

COMPARING MODELS GRM, REFRACTION TOMOGRAPHY AND NEURAL NETWORK



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Introduction



- The general reciprocal method (GRM) assumes a layered model and is effective when the velocity structure is relatively simple and refractors are gently dipping.
- Refraction tomography is capable of modeling the complex velocity structures.
- In contrast to time consuming and complicated numerical methods, neural network is found to be of potential applicability. Neural network ability to establish a relationship between an input and output space is considered to be appropriate for mapping seismic velocity.

Research Purpose



To introduce a new approach to analyze seismic refraction data.

Expectations



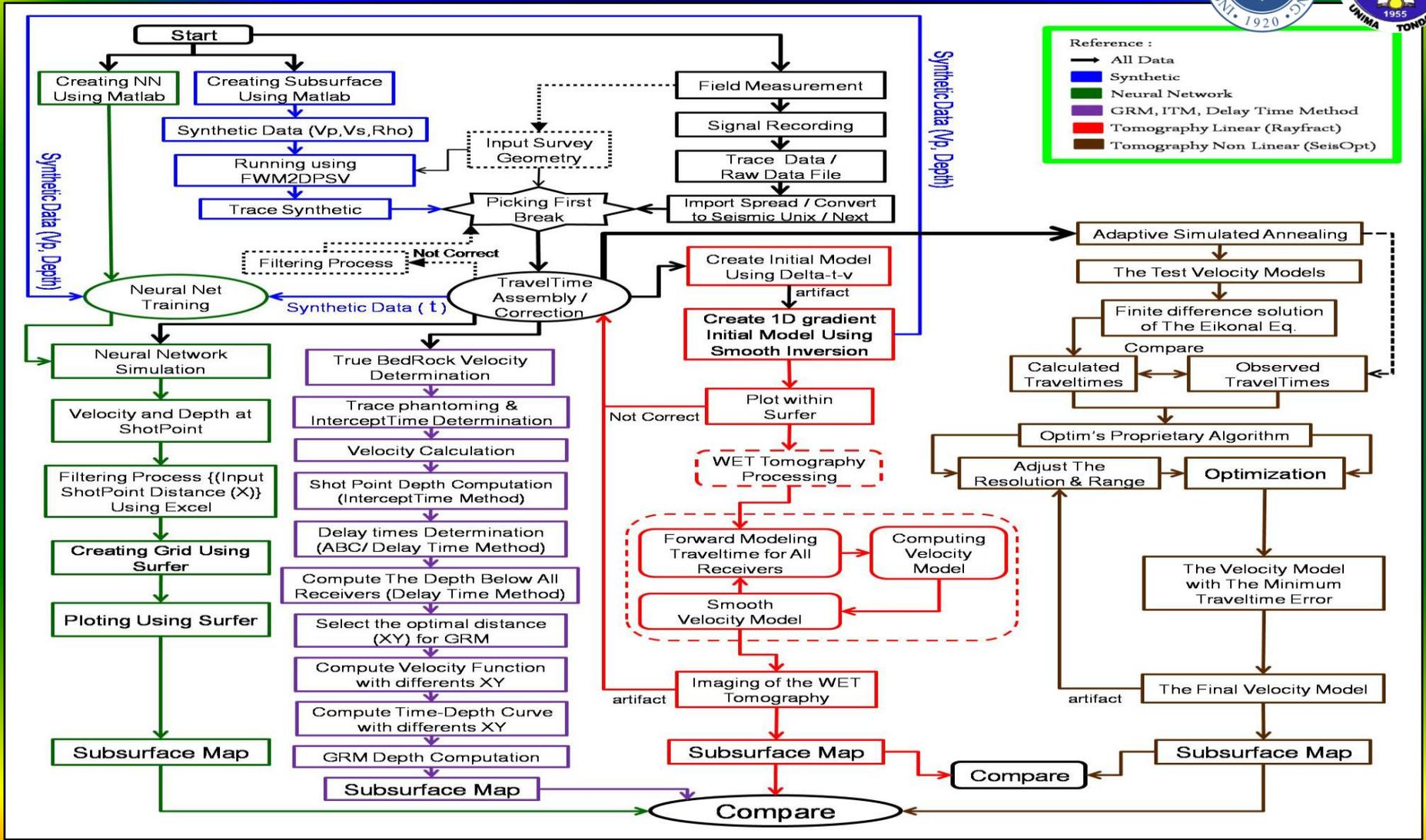
As an innovation in seismic data interpretation.

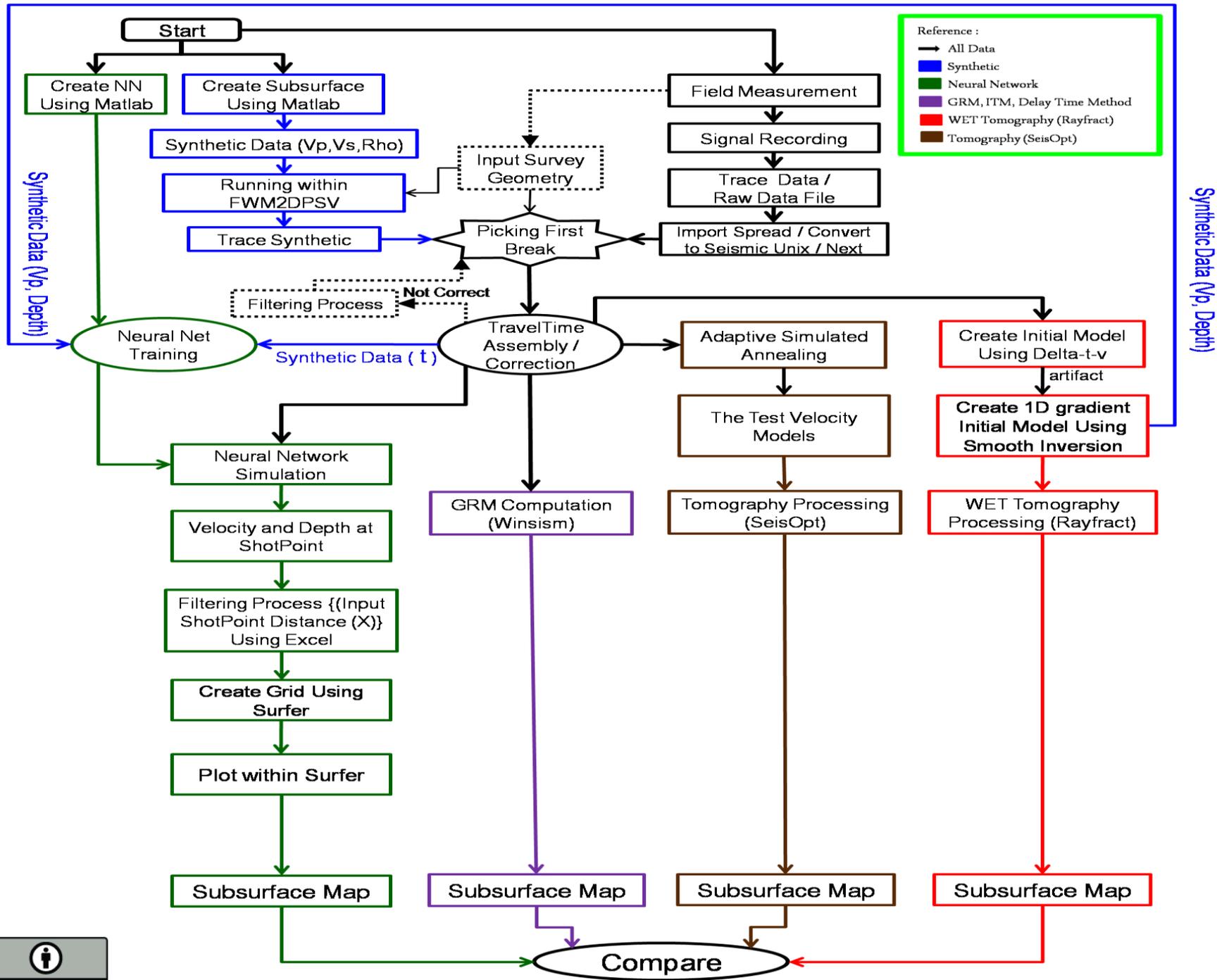
Research Method



1. General Reciprocal Method (GRM):
 - Winsism Software
2. Refraction Tomography Method:
 - Rayfract™ Software
 - SeisOpt@2D Software
3. Neural Network

Research Scheme





Reference :

- All Data
- Synthetic
- Neural Network
- GRM, ITM, Delay Time Method
- WET Tomography (Rayfract)
- Tomography (SeisOpt)

Refraction Tomography



- **Rayfract™ Software:**

 - Inversion Algorithm;*

 - Wavepath eikonal travelttime inversion (WET)

 - Forward Modeling;*

 - Finite-difference solution to the eikonal equation (Qin et al., 1992)

- **SeisOpt@2D Software:**

 - Inversion Algorithm;*

 - Generalized simulated annealing non linear optimization

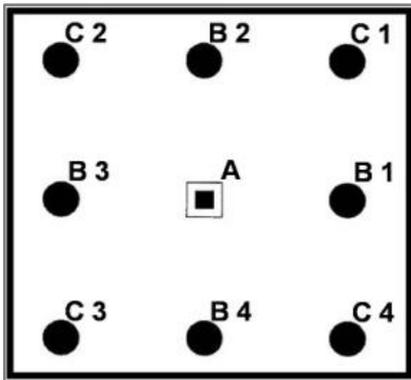
 - Forward Modeling;*

 - Finite-difference solution to the eikonal equation (Vidale, 1988)

Each of the systems contains a components for generating an initial velocity model.

