Comparison of Very Fast Simulated Annealing and Modified Particle Swarm Optimization Inversion Method for 1-D TDEM Data Modelling

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Abstract. Time domain electromagnetic method (TDEM) is a geophysical method that can be applied to a wide range of problem. TDEM data requires non-linear inversion in its modelling because of the complex relationship between data and model. A global approach is an approach in nonlinear inversion calculation which is not sensitive to the initial model and capable of obtaining global minimums. Previous studies proved that one type of inversion method will not give the most satisfactory results for all different types of inversion problems. For this reason, this study was conducted to discuss the performance of global non-linear inversion methods for 1D TDEM data modelling so that future inversion process can be carried out more optimally. In this study, the performance of VFSA and MPSO inversion method in the modelling of synthetic and field 1D TDEM data is compared. The inversion modelling is done multiple times in order to consider the random factor present in both methods and also to compare the result’s variability of each method. From the result of synthetic data inversion, it can be seen that there is a variation of inversion performance between models which is caused by the ambiguity in 1D TDEM. Based on the comparison of the two methods, MPSO performs better in inversion of data with lower level of ambiguity, and vice versa. Overall, it is concluded that the VFSA method performs better than MPSO because it has lower variability and gives better inversion results for data with high ambiguity which is usually the case for real 1D TDEM data.

1. Introduction

Data obtained from TDEM is a response from the variation in resistivity of rock traversed by electromagnetic waves in the form of conductivity contrast [1]. To get the resistivity model from TDEM data, the inversion process needs to be done. TDEM data requires non-linear inversion in its modelling because of the complex relationship between data and models. There are two kinds of approaches to non-linear inversion calculations, namely local and global approaches. The advantage of global approach over local approach is that it is insensitive to the initial model and capable of obtaining global minimums [2]. Because it is not sensitive to the initial model, a global approach can provide good results if a priori data is not available. However, inversion methods that is based on this approach generally...
show inversion performance that varies greatly depending on the problems encountered [3]. Therefore, it is necessary to conduct a study that discusses the details of the performance of inversion methods of non-linear global approaches so that the inversion process in TDEM can be carried out more optimally. In this study, two types of non-linear inversion methods global approach, namely the Very Fast Simulated Annealing (VFSA) method and the Modified Particle Swarm Optimization (MPSO) method is compared.

2. Data and Method

2.1 Data

The data used in this study are 1D TDEM synthetic data and 1D TDEM field data in the Gundih field owned by PT. Pertamina. Synthetic data is generated from forward modelling of synthetic models, while the field data used is data of sounding points for CCS hydrocarbon reservoirs characterization. To compare the performance of VFSA and MPSO inversion methods in modelling various conditions below the earth's surface, two synthetic models with two layers, and two synthetic models with three layers with varying resistivity is used to generate the synthetic data. The specifications of these four models are shown in Table 1.

| Parameter | Synthetic 1 | Synthetic 2 | Synthetic 3 | Synthetic 4 |
|-----------|-------------|-------------|-------------|-------------|
| \( \rho_1 \) (Ohm.m) | 100         | 10          | 100         | 10          |
| \( \rho_2 \) (Ohm.m) | 10          | 100         | 10          | 100         |
| \( \rho_3 \) (Ohm.m) | -           | -           | 100         | 10          |
| \( h_1 \) (m)   | 200         | 100         | 200         | 100         |
| \( h_2 \) (m)   | -           | -           | 100         | 200         |

Field data is used to compare the performance of the VFSA and MPSO methods in real life application, the determination of seal-reservoir layer boundaries, which is part of the characterization for CO2 injection. The field data used in this study is TDEM measurement data for Carbon Capture Storage (CCS) Pilot Project in the Gundih area. The measurement of TDEM is carried out around Jepon-I well located in the area. The average of the current injected in this measurement is 143 A. In this area, the

![Figure 1. Previous interpretation of seismic data around Jepon-1 well. [4]](image-url)
Wonocolo formation acts as a seal layer and the Ngrayong formation is the target reservoir for CO2 injection [4]. Seismic measurements have been carried out around Jepon-1 well with the results of the seismic interpretation shown in Figure 1. The resistivity value of rock lithology used in this modeling is based on a previous research [5]. In accordance with the study, the Ledok Formation is known to have a resistivity value of $20 \, \Omega \cdot m$, the Wonocolo Formation has a resistivity value of $200 \, \Omega \cdot m$, the Ngrayong Formation has a resistivity value of $2 \, \Omega \cdot m$ and the Tuban Formation has a resistivity value of $20 \, \Omega \cdot m$. Based on Figure 1 and the research conducted by Tsuji et al. [6], the boundary between seals and reservoirs is known to be around 750 m to 1200 m. This range of the depth of the seal-reservoir boundary acts as a validation of the inversion modelling results.

