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Artificial Neural Network in Seismic Reflection Method for Measuring Asphalt Pavement Thickness

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Abstract: A non- destructive measurement of asphalt pavement layer thickness using seismic reflection was adopted together with coring test at similar site for comparison. The test was carried out on pavements around university campus's road to measure the asphalt pavement layer thickness. The on-site seismic reflection testing was carried out using three piezoelectric sensors to capture time travel of wave motion, a light ball bearing to produce a high frequency seismic wave source and a data logger for data acquisition. The data processing is conducted in the time domain exclusively using a feedforward artificial neural network (ANN) using MATLAB software. A graphical interface is developed for viewing and extracting the result to make the processing of the seismic data feasible and user-friendly. The seismic reflection method analysis using the ANN successfully measured the asphalt pavement layer thickness. This study of the reflection method for measuring the pavement thickness compared with coring indicates the average accuracy of five testing sites was 93%. It shows that the seismic reflection able to demonstrate the capability to measure thickness of pavement in non-destructive way at a reliable accuracy.

Keywords: NDT, seismic reflection, asphalt pavement thickness, artificial neural network, graphical interface

1. Introduction

The term non-destructive testing or NDT is usually used in the geophysics field to describe the testing and analysis of materials, structures or systems for evaluation without causing any damage to the tested sample. Considering this, the use of NDT shows many advantages and limitations' overcoming (Segovia Ramírez, García Márquez, & Papaelias, 2023). The most important advantage is the nature of the technique, which is non-destructive and non-invasive. In the case of detecting any anomalies, the NDT methods allows for in situ repairing rather than replacing the entire tested material. In addition, the NDT techniques are almost always harmless to the operators, fast and repeatable to conduct, cost-effective and accurate (Gholizadeh, 2016).The seismic reflection is one of the geophysics' NDT methods used for ground exploration, where it can provide a tomography of the subsurface (Nanda, 2016) (Petronio et al., 2023). The seismic reflection principle is analysing the seismic waves that travel from the surface to the targeted subsurface.

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The seismic waves reflect when meeting the targeted subsurface that has difference acoustic impedance (Malehmir et al., 2014). The reflected waves are recorded on the surface using vibration sensors, usually called geophones. The recorded data are stored and then processed to represent the subsurface image (Metwaly, Green, Horstmeyer, Maurer, & Abbas, 2019). Due to the outstanding development in data acquisition and processing equipment and techniques risen in the last few decades, the method can be used on a highly shallow surface subjected to the frequency of seismic source (Hunter, Pullan, Burns, Gagne, & Good, 1984) (Madun, Kamaruddin, & Remmani, 2020) (Zahari et al., 2018).

The top asphalt layer of the road pavement is a crucial character in its life expectancy and general quality. One of the biggest problems faced by the deficiency in the top layer thickness is rutting (Ismael, Joni, & Fattah, 2023). In this case, the lack of thickness in the asphalt layer causes the utilization weight and forces transferred to the base layer and cause it to compress. An example of rutting on the surface of the pavement is shown in Figure.1.

Fig. 1 - Rutting problem on the asphalt surface (Daniel, 2017)

In order to ensure the asphalt layer thickness corresponds to the specification, the pavement coring method is commonly used. The coring process is destructive in nature and time consuming (Figure. 2). Alongside the nature of the method, one of the drawbacks allied with coring is the resulting core holes and localized at a single point of testing (Monazami, Sharma, & Gupta, 2022) (Yin & En, 2009). (Gopaldas, Lodge, & Wright, 2009) investigated the use of smaller cores examination to overcome this issue but found that using cores with a diameter lower than 4 cm, the sample overheats, causing risk to the operator and damaging the cored sample making it hard to measure the pavement asphalt layer thickness accurately. Due to the limitation of coring method, thus this study aims to introduce an alternative method that is quick and non-destructive.

