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Affirmation of Elastic Modulus Derived from Spectral Analysis of Surface Waves Method using Artificial Neural Network

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ABSTRACT

Pavement modulus is believed as one of the important features to characterize the pavement condition, specifically the pavement stiffness. The value of pavement modulus may be calculated using the existing Witczak mathematical dynamic pavement modulus prediction formulae. However, the equation developed by Witczak is heavily impacted by temperature while underestimating the impact of other mixing factors thus, only offering an adequate approximation for the circumstances for which they were designed. In this study, the Spectral Analysis of Surface Wave (SASW) test data was used to develop an Artificial Neural Network (ANN) that accurately backcalculates pavement profiles in real-time. The pavement modulus calculated from the equation was validated by using ANN developed in Matlab software to avoid any mistakes during calculation based on the equation. Three parameters, shear wave velocity, depth and thickness from SASW test data were used as inputs and elastic modulus calculated using Witczak pavement modulus equation was used as an output to train the models developed in ANN. Five segments of pavement are presented in this paper where almost compromise that the greater the depth, the lesser the shear wave velocity as well as pavement modulus. Nine neural network models were developed in this study. The network architecture of 4-80-4 is the most optimized network with the highest correlation coefficient of 0.9992, 0.9994, 1.0, 0.9996 for validation, testing, training and all respectively. The created ANN models' final outputs were reasonable and relatively similar to the real output.

Keywords: SASW; ANN; Pavement Modulus; Network Architecture

INTRODUCTION

According to Gucunski et al. (2000), transportation authorities in the United States have switched their attention from the building of new roads and bridges to the maintenance and restoration of existing ones during the last two decades. A database of information collected, stored, and available for use regarding the systems governed is at the basis of every management system. Data regarding the present state of pavements is an important element of the database. These might contain information on the pavement profile, pavement condition, maintenance and costs.

Geotechnical areas (layering, top of bedrock, depth to water table) and geotechnical materials (stiffness in shear and compression) were characterized using seismic measurements (Stokoe II et al. 2004). Seismic methods can assess thickness as well as strength of the pavement where the strength is estimated from modulus determined by the seismic methods (Cho et al. 2007).

The seismic surface wave method can determine the stiffness and structure anomalies in current road pavement at the same time (Rosyidi, 2015). As a result, this approach has the potential to be improved and developed as a new material assessment device for pavement structures. The non-intrusive nature of the surface-wave technique, along with the ability to detect softer layers beneath stiffer materials and test vast areas quickly and cost-efficiently, has sparked a lot of interest (Stokoe II et al. 2004, Ekstrom, 2011 and Chakraborty et al. 2016).

SPECTRAL ANALYSIS OF SURFACE WAVES (SASW)

Gucunski et al (2000) agreed that the nondestructive Spectral Analysis of Surface Waves (SASW) technique has been used to estimate the elastic modulus profile of pavement layers. The approach is based on the dispersive properties of seismic surface waves in a layered system (waves of various frequencies or wavelengths move through the pavement layers at varying velocities) (Shirazi et al. 2009). The field-testing entails striking the pavement's surface to generate and identify surface waves. An experimental dispersion curve (change in wave phase velocity with frequency or wavelength) is created by processing the recorded data (Shirazi et al. 2006).

The SASW technique is a method for determining the dynamic characteristics of shallow soil layers and layer thicknesses of layered systems, such as soils and pavements, with the added benefit of being completely conducted from the surface (Alimoradi et al. 2011; Ekstrom 2011; Stokoe II et al. 2004 and Chakraborty et al. 2016).

Figure 1 depicts a diagram of the current testing arrangement. An impact source generates surface waves, which are recognized by a pair of receivers and recorded on a compatible recording device (Gucunski and Woods 1992). The WaveForm Analyzer is a recommended instrument for instantaneous inspection of the recorded data because it contains built-in spectrum functions. In need to cover a required range of Rayleigh wavelengths, the test is performed for multiple receivers spacing (Stokoe II et al. 2004 and Rosyidi 2015).

Likewise, using the existing mathematical dynamic modulus pavement modulus prediction formulae or empirical correlation coefficients, the value of pavement modulus may be calculated. In substitution of laboratory testing, many mathematical pavement modulus prediction equations have been devised for characterizing the pavement modulus of asphalt concrete. The Witczak dynamic modulus pavement modulus prediction model, which was developed using multivariate regression analysis of laboratory test data, is the most commonly used (Hamim et al. 2020).

