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.

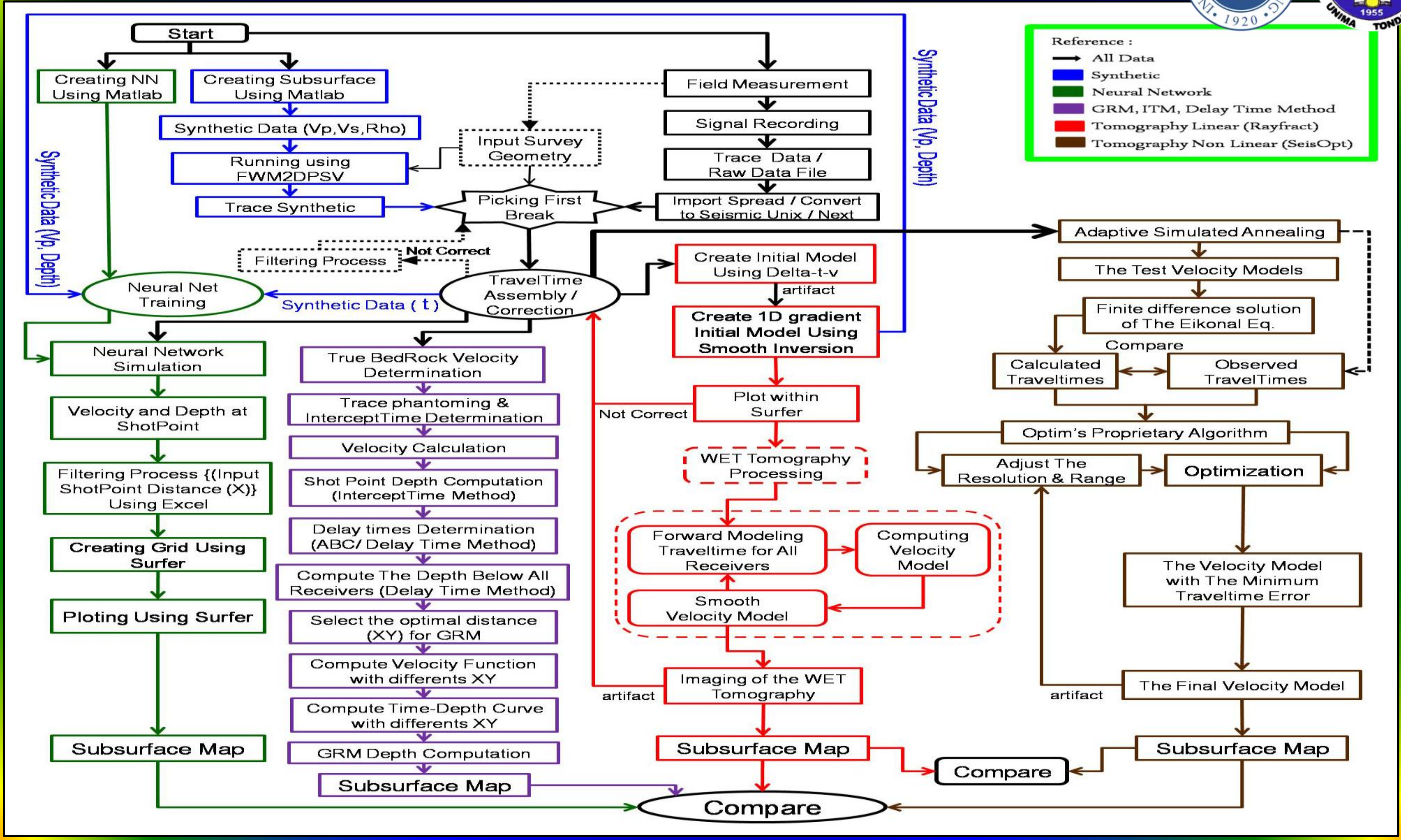
Expectations

As an innovation in seismic data interpretation.

Research Method

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

Research Scheme



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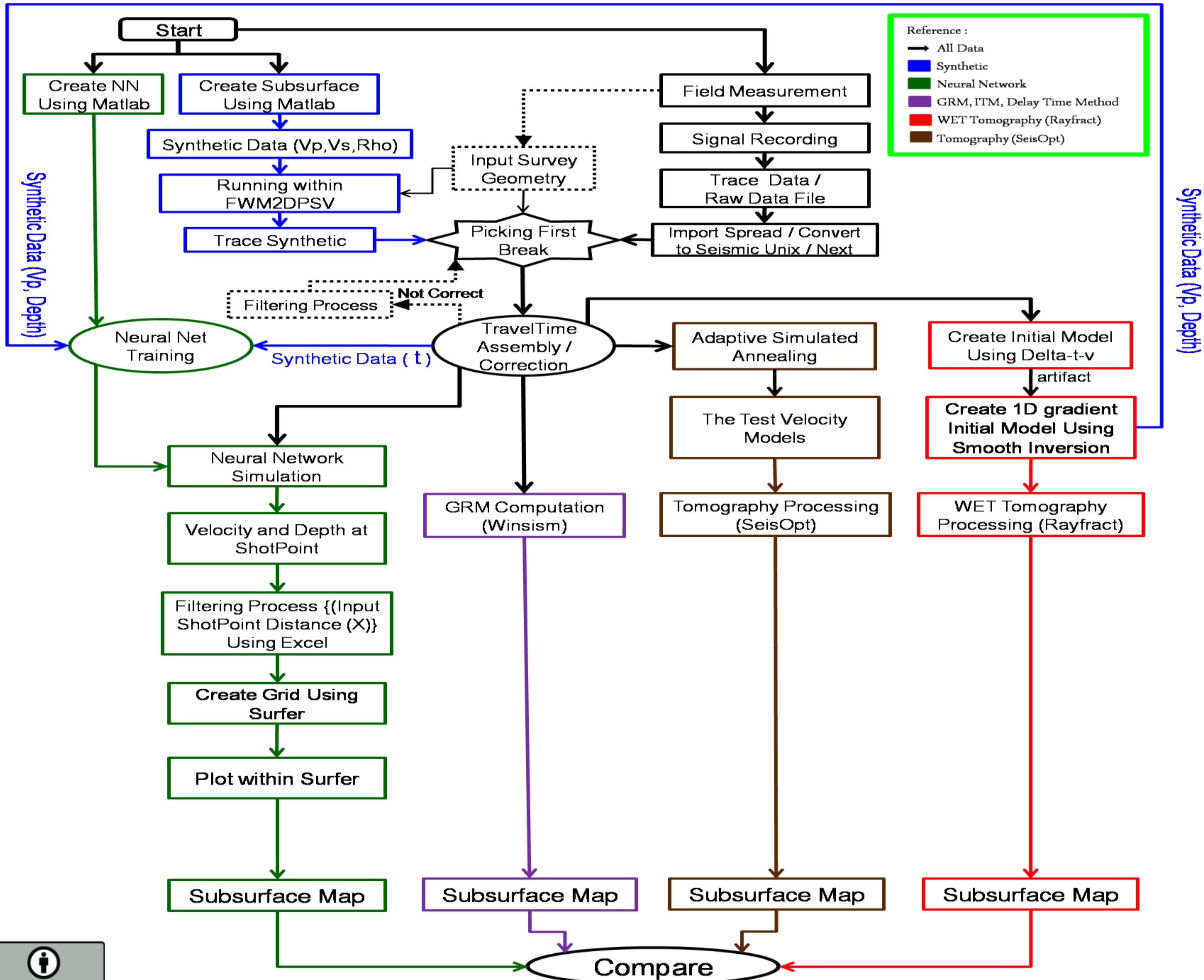

Start
Create NN Using Matlab
Create Subsurface Using Matlab
Synthetic Data (Vp,Vs,Rho)
Running within FWM2DPSV
Trace Synthetic
Field Measurement
Signal Recording
Trace Data / Raw Data File
Import Spread / Convert to Seismic Unix / Next
Input Survey Geometry
Picking First Break
Filtering Process
Not Correct
TravelTime Assembly / Correction
Neural Net Training
Synthetic Data (t)
Synthetic Data (Vp, Depth)
Synthetic Data (Vp, Depth)
Reference :
All Data
Synthetic
Neural Network
GRM, ITM, Delay Time Method
WET Tomography (Rayfract)
Tomography (SeisOpt)
Adaptive Simulated Annealing
The Test Velocity Models
Tomography Processing (SeisOpt)
Create Initial Model Using Delta-t-v
artifact
Create 1D gradient Initial Model Using Smooth Inversion
WET Tomography Processing (Rayfract)
Neural Network Simulation
Velocity and Depth at ShotPoint
Filtering Process {(Input ShotPoint Distance (X)} Using Excel
Create Grid Using Surfer
Plot within Surfer
GRM Computation (Winsism)
Subsurface Map
Subsurface Map
Subsurface Map
Subsurface Map
Compare

Refraction Tomography

- **Rayfract^{TM} Software**:

  Inversion Algorithm;

  Wavepath eikonal traveltime 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

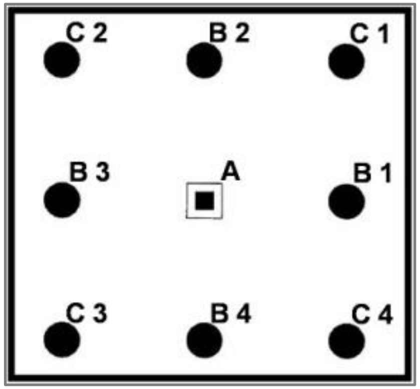
  Forward Modeling;

  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.

