

Integrating Building Information Modeling and Lifecycle Reliability Assessment for Sustainable Building Infrastructure: A Conceptual Framework

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Abstract

Building information models are produced in large numbers during design and construction, yet the information they carry rarely informs how mechanical, electrical and plumbing systems fail, how often they must be maintained, or how much energy they waste as they degrade. This study addresses that disconnect through an integrative review and a conceptual model. Fifty-eight sources spanning building information modeling for facility management, Construction Operations Building information exchange, Industry Foundation Classes, digital twins, model-based energy simulation, life cycle costing and assessment, and reliability engineering of building services were analysed with a structured integrative review protocol. The synthesis shows that facility management research treats asset data as an inventory problem while reliability research treats failure data as a statistical problem, and that the two rarely meet inside the model. The proposed framework links five layers: design, information, reliability, energy and decision. Weibull reliability, hazard, series and parallel system logic, availability, a lifecycle risk index that combines failure probability with weighted consequence, and a net present value life cycle cost are formalised as model-resident functions. Six propositions state testable relationships among information completeness, redundancy, risk ranking and whole-life cost. An illustrative application to a synthetic mid-rise office building shows that risk rankings change with the planning horizon and that redundancy is justified only above an identifiable outage cost. A validation protocol is specified for empirical testing.

Keywords: Building information modeling; Reliability engineering; Facility management; Weibull analysis; Life cycle cost; COBie; Digital twin

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1. Introduction

1.1 Background and Problem Statement

Much of the whole-life cost of buildings lies in mechanical, electrical and plumbing (MEP) services that wear and fail over decades. Building information modeling (BIM) was promoted as the means of carrying structured information into that phase (Eastman et al., 2011; Succar, 2009), yet evidence that models improve operational decisions remains thin (Volk et al., 2014; Pärn et al., 2017), and facility management (FM) staff still re-enter information that existed during design (Becerik-Gerber et al., 2012; Kassem et al., 2015). The Construction Operations Building information exchange (COBie) within the National BIM Standard (National Institute of Building Sciences, 2015) and the ISO 19650 series (ISO, 2018) specify expected life and replacement cost fields, but not how to derive them or link them to the probability and consequence of failure. Reliability engineering supplies the tools: the Weibull distribution (Weibull, 1951; Abernethy, 2006), reliability block logic (Rausand & Høyland, 2004), failure mode, effects and criticality analysis (Liu et al., 2013) and reliability-centred maintenance (Moubray, 1997), applied to HVAC systems (Myrefelt, 2004) and electrical distribution (IEEE, 2007) but largely outside BIM. Decisions such as installing N+1 chillers therefore lack a quantitative lifecycle risk argument that travels with the model.

1.2 Research Gap and Novelty

BIM-for-FM studies address data requirements, interoperability and work orders (Gao & Pishdad-Bozorgi, 2019; Matarneh et al., 2019; Chen et al., 2018); digital twin studies address live sensing and anomaly detection (Q. Lu et al., 2020; Tang et al., 2019; Opoku et al., 2021); and lifecycle sustainability studies address energy simulation, life cycle assessment (LCA) and life cycle costing (LCC) at design stage (Kamel & Memari, 2019; Santos et al., 2019; Soust-Verdaguer et al., 2017). None formalises component reliability as a model-resident quantity that drives maintenance planning, degradation-adjusted energy performance and lifecycle cost together. Cheng et al. (2020) came closest by predicting MEP condition from BIM and Internet of Things data, but their approach presupposes sensor histories that a new building lacks. The novelty of this study is a layered framework in which design-stage BIM objects carry reliability parameters that propagate to availability, risk and cost metrics and feed back into design before documentation is finalised.

1.3 Research Questions and Objectives

Following integrative review practice (Torraco, 2005; Whittemore & Knafl, 2005), three questions are addressed. RQ1: How does the literature connect BIM information structures with the maintenance and lifecycle performance of building services? RQ2: Which reliability and economic constructs make that

connection quantitative, and which BIM data carriers can host them? RQ3: How can a layered framework link design decisions to maintenance, energy and lifecycle risk, and what testable propositions follow? The objectives are to synthesise the relevant literatures, to formalise reliability, availability, risk and cost functions that can be attached to model objects through COBie and Industry Foundation Classes (IFC) property sets (Laakso & Kiviniemi, 2012), to state falsifiable propositions, and to demonstrate internal consistency on a computed scenario.

