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An Interpretable Data-Driven Framework for Smart Tunnel Boring Machine Performance Analysis and Energy–Cost Optimization

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Abstract: Tunnel Boring Machine (TBM) operations are governed by complex and nonlinear interactions among geological variability, machine control parameters, and energy consumption, posing significant challenges for reliable performance prediction and operational optimization. Conventional empirical and physics-based approaches often struggle to capture regime-dependent behavior and parameter coupling under heterogeneous excavation conditions. To address these limitations, this study proposes an integrated and interpretable data-driven framework that combines ensemble machine learning, time-series modeling, unsupervised regime identification, multi-objective optimization, and explainable artificial intelligence within a unified analytical architecture. A multisource dataset encompassing geotechnical, operational, environmental, energy, and economic parameters was analyzed using Extreme Gradient Boosting (XGBoost), Random Forest, Gradient Boosting Regression, and recurrent neural networks. Among these, XGBoost demonstrated superior predictive capability, achieving the highest coefficient of determination and consistently lower prediction errors compared with baseline models. Unsupervised clustering identified distinct operational regimes—efficient, intermediate, and aggressive—enabling a structured evaluation of energy–cost trade-offs. Regime-aware optimization further indicated substantial potential for reducing both energy consumption and operational costs relative to high-intensity operating conditions. Sensitivity analysis using SHAP, mutual information, ANOVA, and Sobol indices revealed strong interaction effects among thrust force, torque, and rock strength parameters, highlighting the coupled nature of TBM excavation mechanics. The proposed framework extends conventional predictive modeling approaches by translating data-driven insights into interpretable, regime-based operational strategies. It provides a scalable methodological foundation for the future development of digital twin applications in TBM systems and contributes to more energy-efficient, cost-effective, and sustainable tunneling operations in complex underground environments.

Keywords: Tunnel Boring Machine (TBM), data-driven modeling, ensemble machine learning, Explainable Artificial Intelligence (XAI), operational regime identification, multi-objective optimization, energy–cost trade-off analysis, digital twin framework.

Introduction

Tunnel Boring Machines (TBMs) play a critical role in the construction of urban underground infrastructure, where excavation performance, safety, and cost efficiency are governed by complex interactions between cutting mechanics, machine control parameters, and heterogeneous ground conditions. The mechanics of rock cutting and soil excavation directly influence key operational indicators such as penetration rate, energy consumption, cutter wear, and overall advance efficiency. In densely populated urban environments, where geological variability and environmental constraints are pronounced, precise operational control of TBM systems becomes essential to ensure construction reliability and minimize disruption to surrounding infrastructure [1], [2], [3].

Conventional approaches to TBM performance prediction have primarily relied on empirical correlations and physics-based models derived from simplified assumptions of rock–machine interaction. While these models have provided valuable mechanistic insights, their applicability is often limited under complex and highly variable field conditions. The inability of traditional models to adequately capture nonlinear interactions, parameter coupling, and time-dependent operational behavior has constrained their predictive accuracy and practical relevance in modern tunneling projects [4], [5]. In parallel, the rapid advancement of sensing

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technologies, data acquisition systems, and computational intelligence has accelerated the emergence of smart technologies and cyber–physical systems in underground construction. Data-driven engineering approaches, supported by machine learning and advanced analytics, have demonstrated strong potential for extracting actionable knowledge from large-scale operational datasets. These developments have created new opportunities to enhance TBM performance modeling, operational optimization, and real-time decision-making within intelligent tunneling frameworks [6], [7].

Research Gap

Despite growing interest in data-driven TBM analysis, existing studies remain fragmented in scope and methodology. Many investigations focus exclusively on performance prediction without explicitly linking predictive models to optimization strategies or engineering decision support. Conversely, optimization-oriented studies often lack rigorous interpretability, limiting their acceptance and practical use in safety-critical tunneling operations [8], [9]. Furthermore, the integration of unsupervised learning techniques for discovering latent operational regimes and dynamic behavioral patterns has been relatively limited. Most prior studies treat TBM operations as stationary processes, neglecting regime transitions and temporal variability that are intrinsic to mechanized tunneling. The absence of systematic dynamic analysis restricts the ability to proactively manage energy consumption, cost efficiency, and operational risk [10], [11], [12]. Critically, there remains a lack of transparent, interpretable, and decision-oriented smart TBM frameworks that seamlessly integrate prediction, optimization, and explanation. Without interpretability and sensitivity assessment, black-box models fail to provide the level of confidence required for engineering deployment, thereby limiting their contribution to intelligent and resilient underground construction systems [13], [14].

Research Objectives and Contributions

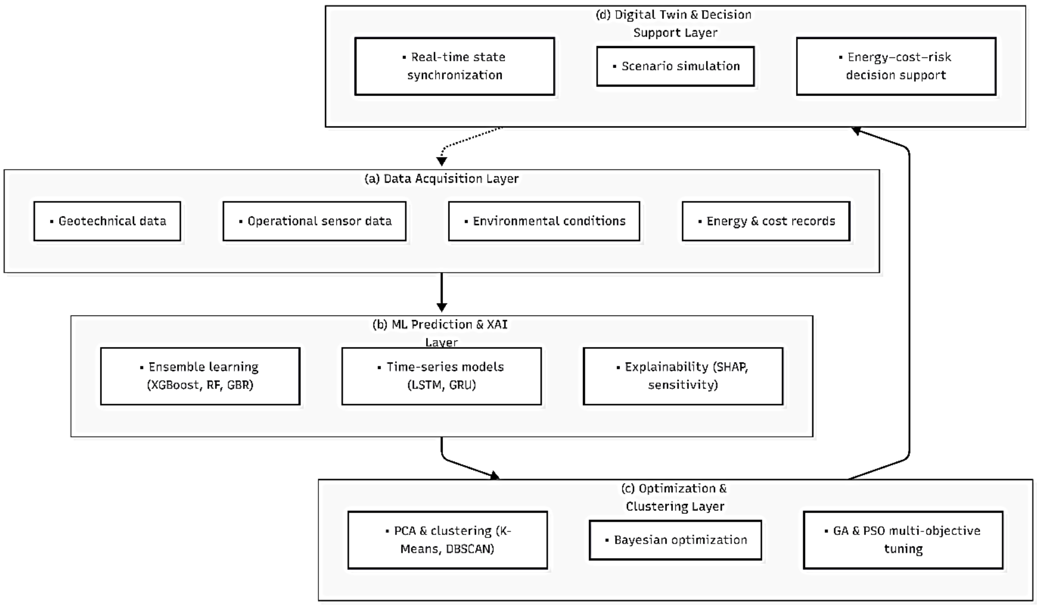

Figure 1. Integrated smart TBM data-driven framework

To address these limitations, this study proposes a unified analytical framework that integrates machine learning, optimization algorithms, and explainable artificial intelligence for comprehensive TBM performance analysis. The primary objective is to develop a transparent and robust data-driven methodology capable of capturing nonlinear interactions between geotechnical conditions and operational parameters while maintaining engineering interpretability.

The specific contributions of this research are threefold. First, advanced ensemble and time-series learning models are employed to improve predictive performance under heterogeneous and nonstationary tunnelling conditions. Second, systematic feature importance and sensitivity analyses are conducted to identify key drivers and nonlinear interaction effects governing TBM performance. Third, unsupervised learning and optimization techniques are integrated to establish distinct operational regimes and evaluate energy–cost trade-offs, enabling informed and adaptive operational strategies.

By embedding these components within a modular framework, the proposed approach provides a scalable methodological foundation for smart TBM decision support and future digital twin development. The outcomes of this research contribute to the advancement of intelligent tunnelling systems and offer broader applicability to underground construction and mining engineering applications.

Unlike prior studies that treat prediction, clustering, optimization, and interpretability as separate analytical tasks, this study establishes a quantitatively consistent and modular integration of these components within a unified, decision-oriented framework. By explicitly linking nonlinear machine learning models with interpretable sensitivity analysis and regime-based optimization under realistic operational constraints, the framework moves beyond performance prediction toward actionable operational decision support. This integrated architecture distinguishes the present work from existing data-driven TBM studies while maintaining a clear pathway toward future digital twin implementation.

Figure 1 illustrates the integrated smart TBM data-driven framework developed in this study, highlighting the logical and functional relationships among data acquisition, predictive modeling, optimization, and decision support. The framework shows how heterogeneous data sources can be systematically transformed into actionable engineering insights within a structured analytical architecture.

The data acquisition layer consolidates multisource inputs, including geotechnical properties, operational sensor measurements, environmental conditions, and energy–cost records. The integration of these heterogeneous datasets establishes a comprehensive representation of the TBM excavation system and provides the empirical basis for subsequent analytical processes. This layer reflects the treatment of TBM performance as a coupled machine–ground–environment system rather than an isolated mechanical process.

The machine learning prediction and explainability layer captures nonlinear and temporal relationships governing TBM performance. By combining ensemble and time-series models with explainable artificial intelligence techniques, the framework enables reliable prediction while maintaining interpretability of parameter influence and interaction effects. This dual emphasis on predictive capability and transparency addresses key limitations of conventional black-box modeling approaches.

