Chapter 1

INTRODUCTION

The seismic refraction is a technique employed in determining a geological structure under the earth surface. Shallow refraction survey could be applied for civil engineering problems whose interested depth less than 100 m. The seismic velocity, which was determined from the seismic refraction measurement, will be used for detailed predicted of rock quality. For example, the interest is focused on seismic sections where lower velocities indicate inferior quality of rock. The lower velocities appear as the weathered and fractured or softer rock (Sjögren, 1984). In the present time, the interpretation techniques such as wave front reconstruction methods, intercept time method, and reciprocal method, are focused on the inversion of scalar travel time data. The accuracy of each technique is depended on the skill and experience of interpreter (Palmer, 2001).

Artificial neural networks can be viewed as computational systems that have been applied in a wide variety of fields to solve problems such as classification, parameter estimation, parameter prediction, pattern recognition, completion, association, filtering and optimization (Brown and Poulton, 1996). This method has been applied to solve many geophysical prospecting problems, such as interpreting of resistivity data (El-Qady and Ushijima, 2001), processing of EM sounding data (Poulton, Sternberg and Glass, 1992; Winkler, 1994), ground-penetration radar (Poulton and El-Fouly, 1991), and recognizing seismic waveforms (Röth and Tarantola, 1994; Dai and Mucbeth, 1995; Ashida, 1996), which has shown a wide potential for solving complex relationship problems that normally needed a skillful and experienced interpreter. The application of neural network in seismic refraction interpretation is an alternative method, which needed to be studied thoughtful.

1.1 Seismic refraction method

Seismic energy was generated at ground surface. The energy penetrates deep into the ground and reaches interface between grounds of different acoustic impedance. Parts of seismic energy travels in top layer ground to receivers directly, called direct wave. Parts of seismic energy travel deep down to interfaces between grounds of different acoustic impedance. There some parts of energy reflected back to overlying layers while others refracted into underlying layers. There some part of energy refracted and traveled back to ground surface. This coming back energy will be monitored and recorded. Actually traveling time of seismic energy from source location to receiver position will be measured. The subsurface information, such as thickness of each ground layer and velocity of seismic wave in each layer can then be derived from the seismic refraction travel time.

1.1.1 Geometry of refraction profiles

The seismic field work is generally carried out with the impact points and detectors placed in a straight line, called in-line profiling system. Offset distance between source and receivers will be designed according to depth of investigation and estimated impedance contrast between ground layers. For measurements on land, a detector, called geophones or seismometers, are sensitive to ground vibrations, while those used under water, called hydrophones, are sensitive to variations in water pressure. The spread length of a seismic refraction survey line is dependent on number of receiver channel in a seismic recording system. In planning a survey this minimum line length is conveniently taken to be about 10 times the estimated depth to the horizon of interest. The impact of the ground motion (or pressure variations) on the detectors is transformed into an electric and transmitted by seismic cables to amplifying unit and a recorder of seismograph. The signals are recorded either on photographic film or on magnetic tape. The instant of an explosion or an impact of a mechanical energy source is conveyed by a cable or via radio signal to the recording equipment. In shallow refraction surveys, the depth of interest seldom exceeds 100 m.

1.1.2 Time-distance graph

The travel time of the wave is plotted with respect to the offset distance of the geophone from the source point, the t-x graphs of two-layer and three-layer horizontal ground are shown in Fig.1.1 a) and 1.1 b).

