# Work Package 5: Monitoring and evaluation of outputs

# Deliverable 5.7.4 (former 5.4.2): Evaluation of existing data and fixing of the measurement protocol

**Beneficiary: IHU (former Eastern Macedonia and Thrace Institute of Technology, EMATTECH)**

**INTERREG V-A COOPERATION PROGRAMME:**

**GREECE – BULGARIA 2014-2020**

The Project is co-funded by the European Regional Development Fund and by national funds of the countries participating in the Interreg V-A "Greece - Bulgaria 2014-2020" Cooperation Programme.

**About this document:**

This deliverable reports on the methods of data acquisition, the methods of evaluation of measurements as well as and the measurements protocols.

**Deliverable Version:** v.4

**Date:** 02/06/2022

**Deliverable Contributors:**

1. Lykourgos Magafas

**Has been reviewed and approved by:** Lykourgos Magafas

# Table of Contents

# 1. Sensor

A sensor is a device used to measure a physical quantity. It converts the measured natural quantity (measured size) usually into an electrical signal. It should be clarified, that the general expression "electrical output signal" of a sensor is either voltage (if the sensor converts the measured size to voltage) or current (if the sensor converts the measured size to current). Some examples of physical quantities commonly measured by sensors are temperature, position and displacement of an object, fluid level, velocity and acceleration of a moving object, force, fluid flow, voltage, current, humidity, radiation and more.

Along with temperature and pressure, level measurement is at the top of measurement needs in our daily lives. Level and volume sensors are used in the case of liquids, which occupy the lower part of the borehole, container or tank in which they are placed and form a horizontal free surface at the top.

# 2. Sensor Options

## 2.1 Vibration Sensor

The measured physical quantity is the frequency slip. A fork or rod vibrates electronically with a specific frequency of piezo-ceramic crystal or similar. When it comes in contact with the measured instrument, this frequency decreases. The electrical part of the device recognizes the change in frequency and creates an output signal based on this change

It is an easy and simple to use instrument. No special or non-existing settings, no moving parts, no restriction on installation, unaffected by the physical characteristics of the measured medium, possibility-test of correct operation. Sticky materials however can cause problems, and solids with high cocometry can clog the fork (both of these disadvantages are minimized by using a vibrating rod-type switch-VIBRATION ROD).

## 2.2 Capacitive Sensor

The measured physical quantity in this case is the capacity. The probe sensor with the metal wall of the tank creates a capacitor that changes its value as a material is added to the tank.

It is a general use method, without moving parts and with quite good accuracy. They are instruments suitable for solid materials. The main disadvantages are that sticky materials can cause problems. Installation can be difficult due to external parameters such as the material of the tank, or the influence of the cable.

## 2.3 Conductive Electrodes

One or more electrodes with different lengths form a probe (measurement stem). They are placed in containers with a conductive liquid. If the level of the material rises to the electrode, it "closes" a circuit between two electrodes and creates an output signal.

## 2.4 Magnetic Immersion Probe

The measuring instrument is a driven float that has a built-in magnet. As the float moves based on the level on a rod, the permanent magnet contained in the float activates reed contacts placed inside the rod, resulting in corresponding output activations.

It is a simple method, easy to install, without maintenance needs and with high reliability of measurements. The buoyancy depends on the size of the float, and the lengths do not exceed 3 to 5 meters.

## 2.5 Float switch

The movement / position of the float as it sinks and lifts based on the liquid level is detected by a built-in switch that gives an output signal.

## 2.6 Ultrasonic Sensor

The sensor measures the time it takes for the ultrasound wave to travel from the sensor to the surface of the material and be reflected back to the sensor. This time is directly related to the distance and therefore the level of the material. The device's electronic unit translates this value into an analog signal.

The sensor does not come into contact with the measured material. The measurement is independent of the density of the material. It has no moving parts and has a solid construction.

The speed of sound depends largely on temperature and pressure. The formation of gas above the surface of the material can affect the speed of sound, the presence of foam absorbs much of the ultrasound. Modern sensors have temperature compensation systems, signal absorption calculation, and measurement belt rejection to reduce the chances of incorrect measurements.

### 2.7 Guided Microwave or Radar

The physical parameter measured is the pulse of driven microwaves. The emitted microwave pulse moves on the metal rod and is reflected back, on the surface of the material. The level of the material is calculated by the electronic unit and is based on the total sending-receiving time of the pulse.

The calibration can be done without being installed. It has no moving parts. Also suitable for solid materials (in the form of powder, granules). High measurement accuracy. Unaffected by temperature, pressure. Adhesives can cause problems.

### 2.8 Hydrostatic Pressure

The measured physical parameter is the pressure of the liquid, which changes with respect to the level. The output signal of the transmitter is proportional to the level of the liquid to be measured. It offers great accuracy in measurement. It has no moving parts, does not require maintenance, is suitable for measurement in waste, viscous materials, etc. Temperature compensation is necessary to change the density.

### 2.9 Magnetic Immersion Probe

As the float moves according to the liquid level on a rod, the permanent magnet contained in the float activates reed contacts located inside the rod that change the total resistance (through the opening and closing of the reed switches). This total resistance is converted by the electronic unit into an output signal proportional to the fluid level. Regarding the advantages and disadvantages, the same applies as for point level measurement.

**For our study, due to their advantages and low cost, we have chosen the ultrasonic sensors, in order to measure the borehole water level.**

## 3. Instrument Calibration

The measurement system consists of an ultrasonic sensor, the necessary cable, the system controller, an internet router for the provision of data via the Internet and a tablet for on-site measurement (Fig. 1 and 2). As mentioned in the deliverable D.4.7.2. for the implementation of the measurements using the ultrasonic sensor, special software was developed for real-time monitoring (Fig. 3.).

