Location instrumentation optimization for disposal cells' deformation monitoring

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ABSTRACT: The Industrial Center for Geological Disposal, Cigéo project, will consist of creating disposal cells, such as tunnels, for high level and intermediate level long-lived radioactive waste. Repository cells type will deform under the rock loading. Although this convergence would be low, its monitoring is mandatory especially in order to know whether the waste packages could be retrievable during secular operating period. The monitoring of the cell shrink shall be made by an optimized instrumentation. The approach consists in determining, by numerical simulation of tunnel sections, the number of sensors to be put in place, their position and their orientation, taking into account their lifetime and precision. A simplified model represents a disposal cell subjected to different loads. This model create allows us to a database of the deformations obtained by the virtual sensors according to the soil stress applied to the repository cell. An inverse model built with a Bayesian approach will allow retrieving the stress of the ground corresponding to a given deformation. The capability of the inverse model to detect the loading condition is the criterion to be optimized. The numerical and inverse models were developed to compare horizontal pressure using a fitness function to classify individual configurations. Genetic Algorithm optimization is then used selection, crossover and mutation to find the best sensors' placement for a given number of sensors.

1. INTRODUCTION

Structural monitoring requires both high-performance instrumentation and adaptation to civil engineering. It also requires an optimal installation of sensors. With the current growth of data processing means, it seems advisable to consider the sensors placement so that their measurements are more adapted to their interpretation. This is also requirement given by the surveillance program of the Cigéo project defined by Andra (French national radioactive waste management agency) for the submission of licensing application. The objective of the work presented here in is to optimize the placement of sensors, which are Vibrating Wire Extensometers, also called VWE. These sensors measure local strain of concrete cells. Sensors location optimization makes it possible to determine the convergence of the cell. As a first step, the load of the rock is determined from the measurements of strains.

Different horizontal stress σ_h are considered in the range between 12 and 18 MPa and the effects on concrete annular deformation of the cell is analyzed. The next step consists, using inverse model, in determining (with uncertainties on the knowledge of the deformations) which loading corresponds to them. For this, a numerical simulation is carried out in order to know the strains of tunnel sections, for given input parameters (loading profile, mechanical properties of rock and concrete). A scan of input parameters allows us to constitute a strain database to be used by the inverse model. This model uses a Bayesian approach, allowing to find the input parameter from strain observation. By varying the number of VWE, as well as their position, the obtained strains are used to feed the database. The ability of the inverse model to identify the loading case, depending on the number and position of the VWE, is the criterion to optimize. The optimal determination of the number and positions of these sensors is carried out by genetic algorithm.

The goal of this study is to find the unknown parameter on the site: the horizontal stress σ_h. Whatever the horizontal stress, the vertical stress σ_v is constant and equal to 12.7 MPa. The considered simplifying assumption, for realization of finite element model, makes it possible to increase the number of iterations in a suitable time.

The optimization of number and positions of VWE uses an irregular fitness function (noise measurement sensors and local minimum) according to Collette and Siarry (2011). They specified that “main resolution methods are metaheuristic algorithms”. Hammouche, Diaf, and Siarry (2010) compared main techniques of these algorithms. The genetic algorithms (GA), developed by Goldberg and Holland (1988), and the particle swarm (PSO), presented by Kennedy and Eberhart (1995), give the best results with rapid convergence in few iterations. For deployment of wireless sensor networks (WSN), Aval and Razak (2012) concluded that GA and PSO are the two most used techniques. Banimelhem, Mowafi, and Aljoby (2013) evaluated the performance of GA to reduce or eliminate formulated holes after initialed and random deployment of stationary nodes. Two simulations of target detections led to conclude that GA can maximize detection coverage by finding the minimum number of additional mobile nodes and best positions on the ground. Fontan (2011) studied the optimization of sensor placement for identification of mechanical parameters of structures from in-situ measurements. He worked by inverse analysis using a PSO metaheuristic chosen for its speed of convergence. In 2006, a challenge was organized to optimize sensors’ placement for detection of contaminants in a water network according to four criteria (time of intrusion detection, population affected by the intrusion, quantity of contaminated water consumed and probability of detection). Most of the participants used metaheuristic methods such as Krause and al. (2008) who implemented a greedy algorithm or Guan and al. (2008), Wu and Walski (2006) and Preis and Ostfeld (2008) who work by GA.

