Decision Intelligence Framework for Sustainable Infrastructure and Industrial Asset Portfolio Prioritization Under Competing Constraints

MD Monasur Rahman[1]; Md Jahedul Islam Arif[2];
Mohammad Mostafijur Rahman[3]; Safaul Islam Rohan[4]

[1]Master of Science in Engineering Management Westcliff University, California, USA
[2]Master of Engineering, Industrial Systems Engineering Lamar University, Beaumont, TX
[3]Master of Engineering Science in Industrial Engineering Lamar University, Beaumont, Texas, USA
[4]Master of Industrial Engineering Lamar University, Beaumont, Texas, USA

[1]ORCiD: https://orcid.org/0009-0009-0452-143X
[2]ORCiD: https://orcid.org/0009-0009-0104-6565
[3]ORCiD: https://orcid.org/0009-0007-6919-5773
[4]ORCiD: https://orcid.org/0009-0003-0726-8958

Publication Date: 2026/09/22

Abstract: Industrial and infrastructure asset portfolios require investment decisions under limited budgets, operational risks, resource constraints, and competing sustainability priorities. This study proposes a decision intelligence framework for portfolio level asset intervention prioritization. The framework integrates Fuzzy Delphi based criterion validation, Pareto screening, Group AHP weighting, Utility Value Analysis, performance-gap assessment, and binary performance-gain knapsack optimization. Eight criteria are considered: asset condition, failure exposure, lifecycle cost, operational importance, resilience contribution, environmental performance, modernization potential, and implementation feasibility. The optimization model selects intervention portfolios according to expected performance gains while considering budget limits, performance requirements, resource constraints, and logical dependencies. Scenario analysis examines portfolio changes under cost, reliability, resilience, sustainability, and digital-modernization priorities. VIKOR, TOPSIS, PROMETHEE, and COPRAS provide alternative rankings, while Spearman correlation assesses ranking stability. A synthetic asset portfolio is used to demonstrate the computational workflow without relying on proprietary organizational data.

Keywords: *Decision Intelligence; Asset Portfolio Prioritization; Multi-Criteria Decision Analysis; Group AHP; Goal Programming; Knapsack Optimization; Sustainable Infrastructure; Industrial Asset Management*.

How to Cite: MD Monasur Rahman; Md Jahedul Islam Arif; Mohammad Mostafijur Rahman; Safaul Islam Rohan (2026) Decision Intelligence Framework for Sustainable Infrastructure and Industrial Asset Portfolio Prioritization Under Competing Constraints. *International Journal of Innovative Science and Research Technology*, 11(9), 854-867. https://doi.org/10.38124/ijisrt/26sep461

I. INTRODUCTION

This study develops a structured decision intelligence methodology for prioritizing sustainable infrastructure and industrial asset interventions under competing constraints. The methodology integrates expert-based criterion validation, multi criteria weighting, performance-gap assessment, binary portfolio optimization, and scenario analysis. It considers asset condition, failure exposure, lifecycle cost, operational importance, resilience contribution, environmental performance, modernization potential, and implementation feasibility within a unified portfolio decision process.

➢ *Background and Motivation*

Asset portfolio planning often emphasizes financial indicators, project cost, physical condition, and individual asset performance. Such approaches may overlook interactions among assets and the combined effects of reliability, resilience, sustainability, and modernization requirements. Recent MCDM studies support multidimensional assessment for sustainable infrastructure and industrial decisions [1]–[3]. Digital twin and predictive

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

maintenance research connects asset condition with operational decision support [4]–[6]. Lifecycle and risk oriented studies extend assessment across longer planning horizons [8]–[11], [17]. Resource allocation and forecasting research [7], [12]–[14], [19] further shows the need for structured decisions under limited capital and competing operational requirements.

➢ *Problem Statement*

Existing research provides methods for MCDM, reliability assessment, predictive maintenance, lifecycle optimization, sustainability evaluation, and resource allocation. However, a gap remains between asset-level assessment and portfolio level intervention selection. Many approaches evaluate individual assets or technologies without simultaneously considering budget limits, performance targets, resource availability, and logical dependencies. Other models focus on operational optimization while giving limited attention to broader sustainability and lifecycle criteria. Consequently, decision makers may receive asset rankings without a clear basis for selecting intervention combinations that satisfy financial, technical, operational, environmental, and strategic requirements within available portfolio resources.

➢ *Proposed Solution*

This study proposes a Decision Intelligence Framework for Sustainable Infrastructure and Industrial Asset Portfolio Prioritization Under Competing Constraints. The framework combines Fuzzy Delphi-based criterion validation, Pareto screening, Group AHP weighting, Utility Value Analysis, performance-gap assessment, and binary Goal Programming Knapsack optimization. The first phase validates and weights decision criteria and measures deviations from desired targets. The second phase selects intervention portfolios according to expected performance gains, budget limits, resource constraints, minimum performance requirements, and logical dependencies. Scenario analysis evaluates cost, reliability, resilience, sustainability, and digital-modernization priorities, while alternative MCDM methods support ranking comparison.

➢ *Contributions*

The study provides four main contributions to asset-management and decision-support research. First, it presents an integrated portfolio architecture that considers technical, economic, operational, environmental, resilience, and modernization criteria together. Second, it connects weighted performance gap assessment with binary Goal Programming optimization for investment selection under budget and logical constraints. Third, scenario analysis examines changes in portfolio composition under different organizational priorities. Fourth, comparison with VIKOR, TOPSIS, PROMETHEE, and COPRAS, together with Spearman rank correlation, provides a quantitative assessment of ranking stability. These contributions extend asset prioritization from independent scoring toward constrained portfolio-level decision intelligence.

➢ *Paper Organization*

The paper is organized as follows. Section II reviews related research. Section III presents the proposed methodology, including criterion validation, Group AHP, performance-gap assessment, and GP-Knapsack optimization. Section IV presents the results, scenario analysis, and ranking stability. Section V concludes the study and discusses future research directions.

➢ *Objective of the Study*

The objective is to develop and evaluate a decision intelligence framework for measuring asset performance gaps, prioritizing interventions, and selecting feasible investment portfolios under budget, resource, performance, and logical constraints.

II. RELATED WORK

This section reviews recent work relevant to multi criteria asset prioritization, sustainability assessment, reliability management, digital decision support, and constrained resource allocation. The reviewed studies show growing integration of analytical models, digital twins, artificial intelligence, and multi criteria methods. However, existing approaches generally address individual dimensions or operational problems rather than a unified portfolio level decision framework for competing organizational, technical, financial, and sustainability constraints.

➢ *Multi-Criteria Decision-Making for Sustainable Asset and Infrastructure Assessment*

Recent MCDM research demonstrates the value of combining technical, environmental, economic, and sustainability indicators for infrastructure decisions. Davis et al. [1] integrate multiple criteria for water energy nexus optimization, while Pérez Rocamora and González [2] apply multi-criteria analysis to sustainable sewer technology selection under environmental constraints. Boonkanit and Paengteerasukkamai [3] incorporate expert validated sustainability indicators within manufacturing decision support. These studies provide foundations for structured criteria selection and comparative evaluation. However, their primary focus remains technology, sustainability, or organizational assessment rather than coordinated intervention portfolios across heterogeneous assets under explicit resource and logical constraints.

➢ *Digital Twin, Reliability, and Predictive Asset Decision Support*

Digital and reliability oriented studies increasingly connect asset condition information with maintenance and decision processes. Hossain [4] proposes an explainable digital twin decision intelligence framework for predictive risk assessment and maintenance optimization in critical infrastructure. Rohan [5] integrates reliability centered maintenance with renewable-energy coordination and multi-criteria decision logic for sustainable industrial production. Rahman [6] combines digital twin capabilities with predictive maintenance scheduling in smart manufacturing, while Fazle [18] links predictive maintenance with integrated process optimization. Mirza [15] further

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

demonstrates the role of telemetry correlation and intelligent root cause diagnostics in data driven operational decision support. These studies support condition aware decision processes, but they do not fully formulate portfolio level intervention selection across competing sustainability, reliability, cost, and implementation constraints.