**Figure 1.** Ultrasonic sensor with 30m cable

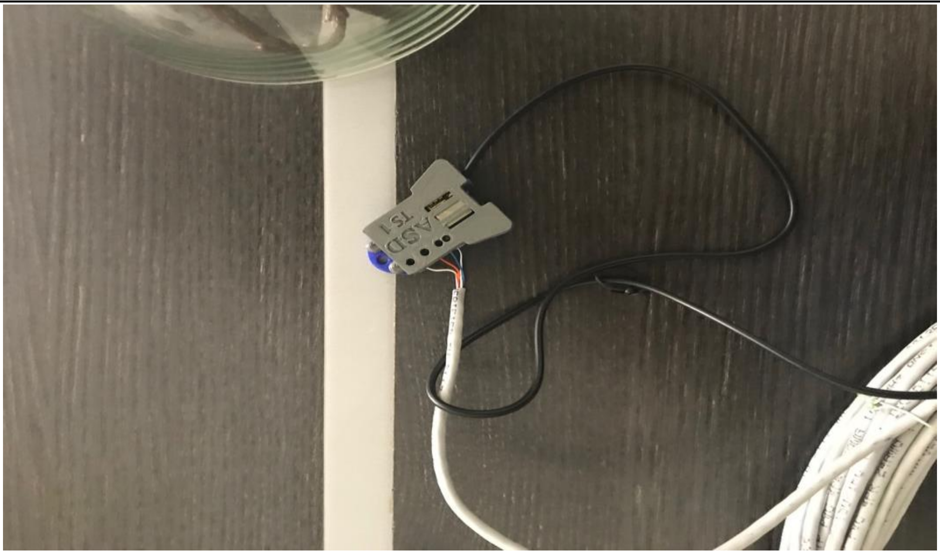

**Figure 2.** The system controler

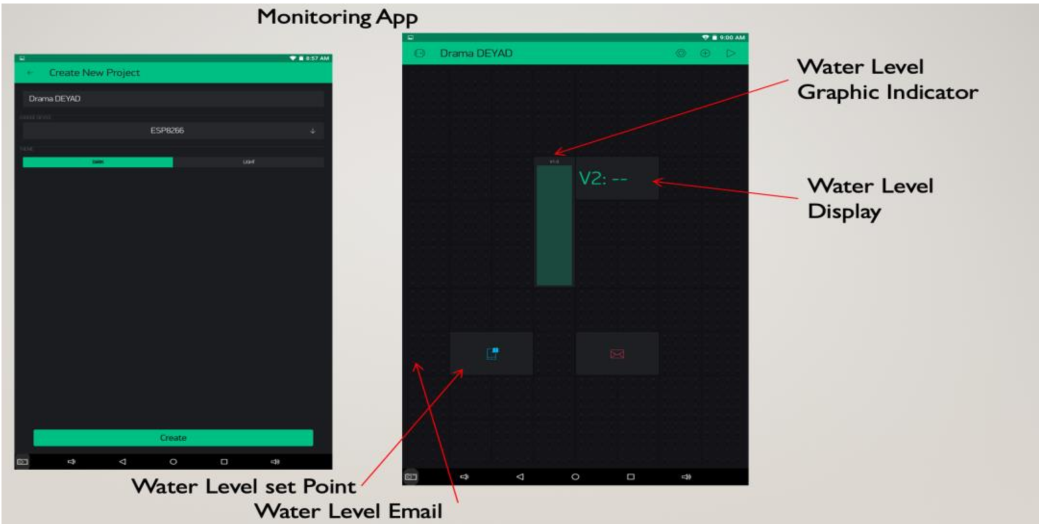


**Figure 3.** Screenshot of software for water level monitoring.

Before performing any measurements, it is necessary to initialize the sensor in order to certify the accuracy of the measurements. For this purpose, a manual meter and a conductivity sensor were used to accurately determine the height of the water level in the borehole. After identifying the height level of the water, the level and the diameter of the drain pipe were registered in the software at the given time. The operation of the system was checked for the next hour.

## 4. Results and Evaluation

The following 3 diagrams (Figures 4,5 and 6) show indicative results for the month of March 2020. The first diagram shows the height of the water in the borehole. The second diagram shows the amount of rain that fell in the city of Drama that month. The last diagram represents both measurements simultaneously. There is a complete correspondence between water levels in drilling and whether there was rain or not.