2. Review Method

2.1 Review Design and Search Strategy

An integrative review was chosen because the evidence spans case studies, prototypes, standards, textbooks and conceptual papers, and the aim is a new conceptualisation rather than a pooled effect (Whittemore & Knafl, 2005; Torraco, 2005). The five stages of Whittemore and Knafl (2005) were followed, as recorded in Table 1.

Table 1. Integrative review protocol following the five-stage structure of Whittemore and Knafl (2005)

Stage	Operationalisation in this study	Output
1. Problem identification	Unit of analysis fixed as the information link between design-stage BIM and lifecycle behaviour of MEP components; five scope boundaries set (building scale, MEP services, O&M outcome, reliability/energy/cost dimensions, model as locus)	Research questions RQ1 to RQ3; inclusion and exclusion criteria
2. Literature search	Targeted searching of literature indexed in Scopus, Web of Science, ASCE Library, ScienceDirect and ITcon; three concept blocks (information, operations, performance); backward citation tracking; direct retrieval of standards; publication year 2024 or earlier	Sources meeting the inclusion criteria
3. Data evaluation	Coding of evidence type, system, phase, information carrier and performance dimension; appraisal of methodological transparency and relevance (high, medium, low)	58 analysed sources with appraisal ratings
4. Data analysis	Constant comparison; grouping of codes into themes; cross-theme comparison; recording of contradictions	Six themes and five integration gaps
5. Presentation	Thematic synthesis, gap statement, layered conceptual framework, formal functions, propositions, illustrative application, validation protocol	Sections 3 to 7 of this paper

The unit of analysis is the link between design-stage models and MEP lifecycle behaviour, scoped as in prior BIM-for-FM reviews (Pärn et al., 2017; Wong et al., 2018) but adding reliability sources. Standards and textbooks that define framework constructs, such as ISO 15686-5 for lifecycle costing (ISO, 2017)

and Rausand and Høyland (2004) for system reliability, were admitted. Scopus, Web of Science, ASCE Library, ScienceDirect and the ITcon archive were searched with information, operations and performance concept blocks, supplemented by citation tracking from anchor reviews (Volk et al., 2014; Gao & Pishdad-Bozorgi, 2019; Matarneh et al., 2019). Inclusion required peer review or standardisation, relevance to a framework layer and publication by 2024. Fifty-eight sources were retained, and together they form the reference list.

Table 2. Representative sources by theme, evidence type and the framework layer each informs

Theme	Representative sources	Dominant evidence type	Framework layer informed
BIM for facility management	Becerik-Gerber et al. (2012); Volk et al. (2014); Kassem et al. (2015); Pärn et al. (2017); Gao and Pishdad-Bozorgi (2019); Matarneh et al. (2019); Wong et al. (2018)	Reviews, survey, case study	Information; Decision
BIM-based maintenance tools	Lin and Su (2013); Motawa and Almarshad (2013); Chen et al. (2018); Wang et al. (2013); Hassanain et al. (2003); Obeta et al. (2023)	Prototypes, case studies	Design; Decision
COBie, IFC and information requirements	National Institute of Building Sciences (2015); ISO (2018); Laakso and Kiviniemi (2012); Patacas et al. (2015)	Standards, evaluation study	Information
Digital twins and sensing	Grieves and Vickers (2017); Khajavi et al. (2019); Tang et al. (2019); Boje et al. (2020); Q. Lu et al. (2020); Cheng et al. (2020); Opoku et al. (2021); Adelanwa et al. (2023)	Conceptual, prototypes, reviews	Information; Reliability
Energy simulation and green BIM	Crawley et al. (2001); Azhar et al. (2011); Wong and Zhou (2015); Gerrish et al. (2017); Y. Lu et al. (2017); Kamel and Memari (2019); Nwafor et al. (2018)	Software, case studies, reviews	Energy
Lifecycle cost and LCA	Fuller and Petersen (1996); Horner et al. (1997); Chew et al. (2004); ISO (2011, 2017); Soust-Verdaguer et al. (2017); Santos et al. (2019); Ogbete and Aminu-Ibrahim (2023)	Standards, reviews, prototype	Decision; Energy
Reliability and maintenance strategy	Weibull (1951); Moubray (1997); Endrenyi et al. (2001); Myrefelt (2004); Rausand and Høyland (2004); Abernethy (2006); Jardine et al. (2006); IEEE (2007); Ahmad and Kamaruddin (2012); Liu et al. (2013); Adaramola et al. (2018); Gideon et al. (2019); Sunday et al. (2020)	Textbooks, standards, empirical, reviews	Reliability; Decision
BIM frameworks and method	Succar (2009); Eastman et al. (2011); Ding et al. (2014); Torraco (2005); Whittemore and Knafl (2005)	Conceptual, textbook, method	All layers; review design

