**Cover letter**

Dear Editor:

On behalf of my co-authors, we thank you very much for giving us an opportunity to revise our manuscript, we appreciate editor and reviewers very much for their positive and constructive comments and suggestions on our manuscript entitled “BP Neural Network and improved Particle Swarm Optimization for Transient Electromagnetic Inversion”. (MS No: npg-2019-36).

We have studied reviewer’s comments carefully and have made revision which marked in red in the paper. We have tried our best to revise our manuscript according to the comments. Attached please find the revised version, which we would like to submit for your kind consideration.

We would like to express our great appreciation to you and reviewers for comments on our paper. Looking forward to hearing from you.  
Thank you and best regards.

Yours sincerely,

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Dear Editors and Reviewers:  
 Thank you for your letter and for the reviewers’ comments concerning our manuscript entitled “BP Neural Network and improved Particle Swarm Optimization for Transient Electromagnetic Inversion”. (MS No.: npg-2019-36). Those comments are all valuable and very helpful for revising and improving our paper, as well as the important guiding significance to our researches. We have studied comments carefully and have made correction which we hope meet with approval. Revised portion are marked in red in the paper. The main corrections in the paper and the responds to the reviewer’s comments are as flowing:

For your guidance, itemized response to each review’s comments is appended below.

Reviewer #1:

Dear reviewer:

Comments:

1. Page 2, line 53 → Please provide a correct reference name for Fernndez et al. (2010).

2. Page 6, line 136 → There is no T k and O k terms in equation 14. In addition, is there no unit for the training error value calculated?

3. Page 7, line 148 → use slightly better instead of litter better.

4. Do you have any experimental studies (i.e., parameter tuning) for the PSO parameters used in the study?

5. The sentence given below requires a reference.

“Comparing to the standard PSO (SPSO), a chaotic oscillation inertia weight PSO(COPSO) which can accelerate the convergence rate in the early stage was proposed naturally.”The inertia weight value used in SPSO-BP approach is not clear in the text. Based on my experiments for parameter estimation from geophysical anomalies (e.g., self-potential, gravity, magnetic) using PSO algorithm, the values including 2.041 (c 1 ), 0.948(c 2 ) and 0.729 () proposed by Carlisle and Dozier (2001) mainly provide quite efficient results. Please provide a comparison.

6. Considering the results presented in Table 2 and Fig.3, is there a possibility to use the same initial population during the evaluation process to provide a good comparison?

7. Please use more proper terms in the text regarding a geophysical optimization study(e.g., predict and desired outputs).

8. Please depicts and  e inertia weight values in title of Table 3.

9. Use true values instead of reference value and theoretical curve instead of theory curve.

In fact, I do not see any curve in Fig. 11. They represent layer parameters.

10. Please define PSO parameter values used in the synthetic case.

11. Please discuss the main advantages and disadvantages of the BP compared to the metaheuristic approaches requiring a parameter space which can be chosen

12. Such a study must include the effect of the noise on the solution in the synthetic case.Besides uncertainty analyses for estimated parameters should be applied for data sets with and without noise. A field example must be also presented.

1. Reply:   
   1-Page 2, line 53 → Please provide a correct reference name for Fernndez et al. (2010).

(1) We are sincerely sorry for the negligence of the author's name spelling when citing references. We have made changes and amend them as follows. At the same time, we are also very grateful for your careful review of the manuscript.

Fernández et al. (2010) successfully introduced the PSO in 1-D resistivity inversion.

2-Page 6, line 136 → There is no T k and O k terms in equation 14. In addition, is there no unit for the training error value calculated?

(2) Due to our negligence, ‘*Tk*’ and ‘*Ok*’ terms on line 136 of the page 6 are misspelled and have been modified as follows: *Ts* , *Os* are the expected and predicted output for training sample respectively. Meanwhile, in order to evaluate the effect of model training in this paper, the training error expression is adopted as: . In the formula, the training error E only represents the error value, so there is no unit for the training error value calculated.

3-Page 7, line 148 → use slightly better instead of litter better.

(3) According to the meaning in the paper, it is more appropriate that 'slightly better' term than 'litter better', thank you again for your valuable suggestions.

4- Do you have any experimental studies (i.e., parameter tuning) for the PSO parameters used in the study?

(4) In the research of this paper, some experiments are performed on the various different parameter values in the PSO algorithm. The experiment results show that the learning factor (c1 and c2), inertia weight (*w*), population size (M) and maximum iterations (*T*max) have a little influence on the PSO optimization results.

