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# A gradient-improved particle swarm optimizer using surrogate modeling

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**Abstract.** An optimization scheme combining a PCE metamodel and a PSO optimizer has been implemented and tested on both a well-posed and an ill-posed ECT configurations. The algorithm has been improved by integrating the information of the gradient of the PCE, improving the quality of the parameter retrieval.

**Keywords.** inverse problems, particle swarm optimization, surrogate modeling, polynomial chaos expansion

*Introduction* Inverse scattering problems can be solved by using optimization, in which a cost function is minimized. The cost function usually measures the error between observations and simulations computed with the sought parameters. However the computational weight of running such an optimization with an exact physical solver is often too much for it to be considered. Metamodels - or surrogate models - aim at replacing the exact physical solver by an approximate mathematical function that describes the physical solver over the search space. This improves the optimization by avoiding to solve the physical problem at each iteration, at the cost of building a set of solutions to the problem over the search space beforehand.

*Method* A Polynomial Chaos Expansion (PCE) is used to surrogate the physical solver. The UQLab toolbox [1] is used to compute the coefficients of the expansion. The main advantage of the PCE metamodeling framework is its closed-form expression, from which its gradient can be computed.

The PCE metamodel is used as an interpolator of the search space and is integrated inside a Particle Swarm Optimizer (PSO). The PSO is a stochastic iterative global optimization algorithm, based on the social behavior of groups of animals[2]. A swarm of particles explores the search space, which is mapped by a cost function. Thanks to the gradient of the metamodel [3], the gradient of the cost function is computed and used to converge faster towards the desired cost function value [4].

*Configurations* The designed method has been tested over two Eddy Current Testing (ECT) configurations. The first one, from an internal L2S-ELEDIA collaboration, has a single rectangular crack with varying depth, length and width. It is made of 1000 points sampled as a uniform grid in the 3-dimensional search space. The second one, from the

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JSAEM [5], has two rectangular cracks with varying depths, lengths and separation gap inbetween. It is made of 500 points sampled by Latin Hypercube Sampling (LHS) over the 5-dimensional search space. This configuration is ill-posed, meaning that the same observation can happen from different sets of parameters.

*Results* To assess the performance of the optimization, the retrieved parameters are compared to their expected values, which gives a measure called reconstruction error. The gradient-improved PSO performed better than the PSO alone both in terms of mean and variance of reconstruction error. Table 1 summarizes these results. The computations have been carried out on an Intel® Xeon® E5-2660, with 2 CPUs, 16 cores each at 2.20 GHz clock speed.

| Number of parameters | Algorithm | Computation time (s) | norm. reconstruction error Mean | norm. reconstruction error Std |
|---|---|---|---|---|
| 3 | PSO | 0.46 | $98.76 \times 10^{-3}$ | $150.8 \times 10^{-3}$ |
| | GPSO | 4.80 | $74.02 \times 10^{-3}$ | $82.12 \times 10^{-3}$ |
| 5 | PSO | 9.07 | $202.6 \times 10^{-3}$ | $356.5 \times 10^{-3}$ |
| | GPSO | 191.57 | $140.7 \times 10^{-3}$ | $305.4 \times 10^{-3}$ |

**Table 1.** Comparison of reconstruction errors of the two algorithms on the two configurations

*Conclusion and further works* The integration of a PCE metamodel inside a particle swarm optimizer has been studied and tested over two ECT configurations, yielding good results. Additionnally, the proposed method has been refined by adding a local search thanks to the information of the gradient of the metamodel.

The current algorithm could be used for uncertainty quantification, and a solution to ill-posedness could be of interest.

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