

Article

A Simulation Optimization Decision Framework for Composite Tunnel Support Design Using FEM, Particle Swarm Optimization, and Multi-Criteria Decision-Making

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Abstract

Tunnel support design in rock masses requires controlling deformation while maintaining structural safety, constructability, and material efficiency under variable geotechnical conditions. This study presents a Simulation–Optimization–Decision Framework (SODF) for preliminary and comparative tunnel support design. The framework integrates FEM-based numerical modeling in PLAXIS 2D, Particle Swarm Optimization (PSO), and a Multi-Criteria Decision-Making (MCDM) model to evaluate composite support systems composed of shotcrete and steel sets. Deformation at the tunnel crown was used as the primary optimization response, while structural feasibility was verified through axial force–bending moment and axial force–shear force interaction envelopes with a minimum safety factor of $FS \geq 1.5$. Two case studies were analyzed using GSI values of 40, 45, 50, and 55. Case 1 considered $E_{rm} = 500,000 \text{ kN/m}^2$, with an additional condition of $250,000 \text{ kN/m}^2$ at $GSI = 40$, whereas Case 2 considered $E_{rm} = 545,000 \text{ kN/m}^2$, with an additional condition of $300,000 \text{ kN/m}^2$ at $GSI = 45$. Three PSO configurations were evaluated to compare the search intensity, the diversity of feasible solutions, and the computational effort. The results showed that feasible configurations were mainly concentrated between 10 and 14 cm of shotcrete thickness in Case 1 and between 10 and 12 cm in Case 2, with frequent selection of 254 mm and 305 mm steel sets. The MCDM analysis indicated that the lowest-deformation alternative does not necessarily coincide with the most suitable engineering alternative when material cost, shotcrete applicability, steel-set maneuverability, and local availability are considered.

Keywords: tunnel support systems; particle swarm optimization; multi-criteria decision-making; PLAXIS 2D



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1. Introduction

The design of tunnel support systems in rock masses is a critical task in underground engineering, where structural stability, safety, and cost efficiency must be ensured simultaneously. Modern tunnel design relies on understanding the mechanical response of

the surrounding rock mass to excavation, particularly in terms of deformation and stress redistribution. In this context, numerical modeling techniques based on the Finite Element Method (FEM) have become essential tools for evaluating tunnel behavior under varying geotechnical conditions [1–7], and the tendency is to automate the workflow to optimize the time of analysis and design [5,7–11].

Among the available computational tools, PLAXIS 2D has been widely adopted for simulating geotechnical problems due to its ability to represent complex material behavior and staged construction processes [4]. However, despite its capabilities, the practical use of FEM-based modeling in tunnel design often remains limited to isolated simulations or manually defined scenarios. This restricts the systematic exploration of design alternatives, making the process time-consuming and reliant on expert judgment.

In parallel, optimization techniques have been introduced to improve engineering design processes. Particle Swarm Optimization (PSO), originally proposed by Eberhart and Kennedy [12], has demonstrated strong performance in exploring complex and high-dimensional solution spaces. In geotechnical engineering, PSO has been applied to calibration and parameter estimation problems, but its integration with numerical simulation tools for automated design exploration remains limited. Recent studies highlight the growing relevance of PSO in engineering applications, particularly for problems requiring efficient search strategies under uncertainty [13–17].

Another important aspect of engineering design is decision-making. Even when multiple feasible solutions are available, selecting the most appropriate alternative requires balancing structural performance with economic, operational, and logistical considerations. Multi-Criteria Decision-Making (MCDM) methods, such as the Analytic Hierarchy Process (AHP) proposed by Saaty [18], provide a structured approach to ranking alternatives based on weighted criteria. However, in many existing studies, optimization and decision-making are treated as separate stages, without a unified framework that connects both processes.

Despite advances in numerical modeling, optimization, and decision analysis, there remains a lack of integrated methodologies that enable systematic, reproducible, and scalable evaluation of tunnel support configurations. Most existing approaches focus on either parametric studies, specific case calibrations, or isolated optimization tasks, without fully integrating simulation, optimization, and decision-making into a single workflow.

To address this gap, this work proposes a Simulation–Optimization–Decision Framework (SODF) for the preliminary and comparative design of composite tunnel support systems in rock masses. The framework combines FEM-based numerical modeling using PLAXIS 2D, Particle Swarm Optimization for the systematic exploration of support configurations, structural feasibility screening through N – M and N – Q capacity envelopes, and a Multi-Criteria Decision-Making model for ranking feasible alternatives according to structural, economic, operational, and logistical criteria. The workflow is implemented in Python through the PLAXIS API, enabling automated model execution, data extraction, feasibility assessment, and decision-oriented evaluation.

The SODF explores composite tunnel support configurations defined by shotcrete thickness and steel-set selection, using tunnel crown deformation as the primary structural response. Its performance is evaluated through two case studies representing different geotechnical scenarios characterized by variations in rock-mass quality and deformability. Specifically, the analysis examines how GSI, E_{rm} , shotcrete thickness, and steel-set selection influence tunnel crown deformation, the distribution of feasible support configurations, and the final decision-oriented rankings. This evaluation provides a basis for assessing the capacity of the SODF to support preliminary and comparative tunnel support design under controlled geotechnical conditions. The novelty of the SODF lies not in the individual use of FEM, PSO, structural verification, or MCDM, but in their sequential integration for

composite shotcrete–steel support design. The framework preserves a direct and traceable connection among geotechnical conditions, numerical response, automated design exploration, structural feasibility screening, and final engineering selection.

The main contributions of this work can be summarized as follows:

- A Simulation–Optimization–Decision Framework (SODF) that integrates FEM-based numerical modeling, PSO-based design exploration, structural feasibility screening, and MCDM-based ranking into a single workflow for composite tunnel support selection.
- An automated computational implementation using Python and the PLAXIS 2D API, which enables reproducible model generation, staged numerical simulation, support configuration, data extraction, and post-processing.
- A systematic exploration of composite support configurations defined by shotcrete thickness and steel-set selection under varying geotechnical conditions, considering the influence of GSI and E_{rm} on tunnel crown deformation and feasible support alternatives.
- A structural feasibility screening procedure that evaluates candidate support configurations using interaction envelopes with a minimum safety factor of $FS \geq 1.5$, ensuring that the optimization process retains only structurally admissible alternatives.
- A decision-oriented evaluation stage that combines tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability, allowing the final support recommendation to reflect both structural performance and practical implementation criteria.

The remainder of this paper is organized as follows. Section 2 reviews previous work on numerical modeling, optimization, and Multi-Criteria Decision-Making for tunnel support design. Section 3 describes the proposed SODF, including project characterization, FEM-based numerical modeling, PSO-based optimization, structural feasibility screening, results analysis, and MCDM-based support selection. Section 4 presents the experimental setup, including the computational environment, geotechnical scenarios, design variables, PSO configurations, objective function, and comparative evaluation strategy. Section 5 reports and discusses the main results, focusing on PSO behavior, feasible support configurations, deformation-based selection, MCDM-based selection, and comparison with related approaches. Section 6 summarizes the main limitations of the study. Finally, Section 7 presents the conclusions and future research directions.

2. Related Work

The design and evaluation of tunnel support systems have been widely studied in geotechnical engineering, with contributions spanning numerical modeling, optimization techniques, and decision-making approaches. However, these components are often developed separately, which limits their effectiveness when addressing complex design scenarios involving geotechnical variability, multiple support alternatives, and practical implementation constraints.

2.1. Numerical Modeling in Tunnel Design

Numerical modeling based on the Finite Element Method has become a standard approach for analyzing tunnel behavior under different geotechnical and construction conditions [1–7]. These methods allow engineers to represent excavation-induced stress redistribution, deformation patterns, plastic zones, and the interaction between the surrounding rock mass and the installed support system. Analytical and numerical studies have therefore provided important information for assessing tunnel stability, particularly in weak or highly deformable rock masses [19,20].

In practical applications, programs such as PLAXIS 2D enable staged excavation, nonlinear constitutive modeling, and the representation of support components such as shotcrete linings and steel sets [21]. Earlier studies demonstrated the usefulness of two-dimensional numerical approaches for evaluating support performance under weak-rock conditions [22]. More recent research has emphasized that reliable support design should combine detailed rock-mass characterization, interpretation of ground behavior, and numerical assessment rather than relying exclusively on empirical classification systems.

For example, Terron-Almenara et al. [23] proposed a hybrid methodology for support design in poor ground conditions that combines geological and geotechnical characterization with analytical and numerical evaluation. Subsequent applications to hard, layered rock masses showed that discontinuities, anisotropy, overbreak, and delamination can strongly influence ground response and may not be adequately represented by conventional classification-based support recommendations [24]. Similar findings were reported for tunnels excavated under low-overburden conditions, where numerical analyses were used together with rock-mass classification systems to evaluate ground stability and support requirements [25]. Recent work on weak rock masses has also shown that estimates of plastic deformation and support loading remain sensitive to the assumptions adopted in analytical and numerical models [26].

These studies demonstrate the value of numerical modeling for examining site-specific ground–support interaction. However, most applications still evaluate a predefined set of cases or support alternatives. This approach can limit the systematic exploration of broader design spaces when multiple geotechnical and structural variables must be considered.

Scripting interfaces provide a means of extending conventional numerical studies by automating model generation, repeated calculations, parameter variation, and result extraction [8,10,11]. Previous implementations using the PLAXIS scripting environment have shown that automated workflows can support structured numerical campaigns and reduce the manual effort associated with repeated simulations [27]. Nevertheless, the integration of automated FEM simulations with optimization and decision-making procedures for the systematic evaluation of composite shotcrete–steel set support configurations remains limited.

2.2. Optimization Approaches in Geotechnical Engineering

Optimization techniques have been increasingly adopted to improve engineering design processes by enabling the exploration of multiple design alternatives [28]. Among these methods, Particle Swarm Optimization (PSO) has gained attention due to its simplicity and effectiveness in handling complex nonlinear problems [12–17].

PSO has been applied in geotechnical engineering for tasks such as parameter calibration, structural optimization, and design improvement. Surveys on PSO highlight its capability to explore high-dimensional solution spaces and converge toward optimal or near-optimal solutions under uncertainty [13]. In the context of underground engineering, optimization approaches have also been used for the shape and reinforcement design of tunnels, demonstrating the potential of metaheuristic methods in structural applications [16,29].

Recent studies have extended conventional numerical optimization by combining numerical simulations with surrogate models, machine learning techniques, and population-based optimization algorithms. Zhang et al. [30] integrated finite element simulations, an RBF surrogate model, and PSO to optimize tunnel support parameters while reducing the number of direct numerical evaluations. Jianting et al. [31] combined FLAC3D simulations with XGBoost models optimized using PSO and other swarm-intelligence algorithms to predict the mechanical behavior of steel-fiber shotcrete linings. Similarly, Niu et al. developed

an automated workflow that integrates FLAC3D, Python, and NSGA-II to optimize tunnel excavation parameters under fractured rock conditions [32]. These studies demonstrate the growing use of surrogate modeling, machine learning, and intelligent optimization in tunnel engineering. However, their applications generally focus on a specific response, material, excavation parameter, or geological condition, and do not necessarily connect the generated alternatives to a subsequent multi-criteria engineering selection stage.