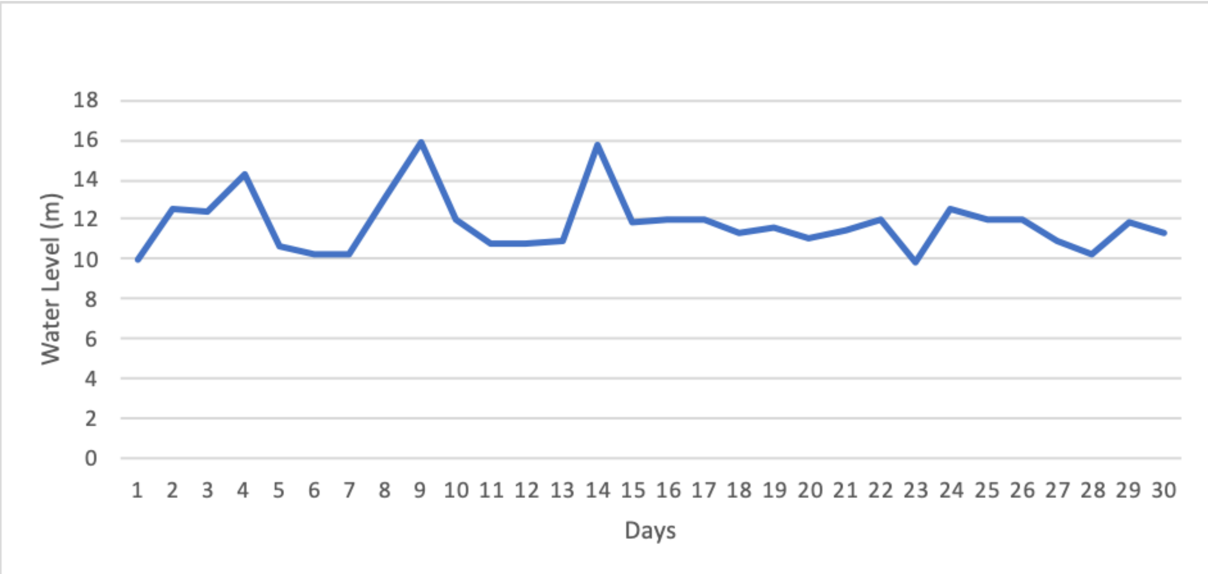


**Figure 4** The height of the water in the borehole during March 2020.

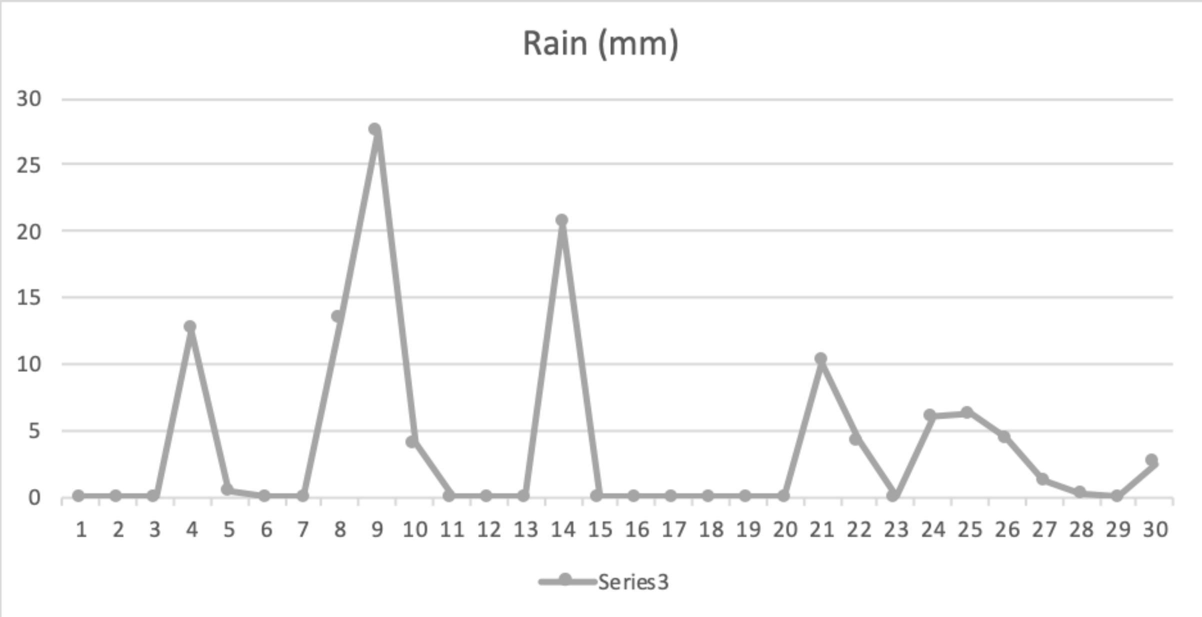


**Figure 5**. The amount of rain that fell in the city of Drama on March 2020.

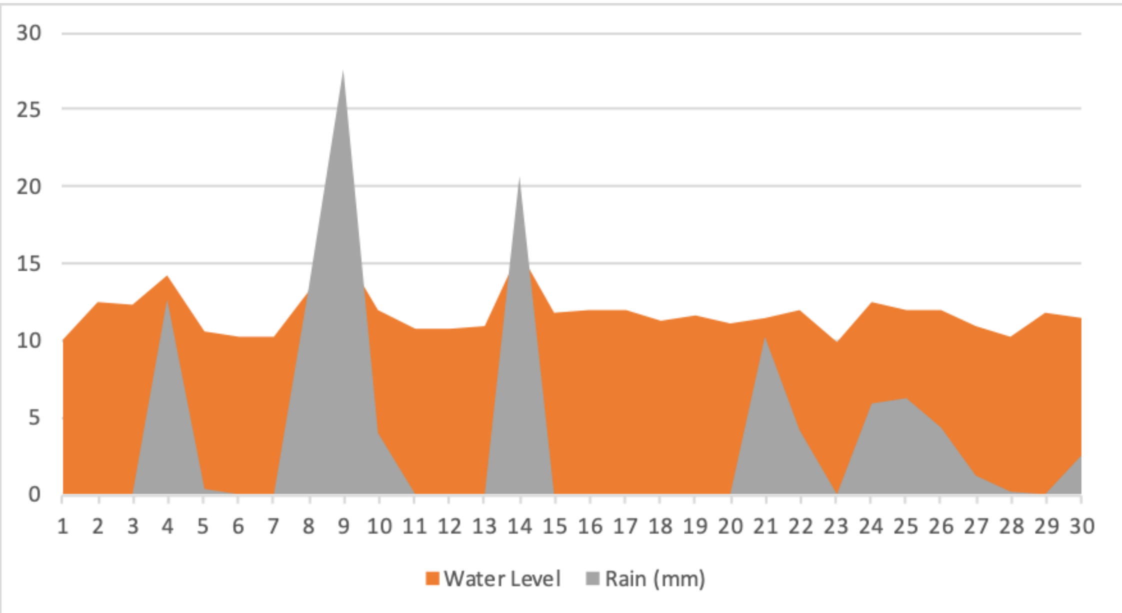


**Figure 6** Combination of figure 4 and 5.

## 5. Additional Evaluation based on Computational Models

In order to detect seasonality as well as periodical phenomena for the height of pump water it was studied the behavior of height as a function of the time (time series) in order to make predictions.