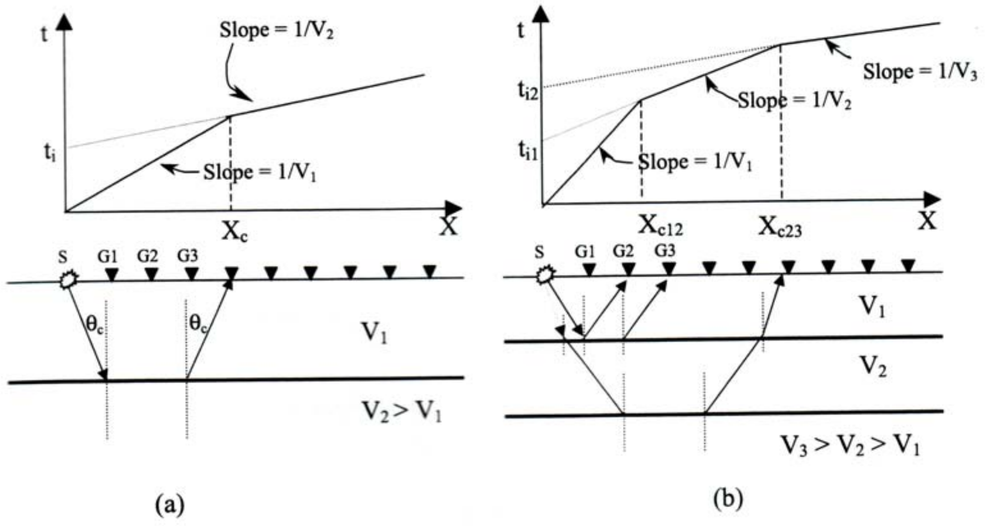


Figure 1.1 Raypath and travel time curve (a) two parallel plane layers, (b) three parallel layers (Wattanasen, 2001).

At the distance X_c (Fig. 1.1a) and X_{c12} (Fig. 1.1b) on t-x graph, direct wave and the refracted wave arrive exactly at the same time. This distance is called the *cross-over distance.* The arrival time of direct wave could be determined from the offset distance traveling and velocity of seismic wave in the top layer ground, as following;

$$t_1 = \frac{X}{V_1} \tag{1}$$

At a distance farther from the crossover distance, the refracted wave will arrive earlier than the direct wave. The arrival time of refraction energy at any offset distance is

$$t_2 = \frac{X}{V_2} + \frac{2h_1 \cos\theta_c}{V_1} \tag{2}$$

The crossover distance can be calculated by equation (1) and (2) at $X = X_c$. The crossover distance is related to thickness of the top layer ground and velocity of seismic energy above and below an interface as following.

$$X_c = 2h_1 \left(\frac{V_2 + V_1}{V_2 - V_1} \right)^{1/2} \tag{3}$$

The thickness of the first layer will be useful for determining the offset distance of seismic survey line. Normally a length of a survey line will be at least three times the crossover distance show linear correlation between travel time, t, and offset distance, x.

The equation (1) and (2) on t-x graph, V_1 and V_2 could be determined from slopes of straight lines representative direct wave and refracted wave sections. The travel time at zero offset distance, called intercept times, is

$$t_i = \frac{2h_1 \cos\theta_c}{V_1} = \frac{2h_1}{V_1 V_2}\sqrt{V_2^2 - V_1^2}\ , \tag{4}$$

where t_i is called the intercept time.

The slopes of graph and intercept time, determined from the t-x graph (Fig.1.1a), could be used to determine the thickness of top layer and seismic velocities of each ground layer.

In case of multi-parallel layers, the travel time of refracted wave from each nth-layer can be written as

$$t_n = \frac{X}{V_n} + t_i^n\ , \tag{5}$$

where t_i^n is an intercept time of nth layer ground on a t-x graph.

The thickness of each layer can be determined from the corresponding intercept time and knowledge of seismic velocities of ground.

$$t_i^n = \frac{2}{V_n}\sum_{k=1}^{n-1} h_k \left(\left(\frac{V_n}{V_k} \right)^2 - 1 \right)^{1/2} \tag{6}$$

where n is the number of layers.

If interface place between subsurface layers are dipping, additional shot point at another of spread end of geophone (Fig.1.2) is needed for determining the dip of the layers.

Considering the shot point S_1 at one end of the spread, called forward shot point, S_1ABS_2, down dip traveling path from S_1 to S_2, is exactly equal to S_2BAS_1, up-dip for the shot point S_2 (reverse shot point). The arrival time of refracted wave, t_d, from S_1 to any offset distance X is given by

$$t_d = \frac{X\sin(\theta_c + \alpha)}{V_1} + \frac{2h_{1d}\cos\theta_c}{V_1} \tag{7}$$

where α is the dip angle of the interface plane between the top and second layer, the second term of equation (7) is the intercept time of the refracted wave on t-x graph at shot S_1 location. When the shot point is at S_2, the "head wave" arrival time of refracted wave at any distance X is