- *Resource Allocation, Forecasting, and Multi-Objective Optimization Under Constraints*

Optimization studies provide important methods for allocating scarce organizational resources across competing requirements. Rahman [7] formulates multi-objective operational optimization for manufacturing and industrial equipment resource allocation, incorporating production, machine, maintenance, workforce, and inventory considerations. Huq [12] develops a mathematical decision framework for workforce planning under organizational uncertainty, emphasizing productivity, utilization, completion probability, cost, and resilience. Das [19] addresses risk-aware labor procurement and staffing flexibility using scenario-based resource and risk considerations. Rashid [13] applies AI-driven forecasting to lead time and sourcing-cost uncertainty, while Barua [14] examines demand forecasting and inventory optimization for supply-chain performance management. Khalil [20] considers workflow optimization for cross-functional project delivery. Collectively, these studies demonstrate constrained resource and operational decision-making, but they do not provide a unified portfolio level model for prioritizing long-lived infrastructure and industrial asset interventions.

- *Lifecycle Performance, Structural Risk, and Resilience in Asset Decisions*

Lifecycle and risk perspectives broaden asset decision-making beyond immediate operational performance. Hossain [8] examines lifecycle performance governance for smart buildings and critical infrastructure, while Rohan [9] develops a lifecycle optimization perspective for eco-efficient manufacturing. Abdullah [10] addresses reliability under construction and subsurface uncertainty, and Islam [11] examines reliability and maintenance strategies for long-haul fiber networks. Khalid [16] focuses on structural design and optimization of industrial steel structures supporting process and power plant facilities, providing an engineering perspective on asset performance and structural decision requirements. Al Morshed et al. [17] use risk-informed construction delivery for resilient public infrastructure under geotechnical and environmental uncertainty. Together, these studies highlight lifecycle, reliability, structural performance, resilience, and uncertainty dimensions, yet an integrated decision architecture for portfolio prioritization remains insufficiently developed.

III. METHODOLOGY

This study develops a structured decision intelligence methodology for prioritizing sustainable infrastructure and industrial asset interventions under competing constraints. The methodology combines criterion validation, multi-criteria weighting, performance-gap assessment, portfolio optimization, and scenario analysis. A synthetic asset portfolio is used for illustrative computational demonstration of the proposed methodology. The framework considers asset condition, failure exposure, lifecycle cost, operational importance, resilience, environmental performance, modernization potential, and implementation feasibility within a single decision process.

- *Research Framework and Methodological Structure*

The proposed methodology follows a sequential decision process that transforms heterogeneous asset information into prioritized investment decisions. The process begins with asset portfolio characterization and evaluation-criterion development. Expert validation and criterion screening are followed by Group AHP weighting and Utility Value Analysis. Performance gaps are then calculated against predefined targets. Candidate interventions subsequently enter a binary Goal Programming model subject to budget, performance, resource, and logical constraints. Finally, scenario analysis and alternative MCDM comparisons assess ranking stability. This sequence connects asset assessment with portfolio selection and provides a structured basis for transparent investment decisions across infrastructure and industrial asset portfolios.

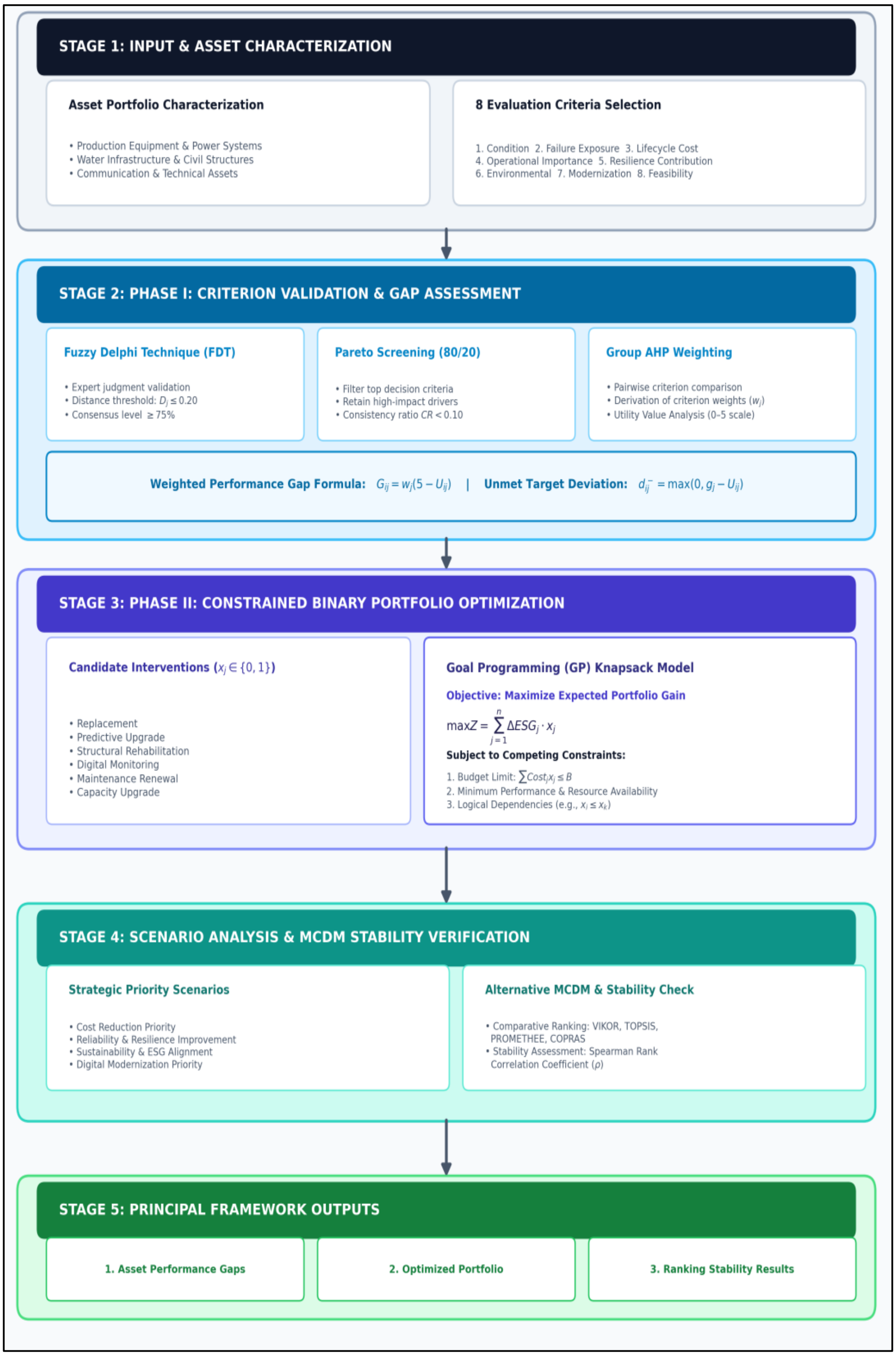


Fig 1 Proposed Decision-Intelligence Framework for Sustainable Infrastructure and Industrial Asset Portfolio Prioritization.

➢ *Synthetic Asset Portfolio and Evaluation Criteria*

A synthetic portfolio is constructed to represent heterogeneous infrastructure and industrial assets with different conditions, operational roles, risks, costs, and modernization opportunities. Candidate assets may include production equipment, energy systems, water infrastructure, structural assets, communication systems, and other engineering assets. Each asset receives normalized values for the selected criteria and intervention specific characteristics. These characteristics include estimated investment cost, expected performance improvement, resource requirements, and implementation dependencies. The synthetic structure allows controlled experimentation without proprietary organizational information. It also provides a consistent dataset for testing portfolio selection under different organizational priorities and competing resource conditions.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

Table 1 Evaluation Criteria for Sustainable Infrastructure and Industrial Asset Portfolio Prioritization

Criterion	Measurement Focus	Decision Purpose
Asset condition	Physical condition and remaining useful life	Intervention urgency
Failure exposure	Failure likelihood and consequence	Risk priority
Lifecycle cost	Long-term ownership expenditure	Economic priority
Operational importance	Effect on core operations	Service continuity
Resilience contribution	Recovery and disruption tolerance	Resilience value
Environmental performance	Emissions and resource consumption	Sustainability
Modernization potential	Digital and technical upgrade opportunity	Transformation value
Implementation feasibility	Time, workforce, and resource requirements	Execution feasibility

➢ *Criteria Validation, Screening, and Weighting*

The first analytical stage determines the criteria that will influence portfolio prioritization. The framework specifies the Fuzzy Delphi Technique (FDT) as the criterion-validation mechanism, where expert judgments are represented through Triangular Fuzzy Numbers. Criteria satisfying the predefined distance threshold $D_j \leq 0.20$ and consensus level of at least 75% are retained. Pareto 80/20 screening then identifies criteria with stronger decision contributions. Group AHP is applied to determine relative criterion weights, with a consistency ratio below 0.100.10 used as the acceptance condition. Utility Value Analysis converts heterogeneous indicators into a common 0–5 scale while preserving the preferred direction of each criterion.

