

Review

Inversion Analysis Method for Tunnel and Underground Space Engineering: A Short Review

Zhanping Song^{1,2,3,*}, Zifan Yang¹ , Runke Huo^{1,2} and Yuwei Zhang^{1,2}

¹ School of Civil Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China; yangzf0925@163.com (Z.Y.); huorkdq@xauat.edu.cn (R.H.); zhangyuwei@xauat.edu.cn (Y.Z.)

² Shaanxi Province Key Laboratory of Geotechnical and Underground Space Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China

³ Institute of Tunnel and Underground Structure Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China

* Correspondence: songzhpyt@xauat.edu.cn; Tel.: +86-131-8608-8693

Abstract: With the rise of the fourth industrial revolution, traditional methods of analyzing investment have been transformed into intelligent methods under big data and the Internet of Things. This has created a new approach to solving practical engineering problems. This paper examines the formation and evolution of the application of inversion theory in tunnel and underground engineering, summarizing research progress using traditional and intelligent inversion analysis methods to identify three types of target unknown quantities in tunnels and underground projects: initial ground stress, support structure load, and tunnel characteristic parameters. It also offers an outlook on how to optimize inversion analysis methods to solve more challenging and complex tunneling problems in the context of informatization, digitalization, and intelligence. In the current research process of tunnel and underground space engineering problems, the inversion theory system has been improved, but inversion analysis methods still face many challenges. These include the low reliability of initial ground stress inversion under complex geological conditions, the lack of indicators to objectively evaluate the accuracy of inversion analysis, and the high costs of intelligent inversion analysis means. Moving forward in the context of big data and the information era, the future development direction for inversion theory and inversion methods in tunnel and underground space engineering is to combine new monitoring technology, computer vision technology, and simulation analysis technology to establish multifaceted intelligent inversion analysis models.

Keywords: tunnel and underground engineering; inverse theory; multiple intelligent inversion model; situation and development



Citation: Song, Z.; Yang, Z.; Huo, R.; Zhang, Y. Inversion Analysis Method for Tunnel and Underground Space Engineering: A Short Review. *Appl. Sci.* **2023**, *13*, 5454. <https://doi.org/10.3390/app13095454>

Academic Editor: Sakdirat Kaewunruen

Received: 20 March 2023

Revised: 25 April 2023

Accepted: 25 April 2023

Published: 27 April 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In the field of tunnel and underground engineering, the main research objects are the characteristics of excavated rock mass and the surrounding geological environment. During the extremely long process of rock mass formation, a large number of cracks and pores will form in the structure. Coupled with the influence of groundwater, the rock mass will become a discontinuous body composed of various media. This results in extremely complex physical and mechanical properties of the rock mass [1,2]. Therefore, it is important to invert the initial ground stress and related parameters from on-site monitoring and measurement of displacement, stress, strain, and other multivariate information. By doing so, a tunnel excavation and support plan can be formulated. With the development of construction technology and measurement means, many researchers have begun using measurement data to invert the initial ground stress, structural load, and material characteristic parameters. This replaces previous test methods and facilitates application in follow-up projects.

The inverse analysis method involves analyzing physical information data (such as displacement, deformation, stress, strain, or load) measured in the field to establish an effective mapping relationship from the data sample space to the model identification space. It comprises two parts. One is the model identification problem of identifying the model structure style closest to the actual deformation law [3] (such as the constitutive model of geotechnical medium) from the change law of monitoring data. The other is a discussion of the inversion model under linear elastic and nonlinear conditions (stress-strain relationship, time and settlement deformation relationship). Various individual mechanical parameters (such as initial ground stress, structural load, and physical parameters) in the inversion system are identified.

Nowadays, many problems are accompanied by inverse problems, such as the most commonly used least square method, which was first proposed by the famous German mathematician Gauss in 1795 to calculate the trajectories of planets and comets [4]. In bridge structure monitoring, researchers use the back analysis method to analyze the building structure under the condition of environmental vibration and strong wind. The performance is evaluated, and the results are close to the measured value [5]. In solid geophysical problems, researchers process geophysical data and extract geological data and physical models that are closest to the actual situation [6]. Combined with the data collected by local seismic stations, the prediction of earthquakes in other areas can be realized, and this process is the inversion of geophysical information. From this it can be seen that in practical engineering problems, the study of inverse problems has higher practical value, but compared with forward analysis, inverse analysis still has the characteristics and difficulties of strong nonlinearity, ill-posedness, and the need for a large amount of calculation.

With the fourth Industrial Revolution, there is a growing focus on scientific and technological innovation and technological renewal in various engineering fields. Scholars are increasingly using intelligent inversion analysis methods based on optimization algorithms, computer vision, and data mining to solve difficulties existing in the inversion analysis method itself. At the same time, the problems faced by rock mechanics, such as “limited discretization of data”, “complexity of failure mechanism”, and “uncertainty of influencing factors” have further promoted the discussion of artificial intelligence (Artificial Intelligence, AI) in geotechnical engineering. Through the in-depth study of AI, a relatively intelligent mechanical analysis and calculation model is obtained, and a computer integrated intelligent system with the ability of self-perception, reasoning learning, and the life cycle management analysis method of tunnel construction process considering sustainable development strategy is established [7,8], so as to solve all kinds of tunnel and underground engineering problems in complex geological environment.

However, current research on the application of inversion theory and its analysis method in tunnel and underground engineering is limited to a specific direction, and there are few summary articles on the application of inversion analysis method in this field. This paper analyzes the reasons for the formation of inversion theory in tunnel and underground engineering, summarizes the development process of inversion theory in four stages, and discusses the main research direction of inversion theory in tunnel engineering. The research progress of domestic and foreign scholars applying traditional and intelligent back analysis methods to inverse analysis of initial ground stress, supporting structure load, and tunnel characteristic parameters is summarized. The paper concludes with a call for realizing the diversification of inversion models and the intellectualization of inversion analysis methods in tunnel and underground engineering in the information and intelligent era. The structure flow chart of the article is shown in Figure 1.

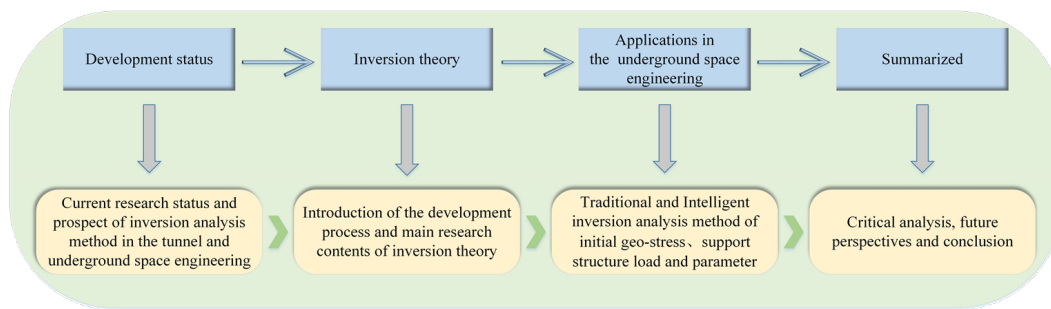


Figure 1. Research frame of inversion analysis method in tunnel and underground space engineering.

2. The Development and Main Research Contents of Inversion Theory

2.1. Development of Inversion Theory

In the 19th century, researchers relied mainly on empirical methods or engineering analogies to solve engineering problems due to the limitations of science and technology. With the introduction of calculus and solid mechanics theory into tunnel and underground engineering, the combination of theory and experience was realized. The previous empirical method was upgraded to a “semi-empirical and semi-theoretical” analysis method. However, the research objects of tunnels and underground engineering are nonlinear, non-homogeneous, and have complex and variable boundary conditions. Therefore, the theoretical analysis method can only solve simple linear problems, and its engineering applicability is poor.

In the middle of the 20th century, efficient simulation methods such as the finite element method, discrete element method, and boundary element method became the main means of model analysis with the development of computer technology. The application of theoretical methods in engineering was also extended. However, the simulation method does not solve the problem of low accuracy of theoretical analysis, and there is a large gap between theoretical analysis results and actual results. There are three main reasons for this gap. First, there is uncertainty in the selection of the characteristic parameters of the surrounding rock. The rock parameters obtained from a few boreholes in the field and indoor and outdoor tests have large deviations from the actual ones. Second, there are more assumptions in constructing the model. In the research process, there is often a tendency to treat the surrounding rock mass as a homogeneous isotropic continuous medium and adopt the load-structure model for numerical calculation with large errors. Third, it is impossible to consider the dynamic construction process. Although the strength reduction method is used in the simulation analysis, which can approximate the excavation process, it cannot be adjusted according to the problems occurring in the field and has poor timeliness.

The complex physical and mechanical properties of engineering research objects lead to more or fewer problems in both field in situ tests and laboratory tests. The analytical method and numerical analysis method also have their inevitable defects, making it necessary for researchers to rely on displacement, stress, and other information from field measurements to determine the characteristic parameters of the surrounding rock. This method of determining the model and parameters based on field monitoring and control information is called inversion analysis.

The inversion analysis method is not only based on relevant theoretical research but also based on actual measurement, which is both theoretical and practical. It can connect the two for solving more complex engineering problems. Since the early 1970s, the research of engineering parameters through on-site monitoring data of tunnels and underground projects has gradually developed. After more than 40 years of effort, the inversion theory has well developed, and a complete theoretical system has formed. Its development process can be broadly divided into four stages.

2.1.1. Establishment Phase

The period from the early 1970s to the early 1980s saw the emergence of inverse theory and its computational modeling. In 1971, Kavanagh et al. [9] pioneered the inversion of elastic modulus and other elasticity parameters of media using the finite element method. During this stage, inversion analysis was applied to tunnel and underground space engineering, for linear elastic problems with simple boundary conditions and a single parameter [10]. Simultaneously, optimization calculation methods such as the simplex method [11], the atlas method, and the quadratic gradient method [12] were also gradually developed.

2.1.2. Evolutionary Phase

The evolutionary phase of inverse theory began in the early 1980s and ended in the early 1990s. During this period, researchers expanded the scope of application and accuracy of inversion analysis with the help of simulation methods such as finite element and discrete element. They also performed regression analysis of the rock stress field and displacement field.

Field monitoring technology developed based on large-scale tunnel and underground space engineering construction provided a basis for the inversion of ground stress. The combination and introduction of numerical computation and field monitoring technology made inversion analysis research more focused on practical engineering applications. As a result, inversion analysis is commonly used in linear elastic, viscoelastic, or elasto-plastic problems.

2.1.3. Innovation Phase

From the early 1990s to the early 21st century, inversion theory underwent an innovative stage. During this period, the uncertainty inversion analysis method, which takes into account the self-randomness of rock and soil, rapidly developed. Inversion analysis also expanded its application scope from single parameter identification problems to rock and soil structure identification. Additionally, a numerical inversion method was proposed by combining the finite element method with the inversion analysis method. This method considers the influence of the design scheme and construction process. Machine learning was introduced into numerical analysis, and a research method was proposed that considers the dynamic changes in the excavation process. The intelligent rock mechanics method was also introduced through the use of genetic algorithms and particle swarm optimization algorithms in the numerical analysis model. This method has been successfully applied in practical engineering.

2.1.4. Intelligent Phase

Continuous innovation in computer technology and field measurement technology since the early 21st century has addressed problems of missing data, low accuracy, and weak dynamics in numerical analysis. As a result, the inversion analysis method has entered the intelligent stage. Researchers have started using a method that combines artificial intelligence technology with the basic theory of tunnel and underground space engineering to carry out intelligent analysis of the mechanical behavior of the rock mass during excavation. This approach enables rapid numerical simulation analysis and research according to different construction methods.

The main feature of the intelligent phase of inversion analysis is the introduction of deep neural networks, which have powerful ability to solve nonlinear problems with low workload, short time consumption, and high accuracy. Large numbers of parameter values are not required in engineering problems, such as parameter identification and deformation prediction. Instead, relevant information about the research object can be obtained through network analysis. A cloud database is established, and after uploading the data, end-to-end intelligent inversion analysis can be performed [13–17].