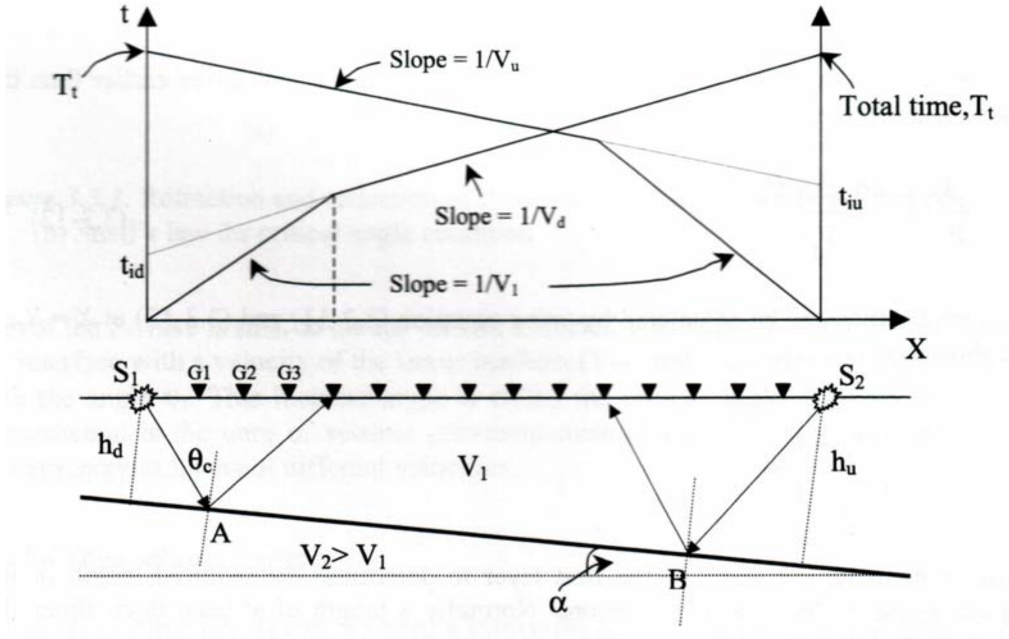


Figure 1.2 Raypath diagram and travel time curves of two-layer earth with dipping interface for a forward shot point (S_1) and reversed shot point (S_2) (Wattanasen, 2001).

$$t_u = \frac{X\sin(\theta_c - \alpha)}{V_1} + \frac{2h_{1u}\cos\theta_c}{V_1} \tag{8}$$

where h_{1u} is the thickness of the first layer at S_2 direct perpendicular to the dipping interface and the second term in equation (8) is the intercept time of the returned refracted wave at shot point location S_2 on t-x graph.

The down dip velocity, V_d, and up dip velocity, V_u, can be determined from slope of the t-x graph, where as the critical angle, θ_c and dipping angle could be determined from the following equations;

$$\theta_c = \frac{1}{2}\left[\sin^{-1}\frac{V_1}{V_d} + \sin^{-1}\frac{V_1}{V_u}\right] \tag{9}$$

and

$$\alpha = \frac{1}{2}\left[\sin^{-1}\frac{V_1}{V_d} - \sin^{-1}\frac{V_1}{V_u}\right] \qquad (10)$$

The velocity of the second layer, V_2, could then be determined from the knowledge of the critical angle, θ_c as following;

$$\sin\theta_c = \frac{V_1}{V_2} \qquad (11)$$

If the dipping angle, α , is very small, the velocity V_2 could be determined from the following equation;

$$\frac{1}{V_2} = \frac{1}{2}\left[\frac{1}{V_d} + \frac{1}{V_u}\right] \qquad (12)$$

Then thickness of the top ground layer below shot points, h_{1d} and h_{1u} could be determined from the corresponding intercept time from one shot point to another.

The total travel time, T_t , time from one shot point to another shot point should be equal. This time is also called reciprocal time and has been used in many interpretation methods, for example the plus-minus method, the delay-time method and the general reciprocal method.

1.2 Artificial neural networks

Artificial neural network is an invented algorithm that simulates the process of human brain. This algorithm can solve several type of problem that is difficult to find correlation between the input and output is not previously known. The mathematical model of a neuron will be introduced and how these artificial neurons will be explained interconnected to form a variety of network architectures.

1.2.1 Neuron Model

A basic biological neuron has three principal components: dendrites, cell body and axon (Fig.1.3). The dendrites are tree-like receptive networks of nerve fibers that transmit electrical signals into the cell body. These incoming signals are summed and analyzed by the cell body and then transmitted by the axon, a long signal fiber to other neurons. The contacted point between an axon of one cell and a dendrite of another cell is called a synapse. At the synapse the signal can be transmitted to the other neurons by a complex chemical process.