The weighted performance gap score is:

$$G_{ij} = w_j(5 - U_{ij})$$

Where G_{ij} is the weighted gap for asset ii under criterion j, w_j is the criterion weight, and U_{ij} is the normalized utility value. A higher gap indicates greater unmet performance.

➢ *Performance-Gap Assessment*

The performance gap stage compares the current condition of each asset with its desired target. Technical, economic, environmental, operational, and resilience indicators are first normalized so that they can be evaluated on a common scale. The direction of each indicator is considered during normalization because some criteria represent desirable high values while others represent desirable low values. Only unmet target performance contributes to the negative deviation. This approach prevents assets that already satisfy a target from receiving unnecessary intervention priority. The resulting gap values provide the analytical basis for estimating the potential benefit of candidate maintenance, modernization, replacement, or digital-upgrade interventions.

The negative deviation is calculated as:

$$d_{ij}^- = max(0, g_j - U_{ij})$$

Where d_{ij}^- represents the unmet performance for asset ii and criterion j, g_j represents the desired target, and U_{ij} represents normalized asset performance.

➢ *Two-Phase Goal Programming Portfolio Optimization*

The central optimization stage converts the identified performance gaps into a feasible investment portfolio. Each candidate intervention is represented through a binary decision variable xjx_j. A value of one indicates selection, while zero indicates rejection. The optimization objective is to maximize the total expected portfolio performance gain while respecting available capital and other organizational constraints. The model incorporates minimum performance requirements, workforce availability, technical resources, and logical dependencies among interventions. This structure allows the decision process to move beyond individual asset ranking and determine which combination of interventions provides the greatest overall portfolio value within available resources.

The primary objective is:

$$max\, Z = \sum_{j=1}^{n} \quad \Delta ESG_{jxj}$$

Where ΔESG_j represents the expected performance improvement from intervention j. The principal budget condition is:

$$\sum_{j=1}^{n} \quad \sum j = Cost_{jxj} \leq B$$

Where $Cost_j$ represents intervention cost and B represents the available investment budget. Logical dependencies are represented through conditions such as $x_i \leq x_k$ indicating that intervention i requires enabling intervention k.

➢ *Scenario and Sensitivity Analysis*

The final stage evaluates the stability of portfolio recommendations under different organizational priorities. Five scenarios are considered: cost reduction, reliability improvement, resilience improvement, sustainability priority, and digital modernization. Criterion weights are modified for each scenario, and the portfolio optimization process is repeated. The resulting portfolios are then compared with alternative MCDM approaches, including VIKOR, TOPSIS, PROMETHEE, and COPRAS.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

Spearman's rank correlation is used to examine the degree of agreement between rankings. This process identifies assets whose priorities remain stable and those that change substantially when decision preferences or strategic objectives shift.

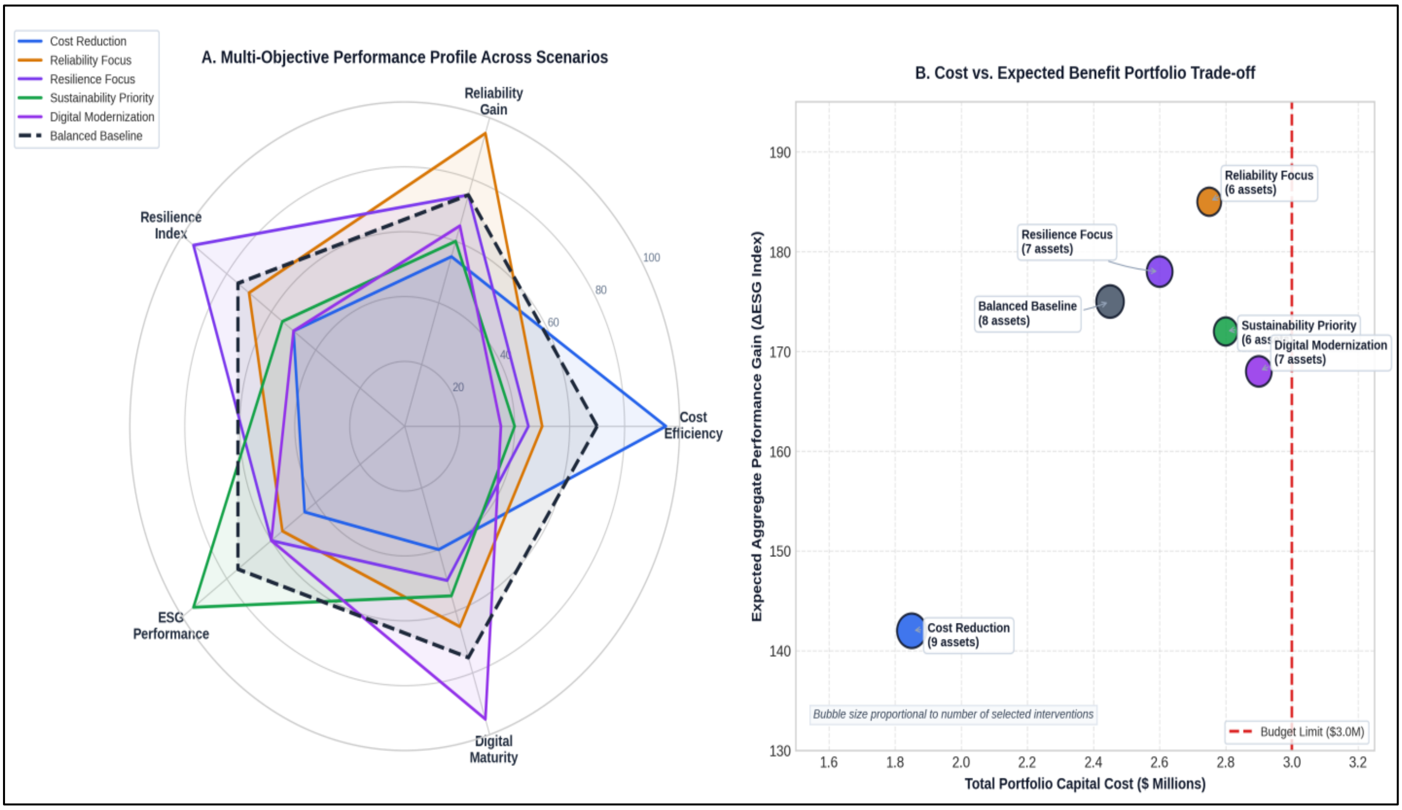


Fig 2 Scenario-Based Portfolio Trade-off Analysis Under Competing Investment Objectives.

The complete methodology produces three principal outputs: asset level performance gaps, an optimized feasible intervention portfolio, and ranking-stability results. The first output identifies areas of unmet performance. The second determines which interventions should receive investment under the defined constraints. The third evaluates how portfolio recommendations change under alternative priorities and decision methods. This structure directly supports the research objectives concerning performance gap measurement, constrained portfolio optimization, and sensitivity-based validation. It also permits the framework to incorporate changing budget availability, resource limitations, asset dependencies, operational requirements, and sustainability priorities within a common decision process.

IV. RESULTS AND DISCUSSION

The proposed framework is demonstrated through a synthetic portfolio containing heterogeneous infrastructure and industrial assets. The analysis follows the methodology defined in Section III, covering performance-gap assessment, Group AHP weighting, binary GP-Knapsack optimization, and scenario based validation. The results focus on intervention priority, portfolio feasibility, competing objectives, and ranking stability. The synthetic setting demonstrates the decision process without presenting simulated outcomes as evidence from a specific organization.