Representative achievements in this stage include Zhu et al. [18], who used on-site monitoring information of the concrete dam of Shuibuya Hydropower Station to invert the dam rockfill parameters. The inverted parameters were used to re-calculate the dam displacement using a multi-group particle swarm optimization algorithm. Liu et al. [19] introduced the particle swarm optimization algorithm (PSO) and Gaussian factor into the pigeon heuristic optimization algorithm (PIO) to improve the elastic parameter inversion problem under the pre-stack amplitude variation with offset algorithm (AVO). Wang et al. [20] proposed an intelligent inversion method of hydrogeological parameters based on the disturbance-inspired equilibrium optimizer (DIEO) to solve the problems of groundwater numerical simulation and sustainable utilization of water resources. The method was verified with three different types of cases, and the results showed that this method can accurately and quickly obtain hydrogeological parameters. Xu et al. [21] and Zhang et al. [22] used intelligent parameter inversion analysis by means of depth network optimization algorithm and numerical analysis to realize multi-means coupling inversion to solve complex engineering problems.

From the above analysis, it can be seen that the first two phases of the development of inversion analysis were limited by the level of field monitoring. The engineering problems were mainly solved by theoretical analysis and numerical inversion analysis methods. After entering the 1990s, the advent of the information age created opportunities for the transmission of various engineering information and the sharing of resources. The rapid development of computer vision has caused deep learning methods to penetrate into various fields. Consequently, in the latter two time nodes, inversion analysis has also entered the intelligent stage, forming an operational technology based on “big data” cloud system as the operation platform and intelligent inversion as the fundamental method to solve the problems of construction parameters and predict engineering disasters.

2.2. The Main Contents of Application Research of Inversion Analysis

According to statistics from relevant departments, the number of completed and opened highway tunnels, railroad tunnels, and urban rail transit in 2020 reached 21,316, 16,798, and 245, respectively. This represents an increase of 153.2%, 125.3%, and 222.7%, respectively, compared to the number of tunnels built in 2015, as shown in Figure 2.

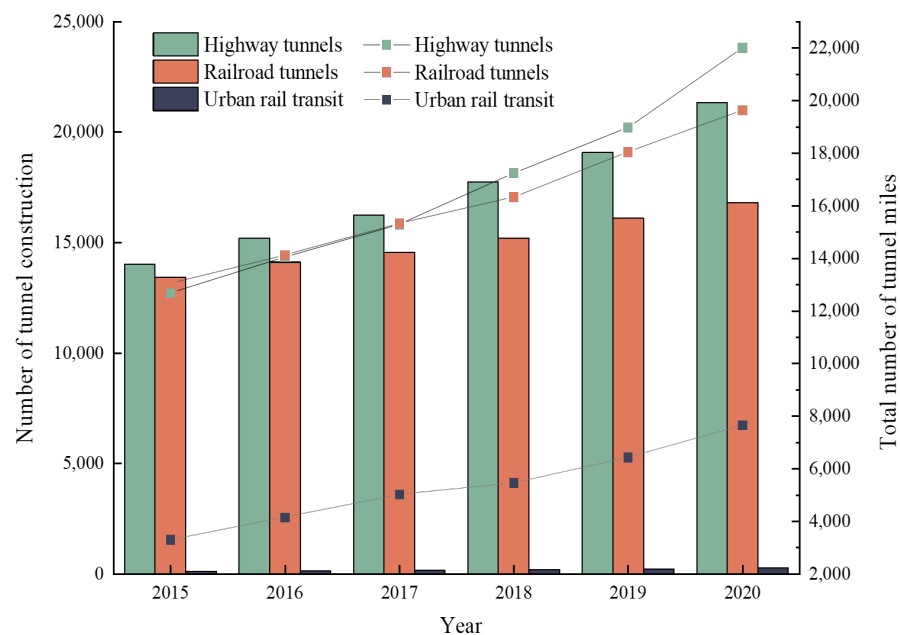


Figure 2. Statistics of highway tunnels, railway tunnels, and urban rail transit in China (2015–2020).

As a large and diverse research branch in the field of civil engineering, research on the computational theory of tunnel and underground engineering has made great progress in recent decades. Through search engines such as CNKI and “Web of Science” a total of 578 related papers were found using the keywords “inversion analysis” and “tunnel and underground space engineering” in the past 20 years. The research directions of inversion analysis in tunnel and underground engineering are summarized in Figure 3a. It is not difficult to see that the proportion of material characteristic parameters and initial geo-stress research is large, accounting for 59% and 28%, respectively, while comprehensive application and supporting structure load account for only 8.13% and 5.02%, respectively.

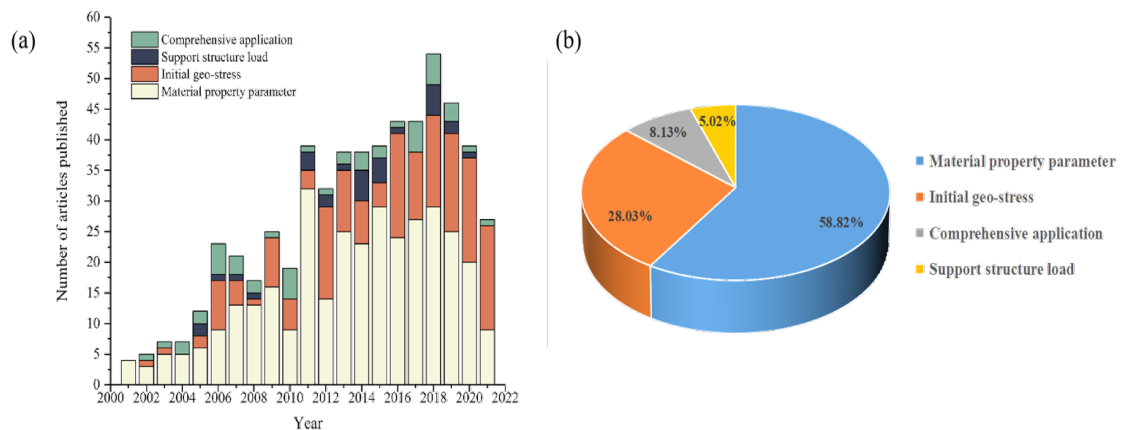


Figure 3. The research on inversion analysis method in tunnel and underground engineering in recent 20 years: (a) Research compositions, (b) Distribution of publications.

Figure 3b presents a graph of literature published in different years. The graph demonstrates that the number of publications for inversion analysis of material property parameters constitutes a significant portion of the total number of publications per year. In contrast, the number of papers on the inversion analysis of initial ground stress has only gradually caught up in recent years. The research results in this field have a certain lag compared to the number of tunnels constructed and lack an effective mechanism to transform the results. However, it is undeniable that inversion theory has become an effective tool for solving tunnel and underground engineering problems. In the future, it will be deeply integrated with the Internet, big data, and intelligent monitoring technology to realize the diversification of inversion analysis methods.

3. Inversion Analysis of Initial Ground Stress

Geo-stress is a type of natural stress that varies spatially and temporally, while initial stress is secondary stress formed relative to the stress redistribution phenomenon during tunnel excavation. In the early 20th century, people began exploring initial ground stress during tunnel and underground space engineering construction. Heim, a Swiss geologist, was the first to propose the existence of initial ground stress within rock strata. He observed and analyzed the construction process of a large section mountain tunnel and concluded that the distribution of initial ground stress is in a state of hydrostatic stress.

In 1915, the Swedish scholar N. Hast first measured the initial geo-stress in the Navia Peninsula. He found that the maximum principal stress in the rock stratum is almost horizontal stress, fundamentally shaking the view that the initial geo-stress is dominated by vertical stress. In the mid-20th century, domestic and foreign scholars used the strain generated in the mining process and geological exploration data in major projects to develop the calculation method of inversion analysis. In China, the founders, mainly Li Siguang and Chen Zongji, began actual measurements of ground stress in the 1950s.

3.1. Traditional Inversion Analysis Method

The 20-year period spanning from 1970 to 1990 marked the first stage of inversion research in China on the initial geo-stress of rock mass. During this stage, the Institute of Geology of the Chinese Academy of Sciences conducted the first research on initial stress inversion analysis. They proposed a finite element atlas method [23] for inversion analysis of initial stress based on mapping. The atlas method approximates the displacement and stress of surrounding rock in practical engineering based on finite element calculation results. By preparing a series of atlases according to commonly used section forms in engineering, the stress and displacement in actual engineering surrounding rock can be projected.

The atlas model includes vertical load q , horizontal ground stress P , horizontal lateral pressure ξ , and weight of surrounding rock. The model structure is shown in Figure 4. While the mapping method is still a good method for conducting rapid inference of elastic stresses and displacements in early studies, it is not suitable for tunnel and underground space engineering with special section shapes and complex geological environments. In such cases, the finite element method or other methods are used to obtain more reasonable and accurate results.

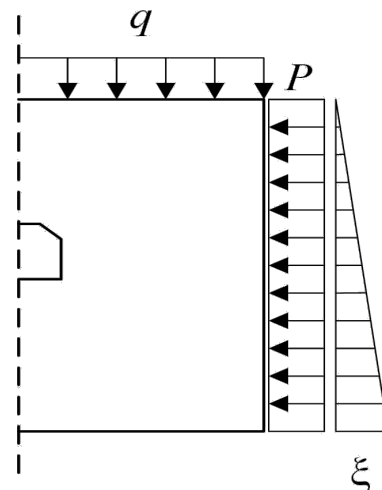


Figure 4. Finite element atlas model [23].

In 1983, Professor Guo Huaizhi of Tianjin University proposed the method of using regression analysis to inverse the initial stress field [24]. The method first establishes a three-dimensional calculation domain coordinate system, as shown in Figure 5, and establishes a finite element calculation model based on the determined geological and topographic survey data and using the factors that may form the initial ground stress field of the rock mass, such as the self-weight of the rock mass, geological tectonic movement, and temperature as the undetermined analysis value, from which the multiple regression relationship between the undetermined analysis value and the measured data is established, as shown in Equation (1):

$$\sigma = f(x, y, z, E, \mu, \gamma, \Delta, U, V, W, T) \quad (1)$$

where σ is the initial stress value, two-dimensional problems represent three stress components, and three-dimensional problems represent six stress components, x, y, z are the coordinate system of the spatial location of topography and geological bodies can be obtained from survey data, E, μ, γ are elastic modulus, Poisson's ratio, and bulk density of rock mass, respectively, which can be obtained by physical testing, Δ is the self-weight factor, U, V , and W are factors of geological structure, and T is the temperature factor.

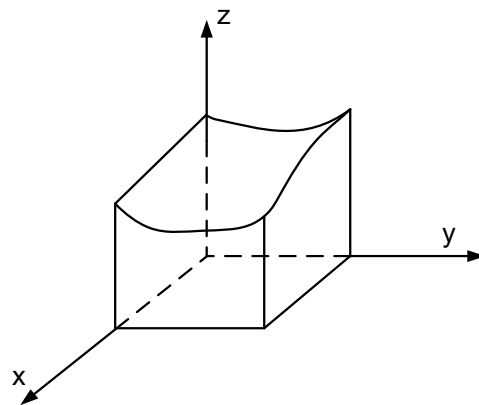


Figure 5. Selection of computational domain coordinates.

The multiple regression equation of Equation (1) is linear due to the complex composition of the initial stress, which is only a gradual approximation method. If the initial stress can be estimated according to the nonlinear regression equation, it can better meet the needs of practical engineering. The general nonlinear regression model is expressed as Equation (2) [25]:

$$y_k = f(x_k, \beta_p) + \varepsilon_k \quad (2)$$

where y_k is the observed value; x_k is a non-random regression coefficient, β_p is a unknown parameter vector and ε_k is a random vector. In Equation (2), the value of k does not correspond to the value of p .

