Optimisation of Excavation Design Using Artificial Intelligence (AI)

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Supervisor: Dr. Abbas Haider

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DEDICATION

Optimisation of Excavation Design Using Artificial Intelligence (AI)

This research work is dedicated to the promotion of artificial intelligence in the field of geotechnical engineering.

ABSTRACT

Optimisation of Excavation Design Using Artificial Intelligence (AI)

Reinforcement learning (RL), considered a section of machine learning, incorporating human-level control, is attracting considerable interests in many fields. Currently, there is a transition from academia to real-world prototypes, with RL-examples like the optimization of a manufacturing process, for real-time steering of hydrocarbon drilling, in optimization of power grids and control systems in general, for UAVs, and in robotics and other autonomous vehicles becoming common. However, there is very little published application of RL to geotechnics in general. Therefore, in this study will present a novel RL-based framework for construction process optimization whereby displacements would be optimized by application of Hoeke-Brown criterion and GSI system to excavation design. Such models can act as decision support for the geotechnical engineer, engineering geologist, geotechnician etc. (design choices, progress-planning) and in the long run such models work towards full automation in underground construction. Hence, the model is one of the first attempt to automate decisions made by the geotechnician in excavation design for underground construction.

Keywords: Reinforcement Learning; Artificial Intelligence; Excavation Design; Tunnels; Geological Strength Index; DQN.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
RL	Reinforcement Learning
TBM	Tunnel Boring Machine
DQN	Deep Q-Learning Network
PSO	Particle Swarm Optimization
ELM	Extreme Learning Machine
WF	Walk Forward
OLS	Ordinary Least Squares
GSI	Geological Strength Index
MDP	Markov Decision Process
ANN	Artificial Neural Networks
NATM	New Austrian Tunnelling Method

CHAPTER 1: INTRODUCTION

Artificial Intelligence has gained wide traction in daily-use and is now being considered an integral part of transforming the way humans live, work and interact with the digital world. Its impact on human lives is profound, with its vast use in the fields of healthcare, manufacturing, retail, finance, sustainability, human resources, security and social media, to name a few.

1.1 Artificial Intelligence (AI) in Construction Automation

Artificial Intelligence (AI) is revolutionizing how humans perceive and relate to the construction industry. AI is incorporating advanced technological innovations into construction and building processes. It is refining, enhancing and simplifying how structures are buildings were once designed, built and maintained. This is proliferating major benefits in the industry, which has led substantial updates and progress safety, accuracy, precision, performance, economy and productivity. This profound impact on construction industry can be categorized into many categories

1.1.1 Efficiently Tackling Complex Construction Projects

With construction automation increasingly being categorized by AI, sophisticated and challenging construction projects can now be dealt with enormous speed and predictability, simultaneously catering to the difficulties of material and labor scarcities, while considerably increasing output and performance. It was noted (*Sacks & Pikas, 2013*) that these breakthroughs are reinventing how humans perceive the construction industry.

1.1.2 Improving Safety in Construction Projects

Autonomous systems are growingly making headways in making construction projects safer for the clients, customers and the intermediaries, alike. These autonomous systems are risingly being assigned hazardous tasks, involving many risks and hazards, that would otherwise have to be performed by human workers. This shift to give more independence to AI in the industry is creating safer environments to work more securely and harmlessly (*Bock & Linner, 2015*).

1.1.3 Resources and Waste Reduction

As AI makes the construction processes more streamlined, reduction in materials is leading to significant declines in costs spread over time (*Akinradewo et al., 2021*). This is how reductions in resources is bringing in economies of scale in construction processes.

1.1.4 High Precision in Measurements

Advances in technologies are making sure measurements in construction industry are accurate to the best possible effort, reducing and minimizing oversights and misjudgements, scalping the need of cost-intensive reworks (*Josephson P E et. al., 1999*). Hence, project quality of construction results are enhanced.

Figure 1 shows the opportunities, trends, difficulties and open research challenges of AI in construction industry.

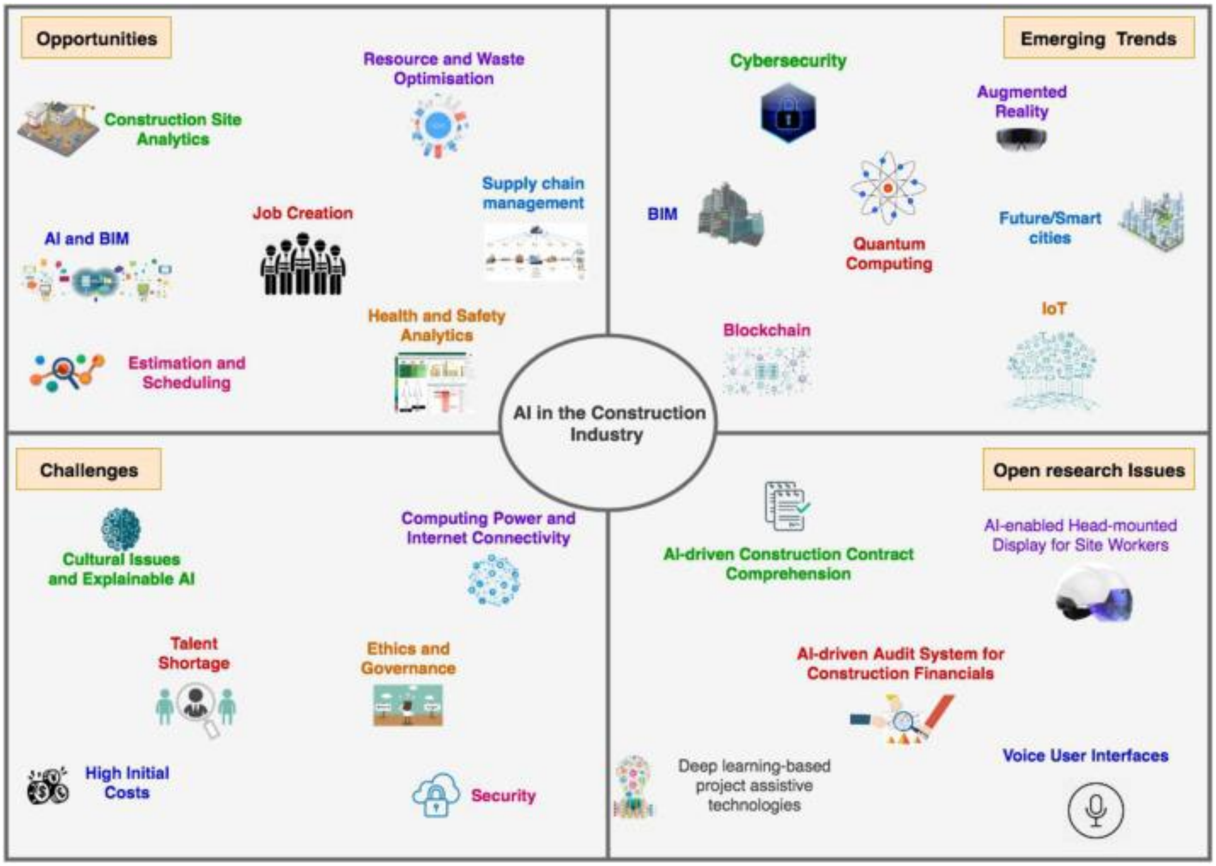

Figure 1. *Opportunities, trends, difficulties and open research issues of AI in construction industry*

1.2 Artificial Intelligence (AI) in Tunnelling

Artificial Intelligence (AI) is also playing a crucial role in optimization of tunnelling operations. Not only are the productivity and performance of tunnelling procedures upgraded, but the overall accuracy of underground construction processes enhanced.

For instance, managing and catering to geological variability has been a complex procedure that has been a stiff task in underground construction. AI processes are now increasingly being utilized to manage these challenges (*Ebrahim and Ewan 2021*).

Secondly, system complexities in construction projects are being simplified by Artificial Intelligence. More accurate decision-making is being carried out, allowing greater level of confidence in controlling intricacies of tunnelling.

Next, budgeting and cost management, is also contributing to a substantial influence on construction procedures (*Cheng 2009*). Streamlining of resource allocation and fiscal planning helps to keep the construction projects meeting expectations financially.

