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RISK-BASED PREDICTIVE MODELLING FOR HIGHWAY PROJECT DURATIONS IN NIGERIA USING MULTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORK

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Abstract:

Across the globe, highway infrastructure plays a pivotal role in national development by supporting the movement of people, goods, and services, making the timely delivery of such projects essential for economic growth and public welfare. Highway infrastructure projects attract huge budgetary allocations; hence, their timely completion is of significant importance. In Nigeria, schedule overruns on highway projects remain a persistent challenge, and previous studies on forecasting highway project duration relied mainly on conventional methods, which have yielded limited accuracy. This study presents a more robust approach to predicting highway construction durations by integrating both contemporary and traditional modelling techniques "Artificial Neural Networks (ANN) and Multiple Linear Regression (MLR)." A dataset comprising 103 completed federal highway projects executed between 2002 and 2022 was compiled using a snowball sampling strategy, drawing from the 2017 Federal Ministry of Works and Housing publication as well as additional inputs from highway engineers and quantity surveyors across Nigeria. For each project, a key professional was selected using the purposive sampling method to solicit detailed information on schedule-related risk factors via a structured questionnaire. These identified risks, combined with historical schedule data for each identified project, were employed as predictor variables for developing the schedule estimation models. Comparative analysis of model performance indicated that the ANN technique produced significantly more accurate duration forecasts than the MLR model. The study contributes to a practical and data-driven predictive tool that can assist government agencies,

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consulting firms, and contractors in enhancing the reliability of schedule planning and mitigating delays in future highway infrastructure delivery.

Keywords:

Artificial Neural Network, Time Forecast, Highway Projects, Multiple Linear Regression, Schedule Risk, Time Estimation

Introduction

A well-defined construction plan forms the foundation for the preparation of reliable project budgets and schedules. For both consultants and contractors, estimating project duration represents a critical component of the planning process. In practice, however, the actual project duration can only be conclusively determined upon project completion. Previous studies by Johnson and Babu (2018) identified persistent challenges affecting construction project success, including cost overruns, time overruns, scope changes, inadequate contingency allowances, and the effects of inflation. Delays in construction project delivery have also been identified as one of the factors adversely affecting overall project performance, often resulting in increased initial cost estimates and reduced productivity levels (Idowu and Aligamhe, 2023). Also, conflicts among contractual parties leading to litigation and arbitration occur due to time overruns of construction projects.

The execution of highway projects demands enormous financial resources, stressing the need for diligent planning to achieve the desired project outcome. Construction project success is mainly determined by cost, time, and quality performance. These indexes have been used to evaluate the performance of the construction sector in most countries (Yaseen et al., 2020). Highway construction projects are intricate, including non-linear feedback mechanisms; hence, an efficient and precise technique for forecasting the duration of projects that accommodates these complexities is essential. Changali et al. (2015) indicate that 98% of megaprojects encounter overruns in their original estimates; Love et al. (2012) state that actual time and cost performance may average 183% and exceed planned estimates by 70%. Time overruns affect highway projects in both developed and developing countries, prompting numerous studies aimed at improving schedule performance in highway construction. Tar and Carr (2000) observed that time overruns occur more frequently in developing countries, largely due to the absence of formalised risk management techniques, while Mousavi et al. (2011) attributed persistent schedule overruns to the scarcity of reliable highway project data.

Consequently, there is a compelling need to move beyond traditional estimation practices by systematically incorporating risk considerations into project planning and execution processes. Highway infrastructure projects are particularly vulnerable to uncertainty, owing to unpredictable subsurface conditions and their wide spatial and geographical coverage, which significantly amplify exposure to diverse technical and environmental risks (Okate and Kakade, 2019). According to Creedy et al. (2010), risk is the occurrence of an unplanned situation that alters the sequence of a planned event. Schedule-related risks constitute a major barrier to the timely delivery of construction projects (Sambasivan and Soon, 2007). Accordingly, systematic analysis of historical schedule deviation records offers a robust basis

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for forecasting future project time performance through the application of contemporary trend-based analytical methods.

Studies conducted by Aligamhe et al. (2024); Debnath and Mourshed (2018) used trend analysis to track cost and time variances (historical data) for predicting future outcomes. This technique can serve as a very useful guide to organisation when developing their cost and schedule estimates. Additionally, a properly documented critical risk register of previous projects can be standardised in order to assure realistic estimates for future similar work. Variations between planned schedule estimate and actual project durations can generate unintended consequences for key project stakeholders. Addressing these persistent challenges necessitates the development of advanced methodological approaches and the adoption of innovative practices aimed at improving schedule reliability (Cabuñas and Silva, 2019). Artificial neural networks (ANNs) possess the capacity to enhance predictive performance through iterative retraining processes, as their architecture is inherently designed for data-driven learning (Manahan Malasan et al., 2021; Waziri et al., 2017). Evidence from a comprehensive review by Kulkarni et al. (2017) further demonstrates that ANN-based techniques are well suited for the development of hybrid modelling frameworks and have been successfully applied across a wide range of construction-related domains, including cost and unit rate estimation, schedule forecasting, risk assessment, productivity analysis, safety management, and dispute resolution. In addition, Alaloul et al. (2018) reported that Neural Networks exhibit strong learning capabilities, enabling reliable pattern recognition and high levels of predictive accuracy.

