The role of three different metaheuristic methods in geophysical data optimization.

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The role of three different metaheuristic methods in geophysical data optimization

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Introduction

There has been an increasing interest in global search methods for solving the geophysical inverse problem during the last decades (Sen and Stoffa, 2013). Several metaheuristic methods have been adopted in the geophysical literature, and ever novel methods are being proposed from non-geophysical studies. These methods are the so-called nature-inspired algorithms based on biological systems and social dynamics of groups of entities such as birds, fish, bats, ants, wolves and so on (Engelbrecht, 2007). These algorithms are original, sophisticated, and efficient in the optimization of geophysical data. The most popular metaheuristics are the genetic algorithm (GA) and particle swarm optimization (PSO), which have been largely adopted (Sen and Stoffa, 2013; Pace et al., 2021). An example of an emerging and promising population-based algorithm is the grey wolf optimizer (GWO) (Mirjalili et al., 2014). Then, the scientific question that arises is if all these algorithms are efficient and useful.

We focused on a comparative analysis among the performances of three metaheuristic methods, that is, GA, PSO and GWO, for the optimization of time-domain electromagnetic (TDEM) data (Pace et al., 2022). The aim of the work is to highlight their advantages and weaknesses because it seems that they have been indistinctly applied to geophysical data so far. Moreover, it is rare the three algorithms are contextually compared.

The three metaheuristic algorithms: GA, PSO, GWO

The GA is an Evolutionary Computation paradigm and mimics the inheritance rules in nature, where the individuals with the best chromosomes survive (and the weakest individuals must die) (Sen and Stoffa, 2013). The PSO algorithm is based on the social behavior of agents sharing knowledge to achieve the best objective of the group, such as escaping from a predator or searching for food (Pace et al., 2019, 2021). The GWO algorithm is based on the social dynamics adopted by a group of wolves attacking a prey while searching for food (Mirjalili et al., 2014).

The comparison among the three methods was performed by setting some common features. The same settings of the algorithms were the objective function, the forward modeling code, the number of candidate solutions sampled, the stopping criterion, the random initialization, the boundary conditions, and the computational resources. The other settings were specific for each algorithm and were chosen following the most recent findings for GA (Pace et al. 2022), PSO (Pace et al. 2019) and GWO (Mirjalili et al., 2014) applied to geophysical data.

A field case study

The methods were first validated on a synthetic example of noise-corrupted data and then applied to two field surveys located in Italy. One field case study is a TDEM sounding located in Stupinigi (Torino district area) acquired for groundwater prospection over a known stratigraphy (coming from a close borehole). The TDEM acquisition was a coincident loop of 50 m length for the loop size. The time range of acquisition was 10^{-5} –10^{-3} s. The 1D model was discretized into 19 layers, whose thickness logarithmically increased with depth. The number of iterations was 500 for PSO and GWO, and 800 for GA since we observed insufficient convergence and minimization. The number of individuals (GA), particles (PSO) and wolves (GWO) were 170, for a proper solution exploration. The boundary conditions of the search space were 1 and 500 Ωm. Each algorithm was independently run 10 times or trials to inspect the variability of the equivalent final solutions and then highlight the solution with the minimum nRMSE. The outcomes of GA, PSO and GWO are shown in in Figs. 1b, 2b and 3b, respectively. The final data misfit (nRMSE) was 0.0764 for GA, 0.0618 for PSO, and 0.0619 for GWO. The lowest runtime and nRMSE were achieved by PSO, while GA had the worst performance. The data fitting is satisfactory for the three methods. There is similarity among the solutions of the PSO and GWO trials, while they significantly differ for GA.

Figure 3c plots the minimization of the objective function along the iterations for GA (black dots), PSO (blue dots) and GWO (pink dots). The trend of the PSO curve is gradual from the highest to the lowest value, meaning good balance between exploration and exploitation of the search space. GA and GWO show a stepped trend that decreases rapidly and becomes flat earlier than PSO, meaning a possible premature exploitation phase.

Conclusions

The performance of three different and widely adopted metaheuristic algorithms were analyzed for the optimization of TDEM data. The comparative analysis reveals that PSO and GWO perform better than GA. GA yields the highest data misfit and an ineffective minimization of the objective function. PSO and GWO provide similar outcomes in terms of both resistivity distribution and data misfits, possibly because they are based on the same computational principle known as Swarm Intelligence. The results prove compelling evidence that both the emerging GWO and the established PSO are highly valid tools for stochastic inverse modeling in geophysics, while GA appears to be less competitive than them.