Song et al. [33] reviewed traditional and intelligent inversion methods in tunnel and underground engineering for identifying unknown quantities such as initial ground stress, support loads, and tunnel-related parameters. Their review shows that coupling numerical simulations with intelligent optimization algorithms has become an important methodological paradigm for solving complex underground-engineering problems, while also identifying the high computational cost of repeated simulation-based evaluations as a major challenge. Although inversion analysis estimates unknown parameters from observed responses, the present SODF addresses a forward design problem in which predefined support configurations are evaluated through FEM simulations and systematically explored using PSO. The two approaches, therefore, share the integration of numerical modeling and intelligent search but differ in their computational objective. In the proposed framework, automation via the PLAXIS 2D API reduces manual intervention, improves traceability, and enables repeated evaluation of support alternatives; however, the computational cost of FEM calculations remains a significant limitation.

Despite these advances, recent approaches commonly concentrate on a particular optimization objective, support component, material property, excavation parameter, or geological setting. Fewer studies integrate automated numerical simulation, systematic exploration of composite support configurations, structural feasibility screening, and multi-criteria ranking into a single workflow.

2.3. Multi-Criteria Decision-Making in Engineering Design

Engineering design problems often involve multiple competing criteria, including structural performance, cost, constructability, operational constraints, and material availability. Multi-Criteria Decision-Making (MCDM) methods provide a structured framework for comparing and ranking feasible alternatives when no single criterion is sufficient to support the final engineering decision.

Recent studies in tunnel and underground engineering have increasingly recognized that support selection cannot be based exclusively on a single mechanical response. Cost, robustness, construction complexity, uncertainty, and operational feasibility may lead to a preferred alternative that differs from the solution obtained through deformation minimization alone. Accordingly, optimization and decision-support methods have been combined to compare alternatives under multiple technical engineering priorities [34,35].

Among the available MCDM methods, the Analytic Hierarchy Process (AHP), introduced by Saaty [18], provides a hierarchical structure for organizing decision criteria and assessing their relative importance. A formal AHP implementation typically derives criterion weights via pairwise comparisons and assesses the consistency of the resulting judgments. However, engineering applications may also use AHP principles as a conceptual reference for structuring criteria and defining their relative priorities when the final weights are established through professional judgment.

In the present study, MCDM is applied after the optimization and structural feasibility screening stages. This separation allows the PSO process to identify low-deformation and structurally admissible configurations, while the decision stage incorporates material cost, shotcrete applicability, steel-set maneuverability, and local availability. The weighting scheme was informed by the hierarchical and relative-priority principles of AHP, whereas

the final baseline weights were assigned through engineering judgment based on the professional experience of the engineer involved in the tunnel support design.

2.4. Research Gap

Recent studies have advanced different components of tunnel support design. Terron-Almenara et al. [24] developed a hybrid methodology combining detailed rock-mass characterization, engineering assessment, and numerical modeling to improve support design under complex ground conditions. Wang et al. [36] proposed an analytical procedure for selecting tunnel support parameters based on surrounding-rock failure modes and convergence–confinement relationships. From an optimization perspective, Zhang et al. [30] integrated finite element simulations, a radial basis function surrogate model, and PSO to improve support parameters while reducing the number of direct numerical evaluations. Jianting et al. [31] combined FLAC3D simulations, machine-learning prediction, and swarm-intelligence algorithms to analyze the mechanical response of steel-fiber shotcrete linings. Niu et al. [32] developed an automated numerical workflow integrating FLAC3D, Python, and NSGA-II to optimize tunnel excavation parameters.

The reviewed literature can be organized into two complementary streams. The first includes analytical and numerical tunnel-design approaches that provide detailed assessments of ground and support behavior but generally examine predefined configurations or focus on specific design conditions. The second includes metaheuristic, surrogate-assisted, and multi-objective approaches that broaden the exploration of design alternatives, although optimization and final engineering selection are often treated as separate stages.

Despite these advances, limited attention has been given to workflows that maintain a direct connection among geotechnical characterization, numerical response, automated exploration of composite support configurations, structural feasibility verification, and multi-criteria engineering selection. This gap is particularly relevant when several combinations of shotcrete thickness and steel-set profiles satisfy the structural requirements but differ in deformation response, material demand, constructability, and logistical feasibility.

The novelty of the proposed SODF does not rely on the individual use of FEM, PSO, structural verification, or MCDM, but on their sequential integration for composite shotcrete–steel support design. Automated FEM simulations generate the structural response, PSO explores candidate configurations, N – M and N – Q capacity envelopes screen structural feasibility, and a weighted MCDM procedure ranks the feasible alternatives using structural, economic, operational, and logistical criteria. This integration preserves traceability from the geotechnical scenario and numerical response to the final engineering selection within a preliminary and comparative design framework.

3. Methodology

This section presents the proposed Simulation–Optimization–Decision Framework (SODF) for the design and evaluation of composite tunnel support systems. The methodology integrates project characterization, numerical modeling, optimization, results analysis, and Multi-Criteria Decision-Making into a unified workflow. The purpose of this structure is to support a systematic and reproducible exploration of support configurations, from defining the geotechnical context to selecting feasible, practically applicable alternatives.

3.1. Framework Overview

Figure 1 presents the general workflow of the proposed methodology. The SODF comprises five sequential phases that structure the analysis, from the initial definition of the tunnel project to the final selection of the support configuration.

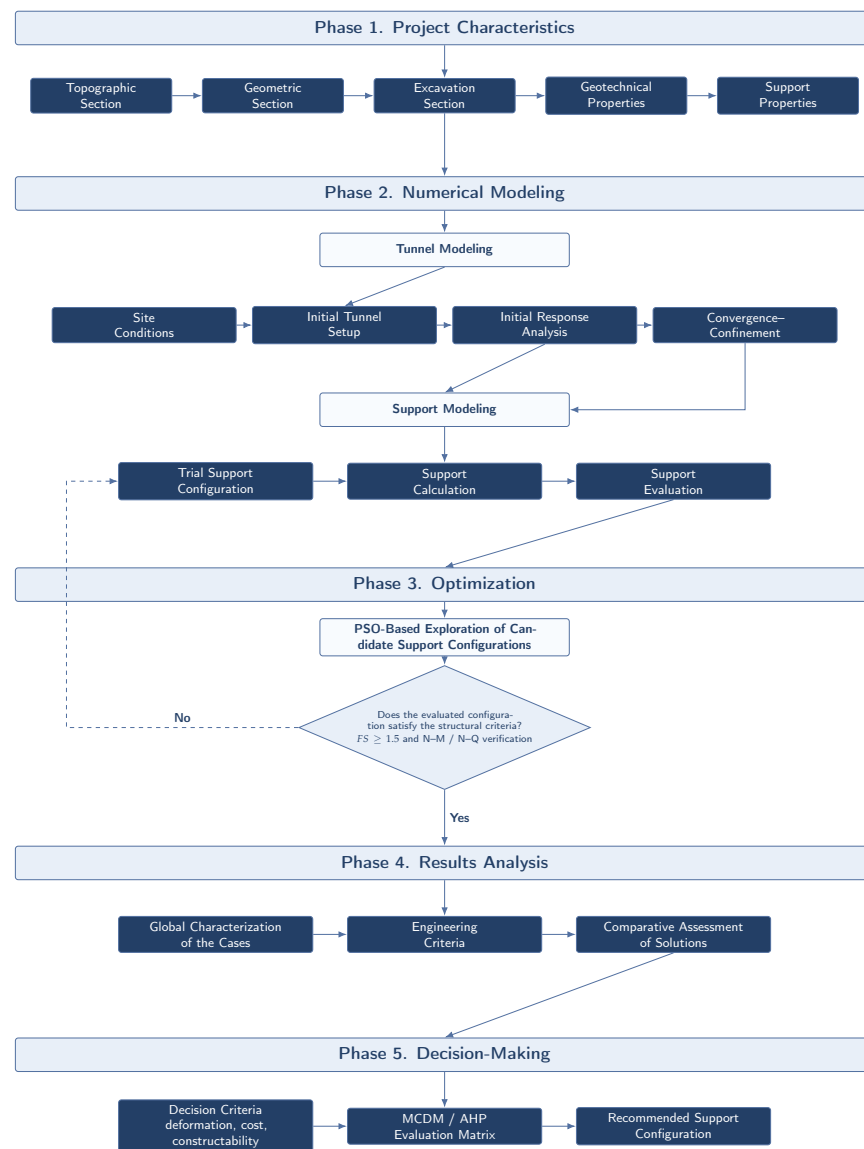


Figure 1. General workflow of the proposed Simulation–Optimization–Decision Framework (SODF).

- **Phase 1: Project Characteristics.** This phase defines the main characteristics of the project and establishes the initial conditions required for the analysis. It includes the geometric, geotechnical, and structural information needed to model the tunnel excavation problem and delimit the design space.
- **Phase 2: Numerical Modeling.** This phase represents the tunnel response using an FEM-based model in PLAXIS 2D. The model considers the geotechnical conditions and the staged construction process defined in the previous phase, with particular attention to deformation at the tunnel crown.
- **Phase 3: Optimization.** This phase explores candidate support configurations using Particle Swarm Optimization (PSO). Each alternative is defined by a shotcrete thickness and an associated steel set. The optimization is guided by tunnel crown deformation, while structural feasibility is evaluated using predefined engineering criteria.
- **Phase 4: Results Analysis.** This phase organizes and analyzes the results obtained from the optimization process. Feasible configurations are grouped and compared based on their deformation response, support characteristics, geotechnical scenario, and PSO configuration, thereby enabling the selection of a representative set of alternatives.
- **Phase 5: Decision-Making.** This phase ranks the feasible alternatives using a Multi-Criteria Decision-Making (MCDM) model. The decision process incorporates structural,

economic, operational, and logistical criteria, aiming to identify a balanced support configuration rather than simply selecting the alternative with the lowest deformation.

The methods integrated into the SODF were selected according to their complementary roles within the tunnel support design problem. FEM modeling in PLAXIS 2D was adopted because it enables representation of rock-mass behavior, staged excavation, support activation, and ground–support interaction, and its Remote Scripting interface supports repeated model execution and automated result extraction through Python. PSO was selected as a derivative-free search method suitable for a simulation-based design problem in which shotcrete thickness is directly explored and, during candidate evaluation, combined with discrete steel-set profiles from the predefined catalog. The N – M and N – Q interaction envelopes were incorporated to verify structural admissibility under combined internal forces and the adopted safety criterion. MCDM was applied after optimization because the final engineering selection involves structural, economic, operational, and logistical criteria that are not represented by tunnel crown deformation alone. AHP principles were used only as a conceptual basis for organizing the decision criteria and their relative priorities. Accordingly, the selected methods perform complementary simulation, exploration, verification, and decision-support functions rather than being considered universally superior to other available approaches.

