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Nonlinear 1D Time-Domain Electromagnetic Inversion using Adaptive Differential Evolution: Application to Volcanic-Hydrothermal System

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ABSTRACT

Time-Domain Electromagnetic (TDEM) subsurface resistivity inversion is a highly nonlinear, ill-posed optimization problem hindered by parameter coupling, layer equivalence, and local minima trapping. To address these challenges, this study presents an advanced stochastic inversion framework based on Improved Linear Population Size Reduction Success-History Based Adaptive Differential Evolution (iL-SHADE). The algorithm incorporates dynamic memory-driven parameter adaptation and linear population size reduction to balance global exploration and local exploitation, eliminating the need for manual tuning of mutation and crossover parameters. Evaluated over 30 independent stochastic runs across four distinct 5-layer synthetic earth models (Ascending, Bell, Bowl, and Descending), iL-SHADE achieved superior solution quality, reaching median misfits of 10^{-8} to 10^{-9} , outperforming standard DE and SHADE by 2 to 4 orders of magnitude. Non-parametric Wilcoxon rank-sum hypothesis testing confirmed that these performance enhancements are statistically significant ($p < 0.01$). Noise robustness assessments demonstrated consistent convergence to noise-floor-bounded minima under Gaussian noise levels up to 20%. Field data validation at Station UZ01 on Unzen Volcano, Japan (1.4 km grounded electric wire transmitter, 2.0 km offset) successfully resolved the 5-layer subsurface structure extending to a depth of 5.6 km. These results demonstrate that

iL-SHADE provides a highly robust, parameter-adaptive optimization framework for reliable electromagnetic imaging in complex volcanic-hydrothermal systems.

Keywords: Time-Domain Electromagnetic (TDEM); adaptive differential evolution (iL-SHADE); nonlinear 1D inversion; non-parametric statistical analysis; volcanic-hydrothermal system.

1. INTRODUCTION

Electrical resistivity has long been recognized as one of the most informative physical properties for characterizing subsurface geological structures (Akingboye, 2025; Xia et al., 2026) because it is highly sensitive to variations in lithology (Nielsen et al., 2026), fluid saturation, porosity (Grana et al., 2026), temperature (Xia et al., 2026), and hydrothermal alteration (Revil & Gresse, 2021). Reliable resistivity imaging is therefore fundamental for a wide range of geophysical applications, including mineral and groundwater exploration (Aizawa et al., 2009; Akingboye, 2025), geothermal reservoir characterization (Aizawa et al., 2009; Revil & Gresse, 2021), environmental investigations (Xia et al., 2026), and volcanic monitoring (Aizawa et al., 2009; Caudron et al., 2023). In volcanic and geothermal systems, subsurface resistivity imaging becomes particularly important because hydrothermal alteration, fracture networks, and fluid circulation generate highly heterogeneous electrical structures that cannot be reliably characterized using surface observations alone (Lin et al., 2023). Among the available electromagnetic methods, Transient Electromagnetic (TEM) or Time-Domain Electromagnetic (TDEM) surveying has become an established technique due to its capability to provide high-resolution resistivity information over a broad depth range while maintaining operational efficiency in complex field environments (Akingboye, 2025; Rulff et al., 2026). By measuring the transient decay of induced electromagnetic fields after the transmitter current is suddenly terminated, TDEM enables the reconstruction of subsurface resistivity distributions that are closely associated with geological and hydrogeological features (Rulff et al., 2026). Consequently, the reliability of geological interpretation derived from TDEM surveys depends critically on the accuracy and robustness of the inversion process used to transform measured transient responses into physically meaningful resistivity models (Hapsoro et al., 2021; Zhang et al., 2025).

TDEM inversion is a highly nonlinear and ill-posed optimization (Hapsoro et al., 2021; Srigitomo et al., 2021) problems in which multiple subsurface models may produce nearly indistinguishable responses. This non-uniqueness is further exacerbated by measurement noise (Falk et al., 2025; Haber et al., 2007), limited data coverage (Falk et al., 2025; Heagy et al.,

2017), and the strong coupling between model parameters (Hapsoro et al., 2021; Wang et al., 1994), resulting in a complex objective function characterized by multiple local minima. Furthermore, strong trade-offs between layer resistivity and thickness are commonly revealing equivalent models that fit the observed responses equally well, thereby increasing inversion ambiguity and reducing model reliability (Franz et al., 2021; Maurya et al., 2023). As model complexity increases, particularly for multilayered resistivity structures commonly encountered in volcanic and geothermal environments, the search space expands substantially, making it increasingly difficult to obtain stable and globally optimal solutions (Horikawa & Kusumoto, 2025; Lindsey & Newman, 2015; Pollack et al., 2021). Such characteristics substantially increase the difficulty of navigating the inversion landscape, where an optimization algorithm must simultaneously preserve population diversity during global exploration while ensuring stable convergence toward physically meaningful solutions. Consequently, the performance of TDEM inversion is governed not only by data quality and forward modelling accuracy, but also by the capability of the optimization algorithm (Hapsoro et al., 2021; Srigutomo et al., 2021) to effectively balance global exploration and local exploitation while maintaining convergence stability.

To overcome the challenges associated with nonlinear and multimodal inverse problems, numerous inversion strategies have been developed over the past decades. Conventional deterministic approaches, such as Gauss–Newton (Blanchy et al., 2020; Chen & Sacchi, 2020), Levenberg–Marquardt (Bergou et al., 2022), and Occam-type (de Groot-Hedlin & Constable, 1990) inversion, have been widely adopted because of their computational efficiency and rapid convergence when the initial model is sufficiently close to the true solution (Laloy et al., 2019; Puzyrev & Swidinsky, 2021). Nevertheless, their performance commonly deteriorates for highly nonlinear inverse problems due to their dependence on initial parameter estimates (Bai et al., 2021) and their susceptibility to becoming trapped in local minima (Puzyrev & Swidinsky, 2021). These limitations have motivated the increasing adoption of global optimization algorithms, including Genetic Algorithms (GA) (Dossi et al., 2021; Ekinici et al., 2023), Particle Swarm Optimization (PSO) (Hapsoro et al., 2021), Simulated Annealing (SA) (Anthony et al., 2022; Brown et al., 2022; Srigutomo et al., 2021), and Differential Evolution (DE) (Price et al., 2005), which employ stochastic search mechanisms to explore the solution space more comprehensively. Among these approaches, DE has attracted considerable attention owing to its simple implementation (Das & Suganthan, 2011; Price et al., 2005; Storn & Price, 1997), relatively small number of control parameters (Das & Suganthan, 2011; Price et al.,

2005), and strong capability to locate near-global solutions across a wide range of continuous optimization problems (Das & Suganthan, 2011), including geophysical inversion.

Although classical DE has demonstrated competitive performance in solving nonlinear optimization problems, its application to TDEM inversion remains challenged by the selection of mutation and crossover parameters, which are typically assigned fixed values throughout the optimization process. The use of static parameter settings frequently lack the flexibility to address the dynamic search requirements that arise during different evolutionary phases (Price et al., 2005; Zhang & Sanderson, 2009), leading to reduced population diversity (Zhu et al., 2020; Zuo & Gao, 2025), premature convergence (Tanabe & Fukunaga, 2013), and stagnation in solving highly nonlinear inverse problems (Tanabe & Fukunaga, 2014). To address these limitations, adaptive variants of DE have been developed to automatically regulate search behavior according to the optimization progress. Success-History based Adaptive Differential Evolution (SHADE) introduces historical parameter memory that continuously updates mutation and crossover factors using successful search experiences (Stanovov et al., 2021; Tanabe & Fukunaga, 2014), thereby this algorithm provides improving the balance between global exploration and local exploitation. Subsequent developments, including Linear Population Size Reduction SHADE (L-SHADE) and its improved variants, further enhance search efficiency through adaptive population control and refined evolutionary strategies, aiming to achieve faster convergence while preserving solution quality in increasingly complex optimization landscapes (Brest et al., 2016).

Despite the remarkable progress achieved by adaptive DE algorithms, their superiority has been demonstrated predominantly on mathematical benchmark functions and generic continuous optimization problems. However, the effectiveness of these adaptive strategies cannot be directly generalized to TDEM inversion, where nonlinear forward responses (Puzyrev & Swidinsky, 2021; Ren & Kalscheuer, 2020), strong parameter coupling (Bai et al., 2021; Glubokovskikh et al., 2023), model equivalence (Liu et al., 2021), and progressively increasing model complexity fundamentally alter the characteristics of the optimization landscape (Hapsoro et al., 2021; Price et al., 2005; Ren & Kalscheuer, 2020). Consequently, it remains insufficiently understood how successive adaptive mechanisms within the DE algorithm influence convergence behavior, solution stability, and inversion accuracy as the complexity of TDEM inverse problems increases. Addressing this knowledge gap requires a systematic evaluation that extends beyond conventional benchmark functions and examines the practical robustness of adaptive search mechanisms under both controlled synthetic models and field geophysical data observations.

Motivated by these challenges, this study systematically investigates the evolutionary progression of adaptive DE strategies for solving TDEM inverse problems. This work investigates how successive developments in adaptive parameter control and population management influence convergence behavior, solution stability, and inversion accuracy across progressively more challenging inversion scenarios. The proposed investigation is conducted using a hierarchical validation framework consisting of synthetic multilayer models with varying complexity, followed by application to TDEM field data acquired from a volcanic environment. By progressively increasing inversion complexity from controlled synthetic models to TDEM field data, the proposed algorithm enables a systematic evaluation of the robustness and practical effectiveness of adaptive search mechanisms under realistic geophysical conditions.

2. METHODS

2.1. TDEM Forward Modeling

Time-Domain Electromagnetic (TDEM) surveying operates on the principle of transient electromagnetic field diffusion resulting from the sudden termination of a primary electric current flowing through a transmitter loop or a grounded horizontal electric dipole (HED) source (Hapsoro et al., 2021; Srigutomo et al., 2021). During the current-on stage, a steady primary magnetic field is established in the subsurface. When the transmitter current is abruptly shut off, induced eddy currents diffuse outward and downward into the conductive subsurface media, generating secondary transient electromagnetic fields that decay over time and are recorded by magnetic field sensors at the surface. Because the transient diffusion rate is inherently governed by the electrical conductivity and geometry of the subsurface structures, the recorded decay response provides essential information regarding the subsurface electrical resistivity distribution.

In this study, the source configuration is modeled as a grounded HED oriented along the x -axis with current moment $I dx$, where I is the injected current intensity and dx represents the dipole length. For a cut-off current waveform shut off at $t = 0$, the source current density distribution $\mathbf{j}_s(\mathbf{r}, t)$ is expressed as (Hapsoro et al., 2021),

$$\mathbf{j}_s(\mathbf{r}, t) = I dx \delta(\mathbf{r} - \mathbf{r}_0)[1 - H(t)]\mathbf{u}_x \quad (1)$$

where $\delta(\cdot)$ is the Dirac delta function, $H(t)$ is the Heaviside step function, $\mathbf{r}_0$ specifies the transmitter location, and $\mathbf{u}_x$ is the unit vector along the dipole direction. Under the quasi-static approximation valid for low-frequency geophysical electromagnetic applications (where

Exploiting the horizontal symmetry of the HED dipole aligned along the x -axis over a 1D horizontally layered earth, the y -component of the vector potential vanishes ($\mathbf{A}_{iy} = 0$), leaving two non-zero components that satisfy decoupled scalar Helmholtz equations,

$$\nabla^2 A_{ix} + k_i^2 A_{ix} = 0 \quad (7)$$

$$\nabla^2 A_{iz} + k_i^2 A_{iz} = 0 \quad (8)$$

By applying boundary conditions across the horizontal layer interfaces, the vertical component of the magnetic field $H_z(s)$ at an offset distance

$$\rho = \sqrt{x^2 + y^2}$$

from the transmitter is obtained via the Hankel transform integral

$$H_z(s) = \frac{I dx y}{2\pi\rho} \int_0^\infty \lambda [e^{-u_0 z} + r_{TE}(\lambda, s)e^{u_0 z}] J_1(\lambda\rho) d\lambda \quad (9)$$

where

$$u_0 = \sqrt{\lambda^2 + s\mu_0\sigma_0} \quad (10)$$

and y denotes the receiver offset in the y -direction, $J_1(\cdot)$ is the first-order Bessel function of the first kind, and $r_{TE}(\lambda, s)$ represents the transverse electric (TE) reflection coefficient evaluated recursively from the layered earth conductivity-thickness model using the recursive impedance formulation (Hapsoro et al., 2021). Numerical integration of Eq. 9 over the spatial wavenumber domain is executed efficiently using digital linear filter algorithms (Anderson, 1979).

To transform the vertical magnetic field response from the Laplace domain $H_z(s)$ into the time domain $h(t)$, the inverse Laplace transform is evaluated numerically using the Gaver–Stehfest algorithm (Hapsoro et al., 2021; Kuznetsov, 2013)

$$h(t) = \frac{\ln 2}{t} \sum_{l=1}^L K_l H_z(s_l), s_l = \frac{l \ln 2}{t} \quad (11)$$

where L is the number of expansion terms (set to $L = 8$ in this study for optimal precision and numerical stability), and the weighting coefficients K_l are computed as

$$K_l = (-1)^{L/2+l} \sum_{k=\lfloor \frac{l+1}{2} \rfloor}^{\min(l, L/2)} \frac{k^{L/2} (2k)!}{\left(\frac{L}{2}-k\right)! k! (k-1)! (l-k)! (2k-l)!} \quad (12)$$

195 The transient decay response $h_-(t)$ recorded post current shut-off ($t \geq 0$) is obtained by
 196 subtracting the dynamic transient response from the steady-state DC field h_{DC} (calculated as s
 197 $\rightarrow 0$)

$$h_-(t) = h_{DC} - h(t) \quad (13)$$

198 Finally, considering fluxgate magnetometer sensors that directly record magnetic flux density
 199 B rather than its time derivative dB/dt (thereby enhancing sensitivity to highly conductive
 200 subsurface targets), the $B_z(t)$ is calculated as (Hapsoro et al., 2021),

$$B_z(t) = \mu_0 h_-(t) \quad (14)$$

201 **2.2. Canonical Differential Evolution**

202 Differential Evolution (DE) is a robust, population-based, stochastic metaheuristic global
 203 optimization algorithm designed for continuous parameter spaces (Price et al., 2005; Storn &
 204 Price, 1997). Canonical DE begins with a N_p -population ($\mathbb{P}$) of candidate solutions represented
 205 as real-valued vectors $\vec{X}$, referred to as individuals. The initial population is generated randomly
 206 from a uniform probability distribution within the predefined $\Omega \subseteq \mathbb{R}^D$, D -dimensional, search
 207 space. Subsequently, DE iteratively evolves the population through mutation, crossover, and
 208 selection at each generation. The iteration is terminated when a specified stopping criterion is
 209 satisfied, for example, the maximum number of iterations or the target error threshold has been
 210 reached. The iterative procedure consists of four sequential phases, follow the procedure of
 211 Price et al. (2005), namely (1) population initialization, (2) mutation phase, (3) binomial
 212 crossover phase, and (4) greedy selection phase.