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



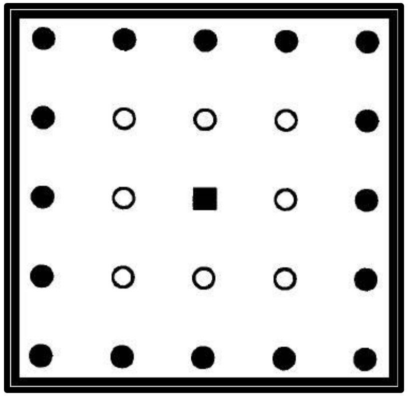
$$t_{Bi} = \frac{h}{2}(S_{Bi} + S_A)$$

$$t_{C_i} = t_A + \left[2(h\bar{S}_\iota)^2 - (t_{Bi+1} - t_{Bi})^2\right]^{1/2}$$

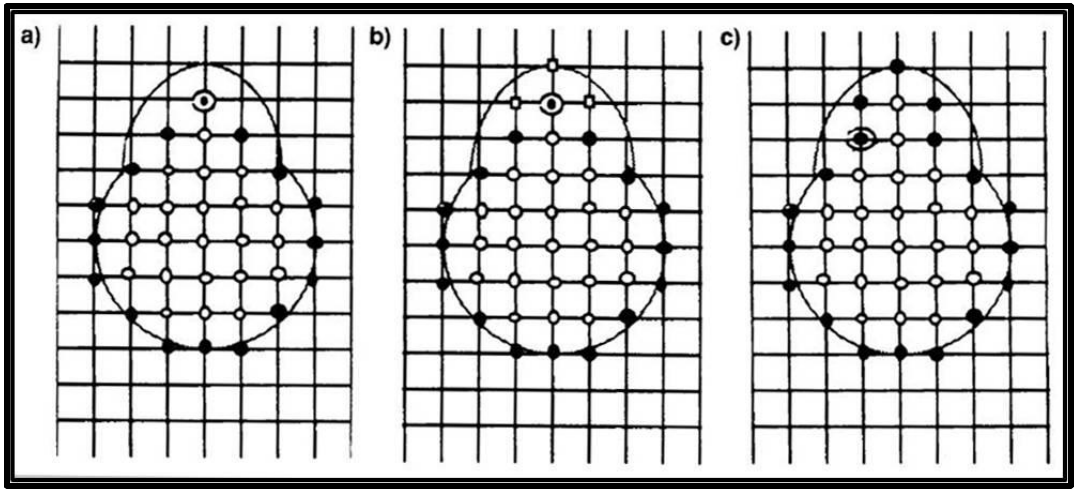
$*$ when $i = 4$; $t_{Bi+1} = t_{B1}$

$*$ $\bar{S}_\iota = \frac{1}{4}(S_A + S_{C_i} + S_{B_i} + S_{B_{i+1}})$

- ***Expanding Square Method*** **(Vidale, 1988)**



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



Wavepath Eikonal Traveltime inversion (WET)

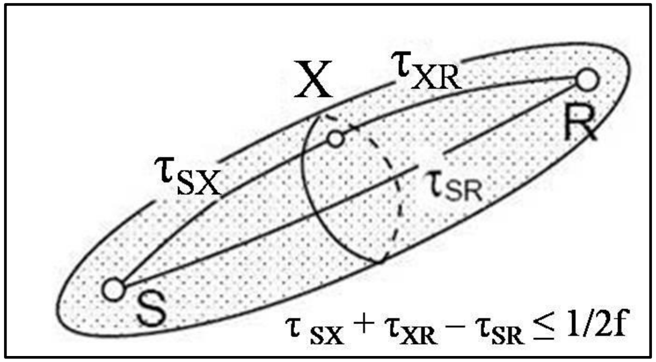
(**Schuster** and **Quintus-Bosz, 1993**)

1. Pick the first-arrival traveltimes from the seismograms ($\boldsymbol{\tau}_{rs}^{obs}$).
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 $\boldsymbol{\tau}_{xs}$ and $\boldsymbol{\tau}_{xr}$. The traveltime residual is computed by

$$\Delta\boldsymbol{\tau} = \boldsymbol{\tau}_{rs} - \boldsymbol{\tau}_{rs}^{obs}$$

3. The source weighting function in equation

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



   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),

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

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)

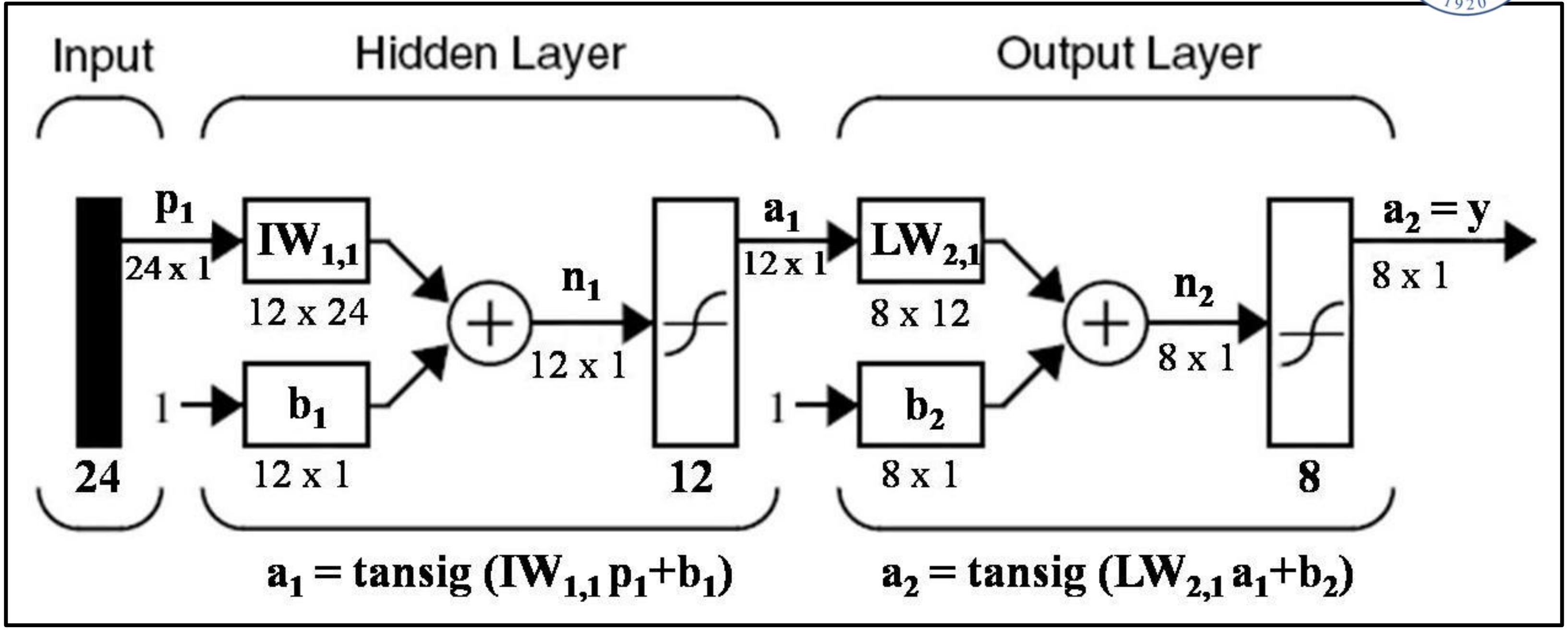
- The NN have the ability to map a space, which is called input space to another one which is called output space.

- 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)

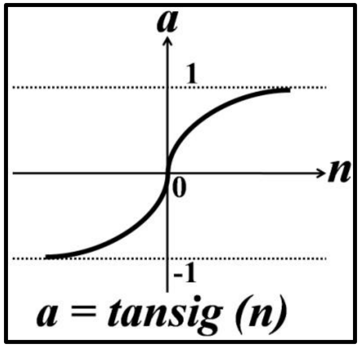
- This study is based on application of feedforward Backpropagation NN, which contains an input, a hidden layer and an output (see Fig).
- Information flows forward from input to hidden layer and then through output (see Fig).
- Connections are only between adjacent layers and there is no connection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

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



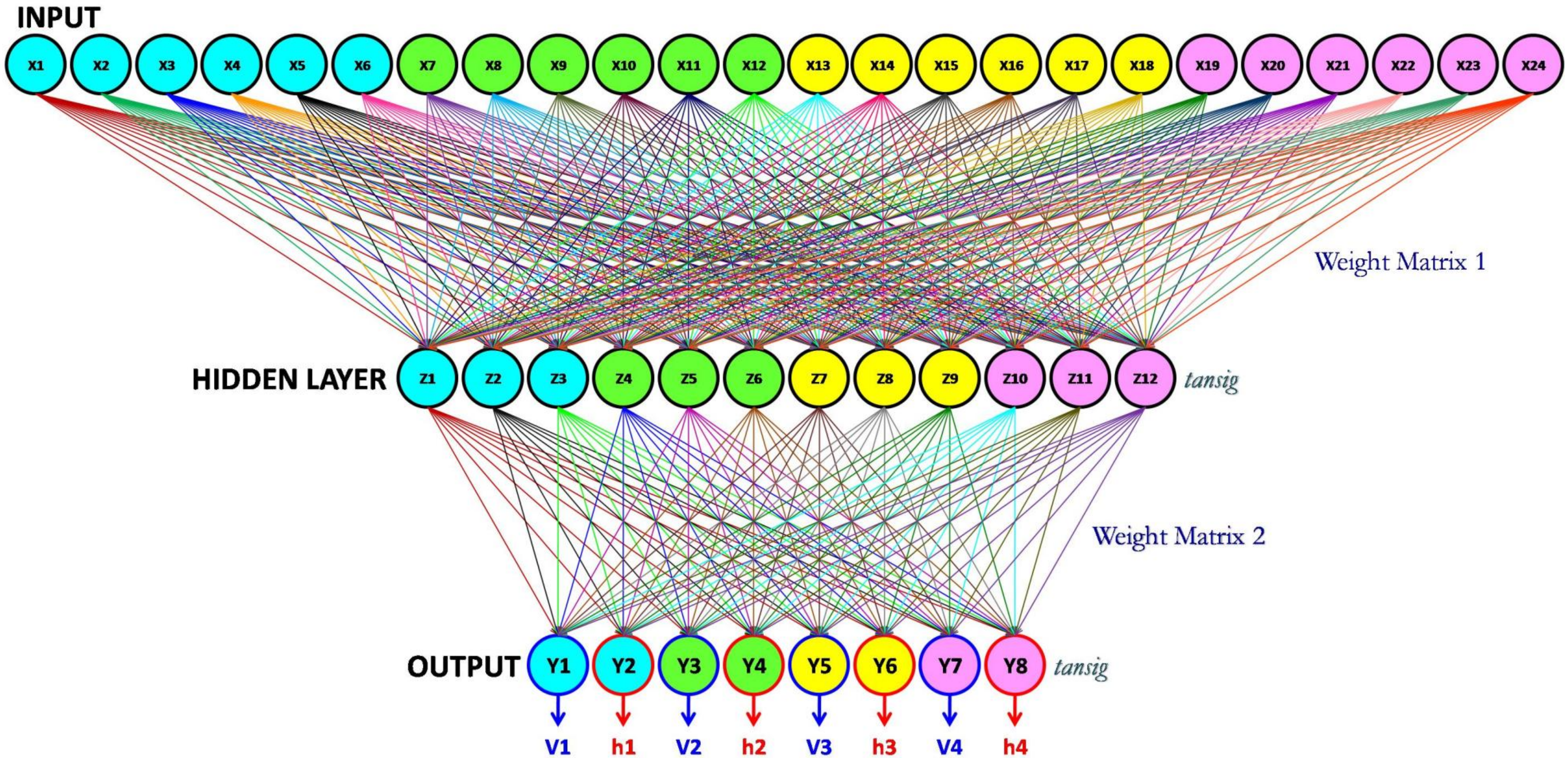
$$n_i = \sum_j W_{ij} a_j \quad \text{... (Eq. 1)}$$

