Chapter 2

METHODOLOGY

The artificial neural network (ANN) was employed to determine shallow subsurface geological structure from shallow seismic refraction data. Neural network has an ability to solve mathematical problem without using the relation between input and output. It learns to solve problem from the training data sets, which comprises input and designed output or target. In the training process, the difference in outputs and targets is in term of mean square error (MSE), is propagated back to the network for adjusting network parameters such as weights and bias. This process is called back-propagation technique. The training process stops when MSE reach a setting goal an MSE value.

The 12 channels seismographs data were synthesized from two-layer earth model. For horizontal interface, there were 24 inputs of 12 offsets and 12 travel times and 3 targets of first layer velocity, second layer velocity, and first layer thickness. For dipping interface and irregular interface, the number of inputs and targets were changed because they had two shot points at both ends of the spread. The networks were separated into depth network of 12 depth targets and velocity network of 2 velocities targets.

Neural network toolbox of Matlab® was employed in designing a network. The synthesized training and testing data sets for horizontal and dipping interface were calculated by making used of this Matlab® program. However, the data sets of irregular interface were obtained from a real field data.

2.1 Materials

2.1.1 Software

1) Neural network toolbox of Matlab Program Version 6.5

2) Seismic Interpretation Program (SIP)

3) Lotus 123

2.1.2 Computer Materials

1) Diskettes

2) CD

3) Hard disks

2.1.3 Field Materials

1) Recording Seismic Data Paper

2.2 Equipment

1) PC Computer Pentium(R) 4 CPU 2.40 GHz, 256 MB RAM

2) Geometric SmartSeis S-42

3) Geophones

4) Seismic cable

5) Measuring tapes 0-50 m length

6) Hammer

2.3 Network design for two-layer structure with horizontal interface

2.3.1 Preparation of training and testing data set for horizontal interface

1) The data sets for training and testing a designed network were calculated from 3780 combination of two-layer earth model (Fig.2.1) which had different velocity in each layer and different thickness of the first layer, as shown in Table 2.1. The first layer velocity (V_1) varied between 350 to 1500 m/s by the step of 20 m/s and the second layer velocity (V_2) varies between 400 to 4000 m/s by the step of 200 m/s. In each pair of layer velocities, V_1, was less than V_2. The thickness of first layer varied between 1 to 10 m with a step of 1 m.

Table 2.1 The model details of synthesizing training data

Layer	Velocity (m/s)	Thickness (m)
First layer	350:20:1500	1-10
Second layer	400:200:4000	-

2) The data sets were synthesized for a spread of 12 geophones. The 24 inputs of a neural network comprised 12 geophone positions with respect to the first shot point (S_1) and arriving times of seismic wave at 12 geophones. The arriving times were calculated from eq.(1) and eq.(2). The spacing between geophones was set to $X_c/3.5$, $X_c/2.5$, and $X_c/1.5$, X_c was cross-over distance defined by eq.(3). In order to be able to determine velocity of direct wave, there should be direct wave information on travel time graph. The targets of a network comprised V_1, V_2, and h_1.

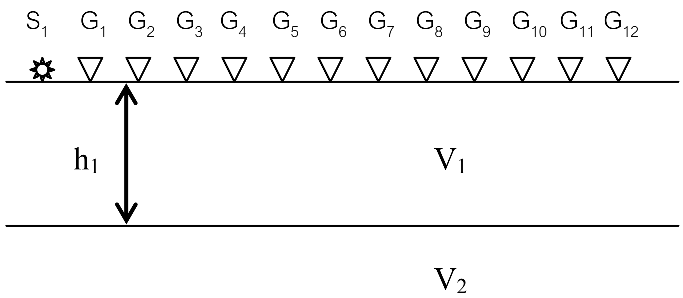

Figure 2.1 Two horizontal layered model

2.3.2 Design architecture network for horizontal interface

1) Two-layer and three-layer architecture neural networks were selected to handle non-separated network. The outputs of the network were V_1, V_2 and h_1.