This study aims to develop predictive models based on ANN and MLR techniques to compare the accuracy of both models in predicting the actual duration of highway construction projects. The importance of federal roads in Nigeria, which make up 54% of the country's total bituminous road network, provides the basis for the study's significance. Road transportation remains the dominant mode for the movement of both people and goods in Nigeria, accounting for approximately 90% of national mobility activities (Anigbogu et al., 2019). Despite the strategic importance of this sector, existing literature provides limited evidence of the application of artificial neural networks in developing schedule prediction models for highway construction projects within the Nigerian context.

Literature Review

Accurate prediction of project duration remains one of the most persistent challenges in construction management, particularly for large-scale infrastructure projects such as highways (Zhasmukhambetova et al., 2025). Unlike building projects, highways are linear, spatially dispersed, and heavily influenced by external conditions such as terrain, weather, regulatory approvals, land acquisition, and socio-political dynamics (Alamgir et al., 2017). As a result, time overruns are not merely operational failures but systemic outcomes of interacting risks (Ahiaga-Dagbui et al., 2017). The literature increasingly recognises that project duration is not only a function of technical scope but also of how risks are identified, quantified, and managed throughout the project lifecycle.

Risk And Uncertainty in Highway Project Scheduling

The theoretical foundation of duration prediction in construction is closely tied to the concepts of risk and uncertainty. While uncertainty refers to incomplete knowledge about future events,

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risk is commonly defined as uncertainty that can be measured in terms of probability and impact (Crane et al., 2024). In highway construction, risks are embedded in virtually every phase of the project, from feasibility and design to procurement, construction, and handover (Zhasmukhambetova et al., 2025). Research shows that traditional deterministic scheduling methods fail to capture this reality, as they assume stable conditions and linear cause–effect relationships (Zhang and Wang, 2023; Padwal, 2025). Consequently, risk-based approaches have emerged to better explain why actual project durations frequently deviate from planned schedules.

Risk-based scheduling emphasizes that delays rarely result from a single factor, but rather arise from the accumulation and interaction of multiple risk events (Yazdani et al., 2025). For example, delayed payments may weaken contractor cash flow, which in turn affects productivity, equipment mobilisation, and subcontractor performance (Chadee et al., 2023). Similarly, unresolved right-of-way issues can trigger design revisions and disrupt construction sequencing. These interdependencies suggest that duration prediction models must be capable of handling both multiple variables and their complex relationships.

Empirical Determinants of Highway Project Duration

A substantial body of empirical research has sought to identify the factors that influence construction project durations, with highway projects receiving particular attention due to their economic significance. Across various geographical zones, studies consistently report that project size, technical complexity, and environmental conditions have a significant impact on duration (Idowu and Aligamhe, 2016; Mirza and Ehsan, 2017). Larger projects with extensive earthworks, bridge structures, and complex interchanges are naturally associated with longer construction periods (Jastino, 2024). However, technical characteristics alone do not sufficiently explain observed delays.

Institutional and managerial factors are repeatedly highlighted as influential. Osipova and Eriksson (2011) revealed that procurement methods, contract types, contractor experience, and project governance structures shape how risks are allocated and managed. In public highway projects, bureaucratic approval processes, funding discontinuities, and weak inter-agency coordination are frequently cited as major contributors to schedule overruns. Environmental factors, particularly weather variability and geotechnical uncertainty, further complicate execution by introducing non-controllable delays.

In developing countries including Sub-Saharan Africa, the literature underscores the prominence of systemic and socio-political risks (Amewu et al., 2024). These include delayed compensation for land acquisition, community resistance, security challenges, and macroeconomic instability (Peng et al., 2021). Studies focusing on Nigeria consistently point to delayed payments, right-of-way challenges, inflationary pressures, and weak risk management practices as dominant causes of highway project delays (Akoh, 2018; Ibrahim, 2023; Kahangirwe and Vanclay, 2024). Much of this evidence, however, remains descriptive or qualitative, highlighting the need for quantitative models that can translate these risk factors into measurable duration outcomes.

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Multiple Linear Regression in Duration Prediction

Multiple linear regression has long been employed as a core analytical tool in construction management research (Yang et al., 2023). Its appeal lies in its transparency and ease of interpretation. By estimating the marginal contribution of each independent variable to project duration, regression models allow researchers and practitioners to identify which factors exert the greatest influence on schedule performance (Selvam et al., 2025). This explanatory power is particularly valuable in public-sector infrastructure projects, where decision-makers often require clear justification for policy or management interventions.

Several studies have successfully applied regression models to predict construction durations using variables such as project size, contract value, contractor experience, and environmental conditions (Alsugair et al., 2023). Extensions of these models incorporate risk-related variables, such as the frequency of design changes or the severity of funding delays, thereby linking risk exposure to schedule outcomes. These efforts demonstrate that regression models can offer meaningful insights into how risk factors shape project timelines.

Studies acknowledge important limitations of multiple linear regression. The method relies on assumptions of linearity, independence, and homoscedasticity, conditions that are rarely fully satisfied in construction datasets (KhairEldin et al., 2025). Highway project data often exhibit nonlinear relationships, multicollinearity among predictors, and heterogeneity across project types and regions. As the number of influencing factors increases, the explanatory clarity of regression models may decline, and their predictive accuracy may suffer. These shortcomings have motivated researchers to explore alternative modelling techniques capable of capturing more complex patterns.