2.2 Forward Modelling

The forward modelling used in this research is the long-grounded wire modelling formulated by Ward and Hohhman [7]. The vertical magnetic field $H_z$ in the frequency domain is formulated with equation (1):

$$
H_z = \frac{I}{4\pi} \int_{-L}^{L} \frac{y}{R} \int_{0}^{\infty} (1 + r_{TE}) e^{\mu_0 z} \frac{3}{\mu_0} J_1(\lambda R) d\lambda dx'
$$

$I$ is the current that is injected by the transmitter and $L$ is the distance from the centre of the transmitter to the two ends of the transmitter. $R$ is the discrete distance of the transmitter cable to the receiver's location which is formulated by $R = \sqrt{x^2 + y^2}$, where $x$ and $y$ are the coordinates of the receiver's location from the centre of the transmitter. The $r_{TE}$ variable is a reflection coefficient that is recursively calculated from the lowest layer towards the top layer of the model. Variable $\mu_0$ is the magnetic permeability in vacuum ($4\pi \times 10^{-7} \, \text{N} / \text{A}$). Equation (1) is calculated using the 1st order of Bassel equation ($J_1$), where $\lambda$ is the integration variable of the Hankel transformation. The calculation of the response value in the time domain is done by doing fourier transform to the magnetic field value as formulated by Mitsuhata et al. [8]. The response of the magnetic field when the current is turned off (step-off response) is calculated by

$$
H_{z,\text{off}} = \frac{-2}{\pi} \int_{0}^{\infty} \text{Im}[H_z(\omega)] \frac{\cos(\omega t)}{\omega} d\omega
$$

2.3 Very Fast Simulated Annealing

The VFSA method is similar to the SA method but uses Cauchy distribution-based perturbation models which is a function of temperature, and a with a faster decrease in temperature $T$ [9]. The model renewal factor ($y_i$) is calculated using equation (3).

$$
y_i = \text{sgn}(u_i - 0.5)T_i \left[ \left(1 + \frac{2u_i - 1}{T_i} \right)^{1/2} - 1 \right]
$$

Variable $u_i$ is a random value that vary from 0 to 1 so that the value of $y_i$ can vary from +1 to -1, and $T_i$ is the temperature of iteration $i$. The model $m$ is updated into $m_{i+1}$ by

$$
m_{i+1} = m_i + y_i(m_{\text{max}} - m_{\text{min}})
$$

Misfit of VFSA method is formulated by Sharma [10] and can be written as equation (5):
The change in of $c_i$ where the best position particle index. Local best ($l_j$) is the best position ever achieved by a particle, whereas global best ($g_i$) is the best position out of all the particles. The search limit is defined as

$$1 \leq j \leq n_{size}$$

where $n_{size}$ is the number of particles. The MPSO method updates $x_j$ and $v_j$ of each particle in iteration $i$ by

$$v_j(i + 1) = \begin{cases} 
  c_1 r_1 (l_j(i) - x_j(i)) + c_2 r_2 (g(i) - x_j(i)), & E(x_j(i + 1)) > E(l_j(i)) \\
  \omega_c v_j(i), & E(x_j(i + 1)) < E(g(i)) \\
  \omega_c v_j(i) + c_1 r_1 (l_j(i) - x_j(i)) + c_2 r_2 (g(i) - x_j(i)), & Others 
\end{cases}$$

$$x_j(i + 1) = v_j(i + 1) + x_j(i)$$

$c_1$ and $c_2$ are user defined constants, while $r_1$ and $r_2$ are random values which vary from 0 to 1. The value of $\omega_c$ in this method is a dynamic number that functions to increase the speed of the inversion process. The change in the value of $\omega_c$ is calculated by

$$\omega_c = \omega_c \text{Max} - (i - 1) \frac{\omega_c \text{Max} - \omega_c \text{Min}}{(\lambda)(i_{\text{max}})}$$

where $\lambda$ is a constant with a value of 0.75, $\omega_c \text{Max}$ and $\omega_c \text{Min}$ is the maximum and minimum value $\omega_c$, and $i_{\text{max}}$ is the maximum iteration. In the first iteration, $\omega_c$ will have a value of $\omega_c \text{Max}$ and in the last iteration, the value of $\omega_c$ is equal to $\omega_c \text{Min}$.
2.5 Inversion Method and Parameters

