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# DEFORMATION ANALYSIS OF GPS AUSCULTATION NETWORK BASED ON GENERALIZED REGRESSION NEURAL NETWORK (GRNN)

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## ABSTRACT

The present paper deals with the use of neural networks in the displacement and deformation fields modelling and analysis. The Generalized Regression Neural Network (GRNN) has proved its efficiency and reliability than the classical methods in the approximation of the displacement function. Based on the strain tensors, the deformation of GPS network is evaluated and represented according to a regular grid. In order to analyse this deformation, the concepts of deformability and deformation reliability are introduced, where the Monte Carlo method is employed to compute the significance degrees of the resulting tensors. At each stage of deformation field process, the GRNN neural network is used to perform an optimum interpolation of displacement field. The application concerns the GPS auscultation network of the Liquefied Natural Gas (LNG) underground tank of GL4/Z industrial complex (Arzew, Algeria). Composed of 119 points surrounding the LNG tank, the GPS network was observed between 2000 and 2006. The data concern the horizontal and vertical displacements of the network points according to local geodetic coordinates (E, N, U). The results show the performance of the adopted neural networks method in the generating and analysis of displacement and deformation fields. The most deformations measured are significant and at the deformability level. They support the physical interpretation by the presence of a rocky area at the WS side (landward) of the LNG tank which leads to compression and swelling, and the role of sea which acts as a warmer of freezing front causing important dilatations at the NE side (seaward).

**Keywords:** Geodesy, Artificial Neural Networks, Deformability, Deformation Significance, GPS Auscultation Network, Generalized Regression Neural Network (GRNN).

## INTRODUCTION

The global navigation satellite system (GNSS) becomes an inevitable technique for deformation monitoring from local to regional scales. Thanks to its low cost and fast positioning with high accuracy, the GNSS contributes effectively in the establishment of homogeneous and precise geodetic networks. The reiteration of the GNSS measurements of the same network permits to compute the displacements vectors. Then the strain tensors can be evaluated according to finite elements constituted from geodetic points which are heterogeneously distributed. This deformation representation makes difficult the interpretation of the results obtained (Merbah et al., 2005; Gourine et al., 2012). The solution adopted consists in assessment of deformation field over regular grid based on artificial neural networks (ANN) approximation (Gourine et al., 2012). Indeed, since several years, the ANN has been applied in diverse fields of geodesy (Miima et al., 2001; Schuh et al., 2002). As for geoid model determination, many studies have been realised (Lin 2009; Gullu et al., 2011). ANN was employed as an approximator for crustal velocity field (Moghtased-Azar, Zaletnyik, 2008) and it was adapted for structural behaviour modelling.
The aim of this present paper deals with the use of the Generalized Regression Neural Network (GRNN) for displacement field generating, deformation field evaluation and deformation reliability. The idea is to obtain the deformation field with ANN and to measure the significance level of the obtained deformation in order to get reliable diagnostic of the studied area. The application area concerns the zone of the Liquefied Natural Gas (LNG) underground tank (GL4/Z industrial Complex – Arzew, ALGERIA). To achieve deformation monitoring, an auscultation network was established by static GPS. It is composed of 119 points where 41 control points are implanted on the Tank structure. Observed between 2000 and 2006, the precision of the points positioning is of about few millimeters. The GPS points are expressed according to the local geodetic system (N, E, U).
The methodology adopted is based on the definition of the network deformation tensors (section 2) as the gradient of the displacements field generated over a regular grid, by the GRNN neural network (section 4). Four deformation primitives describe the way and magnitude of deformation: dilatation, shear and twist; for the 2D, and swelling for 1D. These later should be analysed since random errors in the measurements propagate throughout the calculation and by consequence lead to uncertainties in the strain tensors. The deformation analysis concept (section 3) is performed using the notions of deformability and deformation significance where the Monte Carlo method is employed. It creates

virtual deformations by artificial change of the observations in their confidence level. The GRNN based simulated displacements fields lead to the virtual deformations fields where the reliability of measured deformation is carried out. Finally, the results obtained are presented and discussed in section (6).

## DEFORMATION MODELLING

Assuming infinitesimal deformations and a continuous, homogeneous and elastic medium, the strain tensors of a geodetic network can be defined as following:

### Horizontal Deformation (2D)

The 2D local displacement field around a given point *M(x,y)*, is simply the difference of coordinates of this point between two epochs, as:

$$U(x,y) = \begin{pmatrix} u(x,y) \\ v(x,y) \end{pmatrix} \tag{1}$$

This representation of deformation mainly suffers from dependence to reference frame.
The strain tensor *E(x, y)* is defined as the gradient of the displacement field and is expressed by (Seemkooei 2001; Vaniçek et al., 2001):

$$E(x,y) = \frac{\partial U(x,y)}{\partial X} = \begin{pmatrix} \frac{\partial u}{\partial x}(x,y) & \frac{\partial u}{\partial y}(x,y) \\ \frac{\partial v}{\partial x}(x,y) & \frac{\partial v}{\partial y}(x,y) \end{pmatrix} = \begin{pmatrix} e_{ux} & e_{uy} \\ e_{vx} & e_{vy} \end{pmatrix} \tag{2}$$

