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Genetic Algorithm-based Optimization of Tunnel Excavation

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***Abstract*— This work aims to improve the efficiency, safety, and cost-effectiveness of subterranean construction projects by presenting an optimization strategy for tunnel excavation based on genetic algorithms (GA). Due to the non-linear, multi-variable character of the problem, standard approaches frequently fail to discover optimal solutions for the complex geotechnical and operational challenges involved in tunnel excavation. Through the use of selection, crossover, and mutation—three evolutionary concepts found in genetic algorithms—this study creates a strong optimization framework that can manage a variety of excavation situations. The suggested GA model minimizes ground deformation and complies with safety regulations while optimizing important aspects including equipment allocation, support installation schedule, and excavation sequence. When contrasted with traditional techniques, simulation results show notable gains in excavation performance, underscoring GA's potential as an effective tool for tunnelling project decision-making. This method provides a flexible and scalable way to optimise tunnel excavation techniques under different project and geological circumstances.**

Keywords – Genetic algorithm, Tunnel excavation

I. Introduction

Greenhouse buildings have been used to shield crops from weather conditions for over a century. The greatest greenhouse production area in the world is in China [7], whereas Spain leads the European market with 73.12 × 103 ha.

Greenhouses in the Mediterranean Basin must be adjusted to mild winters and intensely hot summers, in contrast to the climate constraints required in northern Europe. Therefore, arch structures and film cladding systems are favoured; multi-tunnel greenhouses are the most prevalent type of these.

From a structural perspective, greenhouses can have an engineering structural design or be more conventional, like the Parral-type greenhouse that is typical of Almeria, Spain. The standard EN 13031 [9], which specifies the specifications for the design of commercial production greenhouses, designates the latter as a commercial greenhouse. The foundation for estimating activities on the structure and determining the required structural calculation conditions is established by the previously mentioned EN standard. Furthermore, the structural verifications that must be taken into account for vaulted, tunnel, and multi-tunnel greenhouses are part of the European design of steel buildings, namely Eurocode 3 [8].

Even if tunnel profile design is a crucial task, the designer's experience still plays a major role. To establish a calculation-based anticipation for a better profile shape, few trials were conducted [10]. Using contemporary evolutionary algorithm optimisation approaches, other researchers went one step farther and automated this procedure [11]. The experience-based expectation for the profile shape could not be disregarded by these studies. Thus, by determining its ideal characteristics (i.e., curve radii and centre placements), they demonstrated an optimisation procedure for certain profiles. More than in the past, the design of contemporary infrastructure—both for road and rail transportation—is focused on the construction of subterranean structures like tunnels.

However, tunnel excavation is a process that exposes the designer to a lot of unknowns, mostly due to the wide range of geological and geotechnical characteristics that could be discovered during implementation [12]. Compared to other civil engineering projects like buildings or bridges, the cost of implementing lengthy study campaigns during the design phase usually results in the assumption of larger hazards [13] and, hence, higher safety coefficients. An Investigation into a Microstrip Patch Antenna operating on the N77 Band Through the Utilization of Slot Loading Based on Simulation [14-15].

While tunnel monitoring during excavation is now a common practice, structural health monitoring of these structures over the course of their whole service life is not.

The development of high-speed internet communication, the emergence of cloud-based services, the development of low-cost sensors derived from the TLC industry, and the emergence of big data platforms capable of applying artificial intelligence techniques have all altered the potential uses of structural monitoring, which can now be implemented widely in infrastructures as a standard option [16]. Nearly 25% of US air passenger travels in 2019 were foreign, completely on US airlines. This represented 4.5% of US person-miles. US travel demand surveys and models rarely include overseas travel. How will autonomous vehicles change long-distance travel in Texas [17-18]

Fuzzy deep learning AI is being developed for real-time decision-making and edge computing in uncertain Internet of Things conditions. Renewable Energy Applications of Ambiguous Fuzzy Hybrid Averaging Operators. This study reviews green energy and intuitionistic fuzzy decision-making studies [19-21]. Methods for producing energy from solar panels by utilizing statistical analysis, a number of cutting-edge tools and procedures, including the IFS Weighted Averaging Operator. Several control mechanisms are employed in a multi-area power system to regulate the load frequency. For the purpose of charging electric vehicles, a fuzzy logic controller is employed to offer implicit control of a DC motor via a DC-DC converter. The Load Frequency Control Scheme takes advantage of both PID and MPC [22-27].