213 *2.2.1. Population Initialization*

214 During the initialization process, the lower bound $\vec{X}_{\min} = [x_{\min,1}, x_{\min,2}, \dots, x_{\min,D}]$ and
 215 upper bound $\vec{X}_{\max} = [x_{\max,1}, x_{\max,2}, \dots, x_{\max,D}]$ of the search space are defined. An initial
 216 population of N_p candidate solutions is generated by uniformly sampling each model parameter
 217 within its predefined lower and upper bounds. Then, the candidate solution for the j -th
 218 dimension, $j \in \{1, 2, \dots, D\}$, of the i -th individual, $i \in \{1, 2, \dots, Np\}$, is initialized as

$$x_{i,j} = x_{\min,j} + \text{URand}(0, 1) \times (x_{\max,j} - x_{\min,j}), \quad (15)$$

219 where $x_{\min,j}$ and $x_{\max,j}$ denote the lower and upper search bounds of the j -th model parameter,
 220 respectively, and $\text{URand}(0,1)$ is a uniformly distributed random number in the interval $[0,1]$.
 221 This initialization strategy ensures that the initial population is uniformly distributed

throughout the feasible search space, thereby this strategy provides promoting population diversity during the early stage of the optimization process.

2.2.2. Mutation Phase

After initialization, each individual $x_i^{(G)}$ in the in current generation population (G) is referred to as the target vector. During the mutation process, for each target vector, a scaled difference vector is added to a base vector to generate a new vector called the mutant vector $v_i^{(G)}$. The mutation operator constitutes the primary search mechanism in DE, controlling the balance between exploration and exploitation. Three classical mutation strategies commonly adopted in DE-based optimization as shown in Table 1 (Sun et al., 2021).

Table 1. Classical mutation strategies commonly adopted in DE-based optimization.

Name	Mutation Strategies
DE/Rand/1/bin	$\vec{V}_{i,G} = \vec{X}_{r_1,G} + F \cdot (\vec{X}_{r_2,G} - \vec{X}_{r_3,G}),$
DE/Best/1/bin	$\vec{V}_{i,G} = \vec{X}_{best,G} + F \cdot (\vec{X}_{r_1,G} - \vec{X}_{r_2,G})$
DE/Current-to-best/1/bin	$\vec{V}_{i,G} = \vec{X}_{i,G} + F \cdot (\vec{X}_{best,G} - \vec{X}_{i,G}) + F \cdot (\vec{X}_{r_1,G} - \vec{X}_{r_2,G})$

Here, r_1 , r_2 , and r_3 are mutually distinct random integer indices selected from the population $\{1, \dots, N_p\}$ and satisfy

$$r_1 \neq r_2 \neq r_3 \neq i \quad (16)$$

where i is the target vector index. The vector $\vec{X}_{best,G}$ denotes the individual with the lowest objective function value in generation G , while $F \in [0,2]$ is the mutation scaling factor controlling the amplification of the differential vector. Among the classical mutation strategies, DE/rand/1/bin provides strong exploration capability but generally exhibits relatively slow convergence. In contrast, DE/Best/1/bin and DE/Current-to-best/1/bin achieve faster convergence through enhanced exploitation; however, they are more susceptible to premature convergence due to the rapid loss of population diversity (Baig et al., 2023; Popič et al., 2025).

2.2.3. Binomial Crossover Phase

DE employs a binomial crossover operator to recombine the target vector with its corresponding mutant vector in order to enhance population diversity (Chauhan et al., 2025; Yang et al., 2024). This operation generates a trial vector $U_{i,G}$, by selecting each parameter independently from either the mutant or the target vector according to the crossover probability. The crossover rule is defined as

$$u_{i,j,G} = \begin{cases} v_{i,j,G}, & \text{if } \text{Urand}(0,1) \leq CR \text{ or } j = j_{\text{rand}}, \\ x_{i,j,G}, & \text{otherwise,} \end{cases} \quad (17)$$

where $Cr \in [0,1]$ denotes the crossover rate controlling the probability of inheriting parameters from the mutant vector, and $j_{\text{rand}} \in [1, D]$ is a randomly selected parameter index that guarantees at least one decision variable is inherited from the mutant vector. Consequently, the trial vector always differs from the target vector by at least one parameter, thereby preventing redundant offspring and promoting effective exploration of the search space.

2.2.4. Greedy Selection Phase

Following mutation and crossover, both the i -th target vector $x_i^{(G)}$ and the i -th corresponding trial vector $U_{i,G}$ are evaluated using the objective function $f(\cdot)$. A greedy one-to-one selection strategy is then applied to determine the survivor for the next generation (Ghosh et al., 2017; Stanovov et al., 2021). Specifically, the trial vector replaces the target vector only if it produces an equal or lower objective function value (Ghosh et al., 2017). The selection rule is expressed as Eq. 18,

$$\vec{X}_{i,G+1} = \begin{cases} \vec{U}_{i,G}, & \text{if } f(\vec{U}_{i,G}) \leq f(\vec{X}_{i,G}), \\ \vec{X}_{i,G}, & \text{otherwise,} \end{cases} \quad (18)$$

where $f(\cdot)$ is the objective function to be minimized, $f(u_i^{(G)})$ is the fitness of the trial vector, and $f(x_i^{(G)})$ is the fitness of the target vector. The greedy selection mechanism ensures that the objective function value of each surviving individual never deteriorates between successive generations, thereby providing a monotonic improvement in the overall population while preserving the population size.

2.3. Modified Differential Evolution Algorithm for TDEM Inversion

The performance of DE is strongly influenced by its control parameter settings, mutation strategy, and the characteristics of the optimization problem being addressed. Cheng et al. (2023) reported that the recommendations for manually configuring DE parameters are often inconsistent and even contradictory, while the theoretical foundation for selecting optimal parameter values remains limited (Zhu et al., 2020). Furthermore, the population plays different optimization roles throughout the evolutionary process. During the early generations, the population should emphasize aggressive exploration to extensively investigate the search space (Epitropakis et al., 2008; Zuo & Gao, 2025). In contrast, during the later generations, the search should gradually shift toward exploitation by focusing on a narrower region surrounding

promising solutions (Epitropakis et al., 2008; Zuo & Gao, 2025). Consequently, achieving satisfactory optimization performance generally requires problem-specific parameter tuning. However, determining suitable parameter values through manual trial-and-error is computationally expensive and time-consuming (Ekinici et al., 2023; Pamplona et al., 2025; Zhang & Sanderson, 2009).

Instead of manually selecting the control parameters, numerous studies have proposed adaptive variants of DE in which the algorithm automatically adjusts its parameters during the evolutionary process. Zhang & Sanderson (2009) introduced the JADE algorithm, which employs an optional external archive together with the DE/current-to-pbest/1/bin mutation strategy. The mutation strategy is defined as,

$$\vec{V}_{i,G} = \vec{X}_{i,G} + F_i \cdot (\vec{X}_{pbest,G} - \vec{X}_{i,G}) + F_i \cdot (\vec{X}_{r_1,G} - \tilde{\vec{X}}_{r_2,G}) \quad (19)$$

where $\vec{X}_{pbest,G}$ is randomly selected from the top $(100p\%, p \in [0,1])$ best individuals in the current population $\mathbb{P}$, $\vec{X}_{i,G}$ and $\vec{X}_{r_1,G}$ are randomly selected from the current population $\mathbb{P}$, whereas $\tilde{\vec{X}}_{r_2,G}$ is randomly selected from the union of the current population and the external archive $(\mathbb{P} \cup \mathbb{A})$, with $i \neq r_1 \neq r_2$. The DE/current-to-pbest/1/bin mutation strategy effectively balances the exploration and exploitation capabilities of DE (Meng & Pan, 2019; Zhang & Sanderson, 2009). The external archive is initially empty $(\mathbb{A} = \emptyset)$ and subsequently stores parent vectors that are discarded during the selection process in Eq. 18. Once the archive $\mathbb{A}$ reaches its maximum capacity, one archived solution is randomly removed to maintain the predefined archive size, which is typically determined by the archive size ratio $|\mathbb{A}| = |\mathbb{P}|$.

In canonical DE, the scaling factor (F) and crossover rate (Cr) are also known to be highly problem-dependent (Zhang & Sanderson, 2009). Therefore, JADE further introduces adaptive parameter control for both F and Cr (Zhang & Sanderson, 2009), expressed as

$$\left. \begin{array}{l} F = CRand(\mu_F, 0,1) \\ Cr = NRand(\mu_{Cr}, 0,1) \end{array} \right\} \text{where} \left\{ \begin{array}{l} \mu_F = (1 - c) \cdot \mu_F + c \cdot \text{mean}_L(S_F) \\ \text{mean}_L(S_F) = \frac{\sum_{F \in S_F} F^2}{\sum_{F \in S_F} F} \\ \mu_{Cr} = (1 - c) \cdot \mu_{Cr} + c \cdot \text{mean}_A(S_{Cr}) \\ \text{mean}_A(S_{Cr}) = \frac{\sum_{Cr \in S_{Cr}} Cr}{|S_{Cr}|} \end{array} \right. \quad (20)$$

where $CRand(\mu_F, 0,1)$ is a random number generated from the Cauchy distribution with location parameter μ_F and scale parameter 0.1. Meanwhile, $NRand(\mu_{Cr}, 0,1)$ is generated from a normal distribution with mean μ_{Cr} and standard deviation 0.1. The values of $F =$

299 $CRand(\mu_F, 0, 1)$ and $Cr = NRand(\mu_{Cr}, 0, 1)$ are constrained within the interval $[0, 1]$. The
300 functions $mean_L(S_F)$ and $mean_A(S_{Cr})$ denote the Lehmer mean of the set S_F and the arithmetic
301 mean of the set S_{Cr} , respectively. The initial values of $\mu_F = \mu_{Cr} = 0,5$ and c are constants with
302 a default value of 0.1. For each generation G , the successful values of F_i and CR_i from U_i that
303 survive the selection process in Eq. 18 are stored in the sets S_F and S_{Cr} , where $|S_F|$ denotes the
304 number of elements in S_F . The two additional parameters introduced in JADE, namely c and p ,
305 are reported to be relatively insensitive to the optimization problem being solved (Zhang &
306 Sanderson, 2009). Nevertheless, in JADE, unsuccessful values of F and Cr may still influence
307 the adaptation process through S_F and S_{Cr} , potentially guiding the population toward
308 undesirable regions of the search space (Tanabe & Fukunaga, 2013).

309 Subsequently, Tanabe & Fukunaga (2013) improved JADE by introducing the Success-
310 History based Adaptive Differential Evolution (SHADE) algorithm, which records the
311 historical values of S_F and S_{Cr} from previous generations. In SHADE, the historical means of
312 S_F and S_{Cr} are stored in the memory arrays M_F and M_{Cr} respectively, as

$$M_{F,h,G+1} = \begin{cases} mean_{WL}(S_F), & \text{if } S_F \neq \emptyset, \\ M_{F,h,G}, & \text{otherwise} \end{cases} \quad (21)$$

$$M_{Cr,h,G+1} = \begin{cases} mean_{WA}(S_{Cr}), & \text{if } S_{Cr} \neq \emptyset, \\ M_{Cr,h,G}, & \text{otherwise} \end{cases} \quad (22)$$

313 The weighted means $mean_{WL}$ and $mean_{WA}$ are computed using Eq. 23,

$$mean_{WL}(S_F) = \frac{\sum_{k=1}^{|S_F|} w_k \cdot S_{F,k}^2}{\sum_{k=1}^{|S_F|} w_k \cdot S_{F,k}}, \quad (23)$$

314 and Eq. 24,

$$mean_{WA}(S_{Cr}) = \sum_{k=1}^{|S_F|} w_k \cdot S_{Cr,k} \quad (24)$$

315 where $w_k = \Delta f_k / \sum_{k=1}^{|S_{Cr}|} \Delta f_k$ and $\Delta f_k = |f(\vec{U}_{k,G}) - f(\vec{X}|_{k,G})|$ is the fitness improvement
316 obtained by the k -th successful trial vector. The memory M arrays consist of H -entries, with
317 each entry initially assigned a value of 0.5. The index $h \in [1, H]$ indicates the memory position
318 to be updated and is initially set to $h = 1$, then incremented by one at each generation. When h
319 $> H$, the index h is reset to 1. For each generation, the values of F_i and Cr_i are generated by
320 randomly selecting an index r_i from the H -memory entries, and then using $F_i =$
321 $CRand(M_{F,r_i}, 0, 1)$ and $Cr_i = NRand(M_{Cr,r_i}, 0, 1)$, with the resulting values constrained to the

interval $[0, 1]$. The use of historical memories of M_F and M_{Cr} prevents SHADE from being directly affected by S_F and S_{Cr} poor parameter values generated by the probabilistic nature of DE (Tanabe & Fukunaga, 2013).

Furthermore, Tanabe & Fukunaga (2014) proposed an improvement to SHADE. L-SHADE enhances SHADE through the introduction of Linear Population Size Reduction (LPSR) (Tanabe & Fukunaga, 2014). In LPSR, if the population size Np in the first generation is Np_{init} and the population size Np in the final generation is Np_{min} , then

$$N_{G+1} = \text{round} \left[\left(\frac{Np_{min} - Np_{init}}{\text{MaxNFE}} \right) \cdot NFE + Np_{init} \right] \quad (25)$$

Where NFE and MaxNFE denote the current and maximum numbers of objective-function evaluations, respectively. To satisfy Eq. 19, the minimum population size Np is set to $Np_{min} = 4$. With this improvement, L-SHADE won the IEEE CEC 2014 competition on bound-constrained real-parameter optimization, and its subsequent extensions won several CEC competitions in the following years (Ekinici et al., 2023; Ghosh et al., 2022).

In L-SHADE, Eq. 24 is replaced by Eq. 26,

$$\text{mean}_{WL}(S_{Cr}) = \frac{\sum_{k=1}^{|S_{Cr}|} w_k \cdot S_{Cr,k}^2}{\sum_{k=1}^{|S_{Cr}|} w_k \cdot S_{Cr,k}} \quad (26)$$

When the terminal value is reached, M_{Cr} becomes equal to $\perp$, where $\perp$ denotes the terminal value or the maximum value of $S_{Cr} = 0$. Thereafter, $M_{Cr} = \perp$ remains constant until the final generation. If $M_{Cr} = \perp$, then $S_{Cr} = 0$. Finally, the archive size $|\mathbb{A}|$ is also reduced according to $|\mathbb{A}| = r^{\text{arc}} \cdot Np_G$, where r^{arc} is a constant (Tanabe & Fukunaga, 2014).

In this study, the improved version of L-SHADE, namely iL-SHADE (Brest et al., 2016), is employed. iL-SHADE introduces several minor modifications.