2.2 Data Evaluation, Analysis and Synthesis

Each source was coded for evidence type, building system, lifecycle phase, information carrier and performance dimension, and appraised for methodological transparency and relevance (Whittemore & Knafl, 2005); appraisal weighted rather than excluded sources. Constant comparison grouped codes into themes and recorded contradictions rather than resolving them prematurely; for example, COBie deliverables reduce FM data effort (Kassem et al., 2015) but are often incomplete or unverified (Patacas et al., 2015). Table 2 lists representative sources by theme and the framework layer each informs, so that the link from evidence to model is auditable, and the gaps found across the six themes of Section 3 became the design requirements of Section 4 (Torraco, 2005).

3. Thematic Synthesis of the Literature

3.1 BIM for Facility Management and Operations

Becerik-Gerber et al. (2012) identified component location, real-time data access, visualisation, maintainability checking and space management as the principal BIM applications in FM. Later reviews found maintenance management the leading use case but constrained by interoperability and weak return-on-investment evidence (Volk et al., 2014; Pärn et al., 2017; Matarneh et al., 2019), and Gao and Pishdad-Bozorgi (2019) noted that most studies stop at information retrieval. Prototypes have delivered mobile maintenance interfaces (Lin & Su, 2013), case-based maintenance support (Motawa & Almarshad, 2013) and automated work order scheduling (Chen et al., 2018). Wang et al. (2013) showed that FM input at design exposes maintainability problems early, and Obetta et al. (2023) proposed a computerised maintenance management concept that depends on the structured asset records a BIM handover is meant to seed. Throughout this theme, failure probability and consequence are absent or entered as static priority flags, leaving maintenance planning reactive or calendar-based.

3.2 COBie, IFC and Information Requirements

IFC provides a neutral, object-based schema whose history was reviewed by Laakso and Kiviniemi (2012), while COBie (National Institute of Building Sciences, 2015) constrains IFC to an FM handover subset arranged in worksheets such as Type, Component, System, Spare and Job. ISO 19650-1 places these deliverables within organisational, asset, project and exchange information requirements (ISO, 2018). Patacas et al. (2015) found that COBie and IFC carry expected life and replacement cost fields for service life planning but no consistent method to populate them, and Kassem et al. (2015) found that

model-to-CAFM transfer worked technically but required substantial manual verification. Hassanain et al. (2003) anticipated these requirements in an IFC-oriented maintenance model. The data carriers for reliability information therefore exist, particularly the COBie Type and Job sheets and IFC service life property sets, but no accepted method links their content to failure statistics.

3.3 Digital Twins and Sensor Integration

The digital twin concept from product lifecycle management (Grieves & Vickers, 2017) has been adapted to buildings as a model synchronised with its physical counterpart. Khajavi et al. (2019) fed a facade twin from a sensor network, Boje et al. (2020) argued that construction twins need semantic models beyond BIM geometry, Opoku et al. (2021) found most applications still at the monitoring stage, and Tang et al. (2019) reviewed BIM and Internet of Things data-linking methods. Q. Lu et al. (2020) improved pump anomaly detection by combining BIM context with sensor streams, Cheng et al. (2020) predicted MEP condition with machine learning, and Adelanwa et al. (2023) proposed managing design, delivery and operation data as one lifecycle record. All need measurement histories, and no reviewed architecture specifies how design-stage reliability priors are stored or updated.