The most successful methods are Chaos Theory as well as Neural Networks. Both methods are independent. Neural nets can be applied in all kind of data whereas Chaos theory can be applied on non linear. In Figure 7 are presented all type of data. The data used in this study concern a long period, about two years.

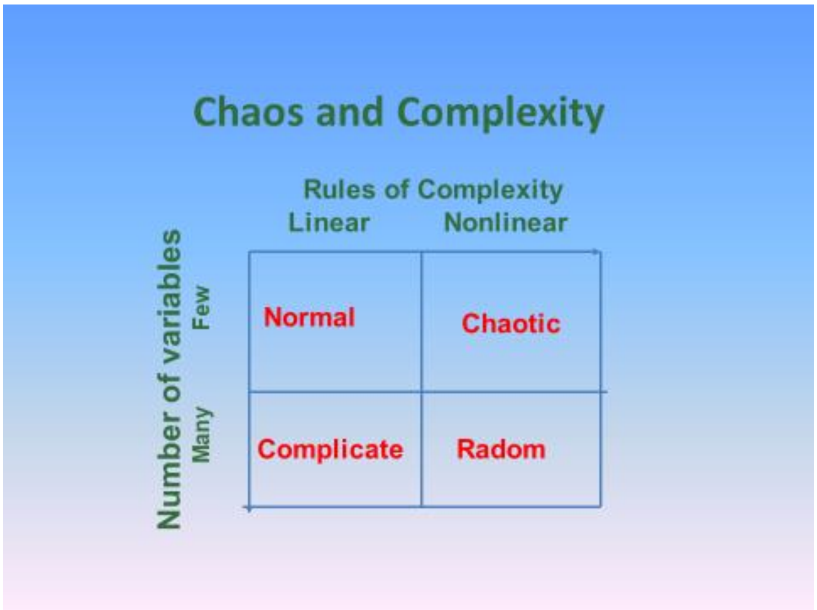


**Figure 7**. The different kind of data

## 5.1 Evaluation according Chaos Theory.

Figure 8 presents the time series of height of pump water. As it is clear, the height (h) presents strong fluctuations with the time which is related mainly with the rainfall.

As mentioned before the reconstruction of the corresponding possible strange attractor is based on Grassberger and Procaccia's method, [1-3]. Using the height of the water in the borehole as a variable, which belongs to a wider natural system and there are other parameters that affect the height. It is important to know if the system is a deterministic chaotic one or a stochastic one. This is proved by the the number of other parameters that

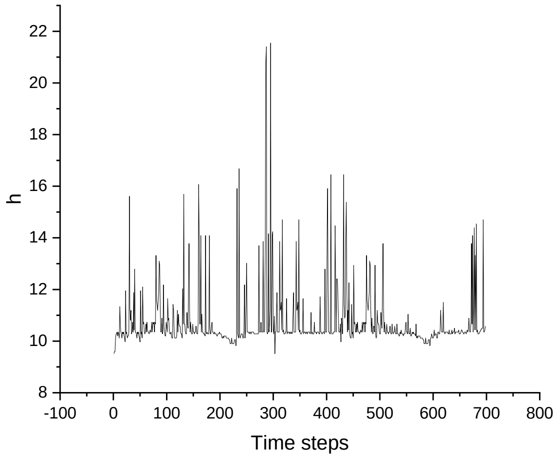


**Figure 8**. The height of the water in the borehole.

means the number of differential equations of first order describing the system. If this number is small then the system is a deterministic chaotic one otherwise is stochastic Using Takens' theorem, [4], in a recorded time series it can be constructed a topological equivalent phase space can be constructed. It is usual phenomenon in time series data to co-exist deterministic chaotic information with random component and noise (in sometimes white noise) [5].

Takens' theorem [4], provide the calculation of the correlation integral calculated,[3] for r→0 and N→∞, by,

$$C(r) = \frac{1}{N_{pairs}} \sum_{\substack{i=1, \\ j=i+1+W}}^{N} H\left(r - \left\| \vec{X}_i - \vec{X}_j \right\|\right) \tag{1}$$

where

N is the number of points, r is the linear dimension of hyperspheres and H is the Heaviside function. The quantity of $N_{pairs}$ is given by the relation:

$$N_{pairs} = \frac{2}{(N-m+1)(N-m+W+1)} \tag{2}$$

Where m is the embedding dimension, $(\vec{X}_i, \vec{X}_j)$ are the number of pairs for which the distance, (Euclidean norm), $\left\|\vec{X}_i - \vec{X}_j\right\|$ is less than r, in an m dimensional Euclidean space,

W is the Theiler window, N is the number of data.

For this time series N=580, $\vec{X}_i$ is a vector which is determined as:

$$\vec{X}_i = \{x_i, x_{i-\tau}, x_{i-2\tau}, \ldots.. x_{i+(m-1)\tau}\} \tag{3}$$

And τ is the time delay (τ=iΔt).

This parameter, τ (time delay), can be estimated by using the average mutual information function I(t) [6,7]. More specifically, the amount of I(t) for the space between x(t) and x(t+τ), is the amount in bits found by values of x(t) through measurements of x(t+τ) . For this case of study, when recording The height of the water in the borehole every minute, the values are highly correlated contrary to 12 hours measurements which results in loss of information. In order to get optimal τ, the suggestion is to take the τ as the first minimum of the mutual information I. For this data set, the first minimum is at τ=3 time steps as depicted in Figure 9. Of course, this value is a starting point. Practically the influence of τ values on correlation dimension estimation, in this region of values is negligible.