- (1) The initial value of M_{Cr} ($h = 1, \dots, H - 1$) is set to 0.8, while one entry in H , corresponding to a pair of M_F and M_{Cr} , is fixed at 0.9.
- (2) The update rules for M_F and M_{Cr} in Eqs. 21 and 26 are replaced by Eqs. 27 and 28,

$$M_{F,h,G+1} = \begin{cases} [\text{mean}_{WL}(S_F) + M_{F,h,G}]/2, & \text{if } S_F \neq \emptyset, \\ M_{F,h,G}, & \text{otherwise} \end{cases} \quad (27)$$

$$M_{Cr,h,G+1} = \begin{cases} [\text{mean}_{WL}(S_{Cr}) + M_{Cr,h,G}]/2, & \text{if } S_{Cr} \neq \emptyset, \\ M_{Cr,h,G}, & \text{otherwise} \end{cases} \quad (28)$$

346 (3) The values of F and Cr are adjusted according to each generation,

$$F_{i,G} = \begin{cases} \min(F_{i,G}, 0.7), & \text{if } G < 0.25 \cdot G_{\max} \\ \min(F_{i,G}, 0.8), & \text{if } G < 0.50 \cdot G_{\max} \\ \min(F_{i,G}, 0.9), & \text{if } G < 0.75 \cdot G_{\max} \end{cases} \quad (29)$$

$$Cr_{i,G} = \begin{cases} \max(Cr_{i,G}, 0.50), & \text{if } G < 0.25 \cdot G_{\max} \\ \max(Cr_{i,G}, 0.25), & \text{if } G < 0.50 \cdot G_{\max} \end{cases} \quad (30)$$

347 (4) The value of p is updated at every generation according to

$$p = \frac{p_{\max} - p_{\min}}{\text{MaxNFE}} \cdot \text{NFE} + p_{\min} \quad (31)$$

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1   $G \leftarrow 1$ , Archive  $\mathbb{A} \leftarrow \emptyset$ ,  $Np \leftarrow Np_{init}$ 
2   $\Omega \leftarrow \{\vec{X} \in \mathbb{R} \mid x_{\min,j} \leq x_j \leq x_{\max,j}, \forall j = 1, \dots, D\}$ 
3  Initialize population  $\mathbb{P}_{G=1} \leftarrow \vec{x}_{i,G}, \dots, \vec{x}_{Np_{init},G}$  randomly within  $\Omega$ . // Eq. 15
4   $M_F \leftarrow \{0.5, \dots, 0.5\}$ ,  $M_{Cr} \leftarrow \{0.8, \dots, 0.8\}$ 
5   $h \leftarrow 1$  // index counter
6  while  $\text{NFE} < \text{MaxNFE}$  do
7       $S_F \leftarrow \emptyset$ ,  $S_{Cr} \leftarrow \emptyset$ 
8      for  $i \leftarrow 1$  to  $Np$  do
9           $r_i \leftarrow$  select from  $[1, H]$  randomly
10         if  $r_i == H$  then  $M_{F,r_i} \leftarrow 0.9$ ,  $M_{Cr,r_i} \leftarrow 0.9$  end if
11          $F_{i,G} \leftarrow \text{CRand}(M_{F,r_i}, 0.1)$ 
12         if  $M_{Cr,r_i} < 0$  then  $Cr_{i,G} \leftarrow 0$  else  $Cr_{i,G} \leftarrow \text{NRand}(M_{Cr,r_i}, 0.1)$  end if
13         if  $G < 0.25 \cdot G_{\max}$  then  $F_{i,G} \leftarrow \min(F_{i,G}, 0.7)$ ,  $Cr_{i,G} \leftarrow \max(Cr_{i,G}, 0.50)$ 
14         else if  $G < 0.50 \cdot G_{\max}$  then  $F_{i,G} \leftarrow \min(F_{i,G}, 0.8)$ ,  $Cr_{i,G} \leftarrow \max(Cr_{i,G}, 0.25)$ 
15         else if  $G < 0.75 \cdot G_{\max}$  then  $F_{i,G} \leftarrow \min(F_{i,G}, 0.9)$  end if
16          $\vec{V}_{i,G} \leftarrow \text{DE/current-to-pbest}/1/\text{bin}$  // Eq. 19
17         Apply Bound Constraint to  $\vec{V}_{i,G}$ 
18          $u_{i,j,G} \leftarrow \text{Binomial Crossover}$  // Eq. 17
19
20     end for
21     for  $i \leftarrow 1$  to  $Np$  do
22         if  $f(\vec{U}_{i,G}) \leq f(\vec{X}_{i,G})$  then  $\vec{X}_{i,G+1} \leftarrow \vec{U}_{i,G}$  else  $\vec{X}_{i,G+1} \leftarrow \vec{X}_{i,G}$  end if // Eq. 18
23         if  $f(\vec{U}_{i,G}) < f(\vec{X}_{i,G})$  then
24             insert  $\vec{X}_{i,G}$  into  $\mathbb{A}$ , insert  $Cr_{i,G}$  into  $S_{Cr}$ , insert  $F_{i,G}$  into  $S_F$ 
25         end if
26         if  $|\mathbb{A}| > r^{\text{arc}} \cdot Np_G$  then Shrink  $\mathbb{A}$  end if
27         if  $S_{Cr} \neq \emptyset$  AND  $S_F \neq \emptyset$  then
28             if  $M_{Cr,h,G} == \perp$  or  $\max(S_{Cr}) == 0$  then  $M_{Cr,h,G+1} \leftarrow \perp$ 
29             else  $M_{Cr,h,G+1} \leftarrow (\text{mean}_{\text{WL}}(S_{Cr}) + M_{Cr,h,G})/2$  end if
30              $M_{F,h,G+1} \leftarrow (\text{mean}_{\text{WL}}(S_F) + M_{F,h,G})/2$ 
31              $h \leftarrow h + 1$ 
32             if  $h > H$  then  $h \leftarrow 1$  end if
33         else
34              $M_{Cr,h,G+1} \leftarrow M_{Cr,h,G}$ ,  $M_{F,h,G+1} \leftarrow M_{F,h,G}$ 
35         end if
36     end for
37      $\text{NFE} \leftarrow \text{NFE} + Np_G$ 
38      $Np_{G+1} \leftarrow$  Population size reduction using LPSR // Eq. 25
39     Update  $p$  // Eq. 31
40      $G \leftarrow G + 1$ 
41 end while

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Fig. 2. Pseudocode of the modified differential evolution algorithm.

The complete implementation procedure of the iL-SHADE algorithm adopted in this study is summarized in Fig. 2. The pseudocode integrates the initialization, mutation, crossover, selection, parameter adaptation, archive management, and linear population size reduction mechanisms described in the preceding sections into a unified optimization workflow.

2.4. Objective Function Formulation of The TDEM Inversion

In order to evaluate the performance, convergence behavior, and optimization stability of the proposed DE algorithm for 1D TDEM data inversion systematically, a comprehensive experimental framework was established using four synthetic 5-layer earth model benchmark profiles as shown in Table 2.

Table 2. Four synthetic 5-layer earth model benchmark profiles as experimental framework.

Model	Benchmark Profiles
Ascending 5-layer	Represents a subsurface environment where electrical resistivity monotonically increases with depth, typical of sedimentary basins overlying resistive crystalline basement
Bell 5-layer	Characterized by a high-resistivity intermediate layer bounded by conductive upper and lower strata, modeling resistive intrusive dykes or dry volcanic formations
Bowl 5-layer	Characterized by a low-resistivity intermediate zone bounded by high-resistivity upper and lower layers, representing hydrothermally altered clay caps in volcanic geothermal systems
Descending 5-layer	Represents a subsurface structure where electrical resistivity monotonically decreases with depth, characteristic of deepening saline aquifers or conductive sedimentary sequences

2.4.1. Model Parameterization and Search Boundaries

For a 1D 5-layer earth model, the subsurface is parameterized by a real-valued model vector $\mathbf{m}$ in $\mathbb{R}^9$,

$$\mathbf{m} = [\sigma_1 \ \sigma_2 \ \sigma_3 \ \sigma_4 \ \sigma_5 \ h_1 \ h_2 \ h_3 \ h_4]^T \in \mathbb{R}^9 \quad (32)$$

where σ_i ($i = 1, \dots, 5$) denotes the electrical conductivity of the i -th layer, while its corresponding electrical resistivity is defined as $\rho_i = 1 / \sigma_i$ and h_j ($j = 1, \dots, 4$) represents the thickness of the j -th layer. Consequently, the inversion model consists of five conductivity

parameters and four thickness parameters, yielding a total of nine unknown model parameters.

The feasible model space is constrained by lower and upper bound vectors,

$$\mathbf{m}_{\min} \leq \mathbf{m} \leq \mathbf{m}_{\max} \quad (33)$$

where

$$\mathbf{m}_{\min} = [0.001 \quad 0.001 \quad 0.001 \quad 0.001 \quad 0.001 \quad 100 \quad 100 \quad 100 \quad 100]^T \quad (34)$$

and

$$\mathbf{m}_{\max} = [1.0 \quad 1.0 \quad 1.0 \quad 1.0 \quad 1.0 \quad 5000 \quad 5000 \quad 5000 \quad 5000]^T \quad (35)$$

Accordingly, the conductivity parameters satisfy

$$0.001 \leq \sigma_i \leq 1.0 \text{ S/m}, \quad i = 1, \dots, 5 \quad (36)$$

which is equivalent to the resistivity range

$$1 \leq \rho_i \leq 1000 \Omega \cdot m \quad (37)$$

while the layer thicknesses satisfy

$$100 \leq h_j \leq 5000 \text{ m}, \quad j = 1, \dots, 4 \quad (38)$$

These constraints define the admissible parameter space explored by the optimization algorithm during the inversion process, ensuring that all candidate models remain physically meaningful and consistent with realistic geological conditions.

2.4.2. Objective Function Formulation

In this study, the observed data vector $\vec{d}_{\text{obs}} \in \mathbb{R}^1$ and the forward function $\vec{G}: \mathbb{R}^n \rightarrow \mathbb{R}^1$ are given. The observed data are used to estimate the model vector $\vec{m} \in \mathbb{R}^n$ from the inverse problem $\vec{G}(\vec{m}) = \vec{d}_{\text{obs}}$. The inversion process aims to determine the optimal subsurface model vector by minimizing the objective function value (misfit) between the observed transient electromagnetic response and the corresponding forward response predicted by the TDEM model over all observation time channels. This inverse problem can be solved by minimizing the objective function, following Hapsoro et al. (2021) and Stoffa & Sen (1991),

$$f(\vec{d}_{\text{obs}}, \delta) = \frac{1}{N} \sum_{m=1}^n \left[\frac{(\vec{d}_{\text{cal}} - \vec{d}_{\text{obs}})}{\delta} \right]^2. \quad (39)$$

where N is the number of observed data, $\vec{d}_{\text{cal}}$ is the calculated response obtained from the iL-SHADE inversion, and δ is the standard deviation derived from the measurement data. An l -layer earth model implies that the minimization is performed in $D = l \times 2 - 1$ dimensional

search space $\Omega \subseteq \mathbb{R}^D$. In the context of 1D TDEM inversion, this search space consists of l resistivity parameters and $(l - 1)$ layer-thickness parameters, or

$$\vec{m} = [\rho_1, \rho_2, \dots, \rho_l, h_1, h_2, \dots, h_{l-1}]. \quad (40)$$

2.5. Real Data Application

To validate the practical best utility algorithm under realistic field conditions, the algorithm was applied to actual field observations recorded at station UZ01 on the eastern flank of Unzen Volcano, Shimabara Peninsula, Kyushu Island, Japan (Srigutomo et al., 2021). The field survey employed a Grounded Electric Source Time-Domain Electromagnetic (Grounded-Source TDEM) configuration to image the subsurface electrical structure at this site, as shown in Fig. 3.

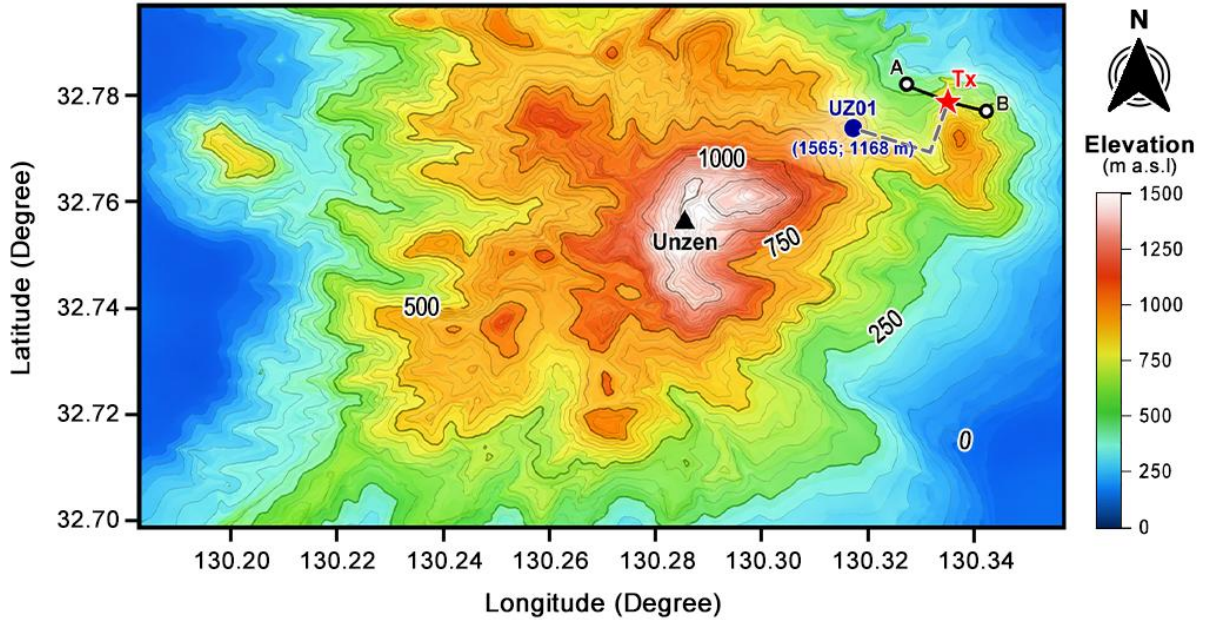


Fig. 3. Coordinates of the UZ01 TDEM receiver stations (blue circles) relative to the transmitter Tx (red star) in the Unzen volcanic area, Shimabara Peninsula, Kyushu, Japan. Coordinates are given in meters in the local cartesian centered at Tx. Points A and B denote locations used to define the transmitter orientation. Background colors and contours indicate topography (elevation in meters).

The survey setup utilized a 1.4 km long grounded electric wire transmitter (Tx) anchored at both ends to inject high-amplitude square-wave current pulses into the earth, while receiver station UZ01 was positioned at an offset distance of approximately 2.0 km from the center of the transmitter wire. The recorded dataset comprises the vertical component of the transient induced magnetic flux density decay, $B_z(t)$, recorded across 158 logarithmic time channels

spanning from early transient diffusion times (10^{-5} s) to late-time decay tails (10^{-1} s). To establish the optimal subsurface model order, single candidate earth model parameterizations were evaluated, namely 5-layer model ($D = 9$).

2.6. Performance Metrics

The performance of each optimization algorithm (iL-SHADE, SHADE, Standard DE) was evaluated over $N_r = 30$ independent stochastic runs per synthetic benchmark profile. Four key performance metrics were defined as shown in Table 3.

Table 3. Key performance metrics.