Several investigations, however, show that Witczak pavement modulus prediction models have a significant dispersion, especially at low and/or high pavement modulus extremes which has been claimed that these models are heavily impacted by temperature while underestimating the impact of other mixing factors (Hamim et al. 2020). As a result, pavement modulus prediction models can only offer an adequate approximation for the circumstances for which they were designed.

Hamim et al. (2020) mentioned that researchers at Iowa State University have conducted many studies over the last decade to create an innovative approach for forecasting pavement modulus using artificial neural networks (ANN). The input parameters given by Witczak et al. while constructing the 1999 and 2006 models were used to design the ANN models.

ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANN) have shown to be excellent tools for describing nondestructive testing (NDT) methods for pavements back-calculation techniques (Gucunski et al. 2000).

ANN is a computer model that is based on the human brain's operations, which is the most sophisticated biological neural network (Alimoradi et al. 2011). In recognition, control, and learning, the human brain outperforms traditional computers in terms of effectiveness, adaptability, and tolerance (Hamim et al. 2020).

In general, a neural network is made up of an interconnected set of artificial neurons (basic processors connected to a large number of other neurons) (S. Mahdevari & S. Rahman 2012). These processing units take data, perform some simple processing on it, and then pass it on to other neurons which then flow of data generates a computational model for processing data (Alimoradi et al. 2011).

Shirazi et al (2009) and Alimoradi et al. (2011) agreed that multilayered networks with linked layers are one of the most frequent forms of neural networks. The number of input parameters (called input nodes), outputs (called output nodes), and hidden nodes grouped in one or more layers that function as computing units of the model make up the architecture of the model. The fundamental architectural network for ANN is depicted in Figure 2.

The input layer is used to feed data into the ANN network. The response to the input is displayed in the output layer. The intermediate or hidden layer is where complex patterns are calculated. All layers have stored neurons, with the number of neurons determined by the user. The number of hidden neurons is determined using the trial-and-error approach. In most situations, the smallest number of neurons necessary to get acceptable results should be used (Hamim et al. 2020).

S. Mahdevari and S. Rahman (2012) said that, in recognition of artificial neural networks' computational power in rule generation and function approximation, as well as their robustness in the area of data classification, a back-propagation artificial neural network had been developed and trained for validating the pavement modulus considered in this study.

The multilayer feed-forward network (MLFN), which is taught using the backpropagation learning technique, is the most well-known ANN. This ANN is popular because of its ease of use, simplicity, and demonstrated usefulness in forecasting or predicting research. The Levenberg-Marquardt (LM) approach is more resilient than traditional gradient descent strategies for training MLFNs. The LM method was chosen to do back-propagation training in this work because it converges faster than traditional gradient descent algorithms, requires no momentum factor or learning rate, and, in most cases, converges when other back-propagation techniques fail (Hamim et al. 2020).

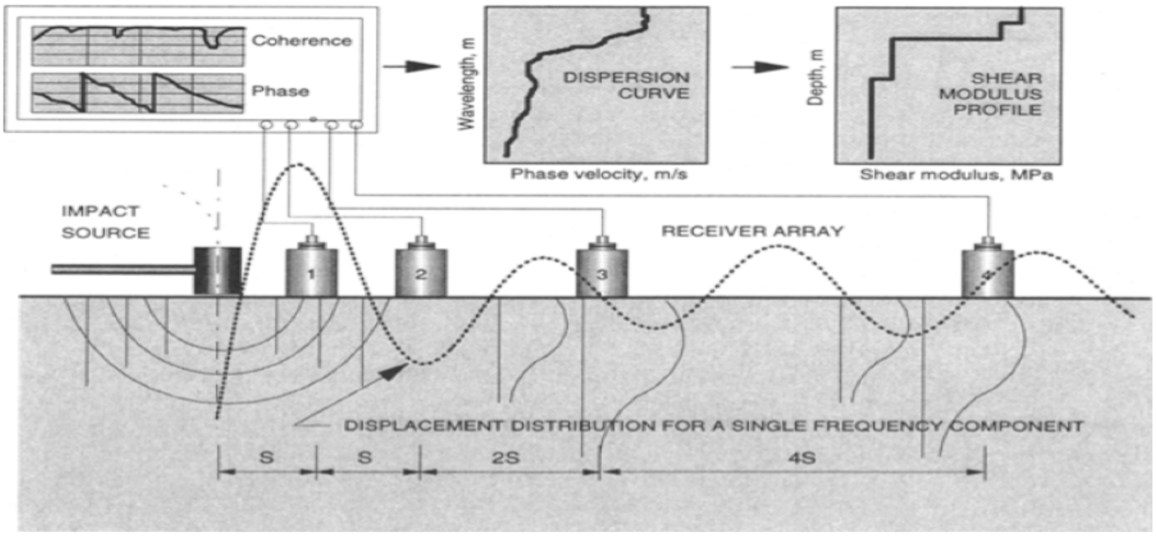

FIGURE 1. Schematic of SASW Test Procedures (N. Gucunski et al. 2000)