Inversion of the synthetic data is performed by iterating the inversion process by ten times for each data to consider the random factor present in both inversion methods. A run is defined as a finished inversion process in which the inversion has reached the defined number of maximum iterations; or if the generated model has reached a misfit value below a defined misfit threshold. The ten runs for both inversion methods each generated ten different models in which the variability of model parameters and misfit values from these two methods are compared. In addition, inversion models are illustrated for qualitative analysis and comparison.

Specifications of the synthetic models used to generate the synthetic data are shown in Table 1. The values of TDEM measurement parameters for the forward modeling calculations are as follows; the injection current is 1 A, the distance between the transmitter is 1 meter, and the distance between the receiver and the transmitter center point (offset) is 200 meters. The inversion parameters of the VFSA and MPSO methods on synthetic data inversion, as shown in Table 2, are obtained through a tuning process.

| Parameter | Synthetic 1 | Synthetic 2 | Synthetic 3 | Synthetic 4 |
|-----------|-------------|-------------|-------------|-------------|
| $T_{oi}$  | 0.1         | 0.1         | 0.2         | 0.2         |
| $nv$      | 10          | 10          | 50          | 50          |
| $ni$      | 100         | 100         | 100         | 100         |
| $ci$      | 1           | 1           | 1           | 1           |
| $CS$      | 0.5         | 0.5         | 0.5         | 0.5         |

VFSA

| Parameter | VFSA         |
|-----------|--------------|
| $ns$      | 10           |
| $ni$      | 100          |

MPSO

| Parameter | MPSO         |
|-----------|--------------|
| $ns$      | 50           |
| $ni$      | 100          |

The resistivity and depth dataspace are uniform for all parameters which is 0.1 ~ 300 $\Omega$m and 0.1 ~ 300 m respectively. To be able to compare the speed of the two inversion methods in achieving the threshold misfit value, the maximum number of iterations $i_{max}$ and misfit threshold for both methods and all synthetic data is made equal and set at 100 and 0.1 respectively. The value of the $nv$ parameter multiplied with $ns$ is also made equal so that the inversion time in one iteration takes similar time.

The inversion for the field data is carried out on 3 TDEM measurement point data named E000N100, E00S100, and E00S200. With similarity to the inversion for the synthetic data, the inversion for the field data was also done in ten runs for each data but does not use a misfit threshold as a criterion to end a run. The inversion parameters used in the inversion of the three fields data are set equal and shown in Table 3. The number of layers to be modelled in each data is four layers and the resistivity and depth dataspace is set equal for all layers, which is 0.1 ~ 400 $\Omega$m and 1 ~ 1200 m respectively.

| Parameter | VFSA        |
|-----------|-------------|
| $T_{oi}$  | 0.3         |
| $nv$      | 50          |
| $i_{max}$ | 100         |
| $ci$      | 1           |
| $CS$      | 0.5         |

MPSO

| Parameter | MPSO        |
|-----------|-------------|
| $ns$      | 50          |
| $i_{max}$ | 100         |

The resistivity and depth dataspace are uniform for all parameters which is 0.1 ~ 300 $\Omega$m and 0.1 ~ 300 m respectively.
3. Result and Analysis

3.1 Synthetic Data Inversion

The summary of synthetic data inversion with VFSA and MPSO in ten runs is shown in Tables 4 and 5. The table depicts the averaged values of each layer’s parameter and total error resulted from both inversion methods. The values are also included with average deviations so that the variability can be clearly observed.