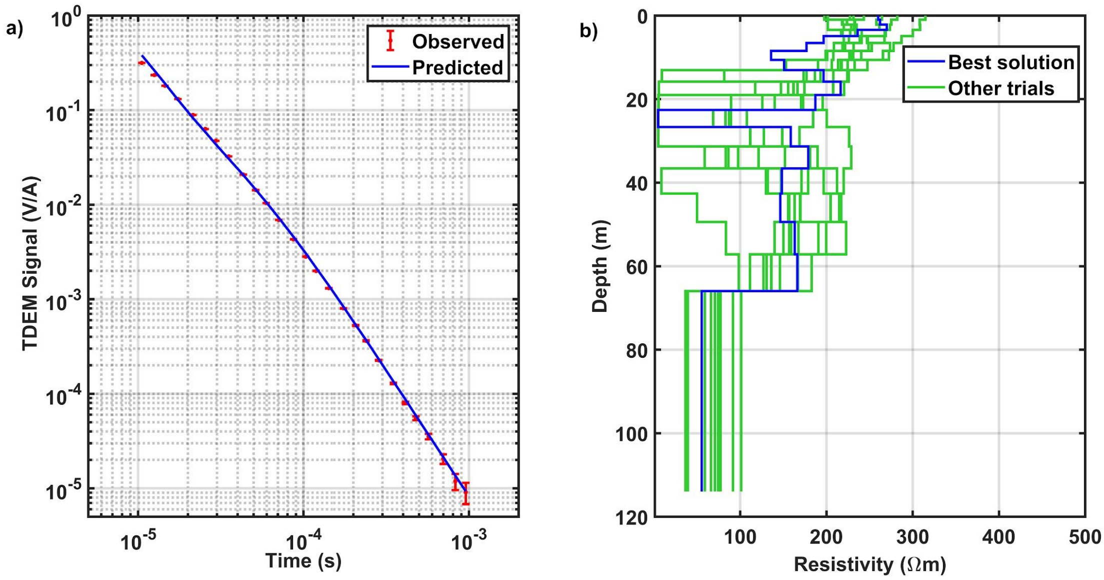

Fig. 1 – The result of GA: a) TDEM observed signal (the red dots with error bars) and GA predicted response (blue line); b) the final resistivity models after 10 trials (the green lines) and the best GA solution highlighted in blue

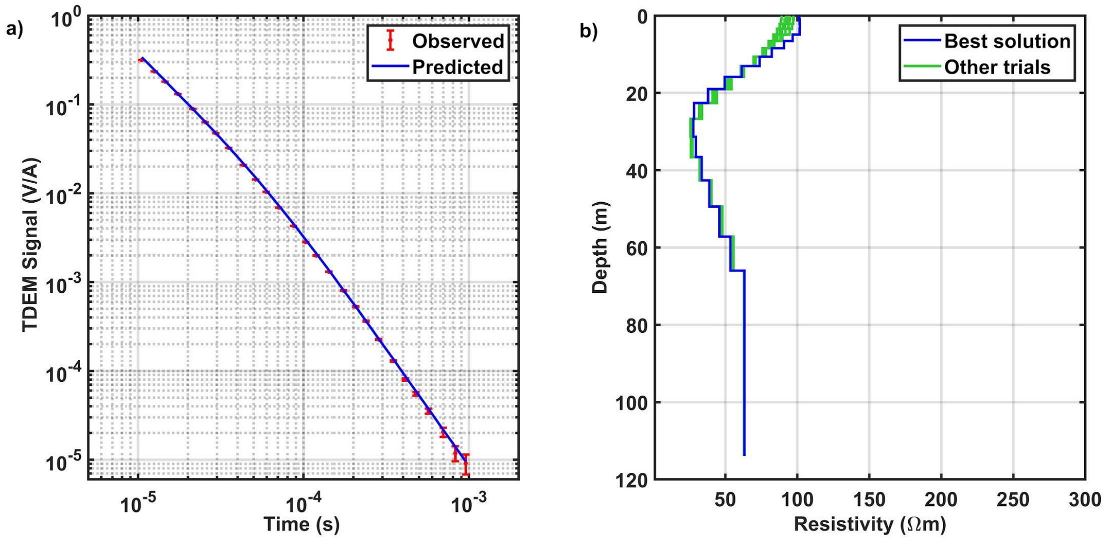

Fig. 2 – The result of PSO: a) TDEM observed signal (the red dots with error bars) and PSO predicted response (blue line); b) the final resistivity models after 10 trials (the green lines) and the best PSO solution highlighted in blue