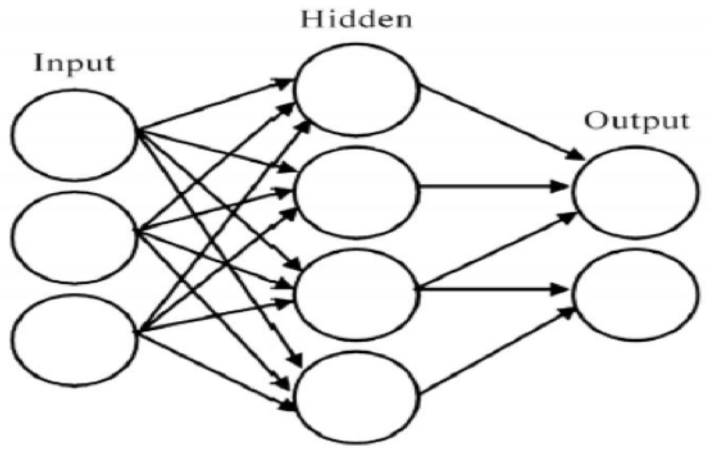

FIGURE 2. A network containing layers of input, hidden and output. (S. Mahdevari & S. Rahman, 2012).

Backpropagation is utilized to construct the ANN models in this study. Backpropagation is a two-mode technique that works in both mapping and learning modes. As mentioned by Gucunski et al. (2000) the information is passed forward from the input to the hidden layer and subsequently to the output in the mapping mode. The learning mode includes both forward and backward processing of data. The connections between the three layers are computed based on the mapping mode, and the estimated output is utilized to compute an error. An evaluation function is used to check the error. If the developer's conditions are not met, the error is propagated backwards from the output to the hidden layer and finally to the input. This adjusts the values of the connections between each of the layers and the whole process repeats. Learning is the term used to describe this process of repetition. The goal of learning is to reduce the difference between the expected and known outputs (the output used in developing the model).

Gucunski et al. (2000) also stated that the quality and quantity of data utilized are the most important aspects in developing any mathematical model as well as creating an ANN model. According to other researchers' experience, up to 70% of the time might be spent "massaging" the data. Data pre-processing, often known as "data mining," is a skill that varies according to developer expertise (J. Liu, 2014). Finding a representative sample of variables with a strong link between the input and output variables is the basic guideline for data mining. Descriptive statistics, data standardization, and data transformations are some of the techniques used to prepare the data. Different combinations of these technologies can be employed depending on the size of the data collection and the number of variables available.

Based on Shirazi et al (2009), a database of exemplars is the bare minimum for developing ANN models (combinations of available input parameters and corresponding outputs to be estimated). There are several commercial software programs that use such a database to "train" an ANN model to estimate the intended outputs from the supplied inputs. The ANN model is seen as a replacement for extremely complicated numerical models or as a stand-in for situations in which the connection between input and output is unclear. In general. training an ANN model is a simple and quick process. Establishing a good and high-quality ANN model, on the other hand, necessitates a thorough examination of various training techniques. Commercial software packages include a significant variety of ANN complicated "training" structures and techniques that are rarely studied by individuals who use them.

In this study, a detailed review of several training techniques was carried out. The pavement modulus was calculated using ANN models of various neural network types and architectures based on various inputs.

The most essential components in developing correct ANN models are selecting proper network design and learning algorithms. The necessary network model for this research application was developed using the ANN toolbox from MATLAB.

MATLAB has an ANN toolbox, which provides programmers with an environment in which to construct desired models. The toolbox's intricacy and versatility make it suitable for an expert, as the user has complete control over the model's parameters and the training session's algorithms (Shirazi et al. 2009). The program includes common training techniques like backpropagation, radial basis, self-organizing, and recurrent networks. The toolkit provides a graphical user interface that helps with model development to some extent (Shirazi et al. 2006). Developed models may be exported to MATLAB's working area for easy integration with other programs.

