COMPARING A UNIVARIATE TIME SERIES APPROACH WITH NEURAL NETWORKS TO PREDICT DEFORMATION OF SOIL MASS

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Abstract: The deforming soil mass of two major lignite mines in Greece is being monitored by conventional underground and surface methods, namely, inclinometers, total station surveying using control targets and differential GPS. While the inclinometer data can indicate the early stages of the landslide process, it provides little information about regressive and progressive movements of the soil mass under consideration. Thus, the effective monitoring of mine benches is based solely on surveying data. This paper describes two different approaches for the detailed analysis of data to predict the deformation rate of the soil mass. In the first approach, univariate time series analysis is used to transform the deformation rate of each survey target into an appropriate ARIMA model. The main limitation of this approach is the white noise which is generated when dealing with low deformation rates. The second approach is implemented through neural networks and a feed forward type is described. Both approaches are implemented through in-house developed open source software and results are given using data from the lignite mines.

1. INTRODUCTION

Two major lignite extraction sites are situated in southern and northern Greece. The deposit at both mining sites has similar geological and mechanical characteristics, consisting of successive layers of low-grade coal and clay materials. This layered structure constitutes an important discontinuity of the soil mass. As mining continues, the equilibrium of the stress state is disturbed, so highwalls and non-working benches have being deformed. However, the stability of highwalls is controlled by overall design, since the benches are kept wide and the total slope angle is maintained as low as possible. Consequently, the deformation of highwalls is merely regressive and no monitoring system has being established. On the contrary, non-working benches are the most vulnerable to collapsing and historical data verify this fact.

The typical mining cycle includes excavation of 20m high benches with bucket wheel excavators (BWE), transportation of coal material by conveyor belts to central stacking places and haul-backing of gangues. It must be emphasized that occurrences of sudden energy release, like excavation by means of explosives and seismic waves are quite rare; therefore, these attributes are not taken into account by the analysis that follows.

The monitoring of non-working benches has being implemented by two independent approaches. The first one comprises mobile inclinometer probes that survey near-vertical boreholes. The data collected by this process is used for the detection of the depth at which the main sliding surface has formed. These are also used to monitor the rate of movement at its early stages. However, as the deformation progresses, the underground installations tend to fail, giving no more data to the monitoring program. The second monitoring approach has being implemented by means of terrestrial and space geodesy. This comprises the most practical monitoring procedure, since the collection of the deformation data is continued up to the collapse of the bench. In particular, a large number of control targets are established at suitable locations on the deforming soil mass. Then, successive distance measurements of the control targets from another stable point in space and time yield the deformation rate of those targets, which extrapolates to the rate of movement of the bench.

The analysis of various deformation cases over a long period of time led to a rule of thumb, concerning the maximum allowable deformation rate of benches in the particular mines. According to Leonardos (2003), when the rate of movement exceeds the threshold value of $10\,{}^{mm}/_{day}$, the bench is under a critical regime and remedial measures should be taken immediately.

The above methodology is not adequate to address the problem of bench failure, whether this failure results to a total collapse of a portion of the soil mass or to the termination of bench's operational life. The rule of thumb was effective for a number of cases, while for others slope failures were reported. Therefore, there is a need for understanding the major parameters that adversely influence the deformation rate of a mining slope and identifying their critical values. Additionally, data collected by surface and underground methods must be associated, as both describe the deformation in a complete way.

In light of this notion, two different mathematical procedures for the analysis of deformation data are presented in this paper. In the first approach, univariate time series analysis is used to transform the deformation rate of each survey target into an appropriate ARIMA model. Univariate time series analysis works on surveying data collected over long periods of time and thus, the short term prediction of future deformation rates is quite feasible. Its main purpose is to simulate the mechanism that initiates and preserves the deformation of benches. The second approach is implemented through neural networks. A feed forward neural network type is combined with decision trees to construct general rules that deformation data follow. Both algorithms are developed and implemented through open source codes. Section 2 of the paper describes the time series analysis performed on data from the mine. Section 3 describes the development of a single and multi-layer perceptron neural network approaches and results are given using data from the mines. Finally, Section 4 summarises the work and provides future directions in this work.

2. TIME SERIES ANALYSIS

A deforming soil mass can be mathematically described as a complex multivariate problem. It is influenced by its geometrical design and various mechanical and hydraulic properties, like the bench height, the shear strength of the sliding surface and the pore water pressures. In simple terms, when a process combines all the above associated variables into one super-variable and the behavior of this super-variable is modeled over time, a time series is generated. The great advantage of this procedure is the reduction of a multivariate problem to a univariate one. Additionally, the stochastic nature of time series is capable of modeling the errors that accompany the measurements of the super-variable. However, by this fusion mechanism, information related to the influence of each parameter on the overall problem of deformation is lost forever.

