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Direct 1D Resistivity Estimation from Data Rescaling Using Cumulative Resistance Models

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Summary

This study presents a novel methodology to transform 1D resistivity data into layered resistivity models without prior information by using the concept of cumulative reference models. The proposed methodology involves deriving an error function that transforms apparent resistance measurements into a cumulative resistance, which is then transformed into a layered resistivity model. We applied the methodology to simulated data from various 1D models with different physical parameters, and the results demonstrate that our method can be used to directly transform the data into a layered resistivity model without requiring prior information. This methodology provides a valuable alternative to inversion methods when one local model is available and multiple measurements are available over an area with similar physical parameters. Furthermore, the retrieved rescaled model can be used as a reference model for the inversion process, reducing computational and economic costs. This study highlights the potential of cumulative reference models for subsurface characterization, providing a new paradigm to study the subsurface with increased efficiency.

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The goal of geophysical prospecting is to accurately characterize the subsurface, typically achieved through inversion processes that use 1D, 2D, or 3D reference models to generate a model of the subsurface that reproduces the measured data. However, the inversion process is highly non-linear, computationally expensive and can be affected by solution non-uniqueness due to the existence of multiple subsurface models that can generate the same surface measurements. Therefore, selecting an appropriate reference model is critical for obtaining an accurate estimate of the subsurface model.

The reference model used as the starting point for a 1D inversion process is typically formulated as a layered system representing the subsurface. However, geophysical measurements represent the cumulative effect of all layers above a given point in depth. As result, some researchers have introduced the concept of cumulative models as a means of incorporating the cumulative effects present in the data into the reference model, resulting in a model that is closely related to measurements. This approach has been successfully applied to retrieve geophysical models for various techniques, such as seismic surface wave dispersion data Socco et al. (2017) and self-potential data Florio (2018) and it is currently being explored for the magnetotelluric method Calderon Hernandez et al. (2022).

The use of cumulative models has proven to be useful in directly transforming geophysical data into an initial approximation of the geophysical model without the need of an inversion process. In this work we explore the idea of using a 1D cumulative resistance model to transform the data measured from a resistivity survey directly into a model. Using Vertical Electric Soundings (VES) as geophysical method, we seek to investigate the feasibility of using the cumulative model to develop a rescaling function that transforms the data directly into a geoelectrical model following what has been developed for other geophysical methods.

Furthermore, we aim to assess whether the rescaling function can be used to retrieve resistivity models using only data derived from 1D resistivity measurements without any prior knowledge. We will examine the applicability of the proposed methodology aiming to retrieve geoelectrical models using only apparent resistivity data by varying the model parameters based on different conditions without modifying the rescaling function previously derived. Through our research, we aim to provide insights into the potential of using cumulative reference models as a practical and efficient approach for transforming the data from resistivity surveys directly into geoelectrical models, and potentially for other geophysical prospecting techniques as well.

Method

We simulated VES data by using a 1D resistivity model and displayed it as a function of the electrode spacing (AB/4) which is used as a pseudopepth.

To use the approach proposed by Socco et al. (2017) for seismic surface waves and by Florio (2018) for self-potential data we transformed the layered model into a cumulative one. For resistivity data this can be done by using the concept of equivalent layers, which transforms a series of horizontal layers into one effective layer with a uniform resistivity value. The equations modeling the equivalent layer are defined by:

$$\rho_{eq} = (T/S)^{1/2} \tag{1}$$

Where T is known as *transverse unit resistance* and S is known as *longitudinal unit conductance*. These parameters are defined by:

$$T = \rho_1 z_1 + \rho_2 z_2 + ... + \rho_n z_n = \sum_{i=1}^{n} \rho_i z_i \tag{2}$$

$$S = \frac{z_1}{\rho_1} + \frac{z_2}{\rho_2} + ... + \frac{z_n}{\rho_n} = \sum_{i=1}^{n} \frac{z_i}{\rho_i} \tag{3}$$

By using equation 1 we calculated the cumulative resistivity values at each point in depth within the electrical model, resulting in a cumulative resistivity model. The cumulative model is physically related to the measured data.