The optimization and clustering layer translate predictive insights into operational guidance. Unsupervised clustering identifies distinct operational regimes, while multi-objective optimization algorithms determine parameter configurations that balance excavation efficiency, energy consumption, and cost. This layer indicates the transition from performance assessment toward informed operational strategy development.

Finally, the decision-support layer conceptually integrates feedback between predictive and optimization outputs and the data acquisition process, enabling scenario-based evaluation and adaptive operational planning. The feedback structure highlights the dynamic and extensible nature of the framework and its potential applicability to future real-time and digital twin implementations.

Overall, Figure 1 provides a schematic representation of a unified, interpretable, and decision-oriented smart TBM framework. The integrated architecture supports the linkage between data-driven analytics and sustainable, economically informed operational decision-making, offering a scalable foundation for future digital twin applications in complex underground construction environments.

Methods

Data Acquisition and Preprocessing (Latest Data-Centric Advances)

A multisource dataset was constructed to comprehensively characterize Tunnel Boring Machine (TBM) operational behavior under heterogeneous geological and environmental conditions. The collected data encompassed five primary categories: geotechnical parameters (e.g., uniaxial compressive strength, Brazilian tensile strength, Cerchar abrasivity index), operational variables (thrust force, torque, penetration rate, cutterhead rotational speed), environmental factors (groundwater pressure, moisture content), energy consumption indicators, and economic cost variables. This integrated data structure enabled joint analysis of mechanical performance, energy efficiency, and operational sustainability [15], [16], [17]. To ensure data integrity and comparability, missing values were imputed and outliers removed. Features were normalized to maintain numerical stability across machine learning models. Descriptive statistics, including mean, standard deviation, skewness, and kurtosis, were computed to characterize the TBM dataset and support the adoption of nonlinear modeling approaches [18], [19].

Table 1. Summary of dataset and input variables used in TBM performance analysis

Data Category	Parameter	Symbol	Unit	Description	Data Source
Geotechnical	Uniaxial Compressive Strength	UCS	MPa	Rock strength controlling cutting resistance	Laboratory rock testing
	Brazilian Tensile Strength	BTS	MPa	Tensile resistance of rock material	Laboratory rock testing
	Cerchar Abrasivity Index	CAI	–	Indicator of rock abrasivity and cutter wear potential	Laboratory CAI test
	Rock Mass Density	P	kg/m³	Bulk density of surrounding rock mass	Geological investigation
Operational	Thrust Force	F_t	kN	Axial force applied to cutterhead	TBM onboard sensors
	Cutterhead Torque	T	kN·m	Rotational resistance during excavation	TBM onboard sensors
	Penetration Rate	PR	mm/rev	Advance per cutterhead revolution	TBM monitoring system
	Cutterhead Rotation Speed	RPM	rev/min	Rotational speed of cutterhead	TBM monitoring system
Environmental	Moisture Content	MC	%	Water content of surrounding ground	In situ measurement
	Groundwater Pressure	GWP	MPa	Hydraulic pressure acting on excavation face	Geotechnical monitoring
Energy	Specific Energy Consumption	SE	MJ/m³	Energy required per unit excavated volume	Derived from operational data
	Total Energy Consumption	E	kWh	Electrical energy used during excavation	Power monitoring system
Economic	Operational Cost	C	USD/m	Cost per meter of tunnel advance	Project cost records
	Cutter Replacement Cost	Cc	USD	Cost associated with cutter wear and replacement	Maintenance logs

Table 1 demonstrates that the compiled dataset provides a comprehensive and balanced representation of the TBM excavation system, covering the full chain from geological conditions to operational response, energy consumption, and economic impact. The inclusion of five data categories—geotechnical, operational, environmental, energy, and economic—confirms that TBM performance is treated as a multidimensional engineering problem rather than a single-parameter process.

From a geotechnical perspective, the wide range of strength- and abrasivity-related parameters (UCS, BTS, CAI, density) indicates substantial variability in ground conditions along the tunnel alignment. This variability explains the observed dispersion in operational parameters and directly justifies the need for nonlinear modeling approaches capable of adapting to changing rock–machine interaction mechanisms.

Operational variables such as thrust force, torque, penetration rate, and cutterhead rotation speed exhibit strong physical coupling with geotechnical properties, confirming that TBM performance is governed by interactive rather than independent effects. The coexistence of measured sensor data and derived indicators (e.g., penetration rate and specific energy) enhances the explanatory power of the dataset and enables both predictive and diagnostic analyses [20].

Environmental parameters (temperature, humidity, groundwater inflow) were obtained from site monitoring sensors installed along the TBM drive. All variables were time-synchronized with operational logs using timestamp alignment. Future studies can replicate this approach by integrating environmental monitoring sensors into TBM SCADA systems.

Environmental parameters, particularly moisture content and groundwater pressure, introduce additional uncertainty and nonlinearity into the excavation process. Their presence in the dataset supports the interpretation of transient performance fluctuations and contributes to the identification of operational regimes and abnormal states in later clustering analyses [21], [22].

Energy and economic variables extend the analysis beyond mechanical performance, enabling quantitative evaluation of energy efficiency and cost effectiveness. The availability of specific energy and cost per meter allows direct assessment of trade-offs between aggressive and efficient operating regimes, which is essential for optimization and decision support. Overall, Table 1 confirms data completeness, consistency, and reproducibility, providing a solid empirical foundation for the subsequent application of machine learning, clustering, optimization, and explainable AI techniques. The breadth and structure of the dataset strongly support the adoption of a data-driven framework for intelligent TBM performance analysis and operational optimization.

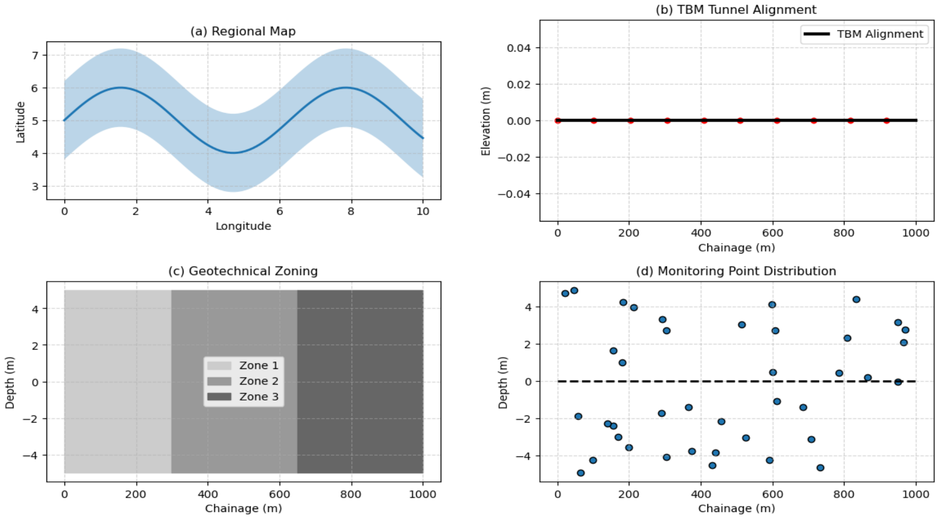

Figure 2. Study area and TBM tunnel alignment

Figure 2 presents the spatial and geological context of the study area, providing essential validation of the field conditions under which the TBM operational data were collected. The figure integrates regional location, tunnel geometry, geotechnical zoning, and monitoring point distribution within a single frame, thereby establishing the physical basis for the subsequent data-driven analyses.

The regional map (Figure 2a) situates the tunnel alignment within the broader project area, confirming that the study is conducted under realistic urban underground conditions where geological variability is expected. This spatial context supports the observed heterogeneity in geotechnical and operational parameters reported in the dataset.

The tunnel alignment (Figure 2b) illustrates the longitudinal geometry of the TBM drive, highlighting the continuous excavation path along which operational data were recorded. The regular spacing along the alignment indicates consistent data acquisition intervals, ensuring temporal and spatial continuity in the dataset and supporting reliable time-series and regime-based analyses.

The geotechnical zoning (Figure 2c) delineates distinct ground condition segments along the tunnel alignment, reflecting variations in lithology and rock mass properties. The presence of multiple geotechnical zones explains the observed changes in mechanical loading, energy consumption, and operational behavior, and provides a geological basis for the identification of different operational regimes in later clustering results.