3.4 BIM-Based Energy Simulation and Green BIM

Energy performance is the sustainability dimension most closely tied to BIM. Azhar et al. (2011) used BIM for LEED documentation, Wong and Zhou (2015) and Y. Lu et al. (2017) found that operational green BIM lags design applications, and Kamel and Memari (2019) reported geometry and zoning errors in BIM-to-energy workflows feeding engines such as EnergyPlus (Crawley et al., 2001). Gerrish et al. (2017) found that models are rarely updated after handover, so predicted and measured performance diverge. Equipment degradation is one driver of that divergence: fouled coils, worn bearings and failed actuators raise energy use long before they cause an outage (Jardine et al., 2006). Envelope design against local climate also fixes plant loads for the life of the building (Nwafor et al., 2018). Energy simulation nonetheless assumes nameplate efficiency throughout, which decouples energy prediction from reliability.

3.5 Lifecycle Cost and Life Cycle Assessment

Lifecycle costing is codified in ISO 15686-5 (ISO, 2017) and NIST Handbook 135 (Fuller & Petersen, 1996), with replacement intervals drawn from the service life planning principles of ISO 15686-1 (ISO, 2011). Santos et al. (2019) integrated LCA and LCC in a BIM environment, and Soust-Verdaguer et al. (2017) identified the model's level of development as a key determinant of BIM-based LCA results. Horner et al. (1997) argued that maintenance strategy should follow element criticality and failure

behaviour rather than fixed schedules, Chew et al. (2004) showed that design decisions on access, materials and configuration fix much of future maintenance cost, and Ogbete and Aminu-Ibrahim (2023) argued that service-intensive facilities must be judged over sustained operation rather than at handover. LCC and LCA treat maintenance and replacement as deterministic schedules from reference service lives, whereas reliability engineering treats them as stochastic events; replacing schedules with expected failure counts is one link the framework provides.

3.6 Reliability Modelling and Maintenance Strategy for Building Systems

The Weibull distribution (Weibull, 1951) represents decreasing, constant and increasing hazard through one shape parameter and is the default life model in engineering practice (Abernethy, 2006). System reliability theory composes components through series, parallel and k-out-of-n structures and defines availability for repairable systems (Rausand & Høyland, 2004). Reliability-centred maintenance selects run-to-failure, time-based or condition-based tasks according to failure pattern and consequence (Moubray, 1997), with condition-based maintenance resting on diagnostics and prognostics (Jardine et al., 2006; Ahmad & Kamaruddin, 2012). Gideon et al. (2019) stressed component interaction in system reliability, Sunday et al. (2020) set out prerequisites for predictive maintenance, and Adaramola et al. (2018) examined condition monitoring of power equipment. The FMEA risk priority number has known weaknesses (Liu et al., 2013). For building services, Myrefelt (2004) analysed HVAC reliability and availability, and IEEE Std 493 compiled failure and repair data for power systems (IEEE, 2007). Motawa and Almarshad (2013) and Chen et al. (2018) used maintenance histories within BIM but did not fit or store failure distributions.

3.7 Synthesis of Gaps

Five gaps become requirements for the framework. An information gap: COBie and IFC carry expected life and replacement cost but no failure distribution parameters or consequence scores (Patacas et al., 2015; National Institute of Building Sciences, 2015). A method gap: no accepted procedure derives those fields, so delivered values are often defaults (Kassem et al., 2015). A system gap: maintenance tools treat components independently, whereas availability depends on configuration and redundancy (Rausand & Høyland, 2004). A coupling gap: energy simulation ignores degradation and lifecycle costing treats maintenance as deterministic (Gerrish et al., 2017; Santos et al., 2019). A feedback gap: operational evidence rarely returns to design, so reliability assumptions are never tested (Wang et al., 2013; Q. Lu et al., 2020). Each layer of the framework in Section 4 closes one or more of these gaps.

