

**JOINT INVERSION OF DIRECT CURRENT RESISTIVITY
AND SEISMIC REFRACTION DATA, USING LOCAL AND
GLOBAL OPTIMIZATION ALGORITHMS WITH
SYNTHETIC AND REAL DATA EXAMPLES**

BY
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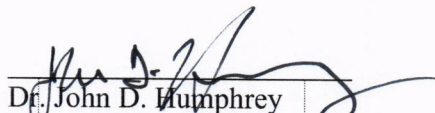
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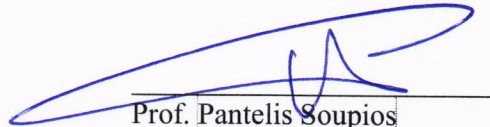
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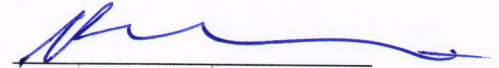
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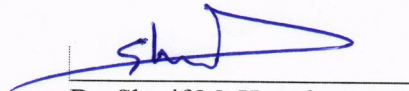


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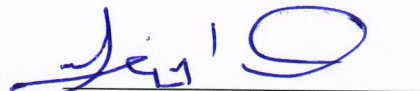


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Dedication:
To my lovely wife, and my parents

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LIST OF ABBREVIATIONS

CGO	: Combined Global Optimization
CSAMT	: Controlled-Source Audio Magnetotelluric
DC	: Direct Current
DCR	: Direct Current Resistivity
DD	: Dipole Dipole
EM	: Electromagnetic
ENE	: East-North-East
ERT	: Electrical Resistivity Tomography
FD	: Finite Difference
FE	: Finite Element
GA	: Genetic Algorithm
GN	: Gauss-Newton
GOM	: Global Optimization Method
GPA	: Genetic Price Algorithm
GPR	: Ground Penetrating Radar
GPS	: Generalized Pattern Search
HPC	: High Performance Computing
IIM	: Individual Inversion Method
JIM	: Joint Inversion Method
LOM	: Local Optimization Method
MBZ	: Megabreccia Zone
MOO	: Multi-Objective Optimization

NE	: North-East
NNW	: North-North-west
NSGA	: Non-Dominated Sorting Genetic Algorithm
NW	: North-West
PNU	: Pre-Neogene Unconformity
PS	: Pattern Search
PSO	: Particle Swarm Optimization
RMS	: Root Mean Square
SA	: Simulated Annealing
SNR	: Signal-To-Noise Ratio
SO	: Surrogate Optimization
SOO	: Single-Objective Optimization
SR	: Seismic Refraction
SSE	: South-South-East
SVI	: Supervirtual Interferometry
SW	: South-West
TEM	: Time Domain Electromagnetic
VFSA	: Very Fast Simulated Annealing
WS	: Wenner-Schlumberger
WSW	: West-South-West

ABSTRACT

Full Name : [Paul Irikefe Edigbue]
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The joint inversion of Direct Current Resistivity (DCR) and Seismic Refraction (SR) data has become a common technique for subsurface exploration due to its high-resolution imaging capabilities. This study focuses on the performance of different optimization algorithms for joint inversion of DCR and SR data, and the application of a proposed combined optimization approach to three synthetic anomalies models (dyke, positive, and combined positive and negative), as well as a case study in the Dammam Dome in Eastern Saudi Arabia. The study also tests different stochastic methods to model DCR and SR data using the combined optimization approach. The study found that the combined optimization approach outperforms both the local and global optimization methods in terms of the percentage of anomaly reconstruction and convergence as shown in the synthetic test results. This approach was found to be particularly effective in handling the non-linear and multi-dimensional nature of the joint inversion problem, and in accurately characterizing the subsurface geology. The study also found that the use of stochastic methods to model DCR and SR data can provide a useful tool for modeling the

uncertainties in the data, and for providing more realistic estimates of the subsurface properties. The case study in the Dammam Dome demonstrated the effectiveness of the combined optimization approach in accurately characterizing the subsurface geology. The results showed that the approach was able to delineate the major geological structures of the area, including faults, fractures, and lithological boundaries. In general, this study provides a comprehensive analysis of the performance of different optimization algorithms for joint inversion of DCR and SR data. The study found that the combined optimization approach is the most effective method for accurately characterizing the subsurface geology.

ملخص الرسالة

الاسم الكامل: بول إريكفي إديجو

عنوان الرسالة: الانعكاس المشترك لمقاومة التيار المباشر وبيانات الانكسار الزلزالي ، باستخدام خوارزميات التحسين المحلية والعالمية مع أمثلة البيانات الاصطناعية والواقعية.

التخصص: الجيوفيزياء

تاريخ الدرجة العلمية: أبريل 2023

أصبح الانعكاس المشترك لبيانات (SR) والانكسار الزلزالي (DCR) أصبح الانعكاس المشترك لبيانات مقاومة التيار المباشر تقنية شائعة للاستكشاف تحت السطحي بسبب قدرات التصوير عالية (SR) والانكسار الزلزالي (DCR) مقاومة التيار المباشر ، وتطبيق نهج التحسين SR و DCR الدقة. تركز هذه الدراسة على أداء خوارزميات التحسين المختلفة لعكس مشترك لبيانات المشترك المقترح على ثلاثة نماذج شاذة تركيبية (السد ، الموجب ، والمجموعة الإيجابية والسلبية) ، بالإضافة إلى حالة الدراسة في باستخدام SR و DCR قبة الدمام بشرق المملكة العربية السعودية. تختبر الدراسة أيضًا طرقًا عشوائية مختلفة لنمذجة بيانات نهج التحسين المشترك. وجدت الدراسة أن نهج التحسين المشترك يتفوق على كل من طرق التحسين المحلية والعالمية من حيث النسبة المئوية لإعادة بناء الانحراف والتقارب كما هو موضح في نتائج الاختبار التركيبي. تم العثور على هذا النهج ليكون فعال بشكل خاص في التعامل مع الطبيعة غير الخطية ومتعددة الأبعاد لمشكلة انقلاب المفصل ، وفي توصيف الجيولوجيا تحت السطحية يمكن أن يوفر أداة مفيدة لنمذجة أوجه SR و DCR بدقة. وجدت الدراسة أيضًا أن استخدام الطرق العشوائية لنمذجة بيانات عدم اليقين في البيانات ، ولتوفير تقديرات أكثر واقعية للخصائص الجوفية. أظهرت دراسة الحالة في قبة الدمام فعالية نهج التحسين المشترك في التوصيف الدقيق للجيولوجيا تحت السطحية. وأظهرت النتائج أن المنهج كان قادرًا على تحديد الهياكل الجيولوجية الرئيسية للمنطقة ، بما في ذلك الصدوع والكسور والحدود الصخرية. بشكل عام ، تقدم هذه الدراسة تحليلًا شاملاً لأداء خوارزميات وجدت الدراسة أن نهج التحسين المشترك هو الطريقة الأكثر فعالية SR و DCR التحسين المختلفة لعكس مشترك لبيانات لتوصيف الجيولوجيا الجوفية بدقة.

CHAPTER 1

Introduction

Joint inversion of seismic refraction and direct current (DC) resistivity data is a powerful and widely used technique in subsurface imaging and characterization. It involves the integration of two complementary geophysical methods to produce a more detailed and accurate subsurface image. Seismic refraction measures the velocity of seismic waves, which is related to the elastic properties of subsurface rocks and the fluids therein, while DC resistivity is related to their electrical conductivities. By combining these two data sets, joint inversion provides a more comprehensive understanding of the subsurface structure and its properties [4]. The inversion algorithms use optimization techniques to estimate the subsurface parameters, such as velocity and resistivity, from the combined seismic refraction and DC resistivity data. These optimization algorithms can be divided into two categories: local and global. Local optimization algorithms rely on an iterative and incremental approach to find the best solution within a limited search space. Global optimization algorithms, on the other hand, use more sophisticated techniques to explore a wider search space and find the global optimum solution [1]. In the local optimization, the inversion process starts with collecting and pre-processing the seismic refraction and DC resistivity data. Next, the two data sets are combined and used as input to the optimization algorithms. The algorithms then iteratively adjust the subsurface parameters until the best fit between the modeled and observed data is achieved. The resulting subsurface parameters provide a detailed and accurate representation of the subsurface structure and its properties [3]. By combining two complementary data sets, joint inversion provides a more comprehensive and accurate understanding of the subsurface, which can help to make more informed decisions about the subsurface [2]. This inversion technique (i.e., joint

inversion of seismic refraction and DC resistivity data) is widely used in a variety of applications, including geological and environmental studies, mineral exploration, and engineering.

One of the challenges in joint inversion is dealing with the non-uniqueness of the solution. Different subsurface models can fit the observed data equally well, and it is often difficult to determine which model is the most realistic. To overcome this challenge, various constraints and priors informations can be added to the optimization problem, such as geological and geometrical constraints, to guide the optimization process towards a more realistic solution. Another challenge in joint inversion is dealing with the noise and errors in the data. Both seismic refraction and DC resistivity data are subject to measurement errors, and these errors can affect the accuracy of the joint inversion results. To address this issue, various data-weighting and error-modelling techniques can be used to account for the noise and errors in the data. Basically, this study considers the creation of new combined local and global optimization algorithms that mitigates the challenges of non-unique and data ambiguity.

1.1 Problem Statement

One of the main limitations of local optimization algorithms is that they are prone to get stuck in local minima. Local optimization algorithms rely on an iterative and incremental approach to find the best solution within a limited search space. However, this approach can lead to finding only a local optimum solution instead of the global optimum solution. In other words, local optimization algorithms may not find the best solution for the entire subsurface, but rather only the best solution for a limited region of the subsurface [1]. Another limitation of local optimization algorithms is that they may not converge to the optimal solution for a large and complex subsurface model. For example, a subsurface model with multiple layers, multiple fluids, and multiple interfaces can be difficult to solve using local optimization algorithms, as these algorithms may not be able to find the correct solution within the limited search space [4]. The sensitivity of local

optimization algorithms to the initial conditions is another limitation. Local optimization algorithms often require a good initial guess of the subsurface parameters in order to converge to the correct solution. If the initial guess is not accurate, the optimization process may converge to a wrong or suboptimal solution [3]. This can make it difficult to use local optimization algorithms for real-time applications, where fast and efficient solutions are required [2]. Therefore, local optimization algorithms have several limitations, including the risk of getting stuck in local minima, difficulty in solving complex subsurface models, sensitivity to initial conditions, and computational intensity. However, the local optimization algorithms are often faster and more efficient than global optimization algorithms, and they can provide a good initial guess of the subsurface parameters.

On the other hand, global optimization algorithms are becoming more popular in the inversion of geophysical data due to their ability to find the global optimum solution for complex subsurface models, instead of just a local optimum solution, as is the case with local optimization algorithms [4]. Moreover, global optimization algorithms are often more robust than local optimization algorithms, as they do not rely on a good initial guess of the subsurface parameters. Instead, they explore the entire search space and find the best solution for the entire subsurface [2]. Despite their efficacy, global optimization algorithms can still be computationally intensive and time-consuming, especially for large and complex subsurface models. This can make them challenging to implement in practice [5]. In addition, global optimization algorithms can still be sensitive to the initial conditions, especially for subsurface models with multiple layers, multiple fluids, and multiple interfaces. This can result in a suboptimal solution if the initial conditions are not accurate [1]. Despite these limitations, global optimization algorithms are still widely used, as they provide a more sophisticated solution for complex subsurface models [5].

By integrating both local and global optimization algorithms, it is possible to leverage the strengths of each algorithm and overcome their weaknesses. For example, local optimization

algorithms can be used to provide a good initial guess of the subsurface parameters, which can be used as the starting point for the global optimization algorithms. This can help to reduce the computational intensity and time required to find the global optimum solution [2].

Therefore, integrating both local and global optimization algorithms can complement each other and provide a more comprehensive solution for joint inversion of seismic refraction and DC resistivity data. This integration can help to reduce the computational intensity and time required to find the global optimum solution, and it can also help to improve the accuracy and robustness of the inversion results [5].

1.2 Research Objectives

The main objective of this study is to improve the resolution of near-surface geologic features by applying data integration involving two geophysical methods, namely; seismic refraction, and direct current resistivity methods. In particular, my main goal is to evaluate the feasibility of applying both local and global optimization algorithms in joint parameter estimation techniques involving seismic refraction and direct current resistivity methods. In addition, I plan to apply hybrid optimization techniques (i.e., use of local optimization during global optimization solution), involving the two geophysical methods, which can run on a parallel computer to optimize the total joint inversion runtime. My specific objectives are as follows:

1. To formulate a joint inversion objective function involving seismic refraction and direct current resistivity methods.
2. To formulate the multi-parameter objective function for the global optimization solution.
3. To apply the optimum regularization parameters during the conventional (local) optimization algorithm to minimize the error function.

4. To apply a hybrid technique (i.e., using local optimization into the global optimization solution) by a genetic algorithm (GA) to search for the global minimum of the objective function.
5. To make the algorithm run on an HPC (High-Performance Computing) system optimizing the computational cost.
6. To apply all suggested methods for data integration to real data.

1.3 Research Questions

This study will provide answers to the following research questions:

- What is the feasibility of jointly estimating model parameters of the two geophysical methods, namely, direct current resistivity and seismic travel-time tomography using local or global (multi-objective algorithm) optimization codes?
- What are the benefits of using global or local optimization methods?
- Will there be any difference in the output between local and global optimization?
- How significant is this difference in terms of the percentage amount of anomaly reconstructed by both optimization techniques?
- How will each optimization algorithm perform in both simple and complex models?
- How can we improve the computational cost of global optimization method, using the genetic algorithm for this type of inverse problem?

1.4 Thesis Structure

The overview of this Ph.D. dissertation report is presented as follows:

Chapter 1 provides an overview of the research topic, presents the research questions and objectives, and outlines the significance of the study. The chapter also provides an overview of the research methodology, data sources from two geophysical methods, and the limitations of the study.

In chapter 2 I review relevant literature on the joint inversion of DCR and SR data, focusing on the principles and theory of the methods used in this study. The chapter also discusses the advantages and limitations of the different optimization algorithms, and provides an overview of previous case studies on the joint inversion of DCR and SR data.

A comprehensive study of the optimization methods used in this study is discussed in chapter 3. Specifically, this chapter presents a comprehensive study of the performance of different optimization algorithms and proposes a new combined optimization algorithm tested on synthetic DCR and SR data. The chapter compares the accuracy, speed, and convergence of local, global, and combined optimization methods, and provides recommendations on the best approach to use for the joint inversion of DCR and SR data.

In chapter 4 I discuss the application of combined local and global optimization algorithms using field direct current resistivity and seismic refraction datasets acquired from Dammam Dome, Eastern Saudi Arabia. The chapter describes the geological setting of the area, the data acquisition, and the processing of the data. The chapter then presents the results of the joint inversion using the combined local and global optimization algorithms and discusses the interpretation of the results.

In chapter 5 I present the methods and results of testing different stochastic methods to model direct current resistivity and seismic refraction data. Specifically, this chapter focuses on the testing of different stochastic methods to model DCR and SR data using the combined local and global optimization algorithms. The chapter compares the performance of the different stochastic methods and provides recommendations on the best approach to use for joint inversion of DCR and SR data in different geological settings.

Chapter 7 summarizes the main findings of the study and answers the research questions and objectives. The chapter also provides recommendations for future research on the joint inversion of DCR and SR data, and discusses the limitations of the study.

1.5 References

1. Al-Qahtani, A. (2011). Joint inversion of seismic refraction and electrical resistivity data. *Journal of Applied Geophysics*, 75(3), 546-551.
2. Chen, X., & Liu, Y. (2015). Joint inversion of seismic refraction and electrical resistivity data using particle swarm optimization algorithm. *Journal of Applied Geophysics*, 115, 1-10.
3. Han, J., & Li, Y. (2017). Joint inversion of seismic refraction and electrical resistivity data using an improved particle swarm optimization algorithm. *Arabian Journal of Geosciences*, 10(12), 563.
4. Liu, Y., & Liu, Y. (2017). Joint inversion of seismic refraction and electrical resistivity data using a modified particle swarm optimization algorithm. *Journal of Applied Geophysics*, 141, 22-31.
5. Zhang, Z., & Gao, S. (2015). Joint inversion of seismic refraction and electrical resistivity data using a hybrid particle swarm optimization and simulated annealing algorithm. *Journal of Applied Geophysics*, 120, 97-107.

CHAPTER 2

Literature Review

2.1 Techniques of Geophysical Inversion

The primary goal of inverting geophysical data is to estimate the parameters of a model that will give a theoretical response similar to the field observations [1,2]. However, it is unusual to have a unique solution since most geophysical inverse problems are ill-posed. Previous studies included regularization constraints in the objective function to solve the problem of instability [3–6]. In some cases, with a regularization term in the objective function, the inversion still faces the challenge of non-uniqueness (i.e., ambiguity) associated with the inverse problem. To reduce uncertainties related to the inversion of a dataset belonging to a single geophysical method, many researchers have applied the concept of joint inversion [7–16] of more than one method, which provides better model resolution than individual inversion [17–19]. Joint inversion can even resolve ambiguity associated with the geophysical method(s) applied in an area with low physical properties contrast [20–22]. Geophysical joint inversion tries to optimize a single objective function formed by a weighted or arithmetic sum of the individual objective functions of corresponding methods [23]. However, the issue of parametric coupling (i.e., model integration) arises when we are dealing with the inversion of datasets acquired with more than one geophysical method [24].

In this study, we apply the structural model coupling approach, which involves the cross-gradient constraint method that is commonly used for geophysical inversion [8]. The basic idea using this approach is that the gradients of relevant model parameters are spatially correlated. The cross-gradient approach has been adapted for the joint inversion of different geophysical data [13–16,25–29]. Wang et al. [17] applied the cross-gradient algorithm in a joint inversion involving both the controlled-source audio magnetotelluric (CSAMT) and magnetic methods. Demirci et al. [15]

formulated an objective function concerning weighted cross-gradient, which limits the dominance of one type of model parameter to another. Zhang et al. [30] utilized the cross-gradient constraint to impose a common structural framework in the joint inversion of EM and acoustic data, which reconstructs the structures satisfactorily.

Furthermore, Yin et al. [31] applied a cross-gradient technique to invert magnetotelluric (MT) and gravity data and tested their algorithm using both synthetic and real datasets. Finally, Jordi et al. [32] introduced a new approach to the crossgradient constraint, which involved the use of an irregular grid in unstructured mesh in the finite element method. They used the method to invert the DCR and ground penetrating (GPR) data. All the above examples used the conventional or local optimization method that incorporated all acquired data within the same Jacobian using a unique objective function for all geophysical methods.

2.2 Applicability of Geophysical Methods in Dammam Dome

Geophysical investigations are most effective in areas with sufficient subsurface geo-logical contrasts, such as layer boundaries and lateral changes, including fractured/faulted or, in general, deformed zones [33]. These contrasts create a specific geophysical response in the field observations (geophysical measurements) and are interpreted with respect to the geological setting of the survey area. Conceptually, the method(s) applied in geophysical exploration depends on the physical properties, the contrast between the anomalies and the surroundings, and the location/geometry of expected anomalies [34]. The Dammam Dome, which has been related to salt and tectonic processes since Jurassic and Cretaceous times [35–37], offers an opportunity to apply both Seismic Refraction (SR) and Direct Current Resistivity (DCR) geophysical methods. It should be mentioned that resistivity (DCR) and seismic methods are suggested as the optimum methods for natural resources exploration, engineering, and environmental purposes [33]. This area has been chosen as case study because extended earthworks are in progress for highway construction. As a

result, an open cutting of the Dammam Dome was exposed, providing a unique opportunity to apply the aforementioned geophysical methods and thus get an insight into the stratigraphy and the well-developed fracture system of the Dammam Dome, as reported by previous studies [35,38–41].

2.3 Features of Local and Global Optimization Methods

Most geophysical inverse problems are non-unique due to the ill-posedness of the problem, and as a result, they must be regularized to reduce inversion instability [42]. In most cases, a regularization term is added to the objective function. Starting from an initial model, usually based on a priori information from the study area, a vector containing corrections to the model parameters is iteratively calculated from the objective function and is used to update the model parameters using an appropriate local optimization algorithm. Sometimes the objective function could have several minima [42,43] that could challenge a local optimization algorithm. This is because the local optimization approaches search for the closest (depending on the starting model) minimum of the objective function [44], which may not necessarily be the global minimum. To overcome this challenge, global optimization methods are sometimes applied. The global optimization algorithms do not require the computation of derivatives, as in the case of the local optimization algorithm. Instead, the forward solution is used iteratively to estimate the value of an error function that needs to be minimized with iterations. Because the global optimization approaches are stochastic and/or heuristic, they mostly avoid being stuck in a local minimum of the error function. However, the global optimization methods require plenty of iterations to obtain an optimum solution using a population of candidate models. This challenge has limited their application, especially in geophysical inversion involving a large geophysical data set and even more when joint inversion or interpretation/modeling of geophysical set is considered. However, applying the global optimization method is becoming more popular with the availability of high-performance computing systems and hybrid techniques [45,46].

2.4 References

1. Oldenburg, D.W.; Ellis, R.G. Inversion of geophysical data using an approximate inverse mapping. *Geophys. J. Int.* **1991**, *105*, 325–353. <https://doi.org/10.1111/J.1365-246X.1991.TB06717.X>.
2. Oldenburg, D.W.; Li, Y. Inversion for Applied Geophysics: A Tutorial. In *Near-Surface Geophysics*; Society of Exploration Geophysicists: Houston, TX, USA, 2005; pp. 89–150.
3. Farquharson, C.G.; Oldenburg, D.W. A comparison of automatic techniques for estimating the regularization parameter in non-linear inverse problems. *Geophys. J. Int.* **2004**, *156*, 411–425. <https://doi.org/10.1111/j.1365-246X.2004.02190.x>.
4. Fomel, S. Shaping regularization in geophysical-estimation problems. *Geophysics* **2007**, *72*, R29. <https://doi.org/10.1190/1.2433716>.
5. Gheymasi, H.M.; Gholami, A. A local-order regularization for geophysical inverse problems. *Geophys. J. Int.* **2013**, *195*, 1288–1299. <https://doi.org/10.1093/GJI/GGT308>.
6. Gündoğdu, N.Y.; Demirci, İ.; Demirel, C.; Candansayar, M.E. Characterization of the bridge pillar foundations using 3d focusing inversion of DC resistivity data. *J. Appl. Geophys.* **2020**, *172*, 103875. <https://doi.org/10.1016/J.JAPPGEO.2019.103875>.
7. Haber, E.; Oldenburg, D. Joint inversion: A structural approach. *Inverse Probl.* **1997**, *13*, 63–77.
8. Gallardo, L.A.; Meju, M.A. Characterization of heterogeneous near-surface materials by joint 2D inversion of dc resistivity and seismic data. *Geophys. Res. Lett.* **2003**, *30*, 1658. <https://doi.org/10.1029/2003GL017370>.
9. Gallardo, L.A.; Meju, M.A. Joint two-dimensional cross-gradient imaging of magnetotelluric and seismic traveltime data for structural and lithological classification. *Geophys. J. Int.* **2007**, *169*, 1261–1272. <https://doi.org/10.1111/j.1365-246X.2007.03366.x>.
10. Linde, N.; Binley, A.; Tryggvason, A.; Pedersen, L.B.; Reil, A. Improved hydrogeophysical characterization using joint inversion of cross-hole electrical resistance and ground-penetrating radar traveltime data. *Water Resour. Res.* **2006**, *42*, W12404. <https://doi.org/10.1029/2006WR005131>.
11. Infante, V.; Gallardo, L.A.; Montalvo-Arrieta, J.C.; Navarro de León, I. Lithological classification assisted by the joint inversion of electrical and seismic data at a control site in northeast Mexico. *J. Appl. Geophys.* **2010**, *70*, 93–102. <https://doi.org/10.1016/j.jappgeo.2009.11.003>.
12. Moorkamp, M.; Heincke, B.; Jegen, M.; Roberts, A.W.; Hobbs, R.W. A framework for 3-D joint inversion of MT, gravity and seismic refraction data. *Geophys. J. Int.* **2011**, *184*, 477–493. <https://doi.org/10.1111/j.1365-246X.2010.04856.x>.
13. Hamdan, H.A.; Vafidis, A. Joint inversion of 2D resistivity and seismic travel time data to image saltwater intrusion over karstic areas. *Environ. Earth Sci.* **2013**, *68*, 1877–1885. <https://doi.org/10.1007/S12665-012-1875-9/FIGURES/6>.
14. Bennington, N.L.; Zhang, H.; Thurber, C.H.; Bedrosian, P.A. Joint Inversion of Seismic and Magnetotelluric Data in the Parkfield Region of California Using the Normalized Cross-

- Gradient Constraint. *Pure Appl. Geophys.* **2015**, 172, 1033–1052. <https://doi.org/10.1007/S00024-014-1002-9/FIGURES/11>.
15. Demirci, İ.; Candansayar, M.E.; Vafidis, A.; Soupios, P. Two dimensional joint inversion of direct current resistivity, radio-magnetotelluric and seismic refraction data: An application from Bafra Plain, Turkey. *J. Appl. Geophys.* **2017**, 139, 316–330. <https://doi.org/10.1016/j.jappgeo.2017.03.002>.
 16. Demirci, İ.; Dikmen, Ü.; Candansayar, M.E. Two-dimensional joint inversion of Magnetotelluric and local earthquake data: Discussion on the contribution to the solution of deep subsurface structures. *Phys. Earth Planet. Inter.* **2018**, 275, 56–68. <https://doi.org/10.1016/j.pepi.2018.01.006>.
 17. Wang, K.P.; Tan, H.D.; Wang, T. 2D joint inversion of CSAMT and magnetic data based on cross-gradient theory. *Appl. Geophys.* **2017**, 14, 279–290. <https://doi.org/10.1007/S11770-017-0615-Z>.
 18. Vozoff, K.; Jupp, D.L.B. Joint Inversion of Geophysical Data. *Geophys. J. Int.* **1975**, 42, 977–991. <https://doi.org/10.1111/j.1365-246X.1975.tb06462.x>.
 19. Autio, U.; Smirnov, M.Y.; Savvaidis, A.; Soupios, P.; Bastani, M. Combining electromagnetic measurements in the Mygdonian sedimentary basin, Greece. *J. Appl. Geophys.* **2016**, 135, 261–269. <https://doi.org/10.1016/j.jappgeo.2016.10.014>.
 20. Demirci, İ.; Gündoğdu, N.Y.; Candansayar, M.E.; Soupios, P.; Vafidis, A.; Arslan, H. Determination and Evaluation of Saltwater Intrusion on Bafra Plain: Joint Interpretation of Geophysical, Hydrogeological and Hydrochemical Data. *Pure Appl. Geophys.* **2020**, 177, 5621–5640. <https://doi.org/10.1007/s00024-020-02573-2>.
 21. Vafidis, A.; Soupios, P.; Economou, N.; Hamdan, H.; Andronikidis, N.; Kritikakis, G.; Panagopoulos, G.; Manoutsoglou, E.; Steiakakis, M.; Candansayar, E.; et al. Seawater intrusion imaging at Tybaki, Crete, using geophysical data and joint inversion of electrical and seismic data. *First Break* **2014**, 32, 107–114. <https://doi.org/10.3997/1365-2397.32.8.76970>.
 22. Shahrukh, M.; Soupios, P.; Papadopoulos, N.; Sarris, A. Geophysical investigations at the Istron archaeological site, eastern Crete, Greece using seismic refraction and electrical resistivity tomography. *J. Geophys. Eng.* **2012**, 9, 749–760. <https://doi.org/10.1088/1742-2132/9/6/749>.
 23. Linde, N.; Doetsch, J. Joint Inversion in Hydrogeophysics and Near-Surface Geophysics. In *Integrated Imaging of the Earth: Theory and Applications*; John Wiley & Sons: Hoboken, NJ, USA, 2016; pp. 117–135.
 24. Meju, M.A. Joint multi-geophysical inversion: Effective model integration, challenges and directions for future research. In *Proceedings of the International Workshop on Gravity, Electrical & Magnetic Methods and Their Applications*, Beijing, China, 10–13 October 2011; pp. 37–37. <https://doi.org/10.1190/1.3659078>.
 25. Athanasiou, E.N.; Tsourlos, P.I.; Papazachos, C.B.; Tsokas, G.N. Combined weighted inversion of electrical resistivity data arising from different array types. *J. Appl. Geophys.* **2007**, 62, 124–140. <https://doi.org/10.1016/J.JAPPGEO.2006.09.003>.
 26. Hu, W.; Abubakar, A.; Habashy, T.M. Joint electromagnetic and seismic inversion using structural constraints. *Geophysics* **2009**, 74, 1ND–Z107. <https://doi.org/10.1190/1.3246586>.