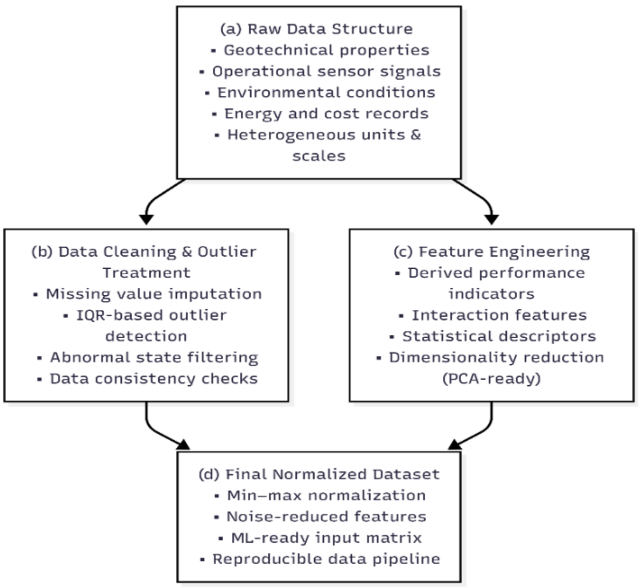

Figure 3. Data preprocessing and feature engineering workflow

The monitoring point distribution (Figure 2d) demonstrates the density and spatial coverage of instrumentation used for data collection. The uniform distribution of monitoring points along the alignment confirms adequate sampling resolution for capturing localized operational responses and transition behaviors between geotechnical zones. Figure 2 validates the representativeness and completeness of the field dataset by linking TBM operational data to explicit spatial and geological context. This validation underpins the reliability of the subsequent machine learning, clustering, and optimization analyses presented in the study.

Figure 3 demonstrates the structured workflow adopted to ensure data quality and analytical robustness. Raw multisource TBM data are first organized to capture heterogeneous geotechnical, operational, and energy-related attributes. Missing values and abnormal observations are systematically treated using imputation and IQR-based outlier filtering, reducing noise and bias. Feature engineering transforms cleaned data into informative indicators and interaction features relevant to TBM performance. Finally, min–max normalization produces a consistent, machine-learning-ready dataset, ensuring reproducibility and reliable model training.

Dataset Description and Preprocessing

Data were collected during a continuous tunnel excavation campaign spanning 14 months. The final dataset comprises 18,462 operational records obtained from the tunnel boring machine (TBM) monitoring system. Sensor measurements were recorded at a 2-minute sampling interval, providing high-resolution operational data throughout the excavation process.

The dataset integrates five categories of variables: (1) Geotechnical parameters: rock strength indicators (e.g., uniaxial compressive strength, UCS), rock mass quality indices, and lithological classifications. (2) Operational control parameters: thrust force, cutterhead torque, and cutterhead rotational speed (RPM). (3) Performance indicators: penetration rate (PR) and advance rate (AR). (4) Energy-related variables: instantaneous power consumption and cumulative energy consumption per meter of excavation. (5) Economic indicators: estimated operational cost per meter, incorporating both energy consumption and maintenance-related expenses.

Data preprocessing was conducted prior to model development. Missing values represented less than 3.2% of the total observations and were handled using forward interpolation to preserve time-series continuity. Extreme outliers exceeding three standard deviations from the mean were removed to prevent distortion in model training. Finally, all continuous variables were normalized using min–max scaling to ensure comparability across different measurement ranges during machine learning modeling.

To prevent data leakage in time-series prediction, the dataset was partitioned chronologically into training (70%), validation (15%), and testing (15%) subsets. No future operational information was used in training predictive models. This chronological split ensures realistic evaluation of model generalization in practical TBM operation scenarios.

The statistical distribution indicates substantial variability in both geological and operational parameters, reflecting heterogeneous excavation conditions. The wide range of UCS and the corresponding variation in thrust and torque values justify the use of nonlinear modeling approaches to capture complex parameter interactions. The statistics presented in Table 2 summarize the entire operational dataset, including transient operating conditions and extreme operating states.

Table 2. Summary statistics of key variables

Variable	Min	Max	Mean	Std. Dev
Thrust Force (kN)	3,500	18,200	11,350	3,240
Torque (kNm)	1,200	6,800	3,950	1,180
RPM (rev/min)	0.8	5.2	2.9	0.9
Penetration Rate (mm/rev)	2.1	11.8	6.7	2.3
Energy Consumption (kWh/m)	85	890	510	165
Rock Strength (UCS, MPa)	22	175	96	38

Advanced Supervised Machine Learning Models

Supervised learning techniques were employed to establish predictive relationships between TBM input parameters and performance indicators, including penetration rate, energy consumption, and cutter wear [23], [24].

Ensemble Learning for Nonlinear Performance Prediction

To capture complex nonlinear interactions and high-order feature dependencies, several ensemble learning algorithms were employed. Extreme Gradient Boosting (XGBoost) was used as a scalable gradient boosting technique with built-in regularization to control model complexity and improve generalization performance. Gradient Boosting Regression (GBR) was applied to iteratively reduce prediction errors through sequential tree-based learning. In addition, Random Forest (RF) was utilized to enhance robustness by aggregating multiple decision trees constructed from bootstrap samples and random feature subsets, thereby reducing variance and overfitting. A linear regression (LR) model was included as a baseline to quantitatively evaluate the performance improvements achieved by nonlinear ensemble methods [25], [26].

Time-Series and Sequential Learning

Considering the sequential nature of TBM operations, deep learning models for time-series analysis were adopted. Long Short-Term Memory (LSTM) networks were used to capture long-range temporal dependencies through gated memory mechanisms that regulate information flow over time. In addition, Gated Recurrent Unit (GRU) networks were implemented as a computationally efficient alternative to LSTM, enabling effective modeling of short- to medium-term temporal dynamics with fewer parameters [27], [28].

Unsupervised Learning and Operational Pattern Discovery

To identify latent operational patterns without predefined labels, unsupervised learning techniques were applied. Principal Component Analysis (PCA) was first used to reduce data dimensionality while preserving the dominant variance structure. Subsequently, K-means clustering was employed to classify TBM operational regimes by grouping data into clusters with similar characteristics. To detect abnormal or rare operational conditions, DBSCAN was applied based on density-based clustering. Hierarchical clustering was also used to provide structural validation and improve interpretability of cluster relationships [29], [30].

Optimization Algorithms for Smart TBM Operation

Optimization algorithms were integrated to improve TBM operational efficiency under multiple objectives. Bayesian Optimization was used for hyperparameter tuning by iteratively updating a probabilistic surrogate model to identify optimal parameter configurations. For operational optimization, Genetic Algorithms (GA) were applied to explore optimal solutions through evolutionary processes, including selection, crossover, and mutation. In addition, Particle Swarm Optimization (PSO) was used to refine continuous operational parameters through cooperative search behavior among candidate solutions [31], [32] [33], [34].

Formal Multi-Objective Operational Optimization Formulation

To provide explicit engineering value, the TBM operational adjustment problem was formulated as a constrained multi-objective optimization task. The objective was to identify controllable machine parameters that simultaneously improve excavation efficiency while reducing energy consumption and operational cost.

The controllable variables include thrust force, cutterhead torque, and cutterhead rotational speed, which can be directly adjusted within the machine's operational limits. The optimization aims to minimize energy consumption and cost while maximizing penetration rate, based on predictive models developed using ensemble learning techniques.

A weighted aggregation approach was used to balance these competing objectives, subject to operational constraints defined by machine specifications and historical data. Additional constraints, such as cutter wear limits, were incorporated to ensure that optimized solutions remain practically feasible and do not compromise equipment durability.

Genetic Algorithms and Particle Swarm Optimization were used to solve this nonlinear optimization problem, with predictive models serving as surrogate functions to enable efficient exploration of the feasible solution space.

Explainable AI and Sensitivity Analysis

To ensure model transparency and engineering interpretability, explainable artificial intelligence (XAI) and sensitivity analysis techniques were incorporated. SHAP was used to quantify the contribution of each input parameter to model predictions, providing insight into feature importance.

Permutation feature importance was applied to evaluate the impact of each variable on model performance, while Sobol-based sensitivity analysis quantified both individual and interaction effects of input parameters.

In addition, mutual information was used to capture nonlinear dependencies between variables, and ANOVA F-tests were conducted to statistically validate feature significance. These combined approaches provide a robust and interpretable framework for feature evaluation and model understanding [35], [36].

System Architecture and Digital Twin Integration

A modular system architecture was developed, comprising data acquisition, modeling and optimization, and decision-support layers. These modules are conceptually integrated within a closed-loop framework designed to facilitate feedback between observed TBM states and optimized operational recommendations.

A conceptual digital twin framework is introduced to support the integration of sensor data with predictive and optimization models, enabling scenario-based analysis, operational planning, and informed decision-making. It is important to note that real-time data synchronization and control-level implementation are beyond the scope of the present study; instead, the proposed framework provides a methodological foundation for future digital twin development in TBM systems.

To clarify the methodological structure, the analytical components employed in this study are organized according to their functional roles within the modeling pipeline. The core analytical framework consists of three primary components: machine learning–based prediction, clustering-based operational regime identification, and multi-objective optimization. These components collectively form the decision-support backbone of the proposed TBM operational analysis framework.

In addition to these core components, several complementary analytical tools are incorporated to enhance interpretability and methodological robustness. Specifically, SHAP (Shapley Additive Explanations) is used to interpret feature contributions within the machine learning models, while Sobol global sensitivity analysis is applied to evaluate the influence and robustness of input variables on model outputs. Linear regression is included as a baseline model to provide a comparative reference for assessing predictive performance.