Within the proposed SODF, FEM provides the numerical response required to evaluate each candidate support configuration, PSO explores the support-parameter space, and MCDM ranks the feasible alternatives. Although the present implementation uses FEM in PLAXIS 2D, the general workflow is not restricted to a single numerical solution method. PLAXIS 2D was selected because it supports staged excavation, support activation, and automated execution and result extraction through its Remote Scripting API.

The following subsections describe the main technical components of the SODF: project characterization, numerical modeling, PSO-based optimization, results analysis and feasible solution screening, Multi-Criteria Decision-Making, and workflow integration.

3.2. Project Characterization

The first stage of the SODF defines the geometric, geotechnical, and structural conditions required to construct the numerical model and delimit the design space. The case study concerns a four-lane road tunnel excavated in a rock mass. The adopted tunnel cross-section has an approximate area of 197 m², a free height of 11.50 m, and a width of 21.10 m. Since the section is not circular, an equivalent diameter was computed to preserve the cross-sectional area and provide a reference value for analytical and numerical modeling:

$$D_{eq} = \sqrt{\frac{4A}{\pi}} \quad (1)$$

where A is the tunnel cross-sectional area. For $A = 197$ m², the equivalent diameter is approximately $D_{eq} \approx 15.85$ m.

The geotechnical characterization considers a homogeneous rock-mass unit for each case study. The rock-mass behavior is represented using the Hoek–Brown failure criterion [37], with parameters including unit weight, rock-mass deformation modulus E_{rm} , Poisson's ratio, uniaxial compressive strength, the intact rock parameter m_i , Geological Strength Index (GSI), and disturbance factor D . The experimental design varies E_{rm} and GSI to represent different levels of rock-mass deformability and quality within the evaluated range.

The composite support system comprises two main components: shotcrete and steel sets [38]. Shotcrete is characterized by its mechanical properties and variable thickness, whereas steel sets are selected from a discrete catalog of IR profiles. To incorporate both

components into the numerical model, the support system is represented through equivalent structural properties, including axial stiffness EA , flexural stiffness EI , Poisson's ratio ν , and unit weight w . These equivalent properties allow the composite behavior of shotcrete and steel sets to be evaluated consistently across the optimization process.

The equivalent-section formulation assumes full composite action between the shotcrete and steel sets. Accordingly, both components are considered to deform compatibly and to transfer internal forces without relative sliding, interface separation, debonding, or delamination. No explicit contact or interface element was introduced between the two support components.

The geometric definition of the model was established from the topographic section, the tunnel cross-section, and the excavation sequence adopted for the staged numerical analysis, as shown in Figure 2.

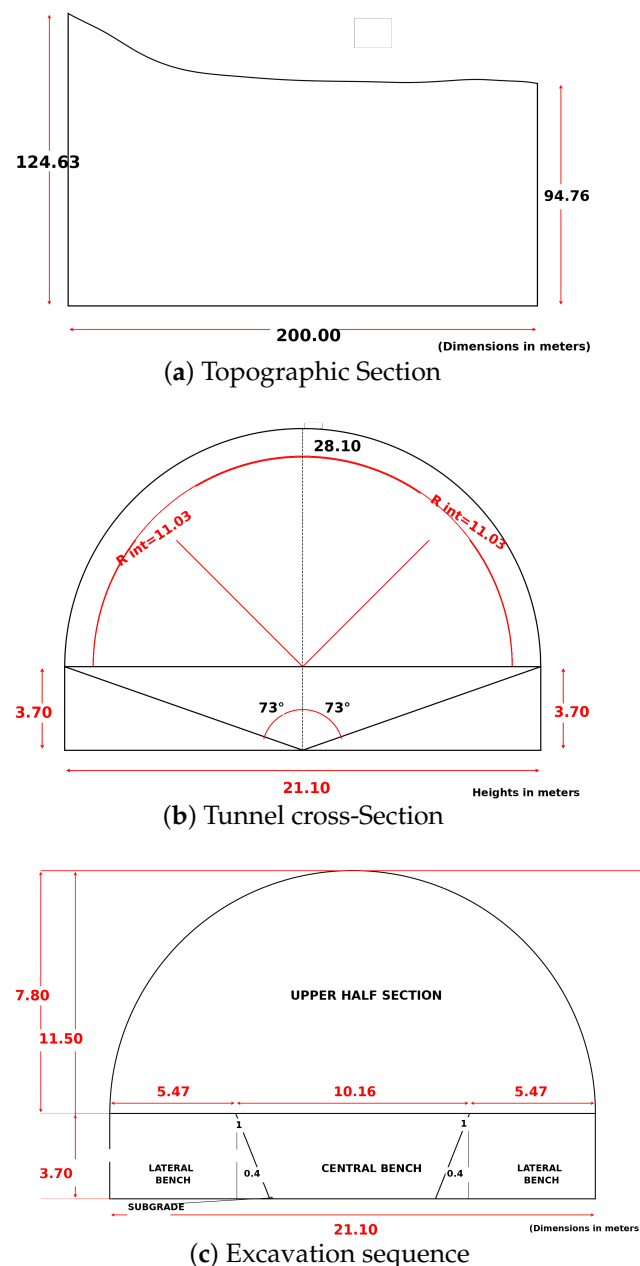


Figure 2. Geometric characteristics used to define the tunnel model: (a) topographic section, (b) tunnel cross-section, and (c) excavation sequence adopted for the staged numerical analysis.

3.3. Numerical Modeling

Numerical simulations were performed using the Finite Element Method (FEM) in PLAXIS 2D. Each stage of the tunnel was modeled as an isotropic elastic domain in static equilibrium under plane strain conditions, considering a homogeneous geotechnical unit and the Hoek–Brown failure criterion to represent the mechanical response of the surrounding rock mass.

Assuming a 2D plane strain state along the longitudinal axis of the tunnel (z -axis, where $\epsilon_{zz} = \gamma_{xz} = \gamma_{yz} = 0$), the static equilibrium in the (x, y) analysis plane is governed by:

$$\begin{aligned}\frac{\partial \sigma_{xx}}{\partial x} + \frac{\partial \tau_{xy}}{\partial y} + b_x &= 0 \\ \frac{\partial \tau_{xy}}{\partial x} + \frac{\partial \sigma_{yy}}{\partial y} + b_y &= 0\end{aligned}\quad (2)$$

where σ_{xx} and σ_{yy} are the normal stresses, τ_{xy} is the in-plane shear stress, and b_i represents the body forces ($b_x = 0$; $b_y = -\gamma_{rock}$).

The yield function $F(\sigma) = 0$ for the rock mass is defined by the Generalized Hoek–Brown criterion [39] in terms of major (σ_1) and minor (σ_3) effective principal stresses:

$$\sigma_1 = \sigma_3 + \sigma_{ci} \left(m_b \frac{\sigma_3}{\sigma_{ci}} + s \right)^a \quad (3)$$

where σ_{ci} is the uniaxial compressive strength of the intact rock, and the rock-mass parameters (m_b, s, a) are derived from the Geological Strength Index (GSI) and the disturbance factor (D):

$$m_b = m_i \exp \left(\frac{\text{GSI} - 100}{28 - 14D} \right) \quad (4)$$

$$s = \exp \left(\frac{\text{GSI} - 100}{9 - 3D} \right) \quad (5)$$

$$a = \frac{1}{2} + \frac{1}{6} \left[\exp \left(-\frac{\text{GSI}}{15} \right) - \exp \left(-\frac{20}{3} \right) \right] \quad (6)$$

The FEM domain boundaries (Γ) are formally constrained as follows: Bottom Boundary (Γ_{inf}): Full displacement restriction ($u_x = 0, u_y = 0$). Lateral Boundaries (Γ_{lat}): Normal roller constraints ($u_x = 0, \tau_{xy} = 0$).

To simulate the 3D arching effect at the tunnel face within the 2D plane strain model, the Longitudinal Displacement Profile (LDP) proposed by Vlachopoulos and Diederichs (2009) is implemented Vlachopoulos and Diederichs [40].

The corresponding numerical model in PLAXIS was constructed from the geometric and geotechnical information defined in the project characterization stage. The modeling process included assigning material properties, defining boundary conditions, generating the finite element mesh, and configuring staged excavation phases. The mesh was generated using 15-node triangular elements, with local refinement around the tunnel contour to improve the representation of stress gradients, plastic zones, and deformation near the excavation boundary. A control node was selected at the tunnel crown to monitor vertical deformation, which was used as the main performance indicator. Figure 3 summarizes the numerical model setup used for the FEM-based simulations.