Finite-difference Solution to The Eikonal Eq.

$$\left(\frac{\partial t}{\partial x}\right)^2 + \left(\frac{\partial t}{\partial z}\right)^2 = S(x, z)^2$$



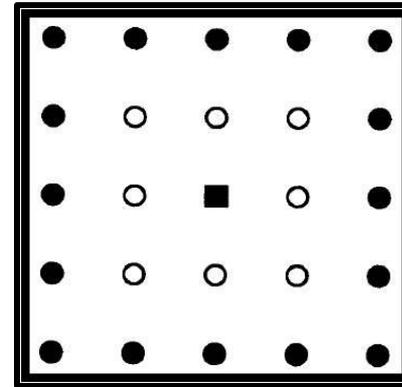
$$t_{Bi} = \frac{h}{2} (S_{Bi} + S_A)$$

$$t_{Ci} = t_A + [2(h\bar{S}_i)^2 - (t_{Bi+1} - t_{Bi})^2]^{1/2}$$

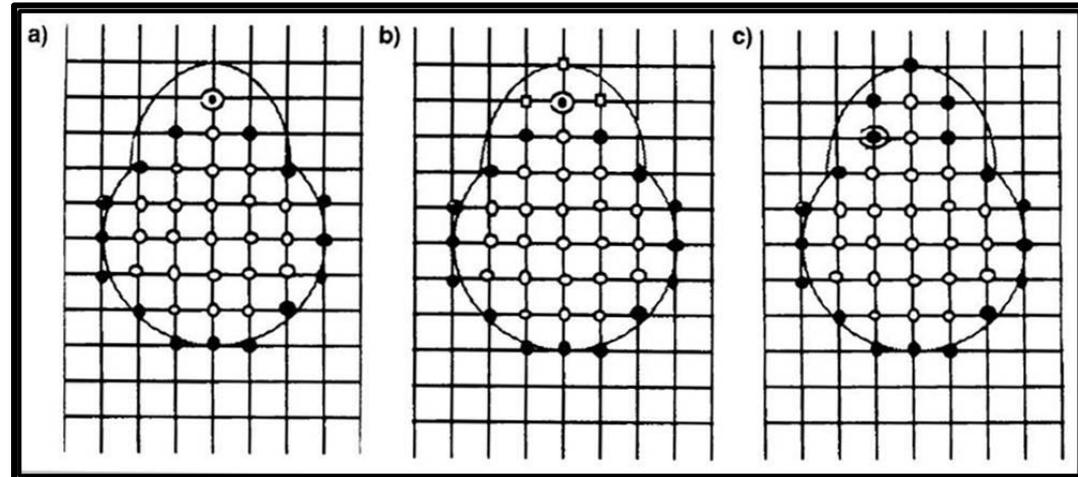
* when $i = 4$; $t_{Bi+1} = t_{B1}$

$$* \bar{S}_i = \frac{1}{4} (S_A + S_{Ci} + S_{Bi} + S_{Bi+1})$$

• *Expanding Square Method* (Vidale, 1988)



• *Expanding Wavefront Method* (Qin et al., 1992)



Wavepath Eikonal Traveltime inversion (WET)

(Schuster and Quintus-Bosz, 1993)

1. Pick the first-arrival traveltimes from the seismograms (τ_{rs}^{obs}).
2. An initial slowness model is proposed and the eikonal equation is efficiently solved by a finite-difference method (Qin et al., 1992) to get τ_{xs} and τ_{xr} . The traveltime residual is computed by

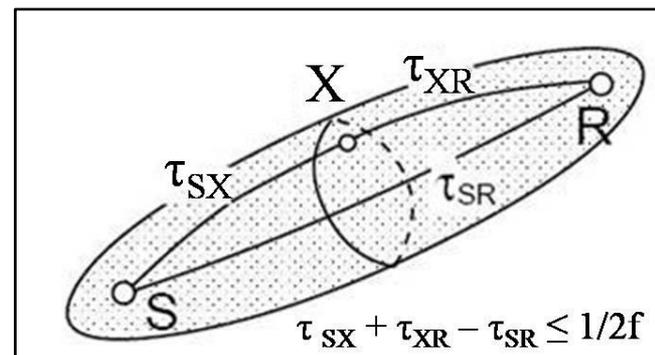
$$\Delta\tau = \tau_{rs} - \tau_{rs}^{obs}$$

3. The source weighting function in equation

$$y(\mathbf{x}) = \frac{2S(\mathbf{x})A''}{A_{xr}A_{xs}} \times W'''(\tau_{xs} + \tau_{xr} - \tau_{rs})$$

is evaluated at all points within the medium.

4. The slowness model is updated and these steps are iteratively repeated until convergence.



Generalized simulated annealing

(Pullammanappallil and Louie, 1994)

1. Compute travel times through an initial model {Using Finite-difference solution to the eikonal equation (Vidale, 1988)}.
2. Determine the least-square error (E_0),

$$E_i = \frac{1}{n} \left[\sum (t_j^{obs} - t_j^{cal})^2 \right]$$

3. Perturb the velocity model by adding random constant-velocity boxes. The boxes can have any aspect ratio and vary between one cell size and the entire model size.
4. Compute the new least-square error (E_1),

$$P_c = \exp[(E_{min} - E_1)^q \Delta E / T]$$

5. Repeat steps 3 through 4 until the optimization converges.

Neural Network (NN)



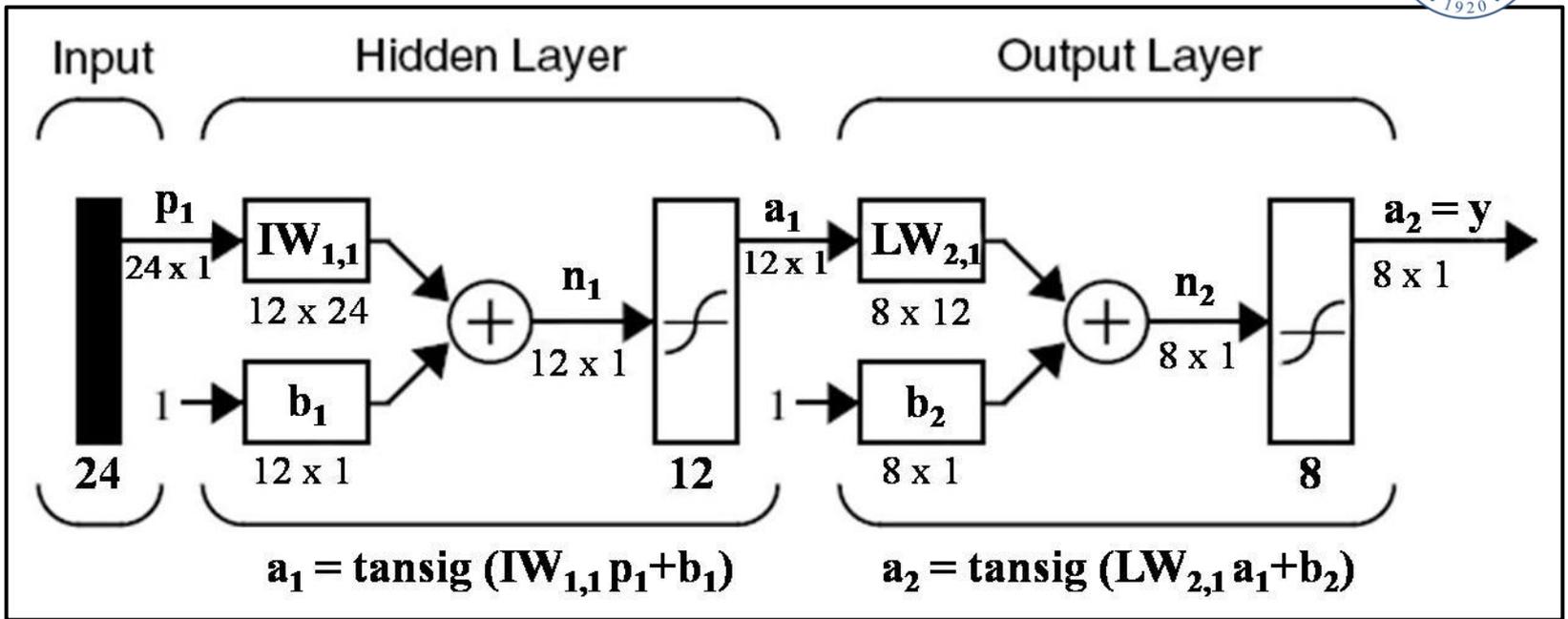
- The NN have the ability to map a space, which is called input space to another one which is called output space.
- NN can be trained to compute desired output patterns according to input patterns. The outstanding characteristic of this technique lies in its ability in computing accurate output patterns even for unknown input patterns.

Neural Network (NN)

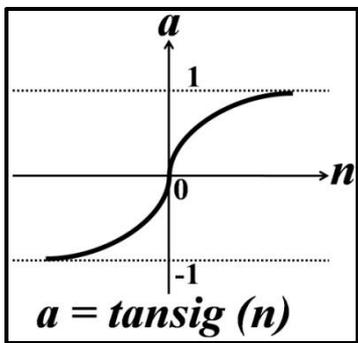


- This study is based on application of **feedforward Backpropagation NN**, which contains an input, a hidden layer and an output ([see Fig](#)).
- Information flows forward from input to hidden layer and then through output ([see Fig](#)).
- Connections are only between adjacent layers and there is no connection between neurons in the same layer ([see Fig](#)).

Neural Network: Structure



•A neuron is a simple processing node which calculates the output a according to an input n . The value of input n for neuron i is the weighted sum of all outputs of neurons in previous layers (Eq. 1). Index j indicates neurons in previous layers.



$$n_i = \sum_j W_{ij} a_j \quad \dots \text{(Eq. 1)}$$

$$a_i = \frac{2}{1 + e^{-n_i}} - 1 \quad \dots \text{(Eq. 2)}$$

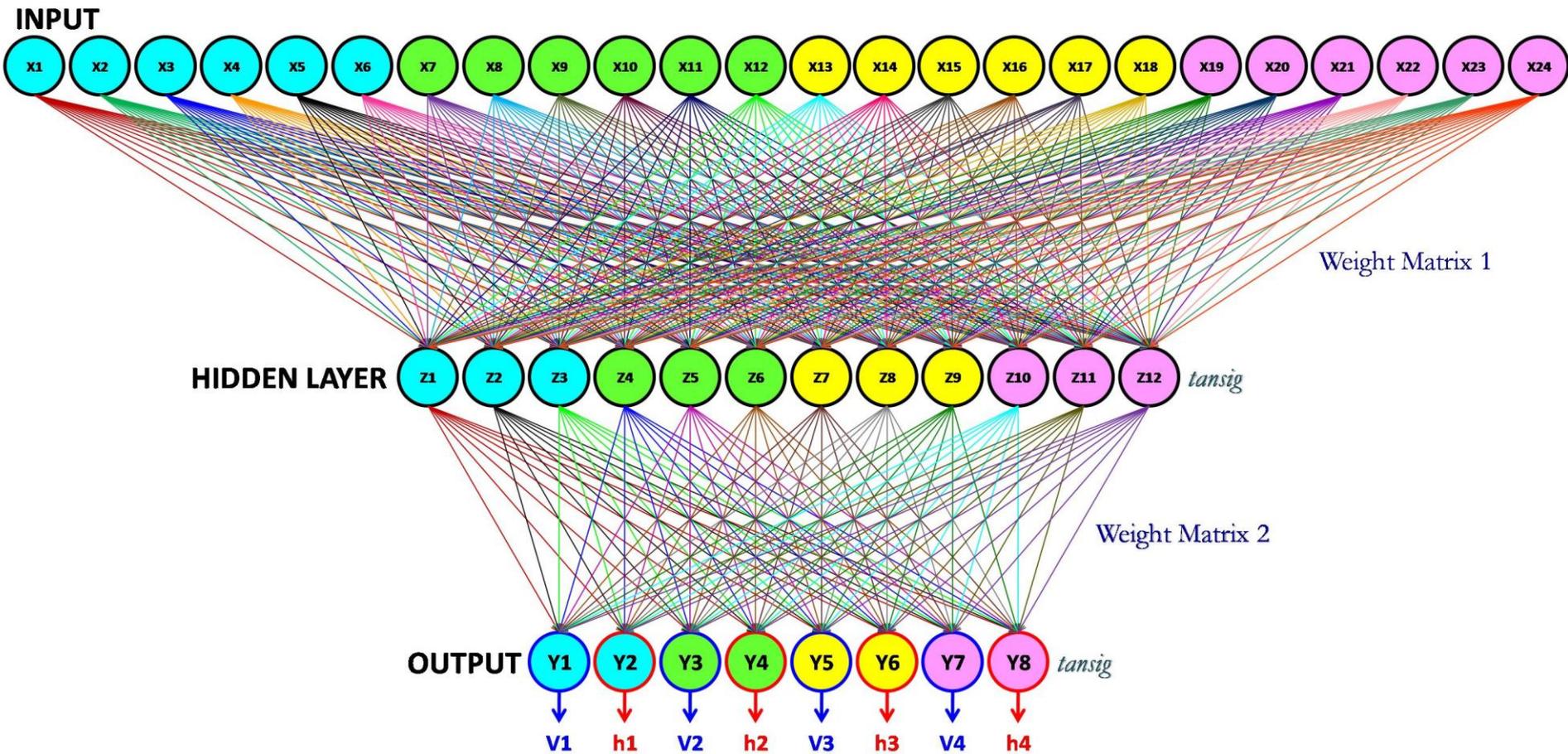
•The value of output a is calculated according to a tan-sigmoidal function as follows (Eq. 2)

Neural Network (NN)



- As the structure and the rules of feedforward flow are defined, the network should undergo the training process.
- The structure and output function do not change during training. Training comprises the process of initializing the weights W (which are the only free parameters in network) so that the error between the computed output and the desired output for all samples is minimized.
- In this study, picked travel times were considered as inputs and the corresponding velocity and elevation as outputs.