The frequent change of the bench stability parameters is reflected on the rate of movement that accompanies each control target of the surveying monitoring system. Thus, the rate of movement is the suitable super-variable for the time series approach. The application of time series analysis over deformation rates for a bench in the Megalopolis lignite site, yielded the results of Figure 1.

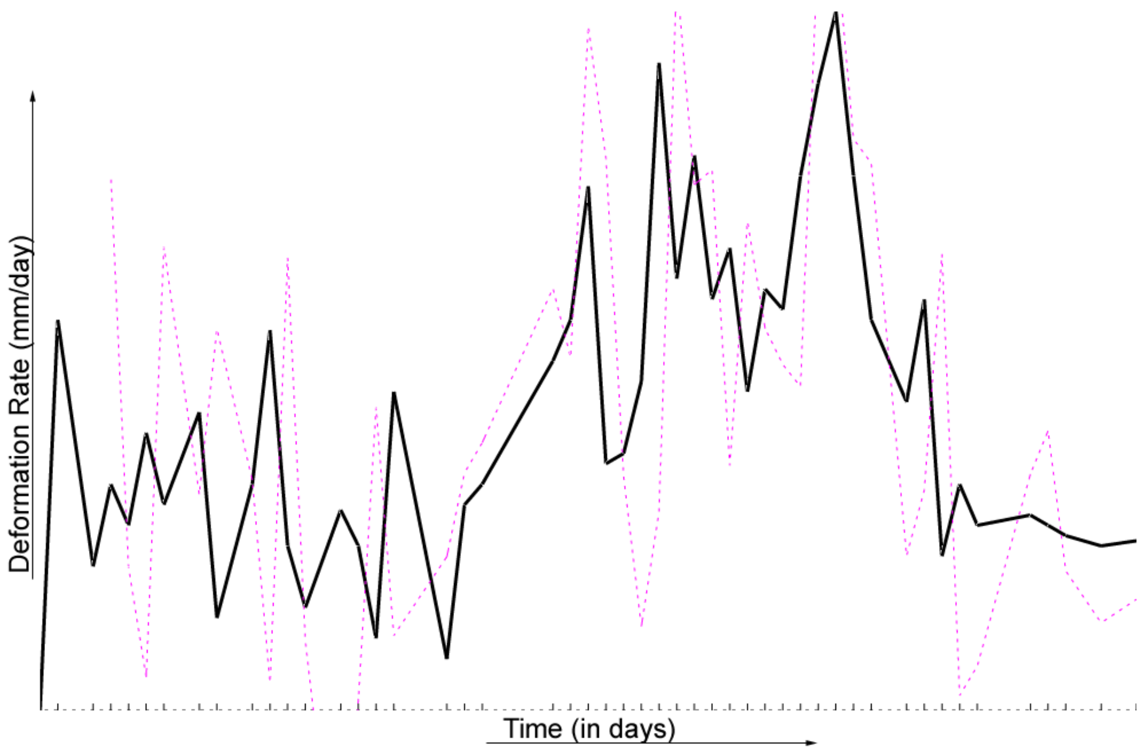


Figure 1 - Deformation rate of bench in Megalopolis lignite mine

In Figure 1, the solid curve describes the rate of movement of one control target that is located at a lignite bench in Megalopolis mine site. By analyzing the data with an ARIMA procedure (the analysis has been conducted by in-house developed software), the corresponding time series model takes the form of equation (1):

$$V_t = 2V_{t-1} - V_{t-2} - 0.45(V_{t-1} - 2V_{t-2} + V_{t-3} - 10.8) + WN_t + 10.8 \tag{1}$$

It is seen that the deformation rate at any time, V_t, can be modeled as a combination of previous deformation rates (V_{t-1} through V_{t-3}) and the associative noise WN_t that describes the errors of the measurements. The constant values are the parameters of the model and are estimated by an appropriate algorithm, such as the moments' or Monte Carlo's method (Box & Jenkins, 1976). By plotting equation (1), depicted by the dotted line in Figure 1, and superimposing it to the measured data, the applicability of the generated model can be assessed.

The data presented in Figure 1 corresponds to a state of progressive movement of the bench. In situations like this, future values of deformation rates are strongly connected to previous ones. Thus, the time series analysis is applied with success. However, when the bench is deforming with low rates, the autocorrelation function is statistically zero most of the time. So, an appropriate stochastic model cannot be constructed.

3. ANALYSIS WITH ARTIFICIAL NEURAL NETWORKS

Artificial neural networks represent a numerical analysis method that uses iterations to converge to a proper solution. In general, the desirable solution minimizes an appropriate error function. The network's architecture resembles the brain in that it consists of a respectable number of computational units that are highly interconnected via weights.

