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Original Research Article

Artificial Intelligence-Driven Electrical Cost Estimation and Budget Optimization for Large-Scale Construction Projects in Saudi Arabia

Mir Shuja Ur Rahman[1]*
[1]Research Scholar

***Corresponding Author**
Mir Shuja Ur Rahman
Research Scholar

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Abstract: Cost estimation for electrical building services becomes increasingly difficult as Saudi construction programmes combine compressed procurement schedules, evolving designs, complex low-current systems and volatile supplier markets. This integrative review examines how artificial intelligence can augment electrical cost estimation and budget optimization without displacing professional engineering judgment. It differentiates estimating accuracy from commercial feasibility and explains why models trained on generic building costs are not automatically transferable to medium-voltage distribution, low-voltage networks, structured cabling, security installations or building automation. The review synthesizes recent construction cost prediction scholarship, Saudi evidence on cost drivers, and related work on digital project information. Its central contribution is a governance-oriented framework integrating a controlled electrical work-breakdown structure, validated historical quantities, contextual price features, interpretable prediction models, procurement risk scenarios and accountable estimator approvals. The analysis finds that predictive algorithms offer substantial promise for early budget range development and tender comparison, yet their reliability depends on scope normalization, temporal validation, uncertainty communication and auditable changes. Practical implementation should begin with narrow trade-specific pilots and progress towards integrated cost intelligence once data quality and organizational safeguards are demonstrated. The study concludes with research priorities for prospective evaluation within Saudi infrastructure programmes.

Keywords: Electrical Cost Estimation, Artificial Intelligence, Saudi Arabia, Construction Tendering, Budget Optimization, Procurement Risk, Vision 2030.

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1. INTRODUCTION

Reliable electrical estimates are indispensable to project investment decisions, procurement strategy, tender competitiveness and construction delivery. Electrical scopes involve more than counting cables and luminaires. Engineers must identify equipment duty, distribution architecture, containment routes, installation constraints, interface responsibilities, commissioning requirements and compliance obligations. A preliminary estimate prepared from limited concept drawings may later become a detailed bill of quantities, a negotiated subcontract price and ultimately a cost-controlled construction budget. Each stage changes the type and reliability of available information. Consequently, numerical prediction alone cannot establish whether an estimate adequately represents the contracted scope.

Saudi Arabia offers an important context for examining this problem. Its infrastructure development agenda encompasses transport facilities, hospitals, commercial environments, industrial installations and sophisticated building-service networks. The National Transformation Program emphasizes stronger infrastructure, digital transformation and private-sector capability as part of Vision 2030 (Saudi Vision 2030, n.d.). Such priorities create legitimate interest in modern estimating systems, but national policy aspirations should not be confused with evidence that a particular algorithm has already improved project outcomes. The present review examines the operational prerequisites and limits of that improvement.

Conventional electrical estimating combines engineering take-off, supplier quotations, historical rates, installation productivity assumptions, contingencies and expert review. These activities are affected by repeated information handovers. Early project concepts may have uncertain load schedules and equipment specifications; tender documents may contain ambiguous scope boundaries; supplier prices may expire before commercial agreement. A change in cable routing, transformer rating, fire-alarm topology or security coverage can alter both quantities and installation labour. Forecast models that omit those mechanisms risk producing a mathematically plausible but contractually incomplete budget.

Construction researchers have increasingly investigated artificial neural networks, regression, case-based reasoning and hybrid forecasting. A bibliometric review identifies seven commonly explored cost-modelling techniques, underscoring the diversity of approaches rather than the superiority of any single algorithm (construction cost modelling review, 2023; source details require confirmation). A review devoted to machine learning in building-project estimation also observes persistent challenges involving data suitability and model development (Wang *et al*., 2024). Those findings motivate a specialized analysis of electrical systems, where equipment price distributions, installation resources and approval processes differ materially from aggregate construction costs.

The practical motivation also arises from Saudi evidence. Mosly (2024) reports that inadequate management, weak estimation and design errors are important reported cost influences in a survey of engineers. An artificial-neural-network study using 135 Saudi projects demonstrates that final-cost prediction is possible with relatively few variables, but its reported changes in error after excluding extreme cases also warn against treating performance figures as universally transferable (Al-Gahtani *et al*., 2024). Thus, the research question is not whether artificial intelligence can generate a cost number, but under which conditions that number becomes defensible engineering advice.

