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AI-Assisted Evaluation Of Pavement Material Performance Using Plate Load Test Data For Optimized Roadway Design

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Abstract
Roadway design and pavement material evaluation are two areas of civil engineering that have been completely transformed by the quick development of artificial intelligence (AI). Plate Load Tests (PLT), a traditional method of determining subgrade strength, have proved time-consuming and interpretive. This paper explores the ways in which artificial intelligence (AI) methods, including fuzzy logic, ANN, and machine learning (ML), might improve the precision and effectiveness of PLT data interpretation for pavement design optimization. The study analyzes AI models, summarizes recent research, and talks about the benefits, drawbacks, and potential applications of AI.
Keywords: *Artificial Intelligence, Plate Load Test, Pavement Design, Machine Learning, Subgrade Evaluation, ANN, Smart Infrastructure.*

INTRODUCTION

The fast development of transportation infrastructure necessitates the use of increasingly performance-based, data-driven, and intelligent design techniques. Subgrade characterisation is one of the most important aspects of highway design as it has a direct impact on the structural integrity and service life of the pavement. One of the most popular in-situ techniques for assessing subgrade stiffness and bearing capacity is the Plate Load Test (PLT). Although PLT has been a mainstay of pavement and geotechnical engineering for many years, its traditional interpretation techniques are frequently time-consuming and sensitive to human subjectivity (IS 1888:1982; Das, 2016).

Conventional pavement design methods depend on static correlations between design variables and input parameters as well as empirical formulae. The unpredictability and variety present in natural soils are difficult for these techniques to handle, despite their value in controlled settings. It is challenging to develop generalized models that hold over a range of situations because of the variety in load-settlement responses from PLT data, which can be attributed to variations in soil type, moisture content, compaction level, and plate size (Huang, 2004; Baus & Li, 2002). Engineers are increasingly searching for more intelligent, automated technologies that offer precise, real-time analysis of material performance as the worldwide movement toward robust and sustainable infrastructure heats up.

In civil engineering, artificial intelligence (AI), especially its subsets such as machine learning (ML), artificial neural networks (ANN), and fuzzy logic, has become a game-changing technology. AI models are significantly more predictive than conventional statistical tools, can identify intricate patterns, and can learn from past data. AI has been used more and more in pavement engineering to evaluate pavement quality, anticipate rutting and cracking, improve mix designs, and, more recently, analyze geotechnical field data such as those from PLT (Gandomi & Alavi, 2016; Kabir et al., 2015).

By facilitating quick interpretation of load-settlement curves and better determination of the modulus of subgrade response (k-value), the use of AI in conjunction with PLT data improves the quality of subgrade evaluation. For example, considering factors like applied load, settlement, moisture content, and soil classification, ANNs have demonstrated great accuracy in forecasting subgrade modulus (Ahmad et al., 2021; Alzubi et al., 2020). These models support performance-based pavement design methodologies and perform better than empirical equations, particularly under variable field circumstances.Furthermore, AI is especially well-suited for real-world pavement applications due to its capacity to manage high-dimensional input, missing data, and nonlinear correlations. AI is able to adjust to regional variations in materials and environmental conditions and encompass a wider variety of variables than deterministic models. Scholars have effectively analyzed PLT data using models such as ensemble approaches, decision trees, and Support Vector Machines (SVM), showing notable gains in interpretability and prediction reliability (Li & Wang, 2020; Reddy et al., 2022).

The objectives of smart infrastructure and digital transformation in the construction industry are further supported by the combination of AI and PLT analysis. AI makes it possible for real-time monitoring, data collecting, and adaptive design techniques when used in conjunction with Internet of Things (IoT) sensors, drones, and GIS systems. According to Yazdani et al. (2022) and Zhang et al. (2019), these technologies are crucial for developing resilient pavement systems that can tolerate rising traffic loads and pressures brought on by climate change.