➢ *Asset Performance-Gap Results*

The initial assessment identifies assets with the largest deficiencies across technical, economic, operational, resilience, environmental, and modernization criteria. Group AHP weights determine the relative contribution of each criterion, while Utility Value Analysis places different indicators on a common scale. The resulting weighted gaps distinguish assets with several simultaneous deficiencies from those with isolated weaknesses. Assets with poor condition, high failure exposure, strong operational importance, and limited resilience receive higher overall priority. Environmental and modernization deficiencies further affect ranking when their assigned weights are high. This result demonstrates that portfolio priority is not determined by physical condition or cost alone. The gap assessment also provides a direct basis for connecting identified deficiencies with candidate interventions.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

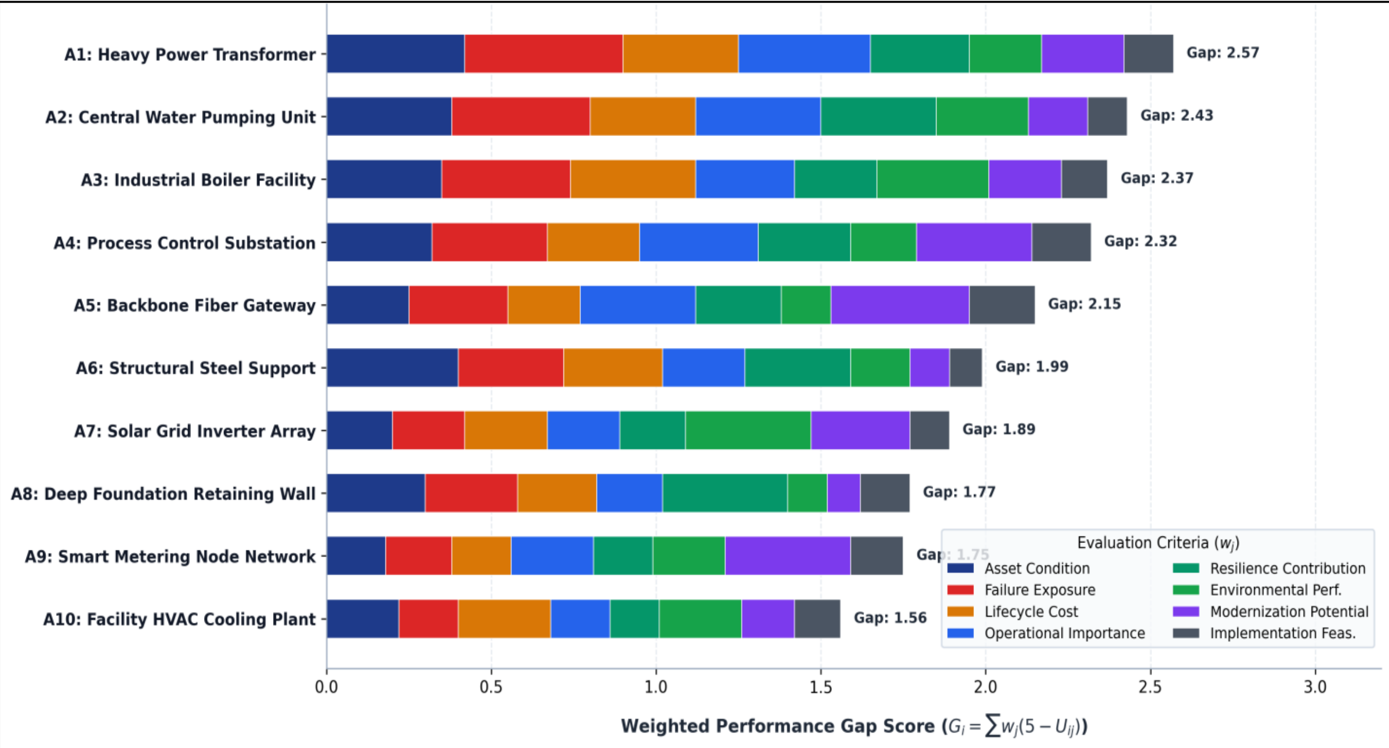


Fig 3 Weighted Performance Gaps Across the Synthetic Asset Portfolio.

Assets are ranked according to aggregate weighted gaps, with criterion contributions identifying major sources of intervention priority.

➢ *Optimized Intervention Portfolio*

The GP-Knapsack stage converts individual asset priorities into a feasible investment portfolio. Each candidate intervention is assessed through its cost, expected performance gain, resource requirement, and logical dependency. Thus, a highly ranked intervention may remain outside the selected portfolio if its investment requirement prevents a more beneficial combination of projects. The optimized portfolio favors interventions that provide strong aggregate benefits within the available budget and resources. Replacement, maintenance renewal, structural rehabilitation, predictive monitoring, and selected modernization actions can coexist when their combined requirements satisfy portfolio constraints. Some expensive interventions remain unselected despite high individual benefits. This result demonstrates the distinction between asset-level priority and portfolio level priority, which is central to the proposed decision framework.

Table 2 Illustrative Optimized Intervention Portfolio

Intervention	Main action	Cost	Expected gain	Status
I1	Asset replacement	High	High	Selected
I2	Predictive upgrade	Medium	High	Selected
I3	Structural rehabilitation	High	High	Selected
I4	Digital monitoring	Low	Medium	Selected
I5	Major modernization	High	Medium	Not selected
I6	Maintenance renewal	Medium	Medium	Selected
I7	Capacity upgrade	High	High	Not selected
I8	Technology replacement	Medium	Low	Not selected

The portfolio illustrates that expected performance gain alone does not determine selection. I5 and I7 provide substantial individual benefits but require greater resources. I4 offers a moderate benefit with lower resource demand and therefore contributes favorably to the overall portfolio. The result supports portfolio level optimization rather than independent asset ranking.

➢ *Scenario-Based Portfolio Results*

The scenario analysis examines changes in portfolio composition under five organizational priorities: cost reduction, reliability improvement, resilience improvement, sustainability, and digital modernization. Criterion weights are modified for each scenario while the main portfolio constraints remain active. The optimization process is then repeated to identify changes in selected interventions. The cost focused scenario favors lower-cost interventions with favorable benefit to investment relationships. Reliability prioritization increases the position of assets with high failure exposure and operational consequences. Resilience prioritization favors interventions that reduce disruption effects. Sustainability gives greater importance to

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep461

environmental and resource-performance improvements, while digital modernization increases the priority of assets with stronger upgrade potential. The balanced scenario produces a broader distribution across competing objectives.