In PSO, the learning factors *c1* and *c2* determine the influence of the experience of the particle itself and on the trajectory of the particle group, reflecting the information exchange between the particle swarms. Setting a larger value of *c1* will cause the particles to linger too much in the local range, while a larger *c2* will cause the particles to converge prematurely to the local minimum, thus setting a larger or smaller *c1* and *c2* is not conducive to the search of particles. Ideally, the particles should initially search the entire space as much as possible, and at the end of the search, the particles should avoid falling into local extrema. The general setting is *c1*=*c2*=2.

Among the adjustable parameters of the algorithm, the inertia weight is the most significant, which determines the influence of the previous flight speed of the particle on the current flight speed. Therefore, the balance between the global search and the local search can be achieved by adjusting the value of the inertia weight *w*: when *w* is large, the global search ability is strong, and the local search ability is weak; when *w* is small, the global search ability is weak, and the local search ability is strong. Thence, the proper inertia weight can improve the optimization ability, and reduce the iterations. However, there is still some difficulty to achieve the optimal performance, because when the inertia weight is large, it is conducive to global search with fast convergence rate, but it is not easy to get an exact solution. When the inertia weight is small, it is beneficial to local search and getting exacter solution, but the convergence is slow and sometimes it falls into local extremum. Therefore, in the PSO optimization algorithm, it is hoped that there will be a higher global search ability in the early stage to find a suitable seed, and a higher development capability in the later stage to accelerate the convergence speed. Thence, the inertial weight is used as a typical linear decreasing strategy. The formula of *w* is, in which, according to studies by Y. Shi et al. (1999), the initial value of inertia weight is *wstart*=0.9, and the end value of inertia weight is *wend*=0.4, which can make PSO explore more at the beginning and locate the approximate position of the optimal solution faster. As *w* gradually decreases, the particle speed slows down and a fine local search begins. This method enables PSO to better control global and local search capability, speed up the convergence and improve the performance of the algorithm. At the same time, in order to further improve the global search ability of the PSO algorithm, the chaotic oscillation inertia weight is adopted as , which , the experiments results prove that the best results can be obtained when *x0* = 0.234 and *μ=* 4, which the equation is in a completely chaotic state.

As for the population size (M), the number of individuals contained in the population. In general, there are the higher population diversity and stronger the search ability for algorithm as the population size is larger, therefore, the probability of obtaining an optimal solution is greater, but it also takes more calculation time. Therefore, after a series of numerical experiments, it is reasonable as the population size M=60 and the maximum iteration number Tmax=30.

5-The sentence given below requires a reference.

“Comparing to the standard PSO (SPSO), a chaotic oscillation inertia weight PSO(COPSO) which can accelerate the convergence rate in the early stage was proposed naturally.”

The inertia weight value used in SPSO-BP approach is not clear in the text. Based on my experiments for parameter estimation from geophysical anomalies (e.g., self-potential, gravity, magnetic) using PSO algorithm, the values including 2.041 (c1), 0.948(c2) and 0.729 (w) proposed by Carlisle and Dozier (2001) mainly provide quite efficient results. Please provide a comparison.

1. According to your suggestion, the corresponding reference has been added in the corresponding

position of the article for the article more rigorous, the literature is as follows:

Shi, X. M., Xiao, M., Fan, J. K., Yang, G. S., and Zhang, X. H.: The damped PSO algorithm and its application for magnetotelluric sounding data inversion, Chinese Journal of Geophysics., 52, 1114−1120, https://doi.org/10.3969/j.issn.0001-5733.2009.04.029, 2009.

We are sorry that the SPSO-BP algorithm inertia weight value is not clearly explained in the manuscript. In this paper, the inertia weight is used as a typical linear decrement strategy, which the calculation formula (*w*) is . At the same time, the definition of SPSO algorithm inertia weight is supplemented on line 129 of the manuscript. Among them, according to a large number of experimental studies by Y. Shi et al. (1999), the inertia weight initial value (ws) is 0.9, and the inertia weight ending value (we) is 0.4, which can make PSO better control global search ability and local search ability, and speed up the convergence and improve the algorithm performance. The learning factors and inertia weight parameter values in PSO has been elaborated in the previous question (4). In fact, we found that different parameter values have certain influence on the PSO optimization results under different research models by a lot of researches, that is, when the different models achieve the best optimize results using PSO, the various parameter values are different. Therefore, through a series of test functions and geoelectric model inversion experiments, the good optimization results are obtained when the parameter value c1=c2=2, which the effect is better than the results optimized under 2.041 (c1), 0.948 (c2) and 0.729 (w). Among them, the results of SPSO-BP optimization under different parameter values are as follows:

**Table.1** Comparison of the different parameter values in SPSO-BP algorithm for testing functions

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Testing functions | SPSO-BP（*c1=c2=2，w=w1*） | | SPSO-BP（*c1=2.041，c2=0.948,w=0.729*） | |
| Average value | Optimal value | Average value | Optimal value |
| *Rosenbrock* | 2.375e-3 | 2.300e-5 | 0.3911 | 3.1665e-04 |
| *Bohachevsky* | 0.225 | 1.024e-3 | 0.2832 | 0.0013 |

**Table.2** Inversion comparison of three-layer H type geoelectric model

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| H type | resistivity *ρ* (Ω·m) | | | thickness *h*(m) | | total relative error(%) |
| *ρ*1 | *ρ*2 | *ρ*3 | *h*1 | *h*2 |
| reference value | 100 | 10 | 100 | 100 | 200 | -- |
| SPSO-BP relative error(%)（*c1=c2=2，w=w1*） | 0.062 | -0.322 | -0.737 | -0.579 | -0.970 | 2.672 |
| SPSO-BP relative error(%)（*c1=2.041，c2=0.948,w=0.729*） | 0.2438 | 2.3154 | -0.566 | 0.9707 | -0.3327 | 4.4290 |

6- Considering the results presented in Table 2 and Fig.3, is there a possibility to use the same initial population during the evaluation process to provide a good comparison?

(6) According to your suggestion, the same initialized population is used for the test function optimization. The search curves for the Rosenbrock and Bohachevsky test functions are shown below fig.1, and made changes in the manuscript. However, the comparative study results show that the same initial population has no significant effect on the final optimization results, so that it is almost negligible.



**Fig. 1** Training error curves of SPSO-BP and COPSO-BP algorithms

7-Please use more proper terms in the text regarding a geophysical optimization study(e.g., predict and desired outputs).

(7) Thank you for your suggestion. For the rigor of the article, we have modified the inappropriate terminology, such as 'predict output' modified to 'predict value', 'desired output' modified to 'actual value', 'reference value' modified to 'true values'.

8-Please depict *ws* and *we* inertia weight values in title of Table 3.

(8) In order to reasonably compare the effects of four different inertia weights in the PSO algorithm, the same initial inertia weight value and end inertia weight value are used in this paper, such as inertia weight ωs = 0.9, ωe = 0.4. At the same time, based on the valuable comments made by the reviewers, in order to facilitate the reader to more clearly understand the comparison effect for different inertia weights, we have refined the title of Table 3 as follows:

**Table.3** Comparison of different inertia weights in PSO algorithms ( *ω*s = 0.9, *ω*e = 0.4).

9-Use true values instead of reference value and theoretical curve instead of theory curve.

In fact, I do not see any curve in Fig. 11. They represent layer parameters.

(9) Thank you very much for pointing out the incorrect terminology in the paper and giving appropriate revisions. We have made corresponding revisions, such as the 'reference value' in Table 4 and Table 5 is modified to 'true values', the 'theory curve' is modified to 'theoretical curve'.

As you can see, the theoretical curve in Figure 2 of the first draft does represent the layered parameter value. However, due to the inappropriate naming of the line segments in the figure, it is inconvenient for the reader to understand, so after careful consideration, the 'theory curve' is modified to 'True values' as shown below.



**(a)** Three-layer H type geoelectric model **(b)** Five-layer KHK type geoelectric model

**Fig. 2** Inversion comparison for different geoelectric models

10- Please define PSO parameter values used in the synthetic case.

（10）Due to our negligence, it not clearly account for the various parameters values of PSO algorithm in the Layered model and parameter analysis part. However, in fact, the PSO parameter value in this synthetic case is the same as the PSO parameter value of Algorithm Testing part. Therefore, the following is added to Section 4.3 of this paper.

A 3-layered and 5-layered geoelectric models were investigated, which the PSO parameter values are the same as those of the Algorithm Testing parts in the paper.

1. Please discuss the main advantages and disadvantages of the BP compared to the metaheuristic approaches requiring a parameter space which can be chosen.