Gudehus G [26] adopts the concept of “releasing load” to analyze the stress present in the current underground cavern excavation. It is considered that the disturbed stress field and displacement field are caused by the unloading effect resulting from the release of the initial ground stress around the tunnel, and the load released is completely determined by the initial ground stress. In addition, in 1983, Bai et al. [27] carried out back analysis of the in situ stress of the dam powerhouse through the disc fracture phenomenon and rockburst phenomenon of the core. In 1989, Xiao et al. [28] proposed the geostress function analysis method. In 1999, Diao et al. [29] put forward the idea of combining artificial intelligence with numerical analysis to estimate the initial geostress.

In the early stage of theoretical research on initial in situ stress inversion, it was assumed that the initial in situ stress field is a uniformly distributed stress field, or a superimposed stress field formed by considering the linear distribution of gravity stress and tectonic stress. However, the engineering application of the initial stress value mainly relies on measured data and in situ stress measurement methods [30]. Therefore, it is difficult to meet the needs of engineering construction when the number of measuring points is small. As a result, researchers proposed an inversion analysis method for the initial geostress of rock mass during tunnel excavation using a small number of measuring points.

3.2. Intelligent Inversion Analysis Method

At the beginning of the 21st century, research on geo-stress inversion of rock masses entered its second stage. Researchers have combined neural networks and numerical analysis to perform initial ground stress inversion analysis [31]. However, for the initial in situ stress field inversion problem under complex geological conditions, the simplified model cannot obtain reasonable and accurate stress parameters due to objective factors such as discontinuity, non-uniformity, and non-elastic-plasticity of the rock mass itself. Therefore, approximating the in situ stress field under general conditions is difficult, and the solution process is very inefficient when considering multi-field coupling problems such as temperature and seepage field.

With the improvement of measurement technology, site construction workers can collect more in situ stress measurement data. The inversion analysis method combined with information theory and new optimization methods has gradually become the main direction of research. At the same time, intelligent algorithms such as machine learning are used to mine the measured data, increasing the generalization analysis ability of the inversion model. Figure 6 shows a technical roadmap of the intelligent inversion analysis method.

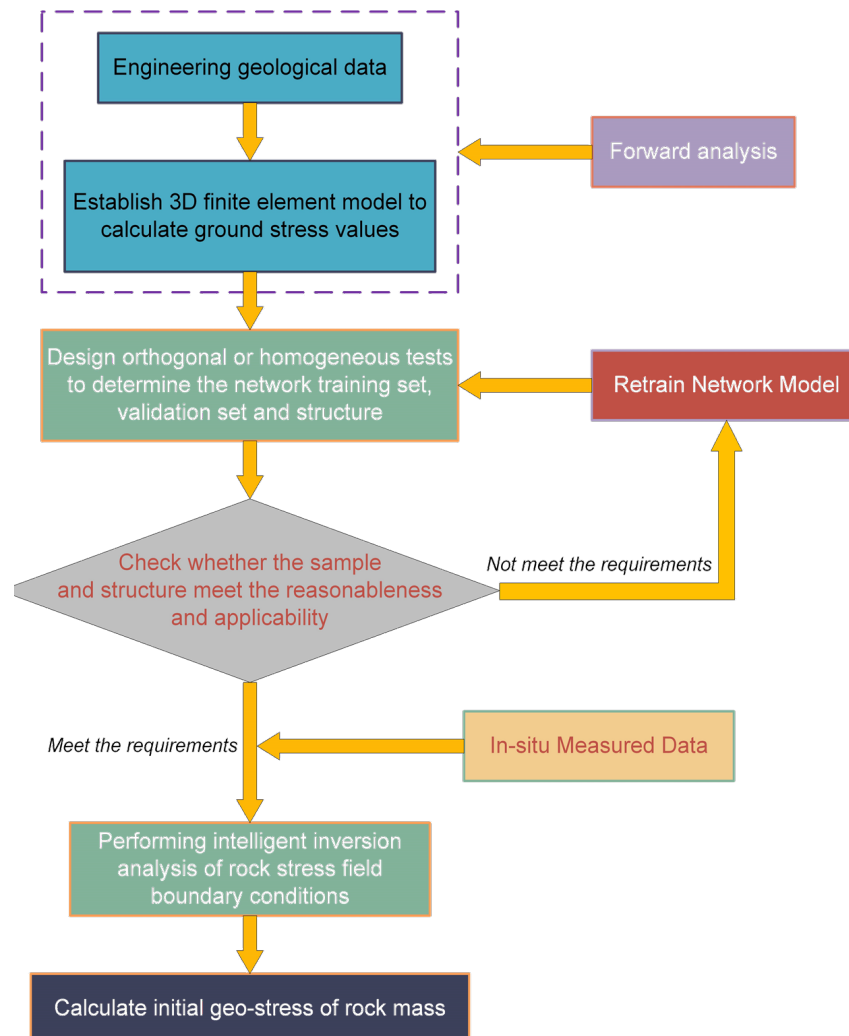


Figure 6. Flow chart of intelligent inversion of initial in situ stress.

In the process of initial geo-stress inversion analysis using intelligent algorithms, the neural network algorithm based on genetic algorithm optimization is one of the most commonly used methods. This algorithm originated from the simulation study of biological systems and drew on the mechanism of biological genetics, which can be more relevant to the mechanism of neural networks using human brain neurons to process information. Its application scope covers optimization problems that are difficult to solve in traditional inversion analysis. Many scholars also choose to use this method to solve the in situ stress distribution of dam bodies [32], underground powerhouses of hydropower stations, and deep-buried tunnels [33]. Jiang et al. [34] proposed a non-linear inversion method of in situ stress, which integrates ground abrasion simulation, elastoplastic calculation, and a neural network. The nonlinear relationship between the boundary conditions to be inverted and the stress can be described by such neural networks, as shown in Equation (3). This method considered the time series conditions of ancient structures and better simulated the strong

erosion of rivers on the ground stress field in the current site area, so that the inversion results have higher credibility.

$$\left. \begin{aligned} & NN(m, x_1, \dots, x_p, n) : R^m \rightarrow R^n \\ & D = NN(m, x_1, \dots, x_p, n)(P) \\ & P = (p_1, p_2, \dots, p_m); D = (d_1, d_2, \dots, d_n) \end{aligned} \right\} \quad (3)$$

where $P = (p_1, p_2, \dots, p_m)$ is the input variable of the neural network, expressed as the stress value at the measurement point, $D = (d_1, d_2, \dots, d_n)$ is the output variable of the neural network, expressed as the displacement boundary condition of the constructed stress field, $NN = (m, x_1, x_2, \dots, x_p, n)$ is the established multilayer neural network structure and m, n are the number of nodes in the input and output layers, respectively.

Deep learning neural networks, such as the radial basis function (RBF) neural network and the generating adversarial network (GAN), are widely used in various tunnel and underground space projects. Zhang et al. [35] proposed a back analysis method of the earth's stress field considering the hydraulic fracturing environment by combining an artificial neural network with a genetic algorithm, based on the principle of the RBF neural network. This method enables the integration of an artificial neural network and an optimization algorithm and effectively reduces the workload of numerical calculation by using the information measured in the field to construct learning samples.

Li et al. [36] proposed a neural network algorithm of GMDH (Group Modeling of Data Handling) for the critical issue of sparse measured sample data of ground stress. This algorithm constructs the boundary condition model under complex geological conditions by combining the nonlinear characteristics of the gravity and tectonic stress fields and fitting nonlinear expressions of the boundary load. The effectiveness of the algorithm was verified by establishing a two-dimensional geological regional model. The author randomly selected 15, 12, 9, and 6 position points as the “field measured stress” points. The abscissa 2, 5, 8, 9, 11, and 14 in the Figure 7 are the serial numbers of measuring points under the above four position points. The results show that the GMDH algorithm has better nonlinear data predictability than the BP neural network. Qian et al. [37] simulated the evolution process of the river valley during excavation by establishing a three-dimensional numerical model of the Shuangjiangkou underground hydropower station. They inputted coordinates, current buried depth, and current lateral stress coefficient into the GAN model as training samples. After nonlinear analysis of the model, the optimized lateral stress coefficient was determined and applied to the reconstruction of the paleo-stress field.

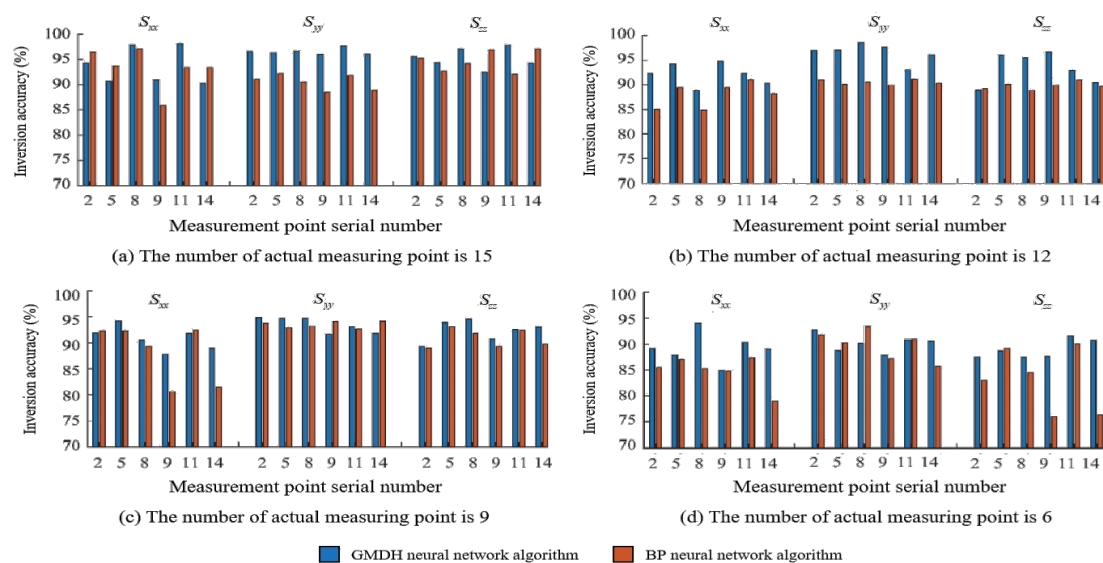


Figure 7. The contrast of inversion accuracy between GMDH and BP neural network [36].

According to the statistical results of some typical engineering cases and simulation analyses (shown in Tables 1 and 2), the intelligent inversion analysis method is superior to the traditional inversion analysis method in terms of calculation error and accuracy. When conducting inversion analysis of the initial ground stress field in complex geological conditions, such as high ground temperature and high ground stress, the optimization method that uses deep learning network architecture can achieve better results than the single neural network algorithm or numerical analysis method. Moreover, intelligent monitoring equipment and numerical simulation software can improve the applicability and accuracy of inversion results. The artificial intelligence method also allows the existing inversion analysis method to select calculation methods based on different geological characteristics and engineering requirements, significantly enhancing the accuracy of inversion results.

Table 1. The statistical results of the simulation cases for initial geo-stress inversion analysis in traditional inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
Atlas method [23]	1580 hoist cavern of Muding copper deposits	Only elastic stress and displacement can be inferred, but for some underground engineering with special section shapes and complex geological conditions, the applicability is poor
Finite element method [27]	Ertan hydropower station	Some deviation in the stress of the part affected by lithology change or local structure
Displacement back analysis [38]	Urumqi Wudong Coal Mine	The actual vertical stress value is smaller than the inverse calculation result, while the minimum principal horizontal stress value is similar to the inverse calculation result
Multiple regression analysis [39]	Daxiangling Tunnel, Ya'an City, Sichuan Province	The regression analysis results are basically consistent with the measured results, and the relative error is controlled within 10%

Table 2. The statistical results of the simulation cases for initial geo-stress inversion analysis in intelligent inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
Artificial neural networks (ANNs) and genetic algorithms (GAs) [35]	Hydropower projects at Huizhou Pumped Storage Power Station	The relative errors between the theoretical and network calculated values of maximum and minimum horizontal soil stress are only 1.01% and 0.24%, respectively.
GMDH neural network algorithms [36]	Xingshan iron mine	The average inversion accuracy reached 84%, and the inversion error of stress components is less than 10% for most of the measuring points
BP neural network [40]	Sichuan-Tibet Railway Tunnel	Compared with the multiple regression analysis method, the average relative error of the inversion results of maximum horizontal principal stress and vertical stress is reduced by 26.44% and 77.27%, respectively.
Segmentation feature capsule Network based on convolution Neural Network Enhancement [41]	China coal mine underground stress database	Mean square error is as low as 0.06%, which is lower than 0.62% of deep neural network prediction algorithms and 0.98% of traditional machine learning algorithms

However, these methods also have problems. Firstly, the calculation process considers too many influencing factors, resulting in a large amount of calculation. Secondly, the stress function applied to the boundary load condition of the model is relatively simple

and cannot reflect the stress field under complex conditions. Additionally, the inversion analysis method based on elastic mechanics theory does not consider the plastic state of rock mass in tunnel and underground engineering construction under deep complex geological conditions. Therefore, it is a matter of urgency to develop new deep rock mechanics theories and methods that consider non-linear factors such as construction [42,43] and the inversion method of in situ stress variation under the influence of major geological conditions such as faults and geological structures [44]. With the help of stress inversion, it is possible to predict and diagnose the diseases of supporting structures [45].