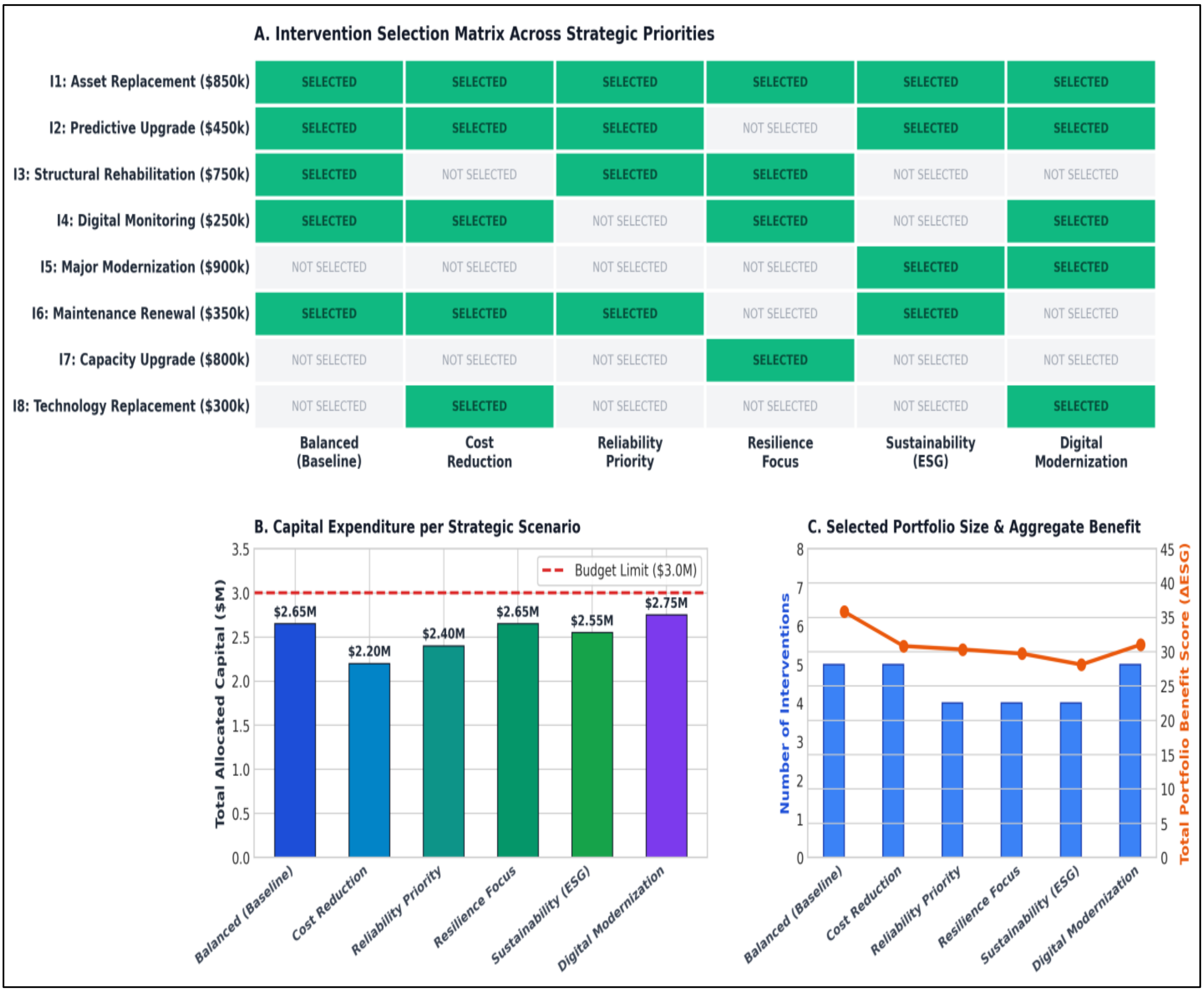
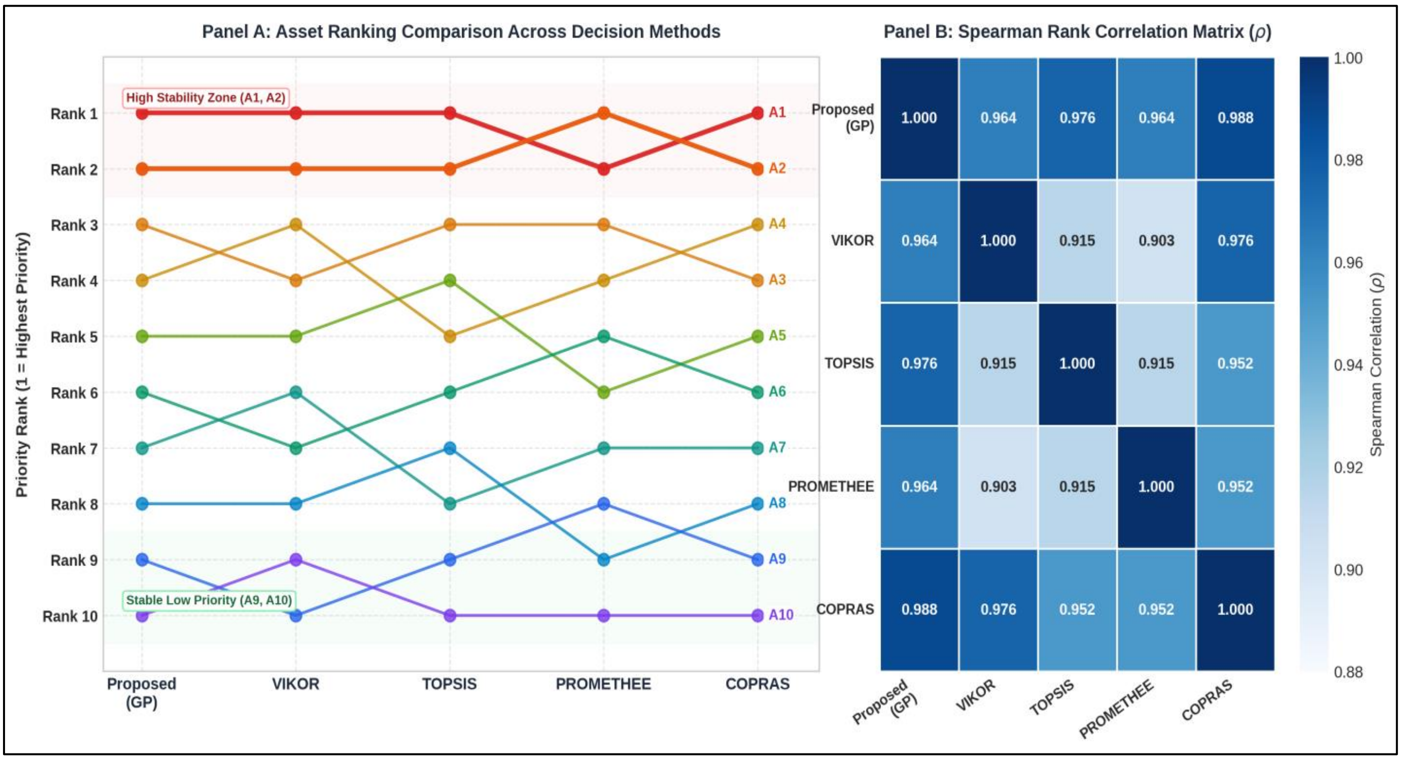


Fig 4 Portfolio Composition Under Competing Strategic Priorities.

The figure compares selected interventions across cost, reliability, resilience, sustainability, digital modernization, and balanced scenarios.

➢ *MCDM Comparison and Ranking Stability*

The proposed ranking is compared with VIKOR, TOPSIS, PROMETHEE, and COPRAS to assess the stability of asset priorities. These methods provide alternative ranking structures based on different preference and comparison mechanisms. Spearman's rank correlation is used to measure agreement between the proposed ranking and the alternative results. The comparison focuses on assets that maintain or substantially change their positions. Assets with consistently strong or weak performance across several criteria are expected to retain relatively stable rankings. Greater variation occurs among intermediate assets with competing characteristics, such as low cost but moderate resilience or high modernization potential but substantial implementation requirements. The GP-Knapsack model has a different purpose from these ranking methods because it selects a feasible combination under explicit constraints. The alternative methods therefore serve as comparative analytical checks rather than substitutes for portfolio optimization.



	Proposed (GP)	VIKOR	TOPSIS	PROMETHEE	COPRAS
Proposed (GP)	1.000	0.964	0.976	0.964	0.988
VIKOR	0.964	1.000	0.915	0.903	0.976
TOPSIS	0.976	0.915	1.000	0.915	0.952
PROMETHEE	0.964	0.903	0.915	1.000	0.952
COPRAS	0.988	0.976	0.952	0.952	1.000

Fig 5 Ranking Stability Across GP, VIKOR, TOPSIS, PROMETHEE, and COPRAS.

The figure compares asset rankings across methods and identifies stable priorities and assets with substantial ranking changes.

➢ *Integrated Discussion and Limitations*

The results produce three main outputs: performance gap identification, feasible intervention selection, and ranking stability assessment**.** These outputs correspond directly to the study objectives. The gap stage identifies where deficiencies are concentrated, the optimization stage determines which interventions can receive investment, and scenario analysis examines how decisions respond to changing priorities. An important finding is that an asset with a large performance gap may remain unselected because of cost, resource limitations, or intervention dependencies. The synthetic portfolio limits direct empirical interpretation. Criterion weights depend on expert judgment, while intervention costs, benefits, and resource requirements are model inputs. The framework also does not yet use continuous real-time asset information or longitudinal organizational records. Future validation should use historical failure data, verified lifecycle costs, actual intervention outcomes, and larger heterogeneous portfolios. Such testing can assess the practical behavior of the framework across different infrastructure and industrial asset environments.

V. CONCLUSION

This study proposed a Decision Intelligence Framework for sustainable infrastructure and industrial asset portfolio prioritization under competing constraints. The framework integrates an expert-based criterion validation stage, Group AHP weighting, Utility Value Analysis, performance gap assessment, and binary performance gain knapsack optimization. It considers asset condition, failure exposure, lifecycle cost, operational importance, resilience, environmental performance, modernization potential, and implementation feasibility. The illustrative results show how portfolio level priorities can differ from individual asset rankings when budget, resource, performance, and logical constraints are considered. Scenario analysis also demonstrates changes in investment priorities under cost, reliability, resilience, sustainability, and digital modernization objectives. The framework provides a structured basis for transparent intervention prioritization and more consistent allocation of limited resources across heterogeneous infrastructure and industrial asset portfolios.