Neural Network: Structure



Neural Network: Structure

The screenshot displays the MATLAB Neural Network Designer interface for a network named 'NetArmstrong'. The network structure is a feed-forward network with three layers: an input layer with 24 neurons, a hidden layer with 12 neurons, and an output layer with 8 neurons. The training parameters are as follows:

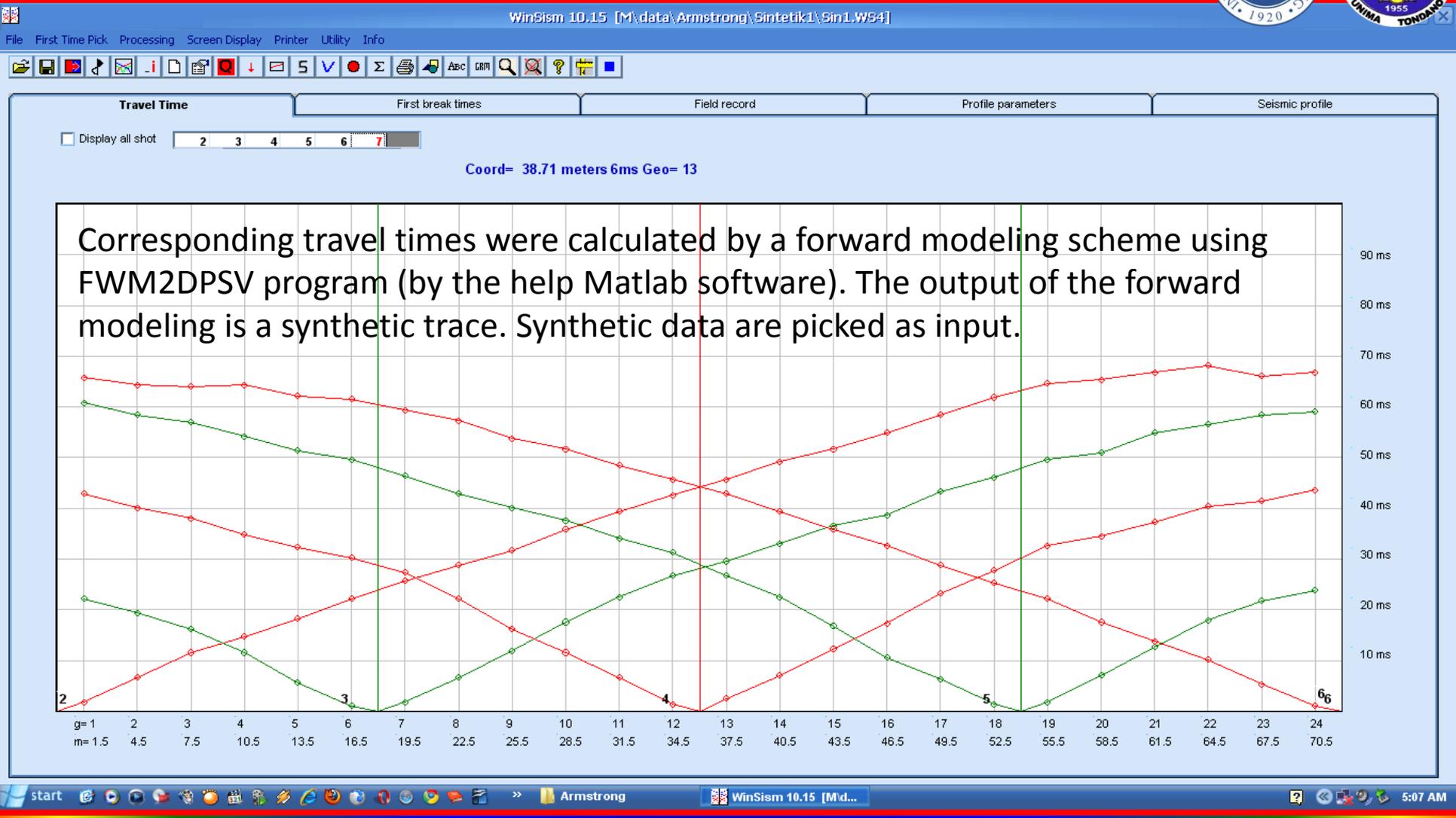
Parameter	Value	Parameter	Value
epochs	4000	max_perf_inc	1.04
goal	1e-005	mc	0.9
lr	0.01	min_grad	1e-006
lr_dec	0.7	show	25
lr_inc	1.05	time	Inf
max_fail	5		

The 'Network Properties' section shows the following settings:

- Network Type: Feed-forward backprop
- Input ranges: ; 0 1; 0 1; 0 1; 0 1]
- Training function: TRAINGDX
- Adaption learning function: LEARNGDM
- Performance function: MSE
- Number of layers: 2
- Properties for: Layer 1
 - Number of neurons: 12
 - Transfer Function: TANSIG