Table 1: Electrical estimation information streams and their principal quality controls

Information stream	Typical content	Quality control
Design information	SLDs, schedules, equipment duty, layout	Revision control and scope reconciliation
Measured quantities	Cables, trays, switchgear, devices	Unit, measurement and duplication checks
Market information	Supplier quotations and labour rates	Date, currency, validity and exclusions
Execution data	Productivity, commissioning and rework	Actual-cost matching by work package
Risk assumptions	Lead times, interface and design changes	Scenario and contingency review

2. Study Aim and Objectives

The aim of this review is to develop an evidence-informed conceptual approach for using artificial intelligence to improve electrical cost estimation and budget optimization across large Saudi construction projects while preserving traceability, contractual completeness and professional accountability.

Five objectives structure the inquiry. First, identify the electrical estimating tasks in which machine learning can provide relevant support. Second, evaluate data sources and technical features required to represent electrical scope and market conditions. Third, compare model families through operational criteria including interpretability, validation and uncertainty rather than reported accuracy alone. Fourth, propose an integrated workflow connecting prediction to tender review, procurement decisions and cost control. Fifth, identify research gaps and governance requirements relevant to Saudi infrastructure delivery.

The corresponding questions are: what additional information makes an electrical estimate reliable; how should predictive models be evaluated across project phases and sectors; what controls prevent historical data leakage and scope mismatch; how can risk-adjusted budgets be linked to procurement and design decisions; and which field studies are necessary before organizational deployment? These questions are exploratory and synthesis-oriented. They do not imply that a new software tool has been built, tested or deployed in the present study.

3. RESEARCH METHODOLOGY

An integrative narrative review was selected because the topic joins technical prediction, construction economics, engineering design, contractual practice and digital governance. A narrowly quantitative synthesis would be inappropriate where studies differ in project types, cost definitions, available inputs and evaluation metrics. The approach therefore focuses on convergent mechanisms, contradictory assumptions and decisions needed to translate research into electrical estimating practice. It does not claim exhaustive retrieval or a statistically pooled treatment effect.

Evidence was identified through targeted searches of publisher platforms, academic search interfaces and official Saudi policy resources. Search combinations included construction cost estimation, machine learning, neural network, building services, electrical systems, building information modelling, early budget, procurement risk, Saudi Arabia, and project cost overrun. Priority was given to research from 2020 to 2025, supplemented by official policy sources and a small number of directly relevant methodological studies. The review uses attributable publications with identifiable titles and persistent links or publisher records. It avoids presenting a fictitious database screening count, reviewer agreement statistic or formal risk-of-bias score.

For inclusion, a source needed to inform at least one of four themes: construction cost prediction methods, Saudi cost determinants, design and digital information integration, or model evaluation and implementation. Studies confined to unrelated financial forecasting were not treated as construction evidence. Publications supplying only promotional claims without a discernible method were excluded from substantive interpretation. The selected works were examined through a common extraction template describing prediction target, project stage, input variables, sample context, performance measure, source limitations and possible electrical application.

Quality was appraised qualitatively. Greater analytical weight was assigned to studies that defined their outcome, described data provenance, explained train-test separation and acknowledged generalization limits. Contextual studies were evaluated for population and survey limitations. Official Vision 2030 information was used only to establish policy direction, not to validate model performance. The synthesis proceeded by comparing estimation stages, identifying recurring failure mechanisms, and constructing a workflow whose safeguards address the documented limitations.

This methodology remains constrained by source heterogeneity and the limited number of studies focused specifically on electrical and low-current trades. Some evidence concerns whole-building or infrastructure costs and is transferred by reasoned analogy. Such transfers are explicitly propositions requiring later testing, rather than established electrical-performance findings. No new project database, interviews, algorithm training or numerical meta-analysis was conducted for this review.

4. The Electrical Estimating Problem

A meaningful prediction target must be specified before a model is trained. At concept stage, an estimator may forecast an order-of-magnitude budget for electrical distribution and specialist systems. During tender preparation, the target may be a priced bill of quantities after vendor comparison and technical compliance review. During execution, the target can become forecast final cost, including committed purchase orders, variations and remaining work. Combining these outcomes in one dataset without explicit stage labels causes target inconsistency. A model predicting approved tender values cannot simply be interpreted as predicting the final out-turn cost.

