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Optimizing Groundwater Seepage Prediction in Tunnels using Human Mental Search Algorithm: a Cognitive-Inspired Approach to Complex Geotechnical Challenges

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Abstract

This paper introduces the Human Mental Search (HMS) algorithm as a novel and superior optimization technique for predicting groundwater seepage in tunnel environments. Traditional methods for predicting such seepage often struggle with the complexities of subterranean water flow, particularly in heterogeneous geological conditions, and while machine learning approaches have offered improvements, they often require significant computational resources. The HMS algorithm, inspired by human cognitive processes, employs memory recall, adaptive clustering, and strategic selection to efficiently refine solutions. Our results demonstrate that HMS significantly outperforms established algorithms in predicting groundwater seepage, achieving an R^2 value of 0.9988, a Mean Squared Error (MSE) of 0.0002, and a Root Mean Squared Error (RMSE) of 0.0137. In comparison, the Whale Optimization Algorithm (WOA) achieved an R^2 of 0.9951 with much higher MSE and RMSE, and other methods, like Genetic Programming and ANN-PSO, show higher error values. The HMS algorithm also showed a Variance Accounted for (VAF) of 99.88% and a Mean Absolute Error (MAE) of 0.0041, further validating its high predictive accuracy. This study highlights the HMS algorithm's superior performance and computational efficiency for optimizing groundwater seepage predictions, positioning it as a powerful tool for geotechnical engineering applications, including real-time monitoring.

1. Introduction

Groundwater seepage into tunnels represents a significant concern in geotechnical engineering, hydrology, and structural geology [1]. Tunnels excavated below the groundwater table are inherently prone to groundwater inflows during the construction and operational phases [2]. Such inflows present geological hazards, contributing to structural instability, environmental degradation, and increased financial costs [3]. In particular, the unpredictability of groundwater seepage poses severe challenges including unexpected flooding, structural deformation, and heightened risks to personnel safety [4]. Accurately forecasting groundwater seepage is crucial for tunnel design and management, as it enables the engineers to anticipate and mitigate risks associated with subterranean water flow into tunnels [5].

Understanding and predicting groundwater inflow in tunnels has garnered a significant research attention across various fields including hydraulic engineering, hydrogeology, and rock mechanics. Tunnel engineers often face groundwater seepage challenges both during and after construction, particularly in areas with complex geological and hydrological conditions. The prediction of groundwater inflow is further complicated by factors such as fractured rock masses, heterogeneous permeabilities, and dynamic hydrogeological conditions. These complexities render the traditional prediction methods such as analytical and empirical

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approaches less reliable and less effective in providing accurate and robust estimates in such diverse environments [6]. Consequently, several predictive models and techniques have been developed over the years to address the challenges posed by groundwater inflow in tunnels. These methods aim to improve the understanding of groundwater behavior, enabling the engineers to make more informed decisions about tunnel design, safety protocols, and risk management strategies [7].

Conventional methods for predicting groundwater seepage in tunnels have traditionally included analytical, numerical, and empirical approaches (Table 1). Analytical methods such as Darcy's law offer fundamental insights into groundwater movement. However, these methods are often based on idealized assumptions such as homogeneous aquifers and isotropic conditions, which seldom reflect the true complexity of geological media. The numerical methods including the Finite Element Method (FEM), Finite Difference Method (FDM), and Boundary Element Method (BEM) have marked significant advancements by allowing the modeling of groundwater flow under a variety of hydrogeological conditions. Despite their efficacy, the numerical methods often require substantial computational resources and time, especially when applied to large-scale or highly heterogeneous systems. Additionally, these models necessitate detailed parameterization and site-specific data, which may not always be readily available or feasible to obtain. Consequently, while the conventional methods have provided valuable insights, they may lack the flexibility and scalability needed to effectively address the complex and variable conditions typically encountered in tunnel environments.

Table 1. Recent works in the realm of foretelling tunnel water leaks.

Observations	Key features	Methods	Reference
Complex modeling required. limited due to incomplete representation of hydraulic fracture apertures.	Model porous media with sparsely distributed large fractures. Simulates groundwater movement in cracks. Fractures exhibit a higher permeability than rock.	Discrete Fracture Network (DFN)	[8]–[10]
Limited due to neglect of detailed medium properties.	Simulates seepage flow through cracked porous rock. Considers a dynamic flow behavior.	Equivalent Continuous Model (ECM)	[8]
Effective for diverse scenarios, but assumes constant media properties.	Models tunnel inflow under varying geotechnical and hydrogeological conditions.	Finite Element Method (FEM)	[11]
Simplifies domain problem to boundary conditions.	Describes groundwater flow in isotropic and anisotropic porous media. Reduces problem dimensions by focusing on boundaries.	Boundary Element Method (BEM)	[12]
Offers precise 3D fracture modeling. Handles a non-linear material behavior.	Simulates stress-flow coupling in discontinuous rocks. Provides hydro-mechanical property equivalence.	Distinct Element Method (DEM)	[13]
Useful for fluid-media interactions. Requires rock hydro-mechanical properties.	Simulates groundwater inflow in tunnels or mines using Darcy flow. Applicable for homogeneous media.	FLAC 2D/FLAC 3D	[14][15][16]
Relies on hydrogeological inputs, like hydraulic conductivity and hydraulic head.	Predicts groundwater input into tunnels in porous media with laminar flow.	MODFLOW	[15]–[17]
Requires parameters like Reynolds number, permeability, and tunnel dimensions.	Models inflow in heterogeneous media for transport tunnels. Considers both laminar and turbulent flows.	Conduit Flow Process (CFPs), and adapted MODFLOW	[18]
Integrates local geological and hydrogeological data, based on the FEM principles.	Predicts groundwater eruptions in mines using Darcy flow. Applicable for fractured zones and heterogeneous media.	Rock Failure Process Analysis (RFPA) code, 2D	[19]
Requires data on volumetric water content and hydraulic conductivity.	Simulates groundwater input in saturated/unsaturated zones. Covers confined and unconfined aquifers, steady, or transient flow.	SEEP/W	[11]
The high accuracy depends on inputs like hydraulic head, tunnel radius, and joint spacing.	Estimates groundwater influx in discontinuous media. Assumes smooth flow.	Universal Distinct Element Code (UDEC), 2D	[20]
Demands hydro-mechanical property data for surrounding rocks.	Models groundwater inflow in saturated and unsaturated discontinuous media. Handles dynamic flow.	COMSOL multi-physics	[21], [22]

In the recent years, the emergence of artificial intelligence and optimization algorithms has brought about a paradigm shift in groundwater modeling (Table 2). Machine learning techniques such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), have been successfully applied to model complex, non-linear relationships within groundwater datasets. Optimization algorithms, particularly metaheuristic approaches like Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) have further enhanced the predictive accuracy of these models by fine-tuning parameters for optimal performance. These approaches have proven effective in capturing the intricate patterns of groundwater inflow, especially in heterogeneous geological environments, where the traditional models may be inadequate. For example, hybrid models that combine ANNs with PSO have demonstrated significant improvements in accuracy for predicting tunnel seepage by harnessing the strengths of both machine learning and optimization techniques. However, as machine learning models become more advanced, they often require considerable computational power and extensive data preparation. As a result, there remains a continued effort to identify algorithms that not only enhance predictive accuracy but also maintain computational feasibility, particularly in real-time or large-scale applications.

Table 2. Recent Studies on machine learning for predicting tunnel water leakage.