In this article, the optimization of VWE position, for a given sensor number, is realized by Genetic Algorithm (GA). The reasons for this choice are that among the metaheuristics, GA and PSO algorithms have been preferred to Ant Colony Optimization (ACO), Simulated Annealing (SA) and Tabu Search (TS) algorithms. This is because they have better robustness and precision and a fast convergence. Compared to PSO method, GA require fewer parameters to adjust. They do not have particle indiscriminate solutions in case of very “flat” search space and they do not require search space. Finally, GA methods have an effective exploration of research area and have potential to address large research areas as well as a great adaptability.

2. MODELING DEFORMATIONS OBSERVED BY SENSORS

The finite element model of cell cross-section provides a database with known input parameters and output values.

2.1. Numerical model

The purpose of this model is to create a database of strains for all VWE location whatever the stress applied to the cell. The cell cross-section takes into account only the coating whose thickness is 30 cm for an extrados diameter of 5m. The numerical model is realized under Cast3M with a coating which is a 2D. The surrounding soil is represented by Winkler resorts, Buco (2007) (Figure 1).

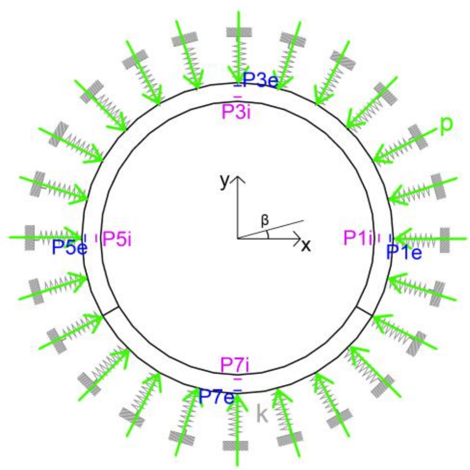

Figure 1 : Modeling cell cross-section.

2.2. Model parameters

To allow for large number of calculations, the numerical model is a simplification of reality. The input parameters are data available at Andra Underground Laboratory Cigéo project site.

2.2.1. Input parameters

The concrete Young's modulus is equal to 39.1MPa and the Poisson's ratio is 0.25. The surrounding soil is represented by springs of variable rigidity depending of soil Young's modulus which varies between 3 and 9 GPa and Poisson's coefficient which is equal to 0.29. Depending on the gallery orientation, horizontal stress varies between 12 and 18 MPa while the vertical stress is constant and equal to 12.7 MPa. On one section, the rigidity of each spring is variable while the horizontal stress is constant. For the database creation, the VWE are set up at all the intrados and extrados degrees and the horizontal stress varies between 12 and 18 MPa, with a step of 1 MPa.

The rigidity is drawn every 45° and the springs' rigidity between two successive samples are calculated by linear interpolation. Due to the risks associated with implementation and concrete pouring, the uncertainty on the angle θ of the VWE position compared to its theoretical orthoradial position is maximum ± 20°. This uncertainty is considered by a standard normal law with ± 20° of sensor orientation error corresponding to ± 3 standard deviations. The sensor intrinsic error of 1.75%, due to its resonance mode is also taken into account, Mei (2016).

2.2.2. Output parameters

The output parameter of the numerical model is the strain distribution for each position of intrados and extrados orthoradial sensors. These VWE positions are represented by points P1 to P7. Letter "e" or "i" represented the position extrados or intrados of the orthoradial VWE (Figure 1).