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

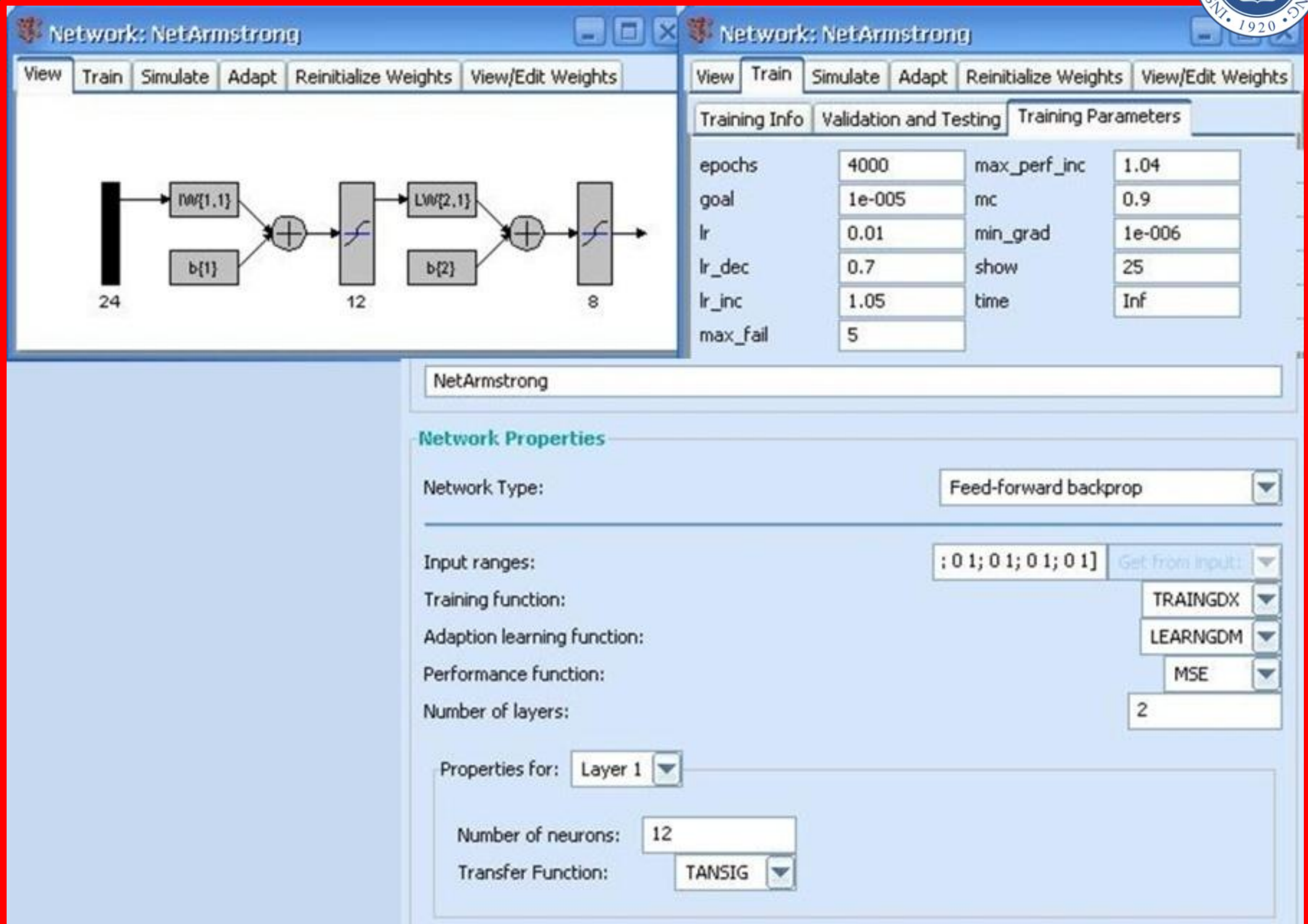
Neural Network (NN)

- 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.

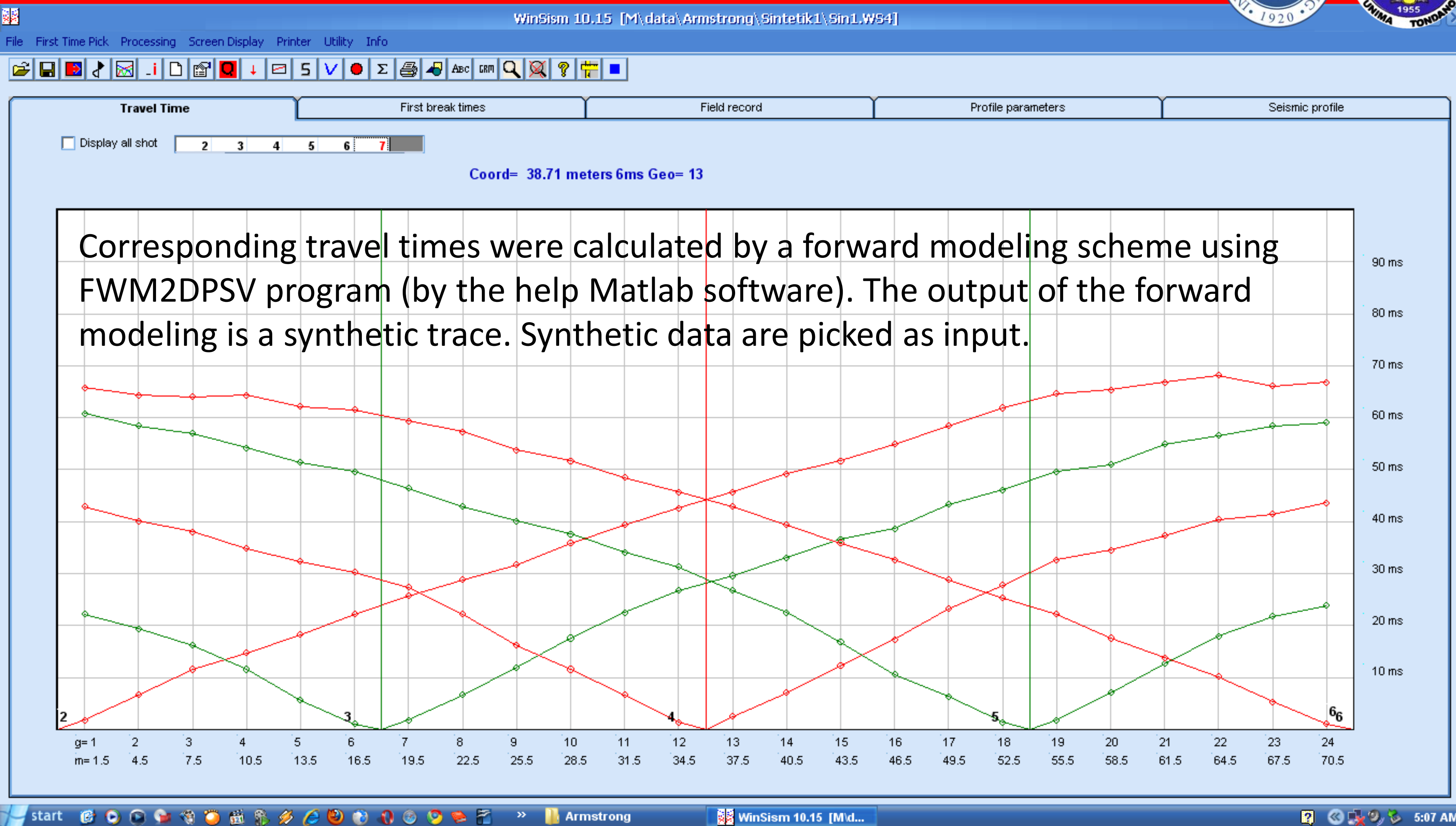
Neural Network: Structure



Neural Network: Structure

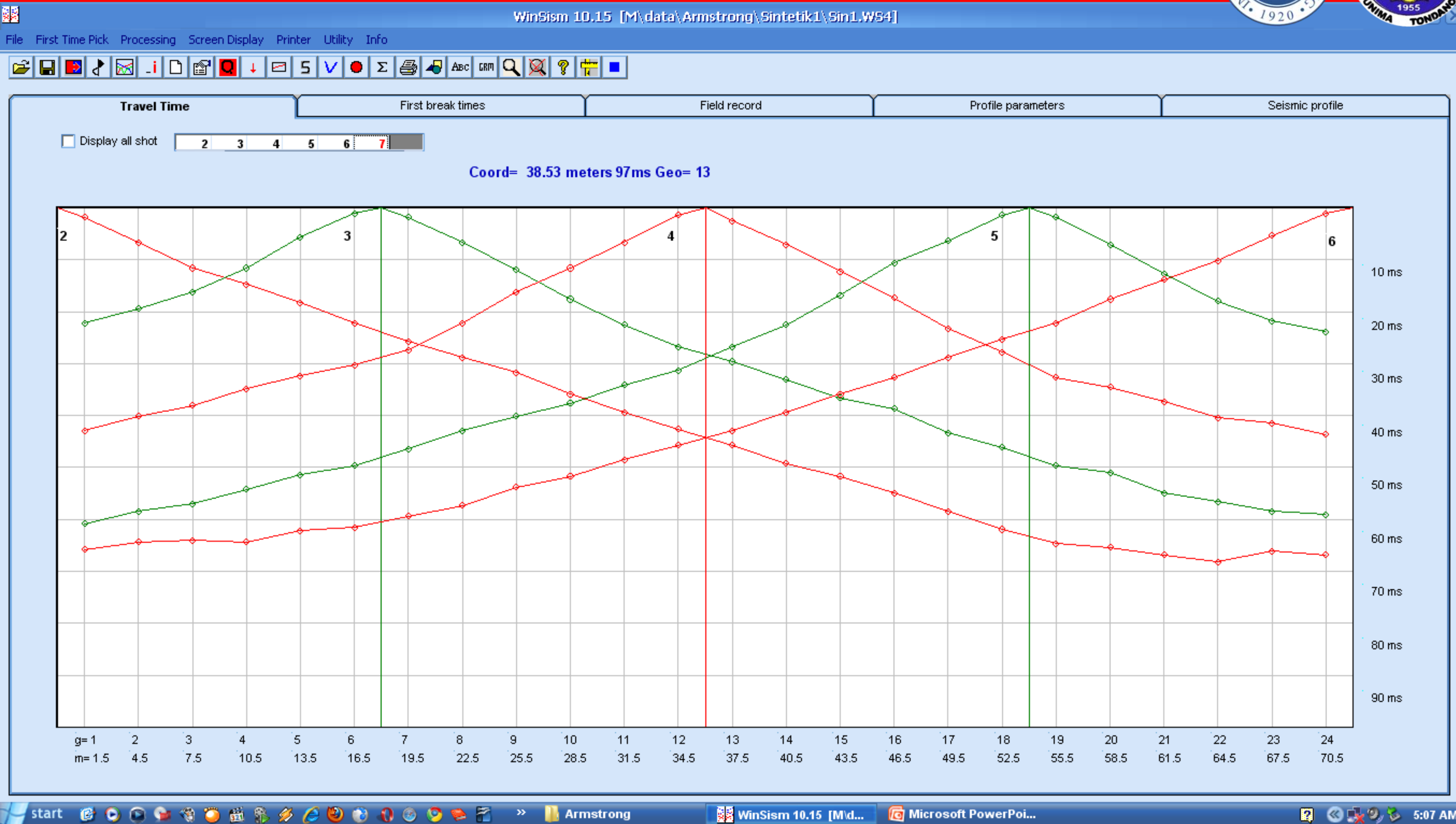


Neural Network: Input Data



Corresponding travel times were calculated by a forward modeling scheme using FWM2DPSV program (by the help Matlab software). The output of the forward modeling is a synthetic trace. Synthetic data are picked as input.