Artificial Neural Networks and Nonlinear Modelling

Artificial neural networks (ANNs) have gained increasing prominence in construction research as a response to the limitations of traditional statistical methods (Xu et al., 2022). ANNs are designed to learn complex, nonlinear relationships from data without requiring predefined functional forms. This flexibility makes them particularly attractive for modelling construction project durations, where interactions among technical, managerial, and environmental factors are rarely linear. Ujong et al. (2022) revealed that the applications of ANNs in predicting construction cost, productivity, and duration with a better predictive performance compared to linear regression models. In highway projects, ANNs have been shown to effectively accommodate variables with complex interdependencies, such as weather conditions interacting with contractor capacity or funding stability. Their ability to handle noisy and multicollinear data further enhances their suitability for real-world construction environments.

Despite these advantages, ANN-based models are not without criticism. A recurring concern in the literature is their lack of transparency. Unlike regression models, ANNs do not produce easily interpretable coefficients, making it difficult for practitioners to understand why a particular prediction is generated. This “black-box” nature can limit stakeholder trust, especially in public infrastructure projects where accountability and interpretability are essential. Furthermore, ANN models require careful calibration and validation to avoid overfitting, particularly when datasets are relatively small, as is often the case in country-specific studies.

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This study presents improvement over existing research by integrating risk-based theoretical insights with both linear and nonlinear modelling techniques within a unified framework specifically developed for Nigerian highway projects. Whereas Leo-Olagbaye and Odeyinka (2020) developed MLR-based cost and schedule risk models for highway projects in Osun State and recommended the adoption of advanced modelling techniques such as neural networks to better address complexity, as their work did not operationalise such methods. Although, Aligamhe et al. (2024) employed both MLR and ANN to model cost-related risks for federal highway projects, their focus remained on cost performance, leaving a gap in the modelling of schedule risks despite their critical influence on project outcomes. This study addresses this gap by developing schedule risk prediction models that systematically incorporates key risk determinants and evaluates the predictive capabilities of MLR and ANN using a common dataset under identical conditions. The novelty of the study lies in its dual-modelling approach, which not only benchmarks the two techniques side-by-side but also provides a practitioner-orientated balance between the interpretability of regression models and Artificial Neural Network models. By moving beyond fragmented, single-method approaches, the study establishes a more rigorous and context-sensitive basis for improving duration forecasting and strengthening risk-informed decision-making in highway infrastructure delivery.

Methodology

This section discussed data collection, data organisation, and data analysis for the research.

Data Collection

A snowball sampling approach was adopted to identify suitable participants and to administer structured pro forma and questionnaires to key stakeholders involved in the delivery of the selected highway projects. The respondents comprised highway engineers and quantity surveyors engaged across the study area in various capacities, including consultancy, contracting, and client representation. Data collection was conducted using both hardcopy instruments and electronic survey formats to maximise response coverage. These professional groups were purposively selected due to their direct involvement in construction and project management functions, particularly in relation to schedule control and cost management during highway project implementation. The demographic and professional characteristics of the respondents are summarised in Table 1.

The dataset employed for model development was derived from historical records of 103 completed federal highway projects. Project identification began with a with the examination of a publication by FMWH in 2017, which documented 229 ongoing and completed highway projects nationwide. This inventory served as the baseline for isolating projects that had been completed at the time of publication, as well as for monitoring additional projects that reached completion prior to January 2022. From this source, 68 projects were initially identified; however, five were subsequently excluded due to insufficient or incomplete data, resulting in 63 eligible completed projects. To enhance the robustness of the dataset and capture more recent project completions, a pilot survey was undertaken, through which an additional 40 completed highway projects were obtained. Consequently, the final sample comprised 103 completed projects, as summarised in Table 3.

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Table 1: Characteristic of Respondents

Variables	Grouping	Distribution (n)	Percentage (%)
Years of post-qualification experience	0-5	9	8.70
	6-10	19	18.40
	11-15	43	41.70
	16-20	27	26.20
	>20	5	4.90
	Total	103	100
Occupational category	Client organisation	49	47.57
	Consulting	26	25.25
	Contracting	28	27.18
	Total	103	100
Locations	South-West	19	18.45
	South-East	17	16.50
	South-South	18	17.48
	North-East	17	16.50
	North-West	13	12.62
	North-Central	19	18.45
	Total	103	100

Identification of Highway Risk Factors

An extensive inventory of potential highway schedule risk variables was compiled based on a prior systematic review of the literature reported by Aligamhe (2024), which initially identified 154 risk factors associated with highway projects. These factors were subsequently evaluated through expert judgement involving professionals with 15–25 years of industry experience, with the objective of screening and isolating those risks specifically related to project scheduling from the broader set of identified variables resulting in identifying 85 schedule risk variables. The refinement process engaged ten specialists with extensive experience in project and construction management, resulting in the identification of 85 schedule-related risk factors. In addition, this procedure strengthened construct validity by systematically screening out duplicated or overlapping variables within the pilot questionnaire.

Relative Importance Index (RII)

Primary data relating to the effects of risk on highway schedule performance were collected using a structured five-point Likert-type scale, ranging from very low (1) to very high (5). The responses obtained were quantitatively analysed using the Relative Importance Index (RII), a technique widely applied in construction management research for prioritising risk factors (Oboirien, 2019; Thaseena and Vishnu, 2017). Risk impact levels were established based on the computed RII values for each factor and subsequently ranked in descending order of significance. Consistent with the Likert-scale framework, risk factors were classified into five categories: very low (RII < 1.5), low (1.5 ≤ RII < 2.5), moderate (2.5 ≤ RII < 3.5), high (3.5 ≤ RII < 4.5), and very high (4.5 ≤ RII ≤ 5.0), following an approach similar to that adopted by El-Sayegh and Mansour (2015).