2.3. Inverse model

The numerical model allows the database creation and the inverse model will determine the only really unknown value: σ_h. This value is found thanks to strain observations given by VWE.

For a strain observation (measured by an VWE at a given location), the inverse model applies a Bayesian principle to find the probability of occurrence of each horizontal stress. The inverse model is based on the database created using the finite element model. Bayesian inference is calculated using the following formula as defined by Bayes (1763):

$$P(\sigma_i|O) = \frac{P(O|\sigma_i)*P(\sigma_i)}{\sum_{j=1}^{7} P(O|\sigma_j)*P(\sigma_j)} \qquad (1)$$

with O the strain observation and σ_i a soil pressure (σ_i = {12, 13, 14, 15, 16, 17, 18}). The denominator serves to normalize the posteriori law.

In the inverse model, the Bayesian approach creates a confidence interval around the value of observed strain O by a sensor [O (1 - 0.1%); O (1 + 0.1%)] and counts the number of stains in this interval. Thus, for each realization of strain in the database, of each stress σ_i, the conditional probability $P(O|\sigma_i)$ amounts to counting the occurrence number in the considered interval. For $P(\sigma_i)$, each pressure value has an equal probability (non-informative law), leading to the hypothesis $P(\sigma_i) = 1/7$.

A single strain observation leads to overlapped distributions, so the inverse model must be able to recover several observations of strain O simultaneously. The observation vector is therefore passed as input parameter of the inverse model by a naive approach whose hypothesis is the independence of the observations. According to Eq. (1), the naive hypothesis makes it possible to write:

$$P(O_1, \dots, O_n|\sigma_i) = P(O_1|\sigma_i) * \dots * P(O_n|\sigma_i) \quad (2)$$

2.4. Results

Results of the finite element calculations allow us to obtain normal laws of local strain at the position of the orthoradial VWE (see Figure 2). By varying the horizontal stress between 12 and 18 MPa with a step of 1 MPa, the numerical model allows us to generate a database of strains.

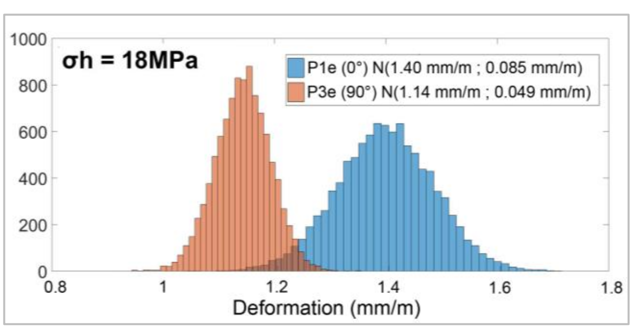

Figure 2 : Normal strain laws at the position of the VWE P1e and P3e (see Figure 1) on a cell cross-section for a stress of 18 MPa.

The inverse model is tested on a growing number of extrados sensors (see Figure 3) and on the influence position of the VWE, for the observation of two sensors (see Figure 4). These graphics represent the evolution of the inverse model for a given number of VWE (Figure 3) or a position of two sensors (Figure 4), for each horizontal stress.

Figure 3 shows the influence of the VWE number to find σ_i from O. For 1 mm/m strain, the sensor placed at 0° (point P1e in Figure 1) gives a pressure of 12 MPa at 45% (light blue curve). Point P3e gives a stress of 12 MPa at only 21% (orange curve). By combining the information of the sensors P1e and P3e, the result is 49% (gray curve) for 12 MPa whereas the point P1e alone already gave a result of 45%. By adding the observation of the sensor located at the second kidney (P5e), the stress of 12 MPa is obtained at 63% (dark blue curve). The addition of a last cross vault sensor does not give more information (yellow curve). Thus, the increase in the number of sensors gives better results but the placement of VWE arch (P3e) and cross vault (P7e) does not give additional information.