In future research, the method of in situ stress monitoring and inversion optimization algorithm can be combined to reduce measurement errors and further improve the theory of multi-scale geostress inversion under complex geological conditions. It is also necessary to explore the inversion analysis method of initial geostress under high geostress conditions and high-altitude cold areas, and other special environments. Additionally, it is important to study the temporal and spatial distribution of rock mass stress under the coupling action of seepage field, stress field, and energy field, and to construct the geostress model needed for deep tunnel excavation and large-scale geotechnical engineering.

4. Inversion Analysis of Supporting Load

In tunnel and underground space engineering, the research on structural load mainly focuses on the analysis of supporting structure load during excavation. In this kind of study, the inversion theory mainly considers the influence of stratum pressure (i.e., the load borne in the process of lining structure contacting with stratum). According to the measured information of displacement and stress, the load acting on the supporting structure is inverted, and the distribution law is further explored.

4.1. Traditional Inversion Analysis Method

The concept of load on supporting structures has undergone three stages, as shown in Figure 8. From the late 19th century until the first half of the 20th century, the support structure was considered to be a structure that only bore loads, without taking into account the magnitude of the action load distributed on it by the surrounding rock resistance and the bearing capacity of the surrounding rock itself. In the 1930s, the load on the support was divided into active load (active surrounding rock pressure) and passive load (the result of surrounding rock pressure constraint on the support). After the 1960s, with the introduction of the New Austrian Tunneling Method (NATM), the surrounding rock became an integral part of the support system. Based on further understanding of the structural nature of the surrounding rock and its loading effects, many scholars have interpreted the nature of the support structure in detail and proposed the tunnel surrounding rock-support synergistic action system.

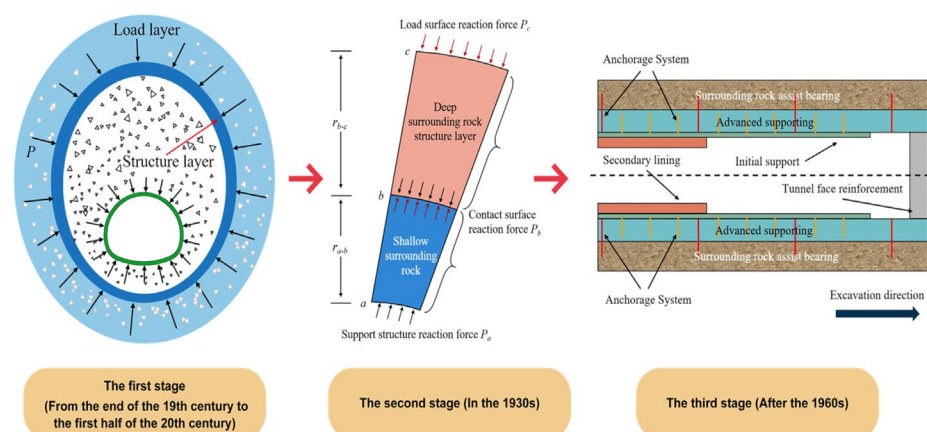


Figure 8. The development process of the load concept on supporting structure [46–48].

In 1977, Professor Kovari [49] from the Department of Rock and Tunnel Engineering at the Zurich University of Applied Sciences conducted the first study on structural load inversion analysis. The main idea was to divide the entire support structure into several parts, establish the relationship between the measured curvature and strain of the support and between the axial force and bending moment of the support, and calculate the distribution of the tangential and normal stress values of the support load. In 1981, the Italian scholar Gioda [50] published an inverse calculation method based on the finite element method, and discussed the inversion analysis of rock pressure considering the effect on retaining structure and the characterization of in situ rock mass material parameters in 1987. The inversion analysis problem is still non-linear, regardless of the linear representation of load and material characteristics, and must be solved by appropriate optimization methods. These articles laid the theoretical foundation for early structural load inversion analysis.

In the 1990s, theoretical research on the inversion of structural support loads began in China, starting with the load inversion of roadway supports and conducting a lot of basic work, followed by in-depth research on the inversion analysis method of tunnel lining load. Liu [51] conducted the inversion analysis of the surrounding rock action pressure on the support lining and concluded that the site measuring point arrangement and boundary conditions directly affect the results of the inversion analysis. Nie [52] proposed a general numerical analysis method for identifying tunnel lining load. This method uses a group of in situ displacement measurements of the sprayed concrete layer for back analysis and calculation, which avoids the complex characteristics of rock mass, and the load value after inversion calculation can effectively reflect the combined effect of tunnel-surrounding rock.

To solve the problem of instability and non-uniqueness of the inverse solution of underground structures, Zhang et al. [53] proposed three kinds of back analysis methods: generalized least square solution estimation, generalized minimum norm solution estimation, and generalized minimum variance solution estimation. These methods greatly improved the accuracy of load inversion of supporting structures. In terms of stability analysis of supporting structures, Song et al. [54] proposed a tunnel structure stability analysis method based on ready-made displacement monitoring data, considering the influence of tunnel buried depth and cross-section. The loads of supporting structures in horseshoe tunnels [55], multi-center circular arch tunnels [56], and shallow eccentric tunnels [57,58] were also studied. However, the above methods are all based on the analysis of two-dimensional plane strain, and there are artificial factors in the setting of boundary conditions, so they are not suitable for load analysis in a complex three-dimensional stress environment.

4.2. Intelligent Inversion Analysis Method

There have been few cases of using neural networks for load inversion analysis of support structures in tunnel construction. Fu et al. [59] introduced a particle swarm optimization algorithm and finite element analysis method into the displacement inversion analysis process of supporting structure load. This provided technical support for the information design and intelligent construction of subway tunnel structures. Liu et al. [60] proposed a TBM shield and surrounding-rock load inversion method based on Newton iteration and finite element theory. The external surface of the TBM shield is divided into regularly curved rectangular cells according to the circumferential or axial components of the column coordinates, and the four nodal load values of the rectangular cells are used as inversion parameters. To analyze the inversion efficiency and stability, the calculation is performed by assuming two cases, such as symmetric linear load and inhomogeneous load distributed on the external surface of the shield (shown in Figure 9). The results show that the inversion algorithm can realize the discrete fitting of the TBM shield surface under arbitrary surrounding rock loads, and the model has high robustness and good error immunity. He [61] proposed a random load inversion method based on probability density evolution theory. Compared with other intelligent optimization algorithms, this method starts from the randomness of monitoring information in practical engineering and uses

random system theory to invert the distribution characteristics of loads in underground structures. Lu et al. [62] proposed a method to inverse the cohesion and internal friction angle of rock mass by grouting, bolt prestress and bolt arrangement based on mechanical analysis, machine learning, and reliability theory. Taking the deep-buried tunnel in loose rock mass as an example, the interaction between deep surrounding rock and support is studied, and its reliability is evaluated.

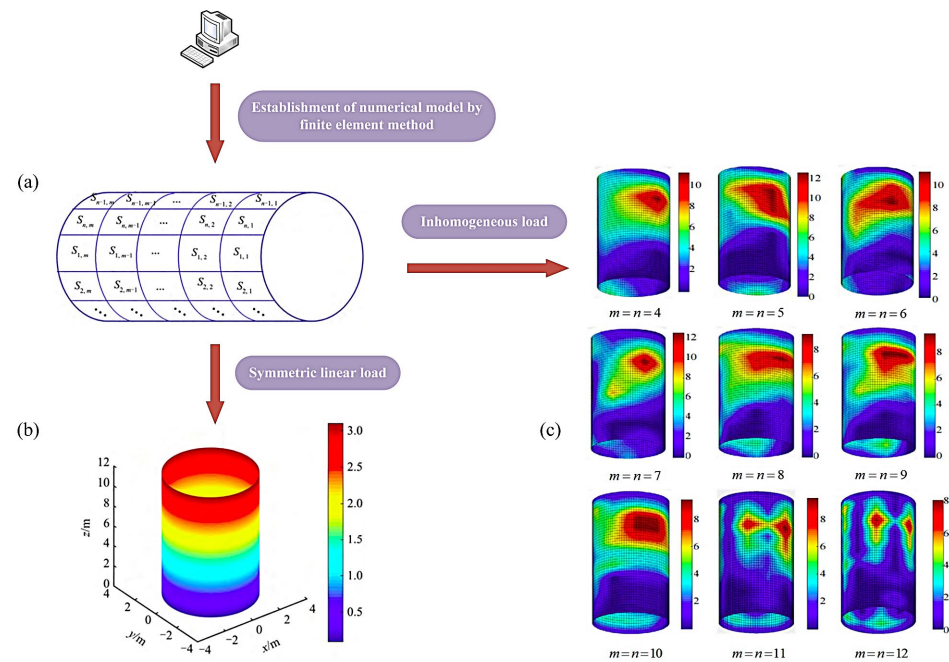


Figure 9. TBM shield and surrounding rock load inversion analysis method: (a) partitions of external shield surface, (b) contour map of identified loads (unit: MPa), (c) inverse results concerning different surface partition schemes (unit: MPa, where m and n are the numbers of shield annular partitions and the number of axial partitions, respectively) [60].

In the field of tunnel and underground engineering, the load back analysis of supporting structure is a practical direction in the inverse theoretical research, and field measurement is the only way to study the stress data of supporting structure. High-precision detection and installation of more efficient measurement tools, such as advanced geological prediction systems (TSP), ground-penetrating radar and optical-fiber sensors, will provide more scientific and accurate observation data for load back calculation. The result of inverse calculation will have higher credibility, which is of great significance for the mechanical analysis of tunnel construction processes. Sui et al. [63] selected distributed optical fiber sensors to monitor the stress and deformation of damaged tunnel lining, and then proposed a more accurate back analysis method to calculate the deformation modes of tunnel arch structures, such as displacement, stress, and load. Zhao et al. [64] relied on the optical-fiber sensor monitoring system of an optical time domain reflectometer to obtain real-time deformation parameters inside the tunnel. Through numerical experiments, the parameters obtained by orthogonal design and uniform design are calculated, and the mapping relationship between tunnel surrounding-rock parameters and monitoring displacement is established. Finally, the parameters are identified based on differential evolution algorithm. Combined with the Dalian Baiyunshan tunnel project, it is proved that this method has strong adaptability.

The representative engineering cases of supporting structures load inversion are listed in Tables 3 and 4, respectively. It is not difficult to find from the above table that for the load inversion analysis, the method adopted by scholars is slightly different from the initial in situ stress inversion. Basically, the finite element theory is taken as the leading factor

and the neural network algorithm as an auxiliary optimization tool, then the structure divides into several units, and finally the calculation under different load conditions is carried out according to different types of optimization analysis methods. However, when the high in situ stress in the surrounding rock and the influence of the structural plane are significant, the selection degree of the support load function combination is complicated, and the number of unit grids is large, which is easy to increase the inversion calculation amount.