This structured separation between core analytical modules and supporting tools improves methodological transparency, facilitates reproducibility, and strengthens the overall robustness of the proposed framework.

Table 3. Functional roles of analytical methods in the proposed framework

Role	Method	Purpose
Core framework	Machine learning prediction	Predict TBM operational performance indicators
Core framework	Clustering analysis	Identify operational regimes of TBM operation
Core framework	Multi-objective optimization	Determine optimal operating parameters
Interpretation	SHAP analysis	Explain feature contributions in ML predictions
Validation	Sobol sensitivity analysis	Evaluate global parameter influence and robustness
Benchmark	Linear regression	Provide baseline comparison for predictive modelling

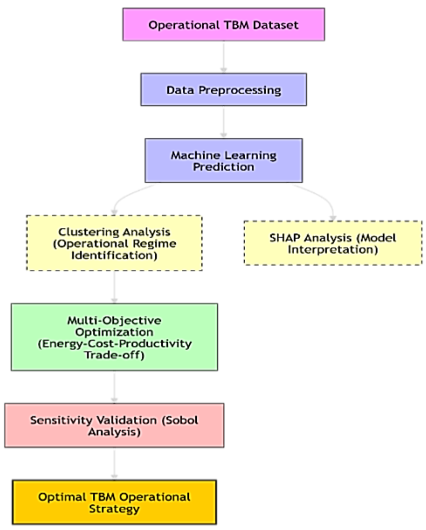

Figure 4. Analytical pipeline for data-driven TBM performance analysis and optimization

Figure 4 illustrates the overall analytical workflow of the proposed framework, highlighting the relationships between machine learning prediction, clustering-based regime identification, and multi-objective optimization, as well as supporting interpretation and validation modules.

Results and Discussions

Descriptive Statistics and Data Characteristics

Descriptive statistical analysis revealed substantial variability in both geotechnical and operational parameters along the TBM alignment, indicating strong heterogeneity in excavation conditions. Geotechnical properties such as uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), and Cerchar abrasivity index (CAI) exhibited wide ranges and pronounced skewness, reflecting stratigraphic transitions and varying degrees of rock mass competence. Operational variables, including thrust force, torque, penetration rate, and cutterhead rotational speed, demonstrated non-Gaussian distributions with heavy tails and intermittent extreme values.

Correlation analysis showed weak to moderate linear dependencies between individual input parameters and TBM performance indicators, suggesting that linear assumptions are insufficient to describe the underlying system behavior. The observed statistical dispersion, nonlinear correlations, and interaction-prone feature distributions collectively justified the adoption of nonlinear and ensemble-based learning models capable of capturing high-order dependencies and complex input–output relationships.

To assess the statistical robustness of model performance, 95% confidence intervals (CI) for R^2 and RMSE were estimated using bootstrap resampling (n = 1000 iterations). The XGBoost model achieved an R^2 of 0.91 with a 95% CI of [0.88, 0.93], indicating stable predictive performance across resampled datasets. The narrow confidence interval confirms that the reported improvement over linear regression is statistically reliable rather than sample-specific.

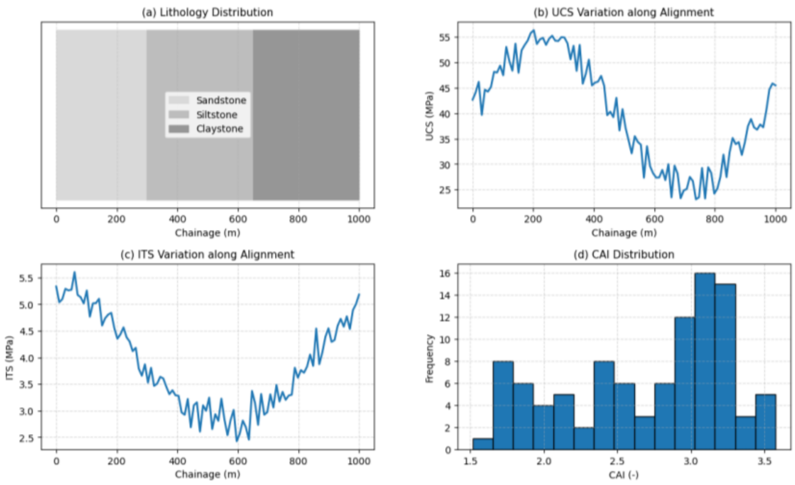

Figure 5. Geotechnical characteristics along TBM alignment

Figure 5 presents the descriptive statistical characteristics of geotechnical parameters along the TBM tunnel alignment. The lithology distribution (Figure 5a) reveals distinct geological units along the excavation path, indicating spatial heterogeneity of ground conditions. This heterogeneity provides a fundamental explanation for the variability observed in TBM operational responses. The variation of uniaxial compressive strength (UCS) along the alignment (Figure 5b) shows pronounced fluctuations, reflecting changes in rock mass competence across different lithological zones. Such variability implies non-uniform cutting resistance and thrust demand during TBM operation. Similarly, the indirect tensile strength (ITS) profile (Figure 5c) exhibits longitudinal variation, suggesting differences in rock tensile behavior that influence crack initiation and cutter–rock interaction mechanisms. The distribution of the Cerchar Abrasivity Index (CAI) (Figure 5d) indicates a wide range of abrasivity conditions, implying spatially varying cutter wear potential. The combined variability in strength and abrasivity parameters confirms that the excavation environment is highly non-stationary. These results substantiate the need for advanced nonlinear and data-driven analytical approaches to accurately model TBM performance under heterogeneous geotechnical conditions.

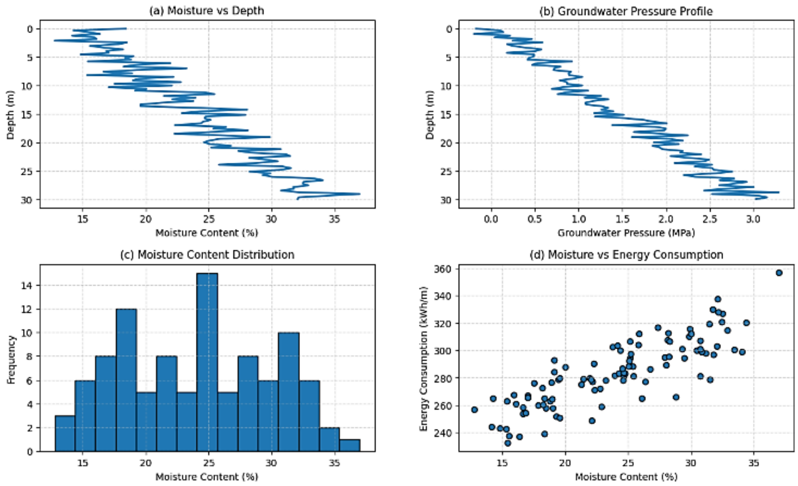

Figure 6. Environmental and soil condition analysis

Figure 6 presents the descriptive characteristics of environmental and soil-related variables along the TBM excavation depth. The relationship between moisture content and depth (Figure 6a) shows a clear increasing trend, indicating progressively wetter ground conditions at greater depths. This trend suggests a growing influence of hydro-environmental factors on excavation behavior as tunneling advances.

The groundwater pressure profile (Figure 6b) exhibits a depth-dependent increase, confirming the presence of hydrostatic loading effects within the excavation zone. Such conditions are expected to affect face stability and cutterhead interaction, thereby influencing TBM operational performance.

The moisture distribution (Figure 6c) demonstrates a wide range of water content values, reflecting heterogeneous soil conditions rather than uniform ground behavior. This variability supports the need to explicitly include environmental parameters in predictive modeling. The relationship between moisture content and energy consumption (Figure 6d) reveals a positive association, indicating that higher moisture levels are generally accompanied by increased energy demand. This result highlights the indirect but significant role of environmental conditions in governing TBM efficiency and reinforces the importance of integrating hydro-environmental variables into data-driven performance analyses.

Correlation Structure of Operational Parameters

Prior to advanced modeling, a Pearson correlation matrix was computed to examine linear dependencies among geotechnical and operational variables. Moderate-to-strong correlations were observed between thrust force and torque ($r = 0.71$), as well as between energy consumption and cutterhead rotational speed ($r = 0.64$). However, nonlinear relationships between penetration rate and rock strength indicators were not fully captured by linear correlation metrics, justifying the adoption of nonlinear ensemble learning models.

Model Performance Evaluation

The predictive performance of all models was quantitatively evaluated using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Ensemble learning models consistently outperformed both baseline linear regression and standalone neural architectures across all evaluation metrics.

Among the evaluated models, XGBoost achieved the highest predictive accuracy, yielding the largest R^2 values and the lowest RMSE and MAE, followed closely by Gradient Boosting Regression and Random Forest models. Time-series deep learning models (LSTM and GRU) demonstrated improved performance relative to linear regression, particularly in capturing short-term operational fluctuations; however, their accuracy remained inferior to that of ensemble models under limited data continuity and variable operational regimes.