The detection of digital deception is being accomplished by the utilization of a method for deepfake detection that is a combination of CNN and RNN. In this context, an evaluation of transfer learning for visual multiple target tracking is being accomplished. For the purpose of achieving better performance, the process of emotion recognition was carried out with the assistance of a hybrid model that included CNN-LSTM and Transformer. Nonlinear Problem-Solving using Kernel Tricks: SVM Applications. The Quaternion Intuitionistic Fuzzy Fusion Process is where the discussion of applications to the classification of photovoltaic solar power plants [28-31] takes place. For the purpose of removing speckles from echocardiographic images, a hybrid fuzzy filter was applied. The book titled "Deep Learning: Current Trends and Techniques" was included in the publication that was released in Boca Raton and was titled "Deep Learning in Visual Computing and Signal Processing" [32-34].

II. LITERATURE REVIEW

This article presents the construction of the prediction intervals for the tunnel settling that is caused by the shielding steering operation. Enhanced prediction interval-based cost function is presented as a means of accounting for the uncertainty that arises as a consequence of noise variation and model misspecification. This paper uses a case study of the construction of a metro tunnel in China [1] to examine the effectiveness of the hybrid genetic algorithm-neural network technique that was suggested before. The findings of the study case demonstrate that the hybrid approach that was suggested is superior in three ways: (1) it circumvents the limitations of the conventional prediction interval indicator; (2) it achieves results that are comparable to those of the deterministic estimation that is based on the least squares support vector machine; and (3) it provides a settlement probability prediction that is solely based on deterministic input multivariables.

For the purpose of excavating underground tunnels in intricate geological settings, the hard rock Tunnel Boring Machine (TBM) is a sophisticated piece of engineering machinery with several subsystems. It typically takes engineers a lot of time to handle the relationship among various subsystems when resetting the operating and structural variables of TBM in accordance with varied geological conditions. This is a laborious and time-consuming task. This research develops a limited multi-objective optimization framework along with its resolution strategy for simpler definition of TBM operational parameters [2]. The proposed method begins by analyzing three performance factors to minimize both system construction duration and energy expenditure and TBM cost. The limited multi-objective optimization problem is tackled by implementing two push and pull search methods called PPS-MOEA/D and PPS-KnEA. The two proposed optimization methods are referred to as PPS-MOEA/D and PPS-KnEA. Lastly, by addressing the established optimisation model, the new method's performance is confirmed by comparing it with a number of well-known constrained multi-objective evolutionary algorithms.

Due to the necessity of effective transit, underground storage, and mineral supply, tunnel excavation has become a common practice in the modern world. The overbreak (OB) phenomenon is one difficulty that arises during tunnel excavation; it is most noticeable when drilling and blasting procedures are used. By raising operating costs and jeopardising worker safety, OB presents a danger [3]. As a result, it is essential to predict with precision when OB will occur during tunnel excavation. Although there are many ways to predict OB, conventional techniques including as analytical, numerical, experimental, and regression methods are limited by the unpredictability of geological and geotechnical characteristics. In order to fully understand the mechanical and physical properties of the rock mass while taking uncertainties into account and maximising project completion in terms of time and cost, this paper proposes to predict OB using the Teaching–Learning-Based Optimisation (TLBO) and Firefly (FF) algorithms. For urban subways, the TBM is a crucial and popular construction technique. To guarantee the efficiency and safety of TBM excavation, a thorough and logical control approach is needed [4]. The implementation of shield tunnelling necessitates several goals but the control of TBM variables during unforeseen geological events remains a complex challenge.