Table 3. The statistical results of engineering cases for supporting structure load in traditional inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
Least-squares method [65]	the Xu FuXiang Station to the Nan-jing Railway Station on subway line 1 in Nanjing City in eastern China	The external load of tunnel structure obtained by back analysis method is more accurate and convenient than that obtained by traditional direct monitoring or classical earth pressure calculation formula, and requires fewer monitoring sensors, but the effect is not good for deep-buried tunnels.
Combining model test and numerical simulation [66]	Foshan Metro Line 2 (Green Island Lake-Liantang)	The consistency between the calculated values and the measured data is analyzed by using the comprehensive error function, and the uniform distribution of the vault load and the parabola distribution of the horizontal load are the most consistent with the test data.
Inversion analysis based on radial displacement and contact stress [67]	Lyjialiang Tunnel in Chongqing	The analysis is limited to the effect of symmetrical loads, and the internal forces of the main support for shallow-buried unsymmetrically-loaded tunnels need to be further explored.
Displacement back analysis [68]	Longsheng Tunnel in Guilin City	The regression analysis results are basically consistent with the measured results, and the relative error is controlled within 10%
Inversion analysis based on initial parameter method [56]	Multi-circular arch tunnel	Considering the time variation of tunnel construction process, and the analytical solution of main support internal force is feasible in tunnel construction

Table 4. The statistical results of engineering cases for supporting structure load in intelligent inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
The particle swarm algorithm [59]	Subway tunnel construction by shield method	The calculation efficiency is high, but for complex rock mass structure, it is still difficult to determine the support load by this method
Inversion method based on probability density evolution theory [61]	Shanghai Metro Line M6	Achieves the correct reflection of the objective system while greatly reducing the difficulty and workload of problem-solving

5. Inversion Analysis of Characteristic Parameter

The types and quantities of characteristic parameters of the surrounding rock are closely related to the deformation behavior of the rock mass under external forces. When the rock mass is in an elastic stress state, Poisson's ratio and elastic modulus are the characteristic parameters of the surrounding rock. When in an elastic-plastic stress state, the internal friction angle and cohesion must be added to fully express the characteristics of the rock mass. Some soft rocks remain in a viscoelastic stress state due to their rheological properties, specifically creep and stress relaxation. Determining the characteristic parame-

ters is equivalent to identifying the constitutive model of the rock mass. Based on this, the problem of identifying various parameters is realized.

Therefore, the inversion analysis of characteristic parameters can be considered an inverse parameter identification problem. For this type of problem, the suitability of the parameter solution must be solved first, including the results for uniqueness, stability, and identifiability. If the forward problem corresponding to the inverse problem has no unique solution, the inverse problem will have no unique solution. When the number of parameters to invert in the structural model is larger than the number of observations, the stability of the inversion analysis solution will be low, and it will be difficult to meet the requirements of construction applications. Meanwhile, the arrangement of observation points and the number of observation data also affect the accuracy and precision of parameter identification.

5.1. Traditional Inversion Analysis Method

The inversion analysis of material characteristic parameters is ultimately attributed to solving the function problem or the minimum residual problem of the sum of squares of minimum values [69]. The traditional inversion analysis method for determining the characteristic parameters of formation materials is mainly based on solving the minimum problem defined by the objective function.

In 1983, one of the main early researchers of the displacement inversion analysis method, Sakurai, a Japanese scholar, established the inverse analysis method of tunnel displacement based on gradient search method and proposed the nonlinear programming theory of the linkage constraints between the identified parameters and the observed data [10], which can be expressed as Equation (4).

$$\min\{J(m, d_m)\}, m \in R^P, d_m \in R^M \quad (4)$$

where R^P is the space of acceptable parameters, m represents the parameter vector to be identified, belonging to space R^P and d_m is the observed data vector, belonging to space R^M .

The work of Colaco et al. [70] optimizes the relationship, uses the norm metric to obtain the objective function of the least square problem for parameter identification, such as the following formula, and compares different kinds of parameter inversion methods.

$$J(p) = (d_m - d_c(m))^T \omega (d_m - d_c(m)) \quad (5)$$

where ω is the weight matrix, considering the influence of the observation data of different observation points on the parameter identification results; $d_c(m)$ is the data vector calculated by the model, which can be regarded as a function of the dependent variable m .

If the computational model of parameter inversion is viewed as an optimization model, the computational process will transform into the problem of solving the optimal solution of the original model. At that time, Levenberg-Marquardt algorithm was proved to be one of the most effective methods to solve unconstrained optimization problems [71], so the least square parameter back analysis method based on this algorithm came into being. Cividini et al. [72] studied the Bayesian method for the inversion of an elastic-plastic parameters of rock mass. Ichikawa and Ohkami [73] used the dual boundary control method (see Figure 10) to study the inversion of elastic parameters. Sun et al. [74] carried out the elastic-plastic inversion analysis of rock mass parameters. This kind of inversion analysis is regarded as an alternative calculation problem of the nonlinear least square method, for which a unique solution of the parameters is found after global optimization design.

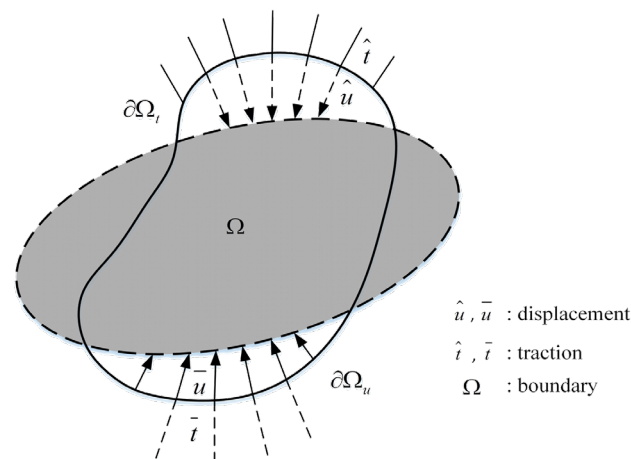


Figure 10. The dual boundary control model [73].

However, due to the uncertainty of observation information, the traditional parameter inversion analysis method cannot obtain practical parameter identification results in the early research stage, and the mathematical formula is cumbersome, which is difficult to apply to practice.

5.2. Intelligent Inversion Analysis Method

The parameter inversion technique has a solid foundation, especially with the increase in the types of field measurement information. The application of uncertain parameter identification methods and intelligent rock mechanics methods makes the result of parameter inversion more unique and reliable. However, the current method based on the optimal solution to solve the parameter inversion analysis problem will invert all the parameters involved in the tunneling project and cause the phenomenon of dimensional disaster. Therefore, it is not realistic to take all the undetermined parameters as the design variables for the inversion analysis, and the relationship between the measurement information and the mechanical parameters is usually highly nonlinear. The singularity of the measurement information will also lead to the deterioration of the uniqueness of the identification parameters.

With the promotion of the finite element analysis method, the use of finite element software combined with deep neural network models such as genetic algorithms [75], particle swarm algorithms [76], and simulated annealing algorithms [77] for parameter inversion analysis has developed rapidly. Deep learning algorithms can achieve an infinite approximation of various functions and establish nonlinear mapping relationships between data to obtain target parameters under complex constraints, effectively avoiding the problem of data dimension disaster.

In the study of parametric inversion analysis using the finite element method combined with an intelligent optimization algorithm, Lee and Kim [78] used the combination of the extended Bayesian and finite element analysis to predict ground response and determine geotechnical parameters. Zhang et al. [79] considered the loss of displacement in the monitoring process, combined the traditional Gaussian process with a particle swarm optimization algorithm, and proposed a new parameter back analysis method based on FLAC^{3D} numerical analysis software, which can evaluate the stability of deep underground geotechnical engineering. In order to make up for the deficiency of traditional neural networks and support vector machines in three-dimensional displacement back analysis, Yan et al. [80] proposed an improved combined kernel Gaussian regression algorithm. With the combination of particle swarm optimization and the algorithm, accurate mapping between geomechanical parameters and rock mass deformation is realized. The simulation example of the Beikou tunnel shows that the recognition accuracy of the algorithm meets the engineering requirements. Wang et al. [81] introduced the elastic-plastic stress-seepage

damage coupling model into the intelligent displacement back analysis and realized the intelligent inversion of tunnel surrounding rock damage parameters. The analysis process, as shown in Figure 11, is divided into three parts, corresponding to (a)–(c), in which part (a) describes the whole calculation process of the intelligent back analysis program. Part (b) briefly explains the implementation process and principal formula of the differential evolution algorithm used in the program, and part (c) shows the calculation results of the elastic-plastic damage mechanical field of surrounding rock and lining after tunnel excavation with and without considering the action of seepage.

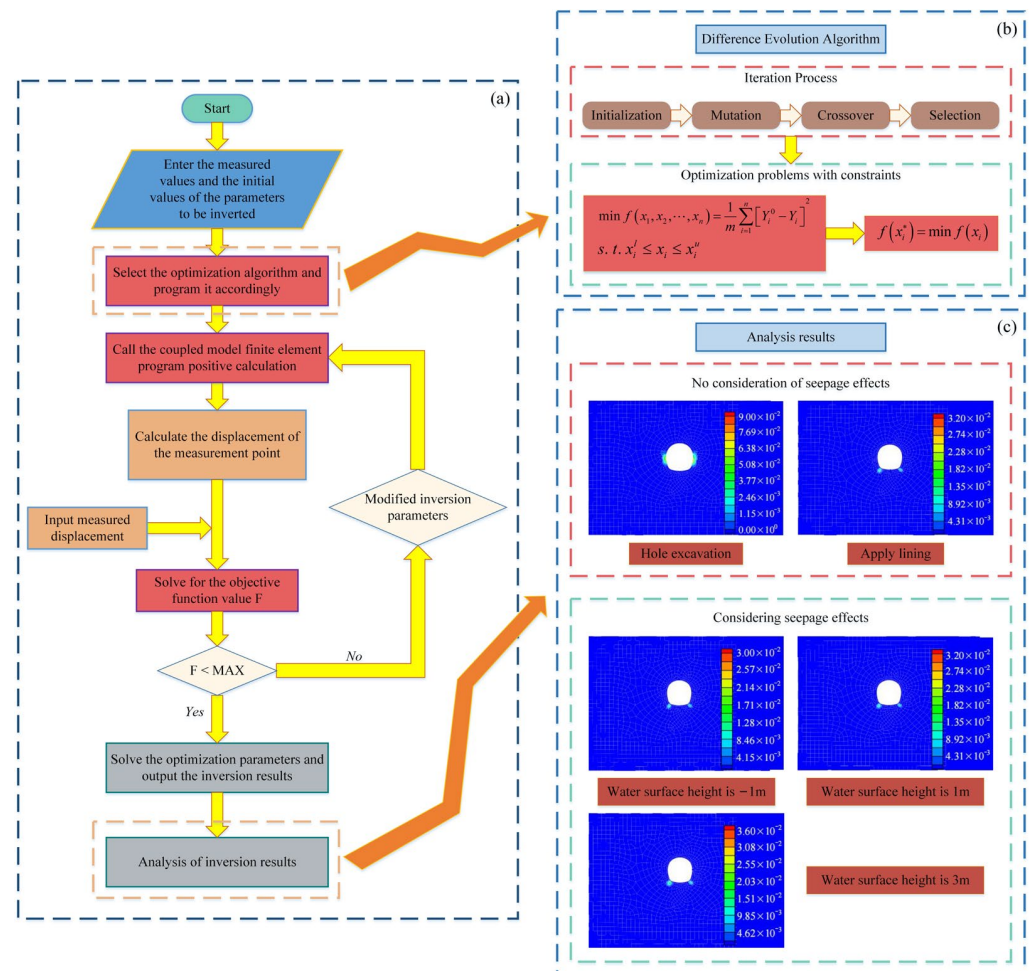


Figure 11. Intelligent inverse analysis of coupling parameters: (a) calculation process of intelligent back analysis program, (b) difference evolution algorithm, (c) calculated mechanical field of elastic-plastic damage in the surrounding rock and lining after tunnel excavation with and without considering the effect of seepage [81].