27. Bastani, M.; Hübert, J.; Kalscheuer, T.; Pedersen, L.B.; Godio, A.; Bernard, J. 2D joint inversion of RMT and ERT data versus individual 3D inversion of full tensor RMT data: An example from Trecate site in Italy. *Geophysics* **2012**, *77*, 1JA-Z106. <https://doi.org/10.1190/geo2011-0525.1>.
28. Gallardo, L.A.; Fontes, S.L.; Meju, M.A.; Buonora, M.P.; De Lugao, P.P. Robust geophysical integration through structure-coupled joint inversion and multispectral fusion of seismic reflection, magnetotelluric, magnetic, and gravity images: Example from Santos Basin, offshore Brazil. *Geophysics* **2012**, *77*, B237–B251. <https://doi.org/10.1190/geo2011-0394.1>.
29. Lochbühler, T.; Doetsch, J.; Brauchler, R.; Linde, N. Structure-coupled joint inversion of geophysical and hydrological data. *Geophysics* **2013**, *78*, ID1–ID14. <https://doi.org/10.1190/geo2012-0460.1>.
30. Zhang, Y.; Zhao, Z.; Nie, Z.; Liu, Q.H. Approach on Joint Inversion of Electromagnetic and Acoustic Data Based on Structural Constraints. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 7672–7681. <https://doi.org/10.1109/TGRS.2020.2983081>.
31. Yin, C.; Sun, S.; Liu, Y.; Ren, X.; Wang, C. Joint inversion of geophysical data and applications. In Proceedings of the Fifth International Conference on Engineering Geophysics, Al Ain, United Arab Emirates, 21–24 October 2019; pp. 232–235. <https://doi.org/10.1190/ICEG2019-059.1>.
32. Jordi, C.; Doetsch, J.; Günther, T.; Schmelzbach, C.; Maurer, H.; Robertsson, J.O.A. Structural joint inversion on irregular meshes. *Geophys. J. Int.* **2020**, *220*, 1995–2008. <https://doi.org/10.1093/GJI/GGZ550>.
33. Reynolds, J. An Introduction to Applied and Environmental Geophysics, 2nd ed.; Willey Blackwell: Hoboken, NJ, USA, 2011; ISBN 978-0-471-48535-3.
34. Anderson, N.; Ismail, A. A generalized protocol for selecting appropriate geophysical techniques. In Proceedings of the Geophysical Technologies for Detecting Underground Coal Mine Voids Forum, Lexington, KY, USA, 20–30 July 2013; pp. 28–30.
35. Hariri, M.M. Fractures system within Dammam Dome and its relationship to the doming process, Eastern Saudi Arabia. *Arab. J. Geosci.* **2014**, *7*, 4943–4956. [CrossRef]
36. Weijermars, R. Surface Geology, Lithostratigraphy and Tertiary Growth of the Dammam Dome, Saudi Arabia: A New Field Guide. *GeoArabia* **1999**, *4*, 199–226. [CrossRef]
37. Tranos, M.D.; Osman, M.S. Rus detachment in Dammam Dome, Eastern Saudi Arabia: A new soft-sediment structure as a ‘sensitive stress sensor’ for the Zagros collision. *Geol. Mag.* **2021**, 1–13. [CrossRef]
38. Steineke, M.; Harriss, T.; Parsons, K.; Berg, E. Geographic Map of the Western Persian Gulf Quadrangle, Kingdom of Saudi Arabia; US Geological Survey: Washington, DC, USA, 1958.
39. Tleel, J.W. Surface Geology of Dammam Dome, Eastern Province, Saudi Arabia. *Am. Assoc. Pet. Geol. Bull.* **1973**, *57*, 558–576. [CrossRef]

40. Hariri, M.; Abdullatif, O. Use of the GIS delineate lineaments from Landsat images, Dammam Dome, Eastern Saudi Arabia. In Proceedings of the XXII International Cartographic Conference (ICC2005), A Coruña, Spain, 9–16 July 2005.
41. Al-fahmi, M. Fractures of the Dammam Dome Carbonate Outcrops: Their Characterization, Development, and Implications for Subsurface Reservoirs. Master's Thesis, University of Massachusetts, Amherst, MA, USA, 2012.
42. Sen, M.K.; Stoffa, P.L. Global optimization methods in geophysical inversion; Cambridge University Press, 2013; ISBN 1139619519.
43. Oldenburg, D.W.; Li, Y. Inversion for Applied Geophysics: A Tutorial. In Near-Surface Geophysics; Society of Exploration Geophysicists, 2005; pp. 89–150.
44. Aleardi, M.; Pierini, S.; Sajeve, A. Assessing the performances of recent global search algorithms using analytic objective functions and seismic optimization problems. *Geophysics* 2019, 84, R767–R781, doi:10.1190/geo2019-0111.1.
45. Chunduru, R.K.; Sen, M.K.; Stoffa, P.L. Hybrid optimization methods for geophysical inversion. *Geophysics* 1997, 62, 1196–1207, doi:10.1190/1.1444220.
46. Soupios, P.; Akca, I.; Mpogiatis, P.; Basokur, A.T.; Papazachos, C. Applications of hybrid genetic algorithms in seismic tomography. *J. Appl. Geophys.* 2011, 75, 479–489, doi:10.1016/J.JAPPGEO.2011.08.005.

CHAPTER 3

Combined Optimization Methods

A Comprehensive Study of Local, Global, and Combined Optimization Methods on Synthetic Seismic Reflection and Direct Current Resistivity Data

Edigbue P., Demirci I., Akca I., Hamdan H.A., Kirmizakis P., Soupios P., Candansayar E., Hanafy S., Al-Shuhail A. A comprehensive study of local, global, and combined optimization methods on synthetic seismic refraction and direct current resistivity data. Applied Sciences. 2022 Nov 15;12(22):11589.

ABSTRACT

Most geophysical inversions face the problem of non-uniqueness, which poses a challenge in the mapping and delineation of the subsurface anomalies. To tackle this challenge, a combined local and global optimization approach is considered for jointly inverting two-dimensional direct current resistivity (DCR) and seismic refraction (SR) data that aim to estimate the corresponding physical model parameters. In this combined approach, the output of the local optimization method is used to determine the search space and tuning parameters for the global optimization algorithm. The multi-objective genetic algorithm (non-dominated sorting genetic algorithm) was utilized to jointly optimize the objective functions of two different methods. Because the genetic algorithm is a population-based optimization method, it requires numerous forward calculations. To deal with the expected high computational cost associated with this approach, parallel computing was utilized for the forward function evaluations to reduce the run time of the entire process. The proposed approach was tested using synthetic two-dimensional resistivity and velocity models that had three different types of anomalies (dyke, positive, and combined positive and negative). The results showed an improvement in the anomaly delineation in the output of the combined local and global optimization method compared with the local optimization method. Additionally, similar

synthetic models were tested using only the single objective global optimization algorithm (conventional global optimization), which showed promising anomaly delineation.

3.1 Introduction

Optimization methods play a crucial role in processing geophysical data and extracting meaningful information. They help to determine the model parameters that best fit the observed data and minimize the objective function, which measures the misfit between the observed and predicted data. The local optimization techniques are applied iteratively to obtain an updated model that minimizes the objective function, which may not be the global solution to the inverse problem. The global optimization algorithm in geophysical inversion might be used to search for a solution space to avoid being stuck in the local minimum of the objective function. For instance, Liu et al. [33] applied the particle swarm optimization (PSO) algorithm in a parametric inversion involving magnetic data. Rani et al. [34] used the genetic price algorithm (GPA) to monitor the movement of contaminants in the subsurface. Additionally, [35] introduced a hybrid approach by using the results of the local optimization method as an input to the genetic algorithm for the modeling of the SR data. This novel algorithm by [35] overcame the problem of being stuck in the local minima. It optimized the computational cost of the genetic algorithm using the multicore parallel computing method.

Similarly, local and global (hybrid) optimization has been applied to complement each other to subdue their shortcomings [35–37]. Most previous work has considered an objective function from a different perspective to perform joint inversion using a global optimization method, such as when using a local optimization algorithm. For instance, Schwarzbach et al. [38] and Ayani et al. [39] considered the objective function for the inversion of electromagnetic data in two terms. First, they tried to minimize the data misfit and the roughness of the model at the same time. Akca et al.

[40] applied a non-dominated sorting genetic algorithm in a joint 1D parametric inversion involving magnetic resonance and vertical electrical sounding.

In previous studies, joint inversion/interpretation was applied by using either local or global optimization methods. Moreover, local and global (hybrid) optimization has been applied to complement each other to subdue their shortcomings. However, based on our knowledge, the joint modeling of different geophysical data by using the results from the inversion (local optimization) to constrain the search space of the global optimization approach has never been reported in the literature. Thus, a procedure that constrains the global part of the combined optimization algorithm by using the local optimization to define a close search space to the real model parameters was proposed and designed. In this way, the search space of the model parameters has been limited to a more reliable range, drastically reducing the computation time.

This study presents the combined local and global optimization approach to jointly model SR and DCR data. With this proposed approach, the multi-objective (i.e., integration of the DCR and SR misfit functions) global optimization algorithm is used for the first time for the two-dimensional joint inversion of two different geophysical datasets, i.e., SR and DCR data. Specifically, in this algorithm, the global part of the combined optimization algorithm is constrained by using the output of the local optimization to define a search space, significantly improving its run time and mitigating model instability. In addition to the improved computational cost that resulted from applying the combined local and global optimization methods, we made the multi-objective global optimization algorithm run on parallel computing. This process further optimized the computational cost and devised the optimum technique using the combined optimization algorithm. We tested and discussed the efficacy of our pro-posed algorithm using synthetic SR and DCR data.

3.2 Optimization Methods

3.2.1 Local Optimization Method

The individual and joint inversion of DCR and SR data are usually regularized with a smoothing function due to the non-uniqueness and instability associated with the inverse process. In the inversion of both DCR and SR methods, the data misfit can be formulated as follows:

$$E(\mathbf{m}) = \|\mathbf{W}_d(\mathbf{d}_{obs} - \mathbf{f}(\mathbf{m}))\|^2, \quad (1)$$

$\mathbf{f}(\mathbf{m})$ is a function that is used to describe forward modeling, $\mathbf{d}_{obs}$ is the observed field record, and $\mathbf{W}_d$ is the weight matrix used to adjust the data anomaly (e.g., high or low amplitudes). Usually, we use norms to quantify the misfit between the observed and calculated data, and the common one used for this type of inverse problem is the L_2 norm because we assume that the error in the data is Gaussian. Therefore, the objective functions for the DCR and SR data are given as follows:

$$\Phi(\mathbf{m}_{dc}) = \|\mathbf{W}_{dc}(\mathbf{d}_{dc} - \mathbf{f}_{dc}(\mathbf{m}_{dc}))\|^2 + \alpha_{dc}\|\nabla^2\mathbf{m}_{dc}\|^2 \quad (2)$$

$$\Phi(\mathbf{m}_{sr}) = \|\mathbf{W}_{sr}(\mathbf{d}_{sr} - \mathbf{f}_{sr}(\mathbf{m}_{sr}))\|^2 + \alpha_{sr}\|\nabla^2\mathbf{m}_{sr}\|^2 \quad (3)$$

where Φ is the misfit or objective function, $\mathbf{d}_{dc}$ and $\mathbf{d}_{sr}$ are the measured data, and $\mathbf{f}_{dc}$ and $\mathbf{f}_{sr}$ is the model response for the DCR and SR methods, respectively. Additionally, $S = \|\nabla^2\mathbf{m}_{sr}\|^2$ is the Laplacian of the model parameter that is transformed into the smoothness matrix by obtaining its Laplacian operator, while α_{dc} and α_{sr} are the regularization parameters that determine the level of the smoothness of resistivity and seismic models, respectively. The joint inversion offers conventional ways of integrating data from different geophysical methods in such a manner that the outcome models are consistent and similar. One of the methods used to accomplish this goal is to apply the cross-gradient constraint proposed by Gallardo et al. [8] in the objective function. The parallel spatial variation in the models (resistivity or seismic velocity) is required to satisfy the cross-gradient constraint [8,13,15]. This means that model anomalies or layer boundaries must

essentially point in the same or opposite direction. Applying the cross-gradient constraint, Equations (2) and (3) become:

$$\Phi(\mathbf{m}_{dc}, \mathbf{m}_{sr}) = \left\| \begin{matrix} \mathbf{W}_{dc}(\mathbf{d}_{dc} - \mathbf{f}_{dc}(\mathbf{m}_{dc})) \\ \mathbf{W}_{sr}(\mathbf{d}_{sr} - \mathbf{f}_{sr}(\mathbf{m}_{sr})) \end{matrix} \right\|^2 + \frac{\alpha_{dc}}{\alpha_{sr}} \left\| \frac{\nabla^2 \mathbf{m}_{dc}}{\nabla^2 \mathbf{m}_{sr}} \right\|^2 + \vec{c} \left\| \frac{\mathbf{m}_{dc}}{\mathbf{m}_{sr}} \right\|^2 \quad (4)$$

subject to $\vec{c}(\mathbf{m}_{dc}, \mathbf{m}_{sr}) = \vec{0}$. Where $\vec{c}(\mathbf{m}_{dc}, \mathbf{m}_{sr})$ is the cross-gradient constraint and can be defined as:

$$\vec{c}(\mathbf{m}_{dc}, \mathbf{m}_{sr}) = \nabla \mathbf{m}_{dc}(x, z) \times \nabla \mathbf{m}_{sr}(x, z) \quad (5)$$

Equation (4) can be minimized by applying the appropriate regularized local optimization algorithm similar to the approach used in [15]. Therefore, the model parameter correction vector can be expressed as:

$$\Delta \mathbf{m} = \mathbf{G}^{-1} \mathbf{n} - \mathbf{G}^{-1} \mathbf{B}^T (\mathbf{B} \mathbf{G}^{-1} \mathbf{B}^T)^{-1} [\mathbf{B} \mathbf{G}^{-1} \mathbf{n} - \mathbf{B} \Delta \mathbf{m}_{i-1} + \vec{c}(\mathbf{m}_{i-1})] \quad (6)$$

where $\mathbf{G}$ and $\mathbf{n}$ are defined as:

$$\mathbf{G} = (\mathbf{J}^T \mathbf{W}^T \mathbf{W} \mathbf{J} + \alpha \mathbf{C}^T \mathbf{C}) \quad (7)$$

$$\mathbf{n} = (\mathbf{J}^T \mathbf{W}^T \mathbf{W} \mathbf{R} - \alpha \mathbf{C}^T \mathbf{C} \mathbf{m}^{i-1}) \quad (8)$$

In Equations (7) and (8), $\mathbf{J}$ is the Jacobean matrix, $\mathbf{W}$ is the weighting matrix, $\mathbf{R}$ is the data residual, $\mathbf{C}$ is the Laplacian operator, and $\mathbf{B}$ is the cross-gradient derivative. The terms given in Equations (7) and (8) may be rewritten for the joint inversion case as follows:

$$\Delta \mathbf{m} = \begin{bmatrix} \Delta \mathbf{m}_{res} \\ \Delta \mathbf{m}_{seis} \end{bmatrix}, \quad \mathbf{G} = \begin{bmatrix} \mathbf{G}_{res} & 0 \\ 0 & \mathbf{G}_{seis} \end{bmatrix}, \text{ and } \mathbf{n} = \begin{bmatrix} \mathbf{n}_{res} \\ \mathbf{n}_{seis} \end{bmatrix} \quad (9)$$

In this inversion approach, a resistivity model is created for the DCR method, while for the slowness model, the inverse of velocity is used for the SR method [15]. Conceptually, the joint inversion process requires the model discretization for all the geophysical methods to be structurally similar.

3.2.2 Global Optimization Method

The global optimization method applied in this study involves the application of the genetic algorithm (GA) for a single objective function case and non-dominated sorting genetic algorithm 2 (NSGA II) for the multi-objective joint optimization approach. The GA is a special case of evolutionary algorithm that simulates the process of biological evolution, and it is adapted to solve an optimization problem [41–43]. The process of the genetic algorithm starts from population initialization, which creates chromosomes (potential solutions with respect to the objective function) using the binary coding scheme. The binary coding scheme is conceptualized in a way that it constitutes a solution to the objective function of the inverse problem [43]. The binary coding system has a bit string or chromosome that describes each element or individual in the population. Each bit in the bit string represents a gene that can be assigned values of 0 or 1, also known as an allele [43]. Two individuals or parents are paired or selected from the initial population to produce two offspring. The higher the fitness value of an individual in the population, the higher the chance of being selected and the better its performance in the evolution loop. Among other selection methods, we apply the tournament selection because it practically depicts natural competition for mating rights among individuals in a population. Crossover involves exchanging information (genetic properties) between two paired models (parents) to create two new models (offspring). Three types of crossover options are available in the code used in this study: single point, two points, and scattered crossover. The final evolution operator used in the genetic algorithm is the mutation. This is the random alteration of genes in a chromosome to introduce diversity in the entire population of the genetic algorithm. This process is usually conducted using a probability index that is appropriately chosen based on the degree of randomness to be allowed and computation cost. The process described above is generally referred to as a single objective genetic algorithm; it is suitable for the inverse problem having one objective function (i.e., applied in the individual

inversion of DCR or SR). All these GA evolution operators (i.e., selection, crossover, and mutation) are used to modify the solution parameters.

As mentioned above, the non-dominated sorting genetic algorithm 2 (NSGA II) is a variant of the GA commonly used to solve multi-objective optimization problems. The NSGA II procedures involve the creation of an offspring population (Q_t) that has an equal size to the initial population (P_t) using the selection, crossover, and mutation processes as shown in Figure 1. After that, (Q_t) and (P_t) are combined to produce (R_t), which is double the size of (P_t). Then, the non-domination (i.e., the optimum set of solutions in all the objective functions) sorting of the entire population (R_t) is performed, and the best non-dominated solutions are selected, which are indicated as $F_1, F_2, \text{ and } F_3$ (levels of non-domination) in Figure 1. The topmost non-dominated solutions are accepted until the initial population size is reached; thereafter, the rest of the non-dominated solutions are rejected because the process cannot accept more than the initial population size. Sometimes only F_1 can satisfy the initial population size requirement, and that will be enough for the next generation (P_{t+1}); then, the rest are rejected (Figure 1). Consequently, the NSGA-II emphasizes both the non-dominated and less crowded points.

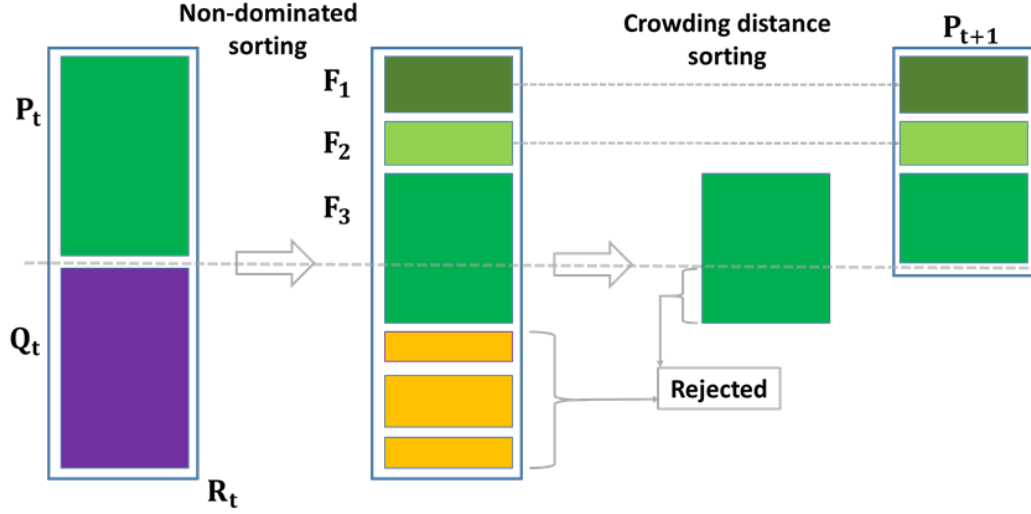


Figure 3.1: Illustration of the non-dominated sorting algorithm 2 (NSGA II). Q_t is the offspring population; P_t is the initial population; R_t is the total population; and F_1 , F_2 , and F_3 are the levels of non-domination solutions.

One of the major challenges in applying the genetic algorithm to the inverse problems that require the simultaneous optimization of more than one objective function is preventing the domination of one objective function to another. Therefore, the multi-objective genetic algorithm was used to search for the optimum solutions that do not dominate (i.e., a set of optimum solutions in both DCR and SR objective functions) each other. The two objectives of the joint inversion of DCR and SR data using the multi-objective global optimization method can be represented similar to Equation (1) as:

$$GA(\mathbf{m}_{dc}) = \|\mathbf{w}_{dc}(\mathbf{d}_{dc} - \mathbf{f}_{dc}(\mathbf{m}_{dc}))\|^2 \quad (10)$$

and

$$GA(\mathbf{m}_{sr}) = \|\mathbf{w}_{sr}(\mathbf{d}_{sr} - \mathbf{f}_{sr}(\mathbf{m}_{sr}))\|^2 \quad (11)$$

The objective functions are used to map the decision variables (model parameters) into an objective space where we delineate solutions that are not dominated or perform optimally in both objectives. These sets of solutions (Pareto sets) align in a pattern known as Pareto optimal solutions or the Pareto front [44]. Basically, the term ‘‘Pareto optimality’’ is used to describe these sets of

solutions, implying that no further optimal solution in both objectives can be obtained. Details about the concept of Pareto optimality and non-domination is discussed by [12]. The NSGA II algorithm sorts the set of solutions as they arrive at the Pareto optimal front. This technique was proposed by [45] to overcome some of the limitations observed in some previous evolutionary multi-objective algorithms. These limitations include computational intricacy, elitism problems, and parameter sharing specifications. The NSGA II only utilizes standard parameters of the genetic algorithm needs, and no extra parameters are needed for its multi-objective base optimization (see the appendix section for the concept of NSGA II).

3.2.3 Combined Local and Global Optimization Method

In the combined optimization algorithm, we used the output of the local optimization method to define the search space for the global optimization technique to speed up and reach the global solution faster. Since the local optimization has been constrained by smoothing terms (i.e., second terms of Equations (2) and (3)), the combined optimization algorithm is linearly constrained by applying the output of the local optimization algorithm to define the lower and upper bounds of the search space. Fundamentally, the search space is determined by modifying the range (minimum and maximum) of the model parameters obtained from the output of the local optimization algorithm. Depending on the quality of the output from the local optimization algorithm, scaling the model parameters up and down by 10 to 30% is recommended to obtain a good result. The variability (10–30%) of the model parameters was selected based on the expected variation in the modeled geophysical properties, such as velocity and resistivity, in Saudi Arabia. This process creates adequate diversity in the initial population for the global optimization algorithm. A flowchart illustrating the combined local and global optimization algorithm is shown in Figure 2. The summary of all terms we used to describe the combined optimization algorithms is presented in Table 1.

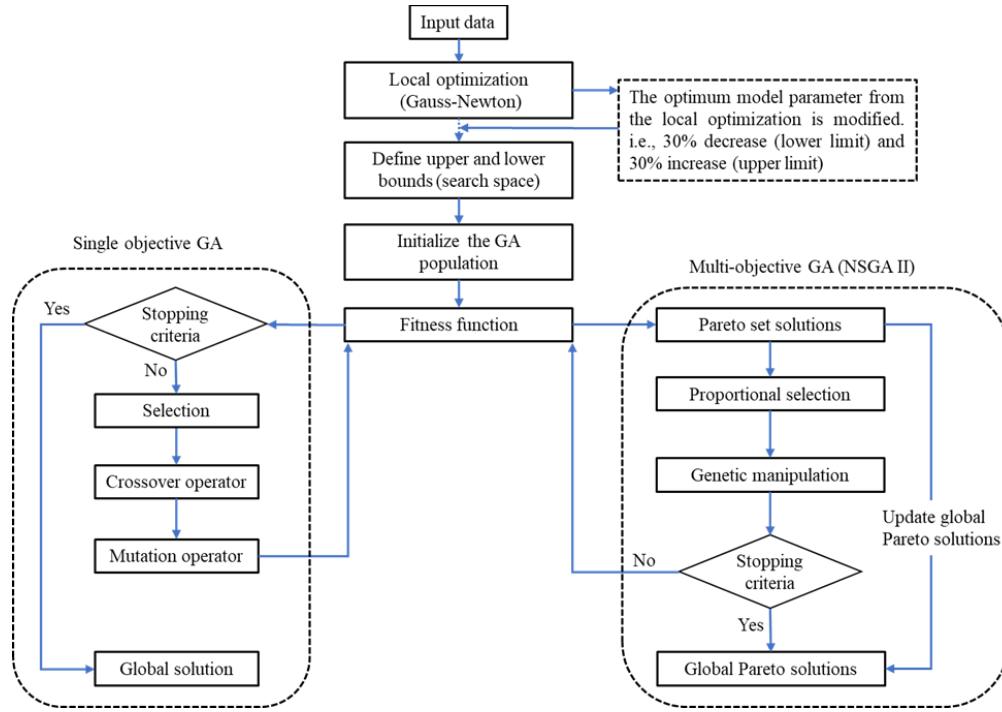


Figure 3.2: Flowcharts of the proposed combined local and global optimization algorithm.

Table 3.1: A summary of all the types of inversion applied in this study, their description, and abbreviations are presented below.

S/N	Inversion Type	Abbreviation	Description
1	Local optimization method	LOM	Optimization involves the derivatives of the objectives, e.g., Gauss–Newton.
2	Global optimization method	GOM	Non-derivation optimization, e.g., genetic algorithm.
3	Individual inversion method	IIM	Inversion of a dataset from one geophysical method using the local optimization, e.g., SR data inversion.
4	Joint inversion method	JIM	Inversion of datasets from more than one geophysical method using the local optimization, e.g., SR and DCR data inversion.
5	Single-objective optimization	SOO	Processing of a dataset from one geophysical method using global optimization, e.g., SR data inversion.
6	Multi-objective optimization	MOO	Processing of dataset from more than one geophysical method using global optimization, e.g., SR and DCR data inversion.
7	Combined (local plus global) optimization method	CGO	Inversion of a dataset from either one or more geophysical methods using the combination of local (to define a search space) with global optimization, e.g., DCR, or SR and DCR data inversion.
8	(Global conventional) optimization method	GOM	Processing a dataset from either one or more geophysical methods using only the global optimization, e.g., DCR, or SR and DCR data inversion.

3.3 Synthetic Test

3.3.1 Synthetic Data

We examined the feasibility of the combined global optimization (CGO) algorithm by using synthetic earth models that simulated three near-surface scenarios. The first model comprised a dyke anomaly with a resistivity of 1250 ohm-m and a two-layered host environment with resistivities of 50 ohm-m and 250 ohm-m. Similarly, a dyke anomaly having a velocity of 2200 m/s and a two-layered host environment with layer velocities of 1000 m/s and 1500 m/s, respectively, was used for the corresponding velocity model (Figure 3a,d). The second model contained two blocks of positive anomalies, having a resistivity of 250 ohm-m and velocity of 2000 m/s, which was greater than the host environment as shown in Figure 3b,e. The third model was similar to the second one, with a higher parameter contrast (higher and lower than the host model anomalies) compared with the host rock, where the block parameters were set as 1250 ohm-m, 2500 m/s (Figure 3c,f). Generally, these models had the same profile length of 240 m in both methods, with a depth of 50 m in the DCR and 60 m in the SR methods. The DCR data were calculated for a setup with equally spaced 49 electrodes 5 m apart using the dipole–dipole (DD) array. The DD array was selected, since it had a fair penetration depth and a very good to excellent lateral resolution. The seismic survey layout was similar to the DCR profile, where we used 49 receivers with 5m spacing and 13 sources with 20m intervals in the SR forward calculations.

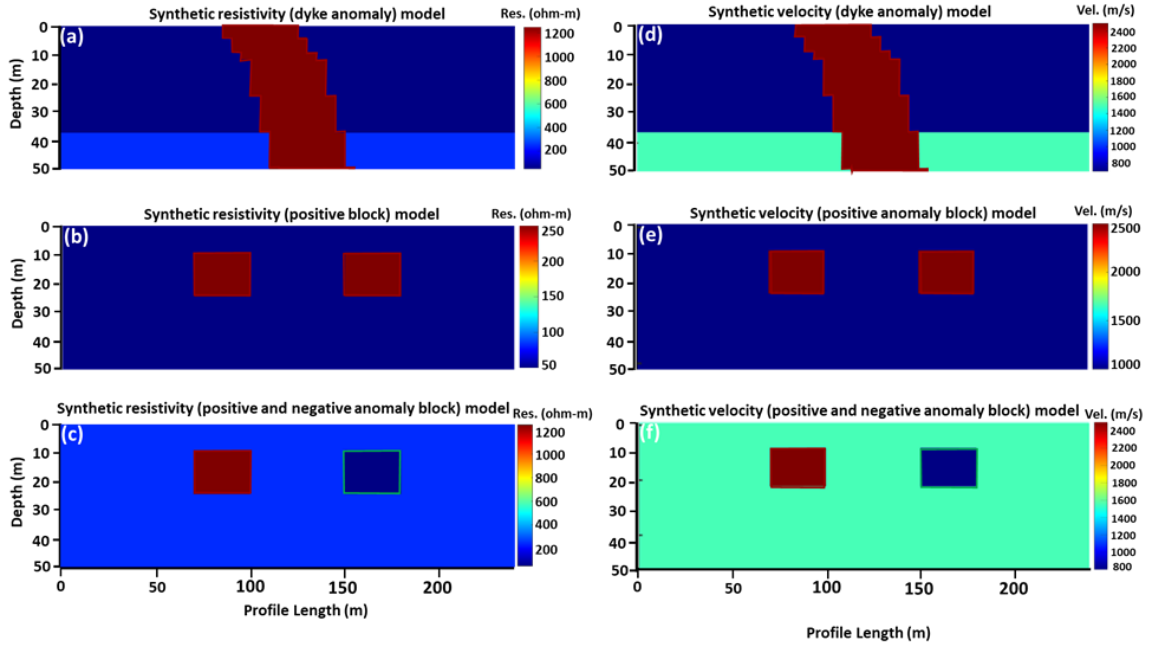


Figure 3.3: Synthetic models for (a) resistivity (dyke anomaly) model, (b) resistivity (positive anomaly) model, (c) resistivity (positive and negative anomalies) model, (d) velocity (dyke anomaly) model, (e) velocity (positive anomaly) model, and (f) velocity (positive and negative anomalies) model. The dark red and green lines are used to mark the anomaly boundaries.

3.3.2 Synthetic Results

To obtain good local optimization (LOM) results, an appropriate regularization parameter was used in addition to adding the smoothing term in the objective function [46,47]. The regularization parameter was determined by obtaining the maximum value of the diagonal matrix in the singular value decomposition of the Jacobian matrix in both the individual and joint inversion of the DCR and SR data. The value of the regularization parameter was modified using a cooling approximation at each iteration. The inversion process started with the initial guess of the model parameters that improved with each iteration. This procedure was used to estimate the model parameter correction vector as applied by [15] and [16]. The LOM was terminated when there was no decrease in error and the RMS dropped below a certain threshold value (convergence criteria). In the combined global optimization (CGO) techniques, a forward modeling algorithm was used to

estimate the theoretical data in both DCR and SR methods; thereafter, the calculated data were compared to the observed field data to compute their misfits. The data misfit (from Equations (10) and (11)) for the DCR method is presented in a simplified form as:

$$M_{dc} = \frac{100 \times \mathbf{W}_{dc} \times (\|d_{dc} - td_{dc}\|_2)}{\|d_{dc}\|_2} \quad (12)$$

where d_{dc} is the observed real data, $\mathbf{W}_{dc}$ is the weighting matrix of the real data, and td_{dc} is the theoretical data. The misfit function for the SR method is defined with a similar annotation as:

$$M_{sr} = \frac{100 \times \mathbf{W}_{sr} \times (\|d_{sr} - td_{sr}\|_2)}{\|d_{sr}\|_2} \quad (13)$$

The combined misfits form the objective function for the multi-objective optimization algorithm that is represented as:

$$M_{dc\ sr} = [M_{dc} \ M_{sr}] \quad (14)$$

Notice that for the multi-objective (MOO) algorithm in Equation (14), the individual misfits are not added together but are simply concatenated to make a two-column matrix of the misfits. In addition, selecting the number of populations and generations is important to improve the model resolution in the CGO algorithm for both methods. Conventionally, the population size of 50 is recommended for the GA, with the number of decision variables less than or equal to five. Otherwise, 200 populations should be used when the decision variable is greater than five. The CGO algorithm is terminated when the average change in the spread of Pareto solutions is less than the function tolerance (i.e., 1×10^{-4} for multi-objective optimization, MOO) and the specified number of generations (i.e., for single objective optimization, SOO).