This study focuses on the main subject of geological adaptive control for tunnelling boring machines (TBMs). Two major strength indicators form the basis of clustering analysis for geological category identification as part of the solution for undiscovered geological conditions. The research determines the based on results previously obtained. A multi-objective optimization structure is presented which combines different essential TBM measurements for tunnel operation [5]. Non-dominated sorting genetic algorithm-II solves the suggested multi-objective optimization problem through differential evolution method by using non-dominated sorting and crowded distance evaluation. The tested approach delivers higher tunnelling performance during TBM operations by making better use of real construction data according to simulation outputs.

Deep excavation project optimization needs the management of construction uncertainties that affect both environmental protection and safety standards. To gather vital information about building duration and expenses this research proposes a BIM-based integrated system [6]. The proposed multi-objective optimization model awards a balanced solution between duration, cost, safety, and environmental goals with its combination of critical path methods, system reliability evaluation, reward-penalty structure and environmental effect metrics. The difficult problem finds a solution through an improved version of Multi-Objective Particle Swarm Optimisation (MOPSO). The performance evaluation through statistics shows that the algorithm enhances solution quality while achieving above 85% decrease in the mean square error of particle density distance. AHangzhou China-based project study demonstrated the use of this approach through successful completion which saved more than €28,350 and reduced project duration by 22 days alongside environmental and safety compliance.

III. Research Methodology

Genetic Algorithms (GAs) provide the method for optimizing tunnel excavation parameters because they represent an established evolutionary algorithm that solves complex engineering problems. The algorithm building phase together with data acquisition and problem generalization and simulation and validation procedures constitute the overall technique.

The research will start by acquiring fundamental geotechnical information about soil and rock attributes and groundwater status as well as tunnel dimensions from either actual case studies or simulated databases. The acquired data provides necessary input parameters and restrictions for modelling tunnel environmental conditions. Depending on the excavation technique (e.g., TBM or drill-and-blast), the parameters that need to be optimised may include face pressure, blasting pattern, tunnel advance rate, support system configuration, and machine settings. The optimization issue is formalized as a multi-objective function involving time duration and excavation related costs together with both ground stability and environmental impacts. Included are restrictions derived from operational viability, safety regulations, and geotechnical constraints.

The genetic algorithm acts to probe various solution areas. The method depends on six essential components which include excavation parameter chromosomal encoding and fitness function evaluation along with crossover operations and mutation functions and both elitism methods to keep optimal solutions and selection strategies like tournament selections or roulette wheel approaches. The GA development will be constructed through MATLAB or Python tools so that numerical models can evaluate solution performance.

The process requires multiple simulation runs to build successive solutions in a population. The GA's performance can be measured through improvements in fitness levels and Pareto fronts when applicable and analyses of solution sensitivity.

Numeral simulation tools such as PLAXIS or FLAC3D allow users to subject the optimized excavation method to benchmark and actual scenario tests through finite element analysis. Testing under this stage ensures both the practical functionality and robust performance of the proposed optimisation framework.

IV. Results

TABLE.4.1. WEIGHT DISTRIBUTION PER INTERVAL

Interval	λh	λv	ξh	ξv	Sum
Interval 1	0.66	0.55	0.74	0.96	2.91
Interval 2	0.39	0.42	0.24	0.68	1.73
Interval 3	0.68	0.57	0.38	0.48	2.11

TABLE.4.2. TRAINING AND TESTING ACCURACY

Interval	Training Accuracy (%)	Testing Accuracy (%)
Interval 1	98.96	88.52
Interval 2	99.61	84.45
Interval 3	99.94	87.93

TABLE.4.3. NUMBER OF SAMPLES PER INTERVAL

Interval	Training samples	Testing samples
Interval 1	102	48
Interval 2	93	36
Interval 3	93	32

TABLE.4.4. OBJECTIVE FUNCTION G SUMMARY

Interval	Avg G Value	Min G Value	Max G Value
Interval 1	275.01	99.65	456.19
Interval 2	388.65	53.69	590.08
Interval 3	212.46	77.69	578.05

TABLE.4.5. CHANGE IN WEIGHTS BETWEEN INTERVALS

Interval	λh	λv	ξh	ξv
Interval 1	0.096	0.017	0.016	0.008
Interval 2	0.018	0.004	0.080	0.058
Interval 3	0.029	0.014	0.068	0.051