This matrix gathers most of the information of displacement field behaviour. However, the interpretation of such a tensor is not obvious but its decomposition may help extracting some characteristic quantities known as deformation primitives. These later represent the deformation, in a more meaningful way. They are usual in material characteristics and mechanics. In this study, the deformation primitives have been chosen are positive scalars, growing with deformation amplitude, as (Gourine et al., 2012):

- Dilatation : $\text{ª} = \frac{1}{2}\left(e_{ux} + e_{vy}\right)$
- Total shear : $\text{¥} = \frac{1}{2}\sqrt{\left(e_{ux} - e_{vy}\right)^2 + \left(e_{uy} + e_{vx}\right)^2}$
- Twist: $\text{¢}\mu = \frac{1}{2}\left(e_{uy} - e_{vx}\right) - \Omega = \mu - \Omega$

where $\Omega$ is rigid rotation which affects the whole area. It represents the global rotation which corresponds to average value of rotations $\mu$ on points of the network.

### Vertical deformation (1D)

Let us denote the vertical displacement of point $M_i$ by $\Delta u_i = [\Delta z_i] = [w_i]$, where $w$ is the displacement in the $z$ vertical direction. The corresponding strain tensor is expressed by Berber (2006) as:

$$E_i = \left\{ \frac{\partial w_i}{\partial z} \right\} \tag{3}$$

It represents the elongation unit, evoking swelling if it is positive, or subsidence if it is negative (Belhadj et al., 2012).

## DEFORMATION ANALYSIS

The methodology adopted for the analysis of geodetic network deformations is based on the study of the significance of the strain tensors in the reliability concept (Michel, Person 2003). Considering a geodetic network as a structure, we can define its deformability as the inverse of its strength in the way that a deformable network is a sensitive network to the observations uncertainties which are due to the accidental errors. In other words, it is a study of network behaviour under the effect of observations variations in their confidence interval. Therefore, any deformation whose magnitude is less than the network deformability is not significant.
In this context, the concept of virtual displacement and virtual deformation (Michel, 2001) is introduced:

- The virtual displacement of a point is defined as the movement of this point due to random changes of observations in their confidence interval.

- The virtual deformation of network is the deformation resulting from the virtual displacements of all points of the network.

Quantifying the deformability of a network is based on virtual deformation primitives which are obtained by simulations of Monte Carlo method (Gourine, 2004). This statistical method consists of creating series of artificial observations sets, simulated from their standard deviations. Then new coordinates of the network points are obtained by adjusting the simulated observations by least squares method. In the following, virtual displacements are determined from which the virtual deformation tensors are processed and finally virtual deformation primitives. The process is repeated according to the number of simulations. The deformability of deformation primitives is defined by:

$$\begin{cases} \text{ª}_{def} = \bar{\text{ª}} + 1.96 \pm_{\text{ª}} \\ \text{¥}_{def} = \bar{\text{¥}} + 1.96 \pm_{\text{¥}} \\ \text{¢µ}_{def} = \text{¢}\bar{\text{µ}} + 1.96 \pm_{\text{µ}} \end{cases} , \tag{4}$$

where:

$\bar{\text{ª}}, \pm_{\text{ª}}$ : mean and standard deviation of simulated dilatations.

$\bar{\text{¥}}, \pm_{\text{¥}}$ : mean and standard deviation of simulated shears.

$\text{¢}\bar{\text{µ}}, \pm_{\text{¢µ}}$ : mean and standard deviation of simulated twists.

This definition lets 97.5% of virtual deformations to be taken into account assuming that the set is following a Gaussian distribution. From the deformability, one can define the degree of significance of the strain tensors. For each measured deformation primitive $(\text{ª}, \text{¥}, \text{¢µ})$, the significance degree is expressed by:

$$\begin{cases} \Sigma_{\text{ª}} = \dfrac{\text{ª} - \text{ª}_{def}}{\text{ª}_{def}} \\ \Sigma\text{¥} = \dfrac{\text{¥} - \text{¥}_{def}}{\text{¥}_{def}} \\ \Sigma_{\text{µ}} = \dfrac{|\text{¢µ}| - \text{¢µ}_{def}}{\text{¢µ}_{def}} \end{cases} , \tag{5}$$

This degree is positive when the measured deformation is meaningful. However, if it is negative, the measured deformation is not significant since it has a smaller magnitude than the deformability. According to (Michel, Person 2003), it depends on:

– The computation process of strain tensors,

– The network geometry configuration and the uncertainties of observations,

– The least squares adjustment of the network at a given time,

– The deformation primitives.

## DEFORMATION BASED GENERALIZED REGRESSION NEURAL NETWORK (GRNN)

Generally, the auscultation geodetic points are geographically distributed with heterogeneous manner, which makes difficult the interpretation of deformation. The use of regular grid is the best way to get a homogenous and continuous representation of the displacement/deformation fields on the whole area (Gourine et al., 2012). In this case, the application of an interpolation function based on the geodetic points permits to approximate the displacement on each node $i$ ($E_i$, $N_i$) of the grid. In this context, the ANN methods have proved their potentials and efficiency compared to classical interpolations (Gourine et al., 2012).