In non-separated network, two-layer networks in a non-separated network had 24 inputs and 3 outputs. The number of neurons in only one hidden layer was varied between 12 to 48 neurons with a step of 6 neurons. The network of 24 inputs, 12 neurons in the hidden layer and 3 outputs can be represented by 24-12-3. The two-layer architecture networks (Fig.2.1 a)) used in this non-separated network were the followings;

- 24-12-3 - 24-18-3 - 24-24-3 - 24-30-3
- 24-36-3 - 24-42-3 - 24-48-3

Three-layer architecture of non-separated networks had 24 inputs and 24 neurons in the first hidden layer; where as the number of neurons in the second hidden layer was varied between 12 to 48 neurons at of 6 neurons. The three-layer architecture networks (Fig.2.1 b)) of the non-separated network were in the followings;

- 24-24-12-3 - 24-24-18-3 - 24-24-24-3 - 24-24-30-3
- 24-24-36-3 - 24-24-42-3 - 24-24-48-3

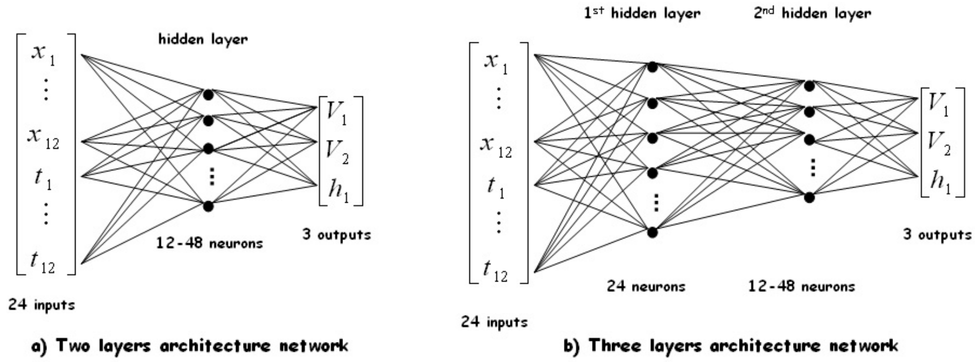

Figure 2.2 Non-separated networks for horizontal interface

2) The hyperbolic tangent sigmoid transfer function (tansig) was used as the transfer function of the only one hidden layer of the two-layer networks and of the first and second hidden layer of the three-layer architecture networks. The linear transfer function (purelin) was used as the transfer function of the output layer of both two-layer and three-layer architecture networks.

3) The normalization and non-normalization training data sets were used in training all designed networks. The normalization training data were normalized by minimum-maximum method (Min-Max method). The normalization process would make the data varying between -1 and 1.

4) Each designed network was trained with the normalization and non-normalization training data sets, which were selected from the synthesized 3780 inputs-outputs pairs in the sequence of 1:11:3780.

5) The designed networks were trained by Levenberg-Marquardt (trainlm) training algorithm. All networks were set the goal (MSE for stopping the training process) and epoch (Maximum iteration for the training process) at 0.01 and 10^6 respectively. For each architecture network, the training process was repeated 10 times in order to check its stability, where the initial parameters such as weight and

bias were changed at the beginning of each time. The training time and the MSE of each case and each training process were recorded.

6) Each trained network was tested with testing data. The testing data sets were selected from the synthesized inputs-outputs pairs in the sequence of 3:111:3780. The MSE of each testing was recorded.

2.4 Network design for two-layer structure with dipping interface

Non-separated network and separated network were designed for two-layer earth with dipping interface. Both networks had the same number of inputs but had difference number of outputs. The non-separated network had 14 outputs of V_1, V_2 and 12 depths to interface below geophones. For separated network, there were depth network and velocity network. The depth network estimated depth at each geophone from the surface to the interface below, so there were 12 outputs in this network. The velocities of top and bottom layers were estimated with the velocity network.

2.4.1 Non-separated network for dipping interface

2.4.1.1 Preparation of training and testing data sets for non-separated network

The data sets for training and testing networks were synthesized from two-layer earth model with dipping interface (Fig.2.3), the model had different velocity for each layer, different depth to interface at shot point (h_{S1} or h_{S2}), and different dipping angle of interface.

1) The training data sets were synthesized from models whose first layer velocity varied from 350 m/s to 800 m/s and second layer velocity varied from 1000 m/s and 4000 m/s with step of 50 and 150 m/s respectively. The depth to interface at shot points (h_{S1} or h_{S2}) was equal to 10 m and the dipping angle of interface varied from 2 to 15 degree, as summarized below.

