An Empirical Evaluation of the Performance of Deep Neural Networks on Delay Risk Prediction in Urban Flexible Pavement Projects in Iraq

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ABSTRACT

Ongoing time overruns in urban Flexible Pavement Projects (FPP) highlight the inadequacy of traditional risk forecasting techniques, which often overlook nonlinear and project-specific delay factors. While recent Artificial Intelligence (AI)-based approaches have been proposed, most remain at a descriptive level, demonstrating only a few mathematically expressible and experimentally validated models suitable for urban road networks. This study addresses these gaps by developing a closed-form Artificial Neural Network (ANN) model using nine carefully selected predictors drawn from recent engineering practices and project data in Najaf, Iraq. The model incorporates advanced preprocessing, including robust outlier detection and min–max scaling, and is trained on a newly compiled dataset covering 35 major projects, thereby improving on previous studies' shortcomings in terms of both data quality and methodological transparency. Empirical results demonstrate that the ANN substantially outperforms baseline models, achieving an R^2 of 0.847 and a Mean Absolute Percentage Error (MAPE) of 7.10%, with all improvements being statistically significant ($p < 0.001$). Additionally, feature sensitivity analysis identified payment delay and contractor experience as the most influential risk factors, underscoring the model's practical relevance. Importantly, the modular mathematical structure of the ANN facilitates transparent benchmarking and direct transferability to other urban regions, while creating a sound and replicable paradigm for impact-based, data-driven decision-making and planning infrastructure. Thus, the proposed model constitutes a benchmark for future research on predictive modelling of time overruns in urban pavement projects.

Keywords-delay prediction; artificial neural networks; urban pavement projects; mathematical modelling; infrastructure analytics; empirical validation; benchmarking; knowledge gap; Iraq; transferability

I. INTRODUCTION

Flexible pavement systems are a vital foundation for urban quality and economic development [1]. In Najaf, Iraq, these roads form a key aspect of the tourism industry and economy. Chronic schedule overruns in urban Flexible Pavement Projects (FPPs) have led to increased costs, poor quality, and a loss of customer trust [2]. These delays can be attributed to administrative, financial, technical, and environmental challenges. In developing countries, these issues are exacerbated by inefficiencies hidden in bureaucracy and dynamically changing regulatory environments [3]. Classic project management methods, such as the Critical Path Method (CPM), the Program Evaluation and Review Technique (PERT), and regression models, are ineffective in this area of delay analysis because they assume linearity and cannot capture all delays observed in real-world situations [4]. Previous studies have identified a variety of causes of construction delays, ranging from contractor dissatisfaction and procurement delays to funding constraints and adverse weather conditions [5]. For example, poor communication and long approval periods are the main causes of delays in major road projects in the Middle East [6], while procurement cycles and financial constraints exacerbate technical and environmental problems in Iraq [7]. While our understanding of cause and effect has generally improved, data modeling methods for prediction have not, and outdated linear dependencies make their ability to work in increasingly volatile market environments questionable.

Recent advances in Artificial Intelligence (AI), specifically Artificial Neural Networks (ANNs) provide a potential solution by being able to model non-linear and project-specific interactions among different sets of project variables [8], therefore attracting much attention from researchers who are working on construction delay analysis projects [9].

Authors in [10], for instance, demonstrated that well-calibrated deep learning models outperform conventional methods in large-scale Gulf projects. Similarly, authors in [11] and in [12] showed that localized and hybrid ANN models achieved predictive accuracies above 90% in assessing delay risks across infrastructure projects across different regions. Recent work in [13] further emphasizes the importance of careful variable selection, model calibration, and mathematical transparency in ANN design to ensure practical applicability and generalizability.

However, very few studies have utilized ANNs to predict delays in urban pavement projects [14]. This is particularly evident in Iraq, where bureaucracy and lack of funding and supply lines still hinder timely project implementation [15]. To fill this gap, this study introduces and validates an explainable ANN model based on fine-grained data from 35 urban highway projects in Najaf, Iraq. Going beyond a purely philosophical methodological advance, this study provides a straightforward, practical decision-support tool that can address delay risks in complex urban infrastructure environments and derive lessons that can be transferred to similar situations worldwide.