2. Methodology

2.1 Equipment Setup

The seismic reflection method detects the first primary wave arrival (P-wave). The discontinuity and difference acoustic impedance between the road base and asphalt layer causes the reflection to occur. The fact that the analysis is conducted in the time domain and the p-wave velocity is the highest velocity than the other types of waves, thus the first arrival must be the p-wave. The on-site configuration setup for the seismic reflection method is demonstrated in Figure.3. The energy source for this experiment is a 5 grams steel ball bearing. As the ball is released and guided with a 1-meter height tube. The steel ball gains its speed and hitting the pavement layer closed to trigger sensor and produced sufficient p-wave seismic energy that propagated through the asphalt layer in a hemispherical form. Piezoelectric sensors at 10kHz frequency are used to record the seismic motion of the surface caused by the seismic waves and convert them to voltage amplitude signals vs time.

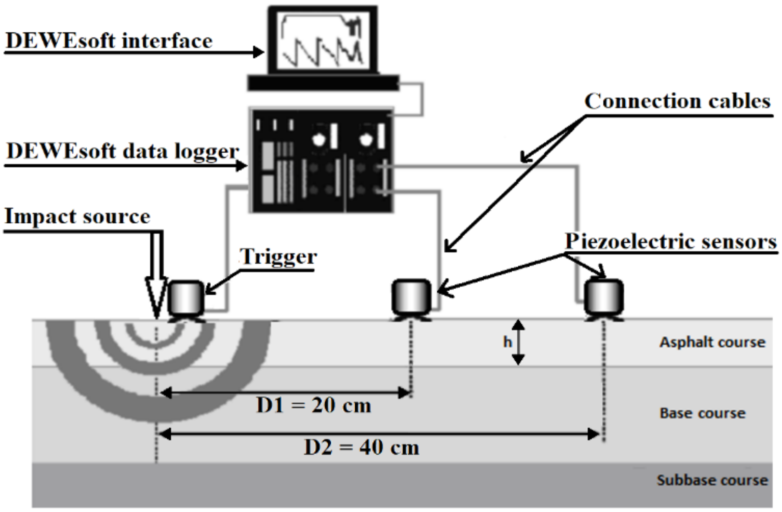

Fig. 3 - The seismic reflection configuration test setup

In this configuration setup, two sensors are placed at D1 and D2 distance from the trigger sensor. The difference distance between the impact source and sensor causes the p-wave motion to arrive at different timing to the first and second sensors. The time taken of p-wave travel to first and second sensors with the geometry of the layer system are used to calculate the thickness of the pavement asphalt layer using the following equation 1:

$$h_r = \sqrt{\frac{D2^2 tr1^2 - D1^2 tr2^2}{4tr2^2 - 4tr1^2}} \quad (1)$$

Where:
D_1 represent the first sensor spacing from the source,
D_2 represent the second sensor spacing from the source,
T_{r1} represent the time taken by the first p wave to arrive at the first sensor,
T_{r2} represent the time taken by the first p wave to arrive at the second sensor,
h_r represents the thickness of the asphalt layer

2.2 Data Acquisition

The tested pavement is measured for ground truth thickness via the conventional coring test across the university campus site. The thickness was found in a range of 10 to 12 cm thickness of all samples. Figure. 4 shows a 10 cm core sample measurement for a selected asphalt pavement site.

Fig. 4 - The cored asphalt sample showing a 10 cm in thickness

The DEWESoft data acquisition system (DAQ) was used in this study. The piezoelectric sensors were connected to the DAQ and displayed in real-time by the DEWESoft X2 recording and analysis interface then converted to MATLAB.mat files extension for further processing as shown in Figure. 5 and Figure.6. The optimum source-receiver spacing distance recommended is equal to two times the targeted depth (Madun et al., 2020). In this study, the spacing of the piezoelectric sensors was set at 0.2 m in the data acquisition setup. This sensor spacing assures that the p-waves arrives at the piezoelectric surface location sooner than other waveforms. Furthermore, the preliminary testing state that under this equipment setup, the ratio of signal to noise for all the sensors is sufficient for a clear reading of the recorded signal.