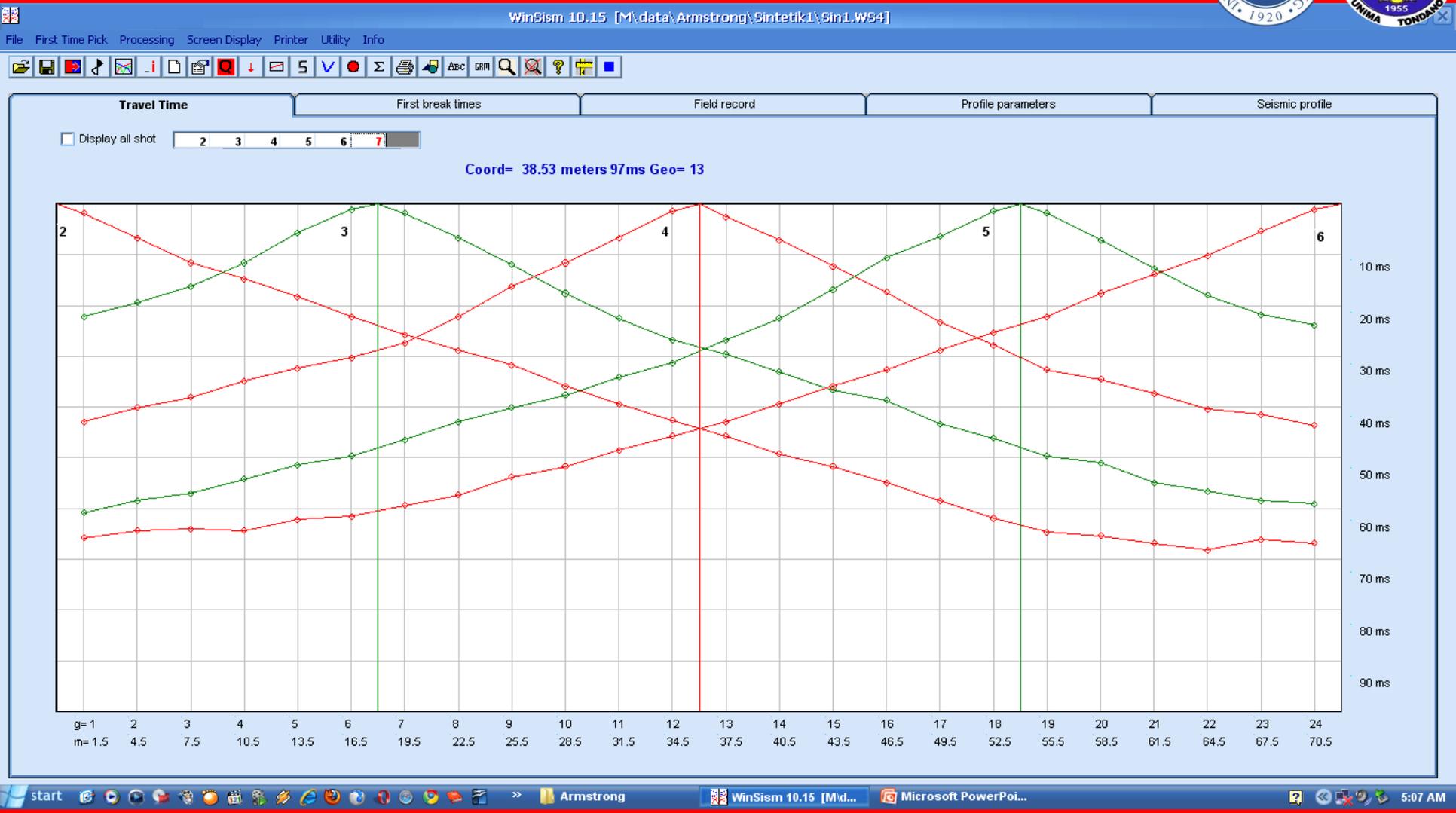


Neural Network: Input Data



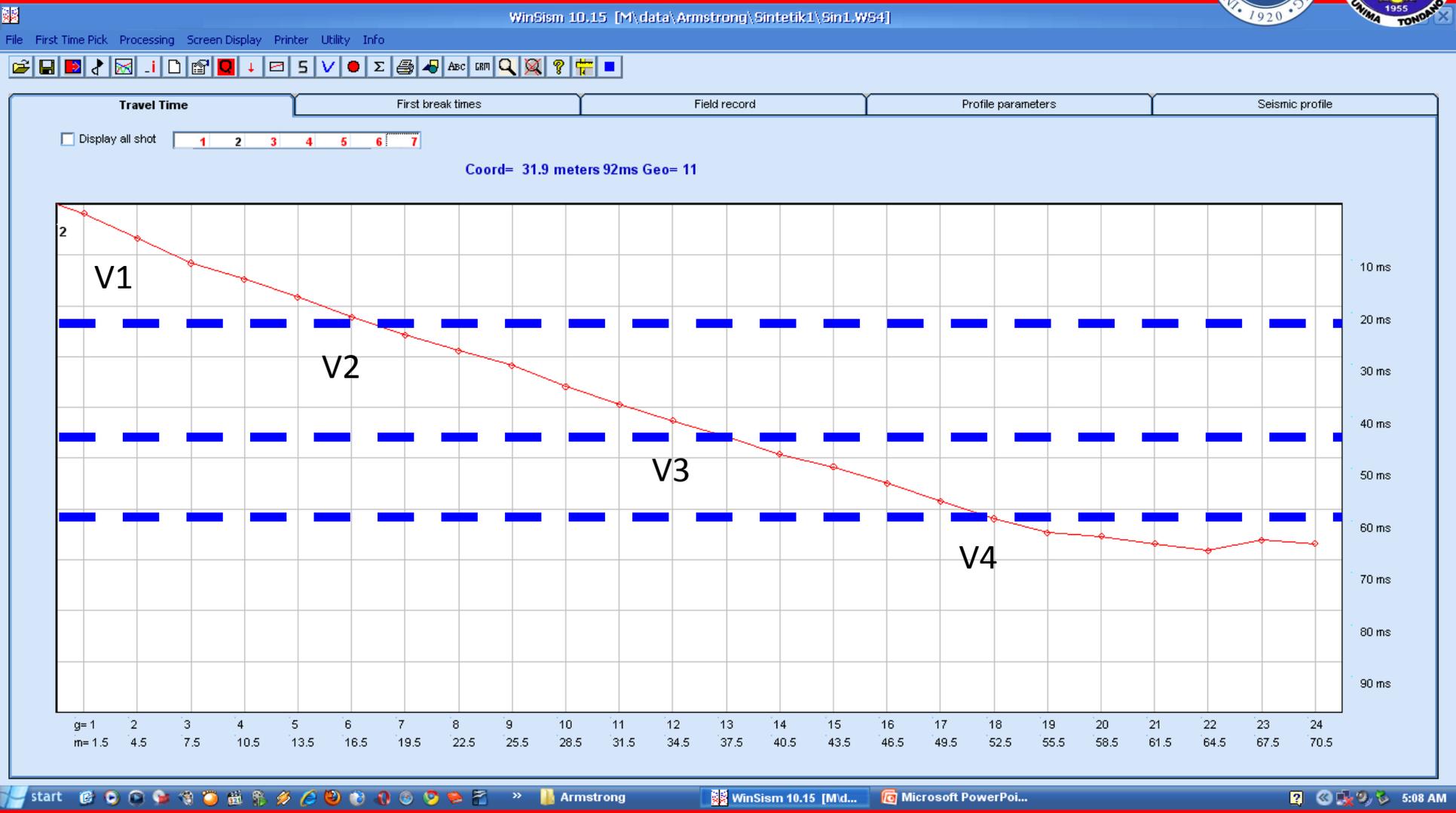


Neural Network: Input Data



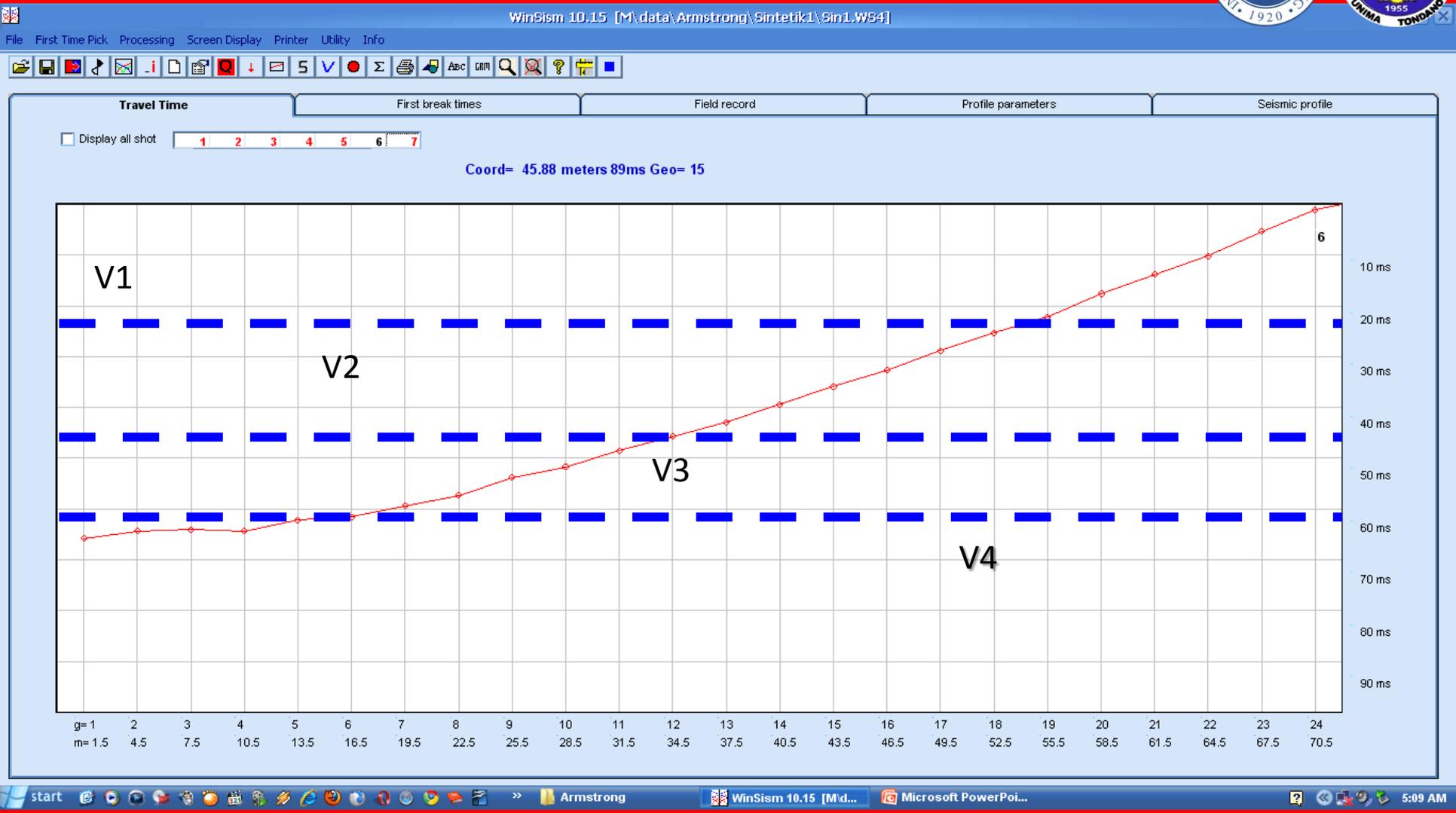


Neural Network: Input Data

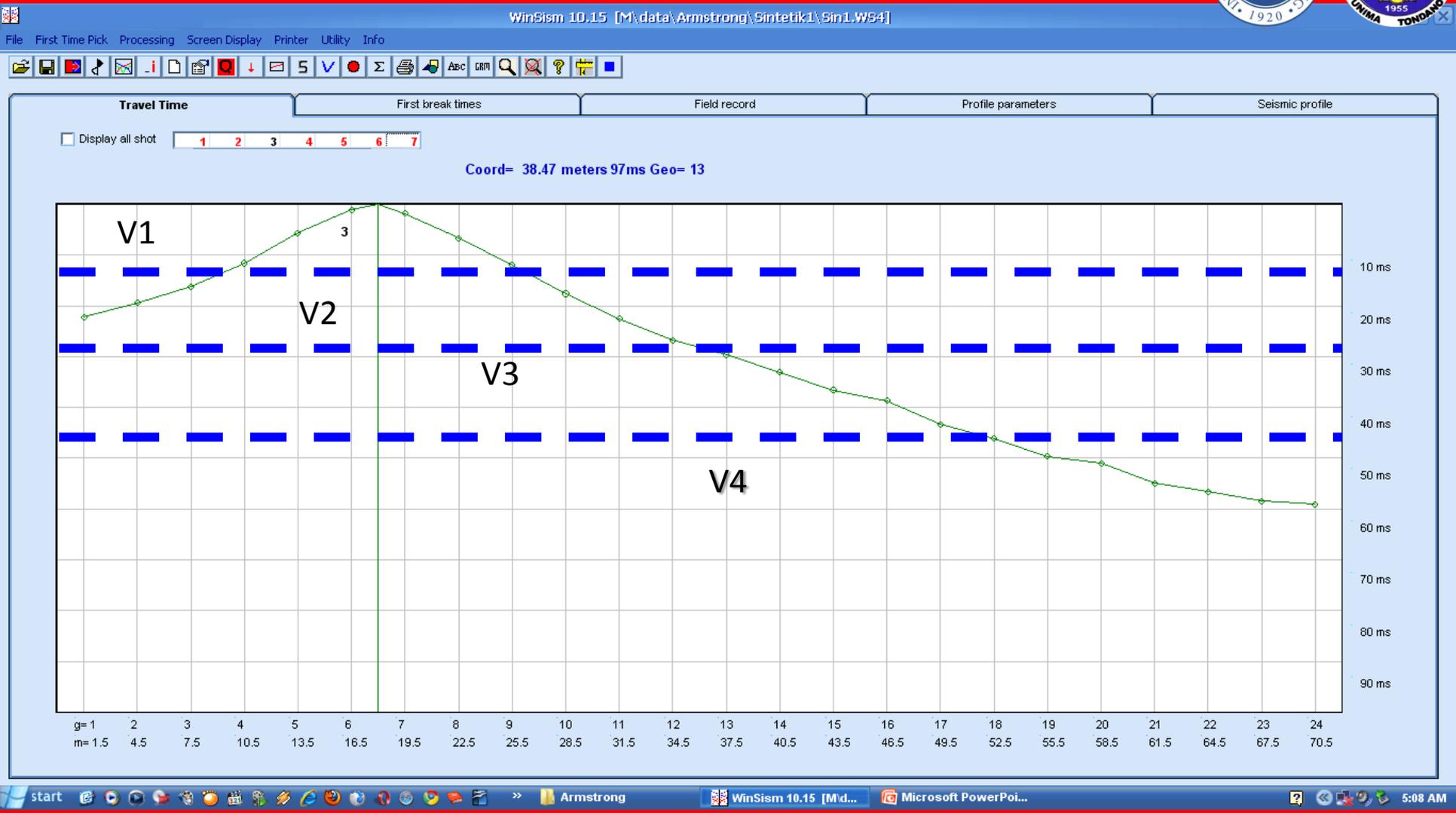




Neural Network: Input Data

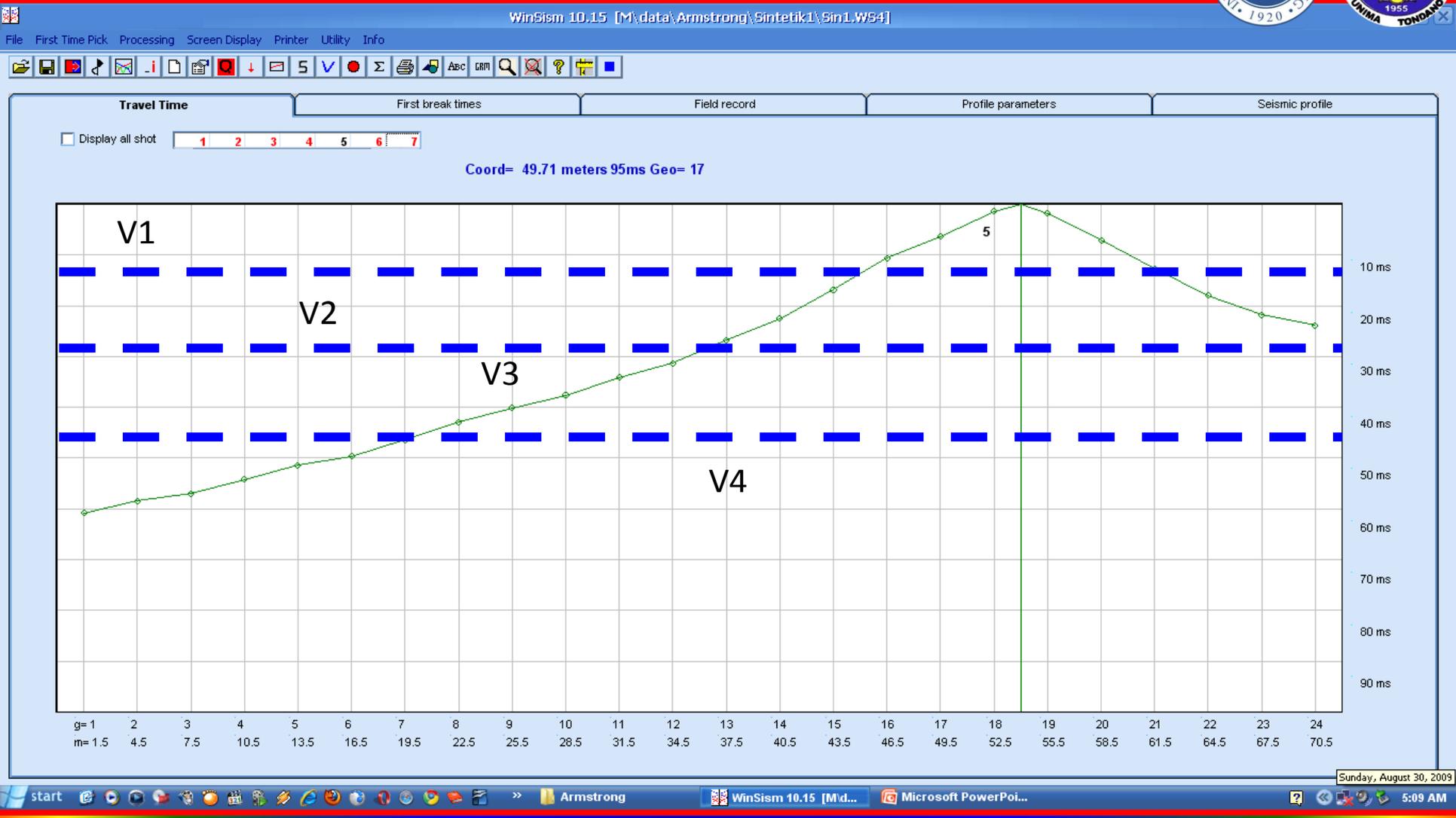


Neural Network: Input Data



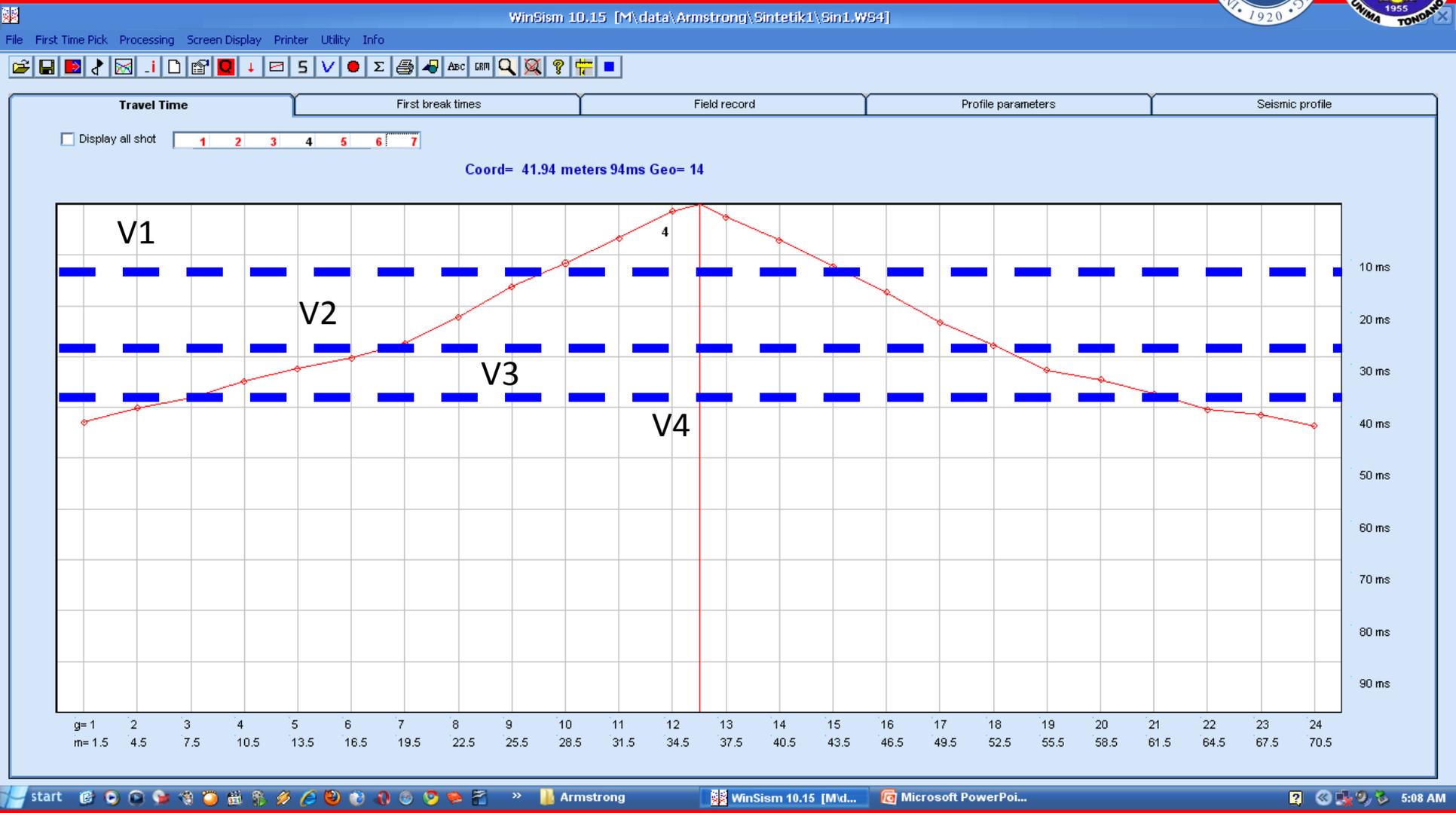