Key Performances	Definition
Minimum misfit	Measures the absolute best solution quality located across all stochastic runs
Median misfit	Represents the central tendency of final misfit values, providing a measure robust against outlier runs
Mean misfit	Calculates the average solution quality across all independent runs
Standard deviation	Measures the dispersion of final misfits around the mean, reflecting algorithmic stability and stochastic repeatability

2.7. Evolutionary Evaluation Framework

The evolutionary evaluation framework incorporates rigorous statistical hypothesis testing, fixed function evaluation budgeting, and noisy data robustness assessments. First, because optimization of misfits across stochastic runs rarely follow a Gaussian normal distribution, pairwise Wilcoxon rank-sum statistical hypothesis testing (a non-parametric test) was performed at a significance level ($\alpha = 0.01$), where an asymptotic p -value < 0.01 rejects the null hypothesis (H_0). This hypothesis confirming that performance enhancements between algorithms are statistically significant. To ensure fair algorithmic comparisons, each stochastic run was allocated a strict maximum computational budget of $N_{\text{eval-max}} = 25,000$ forward function evaluations. Finally, to assess practical resilience against observational field noise, synthetic TDEM transient decay responses for the choosen model were contaminated with four levels of uncorrelated zero-mean Gaussian noise (5%, 10%, 15%, and 20%), establishing a rigorous stress-testing environment for metaheuristic TDEM inversion.

3. SYNTHETIC INVERSION EXPERIMENT

A systematic evaluation was conducted using synthetic benchmark models to rigorously evaluate the performance of the proposed iL-SHADE framework for 1D TDEM data inversion. The performance of iL-SHADE was benchmarked against canonical DE (Standard DE) and SHADE. This section presents the experimental results across statistical robustness, optimization efficiency, magnetic field response fitting, subsurface parameter recovery, pre-inversion sensitivity and parameter tuning studies, and robustness under noisy field conditions.

3.1. Pre-Inversion Studies with The Modal and Sensitivity Analysis

To investigate the search-space characteristics of the TDEM inversion problem, a modality analysis was performed by evaluating the objective function over all pairwise combinations of model parameters. For each parameter pair, the two selected parameters were systematically varied across their entire search ranges, while the remaining seven parameters were fixed at their true values. The analysis was conducted using the Bowl 5-layer model, as described in Table 2. The resulting objective-function landscapes are presented in Fig. 4, where the red cross denotes the location of the true model.

Overall, the parameter pairs produce relatively smooth objective-function landscapes characterized by continuous transitions toward the global optimum. Only a limited number of local minima are observed, indicating that the inversion problem is primarily dominated by broad solution valleys rather than highly multimodal regions. This predominantly unimodal behavior suggests that the problem should, in principle, be efficiently solved by DE and its variants, consistent with the favorable performance of DE reported for numerous benchmark optimization problems. More specifically, the sensitivity analysis reveals that conductivity parameters exert a substantially greater influence on the objective function than layer thicknesses. This is evident from the steep contour gradients associated with parameter combinations involving σ_1 , σ_2 , σ_3 , σ_4 , and σ_5 . In contrast, several parameter combinations exhibit relatively broad minimum regions, indicating lower parameter sensitivity. Such characteristics further justify the use of DE, as its one-to-one selection mechanism preserves trial vectors with objective-function values equal to those of their parent solutions, thereby maintaining diversity and enabling effective exploration of flat regions in the search space (Ghosh et al., 2017).

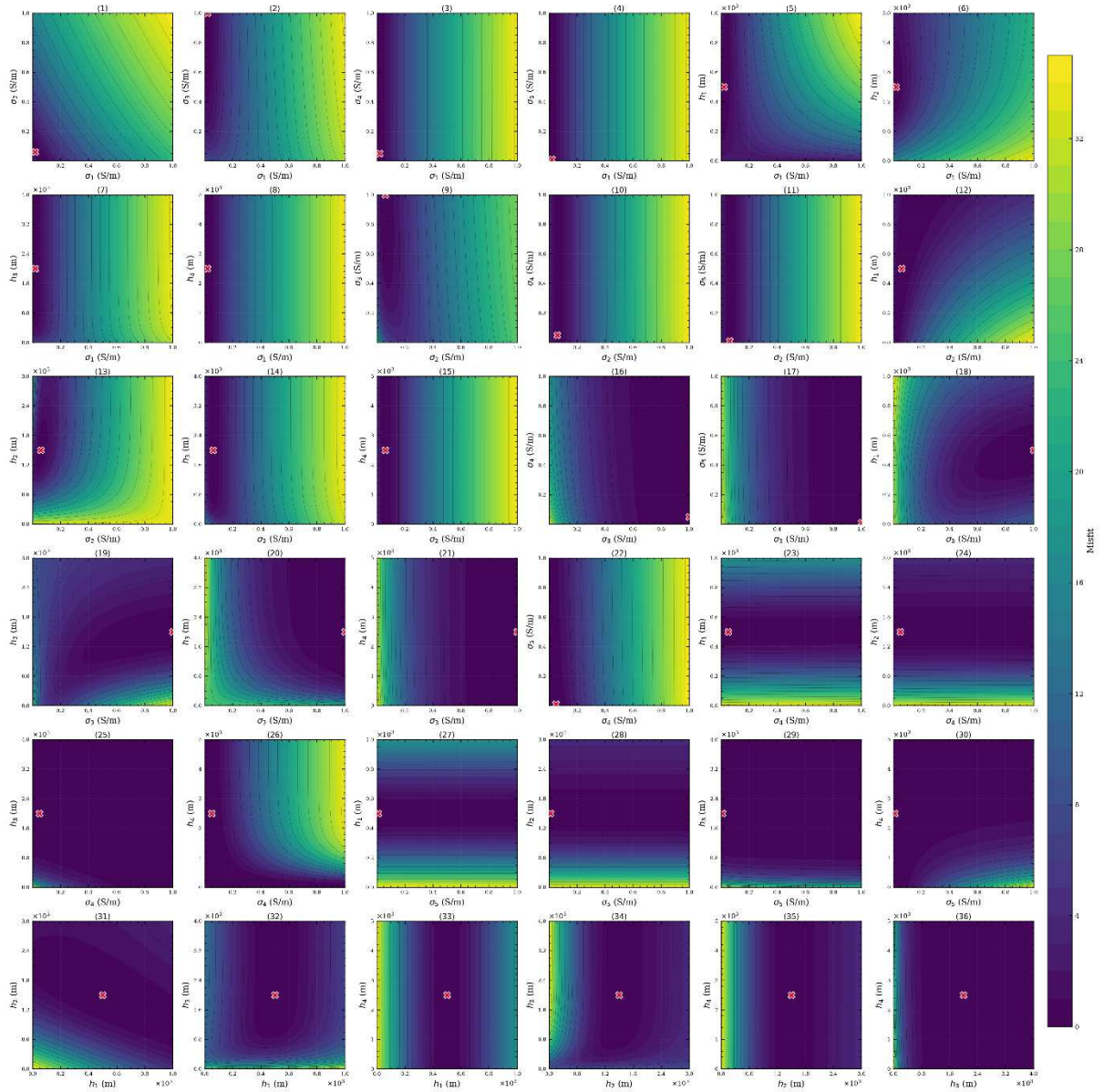


Fig. 4. The result of objective-function landscapes, where the red cross denotes the location of the true model.

Beyond parameter sensitivity, Fig. 4 also reveals significant parameter correlations, manifested as elongated valley-shaped contours. These elongated valleys indicate that variations in one parameter can be compensated by corresponding changes in another parameter while producing nearly identical objective-function values. The strongest correlations are observed between conductivity and layer-thickness parameters, highlighting the inherent trade-off between electrical resistivity and geological layer geometry in TDEM inversion. Such parameter compensation contributes to model non-uniqueness and increases the difficulty of accurately recovering the true subsurface structure, even when the objective-function landscape appears relatively smooth.

3.2. Comparison of DE, SHADE, iL-SHADE on TDEM Synthetic Model

The performance of DE, SHADE, and iL-SHADE was systematically evaluated across four synthetic 5-layer resistivity models. Following (Sungkono, 2020), Ascending (monotonically increasing resistivity with depth), Bell (high-resistivity intermediate layer), and Descending (monotonically decreasing resistivity with depth), and Bowl (low-resistivity intermediate layer) models was used (Table 4). Each algorithm was executed for 30 independent runs per model shape using a maximum budget of 25,000 objective function evaluations.

Table 4. Nine model parameters (five conductivity parameters and four layer-thickness parameters) of the synthetic TDEM layered-earth model.

Model	σ_1 (S/m)	σ_2 (S/m)	σ_3 (S/m)	σ_4 (S/m)	σ_5 (S/m)	h_1 (m)	h_2 (m)	h_3 (m)	h_4 (m)
Ascending	0.01	0.03	0.10	0.30	1.00	500	1500	2000	2500
Bell	0.90	0.05	0.01	0.05	0.50	500	1500	2000	2500
Bowl	0.02	0.06	1.00	0.05	0.01	500	1500	2000	2500
Descending	1.00	0.30	0.10	0.03	0.01	500	1500	2000	2500

3.2.1. Analysis of Statistical Metrics

As presented in Table 5, iL-SHADE demonstrates best performance across all synthetic model configurations. For Ascending 5-layer, Bell 5-layer, and Descending 5-layer, iL-SHADE achieved median misfits of 3.007×10^{-9} , 2.499×10^{-8} , and 2.351×10^{-7} respectively, outperforming Standard DE and classical SHADE by 2 to 4 orders of magnitude. The iL-SHADE produces the lowest median objective function value, indicating that it has a more effective balance between exploration and exploitation in finding solutions that are closer to the true model.

Although Standard DE achieves a relatively low minimum objective function value, the standard deviation of misfits for iL-SHADE remained exceptionally low (e.g., 9.752×10^{-9} for Bell 5-layer) rather than Standard DE, indicating high repeatability and stability across independent random initializations. In the highly non-unique Bowl 5-layer case, while all algorithms experienced increased misfit dispersion due to model equivalence, iL-SHADE achieved the lowest minimum misfit (2.555×10^{-9}) and lowest median misfit (5.979×10^{-9}).

Table 5. The statistical inversion misfits across all synthetic test cases.

Algorithm	Model Profile	Min.	Median	Mean	Std.	Max.
iL-SHADE	Ascending 5-layer	2.592×10^{-9}	3.007×10^{-9}	9.257×10^{-8}	4.849×10^{-7}	2.660×10^{-6}
	Bell 5-layer	1.202×10^{-8}	2.499×10^{-8}	2.584×10^{-8}	9.752×10^{-9}	6.097×10^{-8}
	Bowl 5-layer	2.555×10^{-9}	5.979×10^{-9}	2.483×10^{-2}	5.051×10^{-2}	1.241×10^{-1}
	Descending 5-layer	5.606×10^{-9}	2.351×10^{-7}	2.813×10^{-6}	4.964×10^{-6}	2.133×10^{-5}
SHADE	Ascending 5-layer	1.020×10^{-5}	2.239×10^{-4}	3.065×10^{-4}	2.442×10^{-4}	9.333×10^{-4}
	Bell 5-layer	2.485×10^{-6}	1.487×10^{-5}	5.328×10^{-5}	1.567×10^{-4}	8.681×10^{-4}
	Bowl 5-layer	9.591×10^{-5}	1.738×10^{-3}	1.658×10^{-2}	3.585×10^{-2}	1.242×10^{-1}
	Descending 5-layer	8.082×10^{-5}	4.104×10^{-4}	4.399×10^{-4}	1.763×10^{-4}	7.839×10^{-4}
Standard DE	Ascending 5-layer	8.625×10^{-7}	4.570×10^{-5}	6.304×10^{-4}	1.227×10^{-3}	6.351×10^{-3}
	Bell 5-layer	9.615×10^{-8}	4.156×10^{-7}	2.407×10^{-6}	4.993×10^{-6}	1.790×10^{-5}
	Bowl 5-layer	8.816×10^{-6}	5.549×10^{-4}	2.299×10^{-2}	4.422×10^{-2}	1.242×10^{-1}
	Descending 5-layer	1.296×10^{-5}	9.820×10^{-5}	1.368×10^{-4}	1.138×10^{-4}	3.391×10^{-4}

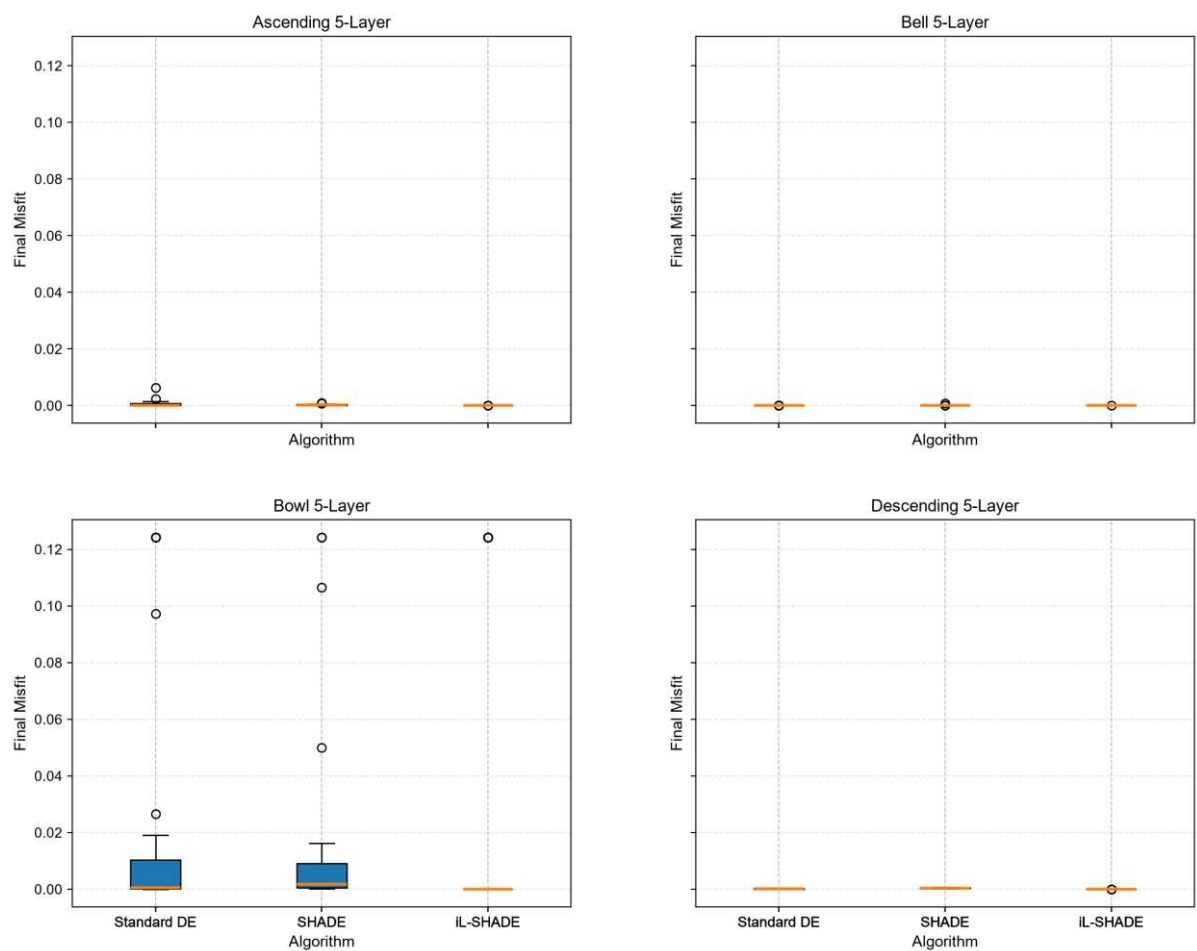


Fig. 5. Comparison of the misfit values obtained by the different algorithms for each model.