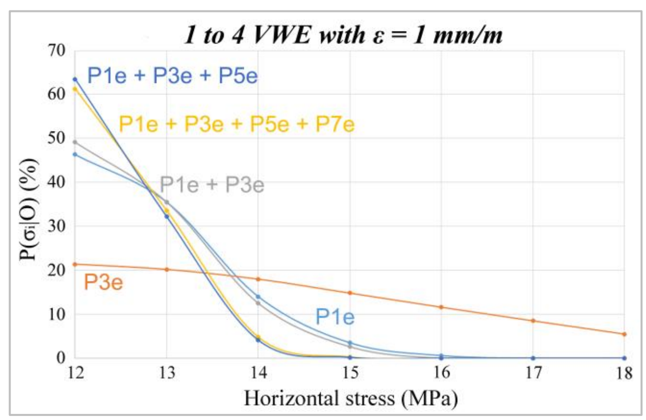

Figure 3 : Result of the inverse model to find the horizontal stress at the origin of a set of strains, according to the number of sensors.

By keeping the position of the four cardinal points for the VWE (Figure 4) the combination of two-by-two sensors varies the results depending on the sensor positions. Arch (P3e) and cross vault (P7e) sensors give the greatest dispersion of results with only 29 % probability of finding a horizontal stress of 12 MPa for strain observation of 1 mm/m (dark blue curve). The combination of kidney/cross vault (P1e/P7e) gives 50 % probability of having a stress of 12 MPa (gray curve). The combination of the two kidneys (P1e/P5e) gives the highest average and the lowest dispersion with 60 % probability of finding 12 MPa (orange curve). This graph comforts the previous assumption that kidney sensors provide more information than arch and cross vault sensors.

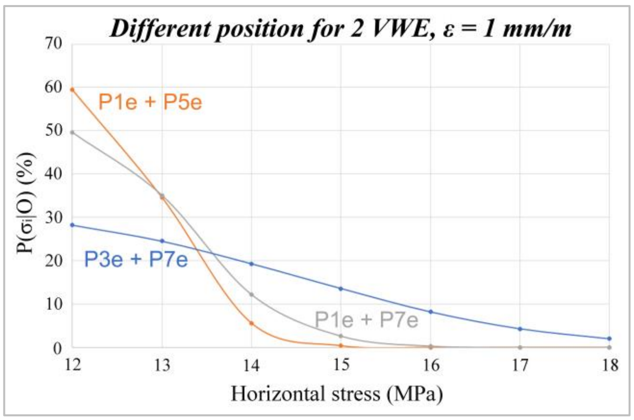

Figure 4 : Result of the inverse model to find the horizontal stress at the origin of a set of deformations, according to the position of sensors.

3. OPTIMIZATION OF THE NUMBER AND POSITION OF SENSORS

The objective of the optimization is to find the best location of VWE allowing to minimize the difference between the stress provided by the inverse model and the stress in the numerical model.

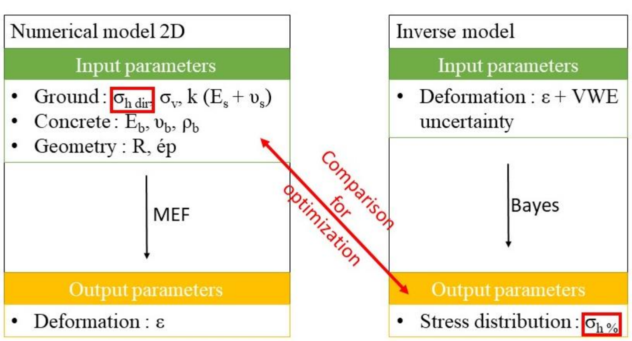

Figure 5 : Implementation of the optimization.