Several ANN models can be formed with various architectures, depending on the number of additional layers and neurons, training algorithms and activation functions. A very interesting characteristic of the ANN is the approximation feature, (Moghtased-Azar, Zaletnyik, 2008), which can be used in the process of deformation field modelling. The proposed ANN, for this study, is based on the Generalized Regression Neural Network (GRNN).

As variant of the Radial Basis Function Neural Network (RBFNN), (Abdul Hannan et al., 2010), the GRNN was proposed by (Spetch, 1993) for smooth approximation and as an alternative to the popular back-propagation training algorithm for feed forward neural networks. Regression can be considered as the least-mean-squares estimation of the value of a variable based on available data. The GRNN is based on the estimation of probability density functions, having a feature of fast training times and can model non linear functions. This method is simple but suffers badly from the curse of dimensionality. GRNN cannot ignore irrelevant inputs without major modifications to the basic algorithm. So GRNN is not likely to be the top choice if there are more than 5 or 6 no redundant inputs (Taboli et al., 2011). The GRNN can be thought of as a normalized RBF network in which there is a hidden unit centered at every training case. Unlike the standard RBF, the weights of these networks can be calculated analytically. As shown in Fig. 1, a GRNN consists of four layers: input layer, pattern layer, summation layer and output layer.

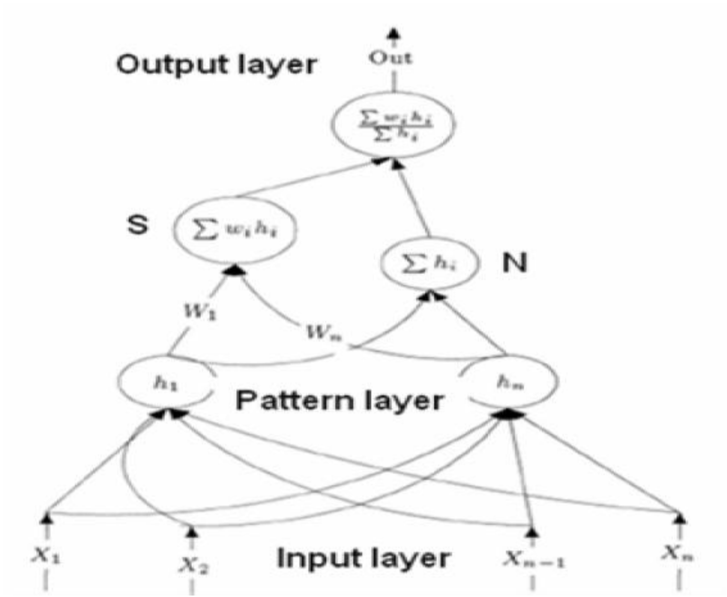



**Figure 1:** Schematic diagram of GRNN architecture

The GRNN process can be described, as in for example (Abdul Hannan et al., 2010), as following: The number of neurons in the input layer is the number of inputs in the proposed problem, and the number of neurons in the output layer corresponds to the number of outputs. The first layer is connected to the pattern layer in which each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. This later has two different types of summation: single division unit and summation units. The summation and output layer together perform a normalization of output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, *S* and *D* summation neurons. *S* summation neuron computes the sum of weighted responses of the pattern layer. *D* summation neuron is used to calculate un-weighted outputs of pattern neurons. The output layer merely divides the output of each *S*-summation neuron by that of each *D*-summation neuron, yielding the estimated value $y'_i$ to an input vector $x$ as:

$$y_i^{'} - \frac{\sum_{i=1}^{n} y_i \cdot e^{-D(x,x_i)}}{\sum_{i=1}^{n} e^{-D(x,x_i)}} \quad , \tag{6}$$

$$D(x, x_i) = \sum_{k=1}^{m} \left( \frac{x_i - x_{ik}}{\pm} \right)^2 , \tag{7}$$

where: $m$ is the number of elements of an input vector, $n$ is the number of the training patterns, $y$ are the weights connection between the pattern layer neurons and the S-summation neurons. $D$ is the Gaussian function and $\sigma$ is known as spread or smoothing factor (SF). This factor provides a smooth transition from one observed value to another, even with sparse data in a multidimensional space. The success of the GRNN depends on the selection of appropriate values of SF (Wasserman, 1993).

The optimum SF is determined after several runs, in the network training process, according to the root mean square error (*RMSE*) of the estimate (Eq. 8), which must be kept at minimum. If a number of iterations passes with no improvement in the *RMSE*, so that SF is determined as the optimum one for that data set. While applying the network to a new set of data, increasing the SF would result in decreasing the range of output values (Spetch, 1993). The GRNN network evaluates each output independently of the other outputs; GRNN network may be more accurate than back-propagation network when there are multiple outputs. GRNN work by measuring how far given samples pattern is from patterns in the training set. The output that is predicted by the network is a proportional amount of all the output in the training set. The proportion is based upon how far the new pattern is from the given patterns in the training set.