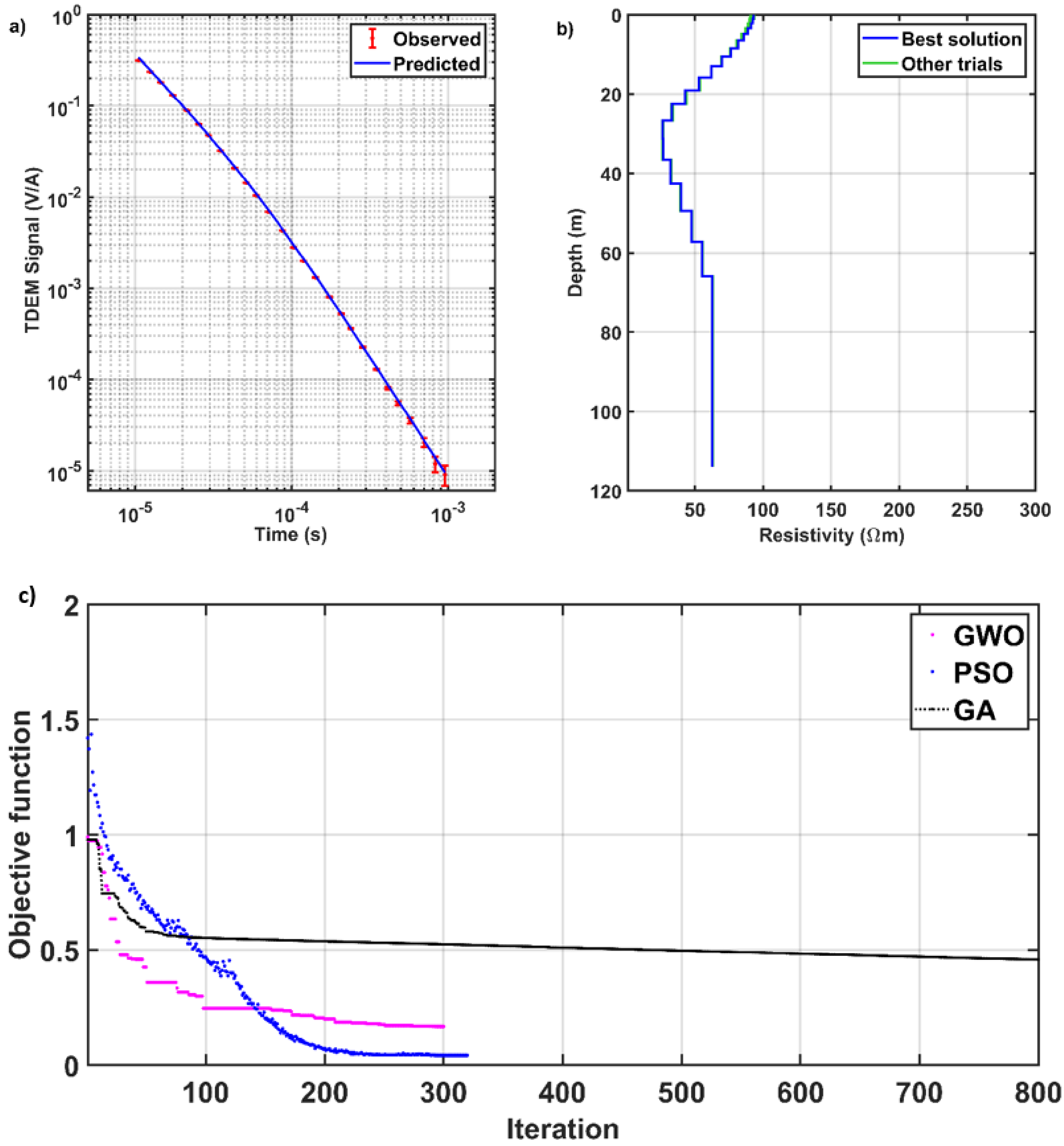

Fig. 3 – The result of GWO: a) TDEM observed signal (the red dots with error bars) and GWO predicted response (blue line); b) the final resistivity models after 10 trials (the green lines) and the best GWO solution highlighted in blue; c) The curves of the objective function minimization for the GWO (pink), PSO (blue) and GA (black) algorithms.

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