Neural Network: Input Data

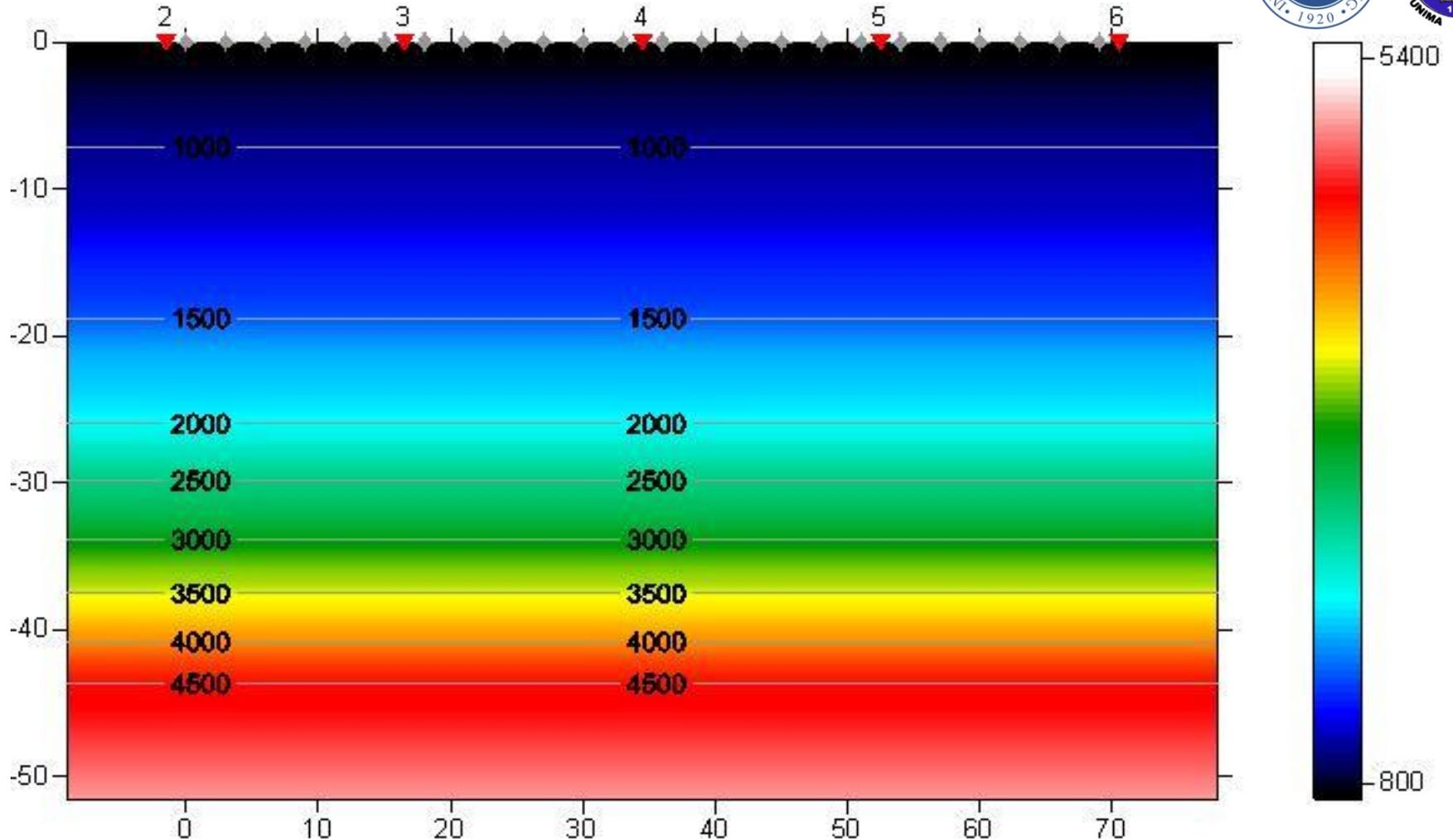




Neural Network: Input Data



Neural Network: Output Target



First break data were also modeled with inversion method, where the velocity and depth of the initial model used as the target data. The corresponding data sets (i.e., arrival times as input and velocity and depth as output) were fed to neural network in order to train the networks.