Electrical estimates also require scope granularity. A medium-voltage package may include transformers, switchgear, protection relays, testing and utility interface requirements. Low-voltage distribution involves main panels, subdistribution, containment, feeders and final circuits. Extra-low-voltage systems may include fire detection, access control, structured cabling, audiovisual infrastructure, public address and operational communications. Building automation adds sensors, controllers, networking and integration tasks. These domains follow different material and labour price dynamics, requiring either trade-specific models or defensible hierarchical estimation methods.

The cost baseline is a contractual and engineering construct. It must identify whether temporary works, permits, utility fees, testing, consumables, supervision, logistics, warranties, design development and contingency are included. An algorithm trained on historical unit rates does not know which obligations were excluded unless the records encode them. Moreover, historical databases frequently mix tender offers, internal budgets, negotiated prices and actual invoices. These observations are not interchangeable. A robust workflow should create explicit data dictionaries defining each cost component, tax treatment, currency, quote date, escalation basis and commercial status.

Quantity take-off is similarly contextual. Cable cost depends on conductor size, insulation, route length, spare capacity and fire performance, while installation cost depends on access, working height, congestion and construction sequence. A single gross-floor-area ratio may be useful for early benchmarking, yet it may obscure those physical determinants. The purpose of artificial intelligence should therefore be to combine simplified early indicators with detailed variables as design maturity improves, not to force every project phase into the same input structure.

Finally, estimating decisions are interdependent. A lower transformer procurement price may be offset by long lead times or compliance risks; a value-engineering proposal may reduce material quantities but increase integration or commissioning cost. Budget optimization must consider lifecycle performance, technical equivalence, programme exposure and quality. The cheapest predicted cost is not necessarily the economically preferable outcome. Treating estimation as a decision-support problem rather than a single-number competition provides the conceptual basis for a safer AI adoption pathway.

Electrical costs are also shaped by technical approval sequences. A substitution cannot be treated as financially valid until required product equivalence, engineering calculations and stakeholder consent are demonstrated. Procurement histories should record not merely accepted prices but rejected offers and reasons for rejection. This information helps distinguish market affordability from compliance failure. Without that distinction, a learning system may repeatedly recommend unrealistically cheap equipment because historical bid data includes quotations that never satisfied the project specification.

5. Predictive Models and Evidence

Existing construction research presents a broad methodological toolkit. Regression models offer transparent baseline relationships but can struggle with nonlinear interactions among building function, design maturity and supply-chain conditions. Artificial neural networks approximate complex relationships and may perform well when trained on sufficiently relevant examples. Tree ensembles can handle mixed numerical and categorical inputs, often providing competitive tabular predictions and feature-importance analysis. Case-based reasoning supports analogical comparison with completed projects, a process already familiar to experienced estimators. Hybrid techniques combine physical quantity information with statistical correction or separate specialist models.

The literature does not justify appointing one universally best method. The 2023 infrastructure-cost bibliometric review finds substantial attention to regression, neural networks and case-based reasoning, and identifies potential value in combined approaches (construction cost modelling review, 2023; source details require confirmation). The 2024 machine-learning review similarly surveys multiple pathways and future development needs (Wang *et al*., 2024). A practical research programme should compare simple and advanced models against the same held-out projects and the same transparent rules. Apparent superiority resulting from richer input data or different exclusions is not a fair algorithmic comparison.

Saudi project studies demonstrate why context matters. The reported neural-network model trained on 135 projects used contract cost, duration and sector to forecast final construction costs (Al-Gahtani *et al.,* 2024). These inputs are attractive when design information is scarce. Yet even a relevant Saudi dataset cannot automatically describe electrical subcontract pricing, airport security systems or industrial cable installations. The appropriate inference is that learning from historical Saudi projects can be useful, not that an electrical-specific model has been validated by the whole-project study.

Another Saudi-focused study developed an integrated causal and system-dynamics approach to project cost prediction, recognizing that interacting cost-risk factors can shape outcomes (An integrated DEMATEL, 2024). This is important because tender prices and execution forecasts respond not only to technical quantities but also to schedule changes, design revisions and managerial decisions. A pure prediction model may capture correlations without representing intervention effects. Combining statistical estimates with explicit risk scenarios could make budget reviews more useful, particularly where project teams must explain why contingency or procurement allowances change.