Song et al. [82] used three-dimensional numerical simulation software to calculate the training and test samples for the component extreme learning machine model. They combined tunnel field displacement and stress monitoring data and, through the optimization of differential evolution algorithm, realized the back analysis of surrounding rock parameters in highway tunnel engineering in Fusong City, Jilin Province. Feng et al. [83] put forward a new displacement back analysis method by combining neural networks, evolutionary algorithms, and numerical analysis methods, and applied it to the establishment of rock mass mechanical parameters of the Three Gorges Project. Wan et al. [84] aimed at the problems of overfitting, local optimization, and poor generalization ability of neural networks. They used a direct optimization algorithm based on a genetic algorithm and improved support vector machine to analyze the rock mechanical parameters and initial

stress of an eccentric tunnel in the shallow section of Zhangshi highway. Liu [85] coupled a genetic algorithm with combined covariance-Gaussian process and, also taking Beikou Tunnel as an example, put forward an optimization method for support parameters, and formed a complete information construction method for tunnel engineering, which was carried out with the prediction results of the genetic algorithm and support vector machine regression coupling algorithm. The results show that this method has the advantages of simple operation, fast processing speed, and high precision.

In general, problems can be solved using artificial neural networks, genetic algorithms, simulated annealing, ant colony algorithms, and hybrid optimization algorithms that improve upon the aforementioned algorithms. However, when there is limited observational data and numerous inversion parameters, the probability of distortion and ill-posed phenomena in the inversion results increases significantly. To address this issue, Tian [86] started with the finite element equilibrium equation and used the local model solution approximation as a global model solution for one or more materials. This approach can reduce errors and solve distortion in the inversion results, greatly expanding the applicability of the original algorithm.

Tables 5 and 6 display the application cases of the traditional inversion analysis method and classical intelligent inversion analysis algorithm in engineering. It can be seen that the improvement measures of various optimization algorithms, such as improved particle swarm optimization algorithm [87], genetic simulated annealing differential evolution algorithm [88], and immune algorithm [89], can further enhance the optimization ability and inversion quality by integrating the advantages of each algorithm and eliminating their disadvantages. These algorithms are widely used in the calculation of various tunnel characteristic parameters.

Table 5. The statistical results of engineering cases for characteristic parameter in traditional inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
A flexible tolerance method [90]	The drilling layout of the Shangmo reservoir project in Gansu Province, China	The maximum errors between the measured and calculated infiltration amounts for each time period are 3.43% and 4.67%, respectively
Combining the orthogonal experimental design and multi-objective optimization back analysis method [91]	A large hydropower station located in the middle reaches of Dadu River in Shimian County, Sichuan Province.	It not only satisfies the engineering accuracy, but also greatly improves the speed of inversion calculation.

Table 6. The statistical results of engineering cases for characteristic parameter in intelligent inversion analysis.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
Support vector regression based on multi-strategy artificial fish swarm algorithm [92]	Heshi Tunnel in Xiushui County, Jiujiang City, Jiangxi Province	The training and testing accuracy of the mechanical parameters of the tunnel surrounding rock is significantly improved, with the relative error only within 0.1%
Deep learning network architecture based on GPRInvNet [93]	Data set of tunnel lining defect types	The location of tunnel lining defects is effectively inverted, but due to the complexity of GPR data, only the contour of defects can be reconstructed
Difference evolution algorithm [94]	Shield Tunnel of Guangzhou Metro Line 9	The maximum error of the inversion results is 20.8% and the minimum is 0.72%

Table 6. Cont.

Inversion Analysis Method	Project Cases	Brief Description of Analysis Results
Neural network algorithm based on genetic algorithm optimization [95–98]	The large underground power station caverns engineering	The error between the calculated displacement value and the actual monitoring value is only within the range of 0.06–0.62 mm.
	Shenzhen Metro Line 13 tunnel project	The average absolute percentage errors of the optimized neural network model for predicting the tunneling speed of the composite stratum dual-mode shield machine are 2.312% 2.926%, respectively, while the standard neural network model is 4.343% 7.240%, respectively.
	Wuyang Tunnel of Xiarong Expressway Project	The predicted displacement is in good agreement with the measured displacement curve
	The underground cavern of Lvchunba railway tunnel	The errors between the numerical values of the vault settlement and clearance convergence of the studied section and the actual monitoring values are 13.2%, −8.3%, −8.9% and 9.4%, respectively.

6. Problems and Prospects of Inversion Analysis Method

The inverse analysis method has been used to solve relevant parameter inversion problems since the 1970s. It has been half a century since its inception, and during this period, many scholars have applied this method to various engineering fields. They continue to innovate and improve. With the rapid development of computer technology and observation methods, numerical analysis methods such as the finite element method and boundary element method, as well as monitoring methods such as ground-penetrating radar and advanced geological prediction TSP systems, have made the research of back analysis in tunnel engineering problems flourish.

Despite this progress, there are still some problems in the current research of tunnel and underground engineering. The main findings are as follows:

1. The reliability of initial geostress inversion in complex geological environments is low. Currently, the stress function used in the back analysis method of initial ground stress is relatively simple. Additionally, the existing theory of rock mechanics based on static research cannot fully reflect the stress field under complex geological conditions, such as high ground stress, high temperature, and long buried depth;
2. Lack of objective indicators to evaluate the accuracy of back analysis. The accuracy of the back analysis results mainly depends on whether the network model can establish an effective nonlinear mapping relationship. However, the types of network models are various, the level of obtaining data is uneven, and the actual engineering types are also different. Therefore, determining an index to objectively evaluate the accuracy of all kinds of back analysis methods has not been solved yet;
3. The process of data processing is difficult to share in real-time. Currently, a large-scale information platform for tunnel monitoring data and geological hazard information sharing has not been established. Furthermore, data mining has a high cost. As a result, some small and medium-sized tunnel projects cannot realize the dynamic optimization of the construction process according to the existing monitoring data. This increases the difficulty of this kind of tunnel construction. However, the quality of on-site data acquisition is also limited by excavation conditions and monitoring equipment. Coupled with the spatio-temporal variability of geological conditions, it is difficult to achieve a relationship between the network model and numerical analysis results in data analysis;
4. Intelligent back analysis methods are costly. The current artificial intelligence technology is not mature, and its way of dealing with problems involves rigorous analysis, calculation, and logical reasoning. This cannot be solved completely without human

intervention. To a large extent, it needs to rely on the expert system to make the final decision, and a lot of human and financial resources will be spent on data mining, collection, and storage in this process.

With the increasing trend of cross-disciplinary fields, the intelligent back analysis method has proven to be highly effective in solving tunnel engineering problems. However, this method does not solely depend on neural networks or optimization algorithms; instead, neural networks serve as a foundational component. Based on this theory, we can consider the following four aspects to realize diverse intelligent back analysis methods, improve the premature convergence of optimization algorithms, and enhance the reliability of inversion results. The main results are as follows:

1. Once the autonomous learning process is established, the inversion computing model can actively understand data and make decisions in complex environments. By combining advanced geological prediction, remote sensing, and the use of electromagnetic or waveform signals, monitoring methods can be improved and optimized to make data analysis more accurate and speed up inversion analysis;
2. To better consider tunnel and underground engineering characteristics and find solutions to problems encountered in engineering practice, we should not be limited to relying on various complex optimization algorithms to obtain accurate inversion results. Optimization algorithms are only one of many excellent tools that need to cooperate with engineering practice to realize their practical value. No matter how accurate a tool is, if it does not match its work, it will not be able to maximize its benefits;
3. By combining numerical analysis software with better flexibility, compatibility, and visualization, as well as simulation technology and intelligent technology with BIM technology, machine learning, computer vision, and other means, the inversion process can expand in the interactive direction, gradually moving from bottom to top applications;
4. Using deep learning to enhance the recognition ability of traditional algorithms for object features under complex structures can investigate the root cause. Intelligence aims to achieve a better imitation of the way of thinking and expression of the human brain, and inversion analysis aims to obtain the predicted results more easily. Real intelligence can obtain the final result without relying on a large amount of data, but it still has to be supported by a large amount of data, meaning that the optimization algorithm of intelligent inversion must be established in a new round;
5. The deep learning network structure should strengthen the expandability of use. Most of the network structures, including fully connected neural networks, convolutional neural networks, and cyclic neural networks, are mainly for supervised learning, which is often limited by artificially labeled sample feature information in the process of use and unable to mine deeper feature information. On the other hand, the unsupervised learning network structure, such as generative countermeasure neural networks, has the ability to extract key information from a large amount of unmarked data and has great potential for development. The use of this kind of network structure can be increased when using intelligent back analysis methods to solve tunnel and underground engineering problems in the future;
6. To achieve a breakthrough in tunnel construction and underground traffic design and construction technology with super-long buried depth under complex conditions, it is necessary to further strengthen countermeasures for large deformation and strong erosion and optimize construction equipment in harsh geological environments. In the process of urban rail transit construction, it is necessary to refine the construction management system, improve the efficiency of network operation and maintenance, and form new construction mode ideas to complete the innovation of tunnel engineering technology and inversion theory.

7. Conclusions

Over time, judging the complex mechanical properties of a discontinuous and non-uniform rock mass becomes increasingly difficult. Laboratory experiments and field measurements alone cannot accurately reflect the actual construction process or the dynamic feedback it generates. In response to the demand for production and construction, and the proposal of the New Austrian method, scholars have begun using the changing trend of monitoring surrounding rock displacement to deduce the properties of rock and soil. As a result, the back analysis method has become an effective means of determining the parameters of calculation models. This paper briefly summarizes the reasons for the formation of back analysis methods and introduces the development process of traditional and intelligent back analysis methods. It then summarizes the traditional and intelligent back analysis of three target unknowns: initial ground stress, load of supporting structures, and characteristic parameters of surrounding rock. The main conclusions are as follows:

1. The back analysis method for initial ground stress is becoming increasingly intelligent and informationized due to the continuous improvement and updating of computer function, as well as the rapid development of neural network and machine learning algorithms. The back analysis method is constantly adjusted and optimized according to the tunnel and underground environment under different geological conditions, and the analysis method suitable for the construction method and construction condition of the project is selected. This ensures a seamless connection between the initial geostress back analysis principle and the actual engineering, and improves the practicability and reliability of numerical analysis methods;
2. The accuracy of back analysis of the load of supporting structures largely depends on the deformation data monitored in the field. Compared to the other two kinds of unknowns, the back analysis of this kind has stronger practical significance and can directly reflect the reliability of engineering design. It also contains fewer uncertain factors and assumptions, which makes the back analysis results more well-posed and reliable;
3. The inversion of tunnel-surrounding rock characteristic parameters is highly ill-posed. To improve the inversion results, more optimization algorithms are needed to analyze unfavorable factors that affect the solution's uniqueness and identifiability. Research methods for this kind of problem are abundant, and the achievements are significant. Currently, the characteristic parameters are obtained by comparing field data with the theoretical model information. With the continuous innovation of computer technology and intelligent calculation methods, and the improvement of field observation accuracy, the inversion results of surrounding rock parameters can be more in line with engineering practice.

Author Contributions: Z.S., R.H. and Y.Z. development the ideas, designed the research methodology. Z.Y. wrote the original version. Z.S. supervised the work, acquired the funds, planned the research and revised the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: The funding support was provided by Shaanxi Innovation Capacity Support Program-Innovation Team (No. 2020TD-005), the Natural Science Foundation of Shaanxi Province (No. 2021JM-373).

Institutional Review Board Statement: No applicable.

Informed Consent Statement: No applicable.