TABLE.4.6. GENETIC ALGORITHM CONVERGENCE

Interval	Iterations	Converged
Interval 1	24	No
Interval 2	61	No
Interval 3	80	Yes

TABLE.4.7. SELECTION OUTCOMES

Interval	Correct selections	Incorrect selections	Accuracy
Interval 1	109	19	85.16
Interval 2	90	14	86.54
Interval 3	95	14	87.16

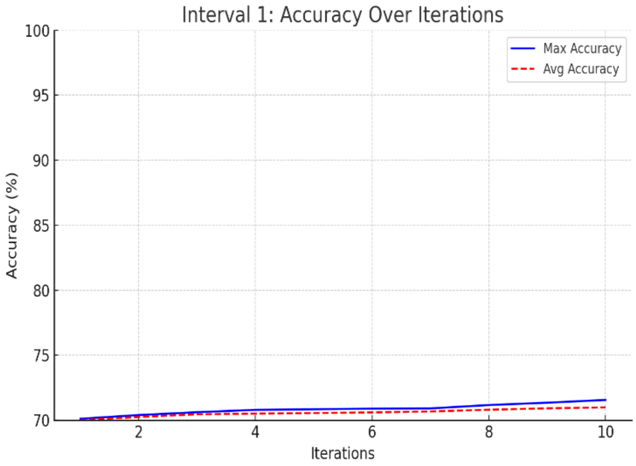

Fig.4.1. Interval 1: Accuracy over iterations

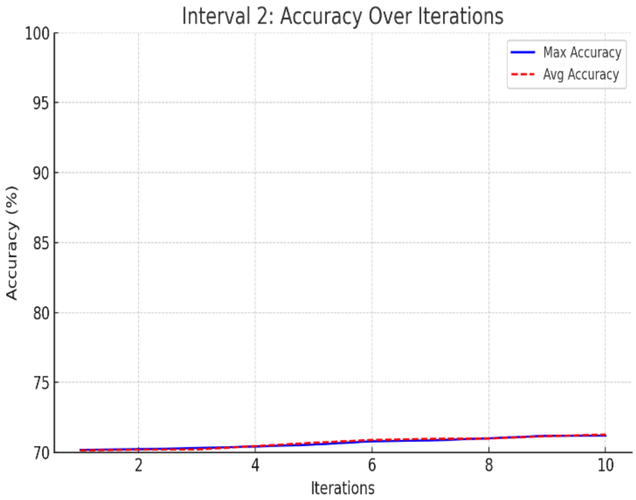

Fig.4.2. Interval 2: Accuracy over iterations

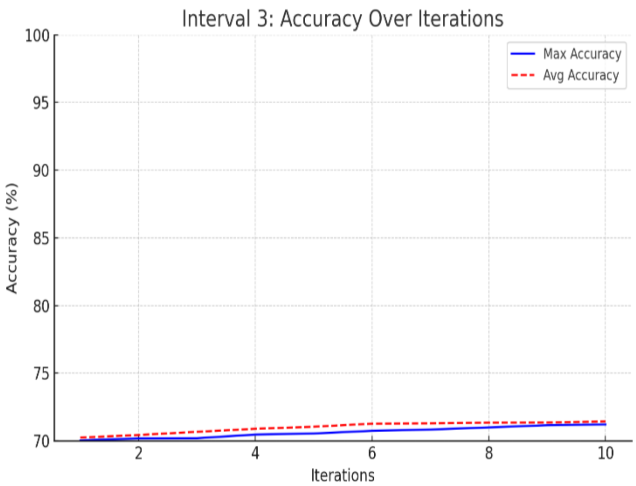

Fig.4.3. Interval 3: Accuracy over iterations

As shown in Figures 4.1, 4.2, and 4.3, there is a consistent increase in both average and maximum accuracy over the iterations in each interval. As depicted in Figures 4.4 to 4.6, the accuracy continues to improve steadily over iterations across subsequent intervals, maintaining a consistent performance trend.