Research on early budget decision-making emphasizes the difficulty of estimation when available inputs remain qualitative (Sadick *et al*., 2024). Such findings suggest a phased feature strategy: conceptual models could use building function, gross area, connected-load intensity and systems complexity; later models could incorporate schedule-derived quantities, supplier quotations, access conditions and testing obligations. Importantly, adding features improves neither accuracy nor fairness automatically. Inputs recorded after a tender decision can leak information about the target and create optimistic retrospective evaluations.

Performance should be described through several complementary measures. Mean absolute error communicates the typical monetary deviation. Mean absolute percentage error is intuitive but unstable around small denominators and can hide expensive absolute mistakes. Root mean squared error emphasizes major deviations that may be commercially consequential. Calibration and interval coverage indicate whether stated uncertainty ranges are credible. Bias analysis reveals systematic underpricing of particular systems, project types or tender phases. For procurement use, one should also evaluate how model advice changes real decisions, not merely how well it reproduces historical outcomes.

Crucially, model explanations must remain interpretable to cost engineers. A prediction accompanied by a ranked influence diagram can support review, but apparent feature importance does not prove causality. For example, a high correlation between facility type and cost may proxy for unmeasured security specifications. Estimators should be able to inspect comparable projects, unit-price changes, major quantity drivers and assumptions. When a prediction conflicts with a certified design or vendor offer, the documented engineering evidence should take precedence.

Model selection also depends on sample size and variable stability. A neural network with many adjustable parameters can fit idiosyncrasies in a small collection of projects. A simpler penalized regression may provide more dependable performance when few comparable tenders exist. Conversely, larger consistent datasets may justify non-linear methods. The evaluation protocol should disclose the size and composition of training, validation and test sets, and repeated experiments should remain constrained by their chronological structure. Confidence in the model should derive from replicable out-of-sample evidence.

6. Data Architecture and Validation

The proposed architecture begins with a standardized electrical work-breakdown structure. Each record should identify the system, design revision, measurement unit, quantity, specification class, installation environment, labour allowance, approved supplier or market quotation and outcome stage. Project metadata should include location, delivery model, procurement date, building function, scale, applicable standards and schedule constraints. A central glossary must separate general abbreviations from operational definitions; otherwise, records from separate projects may share labels while describing materially different work.

Historical data preparation should preserve rather than erase commercial context. Supplier quotations can be linked to their validity windows and technical exclusions. Contract variations should be associated with the design changes that caused them. Purchase-order values should be distinguished from final paid amounts. Abnormal observations should be reviewed by domain specialists before exclusion, because an unusually high price may represent legitimate engineering complexity or adverse site conditions rather than an input error. Removing expensive cases indiscriminately could systematically understate risk for future complex projects.

For electrical projects, feature engineering ought to link physical and commercial variables. Relevant descriptors include transformer count and capacity, distribution-board density, cable-route complexity, emergency power requirements, hazardous-area classifications, building management integration, equipment import exposure and commissioning intensity. These features require consistent collection procedures and may be unavailable at concept stage. Models therefore need explicit missing-data policies and stage-specific feature sets, with unknown values distinguished from zero quantities.

Validation requires temporal and project-level separation. If records from one project appear in both training and testing, the measured performance may reflect familiar project conditions rather than transferable forecasting skill. Random splits are particularly problematic where multiple tender revisions, package prices or supplier records belong to a single scheme. A stronger test trains on older projects and evaluates genuinely later projects, using grouped partitions where related records are kept together. Separate assessment by airport, hospital, industrial and commercial project types can expose poor cross-sector generalization.

An effective minimum-viable pilot might focus on one repeatable electrical package rather than an entire megaproject. For instance, a contractor could evaluate panelboard package rates over a sequence of completed facilities, comparing estimator baselines, model predictions and final approved costs. The pilot should predefine failure thresholds, exclusions and escalation rules. These practices are more informative than a polished dashboard presenting accuracy results without reproducible validation.

7. Proposed Integrated Decision Framework

The review proposes a six-stage framework rather than claiming to report a completed empirical implementation. Stage one is scope governance.

Engineering and estimating teams establish package boundaries, drawing status, applicable standards and measurement rules. Stage two is data assurance, where historical project records and current quotations undergo normalization and technical checks. Stage three is predictive analysis, using baseline statistical models alongside more flexible algorithms only when data sufficiency and validation justify them.