The single objective genetic algorithm runs between 1000 and 1500 generations with an average population size of 250 individuals in both DC-resistivity and SR methods. The SR genetic algorithm runs were completed in about 748, 876, and 1194 min for the dyke, positive, and combined positive–negative anomalies synthetic models, respectively, while the processing times

were measured as 176, 181, and 150 min for DC data. After applying the single objective (SOO) genetic algorithm in both geophysical methods (DCR and SR) separately, we performed the joint parameter estimation using the multi-objective (MOO) genetic algorithm. The non-dominated sorting genetic algorithm (NSGA II) used in the multi-objective global optimization showed that there were feasible solutions depicted by their Pareto optimal fronts (Figure 4). The compromised solution (the green star in Figure 4) was chosen and presented as the output of the MOO method. The NSGA II (for both geophysical methods) ran for about 3136, 2953, and 2891 min for the dyke, positive, and the combined positive and negative anomalies synthetic models, respectively. Figures 5–10 show the results of the local and combined optimization methods for the dyke anomaly model (Figures 5 and 6), positive anomaly (Figures 7 and 8), and the positive and negative anomaly models (Figures 9 and 10). The first column of each of the figures contains the inverted resistivity models, while the second column is the inverted velocity models. In addition, the first row in each figure contains the synthetic models, the second row is the individual (IIM)/single objective (SOO) inverted models, and the third row is the joint (JIM)/multi-objective (MOO) inverted models.

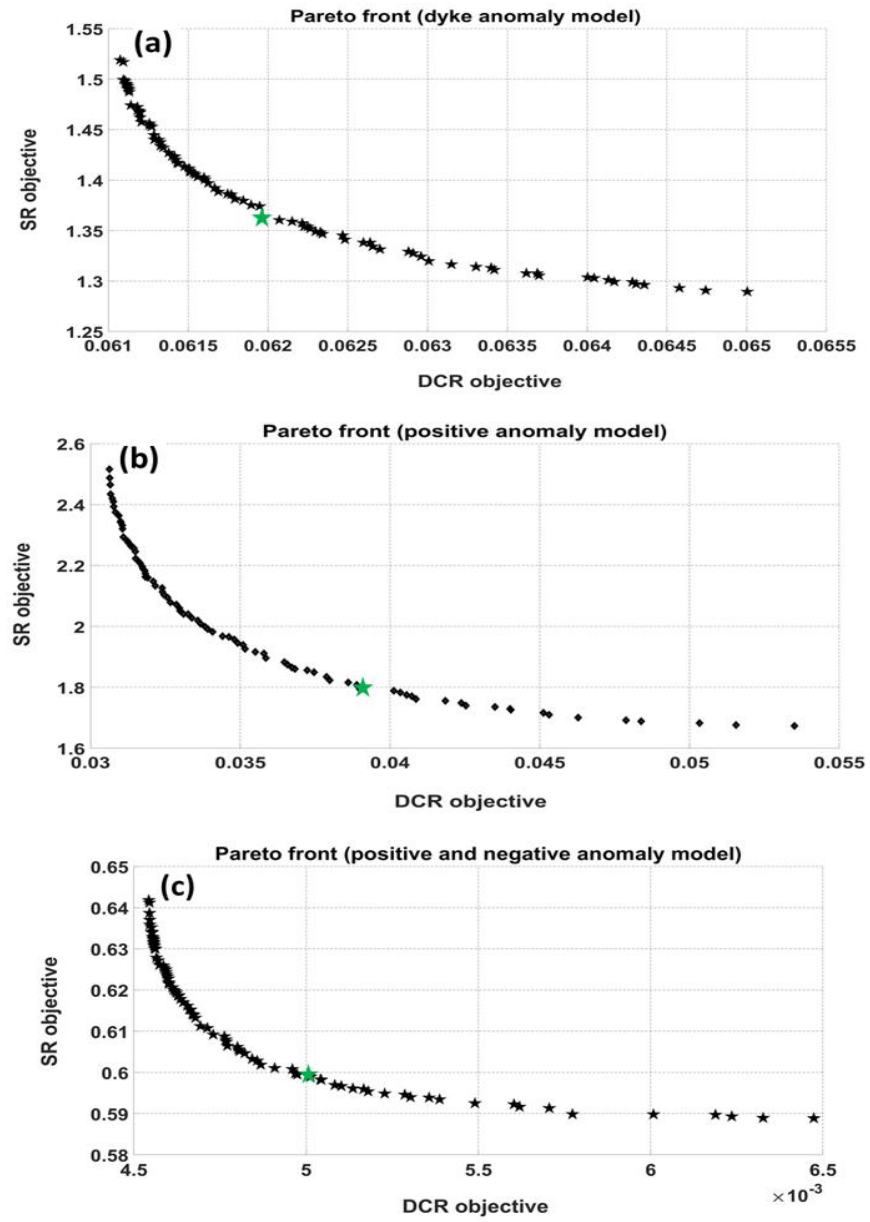


Figure 3.4: Plots of the Pareto fronts showing the compromise solution (green star shape) for (a) a dyke anomaly model, (b) a positive anomaly model, and (c) positive and negative anomalies model.

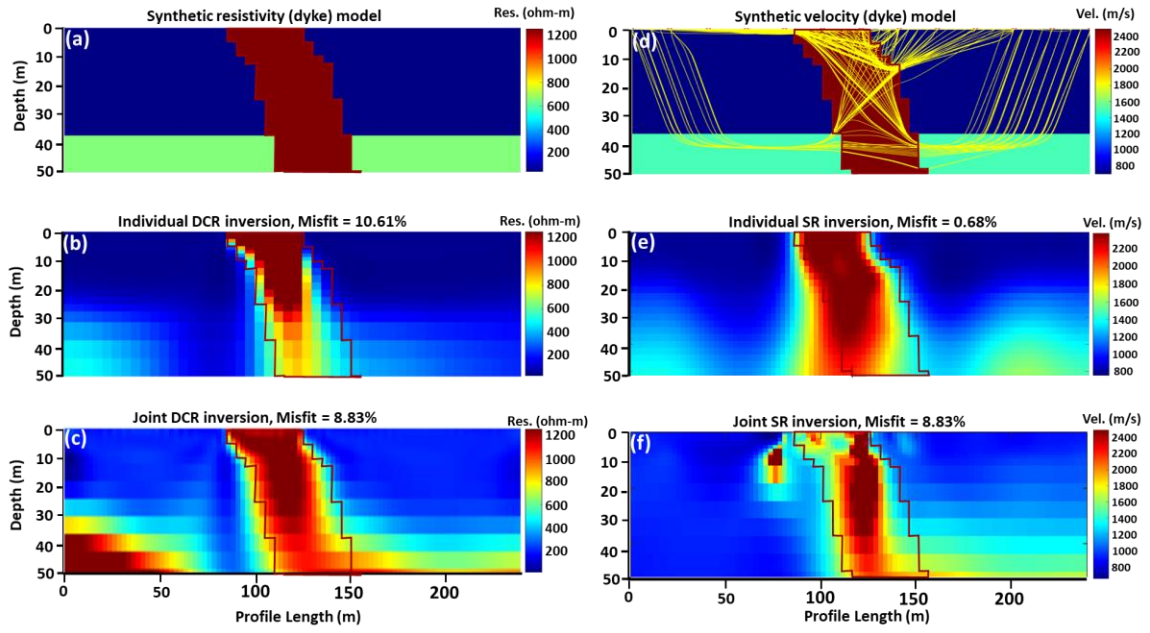


Figure 3.5: Dyke anomaly model inversion using local optimization method; (a) synthetic dc-resistivity model, (b) individual inverted resistivity model, (c) joint inverted resistivity model, (d) synthetic velocity model and its ray path coverage, (e) individual inverted velocity model, (f) joint inverted velocity model. The dark red line is used to mark the anomaly boundary.

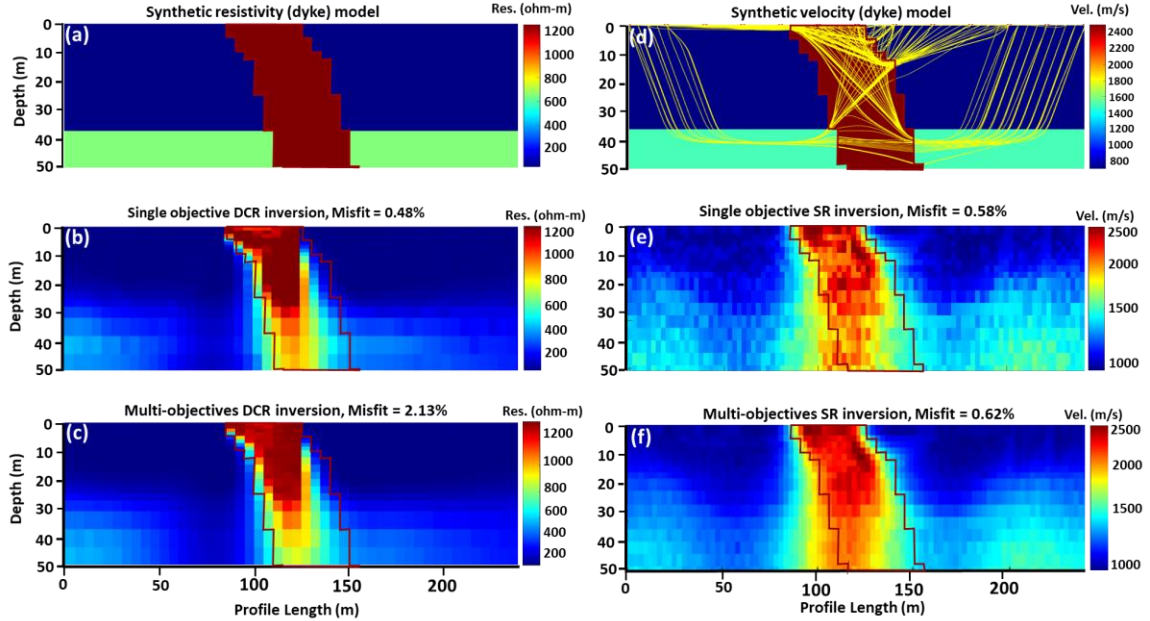


Figure 3.6: Dyke anomaly model inversion using combined optimization method; (a) synthetic dc-resistivity model, (b) single objective inverted resistivity model, (c) multi-objective inverted resistivity model, (d) synthetic velocity model and its ray path coverage, (e) single objective

inverted velocity model, and (f) multi-objective inverted velocity model. The dark red line is used to mark the anomaly boundary.

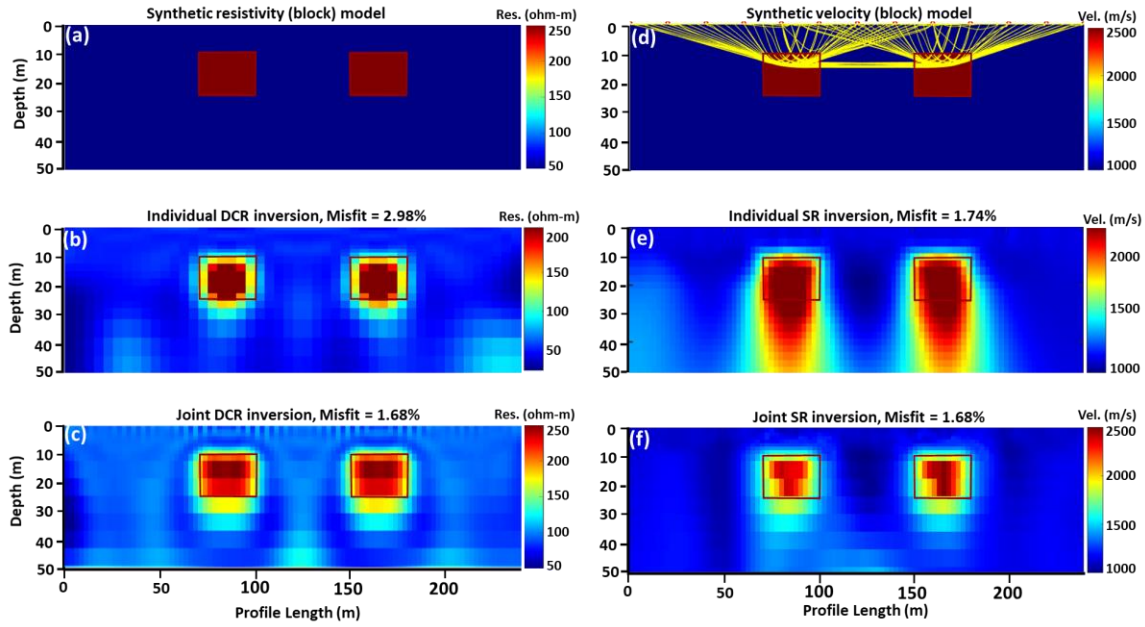


Figure 3.7: Positive anomaly model inversion using local optimization method; (a) synthetic dc-resistivity model, (b) individual inverted resistivity model, (c) joint inverted resistivity model, (d) synthetic velocity model and its ray path coverage, (e) individual inverted velocity model, and (f) joint inverted velocity model. The dark red line is used to mark the anomaly boundary.

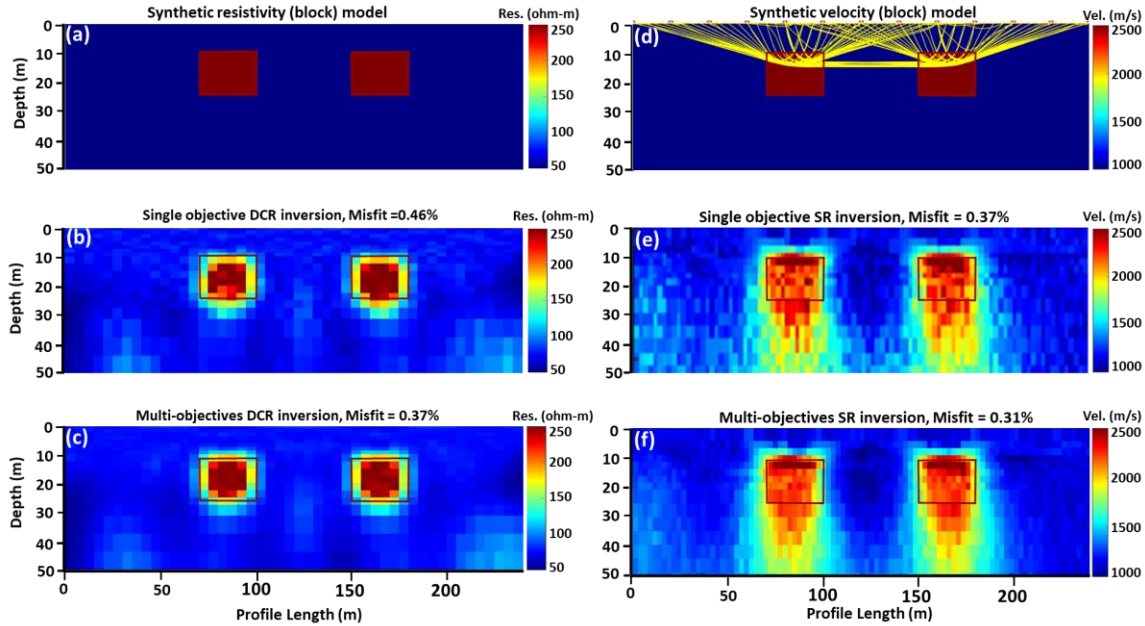


Figure 3.8: Positive anomaly model inversion using combined optimization method; (a) synthetic dc-resistivity model, (b) single objective inverted resistivity model, (c) multi-objective inverted

resistivity model, (d) synthetic velocity model and its ray path coverage, (e) single objective inverted velocity model, and (f) multi-objective inverted velocity model. The dark red line is used to mark the anomaly boundary.

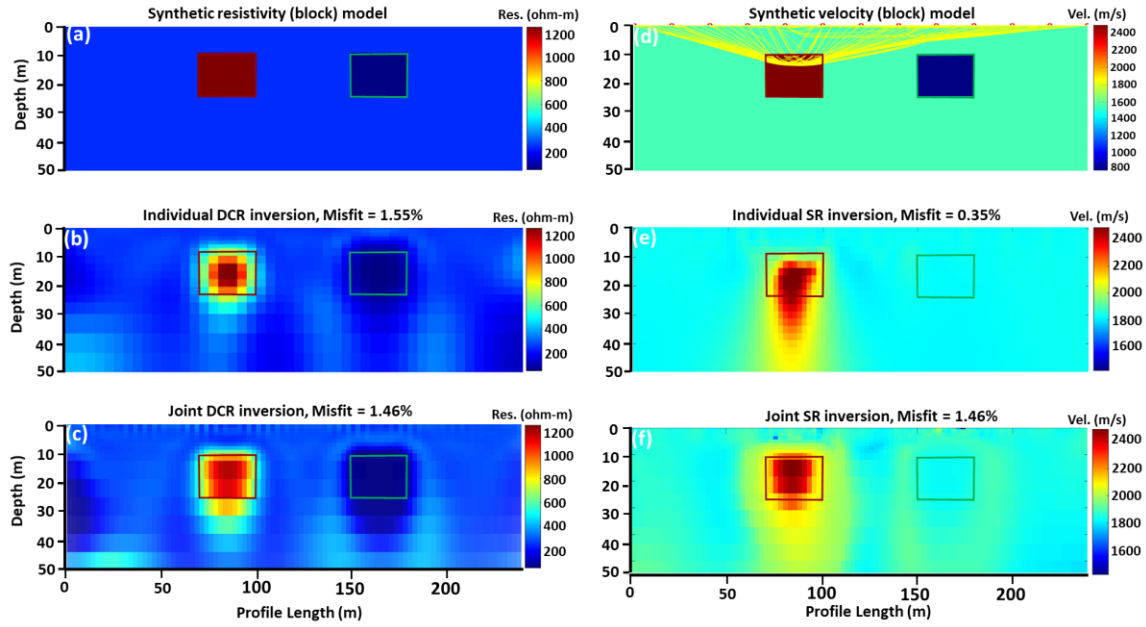


Figure 3.9: Positive and negative anomaly model inversion using local optimization method; (a) synthetic dc-resistivity model, (b) individual inverted resistivity model, (c) joint inverted resistivity model, (d) synthetic velocity model and its ray path coverage, (e) individual inverted velocity model, and (f) joint inverted velocity model. The dark red and green lines are used to mark the anomaly boundary.

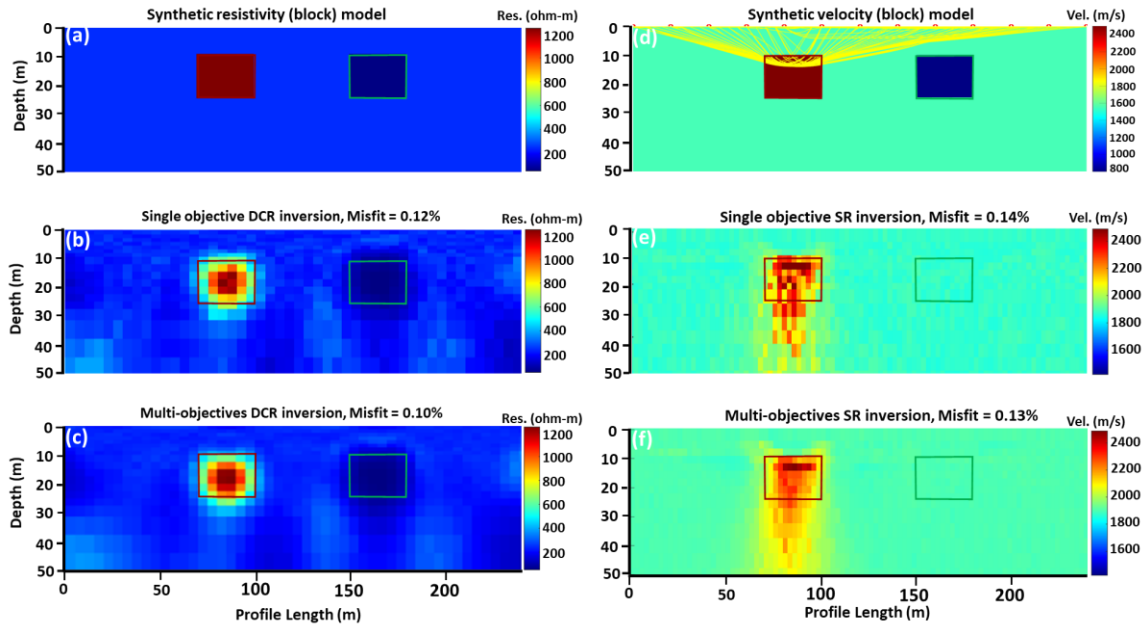


Figure 3.10: Positive and negative anomaly model inversion using the combined optimization method; (a) synthetic dc-resistivity model, (b) single objective inverted resistivity model, (c) multi-objective inverted resistivity model, (d) synthetic velocity model and its ray path coverage, (e) single objective inverted velocity model, and (f) multi-objective inverted velocity model. The dark red and green lines are used to mark the anomaly boundary.

To see the performance of the conventional global optimization (GOM) only using a similar misfit function as applied in the CGO method, we applied the genetic algorithm with a search space defined apart from the local optimization results using the same DCR and SR synthetic models. Applying the single objective genetic GOM algorithm to the resistivity model showed that the GOM technique provided unstable solutions in delineating both DCR and SR anomalies. For example, Figures 11–14 are the outputs of the genetic algorithm application on the dyke anomaly model (for both DCR and SR), the positive anomaly model, and the combined positive and negative anomaly model (for DCR only). Some of the artifacts observed in the results could probably be attributed to the absence of a constraint or model regularization [38]. The genetic algorithm was applied for 200 generations in the case of the SR method and 2500 generations for all DCR models inversion with

a population size of ten times the amount of model parameters [35] in both geophysical methods. This inversion is feasible with the use of high performance and parallel computing (HPPC).

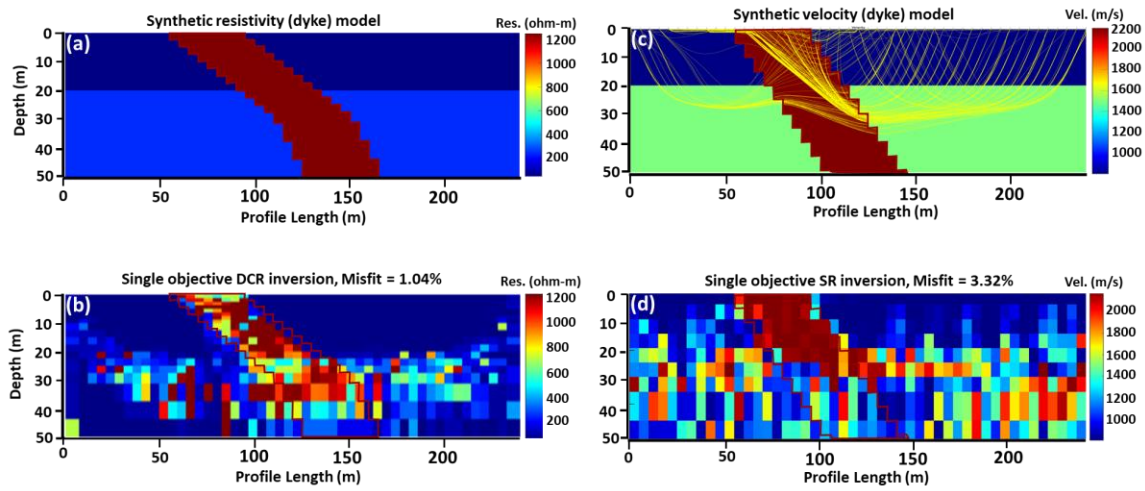


Figure 3.11: Dyke anomaly model inversion using the single objective global optimization method; (a) synthetic dc-resistivity model, (b) single object inverted resistivity model, (c) synthetic velocity model, and (d) single objective inverted velocity model. The dark red line is used to mark the anomaly boundary.

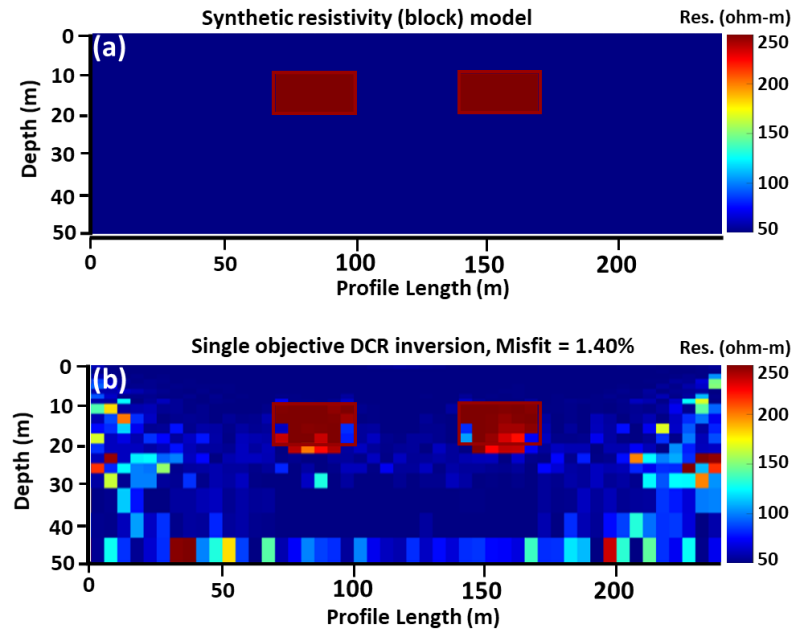


Figure 3.12: Positive anomaly model inversion using the single objective global optimization method; (a) synthetic dc-resistivity model and (b) single object inverted resistivity model. The dark red line is used to mark the anomaly boundary.

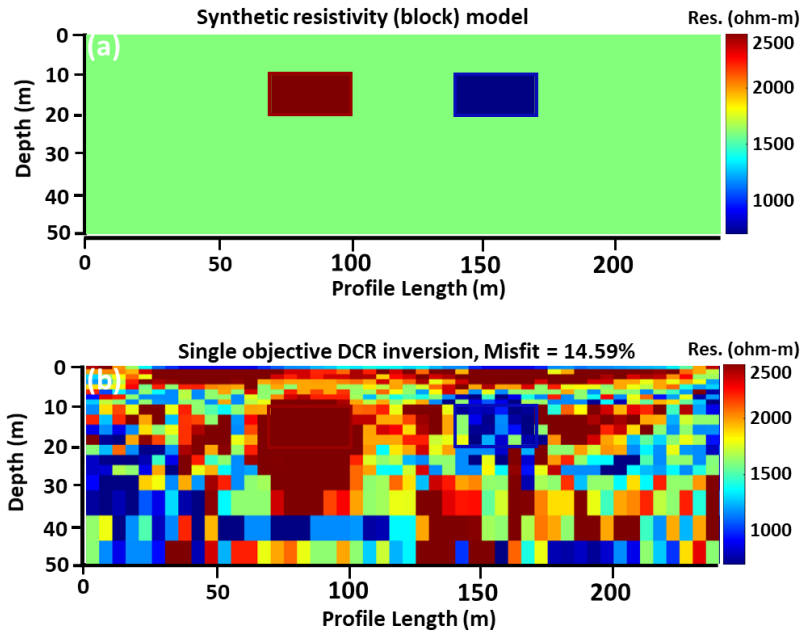


Figure 3.13: Positive and negative anomaly model inversion using the single objective global optimization method; (a) synthetic dc-resistivity model and (b) single object inverted resistivity model. The dark red/blue lines are used to mark the anomaly boundary.

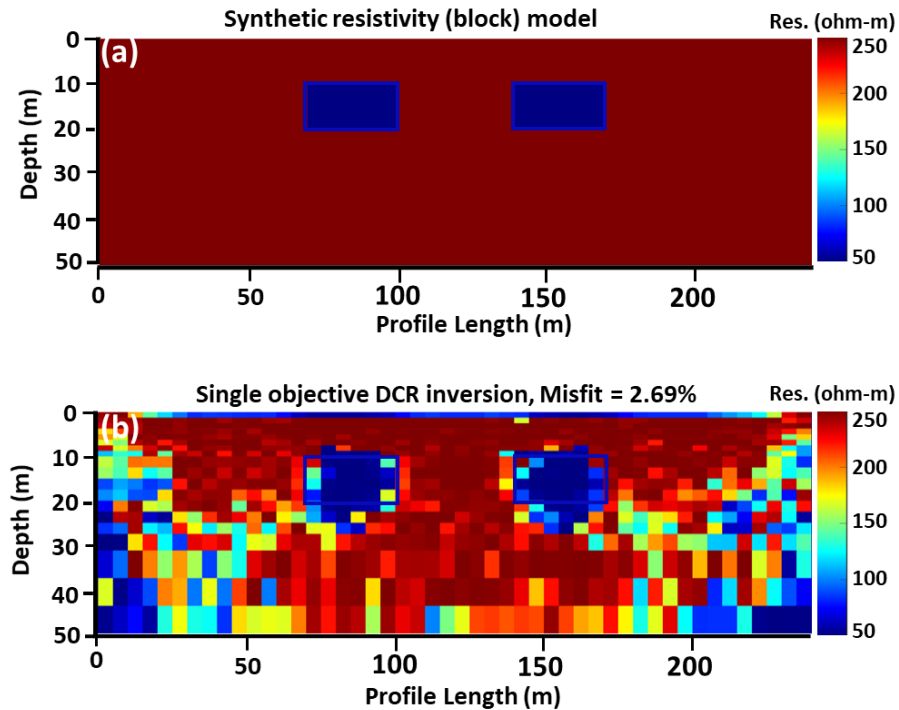


Figure 3.14: Negative anomaly model inversion using the single objective global optimization method; (a) synthetic dc-resistivity model and (b) single object inverted resistivity model. The dark blue line is used to mark the anomaly boundary.

3.4 Discussion

The local optimization algorithm performed optimally in delineating both resistivity and velocity anomalies regarding the tested models. This result is attributed to the application of the smoothing term and appropriate regularization parameters in the objective function to mitigate the effect of the non-uniqueness of the inverse problem. Tables 2–4 summarize the performance of both LOM and CGO algorithms in the inversion involving both DCR and SR methods. Generally, the results from Tables 2–4 show that the CGO improved the misfits compared with the LOM in both the DCR and SR methods but at a relatively high computation cost. Table 5 summarizes the results of the CGO for both (DCR and SR) synthetic models. Despite using a parallel computing approach, the GOM results showed a run time of 6642.15 to 13,962.00 min. This suggests that the most significant challenge with applying the GOM algorithm is the run time.

Table 3.2: Local and global optimization inversion results parameter for both DCR and SR (synthetic dyke anomaly model) methods.

Inversion Type		Methods	No. of Iterations/Generations	Time (min)	Misfit (%)	Target's Reconstruction (%)	
						Geometry	Amplitude
LOM	IIM	SR	10	1.69	0.68	80	95
		DC	8	0.81	10.61	70	97
	JIM	SR	10	10.07	8.83	60	95
		DC	10	10.07	8.83	80	97
CGO	SOO	SR	1000	747.85	0.58	85	100
		DC	1500	175.57	0.48	65	100
	MOO	SR	4000	3136.42	0.62	90	100
		DC	4000	3136.42	2.13	70	100

Table 3.3: Local and combined (local plus global) optimization inversion results parameters for both DCR and SR (synthetic positive anomaly model) methods.