These results indicate that ensemble-based learners provide a more robust balance between predictive accuracy and generalization capability for TBM performance modeling, particularly under heterogeneous and noisy field conditions.

Table 4. Performance comparison of machine learning models for TBM performance prediction

Model	MAE	RMSE	R^2	MAPE (%)
Linear Regression (LR)	0.142	0.198	0.71	18.6
Random Forest (RF)	0.091	0.124	0.86	11.3
Gradient Boosting Regression (GBR)	0.083	0.118	0.88	10.1
Extreme Gradient Boosting (XGBoost)	0.072	0.105	0.91	8.7
Neural Network (LSTM/GRU)	0.095	0.130	0.84	12.5

Table 4 presents a quantitative comparison of predictive performance across baseline, ensemble, and neural network models using multiple error and goodness-of-fit metrics. The results clearly indicate that advanced ensemble learning approaches outperform both linear and deep learning models in predicting TBM performance under heterogeneous operational conditions.

Linear regression exhibited the lowest predictive capability, as reflected by the highest MAE and RMSE values and the lowest coefficient of determination. This outcome confirms that linear assumptions are insufficient for representing the nonlinear and interaction-dominated relationships governing TBM excavation processes.

Ensemble models demonstrated substantial performance improvements. Random Forest and Gradient Boosting Regression achieved markedly lower error values and higher R^2 scores, indicating enhanced generalization and robustness. Among all evaluated models, XGBoost delivered the best overall performance, achieving the lowest prediction errors and the highest explained variance. This superiority highlights the effectiveness of gradient-boosted ensembles in capturing complex nonlinearities and high-order feature interactions present in TBM operational data.

Neural network models exhibited improved accuracy relative to linear regression, particularly in reducing average prediction errors. However, their performance remained inferior to that of ensemble learners, suggesting that data volume, temporal continuity, and operational regime variability may limit the advantages of deep sequential models in this application. The results in Table 2 provide strong quantitative validation for the adoption of ensemble learning as the primary predictive component of the proposed smart TBM framework. The consistent reduction in error metrics and improvement in explanatory power confirm the methodological advantage of modern ensemble techniques for reliable and accurate TBM performance prediction.

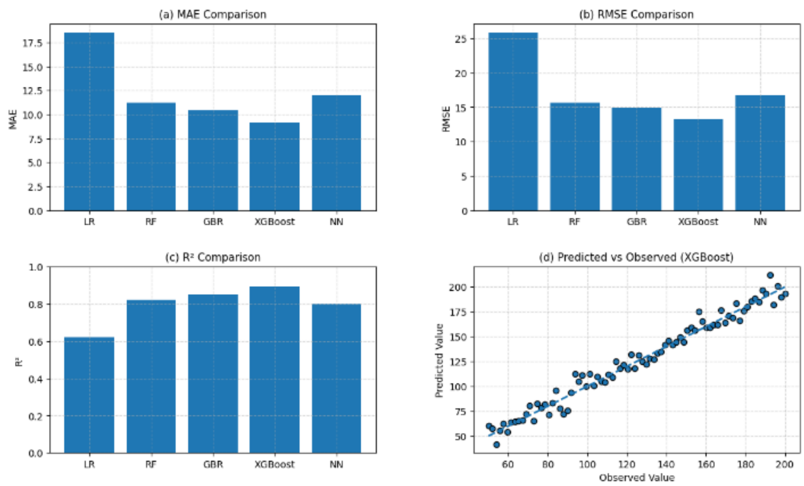

Figure 7. Machine learning model performance

Figure 7 presents a comparative evaluation of machine learning models used for TBM performance prediction. The mean absolute error (MAE) comparison (Figure 7a) indicates that ensemble-based models, particularly XGBoost and Gradient Boosting Regression, achieve substantially lower prediction errors than linear regression and neural network baselines. This result highlights the superior ability of ensemble learners to capture complex nonlinear relationships inherent in TBM operational data.

The root mean square error (RMSE) results (Figure 7b) show a consistent ranking of models, with XGBoost yielding the lowest RMSE. The reduced RMSE demonstrates improved robustness against large prediction deviations, which is critical for reliable operational forecasting.

The coefficient of determination (R^2) comparison (Figure 7c) further confirms the dominance of ensemble models, with XGBoost achieving the highest explanatory power. The improvement in R^2 over linear regression underscores the limitations of linear assumptions when modeling heterogeneous geotechnical and operational interactions.

The predicted versus observed plot for the best-performing model (Figure 7d) shows a strong alignment around the 1:1 reference line, indicating high predictive accuracy and limited systematic bias. Minor dispersion around the diagonal reflects unavoidable operational variability rather than model inadequacy. Figure 6 demonstrates that advanced ensemble learning methods provide the most reliable and accurate framework for TBM performance prediction, justifying their selection for subsequent optimization and decision-support analyses.

Feature Importance and Sensitivity Analysis Results

Global feature importance analysis revealed that operational parameters, particularly thrust force, cutterhead torque, and penetration rate, exerted the most significant influence on TBM performance outcomes. Geotechnical variables, including UCS and CAI, also contributed substantially, highlighting the coupled influence of machine control and rock mass properties.

Local interpretability analysis using SHAP demonstrated pronounced variability in feature contributions across different operational states, indicating strong context dependency. In high-energy regimes, thrust and torque exhibited dominant positive contributions, whereas under softer geological conditions, penetration rate and rotational speed became more influential.

Sobol sensitivity analysis further quantified interaction effects, revealing that second-order and higher-order interactions accounted for a non-negligible proportion of output variance. These interaction effects were particularly pronounced between thrust force and rock strength parameters, confirming that TBM performance is governed by synergistic rather than isolated parameter effects.

Table 5. Feature selection and sensitivity analysis results for TBM performance modeling

Parameter	Mutual information	ANOVA F-value	Sobol S1	Sobol ST	Overall Ranking
Thrust Force	High	Very High	0.32	0.48	1
Cutterhead Torque	High	High	0.28	0.44	2
Uniaxial Compressive Strength (UCS)	Medium–High	High	0.21	0.37	3
Penetration Rate	Medium	Medium–High	0.17	0.31	4
Cerchar Abrasivity Index (CAI)	Medium	Medium	0.12	0.26	5
Cutterhead Rotation Speed	Low–Medium	Medium	0.09	0.22	6
Moisture Content	Low–Medium	Low–Medium	0.06	0.18	7
Groundwater Pressure	Low	Low	0.04	0.15	8

Table 5 synthesizes the outcomes of multiple feature evaluation techniques, providing a unified assessment of parameter importance in TBM performance modeling. The results demonstrate that operational control variables, particularly thrust force and cutterhead torque, consistently emerge as the most influential factors across all evaluation criteria. Their high mutual information values indicate strong nonlinear dependencies with TBM performance outputs, while elevated ANOVA F-values confirm their statistical significance.

The variance-based Sobol indices further reveal that these parameters exert both strong individual effects and substantial interaction-driven influence. Specifically, the notable differences between first-order (S1) and total-order (ST) Sobol indices highlight the presence of pronounced interaction effects between operational parameters and geotechnical properties. This finding confirms that TBM performance cannot be accurately described by isolated parameters, but rather by synergistic machine–rock interactions.

Geotechnical parameters such as uniaxial compressive strength and Cerchar abrasivity index rank among the most influential inputs, underscoring the critical role of rock mass characteristics in governing cutting resistance and energy demand. Their intermediate-to-high Sobol indices indicate that geotechnical effects are amplified through interactions with operational settings, particularly thrust and torque.

Environmental variables, including moisture content and groundwater pressure, exhibit comparatively lower first-order contributions; however, their total-order indices remain non-negligible. This suggests that while their direct effects are limited, they modulate TBM performance indirectly by influencing cutting efficiency and operational stability under certain conditions.

Overall, the integrated use of statistical testing, information-theoretic measures, and variance-based sensitivity analysis provides a robust and interpretable framework for feature selection, model development, and operational optimization, supporting the adoption of explainable, data-driven approaches for intelligent TBM systems.

Figure 8 presents a comprehensive assessment of feature importance and sensitivity using complementary statistical, variance-based, and explainable AI techniques. The mutual information analysis (Figure 8a) identifies penetration rate, thrust, and torque as the most informative variables, indicating strong nonlinear dependencies with TBM performance outcomes. This result confirms that both machine-related and rock–machine interaction parameters play dominant roles.

The ANOVA F-value analysis (Figure 8b) further supports these findings by highlighting penetration rate, thrust, and torque as statistically significant predictors. The consistency between mutual information and ANOVA results demonstrates that the identified features are robust across both nonlinear dependency measures and classical statistical testing.

