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RESEARCH ARTICLE

ASSET CRITICALITY RANKING FOR MISSION-CRITICAL AIRPORT INFRASTRUCTURE: A DECISION MODEL FOR PRIORITIZING PLANNED PREVENTIVE MAINTENANCE

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Abstract

Airports operate thousands of maintainable assets, from airfield ground lighting and baggage sortation to chillers, boarding bridges and uninterr uptible power supplies, yet planned preventive maintenance is often scheduled by manufacturer default or habit rather than by the conseque nce of failure. This paper asks how a transparent, repeatable criticality ranking can be built for mission-critical airport infrastructure and how the resulting ranks should govern the content and frequency of preventive work. Using a design-science approach, it draws six design requirements from thirty peer reviewed studies on criticality assessment multi criteria decision making and infrastructure maintenance published from 2020 to 2025, with two recent decision-framework studies serving as anchors. The resulting model scores each asset against six weighted criteria (safety and regulatory consequence, operational consequence, redundancy, likelihood of failure, detectability and maintainability, and cost consequence), aggregates them into a criticality index, applies a safety override, and maps three tiers to differentiated maintenance strategies and review cycles. An illustrative worked example with nine hypothetical asset classes shows how the index separates assets, how the override lifts a life-safety system that would otherwise sit in the middle tier, and how stable the tiers are when weights shift. The examp le uses invented scores and contains no measured or proprietary airport data. Evaluation against the requirements finds supportive evidence for structured weighting and condition informed likelihood, mixed evidenc e for linking criticality to optimised intervals, and limited evidence on airport-specific consequence scales, which defines a clear agenda for empirical validation.

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Introduction:-

An airport is a system in which a few failures can stop the whole operation. A tripped regulator on an airfield lighting circuit at night, a stalled sortation line in the baggage hall or a failed power supply in an operations room can ground flights or strand passengers within minutes, while the failure of a car park luminaire may pass unnoticed for days. Treating these assets as if they deserved the same preventive attention wastes scarce technician hours on low-consequence equipment and leaves high-consequence equipment exposed.

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Critical infrastructure scholarship stresses that technical failures, natural hazards and malicious acts can cascade from one system to the next (De Felice et al., 2022), and recent work that estimates the system-wide effect of airport outages shows that the importance of an airport depends on its ground infrastructure as well as its position in the network (Wandelt et al., 2025).

Facility and maintenance managers have long used criticality analysis to decide where effort should go. In practice the tools are often weak. A multiple case study in manufacturing found that machine criticality assessments were experience-driven, seldom updated and focused on individual machines rather than on the system they served (Gopalakrishnan et al., 2022). In an estate run by a facilities department, a tutorial account of asset criticality and work order prioritisation showed that the relative importance of each site to the mission of the organisation has to be built into the ranking before work can be sorted sensibly (English & Yunusa-Kaltungo, 2022). Airports add complications of their own, including regulated airside systems, round-the-clock operation, diverse stakeholders and a heavy dependence on safety-related equipment (Javaherikhah & Sarvari, 2025).

The pressure is rising. Passenger volumes, longer operating hours and more automated terminals mean that maintenance windows shrink while the number of connected assets grows. Smart airport systems that rely on sensors and networks bring new dependencies, and the more systems interact, the more a single failure can propagate. In such conditions, the planned preventive programme is one of the few levers a maintenance organisation fully controls, and the question of which assets deserve its most rigorous form becomes a strategic one rather than a clerical one.This paper builds on two recent studies that frame the problem as a decision-model design task. Rios et al. (2025) combined reliability-centred maintenance principles, failure mode and effects analysis, fuzzy logic and multi-criteria decision-making to choose which offshore assets to include in a corrosion maintenance portfolio, and their framework selected a far larger share of highly critical assets than current industry practice. Panwar and Kumar (2021) ranked the failure causes of an industrial subunit using a cloud model and an extended outranking method, rating every failure cause on the chance of failure, non-detection, downtime, spare part criticality and safety risk, with weights for several decision makers. Neither study addresses airports, but together they show that criticality can be made explicit, weighted and linked to maintenance choices.