Inversion Type		Methods	No. of Iterations/Generations	Time (min)	Misfit (%)	Target's Reconstruction (%)	
						Geometry	Amplitude
LOM	IIM	SR	9	1.83	1.74	90	95
		DC	8	0.76	2.98	80	98
	JIM	SR	10	26.51	1.68	75	100
		DC	10	26.51	1.68	90	105
CGO	SOO	SR	1000	876.00	0.37	93	100
		DC	1500	181.09	0.46	85	100
	MOO	SR	4697	2953.45	0.31	95	100
		DC	4697	2953.45	0.37	95	100

Table 3.4: Local and global optimization inversion results parameters for both DCR and SR (synthetic positive and negative anomalies model) methods.

Inversion Type		Methods	No. of Iterations/Generations	Time (min)	Misfit (%)	Target's Reconstruction (%)	
						Geometry	Amplitude
LOM	IIM	SR	11	2.034	0.31	80	90
		DC	8	0.93	1.55	70	90
	JIM	SR	8	20.08	1.46	95	95
		DC	8	20.08	1.46	98	95
CGO	SOO	SR	1500	1193.68	0.14	85	95
		DC	1500	150.22	0.12	80	95
	MOO	SR	3502	2891.43	0.13	97	100
		DC	3502	2891.43	0.10	80	100

Table 3.5: Summary of the convectional global optimization inversion results parameter for both DCR and SR (dyke, positive, positive and negative anomalies model) methods.

Method	Inversion Type	Cores	Population Size	Misfit (%)	Generations	Run Time (min)
DCR	Dyke	16	9500	1.04	2500	6642.15
SR	Dyke	16	4800	3.32	200	6803.45
DCR	Positive	6	9500	1.40	2500	13,962.00
DCR	Negative	6	9500	2.70	2500	11,426.68
DCR	Pos. & Neg.	4	9500	14.51	2500	13,929.15

The results showed that the CGO algorithm inherited some features of the model, such as the geometry and amplitude of the anomaly from the local optimization that reflects in its optimum performance. For example, the amplitude and geometry of the DCR in the Dyke model was reflected in the final output of global optimization (Figure 6). Notice that in Figures 9d and 10d, the ray path avoided the negative anomaly; thus, the ideal model structure cannot be reconstructed with high resolution. This scenario is peculiar with the application of the SR method regarding a low-velocity layer (e.g., cavity) surrounded by a high-velocity media [48].

In the CGO method, using the same size of the synthetic model from the LOM, we observed that obtaining a good inversion result for the SR model using a computer with 12 logical processors configuration (6 cores) takes a longer time than the DCR method. This is because the DCR method produces electrical perturbation and estimates the apparent resistivity of the model at once;

however, the SR method first computes the travel time from one source to all receivers sequentially and thereafter repeats the same procedure for all other available sources. To optimize the computation time of both SOO and MOO, we made the misfit algorithm part of the code to run on parallel computing by using the built-in parallel computing (e.g., `parfor` loop) command in MATLAB. This process enhanced the computation cost of the hybrid global optimization algorithm. For instance, it took 189.75 min to obtain the same result as in Figure 8b (single-objective GA for the positive anomaly DCR model) without parallel computing, whereas it took 55.25 min (71% run time optimization) to obtain the same output with parallel computing. Similarly, running the single objective genetic algorithm for the positive anomaly velocity (SR) model for 100 generations took 664.56 min without parallel computing, whereas it took 75.66 min (89% run time optimization) to obtain the same result with parallel computing. The percentage of run time optimization depends on the population size, number of generations, and type of geophysical method involved. To make the synthetic test challenging for the CGO algorithm, we added 3% Gaussian noise to the data resulting from the positive anomaly model. Although the output did not match noise-free data perfectly, a larger portion of the anomaly was recovered (Figures 15 and 16).

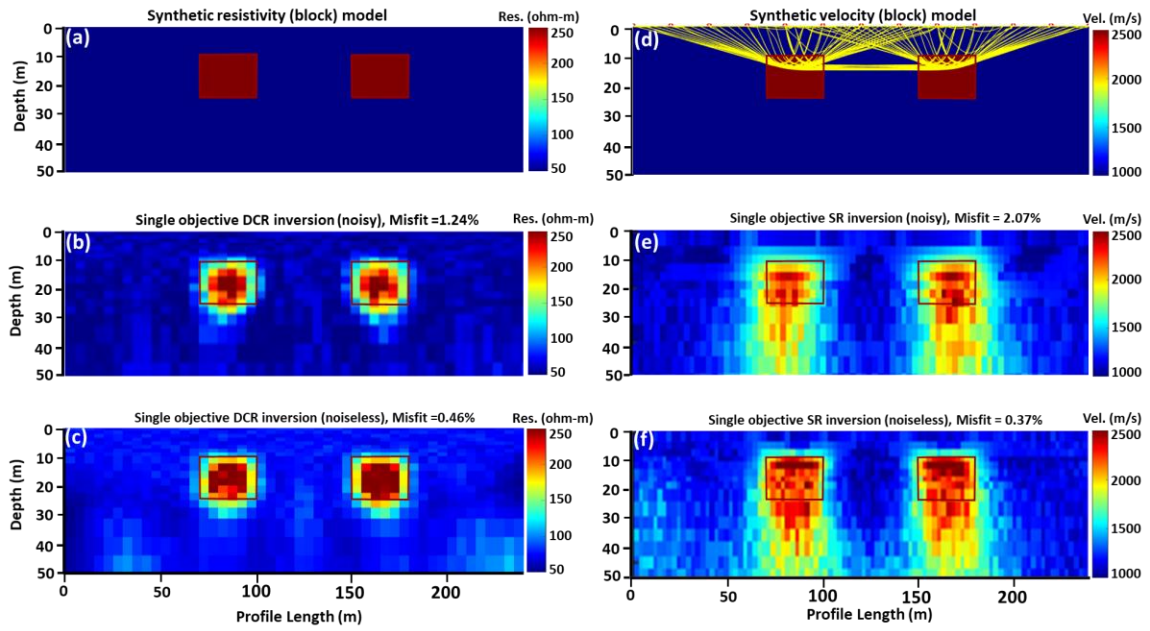


Figure 3.15: Test of the combined optimization algorithm using data (both DCR and SR) with added 3% gaussian noise; (a) synthetic dc-resistivity model, (b) single objective inverted resistivity model (noisy), (c) single objective inverted resistivity model (noiseless), (d) synthetic velocity model, (e) single objective inverted velocity model (noisy), and (f) single objective inverted velocity model (noiseless). The dark red lines are used to mark the anomaly boundary.

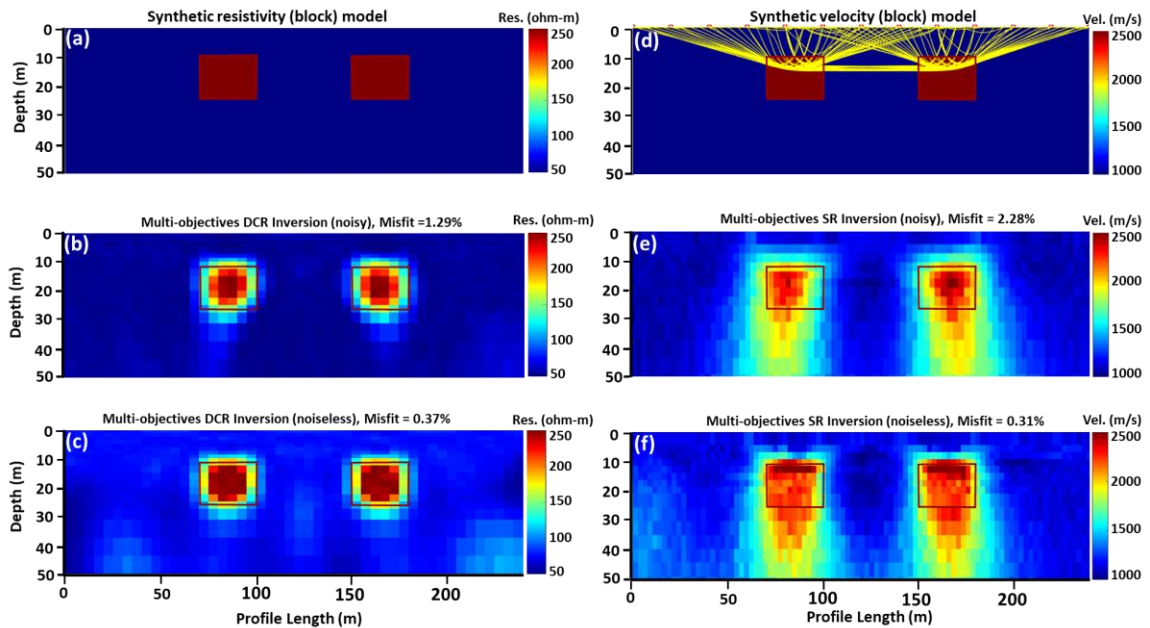


Figure 3.16: Test of the combined optimization algorithm using data (both DCR and SR) with added 3% gaussian noise; (a) synthetic dc-resistivity model, (b) multi-objectives inverted resistivity model (noisy), (c) multi-objectives inverted resistivity model (noiseless), (d) synthetic velocity

model, (e) multi-objectives inverted velocity model (noisy), and (f) multi-objectives inverted velocity model (noiseless). The dark red lines are used to mark the anomaly boundary.

Regarding the GA population size, we observed that the CGO algorithm involving the DCR and SR methods performed better with an increasing number of populations. For example, Figure 15 shows a graduate improvement in the model resolution as the number of populations increased in the DCR genetic algorithm result. Similarly, the CGO algorithm offered a better performance with increasing generations. Notwithstanding, increasing the number of populations and generations prolonged the computation run time (Figure 17).

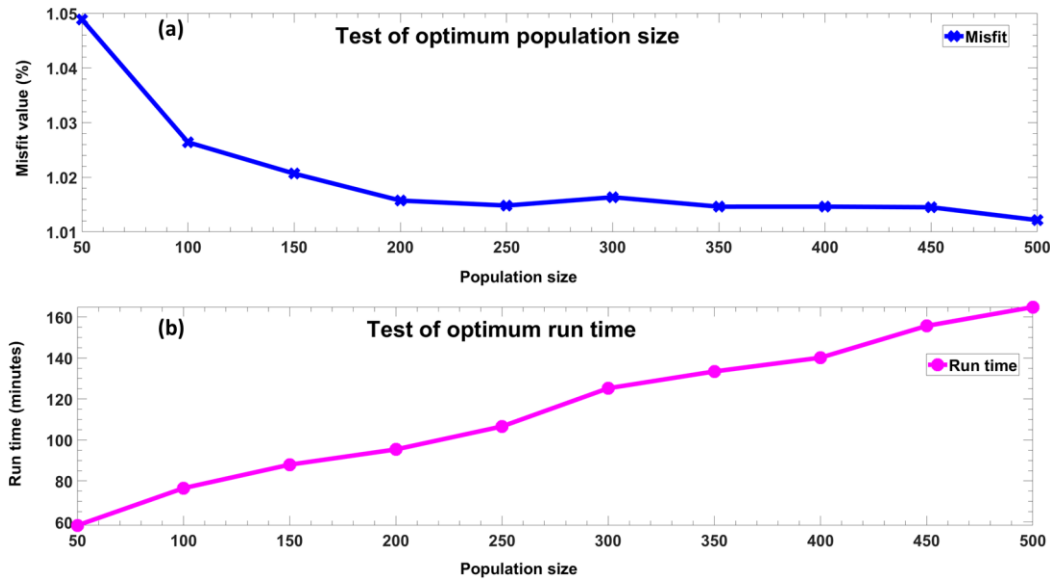


Figure 3.17: Effect of population size on DC-resistivity inversion using the genetic algorithm; (a) test of optimum population size that produces the most significant misfit and (b) test of optimum run time with respect to population size.

Considering these criteria (number of generations, population size, and computation time), we applied an average population size of 500 and 500 generations for both DCR and SR combined global optimization inversion

3.5 Conclusions

The proposed CGO used in this study begins with the application of a local optimization algorithm that requires the use of appropriate regularization parameters incorporated into the DCR and SR objective functions, and it is optimized (using the LOM) to obtain the best model, which will be used as an input model for the combined local–global optimization CGO method. This study applied this concept to obtain the best model parameters for both an individual and joint inversion of the DCR and SR geophysical methods. The CGO algorithm used to overcome the challenges associated with the separate application of LOM and GOM involved the application of the final output (optimum model parameter) of the LOM as the input for the CGO techniques. The global optimization part of the single objective CGO applied the GA to optimize the DCR and SR misfit functions (Equations (13) and (14), respectively) while the NSGA II was used to optimize the resultant misfit from the DCR and SR in the multi-objective optimization algorithm. Apart from the CGO method, which improved the computation run time, we made a part (the misfit function) of the CGO algorithm run on parallel computing. This approach not only contributed to the optimization of the CGO algorithm run time but also provided an opportunity to test the convectional GOM using a computer with 12 logical processor units (six cores). The CGO algorithm was tested with both resistivity and velocity models that had a dyke, two blocks (positive), and two blocks (positive and negative) anomalies. Generally, the CGO algorithm showed an improvement when compared with the local optimization output (Tables 2–4). However, the conventional GOM results showed instability in the delineation of the anomalies in all the tested SR and DCR models, and the model instability was probably due to the use of an unconstrained objective function. However, the CGO method overcame the challenge of model instability since it was linearly constrained by using the LOM’s output to define the search space’s lower and upper bounds. Additionally, the conventional GOM application remained computationally expensive

(especially for the SR method) relative to the CGO techniques. Therefore, this study recommends applying a combined approach (local and global optimization algorithm) when characterizing the subsurface when both DCR and SR data are acquired.

3.6 References

33. Liu, S.; Liang, M.; Hu, X. Particle swarm optimization inversion of magnetic data: Field examples from iron ore deposits in China. *Geophysics* **2018**, *83*, J43–J59. <https://doi.org/10.1190/geo2017-0456.1>.
34. Rani, P.; Piegari, E.; Di Maio, R.; Vitagliano, E.; Soupios, P.; Milano, L. Monitoring time evolution of self-potential anomaly sources by a new global optimization approach. Application to organic contaminant transport. *J. Hydrol.* **2019**, *575*, 955–964. <https://doi.org/10.1016/j.jhydrol.2019.05.093>.
35. Soupios, P.; Akca, I.; Mpogiatis, P.; Basokur, A.T.; Papazachos, C. Applications of hybrid genetic algorithms in seismic tomography. *J. Appl. Geophys.* **2011**, *75*, 479–489. <https://doi.org/10.1016/J.JAPPGEO.2011.08.005>.
36. Akça, I.; Basokur, A.T. Extraction of structure-based geoelectric models by hybrid genetic algorithms. *Geophysics* **2010**, *75*, 1JF–Z16. <https://doi.org/10.1190/1.3273851>.
37. Chunduru, R.K.; Sen, M.K.; Stoffa, P.L. Hybrid optimization methods for geophysical inversion. *Geophysics* **2012**, *62*, 1196–1207. <https://doi.org/10.1190/1.1444220>.
38. Schwarzbach, C.; Börner, R.-U.; Spitzer, K. Two-dimensional inversion of direct current resistivity data using a parallel, multi-objective genetic algorithm. *Geophys. J. Int.* **2005**, *162*, 685–695. <https://doi.org/10.1111/j.1365-246X.2005.02702.x>.
39. Ayani, M.; MacGregor, L.; Mallick, S. Inversion of marine controlled source electromagnetic data using a parallel non-dominated sorting genetic algorithm. *Geophys. J. Int.* **2020**, *220*, 1066–1077. <https://doi.org/10.1093/gji/ggz501>.
40. Akca, İ.; Günther, T.; Müller-Petke, M.; Başokur, A.T.; Yaramanci, U. Joint parameter estimation from magnetic resonance and vertical electric soundings using a multi-objective genetic algorithm. *Geophys. Prospect.* **2014**, *62*, 364–376. <https://doi.org/10.1111/1365-2478.12082>.
41. Holland, J.H. *Adaptation in Natural and Artificial Systems; An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*; Bradford Book: Denver, CO, USA, 1992; ISBN 978-0262581110.
42. Goldberg, D.E. *Genetic Algorithms in Search, Optimization and Machine Learning*; Addison-Wesley Longman Publishing Co., Inc.: Boston, MA, USA, 1989; Volume 7. ISBN 0201157675.
43. Sen, M.K.; Stoffa, P.L. *Global Optimization Methods in Geophysical Inversion*; Cambridge University Press: Cambridge, UK, 2013; ISBN 1139619519.

44. Zidan, A.; Li, Y.E.; Cheng, A. A Pareto Multi-Objective Optimization Approach for Anisotropic Shale Models. *J. Geophys. Res. Solid Earth* **2021**, *126*, e2020JB021476. <https://doi.org/10.1029/2020JB021476>.
45. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197. <https://doi.org/10.1109/4235.996017>.
46. Soupios, P.; Papazachos, C.B.; Vallianatos, F.; Papakostas, T. Numerical treatment and evaluation of inverse problems. *WSEAS Trans. Circuits Syst.* **2003**, *2*, 547–551.
47. Soupios, P.M.; Papazachos, C.B.; Juhlin, C.; Tsokas, G.N. Nonlinear 3-D travelttime inversion of crosshole data with an application in the area of the Middle Ural mountains. *Geophysics* **2001**, *66*, 627–636. <https://doi.org/10.1190/1.1444953>.
48. Carollo, A.; Capizzi, P.; Martorana, R. Joint interpretation of seismic refraction tomography and electrical resistivity tomography by cluster analysis to detect buried cavities. *J. Appl. Geophys.* **2020**, *178*, 104069. <https://doi.org/10.1016/J.JAPPGEO.2020.104069>.

CHAPTER 4

Real Data Example

Application of Combined Local and Global Optimization Algorithms in Joint Interpretation of Direct Current Resistivity and Seismic Refraction

Data: A Case Study of Dammam Dome, Eastern Saudi Arabia

Edigbue P., Demirci I., Akca I., Hamdan H., Kirmizakis P., Soupios P., Tranos M., Abu-Mahfouz I.S., Candansayar E., Hanafy S., Al-Shuhail A. Application of combined local and global optimization algorithms in joint interpretation of direct current resistivity and seismic refraction data: a case study of Dammam Dome, Eastern Saudi Arabia. Sensors. 2022 Nov 30;22(23):9337.

ABSTRACT

The main geological structures in the Dammam Dome are defined by integrating geophysical measurements and applying new methodological approaches. Dammam Dome is characterized by a well-developed fracture/joints system; thus, high complexity of the subsurface is expected. Direct Current Resistivity (DCR) and Seismic Refraction (SR) geophysical survey aimed to map the Dammam Dome's near-surface features. The geophysical data were acquired along two profiles in the northern part of Dammam Dome. To maximize the results from conducting DCR and SR measurements over a complex area, a combined local and global optimization algorithm was used to obtain high-resolution near-surface images in resistivity and velocity models. The local optimization technique involves individual and joint inversion of the DCR and SR data incorporating appropriate regularization parameters, while the global optimization uses single and multi-objective genetic algorithms in model parameter estimation. The combined algorithm uses the output

from the local optimization method to define a search space for the global optimization algorithm. The results show that the local optimization produces satisfactory inverted models, and that the global optimization algorithm improves the local optimization results. The joint inversion and processing of the acquired data identified two major faults and a deformed zone with an almost N–S direction that corresponds with an outcrop were mapped in profile one, while profile two shows similar anomalies in both the resistivity and velocity models with the main E–W direction. This study not only demonstrates the capability of using the combined local and global optimization multi-objectives techniques to estimate model parameters of large datasets (i.e., 2D DCR and SR data), but also provides high-resolution subsurface images that can be used to study structural features of the Dammam Dome.

4.1 Introduction

The primary goal of inverting geophysical data is to generate a model that will give a theoretical response similar to the geophysical field measurements [10]. However, it is unusual to have a unique solution due to the ill-posed characteristics of the most geophysical inverse problem. To reduce uncertainties associated with the inversion of a dataset belonging to a single geophysical method, many researchers have applied the concept of local optimization methods and joint inversion [11–17] or data integration of more than one method, which provides better model resolutions than individual inversions [18–22]. For the local optimization method, the structural data coupling approach, which involves the cross-gradient constraint method, was applied [11]. The local optimization techniques are used iteratively to obtain an updated model that minimizes the objective function, which may not be the global solution of the inverse problem [23,24]. The global

optimization algorithm in geophysical inversion is used to search for a solution space to avoid being trapped in the local minimum of the objective function [25–30]. Global optimization algorithms have been successfully applied to solve geophysical problems involving the gravity method [31,32], Magnetotelluric [33,34], and traveltimes tomography [26]. Among the global optimization applicable to geophysical inversion, the genetic algorithm has been mostly applied because it does not involve complex computation and uses a crossover operator that enables information sharing among the models in the population [35].

Consequently, only the best solutions make it to the next generation. Some studies present integrated local and global optimization algorithms in hybrid form to extract the advantage of both optimization algorithms [25,26]. For this study, the genetic algorithms were used in two different forms. In the first one, the genetic algorithm (GA) for a single objective function case was applied, and for the joint processing of the DCR and SR data, the non-dominated sorting genetic algorithm 2 (NSGA II) for the multi-objective joint optimization approach was used. The use of genetic algorithms in a single objective function is a well-known and controlled problem [26], whereas one of the major challenges in applying the genetic algorithm or global optimization method to a multi-objective function (different geophysical datasets) is the determination of the optimum solutions that do not dominate each other [30].

This study presents the combined local and global optimization approach [36] to jointly invert SR and DCR data to improve the lateral and in-depth resolution and, thus, fully characterize the study area and delineate the presence of anomalous zones. In particular, we aim to outline probable near-surface features such as faults or fractures in

the study area that can be correlated with the background geology (outcrop). This process would provide probable validation for the interpreted resistivity and velocity models. The unique aspect of this study is that it is the first time real DCR and SR datasets are used to test the feasibility of the combined optimization approach, utilizing single and multi-objective methods.

4.2 Materials and Methods

4.2.1 Geology of Study Area

The study area is located on the right side of the road from Al Dhahran to Ad Dammam airport and about 2.7 km north of the King Abdulaziz Center of World Culture–Ithra crossroad, eastern Saudi Arabia (Figure 1a). The exposed sedimentary rocks in the area build up the northern part of the large oval-shaped dome [4]. The latter is the first, and main, hydrocarbon structural trap found in the Eastern Province of Saudi Arabia, and is widely known as the Dammam Dome [3]. More precisely, the Dammam Dome covers an area of ca. 500 km² encompassing the cities of Al Khobar, Al Dhahran, and part of Ad Dammam [3]. Powers et al. [37] grouped the exposed sedimentary rocks of the Dammam Dome into the following formations from bottom to top: (a) Rus Formation; (b) Dammam Formation; (c) Hadruk Formation; and (d) Dam Formation, with the first two formations dated in Eocene, whereas the next two upwards dated to Lower Miocene due to a major unconformity that is generally referred to as the Pre-Neogene Unconformity (PNU) [7] (Figure 1b). Based on the above, the Rus formation can be considered as the bedrock for our geophysical survey. Powers et al. [37] mapped in detail the Dammam Dome, whereas a geological compilation of the Dammam Peninsula from existing source maps [6,7,38] on

a modern road map was compiled by Weijermars [4]. Hariri and Abdullatif [8], Al-Fahmi [9], Al-Fahmi et al. [39], and Hariri [3] have analyzed the fracture patterns of the Dammam Dome, which vary from place to place, but into which the NNW–SSE trending fractures form the regional fracture set. Based on the fracture patterns, Hariri and Abdullatif [8], Al-Fahmi [9], Al-Fahmi, et al. [39], and Hariri [3] concluded that the dome, as part of the interior of the Arabian platform, was far away from the Zagros Mountains belt and therefore was not influenced by the deformation processes taken part along the Zagros due to the convergence between the Arabian and Eurasia plates.

A more recent study by Tranos and Osman [5] dealing with the soft-sediment deformation in the area defined that the site in the Eocene was under a transtension stress regime associated with ENE–WSW compressive stresses, which originated along the Zagros mountain belt due to the collision between the two plates mentioned above. Such a transtensional stress regime was also defined by the orientations of the ENE–WSW striking, km-long, and almost vertical tectonic lines, which were found to cut the Dammam Dome after a geophysical exploration on the King Fahd University campus [40].

The site under investigation is a NE–SW road of ca. 500 m cutting across the sedimentary rocks of the Dammam Formation [7]. The Dammam Formation, coined by Bramkamp in 1941 (unpublished Saudi Aramco report; see Powers et al. [37]), rests conformably on top of the Rus Formation and is subdivided into five members [37]. From bottom to top, these are: (1) Midra Shale; (2) Saila Shale; (3) Alveolina Limestone; (4) Khobar limestone member; and (5) Alat dolomitic limestone/marl member. The three upper members are of Lutetian age (52.0 to 43.8 Ma) [41], whereas the two lower members are of Ypresian age (57.8 to 52.0 Ma) [41].

On the exposed NW slope roadcut (Figure 1c), the predominant feature is an NNW–SSE wide fault zone of ca. 30m that disrupts the rocks of the Dammam Formation. In particular, the bedding seen clearly outside the fault zone cannot be traced within the fault zone due to the intense cataclasis and mingling, processes that make the fault zone appear like a ‘megabreccia’ zone (MBZ) (Figure 1d). As a result, the fault zone disrupts and mismatches the continuation of the bedding. This deformed zone has been recently interpreted by Alkhalifa and Kurison [42] as a karst collapse zone.

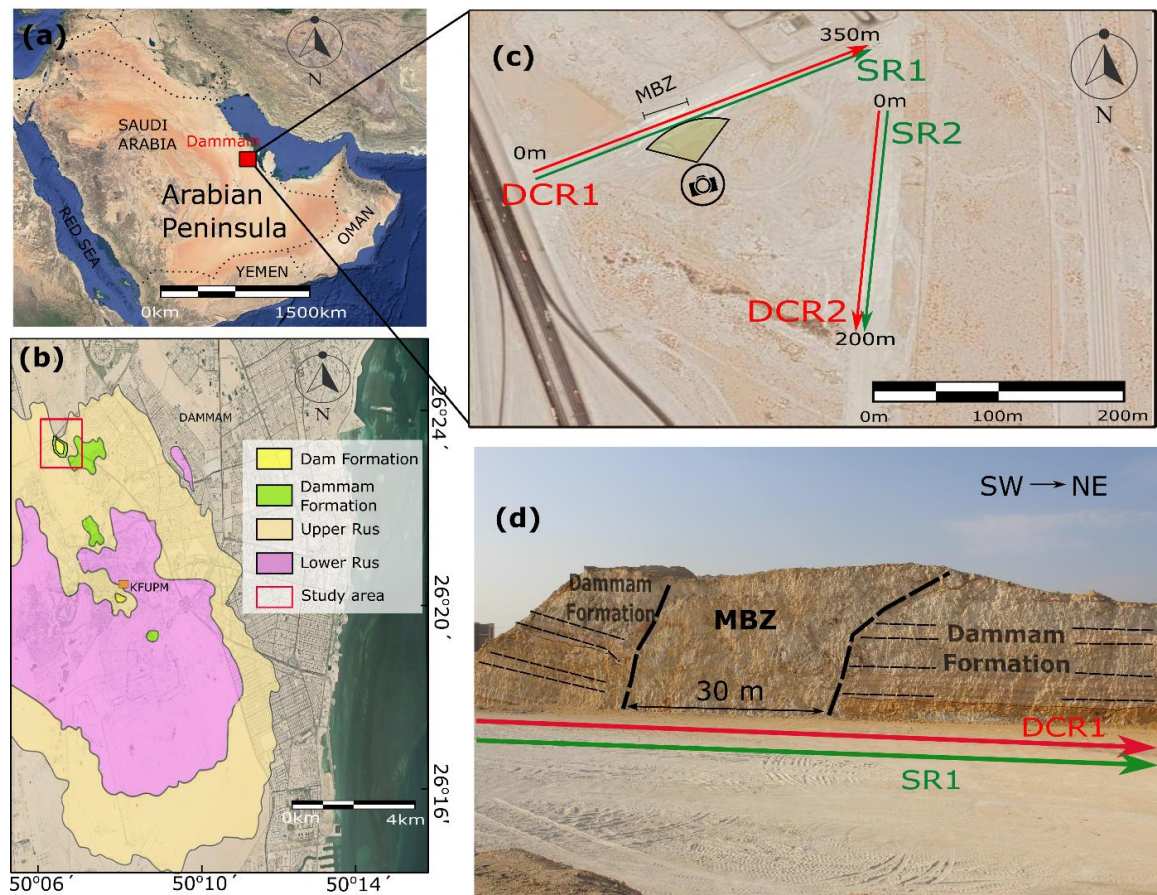


Figure 4.1: Satellite image of the study area and (b) geological map of the wider study area (modified from Weijermars [4]). Red rectangle shows the study area; (c) Field view of the wide ‘megabreccia’ zone (MBZ) disrupting the sedimentary rocks of the Dammam Formation along the roadcut. The location from where the photo for figure (c) is taken, is

shown. The DCR and SR profiles performed herein are shown with red (DCR1, DCR2) and green (SR1, SR2) lines; (d) The stratigraphy of the Dammam formation and the disruption (MBZ) zone of the sedimentary sequence are presented. The DCR1 (red arrow) and SR1 (green arrow) profiles collected along the under-construction road are depicted.

4.2.2 Geophysical Data Acquisition and Quality Control

Two DCR and SR profiles were conducted along road cuts, as shown in Figure 1. Profile 1 is 350 m long and addressed from southwest to northeast, while profile 2 is about 200 m long and acquired from almost north to south in the study area (Figure 1b). DCR data were acquired using the multi-electrode Syscal Pro Switch 96 resistivity instrument, using 75 electrodes with 5 m electrode spacing on profile 1, and 49 electrodes with the same spacing on profile 2. The dipole–dipole (DD) acquisition protocol was used in both DCR profiles 1 and 2 since the DD acquisition protocol provides the best lateral resolution [1,2], and based on the visual evidence mainly lateral changes were expected to be found. For the SR data, 120 shots and receivers at 3 m intervals were used on profile 1, while 40 shots and receivers at 5 m intervals were used on profile 2. The DCR data were converted to a format readable with our Matlab inversion algorithm that prepares the data for inversion. Data preparation for the SR method involves mainly the first arrival picking. The first arrival picking technique, similar to the method applied by Sherif et al. [43], was used in this study, and the supervirtual seismic refraction interferometry (SVI) technique [44,45] was used for part of the SR data, having low signal-to-noise ratio (SNR). After that, the local and global optimization algorithms were applied.

4.3 Optimization Principle

4.3.1 Local Optimization Principle

The forward problem in a geophysical inversion is usually solved to describe the relationship between measured data and theoretical data before considering the inverse problem [10]. The solution to the forward problem includes theoretical computation of model response to the earth perturbation, with the assumption of known model parameters and source and receiver positions related to measured data. The field observations can be described as a function of the model parameters due to earth perturbation, plus a certain amount of noise as shown in Equation (1).

$$F(m) = d_{obs} + n, \quad (1)$$

F is the function that describes the sensitivity of the earth model to the earth perturbation, m is the model parameter or physical property of the earth, and n is noise due to the field survey process. Because the forward operator F can be generally expressed as a differential equation, we often solve the forward problem using numerical solution methods such as FD, FE, and IE.