From the mechanical model and the inverse model, it is possible to compare the two stresses and optimize the VWE's position for a given number of sensors. It consists in minimizing $f = [\sigma_{h\,\%}(\beta_i) - \sigma_{h\,dir}]$ with $\sigma_{h\,\%}$ the horizontal stress provided by the inverse model according to β_i, the location of each sensor and $\sigma_{h\,dir}$ the horizontal stress obtained with the numerical model that the inverse model should be able to find.

3.1. Fitness function

In order to select the best individual in the population, the objective function is:

$$f = \left[(1-\alpha)\frac{\sum_1^7 P\%(\sigma_{h\,\%}-\sigma_{h\,dir})^2}{\sigma_{h\,dir}{}^2}\right] + \alpha[S] \quad (3)$$

The first term is the difference to the target value $\sigma_{h\,dir}$ compared to the results $\sigma_{h\,\%}$ of the inverse model. The second term is the measurement of Shannon's entropy dispersion, Shannon (2001) with:

$$[S] = \frac{-\sum_1^7 P\%_i * \ln(P\%_i)}{-ln\frac{1}{7}} \quad (4)$$

The coefficient α allows us to put more or less weight on one or other of the two parts. *P%* is the occurrence probability of each stress, $\sigma_{h\,\%}$ the stress of the inverse model and $\sigma_{h\,dir}$ the target stress that the inverse model should find.

3.2. Genetic Algorithm

The GA is applied to optimization of sensors placement can be schematized in Figure 6.

From five individuals with four pairs (intrados and extrados) of VWE, drawing angles for each individual is done randomly with a minimum difference of 10° between two consecutive sensors. The first step consists in classifying individuals of this population according to their quality (result of the inverse model and the fitness function). This ranking appears by red numbers in quotation marks. P3 individual is of better quality than P4 individual, which itself is of better quality than P2 individual. Some of these individuals are selected in order to cross them (probability of crossing over Pc) and mutate them (probability of mutation Pm) to create new individuals and thus change the population. The "P" individuals are the parent individuals of the current generation and the "C" individuals are the child individuals created by the process of crossing over and mutation. New individuals are then evaluated (inverse model and objective function) and inserted into the current population. C + P are sorted according to their quality and lower quality individuals are removed for the next generation, in order to keep best individuals and work with constant population. Individuals from this selection step are parents of the next generation.

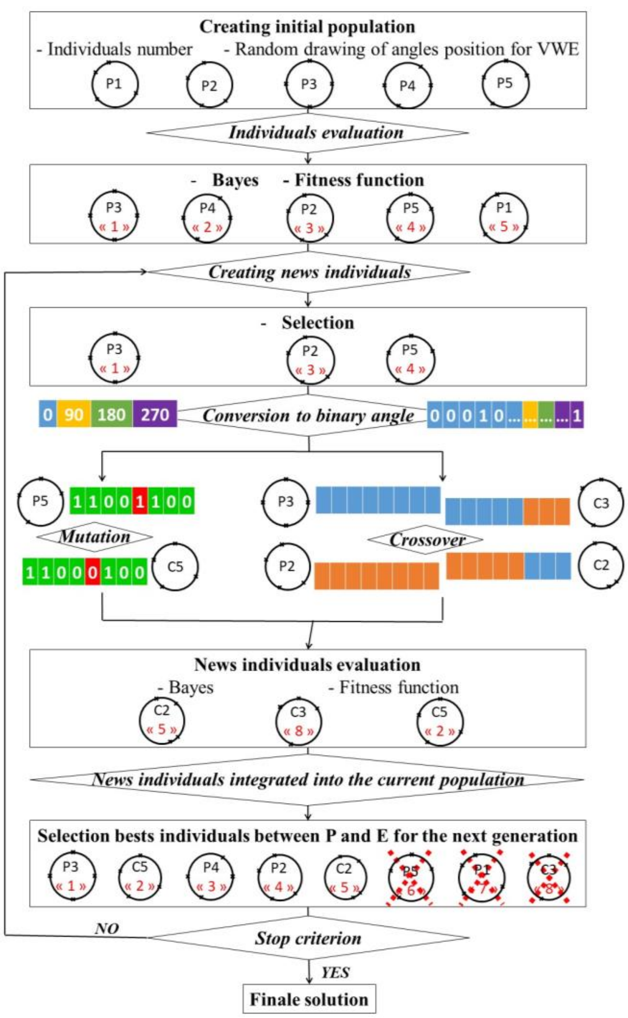

Figure 6 : Diagram of GA principle.