The aim of this study is to design and evaluate a criticality decision model that ranks mission-critical airport assets and uses the ranks to prioritise planned preventive maintenance. Three objectives follow: (O1) to derive design requirements for such a model from recent evidence; (O2) to specify criteria, scales, weighting, aggregation and tier rules that convert criticality into preventive maintenance strategy; and (O3) to demonstrate and evaluate the model through a clearly illustrative scoring example. The corresponding research questions are: RQ1, what must a criticality model for airport infrastructure do to be credible and usable? RQ2, how should criteria be scored, weighted and combined so that the ranking supports preventive maintenance decisions? RQ3, how robust is the resulting tiering, and where is the supporting evidence weakest?Section 2 reviews relevant work, Section 3 explains the design procedure, Section 4 states the requirements, Section 5 presents the model, Section 6 works through the illustrative example, Section 7 evaluates the model and discusses its use, and the final section summarises the answers to the research questions.

Prior Research on Criticality and Prioritisation:-

Criticality assessment in maintenance management:-

Criticality assessment estimates how much a failure would matter and how likely it is. The classic vehicle is failure modes, effects and criticality analysis. Applied to a high-voltage transmission line, it was extended to four severity dimensions, namely efficiency, safety and reliability, environment and finance, with the analytic hierarchy process used to derive an efficiency index (Suwanasri et al., 2021). A methodology for power distribution assets combined functional failure identification under an offshore industry guideline with the analytic hierarchy process so that resources and yearly budgets could be directed to the assets judged most critical (Attanayake et al., 2024). Reviews of distribution system asset management describe the same aim in broader terms, namely to improve reliability and avoid costly outages while controlling maintenance cost (Mirhosseini & Keynia, 2021).

A second strand integrates criticality with established maintenance philosophies. Reliability-centred maintenance and risk-based maintenance are usually applied separately, although they are complementary, and a recent method merges them into a single procedure for maintenance management (da Silva et al., 2023). In healthcare, medical devices have been ranked by criticality for reliability, replacement and maintenance using quality function deployment and fuzzy logic within a multi-criteria model (Amran et al., 2024). These studies agree that criticality should reflect several consequences, not one, and that the method used to combine them must be explicit.

Multi-criteria methods for maintenance prioritization:-

Multi-criteria decision-making offers the machinery for combining unlike consequences. A state-of-the-art review of the transport sector found that such methods complement cost-effectiveness and cost-benefit analysis when projects and policies must be judged against several goals (Yannis et al., 2020). For maintenance strategy selection, a fuzzy model combining DEMATEL, the analytic network process and VIKOR was proposed for safety-critical equipment in sectors including aerospace and energy (Arjomandi et al., 2021). Road and pavement studies use similar tools: one hybrid approach weighted road criteria with the analytic hierarchy process and integrated three outranking variants to prioritise streets for maintenance (Sayadinia & Beheshtinia, 2021), while another combined the hierarchy process with an ideal-solution ranking to choose preventive pavement treatments against service, performance and economic criteria (Liu et al., 2024).

Within facility management, criteria for building maintenance decisions have been identified and ranked as a basis for multi-criteria models, and the same work recorded how condition assessment is currently carried out by practitioners (Besiktepe et al., 2020). Prioritisation is also being moved into maintenance software. One study embedded the analytic hierarchy process in a computerised maintenance management system so that intervention requests are classified automatically rather than by hand, because manual sorting causes delays, extra cost and safety risk (Briki et al., 2025). The common lesson is that weights must be traceable to stakeholder judgement and that the scoring logic should be documented so that it can be audited.

Airport infrastructure and its maintenance:-

Airport maintenance research tends to focus on individual asset classes. Pavement management is the most mature: a condition index for asphalt runways and aprons was proposed to support quality-managed assessment and forecasting (Wesołowski & Iwanowski, 2020), and an airport pavement management system study examined how operating constraints on the airside shape optimal maintenance alternatives, using clustering to define intervention areas (Di Graziano et al., 2024). For electrical systems, the insulation resistance of the navigational lighting system has been described as one of the important indicators of safe operation, and deep learning methods have been proposed to measure it more accurately (Liu et al., 2022). In the baggage hall, technical action research at a major Middle Eastern airport showed that predictive condition-based maintenance improved availability and reliability without heavy capital investment (Koenig et al., 2020).