Neural Network: Input Data



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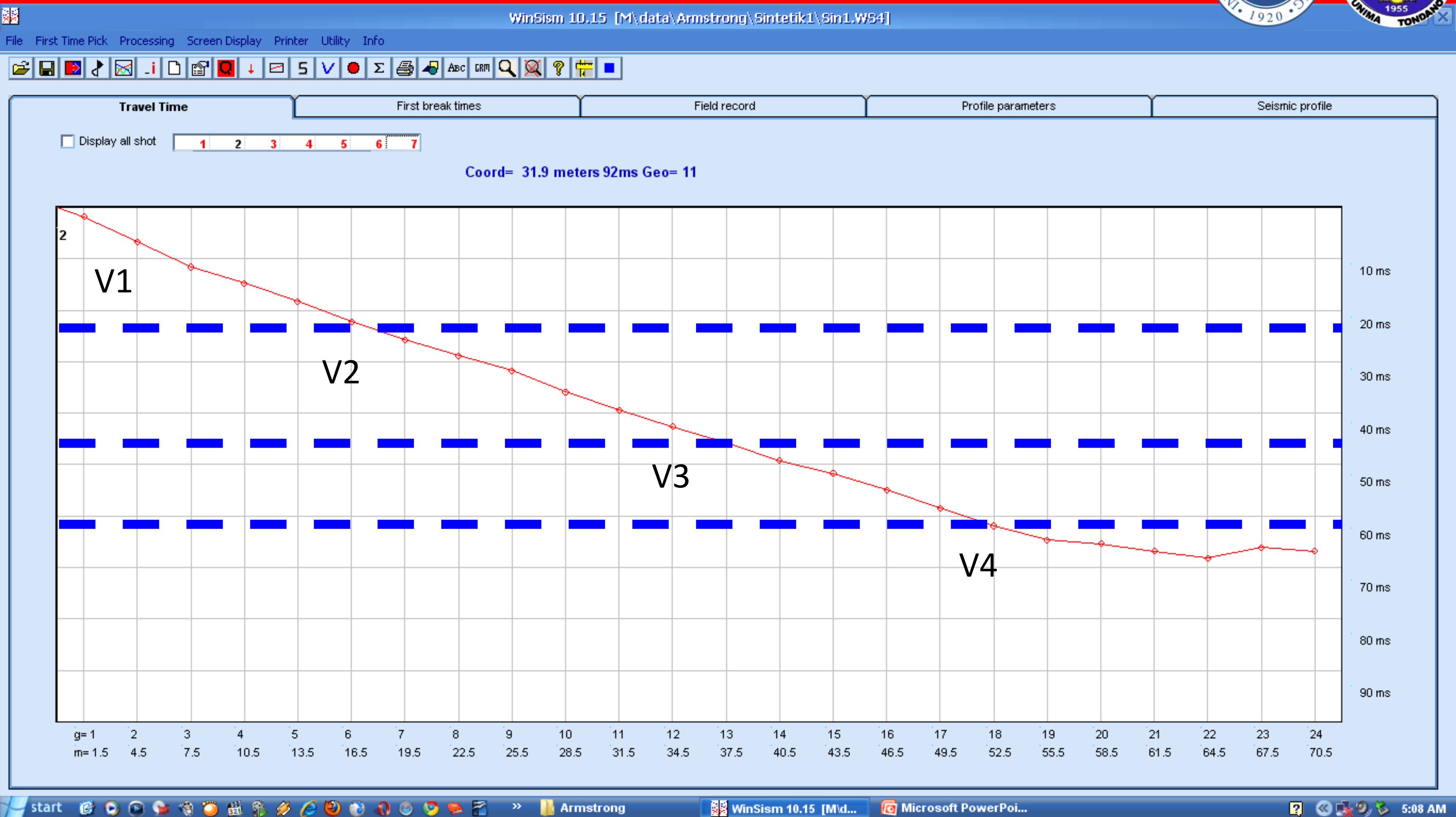
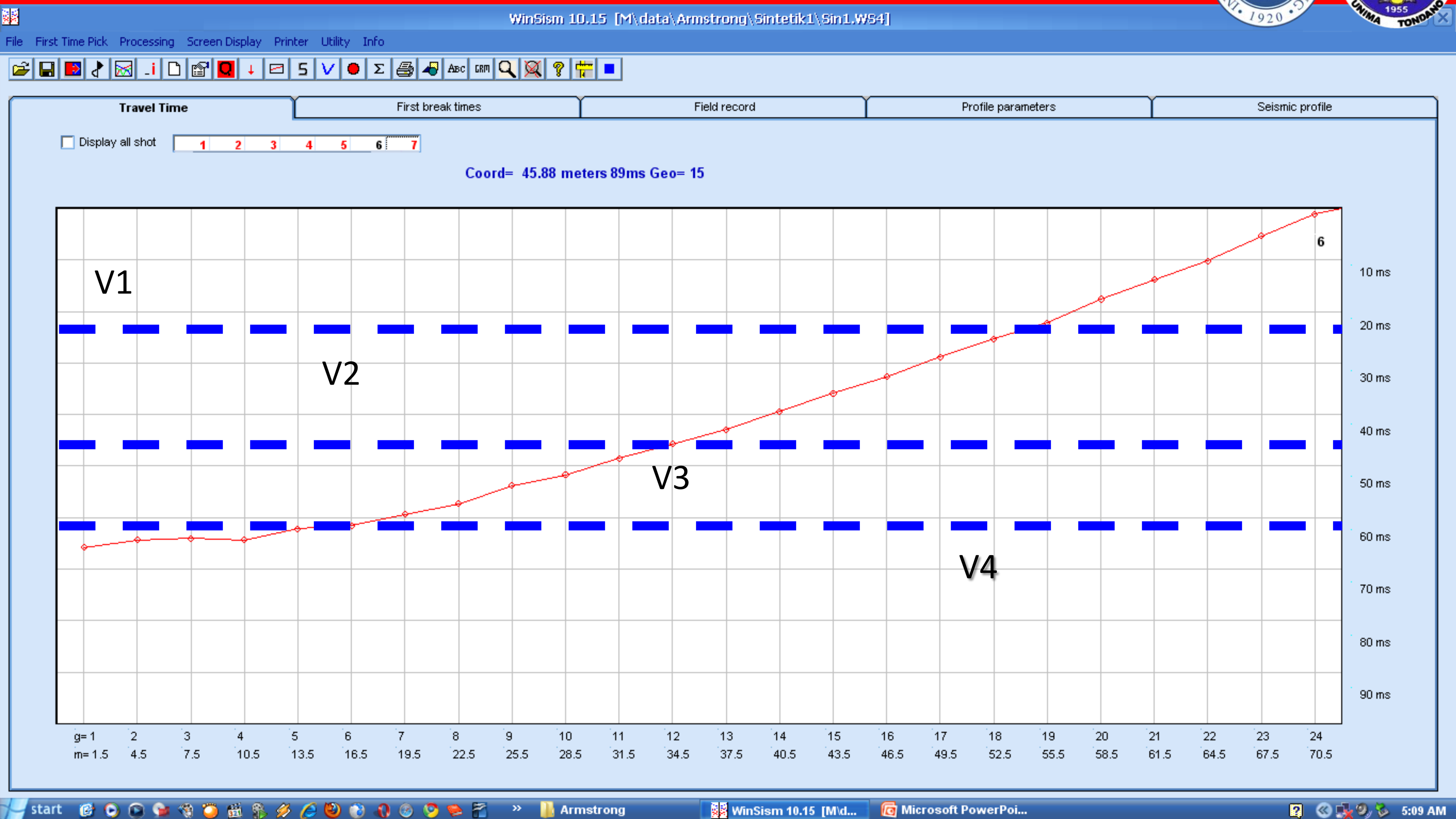
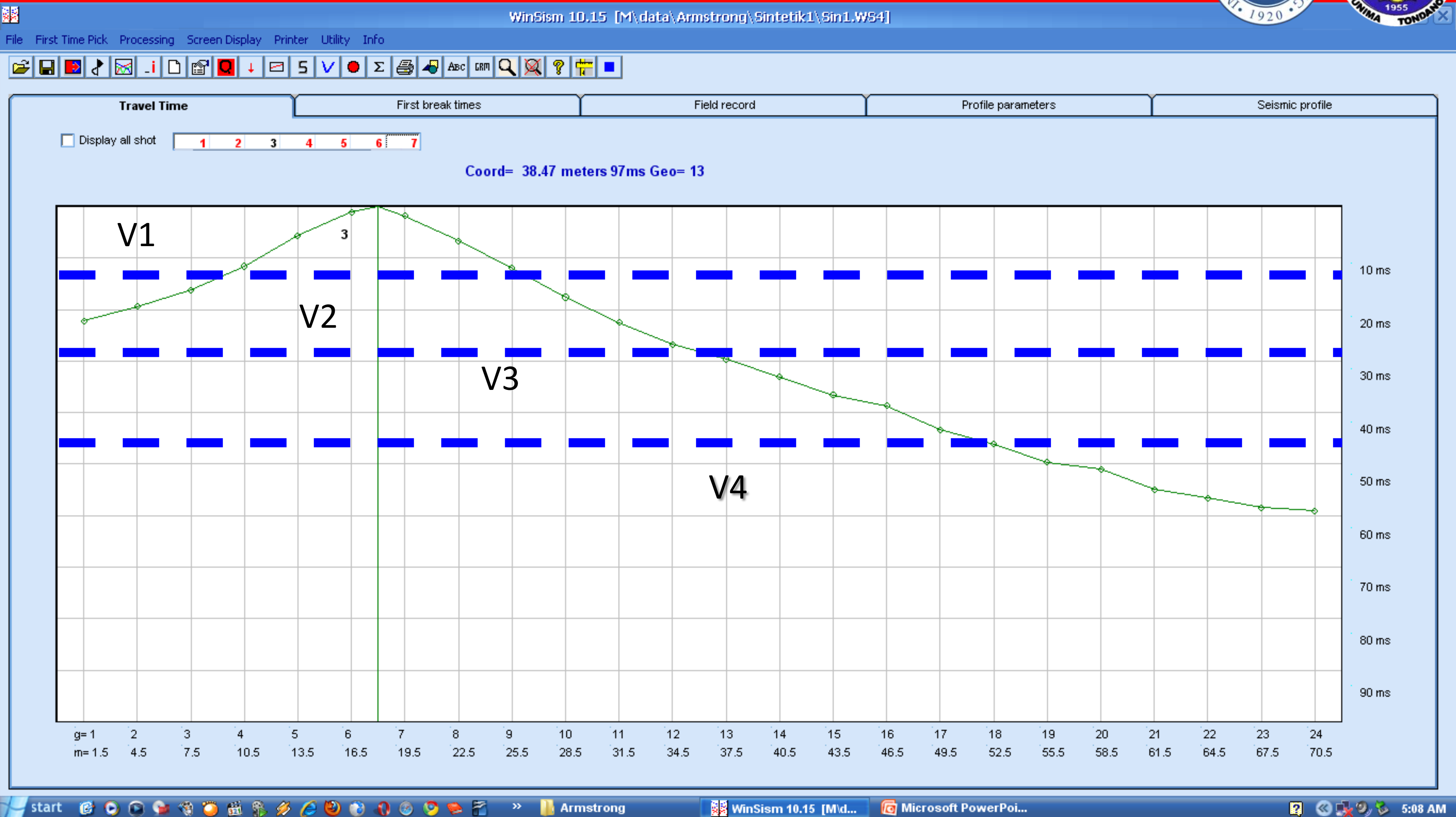
Neural Network: Input Data