The performance of the ANN is determined by the root mean square error (*RMSE*) and the coefficient of determination (°) expressed between observed and estimated output, as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2}{n}}\ , \qquad (8)$$

Where: $y_i$ and $y'_i$ denotes the $i$th observed (actual) and estimated values of output $y$, and $n$ is the number of observations. The coefficient of determination, or correlation coefficient, used to evaluate the performance of the model is obtained by

$$° = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i^{'}\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}\ , \qquad (9)$$

Where: $\overline{y}$ corresponds to the mean of observed values of $y$.

## GRNN APPLICATION TO THE DEFORMATION FIELD MODELLING AND ANALYSIS

### Study Area

The liquefied Natural Gas (LNG) underground reservoir of the SONATRACH industrial enterprise (GL4/Z Complex – Arzew, Algeria), built in 1965, represented more than 50% of storage capacity of the complex of about 38000 $m^3$, figure (2). It was considered as the unique mode of underground LNG storage, operating in the world. With diameter and depth of about 37 m and 36 m, respectively, this tank is located at only 50 m near to the sea. The main characteristic of this kind of storage is the absence of insulation and tightness barrier on the vertical walls and the bottom of the tank, only the gel of water contained in the soil ensures its impermeability (Taibi et al., 2008).
The prevention of industrial hazards, related to this tank, on the complex infrastructures and on the population of Arzew's town, has required a GPS monitoring network to perform a topographic auscultation of this important industrial site.

**Figure 2:** Photo of the underground LNG tank (GL4/Z complex, Arzew – Algeria)

To achieve the geometric auscultation of the tank and its neighbouring, four GPS observation campaigns were carried out by the Division of Space Geodesy, of the Centre of Spatial Techniques (CTS-Algeria), in February 2000, July 2002, July 2004 and February 2006, (Taibi et al., 2008). For this work, the GPS network auscultation, estimated with millimeter precision, consists of 119 common points, between 2000 and 2006 operations.

**Construction of GRNN**

The GRNN neural network was implemented for modelling the fields of horizontal and vertical displacements of the GPS network auscultation of the LNG tank, as shown in figures (3) and (4).

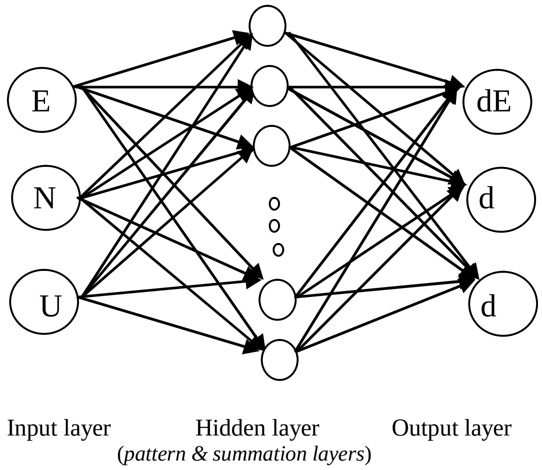



**Figure 3:** Adopted GRNN for displacement field modeling

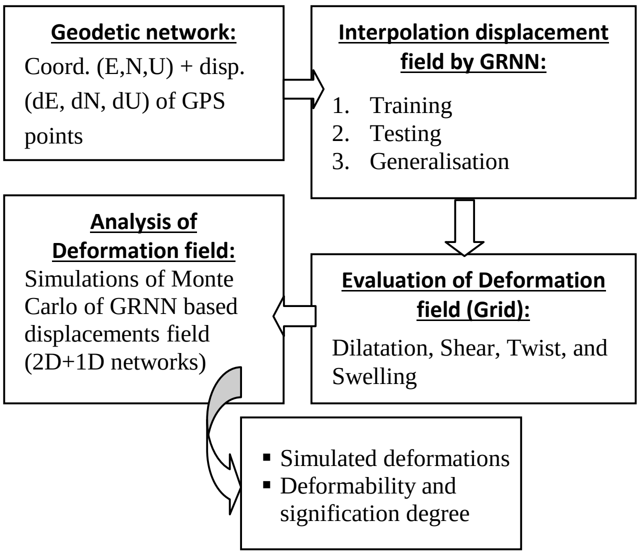



**Figure 4:** GRNN flow based deformation process and analysis

The data used are the local geodetic coordinates (N, E, U) of 119 GPS points and their corresponding displacements (dN, dE, dU), over a period of 06 years

(2000-2006). To test the effectiveness of the employed method, we divide the data into three groups. the first is used to estimate the parameters of the model approximation (Training set composed of 96 points, 81% of all data) and the second is used to test and validate the model (Testing group with 23 points, 19% of all data), as depicted in figure (5). The last one is used to perform the final step for modelling the displacement field, in order to generate the deformation field according to a regular grid. This latter is composed of 323 meshes covering the entire study area. Each mesh represents an area of 10 x 10 m² on the ground.

## RESULTS AND DISCUSSION

The GPS auscultation network is composed of 14 benchmarks (reference points), 64 points survey of the ground near the tank and 41 target points (control points) well distributed over the tank structure, as shown in the figure (5).