Studies that rank airport assets across classes are scarce. Strategies for using building information modelling in airport facility management were ranked by experts with reference to the complexity of the infrastructure and the need for safety (Javaherikhah & Sarvari, 2025), but this concerns technology adoption rather than asset criticality. The gap motivates the present study: airport managers need a single, defensible scale on which a lighting regulator, a chiller and a boarding bridge can be compared.

From criticality to planned preventive maintenance:-

Criticality only adds value if it changes what is done and when. In total productive maintenance, planned maintenance is one of eight pillars, and statistical reliability analysis was found to support its performance (Mohad et al., 2025). A predict-then-optimise approach used historical failures and maintenance records to decide when scheduled preventive interventions should be brought forward (van Staden et al., 2022). A review of maintenance optimisation under Industry 4.0 called for methods that do not require a strategy to be chosen in advance and that can handle large, heterogeneous data sets (Pinciroli et al., 2023).

Condition information is the bridge between static criticality and dynamic scheduling. An asset digitalisation framework linked an asset criticality model with an asset health index fed by sensors, using standard asset definitions so that data remain comparable (Candón Fernández et al., 2025). A holistic framework for power generation assets embedded a health index and life cycle cost estimates in renewal and replacement decisions (Ayu & Yunusa-Kaltungo, 2020). At network level, bridge maintenance was prioritised by combining deterioration modelling, life cycle cost and a criticality measure derived from traffic simulation, which lowered cost relative to a reference tool (Hadjidemetriou et al., 2022). For railway stations, a model linked funding to resulting infrastructure quality and compared different prioritisation approaches for maintenance and replacement (Lampe et al., 2023). Resilience offers a further lens: an availability-based resilience index has been used to compare maintenance strategies and redundancy topologies in fleets of critical equipment (Durán et al., 2020).

Method:-

Design-science procedure:-

The research follows design-science logic, in which an artefact is built to solve a class of practical problems and then evaluated against explicit requirements. The artefact here is a decision model, comprising criteria, scales, weights, aggregation rules and decision rules, together with the procedure for applying it. Four activities were carried out: problem explication from the literature, requirement derivation, artefact design, and demonstration with evaluation. The approach suits the problem because the question is not whether criticality matters, which is accepted, but how a usable model should be constructed for a specific class of infrastructure.

Knowledge base:-

The knowledge base comprises thirty journal studies, each published between 2020 and 2025 and each subject to peer review. Candidates were located in November 2026 by querying an open bibliographic index and checked against publisher registration records for identifiers, dates and retraction notices. Search terms combined asset criticality, maintenance prioritisation, multi-criteria decision-making, reliability-centred and risk-based maintenance, asset health, and airport infrastructure. Studies were retained if they proposed or applied a method for ranking assets, failure causes or maintenance actions, or if they described maintenance of airport or comparable infrastructure. The two anchor studies (Panwar & Kumar, 2021; Rios et al., 2025) were selected because they make the link between weighted criticality and maintenance choice most explicit. Each retained study was coded for the criteria used, the weighting method, the aggregation logic, the use of condition data and the type of validation. Coding was iterative: a first pass recorded what each study did, and a second pass grouped recurring features into candidate requirements, which were kept only if at least two studies from different sectors supported them. Airport-specific studies were read separately to judge which general findings transfer to airside and terminal assets and which need adaptation.

Demonstration and evaluation:-

The model is demonstrated with a worked scoring example covering nine asset classes typical of a large passenger airport. All scores and weights in the example are hypothetical values chosen by the author to show how the model behaves; they are not measurements and do not describe any real airport. Evaluation has two parts. First, each model element is rated against the design requirements according to the strength of supporting evidence in the knowledge base, using the categories supportive, mixed and limited. Second, a simple one-at-a-time weight shift is applied to the illustrative scores to examine whether tier membership is stable. No primary or proprietary data were collected or analysed.

Design Requirements:-

Six requirements emerged from the coded studies. R1, multidimensional consequence: criticality must reflect safety, operational and financial consequences rather than a single severity score, as the transmission and medical device studies show (Amran et al., 2024; Suwanasri et al., 2021). R2, mission alignment: the ranking must reflect what the asset contributes to the mission of the facility, which in an airport means flights and passengers, not only the asset's own condition (English & Yunusa-Kaltungo, 2022; Wandelt et al., 2025).