(1) velocity of the top layer, V_1, from 350 to 800 m/s at a step of 50 m/s
(2) velocity of the bottom layer, V_2, from 1000 to 4000 m/s at a step of 150 m/s
(3) vertical depth to interface at shallow shot point, h_{S1}, at 10 m
(4) dipping angles 2:15 degree

The estimated depth and estimated velocities with each trained network were tested separately. For estimated depth test, each network was tested with data sets, which were synthesized from a model of constant layer velocities, 400 m/s and 1500 m/s for the top and bottom layer respectively and constant h_{S1} at 10 m. The dipping angle of these testing data sets was 2.5, 8.5, and 14.5 degree. The testing data sets were normalized with normalization parameter of training data before applying them to the testing process.

For estimated velocities test, there were two testing data sets, whose layer parameters of the dipping interface model as shown below.

Testing data 1:

(1) velocity of the top layer, V_1, from 350 to 800 m/s at a step of 70 m/s

(2) velocity of the bottom layer, V_2, from 1000 to 4000 m/s at a step of 325 m/s

(3) vertical depth to interface at shallow shot point, h_{S1}, at 10 m

(4) dipping angles 10 degree

Testing data 2:

(1) velocity of the top layer, V_1, from 350 to 800 m/s at a step of 70 m/s

(2) velocity of the bottom layer, V_2, from 1000 to 4000 m/s at a step of 325 m/s

(3) vertical depth to interface at shallow shot point, h_{S1}, at 15 m

(4) dipping angles 10 degree

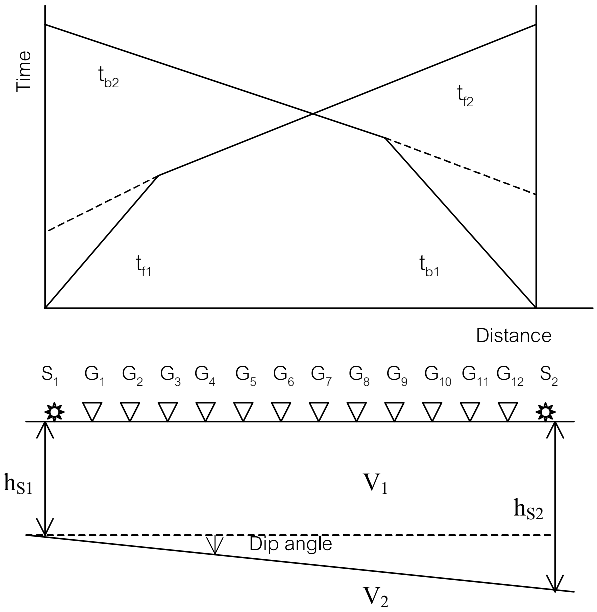

Figure 2.3 Travel time curve and Dipping interface structure model

2) The travel time of seismic wave to each geophone was calculated from eq.(7) to eq.(11). In this dipping case, the travel time were calculated when the shot points were placed at both end of geophone spread. They were called traveling times in forward direction (t_{f1} and t_{f2}) when source was placed at S_1 and in backward direction (t_{b1} and t_{b2}) when source was placed at S_2.

$$\begin{bmatrix} t_{minus}(g1) \\ \vdots \\ t_{minus}(g12) \\ t_{plus}(g1) \\ \vdots \\ t_{plus}(g12) \end{bmatrix} \qquad \begin{bmatrix} x_1 \\ \vdots \\ x_{12} \\ t_{f1} \\ \vdots \\ t_{f12} \\ t_{b1} \\ \vdots \\ t_{b12} \end{bmatrix}$$

a) t_{minus} - t_{plus} inputs **b) Travel time inputs**

Figure 2.4 a) t_{minus}-t_{plus} inputs

b) Travel time inputs

3) There are two types of inputs data sets (Fig.2.4). The first type has 24 values which are 12 differences in time (t_{minus}) and 12 summation of time (t_{plus}) of the forward and backward time. The second input type was composed of the distances from S_1 to each geophone and forward and backward travel time at each geophone. There were 14 outputs of V_1, V_2 and depths to interface at geophones.