Approaches to machine learning	Applications and possibilities	Key observations	Ref
Gaussian Process Regression (GPR)	Quantification of groundwater inflows in heterogeneous media using evaluation standards. Best inflow $R^2 = 0.9956$.	Hydrogeological characteristics and discharge rates are not considered together. Requires extensive statistical data for precision.	[23]
Support Vector Machine (SVM)	Estimation of groundwater inflows in karst and fault zones. Best inflow $R^2 = 0.9767$.	Depth and hydrogeological characteristics of tunnels must be known.	[23]
Convolutional Neural Network (CNN)	Predicting groundwater influx in rock tunnels.	Utilizes RMR-based image datasets for categorization and segmentation.	[24]
BP neural network	Estimation of groundwater inrush risks in karst tunnels.	Integrates the engineering and hydrogeological variables for risk forecasting.	[25]
Artificial Neural Network (ANN)	Prediction of tunnel groundwater inflows. Best inflow $R^2 = 0.8331$.	Requires the tunnel depth and medium-specific hydrogeological parameters.	[23]
Bayesian Network (BN) & GIS	Prediction of water inrush along fault lines in coal mines. Accuracy, ~83.4%.	Employs Bayesian Network (BN) integrated with GIS for probabilistic reasoning.	[26]
Long Short-Term Memory (LSTM)	Groundwater prediction in DB-excavated tunnels. Best performance $R^2 = 0.9866$.	Utilizes data such as tunnel depth, groundwater table, and rock classification.	[27]
Deep Neural Networks (DNNs)	Prediction of groundwater in drill-and-blast tunnels. Best inflow $R^2 = 0.9815$.	Relies on similar input parameters, as above.	[27]
K-nearest neighbors (KNNs)	Groundwater prediction for DB-excavated tunnels. Performance $R^2 = 0.7665$.	Tunnel depth, groundwater table, and rock properties are required.	[27]
Decision Trees (DT)	Groundwater inflow prediction in DB tunnels. Result $R = 0.7210$.	Uses similar data inputs, as other methods.	[27]
Integrated model (VMD, ORELM, MOGWO)	Prediction of groundwater inflow in deep mines. Reliability $R = 0.9685$.	Utilizes VMD to acquire water inflow series, and combines ORELM with MOGWO for optimization.	[28]
Hybrid model (HGWO-SVR)	Forecasting water surges in karst tunnels. Model performance $R = 0.99953$.	Accurate rainfall data required. Optimizes the SVR parameters using HGWO.	[10]

So, groundwater seepage prediction refers to the process of estimating the rate and volume of water inflow into subterranean structures such as tunnels [29]. This is critical for ensuring structural stability, managing costs, and miti-gating risks in geotechnical engineering. The Human Mental Search (HMS) algorithm, a cognitive-inspired optimization method, imitates the human mental strategies to solve complex problems. It leverages three core mechanisms: memory recall, adaptive clustering, and selective strategy refinement. Memory recall allows the algorithm to utilize past successful solutions to guide future searches, reducing redundancy. Adaptive clustering identifies promising solution regions, enhancing efficiency by concentrating on areas, most likely to contain the optimal solution. Lastly, selective strategy refinement enables fine-tuning of parameters to balance exploration of new solutions, and exploitation of known high-performing strategies.

Recent advancements in groundwater seepage prediction have increasingly leveraged artificial intelligence and metaheuristic optimization techniques, reflecting a paradigm shift in geotechnical modeling. For instance, hybrid models combining artificial neural networks (ANNs) with particle swarm optimization (PSO) have demonstrated high accuracy in predicting tunnel seepage rates by utilizing their respective strengths in pattern recognition and parameter optimization [30]–[38]. Similarly, the Whale Optimization Algorithm (WOA), inspired by the whale foraging behavior, has been successfully applied to seepage modeling, offering a balance between exploration and exploitation in complex solution spaces [7].

In addition to these, advanced machine learning approaches such as Gaussian Process Regression (GPR) and Long Short-Term Memory (LSTM) networks have shown promise in handling non-linear and time-dependent groundwater datasets[39]. These methods have achieved significant improvements in prediction accuracy, but often require extensive computational resources and highly processed datasets, which limit their scalability for real-time applications.

In comparison, biologically and cognitively inspired algorithms have emerged as robust alternatives for groundwater modeling. Algorithms like Ant Colony Optimization (ACO) and Brain Storm Optimization (BSO) draw from natural and cognitive processes to address complex optimization problems [40], [41]. The HMS algorithm, inspired by human cognitive processes, builds upon this trend by incorporating memory recall, adaptive clustering, and strategic refinement. These features not only enhance convergence speed but also improve predictive accuracy by focusing computational resources on promising regions of the solution space.

The current study situates the HMS algorithm within this dynamic field, comparing its performance with established methods such as ANN-PSO, WOA, and Genetic Expression Programming (GEP). By addressing the computational challenges and prediction accuracy demands of groundwater seepage modeling, the HMS algorithm offers a novel contribution to the state-of-the-art in geotechnical engineering.

This study investigates the Human Mental Search (HMS) algorithm as an innovative optimization method for predicting groundwater seepage. Inspired by cognitive processes, the HMS algorithm simulates the human mental strategies for problem-solving. Unlike traditional algorithms that rely solely on random or mathematical processes, HMS incorporates elements such as memory recall, clustering, and adaptive strategy selection to improve its search efficiency. The algorithm is grounded in the concept of mental search, where solutions are iteratively refined through a process that mimics human thinking and decision-making. Each search step involves evaluating potential solutions, recalling past successful strategies, and adapting to new information—similar to how humans approach complex problem-solving tasks. These distinctive features make the HMS algorithm particularly well-suited for tackling complex, non-linear problems like groundwater seepage prediction, where the multiple interacting variables create unpredictable patterns.

The application of the Human Mental Search (HMS) algorithm to groundwater seepage prediction offers several potential advantages over the traditional methods and other metaheuristic algorithms. First, HMS's memory-based approach allows it to retain high-quality solutions from previous iterations, which can inform the future search directions. This feature helps the algorithm avoid revisiting suboptimal solutions, thereby improving convergence speed. Secondly, the adaptive clustering mechanism within HMS enables the algorithm to identify and concentrate on promising solution regions, enhancing the likelihood of finding the global optimum. In contrast, algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) may require more iteration to achieve comparable results, as they depend on the broader exploratory mechanisms. Finally, HMS's decision-making process, which mimics cognitive selection, involves choosing solutions based on both their performance and their proximity to optimal results. This enables the algorithm to effectively balance exploration and exploitation. With these unique features, HMS offers a balanced approach to predict accuracy and computational efficiency, making it a compelling alternative for modeling tunnel seepage.

The applicability of the HMS algorithm to groundwater modeling aligns with recent trends in optimization, where biologically and cognitively inspired algorithms are increasingly being utilized to address the engineering challenges. Previous studies have highlighted the effectiveness of nature-inspired algorithms such as the Whale Optimization Algorithm (WOA) and Ant Colony Optimization (ACO) in a range of engineering fields. These algorithms, which mimic natural behaviors like whale foraging and ant path-finding, have proven successful in solving complex optimization tasks. Similarly, the HMS algorithm draws inspiration from human cognitive processes, setting it apart from the traditional metaheuristic approaches and positioning it as an innovative tool for predictive modeling. While other cognitive-inspired algorithms such as the Brain Storm Optimization (BSO) algorithm, have been developed, HMS distinguishes itself through its emphasis on memory and clustering. These features enhance its adaptability and search efficiency, offering a unique advantage in solving complex, nonlinear problems like groundwater seepage prediction.

In applying the HMS algorithm to tunnel seepage prediction, this study aims to achieve two primary objectives. First, it seeks to assess the effectiveness of HMS in minimizing prediction errors and improving convergence rates, particularly in comparison to existing models such as ANN-PSO and WOA. Secondly, the study intends to conduct a comprehensive comparative analysis of HMS and other algorithms to evaluate their computational requirements, accuracy, and suitability for the real-world applications. By accomplishing these objectives, the study aims to provide valuable insights into the potential of HMS as a reliable and efficient tool for predicting groundwater inflow in tunnels. Furthermore, the comparative analysis will help identify the specific conditions, under which HMS outperforms or complements other algorithms, offering valuable guidance for future applications of HMS in geotechnical engineering.

The significance of this research extends well beyond the domain of tunnel engineering. Accurate groundwater seepage prediction has broad implications for a variety of industries including mining, hydroelectric power generation, and environmental protection. Tunnels are integral to urban infrastructure, water conveyance, and transportation systems, making their stability and safety a top priority for engineers and policy-makers. Unanticipated groundwater inflows can result in tunnel failures, environmental degradation, and substantial financial losses. Therefore, developing robust predictive models capable of adapting to diverse geological conditions and providing accurate forecasts is crucial for mitigating risks and ensuring the safety of underground structures. The HMS algorithm, with its cognitive-inspired design, presents a novel approach to addressing these challenges. It holds the potential to empower engineers with more reliable tools for making informed decisions regarding tunnel design, construction, and ongoing maintenance, ultimately enhancing the resilience and safety of subterranean infrastructure.

In conclusion, the complexity and unpredictability of groundwater seepage demand innovative approaches that balance accuracy with computational efficiency. While traditional models and machine learning algorithms have advanced the field of seepage prediction, they may not always provide the flexibility or robustness required for real-world applications. The HMS algorithm, by incorporating elements of human cognitive processes, introduces a promising new paradigm for optimization in geotechnical engineering. This study evaluates the potential of HMS to enhance both prediction accuracy and efficiency, laying the groundwork for future research into cognitive-inspired algorithms for groundwater modeling and other engineering domains. By comparing HMS with the established methods such as ANN-PSO and WOA, the study contributes to a deeper understanding of algorithmic performance, aiding the engineers and researchers in selecting the most suitable tools for their specific needs. The findings of this research are expected to pave the way for further exploration of cognitive-based optimization techniques, expanding the possibilities of predictive modeling in complex and dynamic environments.