We aim to estimate the model parameters that produced the noisy field observations in the inverse process. This task is more complicated than the forward calculations because the field observation is sparse relative to the size of the earth model, making the available resources (data) insufficient. Any solution obtained with these limited resources is non-unique; consequently, we add adequate a priori information about the model and the field observations to arrive at the best solution. One such important information source is the data covariance; the theoretical data should vary similarly to the field observations. Additionally, we impose some constraints or apply a smoothness function to the model to

obtain a more meaningful geologic interpretation. Generally, we formulate the cost function (Φ) by algebraically summing up the data residual and smoothness terms as:

$$\Phi(m_p) = R(m_p) + \alpha_p D(m_p), \quad (2)$$

where R is the data misfit term, D is the stabilizer term which is controlled the smoothness or regularization of model parameters, while α_p is a regularization parameter to balance the weights between data misfit term and stabilizer term, and m_p is a vector representing the model parameter. Specifically, we present the cost function for individual DCR and SR methods as:

$$\Phi(m_{dcr}) = \|W_{dcr}(d_{dcr} - g_{dcr}\Delta m_{dcr})\|^2 + \alpha_{dc}\|(\nabla^2 m_{dcr})\|^2, \quad (3)$$

$$\Phi(m_{sr}) = \|W_{sr}(d_{sr} - g_{sr}\Delta m_{sr})\|^2 + \alpha_{sc}\|(\nabla^2 m_{sr})\|^2. \quad (4)$$

In Equations (3) and (4), W is a weight matrix used for biasing the data, d is the field observations, g is the Jacobean or sensitivity matrix that is used to obtain the theoretical responses at every model perturbation, Δm_p is the model correction vector, and ∇^2 is the Laplacian operator. We minimized the objective function by taking the derivative of the model parameter. Thereafter, the model parameter correction vector for both DCR and SR can be represented as:

$$\Delta m_{dcr} = (g_{dcr}^T W_{dcr}^T W_{dcr} g_{dcr} + \alpha_{dcr} C^T C)^{-1} (g_{dcr}^T W_{dcr}^T W_{dcr} \Delta d_{dcr} - \alpha_{dcr} C^T C m_{dcr}^{i-1}), \quad (5)$$

$$\Delta m_{sr} = (g_{sr}^T W_{sr}^T W_{sr} g_{sr} + \alpha_{sr} C^T C)^{-1} (g_{sr}^T W_{sr}^T W_{sr} \Delta d_{sr} - \alpha_{sr} C^T C m_{sr}^{i-1}), \quad (6)$$

where C is called as smoothing matrix and includes and includes the Laplacian of the model parameters. Equations (5) and (6) can be simplified as follows:

$$\Delta m_{dcr} = G_{dcr}^{-1} n_{dcr}, \quad (7)$$

$$\Delta m_{sr} = G_{sr}^{-1} n_{sr}. \quad (8)$$

We apply the Gauss–Newton optimization algorithm to estimate the model parameter correction vector, and cooling approximation is used to estimate the regularization parameters [46]. Regarding the joint inversion approach, the cross-gradient (structural) constraint is applied as suggested by Gallardo and Meju [11] and Ismail et al. [16,17]. The cross-gradient algorithm considers that the gradient of the model parameters in the joint inversion must be parallel, non-parallel, or equal to zero, which are essential criteria required to satisfy the algorithm. This cross-gradient function for the joint inversion of DCR and SR is given as:

$$\partial(m_{dcr}, m_{sr}) = \nabla m_{dcr} \times \nabla m_{sr}, \quad (9)$$

$$\cong \partial(m_{0dcr}, m_{0sr}) + B \begin{pmatrix} m_{dcr} - m_{0dcr} \\ m_{sr} - m_{0sr} \end{pmatrix}, \quad (10)$$

where ∂ is the cross-gradient function for all the pixels in the model, m represents the model parameters in both DCR and SR methods, and B is the vector of the derivatives of the cross-gradient with respect to model parameters. Therefore, the cost function for the joint inversion is formulated as:

$$\Phi(m_{dcr}, m_{sr}) = R(m_{dcr}, m_{sr}) + \alpha_p D(m_{dcr}, m_{sr}) + \varepsilon \partial(m_{dcr}, m_{sr}), \quad (11)$$

subject to $\Phi(m_{dcr}, m_{sr}) = 0$. In Equation (11), the symbol ‘ ε ’ is used to represent the regularization parameter of the cross-gradient function. The data residual and smoothening terms can be represented as:

$$R(m_{dcr}, m_{sr}) = \|W_{dcr}(d_{dcr} - g_{dcr}\Delta m_{dcr})\|^2 + \|W_{sr}(d_{sr} - g_{sr}\Delta m_{sr})\|^2, \quad (12)$$

$$D(m_{dcr}, m_{sr}) = \|(\nabla^2 m_{dcr} + \nabla^2 m_{sr})\|^2. \quad (13)$$

After performing the minimization of the cost function in Equation (11) as expressed in Demirci et al. [16], the model parameter vector can be represented as:

$$\Delta m = G^{-1}nG^{-1}B^T(BG^{-1}B^T)^{-1}[BG^{-1}n - B\Delta m_{i-1} + \partial(m_{i-1})]. \quad (14)$$

Moreover, the variables Δm , G , and n in Equation (14) can be expressed in matrix form as:

$$\Delta m = \begin{bmatrix} \Delta m_{dcr} \\ \Delta m_{sr} \end{bmatrix}, G = \begin{bmatrix} G_{dcr} & 0 \\ 0 & G_{sr} \end{bmatrix}, \text{ while } n = \begin{bmatrix} n_{dcr} \\ n_{sr} \end{bmatrix}. \quad (15)$$

Similarly, to the individual local optimization algorithm, we apply the Gauss–Newton optimization algorithm to estimate the model parameter correction vector, and cooling approximation is used to estimate the regularization parameters.

4.3.2 Global Optimization Principle

Generally, five (5) global optimization algorithms can be used in geophysical inversion [35]; however, the genetic algorithm was applied in this study due to its computational simplicity and it can be easily adapted to parallel computing [35]. Compared with other stochastic methods applied in 1D full waveform inversion, the genetic algorithm provides optimal performance [47]. Fundamentally, the genetic algorithm uses the evolutionary operators such as selection, crossover, and mutation to compute the solution of an optimization problem [30]. Because the genetic algorithm involves population-based optimization, it is initialized by creating subsets of all the possible solutions in relation to the fitness function of the inverse problem. To obtain the optimality of the global optimization algorithm, both single and multi-objective genetic algorithms were applied. The single objective genetic algorithm involves one fitness function, i.e., only DCR or SR optimization can be run at a time. The binary coding scheme is commonly used to create the initial population for the single objective optimization [35]. Thereafter, genetic algorithm operators are used to search for an optimum solution from the population; this process could be referred to as the stochastic optimization approach.

The multi-objective genetic algorithm is similar to the single objective; however, instead of coding its population, the model parameters are used directly to initialize the

population. In addition, the fitness function is created such that the entire misfit is partitioned according to the number of objective functions, in this case two (i.e., DCR and SR methods). Finally, each portion of the misfit is evaluated with respect to the corresponding fitness functions described in Equations (16) and (17).

$$M_{dcr} = \frac{100 \times (\|d_{dcr} - td_{dcr}\|_2)}{\|d_{dcr}\|_2}, \quad (16)$$

$$M_{sr} = \frac{100 \times (\|d_{sr} - td_{sr}\|_2)}{\|d_{sr}\|_2}, \quad (17)$$

where d is the field observation (real data), while td is the theoretical data for both the DCR and SR methods. The misfit from both DCR and SR objective functions are combined in the multi-objective optimization as:

$$M_{dcr\ sr} = [M_{dcr} \quad M_{sr}]. \quad (18)$$

To perform the multi-objective optimization in a way that the contribution of each misfit function must be optimized to avoid one method dominating the other (i.e., solutions in the DCR and SR objectives domain are not better than each other), the non-dominating sorting genetic algorithm (NSGA II) is applied here. The concept of this algorithm is shown in Appendix A and discussed explicitly in Deb et al. [48], and has been applied in some geophysical-related studies [29,30,36]. In the NSGA II, the basic genetic algorithm operators (i.e., selection crossover, and mutation) were used to create offspring from the initial population and combine both parents and offspring in non-dominated sorting. At the initial stage in this approach, some sets of optimal solutions (non-dominated solutions) arrive at a common front known as Pareto optimal front. These solutions are momentarily set aside in the algorithm while other sets of solutions improve and become non-dominated. Thereafter the principle of elitism [49] is applied to all the non-dominated solutions to determine the sets of optimal solutions that go to the next generation. The combined

optimization algorithms involve the application of the output (model) of the local optimization to define a search space (lower and upper bounds) for the global optimization algorithm. A detailed description of the combined optimization algorithm is presented in Edigbue et al. [50].

4.4 Results

4.4.1 Profile 1

The local optimization results for the individual and joint inversions of both DCR and SR are presented in Figure 2. The resistivity model shows that the DCR method penetrates at a depth of 100 m, while the SR method reached the maximum depth of 60 m. It should be mentioned that we decided not to trim the DCR1 data at 60 m depth to be directly comparable with the SR1, since detecting deep structures was one of this study's objectives. Despite the disparity in depth, both methods show some similarities in the delineating features. The SR method did not significantly trace some of the shallow anomalies, even after applying the joint inversion; this was unlike the DCR method, probably due to the resistivity contrast of these anomalies with respect to the surrounding rock materials. Specifically, surface stratigraphic characteristics, such as the smooth dipping of the layers of the Dammam formation to the east, were detected only on the final inverted individual DCR model. It should be mentioned that the vertical (depth) axis in all final tomographic models is exaggerated by 1.35. Thus, the slope of the layers is much smoother than it appears in the models.

Moreover, low (around 1 Ohm.m.) resistivity vertical structures were depicted at the 150 m and 240 m offset at the DCR final model. From the individual inversion of the seismic refraction data, only the high-velocity structures at the beginning and the end of

the model (the bedrock of the study area) are shown, and a wide (more than 100 m thick, from 120–240 m along the SR1 profile), low-velocity zone was presented. However, after applying the joint inversion of the DC (DCR1) and Seismic (SR1) data, the major anomalies were reconstructed with higher resolution. This could be due to the impact of the structural constraint that is applied in the joint inversion. Generally, the DCR and SR data's joint inversion shows improved structural similarity compared to their individual inversions. Specifically, after applying the joint inversion and using structural constraints, the vertical high resistivity and the in-between low resistivity structure are better depicted, and the shallow structures seem more continuous. The exposed deformed (MBZ) zone and its extent in depth are better seen in the seismic model. In all cases, the final misfit and RMS error are very low, varying from 4.1–5.2% and 0.006–1.6, respectively.

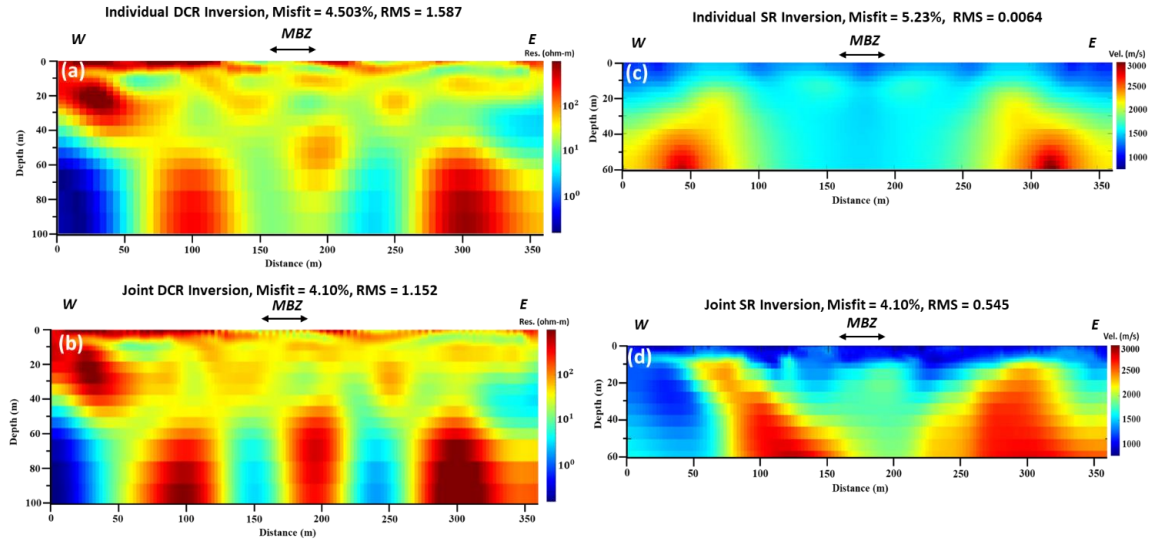


Figure 4.2: DCR and SR inversion using local optimization method: **(a)** individual inverted resistivity model; **(b)** joint inverted resistivity model; **(c)** individual inverted velocity model; and **(d)** joint inverted velocity model. All geophysical models are vertically exaggerated by 1.35.

The final tomographic models using the global optimization results and applying both single and multi-objective algorithms are presented in Figure 3. The outputs of the single objective global optimization for both data sets (Figure 3, upper row) are structurally similar to the local optimization results. This was partially expected since the search space for the next generation was fed by the output of the local optimization algorithm. At best, it shows a slight improvement in the resolution of the DCR and SR models and significantly decreases the misfit and RMS errors. Minor changes and improvements in the final models were observed by using the multi-objective optimization. Only the misfit and RMS errors are lower. The same resistivity and velocity features were depicted.

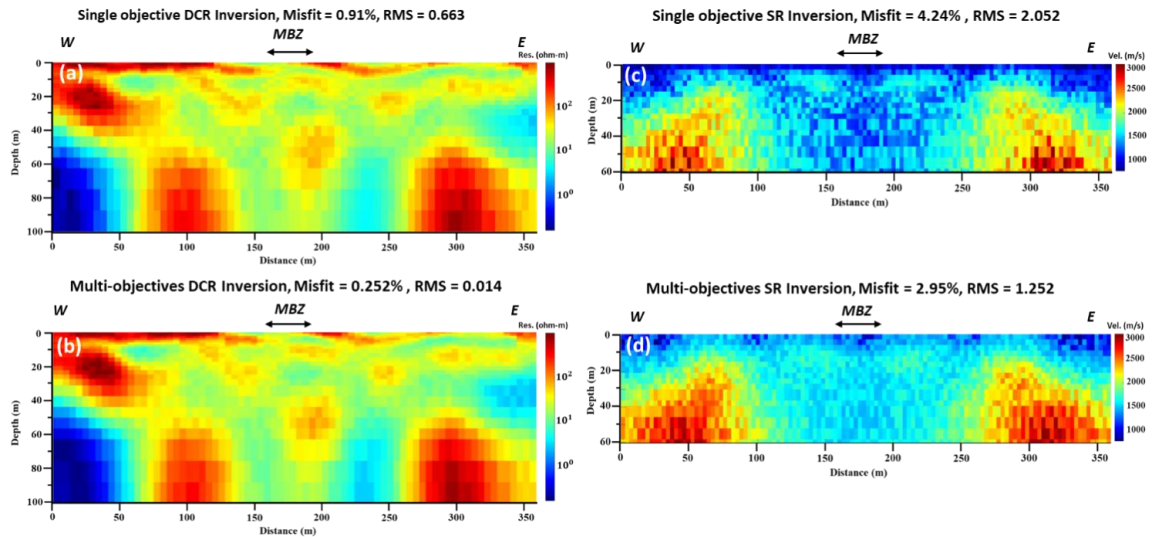


Figure 4.3: DCR and SR inversion using global optimization method: **(a)** single objective optimization resistivity model; **(b)** multi-objectives optimization resistivity model; **(c)** single objective optimization velocity model; and **(d)** multi-objective optimization velocity model. All geophysical models are vertically exaggerated by 1.35.

4.4.2 Profile 2

Both DCR2 and SR2 data were collected along the same profile. The final tomographic results show that the total penetration depth is 50 m for both applied

techniques. Figure 4, (first column, a and b) shows the results of inversion using a local optimization algorithm for individual and joint inversion of both (DCR and SR) geophysical data. Both tomographic models found the bedrock (high resistivity) formations in the southern part of the acquired profile at 20 m below the ground surface. From the final individual/joint inversion DCR models, the bedrock disappears at around 120 m offset from the north (beginning of the profile). A medium resistivity (100 Ohm.m) formation covers the whole area. In the first 50 m of the profile, and from the 20 m depth to the bottom of the model, a very low resistivity (10 Ohm.m) layer was detected. The final misfit and RMS errors for the final resistivity models are low, varying from 4.76–9.24% and 1.59–3.08, respectively.

The seismic tomographic model of Figure 4c shows a 3-layers velocity model: The upper first layer with an average velocity and thickness of 1000 m/s and 10 m, respectively. The second layer, with an average velocity of 1700–2800 m/s, overlays unconformably the bedrock of the study area, which has an average velocity of 2800–4000 m/s. Figure 4d is affected by the joint inversion and incorporation of the structural constraints of the resistivity model/changes to the final resulted velocity model. A low-velocity anomaly at the first 50 m of the profile was reconstructed, similar to the low-resistivity anomaly detected at the same location from the DCR individual and joint inversion. The final misfit and RMS errors for the final velocity tomographic models are acceptable, varying from 3.71–9.24% and 0.002–0.005, respectively.

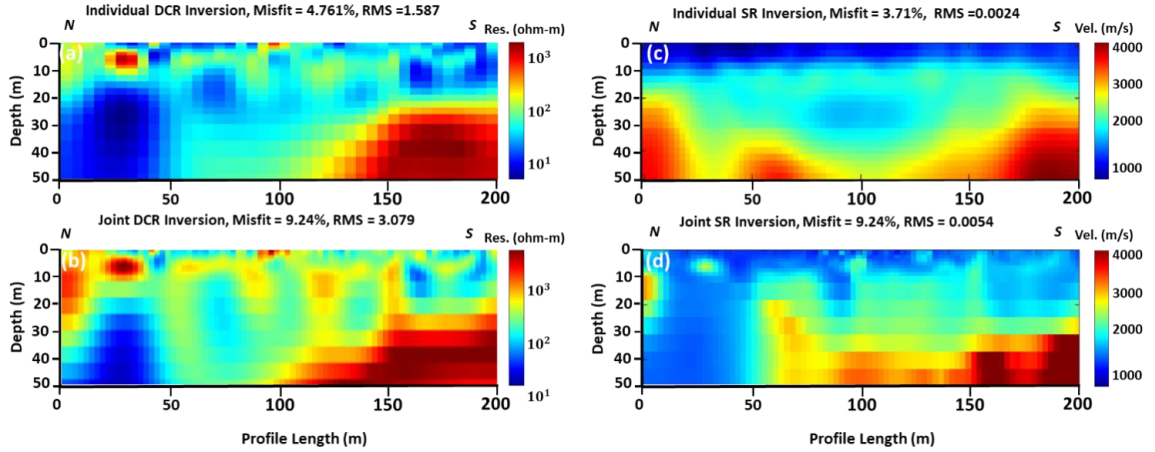


Figure 4.4: DCR2 and SR2 (see Figure 1b for location) inversion using local optimization method: (a) individual inverted resistivity model; (b) joint inverted resistivity model; (c) individual inverted velocity model; and (d) joint inverted velocity model. All geophysical models are vertically exaggerated by 1.35.

Results in Figure 5 shows that the global optimization algorithm slightly improves the output of the local optimization algorithm (individual inversion). For instance, in the local optimization algorithm, RMS in DCR2 is between 1.578 and 3.079, while the RMS is between 0.260 and 0.175 in the global optimization results. Likewise, in the case of SR2, RMS is between 0.0024 and 0.0054 in the local optimization result, while RMS is 0.0036 and 0.0016 in the global optimization results. Structurally, the right part of the resistivity model is similar to the right part of the velocity model. The main difference between the two different solutions, using the local and global optimization techniques, can be identified in the models in Figures 4d and 5d. It seems that the structural constraints of the resistivity models from the use of local optimization are not affected in the same way as the models in the global optimization. Thus, Figure 5d shows a similar model as in Figures 4c and 5c, and only a small lateral discontinuity at around 30 m offset is observed, which is probably in the order of the accuracy/resolution of our model at that depth.

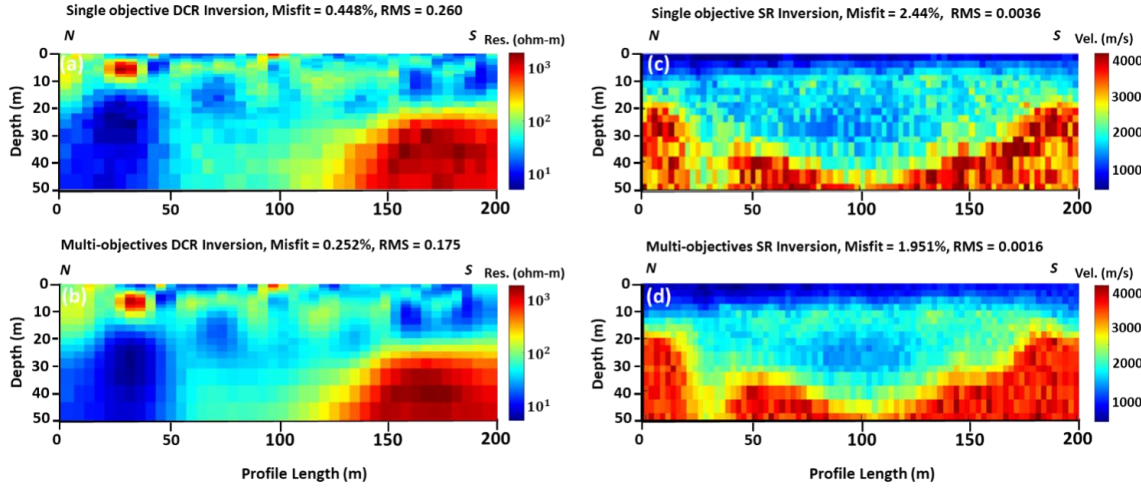


Figure 4.5: DCR and SR inversion using global optimization method: **(a)** single objective inverted resistivity model; **(b)** multi-objectives inverted resistivity model; **(c)** single objective inverted velocity model; and **(d)** multi-objective inverted velocity model. All geophysical models are vertically exaggerated by 1.35.

4.5 Discussions

The application of the local and global optimization methods was proven promising by using a joint geophysical inversion and interpretation of acquired resistivity and seismic data along an open geological section with visible stratigraphy and tectonic features, where the roadcut was used for ground truthing. The exposed ‘megabreccia’ zone (MBZ), the fault zone within the Dammam formation deposits, was confirmed by both the geophysical (DC and Seismic) data but with different resolutions, as expected based on the advantages and disadvantages of the applied geophysical methods and acquisition protocols used. Based on the composition of the Dammam formation, a low to medium (from 10–100 Ohm.m) resistivity is expected. The high resistivity (more than 100 Ohm.m) and velocity (greater than 2500 m/s) structures at both (west and east) sides of the final geophysical (velocity and resistivity) models can be associated with the Rus formation as mapped by Tleel [7] (Figure 1b), and also reported by Alkhalifa and Kurison [42]. Specifically, to the

west of the study area the Rus formation exists in the area, as mapped by Tleel [7], at a distance less than 500 m from the study area.

In particular, DCR1 profile (Figure 6b) shows in depth the continuation of the MBZ zone, but also one more deformed zone was detected between 200–240 m along the profile with the same low resistivity characteristics. Shallow horizontal to sub-horizontal, medium to high resistivity (50–80 Ohm.m) layers are shown with dashed lines in the eastern part of the profile, which agree with the stratigraphy as observed and is shown in Figure 6a. The final resulting velocity (RS1) model has a much lower resolution and can only image the high-velocity Rus formations at the sides of the model and, with low resolution, the wide deformed (low velocity) zone from 110–250 m along the profile.

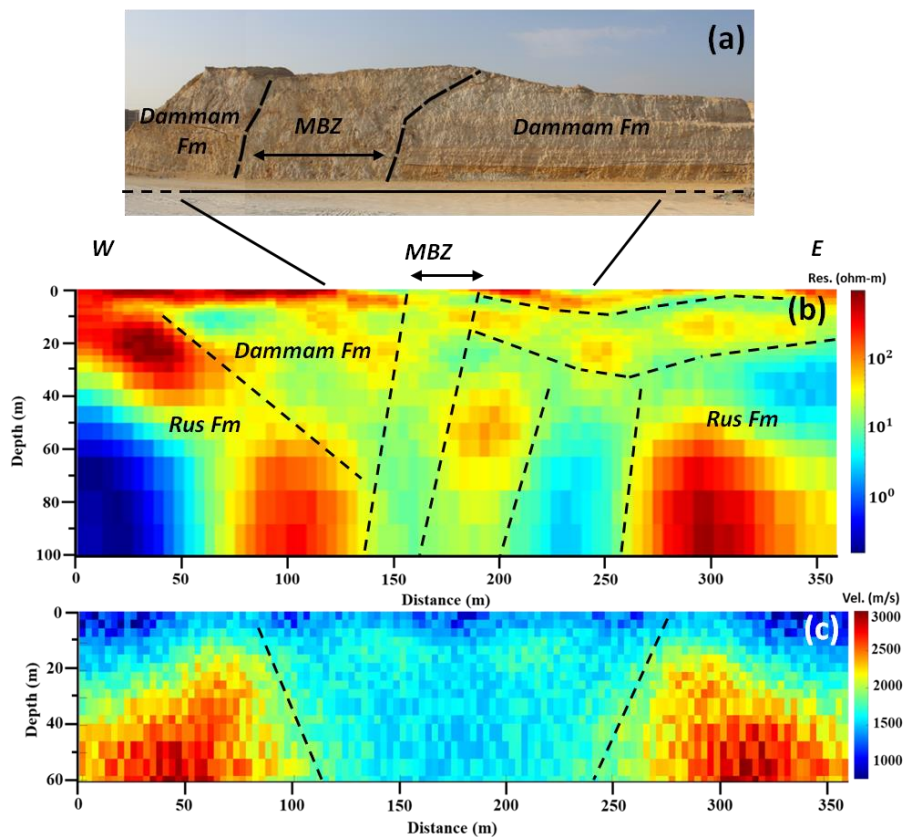


Figure 4.6: Structural interpretation of the resistivity and velocity models from profile 1: **(a)** section of the outcrop (road-cut) showing inclined strata; **(b)** interpreted resistivity

model; and **(c)** interpreted velocity model. Notice that both methods (DCR and SR) map similar structures, especially the faults and the deformed zone. Both geophysical models are vertically exaggerated by 1.35.

Although no prominent outcrop reveals structural information on profile 2, the geophysical results show that the method delineated similar major anomalies. Both DCR and SR models in Figure 7 show the bedrock (resistivity of more than 200 Ohm.m and velocity more than 3000 m/s) in the southern part of the profile at a depth of 20 m below the ground surface. The main difference in the interpretation of the different datasets comes from the northern part of the profile. DCR2 shows a clear low (10 Ohm.m) resistivity anomaly, from top to the bottom of the model. In contrast, the SR2 shows the bedrock along the whole profile (dashed line), with a lateral discontinuity (depicted as a question mark in Figure 7b) at the offset of 35–40 m along the profile SR1. This lateral discontinuity, which in applied geophysics can be considered a fracture/deformed zone, can probably be associated with the very low (10 Ohm.m) resistivity anomaly at the same offset. Since profile 2 has an almost N–S direction, it can be safely assumed that the low detected resistivity and probably lower velocity anomalies are related to a deformed and/or fractured zone of the WSW–ENE direction. This finding agrees with the direction of the subsurface fractures reported by Chavanidis et al. [44], supporting the conclusion that deep and thicker fractured/deformed zones of the WSW–ENE trend, perpendicular to the main axis of the Dammam Dome, exist.

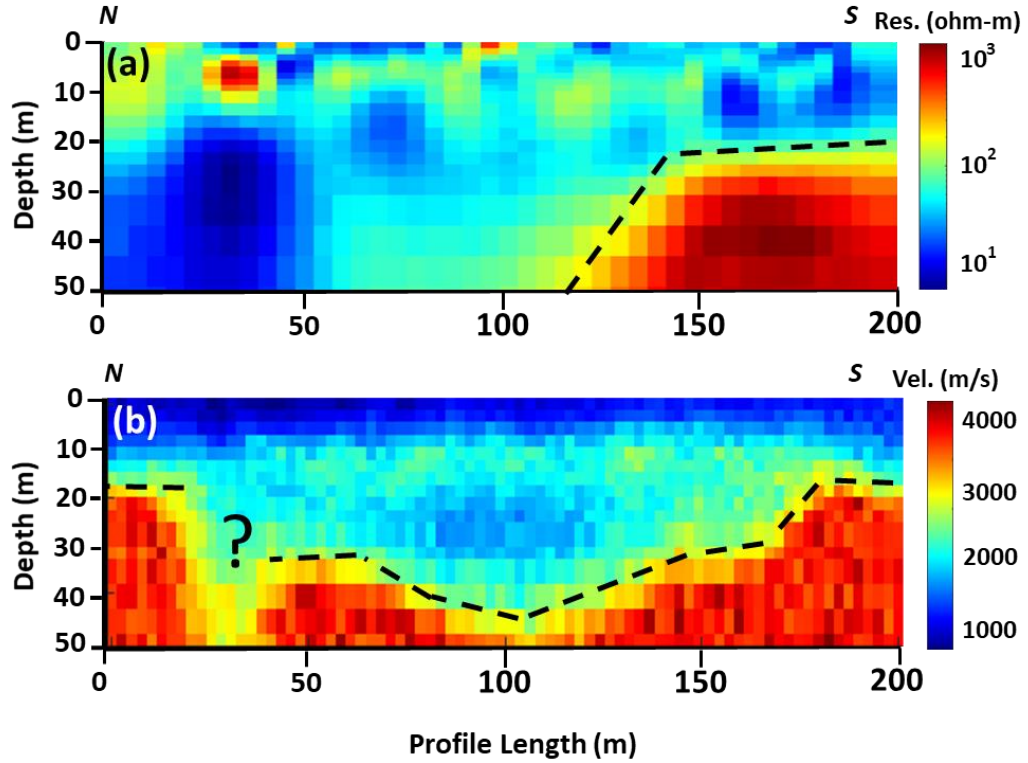


Figure 4.7: Structural interpretation of the resistivity and velocity models from profile 2 (a) interpreted resistivity model; and (b) interpreted velocity model.