The iL-SHADE algorithm consistently achieved the lowest misfit value.

The Bowl 5-layer model appears to be more challenging for all three algorithms than the other three models, as illustrated by the boxplots in Fig. 5. In this case, iL-SHADE achieves extremely low minimum and median objective function values. However, its mean and standard deviation increase substantially due to several runs that fail to converge. A similar pattern is also observed for SHADE and Standard DE. Nevertheless, the median objective function value obtained by iL-SHADE remains approximately five to six orders of magnitude lower than those of both SHADE and Standard DE, indicating that iL-SHADE is constantly performing to identify substantially better solutions in the majority of the optimization runs.

3.2.2. Non-Parametric Statistical Significance (Wilcoxon Rank-Sum Test)

Pairwise Wilcoxon rank-sum test ($p = 0.01$) was performed across all 30 runs per model to verify whether the observed performance enhancements were statistically significant as presented in Table 6. For Bell 5-layer, Ascending 5-layer, and Descending 5-layer, the comparisons between iL-SHADE vs Standard DE and iL-SHADE vs SHADE yielded asymptotic p -values of $p = 3.020 \times 10^{-11}$ ($p \ll 0.01$), rejecting the null hypothesis with extremely high confidence. For Bowl 5-layer, iL-SHADE vs Standard DE yielded $p = 1.430 \times 10^{-5}$ and iL-SHADE vs SHADE yielded $p = 3.157 \times 10^{-5}$, confirming that iL-SHADE provides statistically superior global search capability even under severe non-uniqueness. Overall, the Wilcoxon signed-rank test indicates that iL-SHADE achieves statistically significantly better performance than both Standard DE and SHADE across all synthetic models.

Table 6. Pairwise Wilcoxon rank-sum test across all 30 runs per model.

Model	Algorithm A	Algorithm B	Median A	Median B	Winner	p -value	Effect
Ascending 5-Layer	Standard DE	SHADE	4.570×10^{-5}	2.239×10^{-4}	Standard DE	2.643×10^{-1}	-0.169
	Standard DE	iL-SHADE	4.570×10^{-5}	3.007×10^{-9}	iL-SHADE	4.077×10^{-11}	0.993
	SHADE	iL-SHADE	2.239×10^{-4}	3.007×10^{-9}	iL-SHADE	3.020×10^{-11}	1.000
Bell 5-Layer	Standard DE	SHADE	4.156×10^{-7}	1.487×10^{-9}	Standard DE	8.485×10^{-9}	-0.867
	Standard DE	iL-SHADE	4.156×10^{-7}	2.499×10^{-8}	iL-SHADE	3.020×10^{-11}	1.000
	SHADE	iL-SHADE	1.487×10^{-5}	2.499×10^{-8}	iL-SHADE	3.020×10^{-11}	1.000
Bowl 5-Layer	Standard DE	SHADE	5.549×10^{-4}	1.738×10^{-3}	Standard DE	2.062×10^{-1}	-0.191
	Standard DE	iL-SHADE	5.549×10^{-4}	5.979×10^{-9}	iL-SHADE	1.430×10^{-5}	0.653
	SHADE	iL-SHADE	1.738×10^{-3}	5.979×10^{-9}	iL-SHADE	3.157×10^{-5}	0.627
Descending 5-Layer	Standard DE	SHADE	9.820×10^{-5}	4.104×10^{-4}	Standard DE	1.102×10^{-8}	-0.860
	Standard DE	iL-SHADE	9.820×10^{-5}	2.351×10^{-7}	iL-SHADE	5.494×10^{-11}	0.987
	SHADE	iL-SHADE	4.104×10^{-4}	2.351×10^{-7}	iL-SHADE	3.020×10^{-11}	1.000

3.2.3. Optimization and Convergence Efficiency

All algorithms exhibit a rapid reduction in the objective function value during the early stage of the optimization, indicating that they are capable of identifying promising regions of the search space within the first few thousand function evaluations, as presented in Fig. 6. However, after this initial exploration phase, their convergence behaviors begin to diverge. SHADE tends to stagnate at an earlier stage, resulting in a slower reduction of the objective function value throughout the remainder of the optimization process. Standard DE continues to reduce the objective function gradually, although its convergence rate remains lower than that of iL-SHADE. In contrast, iL-SHADE maintains a steady decrease in the objective function value even after both Standard DE and SHADE have shown a tendency to converge toward relatively stable solutions. In addition to sustaining a higher convergence rate, iL-SHADE also demonstrates greater consistency across repeated optimization runs. This is evidenced by the relatively tight grouping of its convergence curves, which terminate within a similar range of objective function values. By comparison, Standard DE, and particularly SHADE, exhibit a considerably wider dispersion of convergence trajectories.

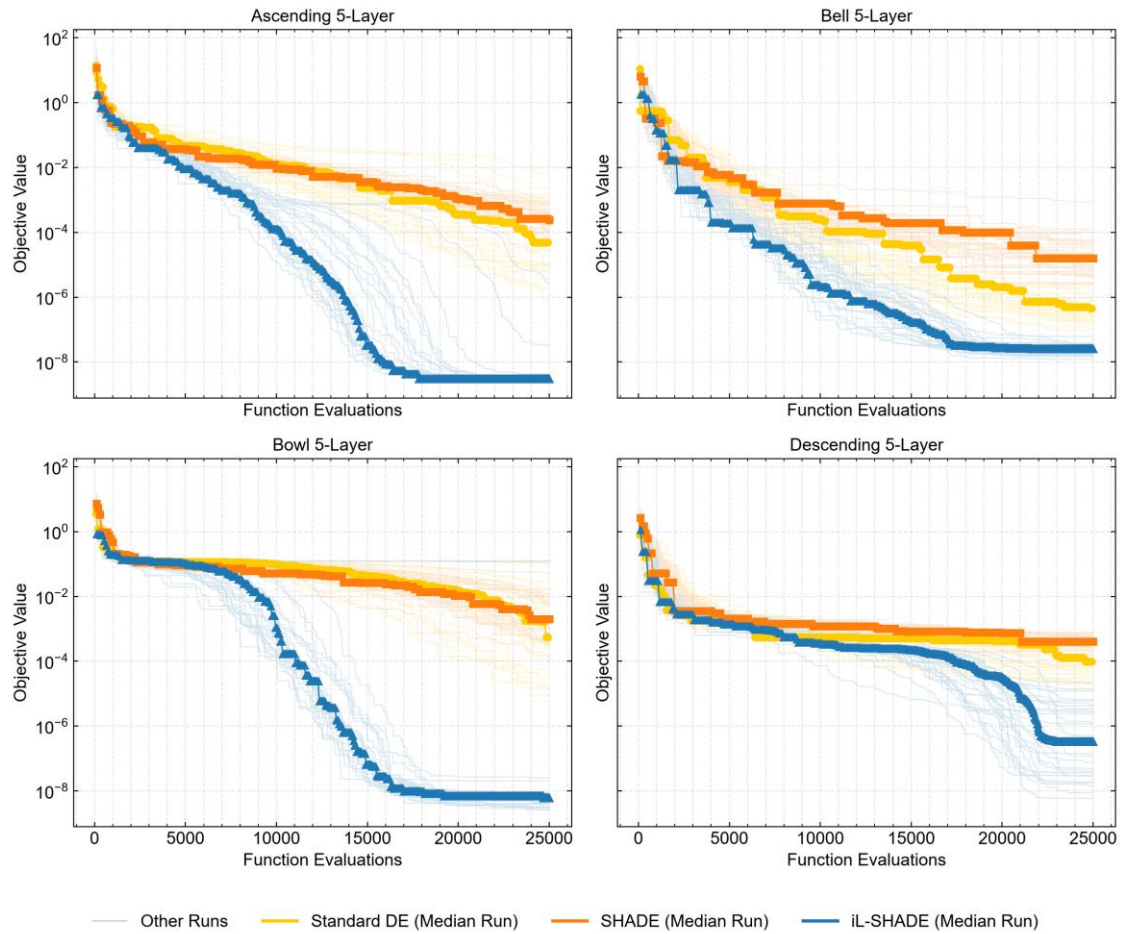


Fig. 6. The evolution of logarithmic objective value curves across function evaluations.

3.2.4. Transient Magnetic Field and Resistivity Response Fitting

The quality of the inversion results was further evaluated by comparing the modeled B_z responses with the synthetic data, as shown in Fig. 7. All three algorithms successfully reproduced the B_z responses generated by the synthetic models with high accuracy time channels ranging from 10^{-3} to 4 seconds.

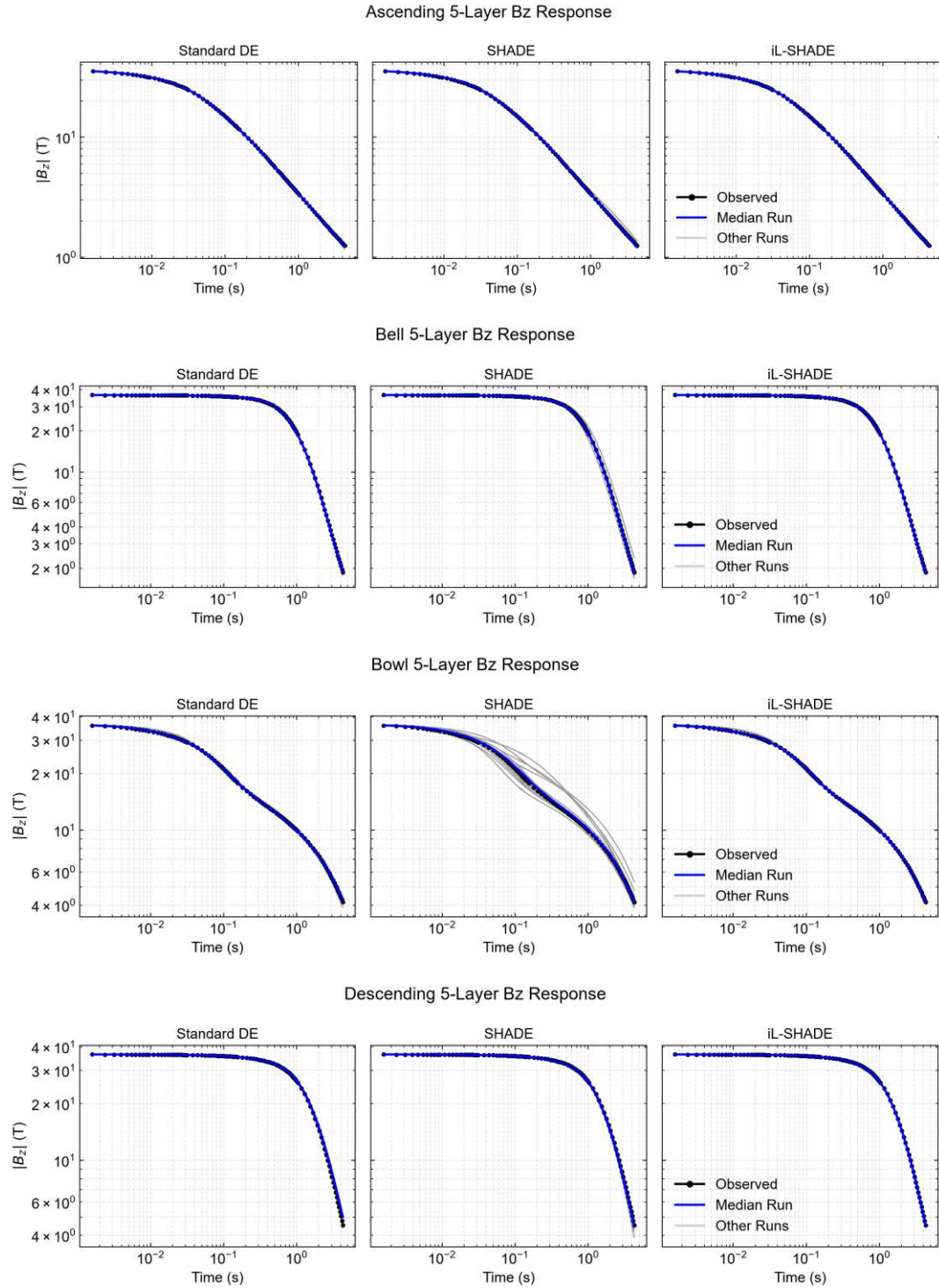
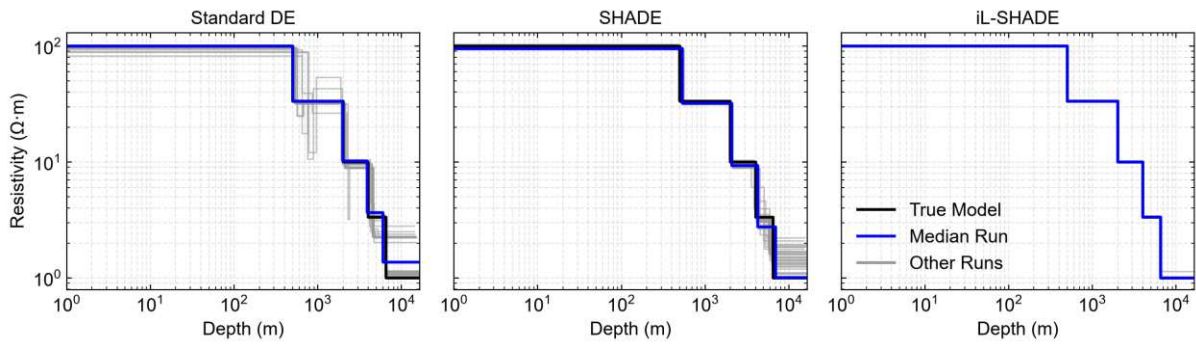
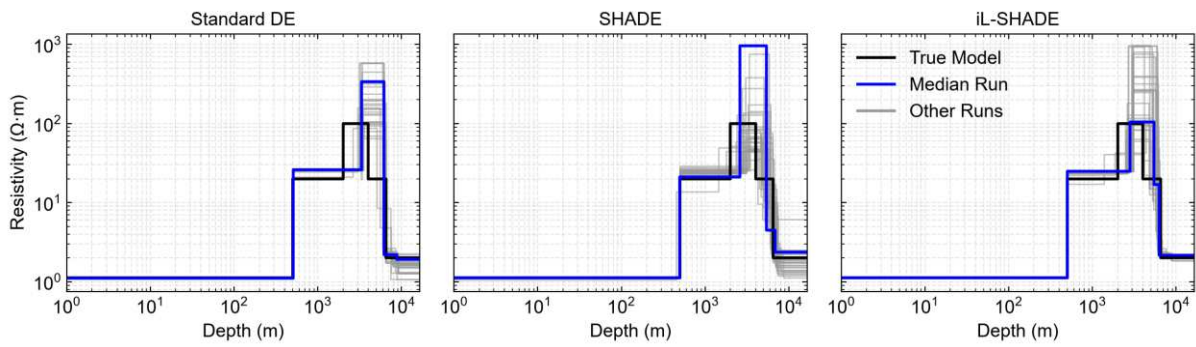


Fig. 7. B_z responses for (a) Ascending 5-layer, (b) Bell 5-layer, (c) Bowl 5-layer, and (d) Descending 5-layer model.