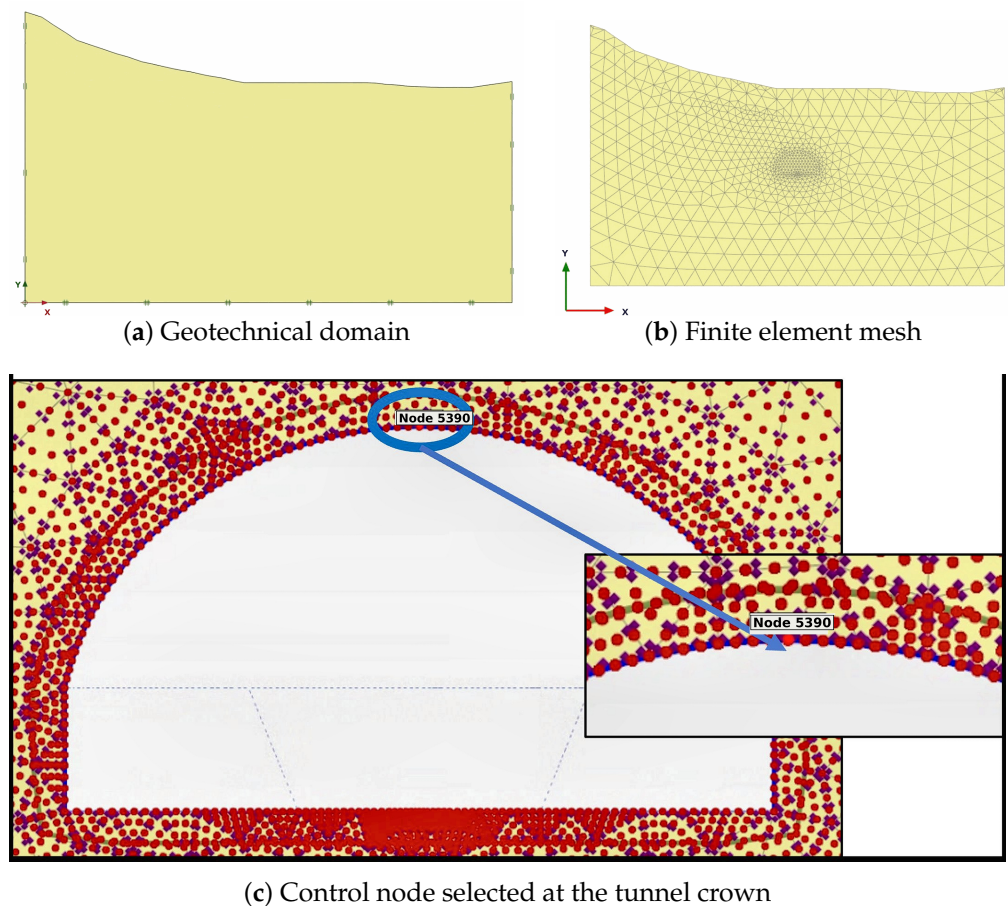
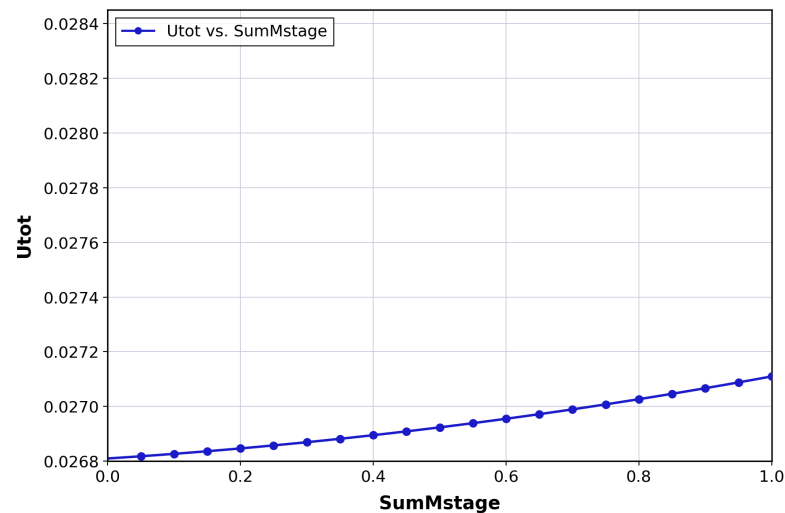


Figure 3. Numerical model setup in PLAXIS 2D: (a) geotechnical domain and assigned material unit, (b) finite element mesh with local refinement around the tunnel contour, and (c) control node selected at the tunnel crown for deformation monitoring.

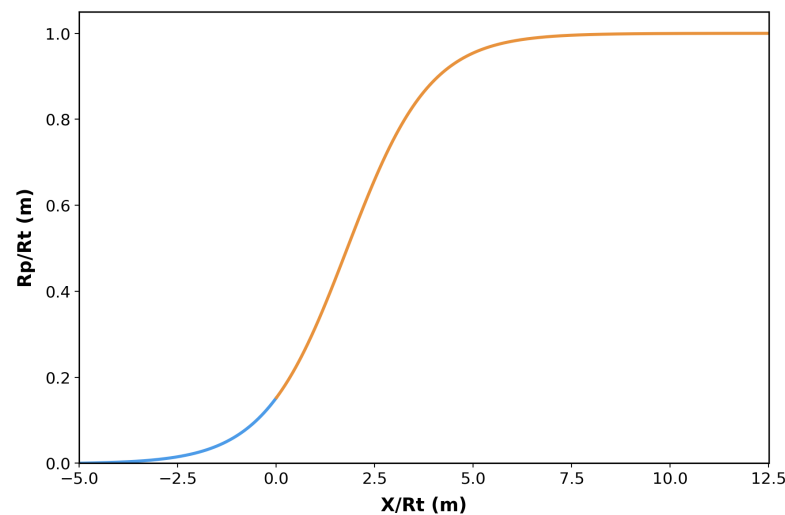
The construction process was first simulated without support to obtain the free deformation response of the rock mass during excavation. This response was then used within a convergence–confinement-based procedure to estimate the target displacement and determine the excavation stage at which the support system should be activated [41]. This step allowed the installation of the support to be linked to the deformation response of the tunnel rather than being assigned arbitrarily. The convergence–confinement-based procedure used to define the support installation stage is summarized in Figure 4.

After defining the support installation stage, the supported model was executed by progressively activating the composite support system. For each evaluated configuration, the corresponding structural properties were computed and assigned to the model based on the corresponding shotcrete thickness and steel-set profile.

The outputs extracted from PLAXIS 2D included the tunnel crown deformation and the internal forces developed in the support system, namely axial force, bending moment, and shear force. These outputs were used to compare unsupported and supported responses and provided the mechanical inputs required for the subsequent optimization and feasibility screening stages.



(a) Excavation advancement vs. crown displacement



(b) Vlachopoulos–Diederichs fitting curve

Figure 4. Convergence–confinement-based procedure used to define the support installation stage: (a) excavation advancement versus crown displacement curve, and (b) Vlachopoulos–Diederichs fitting curve [40] used to estimate the target displacement before support activation.

3.4. Optimization Using Particle Swarm Optimization

Each evaluated candidate represents a composite support configuration composed of shotcrete thickness and a steel-set profile. The PSO search coordinate directly represents shotcrete thickness, whereas the steel-set profile is incorporated from the predefined catalog during candidate evaluation.

The PSO particle was represented as a one-dimensional continuous vector, $\mathbf{x}_i = [t_i]$, where t_i denotes the shotcrete thickness bounded between 10 and 50 cm. Before each numerical evaluation, the thickness value was rounded to the precision used by the computational implementation. A steel-set profile was then selected from the catalog and combined with the particle-defined shotcrete thickness to form the composite support configuration. The corresponding equivalent properties EA , EI , ν , and w were calculated and assigned to the PLAXIS 2D model. Therefore, the PSO search coordinate directly represented shotcrete thickness, whereas steel-set selection was incorporated during the evaluation of each candidate configuration.

The shotcrete thickness was treated as a continuous variable within a range of 10–50 cm, whereas the steel set was selected from a database of 40 IR profiles with pre-

financed geometric and mechanical properties. For each candidate configuration, equivalent structural properties of the composite support system were computed, including axial stiffness, flexural stiffness, Poisson's ratio, and unit weight. The optimization setup is summarized in Table 1.

Table 1. Summary of the PSO-based optimization setup.

Element	Definition
Objective	Minimize tunnel crown deformation
Evaluated support components	Shotcrete thickness and steel-set selection
PSO-encoded	Shotcrete thickness
Shotcrete thickness range	10–50 cm
Steel-set database	40 IR steel profiles
Equivalent properties	EA , EI , ν , and w
Feasibility criteria	Demand points within N – M and N – Q envelopes
Safety factor	$FS \geq 1.5$
PSO configurations	10 particles and 20/40/60 iterations
PSO coefficients	$w = 0.9$, $c_1 = 0.5$, $c_2 = 0.3$
Outputs	Tunnel crown deformation, support properties, feasibility, CSV records

Preliminary exploratory tests were conducted using different combinations of inertia and acceleration coefficients to observe the general behavior of the PSO algorithm. This stage was used to define a consistent parameter configuration for the case-study experiments rather than to perform formal parameter tuning or sensitivity analysis. Accordingly, the coefficients $w = 0.9$, $c_1 = 0.5$, and $c_2 = 0.3$ were fixed across PSO200, PSO400, and PSO600. A systematic comparison of alternative coefficient settings and their influence on convergence, solution diversity, and computational cost remains necessary in future work.

The objective function was defined to minimize deformation at the tunnel crown, which was adopted as the main performance indicator. Structural feasibility was verified by checking whether the induced axial force, bending moment, and shear force remained within the corresponding N – M and N – Q capacity envelopes. A safety factor of $FS \geq 1.5$ was adopted as the acceptance criterion.

Constraint violations were handled through an exterior penalty within the PSO fitness function. For each candidate configuration, the steel-set and shotcrete demand points were checked against the corresponding N – M and N – Q capacity envelopes. A configuration was considered feasible only when all demand points remained within the four envelopes. If any demand point fell outside of an envelope, the candidate was assigned a sufficiently large penalty value. Feasible configurations were evaluated based on tunnel crown deformation, whereas penalized configurations were rendered unfavorable during minimization and therefore excluded from consideration as admissible design alternatives.

The PSO algorithm was implemented in Python and integrated within the numerical simulation workflow. The selected PSO configurations were used to evaluate the trade-off between search intensity, solution diversity, and computational cost.

During each iteration, the algorithm generated a shotcrete thickness value and selected a steel set from the database. The equivalent support properties were calculated, the numerical model was executed, and the structural feasibility criteria were evaluated. All evaluated configurations, including feasible and non-feasible cases, were recorded and exported as CSV files to support traceability and subsequent comparative analysis.

3.5. Results Analysis and Feasible Solution Screening

After the PSO-based optimization process, all evaluated support configurations were organized into structured datasets for post-processing. Each record included the PSO

configuration, geotechnical scenario, shotcrete thickness, selected steel set, tunnel crown deformation, structural feasibility status, and computational information associated with the simulation.

Only configurations satisfying the predefined structural requirements were retained as feasible alternatives. In particular, the induced axial force, bending moment, and shear force were checked against the corresponding N – M and N – Q interaction envelopes, using a minimum safety factor of $FS \geq 1.5$. The feasible configurations were then grouped according to the PSO configuration, geotechnical condition, shotcrete thickness, and steel-set profile. This organization enabled a comparison of results from PSO200, PSO400, and PSO600 in terms of solution coverage, dispersion, and the ability to identify low-deformation support alternatives. The post-processing structure used in this phase is summarized in Table 2.

Table 2. Post-processing structure for feasible support configurations.

Element	Evaluation Role
PSO configuration	Compare PSO200, PSO400, and PSO600 solution sets
Geotechnical scenario	Relate support performance to rock-mass conditions
Tunnel crown deformation	Identify low-deformation support alternatives
Shotcrete thickness	Assess material demand and support efficiency
Steel-set profile	Compare structural capacity and implementation implications
Structural feasibility	Verify N – M and N – Q envelopes with $FS \geq 1.5$
MCDM input variables	Prepare deformation, cost, applicability, maneuverability, and availability indicators
Decision support role	Provide the filtered alternative set for multi-criteria ranking

This stage provides the input required for the subsequent Multi-Criteria Decision-Making process. To align with the final decision phase, the feasible alternatives were evaluated against five criteria: tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability. Thus, the results analysis phase does not directly select the final solution; rather, it produces a filtered and technically consistent set of alternatives for decision-making.

3.6. Multi-Criteria Decision-Making

Once the feasible solution set was obtained, an MCDM model was applied to rank the support alternatives. This stage complements the deformation-based optimization by incorporating structural, economic, operational, and logistical criteria into the final selection process.