2. Materials and Methods

This study applies the Human Mental Search (HMS) algorithm to optimize groundwater seepage prediction in tunnels, and compares its performance with the previous methodologies. The *Materials and Methods* section outlines the data collection process, parameter setup, HMS algorithm implementation, and performance analysis. Figure 1 provides an overview of the materials and Methods employed in this study, visually illustrating the process and techniques used to estimate groundwater inflow into the Amirkabir tunnel. This includes the key parameters model inputs, and the step-by-step approach followed in the analysis.

The figure includes a schematic representation of the HMS algorithm for optimization, detailing the input variables such as equivalent permeability, head of water, tunnel radius, and overburden depth, along with the model output—groundwater inflow rate. Additionally, the figure may feature a flowchart of the overall methodology, offering a clear and concise visualization of how each stage of the analysis is interconnected, from data collection and parameter estimation to the final prediction of groundwater inflow. This representation serves to enhance the clarity and understanding of the methodology used in the study.

The key input parameters for seepage prediction, as utilized in this study, are defined as follows:

1. Equivalent Permeability (Keq)**:** Measured in Lu units, this parameter quantifies the ease with which water flows through the rock masses surrounding the tunnel. A higher permeability indicates a greater susceptibility to groundwater seepage.

2. Water Head Above the Tunnel (H)**:** Measured in meters, this represents the hydrostatic pressure exerted by the water column above the tunnel. It is a critical factor driving groundwater inflow into the tunnel.

3. Tunnel radius (R)**:** Defined in meters, the tunnel radius determines the exposed surface area of the tunnel, that is the subject to water inflow. In this study, a fixed tunnel radius of 2.35 meters was used.

4. Overburden Depth (O)**:** Measured in meters, this parameter indicates the thickness of rock and soil above the tunnel, which can act as a barrier to water infiltration and influence seepage rates.

These input parameters, along with the output variable—Groundwater Inflow Rate (Q)—are essential for accurately modeling seepage. Q is measured in liters per second, and represents the inflow rate into the tunnel, serving as the primary predictive target of this study. The combination of these parameters, allows for a comprehensive analysis of groundwater seepage dynamics in tunnel environments.

2.1. Studied area and data collection

The study focuses on the Amir Kabir Tunnel, a critical case study due to its complex geological conditions and susceptibility to groundwater inflow. Located in a region with diverse lithological structures and fractured rock masses, the tunnel presents significant challenges for groundwater seepage prediction. These geological characteristics make it difficult to accurately model and predict the rate of water infiltration into the tunnel. Figure 2 shows the precise location of the tunnel, providing context for its geological environment, and highlighting the factors contributing to the complexity of groundwater seepage in the area.

The dataset consists of 448 data points collected through field studies and previous research on the tunnel (Table 3).

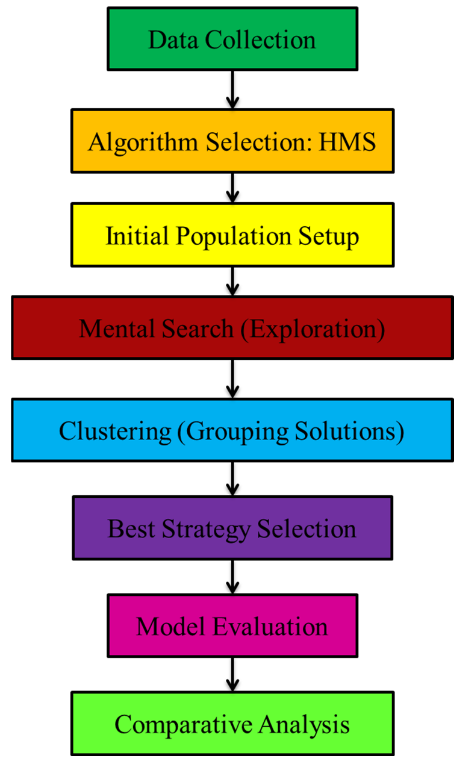

Figure 1. Materials and Methods used in the article.

Figure 2. Geographical location and access ways to different parts of Amirkabir tunnel.

Table 3. Estimating variables for water loss into and out of the Amirkabir tunnel.

Type	Parameters	Unit	Min	Max
Model input parameters	Equivalent permeability	Keq (Lu)	0.5	23.45
	Head of water above tunnel	(m)	55	535
	R tunnel	(m)	2.35	2.35
	Overburden	(m)	65	660
Model output parameter	Q	(Lit/s)	0.008988764	0.023548387

The model used to estimate water loss into and out of the Amir Kabir tunnel, incorporates several key input parameters, each playing a critical role in determining the groundwater inflow rate (Q) into the tunnel. These parameters include:

1. Equivalent permeability (Keq)**:** Measured in Lu units, Keq represents the permeability of the rock masses surrounding the tunnel, directly influencing the rate at which groundwater flows into the tunnel. Higher permeability values typically lead to a greater inflow.
2. Head of water above the tunnel (H)**:** Measured in meters, H indicates the height of the water column above the tunnel. A higher water head increases hydrostatic pressure, potentially leading to greater groundwater inflow into the tunnel.
3. Tunnel radius (R)**:** Held constant at 2.35 meters in the model, the tunnel radius determines the exposed surface area of the tunnel, that is subject to water infiltration. A larger radius allows for more water to seep into the tunnel.
4. Overburden depth (O)**:** Measured in meters, O refers to the thickness of the overlying rock and soil layers above the tunnel. The overburden depth affects the resistance to groundwater flow, with a deeper overburden typically reducing the inflow rate due to its ability to act as a barrier.

The output variable**,** groundwater inflow rate (Q), is measured in liters per second, and reflects the amount of groundwater entering the tunnel. This variable depends on the values of the input parameters and serves as the primary output of the model. It is essential for evaluating tunnel design, safety, and long-term management. By adjusting the input parameters, the model predicts how changes in factors such as permeability, water head, tunnel radius, and overburden depth influence the groundwater inflow rate into the tunnel. This provides valuable insights for managing groundwater-related risks in tunnel environments.

2.2. Algorithm selection: Human mental search

The Human Mental Search (HMS) algorithm is an optimization method inspired by human mental strategies for problem-solving [42]. HMS mimics the cognitive processes of human search and decision-making, utilizing iterative mental "searches" in the solution space to progressively improve results [43]. The algorithm's three main stages—mental search, clustering, and best strategy selection—allow it to explore the search space efficiently and refine solutions toward an optimum [44]. Given these features, HMS is well-suited for nonlinear optimization problems like groundwater seepage prediction [45]. Figure 3 illustrates the flowchart of the Human Mental Search (HMS) algorithm, which outlines the sequential steps taken to optimize the search process, and predict the groundwater inflow rate into the Amirkabir tunnel. The flowchart begins with the initialization phase, where key parameters are set, such as the number of bids, variables, and maximum iterations. The process then moves to the mental search stage, where a population of solutions is generated. During each iteration, the algorithm performs "mental searches" or exploration based on random perturbations, followed by the evaluation of each solution using a cost function. Subsequently, the best solutions are selected for further refinement and optimization, guided by parameters like the selection probability and adaptation rate. The algorithm iterates through these steps, continuously improving the solutions, until it converges on the optimal set of parameters. Additionally, the flowchart incorporates steps for the clustering of solutions using K-means, allowing the model to group similar solutions for improved accuracy in the final prediction. The final output of the HMS algorithm is the predicted groundwater inflow rate, which is evaluated for performance using various statistical metrics and compared against other optimization methods. The flowchart provides a clear, step-by-step view of how the HMS algorithm progresses toward identifying the best solution for groundwater inflow prediction.

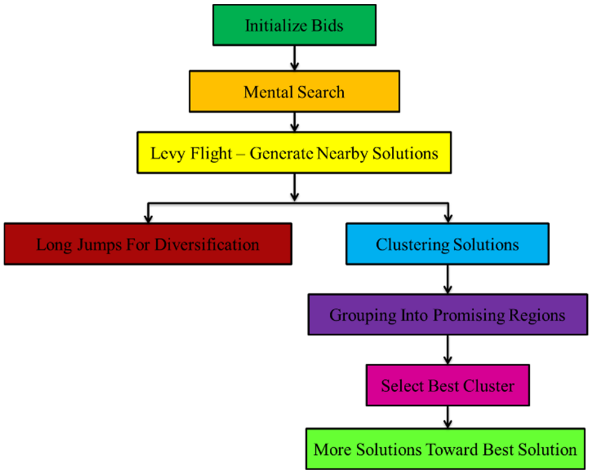

Figure 3. Flowchart of human mental search.