3.1 The structure of the simplest neural network

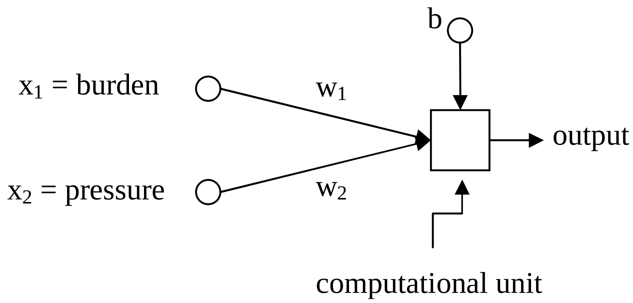
The most basic neural network is the perceptron (Hagan et al., 1996). It is solely used to find a solution for a problem that is linearly separable. Thus, the perceptron is capable of approximating functions that produce a line in 2D space, a plane in 3D space or an imaginary hyperplane in multidimensional spaces.

For simplicity, it's assumed that the stability of a slope depends on two major parameters; the burden and the pore water pressure. Burden is the distance between the face of the slope and its major tension crack. The water pressure is evaluated with standpipe piezometers. This slope is stable when the deformation rate is below a threshold value. However it is likely to fail when this threshold is exceeded. The analysis of historical data reveals this threshold value to be $10\ ^{mm}/_{day}$. Table 1 gives a subset of relevant simulated measurements.

Burden (m)	Water Pressure (at)	Deformation Rate ($^{mm}/_{day}$)
3	2	8
8	0.8	12
7	1.2	10.5
7	0.7	6.4
8	1.4	13.1
8	0.2	7.9

Table 1- Simulated data regarding slope stability

Figure 2 shows a geometrical (left) and a mathematical (right) representation of the suitable perceptron.



Mathematical Presentation

$$Input = \sum x_i \cdot w_i + b$$

$$Output = f(Input)$$

$$f: activation\ function$$

Figure 2 - Rosenblatt's perceptron

Using the in-house developed open source code MoLP (MonoLayer Perceptron) with the data of Table 1, the perceptron learning rule (Rosenblatt, 1958) iterates 217 times, calculating all three parameters of the model, namely $w_1 = 8, w_2 = 31.49\ and\ b = -89$. Now, when a new set of burden and pressure is presented to the network, for example 10m and 0.5at, the perceptron's response is the expected one, producing a value of deformation rate below $10\ ^{mm}/_{day}$.

3.2 Multilayer perceptron neural network (MLP)

Figure 3 presents a more general and realistic case; cascading perceptrons. The Multilayer perceptron neural network **(**MLP) is suitable for solving non-linear problems, when an appropriate learning algorithm exists (Battiti, 1992). This algorithm is the backpropagation and the learning scheme of the algorithm comprises the following steps:

- the memory of the network, i.e. the weights and biases, receives random values
- the input is propagated towards the output and when it reaches that point, the error function is calculated.
- the error is propagated towards the first perceptron of the bank
- all weights and biases are updated.

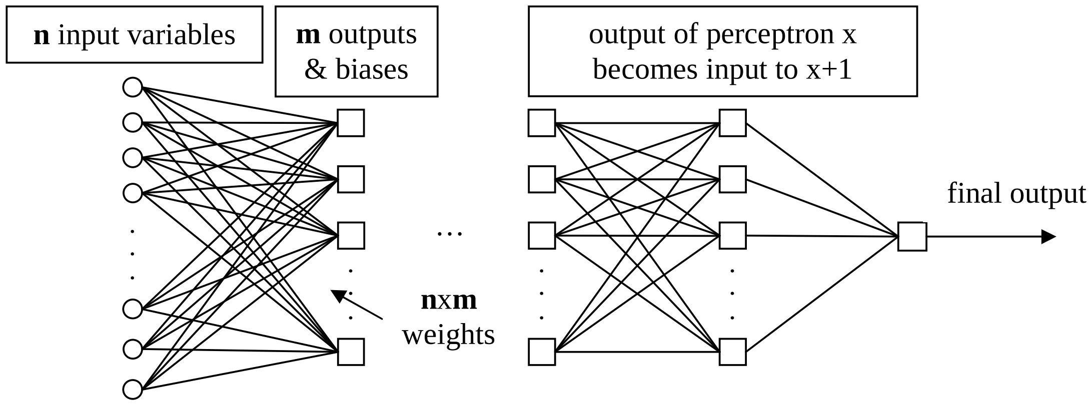


Figure 3 - Cascading Perceptrons or Multi-Layer Perceptron

However, an important problem is that the architecture of each adjacent perceptron in the bank is completely unknown beforehand. Furthermore, an established method for calculating each perceptron's dimensions does not exist. According to Witten and Frank (2005), there must be a relationship between a decision tree constructed from the same instances that are used for the MLP training. Therefore, the initial structure of the MLP bank could be one that resembles the decision tree's structure. Additionally, a more sophisticated network could be constructed by pruning the initial decision tree.