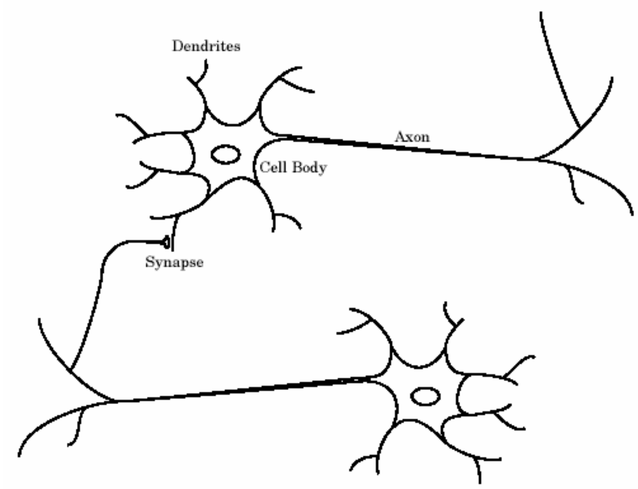


Figure 1.3 Schematic Drawing of Biological Neurons (Hagen *et al.,* 1996)

Single-Input Neuron

A single-input neuron model is shown in Fig. 1.4. The input *p* is multiplied by the scalar weight *w* and sent to the summer. Another input (1) is multiplied by a bias *b* and then passed to the summer. The summer output often referred to as the *net input, n*, is fed into a transfer function *f*, which produces a scalar neuron output *a.*

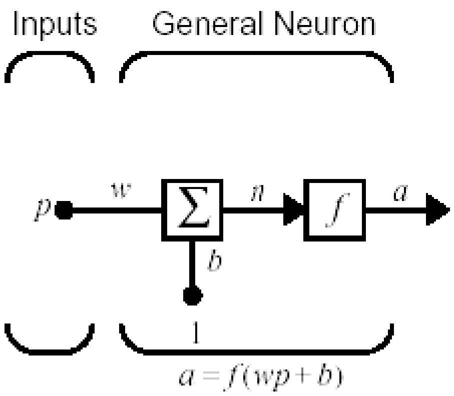


Figure 1.4 Single-Input Neuron (Hagen *et al.*, 1996)

Relating to a biological neuron discussed above, the weight *w* corresponds to the strength of a synapse. The neuron output is calculated by

$$a = f(wp + b) \tag{13}$$

The actual output depends on a transfer function chosen. The bias is much like a weight of a constant input of 1. The w and b are adjustable scalar parameters of a neuron. These parameters will be adjusted by some learning rules, until the neuron output meets the specific goal.

Transfer Functions

A particular transfer function is chosen to meet some specification of the problem that the neuron designed network is attempting to solve. Two important functions used in this study are the linear transfer function and the hyperbolic tangent sigmoid transfer function.

1) The *linear transfer function* (Fig.1.5), the output, a, of the neuron is set equal to the value of the net input, n.

$$\begin{aligned} a &= n \\ a &= purelin(n) \end{aligned} \quad (14)$$

The output (a) and input (p) characteristic of a single-input linear neuron with a bias is shown on the right of Fig.1.5

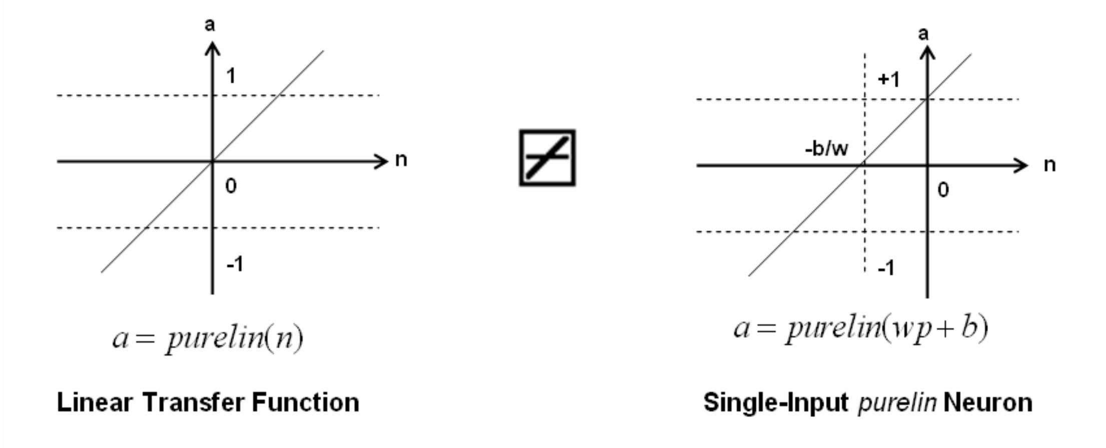


Figure 1.5 Linear Transfer Function

2) The *hyperbolic tangent sigmoid transfer function* (Fig.1.6)