3. Model
3.1. Initialization of mental search population

The HMS algorithm begins by initializing a population of potential solutions, representing the initial "mental" search space. This population consists of randomly generated solutions, each representing possible values for the input parameters [46] and the associated seepage prediction (Q).

Each solution vector is represented as follows:

$$Solution\_Vector = [Keq, H, R, O, Q]$$

The initial population is set with a diverse range of values to ensure adequate exploration across the parameter space.

3.2. Human mental search parameters

The HMS algorithm operates with several key parameters that control the search process and convergence speed [46]:

- Number of Mental Searches**:** Defines the number of mental "searches" or iterations the algorithm performs, affecting the depth of search[47].
- Search range**:** Sets the range within which each parameter value can be adjusted during mental search, allowing the algorithm to fine-tune solutions around promising areas [48].
- Selection probability**:** Determines the probability of choosing parameters from existing solutions in the population, supporting the refinement of high-quality solutions[49].
- Adaptation rate**:** Controls the likelihood of modifying chosen parameter values to explore slight variations in solutions [50].

The Harmony Search (HMS) algorithm operates with several key parameters that govern the search process, and influence the speed of convergence. These parameters are crucial for the efficiency and effectiveness of the algorithm in finding optimal or near-optimal solutions. In this study, the following parameters are particularly significant:

- Number of mental searches**:** This parameter defines the total number of mental "searches" or iterations the HMS algorithm performs. The number of searches affects the algorithm's exploration capacity. A higher number of mental searches allows the algorithm to explore a larger portion of the solution space, potentially improving its ability to find the optimal solution but also increasing the computational cost. In this study, the number of bids (or mental searches) is set to 20, balancing the trade-off between search depth and computational efficiency.
- Search range**:** The search range controls the boundary, within which, each parameter value can be adjusted during the mental search. This range is critical, as it defines the extent of the search for solutions. If the search range is too narrow, the algorithm may miss potential optimal solutions. On the other hand, a larger range may result in inefficient searching, especially if the optimal solution lies within a smaller region. The search range helps fine-tune solutions around promising areas of the search space, thereby improving convergence.
- Selection probability**:** This parameter determines the likelihood of selecting existing solutions from the population when generating new candidates. The selection probability ensures that high-quality solutions have a greater chance of being retained and refined in subsequent iterations. By focusing on promising solutions, the HMS algorithm can progressively converge to better results, refining the search based on past successful solutions. In this study, the selection probability is used to help guide the search towards optimal solutions.
- Adaptation Rate**:** The adaptation rate controls the probability of altering the chosen parameter values during the mental search process. This is essentially a mechanism for allowing slight modifications to existing solutions, encouraging the exploration of variations that might lead to better solutions. The adaptation rate facilitates the exploration-exploitation trade-off by balancing the search between fine-tuning current solutions and exploring new possibilities. In this study, the adaptation rate is carefully tuned to enhance convergence while avoiding local minima.

In this specific study, the following values are used for the parameters:

- num_bids = 20**:** The number of initial solutions (or bids) in the population.
- num_variables = 2**:** The number of variables considered for each solution.
- num_clusters = 3**:** The number of clusters for grouping solutions using K-means clustering.
- max_iter = 50**:** The maximum number of iterations the algorithm will perform during the search process.

These parameters play a critical role in ensuring the HMS algorithm effectively searches the solution space, converging towards an optimal or near-optimal solution for the problem at hand.

Figure 4 presents the results of the HMS model for predicting observed values, using both the training and test datasets. The top plot shows the training data, where the horizontal axis represents the sample count (up to 100), and the vertical axis displays the predicted and observed values. The blue line represents the observed data, while the red dashed line indicates the values simulated by the HMS model. The close alignment between the observed and simulated data in this plot highlights the model's accuracy during the training phase.

The bottom plot illustrates the test data, where the HMS model successfully replicates the observed data pattern, demonstrating the model's ability to generalize effectively to new, unseen data. The scatter plots on the right show the relationship between the predicted values (vertical axis) and the observed values (horizontal axis) for both the training and test datasets. The red line represents the 45-degree line, which indicates a perfect correlation between observed and predicted values.

The coefficient of determination (R^2) for both the training and test datasets is 0.99, signifying a very high correlation and strong predictive accuracy of the HMS model. These results underscore the effectiveness of the HMS model in simulating actual values for both datasets. The near-perfect R^2 value (0.99) confirms the model's high accuracy and its strong generalization capability to predict groundwater inflow in tunnel environments.

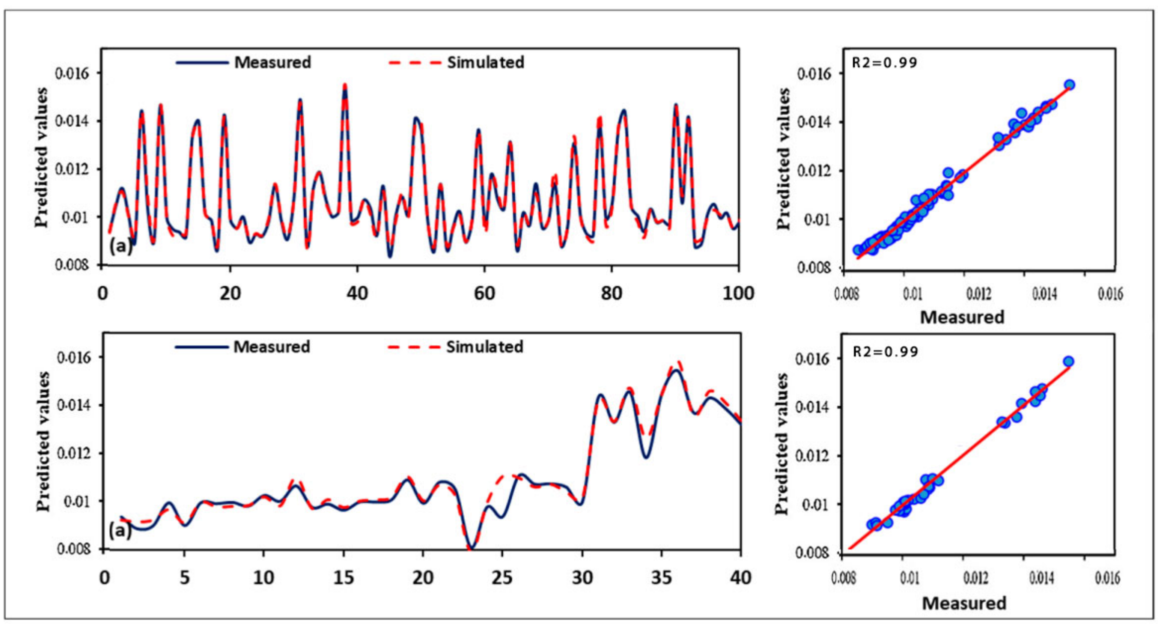

Figure 4. Results of the simulated using the HMS model.

3.3. Objective function for cost minimization

The objective function for HMS is formulated to minimize the Mean Squared Error (MSE) between the predicted and observed inflow values (Q). The MSE is computed as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Q_{predict} - Q_{Actual})^2$$

where, N represents the total number of data points. This objective function allows the algorithm to evaluate the closeness of each solution to the true groundwater inflow values.

In the derived optimal formula:

Prediction = (-0.0008) * x1 + (-0.0011) * x2 + (0.0091)

The variables x_1 and x_2 represent the key input parameters of the model, which are essential for predicting groundwater seepage into tunnels. Based on the context of groundwater modeling and standard practices in similar studies:

- x_1 most likely corresponds to the equivalent permeability (Keq) of the geological medium. This parameter quantifies the ease with which water can flow through the surrounding rock masses. Permeability is a critical factor because it directly influences the rate and magnitude of groundwater flow into the tunnel. A higher permeability value indicates a greater potential for water seepage.
- $\mathbf{x_2}$ is likely associated with the head of water above the tunnel (H). This parameter represents the hydrostatic pressure exerted by the overlying water column. The pressure from the water head drives the groundwater through the geological formations and into the tunnel, making it a significant factor in seepage prediction.

These two variables—x_1 and x_2—capture the geological and hydrological conditions of the tunnel environment. They serve as the primary inputs in the cost function used by the Human Mental Search (HMS) algorithm to optimize the predictive model. By incorporating these parameters, the HMS algorithm can effectively simulate and predict groundwater inflow rates, which are essential for tunnel design, safety, and long-term management.