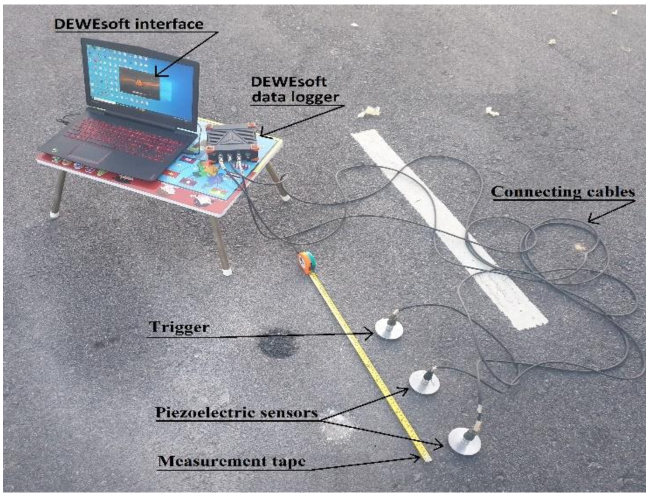

Fig. 5 - The seismic reflection testing setup using the DEWESoft data logger and three piezoelectric sensors, where one acts as a trigger and two as receivers' seismic wave

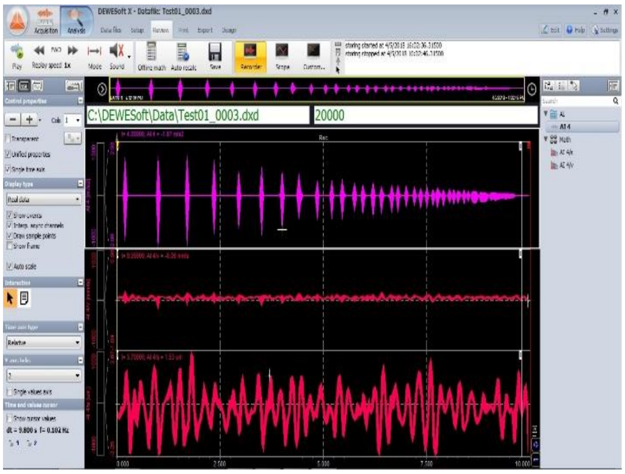

Fig. 6 - Seismic p-wave reflection data acquisition using DEWESoft X2 showing real-time recordings

2.3 The Method for Data Processing

All tables should be numbered with Arabic numerals. Every table should have a caption. Headings should be placed above tables, left justified. Only horizontal lines should be used within a table, to distinguish the column headings from the body of the table, and immediately above and below the table. Tables must be embedded into the text and not supplied separately. Below is an example which the authors may find useful.

The seismic data processing began with recognition the seismic wave coming from the trigger source. A challenge arises due the trigger wave was contaminated with the ambient seismic wave called noise and causes difficulties to select the first p-wave arrival time at the receiver sensors (Monazami et al., 2022) (Alkemade et al., 1978). Thus, to discriminate the noisy seismic wave received by the sensors, an artificial Feedforward neural network was adopted (Yang et al., 2021) (Sazli, 2006). The ANN is developed using MATLAB software aiming to detect the p-wave arrival automatically. Using multiple datasets recorded and manually inserted the time travel for the p-wave from diverse site testing, the ANN is developed and explained in the following four main steps as presented in the pseudo code (Figure7).