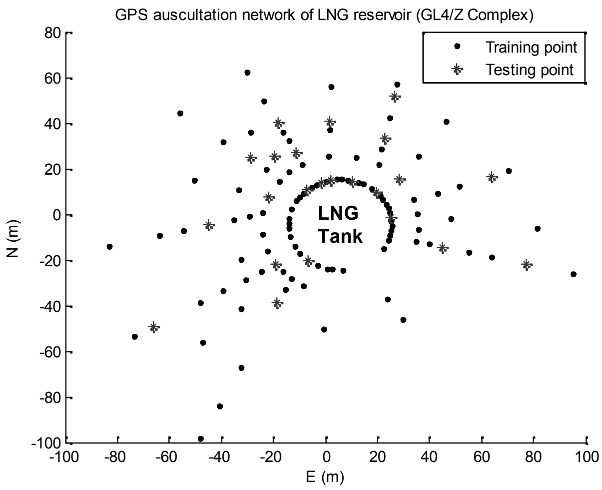



**Figure 5:** GPS auscultation network configuration

The maximum displacements of network points, according to (E, N, U) coordinates, are 112mm, 119mm and 254mm, respectively.

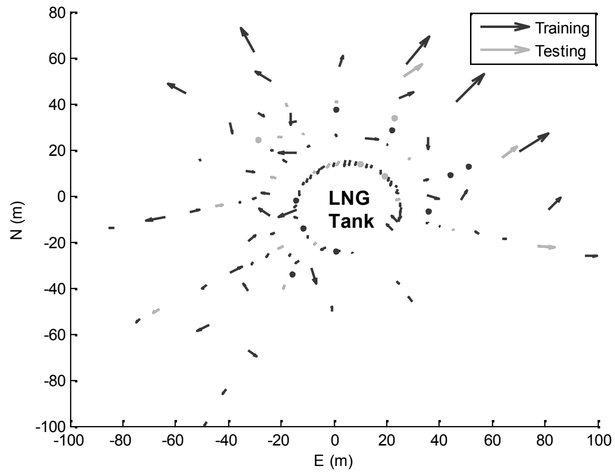



**Figure 6:** 2D displacement vectors of the GPS auscultation points

In order to generate the horizontal and vertical displacement/deformation fields, the GRNN neural network are applied on the GPS auscultation network according to the adopted strategy, figure (4).
Since the spread factor (SF) is the most important feature of GRNN, the network has been trained with different SF until optimum value of SF is achieved. It is chosen on basis of high correlation (close to 1) and high accuracy (minimum values of RSME), in the testing stage.
In figure (7) are depicted the performance parameters of the GRNN according to training and testing steps, with respect to local geodetic coordinates (N, E, U). In this study, the SF values of 14 and 3 have been determined as optimum ones, for horizontal (figure 8) and vertical displacement (figure 9) fields, respectively.