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In addition, the identification of critical schedule-related risk factors for input into the predictive models was guided by the Pareto principle, commonly expressed as the 80:20 rule (see Equation 1). This principle posits that a relatively small proportion of causes is responsible for the majority of observed effects, with approximately 20% of factors accounting for 80% of the outcomes (Grosfeld-Nir et al., 2007). The application of Pareto by firms aids in the development of speedy models using fewer activities in determining the firm's overall productivity (Pandey et al., 2013).

$$TR = \frac{20}{100} X\, N \tag{1}$$

Where: TR = Critical time risk factors; N = Total number of risk factors

Critical Schedule Risk Factors/Independent Variable for Model Development

The independent variables (critical schedule risk factors affecting highway projects in the study area) used for the model development are presented in Table 2 below. These variables represent the critical risk factors impacting the time performance of the identified highway projects being 20% of the schedule risk factors analysed. The dependent variables that are used for the model development consist of historical data on highway time performance.

Table 2: Independent Variables for Model Development

S/No.	REF/Variables	RII	RII classification	Ranking
1	TR 1: Delay in payment by clients	4.53	V. H	1
2	TR 37: Non-availability of spare parts for construction equipment	4.52	V. H	2
3	TR 42: Non-availability of desired plant and equipment	4.39	H	3
4	TR 36: Unavailability of special equipment	4.32	H	4
5	TR 39: Shortage of construction material in the market	4.31	H	5
6	TR 18: Incomprehension of the requirements of the owner by the design team	4.27	H	6
7	TR 53: Lack of communication and coordination between contractor and the other parties	4.25	H	7
8	TR 43: Conflicts	4.2	H	8
9	TR 9: Forced selection of inexperienced contractors	4.16	H	9
10	TR 35: Failure of major construction equipment	4.14	H	10
11	TR 61: Change in government/political changes	4.12	H	11
12	TR 56: Resource management problems	4.12	H	12
13	TR 12: Complexity in project design	4.11	H	13
14	TR 33: Delay in the delivery of materials	4.11	H	14
15	TR 63: Government lack of political will	4.06	H	15
16	TR 66: Lack of legal regulatory framework	4.06	H	16
17	TR 11: Change in design	4.04	H	17

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Historical Data/Dependent Variable for Model Development

The historical highway project time-performance data used to create the predictive models is shown in Table 3. Time overruns were derived and computed using Equation 2. The values for time overruns (in percentage) were divided by 100 to obtain a comparable value with that of Likert scales 1–5, which was used in measuring the schedule risk impact (independent variables).

$$Pto = \frac{icd - acd}{icd} X\ 100 \tag{2}$$

Where: Pto = Time overrun; icd = Initial estimated duration; acd= Actual duration.

Table 3: Dependent Variables for Model Development

S/No.	Project 1D N0.	Length of road (km)	Initial estimated duration (Weeks)	Actual duration (Weeks)	Time overruns (%)	Time performance data (% ÷100)
1	SW 1	19.20	103	165	60.39	0.6039
2	SW 2	31.00	226	343	51.66	0.5166
3	SW 3	22.00	217	344	58.15	0.5815
4	SW4	10.50	182	295	61.90	0.6190
5	SW 5	5.60	62	95	52.67	0.5267
6	SW 6	7.20	221	341	54.09	0.5409
7	SW 7	84.00	204	319	56.08	0.5608
8	SW 8	72.70	169	263	55.53	0.5553
9	SW 9	166.02	156	259	65.42	0.6542
10	SW 10	24.00	228	374	63.77	0.6377
11	SW 11	27.60	193	310	60.89	0.6089
12	SW 12	16.90	139	234	67.98	0.6798
13	SW 13	52.00	227	371	63.73	0.6373
14	SW 14	30.00	287	462	61.14	0.6114
15	SW 15	75.00	182	307	68.33	0.6833
16	SW 16	5.20	104	167	60.05	0.6005
17	SW 17	52.00	226	367	62.37	0.6237
18	SW 18	32.20	78	131	67.21	0.6721
19	SW 19	46.00	35	67	93.54	0.9354
20	SS 1	0.82	26	50	94.81	0.9481
21	SS 2	51.00	187	315	68.71	0.6871
22	SS 3	21.00	104	191	83.34	0.8334
23	SS 4	33.49	130	230	76.38	0.7638
24	SS 5	25.00	130	228	74.67	0.7467
25	SS 6	30.00	130	236	80.64	0.8064
26	SS 7	25.50	96	182	90.14	0.9014
27	SS 8	337.00	17	34	95.99	0.9599
28	SS 9	105.60	104	188	79.99	0.7999
29	SS 10	3.68	57	98	72.90	0.7290
30	SS 11	83.01	156	259	65.40	0.6540