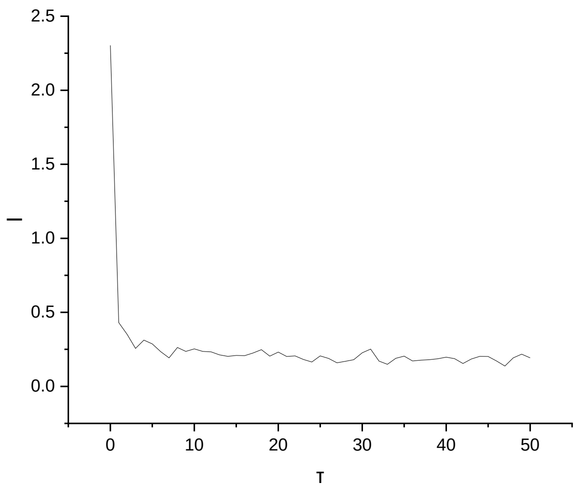


**Figure 9.** The function of Mutual Information (I) versus time delay (τ) for the height of the water in the borehole. The first minimum is at τ=3.

The next step in this evaluation is the estimation of Thailer window (W) [8]. It can be found as the first zero crossing of autocorrelation function. Figure 10 shows the corresponding plot where Theiler window was estimated W=16.

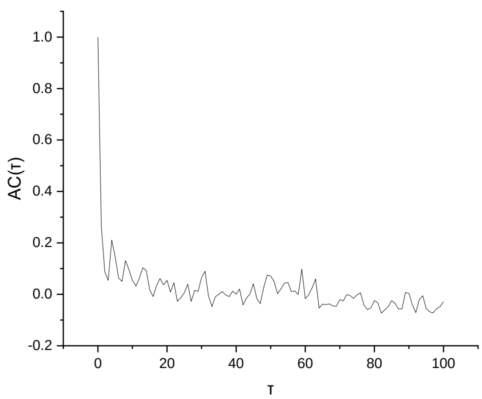


**Figure 10**. Autocorrelation Function versus delay time for Thailer's window estimation.

From the above results for τ=3 and W=16 took place the calculation of correlation integrals for various embedding dimensions. Take into account previous studies [6,9] , where it is supposed that the relation between correlation integral and radius is in form of a power law, then the attractor is a stranger one and v is the correlation dimension. The evaluation results are given in Figure 11 for various embedding dimensions m of the present time series of height.

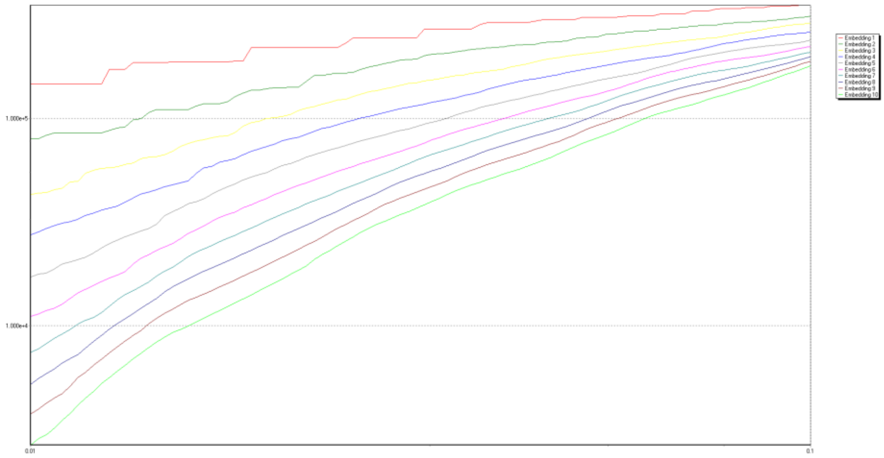


**Figure 11.** Correlation integral C(r) vs. radius r for various embedding dimensions m for the time series for the height of the water in the borehole.

As it is clear from Figure 11, the values of m are followed by a top to bottom sequence. From the slopes of linear parts of these curves the correlation dimensions are estimated for various embedding dimensions m. Figure 12 shows the average slopes v as a function of different embedding dimensions, m. It is obvious that the values of correlation dimension does not saturates with embedding dimension suggesting that the system is stochastic and no one prediction could be take place. The possibility of the existence of strong noise doesn't be excluded.

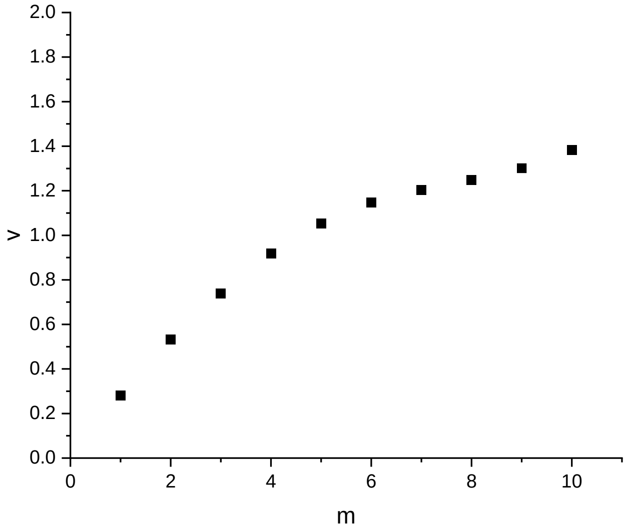


**Figure 12.** Correlation dimension v vs. embedding dimension m

Possibly the previous result can be attributed to the lack of stationarity of time series data. In order to disappear this possibility there were calculated the first differences of this time series according the relation :

$$X(t)=h(t)-h(t-1) \tag{4}$$

Where h(t), h(t-1) are the height of borehole at time t and t-1 respectively. In this way it was created a new time series which was studies its chaotic behavior. Figure 13 shows the new time series of first differences. As it is clear the lack of stationarity is present in the same time series. For this purpose it was applied stationarity test [10] confirming the previous hypothesis.