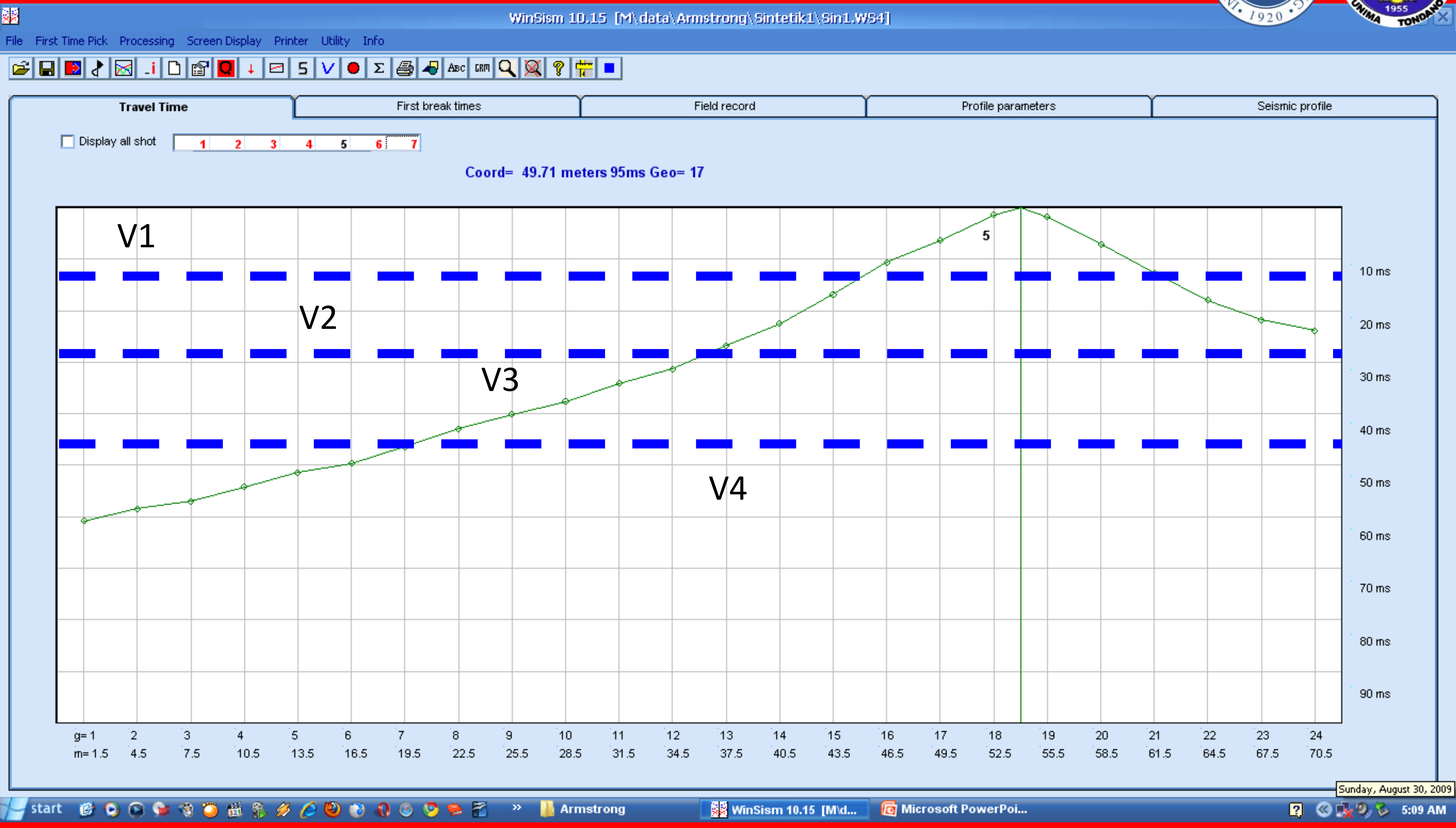
Neural Network: Input Data



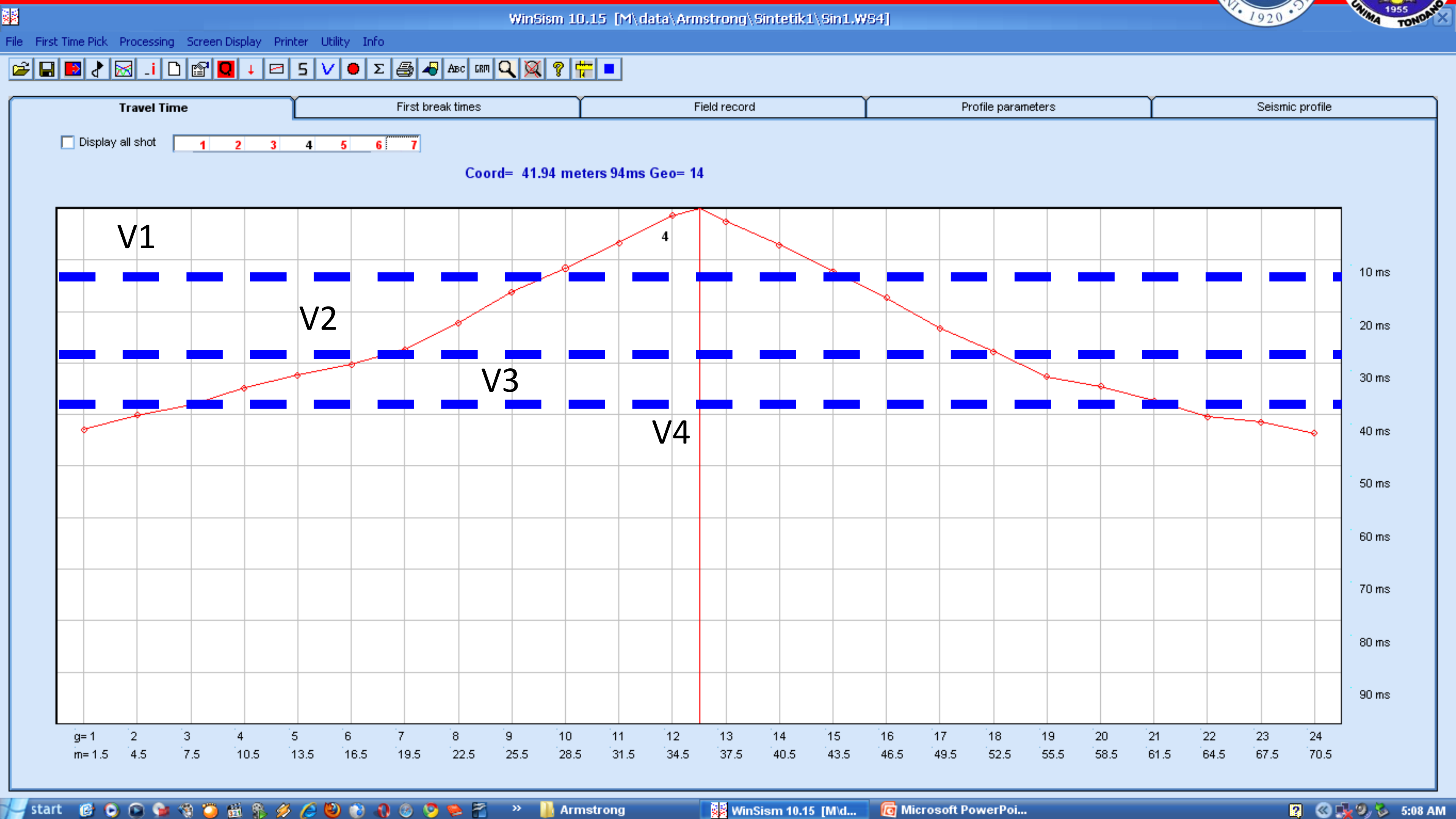
Neural Network: Input Data



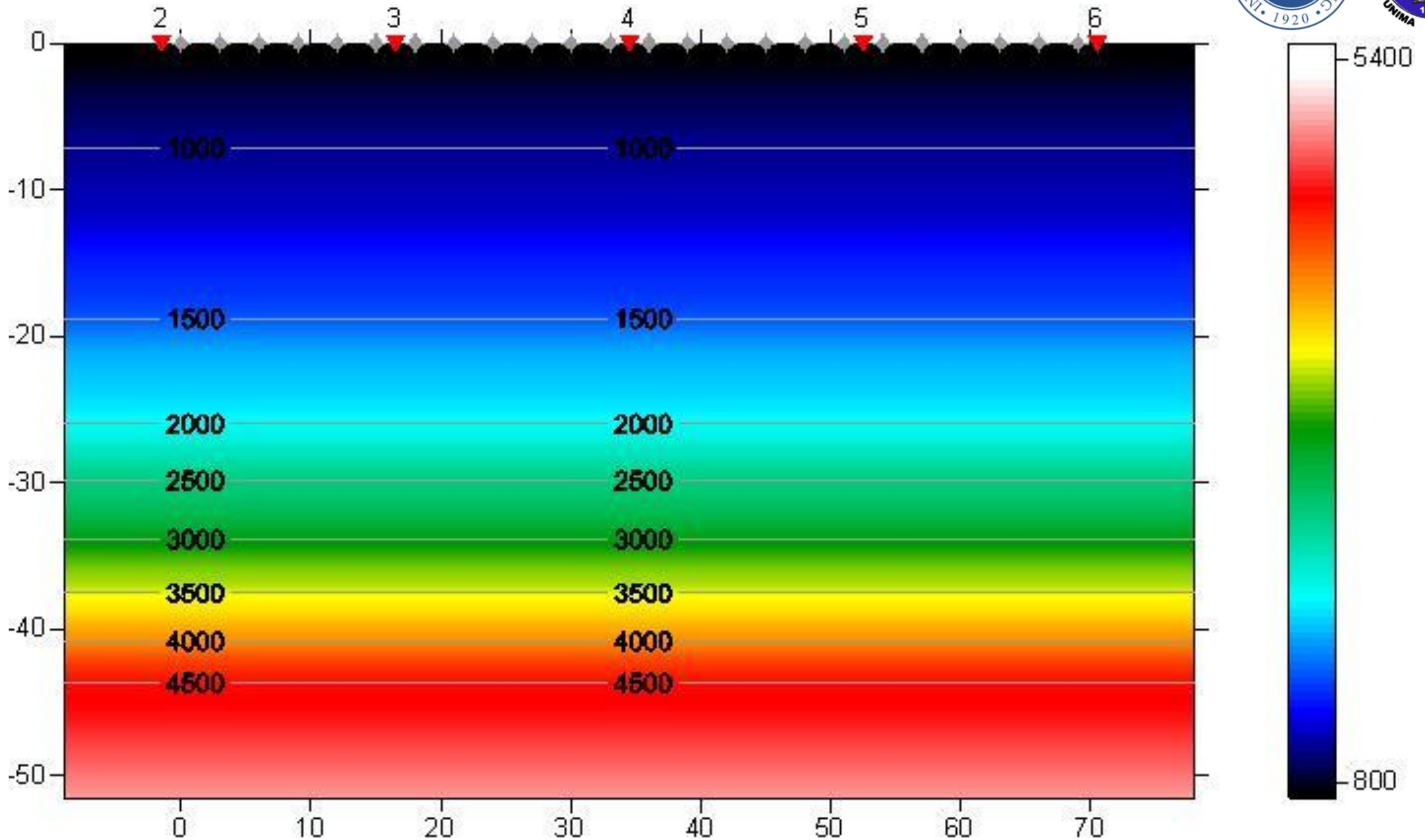
Neural Network: Input Data



Neural Network: Input Data

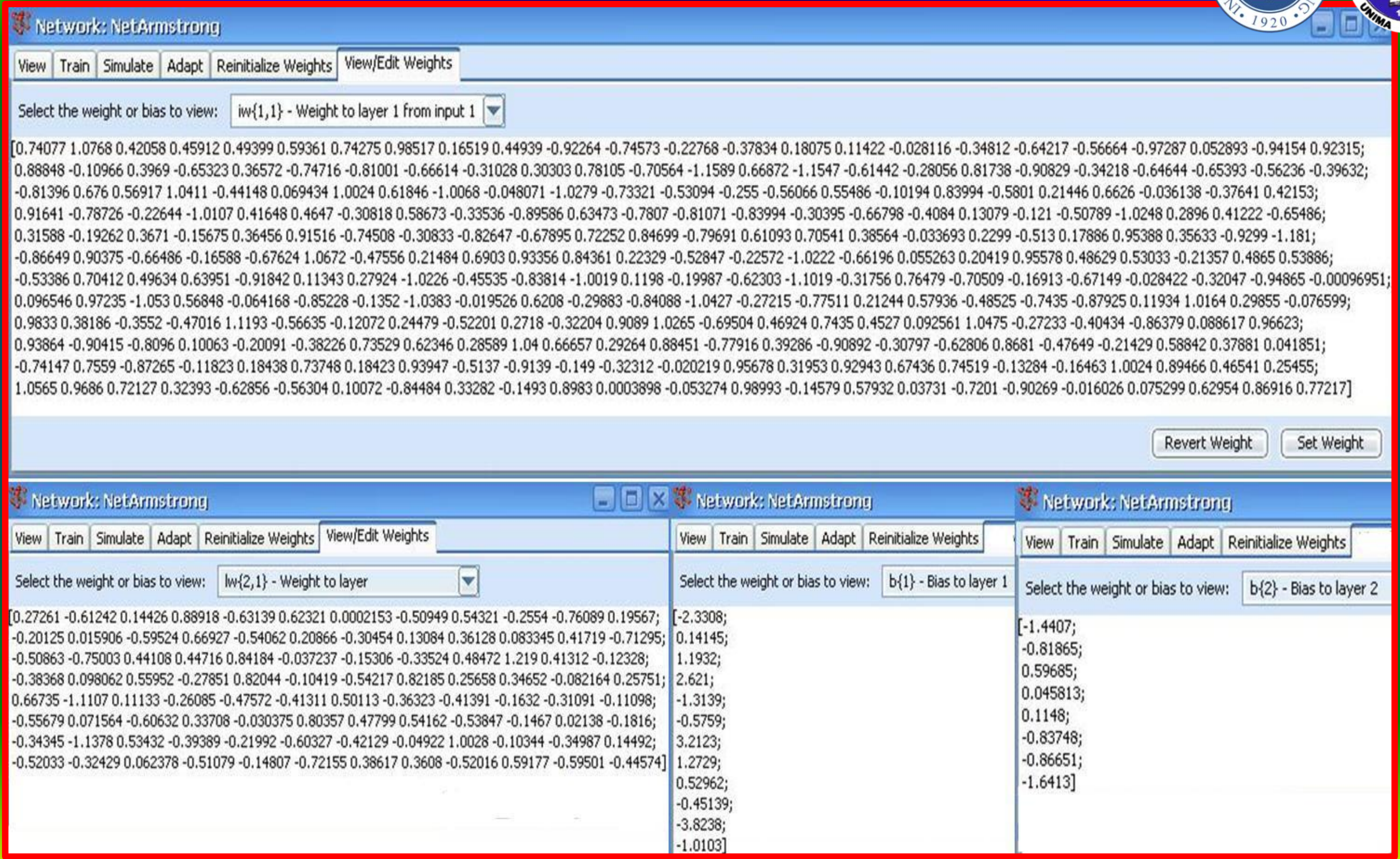


Neural Network: Output Target

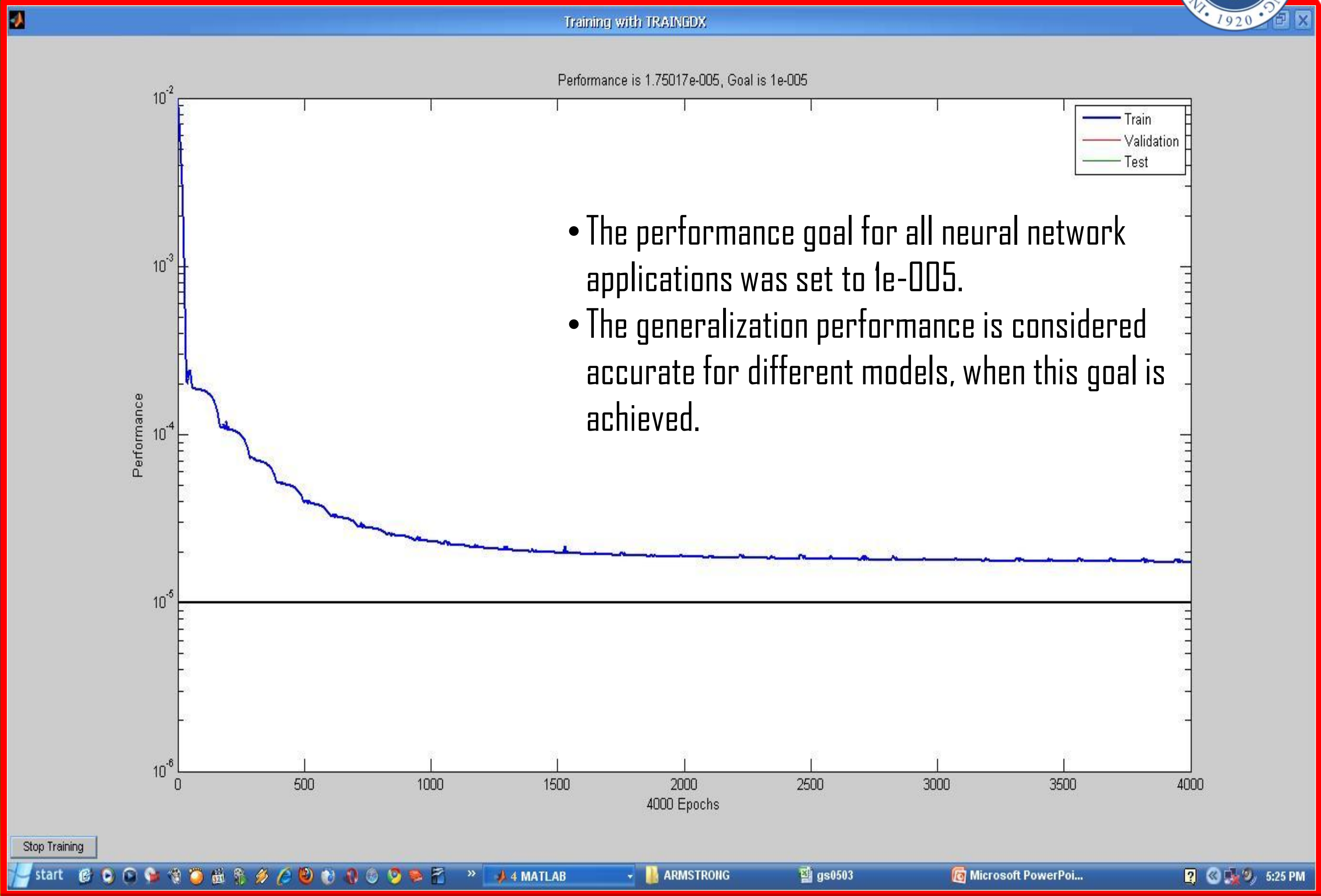


First break data were also modeled with inversion method, where the velocity and depth of the initial model used as the target