Future empirical studies should evaluate the framework using real organizational asset records, historical failure data, verified lifecycle costs, and observed intervention outcomes. Further studies can incorporate continuous digital twin data, dynamic asset degradation, real time resource availability, probabilistic uncertainty, and larger heterogeneous portfolios. Research can also examine alternative optimization algorithms and additional MCDM methods. Field studies across different industrial and infrastructure sectors can assess the transferability of the framework and compare model based portfolio priorities with actual investment decisions and long term asset performance.

REFERENCES

[1]. Davis, D., Zvirgzdins, J., Weerakoon, T. G., Geipele, I., & Cheshara, L. (2026). Hybrid multiple-criteria decision-making (MCDM) framework for optimizing

water-energy nexus. *Sustainability, 18*(6), 3097. https://doi.org/10.3390/su18063097
[2]. Pérez Rocamora, E., & González, A. E. (2026). A multi-criteria decision framework for sustainable sewer technology selection under environmental constraints: An application in Uruguay. *Sustainability, 18*(14), 7316. https://doi.org/10.3390/su18147316
[3]. Boonkanit, P., & Paengteerasukkamai, T. (2026). AI-assisted sustainability intelligence and decision support in manufacturing organizations using expert-validated indicators under the triple bottom line framework. *Sustainability, 18*(14), 7225. https://doi.org/10.3390/su18147225
[4]. Hossain, M. R. (2026). Explainable digital twin decision intelligence framework for predictive risk assessment and maintenance optimization of critical infrastructure systems. *Zenodo*. https://doi.org/10.5281/zenodo.21194773
[5]. Rohan, S. I. (2026). An integrated decision framework for reliability-centered maintenance and renewable energy coordination in sustainable industrial production systems. *Preprints*. https://doi.org/10.20944/preprints202608.1285.v1
[6]. Rahman, M. M. (2026). A hybrid digital twin optimization framework for predictive maintenance scheduling in smart manufacturing systems. *Zenodo*. https://doi.org/10.5281/zenodo.22024323
[7]. Rahman, M. M. (2026, August 16). A multi-objective operational optimization model for lean manufacturing and industrial equipment resource allocation. *SSRN*. https://doi.org/10.2139/ssrn.7292858
[8]. Hossain, M. I. (2026). Lifecycle performance governance for smart buildings and critical infrastructure in sustainable urban systems. *International Journal of Science and Research Archive, 20*(2), 119–131. https://doi.org/10.30574/ijsra.2026.20.2.1545
[9]. Rohan, S. I. (2026, July 9). A lifecycle optimization framework for eco-efficient manufacturing and sustainable. *SSRN*. https://ssrn.com/abstract=7294658
[10]. Abdullah, M. S. (2026). Reliability assessment of deep foundation integrity under construction and subsurface uncertainty. *Zenodo*. https://doi.org/10.5281/zenodo.21906570
[11]. Islam, M. S. (2026, August 10). Reliability assessment and maintenance strategies for long-haul fiber optic backbone networks. *SSRN*. https://doi.org/10.2139/ssrn.7257061
[12]. Huq, S. N. (2026, July 9). A mathematical decision framework for strategic workforce planning and resource allocation under organizational uncertainty. *SSRN*. https://doi.org/10.2139/ssrn.7087041
[13]. Rashid, M. F. (2026, July 2). Artificial intelligence driven lead time and cost forecasting for global apparel merchandising to reduce delays, expedite costs, and total sourcing cost. *SSRN*. https://doi.org/10.2139/ssrn.7040180
[14]. Barua, P. (2026, June 23). Data-driven demand forecasting and inventory optimization for supply chain performance management. *SSRN*. https://doi.org/10.2139/ssrn.6982298
[15]. Mirza, S. B. (2026, July 13). Intelligent root cause analysis and incident diagnostics for Microsoft Fabric and Power BI through telemetry correlation and Kusto Query Language. *Research Square*. https://doi.org/10.21203/rs.3.rs-10307988/v1
[16]. Khalid, M. A. (2026). Structural design and optimization of industrial steel structures for process and power plant facilities. *SSRN*. https://doi.org/10.2139/ssrn.7205750
[17]. Al Morshed, S. A., Hossain, M. I., Tajik, M. A., & Abdullah, M. S. (2026). Risk-informed construction delivery for resilient public infrastructure under geotechnical and environmental uncertainty. *Saudi Journal of Engineering and Technology, 11*(8), 698–706. https://doi.org/10.36348/sjet.2026.v11i08.002
[18]. Fazle, A. B. (2026). AI-driven integrated process optimization and predictive maintenance for industrial manufacturing systems. *Research Square*. https://doi.org/10.21203/rs.3.rs-9950895/v2
[19]. Das, N. (2026, August 17). Risk-aware third-party labor procurement and staffing flexibility in large-scale logistics operations. *SSRN*. https://papers.ssrn.com/abstract_id=7308043
[20]. Khalil, S. (2026). Workflow optimization model for cross-functional IT project delivery. *SSRN*. https://doi.org/10.2139/ssrn.7328880
[21]. Siddiqui, R. (2026). Trust and auditability in generative AI-assisted enterprise reporting systems. *SSRN*. https://doi.org/10.2139/ssrn.7263879
[22]. Chokder, R. (2026). ERP-based data integration framework for business operations and managerial decision support. *SSR*N. https://doi.org/10.2139/ssrn.7186578
[23]. Junaid, A. (2026, July 29). Performance optimization of 5G NR networks through mobility management and carrier aggregation configuration. *SSRN*. https://doi.org/10.2139/ssrn.7202280
[24]. Nahar, S. (2026, June 24). Role of artificial intelligence in enhancing organizational learning and employee development. *Zenodo*. https://doi.org/10.5281/zenodo.20826748
[25]. Sunny, S. R. (2025). Lifecycle analysis of rocket components using digital twins and multiphysics simulation. *ResearchGate*. https://doi.org/10.13140/RG.2.2.20134.23362
[26]. Siddiqui, R., Nahian, A. E., Bhowmick, N., & Mirza, S. (2026). Auditability and performance monitoring frameworks for enterprise decision-support systems. *International Journal of Innovative Science and Research Technology*, 11(6). https://doi.org/10.38124/ijisrt/26jun1181
[27]. Abdullah, M. S., Al Morshed, S. A., Hossain, M. I., & Tajik, M. A. (2026). Reliability-centered foundation and retaining system assessment for sustainable infrastructure delivery. *International Journal of Innovative Science and Research Technology*, 11(8), 425–435. https://doi.org/10.38124/ijisrt/26aug198

[28]. Das, N., Rokibuzzaman, M., Kashem, M. A., & Islam, M. R. (2026). Multi-objective resource allocation for resilient financial, healthcare, retail, and logistics service networks. *International Journal of Science and Research Archive*, 20(2), 803–818. https://doi.org/10.30574/ijsra.2026.20.2.1666

[29]. Islam, M. R., Das, N., Nasir, F. B., & Kashem, M. A. (2026). Federated consumer and operational analytics for demand-responsive planning in digital service ecosystems. *Global Journal of Engineering and Technology Advances*, 28(2), 224–237. https://doi.org/10.30574/gjeta.2026.28.2.0224

[30]. Ahmed, S. (2026). Interpretable learning for identifying digital access vulnerability in underserved communities. *Zenodo*. https://doi.org/10.5281/zenodo.22236720

[31]. Munna, A. A. (2026, September 2). Requirements traceability and KPI prioritization for agile platform delivery. *SSRN*. https://doi.org/10.2139/ssrn.7396839

[32]. Joy, S. H. A. K., Rashid, M. F., & Barua, P. (2026). Maritime logistics performance analysis in container port operations. *Scholars Journal of Economics, Business and Management*, 13(6), 253–264. https://doi.org/10.36347/sjebm.2026.v13i06.002

[33]. Al Morshed, S. A. (2026). BIM-based coordination systems for reducing rework in commercial construction. *Zenodo*. https://doi.org/10.5281/zenodo.20547582