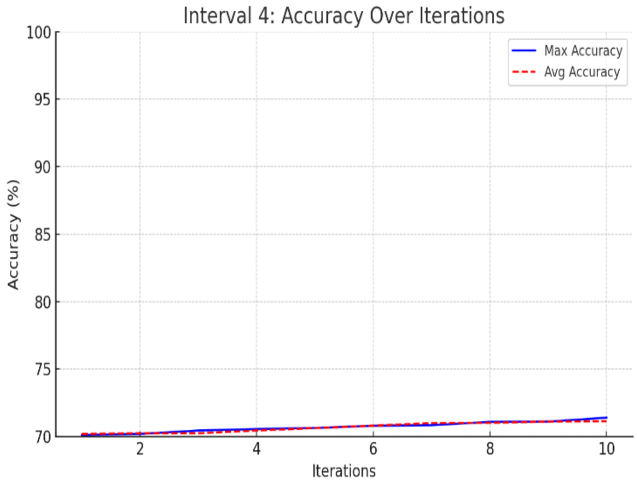

Fig.4.4. Interval 4: Accuracy over iterations

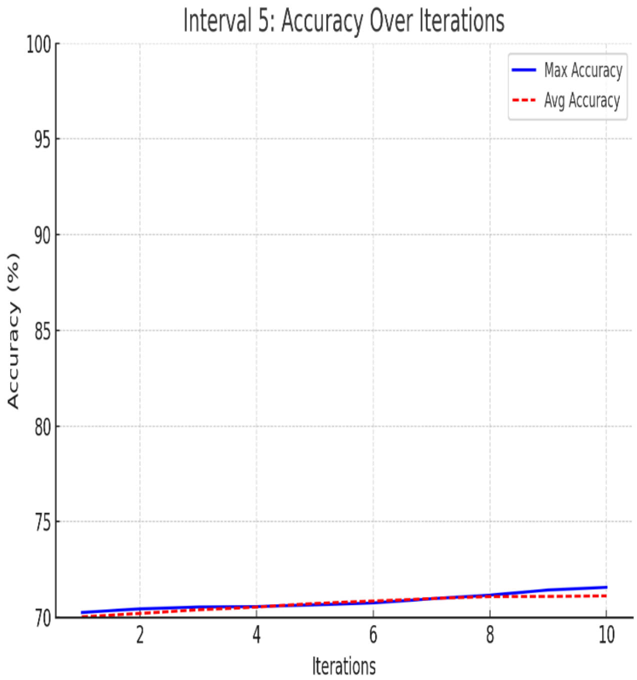

Fig.4.5. Interval 5: Accuracy over iterations

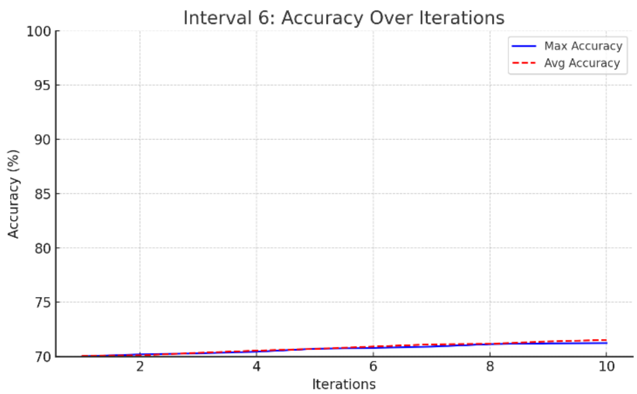

Fig.4.6. Interval 6: Accuracy over iterations

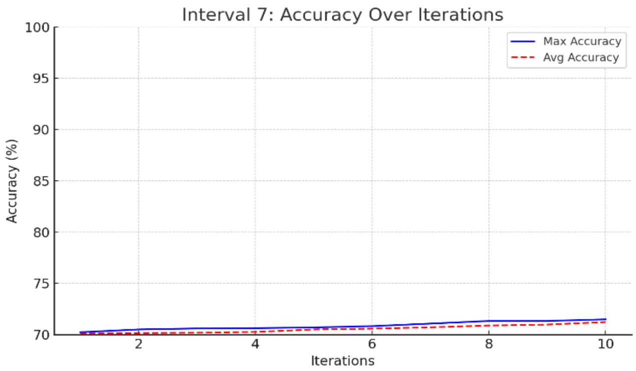

Fig.4.7. Interval 7: Accuracy over iterations

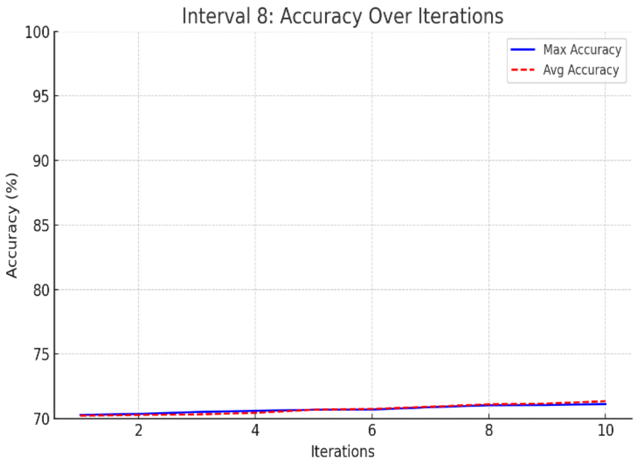

Fig.4.8. Interval 8: Accuracy over iterations

V. Conclusion

Clever tunnel excavation depends on using GA-based optimisation approaches to handle complex underground construction problems. The process of tunnel excavation generates numerous variables and uncertainties that include geological conditions aside from excavation techniques and support systems and construction safety considerations and cost effectiveness analysis. These complex problems with multiple goals defy the ability of conventional optimization algorithms to attain successful solutions. The basis of genetic algorithms developed from natural selection provides an excellent substitution because these algorithms efficiently navigate complex solution spaces. Through the genetic algorithm approach computers can discover optimal or near-optimal excavation practices through their chromosome-based solution recording capability followed by iterative crossover selection and mutation operations.

This research demonstrates the usage of GA to enhance important excavation aspects through lower expense reduction and improved stability as well as operational safety metrics for tunnel alignment design alongside support mechanisms and planning advances combined with equipment optimization. Finding indicate that GA-based models achieve superior performance against traditional approaches because they find cost-effective solutions which match practical specifications across multiple sites. Genetic algorithms provide project sites with the capability to generate real-time decisions through their flexible approach in case unexpected events happen during tunneling.