2.4.1.2 Non-separated network design for dipping interface

1) Two-layer and three-layer architecture networks were designed for the non-separated. There were six different architecture networks of both t_{minus}-t_{plus} input data and travel time input data, as shown below;

Networks for t_{minus}-t_{plus} input data (Fig.2.5):

-24-10-5-14	-24-10-10-14	-24-5-10-14
-24-2-14	-24-5-14	-24-10-14

Networks for travel time input data (Fig.2.6)):

-36-10-5-14	-36-10-10-14	-36-5-10-14
-36-2-14	-36-5-14	-36-10-14

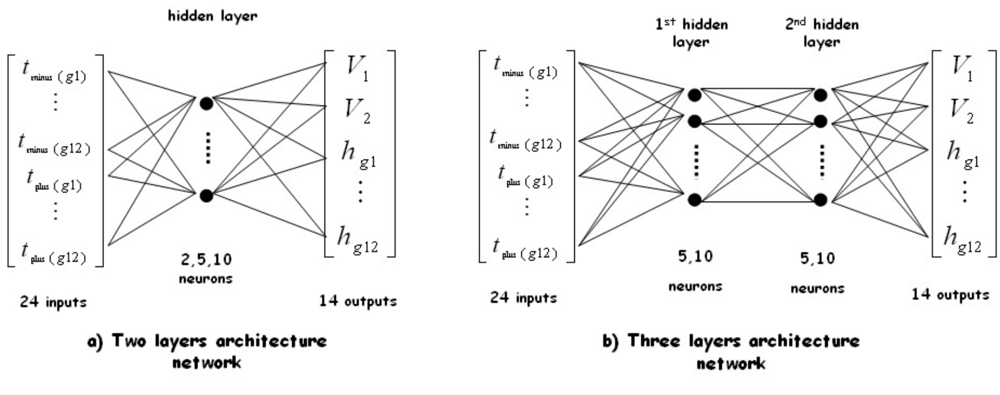

Figure 2.5 Non-separated networks with t_{minus}-t_{plus} input data

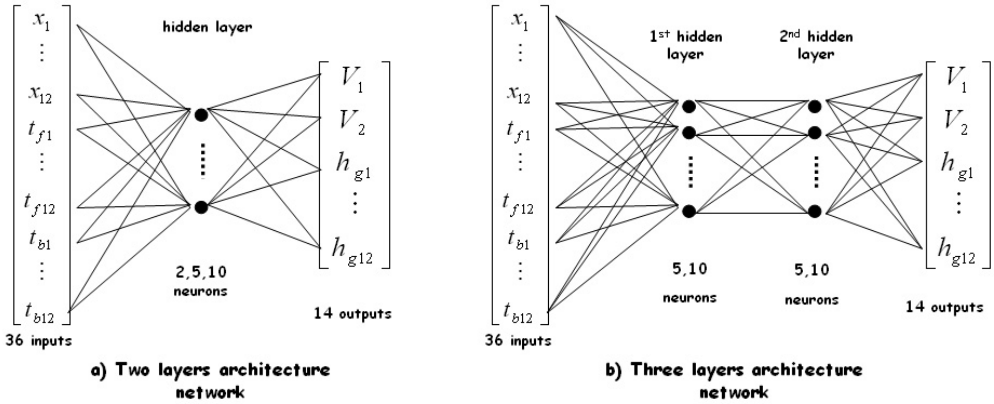

Figure 2.6 Non-separated networks with travel time input data

2) The transfer function of the hidden layer of the network was hyperbolic tangent sigmoid transfer function (tansig) and that of the output layer was linear transfer function (purelin).

3) The normalization data sets were used to train all designed networks. The normalization training data were normalized by minimum-maximum method.

4) The trained networks were tested with corresponding testing data set and errors of predicted depth were recorded.

2.4.2 Depth networks for dipping interface

2.4.2.1 Preparation of training and testing data sets for depth network

The training and testing data sets were synthesized from dipping interface model.

1) The training data sets were calculated from a model of top and bottom velocities varied from 350 to 800 m/s at a step of 50 m/s and from 1000 to 4000 m/s at a step of 150 m/s respectively. The model of dipping interface structure was shown in Fig. 2.3. The depth below one of two shot point was fixed at 10 m and the dipping angle of the interface was varied from 2 to 15 degree.

2) The testing data sets were the same as the testing data of estimated depth test of non-separated networks.

3) The traveling times in forward direction (t_{f1} and t_{f2}) and in backward direction (t_{b1} and t_{b2}) at each geophone of two layers dipping interface model were calculated from eq.(7) to eq.(11).