4. Conceptual Framework Development

The framework organises BIM-resident information and computations into five layers (design, information, reliability, energy and decision), shown in Figure 1. The layering follows BIM frameworks that separate fields, stages and lenses of implementation (Succar, 2009) and the nD view in which model content feeds computable functions (Ding et al., 2014). Information flows upward from design objects through data carriers to reliability and energy computations and then to decision metrics; decisions flow back down as changes to plant configuration, equipment selection or maintainability provisions before the design is frozen. The aim is to make the lifecycle value claimed for BIM (Eastman et al., 2011) measurable rather than asserted.

Upward arrows: information flow to decisions. Downward arrows: decision feedback to design.

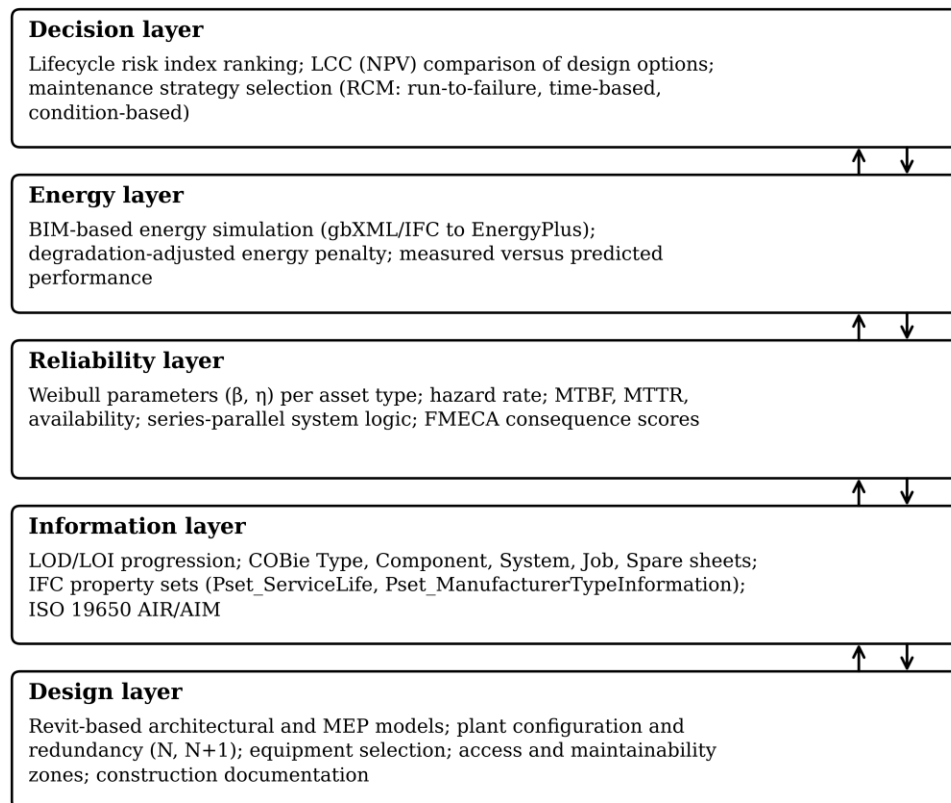


Figure 1. Five-layer conceptual framework integrating BIM and lifecycle reliability assessment

4.1 Design Layer

The design layer comprises the authored architectural and MEP models and the documentation derived from them (Eastman et al., 2011). The decisions that most affect lifecycle reliability are plant configuration (single, duty and standby, or N+1), equipment quality class, distribution topology and maintainability

provisions such as clearances, access routes and plant room location, which are largely fixed at design (Chew et al., 2004) and can be checked with FM input through BIM (Wang et al., 2013). Each MEP family instance becomes a reliability-bearing object linked to a reliability record, and each system is represented as a logical structure of components rather than a drawing grouping, matching the system classification COBie already requires (National Institute of Building Sciences, 2015) and enabling the calculations in Section 4.3.