Figure 2 shows the main research clusters of AI in construction industry

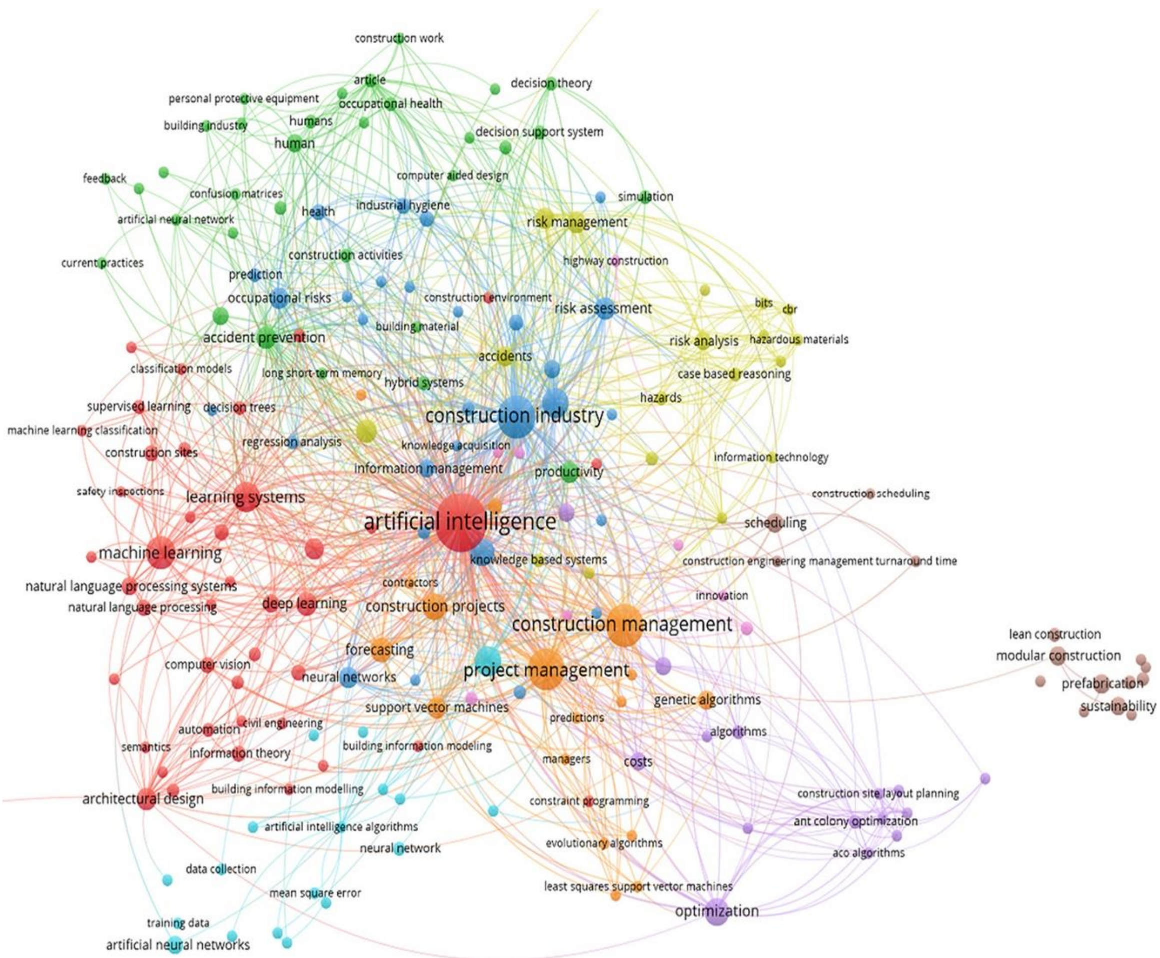

Figure 2. *Main research clusters of Artificial Intelligence in construction industry*

Some of the other key application of Artificial Intelligence in tunnelling include:

1.2.1 Optimization of Drill and Blast Criteria

While proactively adjusting the drill and blast specifications based on real-time environment, AI algorithms can also be used to optimize factors such as timing and quality of explosive materials. This has added to facilitating effectiveness and efficiency of drilling and blasting performance. (*Gao, Zhang, and Liu 2022; Zhou, Chen, and Yang 2019*)

1.2.2 Analyses of Geological Conditions

Another major impact that AI is making on tunnelling operations is the provision of precise prediction in handling ground condition challenges. (*Lin, Yang, and Zhang, 2018*)

1.2.3 Mitigating Operational Complexities

As AI optimizes resource allocation, project supervision is improved by refining project timelines and saving costs. (*Sun and Liu, 2021*)

1.2.4 Scheduling and Project Management

Prospective cost, budget & time overruns are increasingly being identified by AI algorithms, helping to manage scheduling and project management complexities in construction projects. (*Zheng, Chen, and Guo, 2020*)

1.3 Introduction to Reinforcement Learning (RL)

Reinforcement Learning (RL) is a growingly popular section of Machine Learning, in which a software agent learns to maximize preferred reward, by interacting with the environment to take actions (*Sutton and Barto, 2018*). Multiple variety of feedbacks regulate the methodology of an RL-loop.

Figure 3. shows the difference between supervised, unsupervised and reinforcement learning. It can be seen from Figure 3 that supervised learning uses inputs to trace functions to targeted output. However, in reinforcement learning, no target outputs are required; only inputs are fed in.

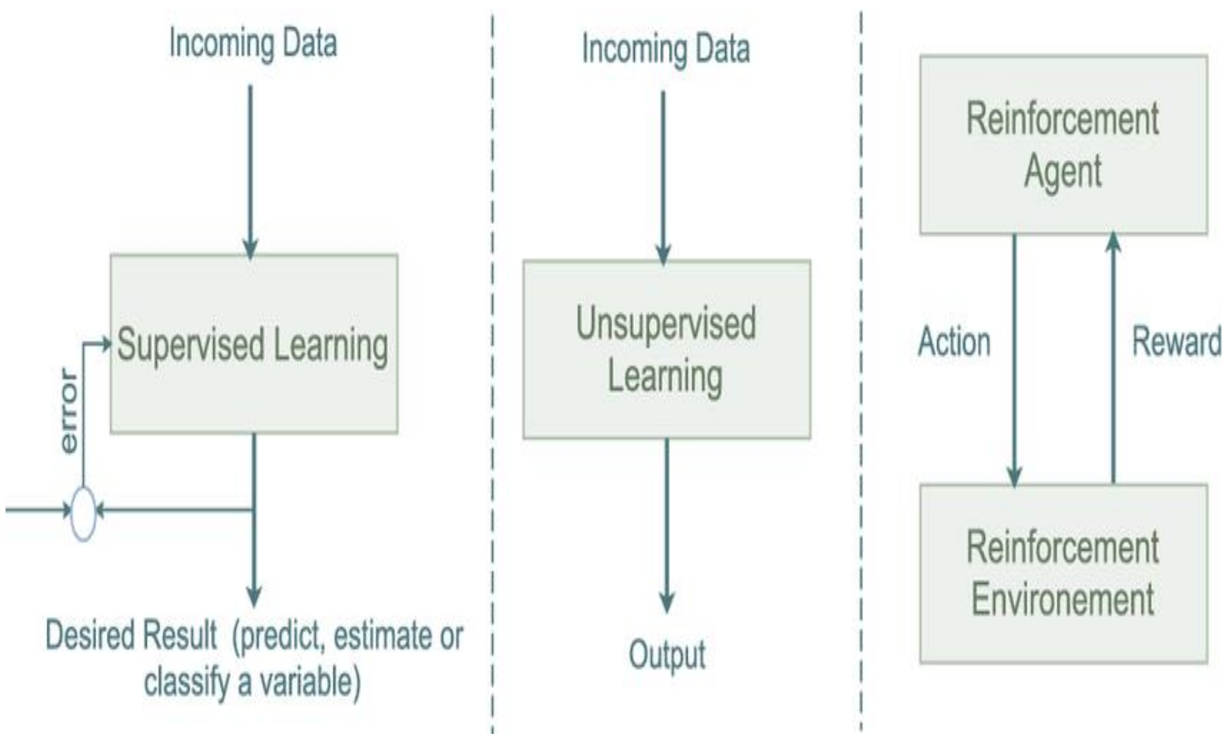

Figure 3. *Difference between Supervised, Unsupervised and Reinforcement Leaning (Fourati et al. 2021)*

Nonetheless, the overarching aim of RL algorithm is achieving balance between Exploration, that is learning on fresh data elements, and Exploitation, that is utilizing data captured in exploration. Framework for an RL algorithm is shown in Figure 4.

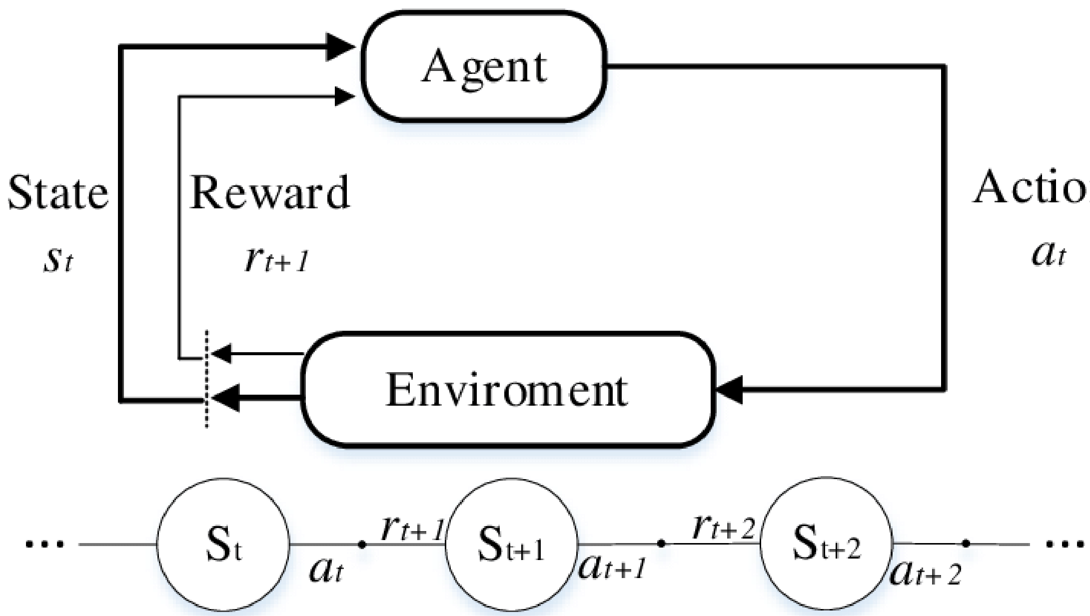

Figure 4. *Basic framework for a Reinforcement Learning algorithm*

It can be observed in Figure 4, that a Reinforcement Learning problem has three main constituents:

1.3.1 Agent

Agent is the constituent which takes actions in the state it is currently in.

1.3.2 Environment

Environment reacts to actions committed by the agent, given new input to it at each step.

1.3.3 Reward

Reward is the response given by the environment, measuring achievement of actions committed by agent.

1.3.4 Other Important Components of Reinforcement Learning Algorithm

Some other important components of an RL algorithm are as follows:

1.3.4.1 State

State is the at-present condition exhibited by the environment.

1.3.4.2 Action

Choices or the possible decisions that the agent can take which in turn influence the environment.

1.3.4.3 Policy

Rules that govern the decisions taken by the agent.

1.3.4.4 Value Function

It estimates the prospective reward / incentive for actions or states, which in effect guide the decisions taken by the agent.

CHAPTER 2: LITERATURE REVIEW

The research work relevant to the project and limitations which highlight the gaps in these research works will be covered in this Chapter. Although, these research papers supplement our comprehension of advances in studies carried out in geotechnical engineering, specifically tunnelling operations, but the research also highlights the opportunities wherein further investigations have been carried out. The below mentioned research studies are utilized to justify the gaps, which necessitate the objectives and aims to carry out research work on optimization of excavation design using artificial intelligence (AI).

2.1 Jia, G. et al., 2023

This study aims to investigate medium-stiff and stiff soils for unsupported excavations of 9m, where adjacent structures are absent. The methodology of the research work is based on predictive modelling (data-based) to classify geology and manage Tunnel Boring Machine (TBM) attitude. As a result of this study, precision and effectiveness of TBM in real-time tunnelling is enhanced. However, the need for adaption to live and variable conditions.