When comparing the cumulative model with the data (figure 1), it is evident that the use of the cumulative approach is a good starting point to transform the resistivity data into a model. However, despite using the cumulative model, the differences between models are significant. Hence we applied the approach used by Calderon Hernandez et al. (2022) for magnetotelluric measurements, which is also based on analyzing the data in the cumulative resistance domain. This approach involves transforming the resistivity data into resistance data, which is a more robust representation of the subsurface resistivity distribution since *"resistivity measurements on the surface are essentially resistance measurements"* Gómez-Treviño (1996). The equation used to transform the data into the cumulative resistance domain is the following:

$$R(z) = \int_0^z \rho(z)dz. \tag{4}$$

As figure 1 shows, the discrepancy between models in the cumulative resistance domain is lower than the discrepancy between models in the resistivity domain.

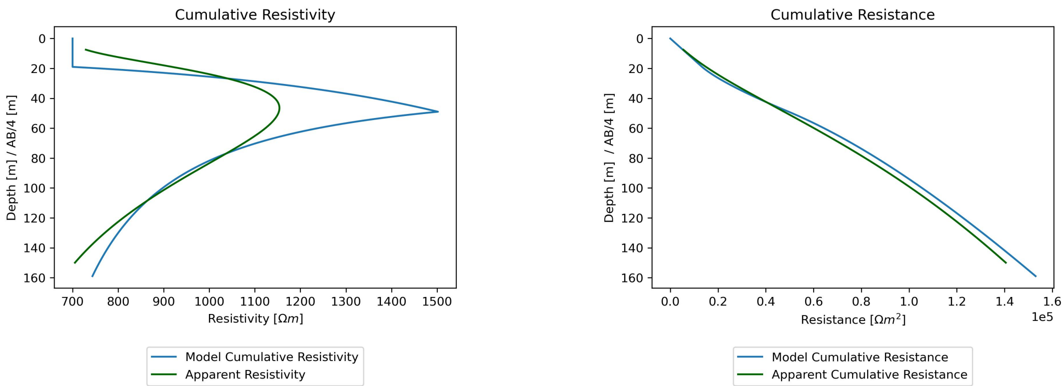

Figure 1: Comparison between the model and the data in the resistivity and the cumulative resistance domains.

In the cumulative resistance domain the difference between models is a Δz for a given value of resistance. The Δz error between models was obtained by:

$$\Delta z(R) = z(R) - z(R_{app}) \quad When \quad R \approx R_{App}. \tag{5}$$

We approximated the Δz function by means of a polynomial regression and we obtained a direct relationship between the resistance data and the cumulative resistance model. This polynomial expression represents an error function that allows the direct transformation between models and data in the cumulative resistance domain.

After rescaling the data into a cumulative resistance, we transformed it into a cumulative resistivity using a numerical derivative. The resulting cumulative resistivity was then transformed into a layered resistivity by solving equation 1 as a layered system is the expected output of any 1D electrical survey.

We evaluated the efficacy of the previously obtained error function by testing its ability to directly transform simulated VES data with varying physical parameters into models, without any introducing any prior information.

Results

We simulated VES data for a 3 layered system using the SimPEG python lybrary, the system had the following characteristics:

Table 1: Parameters of the resistivity model.

Resistivity [Ωm]	**Thickness of the Layer [m]**
750	20
2500	50
450	Half Space

By following the methodology described previously, the Δz error function was retrieved and we used it to transform the simulated data directly into a geoelectrical model. The effectiveness of the approach is illustrated in figure 2, where the blue solid line represents the true model, the green line represents the rescaled model obtained using the error function, and the red line corresponds to the result obtained through a conventional 1D inversion process.

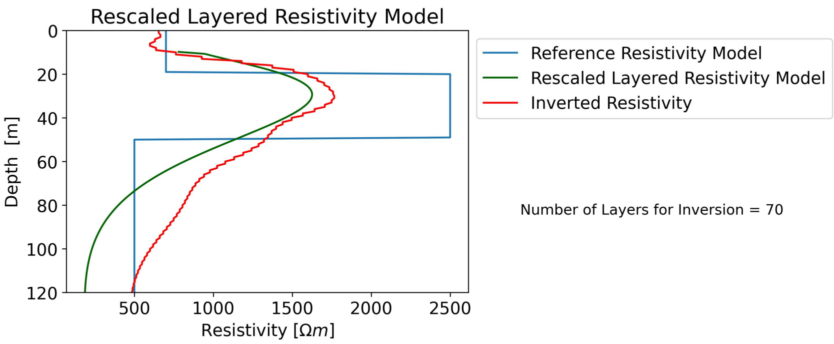

Figure 2: The methodology described in the method section was used to obtain the rescaled resistivity model (green line). The layered model obtained from a conventional 1D inversion process is shown in red. Both results are compared against the true model (blue line) for comparison and assessment.