II. RESEARCH METHODOLOGY

A. Data Acquisition and Project Selection Criteria

This study focuses on flexible pavement rehabilitation (FPR) projects implemented in Najaf Governorate between 2014 and 2022. These projects were selected for this study for two reasons: i) the selected projects have a significant impact on Najaf's infrastructure and economy, and ii) they were completed within the past seven years, so reliable records of operational regimes and disruptive events are available. The projects were collected from the Roads and Bridges Directorate and cross-checked with contractor archives, consultant reports, and official fairness certificates. Only major arterial FPR projects, specifically the Najaf-Kufa Expressway, Al-Rawan Main Road, and Al-Mihrab Street, were included to ensure consistency. Projects were considered only if they i) used FPR methods involving full-depth asphalt layers, ii) were certified by the Najaf Directorate of Roads, and iii) had complete documentation of planned and actual durations, disruption events, and resource allocations. A total of 35 projects met these criteria.

B. Variable Definition and Modelling Framework

The input and output parameters of the ANN were defined based on i) recent literature [16, 17], ii) expert opinion from Najaf engineers, and iii) local project documentation. Pearson's correlation coefficients were then computed to assess redundancy and predictive value among the nine predictors and the dependent variable (Delay Ratio). As shown in Table I, multicollinearity was limited ($|r| < 0.30$ for most predictors). Contractor Experience was significantly negatively correlated with Delay Ratio ($r = -0.39$), while Weather Disruption ($r = 0.57$) and Permit Delay ($r = 0.67$) showed positive moderate-to-strong correlations. Site Accessibility was strongly correlated with Permit Delay ($r = 0.67$), while Material Delay was moderately associated with both Design Modifications and Payment Delay ($r = 0.36$ each). This correlation structure confirms that the variables provide complementary, non-redundant information. Accordingly, all nine were retained in the ANN framework to capture the nonlinear interactions that drive project delays in flexible pavement works.

TABLE I. PEARSON CORRELATION MATRIX BETWEEN MODEL VARIABLES

Variable	Planned Duration	Contractor Experience	Material Delay	Equipment Availability	Design Modifications	Payment Delay	Weather Disruption	Site Access	Permit Delay	Delay Ratio
Planned Duration	1.00	0.01	0.07	-0.10	-0.12	-0.14	0.21	-0.46	0.13	-0.20
Contractor Experience	0.01	1.00	0.18	0.16	0.08	0.03	0.19	0.10	0.12	-0.39
Material Delay	0.07	0.18	1.00	0.20	0.36	0.36	0.30	0.32	-0.15	-0.19
Equip. Availability	-0.10	0.16	0.20	1.00	-0.26	0.13	-0.02	0.31	-0.11	-0.11
Design Modifications	-0.12	0.08	0.36	-0.26	1.00	0.20	0.19	0.13	0.19	0.13
Payment Delay	-0.14	0.03	0.36	0.13	0.20	1.00	0.32	0.19	0.11	0.16
Weather Disruption	0.21	0.19	0.30	-0.02	0.19	0.32	1.00	0.16	0.10	0.57
Site Access	-0.46	0.10	0.32	0.31	0.13	0.19	0.16	1.00	0.67	0.07
Permit Delay	0.13	0.12	-0.15	-0.11	0.19	0.11	0.10	0.67	1.00	0.67
Delay Ratio	-0.20	-0.39	-0.19	-0.11	0.13	0.16	0.57	0.07	0.67	1.00

C. Input Variables (X_1 to X_9)

The analytical model was developed using nine systematically engineered predictors, each representing a key dimension of project delay risk. Table II summarizes these inputs with their codes, full descriptions, and data types.