data. The corresponding data sets (i.e., arrival times as input and velocity and depth as output) were fed to neural network in order to train the networks.

Neural Network: Training



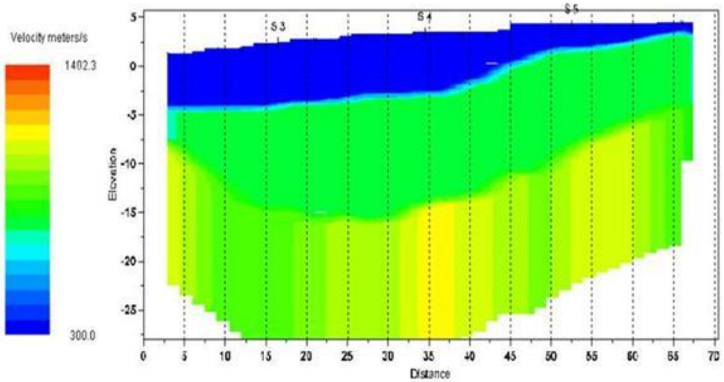
Neural Network: Training



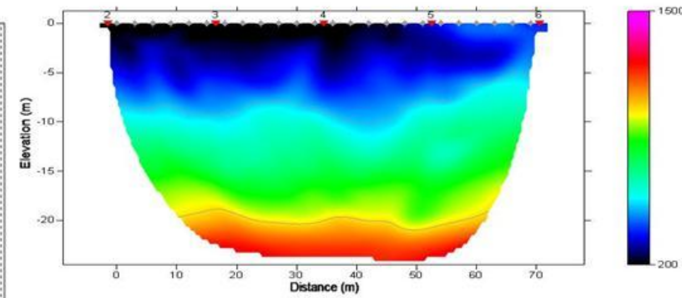
- The performance goal for all neural network applications was set to 1e-005.
- The generalization performance is considered accurate for different models, when this goal is achieved.