The purpose of this review is to examine the many AI approaches that have been used to analyze PLT data and how well they work to maximize the performance of paving materials. It offers a thorough summary of current research, assesses the advantages and difficulties of AI-driven strategies, and identifies areas for further investigation. It is anticipated that the results will help practitioners and researchers embrace cutting-edge computational methods for sustainable, economical, and performance-based road design.

LITERATURE REVIEW

- **Ahmad et al. (2021).**

Using data from the Plate Load Test (PLT), Ahmad and associates created an artificial neural network (ANN) model to forecast the modulus of subgrade response. Variables like applied load, settlement, soil classification, and moisture content were all included in the model. Their findings outperformed conventional empirical models with a prediction accuracy of over 93%. This study demonstrated how well ANNs handle complicated and nonlinear geotechnical information.

- **Li and Wang (2020)**

Li and Wang predicted subgrade modulus using PLT data for a variety of soil types using Support Vector Machine (SVM) models. Plate diameter, soil density, and applied stress were among the multidimensional input characteristics that the model handled well. An 88% correlation between their method and real field data was attained. The effectiveness of SVMs in geotechnical applications with few samples was highlighted in the study.

- **Reddy et al. (2022)**

Reddy et al. modelled the impact of soil characteristics on pavement performance and PLT response using Random Forest (RF) methods. Important affecting elements as dry density, void ratio, and plasticity index were effectively found using the RF model. Compared to linear regression models, it provided better prediction accuracy and interpretability. The study illustrated how ensemble models may be used in geotechnical engineering.

- **Gandomi and Alavi (2016)**

A thorough review of machine learning applications in civil engineering, including pavement evaluation, was given by Gandomi and Alavi. They highlighted how flexible methods like artificial neural networks (ANNs) and genetic programming are for simulating the non-linear behavior of building materials. For incorporating AI into geotechnical procedures, the study was a fundamental resource. The foundation for further study on AI-assisted pavement was established by their findings.

- **Alzubi et al. (2020)**

The use of deep learning models to the interpretation of load-settlement curves derived by PLT was investigated by Alzubi et al. Their algorithm was able to classify soil stiffness with exceptional accuracy after being trained on a dataset consisting of more than 500 test instances. The study demonstrated how deep neural networks can capture complex correlations between test factors. Additionally, it suggested that model resilience was further enhanced by larger datasets.

- **Kabir et al. (2015)**

Kabir and associates looked at modeling pavement subgrade responses using fuzzy logic. Predicting modulus values under ambiguous soil circumstances, including uneven moisture content or mixed soil strata, was made easier by the fuzzy inference approach. For preliminary design in isolated or difficult-to-reach locations, this method worked especially well. Their efforts aided in the creation of intelligent pavement design decision-making systems.

- **Zhang et al. (2019)**

Zhang et al. used PLT and borehole data to spatially map subgrade stiffness by integrating AI and GIS. The technology that resulted made it possible to dynamically visualize pavement performance throughout a network of highways. Their system worked well for developing and maintaining large-scale road systems. It also demonstrated how AI may be used in conjunction with conventional GIS technologies to manage infrastructure assets.

- **Huang (2004)**

The groundwork for comprehending the limits of empirical design methodologies was established by Huang's pavement analysis and design textbook. He underlined how environmental and human variables might cause variation in PLT outcomes. His work emphasizes the necessity for sophisticated techniques like AI to get over the limitations of empirical modeling, even if it is not AI-specific. This underlines the significance of AI in current pavement engineering.

- **Cheng et al. (2021)**

Convolutional neural networks (CNNs) were used by Cheng et al. to decipher real-time load-settlement pictures from automated PLT machinery. When it came to identifying the deformation zone and predicting k-values, the AI model performed exceptionally well. Their technique allowed for the quick and non-contact assessment of soil stiffness. The study was a first step in combining computer vision and artificial intelligence in field testing.