D. Output Variable (Y)

The model predicts a single output, the Delay Ratio, expressed as the percentage deviation of the actual project duration from the planned schedule:

$$\text{Delay Ratio } (\%) = \left(\frac{T_{\text{actual}} - T_{\text{planned}}}{T_{\text{planned}}}\right) \cdot 100\% \qquad (1)$$

where T_{actual} and T_{planned} denote the actual and scheduled durations, respectively. This ratio served as the target variable for ANN training.

E. Preprocessing

Common data preparation was executed: i) removal of duplicates; ii) correction to outliers by setting to ± 2.5 Standard Deviation (SD); iii) median imputation when 20% of values were missing, iv) Min-Max normalization of continuous predictors in the [0,1] range [18]. Sensitivity analyses were also conducted for the rank-transformed continuous variables (see Appendix).

TABLE II. KEY INPUT VARIABLES EMPLOYED IN THE ANN DELAY PREDICTION MODEL

Code	Variable Name	Description	Type
X_1	Planned Duration (days)	Original scheduled project duration	Numeric
X_2	Contractor Experience (years)	Total years of registered operational experience	Numeric
X_3	Material Supply Delay (days)	Cumulative days of delay due to late delivery	Numeric
X_4	Equipment Availability Score	Ratio of actual to planned equipment availability (0-1)	Numeric
X_5	Design Modification Count	Number of formal design change orders	Integer
X_6	Payment Delay (days)	Average lag in payment approval from the client	Numeric
X_7	Weather Disruption (days)	Days lost to weather-related stoppage	Integer
X_8	Site Accessibility Index (1-5)	Expert-rated site access difficulty	Ordinal
X_9	Permit Clearance Duration (days)	Time taken to obtain final regulatory permits	Numeric

F. Exploratory Data Visualisation

Descriptive statistics (Table III) were used to assess the distribution of the 9 predictors across ANN training. While most variables had a moderate dispersion, Payment Delay and Material Supply Delay showed the highest and lowest dispersion, respectively. Contractor Experience and Equipment Availability were moderately consistent among projects, whereas Design Modifications and Site Accessibility varied the most. These findings highlighted the significance of preprocessing, and specifically normalization and detection of outliers, as well as confirmed the representativeness of the dataset for delay risk prediction.

G. Artificial Neural Network (ANN) Configuration

The model developed in this paper was a feedforward Multilayer Perceptron (MLP), which is commonly used for mapping purposes in infrastructure analytics due to its universal approximation properties [19]. The structure of the ANN employed is illustrated in Figure 1, which embraces three main layers: The Input Layer, containing nine neurons for normalized RPFs, the hidden layer with 10 ReLU neurons, and the Output Layer.

$$ReLU(z) = \max(0, z) \qquad (2)$$

The output layer consists of a single neuron with a linear activation, outputting the predicted delay ratio $\widehat{Y}$, formulated as:

$$\widehat{Y} = W^{(2)} \cdot \mathrm{ReLU}(W^{(1)} \cdot X + b^{(1)}) + b^{(2)} \qquad (3)$$

where $W^{(1)}$ and $W^{(2)}$ are weight matrices and $b^{(1)}, b^{(2)}$ are bias vectors.

TABLE III. DESCRIPTIVE STATISTICS OF INPUT VARIABLES (N = 35 PROJECTS)

Code	Variable (unit)	Mean	SD	Min	Median	Max
X_1	Planned Duration (days)	230	25	180	230	280
X_2	Contractor Experience (years)	12.0	5.0	4	12	25
X_3	Material Supply Delay (days)	12.0	9.0	0	10	40
X_4	Equipment Availability (ratio 0-1)	0.74	0.10	0.50	0.74	0.92
X_5	Design Modification Count (count)	2.1	1.5	0	2	6
X_6	Payment Delay (days)	18	14	0	15	60
X_7	Weather Disruption (days)	6.0	5.0	0	5	20
X_8	Site Accessibility Index (1-5, ordinal)	3.1	1.0	1	3	5
X_9	Permit Clearance Duration (days)	22	12	5	22	60