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31	SS 12	0.50	9	16	86.53	0.8653
32	SS 13	30.00	35	67	93.14	0.9314
33	SS 14	55.44	130	223	70.99	0.7099
34	SS 15	6.60	52	99	89.91	0.8991
35	SS 16	338.47	113	204	79.93	0.7993
36	SS 17	470.32	113	204	79.93	0.7993
37	SS 18	18.70	109	173	58.99	0.5899
38	SE 1	46.00	70	70	0.000	0.000
39	SE 2	59.50	182	290	58.97	0.5897
40	SE 3	7.00	26	50	93.40	0.9340
41	SE 4	10.00	26	51	95.64	0.9564
42	SE 5	49.00	130	225	72.37	0.7237
43	SE 6	49.00	130	226	73.70	0.7370
44	SE 7	10.50	26	50	93.73	0.9373
45	SE 8	17.00	70	131	88.23	0.8823
46	SE 9	10.00	26	51	96.58	0.9658
47	SE 10	13.50	39	74	90.35	0.9035
48	SE 11	36.00	78	145	85.84	0.8584
49	SE 12	26.00	61	109	79.20	0.7920
50	SE 13	75.00	104	191	83.38	0.8338
51	SE 14	40.27	130	226	73.73	0.7373
52	SE 15	39.00	78	144	84.26	0.8426
53	SE 16	58.00	17	33	96.52	0.9652
54	SE 17	22.00	104	185	77.81	0.7781
55	NC 1	76.00	78	144	84.43	0.8443
56	NC 2	25.80	52	98	87.61	0.8761
57	NC 3	19.50	287	424	47.60	0.4760
58	NC 4	42.00	235	381	62.20	0.6220
59	NC 5	19.20	9	18	94.47	0.9447
60	NC 6	31.00	96	177	84.45	0.8445
61	NC 7	22.00	104	178	70.76	0.7076
62	NC 8	10.50	235	382	62.98	0.6298
63	NC 9	5.60	104	173	66.06	0.6606
64	NC 10	7.20	52	87	66.73	0.6673
65	NC 11	84.00	104	181	73.44	0.7344
66	NC 12	72.70	61	116	90.60	0.9060
67	NC 13	166.02	78	144	84.69	0.8469
68	NC 14	24.00	78	149	91.02	0.9102
69	NC 15	27.60	39	74	89.32	0.8932
70	NC 16	16.90	104	183	76.11	0.7611
71	NC 17	52.00	130	222	70.63	0.7063
72	NC 18	30.00	130	218	67.05	0.6705
73	NC 18	75.00	209	278	33.33	0.3333
74	NE 1	5.20	65	123	89.11	0.8911
75	NE 2	52.00	78	140	80.09	0.8009
76	NE 3	32.20	174	302	73.49	0.7349
77	NE 4	46.00	182	313	71.80	0.7180

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78	NE 5	0.82	78	138	76.98	0.7698
79	NE 6	51.00	174	310	78.02	0.7802
80	NE 7	21.00	78	144	84.57	0.8457
81	NE 8	33.49	65	123	89.90	0.8990
82	NE 9	25.00	78	147	87.49	0.8749
83	NE 10	30.00	104	190	81.83	0.8183
84	NE 11	25.50	130	217	66.72	0.6672
85	NE 12	337.00	126	229	81.46	0.8146
86	NE 13	105.60	34	64	85.84	0.8584
87	NE 14	3.675	107	175	62.77	0.6277
88	NE 15	83.01	148	269	82.19	0.8219
89	NE 16	0.50	107	180	68.64	0.6864
90	NE 17	30.00	104	193	85.37	0.8537
91	NW 1	55.44	139	235	69.27	0.6927
92	NW 2	6.60	52	97	86.23	0.8623
93	NW 3	338.47	52	100	92.16	0.9216
94	NW 4	470.32	236	370	56.85	0.5685
95	NW 5	18.70	404	629	55.56	0.5556
96	NW 6	46.00	156	255	62.87	0.6287
97	NW 7	59.50	209	334	60.02	0.6002
98	NW 8	7.00	279	469	68.33	0.6833
99	NW 9	10.00	330	539	63.22	0.6322
100	N-W 10	49.00	182	294	60.97	0.6097
101	NW 11	49.00	287	465	61.85	0.6185
102	NW 12	10.50	209	325	55.71	0.5571
103	NW 13	17.00	209	337	61.63	0.6163

Data Partitioning and Model Performance Criteria

Prior to dataset segmentation, outliers were removed to enhance model robustness, resulting in 102 highway projects being retained as the dependent dataset for analysis. Consistent with established practice in related studies (Oboirien, 2019), the dataset was subsequently divided into training and testing subsets using an 80:20 split. This procedure produced 82 project records for model training and 20 records for model validation, which were employed in the development of both the multiple linear regression (MLR) and artificial neural network (ANN) models. The allocation of observations to each subset was performed using random sampling techniques.

Model predictive performance was assessed using three standard error metrics: mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE) as shown in Equations 3, 4, and 5. These indicators were computed by comparing model outputs from the training phase with those obtained during validation, in line with the approach adopted by Glymis et al. (2017). Models exhibiting lower error values across these measures were interpreted as demonstrating superior predictive accuracy.

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Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{i}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

- n = number of observations
- y_i = actual (observed) value
- $\hat{y}_i$ = predicted value
- n = Number of observations
- $|y_i - \hat{y}_i|$ = absolute error for each observation

Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2 \tag{4}$$

- n = number of observations
- A_i = actual (observed) value for the *i-th* observation
- F_i = forecasted or predicted value for the *i-th* observation
- $(A_i - F_i)$ = error (difference between actual and predicted value)
- $(A_i - F_i)^2$ = squared error (squaring removes negatives and penalizes larger errors more strongly)

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2} \tag{5}$$

The square root in RMSE is significant because it converts the error measure back to the same unit as the original data, unlike MSE which is in squared units. This makes RMSE more interpretable, as it shows the typical size of prediction errors directly in meaningful terms for comparison and decision-making

Multiple Linear Regression (MLR)

The formulation of the multiple linear regression (MLR) model was conducted using the regression expression defined in Equation 6 and implemented with the aid of the SPSS statistical software. In constructing the model, the set of critical schedule-related risk factors served as the independent variables, while the corresponding historical records of highway project durations constituted the dependent variables. These input data were sourced from the datasets presented in Tables 2 and 3, respectively.

$$Y = \alpha + \beta 1XT_1 + \beta 2XT_2 + \beta 2XT_3 + \cdots + \beta nXTn \tag{6}$$

Where: Y = Dependent variable; α = Regression constant; β1, β2,… βn=Regression estimates; XT_1, XT_2, XT_3 ... XTn= Independent variables.