Neural Network: Training



Network: NetArmstrong

View Train Simulate Adapt Reinitialize Weights View/Edit Weights

Select the weight or bias to view:

```
[0.74077 1.0768 0.42058 0.45912 0.49399 0.59361 0.74275 0.98517 0.16519 0.44939 -0.92264 -0.74573 -0.22768 -0.37834 0.18075 0.11422 -0.028116 -0.34812 -0.64217 -0.56664 -0.97287 0.052893 -0.94154 0.92315;
0.88848 -0.10966 0.3969 -0.65323 0.36572 -0.74716 -0.81001 -0.66614 -0.31028 0.30303 0.78105 -0.70564 -1.1589 0.66872 -1.1547 -0.61442 -0.28056 0.81738 -0.90829 -0.34218 -0.64644 -0.65393 -0.56236 -0.39632;
-0.81396 0.676 0.56917 1.0411 -0.44148 0.069434 1.0024 0.61846 -1.0068 -0.048071 -1.0279 -0.73321 -0.53094 -0.255 -0.56066 0.55486 -0.10194 0.83994 -0.5801 0.21446 0.6626 -0.036138 -0.37641 0.42153;
0.91641 -0.78726 -0.22644 -1.0107 0.41648 0.4647 -0.30818 0.58673 -0.33536 -0.89586 0.63473 -0.7807 -0.81071 -0.83994 -0.30395 -0.66798 -0.4084 0.13079 -0.121 -0.50789 -1.0248 0.2896 0.41222 -0.65486;
0.31588 -0.19262 0.3671 -0.15675 0.36456 0.91516 -0.74508 -0.30833 -0.82647 -0.67895 0.72252 0.84699 -0.79691 0.61093 0.70541 0.38564 -0.033693 0.2299 -0.513 0.17886 0.95388 0.35633 -0.9299 -1.181;
-0.86649 0.90375 -0.66486 -0.16588 -0.67624 1.0672 -0.47556 0.21484 0.6903 0.93356 0.84361 0.22329 -0.52847 -0.22572 -1.0222 -0.66196 0.055263 0.20419 0.95578 0.48629 0.53033 -0.21357 0.4865 0.53886;
-0.53386 0.70412 0.49634 0.63951 -0.91842 0.11343 0.27924 -1.0226 -0.45535 -0.83814 -1.0019 0.1198 -0.19987 -0.62303 -1.1019 -0.31756 0.76479 -0.70509 -0.16913 -0.67149 -0.028422 -0.32047 -0.94865 -0.00096951;
0.096546 0.97235 -1.053 0.56848 -0.064168 -0.85228 -0.1352 -1.0383 -0.019526 0.6208 -0.29883 -0.84088 -1.0427 -0.27215 -0.77511 0.21244 0.57936 -0.48525 -0.7435 -0.87925 0.11934 1.0164 0.29855 -0.076599;
0.9833 0.38186 -0.3552 -0.47016 1.1193 -0.56635 -0.12072 0.24479 -0.52201 0.2718 -0.32204 0.9089 1.0265 -0.69504 0.46924 0.7435 0.4527 0.092561 1.0475 -0.27233 -0.40434 -0.86379 0.088617 0.96623;
0.93864 -0.90415 -0.8096 0.10063 -0.20091 -0.38226 0.73529 0.62346 0.28589 1.04 0.66657 0.29264 0.88451 -0.77916 0.39286 -0.90892 -0.30797 -0.62806 0.8681 -0.47649 -0.21429 0.58842 0.37881 0.041851;
-0.74147 0.7559 -0.87265 -0.11823 0.18438 0.73748 0.18423 0.93947 -0.5137 -0.9139 -0.149 -0.32312 -0.020219 0.95678 0.31953 0.92943 0.67436 0.74519 -0.13284 -0.16463 1.0024 0.89466 0.46541 0.25455;
1.0565 0.9686 0.72127 0.32393 -0.62856 -0.56304 0.10072 -0.84484 0.33282 -0.1493 0.8983 0.0003898 -0.053274 0.98993 -0.14579 0.57932 0.03731 -0.7201 -0.90269 -0.016026 0.075299 0.62954 0.86916 0.77217]
```

Revert Weight Set Weight

Network: NetArmstrong **Network: NetArmstrong** **Network: NetArmstrong**

View Train Simulate Adapt Reinitialize Weights View/Edit Weights

Select the weight or bias to view:

```
[0.27261 -0.61242 0.14426 0.88918 -0.63139 0.62321 0.0002153 -0.50949 0.54321 -0.2554 -0.76089 0.19567;
-0.20125 0.015906 -0.59524 0.66927 -0.54062 0.20866 -0.30454 0.13084 0.36128 0.083345 0.41719 -0.71295;
-0.50863 -0.75003 0.44108 0.44716 0.84184 -0.037237 -0.15306 -0.33524 0.48472 1.219 0.41312 -0.12328;
-0.38368 0.098062 0.55952 -0.27851 0.82044 -0.10419 -0.54217 0.82185 0.25658 0.34652 -0.082164 0.25751;
0.66735 -1.1107 0.11133 -0.26085 -0.47572 -0.41311 0.50113 -0.36323 -0.41391 -0.1632 -0.31091 -0.11098;
-0.55679 0.071564 -0.60632 0.33708 -0.030375 0.80357 0.47799 0.54162 -0.53847 -0.1467 0.02138 -0.1816;
-0.34345 -1.1378 0.53432 -0.39389 -0.21992 -0.60327 -0.42129 -0.04922 1.0028 -0.10344 -0.34987 0.14492;
-0.52033 -0.32429 0.062378 -0.51079 -0.14807 -0.72155 0.38617 0.3608 -0.52016 0.59177 -0.59501 -0.44574]
```

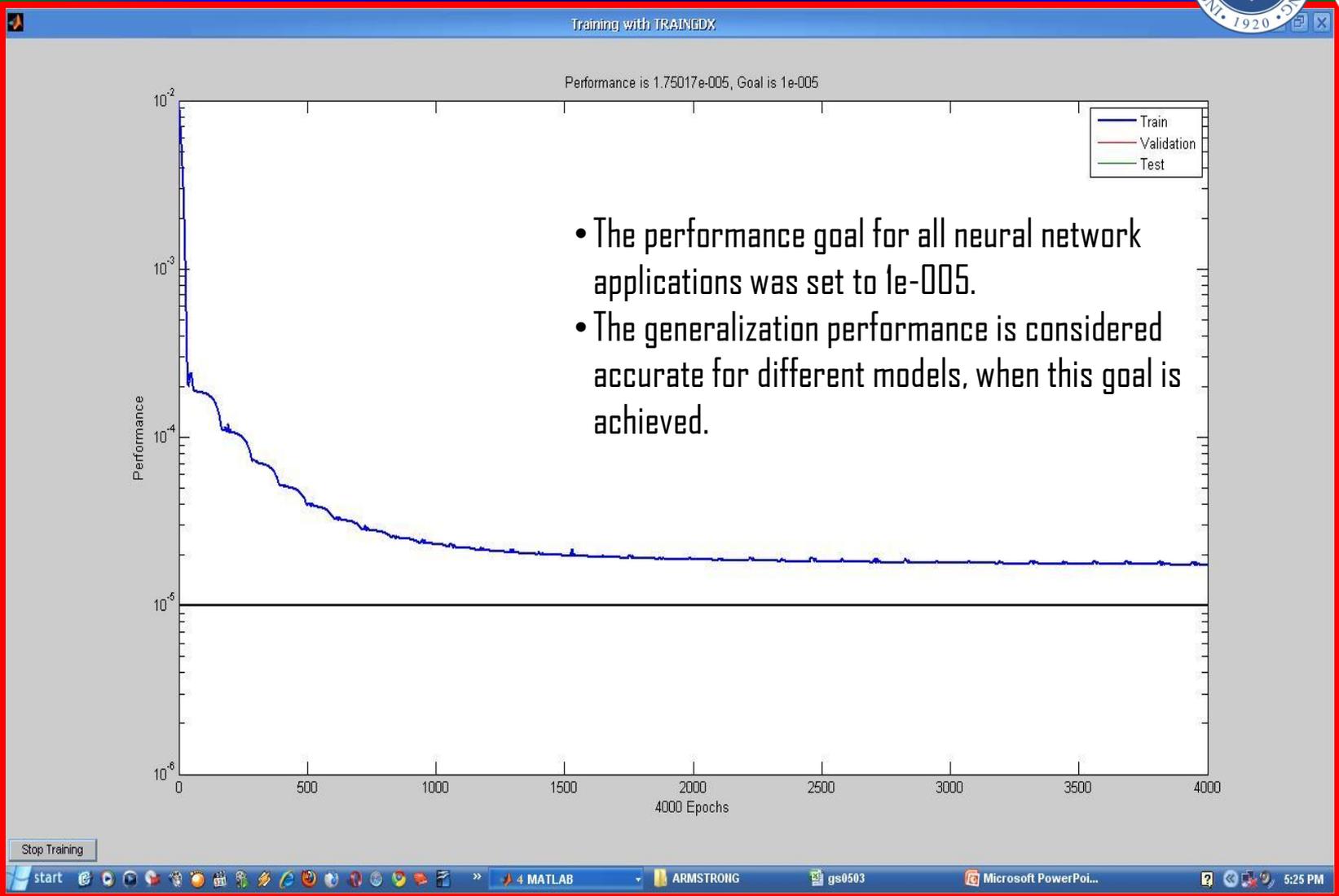
Select the weight or bias to view:

```
[-2.3308;
0.14145;
1.1932;
2.621;
-1.3139;
-0.5759;
3.2123;
1.2729;
0.52962;
-0.45139;
-3.8238;
-1.0103]
```

Select the weight or bias to view:

```
[-1.4407;
-0.81865;
0.59685;
0.045813;
0.1148;
-0.83748;
-0.86651;
-1.6413]
```

Neural Network: Training

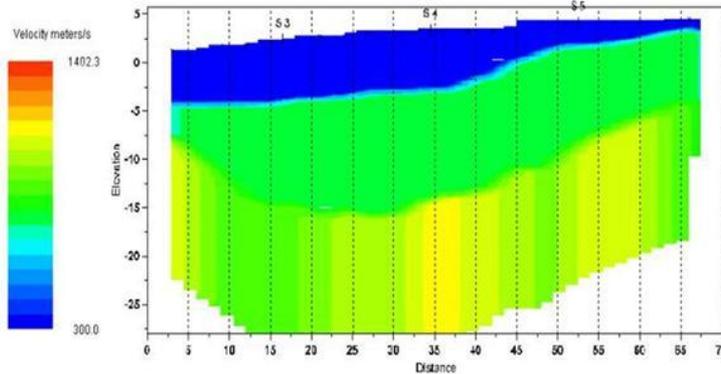


- The performance goal for all neural network applications was set to $1e-005$.
- The generalization performance is considered accurate for different models, when this goal is achieved.