Before applying the MCDM model, the steel-set database was restricted to the P20–P80 range to exclude extreme profiles and focus the comparison on structurally representative and economically attractive alternatives. This filtering step reduced the influence of overdesigned or underdesigned steel sets while preserving technically viable configurations.

Each feasible alternative was evaluated using five criteria: tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability. The weighting scheme was informed by the hierarchical structure and relative-priority principles of the Analytic Hierarchy Process (AHP). However, the final baseline weights were assigned through engineering judgment for the present case studies rather than being derived from a formal pairwise-comparison matrix, an expert survey, or a multi-expert con-

sensus process. A formal AHP consistency-ratio calculation was therefore not performed. Table 3 summarizes the criteria and their corresponding baseline weights.

Table 3. Decision criteria and weights used in the MCDM model.

Criterion	Evaluation Purpose	Weight
Tunnel crown deformation	Measures the structural response of the tunnel after support installation.	35%
Material cost	Estimates the economic impact of shotcrete and steel set use.	25%
Shotcrete applicability	Evaluates the operational effort associated with shotcrete application.	15%
Steel-set maneuverability	Assesses the installation complexity of the selected steel set.	15%
Local material availability	Considers the logistical feasibility of obtaining the required materials.	10%

The baseline weights were established as an engineering-priority scheme for the present case studies. Tunnel crown deformation received the highest weight (35%) because it was treated as the primary indicator of structural response and deformation control. Material cost received the second-highest weight (25%) because of its direct influence on the economic feasibility of the support alternative, while remaining subordinate to structural performance. Shotcrete applicability and steel-set maneuverability were each assigned 15% because both affect construction effort, installation time, equipment requirements, and operational feasibility. Local material availability received 10% because it primarily represents a logistical constraint rather than a direct structural-performance criterion. These values define a baseline decision scenario for the present study and should not be interpreted as universal weights for all tunnel projects.

Material costs were estimated from the required quantities and unit costs of shotcrete and steel sets. Shotcrete applicability is determined by the required volume, the number of application stages, and the estimated application time. Steel-set maneuverability accounted for frame weight, lifting equipment, installation complexity, and estimated handling time, whereas local availability was represented on an ordinal availability scale.

Each alternative was assigned an ordinal score for each criterion according to its relative performance within the evaluated set. Lower scores represented more favorable performance in terms of deformation, material cost, shotcrete application effort, steel-set maneuverability, and local availability. For the availability criterion, a lower coded value represented greater local availability. The criterion scores were multiplied by their corresponding weights and summed to obtain a global score, with lower total scores indicating more favorable alternatives. A single baseline weighting scheme was applied throughout the study, and alternative weighting configurations were not evaluated.

The selected support configuration was not necessarily the one with the minimum deformation but rather the one that provided the most balanced performance across the evaluated design space. Thus, the final decision reflects a compromise between structural safety, deformation control, material efficiency, constructability, and logistical feasibility.

The weighting scheme affects the final MCDM scores and ranking of the feasible alternatives, but it does not alter the FEM-computed responses or the structural feasibility classification obtained from the N – M and N – Q interaction envelopes.

3.7. Workflow Integration and Reproducibility

The five methodological phases were integrated into a single automated workflow implemented through Python scripts and the PLAXIS 2D API. This integration connects model generation, staged numerical simulation, support configuration, optimization, feasibility screening, post-processing, and Multi-Criteria Decision-Making within a reproducible computational environment.

The automated workflow enables multiple support configurations to be evaluated under consistent modeling assumptions, reducing manual intervention and improving traceability across simulations. For each evaluated configuration, the framework records the input parameters, equivalent support properties, numerical response, feasibility status, and decision-related indicators in structured output files.

Overall, the proposed SODF provides a systematic and reproducible procedure for evaluating composite tunnel support systems under varying geotechnical conditions. By linking numerical modeling, PSO-based exploration, feasible solution screening, and multi-criteria ranking, the framework supports a transparent transition from simulation results to engineering decision-making.

4. Experimental Setup

This section describes the experimental configuration used to evaluate the proposed Simulation–Optimization–Decision Framework (SODF). While the methodology defines the computational workflow, the experimental setup specifies the model conditions, design variables, optimization configurations, and evaluation outputs considered in the study.

The experiments were designed to analyze how rock-mass quality, represented by GSI, and rock-mass deformability, represented by E_{rm} , influence tunnel crown deformation and support demand. In addition, the study evaluates how different combinations of shotcrete thickness and steel sets contribute to feasible support configurations, and how the PSO search intensity affects solution diversity and computational cost. Finally, the experimental design provides the basis for applying the MCDM model to prioritize alternatives according to tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability. Table 4 summarizes the main experimental components and evaluated responses.

Table 4. Experimental components and evaluated responses.

Experimental Component	Evaluated Response or Purpose
Rock-mass quality (GSI)	Influence on tunnel crown deformation and support demand.
Rock-mass deformability (E_{rm})	Effect of stiffness variation on tunnel response and feasible support configurations.
Shotcrete thickness	Contribution of shotcrete to deformation control and material demand.
Steel sets	Influence of steel-set stiffness and profile selection on structural performance.
PSO configuration	Effect of search intensity on solution diversity, quality, and computational cost.
Decision criteria	Prioritization of feasible alternatives considering tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local availability.

4.1. Computational Environment

Simulations were performed using Python interfaced with the PLAXIS 2D API. The computational workflow was implemented in a Jupyter Notebook environment, enabling automated model generation, numerical simulation, result extraction, and post-processing.

The experiments were conducted on a workstation equipped with an Intel® Xeon® CPU E3-1240 v5 at 3.5 GHz and 8 GB of RAM. The implementation was performed in Python 3.8.1 and Jupyter Notebook server version 6.4.11. The numerical simulations were performed using PLAXIS 2D version 2023.2.1.1079, which supports remote scripting through the PLAXIS API.

The simulations were executed sequentially on a single workstation, without parallel processing or distributed computing. The Python–PLAXIS integration automates model generation, simulation execution, data extraction, and result storage. The scripts, model configuration files, input data, geometry files, and supporting documentation required to reproduce and extend the computational workflow are available in <https://github.com/MonserratVH/A-Simulation-Optimization-Decision-Framework-for-Composite-Tunnel-Support-Design> (accessed on 5 June 2026), repository provided in the Data Availability Statement.

4.2. Tunnel Model and Geotechnical Scenarios

The experimental study considered a four-lane road tunnel excavated in a rock mass. The numerical model was developed under plane strain conditions using the Hoek–Brown failure criterion to represent the mechanical behavior of the rock mass.

Two case studies were conducted to evaluate the tunnel’s response under different geotechnical scenarios. The selected Geological Strength Index (GSI) values ranged from 40 to 55, indicating low to moderate rock-mass quality. The deformation modulus of the rock mass, denoted as E_{rm} , ranged from 250,000 to 545,000 kN/m², corresponding to relatively weak to moderately competent rock masses.

Case 1 considered scenarios mainly associated with $E_{rm} = 500,000$ kN/m², together with an additional lower-stiffness condition defined by $E_{rm} = 250,000$ kN/m² and GSI = 40. Case 2 considered scenarios mainly associated with $E_{rm} = 545,000$ kN/m², together with an additional condition defined by $E_{rm} = 300,000$ kN/m² and GSI = 45. The selected values of GSI and E_{rm} were evaluated as deterministic geotechnical scenarios intended to represent different levels of rock-mass quality and deformability. The comparison among these scenarios was used to identify changes in tunnel crown deformation and feasible support configurations within the analyzed parameter range. Probability distributions, parameter correlations, and stochastic sampling of the geotechnical properties were not considered. Table 5 summarizes the main geometric, geotechnical, and support-related parameters used to define the experimental domain.

Table 5. Main project characterization parameters.

Parameter	Description
Tunnel type	Four-lane road tunnel excavated in rock mass.
Cross-sectional area	Approximately 197 m ² .
Free height	Approximately 11.50 m.
Width	Approximately 21.10 m.
Equivalent diameter	$D_{eq} \approx 15.85$ m.
Geotechnical model	Homogeneous rock-mass unit represented using the Hoek–Brown failure criterion.
Main geotechnical variables	E_{rm} and GSI.
Support system	Composite system composed of shotcrete and steel sets.
Design variables	Shotcrete thickness and steel-set selection.
Equivalent support properties	EA , EI , ν , and w .

4.3. Design Variables

The support system was defined as a composite comprising shotcrete and steel sets. The design space included two main variables: shotcrete thickness and steel-set selection.

Shotcrete thickness was treated as a continuous variable within the range of 10–50 cm. Steel sets were selected from a discrete catalog of structural IR profiles with predefined mechanical and geometric properties. For each evaluated configuration, equivalent structural properties were computed to represent the composite behavior of the support system, including axial stiffness, flexural stiffness, Poisson's ratio, and unit weight [20]. These equivalent properties were assigned to the PLAXIS 2D model for numerical simulation.

4.4. PSO Configurations

Particle Swarm Optimization (PSO) was used to explore the design space and identify feasible support configurations that minimize tunnel crown deformation. Three PSO configurations were evaluated to analyze the effect of search intensity on feasible solution diversity and computational cost:

- **PSO200:** 10 particles and 20 iterations.
- **PSO400:** 10 particles and 40 iterations.
- **PSO600:** 10 particles and 60 iterations.

The PSO parameters were defined as follows: inertia weight $w = 0.9$, cognitive coefficient $c_1 = 0.5$, and social coefficient $c_2 = 0.3$. These configurations allowed for the effect of increasing the number of evaluations to be assessed while maintaining the same swarm size and coefficient structure.

Because PSO is stochastic, selected configurations were repeated under identical model and optimization conditions to examine algorithmic repeatability. Specifically, Experiments 1 and 3 of Case 1 and Experiments 1 and 4 of Case 2 used the same geotechnical parameters, PSO settings, and design-variable bounds. The repeated runs produced similar minimum-deformation values but different numbers and distributions of feasible solutions, indicating that the best objective values were comparatively stable, whereas the explored feasible set remained sensitive to stochastic particle initialization. These paired repetitions constitute a limited assessment of repeatability rather than a comprehensive statistical stability analysis.

4.5. Objective Function and Feasibility Criteria

The objective function was defined to minimize tunnel crown deformation, which was adopted as the primary indicator of support performance. For each candidate configuration, the numerical model returned the deformation response, which the PSO algorithm used to guide the search.

A configuration was considered feasible only if it satisfied the structural verification criteria established for the composite support system. These criteria included verification against N – M and N – Q interaction envelopes, with a minimum safety factor of $FS \geq 1.5$. Configurations that did not satisfy these structural constraints were excluded from the feasible solution set, while feasible alternatives were retained for comparative analysis and subsequent multi-criteria evaluation.