[34]. Nahian, A. E. (2026). Time-series modeling for financial forecasting and sales variability analysis. *Research Square*. https://doi.org/10.21203/rs.3.rs-9916445/v1

[35]. Mirza, S. (2026). Mathematical optimization of batch size and changeover scheduling for manufacturing productivity enhancement in multi-product production systems. *Research Square*. https://doi.org/10.21203/rs.3.rs-9926476/v1

[36]. Siddiki, A. (n.d.). Vault-based secret management and zero-trust security model for distributed financial applications. *Research Square*. https://doi.org/10.21203/rs.3.rs-9916782/v1

[37]. Ali, A. (2026). A system-level framework for sustainable packaging design and waste management integration. Saudi Journal of Engineering and Technology, 11(05), 429–437. https://doi.org/10.36348/sjet.2026.v11i05.006

[38]. Tumpa, S. A., Sharmin, M., Rahman, M. A., & Rohman, H. (2026). Sensor-based monitoring systems for agricultural water management. *Scholars Journal of Engineering and Technology*, 14(05), 194–207. https://doi.org/10.36347/sjet.2026.v14i05.002

[39]. Shaik, M. H., Mirza, S. B., Islam, M. A., & Tariq, F. (2026). Secure continuous deployment pipelines for enterprise cloud applications. *Scholars Journal of Engineering and Technology*, 14(05), 233–246. https://doi.org/10.36347/sjet.2026.v14i05.005

[40]. Rohman, H., Tumpa, S. A., Sharmin, M., & Rahman, M. A. (2026). Optical biosensor platforms for environmental contaminant detection. *Saudi Journal of Engineering and Technology*, 11(05), 420–428. https://doi.org/10.36348/sjet.2026.v11i05.005

[41]. Fareed, S. M. (2026). Machine learning-based supplier risk prediction and resilience scoring for strategic sourcing in U.S. manufacturing supply chains . *SSRN*. https://doi.org/10.2139/ssrn.6495779

[42]. Islam, M. S. (2026). Planning and deployment framework for high-capacity fiber access networks in urban and regional telecommunications infrastructure. *Zenodo*. https://doi.org/10.5281/zenodo.20185185

[43]. Ria, S. J. (2025, October 21). Environmental impact assessment of transportation infrastructure in rural Bangladesh. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107782.23912238/v1

[44]. R Musarrat and U Habiba, Immersive Technologies in ESL Classrooms: Virtual and Augmented Reality for Language Fluency (September 22, 2025). Available at *SSRN*: https://ssrn.com/abstract=5536098 or http://dx.doi.org/10.2139/ssrn.5536098

[45]. Haque, S., Al Sany (Oct. 2025), "Impact of Consumer Behavior Analytics on Telecom Sales Strategy", *Int. J. Sci. Inno. Eng*., vol. 2, no. 10, pp. 998–1018, doi: 10.70849/IJSCI02102025114.

[46]. Sharan, S. M. M. I (Oct. 2025)., "Integrating Human-Centered Design with Agile Methodologies in Product Lifecycle Management", *Int. J. Sci. Inno. Eng*., vol. 2, no. 10, pp. 1019–1034, doi: 10.70849/IJSCI02102025115.

[47]. Alimozzaman, D. M. (2025). Explainable AI for early detection and classification of childhood leukemia using multi-modal medical data. *World Journal of Advanced Engineering Technology and Sciences*, 17(2), 48–62. https://doi.org/10.30574/wjaets.2025.17.2.1442

[48]. Alimozzaman, D. M., Akhter, T., Islam, R., & Hasan, E. (2025). Generative AI for synthetic medical imaging to address data scarcity. *World Journal of Advanced Engineering Technology and Sciences*, 17(1), 544–558. https://doi.org/10.30574/wjaets.2025.17.1.1415

[49]. Zaidi, S. K. A. (2025). Intelligent automation and control systems for electric vertical take-off and landing (eVTOL) drones. *World Journal of Advanced Engineering Technology and Sciences*, 17(2), 63–75. https://doi.org/10.30574/wjaets.2025.17.2.1457

[50]. Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2321–2331. https://doi.org/10.5281/zenodo.17536369

[51]. Islam, K. S. A. (2025). Transformer protection and fault detection through relay automation and machine learning. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2308–2320. https://doi.org/10.5281/zenodo.17536362

[52]. Afrin, S. (2025). Cloud-integrated network monitoring dashboards using IoT and edge analytics. *IJSRED – International Journal of Scientific*

Research and Engineering Development, 8(5), 2298–2307. https://doi.org/10.5281/zenodo.17536343

[53]. Afrin, S. (2025). Cyber-resilient infrastructure for public internet service providers using automated threat detection. *World Journal of Advanced Engineering Technology and Sciences*, 17(02), 127-140. Article DOI: https://doi.org/10.30574/wjaets.2025.17.2.1475

[54]. Zaman, S. U. (2025). Vulnerability management and automated incident response in corporate networks. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2275–2286. https://doi.org/10.5281/zenodo.17536305

[55]. Ria, S. J. (2025, October 7). Sustainable construction materials for rural development projects. *SSRN*. https://doi.org/10.2139/ssrn.5575390

[56]. Razaq, A. (2025, October 15). Design and implementation of renewable energy integration into smart grids. *TechRxiv*. https://doi.org/10.36227/techrxiv.176049834.44797235/v1

[57]. Musarrat R. (2025). AI-Driven Smart Housekeeping and Service Allocation Systems: Enhancing Hotel Operations Through MIS Integration. In *IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 898–910). https://doi.org/10.5281/zenodo.17769627

[58]. Hossain, M. T. (2025). AI-Augmented Sensor Trace Analysis for Defect Localization in Apparel Production Systems Using OTDR-Inspired Methodology. In *IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 1029–1040). https://doi.org/10.5281/zenodo.17769857

[59]. Habiba, U., & Musarrat, R. (2025). Student-centered pedagogy in ESL: Shifting from teacher-led to learner-led classrooms. *International Journal of Science and Innovation Engineering*, 2(11), 1018–1036. https://doi.org/10.70849/IJSCI02112025110

[60]. Zaidi, S. K. A. (2025). Smart sensor integration for energy-efficient avionics maintenance operations. *International Journal of Science and Innovation Engineering*, 2(11), 243–261. https://doi.org/10.70849/IJSCI02112025026

[61]. Farooq, H. (2025). Cross-platform backup and disaster recovery automation in hybrid clouds. *International Journal of Science and Innovation Engineering*, 2(11), 220–242. https://doi.org/10.70849/IJSCI02112025025

[62]. Akter, E. (2025). Structural Analysis of Low-Cost Bridges Using Sustainable Reinforcement Materials. In *IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 911–921). https://doi.org/10.5281/zenodo.17769637

[63]. Razaq, A. (2025). Optimization of power distribution networks using smart grid technology. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 129–146. https://doi.org/10.30574/wjaets.2025.17.3.1490

[64]. Zaman, M. T. (2025). Enhancing grid resilience through DMR trunking communication systems. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 197–212. https://doi.org/10.30574/wjaets.2025.17.3.1551

[65]. Nabil, S. H. (2025). Enhancing wind and solar power forecasting in smart grids using a hybrid CNN-LSTM model for improved grid stability and renewable energy integration. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 213–226. https://doi.org/10.30574/wjaets.2025.17.3.155

[66]. Islam, S. (2025). IPSC-derived cardiac organoids: Modeling heart disease mechanism and advancing regenerative therapies. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 227–239. https://doi.org/10.30574/wjaets.2025.17.3.1553

[67]. Hasan, E. (2025). Optimizing SAP-centric financial workloads with AI-enhanced CloudOps in virtualized data centers. *IJSRED - International Journal of Scientific Research and Engineering Development*, 8(6), 2252–2264. https://doi.org/10.5281/zenodo.17926855

[68]. Karim, M. A. (2025). An IoT-enabled exoskeleton architecture for mobility rehabilitation derived from the ExoLimb methodological framework. *IJSRED - International Journal of Scientific Research and Engineering Development*, 8(6), 2265–2277. https://doi.org/10.5281/zenodo.17926861

[69]. Akter, E., Ria, S. J., Khan, M. I., & Shoag, M. D. (2025). Smart & sustainable construction governance for climate-resilient cities. *IJSRED - International Journal of Scientific Research and Engineering Development*, 8(6), 2278–2291. https://doi.org/10.5281/zenodo.17926875