Comparing: Line 1

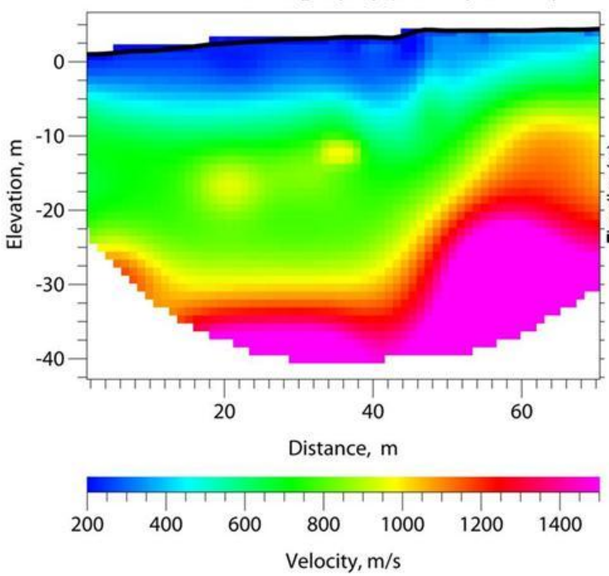
GRM Method (Winsism)



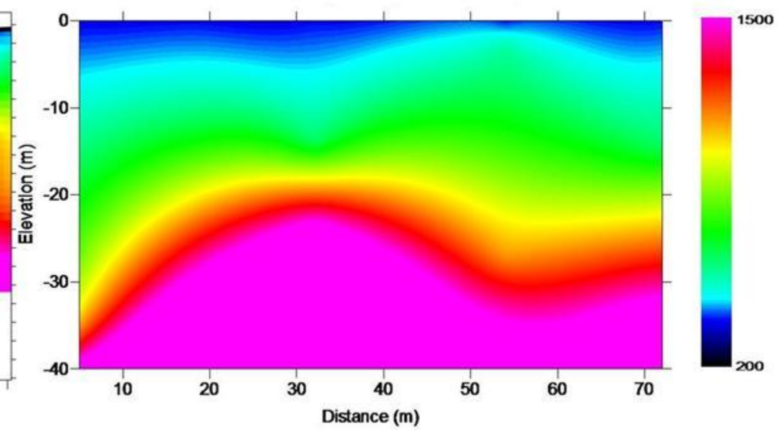
WET Tomography (Rayfract™)



Tomography (SeisOpt@2D)



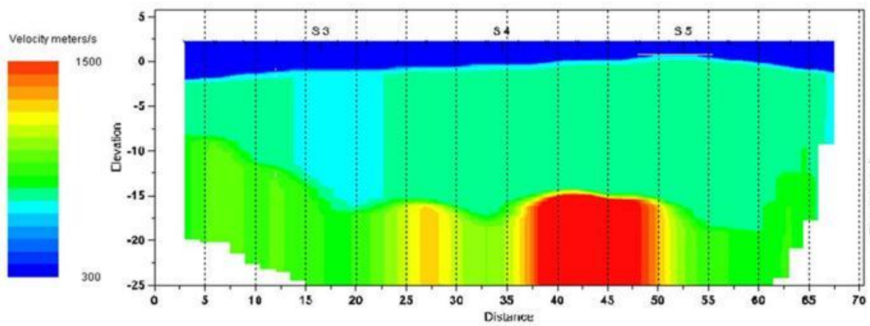
Neural Network



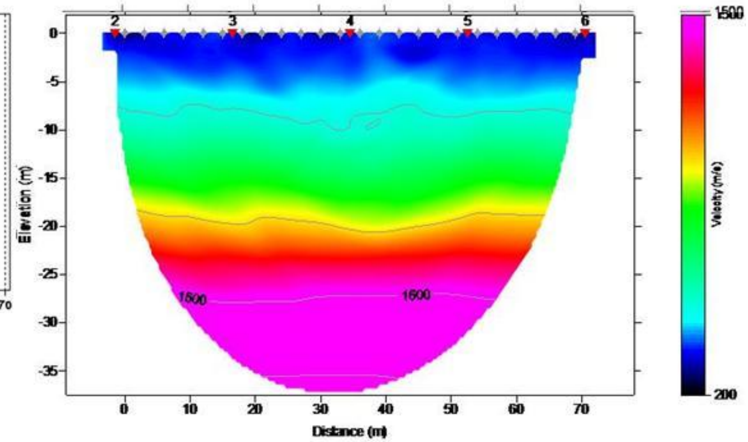
- The first layer shows a velocity of 343-449 m/s and corresponds to ***top soil***. Its thickness varies from 1 m to 5 m.
- The second layer shows velocity in the range of 449 to 837 m/s (Depth 5-10m). It might be associated to **smooth grain above the tuff layer**.
- **Clay Basement** with a velocity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

Comparing: Line 2

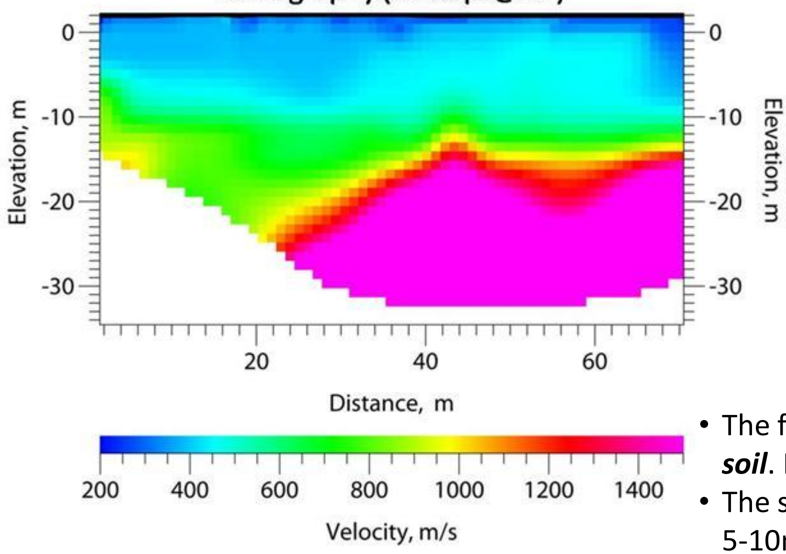
GRM Method (Winsism)



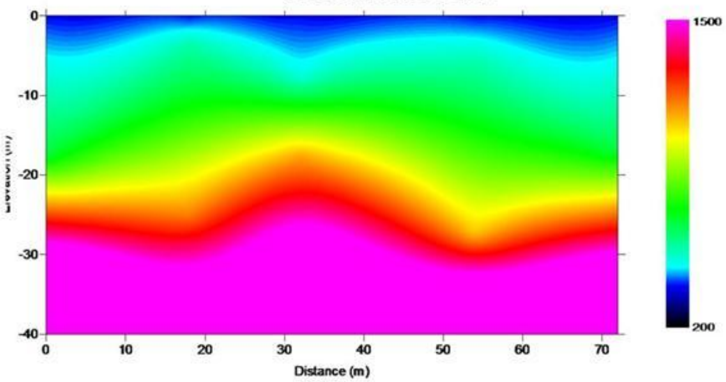
WET Tomography (Rayfract™)



Tomography (SeisOpt@2D)



Neural Network



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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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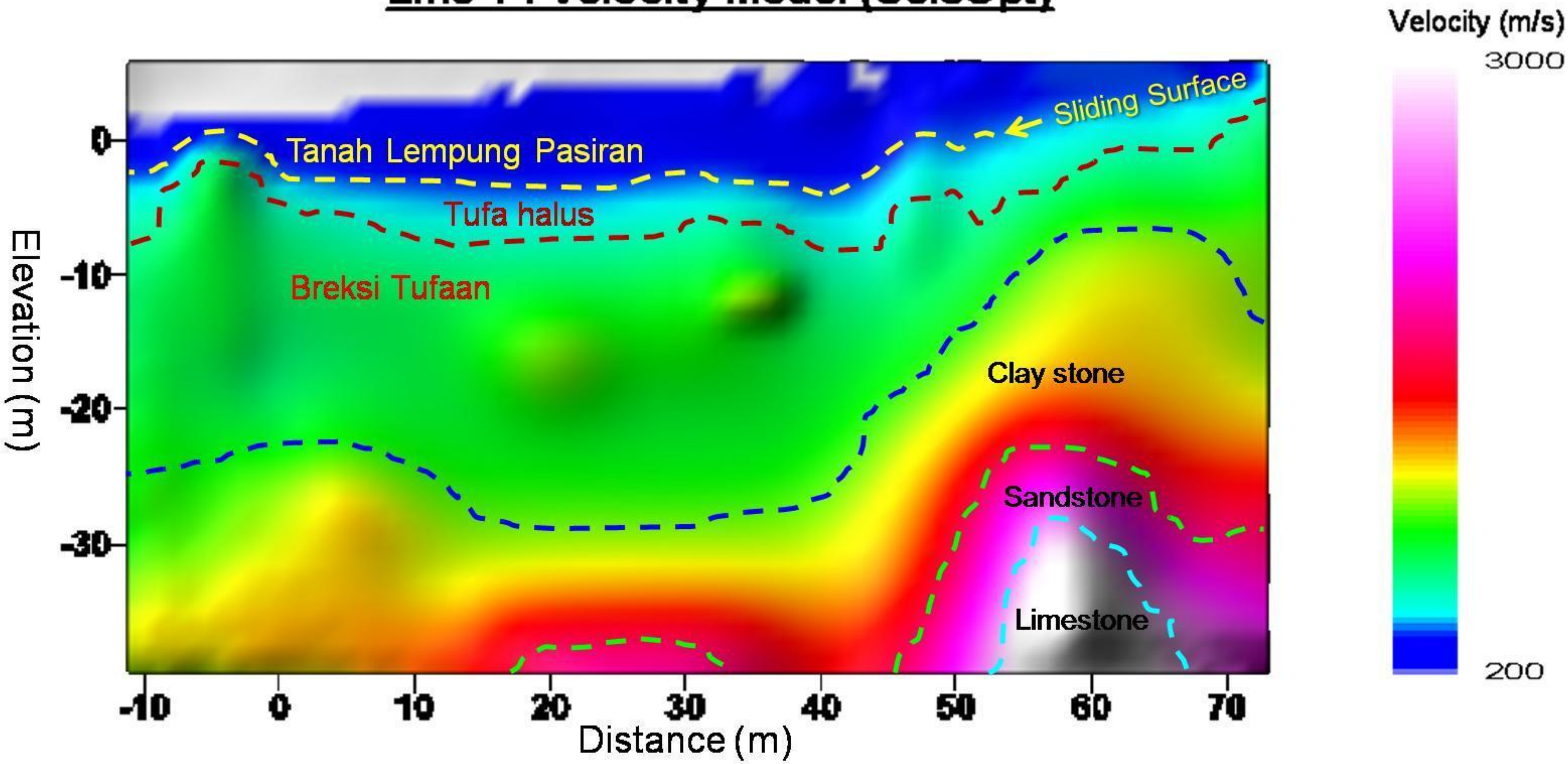
Attachment

Line 1 : Velocity Model (SeisOpt)