4.6. Post-Processing and Comparative Evaluation

The results obtained from PSO200, PSO400, and PSO600 were consolidated for each case study. The post-processing stage focused on organizing the feasible configurations and comparing their behavior according to the main experimental factors. In particular, the analysis considered the distribution of feasible support configurations, the relationship between shotcrete thickness and steel-set selection, the influence of GSI and E_{rm} on

tunnel crown deformation, and the effect of PSO configuration on solution diversity and computational cost.

The feasible configurations were then evaluated from two complementary perspectives. First, the alternatives with the lowest tunnel crown deformation were identified to assess the structural efficiency of the support system and the PSO search's behavior under different configurations. Second, the same feasible alternatives were prepared for the MCDM model, which considered tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability.

This comparative strategy distinguishes between the best alternative according to the optimization objective and the most suitable alternative from an integrated engineering perspective. Therefore, the experimental setup evaluates the extent to which the proposed SODF supports both deformation-based optimization and implementable design decisions.

5. Results and Discussion

This section presents the main results obtained from applying the proposed framework. The analysis is organized around three aspects: the behavior of the PSO configurations, the distribution of feasible support configurations, and the comparison between deformation-based and MCDM-based selection.

The reported results focus on the experiments that generated feasible support configurations. In each case study, one experiment did not produce feasible alternatives within the evaluated search domain, even though the numerical model was executed without calculation or convergence errors. Therefore, the global comparative analysis was performed using the experiments with feasible outputs.

5.1. Optimization Behavior Across PSO Configurations

As described in Section 4, the optimization process was evaluated using three PSO configurations: PSO200, PSO400, and PSO600, corresponding to 200, 400, and 600 support evaluations, respectively. These configurations were used to analyze how search intensity affects the diversity of feasible alternatives, the explored shotcrete thickness range, the selected steel sets, and the computational effort.

Table 6 summarizes the execution times for Experiment 1 of each case study. These times correspond to the complete automated PSO–FEM workflow, including candidate generation, calculation of equivalent support properties, PLAXIS model execution, result extraction, structural feasibility assessment, fitness evaluation, and data storage.

Table 6. Execution times for the representative PSO–FEM experiments.

PSO Configuration	Case 1	Case 2
PSO200	03 h 23 min 46 s	04 h 03 min 54 s
PSO400	07 h 23 min 26 s	08 h 25 min 09 s
PSO600	10 h 25 min 34 s	12 h 05 min 13 s

For PSO600, the total execution time was 10 h 25 min 34 s in Case 1 and 12 h 05 min 13 s in Case 2. As shown in Table 6, the computational effort increased consistently with the number of support evaluations. Although the Python–PLAXIS integration reduced manual intervention, it did not reduce the intrinsic computational cost of the repeated FEM calculations. The reported values correspond to the integrated PSO–FEM workflow rather than to individually timed computational components.

The practical acceptability of these execution times depends on the intended decision context. The present SODF is designed for offline preliminary and comparative support design rather than for real-time operational decisions at the excavation face. Within this

scope, PSO200 provides a reduced exploratory analysis that can be completed in several hours, while PSO400 represents an intermediate analysis that can be executed in a working day or an overnight computation cycle. PSO600 may be reserved for cases where broader exploration is required, and the design schedule permits a longer calculation period. Therefore, the three configurations provide different trade-offs between available decision time, search coverage, and computational effort. However, if the excavation duration exceeds the proposed method execution time, construction-stage decisions remain feasible.

Table 7 is intended as a contextual comparison rather than a direct performance benchmark, because the cited studies differ in numerical model complexity, hardware, design variables, and optimization settings. Nevertheless, the comparison shows that the computational cost observed in the present study is consistent with the recognized burden of direct simulation-based optimization. Surrogate-assisted approaches reduce execution time by replacing repeated high-fidelity simulations with approximate predictive models, particularly when near-real-time responses are required. In contrast, the present SODF retains direct FEM evaluation for every candidate configuration and links the resulting numerical response to structural feasibility verification and multi-criteria ranking. Its contribution, therefore, lies in providing a transparent and traceable offline design workflow rather than in achieving real-time computational performance.

Table 7. Contextual comparison of computational strategies used in simulation-based geotechnical and tunnel-design studies.

Approach	Numerical Strategy	Reported Computational Consideration	Decision Context
Proposed SODF	Direct PLAXIS 2D evaluation of each candidate combined with PSO, structural screening, and MCDM	200–600 direct support evaluations requiring approximately 3.4–12.1 h on a sequential workstation	Offline preliminary and comparative support design
Zhang et al. [30]	FEM simulations combined with an RBF surrogate model and PSO	The surrogate-assisted strategy reduced the calculation cost by approximately 88% relative to repeated direct numerical evaluations	Accelerated optimization of tunnel support parameters
Jürgens and Henke [42]	Direct finite element analyses coupled with PSO and Differential Evolution	The study examined the trade-off between the number of calculation steps, optimization performance, and numerical cost	Offline geotechnical design optimization
Cao et al. [43]	Offline FEM simulations combined with a hybrid RNN–GPOD surrogate model	The FE model was substituted by a computationally efficient surrogate for real-time settlement predictions	Construction-stage decision support for TBM steering

In Case 1, PSO200 concentrated mainly on lower shotcrete thicknesses, typically between 10 and 13 cm. PSO400 produced a more dispersed distribution, including low and intermediate shotcrete thickness values, whereas PSO600 explored a wider range of configurations, including isolated shotcrete thicknesses of up to 22 cm. This behavior indicates that increasing the number of evaluations expands the explored design space and increases the diversity of the identified configurations.

In Case 2, the feasible configurations were more compact. Most solutions were concentrated within shotcrete thicknesses of 10–12 cm, with steel sets mainly located in the 254 mm and 305 mm ranges. For GSI = 50, the results did not indicate the need for shotcrete

The figure illustrates that similar deformation levels can be achieved through different combinations of shotcrete thickness and steel-set selection, reinforcing the need to evaluate the composite support system as a combined structural response rather than as two independent design variables. Table 8 summarizes the observed behavior across the PSO configurations.

Table 8. Summary of optimization behavior across PSO configurations.

PSO Setting	Observed Shotcrete Thickness Range	Observed Steel-Set Pattern	General Behavior
PSO200	Mainly concentrated between 10 and 13 cm in Case 1; in Case 2, explored some upper thickness values between 14 and 16 cm.	More frequent use of lighter or medium steel sets in some scenarios.	Lower search intensity and more limited exploration of the design space.
PSO400	More dispersed distribution, including low and intermediate shotcrete thickness values.	More balanced distribution of steel sets, including intermediate and robust profiles.	Provided a broader and more balanced set of feasible alternatives for subsequent decision analysis.
PSO600	Explored the widest range, including values up to 22 cm in Case 1.	Higher presence of larger steel sets, mainly in the 254 mm and 305 mm ranges.	Increased solution diversity, with higher computational cost.

Overall, PSO400 provided a useful balance between exploration capacity and computational effort, whereas PSO600 increased the diversity of feasible alternatives but at a higher computational cost. This suggests that the choice of PSO configuration should be interpreted as a trade-off between search coverage and computational efficiency.

5.2. Feasible Support Configurations

The feasible support configurations were analyzed in terms of shotcrete thickness, steel-set selection, and tunnel crown deformation. In both case studies, the feasible domain reflected a combined structural response, indicating that the support system's performance depends on the interaction between shotcrete thickness and steel-set stiffness rather than on either variable alone.

In Case 1, the feasible domain was broader and more dispersed. Most feasible solutions were concentrated between 10 and 14 cm of shotcrete thickness, although isolated values reached up to 22 cm. Steel sets in the 305 mm range were the most frequent, followed by 254 mm profiles, while lighter profiles appeared selectively under the more demanding geotechnical scenarios. The global heat map further shows that GSI = 40 accounted for the largest share of feasible combinations, with 45 out of 75 cases (60%), followed by GSI = 45 and GSI = 50, each with 15 cases. Overall, 71% of the Case 1 configurations were concentrated between 10 and 14 cm of shotcrete thickness, confirming that the feasible design space was relatively broad yet centered on moderate thicknesses.

In Case 2, the feasible domain was more compact. Most feasible solutions were concentrated at shotcrete thicknesses of 10–12 cm, whereas thicknesses of 14–16 cm were observed only in isolated cases under more demanding conditions. Steel sets in the 305 mm range clearly predominated, with 254 mm profiles appearing less frequently. The global heat map shows that GSI = 40 represented 36 out of 57 feasible combinations (64%), followed by GSI = 45 with 15 cases (27%) and GSI = 50 with 5 cases (9%). In this case, 88% of the feasible solutions were located between 10 and 12 cm, indicating that the design space became more concentrated and structurally constrained.

Figure 6 summarizes the global distribution of feasible combinations for both case studies. The figure shows that Case 1 admitted a wider range of shotcrete thicknesses and steel sets, whereas Case 2 converged on a narrower set of support alternatives, dominated by moderate shotcrete thicknesses and robust steel sets.