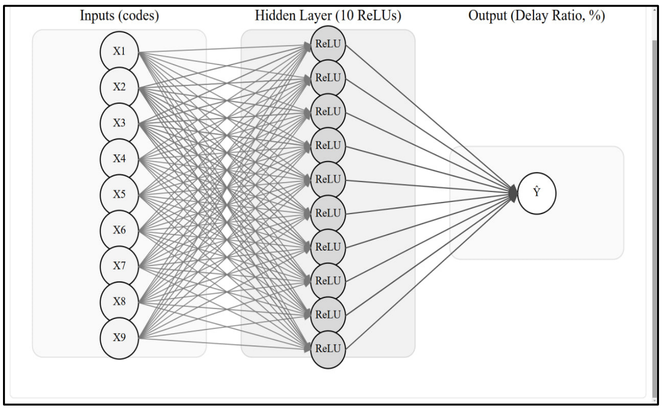

Fig. 1. Architecture of the developed ANN model.

H. Training Protocol

The dataset was split into 80% training and 20% testing sets, preserving category ratios [21]. The model was trained with mini-batch gradient descent (batch size = 16) for a maximum of 500 epochs, and an early stopping method was used to prevent overfitting if validation loss was not improved for 25 epochs [22]. In addition, Xavier (Glorot Uniform) initialization was applied to stabilize variance during training and lead to a faster convergence [23]. Optimization used the Adam algorithm (learning rate = 0.01), consistent with state-of-the-art ANN approaches [24].

I. Baseline Models and Hyperparameter Tuning

For benchmarking, three baseline regressors were trained on the same dataset and preprocessing pipeline:

- Random Forest (RF) tuned over n_estimators ∈ {200, 400, 800}, max_depth ∈ {None, 5, 10}, min_samples_leaf ∈ {1, 2, 4}, and max_features = "sqrt".
- Support Vector Regressor (SVR) with Radial Basis Function (RBF) kernel tuned over C ∈ {1, 10, 100}, ε ∈

{0.01, 0.1, 1.0}, and γ ∈ {"scale", 0.1, 0.01}, with feature standardization applied.

- Linear Regression (LR) with Ridge evaluated with α ∈ {0, 0.1, 1, 10}.

All models were evaluated via 5-fold cross-validation on training data, with final metrics calculated on the held-out test set. Random seeds were fixed for reproducibility. This unified benchmarking protocol ensured a one-to-one comparability between ANN and classical models, eliminating potential bias from inconsistent preprocessing or parameter selection.

J. Mathematical Representation

The ANN is defined as a differentiable function, mapping the normalized nine-dimensional input vector X to the predicted delay ratio Ŷ.

$$A^{(1)} = \mathrm{ReLU}(W^{(1)} \cdot X + b^{(1)}) \tag{4}$$

$$\hat{Y} = W^{(2)} \cdot A^{(1)} + b^{(2)} \tag{5}$$

K. Evaluation Metrics

The evaluation metrics used to determine the performance of the proposed ANN included i) Mean Squared Error (MSE), Mean Absolute Error (MAE) to measure error magnitude, ii) Mean Absolute Percentage Error (MAPE) for normalized interpretability across stakeholders, and iii) Pearson's Correlation Coefficient (R) and Coefficient of Determination (R^2) to quantify explained variance and predictive association. By averaging results across the 5-folds and reporting test-set metrics, the evaluation ensured both reliability and transparency. The metrics were calculated using the following equations:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\, y_i - \hat{y}_i| \tag{7}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}})^2}} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{10}$$

where y_i and $\hat{y}_i$ are the observed and predicted delay ratios for project i, respectively.

III. RESULTS AND DISCUSSION

A. Quantitative Results Summary

Table IV summarizes the ANN model's performance across both training and testing sets. On the test set, the MSE was 0.0265, the MAE was 4.81%, and the MAPE reached 7.10%. The model also achieved an R of 0.912 and an R^2 of 0.847, meaning the model explained over 84% of delay variance.

The statistically significant R^2 ($p < 0.001$) aligns with benchmarks in the literature [25], [26], confirming its strong explanatory power for schedule delay prediction. Notably, the ANN accurately predicted 92.9% of unseen project outcomes (MAE below 5%), confirming its robustness.