The main objective of this study is to validate the pavement modulus (the parameters are taken from SASW results) which was calculated manually using equation where may cause a calculation error.

As a result, this study presents an automated method for pavement modulus calculation testing based on an artificial neural network (ANN) using MATLAB. Using newly produced numerical data, the highest correlation coefficient with the lowest hidden nodes were chosen and verified for confidence. The generated ANN models' final outputs were reasonable and relatively near to the real output.

METHODOLOGY

A SASW field test was initially performed to gather the requisite data. The collected data from the taiway KLIA, Sepang were then evaluated and analyzed using WinSASW software. Figure 3 shows the configuration setup at the site location. Two accelerometers are used as receivers and located 0.3m apart from each other were placed on-site location. The sources were given at a distance of 0.3m, 0.6m, and 1.2m from the first receiver. Based on the signal generated, the measured time histories were recorded.

Figure 4 depicted the flow chart of the methodology. WinSASW for the SASW method is some of the software tools available for respective analysis procedures. WinSASW is based on the dynamic stiffness matrix approach of forward analysis. Optimization techniques like ANN (N. Gucunski et al. 2000), is also being used for automation of analysis procedure.

Field testing, generation of the experimental dispersion curve, and calculation of the pavement stiffness profile from the experimental dispersion curve are the three steps of the SASW tests. The SASW field-testing comprises of striking the surface of a pavement to generate and detect surface waves. The Seismic Pavement Analyzer (SPA) is a device that was created to automate this testing. To create an experimental dispersion curve, the collected signals are processed. This graph depicts the relationship between wave velocity (phase velocity) and frequency (or wavelength). The shear wave velocity, thickness, densities, and Poisson's ratio of each pavement layer are all factors that influence the dispersion curve. The shear wave velocities and layer thicknesses have the greatest impact on the dispersion curves of these parameters.

The final and most difficult, the stage is known as the inversion process (a.k.a. back-calculation). From the experimental dispersion curve, the inversion technique gives an iterative procedure for calculating the shear wave velocity profile. The technique begins by assuming an initial pavement profile (first trial) and utilizing a forward model to construct a theoretical dispersion curve (Shirazi et al. 2009).

The difference between the experimental and theoretical dispersion curves is then repeatedly and automatically reduced to a specified small value. The inversion procedure may not converge or may take too long to converge if the initial experiment is not fairly close (N. Gucunski et al. 2000).

Once a layer's shear wave velocity Vs has been determined, the layer's modulus E may be calculated using equation 1, Witczak pavement modulus equation (Shirazi et al. 2009).

$$E = 2\,\rho {V_s}^2(1+\nu) \tag{1}$$

Where ρ and v = density and Poisson's ratio of that layer.

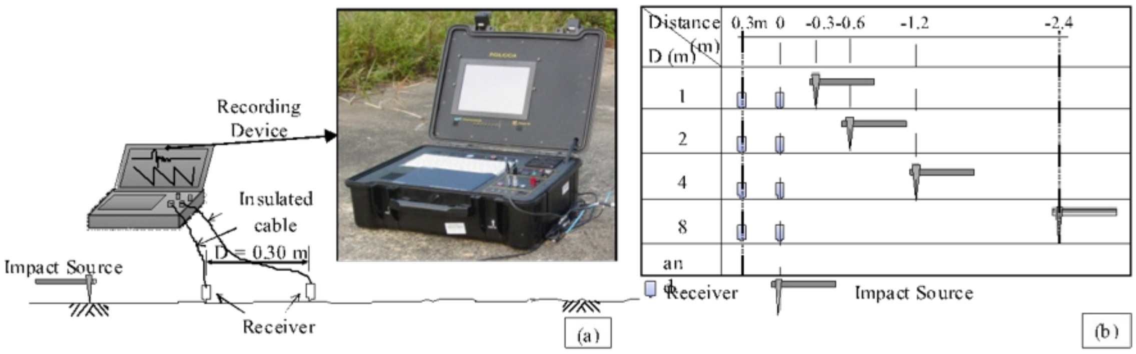

FIGURE 3. (a) Hardware configuration for field measurement and (b) SASW measurement configuration (N. Ismail et al. 2020)