2.2 Ren-Peng Chen et al., 2020

The objective of this research paper is to combine RL based Deep Q-Learning (DQN) and Particle Swarm Optimization (PSO), enhancing Extreme Learning Machine (ELM) anchored settlement forecasting model induced from tunnelling operations. Distinguished improvements are observed over proven (analytical, numerical and empirical) models for enhancing precision and computation cost, nonetheless, further research is required to establish its usefulness under variable tunnelling environments.

2.3 Huang, Z. et al., 2023

The third research focuses on optimization of design of adaptive ground support, using Reinforcement Learning. Performance improvement is notable across varied environments. However, the model depends heavily on real-time information and data.

2.4 Hang-Lo, L. et al., 2021

The investigation explores creating a real-time prediction forecasting methodology for metrics of TBM operations, and utilizes an ARIMAX model, to fulfill this objective. To execute Walk Forward (WF) forecasting, the ARIMAX model is intermixed with variable geological specifications, and it has been found that the ARIMAX is significantly more impressive that Ordinary Least Squares (OLS) in transient TBM thrust projections in less than or equal to 8 rings. However, these predictions are only served to short-term, and do not cater to long-term forecasting.

CHAPTER 3: PROBLEM STATEMENT

To relate this research with the investigations highlighted in previous Chapter, this section will build-up problem definitions.

3.1 Produce Unplanned Geological Data for Effective RL Modelling

Random Walk will be used to produce random geological data, to address the shortcomings of the first paper, which called for developing the necessity to create adaptable models for varied conditions. As a result, sturdier RL-model will be developed to adapt to a multitude of geological environments.

3.2 Translating Geological Strength Index (GSI) Metrics

Data will be normalized and mapped to GSI values. This will address the shortcomings for second research paper, which necessitated the need for adaptation across multiple situations. As a result, a more accurate geological profile will be developed, when real-life geological strength divisions are streamlined with data that is simulated.

3.3 Upgrading Model of Tunnel

When GSI values will be used to upgrade the tunnel profile, computation intensity and dependency on real-time data, as pointed out in the third paper, will be tackled. Necessity for recalibration again and again may be foregone, resultantly, as present geological conditions are reflected.

3.4 Visualization of Results

The data simulated in the problem will be replicated to reflect actual tunnel profile and random walk information. Hence, inclusive outlook of geological understanding may be used to enhance and improve decision-making in long-term.

CHAPTER 4: OBJECTIVES

This Chapter will define the aims of the research that is carried out. The research has been divided into three main parts, which will define the objectives of the investigation.

4.1 Objective 1: Optimization of Excavation Design

This research study will aim to optimize the excavation design. This will be the primary objective of the thesis. Machine Learning techniques, specifically Reinforcement Learning, shall be used to refine excavation design. By integrating GSI empirical design approach into the program, through normalization of random WF, this data will be transformed to simulate geological site conditions into representative rock types.

4.2 Objective 2: Simulating Excavation Series

The second objective of this study is to the usual sequence of excavation and tunnelling, and frame it as an RL-loop. In this reinforcement learning algorithm, the model will self-sufficiently learn optimal strategies by the help of feedback iteratively. This will, in turn, tend to the necessity of creating, precise models, that will adapt to the environment on its own.

4.3 Objective 3: Reducing Cost Time and Contractual Intricacies

Lastly, by using reinforcement learning AI technique, along with GSI design approach, the next goal of this study is to minimize the liabilities during tunnelling and excavation construction processes, which result in extensive delays and cost overruns. In essence, the program will not only improve decision-making on part of geotechnical engineering and contract administration teams, but also provide greater control in efficiently dealing with all the conflicts that may arise during construction processes.

CHAPTER 5: METHODOLOGY

In this Chapter the focus of the research will be on the methodology that is adopted to execute this research. As noted in the previous Chapters, the interdisciplinary nature of this project, at the crossroads of digital technologies and civil engineering, a comprehensive programming the RL-loop and, subsequently, training the agent has been adopted in an extremely delicate way. This has ensured that the results obtained (to be discussed in Chapter 6) are accurate and precise to the best possible degree.

The methodology will first discuss the typical drill / blast procedure, followed by simplifications made in the Loop, the components and decision-making policy adopted, simulation criteria, and then, finally, the training of the reinforcement learning program made.

5.1 Typical Drill and Blast Procedure

In a typical drill and blast procedure, several sequential, iterative and cyclical procedures are followed which make up the bulk of the tunnel construction process. This typical cycle in presented in Figure 4. It can be seen in Figure 4, that the process usually consists of various iterative processes: blasting, mucking and, followed by, installing of supports, performance assessment and refinement of design. Naturally, this process exists as a closed loop, which fulfills the criteria of reinforcement learning technique and may be modeled efficiently according to this procedure.

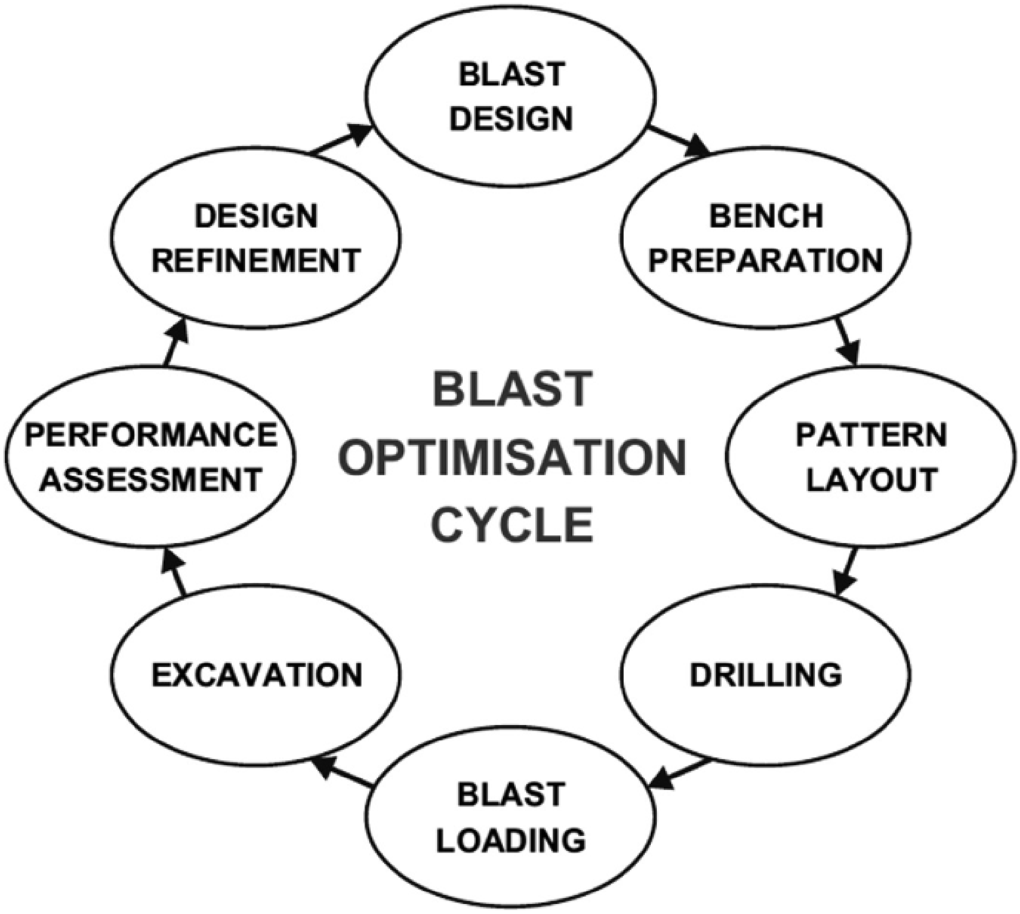

Figure 5. *Typical Drill / Blast Cycle for Construction of Tunnels.*

The loop has been found to be of significant importance, particularly in conventional tunneling construction process This procedure has also been verified by International Tunnelling Association in 2009 (*ITA, 2009*). Hence, the process of decision-making can be optimized by following this procedure, step by step, leading to increase in safety and productivity

5.2 Decision-Making Process in RL-Loop

Excavation sequence is modeled as a simplified reinforcement learning loop, to represent the sequence of excavation outlined in the previous section. The decision-making loop is characterized in Figure 6 below:

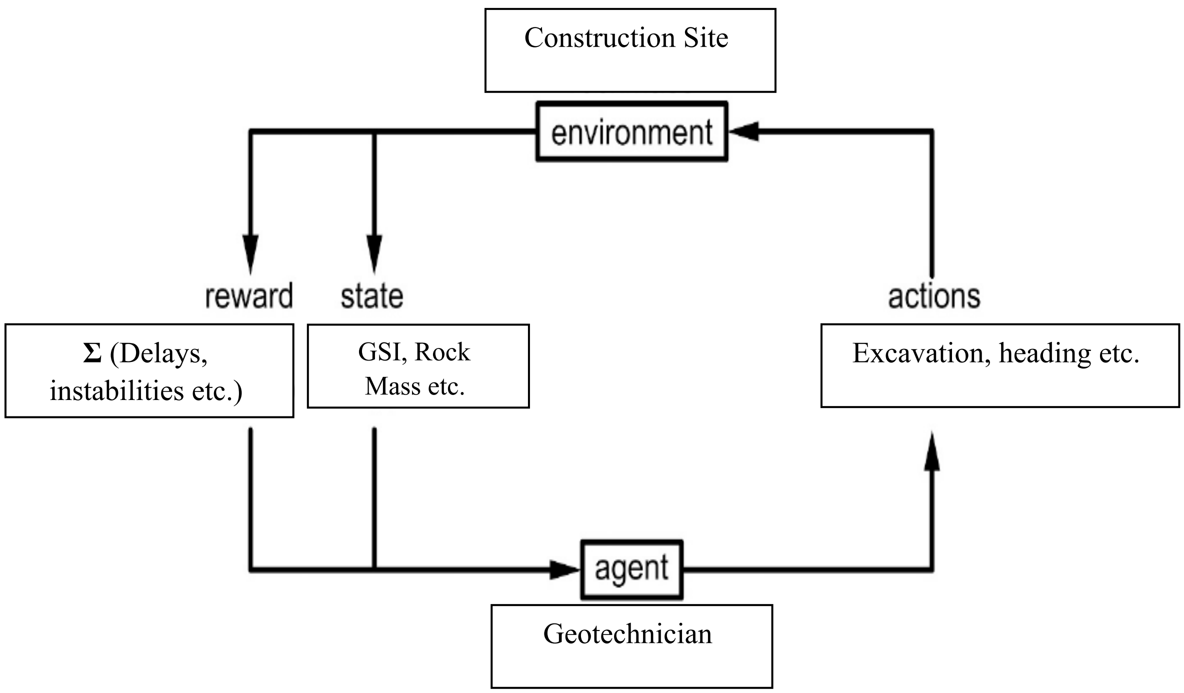

Figure 6 *RL-Loop Schema Adopted in Research Work*

Representation of every component of the schema adopted in the research study is given below:

a) **The Agent**: The decision-making agent is classified as the geotechnician,
b) **The Actions**: Construction processes, such as "excavation of top heading", "excavation of bench" and "installing face support" etc. are classified as the actions.

c) **The Environment**: The GSI empirical design, including the site conditions representative of all construction processes, are the environment.

d) **The Reward**: The unplanned and planned delays, with issues that are encountered throughout the tunnelling / excavation process are the reward. These are the results of the actions of the geotechnician.

e) **The State**: Data and information of forgone and current rockmass situation, inclusive of supports that are installed, are the state.