Stage four translates point predictions into scenario-based budgets. A base case should represent the most defensible available design and market assumptions. Alternative scenarios can account for supplier escalation, lead-time disruption, scope development, labour productivity and value-engineering options. Risks should not be added mechanically when their effects overlap; experienced reviewers need to understand scenario dependencies. Stage five is human challenge and approval, including comparison against supplier offers, quantity benchmarks, technical exclusions and similar completed projects. Stage six is learning and monitoring through comparison of forecasts with awarded prices, purchase commitments and actual closeout costs.

This architecture implies differentiated roles. Quantity surveyors and electrical engineers own scope definitions and bill completeness. Procurement teams validate quotations, lead times and supplier capacity. Data specialists manage reproducible pipelines and monitor model performance. Commercial managers approve contingency and contractual exclusions. Project governance bodies decide when model advice is informative and when exceptions require additional review. Such role separation prevents the false impression that a prediction can independently authorize tender prices.

Budget optimization occurs after technical compliance is established. Candidate designs may be compared through procurement price, installation productivity, energy losses, maintenance access, reliability and operating life. Optimization constraints should prohibit unacceptable departures from safety, client specifications and code requirements. Even if a mathematical solver identifies a cheaper combination of components, engineering specialists must verify that its interfaces, capacities, coordination and maintainability remain suitable. This protects the distinction between cost efficiency and unsafe scope reduction.

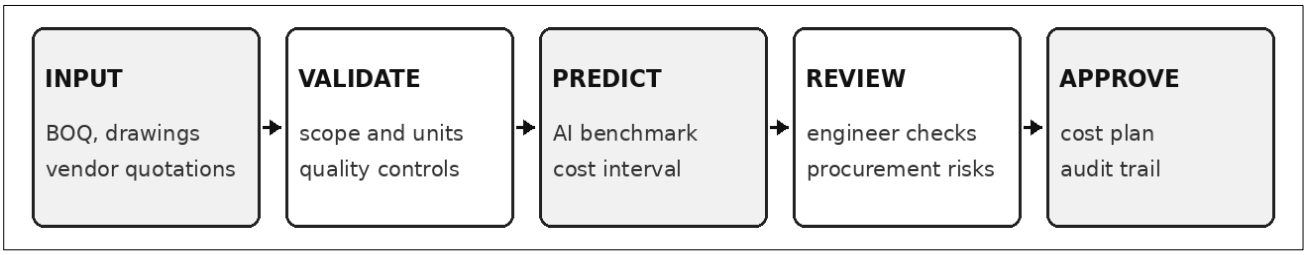


Figure 1: Human-supervised electrical cost estimation workflow

Finally, uncertainty should be communicated as part of the recommendation. Where design maturity is low, a broad and clearly qualified budget range may be more responsible than a precise point estimate. Procurement confidence can increase as vendor quotations become binding and quantities stabilize. Governance thus treats precision as a result of evidence quality, not as a cosmetic feature of software. The framework is intended for empirical testing, not presented as an already-proven Saudi implementation.

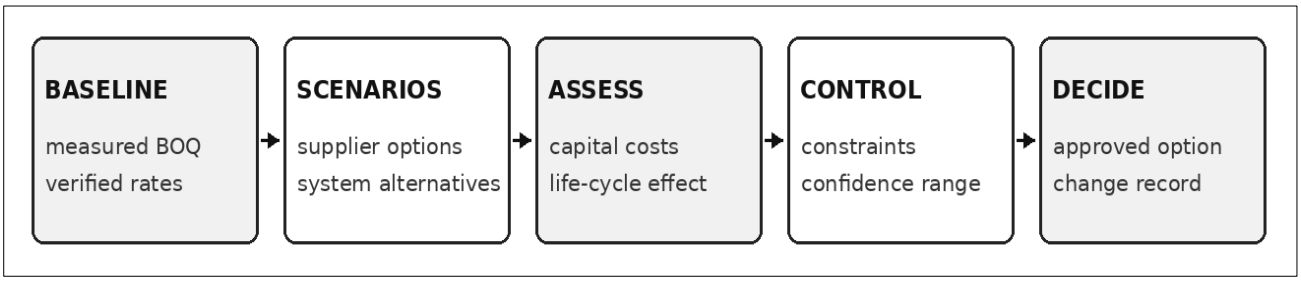


Figure 2: Risk-controlled budget optimisation pathway

8. DISCUSSION

Table 2: Comparative performance and governance criteria for proposed AI estimating models