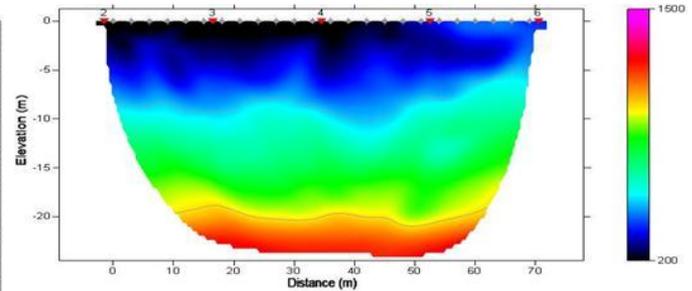
Comparing: Line 1



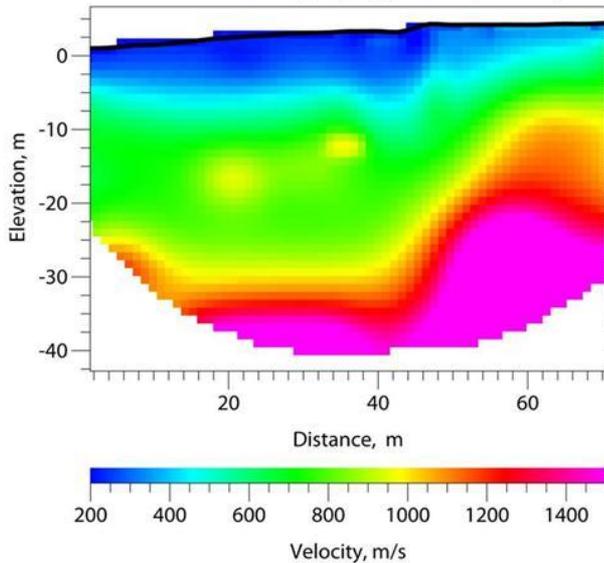
GRM Method (Winsism)



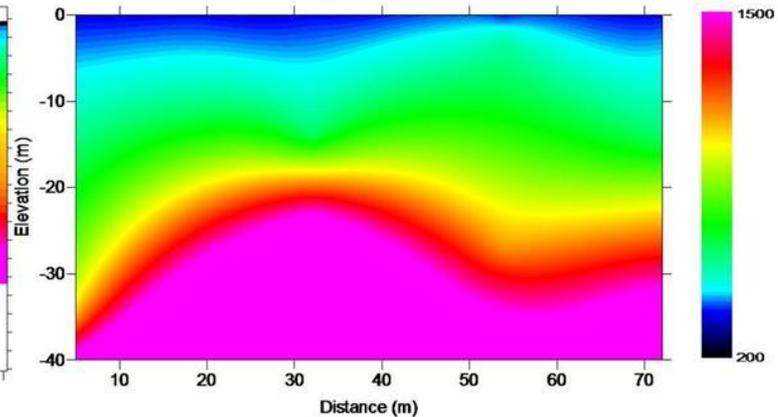
WET Tomography (Rayfract™)



Tomography (SeisOpt@2D)



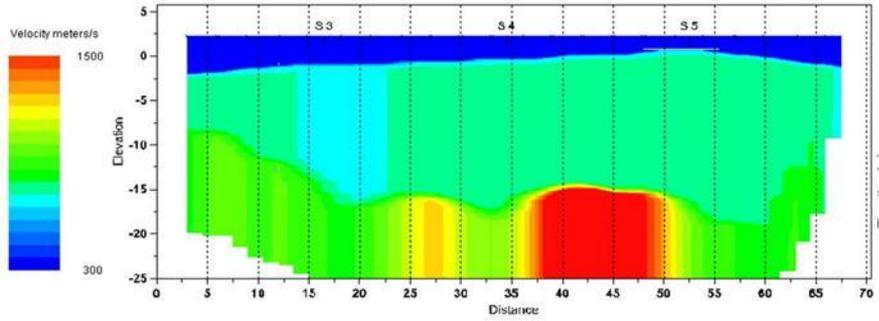
Neural Network



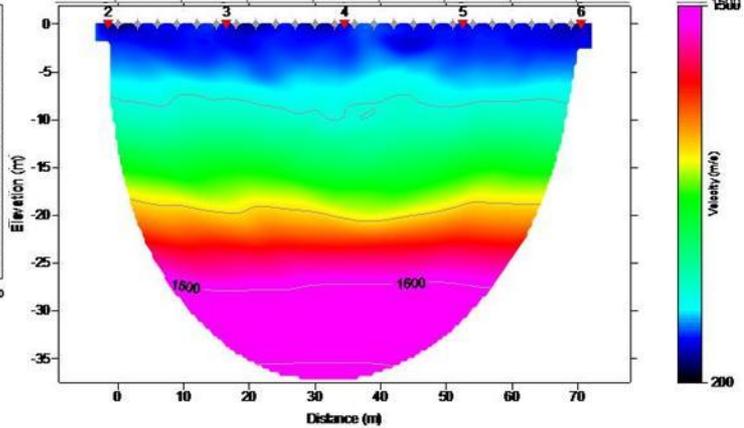
- The first layer shows a velocity of 343-449 m/s and corresponds to **top soil**. Its thickness varies from 1 m to 5 m.
- The second layer shows velocity in the range of 449 to 837 m/s (Depth 5-10m). It might be associated to **smooth grain above the tuff layer**.
- **Clay Basement** with a velocity of 1100-2100 m/s is located at a depth of about 22 m.

Comparing: Line 2

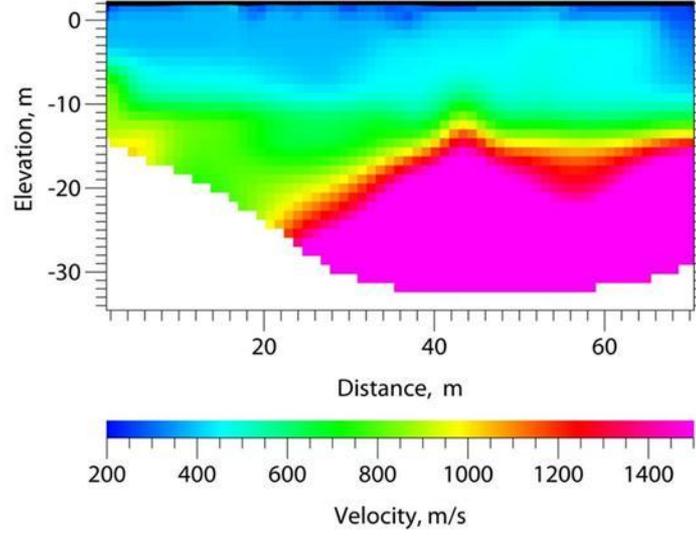
GRM Method (Winsism)



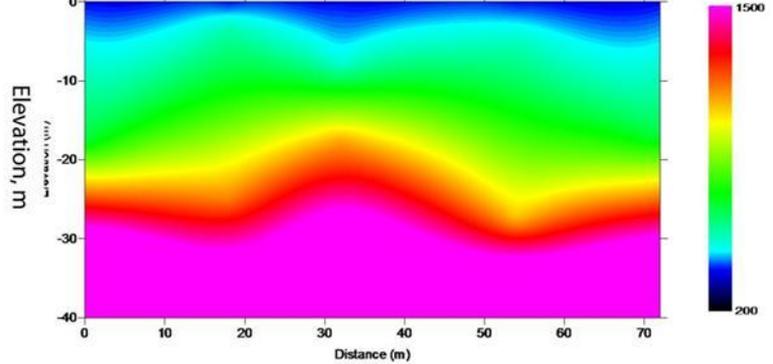
WET Tomography (Rayfract™)



Tomography (SeisOpt@2D)



Neural Network



- The first layer shows a velocity of 343-449 m/s and corresponds to **top soil**. Its thickness varies from 1 m to 5 m.
- The second layer shows velocity in the range of 449 to 837 m/s (Depth 5-10m). It might be associated to **smooth grain above the tuff layer**.
- **Clay Basement** with a velocity of 1100-2100 m/s is located at a depth of about 22 m.

Conclusion



The similarity of those models shows the success of neural network as a new alternative in seismic data interpretation.

Notes



However the results of this research indicated that the velocity errors, **which were in all cases acceptably small** were subject to increase with increasing the depth of the layers.

Therefore, the approach for reducing the velocity error intervals requires further research.