Data Availability Statement: The conclusions used to support this review can be obtained from the corresponding authors as required.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Stille, H.; Palmström, A. Ground behaviour and rock mass composition in underground excavations. *Tunn. Undergr. Space Technol.* **2008**, *23*, 46–64. [\[CrossRef\]](#)
2. Cai, M. Rock Mass Characterization and Rock Property Variability Considerations for Tunnel and Cavern Design. *Rock Mech. Rock Eng.* **2011**, *44*, 379–399. [\[CrossRef\]](#)
3. Swoboda, G.; Ichikawa, Y.; Dong, Q.X.; Zaki, M. Back Analysis of Large Geotechnical Models. *Int. J. Numer. Anal. Met.* **1999**, *23*, 1455–1472. [\[CrossRef\]](#)
4. Stigler, S.M. Gauss and the Invention of Least Squares. *Ann. Stat.* **1981**, *9*, 465–474. [\[CrossRef\]](#)
5. Fujino, Y.; Siringoringo, D.M.; Ikeda, Y.; Nagayama, T.; Mizutani, T. Research and Implementations of Structural Monitoring for Bridges and Buildings in Japan. *Engineering* **2019**, *5*, 1093–1119. [\[CrossRef\]](#)
6. Greenhalgh, S.A.; Bing, Z.; Green, A. Solutions, algorithms and inter-relations for local minimization search geophysical inversion. *J. Geophys. Eng.* **2006**, *3*, 101–113. [\[CrossRef\]](#)
7. Kaewunruen, S.; Lian, Q. Digital twin aided sustainability-based lifecycle management for railway turnout systems. *J. Clean. Prod.* **2019**, *228*, 1537–1551. [\[CrossRef\]](#)
8. Kaewunruen, S.; Sresakoolchai, J.; Yu, S. Global Warming Potentials Due to Railway Tunnel Construction and Maintenance. *Appl. Sci.* **2020**, *10*, 6459. [\[CrossRef\]](#)
9. Kavanagh, K.T.; Clough, R.W. Finite element applications in the characterization of elastic solids. *Int. J. Solids Struct.* **1971**, *7*, 11–23. [\[CrossRef\]](#)
10. Sakurai, S.; Takeuchi, K. Back analysis of measured displacements of tunnels. *Rock Mech. Rock Eng.* **1983**, *16*, 173–180. [\[CrossRef\]](#)
11. Gioda, G.; De Donato, O. Elastic-plastic analysis of geotechnical problems by mathematical programming. *Int. J. Numer. Anal. Methods Géoméch.* **1979**, *3*, 381–401. [\[CrossRef\]](#)
12. Ma, Q.C.; Wang, B.L. Research on Ground Stress Field of Rock Masses by Feedback of In-Situ Displacements Measurement. *Chin. J. Geotech. Eng.* **1990**, *3*, 10–21.
13. Gioda, G.; Maier, G. Direct search solution of an inverse problem in elastoplasticity: Identification of cohesion, friction angle and in situ stress by pressure tunnel tests. *Int. J. Numer. Methods Eng.* **1980**, *15*, 1823–1848. [\[CrossRef\]](#)
14. Plesha, M.E. Constitutive models for rock discontinuities with dilatancy and surface degradation. *Int. J. Numer. Anal. Methods Géoméch.* **1987**, *11*, 345–362. [\[CrossRef\]](#)
15. Zhang, T.; Zhang, Y.; Wang, A.; Wang, R.; Chen, H.; Liu, P. Intelligent Analysis Cloud Platform for Soil Moisture-Nutrients-Salinity Content Based on Quantitative Remote Sensing. *Atmosphere* **2023**, *14*, 23. [\[CrossRef\]](#)
16. Yan, X.; Zhu, Z.; Wu, Q. Intelligent inversion method for pre-stack seismic big data based on MapReduce. *Comput. Geosci.* **2018**, *110*, 81–89. [\[CrossRef\]](#)
17. Yan, X.; Zhang, M.; Wu, Q. Big-data-driven pre-stack seismic intelligent inversion. *Inf. Sci.* **2021**, *549*, 34–52. [\[CrossRef\]](#)
18. Zhu, Y.; Chi, S. The Application of MsPSO in the Rockfill Parameter Inversion of CFRD. *Math. Probl. Eng.* **2016**, *2016*, 1096967. [\[CrossRef\]](#)
19. Liu, H.; Yan, X.; Wu, Q. An Improved Pigeon-Inspired Optimisation Algorithm and Its Application in Parameter Inversion. *Symmetry* **2019**, *11*, 1291. [\[CrossRef\]](#)
20. Wang, W.Y.; Kang, J.T.; Li, K.; Fan, Y.H.; Lin, P. A Novel Intelligent Inversion Method of Hydrogeological Parameters Based on the Disturbance-Inspired Equilibrium Optimizer. *Sustainability* **2022**, *14*, 3267. [\[CrossRef\]](#)
21. Xu, L.; Zhang, T.; Ren, Q. Intelligent Autofeedback and Safety Early-Warning for Underground Cavern Engineering during Construction Based on BP Neural Network and FEM. *Math. Probl. Eng.* **2015**, *2015*, 873823. [\[CrossRef\]](#)
22. Zhang, F.; Jiang, A.; Guo, X.; Yang, X. Creep Parameter Inversion and Long-Term Stability Analysis of Tunnel Based on GP-DE Intelligent Algorithm. *Adv. Mater. Sci. Eng.* **2021**, *2021*, 3769474. [\[CrossRef\]](#)
23. Zang, S.Y. Application of Finite Element Atlas Method in Underground Engineering. *J. Kunming Univ. Sci. Technol.* **1989**, *1*, 30–34.
24. Guo, H.Z.; Ma, Q.C.; Xue, X.C. The Analytical Method of the Initial Stress Field for Rock Masses. *Chin. J. Geotech. Eng.* **1983**, *3*, 64–75.
25. Feng, Z.L. On the Determination of the Load Caused by Excavating Opening. *Chin. J. Geotech. Eng.* **1991**, *3*, 36–42.
26. Gudehus, G.; John, W. *Finite Elements in Geomechanics*; Wiley: New York, NY, USA, 1977; pp. 395–399.
27. Bai, S.W.; Li, G.Y. Research on Stress Field Around Dam Area of Ertan Hydropower Station. *Chin. J. Rock Mech. Eng.* **1982**, *1*, 45–56.
28. Xiao, M.; Liu, Z.M. Inversion Regression Analysis of 3 Dimensional Ground Stress Field for Jinping No.2 Hydropower Station. *Yangtze River* **2000**, *9*, 42–44.
29. Diao, X.H.; Feng, X.T.; Yang, C.X. Key Problem in Numerical Simulation Application in Rock Engineering and Its Development. *Metal Mine* **1999**, *6*, 6–8.
30. Jing, F.; Sheng, Q.; Zhang, Y.; Liu, Y. Study Advance on In-Site Geostress Measurement and Analysis of Initial Geostress Field in China. *Rock Soil Mech.* **2011**, *32*, 51–58.
31. Shahin, M.A.; Jaksa, M.B.; Maier, H.R. Artificial neural network applications in geotechnical engineering. *Aust. Geomech. J.* **2001**, *36*, 49–62.
32. Li, G.; Hu, Y.; Li, Q.-B.; Yin, T.; Miao, J.-X.; Yao, M. Inversion Method of In-situ Stress and Rock Damage Characteristics in Dam Site Using Neural Network and Numerical Simulation—A Case Study. *IEEE Access* **2020**, *8*, 46701–46712. [\[CrossRef\]](#)

33. Zhang, P. In Situ Stress Inversion and Distribution Characteristics of Tunnel Based on Numerical Simulation and Neural Network Technology. *Shock. Vib.* **2021**, *2021*, 5545283. [\[CrossRef\]](#)
34. Jiang, Q.; Feng, X.T.; Chen, J.L. Nonlinear Inversion of 3D Initial Geostress Field in Jinping II Hydropower Station Region. *Rock Soil Mech.* **2008**, *11*, 3003–3010.
35. Zhang, S.; Yuan, Y.; Fang, H.; Wang, F. An application of soft computing for the earth stress analysis in hydropower engineering. *Soft Comput.* **2020**, *24*, 4739–4749. [\[CrossRef\]](#)
36. Li, F.; Zhou, J.X.; Wang, J.N. Back Analysis and Reconstruction Method of In-Situ Stress Field based on Limited Sample Data. *J. China Coal Soc.* **2019**, *44*, 1421–1431.
37. Qian, L.; Yao, T.; Mo, Z.; Zhang, J.; Li, Y.; Zhang, R.; Xu, N.; Li, Z. GAN inversion method of an initial in situ stress field based on the lateral stress coefficient. *Sci. Rep.* **2021**, *11*, 21825. [\[CrossRef\]](#)
38. Shan, P.; Lai, X. An associated evaluation methodology of initial stress level of coal-rock masses in steeply inclined coal seams, Urumchi coal field, China. *Eng. Comput.* **2020**, *37*, 2177–2192. [\[CrossRef\]](#)
39. Zhang, Z.; Gong, R.; Zhang, H.; Lan, Q.; Tang, X. Initial ground stress field regression analysis and application in an extra-long tunnel in the western mountainous area of China. *Bull. Eng. Geol. Environ.* **2021**, *80*, 4603–4619. [\[CrossRef\]](#)
40. Li, X.; Zhou, X.; Xu, Z.; Feng, T.; Wang, D.; Deng, J.; Zhang, G.; Li, C.; Feng, G.; Zhang, R.; et al. Inversion Method of Initial In Situ Stress Field Based on BP Neural Network and Applying Loads to Unit Body. *Adv. Civ. Eng.* **2020**, *2020*, 8840940. [\[CrossRef\]](#)
41. Gao, W.; Lu, X.; Peng, Y.; Wu, L. A Deep Learning Approach Replacing the Finite Difference Method for In Situ Stress Prediction. *IEEE Access* **2020**, *8*, 44063–44074. [\[CrossRef\]](#)
42. Wang, M.; Li, J.; Ma, L.; Huang, H. Study on the Characteristic Energy Factor of the Deep Rock Mass Under Weak Disturbance. *Rock Mech. Rock Eng.* **2016**, *49*, 3165–3173. [\[CrossRef\]](#)
43. Cai, W.; Zhu, H.; Liang, W. Three-dimensional tunnel face extrusion and reinforcement effects of underground excavations in deep rock masses. *Int. J. Rock Mech. Min. Sci.* **2022**, *150*, 104999. [\[CrossRef\]](#)
44. Matsuki, K.; Nakama, S.; Sato, T. Estimation of regional stress by FEM for a heterogeneous rock mass with a large fault. *Int. J. Rock Mech. Min. Sci.* **2009**, *46*, 31–50. [\[CrossRef\]](#)
45. Zhao, C.; Lavasan, A.A.; Barciaga, T.; Kämper, C.; Mark, P.; Schanz, T. Prediction of tunnel lining forces and deformations using analytical and numerical solutions. *Tunn. Undergr. Space Technol.* **2017**, *64*, 164–176. [\[CrossRef\]](#)
46. Oreste, P. Analysis of structural interaction in tunnels using the convergence–confinement approach. *Tunn. Undergr. Space Technol.* **2003**, *18*, 347–363. [\[CrossRef\]](#)
47. Zhang, D.; Chen, L.P. Compound structural characteristics and load effect of tunnel surrounding rock. *Chin. J. Rock Mech. Eng.* **2016**, *35*, 456–469.
48. Sun, Z.Y. The Synergetic Principle and Design Method of Tunnel Support System. Ph.D. Thesis, Beijing Jiaotong University, Beijing, China, 2020.
49. Kovari, K.; Amstad, C.; Fritz, P. Integrated measuring technique for rock pressure determination. *Tunn. Int.* **1978**, *10*, 39–40.
50. Gioda, G.; Sakurai, S. Back analysis procedures for the interpretation of field measurements in geomechanics. *Int. J. Numer. Anal. Methods Géoméché.* **1987**, *11*, 555–583. [\[CrossRef\]](#)
51. Liu, H.H. Support load inversion and safety prediction. *J. Xi'an Inst. Min. Tech.* **1991**, *4*, 1–8.
52. Nie, X.; Zhang, Q. A system of monitoring and dimensioning tunnel support. *Rock Mech. Rock Eng.* **1994**, *27*, 23–36. [\[CrossRef\]](#)
53. Zhang, Z.S.; Chen, Z.Y.; Zhu, W.S. Generalized Inverse Method for Underground Structure Load. *China Civil Eng. J.* **2001**, *2*, 38–42.
54. Song, Z.P. Structural stability evaluation technology of Jiangjuntou tunnel based on displacement back analysis. *Highw. Transp. Sci. Tech.* **2011**, *7*, 144–147.
55. Shreedharan, S.; Kulatilake, P.H.S.W. Discontinuum–Equivalent Continuum Analysis of the Stability of Tunnels in a Deep Coal Mine Using the Distinct Element Method. *Rock Mech. Rock Eng.* **2015**, *49*, 1903–1922. [\[CrossRef\]](#)
56. Yang, Z.; Wang, Y.; Song, L.; Wang, X. Theoretical Study on Internal Forces of Primary Support of Tunnel by considering Time Effect. *Adv. Mater. Sci. Eng.* **2020**, *2020*, 4254178. [\[CrossRef\]](#)
57. Gioda, G.; Locatelli, L. Back analysis of the measurements performed during the excavation of a shallow tunnel in sand. *Int. J. Numer. Anal. Methods Géoméché.* **1999**, *23*, 1407–1425. [\[CrossRef\]](#)
58. Qiu, H.; Qiu, R.; Luo, G.; Ayasrah, M.; Wang, Z. Study on the Mechanical Behavior of Fluid–Solid Coupling in Shallow Buried Tunnels under Different Biased Terrain. *Symmetry* **2022**, *14*, 1339. [\[CrossRef\]](#)
59. Fu, Z.F.; Sun, J.S.; Zuo, C.Q. Back analysis of subway tunnel support load based on particle swarm optimization. *Yangtze River* **2011**, *42*, 70–73.
60. Liu, H.; Liu, Q.S.; Tang, X.H.; Luo, C.; Wan, W.; Chen, L.; Pan, Y. Load identification method of TBM shield-surrounding rock interaction. *Rock Soil Mech.* **2019**, *40*, 4946–4954.
61. He, T. Stochastic Load Identification and Reliability Analysis of Underground Structural. Ph.D. Thesis, Tongji University, Shanghai, China, 2007.
62. Lu, W.; Wang, L.; Song, K.; Sun, H.; Chen, D. Safety Evaluation of Anchoring–Grouting Rock-Support Interaction in Deep Underground Excavation Based on Support Vector Machine Learning. *Iran. J. Sci. Technol. Trans. Civ. Eng.* **2022**, *46*, 3805–3817. [\[CrossRef\]](#)
63. Sui, Y.; Cheng, X.; Wei, J. Distributed fibre optic monitoring of damaged lining in double-arch tunnel and analysis of its deformation mode. *Tunn. Undergr. Space Technol.* **2021**, *110*, 103812. [\[CrossRef\]](#)