R3, traceable weighting: weights must come from a documented procedure that captures the judgement of several stakeholders and can be revisited (Briki et al., 2025; Panwar & Kumar, 2021). R4, condition-informed likelihood: the likelihood of failure should draw on condition and health data where they exist rather than on age alone (Candón Fernández et al., 2025; Gopalakrishnan et al., 2022). R5, actionable output: the ranking must translate into distinct maintenance strategies, task content and intervals, otherwise it remains a register entry (Rios et al., 2025; van Staden et al., 2022). R6, periodic review: criticality changes as systems, redundancy and operations change, so the model must be re-run on a defined cycle and after significant events (Gopalakrishnan et al., 2022; Pinciroli et al., 2023).

The Airport Asset Criticality Decision Model:-

Structure of the model:-

The model has six stages (Figure 1). Stage one builds the asset hierarchy, grouping individual items into maintainable asset classes and recording the function each class serves, for example airside guidance, passenger processing or environmental control. The second stage defines the criteria and scoring scales, after which criterion weights are derived from a structured stakeholder exercise. Each asset class is then scored, and the scores are aggregated into a criticality index. Decision rules, including a safety override, assign each class to a tier in the fifth stage, and the last stage maps tiers to preventive maintenance strategies and sets the review cycle. Condition data, failure history and changes to the operation feed back into stages four and five, so that the ranking does not freeze.



Figure 1. Six-stage airport asset criticality decision model linking ranking to planned preventive maintenance

Criteria and scoring scales:-

Six criteria are used (Table 1). Safety and regulatory consequence (C1) captures harm to people and breach of aerodrome or life-safety obligations. Operational consequence (C2) captures the effect on flights, passenger processing and airline operations. Redundancy (C3) is scored inversely, so that a single-string system with no standby earns a high score. Likelihood of failure (C4) reflects condition, health index, failure history and operating stress. Detectability and maintainability (C5) captures how hard a developing failure is to detect and how long restoration would take, including access restrictions on the airfield. Cost consequence (C6) covers repair cost and indirect costs such as penalties and compensation.Each criterion is scored on a five-point scale with written anchors, because unanchored scales drift between assessors. The anchors in Table 1 are illustrative and should be calibrated locally, for instance by linking operational scores to the expected number of delayed movements. The criteria deliberately mirror those found in the anchor studies, where downtime, non-detection, spare part criticality and safety risk were scored separately (Panwar & Kumar, 2021), and those in facility management criteria sets (Besiktepe et al., 2020).

Table 1. Criteria, illustrative weights and scale anchors used in the criticality model

Code	Criterion	Weight (illustrative)	Score 1 (low)	Score 5 (high)
C1	Safety and regulatory consequence	0.25	No credible harm or compliance effect	Potential injury, loss of life-safety function or breach of aerodrome obligations
C2	Operational consequence	0.22	No effect on flights or passengers	Movements halted or major passenger processing stopped
C3	Redundancy (scored inversely)	0.15	Full standby or alternative available at once	Single-string system with no workaround
C4	Likelihood of failure	0.18	Good health index, stable history	Poor condition, rising failure rate or high operating stress
C5	Detectability and maintainability	0.10	Failure evident early and quick to restore	Hidden failure, restricted access or long restoration

Code	Criterion	Weight (illustrative)	Score 1 (low)	Score 5 (high)
C6	Cost consequence	0.10	Minor repair cost, no penalties	Major repair or replacement with contractual penalties

Weighting:-
Weights are obtained through pairwise comparison by a panel that should include airside operations, terminal operations, engineering and maintenance, safety and finance. The analytic hierarchy process is the default because it is widely understood and offers a consistency check (Attanayake et al., 2024; Liu et al., 2024). Where panel members are uncertain, fuzzy or cloud-based variants can represent the spread of judgement and weight experts by their agreement with the group (Arjomandi et al., 2021; Panwar & Kumar, 2021). The weights in Table 1 are illustrative and place the greatest emphasis on safety and operational consequence, reflecting the mission of an airport, but a different airport could reasonably weight cost or redundancy more heavily.The weighting exercise should be run as a facilitated workshop rather than a survey, so that panel members can challenge one another's reasoning before judgements are recorded. Pairwise judgements whose consistency ratio exceeds the usual tolerance should be revisited with the respondent. Individual weight sets should be kept alongside the aggregated set, because the spread between departments is itself useful information: a large gap between operations and finance on the weight of cost consequence signals a policy question that the model cannot settle on its own.