Several tests were carried out on GA parameters in order to make the optimal choice for calculating the final solution. The example (Table 1) is taken on four pairs of VWE intrados/extrados.

Table 1 : Influence of parameters to be defined.

Test	Size population	Generation number	Generation convergence	Pc	Position				f(*10-5)
					VWE1	VWE2	VWE3	VWE4	
1	50	30	6	0,8	0	102	171	280	1,46
2	50	30	5	0,8	4	95	171	280	1,49
3	100	30	5	0,8	0	102	171	280	1,46
4	100	30	6	0,8	91	171	280	354	1,26
5	100	50	9	0,8	0	102	171	280	1,46
6	100	20	5	0,8	4	95	171	280	1,49
7	100	20	8	0,8	91	171	280	354	1,26
8	100	20	13	0,9	91	171	280	354	1,26
9	100	20	7	0,9	91	171	280	354	1,26
10	50	20	7	0,9	91	171	280	354	1,26
11	50	20	6	0,9	4	95	171	280	1,49
12	100	20	7	0,6	91	171	280	354	1,26
13	100	20	10	0,6	0	102	171	280	1,46

Tests 1 and 2 have the same generation number and the same individual number per generation. The small population size combined with the small generation number prevents the sufficient exploration of research space to obtain the convergence of f towards the global minimum. Tests 3 and 4 retain the generation number and double the individual number. The two results are different but f gives a much lower result. Keeping the population size at 100 and changing the generation number to 50, the test 5 does not give the optimal result already encountered in test 4 despite a population convergence from the 9th generation. Tests 6 and 7 give results for 20 generations since the other simulation tests converged in less than 10 generations. Increasing the crossover probability, Pc, to 0.9 allows a maximum brewing. The purpose to find a compromise between convergence and brewing because a too important admixture can prevent the convergence toward a solution. By keeping the generation number at 20 (the whole population converges in less than 10 generations), tests 8 to 11 show the influence of population size. Only 100 individuals give twice the best result of the fitness function ever met. Tests 12 and 13 show the influence of brewing with a probability of crossing over Pc equal to 0.6. The calculation time is not very variable, so GA parameters chosen are:

- Population size : 100
- Number of generations : 20
- Crossover probability : Pc = 0.9
- Mutation probability : Pm = 0.3

3.3. Results

The results presented here show the influence of the dispersion (α = 0, α = 0.25, α = 0.5 and α = 1) on the value of the fitness function, on the VWE position and the results of the inverse model.

3.3.1. Influence of α value on the VWE number

Figure 7 shows the evolution of the results of the fitness function for 2 to 10 intrados and extrados of VWE as a function of the coefficient α. When α = 0, only the difference to the target value is taken into account and when α = 1, only the measurement of the Shannon entropy dispersion is taken into account. The fitness function gives a results f > 0.001 from 4 VWE whereas for α = 0.25 f = 0.09, for α = 0.5 f = 0.21 and for α = 1 f = 0.41. It is necessary to wait for 5 or 6 VWE to find a fitness function with a weak result when α ≠ 0.