4.6 Conclusions

Both local and global optimization algorithms were applied individually and jointly to achieve the high-resolution resistivity and velocity models presented in this study. The local optimization results show satisfactory outputs as a result of using appropriate regularization parameters for both DCR and SR data inversion. In the combined optimization algorithm, results from the individual local optimization algorithm were used as input to define the search space for the global optimization method. Since the local optimization algorithm performs acceptably, the global optimization method slightly improves the model resolution and RMS error. Subsurface deformational features such as fractures/faults were mapped on both profiles in the study area. Profile 1 reveals significant

NNW–SSE faults, as lateral discontinuity of the resulting tomographic models, observed in both the resistivity and velocity models. Moreover, the observed surface MBZ along the road-cut was confirmed in-depth. The observed anomalies from both resistivity and velocity models for profile 2 show similarities to those in profile 1. Specifically, the interpretation of profile 2 has identified low resistivity and low-velocity anomalies which can be safely related to a deformed zone of WSW–ENE direction. Similar in-trend, subsurface fractures were reported by Chavanidis et al. [44]. It is shown that data integration, or joint geophysical data inversion using the combined local and global optimization methods, can unravel the geology of complex areas in depth. Integrating both DCR and SR data increases the model resolution and provides well-correlated structural similarities in the models. Moreover, these results show the feasibility of applying the combined local and global optimization algorithm to jointly interpret real 2D DCR and SR data, using both single and multi-objective genetic algorithm methods. Although the strength of the genetic algorithm lies in simplicity and adaptability to parallel computers, however, there is a tendency for early convergence (weakness), especially when there is over-mutation and crossover. Future studies may focus on determining the genetic algorithm optimum parameters (i.e., mutation rate and type of crossover) for the inversion of large datasets (e.g., 2D DCR data).

4.7 References

1. Reynolds, J. An Introduction to Applied and Environmental Geophysics, 2nd ed.; Willey-Blackwell: Hoboken, NJ, USA, 2011; ISBN 978-0-471-48535-3.
2. Anderson, N.; Ismail, A. A generalized protocol for selecting appropriate geophysical techniques. In Proceedings of the Geophysical Technologies for Detecting Underground Coal Mine Voids Forum, Lexington, KY, USA, 20–30 July 2013; pp. 28–30.

3. Hariri, M.M. Fractures system within Dammam Dome and its relationship to the doming process, Eastern Saudi Arabia. *Arab. J. Geosci.* **2014**, *7*, 4943–4956. [[CrossRef](#)]
4. Weijermars, R. Surface Geology, Lithostratigraphy and Tertiary Growth of the Dammam Dome, Saudi Arabia: A New Field Guide. *GeoArabia* **1999**, *4*, 199–226. [[CrossRef](#)]
5. Tranos, M.D.; Osman, M.S. Rus detachment in Dammam Dome, Eastern Saudi Arabia: A new soft-sediment structure as a ‘sensitive stress sensor’ for the Zagros collision. *Geol. Mag.* **2021**, 1–13. [[CrossRef](#)]
6. Steineke, M.; Harriss, T.; Parsons, K.; Berg, E. Geographic Map of the Western Persian Gulf Quadrangle, Kingdom of Saudi Arabia; US Geological Survey: Washington, DC, USA, 1958.
7. Tleel, J.W. Surface Geology of Dammam Dome, Eastern Province, Saudi Arabia. *Am. Assoc. Pet. Geol. Bull.* **1973**, *57*, 558–576. [[CrossRef](#)]
8. Hariri, M.; Abdullatif, O. Use of the GIS delineate lineaments from Landsat images, Dammam Dome, Eastern Saudi Arabia. In *Proceedings of the XXII International Cartographic Conference (ICC2005)*, A Coruña, Spain, 9–16 July 2005.
9. Al-fahmi, M. Fractures of the Dammam Dome Carbonate Outcrops: Their Characterization, Development, and Implications for Subsurface Reservoirs. Master’s Thesis, University of Massachusetts, Amherst, MA, USA, 2012.
10. Oldenburg, D.W.; Li, Y. Inversion for Applied Geophysics: A Tutorial. In *Near-Surface Geophysics*; Society of Exploration Geophysicists: Houston, TX, USA, 2005; pp. 89-150.
11. Gallardo, L.A.; Meju, M.A. Characterization of heterogeneous near-surface materials by joint 2D inversion of dc resistivity and seismic data. *Geophys. Res. Lett.* **2003**, *30*, 1658. [[CrossRef](#)]
12. Linde, N.; Binley, A.; Tryggvason, A.; Pedersen, L.B.; Revil, A. Improved hydrogeophysical characterization using joint inversion of cross-hole electrical resistance and ground-penetrating radar traveltimes data. *Water Resour. Res.* **2006**, *42*, W12404. [[CrossRef](#)]
13. Infante, V.; Gallardo, L.A.; Montalvo-Arrieta, J.C.; Navarro de León, I. Lithological classification assisted by the joint inversion of electrical and seismic data at a control site in northeast Mexico. *J. Appl. Geophys.* **2010**, *70*, 93–102. [[CrossRef](#)]
14. Moorkamp, M.; Heincke, B.; Jegen, M.; Roberts, A.W.; Hobbs, R.W. A framework for 3-D joint inversion of MT, gravity and seismic refraction data. *Geophys. J. Int.* **2011**, *184*, 477–493. [[CrossRef](#)]
15. Bennington, N.L.; Zhang, H.; Thurber, C.H.; Bedrosian, P.A. Joint Inversion of Seismic and Magnetotelluric Data in the Parkfield Region of California Using the Normalized Cross-Gradient Constraint. *Pure Appl. Geophys.* **2015**, *172*, 1033–1052. [[CrossRef](#)]
16. Demirci, İ.; Candansayar, M.E.; Vafidis, A.; Soupios, P. Two dimensional joint inversion of direct current resistivity, radio-magnetotelluric and seismic refraction

- data: An application from Bafra Plain, Turkey. *J. Appl. Geophys.* **2017**, 139, 316–330. [[CrossRef](#)]
17. Demirci, I.; Dikmen, Ü.; Candansayar, M.E. Two-dimensional joint inversion of Magnetotelluric and local earthquake data: Discussion on the contribution to the solution of deep subsurface structures. *Phys. Earth Planet. Inter.* **2018**, 275, 56–68. [[CrossRef](#)]
 18. Autio, U.; Smirnov, M.Y.; Savvaidis, A.; Soupios, P.; Bastani, M. Combining electromagnetic measurements in the Mygdonian sedimentary basin, Greece. *J. Appl. Geophys.* **2016**, 135, 261–269. [[CrossRef](#)]
 19. Wang, K.-P.; Tan, H.-D.; Wang, T. 2D joint inversion of CSAMT and magnetic data based on cross-gradient theory. *Appl. Geophys.* **2017**, 14, 279–290. [[CrossRef](#)]
 20. Shahruxh, M.; Soupios, P.; Papadopoulos, N.; Sarris, A. Geophysical investigations at the Istron archaeological site, eastern Crete, Greece using seismic refraction and electrical resistivity tomography. *J. Geophys. Eng.* **2012**, 9, 749–760. [[CrossRef](#)]
 21. Vafidis, A.; Soupios, P.; Economou, N.; Hamdan, H.; Andronikidis, N.; Kritikakis, G.; Panagopoulos, G.; Manoutsoglou, E.; Steiakakis, M.; Candansayar, E.; et al. Seawater intrusion imaging at Tybaki, Crete, using geophysical data and joint inversion of electrical and seismic data. *First Break* **2014**, 32. [[CrossRef](#)]
 22. Demirci, I.; Gündoğdu, N.Y.; Candansayar, M.E.; Soupios, P.; Vafidis, A.; Arslan, H. Determination and Evaluation of Saltwater Intrusion on Bafra Plain: Joint Interpretation of Geophysical, Hydrogeological and Hydrochemical Data. *Pure Appl. Geophys.* **2020**, 177, 5621–5640. [[CrossRef](#)]
 23. Ahmad, M.; Hu, J.-L.; Hadzima-Nyarko, M.; Ahmad, F.; Tang, X.-W.; Rahman, Z.U.; Nawaz, A.; Abrar, M. Rockburst Hazard Prediction in Underground Projects Using Two Intelligent Classification Techniques: A Comparative Study. *Symmetry* **2021**, 13, 632. [[CrossRef](#)]
 24. Ahmad, M.; Katman, H.Y.; Al-Mansob, R.A.; Ahmad, F.; Safdar, M.; Alguno, A.C. Prediction of Rockburst Intensity Grade in Deep Underground Excavation Using Adaptive Boosting Classifier. *Complexity* **2022**, 2022, 6156210. [[CrossRef](#)]
 25. Chunduru, R.K.; Sen, M.K.; Stoffa, P.L. Hybrid optimization methods for geophysical inversion. *Geophysics* **1997**, 62, 1196–1207. [[CrossRef](#)]
 26. Soupios, P.; Akca, I.; Mpogiatis, P.; Basokur, A.T.; Papazachos, C. Applications of hybrid genetic algorithms in seismic tomography. *J. Appl. Geophys.* **2011**, 75, 479–489. [[CrossRef](#)]
 27. Liu, S.; Liang, M.; Hu, X. Particle swarm optimization inversion of magnetic data: Field examples from iron ore deposits in China. *Geophysics* **2018**, 83, J43–J59. [[CrossRef](#)]
 28. Rani, P.; Piegari, E.; Di Maio, R.; Vitagliano, E.; Soupios, P.; Milano, L. Monitoring time evolution of self-potential anomaly sources by a new global optimization approach. Application to organic contaminant transport. *J. Hydrol.* **2019**, 575, 955–964. [[CrossRef](#)]

29. Ayani, M.; MacGregor, L.; Mallick, S. Inversion of marine controlled source electromagnetic data using a parallel non-dominated sorting genetic algorithm. *Geophys. J. Int.* **2020**, *220*, 1066–1077. [[CrossRef](#)]
30. Akca, I.; Günther, T.; Müller-Petke, M.; Başsokur, A.T.; Yaramanci, U. Joint parameter estimation from magnetic resonance and vertical electric soundings using a multi-objective genetic algorithm. *Geophys. Prospect.* **2014**, *62*, 364–376. [[CrossRef](#)]
31. Ekinici, Y.L.; Balkaya, Ç.; Göktürkler, G. Backtracking Search Optimization: A Novel Global Optimization Algorithm for the Inversion of Gravity Anomalies. *Pure Appl. Geophys.* **2021**, *178*, 4507–4527. [[CrossRef](#)]
32. Ramillien, G. Genetic algorithms for geophysical parameter inversion from altimeter data. *Geophys. J. Int.* **2001**, *147*, 393–402. [[CrossRef](#)]
33. Yan, Z.W.; Tan, H.D.; Peng, M.; Kong, W.X.; Wu, P. Three-dimensional joint inversion of gravity, magnetic and magnetotelluric data based on cross-gradient theory. *Chin. J. Geophys.* **2020**, *63*, 736–752. (In Chinese) [[CrossRef](#)]
34. Wang, J.; Tan, Y. 2-D MT inversion using genetic algorithm. *J. Phys. Conf. Ser.* **2005**, *12*, 165–170. [[CrossRef](#)]
35. Sen, M.K.; Stoffa, P.L. *Global Optimization Methods in Geophysical Inversion*; Cambridge University Press: Cambridge, UK, 2013; ISBN 1139619519.
36. Edigbue, P.; Demirci, I.; Hamdan, H.; Al-Shuhail, A.; Akca, I.; Soupios, P.; Candansayar, E. Joint Inversion of Seismic and DC Geophysical Data Using Local and Global Optimization Algorithms. In *Proceedings of the International Petroleum Technology Conference*, Riyadh, Saudi Arabia, 21–23 February 2022; IPTC: Riyadh, Saudi Arabia, 2022.
37. Powers, R.; Ramirez, L.; Redmond, C.; Elberg, E. *Geology of the Arabian peninsula*; US Geological Survey: Washington, DC, USA, 1966; Volume 560.
38. Roger, J.; Giot, D. *Industrial Mineral Resources Map of Ad Dammam, Kingdom of Saudi Arabia*; Ministry of Petroleum and Mineral Resources, Deputy Ministry for Mineral Resources: Jeddah, Saudi Arabia, 1985.
39. Al-Fahmi, M.; Cooke, M.L.; Cole, J.C. Modeling of the Dammam outcrop fractures: Case study for fracture development in salt-cored structures. *GeoArabia J. Middle East Pet. Geosci.* **2014**, *19*, 49–80. [[CrossRef](#)]
40. Chavanidis, K.; Stampolidis, A.; Kirmizakis, P.; Tranos, M.; Fedi, M.; Pasteka, R.; Al-Ramadan, K.; Kaka, S.; Tsokas, G.N.; Soupios, P. Gravity Survey on the Oil-Bearing Dammam Dome (Eastern Saudi Arabia) and Its Implications. *Remote Sens.* **2022**, *14*, 735. [[CrossRef](#)]
41. Palmer, A.R. The Decade of North American Geology 1983 Geologic Time Scale. *Geology* **1983**, *11*, 503. [[CrossRef](#)]
42. Alkhalifa, M.A.; Kurison, C. Karst collapse and gypsum-filled veins in Eocene outcrops, Dammam Dome, Saudi Arabia: Causes and implications. *Geosyst. Geoenviron.* **2023**, *2*, 100109. [[CrossRef](#)]

43. Hanafy, S.M.; Jonsson, S.; Klinger, Y. Imaging normal faults in alluvial fans using geophysical techniques: Field example from the coast of Gulf of Aqaba, Saudi Arabia. In Proceedings of the SEG Technical Program Expanded Abstracts 2014; Society of Exploration Geophysicists: Houston, TX, USA, 2014; pp. 4670–4674.
44. Edigbue, P.; Al-Shuhail, A. Three-dimensional supervirtual seismic refraction interferometry. *Arab. J. Geosci.* **2016**, *9*, 537. [[CrossRef](#)]
45. Hanafy, S.; Gupta, H. Seismic, super-virtual refraction interferometry. In Encyclopedia of Solid Earth Geophysics; Encyclopedia of Earth Sciences Series; Springer International Publishing: Berlin/Heidelberg, Germany, 2020; ISBN 978-3-030-10475-7.
46. Newman, G.A.; Alumbaugh, D.L. Three-dimensional massively parallel electromagnetic inversion-I. Theory. *Geophys. J. Int.* **1997**, *128*, 345–354. [[CrossRef](#)]
47. Sajeve, A.; Aleardi, M.; Galuzzi, B.; Stucchi, E.; Spadavecchia, E.; Mazzotti, A. Comparing the performances of four stochastic optimisation methods using analytic objective functions, 1D elastic full-waveform inversion, and residual static computation. *Geophys. Prospect.* **2017**, *65*, 322–346. [[CrossRef](#)]
48. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197. [[CrossRef](#)]
49. Deb, K.; Agrawal, S.; Pratap, A.; Meyarivan, T. A Fast Elitist Non-dominated Sorting Genetic Algorithm for Multi-objective Optimization: NSGA-II. In Proceedings of the Parallel Problem Solving from Nature PPSN VI; Schoenauer, M., Deb, K., Rudolph, G., Yao, X., Lutton, E., Merelo, J.J., Schwefel, H.-P., Eds.; Springer: Berlin/Heidelberg, Germany, 2000; pp. 849–858.
50. Edigbue, P.; Demirci, I.; Akca, I.; Hamdan, H.A.; Kirmizakis, P.; Soupios, P.; Candansayar, E.; Hanafy, S.; Al-Shuhail, A. A Comprehensive Study of Local, Global, and Combined Optimization Methods on Synthetic Seismic Refraction and Direct Current Resistivity Data. *Appl. Sci.* **2022**, *12*, 11589. [[CrossRef](#)]

CHAPTER 5

Evaluation of Optimization Algorithms

Testing different stochastic methods to model direct current resistivity and seismic refraction geophysical data using a combined local and global optimization algorithms

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Abstract

Global optimization methods have recently become an essential option in the processing and interpretation of geophysical data sets. In this study, we compared the optimization capability of five global optimization techniques in terms of their ability to localize a global solution and computation cost using objective functions for direct current resistivity (DCR), and seismic refraction (SR) data processing and interpretation. The genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), surrogate optimization (SO), and pattern search (PS) optimization techniques were tested. The recently developed combined (global and local) optimization algorithm that uses the local optimization's output to minimize the search space for the global search method and achieve faster convergence is applied to solve the optimization problem for comparison. Because all the optimization algorithms try to minimize the same objective function, we benchmarked the comparison with the result of the local optimization algorithm using the Gauss-Newton (GN) method. The combined optimization algorithms run for 500 iterations

for both synthetic and real data. All the optimization algorithms satisfactorily reconstructed the positive anomalies (synthetic data) and defined a suspected fault (real data). However, considering the result of the local optimization as a benchmark (in terms of misfit and run time), only the GA and PSO satisfactorily reduce the misfit obtained from both DCR and SR inversion using the GN method. Therefore, the GA and PSO should be considered as the proper techniques for inverting the real DCR and SR data sets, with sequential use of local and global optimization methods.

5.1 Introduction

In the hybrid optimization technique, the advantages of the local and global optimization methods are integrated to surmount their challenges [4–7]. In this study, we evaluated some commonly used global optimization algorithms to assess their contributions in a combined (global and local) optimization algorithm of the DCR and SR methods [7,8]. These global search methods include genetic algorithm (GA), particle swarm optimization (PSO), simulated annealing (SA), surrogate optimization (SO), and pattern search (PS) methods. To the best of our understanding, some of these global optimization techniques (e.g., SA, SO, and PS algorithms) have not been combinedly (i.e., using local optimization to define a search space for the global optimization algorithm) applied on a high-dimensional jointly geophysical data inversion (e.g., the DCR and SR data). However, the hybrid form (i.e., integrated local plus global optimization algorithm) of some of these global algorithms (e.g., GA and PSO) have been tested on a high-dimensional geophysical model [5,9]. Also, some of these global search techniques have been compared using analytical, objective functions, and seismic optimizations [3,10]. Generally, we compared the optimization capability of these global search methods in

terms of their misfit output and computation cost using the same objective functions in the DCR and SR data inversion, respectively.

5.2 Optimization techniques

Generally, the combined optimization approach applied in this study is divided into two stages; firstly, we apply the local optimization algorithm to define the search ranges of model parameters for the global optimization algorithms, and secondly, we use this search range to create the initial solutions for each of the global optimization algorithms considered. Demirci et al. [11,12] and Edigbue et al. [8] reported details about the concept of the local optimization algorithm used in this study. Also, Edigbue et. al. [8] provides a detailed description of the combined optimization algorithm involving the GA. This section describes some of the metaheuristic global optimization algorithms we considered in this study. In addition, relevant references are provided for a better understanding of the global search methods applied in this study since we primarily offer their (global methods) overviews and focus on the feasibility study. We evaluated five global optimization algorithms; some are instigated by nature (theory of evolution/or animal behavior), e.g., the genetic algorithm and the particle swarm optimization. At the same time, others are physics-based/artificially instigated, e.g., simulated annealing, surrogate optimization, and pattern search optimization. Each global optimization algorithm begins by creating initial populations randomly distributed within the search range specified using the local optimization algorithms. Then, the model parameter values obtained from the local optimization [2] output are scaled up/down by 50% in both directions to establish the search range in the global optimization stage. A population is a group of decision variables that provide probable solutions to the optimization problem, which are modified at every

iteration until a stopping criteria has been satisfied. Generally, tuning (control) parameters for each global search technique are determined by a trial-and-error approach and references from previous studies. The tuning parameters (e.g., number of iterations and population size) are mostly problem dependent and controlled by experience as a rule of thumb [3].

All the optimization algorithms in this study try to minimize the misfit functions:

$$M_{dcr} = \frac{100 \times (W_{dcr} \|d_{dcr} - td_{dcr}\|_2)}{\|d_{dcr}\|_2} \quad (1)$$

$$M_{sr} = \frac{100 \times (W_{sr} \|d_{sr} - td_{sr}\|_2)}{\|d_{sr}\|_2} \quad (2)$$

where M_{dcr} and M_{sr} are the respective DCR and SR objective functions, W_{dcr} and W_{sr} are the data weights, d_{dcr} and d_{sr} are observed field data, td_{dcr} and td_{sr} are the theoretical data for both DCR and SR methods, respectively. We benchmarked the performances of the combined optimization algorithm with the result of the local optimization algorithm (Gauss-Newton) based on the data objectives given in equations 1 and 2.

5.2.1 Genetic algorithm (GA)

The genetic algorithm (GA) is one of the most popular stochastic optimization techniques often used to solve complex high-dimensional optimization problems. GA is inspired by the concept of natural selection and the survival of the fittest organisms. GA optimization evaluates the models from a randomly created population of candidate solutions concerning the objective function. GA operators such as crossover and mutation are used to update the models and select the optimum solution. Fig. 1 demonstrates the basic operators of GA for binary coded model strings. Because of the simplicity of this algorithm, it has been extensively adapted to solve geophysical inverse problems [1,13].

GA algorithms can reach a global solution because they use analogous information from the previous generations to determine a better solution for the current generation. Because GA is a stochastic process that involves running the algorithm for as many generations as possible, it is computationally expensive. However, with the development of hybrid and combined GA optimization algorithms coupled with parallel computing [5,8], its application has been gaining more popularity in solving large geophysical problems. The simple GA is used for modeling a geophysical problem involving a single objective function. In contrast, another form of GA handles the multi-objective problem, such as the non-dominated sorting genetic algorithm (NSGA II). The main difference is that the cost function value in a single objective is scalar, while that of the multi-objective is a vector that depends on the number of objective functions, as shown in equation 3.

$$Z = \{z \in R^q \mid z_1 = f_1(x), z_2 = f_2(x), \dots, z_q = f_q(x), x \in S\} \quad (3)$$

where $z \in R^q$ is a vector, q is the number of objective functions, and x is the independent variable.

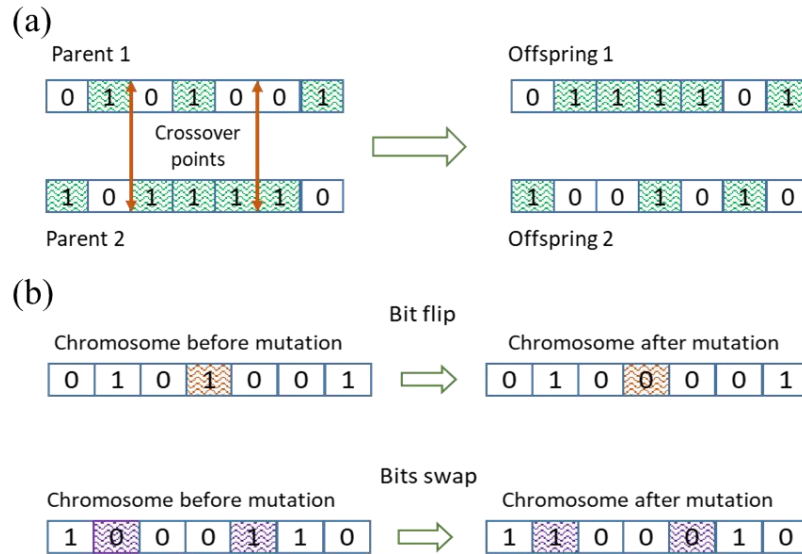


Figure 5.1: Application of GA by using **(a)** the crossover, **(b)** the mutation process.

5.2.2 Particle swarm optimization (PSO)

Particle swarm optimization is one of the population-based evolutionary algorithms motivated by animal social behaviors [1]. Fundamentally, the PSO is controlled by two major criteria, namely, the position and velocity of particles. A detailed review of the applications of PSO and several geophysical examples are found in Pace et al. [14]. PSO has been applied to solve 1D and 2D geophysical problems [15–20]. The operational principle of the PSO is similar to GA; it starts with an initial particle position, $x_i(t)$ and velocity, $v_i(t)$, and after t iterations, $p_i(t)$ is the best particle solution. $g(t)$ is the global solution of all particles, $x_i(t + 1)$ and $v_i(t + 1)$ are the particle's updated position and velocity, respectively (figure 2). This is a genuinely iterative process searching for the best solution with the number of generations. Unlike GA, which uses evolution operators such as crossover and mutation to update models, PSO is regulated by operators that update particle positions and velocities. In addition, new solutions are created using the experiences of each particle and its associated neighbor. Particles keep the memory of their previous optimal positions and velocities that are updated iteratively. PSO particles move towards global best as shown in Figure 2, and the mathematical model describing the swarm optimization is given in equation 4 and 5.

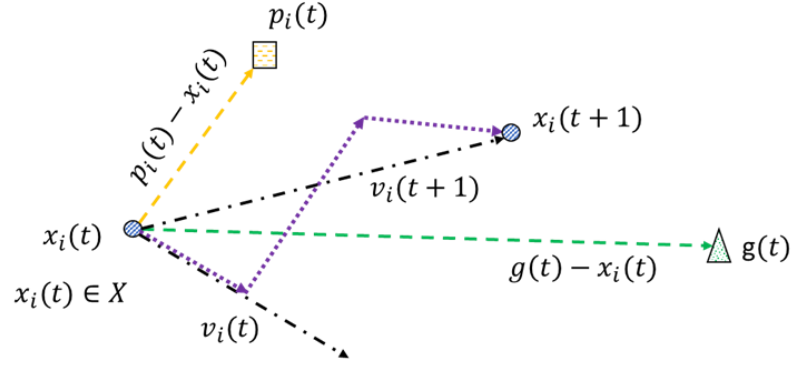


Figure 5.2: Geometrical representation of the particle swarm optimization. The yellow dash line is the particle's personal best vector, the Black dash lines are the particle's initial and updated velocity vectors, and the green dash line is the global best vector of all particles. The purple dash lines show the movement of a particle to a new (better) position.

The PSO uses equations 4 and 5 to update a particle's velocity and position.

$$v_{ij}(t+1) = wv_{ij}(t) + r_1c_1(p_{ij}(t) - x_{ij}(t)) + r_2c_2(g_j(t) - x_{ij}(t)) \quad (4)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (5)$$

where, v_{ij} , p_{ij} and x_{ij} are scalar values in j components of v , p , and x , respectively. w is the inertial coefficient, $r_1, r_2 \sim \mathcal{U}(0,1)$, while c_1 and c_2 are the acceleration coefficients. The first term in equation 4 is the inertial term, the second term is the individual or cognitive component, and the third term is the social component.

5.2.3 Simulated Annealing (SA)

Simulated annealing (SA) was proposed to search for an optimal minimum of an error function with many decision variables [1,21,22]. This global search algorithm is applicable in modeling geophysical data because we usually minimize an error function. Therefore, the application of the SA algorithm has been extended to successfully solve some geophysical problems [23–25]. The working principle of SA optimization is adapted

from material and metallurgical engineering that involves the statistical analysis of metal atoms at a thermal equilibrium undergoing a gradual cooling process (annealing). The metallic particles are randomly dispersed at a high temperature in a liquid state. After that, the system undergoes gradual cooling to make the particles settle in a low-energy level or state, thereby causing complete crystallization. The heated metallic material is allowed to attain thermal equilibrium at every temperature, and Gibbs or Boltzmann probability distribution function is used to describe the state of the particle and its energy as;

$$P(E_j) = \frac{\exp\left(-\frac{E_j}{KT}\right)}{\sum_{i \in R} \exp\left(-\frac{E_k}{KT}\right)} = \frac{1}{Z(T)} \exp\left(-\frac{E_j}{KT}\right) \quad (6)$$

where K is the Boltzmann's constant, T is the temperature, Z is the partition function, and R is the set of all possible configurations.

The fundamental issue is how the material is allowed to cool. The material stops at a local minimum energy level when allowed to cool very rapidly. However, there is a good chance that the material stops at a level close to the global minimum of energy when allowed to cool gradually. Adapting this concept to solve the geophysical problem, the energy function can be replaced with the geophysical error function $E(m)$, where m is the model parameter that minimizes the error function. To avoid calculating the error function at every point in the model domain, some modified versions of the SA algorithm were proposed [21], such as the very fast simulated reannealing (VFSA) techniques used in this study. Given the upper and lower bounds of an error function, the SA algorithm creates a random test point within these bounds and within the limit of the current temperature. Then it evaluates a distance distribution function and randomly changes worse parts of the test point. The objective function is evaluated at this new point to determine whether it is better

or worse than the recent point. Although the new point is accepted in both cases, however, the worse point is accepted using a probability function as;

$$p = \frac{1}{1 + \exp(\frac{\Delta}{\max(T, T_o)})} \quad (7)$$

where Δ is the difference in the values of the objective between the current and the new point, T_o is the initial temperature, and T is the current temperature. Temperature is then updated, and the best point observed so far is stored. The SA algorithm uses reannealing parameters (i.e., temperature scaling) to avoid getting stuck in the local minimum. This process continues until the stopping criteria are fulfilled.

5.2.4 Surrogate optimization (SO)

Fundamentally, surrogates can be described as an approximation to an error or misfit (response) surface so that it simulates an input-output relationship. Instead of directly optimizing the high-fidelity model or error function, surrogate optimization aims to optimize an auxiliary model to speed-up computational cost. Surrogate optimization has been shown to improve the runtime of the optimization of high-dimension models [26–28]. When choosing a surrogate, specific criteria need to be satisfied to obtain dependable surrogates: it should possess a simple structure (few data points) since a complex structure could be very expensive to run, and it should be computationally easy to fit because it needs to be updated as more solutions become available. Furthermore, its predictor should be explicit so that the surrogate can easily optimize. Generally, three surrogates fulfill these conditions: low-order polynomials, basis function models, and Gaussian processes (GPs). In this study, we apply the simple form of surrogate model creation using the basis function method. The fundamentals and concept of surrogate-based optimization are presented in

Queipo et al. [26]. As an overview, given the upper and lower bands of the model parameter, surrogates modeling begins by creating sample points from a quasi-random sequence and evaluating the primary (expensive) objective function at these points. After that, the algorithm makes a surrogate model (auxiliary objective function) by applying the interpolation of a radial basis function [29] over the sample points. More surrogate points are created near the best (minimum) observed point in the initial surrogate model, and a merit function is evaluated at these points [30]. This merit function depends on the function value of the new surrogate points and the intervals between initial and new surrogate points (Eq. 8).

$$f_{merit}(x) = wS(x) + (1 - w)D(x) \quad (8)$$

where $S(x)$ is the scaled surrogate, $D(x)$ is the scaled distance between the sampled and evaluated points, and w is that range from 0 to 1 (i.e., $0 < w < 1$).

The best point evaluated (using the merit function) is selected as the "adaptive point" and is used to assess the primary objective function. After that, the output of the previous evaluation is used to update the surrogate model (Figure 3) and continue another search phase until a termination criterion is observed.

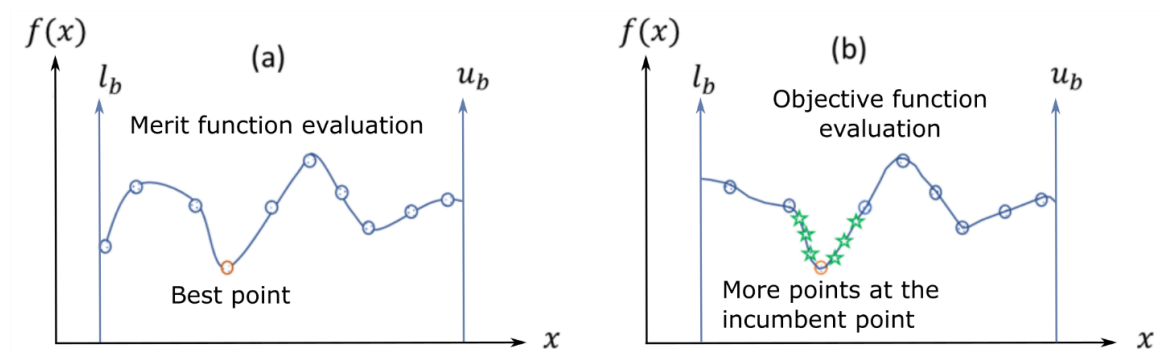


Figure 5.3: Schematic illustration of how the surrogate algorithm searches for minimum: **(a)** Evaluation of the merit function after creating surrogates to obtain the best point, **(b)**

More points are created around the incumbent point, and the objective function is evaluated to update the surrogate model.