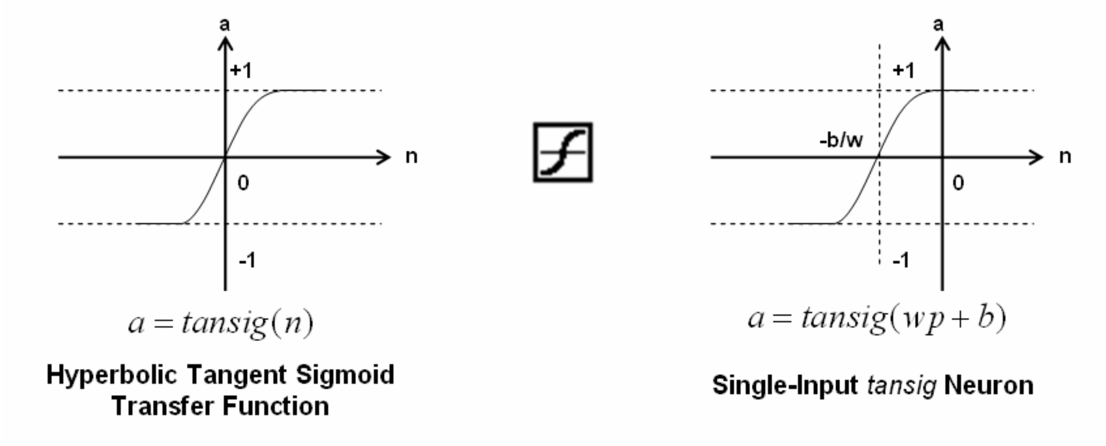


Figure 1.6 Hyperbolic Tangent Sigmoid Transfer Function

The input of this transfer function may have any value between plus and minus infinity and the output will be squashed into the range from -1 to +1, according to the expression:

$$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}} \qquad (15)$$
$$a = \text{tansig}(n)$$

The hyperbolic tangent sigmoid transfer function is a differentiable function. It is commonly used in multilayer networks that are trained using the back-propagation algorithm.

Multiple-Input Neuron

Typically, a neuron can have more than one input. Fig.1.7 shows a neuron with R inputs. The inputs $p_1, p_2, \ldots, p_R$ are each weighted by corresponding elements $w_{1,1}, w_{1,2}, \ldots, w_{1,R}$ of the weight matrix **W.**

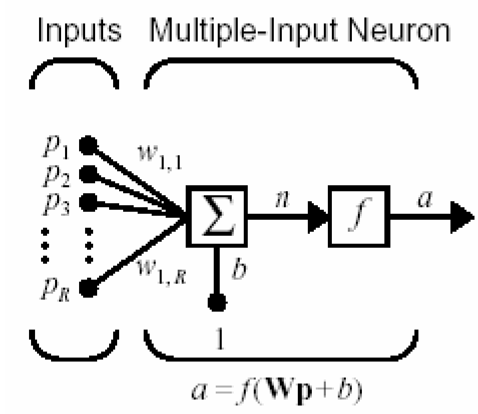


Figure 1.7 Multiple-Input Neuron (Hagen *et al.,* 1996)

The neuron has a bias b, which is summed with the weighted inputs to form the net input n:

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \ldots + w_{1,R}p_R + b\,. \qquad (16)$$

This expression can be written in a matrix form:

$$n = \mathbf{Wp} + b, \qquad (17)$$

The matrix **W** for a single neuron has only one row.
The neuron output can be written as

$$a = f(\mathbf{Wp} + b). \qquad (18)$$

A particular convention in assigning the indices of the elements of the weight matrix has been adopted. The first index indicates the particular neuron destination for that weight. The second index indicates which signal source is fed to the neuron. Thus, the indices in $w_{1,2}$ says that this weight represents the connection of the first neuron with the second source.

1.2.2 Network Architectures

One input neuron may commonly not be sufficient. Five or ten may be needed to operate in parallel, which is called a layer of neurons.

A Layer of Neurons

A single-*layer* network of *S* neurons is shown in Fig.1.8. Note that each of the *R* inputs is connected to each of the neurons and the weight matrix now has *S* rows.

