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Artificial Intelligence-Based Predictive Quality Assurance for High-Voltage Electricity Transmission Infrastructure Projects: A Risk-Based Quality 4.0 Framework

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ABSTRACT

The rapid expansion and modernisation of electricity transmission networks is increasing the scale, complexity and assurance burden of major infrastructure delivery. Conventional quality assurance remains essential but is predominantly reactive, relying on inspections, audits, Inspection and Test Plans (ITPs), Non-Conformance Reports (NCRs) and corrective action after a deviation has occurred or become observable. This paper proposes an Artificial Intelligence-Based Predictive Quality Assurance Framework (AI-PQAF) for high-voltage electricity transmission infrastructure. The framework converts quality information—including NCRs, inspection outcomes, supplier performance, material records, design changes, programme conditions and corrective-action history—into predictive quality intelligence. Machine-learning models are proposed for estimating non-conformance probability and recurrence, while Natural Language Processing (NLP) supports extraction of structured knowledge from unstructured quality narratives. Explainable Artificial Intelligence (XAI) is incorporated to preserve transparency and engineering accountability. Six integrated layers are presented: data acquisition, governance and integration, feature engineering, predictive analytics, risk-based assurance decision support, and continuous learning. A conceptual Quality Risk Index (QRI) combines probability, consequence and recurrence to support dynamic assurance prioritisation. The paper extends Quality 4.0 thinking into electricity transmission construction and establishes a defensible methodology for future empirical validation using anonymised project datasets.

Keywords—Artificial Intelligence, Quality 4.0, Predictive Quality Assurance, Electricity Transmission, Machine Learning, Non-Conformance, ISO 9001, Explainable AI, Risk-Based Assurance

1. INTRODUCTION

Electricity transmission infrastructure is undergoing accelerated transformation as network operators respond to decarbonisation, renewable-energy integration, electrification and increasing expectations for system resilience. The delivery of overhead lines, substations and associated works therefore involves large volumes of engineering activity distributed across multiple organisations, suppliers, work fronts and technical disciplines.

Quality assurance in this environment must control design information, materials, manufacturing, transportation, storage, installation, testing, commissioning and documentary evidence. Established mechanisms such as ITPs, surveillance, audits, material inspections and NCRs remain indispensable. Their principal limitation is that they generally reveal quality risk after a deviation has occurred or become visible.

Large infrastructure programmes nevertheless generate substantial quality information. NCR registers contain defect categories and root causes; inspection records describe conformity outcomes; supplier records reveal delivery and manufacturing trends; assurance findings identify systemic weaknesses; and programme, design and environmental information provide contextual variables. The central proposition of this paper is that these datasets can be transformed from retrospective compliance evidence into predictive intelligence.

2. Research Problem And Gap

Conventional quality assurance can be represented as a reactive sequence: construction activity, inspection, defect identification, NCR, root-cause investigation, corrective action and closure. A predictive system instead analyses historical quality data and current project conditions before directing targeted assurance and preventive intervention.

Three practical gaps motivate the framework: quality information is often fragmented across systems; NCR data are commonly used for closure reporting rather than predictive learning; and assurance frequencies may be fixed rather than dynamically adjusted to changing risk. Recent Quality 4.0 research highlights the need to integrate technology, process and people rather than treat digital tools as isolated solutions [1]. Interpretable machine-learning research has also shown that construction defect narratives can be classified and explained using structured text analytics [2].

3. Aim, Objectives And Research Questions

The aim is to develop a conceptual AI-enabled framework for predicting and preventing quality non-conformances in high-voltage electricity transmission infrastructure.

Objectives are to identify predictive quality information; define an integrated data and analytics architecture; introduce a Quality Risk Index; incorporate machine learning, NLP and XAI into assurance planning; align the model with ISO 9001 governance; and establish a methodology for subsequent empirical validation.

The research questions are: (RQ1) Which project variables provide meaningful predictors of non-conformance? (RQ2) How can historical NCR and inspection data be converted into preventive intelligence? (RQ3) How should predictive outputs be integrated into risk-based assurance without displacing professional judgement? (RQ4) What governance controls are required for trustworthy and traceable AI-supported quality decisions?

4. CONCEPTUAL FOUNDATIONS: QUALITY 4.0 AND PREDICTIVE ASSURANCE

Quality 4.0 describes the convergence of established quality-management principles with digital technologies such as artificial intelligence, machine learning, cloud platforms, IoT, computer vision and advanced analytics. Its value lies not in technology adoption alone but in connecting data, processes and human decision-making [1].

Machine-learning models can identify multidimensional relationships among supplier performance, activity type, design change, programme pressure and prior quality outcomes. Candidate models include logistic regression, decision trees, random forests, gradient boosting, support-vector machines and neural networks. For engineering assurance, however, raw predictive accuracy is insufficient. False negatives, calibration, explainability and consequence weighting are critical because incorrectly classifying a high-consequence activity as low risk can be more serious than generating additional inspection activity.

NLP is particularly relevant because a significant proportion of quality knowledge exists in unstructured form: NCR descriptions, audit observations, corrective-action narratives, inspection comments and

supplier correspondence. Interpretable text classification provides a mechanism for turning such narratives into structured defect categories while retaining traceability [2].