4) Two types of input data sets, t_{minus}-t_{plus} inputs and travel time input, were synthesized for the training and testing data sets. The outputs were the depth to interface beneath geophones.

2.4.2.2 Depth network design for dipping interface

1) Two-layer and three-layer architecture networks were designed for t_{minus}-t_{plus} and travel time input data. There are six different architecture networks for both t_{minus}-t_{plus} inputs and travel time inputs, which were similar to non-separated networks, as shown below.

Networks for t_{minus}-t_{plus} input data (Fig.2.7):

-24-10-5-12 -24-10-10-12 -24-5-10-12

-24-2-12 -24-5-12 -24-10-12

Networks for travel time input data (Fig.2.8):

-36-10-5-12 -36-10-10-12 -36-5-10-12

-36-2-12 -36-5-12 -36-10-12

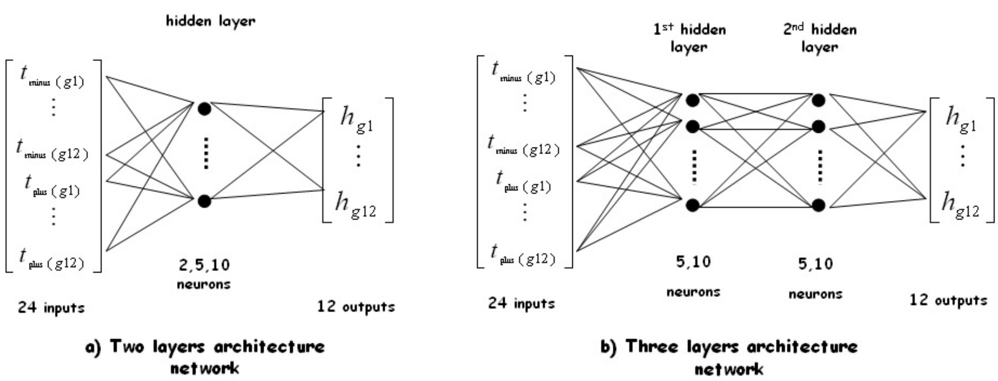

Figure 2.7 Depth networks of t_{minus}-t_{plus} inputs

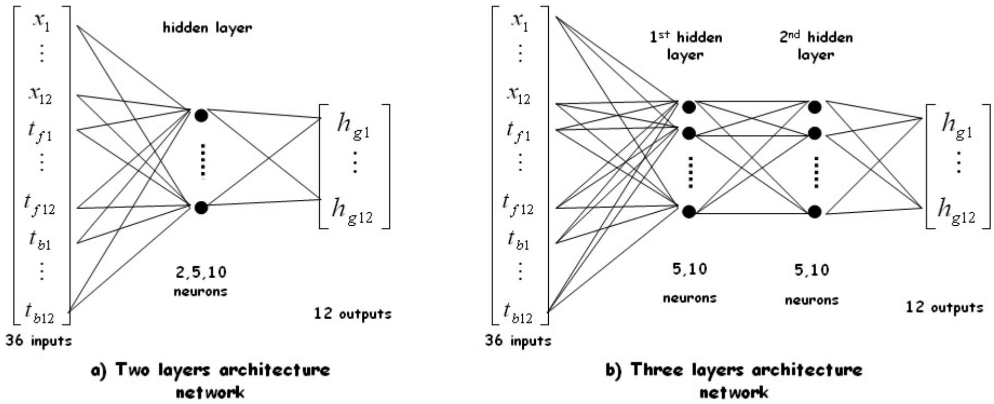

Figure 2.8 Depth networks of travel time inputs

2) The transfer function in the hidden layers of the network was hyperbolic tangent sigmoid transfer function (tansig) and that is the output layer was linear transfer function (purelin).

3) The normalization and training data were applied to train all architecture networks. Each designed network was trained with Levenberg-Marquardt training algorithm (trainlm). The goal and epoch were set at 0.01 and 10^6 respectively.

4) The trained networks were tested with testing data set and errors of predicted depths were recorded.

2.4.3 Velocity networks for dipping interface

2.4.3.1 Preparation of training and testing data sets for velocity network

The training and testing data sets were calculated. The training and testing data sets varied dipping angle from 2 to 15 degree. The data sets were calculated at different velocities of top and bottom layers, by keeping depth to interface below S_1 fixed at 10 m.