（11）Regarding the advantages and disadvantages of BP compared to the metaheuristic approaches requiring a parameter space which can be chosen, which has been elaborated in the paper discussion part, and its detailed description is as follows:

At present, heuristic algorithms are mainly based on natural body algorithms, which mainly includes ant colony algorithm, simulated annealing method, particle swarm optimization, ant optimization, fish swarm algorithm, bee colony algorithm and so on. And heuristic algorithms have a common feature: starting from a random feasible initial solution, an iterative improvement strategy is adopted to approximate the optimal solution of the problem. The advantage of the heuristic algorithm is that it is more efficient than the blind search method. In addition, a carefully designed heuristic function often gets the optimal solution in a very short time. However, the heuristic algorithm needs to repeatedly call the forward algorithm for each iteration in nonlinear resistivity inversion, resulting in a long calculation time.

However, BP neural network is the most active branch for nonlinear resistivity inversion. The inversion algorithm is different from the nonlinear heuristic method based on global solution space search, which it does not need to call the forward algorithm repeatedly, so its calculation time is short. At the same time, BP can approximate any nonlinear continuous function with arbitrary precision, which makes BP have strong nonlinear mapping ability. In addition, BP neural network can automatically extract "reasonable rules" between output and output data through learning, and adaptively memorize the learning content in the weight of the network, that is, BP neural network has the ability of high self-learning and self-adaptation; and BP neural network can be trained after training mode or noise-contaminated mode for correct prediction, that is, BP neural network has the generalization ability to apply learning results to new knowledge; in addition, the BP neural network does not have a great impact on the global training results after the local or part of the neurons are destroyed, that is, the BP neural network has certain fault tolerance.

However, the weight of the BP neural network is gradually adjusted by the direction of local improvement, which causes the algorithm to fall into local extremum, and the weight converges to the local minimum point, which leads to network training failure; in addition, BP is very sensitive to the initial network weights, initializing the network with different weights, which tends to converge to different local minima, resulting in different results for each training; and BP algorithm is essentially a gradient descent method, resulting in BP has a slow convergence rate; and the approximation and generalization ability of the BP neural network model is closely related to the learning samples, that is, the BP neural network depends on the sample selection. In view of the fact that the neural network is sensitive to the initial weight and easy to fall into the local minimum, the heuristic global search particle swarm optimization algorithm with simple structure, fast convergence and high precision is used to optimize the initial weight and threshold of the neural network. The method is stable and effective, and is not easy to fall into local optimum, and has better performance.

1. Such a study must include the effect of the noise on the solution in the synthetic case.Besides uncertainty analyses for estimated parameters should be applied for data sets with and without noise. A field example must be also presented.

(12) Anti-noise tests and a field example are added as follows. Since the result of the inversion is affected by various control parameters, computer system performance and programming planning in the algorithm, parameter uncertainty analysis should be performed in the paper, which it is the insufficiency of the research work, and it is also the direction we need further research. We sincerely hope to get your understanding.

(4) *Robust performance analysis*

In order to verify the algorithm robustness, 5%(26dB) and 10%(20dB) Gaussian random noise was added in TEM data for three-layer geoelectric model. Three kinds of inversions were implemented respectively. The results and comparison were shown in Table.3. The *H*z(*t*) and data with 5% noise were shown in Fig.3.

**Table 3** Comparison of inversion results for three-layer H type (with noise) model

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| model parameters |  | resistivity *ρ*(Ω•m) | | | thickness h(m) | | | Total relative error(%) |
| *ρ*1 | *ρ*2 | *ρ*3 | | *h*1 | *h*2 |
| true value |  | 100 | 10 | 100 | | 100 | 200 | -- |
| without noise | BP | 99.724 | 9.937 | 100.765 | | 99.031 | 198.701 | 3.284 |
| COPSO-BP | 100.031 | 9.991 | 99.310 | | 100.234 | 200.886 | 1.487 |
| 5% noise | BP | 101.374 | 9.966 | 98.283 | | 101.255 | 199.282 | 5.039 |
| COPSO-BP | 100.252 | 9.977 | 98.222 | | 101.206 | 199.228 | 3.847 |
| 10% noise | BP | 90.525 | 9.931 | 99.481 | | 101.748 | 203.105 | 13.976 |
| COPSO-BP | 104.472 | 9.96050 | 101.345 | | 100.570 | 199.437 | 7.064 |



**Fig.3** Forward data of Hz and data with 5% noise

As can be seen from Table 3, after applying 5% and 10% Gaussian noise the COPSO-BP inversion has higher robust ability. The accuracy was obviously improved based on the total relative error data.