Also it was calculated the function of Mutual Information (I) versus time delay (τ) for the height of the water in the borehole and the result showed that the first minimum is at τ=1. This is presented in Figure 14. As it is clear the first minimum it is extremely low value indicating lack of chaotic behavior.

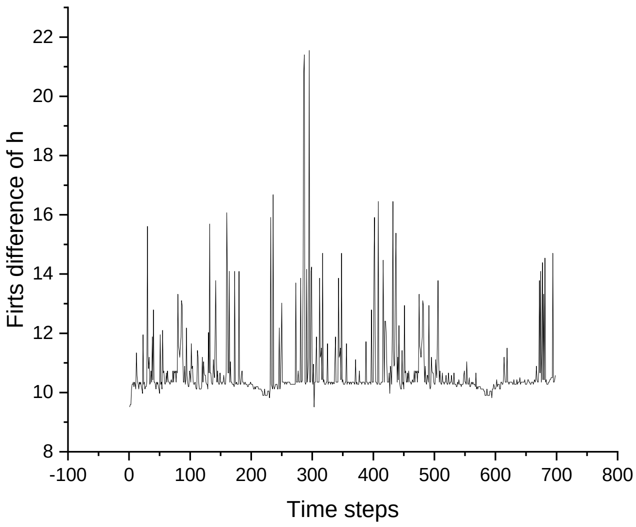


**Figure 13.** The time series of first differences oh height of borehole.

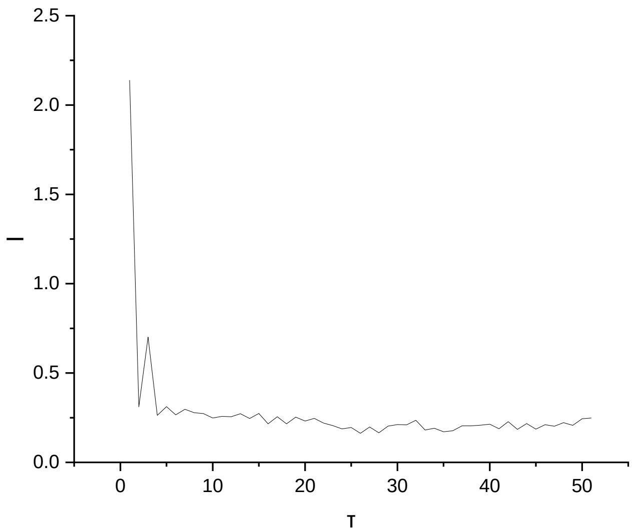


**Figure 14** The function of Mutual Information (I) versus time delay (τ) for the height of the water in the borehole.

Next step was to calculated the dependence of Autocorrelation Function versus time delay τ and the results are presented in Figure 15. It was found that the Thailer window is extremely low (W=3) suggesting the lack of chaotic dynamic.

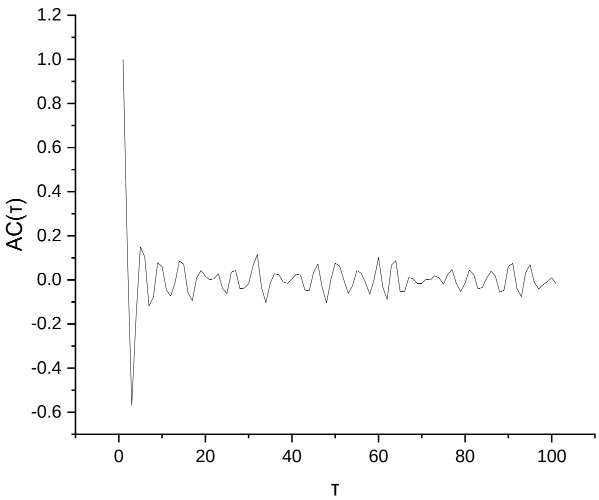


**Figure 15.** Autocorrelation Function versus delay time for Thailer's window estimation.

Finally it was calculated the Correlation dimension **v** vs. embedding dimension **m** for the first differences time series [11,12]. The results are presented in Figure 16. It is obvious that this time series is not chaotic one since does not presents saturation characteristic. Consequently, the time series oh height of borehole as well as the first differences are no chaotic and it is impossible to make prediction.

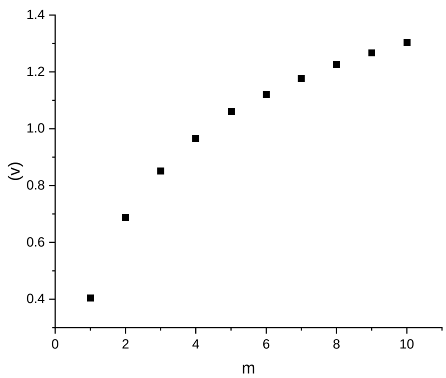


**Figure 16**. Correlation dimension v vs. embedding dimension m

## 5.2 Neural networks

In the present work it was used the Nonlinear Autoregressive Network (NAR Network) since it is the more effective for time series predictions[13,14]. In Figure 17 it is presented a typical Neural Network where it is shown the three different levels, the input, Intermediate or hidden and Output.