1) For the training data sets, the velocity of the first layer, V_1, and the velocity of second layer, V_2, varied from 300 to 800 m/s at steps of 50 m/s and from 1000 to 4000 m/s at the steps of 150 m/s respectively. Two different testing data sets as the part of velocity test of non-separated network were calculated from the model parameters, as shown below;

Testing data 1:

(1) velocity of the top layer, V_1, from 350 to 800 m/s at a step of 70 m/s

(2) velocity of the bottom layer, V_2, from 1000 to 4000 m/s at a step of 325 m/s

(3) vertical depth to interface at shallow shot point, h_{S1}, at 10 m

(4) dipping angles 10 degree

Testing data 2:

(1) velocity of the top layer, V_1, from 350 to 800 m/s at a step of 70 m/s

(2) velocity of the bottom layer, V_2, from 1000 to 4000 m/s at a step of 325 m/s

(3) vertical depth to interface at shallow shot point, h_{S1}, at 15 m

(4) dipping angles 10 degree

2) The forward and backward travel time to each geophone was calculated from eq.(7) to eq.(11).

3) Two types of inputs data, plus-minus time and travel time, were prepared as input of the designed velocity network. The outputs of velocity network were V_1 and V_2.

2.4.3.2 Velocity network design for dipping interface

1) The designed networks for t_{minus}-t_{plus} inputs and travel time inputs were shown below.

Networks for t_{minus}-t_{plus} input data (Fig.2.9):

-24-10-5-2	-24-10-10-2	-24-5-10-2
-24-2-2	-24-5-2	-24-10-2

Networks for travel time input data (Fig.2.10):

-36-10-5-2	-36-10-10-2	-36-5-10-2
-36-2-2	-36-5-2	-36-10-2

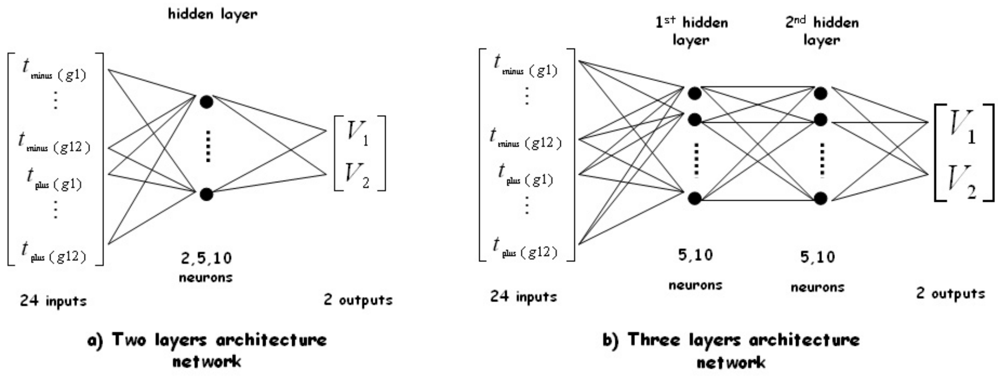

Figure 2.9 Velocity networks of t_{minus}-t_{plus} inputs

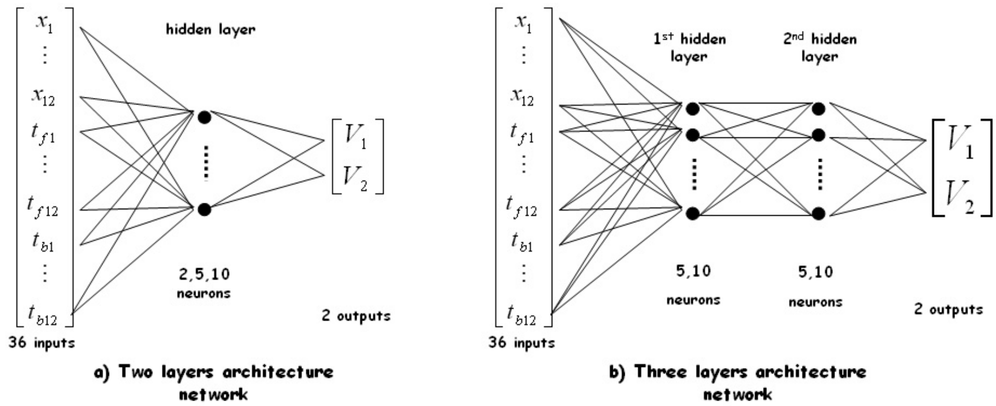

Figure 2.10 Velocity networks of travel time inputs

2) For all networks, the transfer function of hidden layers was the hyperbolic tangent sigmoid function (tansig) and the transfer function of the output layer was the linear transfer function (purelin).