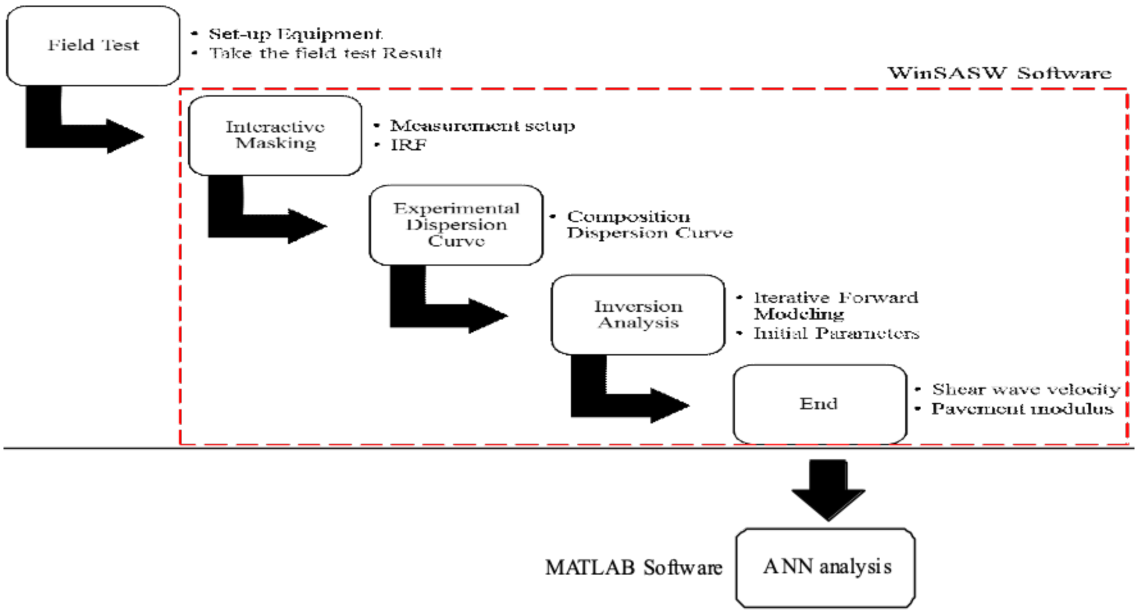

FIGURE 4. Flow chart of the Methodology

DEVELOPMENT OF ANN MODEL

ANN models are used to reduce the inaccuracies in the anticipated correlation coefficient. The data set available is the initial stage in the data mining process (N. Gucunski et al. 2000). There were 28 set examples of shear wave velocity profiles in the synthetic data set used in this investigation. Shear wave velocity, depth, and thickness were the three variables in the input variable set. The elastic modulus was the only variable in the output. Because field tests can reliably determine depth and thickness, they were utilized to normalize the shear wave velocity and perhaps enhance their relationship to the input variables, resulting in more accurate ANN models (D. Shukla and C. Solanski 2020).

The ANN models in this study were created using the MATLAB R2015b computer software. A total of 475 datasets were randomly divided into three groups: 70% for training, 15% for validation, and 15% for testing. For the MLFN model, the 'nftool' command may be used to access the Neural Network Toolbox. The number of neurons in the one hidden layer was found by trial-and-error methods of 10, 20, 30, 40, 50, 60, 70, 80, and 90 hidden nodes.

The neural network was trained and tested using 475 data points. 70 % of the total data were chosen at random for network training, while the remaining 30% of the data was utilized to test and validate the network (Alimoradi et al. 2011). As shown in Table 1, each data point is a vector comprising three input values: shear wave velocity, depth, and thickness. The pavement modulus value obtained from equation 1 is the intended network output. The network's input layer takes data from three nodes, and the network's final layer creates an output. For training, the Levenberg Marquardt (LM) algorithm is employed.

TABLE 1. Example of 1 set of data obtained from SASW

INPUT		OUTPUT	
VELOCITY	DEPTH	THICKNESS	MODULUS
1519.52633	0	0	13299611141
1519.52633	0.025	0.025	13299611141
1577.04318	0.075	0.05	14325495504
1897.17524	0.1	0.05	20731817614
1863.52462	0.15	0.1	20002890294
1511.50431	0.2	0.1	13159556808
1128.05199	0.25	0.15	7329607443
961.86128	0.3	0.15	5329020223
1022.0105	0.4	0.25	6016351462
1067.89313	0.5	0.25	6568679446
1059.96974	0.6	0.35	6471566494
1059.96974	0.7	0.35	6471566494
1059.96974	0.9	0.55	6471566494
1059.96974	1.1	0.55	6471566494
1059.96974	1.3	0.75	6471566494
1059.96974	1.5	0.75	6471566494

RESULTS AND DISCUSSION

EXPERIMENTAL DISPERSION CURVE

An experimental dispersion curve is determined using the phase of the transfer functions between the receiver signals (M. Schevenels et al. 2008 and Chakraborty et al. 2016). All such dispersion curves for different test offsets and orientations are statistically combined and a representative EDC for the test site is finally generated (A. Goel and A. Das, 2008). Dispersion curves for several receiver spacing and two directions are statistically combined to define an average dispersion curve, as described by Nazarian inGucunski and Woods (1992).