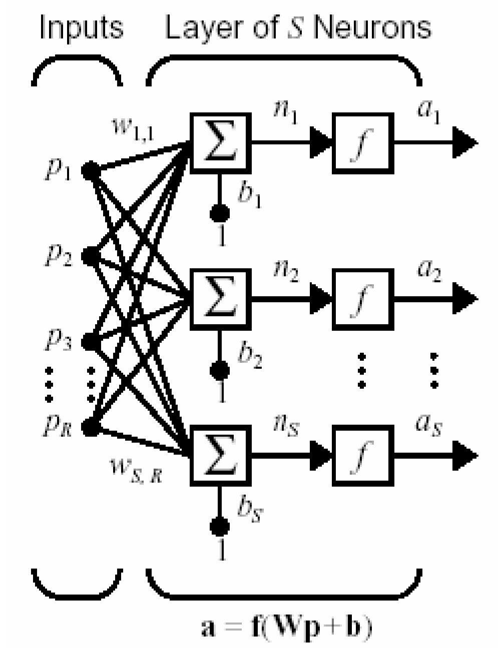


Figure 1.8 Layer of *S* Neurons (Hagen *et al.*, 1996)

Each layer has the weight matrix, the summers, the bias vector **b**, the transfer function boxes and the output vector **a.** Each element of input vector **p** is connected to each neuron through the weight matrix **W.** Each neuron has a bias b_i, a summer, a transfer function *f* and an output a_i. The outputs of each neuron in the layer form an output vector **a**, i.e.

$$a = f(wp + b)$$

The weight matrix, **W**, of a layer of *S* neurons for an input vector of *R* elements is a matrix of *S* rows and *R* columns as shown below

$$\mathbf{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ \vdots & \vdots & & \vdots \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix}. \tag{19}$$

As noted previously, the row index of an element of matrix **W** indicates the destination neuron associated with that weight, while the column index indicates the input source for that weight.

Multiple Layers of Neurons

Now consider a network with several layers. Each layer has its own weight matrix **W**, bias vector **b**, net input vector **n** and output vector **a.** The superscripts on them indicate layers. This notation is used in the three-layer network as shown in Fig.1.9.

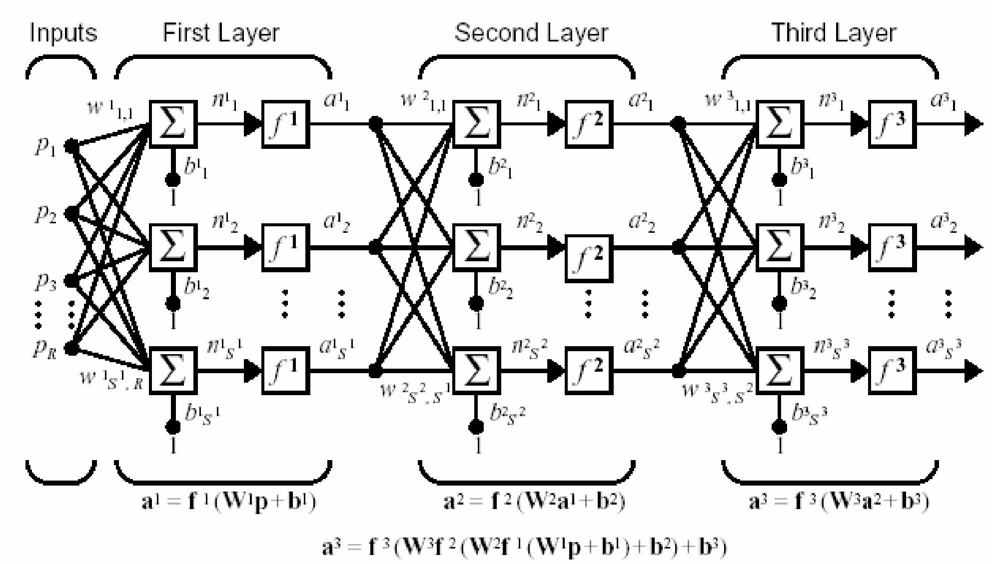


Figure 1.9 Three-Layer Network (Hagen *et al.,* 1996)

A layer of a network output is called an *output layer,* the third layer in Fig.1.9. The other two layers of neurons are called *hidden layers*, the first and second layer in Fig.1.9.

1.2.3 Back-Propagation Artificial Neural Network (BP-ANN)

The Artificial Neural Network (ANN) functions as a non-linear dynamic system that learns to recognize patterns, or to approximate a value, through training. The network (Fig. 1.9) has two major components: neurons and connections, which are weighted links between the neurons. Upon exposure to training examples, the neurons in an ANN compute the activation values and transmit these values to each other in a manner that depends on the learning algorithm being used.

In BP-ANN learning process, the difference between the network output and the corresponding target of a training data set will be calculated. This difference information will be used to adjust weight and bias of the network. This new output of network of the same input data set will be calculated the difference of output and target will be fed back to adjust weight and bias again until network output approach the target values.