3) The normalization training data were applied to train all architecture networks. Each designed network was trained with Levenberg-Marquardt training algorithm (trainlm). The goal and epoch were set at 0.01 and 10^6 respectively.

4) The trained networks were tested with testing data and errors of each predicted depth were recorded and analyzed.

2.5 Network design for two-layer structure with irregular interface

The networks for irregular interface two-layer earth model were separated into the depth network and velocity network, because depth and velocities had different order of magnitude. The depth network was designed to determined depths to interface vertically below geophone positions, where as the velocity network was designed to determine velocities of the top and bottom layers of the two-layer earth.

2.5.1 Depth network for irregular interface

2.5.1.1 Training and testing data sets

1) The training and testing data sets were real field data obtained from the shallow seismic refraction survey in Thung Pho-Thung Khamin Tin Mining area (Changlow, 2002). The survey layout was the followings; number of geophones was 24, geophone spacings were 2, 4 and 5 meters, all geophones were placed on the flat terrain and the end-end shooting was employed in data acquisition. The true depths to interface below geophones were obtained from the interpretation of seismic data with interpretation software, namely: Seismic Interpretation Program or "SIP". These true depths, which were obtained from interpretation with SIP program, were used as for the targets of the training process.

2) There were altogether 24 training data sets whose depths to interface ranged from 1.8 to 10.0 m; 4 data sets for shallow interface, 1.8 to 2.5 m, 10 data sets for intermediate interface depth, 5.0 to 7.0 m, and 10 data sets for deep interface depth, 9.0 to 10.0 m.

3) There were 3 testing data sets, the first one for an average interface depth of 2.0 m, the second one for an average interface depth of 6.0 m and the last one for an average interface depth of 10.0 m.

2.5.1.2 Depth network architectures

1) Two-layer and three-layer network architectures were chosen for this study. In all architecture, there are 72 input elements and 24 output elements. The 72 input elements comprise 24 elements of geophone positions with respect to a shot point (S_1) and 48 elements of forward and backward travel times. There are 24 output elements of depths to interface at geophone locations.

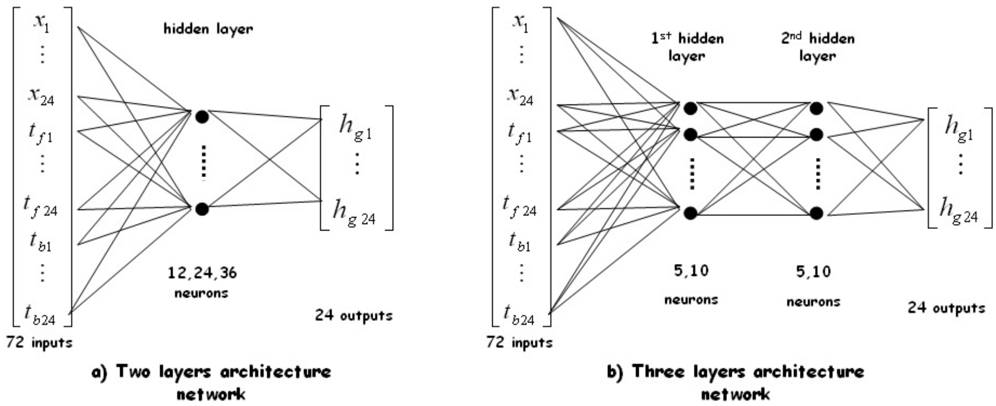

Figure 2.11 Irregular Interface depth network

2) In two-layer network, three architectures were employed in the study. They are 72-12-24, 72-24-24 and 72-36-24. The number of neurons in hidden layer was intentionally increased from 12 to 36 at a step of 12 to find out a correlation between accuracy of network output and the number of neurons in the hidden layer.