Evaluation dimension	Suggested indicator	Management interpretation
Prediction quality	MAE, RMSE and WAPE	Check trade-level error and impact of outliers
Generalisation	Project-group / time-held-out testing	Avoid repeating information from related tenders
Uncertainty	Interval coverage and error by phase	Match contingencies to design maturity
Governance	Override logs and explanation review	Document engineer approval and model changes

Three major insights emerge from the synthesis. First, electrical estimation is distinguished by the interaction of physical system architecture and commercial procurement. Aggregate construction datasets can illuminate overarching patterns but may conceal trade-specific quantities, testing responsibilities and integration costs. Second, predictive model evaluation must be designed around the intended decision. An early conceptual budget, a tender reconciliation and a final-cost forecast require different targets, validation windows and tolerances. Third, adoption depends as much on organizational governance as on algorithm selection.

The Saudi context strengthens these conclusions without making them exclusive to the Kingdom. Large and technically varied projects can create opportunities to standardize historical cost knowledge across future programmes. At the same time, inconsistent data ownership, fragmented subcontract packages and changing specifications can limit information reuse. Mosly's Saudi engineering survey highlights management and design-related cost determinants (Mosly, 2024), suggesting that better prediction should be pursued alongside improved document control and commercial coordination rather than as an alternative to those disciplines.

AI can potentially identify anomalies in rates, provide comparative benchmarks and support earlier recognition of cost exposure. However, correlations from historical projects reflect past procurement conditions and design choices. If new supplier technologies, regulatory requirements or project delivery arrangements shift the operating environment, statistical relationships may no longer hold. This problem of distribution shift is especially material where projects involve novel building functions or unprecedented integration demands. Model monitoring should therefore include triggers for retraining, suspension and expert escalation.

Meaningful value should ultimately be evaluated through commercial outcomes. A model could lower retrospective percentage error without improving negotiations, procurement timing or approved budget reliability. Conversely, a modest prediction improvement could be valuable if it highlights overlooked system interfaces or flags quotations likely to expire. Future evaluations should therefore test decision quality, cost of implementation, estimate preparation time, dispute frequency and post-award forecast stability alongside standard accuracy metrics.

9. Future Directions

The most evident research gap is the scarcity of independently validated, electrical-trade-specific Saudi datasets. Studies of complete buildings and infrastructure schemes cannot resolve whether predictive signals for transformer packages, low-current systems or building automation are stable. Future researchers should assemble anonymized records with explicit technical scopes, quantities, quote dates and cost outcomes. Multi-organization participation could improve representativeness, provided commercial confidentiality and common definitions are maintained.

A second gap is prospective evaluation. Many model comparisons are retrospective, but actual tender environments involve incomplete drawings, late clarifications, supplier negotiation and managerial constraints. A prospective study could record the information available at each tender milestone and compare model advice against estimator decisions without exposing the organization to uncontrolled pricing changes. This would show whether a tool is genuinely useful when information is scarce rather than when all final project records are already known.

Third, research should compare uncertainty methods and human-model collaboration. Evidence is needed on whether calibrated intervals improve contingency decisions, whether explanations reduce inappropriate reliance and how much specialist review is required to identify scope errors. Experimental designs can compare blinded estimates, AI-supported estimates and consensus reviews while recording time, confidence and decision changes. The purpose should be to identify safe operating arrangements, not merely to demonstrate that a sophisticated algorithm can beat an arbitrary baseline.

Fourth, budget optimization requires lifecycle evaluation. A procurement saving that increases losses, maintenance burden or reliability risk should not count automatically as a positive outcome. Research could integrate electrical asset performance and operating-cost assumptions with purchase and installation estimates. Such work would be especially relevant to infrastructure programmes expected to operate for decades, but it needs verified technical inputs and transparent discounting assumptions.

10. Recommendations and Limitations

For contractors, the recommended first action is not purchasing a general AI platform but cleaning historical electrical cost records. A controlled coding system, a library of exclusions and a reliable link between design revisions and prices can create immediate operational value. Estimating teams should select a limited package and establish baseline performance using existing expert and spreadsheet methods before introducing predictive models. Management should evaluate the cost of data preparation against achievable decision benefits.