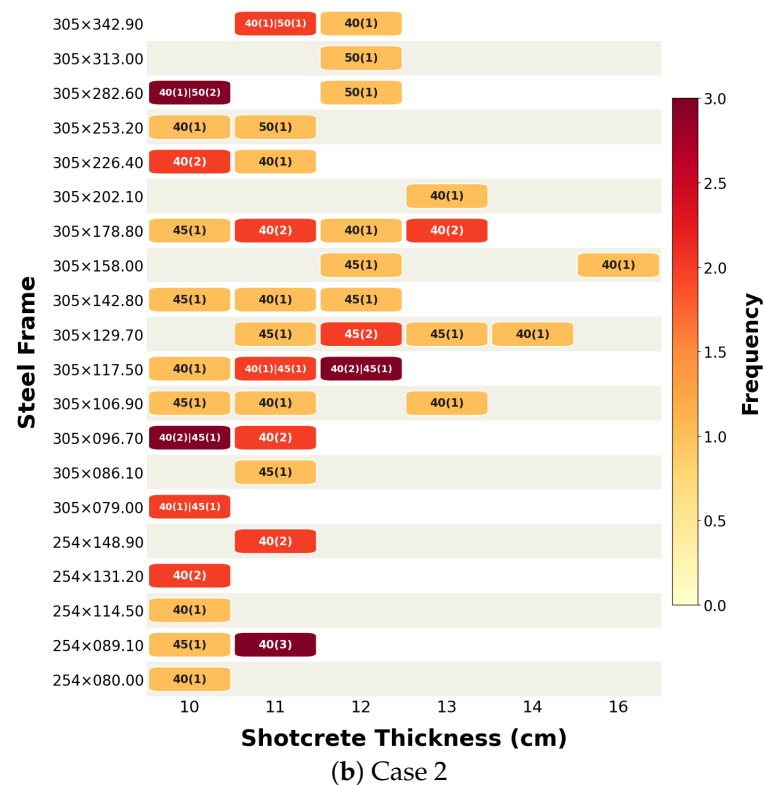
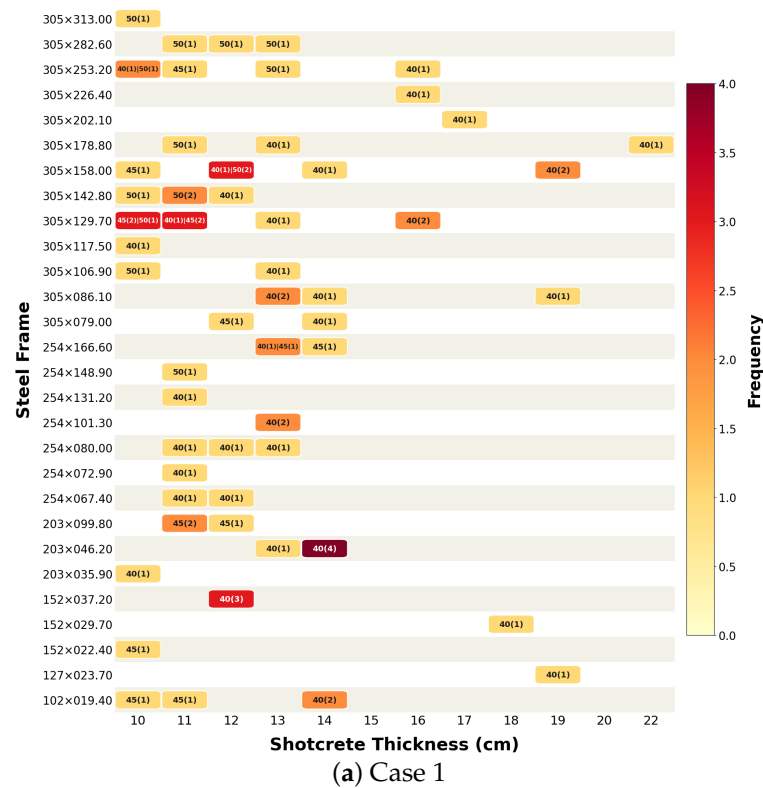


Figure 6. Global heat maps of feasible support configurations: (a) Case 1 and (b) Case 2. The maps summarize the frequency of feasible combinations across shotcrete thickness, steel-set selection, and geotechnical conditions.

Table 9 summarizes the main patterns observed in the feasible support configurations.

Table 9. Summary of feasible support configurations by case study.

Case	Shotcrete Thickness Pattern	Steel-Set Pattern	Observed Design Domain
Case 1	Most feasible solutions were concentrated between 10 and 14 cm; isolated values reached up to 22 cm.	Predominance of 305 mm steel sets, followed by 254 mm steel sets; lighter profiles appeared selectively.	Broader design domain with greater dispersion of feasible configurations.
Case 2	Most feasible solutions were concentrated between 10 and 12 cm; values at 14–16 cm appeared only in isolated cases under more demanding conditions.	Predominance of 305 mm steel sets, with 254 mm steel sets also present in relevant configurations.	A more compact design domain, with feasible alternatives concentrated within a narrower range.

These results indicate that the feasible design space is not governed solely by increasing shotcrete thickness. Instead, the recurrent presence of 254 mm and 305 mm steel sets suggests that the structural role of the steel set is a key factor in defining feasible support configurations. Consequently, the support system should be interpreted as a composite solution in which shotcrete thickness and steel-set selection act jointly to control tunnel crown deformation and satisfy the structural feasibility criteria.

5.3. Deformation-Based Selection Versus MCDM-Based Selection

The feasible alternatives were compared from two complementary perspectives. First, the configurations with the lowest tunnel crown deformation were identified to assess the structural response obtained from the PSO-based optimization. Second, the same feasible alternatives were evaluated using the Multi-Criteria Decision-Making (MCDM) model, which incorporated tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability.

This comparison is important because the minimum-deformation alternative does not necessarily represent the most suitable solution. A configuration may provide a slightly lower deformation but require a less favorable steel set, greater material demand, higher cost, or more complex installation conditions. Conversely, the MCDM model allows alternatives with balanced structural, economic, operational, and logistical performance to be prioritized. Table 10 summarizes the comparison between deformation-based selection and MCDM-based selection for the two case studies.

Table 10. Comparison between deformation-based selection and MCDM-based selection.

Case	Deformation-Based Selection	MCDM-Based Selection	Selection Agreement
Case 1	Lowest-deformation alternatives were associated with shotcrete thickness values around 13–14 cm and variable steel sets, ranging from lighter to intermediate profiles.	Steel set 203 × 99.80 with 11 cm shotcrete thickness.	Partial
Case 2	Lowest-deformation alternatives were mainly associated with shotcrete thickness values between 10 and 13 cm and steel sets in the 254–305 mm range.	Steel set 254 × 114.50 with 10 cm shotcrete thickness.	Partial

The comparison shows that the MCDM-selected alternatives did not fully coincide with the configurations identified by minimum tunnel crown deformation. In Case 1, the deformation-based alternatives were associated with slightly higher shotcrete thicknesses, whereas the MCDM selected a configuration with 11 cm of shotcrete and a 203×99.80 steel set. This indicates that a moderate support configuration can be preferred when cost, shotcrete applicability, maneuverability, and availability are included in the ranking process. In Case 2, the deformation-based alternatives were located mainly between 10 and 13 cm of shotcrete thickness and were associated with 254–305 mm steel sets. The MCDM selected the 254×114.50 steel set with 10 cm of shotcrete, which is consistent with the more compact feasible design domain observed in this case. This result suggests that, under the evaluated geotechnical conditions, a low shotcrete thickness combined with an intermediate-to-robust steel set can provide a balanced engineering alternative.

Overall, these results confirm that tunnel support selection should not be interpreted only as a deformation-minimization problem. The PSO stage identifies feasible configurations that satisfy structural requirements and minimize tunnel crown deformation, whereas the MCDM stage adds a decision layer incorporating implementation-related criteria. Therefore, the final support configuration represents a compromise between structural performance, material efficiency, constructability, and logistical feasibility.

5.4. Discussion

The results show that the tunnel support design problem cannot be interpreted only as a deformation-minimization task. Although tunnel crown deformation was the main response used to guide the PSO-based search, the final selection of a support configuration also depends on structural feasibility, computational effort, and implementation-related criteria, including material cost, shotcrete applicability, steel-set maneuverability, and local material availability. Therefore, the proposed SODF provides value not only by identifying low-deformation alternatives, but also by organizing them into a decision process that distinguishes between structurally efficient and engineering-suitable alternatives.

The comparison among PSO200, PSO400, and PSO600 indicates that search intensity affects the diversity of feasible configurations. Increasing the number of evaluations expanded the design space explored, but did not necessarily yield a proportional improvement in the final engineering decision. This behavior suggests that higher search intensity can be useful when broader exploration is required, particularly under uncertain or demanding geotechnical conditions. However, within the evaluated scenarios, a more moderate configuration may provide a better trade-off between solution diversity and computational efficiency.

The feasible support configurations also indicate that the response of the composite support system is governed by the interaction between shotcrete thickness, steel-set stiffness, and the adopted rock-mass conditions. Case 1 exhibited a broader feasible domain, whereas Case 2 showed a more compact distribution of feasible configurations. This contrast suggests that changes in rock-mass quality and deformability can either expand or restrict the set of structurally admissible alternatives. Recent studies have similarly shown that tunnel support requirements are strongly influenced by the ground structure, discontinuity conditions, stress confinement, tunnel geometry, and the interaction between the rock mass and the installed reinforcement [24,25]. Therefore, the feasible design space should be interpreted as the result of the combined ground–support response rather than as a direct consequence of increasing a single support variable.

A relevant finding is that increasing shotcrete thickness was not the only mechanism for controlling tunnel crown deformation. The repeated selection of intermediate-to-robust steel sets suggests that the steel component's stiffness contribution plays an important role in the composite response. Among several feasible alternatives, deformation control was achieved through a combination of moderate shotcrete thickness and an appropriate steel set, rather than by systematically increasing shotcrete thickness. This interpretation is consistent with recent tunnel support studies in which shotcrete, bolts, reinforced ribs, and other support components are evaluated as interacting elements whose performance depends on both the ground behavior and the overall support arrangement [24,26]. Accordingly, shotcrete thickness and steel-set selection should be assessed jointly within the scope of the composite support system considered in this study.

The comparison between deformation-based selection and MCDM-based selection further shows that the minimum-deformation alternative does not necessarily coincide with the most suitable engineering alternative. In both case studies, the MCDM-selected alternatives differed from the configurations identified only by minimum tunnel crown deformation. This indicates that slightly higher deformation may be acceptable when the selected configuration provides a better overall balance across structural, economic, operational, and logistical criteria.

This distinction is important from an engineering perspective. A support configuration with the lowest deformation may be structurally attractive, but it can also imply higher material demand, less favorable installation conditions, or reduced operational practicality. Conversely, an MCDM-selected alternative may not be the absolute minimum-deformation solution, but it can provide a more balanced and implementable configuration. Thus, the MCDM model complements the PSO stage by adding a decision layer that incorporates practical constraints that are not directly represented in the deformation-based objective function.

In summary, the results indicate that moderate shotcrete thicknesses, combined with appropriately selected steel sets, were repeatedly found to be among the feasible and decision-preferred configurations. The PSO stage was effective for exploring the design space and identifying structurally feasible alternatives, while the MCDM stage supported the selection of alternatives with greater overall engineering suitability. Under the evaluated conditions, this separation between optimization and decision-making is relevant because it prevents the final support recommendation from being based solely on a single mechanical response. Instead, it promotes a more integrated interpretation of structural performance, material efficiency, constructability, and logistical feasibility. These findings also provide a basis for comparing the proposed SODF with recent approaches to tunnel support optimization and decision-making, thereby clarifying its methodological position in the current literature.

5.5. Comparison with Related Approaches

Recent studies on tunnel support design have increasingly incorporated numerical simulation, optimization, surrogate modeling, and decision-support methods. However, many existing approaches emphasize particular components of the design process, such as support parameter optimization, analytical support design, numerical assessment of ground behavior, or engineering decision support. In contrast, the proposed SODF integrates numerical modeling, PSO-based exploration, structural feasibility screening, and MCDM-based ranking within a single computational workflow.

Table 11 summarizes the position of the proposed SODF relative to representative tunnel design and optimization approaches in terms of modeling basis, search strategy, evaluation procedure, and application scope.

Table 11. Comparison of representative tunnel design and optimization approaches with the proposed SODF.