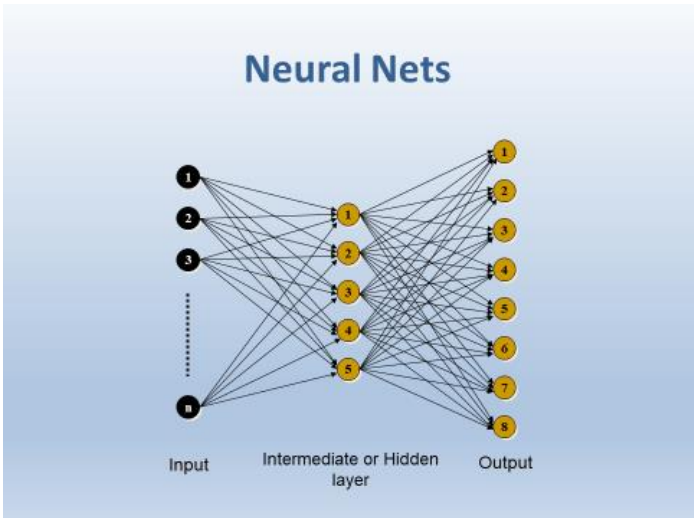


**Figure 17.** Typical structure of a Neural Network

The future values of a time series $y(t)$ are predicted only from past values of that series. This form of prediction is called nonlinear autoregressive, or NAR, and can be written as follows:

$y(t) = f(y(t-1), ..., y(t-d))$

You can use this model to predict specific time series but without the use of a companion series.

### Neural Network Architecture

We construct a neural network with 1 input layer , 1 hidden layer and 1 output layer

The number of neurons at input layer are characterized as feedback delays . As feedback Delays we used the time delay from the first zero crossing of autocorrelation function which is 16 so

Input layer size=16 or feedback Delays=16

As a rule of thumb the number of neurons in hidden layer was closed to be the half of number of neurons of input layer so the

Hidden layer size=8

As learning rule the Levenberg-Marquardt backpropagation selected.

### Levenberg-Marquardt Algorithm

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm [14] was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as:

$$\mathbf{H} = \mathbf{J}^T\mathbf{J} \tag{5}$$

and the gradient can be computed as:

$$\mathbf{g} = \mathbf{J}^T\mathbf{e} \tag{6}$$

where $\mathbf{J}$ is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \left[\mathbf{J}^T\mathbf{J} + \mu\mathbf{I}\right]^{-1}\mathbf{J}^T\mathbf{e} \tag{7}$$

When the scalar $\mu$ is zero, this is just Newton's method, using the approximate Hessian matrix. When $\mu$ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, $\mu$ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function.

This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights). It also has an efficient implementation in MATLAB® software, because the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB environment.

In MATLAB environment the function supports training with validation and test vectors if the network's NET.divideFcn parameter property is set to a data division function. Validation vectors are used to stop training early if the network performance on the validation vectors fails to improve or remains the same for max_fail epochs in a row. Test vectors are used as a further check that the network is generalizing well, but do not have any effect on training.trainlm can train any network as long as its weight, net input, and transfer functions have derivative functions.

Training stops when any of these conditions occurs:

- The maximum number of epochs (repetitions) is reached.

- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min_grad.
- Validation performance (validation error) has increased more than max_fail times since the last time it decreased (when using validation).

This is the implementation of MATLAB code

```
% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivision
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'time';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
```

The 70%of data are used for training the 20% of data are used for validation and the 20% are used for testing.

As performance function the Mean Squared Error function selected

This is the implementation of MATLAB code

```
% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'mse';  % Mean Squared Error
```

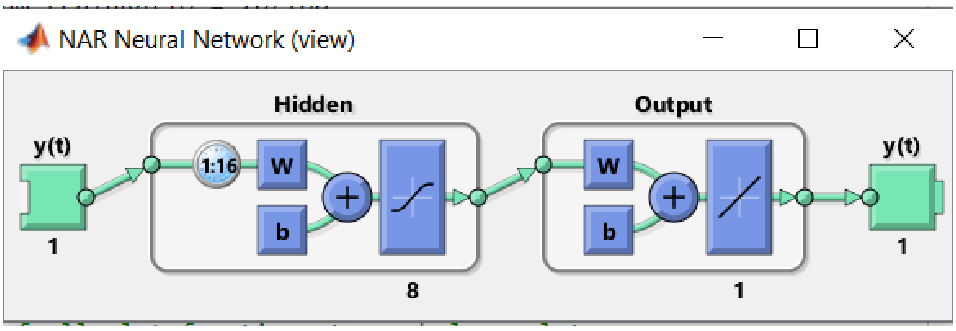

**Figure 18**. The operation structure of NAR Neural Network

The results of the calculations are presented in Figures 19 and 20. More specifically Figures 19 shows the education of the Network and the residuals that is an index suggesting the success of the approximation. It is clear that in the main part of the data the residuals are small numbers confirming that the model is acceptable. Figure 20 shows the forecasting for the time series that it is very good for 5 steps prediction, that is very interesting for this application.