- **Das (2016)**

Das's geotechnical engineering textbook included standard PLT techniques and its drawbacks, such as scale effects and irregularities in stress distribution. Although the manual interpretation approaches had a solid theoretical foundation, they were found to be subjective. This emphasizes how important AI-based objective systems are for evaluating PLT data. It acts as a standard by which to compare conventional and AI-enhanced methods.

- **Jain and Ghosh (2018)**

In order to estimate soil stiffness from PLT data, Jain and Ghosh created a hybrid AI model that combines Genetic Algorithm (GA) and Artificial Neural Networks (ANN). The ANN's design was improved by the GA for increased convergence and performance. When compared to independent ANN models, their model demonstrated superior generalization. The creation of hybrid intelligence models for engineering applications was promoted by this work.

- **Singh et al. (2020)**

Singh et al. investigated the potential application of AI models for identifying anomalies and outliers in PLT datasets. To help with quality control, they grouped related soil behaviors using clustering methods like k-means. This increased design safety margins in addition to data dependability. Their efforts are beneficial for pre-processing big PLT datasets.

- **Yazdani et al. (2022)**

Yazdani and his colleagues used AI models in conjunction with Internet of Things (IoT) sensors to assess pavement subgrade reactivity. An ANN was used to handle real-time data from sensor-embedded plates in order to estimate the modulus instantly. The study demonstrated how the combination of AI and IoT can turn traditional field testing into intelligent infrastructure monitoring instruments.

- **Wang and Zhang (2017)**

Wang and Zhang used machine learning in conjunction with Principal Component Analysis (PCA) to lower the dimensionality of PLT datasets. Regression models for modulus prediction were then trained using the condensed input set. Their approach improved computational efficiency by using fewer parameters while maintaining 95% accuracy. This demonstrates how AI may improve the procedures for gathering and analyzing data.

➢ **Basu and Dey (2021)**

Basu and Dey used PLT and lab data to assess several AI soil classification methods. In their investigation, logistic regression, decision trees, and ANN models were examined. While decision trees provided superior interpretability, ANN was determined to be the best successful at capturing nonlinear behavior. Practitioners were assisted in choosing appropriate AI tools by this comparison analysis.

➢ **Gautam et al. (2018)**

Gautam et al. used artificial intelligence (AI) to create a decision support system for designing pavement layer thickness. The method produced ideal pavement constructions by combining traffic and environmental data with stiffness values determined by PLT. It drastically cut down on manual labor and design time. Their efforts illustrated how AI can streamline the whole design process.

➢ **Mitra and Saha (2020)**

Mitra and Saha used ensemble machine learning techniques like XGBoost to evaluate PLT datasets. When it came to forecasting settlement at different stress levels, their methodology outperformed traditional regression models. Even with small to medium-sized geotechnical datasets, the study demonstrated the effectiveness of boosting approaches.

➢ **Omar et al. (2019)**

A knowledge-based AI system was developed by Omar et al. to suggest appropriate subgrade treatments based on soil categorization and PLT findings. The system recommended compaction or chemical stabilization techniques using fuzzy logic and expert guidelines. In places without access to qualified geotechnical engineers, this method was beneficial.

➢ **Rahman and Islam (2021)**

Rahman and Islam suggested a cloud-based framework for machine learning-based PLT data management and analysis. Their solution offered automatic reporting capabilities and centralized access to field data. It encouraged real-time decision-making and improved field and design team communication.

➢ **Sharifi et al. (2017)**

Sharifi et al. calculated the elastic modulus in reverse using PLT data and field deflection using artificial intelligence. Bayesian networks were used in their model to account for previous knowledge and uncertainty. It increased modulus estimation's dependability, particularly in intricate soil conditions with sparse data.

Overview Of Plate Load Test (Plt)

In the PLT, a rigid plate is placed on the ground, and a load that increases progressively is applied while the corresponding settlements are measured. The load-settlement curve, which yields the modulus of subgrade response (k-value), is the main output.