Aggregation, tiers and the safety override:-
The criticality index is the weighted sum of the six scores and ranges from 1 to 5. A weighted sum is chosen for transparency; outranking methods offer more nuance where criteria are not fully compensatory (Sayadinia & Beheshtinia, 2021; Yannis et al., 2020), but they are harder to explain to non-specialists. Three tiers are proposed: Tier A for an index of 3.80 or above, Tier B from 2.80 to 3.79, and Tier C below 2.80. These thresholds are illustrative and should be set so that Tier A remains small enough to resource properly.Compensatory aggregation has a known weakness: a very high safety score can be diluted by low scores elsewhere. The model therefore applies a safety override, so that any asset class scoring 5 on C1 enters Tier A whatever its index. This reflects the principle in risk-based approaches that intolerable consequences should not be traded against cost (da Silva et al., 2023). Assets lifted by the override are flagged so that reviewers can see why they sit in the top tier.

Linking tiers to preventive maintenance:-
Tier A assets receive a reliability-centred analysis of failure modes, time-based tasks at the most demanding of statutory, manufacturer or analysis-derived intervals, condition monitoring where a measurable precursor exists, critical spares held on site and the fastest response target in the service agreement. The baggage case shows the value of adding condition monitoring to high-consequence systems (Koenig et al., 2020), and measurement of lighting insulation resistance offers a precursor for airfield circuits (Liu et al., 2022). Tier B assets receive time-based preventive maintenance with condition checks, and their intervals are reviewed against failure history, an approach consistent with the use of records to advance or defer scheduled work (van Staden et al., 2022). Tier C assets receive statutory inspections and light routine tasks, with run-to-failure accepted where failure is safe and cheap to correct.The mapping also governs work order priority. When reactive requests compete with preventive work, the tier of the affected asset can be combined with work urgency and a time factor, as proposed for facilities estates (English & Yunusa-Kaltungo, 2022), and the rule can be embedded in the maintenance management system so that requests are sorted consistently (Briki et al., 2025).

Tier membership should also shape how the preventive programme is resourced. Tier A tasks are scheduled first in each planning period and protected from deferral; Tier B tasks may be deferred within a defined tolerance when resources are short, with the deferral logged; Tier C tasks are the first to be rescheduled. This ordering makes the consequences of a shortfall in labour or budget explicit, which is the same logic that links funding scenarios to infrastructure quality in station asset management (Lampe et al., 2023). It also gives contract managers a clear basis for specifying outsourced maintenance, since service levels can be written by tier rather than by asset type.

Review and updating:-
Criticality is reviewed annually and after triggering events, which include a major failure, a change in redundancy, a new terminal or airside configuration, or a material change in the health index of an asset class. Asset health indices and life cycle cost estimates make the likelihood and cost criteria dynamic (Ayu & Yunusa-Kaltungo, 2020; Candón Fernández et al., 2025). Network-level studies of bridges and stations show that such updating can be linked to

budgets, so that the consequences of underfunding a tier become visible (Hadjidemetriou et al., 2022; Lampe et al., 2023).

Illustrative Worked Scoring Example:-

To show how the model behaves, nine asset classes typical of a large passenger airport were scored using the weights in Table 1. The scores in Table 2 are hypothetical and were chosen to represent plausible but invented situations; they are not derived from any airport, and different assumptions would produce different results. Figure 2 plots the resulting indices against the tier thresholds.In the example, two classes reach Tier A on their index alone: the constant-current regulators that feed airfield ground lighting (3.94) and the uninterruptible power supplies serving operational systems (3.94). Both pair high safety and operational scores with limited redundancy. The fire detection and alarm system scores only 3.19, because in the example it is assumed to be in good condition and easy to test, but its safety score of 5 triggers the override and lifts it to Tier A. This is exactly the case the override is designed for: a compensatory index would otherwise place a life-safety system in the same tier as boarding bridges.