3.3 Modeling bench behavior

Table 2 gives an example of geometrical and geotechnical data that was collected in order to assess the deformation rate of a lignite slope in Ptolemaida extraction site.

Instances / **Parameters**	1	2	3	4	5	…	77	…	100
Slope height (m)	19	18	19	20	17		19		18
Slope angle (degrees)	65	71	69	70	65		70		67
Burden (m)	9	12	13	6	13		9		8
BWE position	3	3	2	2	4	.	1	.	2
Inclinometer (mm)	147	82	142	82	146	.	147	.	82
Pore pressure (psi)	18.3	16.5	17.7	16.8	17.3	.	16.1	.	18.2
Target Output									
Deformation Rate (mm/day)	24.27	20.55	9.95	3.76	10.96		16.12		5.91

Table 2 - Parameters for modeling slope behavior

In Table 2 it is assumed that 6 independent variables are adequate to describe the deforming state of the slope. The combination of slope height, angle and burden indicates the unit volume of soil mass that slides. The bench number on which the nearest BWE operates plays the role of an instant disturbing factor. Last but not least, two parameters from the underground monitoring program are taken into account; the first is the cumulative displacement of the inclinometer probe at the depth of the main sliding surface. The second is the pore water pressure at the same depth. Just a subset of the 100 examples is presented in Table 2. The goals of the analysis that follows, which is implemented by the in-house open source code "MLP" are

- the building of an intelligent system, which is capable of learning by example and performing appropriately upon similar cases
- the prediction of deformation rates, as an award of the latter training procedure

Data in Table 2 is represented by the flat file "pt slope". This file is fed to the "MLP" code and a decision tree is generated. Tree's structure follows the architecture 1 – 2 – 4, where each number describes the corresponding tree nodes from top down. It's assumed that the same architecture must be followed by the neural network itself, as a first approximation of its own architecture. Thus, Figure 4 shows a geometrical image of what is constructed in computer's memory

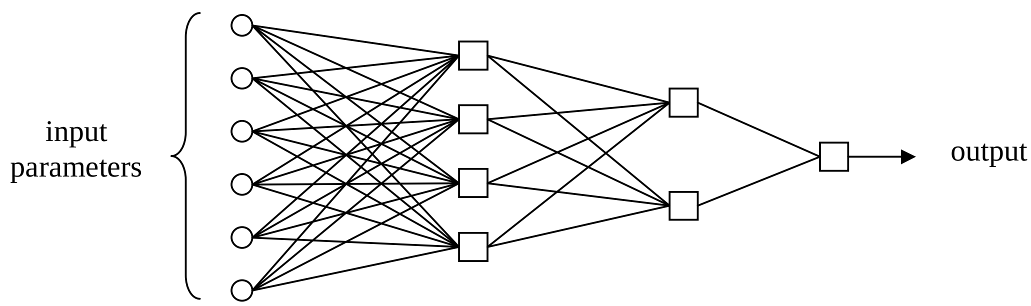


Figure 4 - MLP for deformation rate training & prediction

The "MLP" code has to evaluate a number of 41 memory parameters (34 weights and 7 biases). After the end of execution those parameters are calculated and the program is fed again with a new instance, this time without its target value. This instance assumes the following values; slope height = 17m, slope angle = 70 degrees, burden = 5m, BWE position = 3, inclinometer = 80mm & pore pressure = 16.1psi. The response of the network is 2.79mm/day, when the expected value is 3.5mm/day.

The final stage of analysis is concerned with the reevaluation of network's architecture. According to Witten and Frank (2005), a large number of network parameters result to a network that is highly specialized on its own training data, a situation that is characterized as the overfitting problem (Frank, 2000). Thus, by pruning the initial decision tree, the new 1 – 2 – 2 tree is constructed. Ultimately, the revised neural network has the architecture 6 – 2 – 2 – 1 or 23 memory parameters have to be calculated. After the end of execution, the network is fed with the previous case data and its response is 3.1mm/day, which is really close to the expected output.

4. CONCLUDING REMARKS

The challenging issue of modeling the deformation rate of soil mass has been approached by two different methods. Time series analysis builds a dynamic stochastic function, based on the data at hand; when the trend of data changes, the function adapts itself to the new status. However, the building process is not based solely on the underlying data, as it makes use of statistical assumptions that do not hold in every circumstance.

On the other hand, the neural network approach conducts the modeling without prior information about the data or any statistical assumptions. After a number of iterations, the memory parameters – weights and biases – are changing according to the stimulus they had been given. It's solely a data driven method that can be applied with success to deformation problems in general.

Future work will concentrate on more neural network training algorithms and optimization of nets and decision trees.

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