Applications

- Estimating bearing capacity.
- Designing rigid pavement thickness.
- Assessing soil improvement techniques.

Limitations

- Time-consuming.
- Affected by soil heterogeneity.
- Inconsistent data interpretation.

Need For Ai In Pavement Engineering

Conventional pavement design techniques depend on simple models and empirical correlations, which frequently ignore the intricate behavior of materials. AI tackles these issues by:

- Data-driven prediction models.
- Real-time analysis.
- Pattern recognition in large datasets.
- Adaptive learning from new data.

Conventional pavement design techniques frequently ignore the complicated behavior of materials in favor of empirical correlations and oversimplified models. These issues are addressed by AI via:

Ai Techniques Used With Plt Data

Artificial Neural Networks (ANN)

By simulating nonlinear correlations between input data (such as soil type, moisture content, and plate size) and output variables (such as settlement and k-value), artificial neural networks (ANNs) mimic the function of the human brain.

- **Example:** An ANN trained on PLT results from different soil types can predict subgrade stiffness with >90% accuracy.

Support Vector Machines (SVM)

SVMs work effectively with high-dimensional input variables and small datasets for classification or regression problems.

Fuzzy Logic Systems

helpful when working with ambiguous or imprecise data. Fuzzy systems enhance decision-making by modeling uncertainty in soil parameters.

Decision Trees & Random Forests

These models are helpful for determining important factors influencing PLT results and for decomposing complicated decisions into simpler ones.

Case Studies and Applications

Table 1 Case Study and Applications

Study	AI Model Used	Accuracy	Parameters	Outcome
Ahmad et al. (2021)	ANN	93.5%	Soil index, moisture, load	k-value prediction
Li & Wang (2020)	SVM	88%	Plate diameter, depth, load	Subgrade modulus
Reddy et al. (2022)	Random Forest	90%	Soil type, stress	Performance classification

Observation: AI models outperform empirical methods, especially in heterogeneous soil conditions and layered subgrades.

Benefits Of Ai-Assisted Plt Evaluation

- **Accuracy:** Reduces error in interpreting load-settlement data.
- **Time Efficiency:** Minimizes time spent in field-testing analysis.
- **Predictive Capability:** Anticipates future pavement behavior based on trained data.
- **Design Optimization:** Enables dynamic adjustment of design thickness and materials.

Challenges And Limitations

Despite its advantages, several challenges hinder the full-scale implementation of AI in pavement design:

- **Data Availability:** High-quality, labeled datasets are essential but often limited.
- **Model Overfitting:** Improper training can cause models to perform poorly on unseen data.
- **Interpretability:** Some AI models, especially deep learning networks, act as "black boxes."
- **Standardization:** Lack of standard AI protocols in civil engineering codes.

Integration With Other Technologies

AI in pavement evaluation can be further enhanced when combined with:

- **GIS (Geographic Information Systems):** For spatial mapping of pavement performance.
- **IoT Sensors:** Real-time data collection from instrumented test sites.
- **BIM (Building Information Modeling):** Integration of AI-generated parameters into infrastructure models.

Future Scope And Research Directions

- **Hybrid Models:** Combining multiple AI techniques for better performance.
- **Automated Testing Systems:** Use of robotics for real-time data collection and AI interpretation.
- **Standardized Databases:** Creation of centralized PLT result repositories for model training.

- **AI-Driven Pavement Management Systems:** Integration with life-cycle costing and maintenance planning.

CONCLUSION

Pavement engineering has advanced significantly using AI-assisted PLT data assessment. Roadway design may be optimized thanks to its precise, quick, and intelligent insights on subgrade behavior. The future of pavement evaluation is in fully automated, adaptable, and intelligent systems that have the potential to completely transform civil infrastructure thanks to ongoing advancements in AI algorithms, sensor technology, and data integration.

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