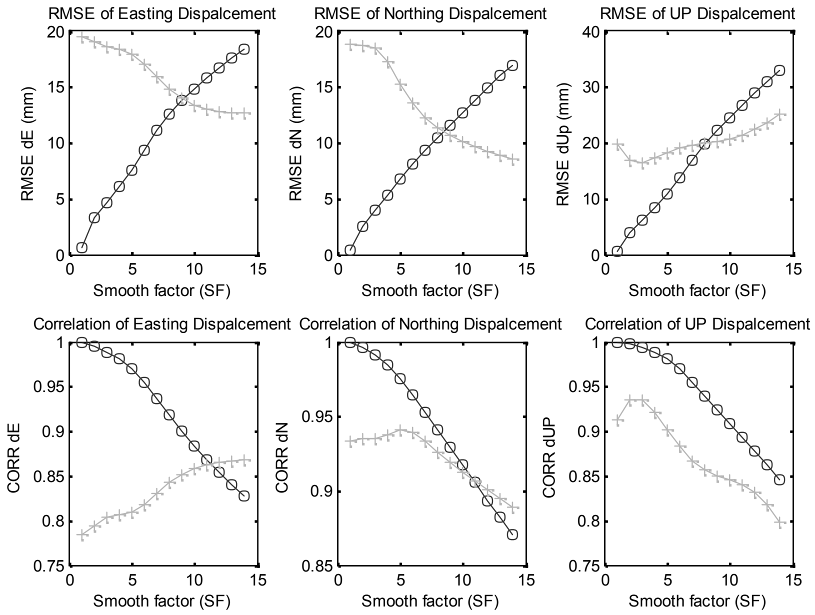



**Figure 7:** GRNN neural network performance results according to training and testing stages

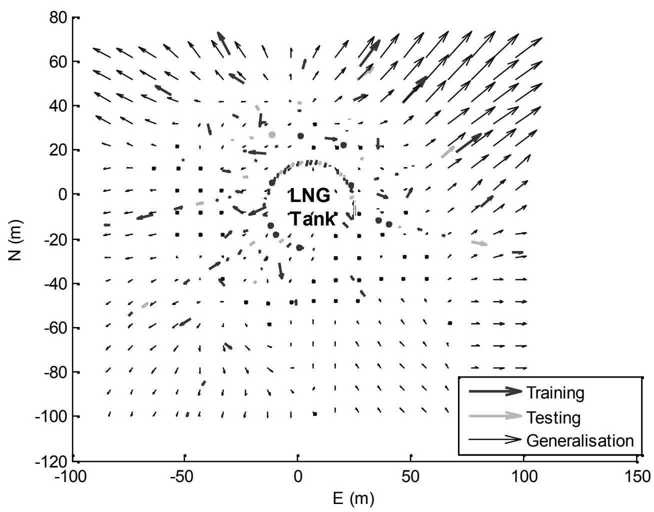



**Figure 8:** Horizontal displacement filed according to GRNN neural network with SF = 14

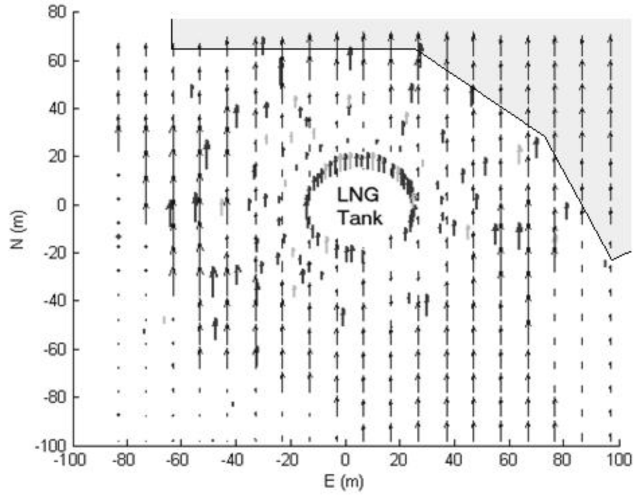



**Figure 9:** Vertical displacement filed according to GRNN neural network with SF = 3

Figure (10) illustrates the vertical displacement field obtained by GRNN neural network. It shows clearly a swelling phenomenon at the landward (in the West and South directions) more important than the seaward (in East and North the directions).

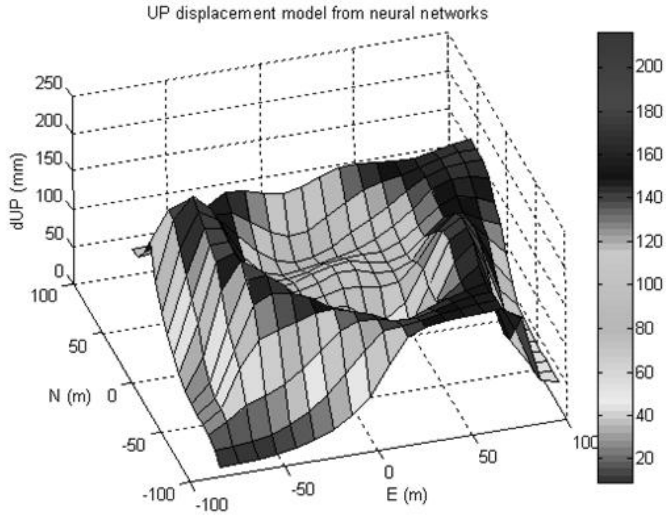



**Figure 10:** 3D visualization of vertical displacement model from GRNN neural network

Figure (11) provides the representation of the 2D deformation field of the GPS auscultation network, in terms of strain tensors primitives, as described in section (2.1), with respect to the obtained displacement field from GRNN network.

The shear expresses the change in configuration (e.g., a square becomes a lozenge). The shear value increases with increasing strain tensors; therefore, we have found regions of high deformation of about 1000–2000 ppm which are around the tank (North and East sides), except for the South and West sides where the shear is weak and at level of 200 ppm.

The dilatation is represented by circles with radii proportional to the deformations amplitudes. The red circles are dilatations and the blue ones are compressions. A dominant dilatation phenomenon characterizes the GPS auscultation network, in the 2000-2006 period. Large dilatations, at level of 3000–4700 ppm are located in the North and East areas of the tank while a weak compression is observed at its neighbourhood in NW and SE directions.

The twist is represented by vertical segments whose lengths correspond to rotations modules. The red and blue arrows are, respectively, positive and negative rotations. The maximum values are of about 790 dmgon.