2.4 Pseudo Code and Steps for Artificial Feedforward Neural Network

In computer programming, a pseudocode is a primary coding language to describe the flow of a given algorithm. Pseudocodes are usually written using a standard programming language and symbols. However, it is not a working machine coding; it is for human reading only. The sole purpose is to omit steps and critical details in the original machine coding algorithm. In this study, the pseudocode is written to illustrate the sequence steps for data processing from the seismic reflection data using a Feedforward layers ANN algorithm (Figure. 7). This pseudocode is essentially a shortened form of the complete ANN code to calculate the reflected p-wave first arrival time. The pseudocode is divided into four main steps; the steps and its outputs are demonstrated below:

```
Input: upload data
finding signal range
data normalization  : STEP1
while find averaged signal STEP2 = 1 do
    find starting point (Maximum signal averaged point )
    if s_avg1(k)<max_s1
        s_str1(k) = 0;

    else
        s_str1(k) = s_avg1(k);
        save_k1 = k;        (save new averaged signal )
        break;
    end
end
        load saved signal with actual time for NN training  : STEP3
        tanh activation function ( weights)
          if  error  is > 0.1  then
            back_Step2 ← 0
        end
    end

while testing STEP3 = 1 do
    use NN training parameters for NN testing  : STEP4
     if size_t >157
        add_d1 = ceil((size_t-157)/2);
        save_t1
     elseif size_t <157
        add_d1 = ceil((157-size_t));
        save_t1
end
    Output the time of first arrival of p wave for the three signals t1, t2 and t3
    end
end
```

Fig. 7 - Pseudocode and steps for artificial feedforward neural network

Step 1: Finding the range of starting point for a given .mat file using an averaged method, normalizing the given data between 0 and 1.

Step 2: Calculating the average of each two head-to-head points and plot them, where all the starting points lie before the peak point of the impact energy reach the maximum and all the noisy values are rounded to zero. Saving and normalizing the new averaged dataset between 0 and 1.
PS: The above steps are repeated for all the datasets used for training the ANN and saving the range of the starting points.