Table 4. Inversion summary for Synthetic Data 1 and 2

| Parameters | Synthetic 1 | Synthetic 2 |
|------------|-------------|-------------|
|            | VFSA        | MPSO        | VFSA        | MPSO        |
| \( \rho_1 (\Omega m) \) | 100.982 ± 2.231 | 100.002 ± 0.004 | 9.956 ± 0.224 | 11.126 ± 2.406 |
| \( \rho_2 (\Omega m) \) | 10 ± 0.15 | 10 ± 0.001 | 100.189 ± 2.085 | 104.314 ± 8.984 |
| \( h_1 \) (m) | 200.617 ± 4.34 | 199.992 ± 0.016 | 99.095 ± 3.7 | 123.884 ± 50.81 |
| Error | 0.114 ± 0.061 | 0 ± 0 | 0.089 ± 0.039 | 0.34 ± 0.684 |

Table 5. Inversion summary for Synthetic Data 3 and 4

| Parameters | Synthetic 3 | Synthetic 4 |
|------------|-------------|-------------|
|            | VFSA | MPSO | VFSA | MPSO |
| \( \rho_1 (\Omega m) \) | 100.843 ± 2.404 | 88.963 ± 24.666 | 10.023 ± 0.239 | 8.273 ± 3.644 |
| \( \rho_2 (\Omega m) \) | 11.659 ± 3.938 | 64.061 ± 111.534 | 166.677 ± 74.102 | 134.829 ± 76.971 |
| \( \rho_3 (\Omega m) \) | 100.926 ± 2.18 | 91.415 ± 19.653 | 10.031 ± 0.146 | 10.522 ± 1.151 |
| \( h_1 \) (m) | 191.908 ± 19.936 | 156.491 ± 78.887 | 102.305 ± 4.719 | 80.532 ± 41.997 |
| \( h_2 \) (m) | 126.044 ± 50.218 | 102.387 ± 36.801 | 190.085 ± 11.738 | 188.881 ± 74.434 |
| Error | 0.152 ± 0.062 | 0.459 ± 0.887 | 0.107 ± 0.043 | 0.208 ± 0.416 |

Table 6 depicts the average number of iterations performed by both methods until it has created models with misfit lower than the defined misfit threshold. It is to be noted that the results from the table does not average the runs that reached max iterations, instead it is depicted as the number of “failed runs” which are runs that has not reach the misfit threshold before performing the defined maximum amount of iterations.

From Tables 4 and 5, it is shown that the average result of Synthetic Data 1 inversion modeling using the MPSO method is better than the VFSA method. On the other hand, for Synthetic Data 2, 3 and 4, the VFSA method provides better average inversion modeling results than the MPSO method. The inversion models created using the MPSO method has a relatively high averaged deviation compared to that created using the VFSA method.

Table 6. Average iterations elapsed to reach misfit threshold

| Model       | Iterations (VFSA) | Iterations (MPSO) | Failed Runs (VFSA) | Failed Runs (MPSO) |
|-------------|-------------------|-------------------|--------------------|--------------------|
| Synthetic 1 | 39                | 16                | 0                  | 0                  |
| Synthetic 2 | 43                | 24                | 0                  | 2                  |
| Synthetic 3 | 54                | 18                | 0                  | 2                  |
| Synthetic 4 | 35                | 18                | 0                  | 2                  |
From Table 6, it is found that for all the synthetic data, the MPSO method requires fewer number of iterations than the method VFSA to reach the misfit threshold. However, MPSO experienced 2 failed runs on Synthetic Data 2, 3, 4, while VFSA does not result any failed runs at all.

Two figurative illustrations of the best and worst models from Synthetic Data 3 created using both methods are depicted in Figure 2 and 3. From Figure 2, it is shown that the best model created using MPSO is more accurate, and could even be considered as near-perfect. In contrast, Figure 3 clearly shows that the model from MPSO deviates distantly from the actual values of the synthetic model, whereas VFSA’s model is more acceptable as it still detects a resistive layer for the second layer.

**Figure 2.** Best inversion models for Synthetic Data 3

**Figure 3.** Worst inversion models for Synthetic Data 3

Based on the overall results of synthetic data inversion, the inversion with both methods shows a highly varied results based on how ambiguous the synthetic data is to be modelled. Synthetic Data 1 is
considered to have the least factor of ambiguity as it is the easiest one to be modelled, which is proven by the overall low deviation numbers compared to the other three models as shown in Table 3 and 4. The MPSO excels in modelling Synthetic Data 1 in terms of speed and accuracy but failed to generate consistent models when faced with Synthetic Data 2, 3, and 4 which has higher factor of ambiguity. From Table 5, it is shown that the MPSO shows a relatively small number of iterations needed to reach the misfit threshold but experienced several failed runs in Synthetic Data 2, 3, and 4. The failed runs is thought-out to be a case of premature convergence, which is when the particles in the swarm converged too early before comprehensively exploring the dataspace. This results in particles flocking in an area that is distant from the actual true values. The VFSA method shows more consistent results as it does not perform any failed runs at all in modelling all the Synthetic data. Its worst-generated models that slightly varies from the actual synthetic data is believed to have been caused by the ambiguity of TDEM, rather than the VFSA method itself, because the misfit is still below the threshold which means that the defined misfit is not low enough for the Synthetic Data to be accurately modeled. Unlike MPSO, the VFSA methods allow for an extensive range of exploration at high temperatures.