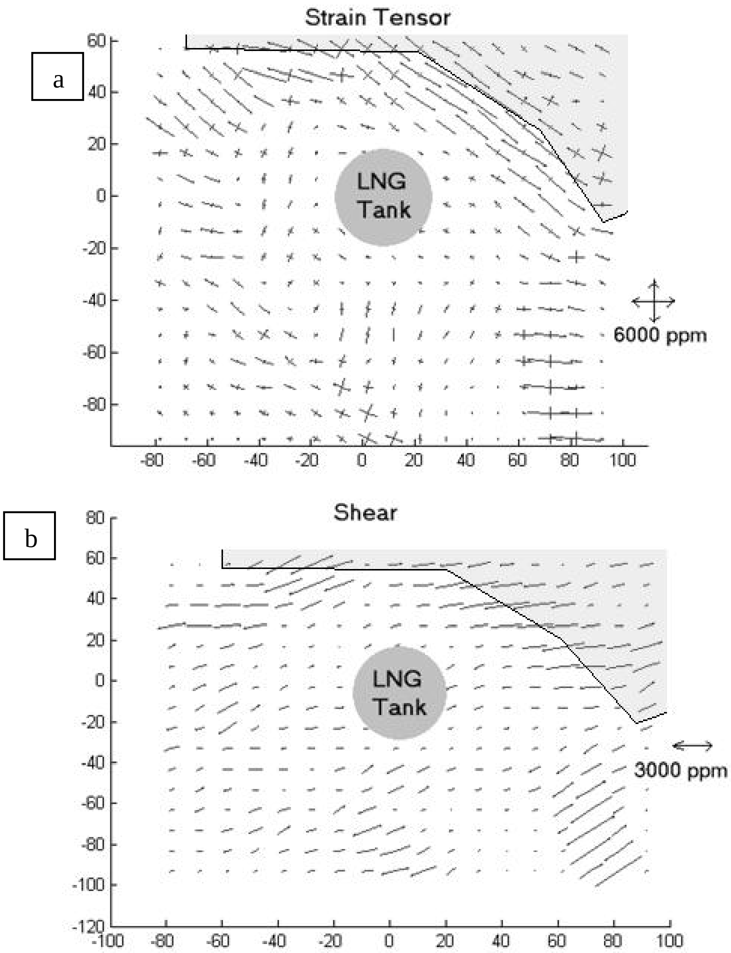



**Figure 11:** 2D Deformation primitives of the LNG Tank auscultation network.
(a) Strain tensor, (b) shear, (c) dilatation and (d) twists. (*Continued*)

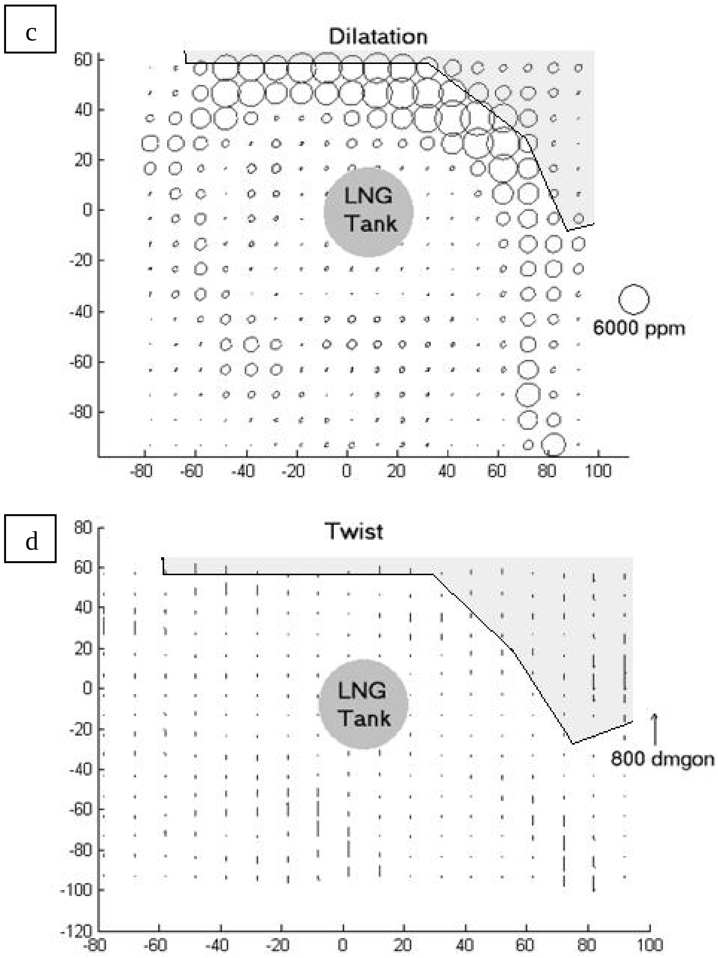



**Figure 11:** (*Continued*)

The vertical deformation field obtained by GRNN neural network of the LNG tank auscultation network is illustrated in figure (12). We note an important swelling at the landward of about 0.4. The tank structure is subject to an uprising of about 0.05.

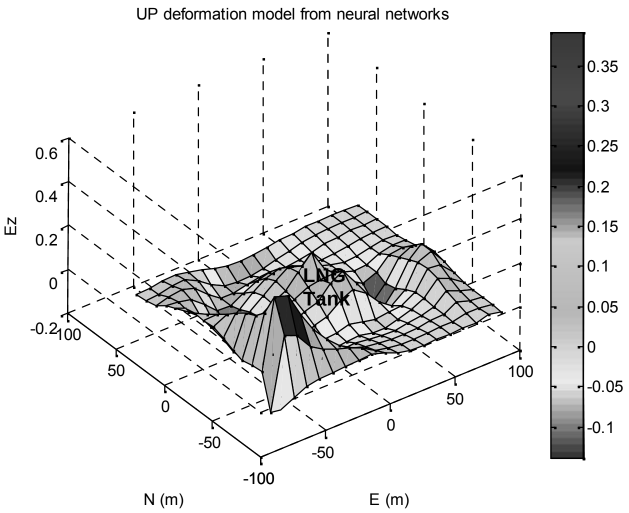
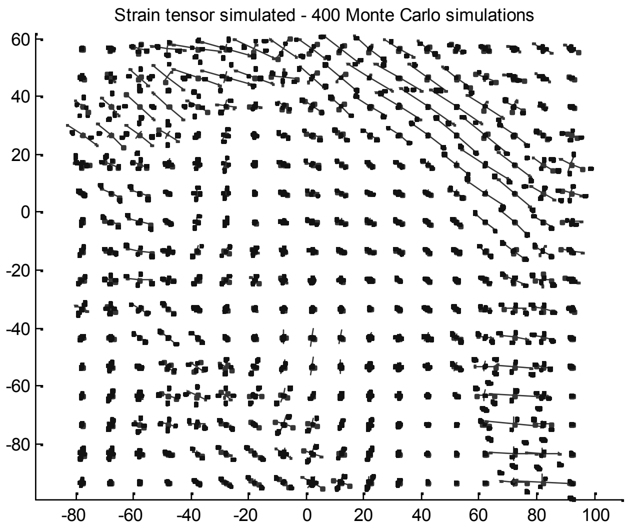



