown in figure 1. During the back propagation training, the connection weights are adjusted to reduce the output error [14, 15].

Figure 1. Backpropagation neural network with architecture 10x4x2.

The ANNs are being widely used to analyze and solve problems in a number of applications in various scientific areas, especially during recent years. PPV assessment is a non-linear and complex
problem due to the characteristics, the special features and the uncertainty of ground medium and the 
complex attenuation laws of the blast wave [16, 17]. Artificial Intelligence (AI) based models and 
more particularly ANNs are successfully employed by some researchers to solve this difficult non-
linear problem. Some notable examples are the work of Lu in 2005 used Artificial Neural Networks to 
control and model the ground shock of underground blasting operations [18], the research of 
Khandewal and Singh where in 2006 carried out a neural network approach to forecast blast-induced 
ground vibrations and frequency at an opencast mine [19] whereas, one year later they made an 
evaluation of blast-induced ground vibration predictors including an ANN method [20]. In 2009 
Mohamed applied the ANN method to predict and control blasting vibrations in Assiuts (Egypt) 
limestone quarry [21]. Also, Dehghani and Ataei-pour developed a model in 2011 to predict peak 
particle velocity in a blasting operation using the ANN method and dimensional analysis [16], while 
Prashanth and Devadas used Artificial Neural Networks to predict blast-induced peak particle velocity 
in 2018 [22].

4. PPV assessment in the LTCP construction site
The paper deals with the vibration assessment and the adoption of a limited threshold PPV for the 
underground blasting operations related to the construction of a shallow tunnel in the vicinity of many 
old derelict buildings which are declared as industrial monuments in the Lavrion Technological and 
Cultural Park (LTCP). The access tunnel constructed in the LTCP is part of an underground hazardous 
repository that has been developed to hold hazardous wastes deriving from the de-pollution of 
the former metallurgical plant, which used to exist and operate in the LTCP site for almost a century. 
The 4,5m width access tunnel starts at the level of +34m and leads towards the main storage complex 
with maximum slope gradient of 11% and total length of approximately 175m (figure 2).

Figure 2. General layout of the tunnel and the underground structures with relation to the above 
ground buildings in the LTCP site [10].
The development of the tunnel was implemented with mechanical excavation for around the first half of its length when more competent geological formations were encountered at the tunnels front and the use of explosives was required. However, the close vicinity of the tunnel to historical buildings raised concerns about potential blast-induced vibration problems to them.

A total of 19 test blasts took place during a two-month period providing the data needed in order to assess the damage risk and to adjust the blasting pattern and parameters for a productive rock extraction through blasting. In all cases the explosive material was gelatin dynamite in 0.21 kg cartridges while NONEL LP millisecond delay caps had been used to initiate the blast. Also, the blast hole’s diameter was set to be 38 mm, aiming at the lowest possible charge per delay [10].

5. Optimum ANN architecture for PPV prediction

The main target of this research is the creation of an ANN capable of predicting the PPV of the ground medium at a certain location after a blast. For that to be achieved, a number of known input-output data collected from the site of interest were used. The ANN method that was followed in order to predict the PPV was implemented with the help of the Neural Network Toolbox on Matlab. The input parameters were two, the distance (D) and the charge per delay (W), whilst the output parameter was one, the peak particle velocity (PPV), which is the main target of investigation.

The blast induced vibrations at the LTCP site were monitored by the NTUA team using a total of 6 seismographs, namely Instantel’s BlastMate III, Mini Mate and Mini Mate Plus. By establishing a monitoring network that covered the area under investigation, 51 data records were collected, including blast characteristics, distance from the blast site, as well as measured PPV at the monitoring point [10]. These data (D, W, PPV) are the basis of the analysis and the training and testing subsets were discriminated and selected from them. More particularly, out of the total 51 recorded data, 35 pairs of data (60%) were used in the training of the ANN and in the forming of its structure while the remaining 16 pairs of data (40%) were used to test the models and benchmark the accuracy between the ANNs generalizations and actual measured PPV values.

In order to determine the optimum network in terms of optimized topology and overall accuracy performance, the root mean squared error \( \text{RMSE} = \sqrt{\frac{1}{N} \sum (O_i - T_i)^2} \), is used (\( O_i, T_i \) and \( N \) represent the actual output, the predicted output and the number of the data pairs, respectively), along with the assessment of Pearson’s correlation coefficient (\( R \)) value.

At first, the maximum and the minimum value for each parameter were identified in the training subset. This is important so as to include data covering the whole range of the values found in the ANNs training stage. In this way the neural network sets an upper and a lower limit, trains within this range and can have a more representative generalization response, addressing the whole spectrum of potential value range.