The review has important limitations. It is an integrative, interpretive synthesis, not a registered systematic review or meta-analysis. The reviewed evidence is heterogeneous and relatively sparse for electrical trade-specific prediction. No new Saudi project dataset was accessed, and no numerical claims of achieved savings or model improvements arise from this manuscript. Some recommendations derive from engineering reasoning extrapolated from whole-project studies. They must be validated before being treated as performance evidence or operational procurement rules.

11. CONCLUSION

Artificial intelligence offers a credible opportunity to strengthen electrical cost estimation in Saudi large-scale construction, but its value is conditional. Reliable outcomes depend on accurate scope representation, harmonized historical records, appropriate validation, explicit uncertainty and accountable engineering review. Generic construction forecasting research provides a starting point, not a substitute for electrical-specific evidence. The proposed six-stage framework connects controlled data and predictive analysis with commercial scenarios, specialist approval and continuous learning. Its contribution is a structured implementation hypothesis that future Saudi field studies can test. Progress should be measured by defensible decisions and stronger budget governance rather than software sophistication alone.

Policy and Implementation Safeguards

Information exchange should follow documented data responsibilities and agreed model deliverables (ISO 19650-1, 2018; ISO 19650-2, 2018). Risk registers and model governance should remain subject to management review (ISO 31000, 2018; NIST, 2023; ISO/IEC 42001, 2023). Electrical design and operating assumptions should be checked against relevant Saudi codes (Saudi Building Code National Committee, 2018), while whole-life consequences should be considered where alternatives differ in energy use or maintenance requirements (ISO 15686-5, 2017; ISO 50001, 2018).

Published Saudi Project Datasets: Case-Study Comparison

A Saudi construction-cost forecasting investigation by Alsugair, Alsanabani and Al-Gahtani (2023) examined 34 completed projects and compared artificial-neural-network predictions against two linear-regression models. The authors reported a lower mean absolute percentage error (MAPE) for the neural network, although its reported MAPE below 8.5% followed filtering observations with absolute percentage error above 35%. These figures are the published authors' results, not a model trained for the present paper. DOI: https://doi.org/10.3390/buildings13030786.

A separate analysis of 135 Saudi projects by Al-Gahtani *et al*., (2024) used contract cost, duration and sector to predict final construction costs. The paper reported average MAPE of 18.7%, falling to 8.7% after excluding cases with absolute percentage error exceeding 35%. The comparison highlights the need to report original-sample and filtered-sample performance separately. It does not establish superior electrical trade-package predictions. DOI: https://doi.org/10.1080/13467581.2023.2294883.

Required independent experimental test: obtain permission to use historical anonymised electrical project records, including project-group identifiers, tender date, measured quantities, approved conventional estimate and final comparable cost. Fix a chronological train/validation/test split; train a specified model (for example gradient-boosted trees) using only information available at tender stage; evaluate against the conventional estimate and a transparent regression baseline on the same held-out projects. Report sample size, MAE, WAPE, RMSE, confidence intervals, project-level errors and preprocessing code. No original training, holdout testing or verified client project dataset has yet been supplied; therefore the present manuscript cannot claim its own model accuracy or case-study savings.

Research-Data Transparency Statement

This manuscript reviews published evidence and proposes an engineering framework. No undisclosed client records are claimed, and no original project-specific empirical results are represented as observed outcomes. Reproducing or extending the framework with confidential project data requires documented access, anonymisation, technical validation and appropriate permission.

