Computational intelligence-based approaches to the integrated study of the Acoculco Caldera (Mexico): particle swarm optimization of MT, TEM and VES data

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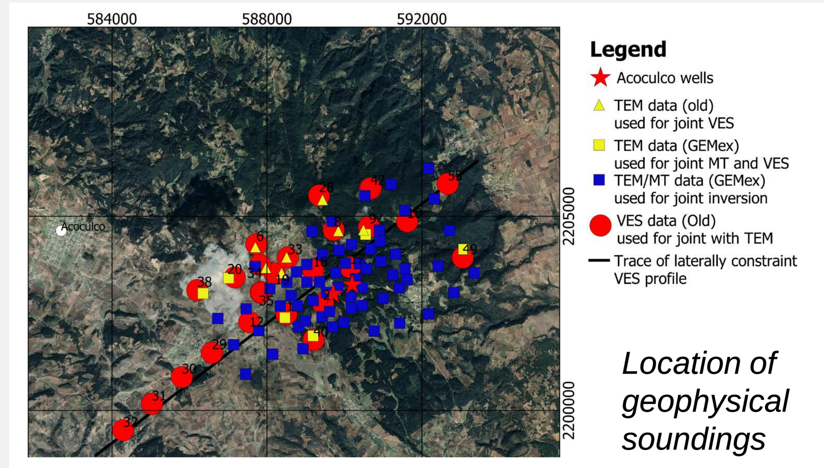
Summary

We present the results of an innovative approach applied to geophysical data available in the Acoculco geothermal field. We exploit computational intelligence (CI) methods for the quantitative data integration of different datasets, by jointly solving the inverse problem of transient electromagnetic (TEM), vertical electrical sounding (VES) and magnetotellurics (MT). We adopted the particle swarm optimization (PSO), a metaheuristic algorithm that seeks for the global solution to the problem.
The need for an accurate integration of multiple geophysical data comes from the possibility to overcome specific limitations of a single method.
The possibility to apply computational intelligence metaheuristics for the geophysical study of geothermal fields was successfully demonstrated.
We have interpreted a dataset of 59 MT and TEM coupled soundings and 20 VESs acquired in the Acoculco Caldera. Different approaches were tested, and the results contributed to the understanding of the Acoculco geothermal field.
The main results are: i) the identification of the static shift of MT curves by means of joint optimization of TEM and MT data, ii) the computation of a 2D laterally-constrained resistivity profile from VESs with external information, iii) the computation of 1D resistivity models from joint VES and TEM data

1 Introduction

The understanding of the physical conditions at depth in complex geothermal systems such as the Acoculco Caldera, is a challenge for the exploration geophysics.
Finding an Earth model explaining different measured data is of help in the geothermal exploration.
The joint inversion of multiple data sets can significantly improve their modelling by overcoming the intrinsic limitations of each geophysical method. Joint inversion is affected by non-uniqueness, nonlinearity and ill-posedness in addition to the issue of data compatibility.
The methods for solving the inverse problem can be classified into deterministic (standard convention) and probabilistic. Computational intelligence-based algorithms have been proposed because they deploy a multi-objective MO optimizer to solve the problem.
We implemented the particle swarm optimization PSO algorithm in order to jointly analyze different type of geophysical datasets (VES, TEM, MT) to study the Acoculco Caldera