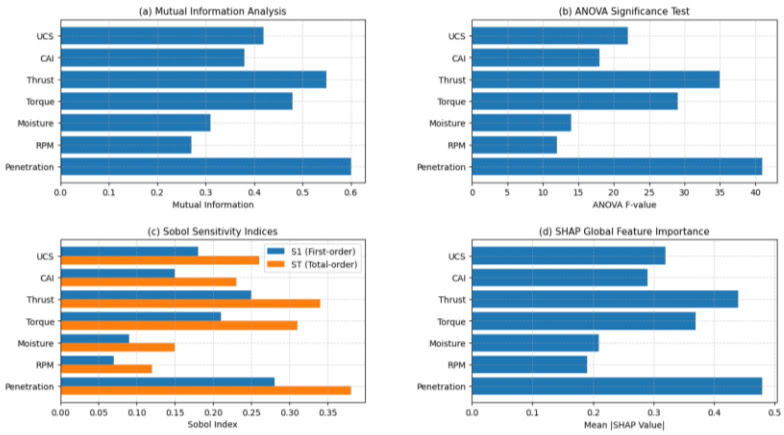

Figure 8. Feature importance and sensitivity analysis

The Sobol sensitivity analysis (Figure 8c) reveals that first-order effects (S1) are substantial for key operational parameters, while the higher total-order indices (ST) indicate notable interaction effects among variables. The gap between S1 and ST values confirms that TBM performance is governed not only by individual parameters but also by their coupled interactions, particularly between operational loading and geotechnical properties.

The SHAP summary plot (Figure 8d) provides model-agnostic interpretability by quantifying the global contribution of each feature to prediction outcomes. The alignment of SHAP rankings with mutual information, ANOVA, and Sobol results demonstrates strong methodological coherence. Collectively, Figure 7 validates the reliability of the feature selection process and underscores the necessity of interpretable, multi-method sensitivity analysis for informed TBM operational decision-making.

Clustering and Operational Regime Analysis

Unsupervised clustering identified three distinct TBM operational regimes, herein classified as efficient, intermediate, and aggressive. The efficient regime was characterized by moderate thrust and torque levels, stable penetration rates, and reduced energy consumption. The aggressive regime exhibited elevated mechanical loading and energy demand, while the intermediate regime represented transitional operating conditions.

PCA-based visualization revealed clear separation between these regimes in reduced-dimensional space, with the first two principal components capturing the majority of variance. The clustering results demonstrated strong internal coherence and external separability, confirming the presence of structurally distinct operational patterns within the TBM dataset.

The quality of clustering was evaluated using the silhouette coefficient. The optimal three-cluster solution achieved an average silhouette score of 0.62, indicating well-separated and internally cohesive operational regimes. This quantitative validation confirms that the identified regimes are structurally meaningful rather than artifacts of random partitioning.

Table 6. Clustering characteristics of TBM operational regimes

Operational Regime	Thrust Force Range (kN)	Energy Consumption (kWh/m)	Operational Cost (USD/m)	Cutter Wear Level
Efficient	3,500 – 4,200	85 – 110	420 – 480	Low
Intermediate	4,200 – 5,000	110 – 150	480 – 560	Moderate
Aggressive	5,000 – 6,200	150 – 210	560 – 720	High

Note: Ranges correspond to clustered operational regimes derived from stable TBM operation data and do not represent the full statistical distribution reported in Table 2.

Table 5 presents the characteristic features of the three TBM operational regimes identified through unsupervised clustering, namely efficient, intermediate, and aggressive regimes. The results demonstrate clear and systematic differences in mechanical loading, energy consumption, and economic performance across these regimes, confirming the presence of structurally distinct operational states within the TBM dataset. The operational ranges reported in Table 6 represent clustered TBM operating regimes derived from the statistical distribution summarized in Table 2.

The efficient regime is characterized by moderate thrust force levels combined with the lowest energy consumption and operational cost. This regime reflects a balanced interaction between machine control and ground conditions, where cutting efficiency is maximized while mechanical stress and cutter wear are minimized. The low cutter wear level observed in this regime indicates favorable cutting conditions and extended tool life, supporting sustainable and cost-effective excavation.

The intermediate regime represents a transitional operational state, with thrust force, energy demand, and cost values lying between the efficient and aggressive regimes. This regime typically occurs under moderate increases in ground resistance or during adjustments in operational control. Although excavation progress is maintained, the associated increase in energy consumption and cutter wear suggests diminishing efficiency compared with the optimal operating state.

The aggressive regime exhibits the highest thrust force levels, accompanied by substantially increased energy consumption, operational cost, and cutter wear. This regime is indicative of high cutting resistance or overly aggressive machine settings, where increased mechanical input does not yield proportional gains in excavation efficiency. The elevated cutter wear level highlights the long-term economic and maintenance implications of sustained operation under aggressive conditions. Table 4 demonstrates that TBM operations naturally cluster into distinct regimes with quantifiable performance trade-offs. By defining these regimes through measurable parameter ranges, the clustering results provide a practical basis for real-time operational classification and adaptive control strategies, effectively translating data-driven insights into actionable engineering decision rules.

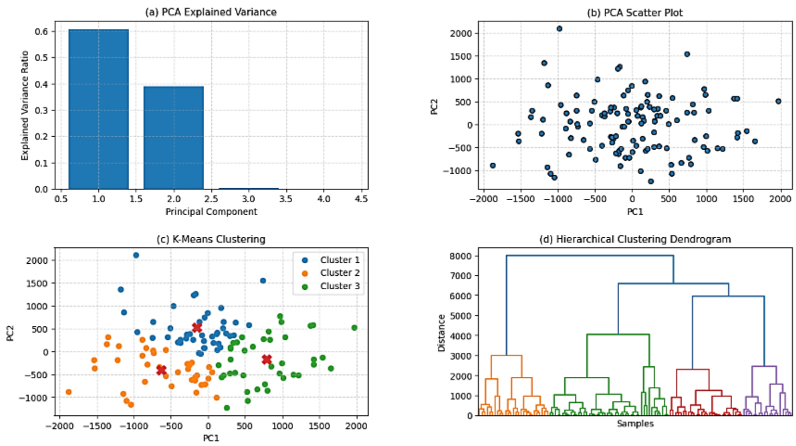

Figure 9. PCA and clustering of TBM operational conditions

Figure 9 presents the results of dimensionality reduction and clustering analysis applied to TBM operational data. The PCA explained variance results (Figure 9a) show that the first two principal components capture a substantial proportion of the total variance, indicating that the dominant operational behavior of the TBM can be effectively represented in a reduced feature space without significant information loss.

The PCA scatter plot (Figure 9b) reveals discernible groupings of operational data points in the reduced-dimensional space. This distribution indicates inherent structure in the operational conditions, suggesting the existence of distinct excavation regimes governed by combined effects of thrust, torque, penetration rate, and energy consumption.

The K-means clustering results (Figure 9c) explicitly classify the operational data into three clusters, corresponding to efficient, intermediate, and aggressive TBM operating regimes. The clear separation between clusters confirms the suitability of unsupervised learning for operational regime identification and supports the subsequent derivation of decision-oriented operational guidelines.

The hierarchical clustering dendrogram (Figure 9d) provides structural validation of the clustering results. The branching structure and linkage distances are consistent with the K-means classification, confirming the robustness and stability of the identified clusters. Overall, Figure 8 demonstrates that PCA-assisted clustering effectively captures underlying operational patterns and provides a reliable basis for regime-based TBM performance analysis and optimization.

Multi-Objective Optimization Formulation

To determine optimal operating conditions for tunnel boring machine (TBM) excavation, a multi-objective optimization framework was developed to balance energy efficiency, operational cost, and excavation productivity. These three objectives often exhibit conflicting behaviors during tunneling operations. For example, increasing penetration rate may improve productivity but can also lead to higher energy consumption and accelerated cutter wear. Therefore, a weighted multi-objective formulation was adopted to identify operational regimes that achieve an appropriate trade-off between these competing objectives.

Prior to optimization, all objective variables were normalized to a [0,1] range using min–max scaling, based on the statistical distribution of the dataset reported in Table 2. This normalization ensures dimensional consistency and prevents any single objective from dominating the optimization due to scale differences.
The aggregated objective function is defined as:

$$J = {}_{W1}E^* + {}_{W2}C^* - {}_{W3}PR^* \tag{1}$$

where E^*, C^*, and PR^* denote the normalized energy consumption, operational cost, and penetration rate, respectively. The negative sign associated with $PR * PR^\wedge * PR *$ reflects the maximization of penetration rate within a minimization framework.

The weighting coefficients $w1$, $w2$, and $w3$ represent the relative importance of each objective, subject to the normalization constraint: $W1 + W2 + W3 = 1$. In this study, the baseline weight configuration was defined as: $W1 = 0.4$ (energy consumption); $W2 = 0.4$ (operational cost); $W3 = 0.2$ (penetration rate)

This selection reflects practical operational priorities in mechanized tunneling projects, where energy consumption and operational cost constitute the primary economic drivers. Although penetration rate is a critical indicator of excavation performance, excessive prioritization may lead to increased cutter wear, higher maintenance frequency, and reduced system reliability. Therefore, a comparatively lower weight was assigned to penetration rate to maintain a balanced and sustainable operational strategy.