References

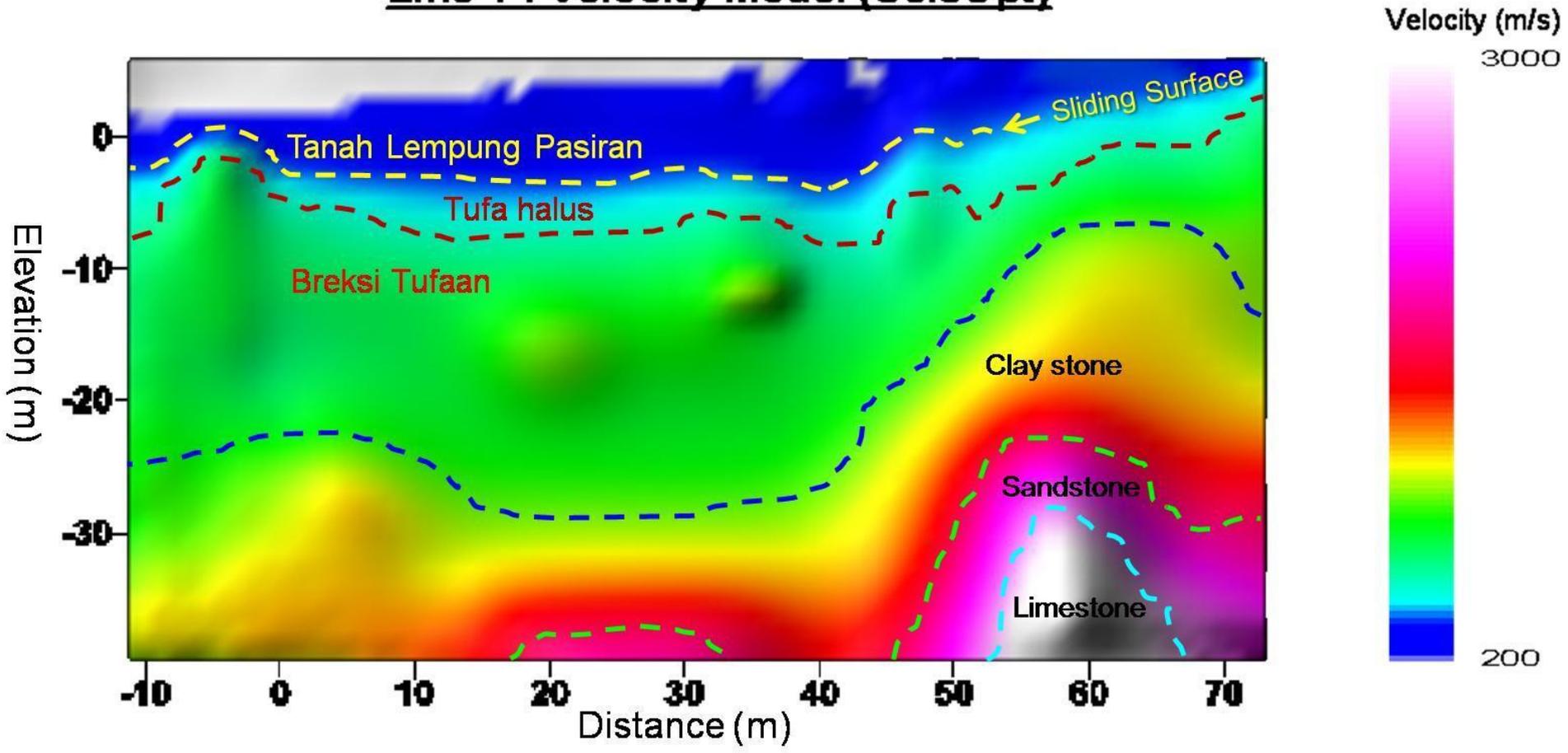


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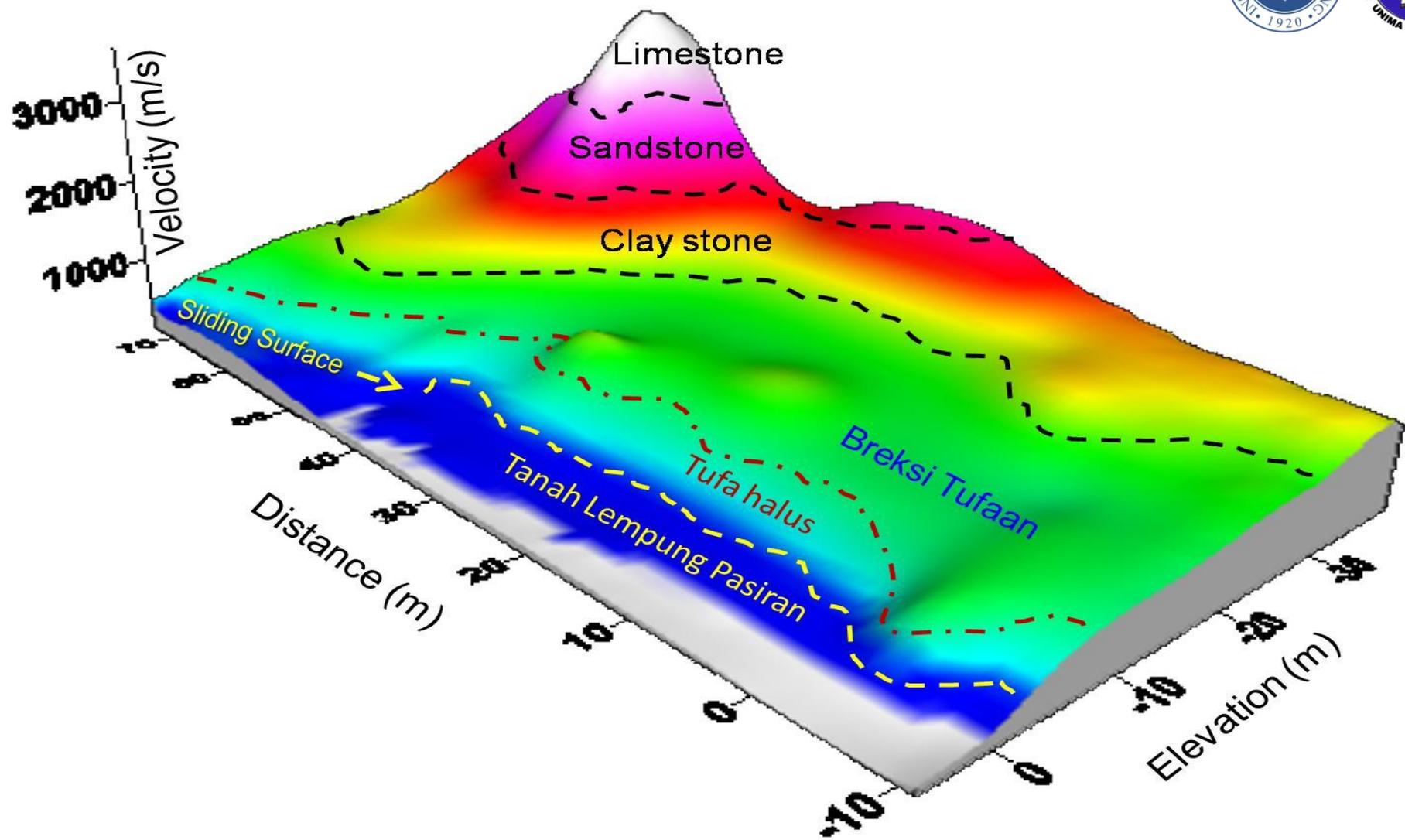
Attachment



Line 1 : Velocity Model (SeisOpt)

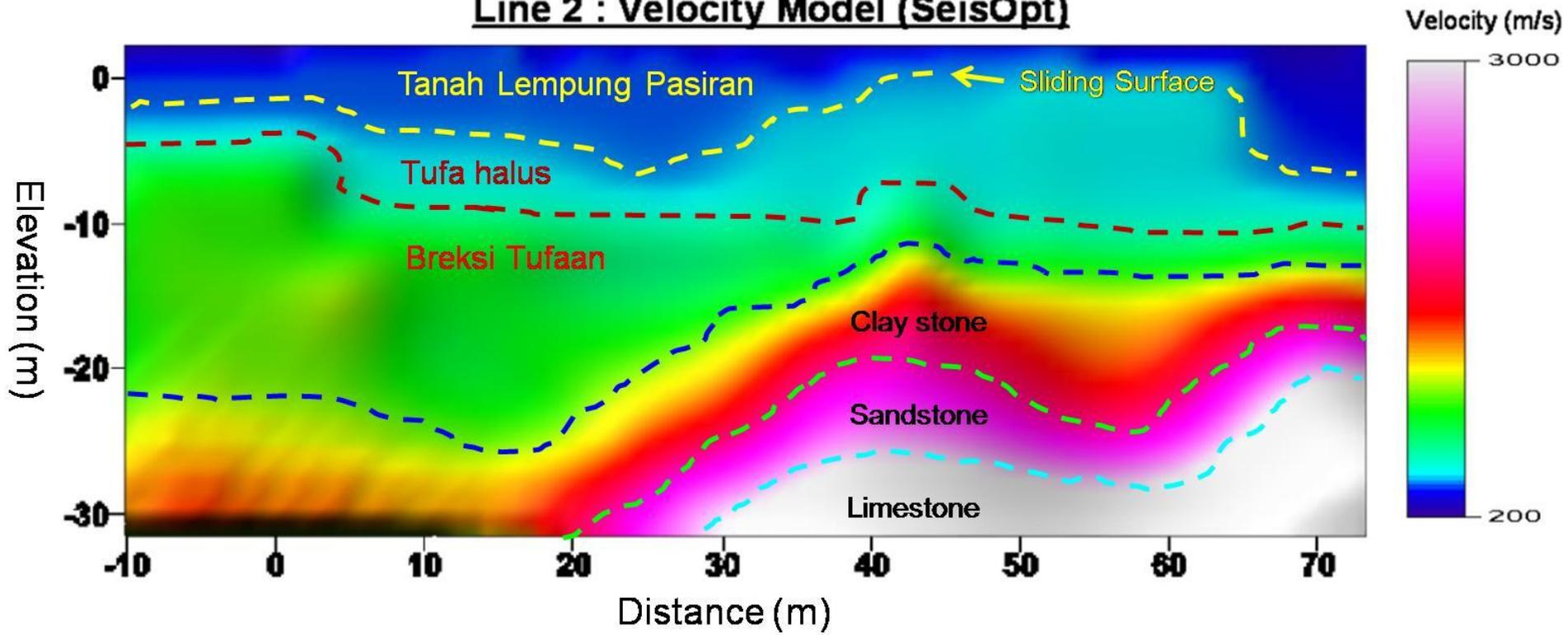


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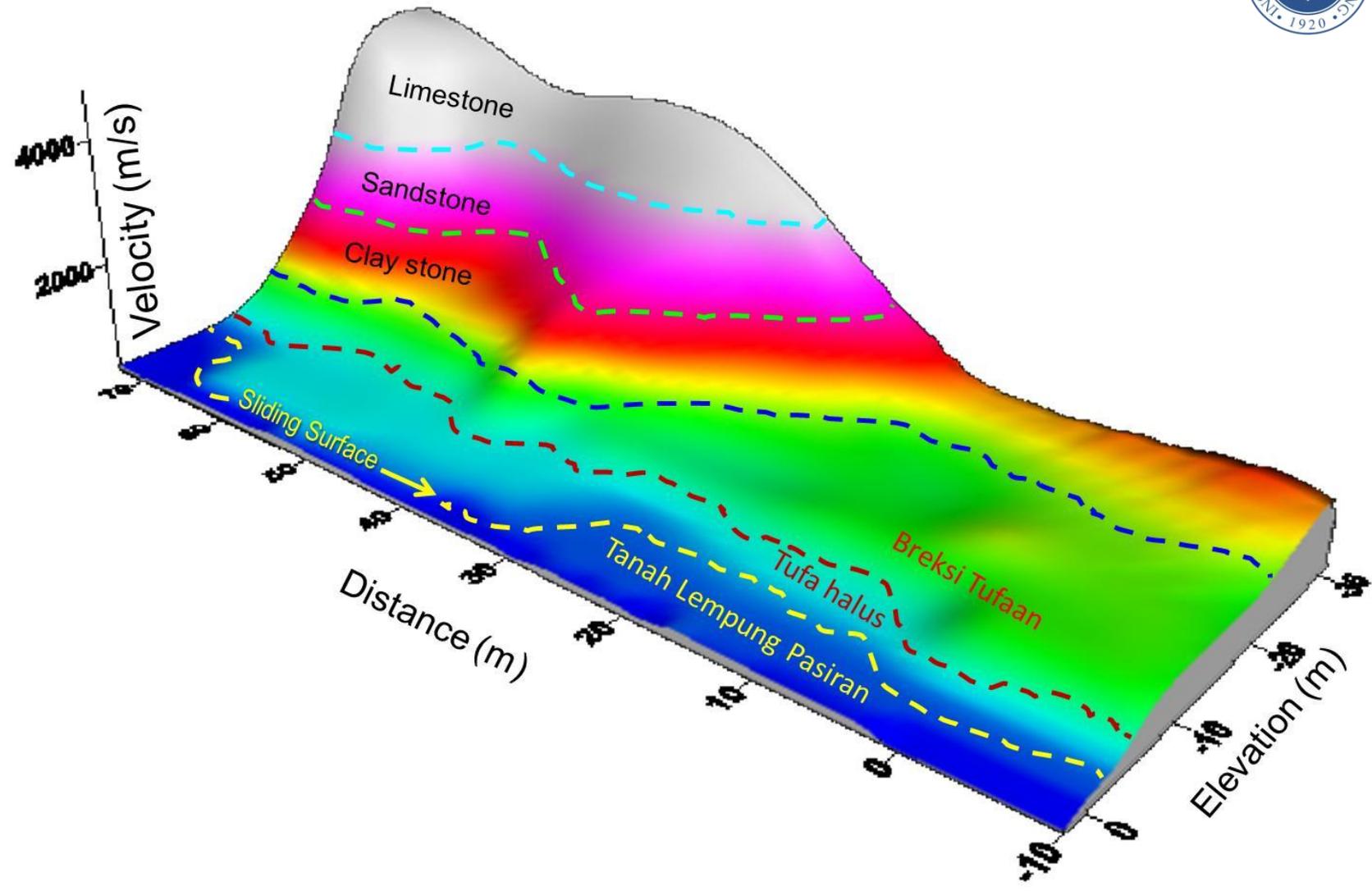


Attachment

Line 2 : Velocity Model (SeisOpt)



Attachment





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Thank You