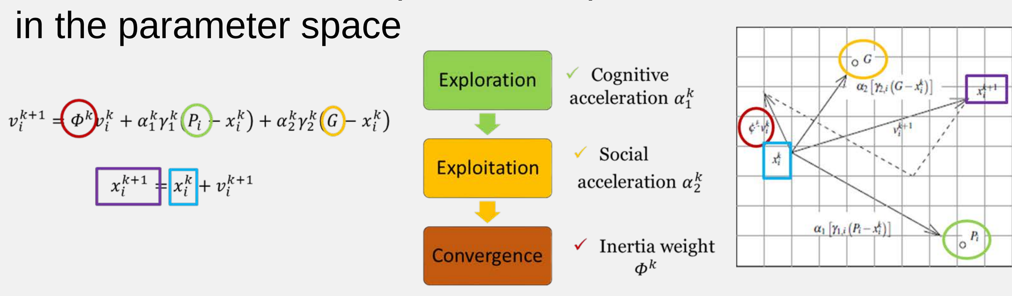
Location of geophysical soundings

The Acoculco geothermal system is a volcanic super-hot system located in the Tulancingo–Acoculco Caldera Complex. The surface geology is the expression of the volcanic evolution of the Caldera. The pervasive hydrothermal alteration is that of a typical fluid-rock interactions in volcanic settings with the a shallow advanced argillitic zone down to the propilytic zone closer to the heat source

2 Methods

PSO is a heuristic optimization method (Kennedy and Eberhart, 1995) based on two main concepts:
1) simulation of the swarm intelligence
2) evolutionary computation

The elements (or "particles"), that compose the swarm, explore the solution space of the problem.
The particle with best fitness value, i.e. a high quality solution, will be the leader of the group around which other particles will move. The swarm represents a population of Earth models. PSO searches for optima by updating each particle according to certain parameters called position (x) and velocity (v). Movement of particles is not entirely random; each particle is attracted towards both its own personal best position, in terms of fitness of the solution, and the swarm's best position of particles, which are vectors in the parameter space



PSO algorithm: position and velocity update at k+1 iteration

Laterally-constrained optimization of VES with external information

We exploit the methodology described in Godio and Santilano (2018). The resistivity value of the ith parameter of the jth 1D model is updated, iteration by iteration, according to the adaptive behaviour of PSO. The aim is the minimization of the following objective function:

$$\Psi\,(\mathbf{m}) = \left(a\left\|\boldsymbol{\rho}_{\mathbf{a,o}} - \boldsymbol{\rho}_{\mathbf{a,p}}\right\|_2\right) + \lambda\,\|\partial\mathbf{m}\|_2 \;\Big]$$

A-priori or external information of the search space can be introduced to reduce the ambiguities of the solutions.
An innovative approach is here tested: a small part of the swarm particles is initialized with a-priori information in order to influence the oscillation centre and the direction of the swarm.
This approach is not a strong constraint.
For the study of the Acoculco Caldera, we have inserted as a-priori information the resulting model of the adjacent VES soundings and information from well logs

Joint optimization of TEM and MT data

The "static shift" galvanic distortion of MT data is caused by small-scale heterogeneities. The effect is a shift of the MT apparent resistivity curve for an unknown multiplier. Our work is intended to help overcome this problem by providing a quantitative estimate of the static shift using PSO optimization.
We exploit the methodology and the Matlab software package described in Santilano et al. (2018) for the 1D simultaneous optimization of TEM+MT data. The method adopts a joint data set in the frequency domain composed of the MT data and the converted TEM data. The following objective function is directly minimized to train the particles (each model):

$$\Psi(\mathbf{m}) = \left(\begin{array}{c} a\left\|(\mathbf{S}\,\boldsymbol{\rho}_{\mathbf{a,o}}) - \boldsymbol{\rho}_{\mathbf{a,p}}\right\|_2 + b\left\|\boldsymbol{\phi}_{\mathbf{a,o}} - \boldsymbol{\phi}_{\mathbf{a,p}}\right\|_2 + \\ + c\left\|\boldsymbol{\rho}_{\mathbf{a(TEM),o}} - \boldsymbol{\rho}_{\mathbf{a(TEM),p}}\right\|_2 \end{array}\right) + \lambda\|\partial\mathrm{m}\|_2 \Big]$$

The parameter S (static shift) is included in the model parameters to be optimized.
The complete GEMex dataset was analysed