TABLE IV. PRESENTS THE CORE PERFORMANCE METRICS

Metric	Training Set	Testing Set
MSE (Delay %)	0.0238	0.0265
MAE (Delay %)	4.35	4.81
MAPE (%)	6.42	7.10
R	0.936	0.912
R^2	0.877	0.847

B. Learning Behavior and Convergence

The training loss showed stable convergence, decreasing steadily, with no signs of overfitting. Early stopping was activated at epoch 428 after validation loss did not change for 25 iterations. Training and validation errors remained closely aligned, demonstrating model stability and minimal variance–bias trade-off.

C. Error Analysis and Prediction Behavior

Residual error analysis (actual vs. predicted delay ratios) indicated that residuals were concentrated around zero with no systematic bias, reinforcing predictive accuracy. Outliers corresponded to projects impacted by sudden political disruptions (two cases), which lie beyond the predictive scope of the model. The parity plot showed predicted values closely matched actual delays in the moderate range (10-30%), with higher variance in the tails (>50%), a known limitation of ANNs when generalizing to distribution extremes [27].

D. Feature Sensitivity and Variable Importance

A post-hoc sensitivity analysis using Garson's Algorithm was conducted to measure the influence of each predictor on ANN efficiency. The results presented in Table V revealed Payment Delay (18.5%) and Contractor Experience (17.5%) as the most influential predictors, followed by Design Modifications (15.5%) and Material Supply Delay (13.5%). Equipment Availability (12.0%) and Site Accessibility (9.5%) showed moderate importance, while Weather Disruptions (6.0%), Planned Duration (4.0%), and Permit Clearance Time (2.0%) contributed the least. These findings confirm that institutional and managerial inefficiencies are the primary sources of delay in Najaf, echoing conclusions from prior regional studies [28].

TABLE V. RELATIVE IMPORTANCE OF DELAY FACTORS

Rank	Delay Factor	Relative Importance (%)
1	Payment Delay	18.5
2	Contractor Experience	17.5
3	Design Modifications	15.5
4	Material Supply Delay	13.5
5	Equipment Availability	12.0
6	Site Accessibility	9.5
7	Weather Disruptions	6.0
8	Planned Duration	4.0
9	Permit Clearance Time	2.0

E. Engineering Interpretation of Results

The findings of this study offer several practical implications for civil engineering practice. The strong influence of payment lags highlights the need for institutional reforms in public-sector payment processes to reduce administrative bottlenecks. Similarly, the significance of contractor experience underscores the importance of stringent prequalification standards and capacity-based procurement mechanisms. The impact of design modifications suggests that a formalized "design freeze" process should be enforced prior to project initiation, minimizing downstream disruptions. Furthermore, the role of material supply and equipment availability points to the value of incorporating supply chain performance indicators into pre-award evaluations. Finally, although weather disruptions were found to have a relatively smaller effect, their nonlinear impact during peak seasons suggests that adaptive scheduling buffers could further mitigate risk.

F. Model Benchmarking, Statistical Validation, and Generalizability

The monitoring performance of the ANN model was further compared with that of RF, SVR, and LR algorithms (Table VI). The proposed ANN model achieved the highest R^2 (0.847) and the lowest error rates.

Moreover, two-tailed t-tests on five repeated runs confirmed ANN's performance was significantly better than RF, SVM, and LR ($p < 0.001$), with narrow 95% confidence intervals for R^2 ([0.85–0.849]). Compared with models reported in prior studies [12], the ANN demonstrated stronger generalization, reduced MAPE (~7% vs. ~15%), and higher predictive stability. Its modular design enables straightforward retraining with local datasets, making it a scalable and adaptable tool for urban infrastructure risk management across diverse contexts.