4.2 Information Layer: LOD, COBie and IFC

The information layer specifies where reliability data live and when they mature, within the exchange and asset information requirements of ISO 19650-1 (ISO, 2018).

Table 3. Reliability attributes added to the information layer and their proposed data carriers

Attribute	Level	Proposed carrier	Used in
Weibull shape β	Type	COBie Type (custom attribute); IFC custom property set	Equations (1) to (3), (10)
Weibull scale η (years)	Type	COBie Type (custom attribute); IFC custom property set	Equations (1) to (3), (10)
Parameter source and status (prior, manufacturer, fitted)	Type	COBie Type (custom attribute)	Validation Stage 2
Mean time to repair (hours)	Type	COBie Type (custom attribute); linked to access zone in model	Equation (6)
Consequence scores S, D, E, R (1 to 5)	Type or Component	COBie Type or Component (custom attributes)	Equations (7), (8)
Energy penalty fraction ϕ	Type	IFC custom property set	Equation (9)
Installation date, serial number	Component	COBie Component (InstallationDate, SerialNumber)	Service age t
System membership and redundancy structure	System	COBie System; custom redundancy descriptor (series, parallel, k-out-of-n)	Equations (4), (5)
Expected life and replacement cost	Type	COBie Type (ExpectedLife, ReplacementCost)	Equation (11)
Selected maintenance policy and interval	Type	COBie Job (TaskType, Frequency)	Decision layer

Table 3 lists the added attributes. At type level, Weibull parameters with a source reference, mean time to repair (MTTR) and consequence scores are stored as custom properties mapped to the COBie Type sheet and IFC property sets, beside the existing expected life and replacement cost fields (Patacas et al.,

2015). At component level, installation date anchors the age clock; at system level, the COBie System sheet gains a redundancy descriptor (series, parallel, k-out-of-n); and Job sheet entries hold the maintenance tasks selected later in the decision layer. Extending IFC through property sets, the practical route for domain-specific data (Laakso & Kiviniemi, 2012), avoids schema change.

4.3 Reliability Layer

The reliability layer converts stored parameters into time-dependent metrics. Component life is modelled with the two-parameter Weibull distribution (Weibull, 1951; Abernethy, 2006), whose reliability function is given in Equation (1).

$$R(t) = \exp \left[- \left(\frac{t}{\eta} \right)^{\beta} \right] \quad (1)$$

In Equation (1), $R(t)$ is the probability that the component survives to service age t in years, η is the characteristic life (the age by which 63.2 per cent of a population has failed) and β is the shape parameter: values below one indicate infant mortality, near one random failure and above one wear-out (Rausand & Høyland, 2004). The hazard function and the mean time between failures for a component renewed on failure are given in Equations (2) and (3).

$$h(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad (2)$$

$$\text{MTBF} = \eta \Gamma \left(1 + \frac{1}{\beta} \right) \quad (3)$$

Here $h(t)$ is the hazard rate in failures per year and Γ is the gamma function. Time-based replacement is effective only when $h(t)$ increases with age, that is, when β exceeds one (Moubray, 1997). System reliability follows from the logical structure recorded in the information layer; for n components in series and m redundant units in parallel it is given by Equations (4) and (5).

$$R_s(t) = \prod_{i=1}^n R_i(t) \quad (4)$$

$$R_p(t) = 1 - \prod_{j=1}^m [1 - R_j(t)] \quad (5)$$

In Equations (4) and (5), $R_i(t)$ and $R_j(t)$ are the reliabilities of the individual components, $R_s(t)$ is the reliability of a series chain in which any failure interrupts service, and $R_p(t)$ is the reliability of a parallel group that fails only when all members fail. Mixed structures, such as $N+1$ chillers feeding a single distribution loop, are evaluated by nesting the two expressions (Rausand & Høyland, 2004). Because building services are repaired rather than discarded, steady-state availability is also required, as defined in Equation (6), where $MTTR_i$ is the mean time to repair including diagnosis, parts procurement and

restoration, a quantity strongly influenced by design-stage access provisions and spares strategy (IEEE, 2007).