Artificial Neural Network (ANN)

Artificial neural networks (ANNs) Artificial neural networks (ANNs) have been widely recognised as effective predictive techniques for addressing complex non-linear relationships

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in modelling applications (Datt, 2012). A fundamental strength of ANN lies in its capacity to learn from empirical data and subsequently generalise acquired knowledge to unseen cases, thereby enhancing predictive reliability (Glymis et al., 2017; Jasim et al., 2020). The ANN modelling process typically involves several sequential stages, including network architecture specification, learning rule selection, model training, and performance testing. The choice of an appropriate network configuration is largely influenced by the problem context, data characteristics, model complexity, and sample size. Consequently, the development of a suitable ANN architecture often requires multiple iterative trials before optimal performance is achieved, as architecture selection remains inherently challenging. In this regard, guidance provided by Hegazy et al. (1994) suggests that a stable ANN structure may be approximated by selecting the number of hidden neurons as roughly half of the combined input and output nodes; this heuristic informed the determination of the ANN architecture adopted in this study.

Results and Discussion

Critical Schedule Risk Factors

As previously shown in Table 2, seventeen critical schedule risk factors were established based on the 80:20 Pareto rule. Both payment delays by clients and the non-availability of spare parts for construction equipment have high RIIs of 4.53 and 4.52, suggesting that they are major schedule risk factors. Prolonged delays in interim payments often compel contractors to suspend on-site construction activities, thereby exerting a direct adverse effect on overall project schedules. Highway construction is inherently equipment-intensive, necessitating substantial investment in heavy machinery that is typically costly to procure or lease. Moreover, the reliance on imported components for equipment maintenance frequently introduces additional delays due to challenges associated with sourcing and timely delivery of spare parts. Several other schedule-related risk factors were also assessed as highly significant, with Relative Importance Index (RII) values ranging between 4.00 and 4.50, as presented in Table 2).

Multiple Linear Regression (MLR)

The developed MLR schedule prediction model incorporated ten critical schedule-related risk factors as independent variables, while seven initially identified risks were excluded due to strong interrelationships among the predictors. Assessment of the regression outputs, summarised in Table 4, reveals high variance inflation factor (VIF) values alongside correspondingly low tolerance levels, both of which signify the presence of substantial multicollinearity within the retained variables. Furthermore, the results suggest that the ten selected predictors collectively account for only 9.4% of the variance associated with schedule overruns. Detailed regression coefficients and model statistics are reported in Table 4, and the fully specified MLR expression obtained by substituting the estimated parameters into the general regression formulation (Equation 6) is presented as Equation 7.

$$\begin{aligned} Yt = 0.581 + 0.071XT_1 + 0.137XT_2 + 0.035XT_3 - 0.045XT_4 \\ - 0.016XT_5 - 0.012XT_6 - 0.115XT_7 + 0.033XT_8 \\ - 0.059XT_9 + 0.042XT_{10} \end{aligned} \tag{7}$$

Where Yt = forecast time overrun (dependent variables); $XT_1, XT_2, XT_3 \ldots XT_{10}$ = critical risk (independent variables).

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Table 4: MLR Model Development Output

Model	Unstandardised Coefficients		Standardised Coefficients	T	Sig.	95.0% CI of B		Collinearity Statistics	
	B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
(Constant)	.581	.674		-.863	.391	-1.924	.761		
Delay in payment by client (XT_1)	.071	.176	.274	.407	.685	-.279	.421	.028	35.476
Forced selection of inexperienced contractor (XT_2)	.137	.145	.359	.946	.347	-.152	.427	.088	11.301
Change in design (XT_3)	.035	.090	.285	.392	.696	-.145	.215	.024	41.250
Complexity in Project design (XT_4)	-.045	.089	-.176	-.503	.617	-.222	.133	.104	9.583
Incomprehension of the requirements of the owner by the design team (XT_5)	-.016	.063	-.162	-.250	.803	-.141	.110	.030	33.104
Failure of major construction equipment (XT_6)	-.012	.089	-.072	-.137	.891	-.190	.165	.046	21.642
Non-availability of spare parts for construction equipment (XT_7)	.115	.090	.442	1.276	.206	-.065	.295	.106	9.390
Unavailability of special equipment (XT_8)	.033	.108	.230	.306	.761	-.183	.249	.023	44.413
Change in government/political changes (XT_9)	-.059	.119	-.366	-.498	.620	-.296	.177	.024	42.381
Lack of legal regulatory framework (XT_{10})	.042	.074	.235	.563	.575	-.106	.189	.073	13.673

Validation of MLR Model

The validation phase involved applying the developed regression expression (Equation 4) to a test sample comprising 20 highway projects. Predicted project durations were generated and subsequently compared with the corresponding observed completion times, as presented in Table 7. The validation outcomes of the MLR model, summarised in Table 5, suggest that the estimated durations generally fall within a plus or minus 15.0% margin of the actual project durations. Notwithstanding this level of agreement, the coefficient of determination (R^2) obtained during model training was 0.094, indicating that the explanatory variables accounted for only 9.4% of the variation in project duration. This limited explanatory power further underscores the inherent limitation of MLR techniques in adequately capturing the complex relationships between dependent and independent variables in highway project scheduling contexts.