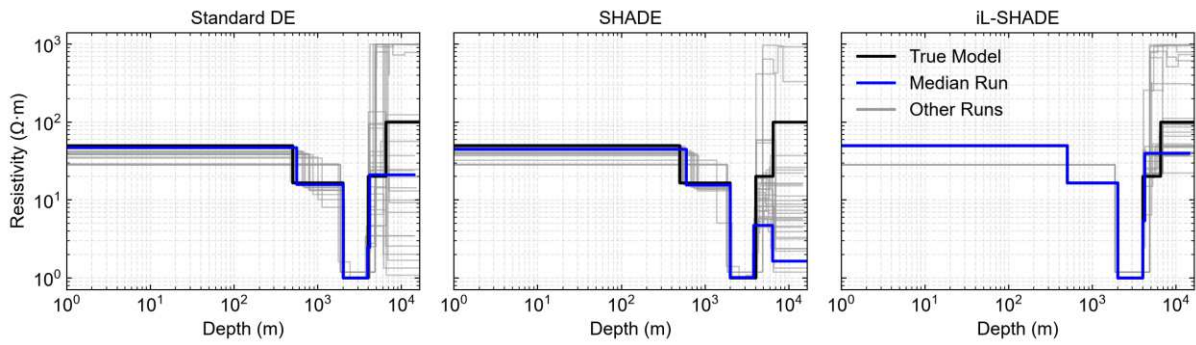
Ascending 5-Layer Resistivity Model



Bell 5-Layer Resistivity Model



Bowl 5-Layer Resistivity Model



Descending 5-Layer Resistivity Model

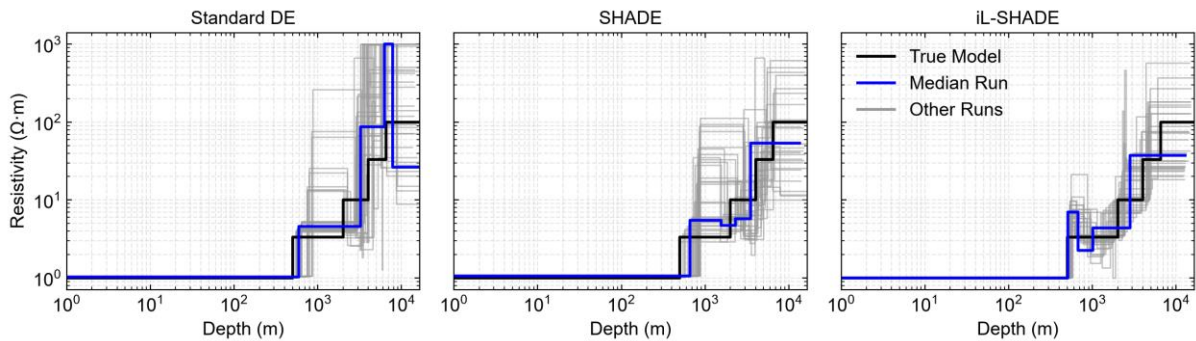


Fig. 8. Resistivity responses for (a) Ascending 5-layer, (b) Bell 5-layer, (c) Bowl 5-layer, and (d) Descending 5-layer model.

In nearly all cases, the median inversion response closely overlaps the synthetic-model response. The primary difference among the algorithms is reflected in the consistency of the inversion results across repeated optimization runs. For the Ascending 5-layer, Bell 5-layer, and Descending 5-layer models, the spread of the inversion response curves is relatively small for all three algorithms, although SHADE still exhibits slightly greater variability than Standard DE and iL-SHADE.

In contrast, the Bowl 5-layer model reveals much more pronounced differences. Several optimization runs produced by SHADE generate B_z responses that deviate noticeably from the observed data, particularly over the intermediate and late time channels, whereas the majority of the iL-SHADE responses remain closely aligned with the observed curve. Standard DE also demonstrates relatively good consistency for this model. These differences are more clearly illustrated in the recovered model parameter plots shown in Fig. 8. SHADE produces several inversion models with deep-layer resistivity estimates that deviate substantially from the true model. Standard DE also exhibits relatively large variability in the recovered model parameters. By contrast, most inversion results obtained by iL-SHADE preserve a consistent model structure, although a few solutions still exhibit deviations in the deepest layer.

The superior performance of iL-SHADE across the various evaluation aspects in Sections 3.2.1 to 3.2.4, demonstrates that the combination of success-history-based parameter adaptation and Linear Population Size Reduction (LPSR) effectively improves the balance between exploration and exploitation during the optimization of synthetic TDEM models. Therefore, iL-SHADE was selected for all subsequent experiments conducted in this study.

3.3. Parameter Tuning Analysis and p -best Influenced

Although iL-SHADE demonstrated superior performance compared with Standard DE and SHADE in the previous experiments, its performance is still influenced by several configurable parameters. Therefore, parameter tuning is required to determine the configuration that is most suitable for the characteristics of the TDEM inversion problem. The parameters considered in this study are the initial population size and the range of the p -best parameter. The initial population size was selected because no general guideline exists for determining an appropriate population size at the beginning of the optimization process, whereas the p -best range was selected because it determines how explorative or exploitative the search behavior of iL-SHADE will be. For the parameter-tuning procedure, the 5-layer Bowl synthetic model was adopted because it was identified as the most challenging model in the Section 3.2.

The first stage evaluates the effect of the initial population size while keeping the remaining parameters unchanged. Five population-size configurations were examined, namely 9D, 12D, 15D, 18D, and 21D, where D denotes the dimensionality of the inversion problem. For each configuration, the inversion was performed 15 times. All configurations employed a p -best range of 0.10–0.20, while the remaining parameters followed the default iL-SHADE settings. A summary of the experimental results is presented in Table 7. Among the tested configurations, 21D yields the lowest median objective function value. The 21D configuration also exhibits a relatively small standard deviation compared with the other configurations, as illustrated in Fig. 9a.

Table 7. the experimental results for different initial population-size configurations (9D, 12D, 15D, 18D, and 21D) using the iL-SHADE algorithm.

Experiment	Np_{init}	p_{min}	p_{max}	runs	med.	mean	std.	min	max
2A	81	0.10	0.20	15	1.175×10^{-8}	0.033106	0.056826	3.704×10^{-9}	0.124147
	108	0.10	0.20	15	9.197×10^{-9}	0.049659	0.062954	2.452×10^{-9}	0.124150
	135	0.10	0.20	15	1.388×10^{-8}	0.033106	0.056827	2.726×10^{-9}	0.124149
	162	0.10	0.20	15	1.003×10^{-8}	0.041383	0.060579	3.779×10^{-9}	0.124152
	189	0.10	0.20	15	4.450×10^{-9}	0.016553	0.043683	3.335×10^{-9}	0.124149
2B	189	0.05	0.15	20	8.458×10^{-9}	0.037245	0.058371	3.216×10^{-9}	0.124152
	189	0.10	0.20	20	5.304×10^{-9}	0.012415	0.038212	2.608×10^{-9}	0.124151
	189	0.15	0.25	20	7.533×10^{-9}	0.018622	0.045482	3.204×10^{-9}	0.124152
	189	0.20	0.30	20	7.853×10^{-9}	0.018623	0.045481	2.984×10^{-9}	0.124151
	189	0.25	0.35	20	5.941×10^{-9}	0.012426	0.038209	2.830×10^{-9}	0.124151

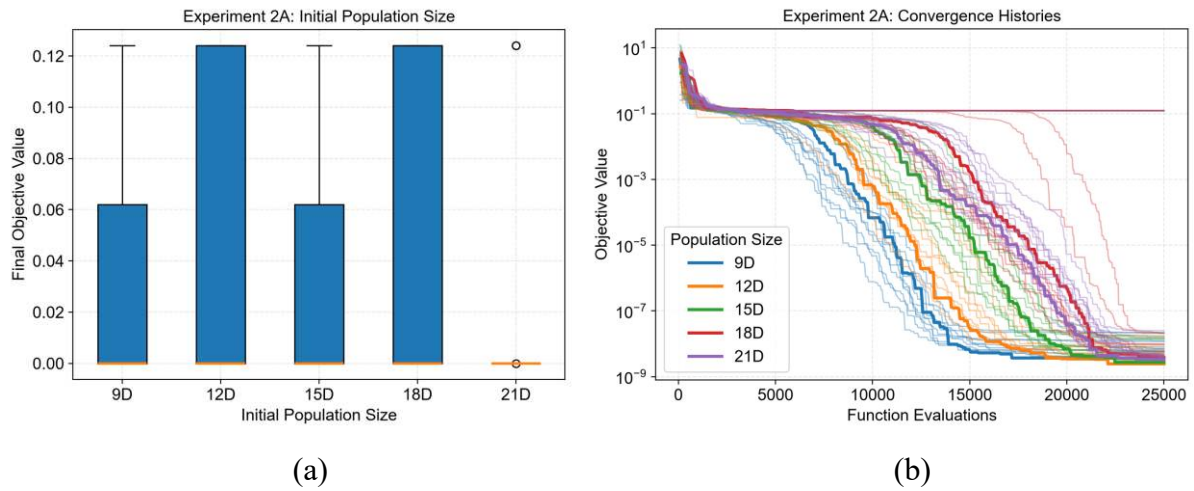


Fig. 9. The experimental results of 2A. (a) Final objective value of initial population size, which reveals the minimum value for the 21D model and (b) convergence histories.

The convergence curves shown in Fig. 9b reveal distinct differences between configurations with smaller and larger initial population sizes. Configurations with smaller populations, particularly 9D and 12D, achieve a rapid reduction in the objective function value during the early stage of the optimization. However, several optimization runs stagnate before reaching the best solutions, resulting in greater performance variability. In contrast, configurations with larger initial population sizes, such as 21D, exhibit a slightly slower convergence during the exploration phase but continue to refine the solutions throughout the later stages of the optimization. Consequently, the majority of the optimization runs eventually converge to a very low range of objective function values with considerably smaller variability.

The parameter-tuning process was subsequently continued by evaluating the effect of the p -best range. This parameter determines the proportion of the best individuals that can be selected as target vectors in the current-to-pbest mutation strategy, thereby directly governing the balance between exploration and exploitation. Five p -best ranges were evaluated, namely 0.05–0.15, 0.10–0.20, 0.15–0.25, 0.20–0.30, and 0.25–0.35. All configurations employed an initial population size of 21D.

The distribution of the objective function values and the corresponding convergence behavior are presented in Fig. 10a. Unlike the initial population size, variations in the p -best range have a relatively minor effect on the quality of the final solutions. All configurations achieve median objective function values on the order of 10^{-9} . Fig. 10b further demonstrates that each p -best range is capable of identifying solutions close to the global optimum with nearly identical convergence behavior. Nevertheless, the 0.10–0.20 configuration exhibits the best overall performance, achieving the lowest median objective function value and the smallest standard deviation among all configurations.

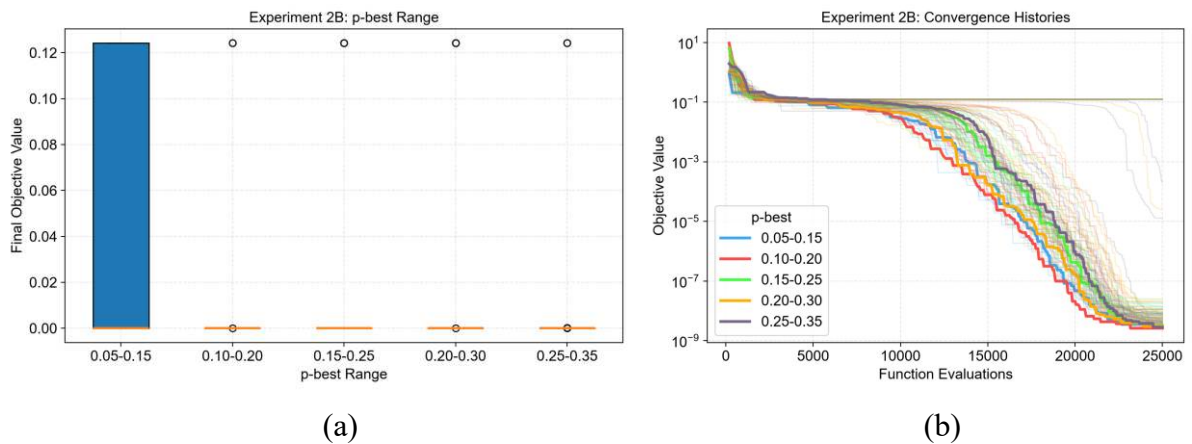


Fig. 10. The experimental results of 2B initial population size of 21D. (a) Final objective value of p -best range and (b) convergence histories.

3.4. Robustness Under Noisy Field Conditions

In practical TDEM surveys, measured data are inevitably contaminated by noise originating from various sources, including environmental electromagnetic interference, acquisition instruments, and field conditions (Horikawa & Kusumoto, 2025; Lindsey & Newman, 2015; Pollack et al., 2021). To evaluate the practical applicability of iL-SHADE under realistic survey conditions, four levels of independent Gaussian noise (5%, 10%, 15%, and 20%) were added to the 5-layer Bowl model using the same random seed. The 5-layer Bowl synthetic model was selected again because it exhibits the highest objective function variability among the synthetic models. The inversion experiments were repeated until the results reached saturation, beyond which no additional variation was observed. In this study, saturation was achieved after 10 optimization runs. The objective function values obtained from all noisy-data experiments are summarized in Table 8. As shown in Table 8, the increase in the objective function value associated with increasing noise levels is relatively small, amounting to less than 0.35% across the entire range of noise levels evaluated. Furthermore, the standard deviation remains on the order of 10^{-6} to 10^{-5} indicating that, in this case, the increased noise does not lead to a deterioration in the consistency of the inversion process.

Table 8. The objective function value under synthetic Gaussian noise levels.

Noise Level	Median	Mean	Std	Min	Max
5%	0.806587	0.806587	0.000003	0.806584	0.806591
10%	0.807272	0.807272	0.000002	0.807268	0.807275
15%	0.808688	0.808688	0.000001	0.808685	0.808690
20%	0.809341	0.809361	0.000044	0.809339	0.809445

Fig. 11 shows that the inverted B_z responses closely follow the synthetic data across all noise levels. As the noise amplitude increases, the dispersion of the observed data points becomes more pronounced. However, the inversion responses remain capable of capturing the overall trend of the B_z signal. This behavior is also reflected in the recovered resistivity models. At noise levels of 5% and 10%, the recovered models almost completely overlap the true synthetic model, indicating that all subsurface layers are successfully reconstructed. When the noise level increases to 15% and 20%, deviations begin to appear in the estimated resistivity of the shallow layers as well as in the positions of several layer interfaces.