**Figure 12:** Vertical strain deformation of the LNG Tank auscultation network.

In order to analyse the obtained horizontal and vertical tensors, we perform deformations reliability as described in section (3). The following figure illustrates 400 Monte Carlo simulations of strain tensors.

a



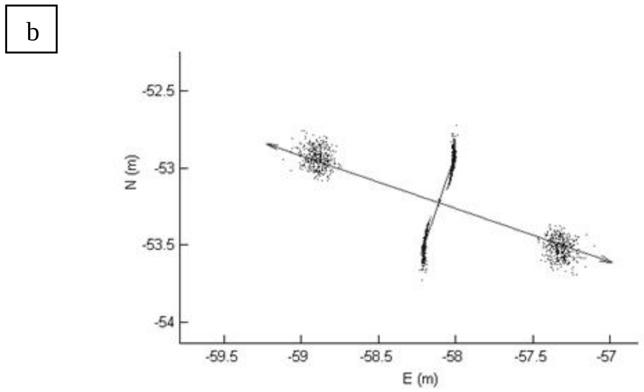



**Figure 13:** Simulated deformations field. (a) Simulated strain tensors with 400 Monte Carlo simulations. (b) Representation of virtual strain tensors with respect to the measured one

In figure (13.b), the clouds of points, surrounding the principal axes of strain tensors, represent the error domains obtained with 400 simulations of Monte Carlo method taking into account the RMS of each points coordinates.
According to the results of significance degree of different deformations, figure (14), the most values are greater than zero which means that the evaluated deformations are significant.

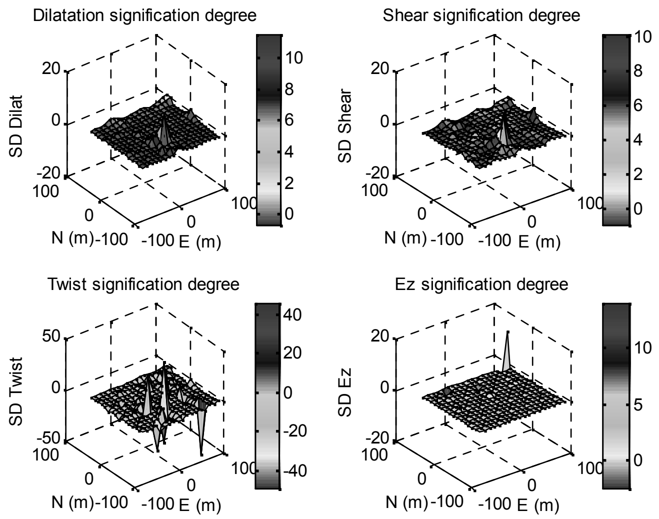



**Figure 14:** Reliability of horizontal and vertical deformations according to their significance degrees

The physical interpretation of the obtained results according to the horizontal and vertical displacement/deformation fields comforts the following hypotheses:

- Proximity to the sea (seaward): the sea acts as a warmer with a limitation of soil freezing which favorites the dilatation phenomenon (cf. figure 11.c).
- Soil (landward): supposition of the presence of a rocky area, near to the LNG Tank in the WS side, which opposes to the progression of the freezing front. This implies a compression phenomenon and swelling of the concerned area (cf. figure 11.c and figure 12).

## CONCLUSIONS

Through this paper, the GRNN neural network method was successfully applied in the deformation modeling and analysis of the LNG tank GPS auscultation network.

Our results show, in one hand, the performance of the adopted neural networks method in the generating and analysis of displacement and deformation fields with respect to the choice of the optimum smooth factor (SF), and in other hand, that the most deformations measured are significant and at the network deformability level.

The studied area is characterized by important dilatations and shears of about of 3000–4700 ppm and 1000–2000 ppm, respectively, at the NE side (seaward) of the network. However, we have observed an important swelling of around 0.4, at the WS side (landward). The tank structure is subject to an uprising at level of 0.05.

These results support the hypothesis of the role of sea which acts as a warmer of freezing front causing important dilatations at the seaward of the LNG tank, and the presence of a rocky area in the landward which leads to compression and swelling.

## ACKNOWLEDGMENTS

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