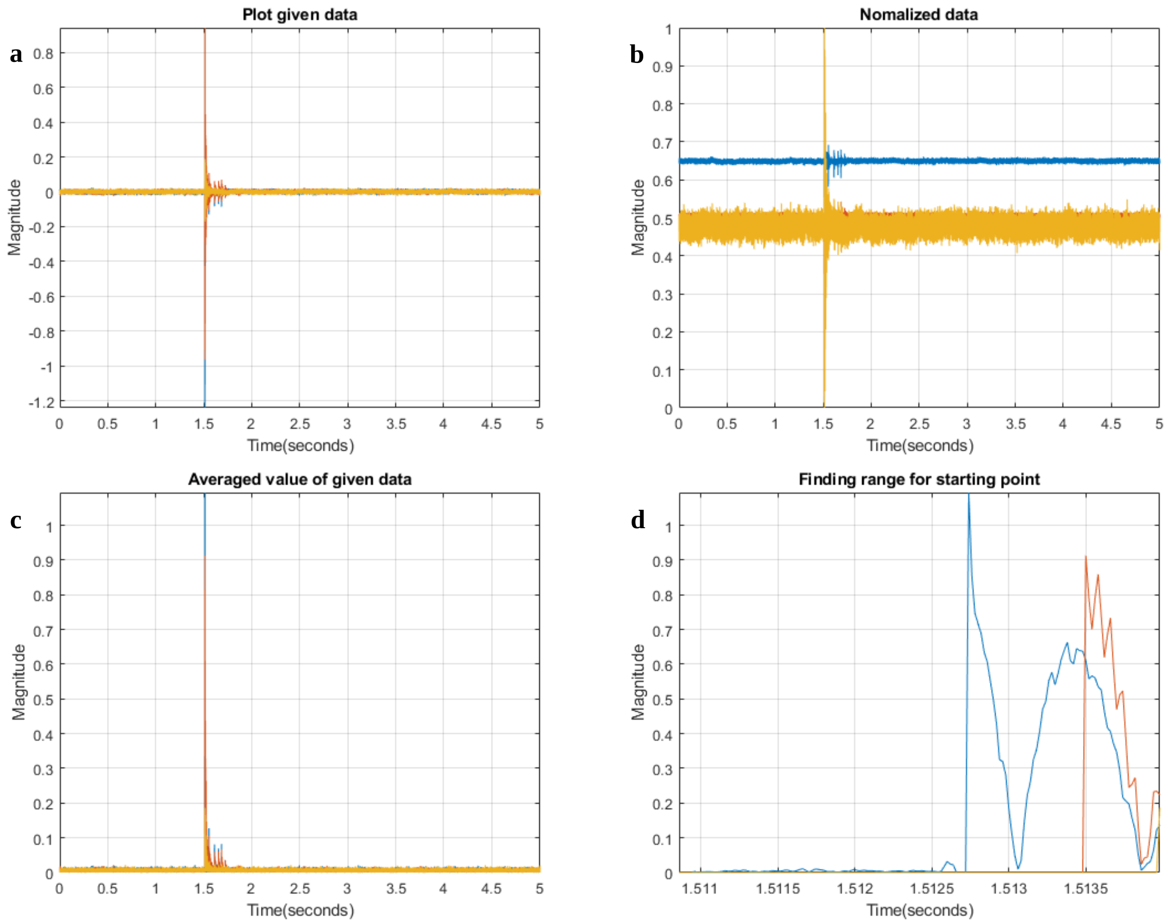

Fig. 8 - Step one and 2 output for the artificial Feedforward neural network; (a) plot of the raw data recording; (b) raw data normalisation between 0 and 1; (c) averaged value plot of the normalized data; (d) range selection for the starting point

Step 3: ANN learning; the learning and training can start when the range of starting points is achieved for all data sets used. When the training is over, weight values are retrieved from the ANN results. The time for an unknown dataset not used in ANN training can be calculated using these values. The parameters used for this ANN are illustrated in table 1.

Table 1 - Parameters used in ANN training

No.	Parameter	Value
1	Inputs count	157
2	outputs count	3 (t1, t2 and t3)
3	hidden neurons	25
4	Hidden layers	5
5	Iterations	5000
6	rate of training	0.001
7	Momentum term	0.02

The graph in Figure. 9 shows that the training has been successfully completed. The ANN has been trained correctly as the error limit approaches zero, and the results for finding the starting point match the desired one. After this section, the optimal weight values are saved as 'w.mat' and 'v.mat' in MATLAB matrix form. Both files are used to calculate the time for any new data set when loading a new data set.

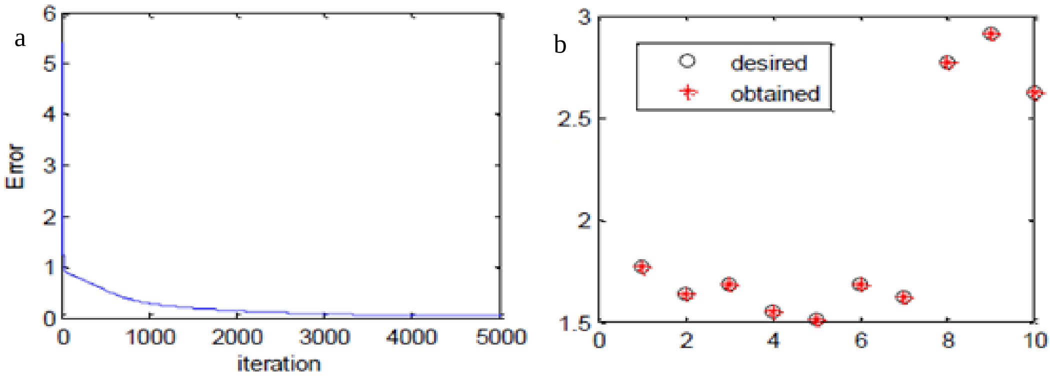

Fig. 9 - Artificial Feedforward neural network learning; (a) error behaviour vs iteration learning; (b) ANN output results after learning completion

Step 4: Using the weight values extracted from the training to write the main code for any new dataset. The output of test file is used to verify the accuracy of the learning process. The acquired results are presented in Table 2 showing the calculated time. It is concluded that the ANN has successfully calculated the desired results.