5.2.5 Pattern search (PS)

Fundamentally, the pattern search (PS) algorithm estimates a set of points (cost function values) around an existing point to determine the next optimum location. This system of setting points around a current point is known as meshing, which is modified (scale up/down) in subsequence iterations depending on the solution optimality. The concept of the PS algorithm is elaborated in Audet & Dennis [31]. Some geophysical application of the PS algorithm includes Song et al. [32,33]. Song et al. [33] provide the optimum PS parameters in the inversion of high-frequency surface waves. In this study, we applied the generalized pattern search (GPS) algorithm that begins with evaluating an initial model parameter vector provided by the user. After that, GPS creates a mesh around the initial point by evaluating updated model parameters produced using directional vectors and the initial model parameters. The GPS algorithm then investigates the mesh to obtain the best solution and proceeds to the location of the optimal solution if found within the mesh. The mesh size is contracted in the next iteration, and similar meshing (exploration) and objective function evaluation processes are repeated (exploitation). If the optimal solution is not found within the mesh, a mesh expansion occurs, and the solution optimality search is restarted. This way, the GPS algorithm avoids being stuck in the local minimum until the global solution is obtained. For example, assume a user-provided model parameter vector (x_o) of size $n=2$ (number of independent variables), and the GPS directional vector ($[1\ 0], [0\ 1], [-1\ 0], [0\ -1]$), then exploration and exploitation processes are presented in Figure 4. Finally, the computation of initial mesh points is illustrated in equations 9a-e.

$$f(x_0) = 2.1 \quad (9.a)$$

$$f(x_0 + z_t \times [1 \ 0]) = f(x_1) = 3.1 \quad (9.b)$$

$$f(x_0 + z_t \times [0 \ 1]) = f(x_2) = 3.1 \quad (9.c)$$

$$f(x_0 + z_t \times [-1 \ 0]) = f(x_3) = 3.1 \quad (9.d)$$

$$f(x_0 + z_t \times [0 \ -1]) = f(x_4) = 2.4 \quad (9.e)$$

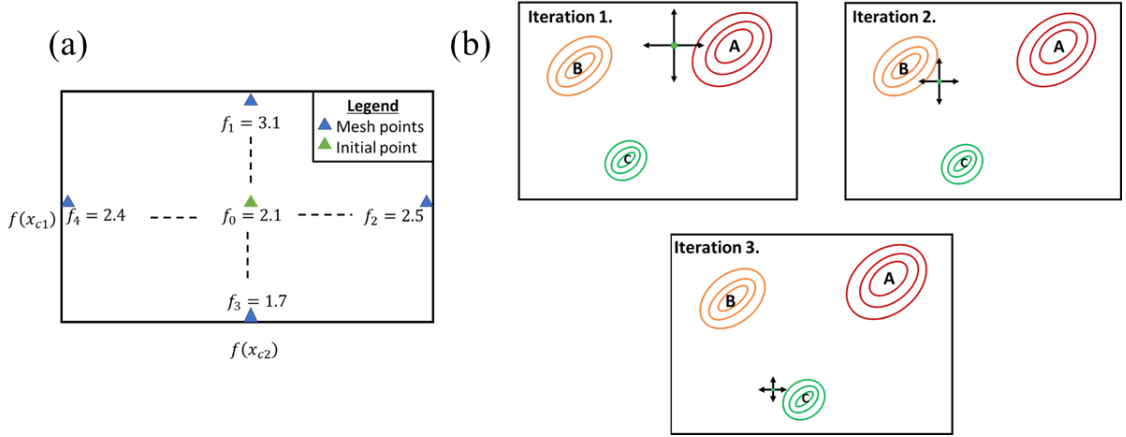


Figure 5.4: Illustration of **(a)** the exploration stage of the PS algorithm, and **(b)** how the PS algorithm approach convergence (exploitation). Notice that at every iteration, the search direction moves towards a better solution and contrasts the mesh as it approaches the global minimum, as in iteration 3.

5.3 Synthetic data example

We created two-dimensional (2D) resistivity and velocity models with two positive anomalies to produce test data sets. The resistivity model is 240 m long with a depth extension of 50 m, and 49 electrodes with 5 m spacing were used to simulate apparent resistivity data using the dipole-dipole array configuration to achieve the highest lateral resolution. The velocity model used is similar to the resistivity model in size and anomalies; where 13 sources and 49 receivers with 5 m spacing were used to simulate the SR data. Gaussian noise with a standard deviation of 3% is added to the datasets (DCR and SR) to simulate field data. These data sets (DCR and SR) were first inverted using the Gauss-

Newton local optimization algorithm starting with homogenous halfspaces with physical parameters of 100 ohm.m and 1000m/s respectively. Then, the final inverted resistivity and velocity models were used to define the search spaces of global algorithms as explained earlier by giving a 50% margin to the estimated cell resistivities and velocities. For comparison, we set the same number of iterations and population size, since these two parameters have significant effect in the convergence of the global methods. The combined algorithm uses two stopping criteria: the average distance between the set of solutions and the number of iterations/generations. The value of $1e-4$ is specified for the average distance, especially for GA, while the population size is 200, and 500 is used as the maximum number of iterations per generation, for all the combined optimization algorithms. Finally, the number of unknown (model) parameters was 950 and 768 for the DCR and SR models, respectively. The combined optimization is prepared to run in parallel (i.e., using a six cores computer) during execution to reduce the computation cost. Results (resistivity and velocity models) from all the combined optimization techniques for both DCR and SR methods are shown in Figures 5 and 8, respectively.

Starting with the DCR method, the misfits obtained are 7.56%, 1.28%, 1.24%, 2.09%, 2.49%, and 1.65% for the GN, GA, PSO, SA, SO, and PS optimization algorithms, respectively (Figure 5). In figure 6, the performances of these DCR optimization algorithms with respect to the misfit and computation cost are presented as bar charts. The DCR local (GN) optimization has the highest misfit value (7.56 %) but the least computation cost (0.75 minutes). The PSO has the least misfit value (1.24 %) but with a computation cost of 51.76 minutes. In the composite plots of all the DCR combined optimization algorithms presented in figure 7, the PSO and GA appear to have optimum

performance after 500 iterations. Comparing all the DCR combined optimization algorithms with the local optimization algorithm, the results show that all the combined algorithms improve the GN misfit level between 67% (SO) and 84% (PSO), but their computation costs are significantly high. Looking at these factors, misfit, and computation cost, the combined PSO algorithm is considered more prolific among all the DCR combined optimization algorithms.

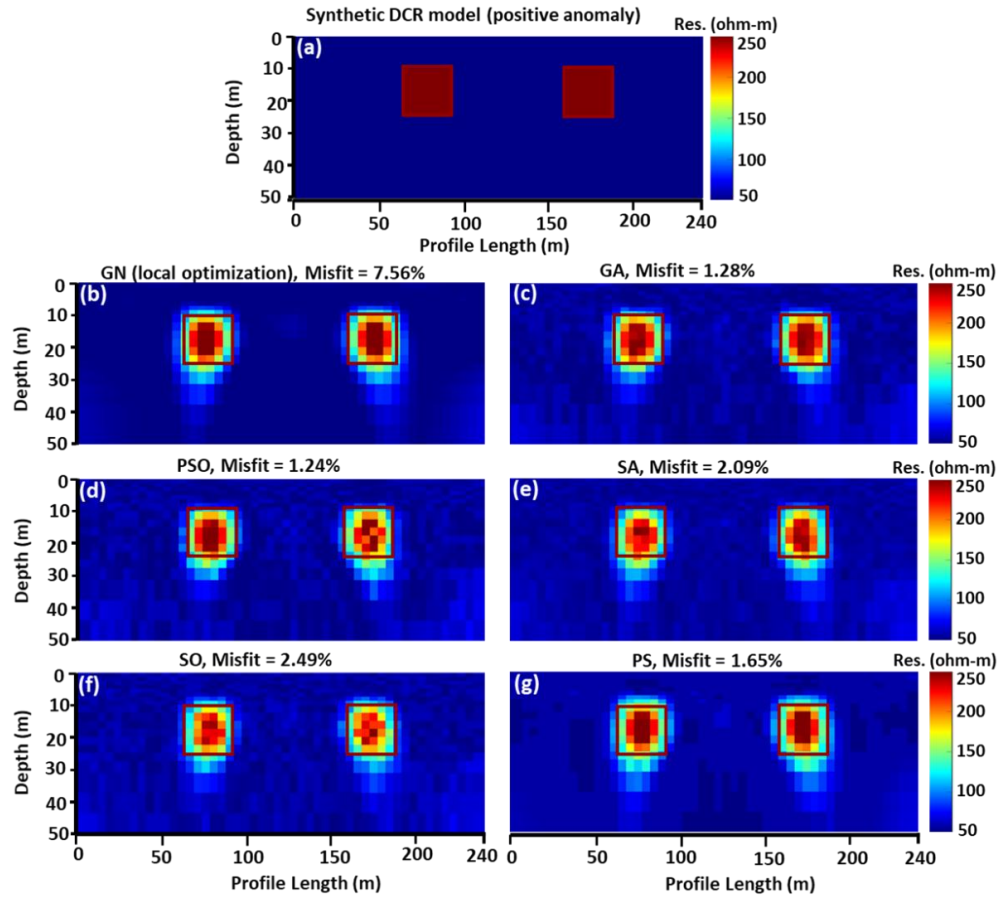


Figure 5.5: Inverted resistivity (DCR method) models using (a) synthetic DCR model (positive anomaly), (b) local optimization using the Gauss-Newton (GN) method, and the combined local with global optimization using (c) genetic algorithm, (d) particle swarm optimization, (e) simulated annealing, (f) surrogate optimization, and (g) pattern search

algorithm. Using the GN as a reference, all the combined algorithms reduce the misfits by about 67% below the misfit of the GN optimization.

This result is presented as a plot of the error function with several iterations and the misfits' bar chart of all the combined algorithms for better comparison.

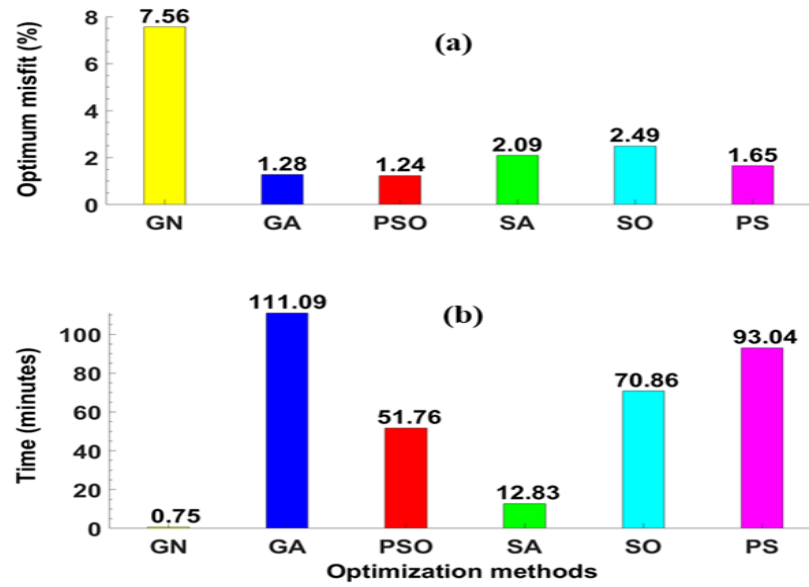


Figure 5.6: Bar chart depicting the performances of all the DCR optimization algorithms in terms of **(a)** optimum misfit and **(b)** computation cost (time).

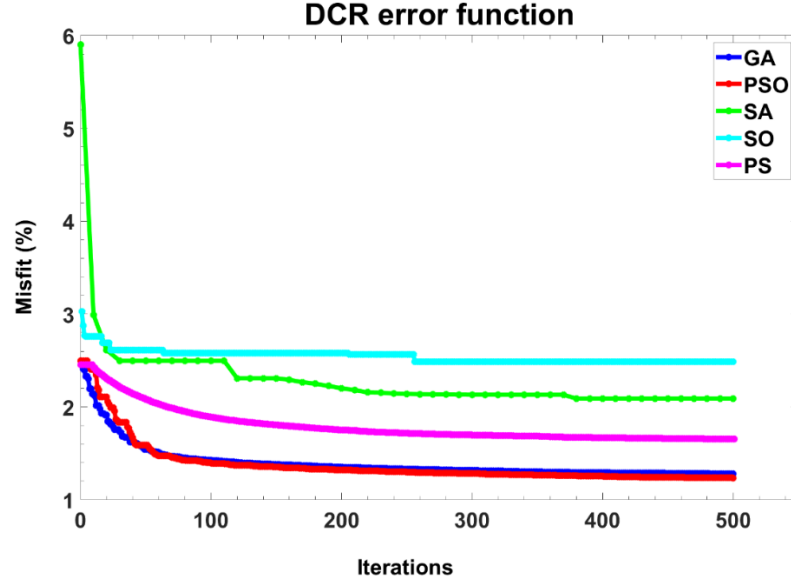


Figure 5.7: Misfit trend with the number of iterations for the DCR error function. The combined PSO (red) algorithm shows the minor misfit after 500 iterations.

Applying similar analysis for the SR method, the misfits obtained are 1.86%, 1.79%, 1.76%, 2.33%, 2.65%, and 2.06% for the GN, GA, PSO, SA, SO, and PS optimization algorithms, respectively (Figure 8). In addition, the performances of these SR optimization algorithms with respect to the misfit and computation cost are presented as bar charts (Figure 9). The SR local (GN) optimization has the misfit value of 1.86% and the least computation cost (1.51 minutes), while the PSO has the least misfit value (1.76 %) but with a computation cost of 988.07 minutes. In the composite plots of all the SR combined optimization algorithms presented in figure 10, the PSO and GA appear to have optimum performance after 500 iterations. Comparing all the SR combined optimization algorithms with the local optimization algorithm, the results in Figures 8 and 9 show that the combined algorithms improve the GN misfit by levels between 3.8% (GA) – 5.4% (PSO), but their computation costs are significantly high. Commenting on these factors,

misfit, and computation cost, the combined GA and PSO algorithm are considered more prolific among all the DCR combined optimization algorithms.

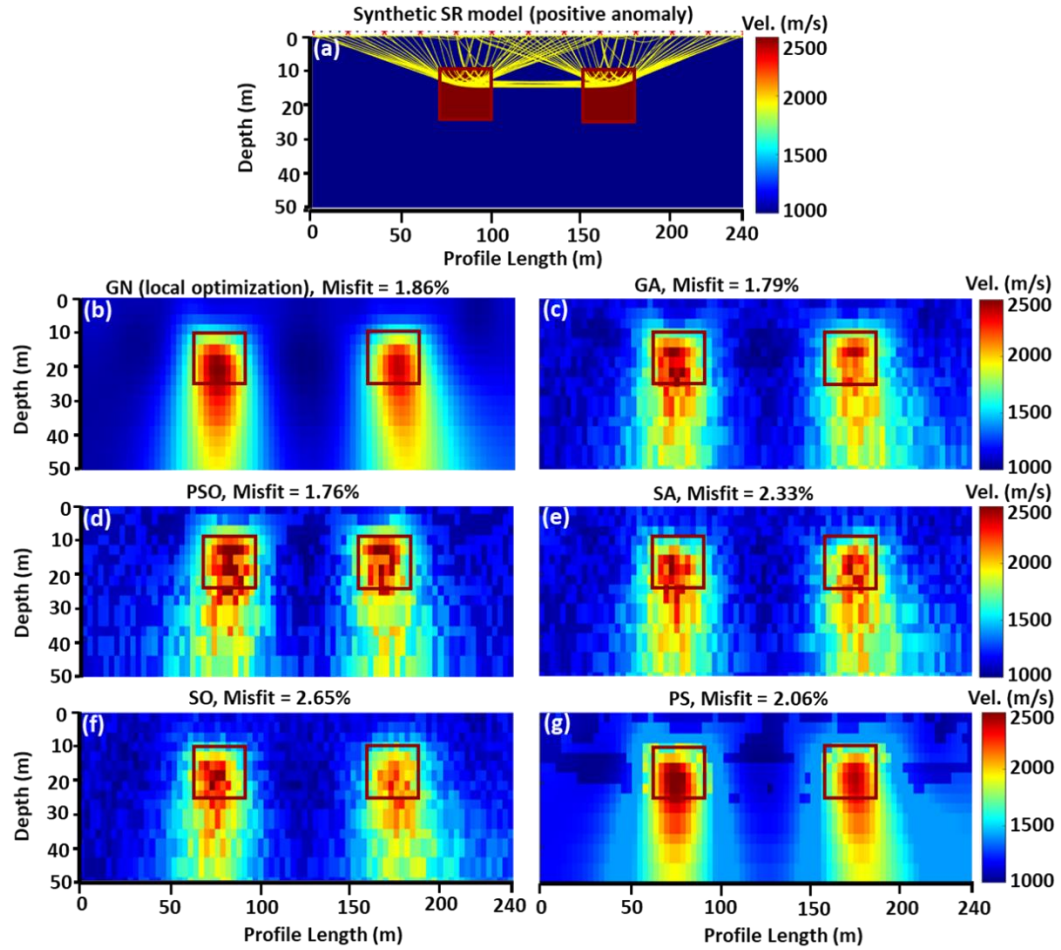


Figure 5.8: Inverted velocity (SR method) models using (a) synthetic SR model (positive anomaly), (b) local optimization using the Gauss-Newton (GN) method, and the combined local with global optimization using (c) genetic algorithm, (d) particle swarm optimization, (e) simulated annealing, (f) surrogate optimization, and (g) pattern search algorithm. Using the GN as a reference, only the combined algorithms using GA and PSO reduce the misfits by about 3.8% and 5.4% below the misfit of the GN optimization.

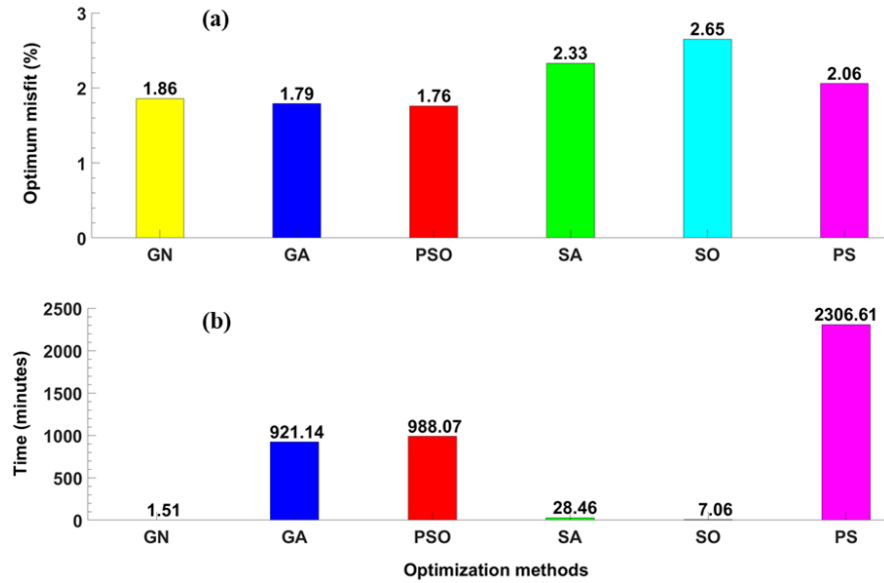


Figure 5.9: Bar chart depicting the performances of all the SR optimization algorithms in terms of (a) optimum misfit and (b) computation cost (time). GN is the Gauss-Newton local optimization.

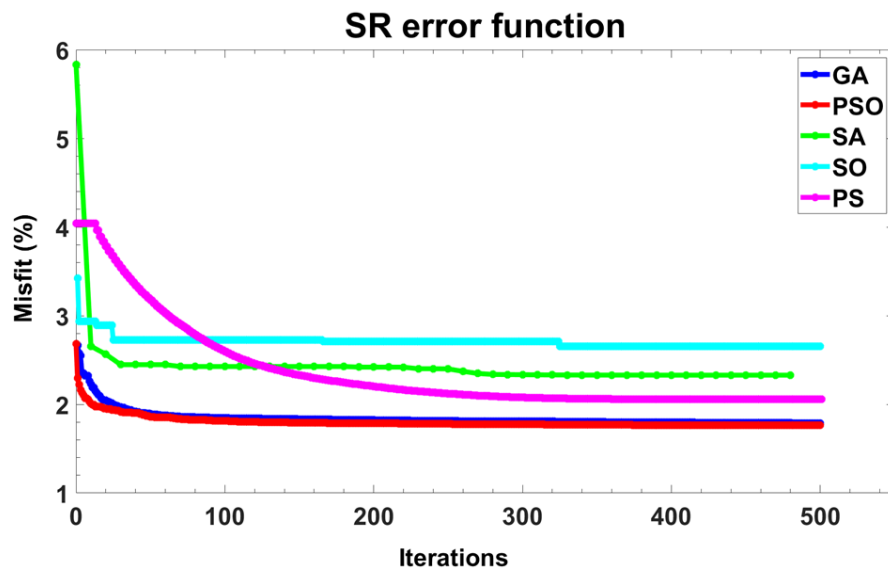


Figure 5.10: Misfit trend with the number of iterations for the SR error function. The combined PSO (red) algorithm shows the least misfit after 500 iterations.

5.4 Field Data Example

The combined optimization algorithms are tested using data acquired across an active fault in the Gulf of Aqaba (Figure 11a), Saudi Arabia [34]. Details about the formation and occurrence of the rupture (fault) found in the study area after the occurrence of an earthquake in 1995 are presented in Hanafy et al. [34], Li et al. [35], and Hanafy & Schuster [36]. Although the ruptured zone has been covered with sediments over time, part of the fault rupture is still visible at the surface (Figure 11b). The fault zone is expected to have a good contrast, as a lateral discontinuity, with the host formation and cause a detectable anomaly for the DCR and SR geophysical methods.

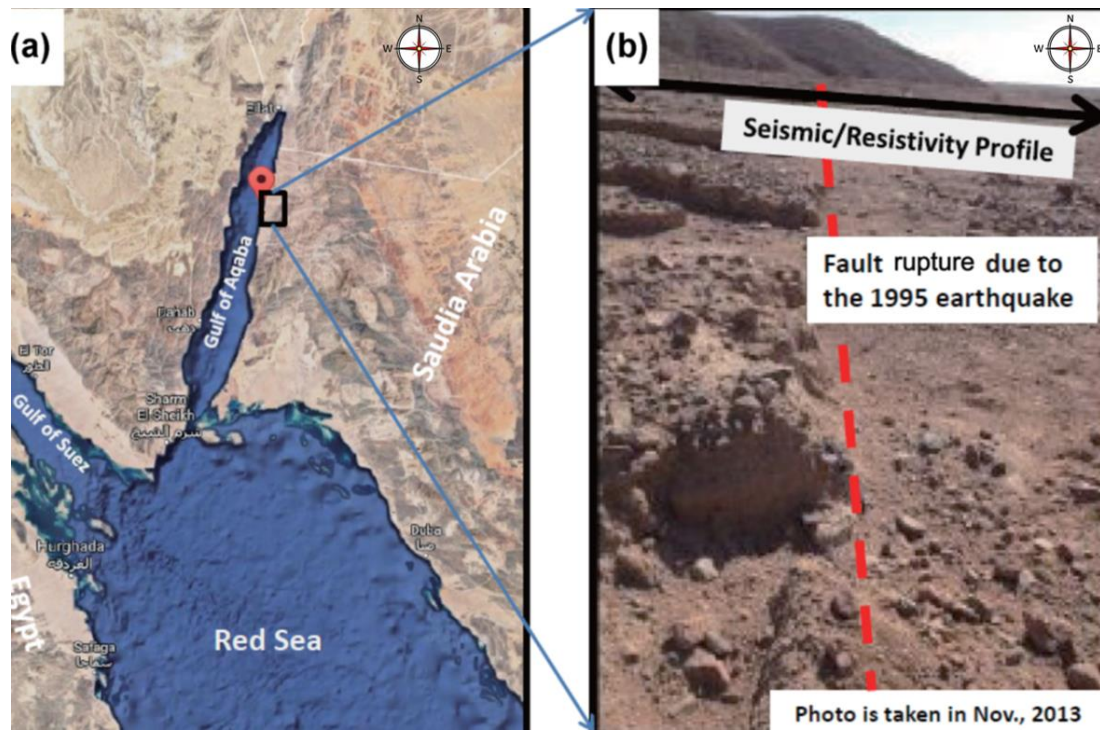


Figure 5.11: Google map showing the study location relative to the gulf of Aqaba, **(b)** field photo showing the location of DCR and SR profiles (thick black line), and the orientation of the fault rupture (broken red line) created during an earthquake in 1995 (modified after Li et al. [35]).

The DCR and SR profiles were created perpendicular to the fault plane (Figure 11b) for better delineation of the fault anomaly. The DCR profile length is 200 m with 41 electrodes and 5 m electrode spacing, and data were acquired using the Wenner-Schlumberger (WS) array configuration. The WS array is the best choice to achieve a simultaneously fair signal-to-noise ratio, lateral resolution, and field setup. Similarly, the SR profile is 200 m long with 21 sources and 10 m spacing, 81 receivers, and 2.5 m receiver spacing. The first break of SR data was picked manually, and the supervirtual interferometry (SVI) technique [35,37] is used for the portion of the SR data having a low signal-to-noise (SNR) ratio. In comparison with the field layout presented by Hanafy et al. [34], the portion of data used, is shown in figure 12.

The local optimization (Gauss-Newton) algorithm was used to optimize the inversion of the individual DCR and SR data. The optimum misfit of 3.35% and 3.73% were obtained after eight (8) iterations for both DCR and SR methods, respectively. From the inverted results, resistivity and velocity tomograms show the subsurface characteristics of the mapped fault on the surface (Figure 13). This result agrees with the study carried out in the same location by Hanafy et al. [34] (figure 12), Hanafy & Schuster [36], and Li et al. [35]. The combined optimization algorithm was carried out similarly to the synthetic examples, using the same objective function for all the methods. For the DCR method, we specify the search range using a 50% model parameter increase/decrease for the lower and upper limits. Also, we apply 500 iterations as the termination criteria because, beyond the limit, the global optimization techniques did not show significant improvement (Figure 14). The DCR combined optimization algorithm results are presented in Figure 13, and compared to the inverted result from local optimization techniques using the Gauss-

Newton (GN) algorithm. This result shows that all the combined optimization algorithms involving the GA, PSO, SA, SO, and PS, reduce the misfit below the threshold of the GN result. However, only the GA and PSO significantly reduce the misfit of the GN by 7.5% and 7.8%, respectively (Figure 15a). Incidentally, the computation cost for the GA (23.22 minutes) and PSO (24.61 minutes) are the highest compared with the computation cost from other combined methods (Figure 15b). For the SR method, the results of the combined optimization algorithms compared to the result of the GN algorithm are presented in Figure 16. Only the GA and PSO reduce the misfits below the threshold of the misfit of the GN (local optimization) algorithm after 500 iterations. On the other hand, the combined GA and PSO algorithms substantially reduce the misfits of GN results by 18.5% and 19.6%, respectively (Figures 17 and 18). Also, the combined GA, PSO, and PS algorithms show relatively high computation costs of 2505.78, 2781.19, and 3012.88 minutes respectively (Figure 18b).

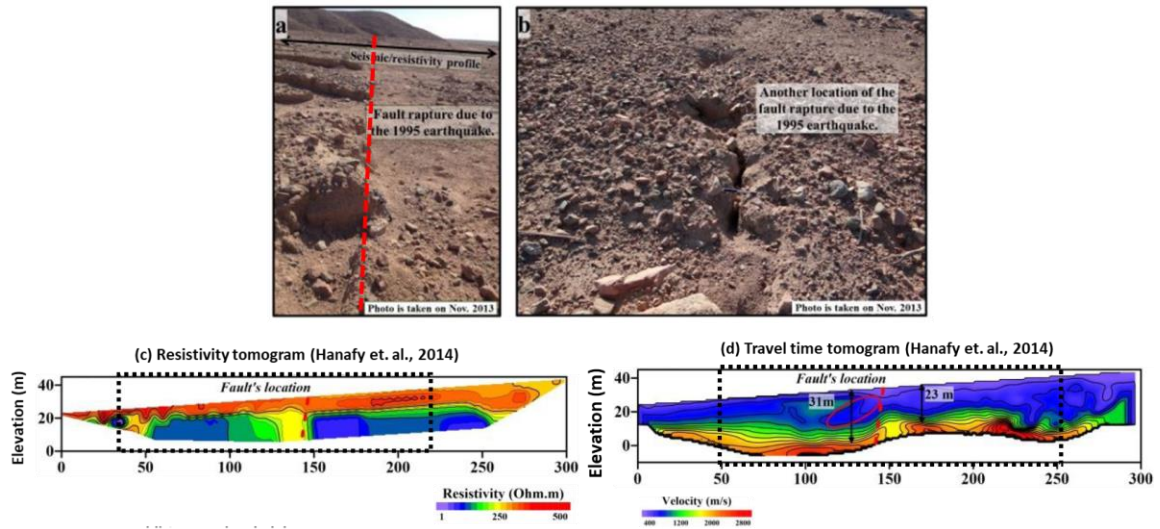


Figure 5.12: (a, b) The field photo shows the fault rupture's location, and (c, d) the inverted DCR and SR data indicating the location of the fault on both the resistivity (c) and velocity (d) model. The black dash rectangles indicate the corresponding data portion used in this study relative to Hanafy et. al., 2014.