Joint optimization of VES/TEM data: the multi objective PSO

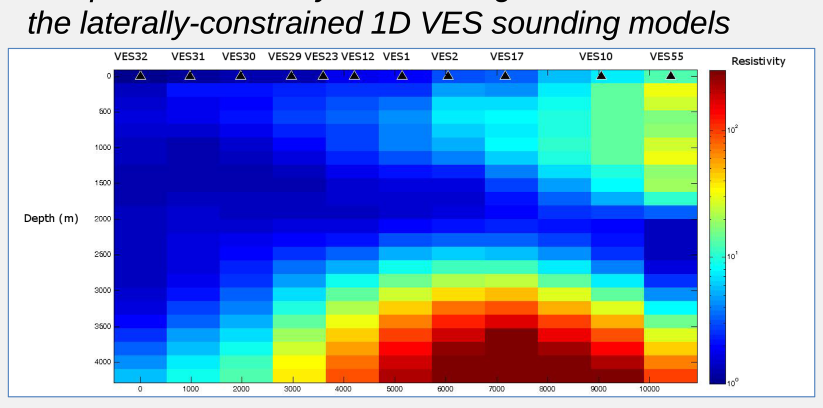
This method (Pace et al., 2019) is the result of the collaboration between the Politecnico di Torino and CNR.
This MOPSO approach implies the use of two different objective functions; one for each method (VES and TEM).
Several solutions are evaluated during the optimization and the best solution is identified. In this case, the set of solutions is selected as best trade-off according to the Pareto optimality concept. A time-variant MOPSO was implemented.
The advantage is to find an Earth model that explains both TEM data, sensitive to conductors and VES data, sensitive to resistors

3 Results

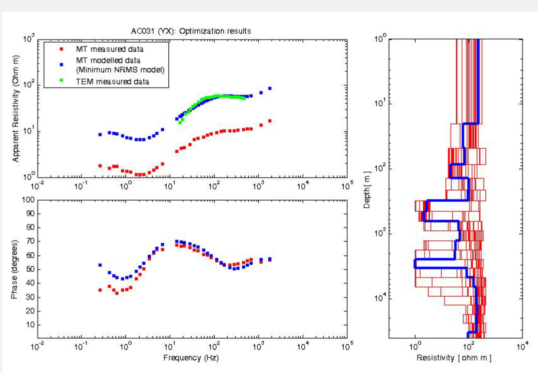
Example of settings for PSO of ACVES17 with external information

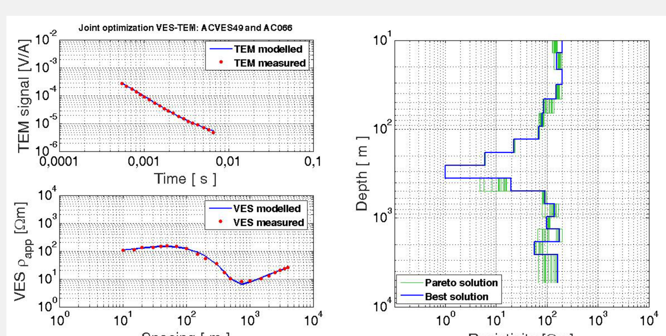
Resistivity (Ω m) boundaries	LB=1; UB=1500
Initial population	500
External (a-priori) information	Models from ACVES02 and 10 Model from well EAC-2
Number of particles with a-priori information inserted in the swarm	5% of the swarm for each model (total 15%)
Generations (iterations)	150
λ (Lagrangian multiplier)	10^{-3}

Interpolated resistivity model along Profile LL1 from the laterally-constrained 1D VES sounding models



Joint PSO of AC031 MT and TEM data. The results of 25 runs are shown in red, and the minimum RMS model is in blue.





Resistivity model from joint PSO of the soundings ACVES49 and AC066.

4 Conclusions

We have successfully demonstrated the possibility to apply computational intelligence metaheuristics for the geophysical study of geothermal fields. Different approaches have been tested and the related results can be of help for the understanding of a complex system such as the Acoculco geothermal field. The main results of this research are:
1) the identification of the static shift of MT curves
2) the computation of a VES laterally-constrained resistivity profile with external information inserted as part of the swarm in the optimization
3) the computation of models from the joint PSO of VES and TEM data

5 References

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