5.2.1 Markov Decision Process (MDP)

The application of Reinforcement Learning problem, and all the elements, will undertake the Markov property (*Sutton and Barto, 2018*). Resultantly, each point in the decision will be taken as a distinctive state in the MDP, as the process of excavation will be broken up into a sequence of choices. The program will then oscillate or transition between the states, rooted in the actions taken by the agent (the geotechnician), which then affects the upcoming states.

Use of MDP enables the simulation of dynamic excavation conditions, where decisions are constantly changing and so must adapt to the changing environment. Eventually, this process optimizes the effectiveness of productivity and safety during construction, as the agent is now the master of managing its own luck, reducing randomness in the rewards of the state that it is in.

5.3 Simplifications Made in the Research Study

Some important simplifications were made in the study to reduce the complexity of operations, computation time and make it as close to the real-time scenario as possible (adapted from *Erharter GH, 2021*):

a) Only two partial excavation techniques are available: top heading and bench and invert, assigned with a specific tunnel geometry.

b) Stability is considered okay for parts where excavation has already taken place, and the construction process does not include tunnel lining installation,

c) Other type of supports for rocks (shotcrete or radial bolts) are not taken into consideration in this study,

d) To evaluate the conditions of stability in the excavated area, face pressure equation (*Vermeer PA, 2002*) for tunnelling with open face is used. This is an effective solution (analytically) as the stability assessment provided by the equation is computationally stable. The equation is given below:

$$\rho f = \gamma_r D^* + \left(\frac{2 + 3^* \left(\frac{d}{D}\right)^{6^* \tan \emptyset'}}{18^* tan\emptyset^*} - 0.05 \right) - \frac{c'}{\tan \emptyset'}$$

Where,

ρf: Required pressure, $\rho f < 0$ indicates stable condition and $\rho \geq 0$ indicates unstable conditions,

γ_r	Unit weight of the rock mass,
D:	Equivalent diameter of the tunnel,
d:	Unsupported advance length,
c':	Effective cohesion,
φ':	Effective friction angle.

e) Only X-sectional area is taken in the study and the assessment does not account longitudinal changes,

f) Only two advance lengths are applicable (2m and 4m) for one blasting round per round of excavation.

5.4 Simulation in the Research Study

The objective of the simulation is to train RL-agents to conduct tunnelling construction sequence as efficiently as possible. To simulate the longitudinal sectional of the specific length (t_l), different ground conditions may ensue. The agent is oblivious to the ground types before it commits or takes an action. It is only alerted of the ground type when it proceeds ahead with excavation, step by step. The ground types are based on the GSI empirical design approach.

Therefore, the primary goal of the agent is that the reward is to be maximized. This is achieved when top heading and bench excavation of tunnel is accomplished.

5.4.1 Geotechnical Case

The geotechnical scenario of the research is as based on the tunnel cross-section in Figure 7 (adapted from *Erharter GH, 2021* for simplification).

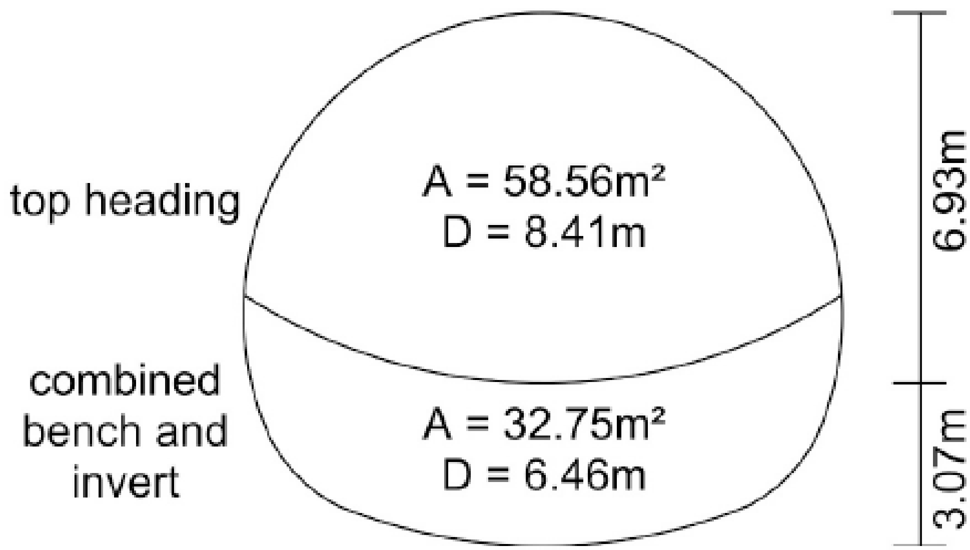

Figure 7. *X-Section of the Tunnel Used in Research (Erharter GH, 2021)*

The agent can take multiple actions during the excavation process, like excavation of top heading of 2m length, excavation of bench with 4m advance length etc. A penalty is also given if distance between top heading and bench face is larger than 50m.

Ground type is defined by the Geological Strength Index (GSI) Empirical Design Approach, based on following surface conditions and rock mass structure as shown in Table 1.

Structure Type	Good Surface	Fair Surface	Poor Surface	Very Poor Surface
Blocky/Seamy	75-90	65-75	55-65	45-55
Very Blocky	65-75	55-65	45-55	35-45
Blocky/Disturbed	55-65	45-55	35-45	25-35
Disintegrated	45-55	35-45	25-35	15-25

Table 1. *Rock Mass Structure and Surface Conditions Simulated in the Program.*

For every WF, rock mass structure and surface conditions are randomly selected, followed by calculation of values of GSI derived from chosen criteria and normalized WF value. Purpose of normalized WF value is to include variability in GSI value so that real-world changes in geological conditions may be simulated.

Based on these principles, GSI can be adjusted more precisely. Thus, the aforementioned methodology outlines the geotechnical scenario, which is working behind the scenes in this RL-simulation, in together with the environment and the agent.

5.4.2 Agent

In this section, shift is made to function of geotechnician as agent. In real-world scenarios, the geotechnicians themselves observe the geotechnical parameters of rock mass behaviors, which in turn impact the critical decisions taken. However, in the methodology adopted in this research, this role of geotechnical engineers making decisions on site, is taken on by the 'RL agent,' which uses Deep Q-Learning Network (DQN) to make decisions.

5.4.2.1 Deep Q-Learning Network

DQN is a deep RL technique, whereby, classical Q-Learning competencies are enhanced by replacement of function approximator of deep ANN in the Q-table. The neural network is called Q-Network, whereas the estimated value function is called Q-value. By constantly learning and reinforcing from the environment, the RL-agent keeps on updating the decisions taken as the construction proceeds ahead, to enhance safety. Basic working is based on the basis that the initial stage is inserted into the neural network, which returns output as Q-value of every action taken. Therefore, DQN can manage multi-dimensional spaces of states, as is usually faced in tunnelling processes.

Since correlation of RL with environment is highly dependent, therefore issues are caused during the training process. To mitigate these correlations Experience Replay is used which separates the correlations in samples used in training, thereby encouraging faster convergence with better quality. The agent is enabled to learn from various transitions using past stored data or ‘experiences,’ enhancing efficiency.

In light of the aforementioned discussion on experience replay, DQN may be considered as a method using ‘off-policy,’ grounded upon Bellman’s Equation given below:

$$Q^*(s,a) = \mathbb{E}_{s'}[r + \gamma \max_{a'} Q^*(s',a')|s,a]$$

Where,

Q*(s,a): State ‘s’, after an Action ‘a’ is taken,

r + γQ*(s', a'):	maximum value of best possible expected value,
s':	state at next stage,
a':	action at next stage.

5.4.2.2 $\mathcal{E}$-Greedy Action Selection Criteria

$\mathcal{E}$-Greedy balances the contest between exploration and exploitation, as it randomly chooses between both. $\mathcal{E}$ = 0 refers to the RL-agent acting randomly, whereas when it tends towards 0, it starts to take greedy actions. Hence, a balance between both is necessary. Exploration is the process which enables the RL-agent to improve the knowledge it has stored currently about each action, leading to long-term reward by allowing the RL-agent to make more informed decisions. Exploitation, conversely, maximizes rewards through exploitation of RL-agent's estimates of present action values, by selecting greedy actions.

$$Q(S_t, A_t) \leftarrow \; Q(S_t, A_t) + \propto [R_{t+1} + \gamma \max_a Q\ (S_{t+1}, a) - Q(S_t, A_t)]$$

In this research, ε is set to 0 initially. Then r (a number) is randomly drawn from a normal distribution ranging from 0 to 1. If (if $r \leq \mathcal{E}$), the action taken by the RL-agent is random, if $r > \mathcal{E}$ action is committed on prior action of the RL-agent.