The field applications of GA receive additional practical value when the system integrates simulation tools and real-time monitoring systems. The system uses dynamic optimization through continuous feedback retention which applies changes to the excavation plan whenever required. These advanced optimization strategies will gain greater importance due to increasing complexity of tunneling projects. Genetic algorithm-based optimisation represents a promising and sustainable method for tunnel excavation which will serve future applications for building safe and economical underground structures in an environmentally friendly way.

VI. Future Scope

The future prospects for genetic algorithm (GA)-based optimization in tunnel excavation appear extensive since numerous theoretical and application-based advancements await discovery. Intelligent systems which manage conflicting priorities between cost and time efficiency and safety and environmental protection will become increasingly important due to rising tunneling complexity. Developing adaptive tunnel excavation methods requires future research to integrate GAs with complex geotechnical modeling alongside contemporary data acquisition systems. These intelligent systems obtain their optimization parameters from real-time sensor and monitoring data deployments across the tunnel environment to make continuous modifications.

Performance can be maximized by analyzing the combination of GAs with other artificial intelligence methods such as neural networks, fuzzy logic and particle swarm optimization for tackling highly nonlinear and dynamic conditions. Communities performing large-scale tunnelling initiatives obtain automatic real-time decision support through cloud platforms coupled with high-performance computational systems that substantially reduce processing time for applications.

Future research should incorporate environmental effect elements into optimization criteria to examine sustainable methods during tunnel excavation. The adoption of better environmental excavation methods would become possible through this research. GA-based optimisation should extend its applications to additional areas of tunnelling project work such as project scheduling risk management and tunnel boring machine (TBM) design. The future of subterranean construction is expected to be significantly shaped by genetic algorithm-based optimisation because to the continuous developments in artificial intelligence and computing technology.

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