64. Zhao, J.; Feng, J.; Ren, L. Inversion Calculation Analysis of Operational Tunnel Structure Based on the Distributed Optical-Fiber Sensing System. *Adv. Civ. Eng.* **2017**, *2017*, 6159095. [\[CrossRef\]](#)
65. Yan, Q.; Zhang, W.; Zhang, C.; Chen, H.; Dai, Y.; Zhou, H. Back Analysis of Water and Earth Loads on Shield Tunnel and Structure Ultimate Limit State Assessment: A Case Study. *Arab. J. Sci. Eng.* **2018**, *44*, 4839–4853. [\[CrossRef\]](#)
66. Niu, H.; Weng, X.; Tian, C.; Wang, D. Model Test and Back Analysis of Shield Tunnel Load Distribution in Soft Clay. *Adv. Mater. Sci. Eng.* **2021**, *2021*, 9992348. [\[CrossRef\]](#)
67. He, W.Z.; Xu, L.S.; Wang, L.L. Theoretical Back Analysis of Internal Forces of Primary Support in Deep Tunnels. *J. Eng. Sci. Technol. Rev.* **2019**, *12*, 18–26. [\[CrossRef\]](#)
68. Liu, Y.; Zhang, X.; Li, J.; Zhang, Z.; Zhang, H. Performance Assessment of Arch-shaped Primary Lining during Construction in Weak Rock Shallow-buried Tunnel. *KSCE J. Civ. Eng.* **2018**, *23*, 433–443. [\[CrossRef\]](#)
69. Neuman, S.P. Calibration of distributed parameter groundwater flow models viewed as a multiple-objective decision process under uncertainty. *Water Resour. Res.* **1973**, *9*, 1006–1021. [\[CrossRef\]](#)
70. Colaco, M.J.; Orlande, H.R.B. Comparison of Different Versions of the Conjugate Gradient Method of Function Estimation. *Numer. Heat Transf. Part A Appl.* **1999**, *36*, 229–249. [\[CrossRef\]](#)
71. Moré, J.J. The Levenberg-Marquardt algorithm: Implementation and theory. In *Numerical Analysis: Proceedings of the Biennial Conference Held at Dundee, Dundee, UK, 28 June–1 July 1977*; Springer: Berlin/Heidelberg, Germany, 2006; pp. 105–116.
72. Cividini, A.; Maier, G.; Nappi, A. Parameter estimation of a static geotechnical model using a Bayes' approach. *Int. J. Rock Mech. Min. Sci. Géoméch. Abstr.* **1983**, *20*, 215–226. [\[CrossRef\]](#)
73. Ichikawa, Y.; Ohkami, T. A Parameter Identification Procedure as a Dual Boundary Control Problem for Linear Elastic Materials. *Soils Found.* **1992**, *32*, 35–44. [\[CrossRef\]](#)
74. Sun, J.; Huang, W. Optimization method for elastoplastic inversion of rock mechanics parameters. *Chin. J. Rock Mech. Eng.* **1992**, *3*, 221–229+317.
75. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, 2nd ed.; MIT Press: Cambridge, UK, 1992.
76. Kennedy, J.; Eberhart, R.C. A discrete binary version of the particle swarm algorithm. In *Proceedings of the 1997 IEEE International Conference on Systems, Man, and Cybernetics Computational Cybernetics and Simulation*, Orlando, FL, USA, 12–15 October 1997; Volume 5, pp. 4104–4108.
77. Metropolis, N.; Rosenbluth, A.W.; Rosenbluth, M.N.; Teller, A.H.; Teller, E. Equation of State Calculations by Fast Computing Machines. *J. Chem. Phys.* **1953**, *21*, 1087–1092. [\[CrossRef\]](#)
78. Lee, I.-M.; Kim, D.-H. Parameter estimation using extended Bayesian method in tunnelling. *Comput. Geotech.* **1999**, *24*, 109–124. [\[CrossRef\]](#)
79. Zhang, Y.; Su, G.; Liu, B.; Li, T. A novel displacement back analysis method considering the displacement loss for underground rock mass engineering. *Tunn. Undergr. Space Technol.* **2020**, *95*, 103141. [\[CrossRef\]](#)
80. Yan, H.; Liu, K.; Xu, C.; Zheng, W. A novel method for identifying geomechanical parameters of rock masses based on a PSO and improved GPR hybrid algorithm. *Sci. Rep.* **2022**, *12*, 5670. [\[CrossRef\]](#)
81. Wang, J.X.; Jiang, Y.N.; Song, Z.P. Research on coupled elastoplastic stress-seepage-damage model of rock (II): Parameter in-version and numerical simulation. *Rock Soil Mech.* **2015**, *36*, 3606–3614.
82. Song, Z.-P.; Jiang, A.-N.; Jiang, Z.-B. Back Analysis of Geomechanical Parameters Using Hybrid Algorithm Based on Difference Evolution and Extreme Learning Machine. *Math. Probl. Eng.* **2015**, *2015*, 821534. [\[CrossRef\]](#)
83. Feng, X.-T.; Zhang, Z.; Sheng, Q. Estimating mechanical rock mass parameters relating to the Three Gorges Project permanent shiplock using an intelligent displacement back analysis method. *Int. J. Rock Mech. Min. Sci.* **2000**, *37*, 1039–1054. [\[CrossRef\]](#)
84. Wan, L.Y.; Zhang, X.F.; Liu, K.Y. Intelligent displacement back analysis method of three-dimension applied in unsymmetrical pressure tunnel with shallow depth. *Appl. Mech. Mater.* **2011**, *90*, 2286–2291. [\[CrossRef\]](#)
85. Liu, K.; Liu, B. Intelligent information-based construction in tunnel engineering based on the GA and CCGPR coupled algorithm. *Tunn. Undergr. Space Technol.* **2019**, *88*, 113–128. [\[CrossRef\]](#)
86. Tian, M. *Intelligent Inversion Algorithms and Application*. Ph.D. Thesis, Dalian University of Technology, Dalian, China, 2006.
87. Fang, W.H. Back-analysis improved particle Swarm optimization algorithm on mechanical parameters of divisional geotechnical engineering material. *Appl. Mech. Mater.* **2012**, *182*, 1647–1653. [\[CrossRef\]](#)
88. Yang, L.; Li, Z.-D. Inverse Analysis of Rock Creep Model Parameters Based on Improved Simulated Annealing Differential Evolution Algorithm. *Geotech. Geol. Eng.* **2019**, *37*, 639–649. [\[CrossRef\]](#)
89. Wang, J.; Sun, J.; Kou, H.; Lin, Y. Multiparameter Inversion Early Warning System of Tunnel Stress-Seepage Coupling Based on IA-BP Algorithm. *Adv. Civ. Eng.* **2021**, *2021*, 1566693. [\[CrossRef\]](#)
90. Gan, L.; Chen, G.; Shen, Z. A New Approach to Permeability Inversion of Fractured Rock Masses and Its Engineering Application. *Water* **2020**, *12*, 734. [\[CrossRef\]](#)
91. Yang, W.D.; Gao, X.C.; Zhang, Y.M. Research on Back Analysis of Parameters for Excavation of the Underground Cavern Group of A Large-scale Hydro-power Station by Using Orthogonal Optimization. *Appl. Mech. Mater.* **2012**, *170*, 3356–3360. [\[CrossRef\]](#)
92. Zhuang, D.; Ma, K.; Tang, C.; Liang, Z.; Wang, K.; Wang, Z. Mechanical parameter inversion in tunnel engineering using support vector regression optimized by multi-strategy artificial fish swarm algorithm. *Tunn. Undergr. Space Technol.* **2018**, *83*, 425–436. [\[CrossRef\]](#)

93. Liu, B.; Ren, Y.; Liu, H.; Xu, H.; Wang, Z.; Cohn, A.G.; Jiang, P. GPRInvNet: Deep Learning-Based Ground-Penetrating Radar Data Inversion for Tunnel Linings. *IEEE Trans. Geosci. Remote Sens.* **2021**, *59*, 8305–8325. [[CrossRef](#)]
94. Zhang, K.; Lyu, H.-M.; Shen, S.-L.; Zhou, A.; Yin, Z.-Y. Evolutionary hybrid neural network approach to predict shield tunneling-induced ground settlements. *Tunn. Undergr. Space Technol.* **2020**, *106*, 103594. [[CrossRef](#)]
95. Di, S.; Zhang, Y.; Zhou, H.; Liu, J. Research on dynamic inverse method of surrounding rock mechanical parameters of large underground caverns in excavation. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *711*, 012071. [[CrossRef](#)]
96. Shi, Q.; Song, P.; Tan, Z.; Qiu, Q.; Liu, H.; Peng, B.; Kerzhaev, A.P.; Yu, G.; Chen, Z.; Kovalenko, M.D.; et al. GA-BP Neural Network Prediction Model for Tunneling Speed of Shield Machine with Composite Formation Dual Mode (TBM-EPB). In Proceedings of the 2022 International Conference on Computational Infrastructure and Urban Planning, Nanchang, China, 18 June 2022; pp. 1–4. [[CrossRef](#)]
97. Zhang, J.; Guo, X.; Ke, X. A multi-information intelligent identification method of rock mechanics parameter and application in underground engineering. In Proceedings of the 2009 2nd IEEE International Conference on Computer Science and Information Technology, Beijing, China, 8–11 August 2009; pp. 90–94.
98. Wang, G.F.; Zhao, W.; Guan, Y.P.; Li, S.G. Application of GA-BP to Back Analysis of Rock's Parameters. *Adv. Mater. Res.* **2013**, *671*, 175–179. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.