The baggage sortation system (3.62), the central chiller plant (3.35) and the passenger boarding bridges (3.25) sit in Tier B. The baggage system scores highly on operational consequence and redundancy but lower on safety, so in the example it lands near the top of the middle tier, suggesting a candidate for condition monitoring even without Tier A status. Potable water booster pumps (2.65), terminal escalators (2.43) and landside car park lighting (1.61) fall into Tier C.

A one-at-a-time sensitivity check moved 0.05 of weight from safety to cost. Under that shift, the chiller index rises from 3.35 to 3.50 and the baggage index from 3.62 to 3.72, while the indices for airfield regulators and power supplies fall slightly to 3.84 and 3.89. No asset changes tier, and the fire alarm system remains in Tier A through the override. In this illustrative case, the tiering is therefore robust to a moderate change in weighting, although assets close to a threshold would need closer examination in a real application.The example also shows what the model does not do. It does not say how often a chiller should be serviced; it says that the chiller belongs with assets whose intervals should be reviewed against failure history and whose spares need not be held at the same level as those for airfield regulators. Nor does it replace engineering judgement on individual failure modes. Its value lies in giving a consistent first answer to the question of where rigour should be applied, which the detailed analyses in each tier can then refine.

Table 2. Illustrative worked scoring example (hypothetical scores, not measured airport data)

Asset class	C1	C2	C3	C4	C5	C6	Index	Tier
Airfield lighting regulators	5	5	3	3	3	3	3.94	A
Uninterruptible power supplies	4	5	4	3	4	3	3.94	A
Fire detection and alarm	5	4	2	2	2	2	3.19	A (override)
Baggage sortation system	2	5	4	4	3	4	3.62	B
Central chiller plant	2	4	3	4	3	5	3.35	B
Passenger boarding bridges	3	4	2	4	3	3	3.25	B
Potable water booster pumps	3	3	2	3	2	2	2.65	C
Terminal escalators	3	2	2	3	2	2	2.43	C
Landside car park lighting	2	1	1	3	1	1	1.61	C

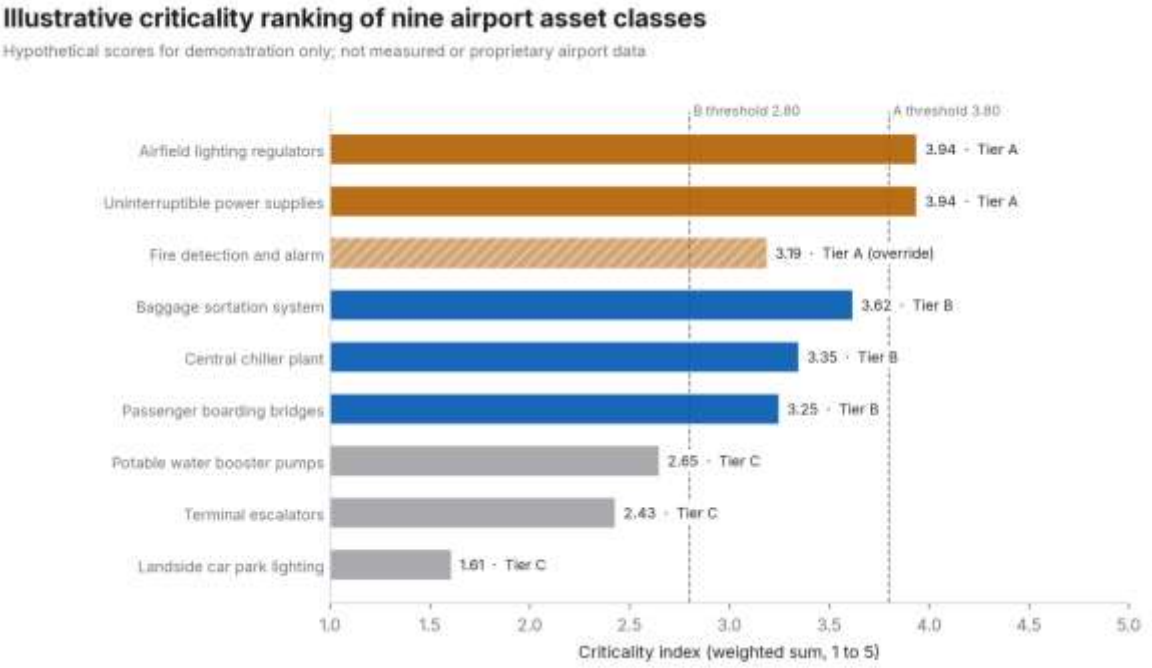

Figure 2. Criticality index and tier for the illustrative worked example (hypothetical scores, not measured data)