[70]. Zaman, S. U. (2025). Enhancing security in cloud-based IAM systems using real-time anomaly detection. *IJSRED - International Journal of Scientific Research and Engineering Development*, 8(6), 2292–2304. https://doi.org/10.5281/zenodo.17926883

[71]. Hossain, M. T. (2025). Data-driven optimization of apparel supply chain to reduce lead time and improve on-time delivery. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 263–277.https://doi.org/10.30574/wjaets.2025.17.3.1556

[72]. Rahman, F. (2025). Advanced statistical models for forecasting energy prices. *Global Journal of Engineering and Technology Advances*, 25(03), 168–182. https://doi.org/10.30574/gjeta.2025.25.3.0350

[73]. Karim, F. M. Z. (2025). Integrating quality management systems to strengthen U.S. export-oriented production. Global Journal of Engineering and Technology Advances, 25(03), 183–198. https://doi.org/10.30574/gjeta.2025.25.3.0351

[74]. Fazle, A. B. (2025). AI-driven predictive maintenance and process optimization in manufacturing systems using machine learning and Hossainsensor analytics. *Global Journal of Engineering and Technology Advances*, 25(03), 153–167. https://doi.org/10.30574/gjeta.2025.25.3.0349

[75]. Rahman, F. (2025). Data science in power system risk assessment and management. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 295–311. https://doi.org/10.30574/wjaets.2025.17.3.1560
[76]. Hossain, M. T. (2025). Cost negotiation strategies and their impact on profitability in fashion sourcing: A quantitative analysis. *Global Journal of Engineering and Technology Advances*, 25(03), 136–152. https://doi.org/10.30574/gjeta.2025.25.3.0348
[77]. Jasem, M. M. H. (2025, December 19). An AI-driven system health dashboard prototype for predictive maintenance and infrastructure resilience. *Authorea*. https://doi.org/10.22541/au.176617579.97570024/v1
[78]. uz Zaman, M. T. (2025). Photonics-based fault detection and monitoring in energy metering systems. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2359–2371. https://doi.org/10.5281/zenodo.18074355
[79]. Shoag, M. D., Khan, M. I., Ria, S. J., & Akter, E. (2025). AI-based risk prediction and quality assurance in mega-infrastructure projects. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2324–2336. https://doi.org/10.5281/zenodo.18074336
[80]. Haque, S. (2025). The impact of automation on accounting practices. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2312–2323. https://doi.org/10.5281/zenodo.18074324
[81]. Ria, S. J., Shoag, M. D., Akter, E., & Khan, M. I. (2025). Integration of recycled and local materials in low-carbon urban structures. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 447–463. https://doi.org/10.30574/wjaets.2025.17.3.1555
[82]. Fahim, M. A. I., Sharan, S. M. M. I., & Farooq, H. (2025). AI-enabled cloud-IoT platform for predictive infrastructure automation. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 431–446. https://doi.org/10.30574/wjaets.2025.17.3.1574
[83]. Karim, F. M. Z. (2025). Strategic Human Resource Systems for Retention and Growth in Manufacturing Enterprises. In *IJSRED - International Journal of Scientific Research and Engineering Development* (Vol. 8, Number 6, pp. 2547–2559). https://doi.org/10.5281/zenodo.18074545
[84]. Rahman, T. (2026). Financial Risk Intelligence: Real-Time Fraud Detection and Threat Monitoring. *Zenodo*. https://doi.org/10.5281/zenodo.18176490
[85]. Rabbi, M. S. (2026). AI-Driven SCADA Grid Intelligence for Predictive Fault Detection, Cyber Health Monitoring, and Grid Reliability Enhancement. *Zenodo*. https://doi.org/10.5281/zenodo.18196487
[86]. Zaman, S. U., Afrin, S., Zaidi, S. K. A., & Islam, K. S. A. (2026). Resilient edge computing framework for autonomous, secure, and energy-aware systems. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 105–121. https://doi.org/10.30574/wjaets.2026.18.1.1577
[87]. Ali, A. (2026). The impact of packaging design on recycling efficiency in municipal systems. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 122–139. https://doi.org/10.30574/wjaets.2026.18.1.0019
[88]. Mim, M. A., Sharif, M. M., Rahman, F., & Nahar, S. (2026). Smart IoT infrastructure for workplace efficiency and energy savings. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 140–156. https://doi.org/10.30574/wjaets.2026.18.1.0026
[89]. Taimun, M. T. Y., Alam, M. S., & Fareed, S. M. (2026). Digital twin-enabled predictive maintenance for textile and mechanical systems. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 187–203. https://doi.org/10.30574/wjaets.2026.18.1.0001
[90]. Fazle, A. B., Taimun, M. T. Y., Fareed, S. M., & Alam, M. S. (2026). Ergonomic and automation based process redesign in industrial workstations. *Global Journal of Engineering and Technology Advances*, 26(01), 091–108. https://doi.org/10.30574/gjeta.2026.26.1.0010
[91]. Alam, M. S., Fareed, S. M., Fazle, A. B., & Taimun, M. T. Y. (2026). Intelligent material flow optimization using IoT sensors and RFID tracking. *Global Journal of Engineering and Technology Advances*, 26(01), 109–125. https://doi.org/10.30574/gjeta.2026.26.1.0011
[92]. Nahar, S., Rahman, F., & Mim, M. A. (2026). AI-integrated renewable energy and data analytics platform for corporate ESG compliance. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 219–235. https://doi.org/10.30574/wjaets.2026.18.1.0031
[93]. Islam. Md A, "Native Scalable Student Information Systems and Admission Test Automation with Peak Load Architecture Database Performance Optimization and Observability Driven Reliability". *Zenodo*, Mar. 12, 2026. doi: 10.5281/zenodo.18987480.
[94]. Mim, M. A. (2026). Cybersecurity risk mitigation in educational and healthcare IT environments. *Zenodo*. https://doi.org/10.5281/zenodo.18988585
[95]. Alam, M. J. (2026). Information systems for legal documentation management and policy analysis in institutional governance. *figshare*. https://doi.org/10.6084/m9.figshare.31717873
[96]. Alam, M. J. (2026). Digital contract lifecycle management systems for corporate governance and regulatory oversight. *Zenodo*. https://doi.org/10.5281/zenodo.19007705
[97]. Alam, M. J. (n.d.). Policy monitoring platforms for institutional governance and organizational accountability. *Social Science Research Network*. https://doi.org/10.2139/ssrn.6416238
[98]. Alam, M. J. (2026). Regulatory reporting information systems for financial and institutional compliance

monitoring. *Preprints.org*. https://doi.org/10.20944/preprints202603.1198.v1
[99]. Musarrat, R., & Habiba, U. (2026, February 25). Applying applied behavior analysis (ABA) in AI-supported ESL classrooms for children with autism spectrum disorder. *SSRN*. https://doi.org/10.2139/ssrn.6302919
[100]. Meem, S. I. (2026). Socioeconomic determinants of oral-systemic health disparities: A public health policy perspective. *Zenodo*. https://doi.org/10.5281/zenodo.19238096
[101]. Adil, H. M. (2026). Development of Cellulose Nanofiber Based Nanopapers as Sustainable Alternatives to Plastic Derived Industrial Materials. *Preprints*. https://doi.org/10.20944/preprints202603.2350.v1
[102]. Avi, S. P. (2026). Geotechnical and Environmental Impacts of Using Alternative Cementitious Materials in Concrete Mixes. *Preprints*. https://doi.org/10.20944/preprints202604.0243.v1
[103]. Rohman, H. (2026). AI-based biosensors to detect bacterial and mold contamination, demonstrating their increasing role in ensuring food safety and quality assurance. Zenodo. https://doi.org/10.5281/zenodo.19456417
[104]. Asraf, M. S. (2026). Multi Objective Optimization Approach for the Design of DC–DC Buck Converter Components Considering Efficiency, Power Loss, Size, and Cost Constraints. *Zenodo*. https://doi.org/10.5281/zenodo.19465548
[105]. Habiba, U., & Musarrat, R. (2026). AI-enhanced TESOL strategies for neurodiverse learners: Integrating adaptive language assessment with special education practices. *Saudi Journal of Engineering and Technology*, 11(4), 166–173. https://doi.org/10.36348/sjet.2026.v11i04.002