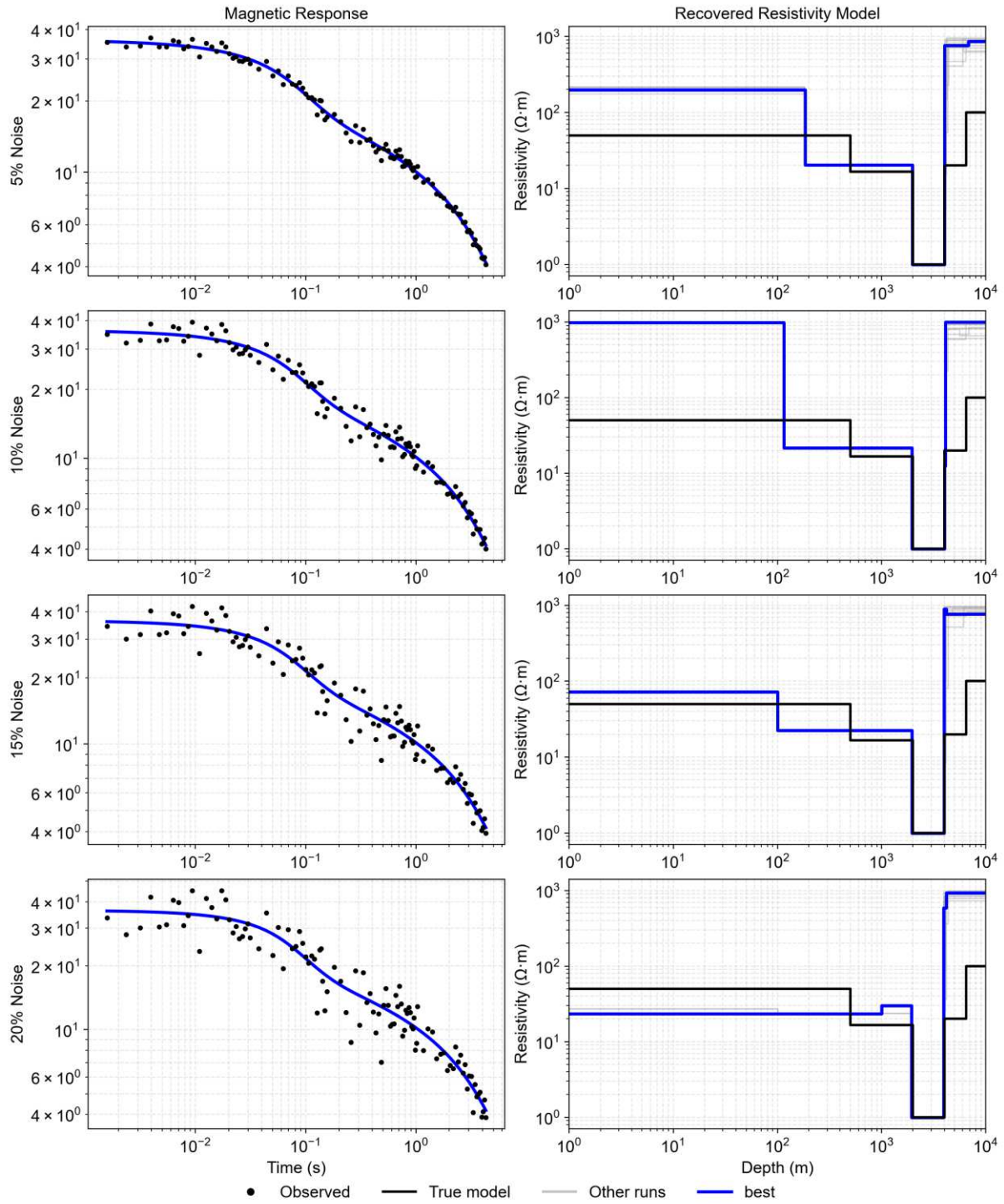


Fig. 11. Addition of noise to the vertical magnetic field data and the inverted resistivity models. Comparison between (up-to-down) 5%, 10%, 15%, and 20% noisy data and the calculated data (left side). Comparison between the test model and the inverted resistivity model for the vertical magnetic field data respectively (right side).

3.5. Layer Mismatch

In practical TDEM applications, the number of subsurface layers is generally unknown. Therefore, it is necessary to evaluate the capability of iL-SHADE to handle discrepancies between the true subsurface model and the inversion model. In this experiment, the synthetic data were generated using a 3-layer Bowl model, whereas the inversion was performed using a 5-layer model. Consequently, iL-SHADE was provided with two additional layers that do not physically exist in the true model. This experiment aims to evaluate whether the algorithm can still reconstruct the correct subsurface structure without performance degradation resulting from the increased number of parameters to be optimized.

Similar to the comparative study presented in the previous section, 30 independent inversion runs were performed using the 3-layer Bowl model. The resulting objective function values yielded a median of 1.809×10^{-9} , a mean of 1.831×10^{-9} , a standard deviation of 1.390×10^{-10} , a minimum of 1.568×10^{-9} , and a maximum of 2.126×10^{-9} . As illustrated in Fig. 12, the inverted B_z response almost completely overlaps the synthetic data. Examination of the recovered model parameters further shows that, although the inversion model consists of five layers, the recovered structure still represents the principal characteristics of the true three-layer synthetic model. The two additional layers available in the inversion model do not develop into significant geological structures. Instead, they exhibit very small thicknesses and therefore contribute negligibly to the final recovered model.

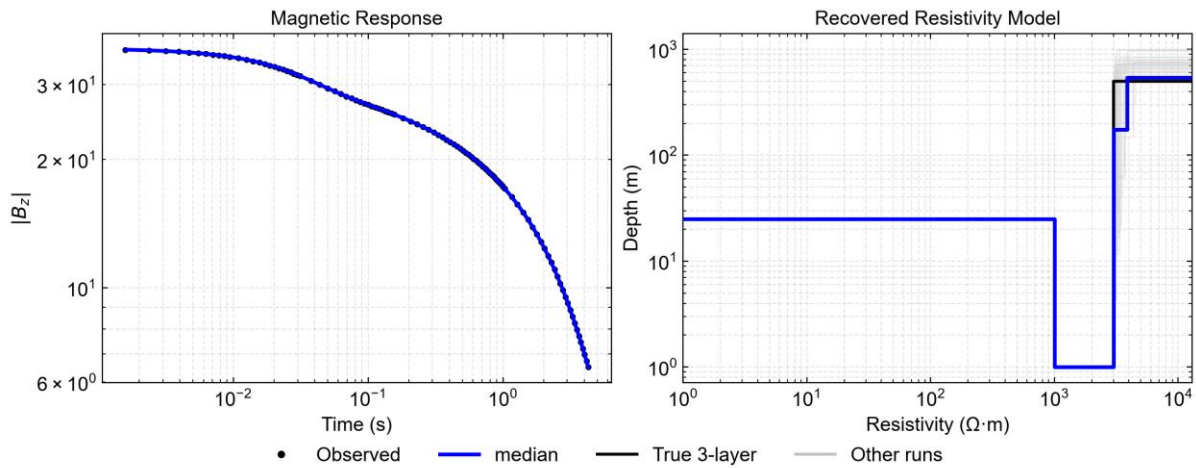


Fig. 12. Inversion of synthetic data in the form of a vertical magnetic field. Comparison between the synthetic (observed) data and the inverted data (left side). Comparison between the test model that generated the synthetic data (blue line) and the inverted resistivity models (black lines) (right side).

4. FIELD DATA VALIDATION

Following the synthetic benchmark experiments, the proposed iL-SHADE inversion framework was further evaluated using field TDEM data to assess its performance under realistic geological conditions. The field dataset was acquired at station UZ01, located on the eastern flank of Unzen Volcano in the Shimabara Peninsula, Kyushu Island, Japan (Srigutomo et al., 2021).

4.1. Comparison of Observed and Calculated TDEM Data Responses

The response of calculated data from the inverted 5-layer model vector is properly fit to the observed transient magnetic field decay $B_z(t)$ at station UZ01 across all 158 time channels, as displayed in Fig. 13 and 14. In early-to-intermediate time channels (10^{-5} to 10^{-2} s), the response of calculated data is properly fit to the observed data with less than 0.1% error. In late-time channels (10^{-2} to 10^{-1} s), despite lower signal-to-noise ratios, the calculated response closely tracked the physical decay trend. Overall, the inverted 5-layer model reproduces the observed electromagnetic transient response with a final RMS misfit of 24.388, validating the forward modeling accuracy and optimization robustness.

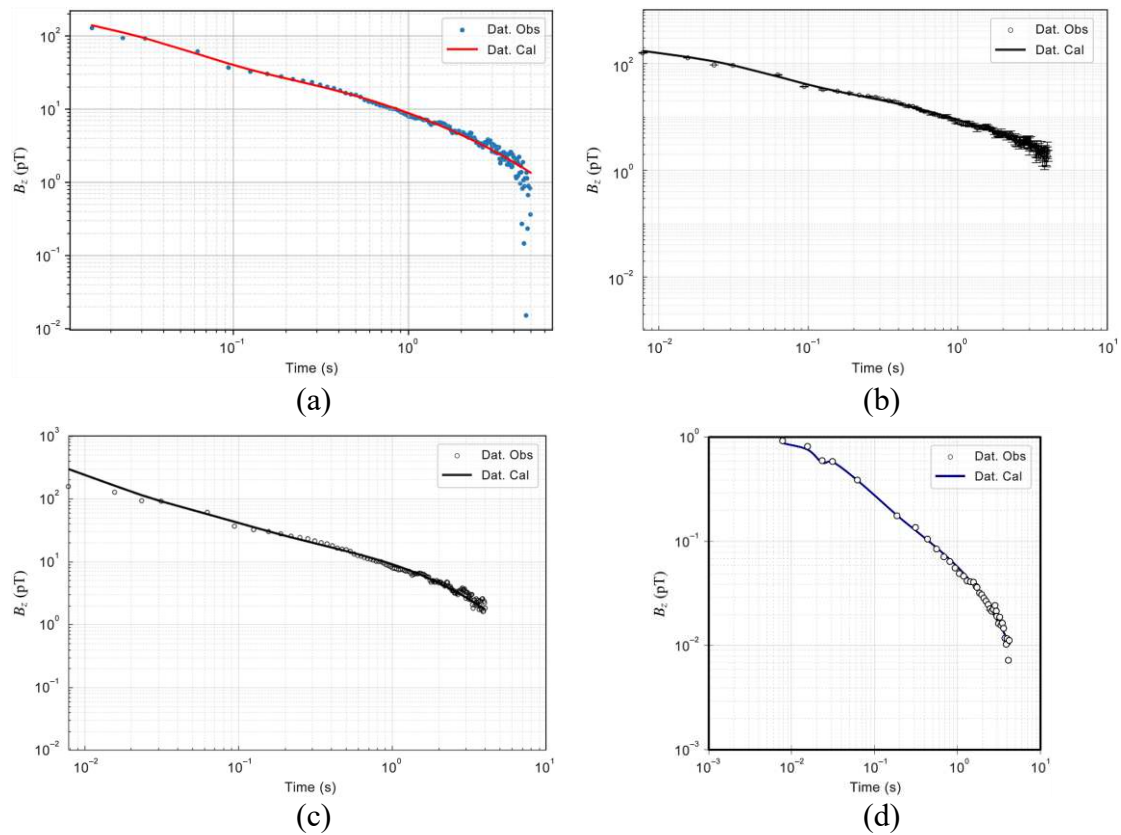


Fig. 13. Comparison between the calculated and observed data response of transient magnetic field decay B_z at station UZ01 for (a) iL-SHADE, (b) PSO (Hapsoro et al., 2021), (c) VFSA (Srigutomo et al., 2021), and (d) Occam (Srigutomo et al., 2008) inversion.

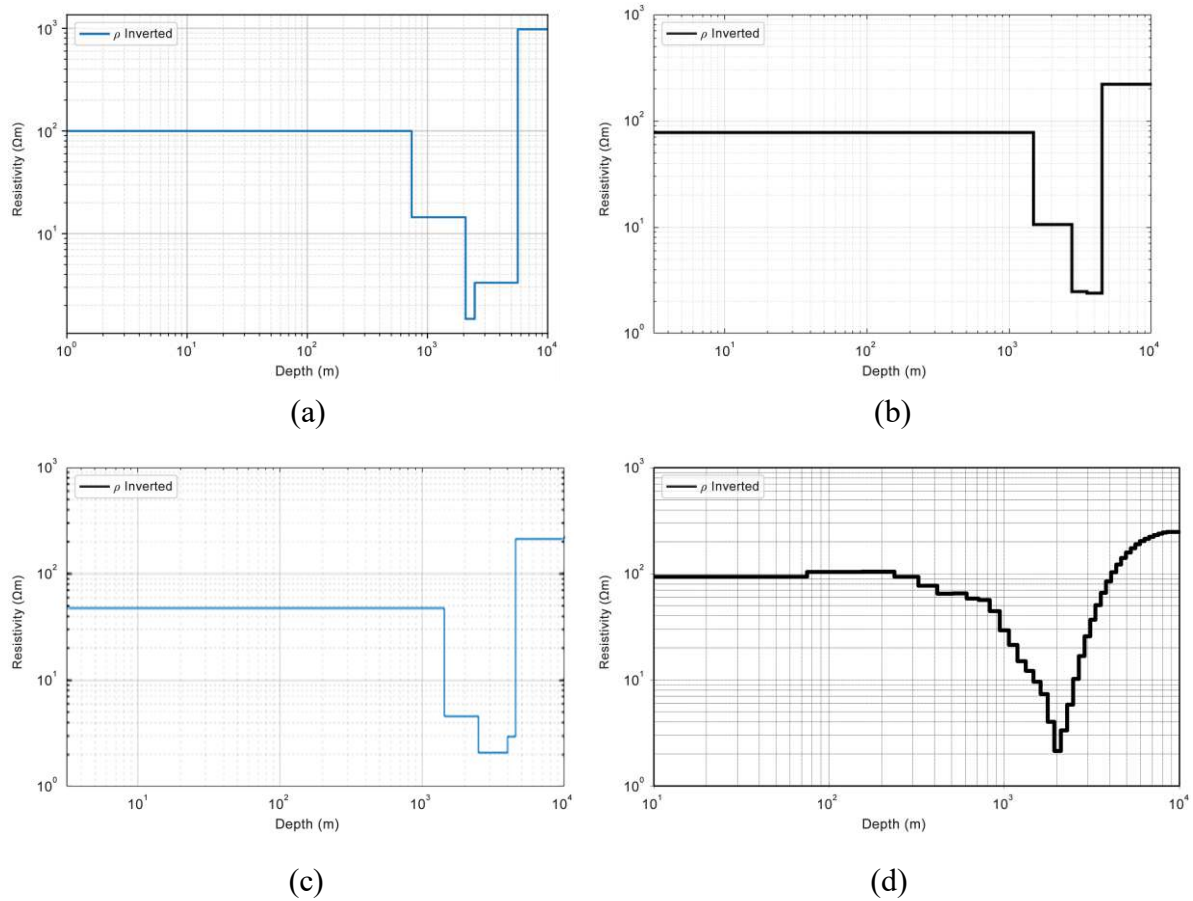


Fig. 14. Comparison between the calculated and observed response of resistivity model vs depth at station UZ01 for (a) iL-SHADE, (b) PSO (Hapsoro et al., 2021), (c) VFSA (Srigutomo et al., 2021), and (d) Occam (Srigutomo et al., 2008) inversion.