1.2.4 Training Algorithm

The training process of basic back-propagation may take days of weeks of computers time. This has encouraged considerable research on methods to accelerate the convergence of the algorithm. The research on faster algorithms falls roughly into two categories, which are the development of heuristic techniques and the development of standard numerical optimization techniques. The Levenberg-Marquardt algorithm is one of the most successful numerical optimization techniques, which is a variation of Newton's method. The Newton's method was designed for minimizing functions, which are sums of square of other nonlinear functions. This is very well suited to neural network training where the performance index is the mean square error.

Newton's method is based on the second-order Taylor series:

$$F(\mathbf{x}_{k+1}) = F(\mathbf{x}_k + \mathbf{\Delta x}_k) \cong F(\mathbf{x}_k) + g_k^T \mathbf{\Delta x}_k + \frac{1}{2}\mathbf{\Delta x}_k^T A_k \mathbf{\Delta x}_k \tag{20}$$

The principle behind Newton's method is to locate the stationary point of this quadratic approximation to *F(***x***)*. The derivative of this quadratic function with respect to $\mathbf{\Delta x}_k$ was taken and set it equal to zero.

$$\begin{aligned} \mathbf{g}_k + \mathbf{A}_k \mathbf{\Delta x}_k &= 0 \\ \mathbf{\Delta x}_k &= -\mathbf{A}_k^{-1} g_k \end{aligned} \tag{21}$$

Newton's method is then defined:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{x}_k - \mathbf{A}_k^{-1}\mathbf{g}_k \\ \mathbf{A}_k &\equiv \nabla^2 F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}_k} \end{aligned} , \tag{22}$$

where $\mathbf{A}_k$ is the Hessian matrices, which is the matrices of second derivative of $F(\mathbf{x})$ and $\mathbf{g}_k$ is the gradient $\mathbf{g}_k \equiv \nabla F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}_k}$ or first order derivative of $F(\mathbf{x})$.

If $F(\mathbf{x})$ was assumed to be a sum of squares function:

$$F(\mathbf{x}) = \sum_{i=1}^{N} v_i^2 = \mathbf{v}^T(\mathbf{x})\mathbf{v}(\mathbf{x}) \tag{23}$$

The gradient can therefore be written in matrix form:

$$\nabla F(\mathbf{x}) = 2\mathbf{J}^T(\mathbf{x})\mathbf{v}(\mathbf{x}), \tag{24}$$

where

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} \frac{\partial v_1(\mathbf{x})}{\partial x_1} & \frac{\partial v_1(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial v_1(\mathbf{x})}{\partial x_n} \\ \frac{\partial v_2(\mathbf{x})}{\partial x_1} & \frac{\partial v_2(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial v_2(\mathbf{x})}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial v_N(\mathbf{x})}{\partial x_1} & \frac{\partial v_N(\mathbf{x})}{\partial x_2} & \cdots & \frac{\partial v_N(\mathbf{x})}{\partial x_n} \end{bmatrix}. \tag{25}$$

The Hessian matrix can then be expressed in matrix from;

$$\nabla^2 F(\mathbf{x}) \cong 2\mathbf{J}^T(\mathbf{x})\mathbf{J}(\mathbf{x}), \tag{26}$$

The Levenberg-Marquardt algorithm is

$$\mathbf{x}_{k+1} = \mathbf{x}_k - [\mathbf{J}^T(\mathbf{x}_k)\mathbf{J}(\mathbf{x}_k) + \mu_k \mathbf{I}]^{-1}\mathbf{J}^T(\mathbf{x}_k)\mathbf{v}(\mathbf{x}_k), \tag{27}$$

where μ_k is the constant.

1.3 Literature Review

The seismic refraction method has been used for many years to map rock layers of interest in problems associated with petroleum exploration (Palmer, 2001), mining, civil engineering and deep crustal studies (Scott, 1973). It can be used in determining depths and types of layered earth. Shallow refraction survey is frequently employed in civil engineering problem (Sjögren, 1984).

The propagation speed of seismic waves through the earth depends on the elastic properties and density of the material. Concept of refraction method begins by generating elastic wave in to the ground. The wave propagates through the ground and arrival time at each geophone is recorded. The travel time of the wave is plotted with respect to the distance of the geophone from the source point. This t-x graph is used for determining number of ground layers and approximating velocity and thickness of each ground layer (Parasnis, 1997).