To maintain a balance between exploration and exploitation, a decay function is also included in the training of the program:

$$\varepsilon_{i+1} = \varepsilon_i * \varepsilon_d$$

Where,

ε_{i+1}: Epsilon for upcoming episode

ε_i: Epsilon for at-present episode

ε_d: Epsilon decay rate

Therefore, the $\mathcal{E}$-Greedy Action Selection Criteria ensures that full exploration of the environment is made by the RL-agent in the beginning, and the knowledge stored is then exploited towards the end of the training regime.

5.4.3 Environment

The rockmass conditions and construction processes (the state), along with feedback from iteration of excavation productivity (reward), is the representation of environment. The RL-agent simulates the role of real-world geotechnician in this environment.

5.4.4 System of Reward

Rewards are used to convey to the RL-agent if its actions are maximizing the return (cumulative reward over the entire episode), which in this case is excavating the whole tunnel. A negative reward or penalty is also given if the agent does not perform according to criteria defined.

The reward system in this research is based on a pre-listed condition in the code. The agent gives a reward if all pre-defined conditions are met, and a breakthrough is achieved. This reward system is based on engineering experience from field knowledge.

5.5 Training of the Reinforcement Learning Problem

In real-life situation, a geotechnical engineer will be knowledgeable of all the action it has to take, based on safety, logistical and technical parameters to execute the tunnel construction operations with best possible strategy. However, in reinforcement learning, an untrained RL-agent is oblivious to all the metrics. Therefore, training on predefined schema or methodology (mentioned previously has to be carried out)

Resultantly, the problem was coded in Python programming language (with all its associated libraries) on Visual Studio (VS) Code source-code editor. Training was done on a cluster of NVIDIA A100 GPU to optimize computational performance and obtain results with more speed. Figure 8 below shows screenshots of computer screens, when training of reinforcement learning problem was in progress.

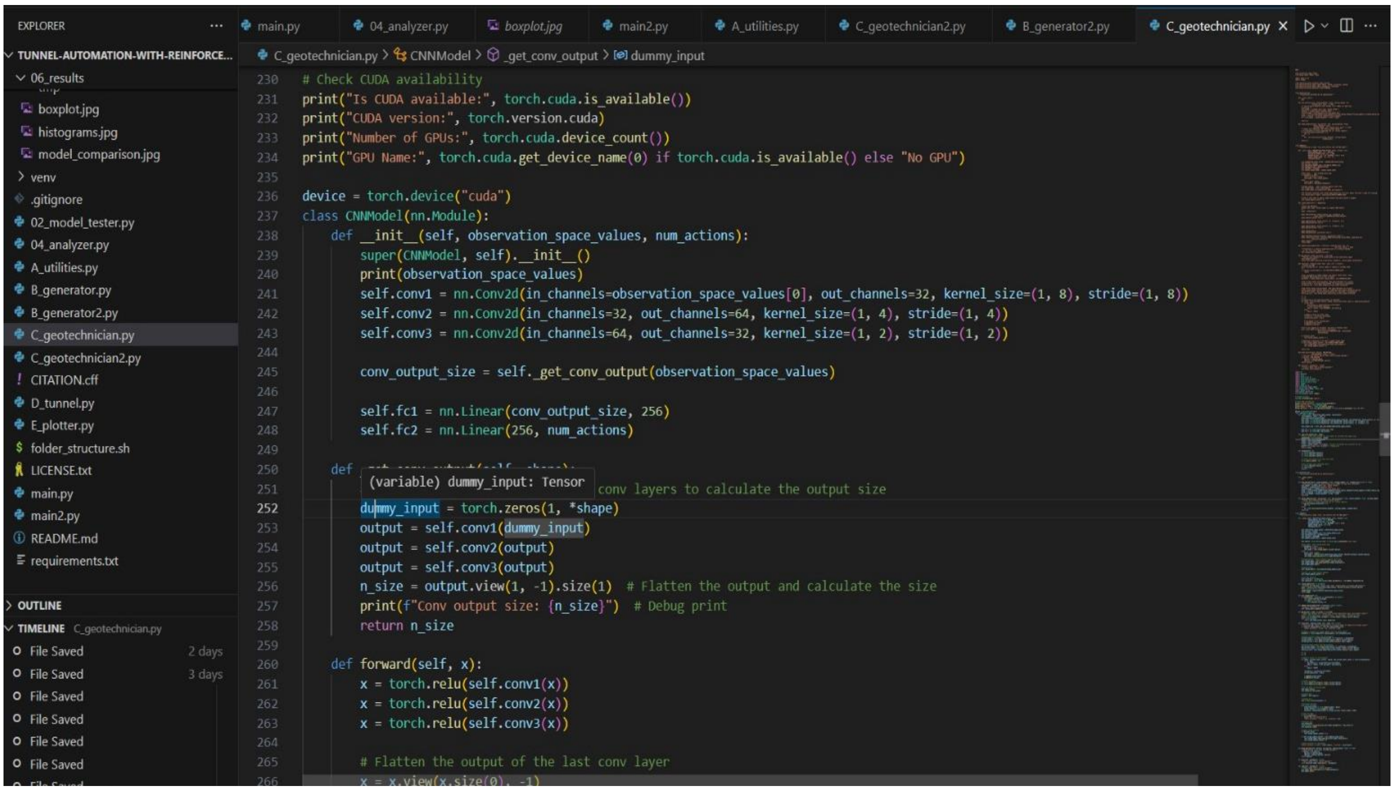

***Figure 8**. Screenshot of Screen Containing Code Written in Python Programming Language, on Visual Studio (VS) Source-Code Editor.*