Two different training algorithms were applied; the first one was Matlab’s default option, the Levenberg – Marquardt backpropagation algorithm (trainlm), while the second was the Resilient Backpropagation algorithm (trainrp). The testing procedure included the development of a number of ANN architectures, to assess the optimum one that could provide the best results. These had variations in the number of hidden layers as well as in the number of the neurons present in each one of them.

More particularly, a total of 73 ANNs were created having different architectures starting from the simplest of 1 hidden layer – and from 3 to 17 neurons in it – up to 3 hidden layers, having up to 6 neurons in each one of them. Every network was tested using the Levenberg – Marquardt algorithm at least 5 times, while in many cases the tests were conducted up to 15 times in order to pursue best performance. After the evaluation of the results obtained, the ANNs having architectures that performed better than the others were re-trained with the Resilient Backpropagation algorithm and re-tested against the testing subset. In this step 22 ANNs were selected the re-trained.

This process identified two ANNs that exhibited the best generalization performance. The first was the network with architecture of 2x6x3x1 (2 hidden layers having 6 and 3 neurons, respectively), trained with the Resilient Backpropagation algorithm, which presented the minimum RMSE, the
higher R and, hence, was considered as the optimum ANN model. Furthermore, the second network with architecture of 2x9x1 (1 hidden network with 9 neurons), trained with the Levenber – Marquardt backpropagation algorithm yielded also very satisfying results. Their details in terms of RMSE and R, are shown in Table 1, while the actual generalization of these ANNs, with respect to the measured PPV values of the testing subset are presented in Table 2.

| Table 1. Comparative assessment of the two ANNs that yielded the best testing results. |
|-------------------------------------------------|
| **ANN architecture (training algorithm)** | **RMSE** | **R** |
| 2x6x3x1 (trainrp) | 1.4029 | 0.96730 |
| 2x9x1 (trainlm) | 1.6210 | 0.95768 |

| Table 2. Measured and predicted PPV values (mm/s) from the best ANN networks (testing subset). |
|-------------------------------------------------|
| **id** | **PPV Values (measured)** | **ANN 2x6x3x1 – PPV Predicted Values** | **ANN 2x9x1 – PPV Predicted Values** |
| 1 | 0.32 | 1.23 | 0.17 |
| 2 | 1.24 | 2.07 | 2.71 |
| 3 | 4.32 | 2.40 | 3.81 |
| 4 | 7.62 | 8.28 | 7.96 |
| 5 | 9.91 | 10.76 | 10.42 |
| 6 | 19.8 | 19.18 | 17.53 |
| 7 | 1.20 | 1.85 | 1.29 |
| 8 | 1.13 | 1.85 | 1.29 |
| 9 | 6.22 | 5.66 | 7.12 |
| 10 | 0.21 | 1.94 | 0.83 |
| 11 | 2.28 | 1.82 | 1.33 |
| 12 | 13.97 | 16.73 | 18.4 |
| 13 | 1.60 | 1.31 | 1.14 |
| 14 | 0.83 | 1.39 | 0.65 |
| 15 | 9.40 | 7.32 | 6.98 |
| 16 | 8.13 | 5.31 | 5.79 |

6. **ANN response vs. empirical Scaled Distance predictors**

The 16 data pair of the ANN’s testing subset are also used to evaluate the performance of the PPV value predictions as made using the empirical scaled distance models. Benardos et al. [10] have already performed the scaled distance analysis and have proposed the scaling law predictors using the square and cube-root equations, from which the constants K and m are determined.

As identified, by the conventional scaled distance analysis, the equations describing the PPV values are given as follows:

$$PPV = 660 \left( \frac{D}{\sqrt{W}} \right)^{-1.41} \quad (4)$$

and

$$PPV = 836 \left( \frac{D}{\sqrt{W}} \right)^{-1.45} \quad (5)$$
For the benchmarking between these 2 predominant methodologies, the AI and the empirical one, the ANN network with architecture of 2x6x3x1, which has been identified as the optimum model is used. The two SD predictors are also yielding satisfying results but it can be clearly seen that the ANNs performance is far better. The cube-root equation is slightly better between the two SD models, however, the ANN’s RMSE values are considerably lower, while the attained R is higher (Table 3). This is also obvious with the help of the data presented in Table 4. In there the actual PPV measurements (mm/s), the ANNs output as well as the PPV value estimation using the 2 conventional scaling law predictors are given. Almost in every case the ANN’s response is better than the one of the empirical equations.