Table 2 - ANN testing results

P wave arrival time	Actual time (ms)	Calculated time using ANN (ms)
t1	1766.70	1766.67
t2	1766.76	1766.72
t3	1766.77	1766.76

2.5 Graphical User Interface and Data Output

To facilitate the data processing phase, a GUI was programmed for this method. The graphical icons and visual indicators for in signal processing in MATLAB (Jamil, Oussama, Hafizah, Abd Wahab, & Johan, 2019; Smith, 2006). The GUI was developed primarily to automate the asphalt pavement thickness measurement by the seismic reflection method. The ANN learning technique as a call-back function inside the GUI where the user can directly read the results from the analysis. Figure. 10 shows the application window of the created GUI using MATLAB.fig and .m extensions. The GUI displays three push buttons and two key-in fields for sensor spacing used to acquire the data when testing, the first button is the file attachment where the user can attach the testing file with the '. mat' extension, and the second is to calculate the results. The data is presented in the time domain. After calculation, the time for the three sensors' first arrival and the thickness is shown. The clear button is to clear all the results and the data stored to apply a new data file for new results calculations.

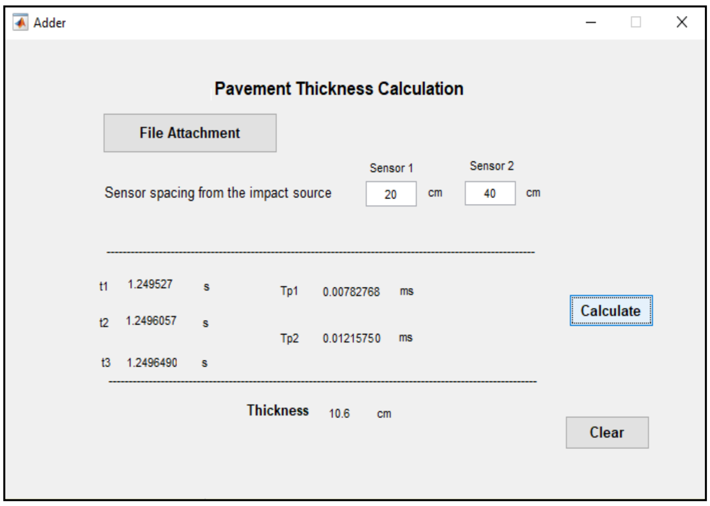

Fig. 10 - The display GUI application window

3. Results and Discussions

The data acquisition was conducted at five locations surrounding the university campus. The data acquisition system (DEWESoft mini) was connected to all three piezoelectric sensors. DEWESoftX2 interface was used to visualize the real-time data recording by the sensors. The recorded data was extracted and converted to MATLAB software extension for processing using the GUI. Table 3 recapitulates all the measurements from the seismic reflection using the developed seismic data processing programme. The method successfully obtains the thickness of the pavement sites with the average accuracy of 93%. The use of the seismic reflection data processing programme via MATLAB based has able to automate the seismic reflection data processing to measure the asphalt pavement thickness. It worth to note that noisy areas should be avoided when acquisitioning the data.

Table 3 - The results directly extracted from the automated data processing

Testing location	Pavement thickness core sample (cm)	Pavement thickness using seismic reflection method (cm)	Accuracy
1	10.00	10.86	91%
2	10.00	10.48	95%
3	10.00	11.32	87%
4	12.00	11.46	96%
5	12.00	12.48	96%
		Average	93%

4. Conclusion

The feedforward artificial neural network successfully identified the first p-wave time arrival at receives with high confident level. In addition, the period of signal processing can be shortened via automated process using GUI. The GUI in this method as a user interface for the ANN is considered an added value to the method, where it can directly measure the thickness of the material even with limited experience from the user. Correspondingly the seismic reflection method provides good withstanding results with fast execution of the acquisition/processing application. The results' accuracy assures the ANN's capability in various test locations' targeted depths. The overall method shows high potential as an alternative thickness measurement tool with fully automatic data processing technique as a non-destructive quality assurance.

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