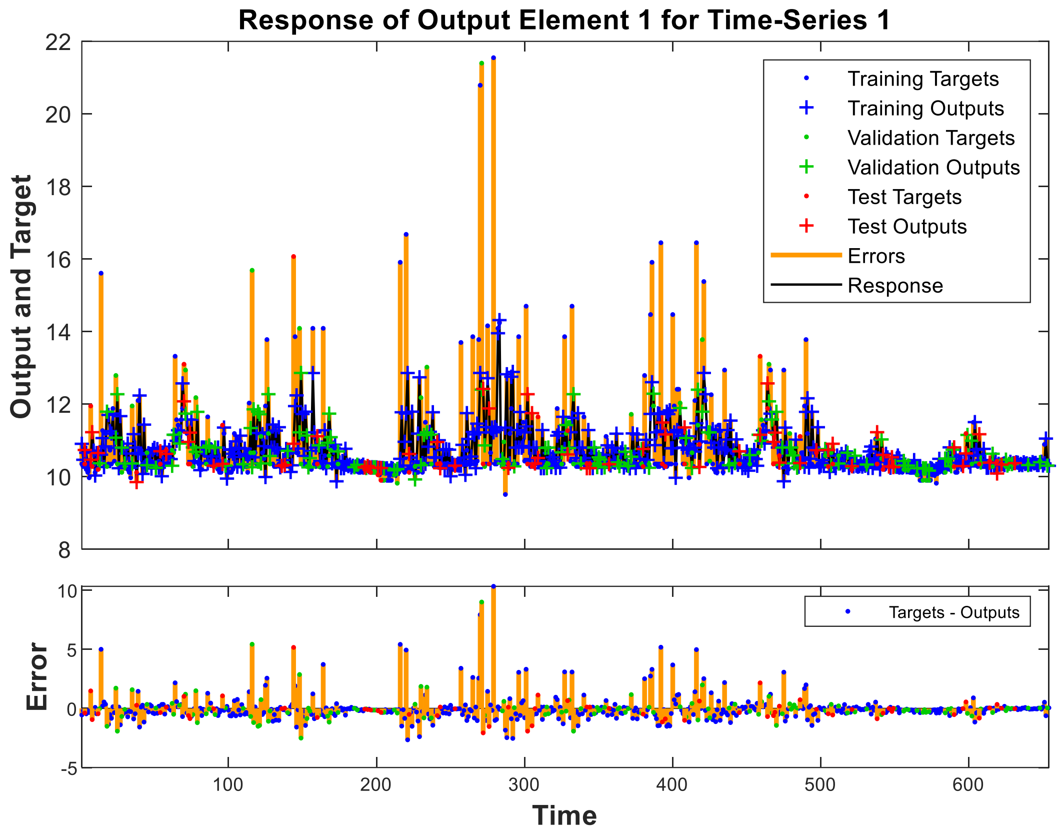


**Figure 19**. The time series of height of boreholes and the residuals of the education of time series.

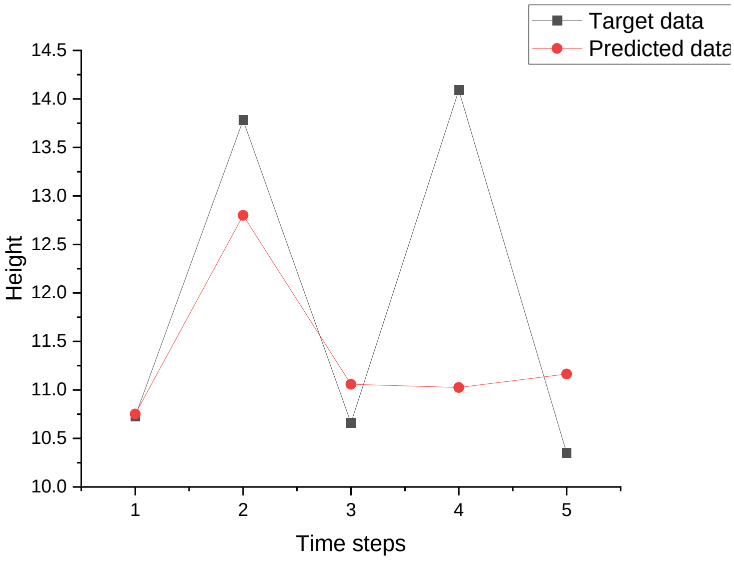


**Figure 20**. The prediction of time series and the real values (Target data).

## REFERENCES


1. Magafas, L., Hanias, M., Tavlatou, A., Kostantaki, P. (2017). Non–Linear properties of VIX Index. *International Journal of Productivity Management and Assessment Technologies, 5(2),*16-24*.*

2. Hanias, M.P., Avgerinos, Z., Tombras, G.S.(2009). Period Doubling, Feingenbaum Constant and Time - Series Prediction in an Experimental Chaotic RLD Circuit. *Chaos Solitons & Fractals, 40, 1050-1059.*

3. Hanias, M., Magafas, L., Konstantaki, P. (2013). Non-Linear Analysis of S&P Index. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 8(4),* 125-135

4. Takens, F. (1981). Dynamical Systems and Turbulence. *Lecture Notes in Mathematics, 898,* 366-381*.*

5. M.Faggiani, (2014). Chaotic time series analysis in economics: Balance and perspectives, Chaos **24**, 042101.

6. Abarbanel, H.D.I.(1996). *Analysis of observed chaotic data. Springer*, New York.

7. Fraser, A.M., Swinney, H.L.(1986). Independent coordinates for strange attractors for mutual information. *Physics Review, A33, 1134-1140*.

8. Kantz, H., Schreiber, T. (1997). *Nonlinear Time Series Analysis*. Cambridge University Press.

9. Sprott, J.C.(2003). *Chaos and Time series Analysis.* Oxford University Press.

10. BR Hunt, E Ott, JA Yorke, (1997). Differentiable generalized synchronization of chaos, Physical Review **E55**, 4029.

11. Provenzale, A., Smith, L.A., Vio,R., Murante, G.(1992). Distinguishing between low dimensional dynamics and randomness in measures time series. *Physica, D58,* 31-49*.*

12. Schouten, J.C., Takens,F., Bleek, C.M. (1994). Estimation of the dimension of a noisy attractor. *Physics Review, E50, 3,* 1851-1861*.*

13. Marquardt, D., “An Algorithm for Least-Squares Estimation of Nonlinear Parameters,” SIAM Journal on Applied Mathematics, Vol. 11, No. 2, June 1963, pp. 431–441.

14. Hagan, M.T., and M. Menhaj, “Training feed-forward networks with the Marquardt algorithm,” IEEE Transactions on Neural Networks, Vol. 5, No. 6, 1999, pp. 989–993, 1994.

**The contents of the report are sole responsibility of IHU (former Eastern Macedonia and Thrace Institute of Technology, EMATTECH) and can in no way be taken to reflect the views of the European Union, the participating countries the Managing Authority and the Joint Secretariat.**