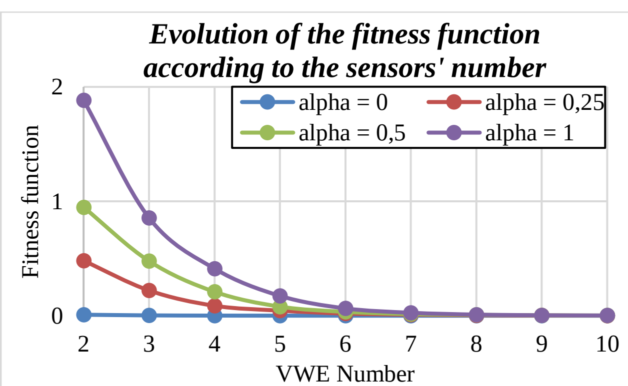

Figure 7 : Results of the fitness function according to the number of VWE for various α values.

3.3.2. Influence of α weighting on the VWE's position

In the example of 4 pairs of sensors, the results, as a function of α, are presented in Table 2. The measurement of the dispersion influences the optimization of the VWE's position.

Table 2 : VWE positon and fitness function results according to α.

α	VWE 1	VWE 2	VWE 3	VWE 4	f
0	22	53	205	352	0.001
0.25	159	178	204	355	0.087
0.5	33	159	178	204	0.209
1	33	159	178	204	0.411

3.3.3. Influence of α weighting on the results of the inverse model

Comparing the results of the inverse model, the best individual selected by optimization for α = 0 and α = 0.5 gives the graphs presented in Figure 8 and Figure 9.

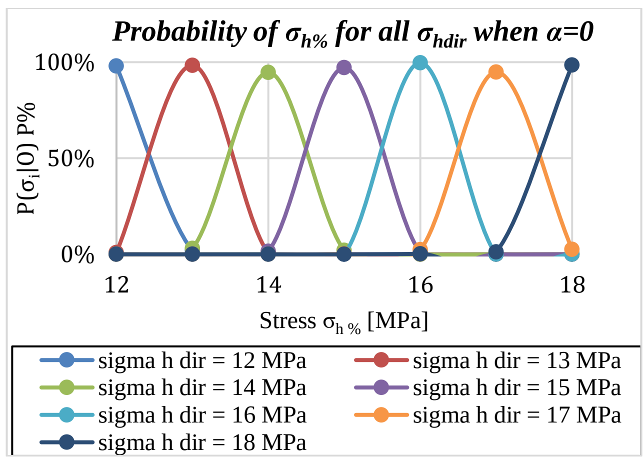

Figure 8 : Inverse model for α = 0.

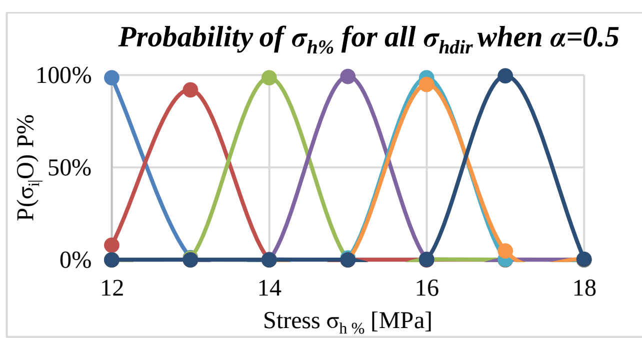

Figure 9 : Inverse model for α = 0.5.

When the fitness function only takes into account the difference regarding the target value (Figure 8), the inverse model finds the loading applied on the cells in more than 95 % of the cases. By adding the measure of the dispersion (Figure 9), the inverse model does not give good results and even goes so far as to error (for $\sigma_{h\ dir}$ = 17 and 18 MPa, orange and dark blue curves). Taking into account the dispersion decreases the efficiency of the inverse model.

4. CONCLUSION

The finite element model allows the construction of a database exploitable by the inverse model. This one serves to find the horizontal stress producing deformation of the cell. The optimization of the number and the position of VWE is done by GA for 2 to 10 couples of sensors. The results showed that the dispersion plays a significant role on the number and the position VWE as well as on the results of the inverse model.

Further research will focus on modifying the methodology for optimizing VWE locations to find the deformed shape of the cell.

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