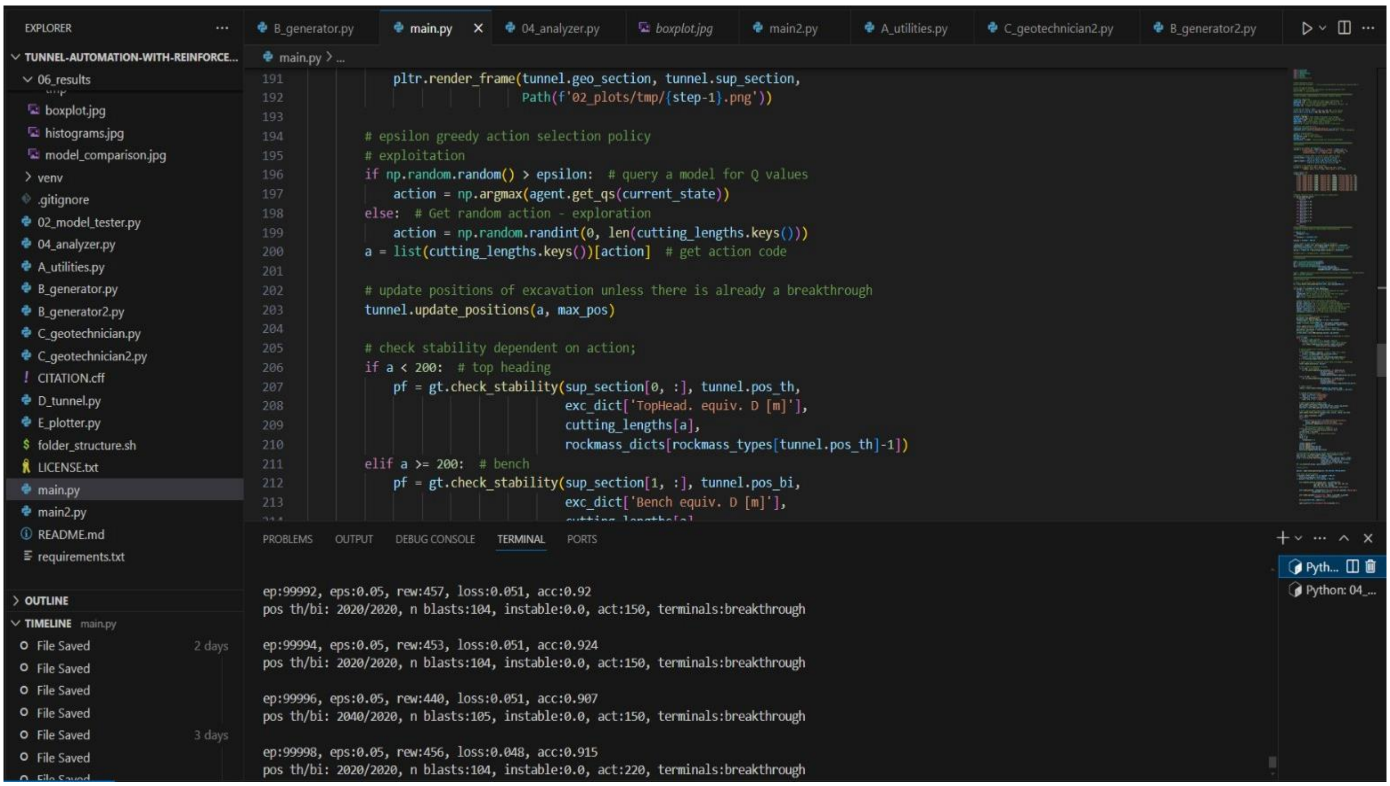

Figure 9. *Screen Showing Python Code and Its Training In Progress.*

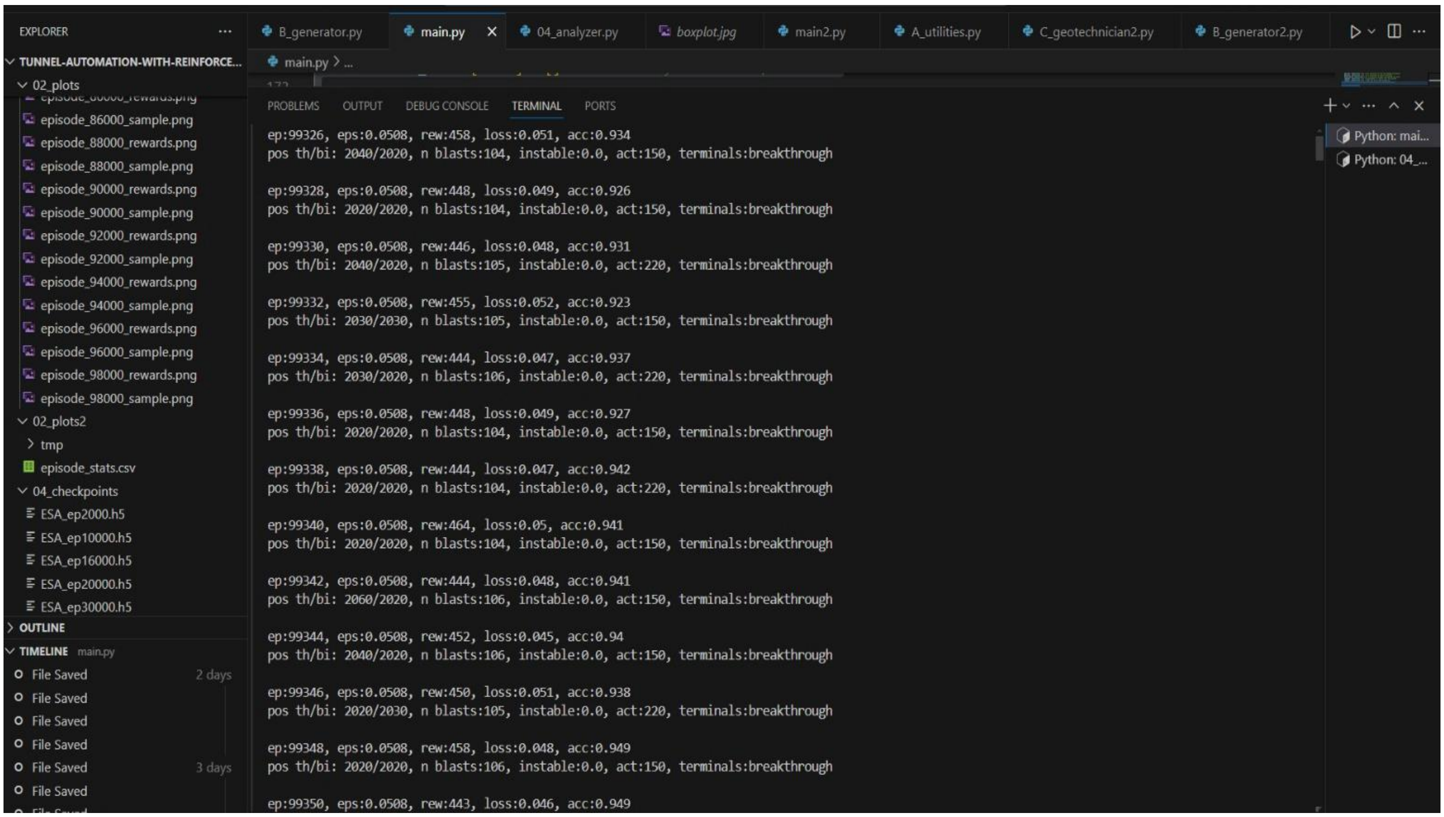

Figure 10. *Screen Showing the Python Code Under Training for 100,000 Episodes.*

CHAPTER 6: RESULTS AND DISCUSSIONS

This Chapter will present the results obtained from training of RL-agent on the methodology fixed in Chapter 5.

6.1 Log of RL-Agent's Training Regime

The figures below show the recordings of training of Agents for 2,000, 30,000 and 100,000 episodes. An episode is referred to as the recordings of actions and states that an RL-agent achieves from beginning state to final state.