4.2. Geological and Geothermal Interpretation of the Recovered Resistivity Profile

The optimal 5-layer subsurface electrical resistivity profile recovered by iL-SHADE at station UZ01 is detailed in Table 9. The model reveals a classic volcanic-hydrothermal system structure extending from the surface down to a depth of 5.6 km.

Table 9. Details the recovered 5-layer subsurface electrical resistivity model for station UZ01.

Subsurface Layer	Conductivity σ (S/m)	Resistivity ρ ($\Omega\cdot\text{m}$)	Layer Thickness h (m)	Depth Range (m)
Layer 1	0.010011	99.89	738.5	0.0 – 738.5
Layer 2	0.069224	14.45	1337.1	738.5 – 2075.6
Layer 3	0.676347	1.48	400.2	2075.6 – 2475.7
Layer 4	0.300872	3.32	3160.7	2475.7 – 5636.5
Layer 5 (Basement)	0.001023	977.67	<i>infinity</i>	> 5636.5

The inverted resistivity structure at station UZ01 reveals five distinct geological units down to a depth exceeding 5.6 km. The surficial unit (Layer 1, extending from 0 to 738.5 m) exhibits a relatively high resistivity of $\rho_1 \sim 99.89 \, \Omega\cdot\text{m}$, representing dry, porous, unaltered volcanic debris and alluvial fan deposits of the Younger Unzen complex situated above the local water table. Beneath this surficial layer, Layer 2 (738.5–2075.6 m) displays a moderate resistivity of $\rho_2 \sim 14.45 \, \Omega\cdot\text{m}$, corresponding to weathered pyroclastic flow units and volcanic breccias with partial groundwater saturation. At intermediate depths, Layer 3 (2075.6–2475.7 m) is characterized by a striking conductive anomaly with an ultra-low resistivity of $\rho_3 \sim 1.48 \, \Omega\cdot\text{m}$ over a thickness of 400.2 m. In active volcanic geothermal systems, such pronounced conductive zones are diagnostic of intense hydrothermal clay mineral alteration, predominantly smectite and illite-smectite mixed-layer clays formed by low-to-moderate temperature (100–200 °C) fluid-rock interaction (Revil & Gresse, 2021), which creates an impermeable hydrothermal cap rock. Immediately underlying this clay cap, Layer 4 (2475.7–5636.5 m) maintains a low resistivity of $\rho_4 \sim 3.32 \, \Omega\cdot\text{m}$ over a 3.16 km thick interval, delineating a high-temperature, fluid-saturated geothermal reservoir containing conductive saline hydrothermal fluids. Finally, at depths greater than 5.6 km, Layer 5 exhibits a sharp increase in resistivity to $\rho_5 \sim 977.67 \, \Omega\cdot\text{m}$. This high-resistivity basement halfspace represents dense, unaltered pre-volcanic basement rocks or a deep igneous intrusive body associated with the magmatic heat source driving the Unzen volcanic geothermal engine.

5. DISCUSSION

The numerical findings and field data inversions presented in this study demonstrate the remarkable efficacy of the iL-SHADE framework for solving nonlinear 1D TDEM inverse problems. By synthesizing synthetic benchmark evaluations across four distinct 5-layer subsurface profiles (Ascending 5-layer, Bell 5-layer, Bowl 5-layer, Descending 5-layer) with actual field observations at station UZ01 (Unzen Volcano, Japan), this section discusses the evolutionary mechanics governing search adaptivity, the physical implications for overcoming subsurface non-uniqueness and layer equivalence, the core scientific novelties introduced by this work, and practical considerations for geophysical exploration.

5.1. Evolutionary Mechanics of Parameter Adaptation and Population Management

The performance of population-based stochastic optimization algorithms is fundamentally governed by how effectively they balance global exploration and local exploitation throughout the evolutionary process (Epitropakis et al., 2008). In canonical DE (Storn & Price, 1997), the mutation scaling factor (F) and crossover rate (Cr) are assigned

static, fixed values prior to optimization. However, as demonstrated by the pre-inversion sensitivity studies in Section 3.1, static parameter configurations lack theoretical justification and fail to accommodate the dynamic search requirements of highly nonlinear objective function landscapes (Cheng et al., 2023). Static settings frequently lead to rapid loss of population diversity, premature convergence to sub-optimal local minima, or evolutionary stagnation when navigating narrow, elongated misfit valleys.

The adaptive evolutionary trajectory evaluated in this study, progressing from canonical DE to JADE (Zhang & Sanderson, 2009), SHADE (Tanabe & Fukunaga, 2013), and ultimately iL-SHADE (Tanabe & Fukunaga, 2014), represents a fundamental paradigm shift in metaheuristic geophysical inversion. By incorporating historical memories (M_F , M_{Cr}) of successful mutation and crossover parameters, SHADE continuously updates parameter probability distributions based on successful evolutionary experiences. This mechanism prevents the optimization process from being derailed by stochastic parameter perturbations that yield poor fitness values (Tanabe & Fukunaga, 2013).

Furthermore, iL-SHADE integrates LPSR, which dynamically decreases the population size N_p according to a linear schedule based on the remaining evaluation budget. In early generations, a large initial population maximizes global exploration and search space coverage, preventing the algorithm from becoming trapped in early local minima. As evolution proceeds, non-promising individuals are progressively eliminated, concentrating the remaining computational budget on high-performing individuals surrounding the global minimum. This dual mechanism enables iL-SHADE to achieve median misfits as low as 10^{-8} to 10^{-9} across synthetic test cases, outperforming canonical DE and standard SHADE by 2 to 4 orders of magnitude.

5.2. Implications for Nonlinear TDEM Inversion and Subsurface Equivalence

TDEM inversion is a highly nonlinear, ill-posed inverse problem characterized by strong parameter coupling and severe non-uniqueness. In 1D layered earth models, this non-uniqueness manifests primarily as layer equivalence, where multiple combinations of layer resistivity (ρ_i) and thickness (h_i) yield electromagnetic transient decay curves B_z that fit field observations equally well within measurement noise tolerances (Nielsen et al., 2026). For instance, in conductive thin layers, the transient response is primarily governed by the longitudinal conductance ($S_i = h_i / \rho_i$), making it difficult to uniquely resolve ρ_i and h_i independently.

Conventional deterministic inversion methods, Gauss–Newton (Blanchy et al., 2020; Chen & Sacchi, 2020), Levenberg–Marquardt (Bergou et al., 2022), and Occam-type (de Groot-Hedlin & Constable, 1990) inversion, address ill-posedness by linearizing the forward operator around an initial model and applying spatial smoothness regularization constraints. While computationally efficient, these local gradient-based methods are heavily dependent on the choice of starting model and often smooth out sharp lithological boundaries, producing overly smoothed resistivity profiles that may obscure localized geothermal targets.

Conversely, classical stochastic global optimization algorithms explore the search space without requiring initial model assumptions or gradient calculations (Hapsoro et al., 2021). However, when applied to complex 5-layer resistivity models (e.g., the Bowl 5-layer profile), standard metaheuristics often suffer from severe performance deterioration due to fixed hyperparameter settings. The modal analysis and misfit surface mapping conducted in this study reveal that iL-SHADE successfully navigates narrow, highly nonlinear parameter trade-off valleys without requiring ad-hoc regularization penalty terms. In the highly non-unique Bowl 5-layer case, iL-SHADE achieved the lowest minimum misfit (2.555×10^{-9}) and lowest median misfit (5.979×10^{-9}). This demonstrates that historical parameter adaptivity and current-to-pbest mutation strategies effectively preserve population diversity along equivalent parameter directions, allowing the algorithm to locate global optimal parameter combinations that satisfy both geophysical data fit and physical structural plausibility.

5.3. Primary Scientific Novelties and Methodological Contributions

5.3.1. *Adaptation of iL-SHADE to TDEM Data Inversion*

While adaptive DE variants have been benchmarked on standard mathematical test functions and applied to 3D gravity basement reconstruction (Ekinci et al., 2023), their performance had not been systematically investigated for TDEM diffusion equations. This work provides the first comprehensive evaluation demonstrating that iL-SHADE dual-adaptation framework successfully resolves the nonlinear diffusion physics and parameter coupling inherent in TDEM transient decay responses.

5.3.2. *Empirical Hyperparameter Guidelines for Metaheuristic TDEM Inversion*

A major barrier to adopting metaheuristic optimization in routine geophysical workflows is trial-and-error manual tuning of algorithmic hyperparameters (Pamplona et al., 2025). This study establishes clear guidelines, which $N_p = 21 \times D$ combined with an archive threshold of $p \in [0.10, 0.20]$. These baseline settings achieved an inversion success rate on the

challenging Bowl 5-layer model, providing geophysicists with a robust, standardized configuration.

5.3.3. *Rigorous Non-Parametric Statistical Verification and Noise Robustness*

This research conducted 30 independent stochastic runs per model profile and applied pairwise Wilcoxon rank-sum statistical hypothesis testing ($\alpha = 0.01$). This findings reveals a better model compared to previous studies that evaluate algorithms using a single optimization run. The resulting asymptotic p -values ($p = 3.020 \times 10^{-11}$, $p \ll 0.01$) provide mathematical proof that iL-SHADE superiority over canonical DE and standard SHADE is statistically significant.

5.4. **Geophysical Insights from Volcanic-Hydrothermal Application (Unzen Volcano)**

The practical utility of the proposed inversion framework is compellingly demonstrated by its application to actual field data from station UZ01 on the eastern flank of Unzen Volcano, Japan (Hapsoro et al., 2021). Volcanic edifices host complex hydrothermal systems characterized by strong lateral and vertical heterogeneity, fluid circulation, and clay mineral alteration zones (Aizawa et al., 2009; Caudron et al., 2023). The 5-layer subsurface electrical resistivity profile recovered by iL-SHADE at station UZ01 (Table 9) provides a detailed, physically consistent image of the volcanic-hydrothermal architecture down to depths up to 5.6 km.

5.5. **Practical Considerations, Limitations, and Future Research Directions**

5.5.1. *Limitation of Computational Budget for Multi-Dimensional inversion*

In 1D layered earth formulations, forward modeling requires evaluating Hankel transform integrals, which compute rapidly (~ 100 runs/second per CPU core). Extending iL-SHADE to 2D or 3D TDEM forward modeling will increase computational cost significantly. Future work should integrate High-Performance Computing (HPC), GPU parallelization, or surrogate machine learning acceleration (Akingboye, 2025).

5.5.2. *Multi-Physics Joint Inversion*

Although 1D TDEM soundings provide excellent vertical resolution for conductive shallow-to-intermediate layers, their sensitivity to deep resistive basements is naturally diminished due to signal attenuation. Integrating iL-SHADE into a joint inversion framework combining TDEM with Magnetotelluric (MT) soundings or gravity anomalies (Ekinici et al., 2023) will further suppress layer equivalence and refine deep basement boundary resolution.

6. CONCLUSION

This study presented a systematic, highly robust global optimization framework for solving nonlinear 1D TDEM data inversion using by applying iL-SHADE. By integrating historical memories of successful mutation and crossover factors (M_F , M_{Cr}) with dynamic LPSR, iL-SHADE effectively overcomes the severe non-uniqueness, parameter coupling, and premature convergence challenges inherent in TDEM inverse problems.

Across four distinct 5-layer synthetic benchmark models (Ascending 5-layer, Bell 5-layer, Bowl 5-layer, Descending 5-layer), iL-SHADE consistently achieved median misfits ranging from 10^{-8} to 10^{-9} , outperforming canonical Differential Evolution (Standard DE) and classical SHADE by 2 to 4 orders of magnitude. In the highly non-unique Bowl 5-layer profile, iL-SHADE achieved the lowest minimum misfit (2.555×10^{-9}) and lowest median misfit (5.979×10^{-9}).

Pairwise Wilcoxon rank-sum statistical hypothesis testing across 30 independent stochastic runs per model confirmed that iL-SHADE performance superiority is statistically significant ($p = 3.020 \times 10^{-11}$, $p \ll 0.01$), achieving better results across all model profiles. Under synthetic Gaussian noise levels up to 20%, iL-SHADE with predictable, linear error scaling (0.8066 to 0.8094 misfit), demonstrating exceptional numerical stability.

Pre-inversion sensitivity studies established an initial population size multiplier of $N_p = 21 \times D$ (where D is model dimension) combined with a greedy archive selection threshold of $p \in [0.10, 0.20]$ as the optimal baseline configuration. These empirical guidelines eliminate the costly, trial-and-error manual hyperparameter tuning traditionally required in metaheuristic geophysical inversion.

Application to actual TDEM field observations at station UZ01 (Unzen Volcano, Japan) successfully imaged a 5-layer volcanic-hydrothermal system down to depths > 5.6 km. The inverted model accurately resolved a 400.2 m thick, ultra-conductive smectite alteration clay cap ($\rho_3 \sim 1.48 \Omega \cdot m$) sealing a fluid-saturated geothermal reservoir ($\rho_4 \sim 3.32 \Omega \cdot m$) above a deep resistive volcanic basement ($\rho_5 \sim 977.7 \Omega \cdot m$).

In summary, iL-SHADE provides a highly efficient, accurate, and automated global optimization framework for TDEM subsurface resistivity imaging, offering substantial practical utility for mineral exploration, groundwater assessment, and volcanic geothermal reservoir characterization.

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8. AUTHOR CONTRIBUTIONS

The authors' contributions are structured according to the CRediT (Contributor Roles Taxonomy) guidelines. C.A.H. contributed to conceptualization, methodology, software development (MATLAB core implementation), investigation, validation, formal analysis, writing of the original draft, review and editing of the manuscript, supervision, and funding acquisition. F.Q.S. contributed to software development (Python analysis codebase), data curation, validation, formal analysis, visualization, and writing of the original draft, as well as review and editing. M.K.R. contributed to conceptualization, methodology, formal analysis, visualization, writing of the original draft, review and editing, and project administration. W.S. contributed to methodology, data curation, manuscript review, and validation.

9. CONFLICT OF INTEREST

The authors declare that they have no financial interests or personal relationships that could have appeared to influence the work reported in this paper. All analyses and interpretations presented in this study are based solely on academic purposes, without any external influence from commercial, financial, or political entities. The authors have acknowledged and addressed any potential bias that may arise from the data or methodology used, ensuring the integrity of the research findings.

10. DATA AVAILABILITY

The datasets generated during the current study are not publicly available due to institutional data access restrictions but are available from the corresponding author upon reasonable request.

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