REFERENCES

- Mosly, I. (2024). Construction cost-influencing factors: Insights from a survey of engineers in Saudi Arabia. Buildings, 14(11), 3399. https://doi.org/10.3390/buildings14113399
- Mosly, I. (2025). Multivariate analysis of factors influencing construction costs in Saudi Arabia. Buildings, 15(5), 687. https://doi.org/10.3390/buildings15050687
- Salleh, H., et al. (2024). Application and prospect of machine learning techniques in cost estimation of building projects. Engineering, Construction and Architectural Management. https://doi.org/10.1108/ECAM-05-2024-0595
- International Organization for Standardization. (2018). ISO 19650-1:2018: Organization and digitization of information about buildings and civil engineering works, including building information modelling—Concepts and principles. https://www.iso.org/standard/68078.html
- International Organization for Standardization. (2018). ISO 19650-2:2018: Organization and digitization of information about buildings and civil engineering works, including building information modelling—Delivery phase of the assets. https://www.iso.org/standard/68080.html
- International Organization for Standardization. (2015). ISO 9001:2015: Quality management systems—Requirements. https://www.iso.org/standard/62085.html
- International Organization for Standardization. (2018). ISO 31000:2018: Risk management—Guidelines. https://www.iso.org/standard/65694.html
- International Organization for Standardization. (2017). ISO 15686-5:2017: Buildings and constructed assets—Service life planning—Life-cycle costing. https://www.iso.org/standard/61148.html
- International Organization for Standardization. (2018). ISO 50001:2018: Energy management systems—Requirements with guidance for use. https://www.iso.org/standard/69426.html
- National Institute of Standards and Technology. (2023). AI Risk Management Framework (AI RMF 1.0), NIST AI 100-1. https://doi.org/10.6028/NIST.AI.100-1
- National Institute of Standards and Technology. (2024). Artificial Intelligence Risk Management Framework: Generative Artificial Intelligence Profile (NIST AI 600-1). https://doi.org/10.6028/NIST.AI.600-1
- International Organization for Standardization and International Electrotechnical Commission. (2023). ISO/IEC 23894:2023: Information technology—Artificial intelligence—Guidance on risk management. https://www.iso.org/standard/77304.html
- International Organization for Standardization and International Electrotechnical Commission. (2023). ISO/IEC 42001:2023: Information technology—Artificial intelligence—Management system. https://www.iso.org/standard/81230.html
- Royal Institution of Chartered Surveyors. (2021). NRM 1: Order of cost estimating and cost planning for capital building works (3rd ed.). RICS.
- Royal Institution of Chartered Surveyors. (2021). NRM 2: Detailed measurement for building works (2nd ed.). RICS.
- Royal Institution of Chartered Surveyors. (2021). NRM 3: Order of cost estimating and cost planning for building maintenance works (2nd ed.). RICS.
- American Society for Testing and Materials. (2024). ASTM E917: Standard practice for measuring life-cycle costs of buildings and building systems. ASTM International.
- Saudi Building Code National Committee. (2018). Saudi Electrical Code (SBC 401). Kingdom of Saudi Arabia.
- Saudi Building Code National Committee. (2018). Saudi Energy Conservation Code—Commercial (SBC 601). Kingdom of Saudi Arabia.
- Project Management Institute. (2021). A guide to the Project Management Body of Knowledge (PMBOK Guide) (7th ed.). Project Management Institute.
- International Energy Agency. (2024). Energy Efficiency 2024. https://www.iea.org/reports/energy-efficiency-2024
- Saudi Vision 2030. (2024). Vision 2030 annual report 2024. Kingdom of Saudi Arabia. https://www.vision2030.gov.sa/
- Organisation for Economic Co-operation and Development. (2019). OECD principles on artificial intelligence. https://oecd.ai/en/ai-principles
- International Organization for Standardization. (2018). ISO 16739-1:2018: Industry Foundation Classes (IFC) for data sharing in the construction

and facility management industries. https://www.iso.org/standard/70303.html

- International Organization for Standardization. (2022). ISO 29481-1:2022: Building information models—Information delivery manual—Methodology and format. https://www.iso.org/
- Verified additional research references
- Alsugair, A. M., Alsanabani, N. M., & Al-Gahtani, K. S. (2023). Forecasting the final contract cost on the basis of the owner's cost estimation using an artificial neural network. Buildings, 13(3), 786. https://doi.org/10.3390/buildings13030786
- Al-Gahtani, K. S., Alsugair, A. M., Alsanabani, N. M., Alabduljabbar, A. A., & Almohsen, A. S. (2024, online publication). ANN prediction model of final construction cost at an early stage. Journal of Asian Architecture and Building Engineering. https://doi.org/10.1080/13467581.2023.2294883
- Wang, R., Salleh, H., Lyu, J., Abdul-Samad, Z., Mohd Radzuan, N. F., & Wen, K. C. (2024, online publication). Application and prospect of machine learning techniques in cost estimation of building projects. Engineering, Construction and Architectural Management. https://doi.org/10.1108/ECAM-05-2024-0595.