$$A_i = \frac{MTBF_i}{MTBF_i + MTTR_i} \quad (6)$$

4.4 Lifecycle Risk Index

Consequence matters as much as failure probability in setting maintenance priority, the core argument of both FMECA and reliability-centred maintenance (Moubray, 1997; Liu et al., 2013). The framework scores consequence on a five-point ordinal scale for life safety and compliance (S), disruption to occupants and business function (D), energy and environmental penalty (E), and direct repair cost and duration (R), aggregated with weights as in Equation (7). The lifecycle risk index (LRI) of component i over planning horizon T is the product of cumulative failure probability and weighted consequence, as in Equation (8).

$$C_i = \sum_{k \in \{S,D,E,R\}} w_k s_{ik}, \sum_k w_k = 1 \quad (7)$$

$$LRI_i(T) = F_i(T) \cdot C_i = [1 - R_i(T)] C_i \quad (8)$$

In Equation (7), C_i is the weighted consequence score of component i , s_{ik} is its score on dimension k and w_k is the weight of dimension k , with weights summing to one. In Equation (8), $F_i(T) = 1 - R_i(T)$ is the probability of at least one failure by horizon T . Unlike the conventional risk priority number, which multiplies ordinal scores and is sensitive to scale distortions (Liu et al., 2013), the LRI uses a probability derived from a fitted distribution, so its likelihood term is on a ratio scale and changes with the planning horizon. The weights are an owner decision recorded in the organisational information requirements (ISO, 2018), so different owners can rank the same model differently without altering its reliability data.

4.5 Energy Layer

The energy layer couples reliability with energy performance. BIM-based energy simulation translates model geometry and system definitions into an energy model, typically through gbXML or IFC into an engine such as EnergyPlus (Crawley et al., 2001; Kamel & Memari, 2019). Conventional workflows assume nameplate efficiency throughout the study period, which is one reason predicted and measured performance diverge (Gerrish et al., 2017). The framework introduces a degradation-adjusted annual energy estimate, given in Equation (9), in which E_0 is the simulated baseline annual energy use, $F_i(t)$ is the cumulative failure or degradation probability of component i at year t , and ϕ_i is the fractional energy penalty attributed to component i when it is in a degraded state, for example the additional fan power drawn by a fouled coil or the simultaneous heating and cooling caused by a failed damper actuator. Values

of φ_i can be estimated from fault impact studies associated with condition monitoring and diagnostics (Jardine et al., 2006), and they connect the E dimension of the consequence score to a quantitative energy outcome.

$$E(t) = E_0[1 + \sum_i \varphi_i F_i(t)] \quad (9)$$

4.6 Decision Layer and Life Cycle Cost

The decision layer turns reliability, energy and risk outputs into choices: which components warrant condition monitoring, which can run to failure, which design options justify their capital cost and which spares to hold. Lifecycle cost follows ISO 15686-5 (ISO, 2017) and NIST Handbook 135 (Fuller & Petersen, 1996). Under minimal repair, the expected cumulative number of failures equals the cumulative hazard (Rausand & Høyland, 2004), as shown in Equation (10), and the net present value of lifecycle cost is given by Equation (11).

$$N_i(t) = \int_0^t h_i(u) du = \left(\frac{t}{\eta_i}\right)^{\beta_i} \quad (10)$$

$$LCC = C_0 + \sum_{t=1}^N \frac{E_t + M_t + P_t + D_t}{(1+r)^t} \quad (11)$$

In Equation (10), $N_i(t)$ is the expected number of failures of component i by year t . In Equation (11), C_0 is initial capital cost, N is the study period in years, r is the real discount rate, E_t is annual energy cost, M_t is expected corrective maintenance cost (the sum over components of unit repair cost c_i multiplied by expected failures in year t , $N_i(t) - N_i(t-1)$), P_t is planned maintenance cost, and D_t is the monetised cost of service outage (outage hours multiplied by an owner-specified cost per hour). This formulation replaces the deterministic replacement schedules of conventional LCC with expected failure counts, closing the coupling gap identified in Section 3.7 (Santos et al., 2019).