3) In three-layer network, the other three architectures were employed in the study. They are 72-15-10-24, 72-10-10-24 and 72-10-15-24. Note that there are three sets of neurons in the hidden layers. In the first set, number of neurons of the 1st hidden layer is greater than that of the second hidden layer. In the second set, the number of neurons in both hidden layers was equal whereas in the third set, the number of neurons of the first hidden layer is less than that of the 2nd hidden layer. These were done in order to find out a correlation between accuracy of network output and a suitable number of neurons in both hidden layers.

4) The hyperbolic tangent sigmoid function or "tansig" and the linear function or "purelin" were used as the transfer function of hidden layers and output layer respectively.

5) All datasets were normalized by minimum-maximum normalization method before feeding to the designed networks. The Levenberg-Marquardt training algorithm or "trainlm" was used in training the networks by setting goal and epoch of training at 0.01 and 10^6 respectively.

6) The trained networks were tested by the testing datasets. The mean and standard deviation of error obtained from each network will be compared and the

network that has the least mean of error or the least standard deviation of error will be chosen as a good depth network.

2.5.2 Velocity network for irregular interface

2.5.2.1 Training and testing datasets

The training and testing data sets for velocity networks were similar to those used in the depth networks, except that true velocities of the top and bottom layers were assigned as targets in training and testing data sets, instead of the depths vertically below geophones. The true velocities of the top and bottom layers were also determined from the SIP program.

2.5.2.2 Velocity network architectures

1) Two-layer and three-layer network architectures were selected in designing velocity network. All designed architectures have 72 input elements and 2 output elements. The output elements are velocities of the top and bottom layers of two-layer earth, whereas 72 input elements were composed of 24 geophone coordinates, 24 forward arrival times and 24 backward arrival times, as shown in Fig.2.12.

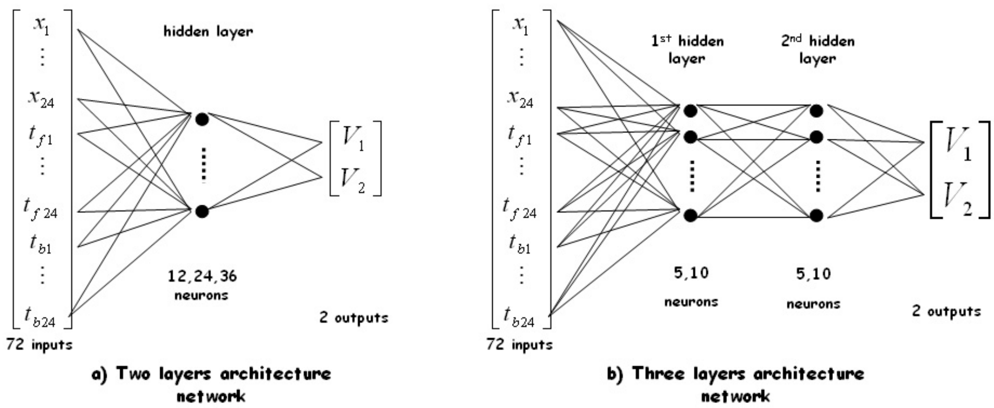

Figure 2.12 Irregular Interface velocity network

2) In two-layer network, three architectures were employed in the study. They are 72-12-2, 72-24-2 and 72-36-2. Note that the number of neurons in hidden layer was increased from 12 to 36 at a step of 12. In three-layer network, the other three architectures were employed in the study. They are 72-15-10-2, 72-10-10-2 and

72-10-15-2. Note that there are three sets of neurons in the hidden layers. In the first set, number of neurons of the first hidden layer is greater than that of the second hidden layer. They are equal in the second set and the number of neurons in the first hidden layer is less than that of the second hidden layer in the third set

3) The hyperbolic tangent sigmoid function or “tansig” and the linear function or “purelin” were used as the transfer function of hidden layers and output layer respectively.

4) All datasets were normalized by Min-Max normalization method before feeding to the designed networks. The Levenberg-Marquardt training algorithm or “trainlm” was used in training the networks by setting goal and epoch of training at 0.01 and 10^6 respectively.

5) The trained networks were tested by the testing datasets. The mean and standard deviation of error obtained from each network will be compared and the network that has the least mean of error or the least standard deviation of error will be chosen as a good velocity network.