5. PROPOSED AI-PQAF ARCHITECTURE

The AI-PQAF contains six connected layers. Layer 1 captures quality information from NCRs, ITPs, inspections, material receiving records, supplier assessments, audits, design changes, RFIs, programme data and commissioning results. Layer 2 governs validation, standardisation, anonymisation, classification, access control and secure integration.

Layer 3 performs feature engineering. Potential features include supplier NCR frequency, delivery damage rates, corrective-action effectiveness, activity type, previous inspection failure, design revision frequency, work intensity, open-NCR burden, NCR ageing, environmental exposure and recurrence history. Layer 4 applies predictive analytics to estimate the probability of non-conformance for a defined activity or asset.

Layer 5 converts predictions into decision support through risk-ranked dashboards and assurance priorities. Layer 6 closes the learning loop by comparing predicted risk with actual outcomes, evaluating the model and retraining it where justified.

6. QUALITY RISK INDEX

A conceptual Quality Risk Index is proposed to combine predicted probability, engineering consequence and recurrence potential:

6.1 QRI Formulation

QRI = P × C × R, where P is predicted probability of non-conformance, C is consequence weighting and R is a recurrence factor. The index may subsequently be normalised to a 0–100 scale. Thresholds should not be imposed arbitrarily; they must be calibrated using real project data and competent engineering judgement.

7. RISK-BASED ASSURANCE DECISION SUPPORT

Predictive outputs should support, not automate, quality decisions. A dashboard could display high-risk activities, recurring defect categories, supplier trends, overdue corrective actions, predicted non-conformance probability and assurance priorities. This allows limited assurance resources to be targeted towards activities where failure is both more probable and more consequential.

An indicative four-band response model is: routine assurance, enhanced monitoring, targeted intervention and priority engineering review. The classification would remain advisory until validated against empirical project outcomes.

8. EXPLAINABLE AI AND HUMAN OVERSIGHT

Engineering organisations require reasons, not merely predictions. XAI techniques such as SHAP can identify which input variables contributed most strongly to an individual risk score. A prediction may, for example, be driven by repeated supplier NCRs, recent design revisions, prior inspection failure, accelerated programme conditions and incomplete pre-activity checks.

The governing principle is that AI recommends and competent engineering professionals decide. Model outputs must remain auditable, challengeable and subordinate to statutory, contractual and technical requirements.

9. PROPOSED VALIDATION METHODOLOGY

Future empirical validation should use anonymised and organisation-approved infrastructure quality data. A representative dataset should be divided into training, validation and test subsets, or evaluated through

cross-validation where dataset size is constrained. Candidate models should be compared using precision, recall, F1 score, ROC-AUC, calibration and confusion matrices.

Particular attention should be given to false-negative rates for critical defects. Model performance should also be tested across suppliers, work packages and project stages to identify dataset shift or systematic bias. The research should compare conventional fixed-frequency assurance against AI-supported risk-based assurance using measurable outcomes such as defect recurrence, inspection yield, rework and closure effectiveness.

10. ISO 9001 ALIGNMENT AND GOVERNANCE

AI-PQAF is intended to strengthen, not replace, an established quality management system. Predictive risk identification supports ISO 9001 clause 6.1; controlled datasets support documented-information requirements; supplier analytics support external-provider controls; structured NCR analysis reinforces control of nonconforming outputs; and predictive quality indicators contribute to monitoring, evaluation, corrective action and continual improvement.

Implementation also requires cybersecurity, confidentiality controls, model versioning, change control, data lineage, access governance, validation records and defined accountability. Poor-quality input data will produce unreliable outputs; therefore, data governance is a quality requirement in its own right.

11. DISCUSSION

The framework changes the primary question from 'Did the activity conform?' to 'Where is non-conformance most likely to occur next, why, and what preventive assurance is justified?' This does not diminish inspection or engineering judgement. Instead, it uses accumulated project knowledge to allocate assurance effort more intelligently.

The principal conceptual contribution is the integration of construction Quality 4.0, predictive analytics and explainable decision support within the specific context of electricity transmission delivery. The framework also creates a research pathway for testing whether historical quality information can materially improve prevention rather than merely support retrospective reporting.

12. LIMITATIONS AND FUTURE WORK

The framework is conceptual and has not yet been validated using a transmission-project dataset. Its effectiveness will depend on data completeness, consistency, taxonomy quality and organisational readiness. Future work should evaluate alternative algorithms, establish validated QRI thresholds, test model transferability between work packages and quantify impacts on NCR recurrence, rework, assurance efficiency and supplier performance.

13. CONCLUSION

This paper proposes an Artificial Intelligence-Based Predictive Quality Assurance Framework for high-voltage electricity transmission infrastructure. By integrating quality data, machine learning, NLP, XAI and risk-based assurance planning, the model shifts quality management towards anticipatory defect prevention while preserving professional engineering judgement. Empirical validation is required before operational deployment, but the framework provides a structured basis for predictive Quality 4.0 research in major electricity infrastructure.

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