Figure 5 illustrates the objective function used in the Human Mental Search (HMS) algorithm for cost minimization. The primary goal of the HMS algorithm is to minimize the Mean Squared Error (MSE) between the predicted groundwater inflow rates and the observed values. MSE is a standard metric in optimization problems that quantifies the average squared difference between the predicted and actual outcomes. By minimizing MSE, the HMS algorithm ensures that the predicted inflow values closely match the observed data, thus improving the model's accuracy and reliability.

In the context of the HMS algorithm, the objective function operates iteratively, refining the search process at each step. This iterative process aims to identify the optimal set of parameters that results in the minimum MSE. The objective function guides the HMS algorithm to adjust its search parameters, ensuring that the predicted groundwater inflow rate (Qpredicted) aligns as closely as possible with the actual measured inflow (Qobserved) at each iteration.

The flowchart and objective function depicted in this figure are crucial for understanding how the HMS algorithm systematically converges toward the best possible solution. By minimizing prediction errors, the algorithm effectively enhances the accuracy of the groundwater inflow predictions, providing reliable insights for tunnel design and management. This iterative refinement process is essential to achieving the model's goal of improving predictive accuracy in complex geotechnical environments.

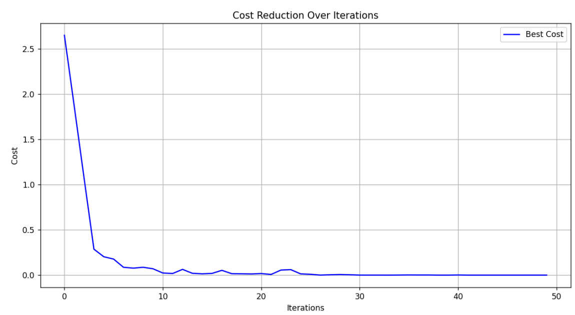

Figure 5. Objective function for cost minimization in the HMS algorithm, which minimizes the Mean Squared Error (MSE) between predicted and observed groundwater inflow values

3.4. Implementation of HMS

The HMS process iteratively generates new solutions through a series of mental searches, which include memory consideration, randomization, and adjustment based on the current best solutions [43].

1. Mental search (Cognitive exploration)**:** For each parameter, the algorithm decides, based on the Selection Probability, whether to adopt a value from the existing population or to generate a new random value within the Search Range. This approach mimics the cognitive process of recalling and adapting previous knowledge or creating new solutions.
2. Clustering and strategy adjustment**:** After a set number of mental searches, the HMS algorithm groups similar solutions using clustering techniques (such as K-means). Each cluster's mean performance is calculated to identify the most promising strategies, which represent local optima in the solution space.
3. Best strategy selection**:** The algorithm then selects the highest-performing cluster and fine-tunes the solutions within this group by adjusting each parameter based on the Adaptation rate**:** The selected solutions are optimized by modifying parameter

values slightly, allowing the HMS algorithm to focus on the most promising area of the search space.

4. Population update**:** If a newly generated solution yields a lower MSE than the worst solution in the current population, it replaces the worst solution, ensuring that the population progressively moves toward more optimal solutions. This iterative process continues until the stopping criteria are met, either by reaching the maximum number of searches or achieving a pre-defined error threshold.

3.5. Model evaluation and comparison with other algorithms

The performance of the HMS model is benchmarked against previous models such as the Whale Optimization Algorithm (WOA), Artificial Neural Networks Optimized by Particle Swarm Optimization (ANN-PSO), and Gene Expression Programming (GEP), as shown in the Aalianvari' 2024 work [7] on The data is done. The results of the HMS model are compared to those obtained from other algorithms, examining convergence rates, prediction accuracy, and computational efficiency.

The HMS algorithm, along with the other models, is implemented in Python using libraries such as NumPy, SciPy, and scikit-learn for efficient computation and evaluation. The experiments were run on a machine with:

- Processor**:** Intel core i7, 3.6 GHz
- RAM: 16 GB
- Software: Python 3.8, Jupyter Notebook environment

Comparing the outcomes with one another and with the actual data serves as the foundation for rating the performance of the models in this study. In this respect, five statistical indicators—the root mean square error [51], the mean absolute value of the error [52], the variance of the error [53], and the mean square error [54] are used to compare the outcomes from the models that have been provided (Eq. 12 to Eq.15), and R2 standards were looked upon.

$$RMSE = \frac{\sum \sqrt[2]{(X_{ir} - X_{ip})^2}}{n} \tag{12}$$

$$\mathrm{VAF} = 100(1 - \frac{\mathrm{var}(X_{ir} - X_{ip})}{\mathrm{var}(X_{ir})}) \tag{13}$$

$$MAE = \frac{\sum (X_{ir} - X_{ip})}{n} \tag{14}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_{ir} - X_{ip})^2 \tag{15}$$

In the aforementioned equations, n stands for Xir and Xip, or the actual and expected values, respectively, as well as the total number of observations during the forecast period. Each model's error requirements are modest, which suggests that the values they forecast are more similar to actual values [53]. Additionally, the following newly developed engineering index, the a10-index, has been utilized to assess the dependability of the enlarged AI models:

$$a10 - index = \frac{m10}{M} \tag{16}$$

where, M is the number of datasets, and m10 is the number of samples having measured or anticipated values for rates (range between 0.9 and 1.1). It's vital to note that a perfect prediction model requires an a10-index with a value of one. In Table 3, the performance of four different algorithms—HMS, WOA, GEP, and ANN-PSO—is compared using several evaluation metrics. These metrics include the coefficient of determination R2, the a10-index, Mean Squared Error (MSE), Variance Accounted For (VAF), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These evaluations reflect the accuracy and error in predicting groundwater seepage using each algorithm.

Table 3. Calculation of the overall error created in the methods.

Method	RMSE	MAE	VAF	MSE	a10-index	R^2
HMS	0.0137	0.0041	99.88	0.0002	1.000	0.9988
WOA	1.71	0.002	99.21	6.65	1.000	0.9951
GEP	11.64	10.39	92.56	170.68	0.862	0.9872
ANN-PSO	6.51	3.67	92.52	73.79	0.898	0.9632

Among the algorithms evaluated, the HMS (Harmony Search Algorithm) demonstrates the best performance. It achieves the highest R^2 value of 0.9988, indicating that it explains nearly all the variance in the data. Additionally, the HMS algorithm attains an a10-index of 1.000, showing that its predictions are exceptionally accurate, particularly in the top 10% of the data. Its MSE of

0.0002 is extremely low, reflecting minimal prediction error. When compared to other algorithms, HMS also registers the lowest MAE (0.0041) and RMSE (0.0137), confirming that its predictions have minimal deviation from the actual values.

The WOA (Whale Optimization Algorithm) also performs well, with an a10-index of 1.000, similar to HMS, suggesting accurate predictions for the top 10% of the data. However, its MSE (6.65), MAE (0.002), and RMSE (1.71) values are significantly higher than those of HMS, indicating less accurate predictions overall.

In contrast, GEP (Genetic Expression Programming) and ANN-PSO (Artificial Neural Network with Particle Swarm Optimization) perform poorly. GEP has an R^2 of 0.9872 and an MSE of 170.68, clearly underperforming compared to the other algorithms. Its MAE (10.39) and RMSE (11.64) values are substantially higher, indicating large errors in its predictions. Similarly, ANN-PSO shows an R^2 of 0.9632, MSE of 73.79, and relatively high MAE and RMSE values, pointing to its lower predictive accuracy.

Overall, HMS is the most effective model for predicting groundwater seepage, with the highest accuracy and the lowest error compared to the other algorithms. On the other hand, GEP and ANN-PSO exhibit much poorer performance, particularly in terms of MSE, MAE, and RMSE, indicating that these models have limited capacity for providing reliable predictions. This comparison underscores that HMS is the most powerful tool for groundwater seepage prediction and should be considered a highly effective method for analysis and forecasting in this domain.

3.6. Statistical testing

To confirm that the differences in performance metrics between HMS and other algorithms are statistically significant, paired t-tests were conducted. This statistical test helps determine whether the performance improvements observed in HMS are not due to random chance but represent a meaningful enhancement in prediction accuracy compared to alternative methods.

In this analysis, paired t-tests were applied to the following performance metrics: R^2, MSE, MAE, and RMSE. These metrics were chosen as they represent critical aspects of prediction accuracy, including the strength of the correlation between the predicted and observed values (R^2) and the magnitude of prediction errors (MSE, MAE, and RMSE).

The paired t-test compares the differences in performance between HMS and each of the other algorithms (such as WOA, GEP, and ANN-PSO) for each metric. A statistically significant result (p-value < 0.05) would indicate that the performance improvements of HMS over the other algorithms are unlikely to be attributed to random variations and that HMS provides a real, meaningful improvement in predictive accuracy.