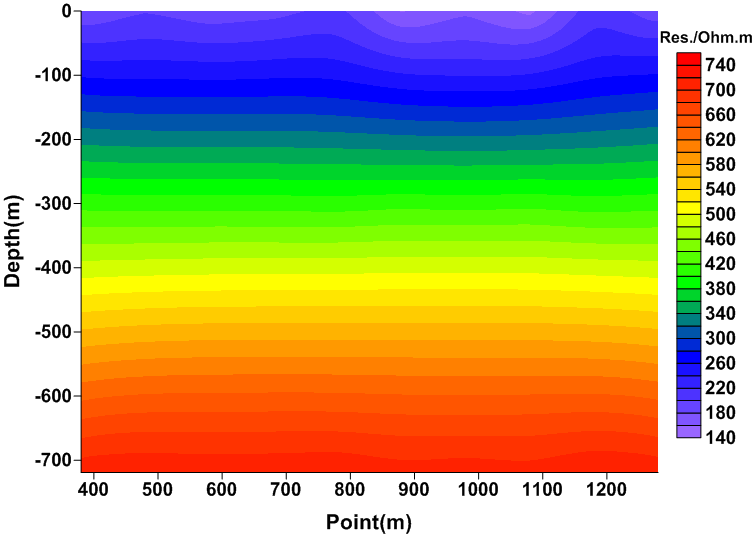
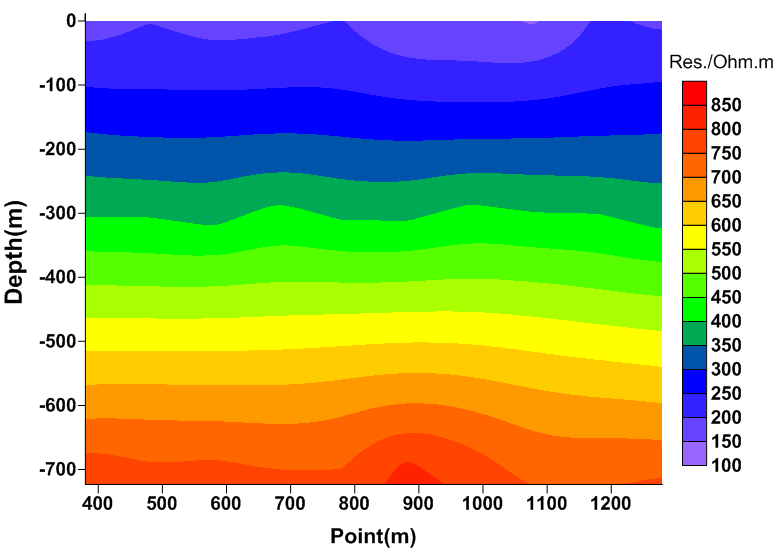
**4.4** **Field example analysis**

In order to test the effectiveness of the method, a transient electromagnetic vertical magnetic field (Hz) with 10 measuring points at the 380m to 1280m of the No. 1 line from a mining area in Anhui Province was selected. After the data processing, the inversion was performed using the 3-layer neural network model in the previous section, and the results of BP and COPSOBP inversion were compared.Figure 4 shows the comparison between the surveyed data and the inversion data at 380m of the No. 2 line in the mining area.Figure 6 displays the pseudo-sections of the 10 sets of inversion data combined with the geological data interpolation smoothing.It can be seen from Fig. 5 that the first layer is a low resistivity (100~200 Ω·m), which is inferred to be the second layer (T2g22) gray dolomite of the Middle Triassic old Malague section, with a thickness of about 200 m; the second layer is the second highest resistivity (300~400 Ω·m), which is surmised to be the first layer (T2g21) dolomite of the Middle Triassic old Malaga section, with a thickness of about 400m;the third layer is high resistivity (600~800Ω·m), which is speculated to be the 6th layer (T2g16) limestone dolomite of the Middle Triassic old group.The results are basically consistent with the geological conditions of the mining area, indicating the feasibility and effectiveness of the neural network method.And the results of COPSO-BP inversion are better than those of BP, which the inversion position is more accurate, the shape and spacing are clearer, and the resistivity of each layer is more consistent with the those of the actual geological model.



(a) BP (b) COPSOBP

Figure 4. 1D inversion forward results. (a) BP; (b) COPSOBP.



1. BP (b) COPSO-BP

Figure 5. Inversion results of BP (a) and COPSO-BP (b).

We tried our best to improve the manuscript and made some changes in the manuscript. These changes will not influence the content and framework of the paper. And here we did not list the changes but marked in red in revised paper.  
 We appreciate for Editors/Reviewers’ warm work earnestly, and hope that the correction will meet with approval.

Once again, thank you very much for your comments and suggestions.