INVERSION ANALYSIS

The dynamic shear modulus of the soil is determined by solving an inverse problem (Chakraborty et al. 2016). Stress-wave propagation theory is used in an inversion process. The propagation theory simulates a theoretical dispersion curve and compares it to an experimental dispersion curve. As a result, the experimental dispersion curve is compared to the theoretical dispersion curve. The pavement profile is modified and a new theoretical dispersion curve is produced if the two dispersion curves do not match. The related profile has then deemed the representative pavement profile after an interactive iteration technique, i.e., maximum likelihood method, is performed until the two curves match (A. Goel and A. Das, 2008 and Rosyidi, 2015)

PAVEMENT MODULUS

The material stiffness of pavement, i.e., stiffness modulus, E can be obtained from the following relationship between the shear wave velocity (VS), the gravitational acceleration (g), the density (ρ) and the Poisson ratio (ν) (A. Goel and A. Das, 2008 and Rosyidi, 2015) as stated in equation 1.

Thus, a range of R-wave frequency components propagating in a multi-layered media can provide information on its stiffness profile if the corresponding phase velocities are measured; which is the objective of all surface-wave tests (A. Goel and A. Das, 2008).

The experimental dispersion curve is shown in Figure (a) while the shear wave profile from the result of the inversion process in the SASW method on the existing pavement is shown in Figure (b) from Figure 5 to Figure 9. Using equation 1, its equivalent dynamic elastic modulus profile is given in Figure (c) for each segment. Five segments are presented in this paper from 28 segments that have been done in this research to represent the SASW test data.

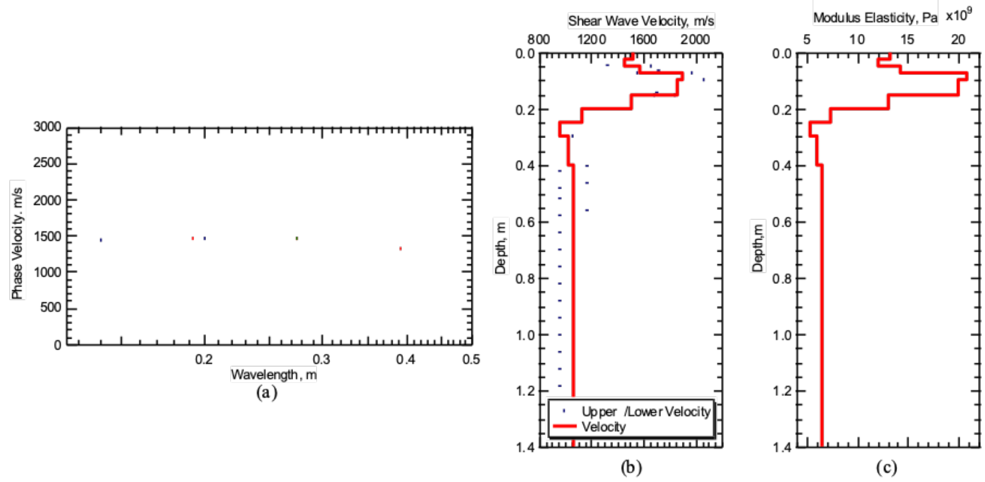

FIGURE 5. Segment 1 of (a) Dispersion Curve, (b) Shear Wave Velocity Profile, and (c) Modulus Profile