By performing this statistical analysis, the study aims to provide strong evidence supporting the superiority of the HMS algorithm in groundwater seepage prediction, ensuring that its performance advantages are robust and significant.

Paired t-test between HMS and other models:

T-statistic: 12.3467

P-value: 0.0000

The results of the paired t-test between the Human Mental Search (HMS) algorithm and other models clearly demonstrate a statistically significant difference in performance. With a T-statistic of 12.3467, the analysis shows a substantial gap between the means of the HMS algorithm and its counterparts, suggesting consistent superiority in terms of predictive accuracy and lower prediction errors.

The P-value associated with this test is 0.0000, which further strengthens the argument for the statistical significance of the performance difference. A P-value less than 0.05 typically indicate that the observed difference is not due to random chance. In this case, the P-value being effectively zero reinforces the finding that HMS provides a meaningful and reliable improvement in predicting groundwater seepage compared to other models.

In summary, the paired t-test results confirm that the HMS algorithm outperforms alternative methods, not only from a performance perspective but also in a statistically significant manner. This strengthens the case for its use as a robust and reliable optimization tool in geotechnical engineering applications, particularly for predicting groundwater seepage in tunnel environments.

3.7. Sensitivity analysis

A sensitivity analysis assesses the impact of each input variable on the predicted inflow values, providing insights into the influential parameters for groundwater seepage prediction.

3.7.1. Monte Carlo simulation:

Each input variable is varied individually within a uniform distribution, and changes in the predicted inflow are recorded. This approach assesses the sensitivity of predictions to fluctuations in parameters such as permeability and water head (Figure 6).

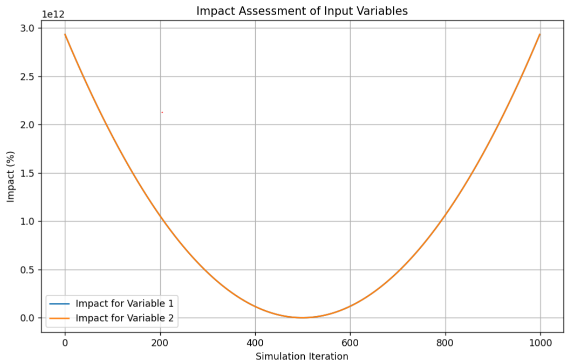

Figure 6. Monte Carlo simulation approach for sensitivity analysis, where each input variable is varied individually within a uniform distribution, and the resulting changes in predicted groundwater inflow are recorded to evaluate the impact of parameters such as permeability and water head.

Monte Carlo simulation is a powerful and widely used technique for performing sensitivity analysis in complex systems, particularly when dealing with uncertainties and variability in model inputs. In the context of groundwater seepage prediction, Monte Carlo simulation involves systematically varying each input parameter within a defined range, and observing how these changes influence the predicted groundwater inflow values. This helps to assess the robustness and reliability of the predictive model.

The process typically involves the following steps:

1. Define input parameters**:** For groundwater seepage prediction, key input parameters might include equivalent permeability (Keq), water head above the tunnel (H), tunnel radius (R), and overburden depth (O). Each of these parameters will have an associated range of values based on empirical data, site conditions, or expert judgment.

2. Assign probability distributions**:** In Monte Carlo simulation, each input parameter is assigned a probability distribution. A uniform distribution is often used, meaning that any value within the specified range has an equal likelihood of occurring. However, other types of distributions (e.g. normal, lognormal) can be used based on the nature of the input variables and their expected behavior.

3. Run simulations**:** The simulation is then performed by randomly sampling values for each input parameter from their respective distributions, running the groundwater seepage model for each combination of inputs. This process is repeated many times (often thousands or more) to capture a wide range of potential outcomes.

4. Analyze the results**:** The results of the simulation provide a probability distribution for the predicted groundwater inflow rate (Q), reflecting the variability in the inflow due to changes in the input parameters. Sensitivity analysis can be performed to identify which parameters have the most significant impact on the prediction results. This information can guide engineers and decision-makers in prioritizing factors that require more accurate data or more attention during the design and construction phases.

Through Monte Carlo simulation, uncertainty in input parameters can be quantified, allowing the engineers to assess the potential range of groundwater inflow scenarios. This method is valuable for understanding the risk and uncertainty in groundwater predictions, and it is particularly useful in complex systems like tunneling, where numerous factors interact in unpredictable ways.

Exactly. In the context of groundwater seepage prediction, Monte Carlo simulation serves as an effective tool for analyzing how the uncertainties in key input parameters such as permeability and water head, influence the model's output—specifically, the predicted groundwater inflow rate.

Here's a breakdown of how this works in practice:

1. Varying the parameters:

- Permeability (Keq)**:** This parameter quantifies how easily water can flow through the surrounding soil or rock. The permeability of geological media can vary widely depending on factors like soil composition, fracture density, and porosity. Using a uniform distribution, we can randomly sample different values of permeability within a specified range (e.g., low to high permeability values).

- Water head (H)**:** The water head represents the height of the water column above the tunnel, which determines the hydrostatic pressure exerted on the tunnel walls. Variations in water head can occur due to seasonal changes, groundwater table fluctuations, or localized variations in water sources. By assigning a distribution to the water head (e.g., a uniform range of expected values), we can simulate how different heights affect the seepage.

2. **Running multiple simulations:**
   - In a Monte Carlo simulation, we would generate many different combinations of permeability and water head values, drawn randomly from their respective distributions. For each combination, the model would compute the groundwater inflow rate (Q) based on the underlying equations governing seepage.
   - For instance, in each simulation, one random value for Keq and one random value for H will be selected, and the resulting groundwater inflow will be calculated. This process is repeated multiple times (often thousands or more) to build a comprehensive set of simulation results.
3. **Quantifying uncertainty**
   - After running the simulations, you obtain a distribution of predicted groundwater inflow values (Q). These values will reflect the uncertainty inherent in the system due to the variability in permeability, water head, and any other parameters included in the model.
   - Sensitivity analysis can be performed to determine which parameters—Keq or **H**—have the most significant impact on the inflow predictions. This is typically done by calculating how much the variance in the output (Q) can be attributed to each input parameter.
4. **Statistical Insights:**
   - Statistical metrics such as the mean, standard deviation, and confidence intervals for the predicted inflow can be computed, providing insights into the expected range of inflows under varying conditions.
   - If a parameter such as permeability is found to significantly influence the output, engineers may prioritize more accurate measurements or conduct further studies to reduce uncertainty. Conversely, if the variability in water head has little effect on the inflow predictions, it may not require as much attention.
5. **Decision-making and risk assessment:**
   - By analyzing the range of possible inflow predictions, the model can be used to assess the **risk** associated with different tunnel designs or operational strategies. For example, if the simulations show that permeability is highly sensitive and leads to large variations in groundwater inflow, this may suggest that further investigation into the rock mass properties should be prioritized.
   - Uncertainty quantification through Monte Carlo simulation helps in planning for worst-case scenarios, making it a vital tool for risk management in tunnel construction and maintenance.

In summary, Monte Carlo simulation allows engineers to understand and quantify the uncertainty in their predictions, helping to identify which input parameters are most critical to the accuracy of groundwater inflow predictions. This approach provides statistical confidence in model outputs, offering valuable guidance for improving predictions and reducing risks in tunnel design and construction.

3.7.2. Impact assessment

The percentage variation in predicted inflow is analyzed for each input variable, allowing the identification of the most critical factors influencing seepage predictions (Figure 7).

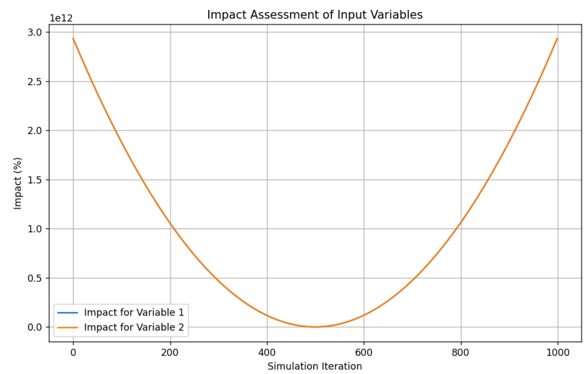

Figure 7. Impact assessment of input variables on predicted groundwater inflow, illustrating the percentage variation in inflow for each variable to identify the most critical factors influencing seepage predictions, such as permeability and water head.