Table 3. Comparison between the empirical equations and the ANN in terms of RMSE and R.

| Model                        | RMSE  | R    |
|------------------------------|-------|------|
| ANN (2x6x3x1)                | 1.4029| 0.9673|
| SD - Square-root equation    | 3.4893| 0.9167|
| SD - Cube-root equation      | 3.4053| 0.9023|

Table 4. Comparison between measured and predicted PPV values (mm/s) from the ANN and the SD empirical models.

| id  | Measured PPV | ANN (2x6x3x1) generalization | Square-Root Equation prediction | Cube-Root Equation prediction |
|-----|--------------|------------------------------|--------------------------------|-----------------------------|
| 1   | 0.32         | 1.23                         | 2.02                           | 2.27                        |
| 2   | 1.24         | 2.07                         | 1.24                           | 1.37                        |
| 3   | 4.32         | 2.40                         | 2.45                           | 2.61                        |
| 4   | 7.62         | 8.28                         | 3.10                           | 3.08                        |
| 5   | 9.91         | 10.76                        | 8.26                           | 9.13                        |
| 6   | 19.8         | 19.18                        | 10.47                          | 10.74                       |
| 7   | 1.20         | 1.85                         | 1.45                           | 1.53                        |
| 8   | 1.13         | 1.85                         | 1.45                           | 1.53                        |
| 9   | 6.22         | 5.66                         | 3.49                           | 3.35                        |
| 10  | 0.21         | 1.94                         | 2.21                           | 2.10                        |
| 11  | 2.28         | 1.82                         | 2.09                           | 1.98                        |
| 12  | 13.97        | 16.73                        | 10.16                          | 10.62                       |
| 13  | 1.60         | 1.31                         | 1.80                           | 1.79                        |
| 14  | 0.83         | 1.39                         | 2.29                           | 2.25                        |
| 15  | 9.40         | 7.32                         | 3.58                           | 3.56                        |
| 16  | 8.13         | 5.31                         | 4.10                           | 4.10                        |

A clearer graphical presentation of these results can be seen in figures 3 and 4. The first one (figure 3) actually presents the data from Table 4 and is provides an easy way to comprehend how well each method behaves in accurately estimating the PPV values. The closest to the measured values the better and the ANN model is closely following the measured PPV values.
Figure 3. Dispersion of measured and predicted PPV values (ANN, SD models) in the whole testing dataset.

Figure 4. Measured vs. predicted PPV values of the ANN and SD models.

Finally, figure 4 is showing the data scattergram of the measured vs. the predicted PPV values for the testing subset. From this it can be clearly seen that the ANN responses are better positioned and closer to the 1:1 line, which denotes a better accuracy of predictors. Furthermore, the accuracy of the ANN’s responses is consistent throughout the value range examined, from 0 to 20 mm/s, exhibiting that the
ANN is capable of capturing the behavior of the modeled phenomenon pretty well. On the contrary, the empirical SD predictors are not that well placed, and they have a tendency to underestimate the PPV values especially in the upper range of values.

7. Conclusions
Artificial Neural Networks (ANNs) are capable of capturing the behavior of the modeled parameters and provide greater insight and more accurate generalization responses in problems of complex phenomena. This generally accepted clause was also proved in the analysis presented in this paper where PPV values were accurately predicted by the ANN model. The developed ANNs used two input parameters, the distance from the point of blasting (D) and the charge per delay (W) and had one output parameter, the peak particle velocity (PPV). Even with such minimal inputs the head to head comparative assessment between the ANN and the empirical derived equations and SD models proved that AI applications are far better at describing the problem and far more efficient in providing accurate outputs. Thus, the trained model can be effectively used at the proper design of the blasting activities and it can succeed in optimizing the production activities, attaining less time and lower cost conditions, while minimizing blast-induced ground vibration impacts.

In the case study analyzed this is of paramount importance as the vicinity of heritage buildings to actually any work or operation undertaken in the site requires a higher level of accuracy, so as to proactively mitigate all vibration risks. The ANN model for PPV prognosis is capable of providing such level of detail in the design of the blasting operations there allowing for the optimum fine tuning of the blast design and moreover can deliver a greater confidence and assurance that everything will eventually go as planned.

Nevertheless, it should be noted that an imperative issue to consider in all AI applications is the presence of a well-maintained database, having a great number of data, representative of the modelled phenomenon. The above is a major prerequisite so as to have a well-trained and accurate model. In all other cases where one is just mixing numbers and is throwing in data of questionable accuracy and origin, the results of AI models can be perceived as accurate, but most certainly would end up inflicting detrimental consequences.

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