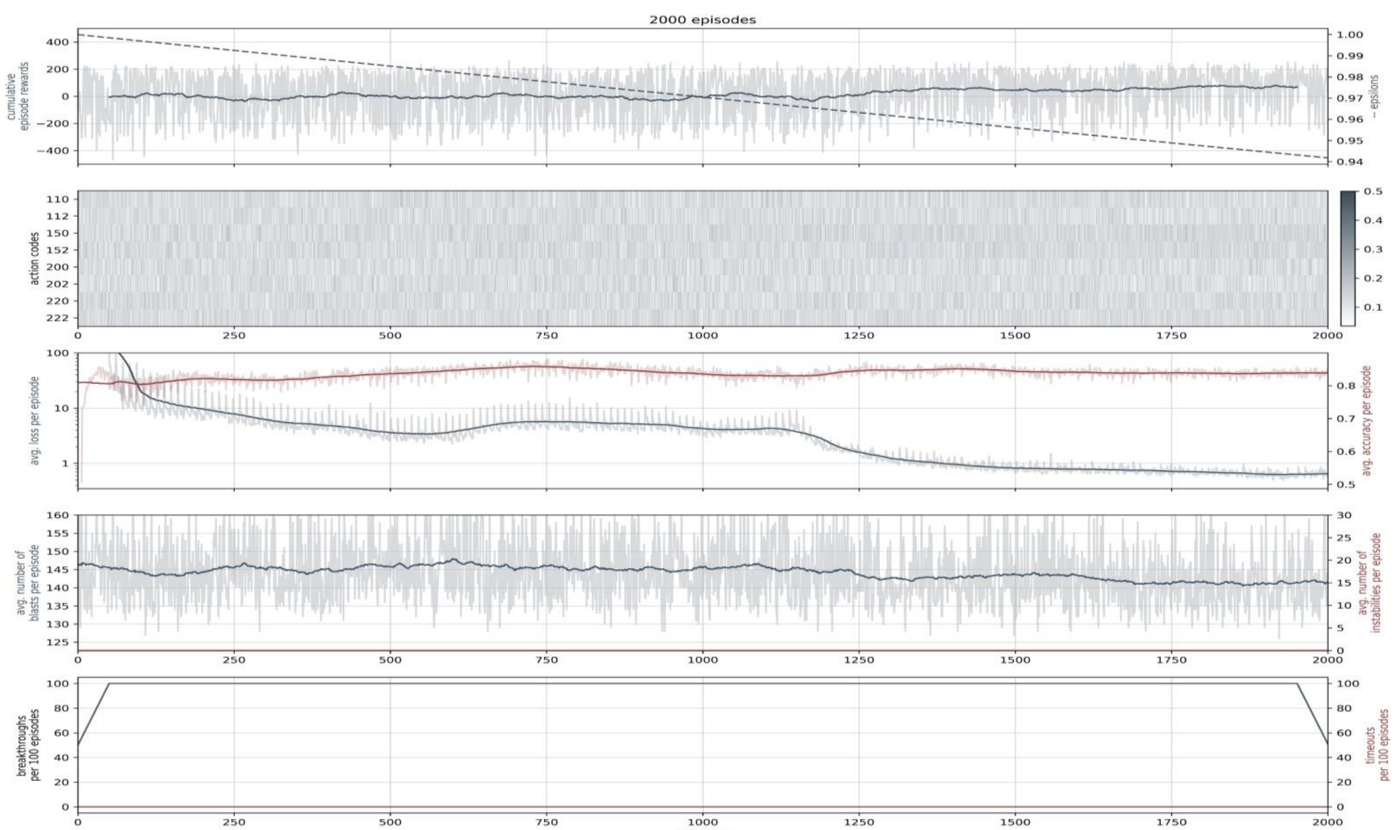

Figure 11. *Log for RL-Agent's Training (**2,000 Episodes**)*

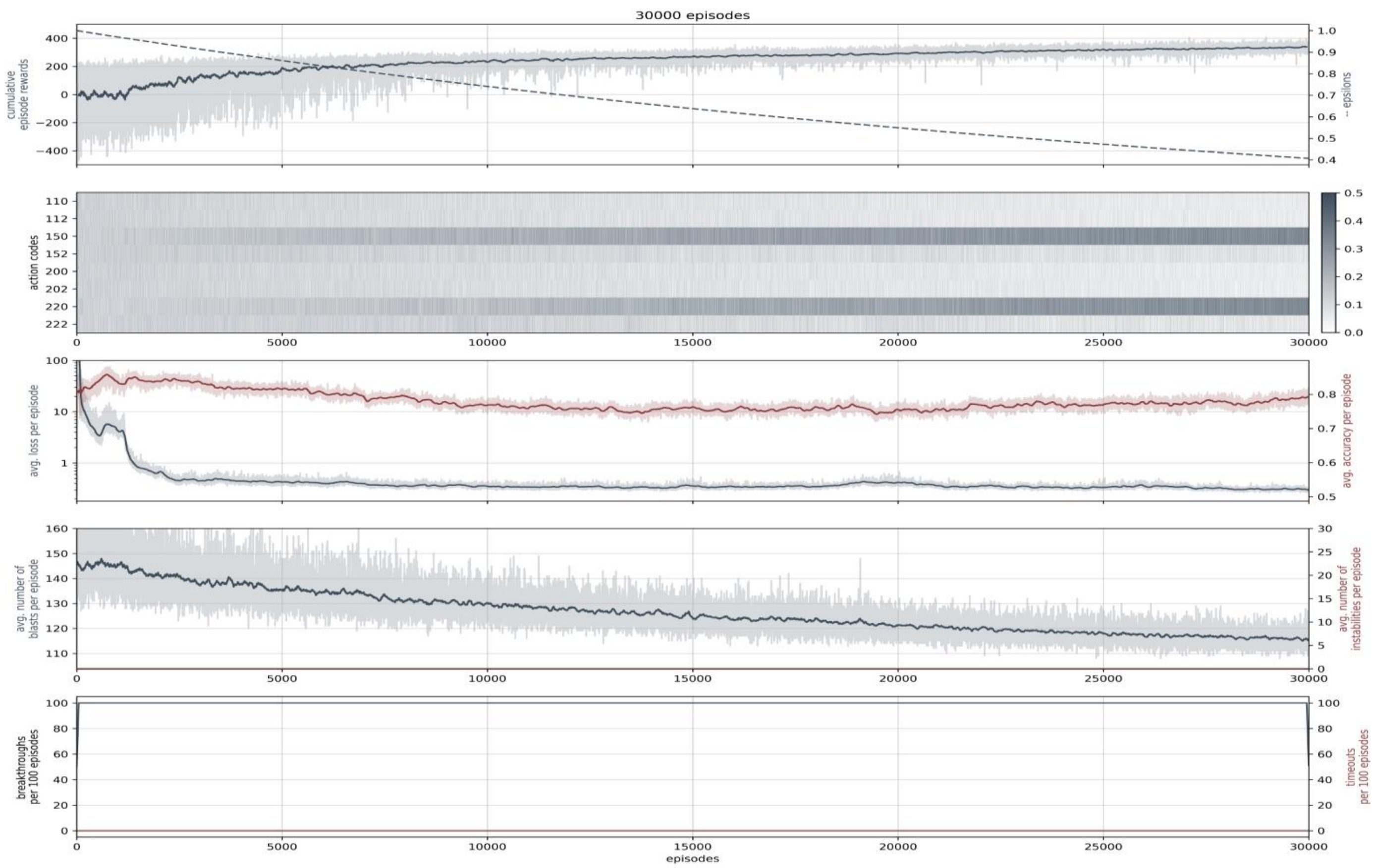

Figure 12. *Log for RL-Agent's Training (**30,000 Episodes**)*

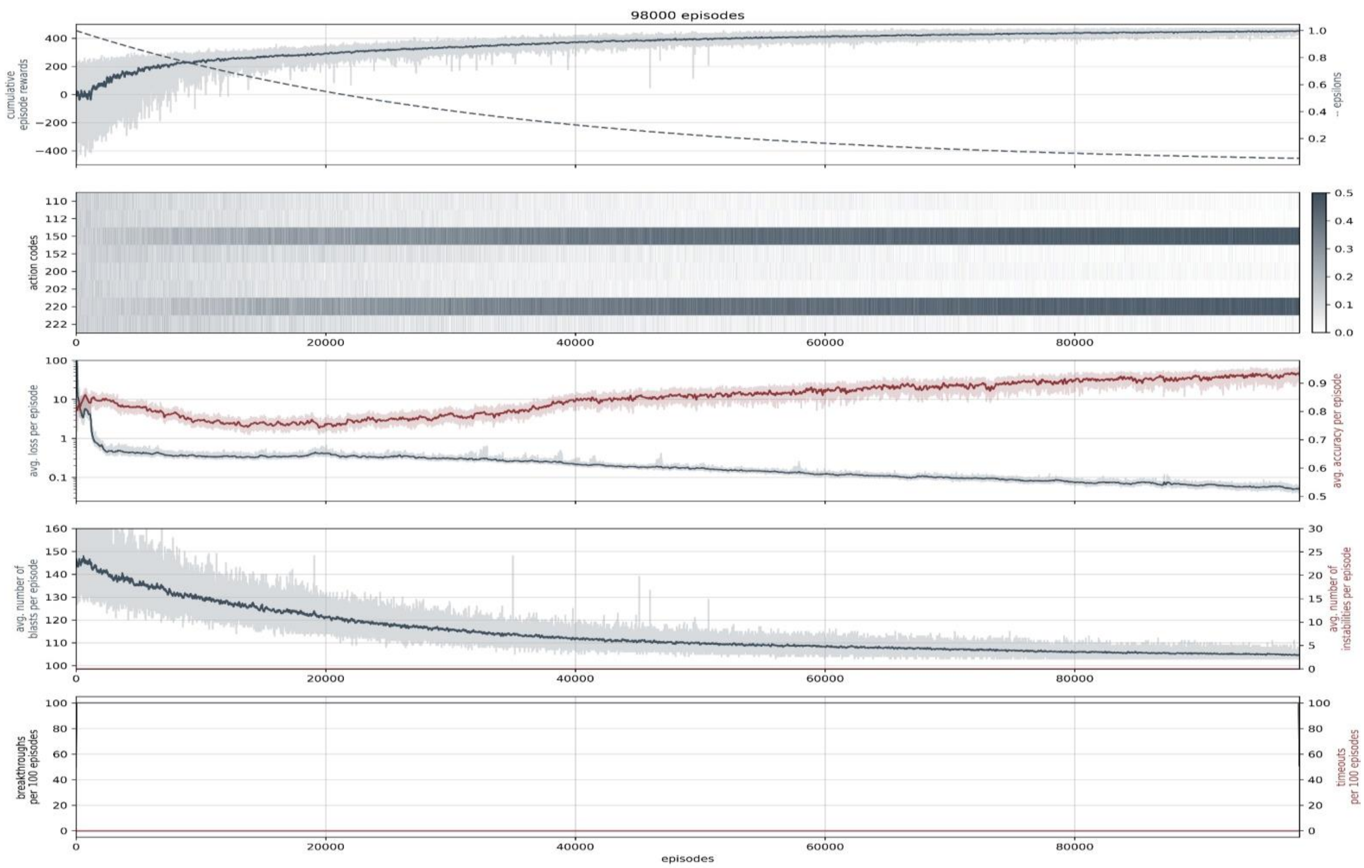

***Figure 13**. Log for RL-Agent's Training (**100,000 Episodes**)*

6.1.1 Discussion on Results

For Figures 11,12 and 13 above, the first row shows rewards / episode and epsilons; the second row shows action codes; the third row shows average loss and accuracy per episode; the fourth row shows average number of blasts and instabilities per episode; the fifth row shows breakthroughs and timeouts per episode.

It can be seen from the first row in Figure 11, that the number of rewards per episode a fairly constant trend, whereas the epsilon decays to a value of 0.942. However, in Figure 12, it can be seen that the reward shows a increasing trend and then reaches a fairly constant value; likewise, the epsilon also decays dramatically to a value of 0.410. In Figure 13, that maximum reward of 400 is achieved by the RL-agent on 100,000 episodes, whereas epsilon also balances and reaches a value close to 0, showing high levels of convergence.

For the second row, It can be seen in Figures 11, 12 and 13, that as the training progress to 100,000 episodes, the RL-agent becomes more clear in the decision-making process. It becomes aware of the action-state-environment loop, and is taking clearer actions, with greater control and consistency.

In the third row of Figure 11, that the average accuracy of the training remains fairly high, which shows a downward trend in Figure 12 for 30,000 episodes but increases again significantly in Figure 13 for 100,000 episodes. The average loss per episode is also observed to be less than 0.5 for Figures of 30,000 and 100,000 episodes.

Fourth row of Figure 12 shows that the average number of blasts per episode remains fairly constant for 2,000 episodes. However, as the training progresses and the agents learns on the RL-loop, the number of blasts decreases significantly (less than 5 for 100,000 episodes). Moreover, it can also be observed that the average number of instabilities per episode is very much closer to zero, for all three Figures of 2,000, 30,000 and 100,000 training episodes. This has shown that the agent has learnt to economize the drill and blast design, tending towards achieving economies of scale and reducing the time required to execute and blasting intensive design.

For the fifth rows, it can be seen that breakthroughs are achieved for all episodes and there have been no timeouts for all three Figures 11, 12 and 13.

6.2 Histogram for RL-Agents Performance for Random Moves

The figures below show the histograms for RL-Agents performance for completely random moves for checkpoints at 30,000 and 100,000 episodes. recordings of training of Agents for 2,000, 30,000 and 100,000 episodes. A fixed ε of greater than zero was chosen to enable RL-Agent to deal with unexpected situations during training.

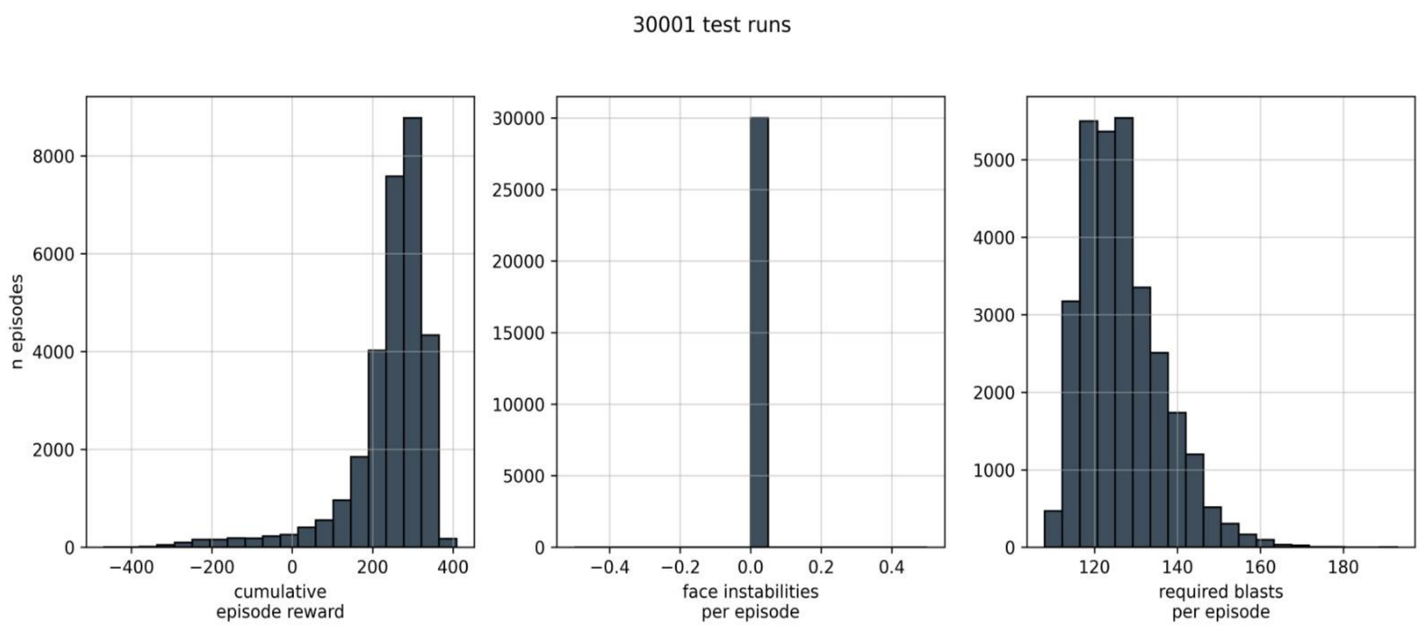

Figure 14. *Performance of RL Agent for* ***30,000 Episode*** *Training Regime, with Completely Random Moves (****ε = 1****).*