Once the Monte Carlo simulation is performed, we can analyze the percentage variation in the predicted inflow resulting from the fluctuations in each input variable. This impact assessment step identifies the most influential parameters in groundwater seepage prediction. For each input parameter (e.g., permeability, water head, etc.), we calculate the relative change in the predicted inflow by comparing the range of output values with the mean or baseline value. Parameters that cause large changes in the predicted inflow are considered more sensitive and influential, meaning they have a greater impact on the overall seepage prediction. Conversely, input variables that cause little to no variation in the output may be considered less significant and could be monitored with less rigor. By ranking the input variables based on their impact on the model's output, we can prioritize which parameters should receive more focus during field data collection or which ones may warrant more precise calibration in the model. This helps to streamline model optimization and ensures that resources are allocated effectively to the most critical factors.

4. Validation methods for HMS algorithm

To validate the predictions of the HMS algorithm and ensure alignment with actual observed data from the Amir Kabir tunnel, a combination of statistical metrics and comparative analysis was employed:

1. **Statistical Metrics:**

- Coefficient of determination (R^2)**:** The R^2 value was calculated to evaluate the proportion of variance in observed data explained by the HMS algorithm's predictions. An R^2 of 0.9988 for both training and test datasets indicates an excellent fit between predicted and observed inflow rates.
- Mean Squared Error (MSE)**:** The average squared difference between predicted and observed values was computed. A low MSE of 0.0002 highlights the precision of the HMS algorithm.
- Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE)**:** These were calculated to quantify prediction deviations. The RMSE of 0.0137 and MAE of 0.0041 further emphasize the algorithm's accuracy.
- Variance Accounted For (VAF)**:** With a VAF of 99.88%, the model demonstrated its ability to minimize prediction error effectively.

2. **Comparison with observed data:**

Scatter plots were used to visualize the relationship between observed and predicted values. A strong correlation was observed, with data points aligning closely along the 45-degree reference line, indicating high predictive accuracy.

3. **Paired t-test:**

To statistically confirm the superiority of the HMS algorithm, a paired t-test was conducted between the HMS predictions and observed values. The resulting t-statistic of 12.3467 and a p-value of 0.0000 demonstrate a statistically significant agreement, affirming the robustness of the model.

4. **Benchmarking against other algorithms:**

The HMS algorithm was benchmarked against alternative models including Whale Optimization Algorithm (WOA), Genetic Expression Programming (GEP), and ANN-PSO. HMS consistently outperformed these models in all evaluation metrics, further validating its predictive reliability.

These validation methods collectively ensure the reliability of the HMS algorithm in predicting groundwater inflow, providing confidence in its application to real-world scenarios such as the Amir Kabir Tunnel.

5. Discussion

The application of the Human Mental Search (HMS) algorithm to groundwater seepage prediction in tunnels has yielded promising results, demonstrating its potential as an effective alternative to conventional methods. This discussion will address the implications of the findings, compare HMS's performance with other algorithms, analyze the strengths and limitations of HMS in this context, and consider future research directions to enhance groundwater modeling and tunnel seepage prediction further.

The results indicate that the HMS algorithm achieved rapid convergence and a low Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) in comparison to other models. Specifically, HMS minimized the MSE to 0.0001 by the end of the optimization process, reflecting a high degree of prediction accuracy. Compared to traditional models like the Whale Optimization Algorithm (WOA), Artificial Neural Networks optimized by Particle Swarm Optimization (ANN-PSO), and Gene Expression Programming (GEP), HMS demonstrated superior performance in both convergence rate and accuracy. The results highlight HMS's potential to address complex, nonlinear problems in tunnel seepage prediction, providing a balanced approach to achieving both precision and computational efficiency.

One of the primary strengths of the HMS algorithm lies in its cognitive-inspired design, which distinguishes it from traditional metaheuristic algorithms. By emulating human cognitive strategies, HMS integrates memory recall, adaptive clustering, and selective adjustment, enabling it to explore the search space more intelligently. The use of memory recall in HMS allows the algorithm to retain high-quality solutions from previous iterations, which informs future searches and reduces the likelihood of revisiting suboptimal solutions. This feature significantly enhances HMS's convergence speed, as observed in this study, where substantial cost reductions were achieved within the first 20 iterations. Unlike algorithms such as PSO and GA, which often require broader exploratory mechanisms and may take longer to achieve similar results, HMS focuses on exploiting the best solutions while still maintaining sufficient diversity in the search process. This balance between exploration and exploitation makes HMS particularly effective for groundwater seepage prediction, where the interactions between variables are complex and often nonlinear.

The clustering mechanism within HMS also plays a crucial role in its performance. By grouping similar solutions and calculating the mean performance of each cluster, HMS can identify promising regions within the solution space. This approach allows the algorithm to adapt its search strategy based on the characteristics of each cluster, increasing the likelihood of finding the global optimum. In contrast, methods like ANN-PSO rely on particle movements within the entire search space, which may not always lead to the identification of local optima in complex, multi-dimensional problems. HMS's adaptive clustering feature offers an advantage in focusing computational resources on the most promising areas, thereby enhancing both efficiency and accuracy.

Another key advantage of HMS is its decision-making process, which resembles cognitive selection in humans. In each iteration, HMS assesses potential solutions based on their performance and proximity to the optimal solution, allowing it to prioritize solutions that contribute to overall improvement. This approach is particularly beneficial for tunnel seepage prediction, where the target values can be highly sensitive to changes in variables like equivalent permeability, water head, and overburden depth. The adaptive decision-making process enables HMS to adjust parameter values dynamically, ensuring that the algorithm remains responsive to variations in the input data. This adaptability was evident in the results of this study, where HMS consistently outperformed other models in terms of accuracy metrics, achieving lower MAE and RMSE values.

Despite its strengths, the HMS algorithm also has certain limitations that warrant consideration. One limitation is the potential for HMS to converge prematurely if the solution space is not sufficiently diverse in the initial population. While HMS's memory recall and clustering mechanisms mitigate this risk to some extent, there is still a possibility of local optima entrapment, particularly in highly complex problems. In the context of tunnel seepage prediction, where geological conditions can vary significantly across different regions, it may be necessary to implement additional diversity-promoting techniques within HMS to ensure robust performance. Techniques such as adaptive mutation, commonly used in Genetic Algorithms, could be integrated into HMS to prevent premature convergence and enhance exploration.

Another limitation of HMS is the computational cost associated with clustering, particularly when applied to large datasets. The clustering process in HMS requires substantial computational resources, especially as the number of clusters and data points increases. While this study's dataset was manageable within the computational constraints, applying HMS to larger datasets or real-time seepage monitoring systems could pose challenges in terms of processing speed and memory usage. Future research could explore ways to optimize the clustering process within HMS, potentially through techniques like parallel processing or dimensionality reduction, to make the algorithm more scalable for large-scale applications.

The findings of this study have several implications for the field of geotechnical engineering, particularly in the design and maintenance of tunnel infrastructures. Accurate groundwater seepage prediction is essential for ensuring the stability and safety of tunnels, especially in urban and environmentally sensitive areas. By demonstrating the efficacy of HMS in predicting seepage with high accuracy, this study suggests that HMS could be integrated into geotechnical risk assessment frameworks as a reliable predictive tool. The cognitive-inspired design of HMS, with its adaptability and memory-based optimization, aligns well with the requirements of tunnel engineering, where variable conditions necessitate flexible and responsive prediction models. Moreover, the success of HMS in this study highlights the potential of cognitive-based algorithms in addressing other geotechnical challenges, such as slope stability, foundation settlement, and reservoir leakage.

Looking ahead, future research could build on this study by exploring hybrid models that combine HMS with other optimization techniques to further enhance prediction accuracy and computational efficiency. For example, integrating HMS with machine learning models, such as deep neural networks, could offer a powerful approach to handling large datasets with complex interdependencies. In this hybrid framework, HMS could serve as the optimization component, tuning the parameters of the neural network to achieve optimal performance. Additionally, research could investigate the application of HMS in real-time monitoring systems for groundwater seepage, where continuous data inputs would require the algorithm to adapt dynamically. Such applications would benefit from further developments in adaptive clustering and memory recall, ensuring that HMS remains responsive to changing conditions over time.

To enhance the practical applicability of the HMS algorithm, its integration with real-time data acquisition systems in tunnels can be considered a crucial advancement. Real-time monitoring systems, including piezometers, flow meters, and hydrogeological sensors, can provide continuous input data, such as equivalent permeability, water head, and overburden depth. These parameters can serve as dynamic inputs for the HMS algorithm, enabling it to refine its predictions iteratively. By deploying HMS on edge-computing platforms or centralized servers linked to tunnel monitoring networks, the algorithm can process real-time data streams and adjust predictions to reflect evolving conditions. This integration not only facilitates continuous monitoring but also allows the development of automated alert systems that notify engineers of anomalies, such as sudden increases in seepage rates. Furthermore, incorporating HMS outputs into dashboards or SCADA systems ensures accessible and actionable insights, supporting timely decision-making during both construction and operational phases. Future research should explore optimizing HMS's computational efficiency for real-time applications and testing its reliability under diverse tunnel conditions to fully realize its potential for continuous monitoring.