Study	Modeling Basis	Search Strategy	Evaluation and Decision	Application Scope
Terron-Almenara et al. [24]	Geological characterization and numerical modeling	No formal optimization	Engineering assessment of ground and hybrid-support response	Site-specific support design in layered and complex ground
Zhang et al. [30]	FEM and RBF surrogate model	Particle swarm optimization	Assessment through mechanical-response indicators	Surrogate-assisted optimization of support parameters in weak interlayers
Wang et al. [36]	Convergence–confinement analytical model	Parametric sensitivity analysis	Assessment of ground–support response and failure modes	Rapid preliminary support design
Jianting et al. [31]	FLAC3D simulations and machine learning	Swarm-based model tuning	Prediction-performance evaluation	Prediction of steel-fiber shotcrete response
Niu et al. [32]	FLAC3D and Python automation	NSGA-II multi-objective optimization	Pareto-based comparison of candidate solutions	Automated optimization of excavation step height
Proposed SODF	PLAXIS 2D simulations integrated through the Python API	PSO-based exploration of support configurations	Structural feasibility screening using N – M and N – Q envelopes, followed by MCDM ranking	Preliminary selection of composite shotcrete–steel support configurations

Taken together, the approaches summarized in Table 11 show that the proposed SODF differs from methods centered on a single modeling, optimization, or evaluation stage by integrating numerical simulation, automated search, structural feasibility screening, and multi-criteria ranking within the same workflow. This integration preserves the connection among geotechnical conditions, numerical response, feasible support configurations, and the final engineering selection while maintaining the framework as a tool for preliminary and comparative design.

Beyond this methodological positioning, Table 12 examines whether the main behavioral trends identified by the SODF are consistent with those reported in previous tunnel support studies.

Table 12. Qualitative comparison between the SODF results and previous tunnel support studies.

Study	Evidence Basis	Main Finding	Relation to the SODF Results
Carranza-Torres and Diederichs [20]	Analytical composite-liner model	Shotcrete and steel sets contribute jointly to the structural response.	Supports the combined assessment of shotcrete thickness and steel-set stiffness.
Terron-Almenara et al. [24]	Numerical and engineering assessment in layered rock	Support requirements vary with ground conditions and rock–support interaction.	Consistent with the reduction of feasible configurations under more demanding conditions.
Terron-Almenara et al. [25]	Case-based numerical assessment	Tunnel response and support demand depend on site and excavation conditions.	Consistent with the variation of feasible support combinations across the analyzed scenarios.
Terron-Almenara and Panthi [26]	Numerical analysis under plastic deformation	Support performance depends on the complete support system rather than on a single component.	Consistent with the finding that increasing shotcrete thickness alone is not always the preferred response.
Proposed SODF	Automated FEM, PSO exploration, structural screening, and MCDM	Feasible solutions arise from different combinations of shotcrete thickness and steel-set stiffness.	The observed trends are qualitatively consistent with previous analytical and numerical studies.

The qualitative assessment indicates that the main trends obtained with the SODF are consistent with previous analytical, numerical, and case-based investigations. In particular, the results emphasize the combined rock mass–support response and the dependence of feasible support configurations on ground conditions. Nevertheless, this qualitative agreement does not constitute direct validation. Field monitoring data and site-specific calibration remain necessary to assess the quantitative predictive capacity of the framework.

6. Limitations

The results presented in this study should be interpreted within the assumptions and scope of the proposed Simulation–Optimization–Decision Framework (SODF). Although the workflow provides a systematic procedure for evaluating composite tunnel support configurations, several limitations must be acknowledged:

- **Two-dimensional numerical model.** The simulations were performed under plane strain conditions; therefore, tunnel-face effects, longitudinal deformation, construction advance, and spatial variability along the alignment were not explicitly represented.
- **Mesh verification.** The numerical model employed 15-node triangular elements with local refinement around the tunnel contour. However, a systematic mesh-convergence analysis was not performed. Therefore, the sensitivity of tunnel crown deformation and support internal forces to mesh density remains to be quantified in future work.
- **Homogeneous geotechnical unit.** Each case study considered a homogeneous rock-mass unit. Although GSI and E_{rm} were varied, stratigraphic heterogeneity, discontinuities, faults, anisotropy, groundwater, and spatially variable properties were not represented. Since these features can substantially affect ground behavior and support requirements [24,25], the identified configurations should not be generalized to complex geological settings without additional characterization and numerical evaluation.
- **Deterministic representation of geotechnical variability.** The geotechnical scenarios were defined using discrete deterministic values of GSI and E_{rm} , without probability distributions, parameter correlations, or stochastic spatial variability. PSO repeatability was assessed only through paired repeated runs; therefore, additional independent runs and formal sensitivity analyses are required to evaluate geotechnical and algorithmic uncertainty.
- **Limited design space.** The design domain included only shotcrete thickness and steel-set selection. Steel-set spacing, rock-bolt parameters, reinforcement mesh, drainage measures, and alternative support components were not optimized. Support installation timing was estimated using the convergence–confinement procedure and then kept fixed. Consequently, the resulting configurations represent preliminary and comparative alternatives rather than complete site-specific support designs.
- **Perfect composite-action assumption.** The equivalent stiffnesses assumed full compatibility between shotcrete and steel sets. Sliding, partial contact, debonding, and delamination were not explicitly modeled. Imperfect interaction could reduce the effective stiffness and increase tunnel deformation; therefore, this assumption should not be regarded as inherently conservative.
- **Single-objective optimization stage.** The PSO stage minimized tunnel crown deformation. Material cost, shotcrete applicability, steel-set maneuverability, and local availability were incorporated afterward through MCDM rather than within a multi-objective optimization formulation.
- **Lack of comparative algorithmic benchmarking.** The study evaluated three PSO configurations but did not compare PSO with alternative state-of-the-art algorithms over a standardized benchmark set. The results, therefore, characterize PSO within the proposed SODF but do not establish its comparative superiority.

- **Fixed and non-expert-validated MCDM weighting scheme.** The final ranking used a single baseline set of weights established through engineering judgment for the present case studies. The weights were not derived from a formal panel of geotechnical, structural, construction, cost, and logistics experts, and no multi-expert consensus or formal pairwise-comparison process was conducted. Alternative weighting configurations were also not evaluated; therefore, the representativeness of the adopted priorities and the stability of the selected alternative and ranking order under different decision perspectives remain to be assessed.
- **Numerical verification without field calibration.** The N – M and N – Q interaction envelopes assess structural admissibility within the numerical model but do not constitute field validation. The reported results should therefore be interpreted as preliminary and comparative. Application to an actual tunnel project would require site-specific characterization, calibration, and verification using construction observations and monitoring data.
- **Offline computational implementation.** The current sequential PSO–FEM implementation requires several hours to complete. However, when the time available before the corresponding construction-stage decision exceeds the execution time of the selected PSO configuration, the workflow may still be used to support that decision. Applications requiring immediate responses would require computational acceleration through parallel processing, adaptive search strategies, reduced-order models, or surrogate-assisted evaluation.

Despite these limitations, the proposed SODF provides a structured basis for simulation-driven support selection. The framework is particularly suitable for preliminary and comparative design stages, where multiple support alternatives must be evaluated consistently before conducting more detailed site-specific analyses.

7. Conclusions

This paper presents a Simulation–Optimization–Decision Framework (SODF) for the preliminary and comparative evaluation of composite tunnel support systems in rock masses. The proposed workflow integrates FEM-based numerical modeling in PLAXIS 2D, Particle Swarm Optimization (PSO), structural feasibility screening, and a Multi-Criteria Decision-Making (MCDM) model to support the comparison of shotcrete and steel-set configurations under controlled geotechnical conditions.

The results showed that feasible support configurations are governed by the combined response of shotcrete thickness, steel-set selection, and rock-mass conditions. Case 1 exhibited a broader feasible design domain, whereas Case 2 showed a more compact distribution of feasible alternatives. In both cases, moderate shotcrete thicknesses combined with appropriately selected steel sets were repeatedly observed among the feasible configurations, indicating that support performance should be interpreted as a composite structural response rather than as the isolated effect of a single design variable.

The comparison among PSO200, PSO400, and PSO600 confirmed that search intensity affects both the diversity of feasible alternatives and the computational effort required to obtain them. Within the evaluated scenarios, PSO400 offered a suitable compromise between design space coverage and computational efficiency, while PSO600 expanded the range of feasible configurations at a higher computational cost.

The MCDM stage showed that the minimum-deformation alternative does not necessarily coincide with the most suitable alternative within the evaluated decision context. By incorporating tunnel crown deformation, material cost, shotcrete applicability, steel-set maneuverability, and local material availability, the decision process favored alternatives that balanced structural performance with implementation feasibility. This

distinction reinforces the importance of separating deformation-based optimization from final engineering selection.

The proposed SODF provides a reproducible and traceable procedure for comparing feasible composite support configurations during the preliminary and comparative design stages. Its main contribution lies in linking numerical simulation, optimization, structural feasibility screening, and multi-criteria ranking within a single workflow, allowing the transition from mechanical response evaluation to decision-oriented support selection. The framework is not intended to replace final site-specific tunnel support design, which requires detailed geological and geotechnical characterization, numerical verification, field calibration, construction-stage observations, and engineering judgment.

Future work should extend the framework to incorporate additional support variables, including steel-set spacing, rock-bolt layout, mechanical properties, reinforcement mesh configuration, support installation timing, drainage measures, and alternative support components. These extensions would allow for the evaluation of interactions among support components and construction decisions within a broader, more representative design domain. Computational acceleration through parallel execution, adaptive evaluation strategies, or validated surrogate models should also be investigated when shorter decision times are required. Further developments should also include sensitivity analyses of the PSO parameters and stopping criteria, along with comparisons with alternative metaheuristic and multi-objective optimization algorithms across a broader, standardized set of geotechnical and support-design instances. These comparisons should consider solution quality, convergence behavior, coverage of feasible solutions, computational cost, and statistical stability. The weighting scheme affects the final MCDM scores and ranking of the feasible alternatives, but it does not alter the FEM-computed responses or the structural feasibility classification obtained from the N – M and N – Q interaction envelopes. Future studies should strengthen the MCDM stage by involving experts in geotechnical engineering, structural design, construction, cost assessment, and logistics. Criterion weights should be derived through a formal elicitation process, such as pairwise comparisons or a structured multi-expert consensus procedure, together with an assessment of judgment consistency. The stability of the MCDM results should likewise be examined by evaluating whether the selected alternative and ranking order remain consistent under different structural, economic, constructability, and logistical weighting priorities. Finally, calibration and validation against field monitoring data and additional case studies will be necessary to assess the applicability of the framework under more complex geological, hydrogeological, and construction conditions.

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for-Composite-Tunnel-Support-Design (accessed on 5 June 2026). Reproduction of the numerical simulations requires a valid licensed installation of PLAXIS 2D with Remote Scripting enabled.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytic Hierarchy Process
API	Application Programming Interface
FEM	Finite Element Method
FS	Factor of Safety
GSI	Geological Strength Index
MCDM	Multi-Criteria Decision-Making
PSO	Particle Swarm Optimization
SODF	Simulation–Optimization–Decision Framework

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