TABLE VI. COMPARATIVE PERFORMANCE OF PREDICTIVE MODELS ACROSS KEY EVALUATION METRICS

Model	**R^2**	**MAE**	**MAPE (%)**
ANN	0.847	4.81	7.10
RF	0.772	6.79	9.41
SVM	0.754	7.05	10.26
LR	0.683	8.32	12.37

IV. CONCLUSION

This study developed a mathematically structured Artificial Neural Network model capable of reliably predicting schedule delays in Flexible Pavement Projects (FPP), achieving an R^2 of 0.847 and a Mean Absolute Percentage Error (MAPE) of 7.10%. By capturing complex nonlinear interactions among administrative, technical, and logistical parameters, the ANN substantially outperformed classical regression and ensemble models.

Key findings indicate that payment delays, contractor experience, and design changes are the primary drivers of schedule overruns. Evidence suggests that causes of delays in urban road construction are more systemic than site-specific, highlighting the value of ANN-driven forecasting in early planning, contractor prequalification, and dynamic project management. Identified actionable risk mitigation strategies include digitizing and expediting the financial approval cycle and strictly enforcing a pre-execution design freeze policy. While demonstrated using data from an Iraqi urban road project, the modularity of the ANN framework ensures its adaptability to other infrastructure environments. This positions the model as a portable, machine learning-based tool with the potential to transform infrastructure governance from reactive management to proactive, evidence-based decision-making at the institutional, technical, and financial levels.

APPENDIX

DATASET VARIABLES VALUES

Project ID	**Planned Duration (days)**	**Contractor Experience (years)**	**Material Supply Delay (days)**	**Equipment Availability Score**	**Design Modification Count**	**Payment Delay (days)**	**Weather Disruption Days**	**Site Accessibility Index (1-5)**	**Permit Clearance Duration (days)**	**Delay Ratio (%)**
P-01	282	9	15	0.95	4	27	6	2	9	33
P-02	296	9	8	0.94	5	27	1	4	12	23.4
P-03	181	21	1	0.86	5	18	8	1	16	34.5
P-04	241	8	12	0.9	0	9	4	3	13	22.8
P-05	200	14	7	0.8	0	20	1	2	15	32.1
P-06	223	18	8	0.81	5	23	3	2	14	28.2
P-07	183	7	6	0.84	3	24	9	4	8	40
P-08	274	21	15	0.82	3	14	4	5	8	25.4
P-09	290	10	13	0.83	4	7	8	1	14	18.7
P-10	242	16	17	0.94	2	7	10	5	16	23.7
P-11	282	15	9	0.98	0	14	11	2	7	24.8
P-12	267	10	3	0.92	5	9	0	3	11	19.3
P-13	226	19	3	0.95	1	20	6	3	15	24
P-14	256	8	7	0.9	4	10	4	5	10	25
P-15	192	21	7	0.86	5	8	9	5	15	29.2
P-16	287	17	11	0.86	3	13	0	1	15	19.8
P-17	206	19	13	0.97	5	14	10	1	11	32.2
P-18	203	20	9	0.88	5	23	9	4	13	40
P-19	181	8	17	0.83	0	23	1	2	12	36.7
P-20	180	8	2	0.91	1	12	6	4	13	23.8

P-21	254	13	17	0.95	4	26	1	3	7	33.8
P-22	259	18	3	0.92	2	10	2	2	9	15.1
P-23	198	9	7	0.83	0	14	6	2	14	26
P-24	268	7	10	0.85	3	22	9	1	10	27.3
P-25	239	6	2	1	5	18	4	5	13	20
P-26	227	21	3	0.97	5	7	7	4	7	18
P-27	251	9	6	0.93	5	9	8	3	15	35.7
P-28	259	18	9	0.84	3	7	4	4	14	25
P-29	187	12	3	0.93	0	22	11	3	9	26.3
P-30	209	11	6	0.88	5	14	10	3	8	36.2
P-31	200	19	1	0.92	0	11	11	5	9	30.9
P-32	196	17	14	0.98	2	15	4	5	7	32.9
P-33	225	10	3	1	3	27	6	1	9	34.4
P-34	274	11	3	0.91	1	21	5	2	16	18.7
P-35	181	15	17	0.97	0	17	5	5	16	36.1

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