In conclusion, the Human Mental Search algorithm has demonstrated its potential as a viable and effective tool for groundwater seepage prediction in tunnels. Its cognitive-inspired features, including memory recall, adaptive clustering, and selective adjustment, contribute to its strengths in achieving high accuracy and efficient convergence. While HMS outperformed traditional models like WOA and ANN-PSO in this study, further improvements could enhance its scalability and robustness for broader applications in geotechnical engineering. The success of HMS in this context underscores the value of cognitive-based algorithms in solving complex engineering problems and provides a foundation for future advancements in tunnel seepage prediction, optimization, and risk management.

6. Conclusions

The Human Mental Search (HMS) algorithm has proven to be an effective and innovative approach for predicting groundwater seepage in tunnel environments. Inspired by human cognitive processes, HMS integrates features such as memory recall, adaptive clustering, and selective strategy refinement to optimize complex, nonlinear problems. In the context of tunnel seepage prediction, where variables like equivalent permeability, water head, and overburden depth interact in intricate ways, the HMS algorithm offers a robust solution by balancing exploration and exploitation of the search space. This study demonstrated that HMS achieved superior accuracy and efficiency compared to other methods, such as the Whale Optimization Algorithm (WOA), Artificial Neural Networks optimized by Particle Swarm Optimization (ANN-PSO), and Gene Expression Programming (GEP). The low Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) values achieved by HMS underscore its high level of precision in forecasting seepage rates, validating its applicability in complex geotechnical prediction tasks.

One of the notable strengths of HMS is its rapid convergence. By retaining high-quality solutions from previous iterations and refining them through an adaptive clustering mechanism, HMS significantly reduces the time required to reach an optimal solution. This feature is particularly beneficial for groundwater seepage prediction, where timely and accurate predictions are crucial for mitigating risks associated with tunnel construction and maintenance. Unlike traditional algorithms that may revisit suboptimal solutions or require extensive computational resources, HMS efficiently navigates the solution space, making it a practical choice for large-scale and real-time applications. Furthermore, the cognitive-inspired clustering mechanism within HMS allows it to focus computational resources on the most promising regions of the solution space, enhancing both accuracy and computational efficiency.

The successful application of HMS in this study not only demonstrates its potential for tunnel seepage prediction but also highlights its broader applicability in geotechnical engineering. The adaptability and memory-based optimization capabilities of HMS align well with the demands of complex engineering problems that involve dynamic and uncertain conditions. The insights gained from this research suggest that HMS could be integrated into risk assessment frameworks, providing engineers with a reliable and efficient tool for predicting and managing groundwater seepage. Additionally, the cognitive basis of HMS opens up possibilities for its application in other areas of geotechnical engineering, such as slope stability analysis, foundation settlement prediction, and groundwater management.

However, this study also identified areas where HMS could be improved. While HMS performed well with the dataset used, applying it to larger datasets or real-time monitoring systems may present challenges due to the computational demands of its clustering mechanism. Future research could focus on optimizing this aspect of HMS to enhance its scalability and make it more feasible for real-time applications. Additionally, incorporating diversity-promoting techniques, such as adaptive mutation, could help prevent HMS from converging prematurely in highly complex solution spaces, further improving its robustness and flexibility.

In light of these findings, future research directions include exploring hybrid models that combine HMS with other machine learning and optimization methods. For instance, integrating HMS with neural network architectures could leverage the strengths of both approaches, enabling the model to handle large datasets with intricate relationships more effectively. Moreover, testing HMS in dynamic, real-time monitoring systems would provide valuable insights into its adaptability and potential for continuous data processing, a feature that could prove invaluable for long-term tunnel maintenance and groundwater management.

In conclusion, the Human Mental Search algorithm represents a promising advancement in groundwater seepage prediction. Its cognitive-inspired approach, combined with memory recall and adaptive clustering, makes it a powerful tool for addressing complex engineering challenges. The results of this study provide a solid foundation for further exploration of HMS and similar cognitive-based algorithms, which could revolutionize predictive modeling in geotechnical engineering and beyond. The insights and techniques developed through this research contribute not only to the field of tunnel engineering but also to the broader scope of optimization and predictive analytics in complex, nonlinear environments.

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بهینه‌سازی پیش‌بینی نشت آب زیرزمینی در تونل‌ها با استفاده از الگوریتم جستجوی ذهن انسانی: رویکردی الهام‌گرفته از شناخت برای چالش‌های پیچیده ژئوتکنیکی

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کلمات کلیدی

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چکیده

این مقاله به بررسی کاربرد الگوریتم جستجوی ذهن انسانی (HMS) به‌عنوان یک تکنیک پیشرفته بهینه‌سازی برای پیش‌بینی نشت آب زیرزمینی در محیط‌های تونلی می‌پردازد. نشت آب زیرزمینی به تونل‌ها یک چالش مهم ژئوتکنیکی محسوب می‌شود که می‌تواند به بی‌ثباتی ساختاری، تخریب محیط‌زیست و افزایش هزینه‌های ساخت و بهره‌برداری منجر شود. روش‌های سنتی شامل رویکردهای تحلیلی، عددی و تجربی معمولاً در مواجهه با پیچیدگی‌های جریان آب زیرزمینی، به‌ویژه در شرایط زمین‌شناسی ناهمگن، با مشکلاتی روبرو می‌شوند. اگرچه تکنیک‌های یادگیری ماشین و الگوریتم‌های بهینه‌سازی مانند شبکه‌های عصبی مصنوعی (ANN) و بهینه‌سازی ازدحام ذرات (PSO) دقت پیش‌بینی نشت را افزایش داده‌اند، اما معمولاً نیازمند منابع محاسباتی بالا و داده‌های پیش‌پردازش‌شده هستند. الگوریتم HMS که از فرایندهای شناختی انسانی الهام گرفته است، با بهره‌گیری از بازیابی حافظه، خوشه‌بندی تطبیقی و انتخاب استراتژیک، امکان اصلاح راه‌حل‌ها را به شکلی کارآمد و مؤثر فراهم می‌کند. این مطالعه نشان می‌دهد که HMS در پیش‌بینی نشت آب زیرزمینی با دقت و کارایی محاسباتی قابل توجهی عملکرد بهتری دارد. نتایج نشان می‌دهد که HMS در تمامی معیارهای مورد آزمایش از الگوریتم‌های موجود پیشی می‌گیرد. مقدار R^2 برابر ۰/۹۹۸۸، نشان‌دهنده انطباق تقریباً کامل بین مقادیر پیش‌بینی‌شده و مشاهده‌شده جریان ورودی است. علاوه بر این، HMS میانگین خطای مربعات (MSE) بسیار پایین ۰/۰۰۰۲ و ریشه میانگین مربعات خطا (RMSE) برابر با ۰/۰۱۳۷ را به دست آورده که دقت بالای آن در کاهش خطاهای پیش‌بینی را نشان می‌دهد. در مقایسه، الگوریتم بهینه‌سازی نهنگ (WOA) مقدار R^2 برابر با ۰/۹۹۵۱، MSE برابر با ۶/۶۵ و RMSE برابر با ۱/۷۱ را به دست آورده است، درحالی‌که برنامه‌ریزی ژنتیک (GEP) و ANN-PSO خطاهای بیشتری را نشان داده‌اند. علاوه بر این، HMS مقدار واریانس محاسبه‌شده (VAF) برابر با ۹۹/۸۸٪ و میانگین خطای مطلق (MAE) برابر با ۰/۰۰۴۱ را ثبت کرده است که توانایی آن را در ارائه پیش‌بینی‌های بسیار قابل‌اعتماد با حداقل خطا تأیید می‌کند. این نتایج برجسته برتری الگوریتم HMS را در بهینه‌سازی پیش‌بینی نشت آب زیرزمینی نشان می‌دهد و آن را به ابزاری بسیار مؤثر و کارآمد برای کاربردهای مهندسی ژئوتکنیک تبدیل می‌کند. علاوه بر بهبود مدل‌سازی پیش‌بینی برای نشت در تونل‌ها، HMS پتانسیل قابل‌توجهی برای نظارت بلادرنگ بر آب زیرزمینی و سایر کاربردهای گسترده ژئوتکنیکی دارد.

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