To further assess the applicability of the rescaling function to correct apparent resistivity measurements for other models, we created several 1D models with varying resistivity, position, and thickness of the target layer. Using these models, we generated 1D apparent resistivity data and applied the rescaling function obtained from the model shown in figure 2 to the new data without any a priori knowledge about the new model parameters. The results of the rescaling process are presented in figures 3 and 4, where they are compared to the resistivity models obtained by conventional inversion processes and the true resistivity models.

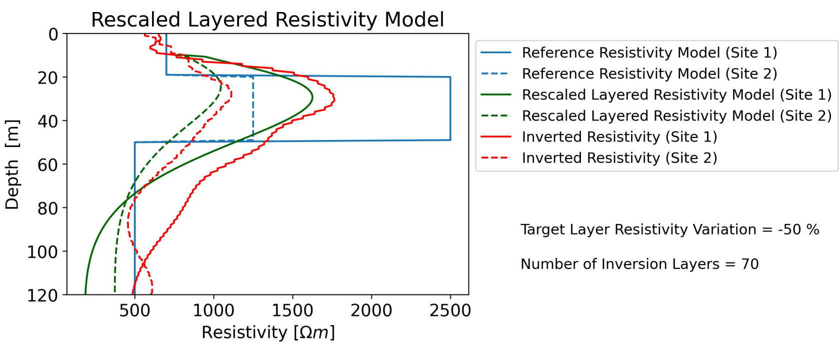

Figure 3: Rescaled resistivity model a for modified model in which the resistivity of the target layer is 50% lower compared to the resistivity of the target layer found in the reference model (Figure 2). The polynomial used to retrieve the electrical model was the one obtained for Figure 2.

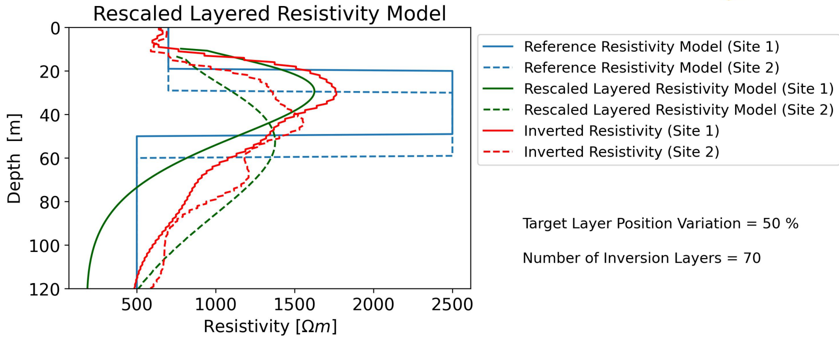

Figure 4: Rescaled resistivity model for a nearby zone in which the position of the target is shifted 50% compared to the position of the target layer found in the reference site. The polynomial used to retrieve the electrical model was the one obtained for Figure 2.

In figures 3 and 4 the model used to derive the polynomial function is shown in solid blue, while the modified true model is shown in dashed blue. The rescaled model for the original model is shown in solid green, while the model retrieved by rescaling the data simulated using the dashed blue model is shown in dashed green. The results of a conventional inversion process for the modified model are shown in dashed red.

The study demonstrates the feasibility of using cumulative reference models to derive a rescaling function for transforming 1D apparent resistivity measurements into 1D resistivity models, without the need for an inversion process. By leveraging the relationship between apparent resistance data and subsurface resistance, the proposed approach provides a practical and efficient method for generating accurate geophysical models in less time compared to conventional inversion processes. The method has the potential to enable rapid interpretation of VES data for real-time monitoring as is able to track changes in the physical parameters of the target layer without introducing any a priori information.

Conclusions

In conclusion, the proposed methodology demonstrates the potential of using cumulative reference models as a practical and efficient approach for transforming data from resistivity surveys directly into geoelectrical models as it has been tested for 1D resistivity surveys and for 1D MT measurements. This approach can serve as a valuable alternative to conventional inversion methods when local models are available and numerous measurements are available over an area with similar physical parameters. Moreover, the model retrieved by the rescaling tool can serve as a reliable reference model for the inversion process, thus saving computational and economic resources in more complex scenarios. Therefore, this study offers important insights into the potential of using cumulative models as a powerful tool for subsurface characterization.

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