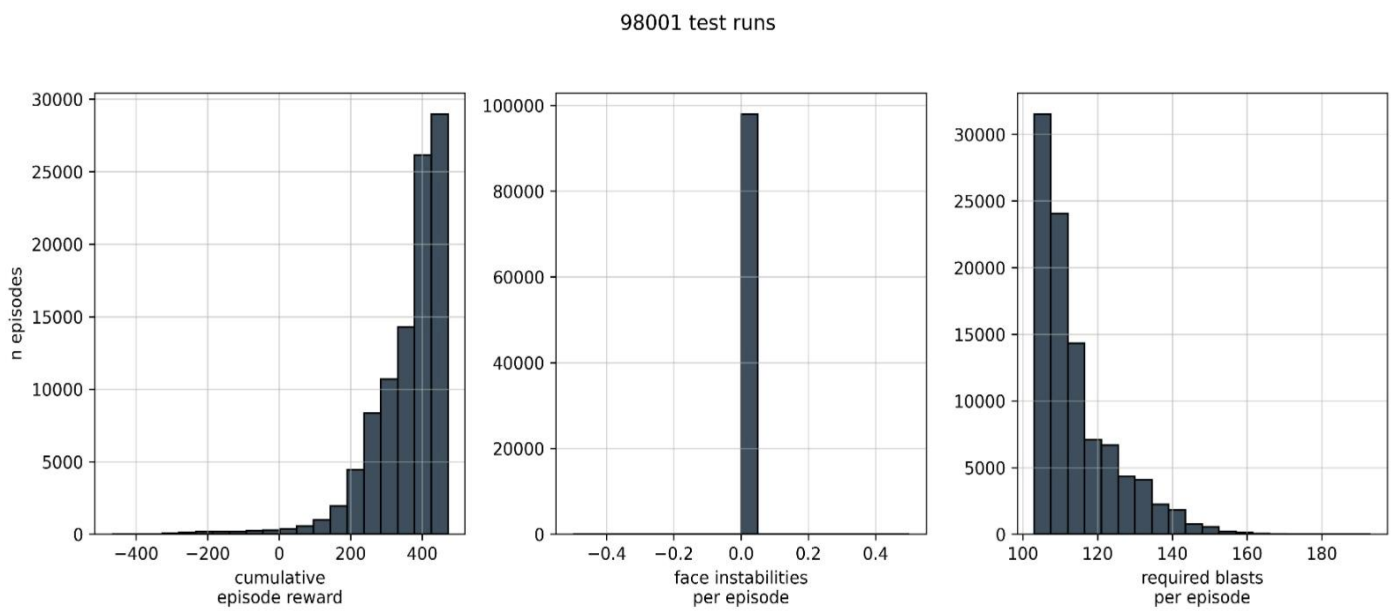

Figure 15. *Performance of RL Agent for* ***100,000 Episode*** *Training Regime, with Completely Random Moves* ***(ε = 1)***

6.2.1 Discussion on Results

Figures 14 and 15 shows that the cumulative reward for every episode increases as the training progresses. It can also be seen that face instabilities are nearly zero for all episodes. Furthermore, the required number of blasts also reduce as training proceeds ahead to the required number of episodes.

The histograms of Figure 14 and Figure 15 reinforce and confirm the results obtained in the previous section, showing that the RL-Agent has learnt to reduce the number of blasts and face instabilities per episode, as it efficiently trains on the methodology outlined in Chapter 5 producing excellent results.

Additionally, when compared to histograms quoted in previous research (*Erharter GH, 2021*), the performance of this program is significantly better, as the previous research are based on isotropic, continuous and homogenous formations of soil / rock, whereas this study properly investigates the action-state-environment loop using empirical design approaches.

6.3 Boxplot of Actions Committed by the RL-Agent Throughout the Specified Episodes

The figures below show the Boxplots that RL-Agent uses for each action throughout the specified number of episodes.

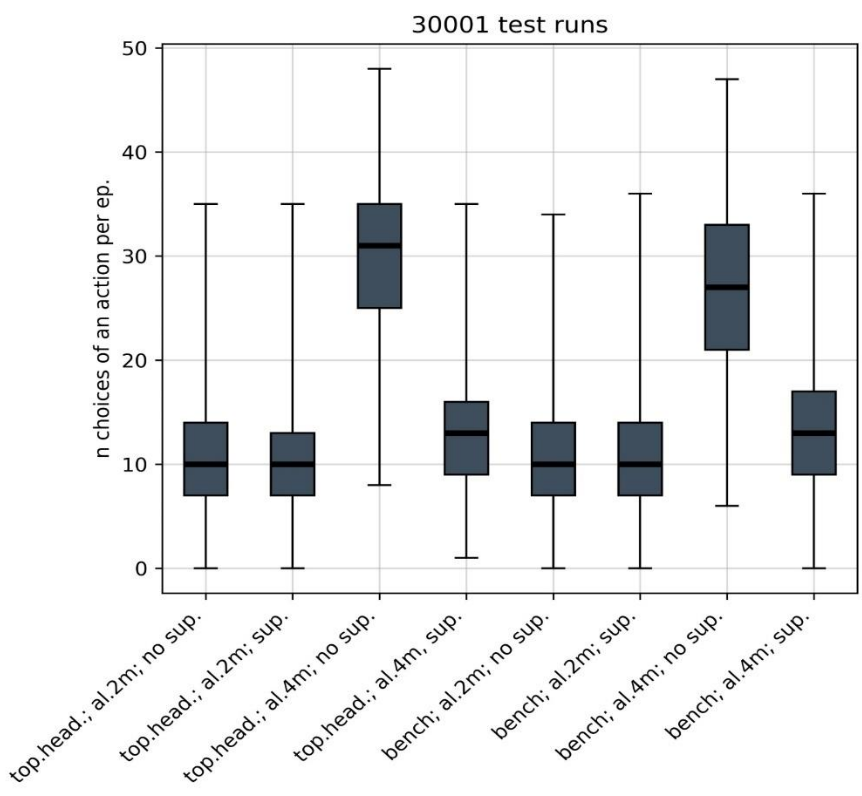

Figure 16. *Boxplot for Each Action Committed by RL-Agent During* ***30,000 Episodes.***

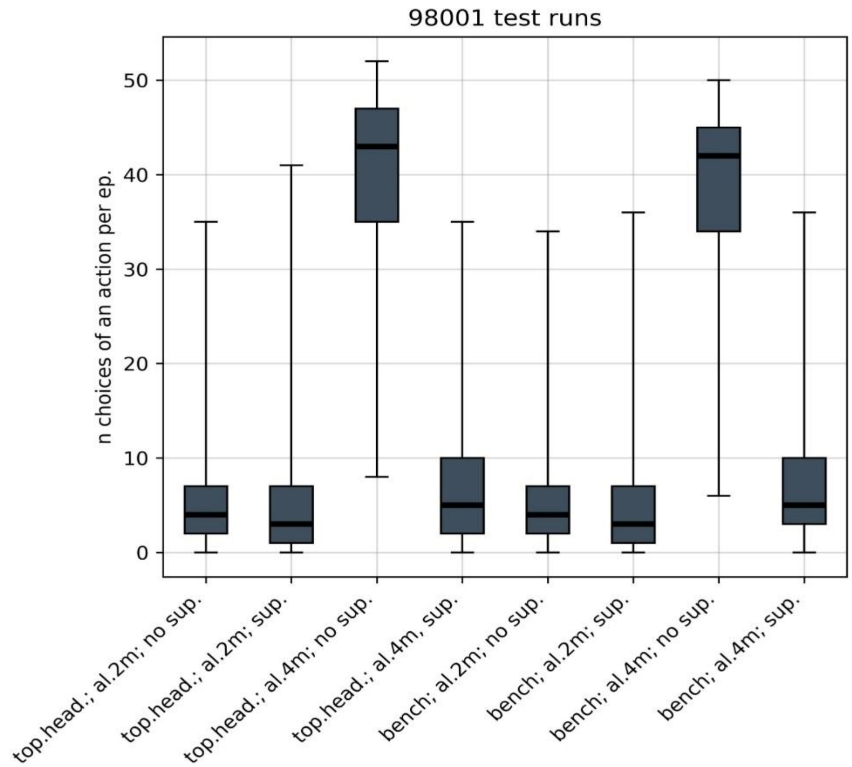

Figure 17. *Boxplot for Each Action Committed by RL-Agent During* ***100,000 Episodes****.*

6.3.1 Discussion on Results

Figures 16 and 17 show that the RL-Agent prefers long advance lengths, that too without any face support in all excavation types. This shows that the RL-agent is preventing support measures that may be too much for the sustenance of excavation required.

Further, it can also be seen that advance lengths of smaller size are also used sometimes, choosing actions with no supports on face. This means that the RL-agent is now aware that advance lengths of shorter magnitude, in underlying geological conditions, do not result to face instabilities.

CHAPTER 7: SUMMARY OF RESEARCH WORK

This research has demonstrated how reinforcement learning could be effectively applied to tunnel construction process. RL may require an initial experience in programming language, but its utility overshadows the initial knowledge capital investment. RL is a growing field of machine learning, and will have lots of opportunities in construction automation, specifically in the field of geotechnical engineering in the future.

This research has shown that reinforcement learning can be efficiently used to simulate a tunnel construction site. The training carried out by the program and resultant outcomes portray that significant economies of scale in terms of cost, time and contractual intricacies can be achieved if this methodology is used.

The research simulates real-world geological conditions effectively and proves outcomes that are comparable to real life tunnel construction process, by simulating the decision-making ability of a geotechnical engineer. The processes are also comparable to models that are currently in widespread use in construction of tunnels and underground spaces.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

This Chapter will present the conclusion, and recommendations of the investigations carried out in this research work.

8.1 Conclusions

This research study has strongly demonstrated that reinforcement learning can not only be utilized to create a working simulation, but that the RL-agent is also able to connect with the environment, realistically, to model conventional tunnel construction processes.

Further, the policy establish by the RL-agent tends to align with real-world tunnelling applications, reducing the blasting amount required, preferring long advance lengths, face support minimization and reducing difference between bench excavation and top headings.

By working economically, in an efficient way, the reality that RL-agents can find construction strategies comparable to tunnelling in real life, shows that reinforcement learning may be applied successfully to problems of this nature.

Lastly, parallels are also observed with models, such as NATM, which minimizes excavation support by use of partial excavation techniques.

8.2 Recommendations

As noted in previous section, the main aim of this research is fulfilled, however, improvements can be made to develop an advance programming code, with advance geological and geotechnical parameter, that is able to model the complete construction site.\

Finally, the code could be optimized to reduce the the computational complexity, so the power required and time to complete the training may be minimized.

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