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Table 5: Model Performance (MLR)

Model	Partitions	R^2	MSE	MAE	RMSE
Duration (Yt)	Train	0.094(9.4%)	0.015	0.109	0.124
	Validate	0.280(28.0%)	0.033	0.150	0.182

ANN Model Development

A suitable artificial neural network (ANN) architecture was developed after multiple iterative trials, as summarised in Table 6. The optimal model, which yielded the lowest prediction error, adopted a multilayer feed-forward configuration with two hidden layers comprising six and three neurons, respectively, corresponding to a 17–6–3–1 network structure (see Figure 1). In this configuration, the selected schedule-related risk factors served as the input (independent) variables, while Yt represented the output (dependent) variable, denoting the predicted project duration. For model training and validation, the dataset was partitioned using an 80:20 ratio, resulting in 82 observations for training and 20 for testing. The mathematical formulation underlying the ANN model is presented in Equation 8.

$$\begin{aligned}\text{Build the Neural model. NeuralModel3neuralnet(YtTR1} &+ \text{TR37} \\ &+ \text{TR42} + \text{TR36} + \text{TR39} + \text{TR18} + \text{TR53} + \text{TR43} \\ &+ \text{TR9} + \text{TR35} + \text{TR56} + \text{TR61} + \text{TR12} + \text{TR33} \\ &+ \text{TR66} + \text{TR63} + \text{TR11}, \text{data} = \text{train}, \text{hidden} \\ &= \text{c(6,3)}, \text{err. fct} = \text{"sse, threshold} \\ &= 0.05, \text{linear. output} \\ &= \text{T) plot(NeuralModel3, rep} = \text{"best")}\end{aligned} \tag{8}$$

Table 6: Determining Suitable ANN Architecture Through Trials-Sensitivity Analysis

Models	Model Architecture	Partition	R^2	MSE	MAPE	RMSE
1	17-10-5-1	Training	0.49	0.01693	11.424	0.13011
		Validation	2.00	0.02271	12.221	0.15070
2	17-8-4-1	Training	2.41	0.01660	11.432	0.12883
		Validation	1.20	0.02312	12.158	0.15205
3	17-6-3-1	Training	0.21	0.01700	11.429	0.13038
		Validation	13.18	0.02207	12.065	0.14855
4	17-5-2-1	Training	2.10	0.01665	11.375	0.12901
		Validation	4.70	0.02361	12.731	0.15365

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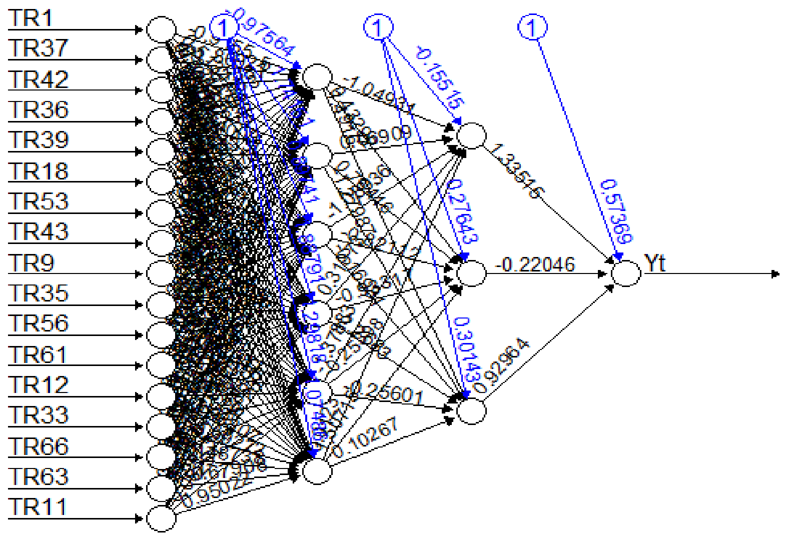

Figure 1: Most Suitable ANN Model Architecture (17-6-3-1)

ANN Model Validation

In research, the validation of a developed ANN is typically done by comparing the outcomes to actual performance, with test performance being recorded Model validation and accuracy assessment constitute critical stages in the model development process. As emphasised by Dysert (2001), ensuring the reliability and precision of a predictive model requires rigorous verification procedures, including the use of distinct datasets for training and validation to avoid biased performance evaluation. Outputs are treated as the model, which may later be expanded and abstracted for usage upon the attainment of model stability, and the output data is then established. A subset of 20 projects, drawn from the total of 102 cases presented in Table 2, was reserved for model validation. The artificial neural network (ANN) was applied to this independent dataset to generate predicted project durations, which were subsequently evaluated against the corresponding observed completion times. Model performance was assessed through a comparative analysis of the resulting percentage prediction errors, as reported in Table 7.

ANN and MLR Model Validation Results Compared

The results in Table 7 and Figure 2 show that the ANN model has better prediction accuracy than the MLR model. The prediction values are more closely related to the observed values when compared with the MLR model. Furthermore, only four points out of twenty deviated from the observed data pattern; thus, the output of the ANN model closely resembles the observed data. The inadequate relationship mapping expressed in the MLR model graph shows the presence of a non-linear or unknown relationship between the dependent and independent variables.

$$Pe = \frac{(apt - ppt)}{apt} X\ 100 \tag{9}$$

Where Pe = percentage error; apt = actual project time; ppt = predicted project time.