There are many interpretation methods for analyzing velocity and thickness of ground layer from refraction data. The wavefront reconstruction method retrace the emerging forward and reverse wavefronts down into the subsurface. The refractor interface is located at the positions where the sum of the forward and reverse wavefronts is equal to the reciprocal time. Another long-standing technique is the intercept time method. This method is essentially a ray-tracing approach applied to a subsurface model consisting of homogeneous layers with uniform wave speeds separated by plane dipping interfaces. The angle of emergence of each ray is readily determined from the simple application of Snell's law. The intercept time method is included within group of techniques known as the reciprocal method. These methods are also known as the ABC method in the Americans and plus-minus method in Europe (Bleistein H. and Gray S.H., 2001). The reciprocal methods can be used to compute depths below each detector position while the ITM can be used to compute only depth and wave speed in ground below at the shot point.

Artificial Neural Network (ANN) is a computational algorithm which emulates the process of neural system in the human brain. The applications of neural network are expanding because its works well in solving problems, such as breast cancer cell analysis, credit application evaluators, flight path simulations and automobile automatic guidance systems (Hagan *et al.,* 1996). Neural networks have been applied to solve geophysical problems, for example, interpretation of logging, processing of EM sounding data, ground penetration radar, recognizing seismic waveforms, and interpreting resistivity data.

Normally, artificial neural networks consist of one input layer, at least one hidden layer and one output layer. ANNs can be interconnected in many different ways leading to a variety of architectures, learning rules and abilities (El-Qady and Ushijima, 2001). Back-propagation (BP) is one of the most common neural network algorithms. In the training process of BPNNs, the error at the outputs of the networks is back-propagated from the output layer to the hidden layer and input layer. These errors are used for updating weights and bias of network in such a way that the total error is reduced. This process is repeated as required until the global minimum is reached.

There are many applications of neural network to solve geophysical problem. Dai and MacBeth (1997) develop back-propagation neural network (BPNN) to identify P- and S- arrivals from recordings of local earthquake data. The BPNN is trained by selecting trace segments of P- and S-waves and noise bursts. After training, the network can automatically identify the type of arrival on earthquake recordings. Compared with manual analysis, a BPNN trained with nine group of data can correctly identify 82.3 % of the P-arrivals and 62.6 % of the S-arrivals from one seismic station, and when trained with five data groups of another seismic station, it can correctly identity 76.6 % of the P-arrivals and 60.5 % of S-arrivals.

The application of neural network in DC resistivity inversion is developed by El-Qady and Ushijima (2001). In their work, the neural network approach was successfully employed to solve both 1D and 2D resistivity inverse problem.

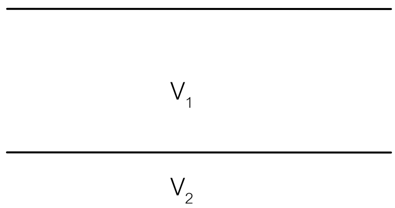
Moreover, Helle *et al*. (2001) applied ANN in estimating porosity and permeability form well logs data. Two separate BP-ANNs were used to model porosity and permeability. The porosity network was a simple three-layer network using sonic, density and resistivity logs as inputs. The permeability network was a complex network with four inputs of density, gamma ray, neuron porosity and sonic logs with more neurons in the hidden layer. The mean difference between the predicted porosity and helium porosity from core plugs is less than 0.01 fractional units. For the permeability network a mean difference is approximately 400 mD.

1.4 Objective

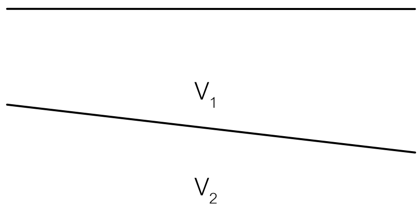
The objective of this research works is to find out a possibility of using neural network in interpreting shallow seismic refraction data of shallow subsurface geological structure.

1.5 Scope of research

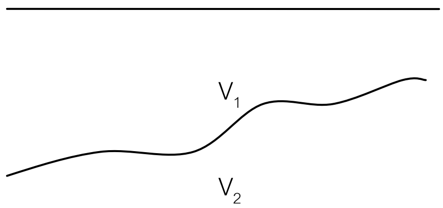
The research is aim at application of neural network in shallow seismic refraction interpretation. The Back-Propagation neural networks (BP-ANNs) are employed in the study. The study will address three different types of geological structures (Fig.1.10), namely; two-horizontal layers structure, two layers dipping interface structure, and two layers irregular interface structure, which all of the structures have horizontal surface.



a) Two-horizontal layers structure



b) Two layer dipping interface structure



b) Two layers irregular interface structure

Figure 1.10 Three different types of interested structures