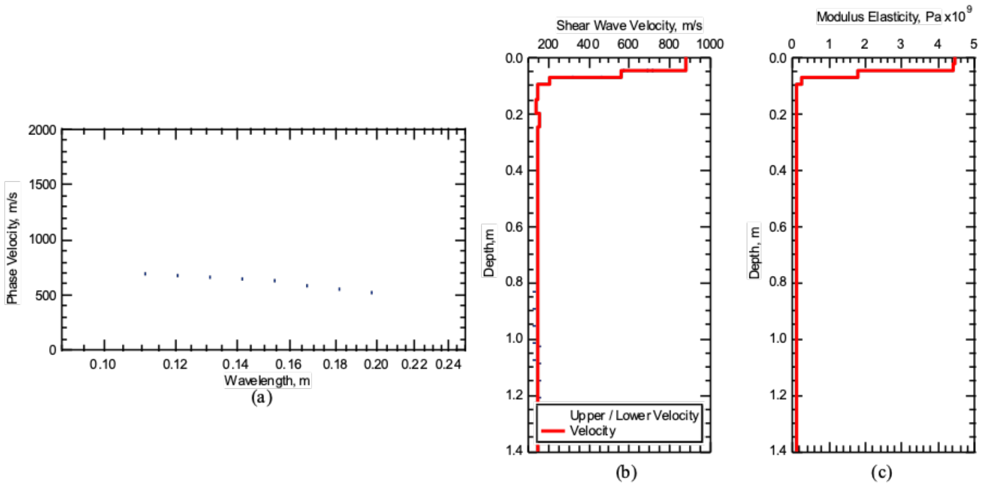

FIGURE 6. Segment 2 of (a) Dispersion Curve, (b) Shear Wave Velocity Profile, and (c) Modulus Pr

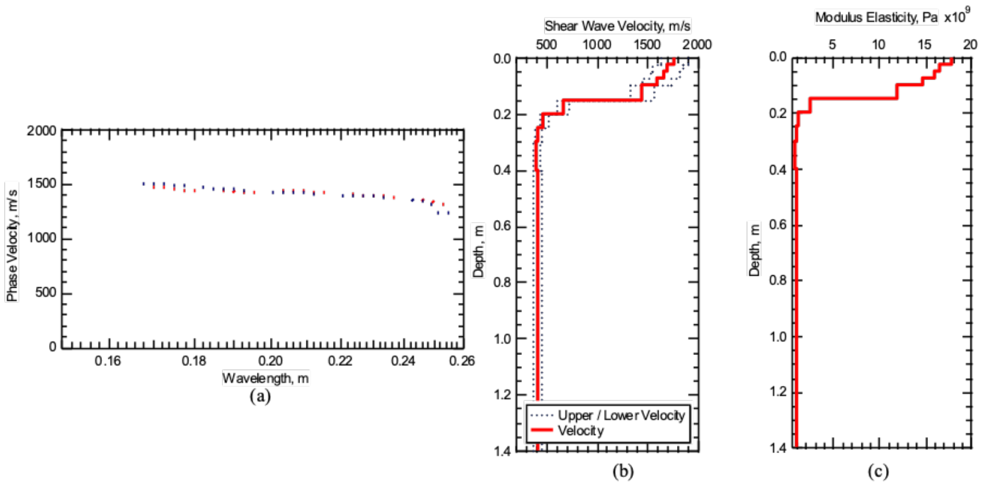

FIGURE 7. Segment 3 of (a) Dispersion Curve, (b) Shear Wave Velocity Profile, and (c) Modulus Profile

Rosyidi (2015) mentioned that higher elastic modulus values are observed in the subbase layer, which has more uniform soil densities that can be contributed by compaction. The lower elastic modulus can be found in the subgrade layers, which have numerous structural flaws.

If there is any deterioration at the pavement, the shear wave velocity profile and modulus profile of the pavement will deviate. As per Figure 5 shown at 0.1m to 0.2 m and Figure 9 at 0.25m to 0.3m, the shear wave velocity and the modulus is higher which mean the layer in between is stiffer. As for Figure 5, the layer in between depth 0.0m to 0.1m is less stiff than 0.1m to 0.2m where from the beginning, the stiffness of pavement is lower than 0.1m to 0.2m and keep decreasing as the depth increases. Meanwhile, in Figure 9, the shear wave velocity and the modulus of pavement is decreasing from 0.0m until 0.25m to 0.3m and keep decreasing after that. It may be due to greater compaction at that depth compare to the layer before for both cases or pipe leaking which cause the layer less stiff at 0.15m to 0.25m in Figure 9.

The training procedure is usually iterative. Following the learning phase, the model is validated, and the training is repeated until the output for a new model is adequate, based on the findings received. The first iteration, however, was sufficient to yield excellent results due to the output normalization and good correlation coefficient values. Based on the validation set, the neural network model with the best level of accuracy was chosen (N. Gucunski et al. 2000).

The determinant indices are the correlation coefficient (R) between the anticipated and desired values, as well as the number of hidden nodes utilized, when appropriate. Shirazi et al (2006) stated that the best model was the one with the greatest correlation coefficient and the fewest hidden nodes and the time it would take to build the network was not taken into account.