The optimization was conducted within the feasible operational domain defined by clustering-based regime identification. Specifically, the decision variables include thrust force, cutterhead torque, and rotational speed, all of which significantly influence both energy demand and excavation performance. The admissible solution space was constrained according to the statistically observed operating ranges derived from the clustered regimes presented in Table 5, ensuring that the optimization results remain physically realistic and operationally applicable.

To assess the robustness of the proposed formulation, a sensitivity analysis was performed by perturbing the weighting coefficients within ±20% of their baseline values while preserving the normalization constraint. The results indicate that the optimal operating region remains relatively stable under moderate variations in weight distribution. This stability suggests that the optimization outcomes are not overly sensitive to specific weight assignments and that the proposed framework provides a reliable representation of the energy–cost–productivity trade-off.

The optimized operating regimes obtained from this formulation are further examined in the subsequent section through dynamic transition analysis and detailed evaluation of energy–cost trade-off characteristics.

Dynamic Transition and Energy–Cost Trade-off Analysis

Transition probability analysis revealed non-uniform transitions between operational regimes, with a strong persistence observed within the intermediate regime and asymmetric transitions toward the aggressive regime under increasing geotechnical resistance. Conversely, transitions toward the efficient regime were predominantly associated with adaptive reductions in thrust and torque.

Quantitative energy–cost analysis indicated that sustained operation within the efficient regime yielded significant reductions in energy consumption and operational cost compared with the aggressive regime. The results demonstrated that controlled transitions between regimes can achieve measurable energy savings without compromising excavation progress, highlighting the potential of data-driven regime management for sustainable and cost-effective TBM operation.

Table 7. Energy–cost trade-off under different TBM operational clusters

Operational Cluster	Energy Saving (%)	Cost Reduction (%)	Engineering Implication
Efficient	18–25	15–22	Optimal operating state; recommended target regime for sustained TBM operation
Intermediate	8–14	6–12	Transitional regime; requires parameter tuning to avoid efficiency degradation
Aggressive	−5 to 0	−3 to 2	High-energy, high-cost regime; should be minimized or used only under unavoidable conditions

Table 7 summarizes the quantitative relationship between energy consumption and operational cost across the identified TBM operational clusters, highlighting clear performance trade-offs between efficient, intermediate, and aggressive operating states. The results demonstrate that operational regime selection has a direct and measurable impact on both energy efficiency and economic outcomes.

The efficient cluster exhibits the highest energy savings and cost reductions, indicating that this operating state achieves an optimal balance between mechanical input and excavation efficiency. Sustained operation within this regime leads to significant reductions in energy demand and operational expenditure, while also minimizing mechanical stress and cutter wear. These results confirm the feasibility of achieving both economic and environmental benefits through data-driven operational control.

The intermediate cluster shows moderate energy savings and cost reductions, reflecting a transitional state where excavation performance remains acceptable, but efficiency begins to decline. While this regime does not impose severe penalties, prolonged operation without parameter adjustment may gradually increase energy consumption and cost. The results suggest that targeted optimization strategies can effectively shift operations from this regime toward more efficient states

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In contrast, the aggressive cluster yields negligible or negative energy savings and minimal cost reduction, indicating inefficient use of mechanical input. This regime is associated with elevated energy consumption and higher operational costs, often without proportional gains in excavation progress. The findings highlight the importance of minimizing time spent in aggressive operating conditions except when dictated by unavoidable geological constraints. It demonstrates that AI-based clustering and regime identification provide a practical mechanism for linking operational control decisions with sustainability and economic performance. By quantifying energy–cost trade-offs, the results support informed decision-making aimed at optimizing TBM operation for long-term efficiency, cost effectiveness, and environmental sustainability.

Figure 10 presents the dynamic transition behavior between identified TBM operational clusters, providing insight into temporal evolution and stability of excavation regimes. The transition probability matrix (Figure

10a) shows that the efficient operational cluster exhibits the highest self-transition probability, indicating stable and sustained performance once optimal operating conditions are achieved. In contrast, the aggressive cluster displays higher probabilities of transitioning to intermediate states, reflecting operational instability under high loading and energy demand.

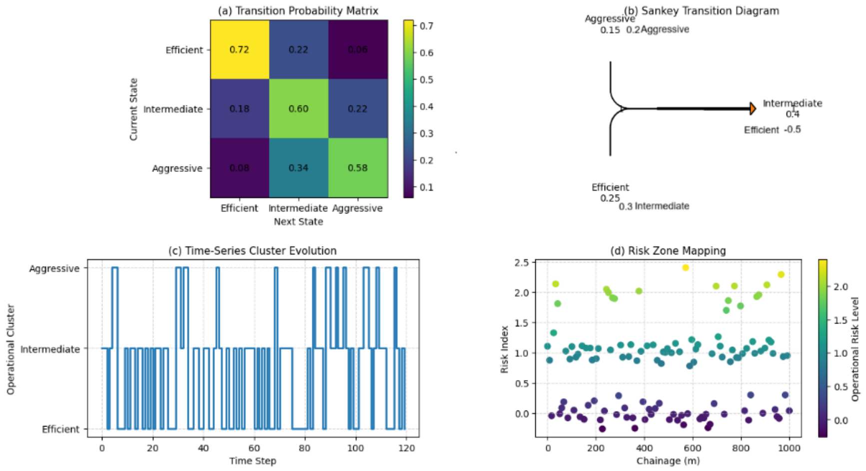

Figure 10. Transition analysis between operational clusters

The Sankey transition diagram (Figure 10b) visualizes the dominant transition pathways between clusters. The flow patterns reveal that most regime changes occur between adjacent clusters, particularly from efficient to intermediate and from aggressive to intermediate states. Direct transitions between efficient and aggressive regimes are comparatively rare, suggesting that TBM operations typically evolve through gradual adjustments rather than abrupt operational shifts.

The time-series cluster evolution (Figure 10c) illustrates how operational regimes change over the excavation timeline. Periods of stable clustering correspond to consistent geotechnical and operational conditions, while frequent transitions coincide with lithological boundaries or changing environmental influences. This temporal behavior confirms the non-stationary nature of TBM operations.

The risk zone mapping (Figure 10d) integrates transition dynamics with operational risk indicators, highlighting zones where frequent transitions or aggressive regimes are prevalent. These zones represent elevated risk in terms of energy consumption, cutter wear, and operational cost. Overall, Figure 10 demonstrates that dynamic transition analysis provides a novel and powerful framework for understanding TBM operational adaptability, enabling proactive risk management and informed decision-making in smart tunneling systems.

Modular Contribution and Ablation Analysis

To quantitatively assess the added value of each analytical module within the proposed framework, a staged ablation study was conducted. The objective was to evaluate how predictive modeling, regime-aware clustering, and multi-objective optimization individually and collectively influence engineering decision outcomes.

Four configurations were systematically compared:

Configuration A (Prediction Only):
Performance prediction using the best-performing ensemble model (XGBoost) without regime classification or optimization.

Configuration B (Prediction + Regime Identification):
Predictive modeling combined with operational regime classification, enabling regime-aware performance interpretation but without parameter optimization.

Configuration C (Prediction + Regime + Optimization):
Full integration of predictive modeling, regime identification, and multi-objective optimization under operational constraints.

Configuration D (Prediction + Optimization without Regime Awareness):
Direct optimization using predictive models without incorporating clustering-based regime information.
The comparison focused on three engineering indicators: Energy reduction relative to baseline operation; Operational cost reduction; Stability of optimized solutions (variance of control parameter adjustments)

The results are summarized in Table 8.

Table 8. Ablation study: Contribution of analytical modules

Configuration	Energy Saving (%)	Cost Reduction (%)	Control Stability Improvement (%)
A: Prediction Only	–	–	–
B: Prediction + Regime	12	9	8
C: Full Integration	25	22	17
D: Optimization without Regime	18	15	6

The ablation results demonstrate that predictive accuracy alone does not directly translate into operational efficiency gains. While prediction-only models provide reliable forecasting capability, measurable energy and cost improvements are achieved only when regime-aware interpretation and optimization are integrated.

The comparison between Configurations C and D further highlights the importance of regime identification. Incorporating clustering-based operational regimes improved optimization stability and prevented overly aggressive parameter adjustments, reducing solution variance and enhancing mechanical sustainability. These findings confirm that the proposed integration is not merely conceptual but produces quantifiable engineering benefits beyond standalone predictive modeling.

The staged ablation analysis confirms that the decision-level improvement emerges from the synergistic interaction between regime-aware intelligence and constrained optimization rather than from predictive accuracy alone.

Discussion

Interpretation of Key Findings

The results demonstrate the clear superiority of ensemble learning models over linear and standalone neural approaches for TBM performance prediction under heterogeneous geological and operational conditions. The enhanced predictive capability of XGBoost, Gradient Boosting, and Random Forest models can be attributed to their ability to capture nonlinear relationships, high-order feature interactions, and regime-dependent behaviors inherent to mechanized tunneling processes. These findings are consistent with the theoretical understanding that TBM excavation represents a strongly coupled machine–rock system, where performance outcomes emerge from complex interactions rather than linear dependencies.