Evaluation and Discussion:-

Evaluation against the requirements:-

Evidence for multidimensional consequence scoring (R1) and traceable weighting (R3) is supportive: many studies across energy, transport, healthcare and industry apply weighted criteria with documented elicitation (Amran et al., 2024; Arjomandi et al., 2021; Attanayake et al., 2024; Liu et al., 2024; Sayadinia & Beheshtinia, 2021; Suwanasri et al., 2021). Evidence for condition-informed likelihood (R4) is also supportive, with frameworks linking health indices and monitoring data to criticality and to renewal decisions (Ayu & Yunusa-Kaltungo, 2020; Candón Fernández et al., 2025; Gopalakrishnan et al., 2022).

For actionable output (R5), the evidence is mixed. Several studies connect criticality to strategy choice or portfolio selection (Rios et al., 2025; da Silva et al., 2023), and others optimise intervals from failure data (Mohad et al., 2025; van Staden et al., 2022), but few close the loop from a criticality tier to a full preventive programme with intervals, spares and response targets. Evidence for periodic review (R6) is mixed as well, because the need is widely stated but the triggers and frequency are seldom tested. Evidence for mission alignment in airports (R2) is limited: system-level indices exist (Wandelt et al., 2025) and asset-class studies exist (Di Graziano et al., 2024; Koenig et al., 2020; Wesołowski & Iwanowski, 2020), but no study in the knowledge base calibrates operational consequence scales for terminal and airside assets together.

Contribution and implications for practice:-

The model contributes a single, explicit scale for comparing unlike airport assets and a rule set that converts that scale into differentiated preventive maintenance. Its novelty lies less in any single technique than in the combination: anchored scales, a stakeholder weighting exercise, a compensatory index with a non-compensatory safety override, and tier rules that govern task content, intervals, spares and response. For maintenance managers, the immediate implication is that the preventive programme can be justified asset class by asset class, which supports budget negotiation and audit. Introducing the model need not wait for perfect data. A first pass can use expert scores for likelihood and detectability, with condition data substituted as they become available, and the register can be built for the highest-consequence functions first, namely airside guidance, power and life safety, before extending to the terminal and landside estate. For operations, the ranking clarifies which failures warrant the most demanding response, which aligns with the resilience view that maintenance strategy and redundancy jointly shape recovery (Durán et al., 2020). For digital programmes, the model indicates where sensors and health indices offer the most value, namely on Tier A and upper Tier B assets with measurable precursors.

Limitations and Further Research:-

The study has clear limits. The model has not been applied at a real airport, and the worked example relies on invented scores, so it demonstrates behaviour rather than validity. The knowledge base is drawn largely from sectors other than aviation, and the criteria may need adaptation for airside regulation, security systems and concession-operated assets. The weighted sum assumes that criteria can compensate for one another, which the override only partly corrects. Future work should calibrate the scales with airport operational data, test inter-rater reliability across assessors, compare the weighted sum with outranking methods on the same asset register, and link tier membership to observed availability and cost over several maintenance cycles. Coupling the ranking with optimisation of intervals, as suggested by maintenance optimisation research (Pinciroli et al., 2023), is a natural next step.

Conclusion:-

Planned preventive maintenance at airports should be shaped by the consequence of failure, not by habit. This paper has designed a criticality decision model for mission-critical airport infrastructure that scores asset classes against six weighted criteria, combines them into an index, protects life-safety systems through an override, and maps three tiers to distinct maintenance strategies and review cycles. Addressing RQ1, the model meets six requirements derived from recent research: multidimensional consequence, mission alignment, traceable weighting, condition-informed likelihood, actionable output and periodic review. Addressing RQ2, a documented pairwise weighting exercise and anchored five-point scales offer a practical balance between rigour and usability. On RQ3, the illustrative example suggests that the tiering is stable under moderate weight shifts, while the evidence is weakest on airport-specific consequence scales and on the link from tiers to optimised intervals. Applied with real data and tested over time, the model offers airport operators a defensible basis for directing preventive effort where it protects flights, passengers and safety most.

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