The MFB models implemented 10 to 90 (with sequences of 10) hidden nodes. The results of training, validation, testing and all performance are presented in Table 2. In this table, R is the correlation coefficient between the self-calculated and the automated ANN pavement modulus values. As shown in Table 2, during testing, a correlation coefficient of greater than 0.95 was fully obtained. This shows that the modulus values in the test data were practically well-correlated with the network predictions as prescribed by S. Mahdevari and S. Rahman (2012). The problem with using the equation to calculate the pavement modulus, some parameters may mistakenly use, thus wrong calculation is done. When the correlation coefficient is 1, implying a good network performance. This can be seen for network architecture of 4-90-4 or the nearest is 4-80-4. The proposed neural network could modify the prediction of pavement modulus.

H. Al-Adhami and Gucunski (2021) described in their paper, the effectiveness of the ANN models to forecast the pavement modulus varied depending on the network design. According to the results of the comparison, the recently created ANN models based on the SASW database, provide sufficient accuracy and can reliably forecast pavement modulus for practical applications.

Most artificial neural networks were capable of producing relatively robust results, based on the validation of those models in Table 2. The ANN models, in particular, are extremely well approximated.

Nine artificial neural network models were created. The findings of the models are shown in Table 2 as results. Table 2 compares each model's output to the requested data. It also describes the hidden layer's design and gives a value for the model's performance based on the correlation coefficient function. The following is a summary of the model's findings:

1. Almost network architecture shows a correlation coefficient of more than 0.95 except for 4-10-4, 4-20-4 and 4-30-4. This shows that the model is both reliable and strongly correlated.
2. As for training, the network architecture of 4-90-4 has the highest R of 1.0 followed by 4-80-4.
3. Meanwhile for the validation, testing and all R. network architecture has the highest values for 0.9992, 0.994, and 0.9996 respectively. Thus, the best model developed for this study is the network architecture of 4-80-4.
4. While the lowest correlation coefficient for training, validation, testing and all are 0.9722 (4-30-4), 0.9493 (4-20-4), 0.9322 (4-30-4) and 0.9642 (4-20-4) respectively. Thus, the worst network architecture developed for this study is 4-20-4.

TABLE 2. Performance of ANN models in determining the pavement modulus.

Network Architecture	R			
	Training	Validation	Testing	All
4-100-4	0.97677	0.9494	0.95544	0.97228
4-20-4	0.97444	0.9493	0.98276	0.96424
4-30-4	0.97219	0.97738	0.93229	0.96502
4-40-4	0.99758	0.9972	0.99299	0.99576
4-50-4	0.98692	0.98351	0.98903	0.98689
4-60-4	0.99593	0.99632	0.99636	0.99576
4-70-4	0.99365	0.99253	0.9951	0.99286
4-80-4	0.9999	0.99915	0.99937	0.99963
4-90-4	1	0.99621	0.99882	0.99804

CONCLUSION

The main objective of this study is to validate the Witczak pavement modulus calculated by equation 1 using ANN is achieved. The data taken at taxiway KLIA, Sepang by using SASW were used in this study. An ANN based on the backcalculation of a pavement modulus profile was created to enhance the speed and automate the modulus calculation.

It may be determined from the recorded seismic signals, that the weak recorded seismic wave signal is an impact of ambient noise, which might be caused by ground or road noise, as well as man-made vibration. This indicates that the system's input signals or actions at different times were not similar which is why many errors can be occurred if the modulus were calculated manually by using the equation.

The following is a summary of the study's major findings:

1. Based on the examination of ANN model performance using numerical data, the final findings for the ANN models created using the SASW database provides adequate accuracy. As a result, the proposed automated method for modulus computation can compute the pavement modulus with acceptable precision for practical applications without utilizing the equation.
2. It was proved that the pavement modulus is affected by each pavement layer characteristics (shear wave velocity, thickness, and depth).

ANN was successfully applied to overcome the mistakes that could be done when self-calculated the pavement modulus using the equation. The network uses depth, thickness and shear wave velocity as input variables to understand the relationship between them and calculated pavement modulus as an output. Results show good correlation coefficients between calculated and predicted values of pavement modulus for both performances of network architecture 4-80-4 and 4-90-4. The ANN results gained in this study can be used in the future to increase the accuracy of ANN models.

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DECLARATION OF COMPETING INTEREST

None

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