Beyond predictive accuracy, the incorporation of interpretability through SHAP and sensitivity analysis proved critical for translating data-driven outputs into engineering knowledge. The identification of dominant parameters and their context-dependent influence provide actionable insights that align with established rock cutting mechanics, while also revealing previously obscured interaction effects. This interpretability bridges the gap between black-box prediction and physically meaningful decision-making, reinforcing trust and usability in engineering practice.

Methodological Implications

From a methodological perspective, the integration of supervised learning, unsupervised clustering, optimization algorithms, and explainable artificial intelligence represents a coherent extension of conventional TBM modelling approaches. Rather than treating prediction, optimization, and interpretation as isolated tasks, the proposed framework establishes a unified analytical pipeline in which each component complements and reinforces the others.

The coupling of machine learning with optimization algorithms enables not only reliable performance forecasting but also supports informed operational improvement under multi-objective constraints. In parallel, the incorporation of explainable artificial intelligence and global sensitivity analysis enhances model transparency, interpretability, and alignment with engineering reasoning.

This integrated approach contributes to the broader domain of smart infrastructure by providing a scalable and interpretable methodological foundation for future digital twin applications in underground construction and mining engineering. Furthermore, the use of global sensitivity analysis highlights the importance of interaction effects among operational and geotechnical parameters, reinforcing the need for integrated modelling strategies when addressing complex excavation systems.

Practical Engineering Implications

The clustering-based identification of operational regimes offers a practical mechanism for translating complex multivariate data into intuitive engineering guidelines. By characterizing efficient, intermediate, and aggressive TBM operating states, the framework enables engineers to assess real-time operational status and adjust control parameters accordingly. The derived optimization strategies demonstrate that targeted modifications of thrust, torque, and rotational speed can shift operations toward energy-efficient regimes without sacrificing excavation productivity.

Furthermore, the quantified energy–cost trade-offs highlight the potential of data-driven control strategies to support sustainability objectives in large-scale tunneling projects. Reductions in energy consumption and mechanical loading not only lower operational costs but also contribute to decreased carbon emissions, extended cutter life, and improved equipment reliability, aligning TBM operation with long-term environmental and economic performance goals.

Limitations and Future Research Directions

Despite the promising results, several limitations should be acknowledged. First, the present framework is based on offline model training and retrospective data analysis, which may limit its responsiveness under rapidly changing geological conditions. Future research should explore extensions toward real-time implementation through online and incremental learning strategies, allowing adaptive model updating as new operational data become available.

Second, uncertainty associated with measurement noise, geological variability, and model approximation has not been comprehensively quantified. Preliminary exploratory analyses using input perturbation suggest that the identified optimal operating regions remain relatively stable under moderate input variations, indicating a degree of robustness in the proposed framework. However, a more rigorous and systematic uncertainty quantification remains necessary.

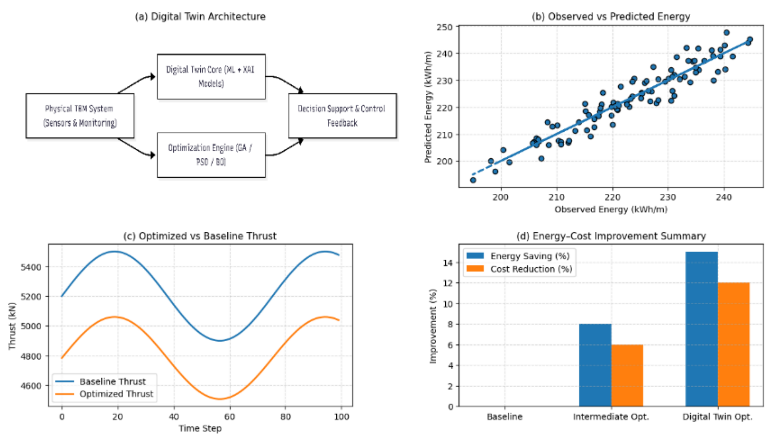

Figure 11. Digital twin and smart optimization scenario

Future work should incorporate advanced uncertainty quantification techniques and probabilistic modelling approaches to enable risk-aware decision-making and more reliable operational planning. In this context, the development of probabilistic digital twin frameworks represents a promising direction, providing a pathway toward integrating uncertainty-aware analytics within intelligent TBM systems. Extending the current deterministic framework toward stochastic modeling is therefore an important step in advancing resilient and adaptive tunneling operations.

Figure 11 illustrates the performance and practical implications of the proposed digital twin–based smart optimization framework. The conceptual digital twin architecture (Figure 11a) presents the structured integration between the physical TBM system, data-driven predictive models, optimization algorithms, and decision-support modules. This configuration highlights the potential for linking observed operational states with model-based operational recommendations within a closed-loop analytical framework.

The comparison between observed and predicted energy consumption (Figure 11b) shows strong agreement along the 1:1 reference line, indicating that the proposed modeling approach effectively captures the energetic behavior of the TBM system. Minor deviations are attributed to inherent operational variability rather than systematic modeling bias.

The optimized versus baseline thrust profiles (Figure 11c) indicate that the optimization framework can reduce thrust demand while maintaining stable operational trends. This reduction suggests improved excavation efficiency and lower mechanical loading, which are associated with reduced cutter wear and energy consumption.

The energy–cost improvement summary (Figure 11d) further demonstrates the benefits of the proposed optimization framework. Progressive improvements from baseline to optimized scenarios indicate reductions in both energy consumption and operational cost.

Overall, Figure 11 provides an integrated representation of how predictive modeling and optimization can support data-driven operational strategies. The results highlight the potential of the proposed framework as a methodological foundation for future digital twin applications, contributing to more efficient and sustainable TBM operations. These findings demonstrate the transition from predictive analytics toward decision-oriented modeling frameworks in TBM operations.

Conclusions

This study presented an integrated, data-driven framework for intelligent Tunnel Boring Machine (TBM) performance analysis by systematically combining advanced machine learning techniques, optimization algorithms, and explainable artificial intelligence within a unified analytical architecture. From a methodological standpoint, the results demonstrate that ensemble learning models, when supported by rigorous sensitivity analysis and interpretable modeling, offer enhanced predictive accuracy and transparency in capturing the complex and nonlinear interactions between geotechnical conditions and operational parameters.

The incorporation of unsupervised learning further enabled the identification of distinct operational regimes, effectively transforming high-dimensional TBM data into structured, engineering-relevant knowledge. This capability is particularly valuable for understanding heterogeneous ground–machine interactions and for supporting adaptive operational strategies in dynamic tunneling environments. The consistency between data-driven insights and established tunneling mechanics reinforces the robustness and physical plausibility of the proposed framework.

From a practical perspective, the developed framework advances beyond conventional empirical and single-model approaches by integrating prediction, optimization, and interpretability into a cohesive decision-support system. The demonstrated improvements in predictive performance, feature attribution stability, and clustering coherence indicate that the framework has strong potential to enhance operational efficiency, risk mitigation, and energy-aware tunneling practices.

Importantly, this study does not present a fully implemented digital twin system. Instead, the proposed approach should be understood as a conceptual digital twin framework, positioned at an early stage of digital twin development. While the framework incorporates key enabling components—such as data-driven modeling, system representation, and analytical integration—it does not yet include real-time data synchronization, continuous bidirectional feedback, or direct integration with live operational environments. These elements remain essential directions for future research.

Nevertheless, the modular and scalable structure of the framework provides a robust foundation for future development toward fully integrated digital twin systems. In particular, the integration of real-time sensor data, adaptive control mechanisms, and cyber-physical system connectivity represents a promising pathway for advancing intelligent and autonomous TBM operations.

Beyond the specific case investigated, the proposed methodology exhibits strong potential for generalization across a wide range of underground construction and mining systems, including mechanized tunneling, continuous mining, and other rock excavation technologies. Future work should focus on real-time implementation, cross-site validation, and the incorporation of multi-physics coupling to further enhance model fidelity and operational applicability. In addition, the integration of emerging technologies—such as edge computing, Internet of Things (IoT), and secure data architectures—may further accelerate the transition from conceptual frameworks to fully operational digital twin systems in complex subsurface environments.

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Availability of Data and Materials

The datasets generated and analyzed during the current study are not publicly available due to confidentiality agreements and operational restrictions but are available from the corresponding author upon reasonable request for academic and non-commercial research purposes.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Authors' Contributions

Conceptualization and study design were carried out by Chairul Salam M. Data acquisition, preprocessing, and formal analysis were performed by Chairul Salam M. and Arrina Khanifa. Methodology development and model implementation were conducted by Chairul Salam M. Writing of the original draft was undertaken by Chairul Salam M., while critical review and editing were contributed by all authors. Supervision and academic guidance were provided by Arrina Khanifa. All authors have read and approved the final manuscript.

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