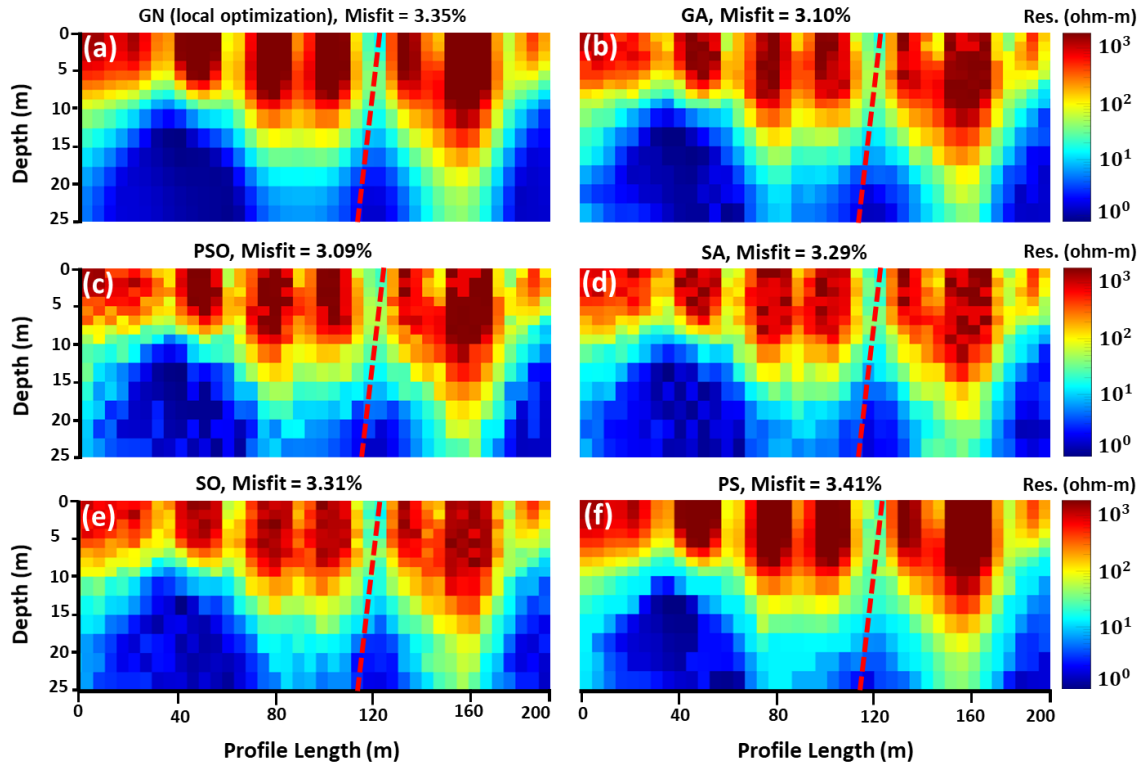


Figure 5.13: Inverted resistivity (real DCR data) models using (a) local optimization, Gauss-Newton (GN) method, and the combined local with global optimization using (b) genetic algorithm, (c) particle swarm optimization, (d) simulated annealing, (e) surrogate optimization, and (f) pattern search algorithm. The red dash lines indicate fault locations.

Using the GN as a reference, all the combined algorithms, except the pattern search (PS) algorithm, reduce the misfits below the misfit of the GN optimization.

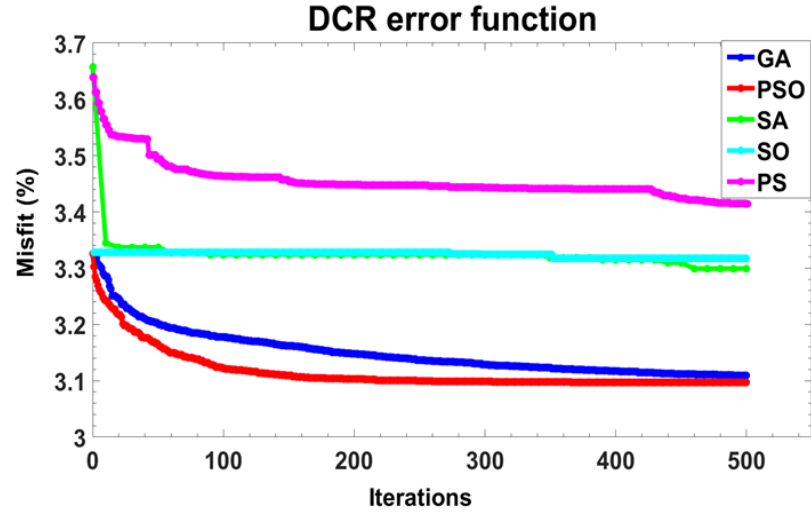


Figure 5.14: Misfit trend with the number of iterations for the DCR error function. The combined PSO (red) algorithm shows the minor misfit after 500 iterations.

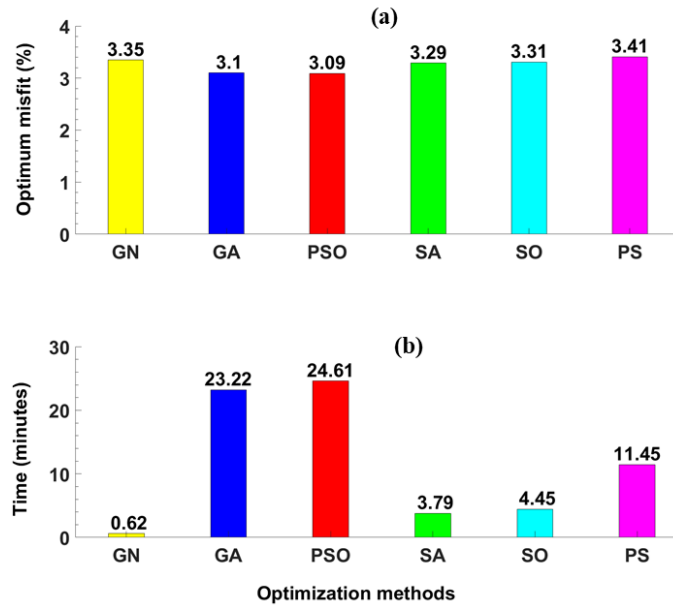


Figure 5.15: Bar chart showing the performances of all the DCR (real data) optimization algorithms in terms of **(a)** optimum misfit and **(b)** computation cost (time). GN is the Gauss-Newton local optimization algorithm.

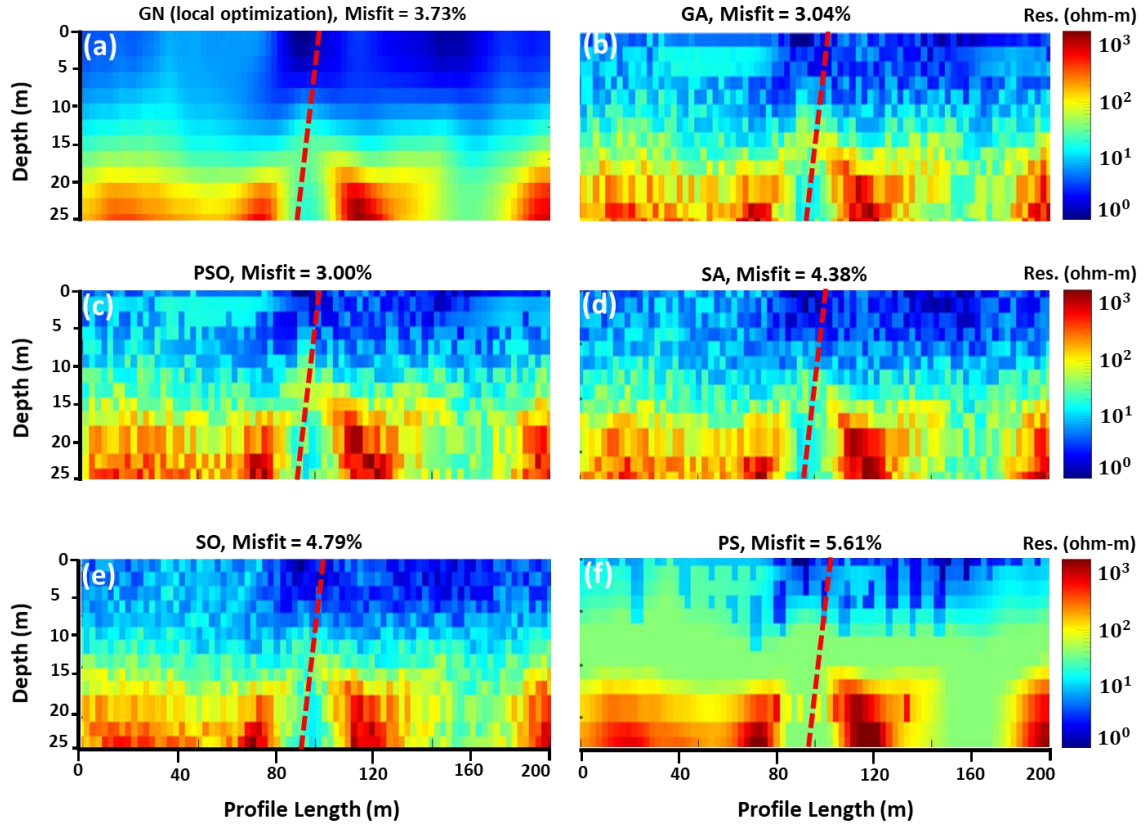


Figure 5.16: Inverted velocity (real SR data) models using **(a)** local optimization, Gauss-Newton (GN) method, and the combined local with global optimization using **(b)** genetic algorithm, **(c)** particle swarm optimization, **(d)** simulated annealing, **(e)** surrogate optimization, and **(f)** pattern search algorithm. The red dash lines indicate fault locations. Using the GN as a reference, only the combined algorithms using GA and PSO reduce the misfits by about 18.5% and 19.6% below the misfit of the GN optimization.

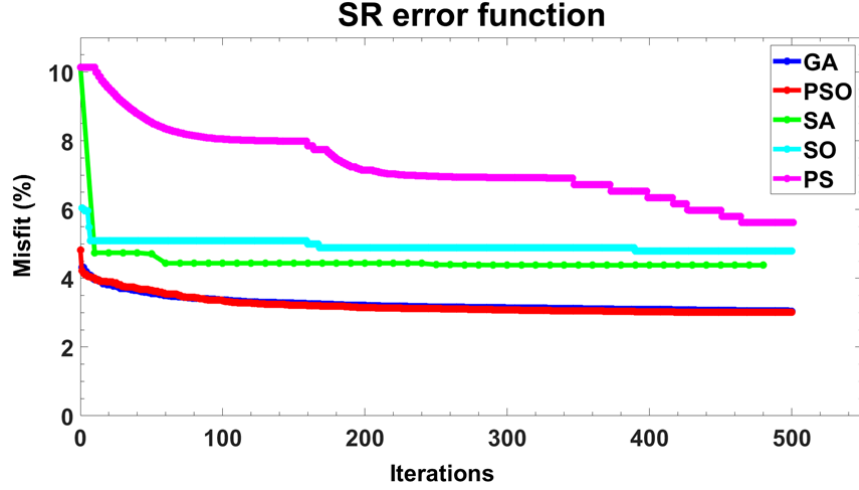


Figure 5.17: Misfit trend with the number of iterations for the SR error function. The combined PSO (red) algorithm shows a minor misfit after 500 iterations.

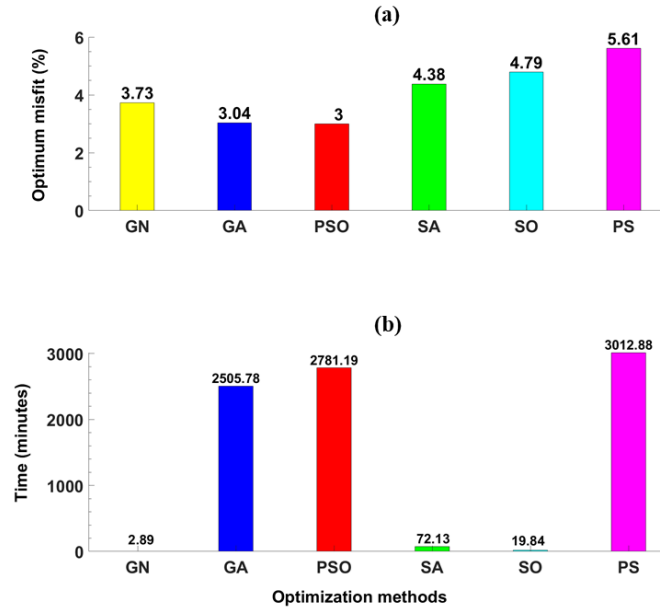


Figure 5.18: Bar chart showing the performances of all the SR (real data) optimization algorithms in terms of **(a)** optimum misfit and **(b)** computation cost (time). GN is the Gauss-Newton local optimization algorithm.

5.5 Conclusions

In the inversion of both DCR and SR data, we compared the performances of the combined GA, PSO, SA, SO, and PS optimization algorithms using the same objective

function. Local optimization using the Gauss-Newton techniques is carried out and applied as a baseline for the combined optimization algorithms. The combined optimization algorithms involve the application of the output (model parameter) from the local optimization to define a search space for the global optimization algorithms. Generally, preliminary interpretations show that the local optimization satisfactorily mapped the positive anomaly (synthetic test) and the suspected fault in the field data example. The performances of these combined algorithms are benchmarked with the result of the local optimization algorithm since they all optimize the same objective function in both DCR and SR methods. All the combined algorithms run for 500 iterations with a population size of 200 in synthetic and real data examples. This allows for an optimum run time, as shown in the error function plots that are asymptotically linear at 500 iterations (i.e., successful convergence). Considering misfit values and computation run time, only the GA and PSO satisfactorily reduce the GN misfits within the tolerable run time compared with other combined optimization algorithms (i.e., SA, SO, and PS). Therefore, the GA and PSO may be considered when applying the combined optimization algorithm for high-dimension DCR and SR data inversion.

5.6 References

1. Sen, M.K.; Stoffa, P.L. *Global optimization methods in geophysical inversion*; Cambridge University Press, 2013; ISBN 1139619519.
2. Oldenburg, D.W.; Li, Y. Inversion for Applied Geophysics: A Tutorial. In *Near-Surface Geophysics*; Society of Exploration Geophysicists, 2005; pp. 89–150.
3. Aleardi, M.; Pierini, S.; Sajeve, A. Assessing the performances of recent global search algorithms using analytic objective functions and seismic optimization problems. *Geophysics* **2019**, *84*, R767–R781, doi:10.1190/geo2019-0111.1.
4. Chunduru, R.K.; Sen, M.K.; Stoffa, P.L. Hybrid optimization methods for geophysical inversion. *Geophysics* **1997**, *62*, 1196–1207, doi:10.1190/1.1444220.

5. Soupios, P.; Akca, I.; Mpogiatis, P.; Basokur, A.T.; Papazachos, C. Applications of hybrid genetic algorithms in seismic tomography. *J. Appl. Geophys.* **2011**, *75*, 479–489, doi:10.1016/J.JAPPGEO.2011.08.005.
6. Başokur, A.T.; Akça, I.; Siyam, N.W.A. Hybrid genetic algorithms in view of the evolution theories with application for the electrical sounding method. *Geophys. Prospect.* **2007**, *55*, 393–406, doi:10.1111/j.1365-2478.2007.00588.x.
7. Edigbue, P.; Demirci, I.; Hamdan, H.; Al-Shuhail, A.; Akca, I.; Soupios, P.; Candansayar, E. Joint Inversion of Seismic and DC Geophysical Data Using Local and Global Optimization Algorithms. In Proceedings of the International Petroleum Technology Conference; IPTC: Riyadh, Saudi Arabia, 2022.
8. Edigbue, P.; Demirci, I.; Akca, I.; Hamdan, H.A.; Kirmizakis, P.; Soupios, P.; Candansayar, E.; Hanafy, S.; Al-Shuhail, A. A Comprehensive Study of Local, Global, and Combined Optimization Methods on Synthetic Seismic Refraction and Direct Current Resistivity Data. *Appl. Sci.* **2022**, *12*, 11589, doi:10.3390/app122211589.
9. Akça, I.; Basokur, A.T. Extraction of structure-based geoelectric models by hybrid genetic algorithms. *Geophysics* **2010**, *75*, doi:10.1190/1.3273851/ASSET/IMAGES/LARGE/8.JPEG.
10. Sajeve, A.; Aleardi, M.; Galuzzi, B.; Stucchi, E.; Spadavecchia, E.; Mazzotti, A. Comparing the performances of four stochastic optimisation methods using analytic objective functions, 1D elastic full-waveform inversion, and residual static computation. *Geophys. Prospect.* **2017**, *65*, 322–346, doi:10.1111/1365-2478.12532.
11. Demirci, İ.; Dikmen, Ü.; Candansayar, M.E. Two-dimensional joint inversion of Magnetotelluric and local earthquake data: Discussion on the contribution to the solution of deep subsurface structures. *Phys. Earth Planet. Inter.* **2018**, *275*, 56–68, doi:10.1016/j.pepi.2018.01.006.
12. Demirci, İ.; Gündoğdu, N.Y.; Candansayar, M.E.; Soupios, P.; Vafidis, A.; Arslan, H. Determination and Evaluation of Saltwater Intrusion on Bafra Plain: Joint Interpretation of Geophysical, Hydrogeological and Hydrochemical Data. *Pure Appl. Geophys.* **2020**, *177*, 5621–5640, doi:10.1007/s00024-020-02573-2.
13. Sesum-Cavic, V.; Kratica, J.; Tošić, D. Solving the geophysical inverse problem using genetic algorithms. *Yugosl. J. Oper. Res.* **2000**, *10*, 283–292.
14. Pace, F.; Santilano, A.; Godio, A. A Review of Geophysical Modeling Based on Particle Swarm Optimization. *Surv. Geophys.* **2021**, *42*, 505–549, doi:10.1007/s10712-021-09638-4.
15. Grandis, H.; Maulana, Y. Particle Swarm Optimization (PSO) for Magnetotelluric (MT) 1D Inversion Modeling. *IOP Conf. Ser. Earth Environ. Sci.* **2017**, *62*, 12033, doi:10.1088/1755-1315/62/1/012033.
16. Pace, F.; Santilano, A.; Godio, A. Particle swarm optimization of 2D magnetotelluric

- data. *Geophysics* **2019**, *84*, E125–E141, doi:10.1190/geo2018-0166.1.
17. Essa, K.S.; Géraud, Y.; Diraison, M. Fault parameters assessment from the gravity data profiles applying the global particle swarm optimization. *J. Pet. Sci. Eng.* **2021**, *207*, 109129, doi:10.1016/j.petrol.2021.109129.
 18. Essa, K.S.; Elhussein, M. Interpretation of Magnetic Data Through Particle Swarm Optimization: Mineral Exploration Cases Studies. *Nat. Resour. Res.* **2020**, *29*, 521–537, doi:10.1007/s11053-020-09617-3.
 19. Pekşen, E.; Yas, T.; Kiyak, A. 1-D DC Resistivity Modeling and Interpretation in Anisotropic Media Using Particle Swarm Optimization. *Pure Appl. Geophys.* **2014**, *171*, 2371–2389, doi:10.1007/s00024-014-0802-2.
 20. Song, X.; Tang, L.; Lv, X.; Fang, H.; Gu, H. Application of particle swarm optimization to interpret Rayleigh wave dispersion curves. *J. Appl. Geophys.* **2012**, *84*, 1–13, doi:10.1016/j.jappgeo.2012.05.011.
 21. Sen, M.K.; Stoffa, P.L. Nonlinear seismic waveform inversion in one dimension using simulated annealing. In Proceedings of the SEG Technical Program Expanded Abstracts 1990; Society of Exploration Geophysicists, 1990; pp. 1119–1122.
 22. Kirkpatrick, S.; Gelatt, C.D.; Vecchi, M.P. Optimization by Simulated Annealing. *Science* (80-.). **1983**, *220*, 671–680, doi:10.1126/science.220.4598.671.
 23. Zhao, L.-S.; Sen, M.K.; Stoffa, P.; Frohlich, C. Application of Very Fast Simulated Annealing to the Determination of the Crustal Structure Beneath Tibet. *Geophys. J. Int.* **1996**, *125*, 355–370, doi:10.1111/j.1365-246X.1996.tb00004.x.
 24. Sharma, S.P. VFSARES—a very fast simulated annealing FORTRAN program for interpretation of 1-D DC resistivity sounding data from various electrode arrays. *Comput. Geosci.* **2012**, *42*, 177–188, doi:10.1016/j.cageo.2011.08.029.
 25. Sharma, S.P.; Kaikkonen, P. Two-dimensional non-linear inversion of VLF-R data using simulated annealing. *Geophys. J. Int.* **1998**, *133*, 649–668, doi:10.1046/j.1365-246X.1998.00523.x.
 26. Queipo, N. V.; Haftka, R.T.; Shyy, W.; Goel, T.; Vaidyanathan, R.; Kevin Tucker, P. Surrogate-based analysis and optimization. *Prog. Aerosp. Sci.* **2005**, *41*, 1–28, doi:10.1016/j.paerosci.2005.02.001.
 27. Koziel, S.; Ciaurri, D.E.; Leifsson, L. Surrogate-Based Methods. In *Computational Optimization, Methods and Algorithms*; Springer: Berlin, Heidelberg, 2011; pp. 33–59 ISBN 978-3-642-20859-1.
 28. Chandra, R.; Azam, D.; Kapoor, A.; Müller, R.D. Surrogate-assisted Bayesian inversion for landscape and basin evolution models. *Geosci. Model Dev.* **2020**, *13*, 2959–2979, doi:10.5194/gmd-13-2959-2020.
 29. Gutmann, H. A Radial Basis Function Method for Global Optimization. *J. Glob. Optim.* **2001**, *19*, 201–227, doi:10.1023/A:1011255519438.

30. Wang, Y.; Shoemaker, C.A. A General Stochastic Algorithmic Framework for Minimizing Expensive Black Box Objective Functions Based on Surrogate Models and Sensitivity Analysis. **2014**.
31. Audet, C.; Dennis, J.E. A Pattern Search Filter Method for Nonlinear Programming without Derivatives. *SIAM J. Optim.* **2004**, *14*, 980–1010, doi:10.1137/S105262340138983X.
32. Song, X.; Gu, H.; Zhang, X.; Liu, J. Pattern search algorithms for nonlinear inversion of high-frequency Rayleigh-wave dispersion curves. *Comput. Geosci.* **2008**, *34*, 611–624, doi:10.1016/j.cageo.2007.05.019.
33. Song, X.; Li, D.; Gu, H.; Liao, Y.; Ren, D. Insights into performance of pattern search algorithms for high-frequency surface wave analysis. *Comput. Geosci.* **2009**, *35*, 1603–1619, doi:10.1016/j.cageo.2009.01.007.
34. Hanafy, S.M.; Jonsson, S.; Klinger, Y. Imaging normal faults in alluvial fans using geophysical techniques: Field example from the coast of Gulf of Aqaba, Saudi Arabia. In Proceedings of the SEG Technical Program Expanded Abstracts 2014; Society of Exploration Geophysicists, 2014; pp. 4670–4674.
35. Li, J.; Hanafy, S.; Schuster, G.T. Parsimonious surface wave interferometry. *Geophys. J. Int.* **2018**, *212*, 1536–1545, doi:10.1093/gji/ggx467.
36. Hanafy, S.; Schuster, G.T. Parsimonious refraction interferometry and tomography. *Geophys. J. Int.* **2017**, *209*, 695–712, doi:10.1093/gji/ggx042.
37. Edigbue, P.; Al-Shuhail, A.; Hanafy, S.M. Three-dimensional supervirtual seismic refraction interferometry: A case study in western Saudi Arabia. *Geophysics* **2021**, *86*, B123–B133, doi:10.1190/geo2020-0310.1.

CHAPTER 6

Conclusions and Recommendations

6.1 Conclusions

In this study, I have presented a comprehensive study of joint inversion of direct current (DCR) resistivity and seismic refraction (SR) data, using both synthetic and real data. I have investigated the performance of local, and global optimization algorithms, and propose a new combined optimization method used for joint parameter estimation of DCR and SR data. I also tested different stochastic methods to model DC resistivity and seismic refraction geophysical data using combined local and global optimization algorithms. I have also presented a case study of the Dammam Dome in Eastern Saudi Arabia to demonstrate the effectiveness of integrating geological and geophysical mapping techniques.

The results of this study have shown that the proposed algorithm, which uses a combination of local and global optimization methods, outperforms the individual local and global methods in terms of accuracy and efficiency in joint interpretation. The combined optimization algorithms also exhibit a greater capability to identify and resolve ambiguities in the data. Additionally, the analysis of different stochastic methods showed that the combined optimization algorithms with stochastic modeling provided better modeling of the data and resulted in more accurate inversion results.

The case study of the Dammam Dome demonstrated the applicability of the proposed methodology in a real data scenario. The inversion results provided valuable

geological and geophysical information, including the location, depth, and extent of subsurface structures.

The results of the comprehensive study of joint inversion of DC resistivity and seismic refraction data using the combined optimization algorithm present the feasibility of jointly estimating model parameters of two geophysical methods presented in chapter 3. Also, results from this study demonstrate the efficiency and effectiveness of the combined optimization algorithms and the importance of stochastic modeling in joint interpretation. These points summarize the novelty of this study and provide responses to the research questions from chapter 1.

Although this study has made significant contributions to solving geophysical optimization problems, there are still limitations and challenges that need to be addressed. One of the main challenges is the acquisition of high-quality data, as the accuracy and reliability of the inversion results are highly dependent on the quality of the input data. Furthermore, the computational requirements of the combined optimization algorithms may limit their use in large-scale applications, and therefore, more research is needed to enhance their efficiency. Also, this study presents the application of the combined optimization algorithm on the Damman Dome, however, examples from different geological settings are needed to show the robustness of the combined optimization algorithm. Further research could be conducted to explore the applicability of the proposed combined optimization algorithm with different data types.

6.2 Recommendations

Based on the findings of this study, there are several recommendations that could be made for future research.

First, I recommend that further research be conducted to investigate the applicability of the proposed methodology in different geological settings and with different data types. While this study has demonstrated the effectiveness of the combined optimization algorithms in the joint interpretation of DC resistivity and seismic refraction data, there may be variations in the performance of the algorithms in different geological contexts. Therefore, further investigation is necessary to establish the generalizability of the proposed methodology.

Second, I recommend that efforts be made to improve the acquisition of high-quality data. As mentioned in the Conclusions, the accuracy and reliability of the inversion results are highly dependent on the quality of the input data. Therefore, research should focus on improving the data acquisition techniques and data quality control measures to ensure that the data used in the joint interpretation process are of high quality.

Third, I recommend that further research be conducted to enhance the efficiency of the combined optimization algorithms. While this study has demonstrated the superiority of the combined optimization algorithms in terms of accuracy, their computational requirements may limit their use in large-scale applications. Therefore, further research is needed to develop more efficient algorithms that can handle large-scale data sets in a reasonable amount of time.

Finally, I recommend that the proposed methodology be used in practice to aid in subsurface exploration and exploitation. The results of this study demonstrate the practical application of the proposed methodology in subsurface characterization, with significant implications for groundwater exploration, mineral exploration, and geotechnical engineering. Therefore, I recommend that practitioners in these fields utilize the proposed

methodology to enhance their understanding of the subsurface and make more informed decisions.

In conclusion, the findings of this study provide a basis for future research and practice in the field of geophysics. I hope that my recommendations will inspire further research and development in this field and contribute to the development of more accurate and efficient methods for subsurface characterization.

Vitae

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Paul Edigbue is an accomplished geophysicist with a strong academic and professional background in the field. He earned his Bachelor's degree in Geophysics from the prestigious Federal University of Technology Akure (FUTA), Nigeria in 2008. Paul began his professional career in 2010 at Beacon Geo-consult, Akure, Nigeria, where he worked as a geophysicist for a year and a half. He then joined FUTA in 2011 as a Technologist, where he worked for two years. In recognition of his academic excellence, Paul received a scholarship in 2013 to pursue a Master's degree in Geophysics at the esteemed King Fahd University of Petroleum & Minerals (KFUPM), Dhahran, Saudi Arabia, which he completed in 2015. While pursuing his MSc, he served as an intern with the Seplat Petroleum Development Company in Lagos, Nigeria in 2014. Upon completing his Master's program, Paul worked as a geophysicist for one and a half years with Jubail Engineers Contracting, Saudi Arabia.

Paul Edigbue is a highly regarded Ph.D. researcher at the King Fahd University of Petroleum & Minerals in Saudi Arabia. With a strong academic background in geophysics, as well as extensive professional experience, he is an accomplished expert in his field. His current research focuses on geophysical imaging, near-surface investigation, and multi-physics inversion. Specifically, Paul work to improve optimization algorithms for the joint inversion of direct current resistivity and seismic refraction data.

Through his research, Paul has developed a new combined optimization algorithm that surpasses existing conventional local and global optimization algorithms. This innovative approach leverages the output of the local optimization to define a search space for the global optimization algorithm. His work has been validated through the use of synthetic and real data for 2D direct current resistivity and seismic refraction data. This research has led to the publication of four peer-reviewed manuscripts in prestigious ISI journals, as well as a conference paper presentation.

Paul is a proud member of several professional organizations, including the Society of Exploration Geophysicists (SEG), the Society of Petroleum Engineers (SPE), the Association of Petroleum Geologists (AAPG), and the Dhahran Geosciences Society (DGS). His research expertise and professional affiliations demonstrate his commitment to advancing the field of geophysics, and his contributions are poised to make significant impacts on the industry.

Journal Publications during Ph.D time:

1. **Edigbue P.**, Demirci I., Akca I., Hamdan H.A., Kirmizakis P., Soupios P., Candansayar E., Hanafy S., Al-Shuhail A. A comprehensive study of local, global, and combined optimization methods on synthetic seismic refraction and direct current resistivity data. Applied Sciences. 2022 Nov 15;12(22):11589.

2. **Edigbue P.**, Demirci I., Akca I., Hamdan H., Kirmizakis P., Soupios P., Tranos M., Abu-Mahfouz I.S., Candansayar E., Hanafy S., Al-Shuhail A. Application of combined local and global optimization algorithms in joint interpretation of direct current resistivity and seismic refraction data: a case study of Dammam Dome, Eastern Saudi Arabia. *Sensors*. 2022 Nov 30;22(23):9337.
3. **Edigbue P.**, Demirci I., Akca I., Al-Shuhail A., Hamdan H., Kirmizakis P., Candansayar E., Hanafy S., Soupios P. Testing different stochastic methods to model direct current resistivity and seismic refraction geophysical data using a combined local and global optimization algorithms. *Arabian Journal of Science and Engineering (AJSE)*. 2023.
4. **Edigbue P.I.**, Al-Mashhor A.A., Plougarlis A., Soupios P., Tranos M., Kaka S., Al-Shuhail A., Al-Garni M. Geological and geophysical investigations of an engineering site characterization for construction purposes in Western Saudi Arabia. *Journal of Applied Geophysics*. 2021 May 1;188:104307.
5. **Edigbue P.**, Al-Shuhail A., Hanafy S.M. Three-dimensional supervirtual seismic refraction interferometry: A case study in western Saudi Arabia 3D semiautomatic SVI and a case study. *Geophysics*. 2021 May 1;86(3):B123-33.
6. Chan S.A., **Edigbue P.**, Khan S., Ashadi A.L., Al-Shuhail A.A. Viscoelastic model and synthetic seismic data of eastern Rub'Al-Khali. *Applied Sciences*. 2021 Feb 4;11(4):1401.

Conference Presentation:

1. **Edigbue P.**, Demirci I., Hamdan H., Al-Shuhail A., Akca I., Soupios P., Candansayar E. Joint inversion of seismic and dc geophysical data using local and global optimization algorithms. Presented at the International Petroleum Technology Conference 2022 Feb 2021, Riyadh, Saudi Arabia. Published by OnePetro.