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Table 7: Comparison Of Actual, MLR (Predicted) And ANN (Predicted) Schedule Overruns

Test data S/N (see Table 2)	Actual schedule overrun/Test dataset	MLR-Predicted	MLR-Percentage Error (%)	ANN-Predicted	ANN - Percentage Error (%)
1	0.6039	0.8898	-47.3477	0.6458	-6.9306
4	0.6190	0.7616	-23.0341	0.6217	-0.4299
6	0.5409	0.7876	-45.6166	0.7058	-30.4790
9	0.6542	0.6911	-5.6405	0.6633	-1.3976
10	0.6377	0.7876	-23.5126	0.6358	0.3050
18	0.6721	0.7746	-15.2564	0.7008	-4.2645
29	0.7290	0.7746	-6.2604	0.7257	0.4527
45	0.8823	0.7616	13.6823	0.7958	9.8083
53	0.9652	0.7275	24.6283	0.7458	22.7351
60	0.8445	0.7746	8.2726	0.7997	5.3107
69	0.8932	0.6514	27.0708	0.8622	3.4680
70	0.7611	0.7026	7.6898	0.7588	0.3043
73	0.3333	0.7876	-136.3156	0.7457	-123.7456
77	0.7180	0.7876	-9.6992	0.7272	-1.2780
78	0.7698	0.7616	1.0677	0.7568	1.6938
82	0.8749	0.6868	21.4958	0.8755	-0.0736
83	0.8183	0.7026	14.1424	0.8003	2.2026
86	0.8584	0.6868	19.9868	0.8556	0.3299
90	0.8537	0.7616	10.7906	0.8558	-0.2414
97	0.6002	0.7616	-26.8879	0.6248	-4.0921

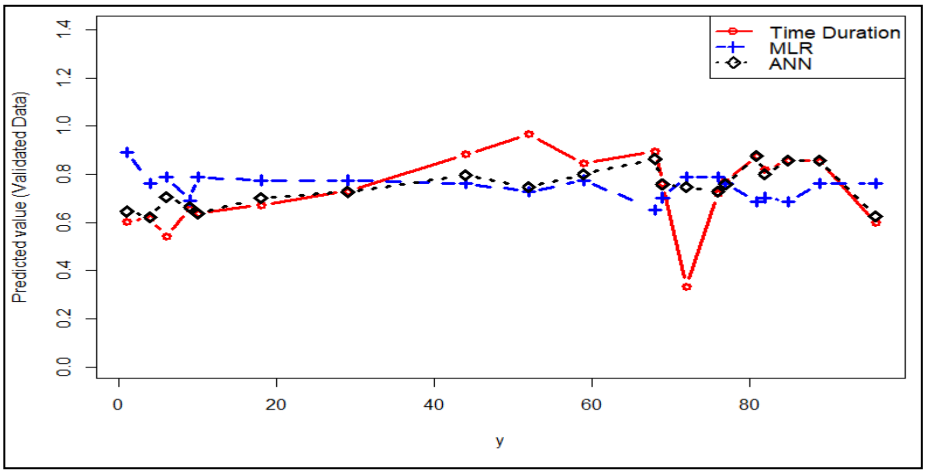

Figure 2: Comparison Of MLR And ANN Predicted Models Performance with Actual Schedule Overruns

Conclusion

- This study successfully developed predictive models that incorporates schedule-related risk variables to estimate highway construction durations, providing a valuable decision-support tool for clients, consultants, and contractors.

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- The study enhances understanding of how various risk combination influence project timelines, thereby improving planning accuracy during early project development and tender preparation.
- The ANN predictive model performed better than MLR predictive model, proving its capability to capture nonlinear and complex interactions among schedule-related risk factors.
- The study provides direction for future research, encouraging scholars to further explore and refine ANN applications within the Nigerian highway construction context.
- Major causes of highway project delays were identified to include delayed payment to the contractor by the client, shortages of spare parts, and equipment.
- Timely payments were shown to be vital in minimising the occurrences and impact of cost overruns on highway project delivery. This underscores the need for policy reforms that will discourage prolonged payment arrears that will in turn restore contractor confidence, thereby motivating investment in modern construction machinery.
- The MLR model retained only 10 out of the 17 independent variables, indicating a high level of multicollinearity among the variables. With a mean absolute percentage error (MAPE) of 15.00%, the MLR model has a predictive accuracy of 85.00% thereby meeting Lewis's (1982) threshold for good forecasting performance.
- The ANN model effectively accommodated all 17 independent variables, demonstrating its ability to handle multicollinearity and nonlinear relationships inherent in highway project data. With a mean absolute percentage error (MAPE) of 12.07%, the ANN model has a predictive accuracy of 87.93% thereby meeting Lewis's (1982) threshold for good forecasting performance. This validation outcomes further demonstrate the potential of the ANN approach in reliably estimating the actual durations of future federal highway construction projects in Nigeria.
- It is recommended that highway experts should actively participate in the creation and calibration of ANN-based predictive models, as this kind of cooperation may enhance model performance, practical relevance, and applicability under actual project circumstances
- To further improve schedule forecasting accuracy, future research may take into account the use of robust predictive modelling techniques such as the Deep Neural Network (DNN). Also, future studies could deploy other statistical approaches other than the Pareto principles of 80/20 rule used in this study to determine critical schedule risk factors.

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