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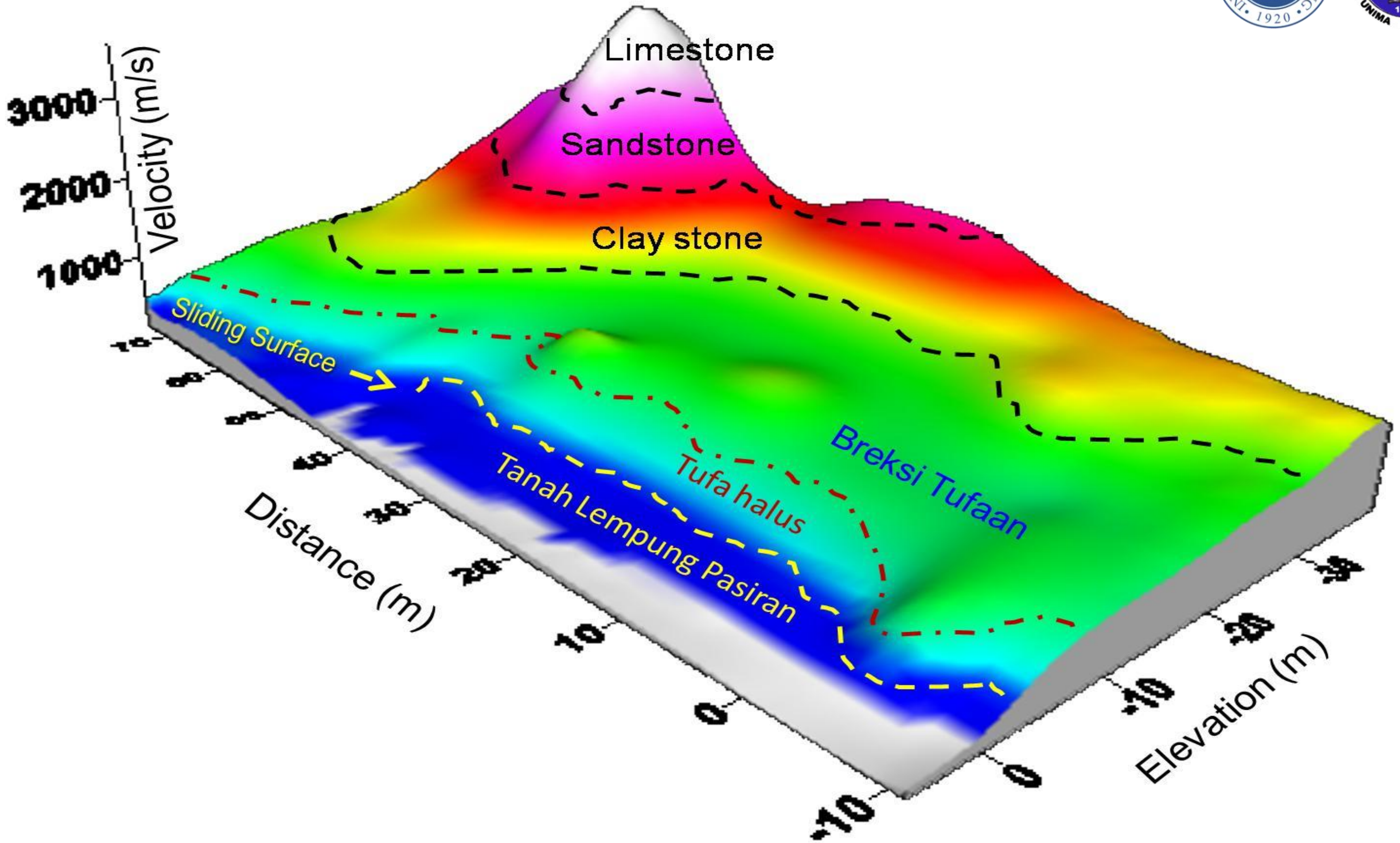
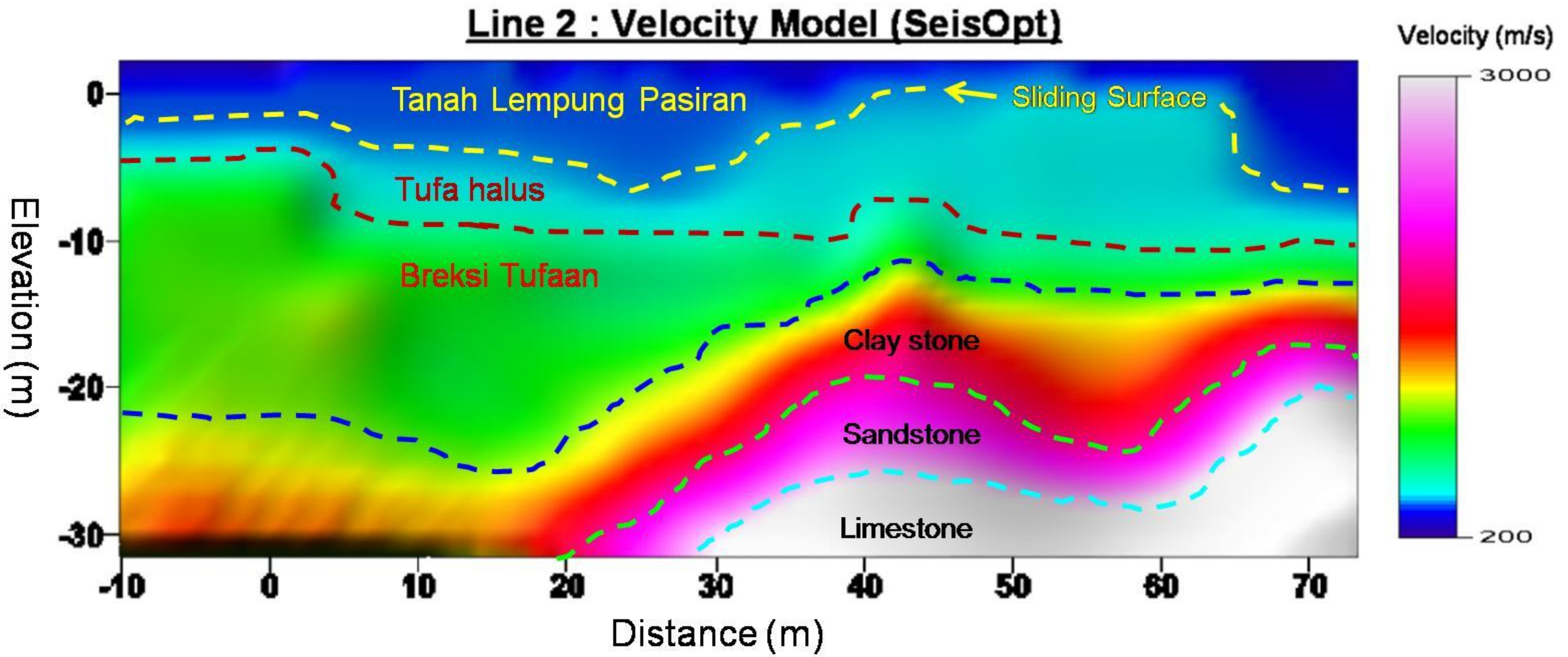
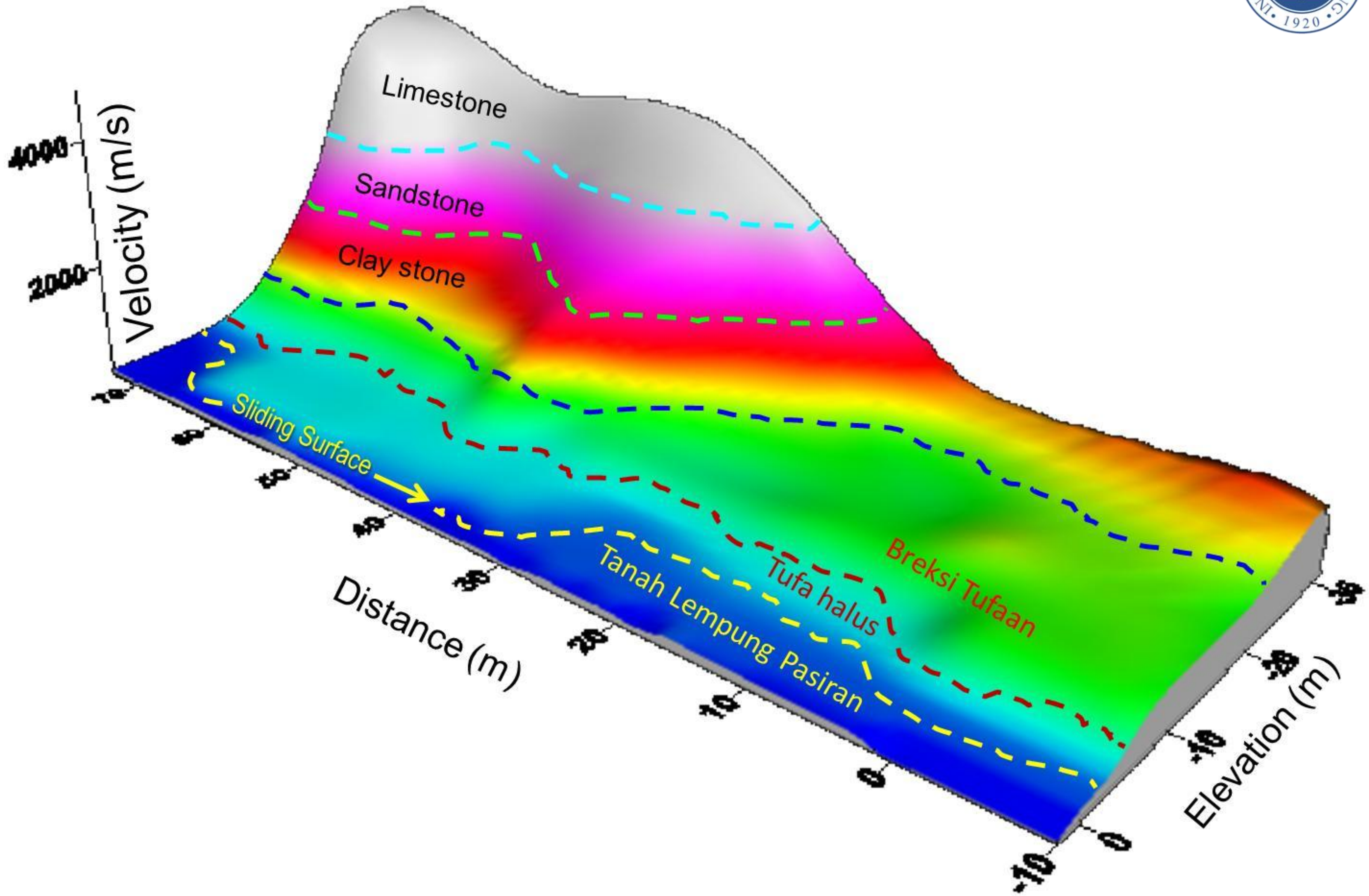

Limestone
Sandstone
Clay stone
Velocity (m/s)
3000
2000
1000
Sliding Surface
Breksi Tufaan
Tufa halus
Tanah Lempung Pasiran
Distance (m)
30
20
10
0
-10
Elevation (m)
0
-10
20
30

Attachment


Line 2 : Velocity Model (SeisOpt)
Velocity (m/s)
3000
200
Tanah Lempung Pasiran
Sliding Surface
Tufa halus
Breksi Tufaan
Clay stone
Sandstone
Limestone
Elevation (m)
0
-10
-20
-30
-10
0
10
20
30
40
50
60
70
Distance (m)

Attachment


Limestone
Sandstone
Clay stone
Sliding Surface
Breksi Tufaan
Tufa halus
Tanah Lempung Pasiran
Velocity (m/s)
4000
2000
Distance (m)
70
60
50
40
30
20
10
0
-10
Elevation (m)
0
-10
-20
-30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