3.2 Field Data Inversion

The summary of field data inversion with VFSA and MPSO in ten runs is shown in Table 7. A selection of the best-fitting model was carried out with consideration of error values, suitability to field conditions, and the average parameter values and standard deviations. The plot best-fitting model of both methods for field data E000N100 is shown in Figure 4.

| Parameters | VFSA       | MPSO       | VFSA       | MPSO       | VFSA       | MPSO       |
|------------|------------|------------|------------|------------|------------|------------|
| \( \rho_1 \) (\( \Omega \)m) | 41.4 ± 4.7 | 56.2 ± 11.9| 34.9 ± 6.7 | 40.6 ± 6.6 | 25.8 ± 3.9 | 44.1 ± 6.6 |
| \( \rho_2 \) (\( \Omega \)m) | 387.5 ± 10.7| 236.3 ± 81.1| 319.9 ± 82.6| 258.6 ± 61.7| 340.9 ± 53.6| 248.1 ± 86.9 |
| \( \rho_3 \) (\( \Omega \)m) | 27.6 ± 37.9 | 40.9 ± 42.4 | 17.9 ± 31.7 | 15.8 ± 25.9 | 13.5 ± 26.7 | 7.4 ± 12.5 |
| \( \rho_4 \) (\( \Omega \)m) | 18.2 ± 22.5 | 23.4 ± 31 | 36.3 ± 26.9 | 29 ± 25.9 | 8.8 ± 13.6 | 40.1 ± 29.7 |
| \( h_1 \) (m) | 182 ± 31 | 304.2 ± 197.7 | 256.9 ± 86.6 | 443.2 ± 206 | 137 ± 30.6 | 400.5 ± 206.7 |
| \( h_2 \) (m) | 872.8 ± 130.2 | 642.3 ± 326.6 | 432.9 ± 114.8 | 290.5 ± 130.7 | 641.2 ± 92.1 | 477.4 ± 186 |
| \( h_3 \) (m) | 815.9 ± 481.5 | 758.3 ± 375.2 | 1090.6 ± 430.5 | 835.7 ± 349.7 | 637.4 ± 276.6 | 544.4 ± 253.4 |
| \( \text{Error} \) | 0.367 ± 0.054 | 0.689 ± 0.241 | 0.371 ± 0.086 | 0.496 ± 0.135 | 0.244 ± 0.045 | 0.58 ± 0.154 |

The results from Table 7 shows inversion models with notably higher values of average deviation and error, which is expected because of the noise present in the field data. Overall, the average values of each layer’s parameters are similar for both methods and represents the lithologies of the subsurface layers as described in Section 2.1. The average error of models from MPSO method is higher than VFSA for all the field data. Similar to the synthetic data inversion, MPSO appears have struggle in modelling the field data which has high factor of ambiguity because of noise and possibly error from the TDEM instruments.

Figure 4 shows how both methods are able to correctly create an inversion model with seal-reservoir boundary corresponding to the previous study by Tsuji et al. [6], which is located at a depth between 750 m and 1200 m. It is to be noted that several of the other inversion models does not fit the validation of the previous study, therefore it is better do more runs on field data which will make the average values of the parameters to be more representative to the actual condition of the subsurface.
4. Conclusion

Compared to the MPSO method, the VFSA method shows an overall better performance in modelling the synthetic data as it provided more consistent results with lower variability. Both inversion methods show their capability in modelling the field data by being able to create models that corresponds to the previous study, but the MPSO methods has an overall higher variability of inversion model parameters. The MPSO shows inadequacy of modelling the TDEM synthetic data with high level of ambiguity, as it is proven to have experienced premature convergence several of times. A finer tuning of inversion parameters and a better strategy of particles initiation for the MPSO is needed for it perform appropriately for data with high ambiguity, while parameters inversion of VFSA may only need a little bit of adjustment for other data. The number of runs may also need to be increased to provide more representative averaged results.

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