Policy selection follows reliability-centred maintenance (Moubray, 1997): components with β at or below one and low consequence run to failure with spares held; components with β above one and moderate to high consequence are renewed at an interval where the hazard approaches an owner-specified threshold; and components with observable degradation, such as vibration or supply temperature deviation, receive condition-based maintenance (Jardine et al., 2006; Ahmad & Kamaruddin, 2012). Recording the policy in the COBie Job sheet aligns the handover maintenance plan with the design's reliability assumptions.

5. Research Propositions

5.1 Propositions on Information and Configuration

The framework implies six propositions, each falsifiable and linked to measurable constructs (Torraco, 2005). P1 (information completeness): projects whose handover models carry reliability attributes for critical MEP types will show a lower ratio of corrective to planned maintenance hours in the first five years of operation than projects whose COBie data are limited to expected life, extending the finding that structured handover data reduce FM effort (Kassem et al., 2015). P2 (configuration sensitivity): for components with shape parameters above one, N+1 redundancy will raise availability more than an equal-cost quality upgrade, because redundancy acts on the product structure of Equation (5) whereas quality acts only on η (Rausand & Høyland, 2004). P3 (maintainability and repair time): design-stage access provisions recorded in the model will explain a significant share of variance in observed MTTR across comparable equipment types (Chew et al., 2004).

5.2 Propositions on Decision Outcomes

P4 (horizon dependence): LRI rankings will differ materially between five-to-ten-year and twenty-year horizons, with high-consequence wear-out components rising as the horizon extends, an effect that the static priority flags of most BIM-for-FM systems cannot represent (Motawa & Almarshad, 2013; Chen et al., 2018). P5 (energy coupling): energy use predicted with Equation (9) will track measured use more closely in years five to fifteen than constant-efficiency predictions, narrowing the performance gap reported by Gerrish et al. (2017). P6 (cost justification threshold): for any redundancy or reliability upgrade there is an outage cost per hour above which the option minimises lifecycle cost under Equation (11), and owners who record this threshold will make more consistent capital decisions than those relying on rule-of-thumb redundancy policies (Horner et al., 1997; ISO, 2017). Prior studies support parts of these propositions but none has tested them jointly inside a model environment (Gao & Pishdad-Bozorgi, 2019; Matarneh et al., 2019).

6. Illustrative Application

6.1 Scenario Definition and Component Parameters

The synthetic scenario is a seven-storey office building of about 9,000 square metres with a central chilled water plant, a gas-fired condensing boiler, variable air volume (VAV) air handling, a building management system (BMS), domestic water boosting, a fire pump and a main low-voltage switchboard.

It does not describe a real facility: parameters are plausible in light of published reliability compilations (IEEE, 2007; Myrefelt, 2004) and Weibull guidance for mechanical wear-out (Abernethy, 2006) but are not fitted to field data, and every value was computed in Python from Equations (1) to (8), (10) and (11). Table 4 lists, for twelve component types, the Weibull parameters, MTTR, consequence scores and derived quantities. Consequence weights (S 0.35, D 0.30, E 0.20, R 0.15) reflect owner information requirements (ISO, 2018), and the base horizon is $T = 10$ years. Shape parameters range from infant mortality (BMS controller, $\beta = 0.9$) through random failure (VAV actuators, $\beta = 1.2$) to strong wear-out (switchboard, $\beta = 2.8$), matching the failure patterns of reliability-centred maintenance (Moubray, 1997).

Table 4. Component parameters, derived reliability metrics and lifecycle risk ranking for the illustrative mid-rise building (synthetic data)

ID	β	η (yr)	MTTR (h)	S/D/E/R	C	MTBF (yr)	A	R(10)	LRI(10)	Rank T=10	Rank T=20
DWB	1.3	8	10	2/4/1/2	2.40	7.4	0.99985	0.263	1.77	1	4
CHWP	1.4	9	16	1/4/2/2	2.25	8.2	0.99978	0.314	1.54	2	6
BMS	0.9	16	8	2/4/4/2	3.00	16.8	0.99995	0.519	1.44	3	7
CWP	1.4	10	16	1/4/2/2	2.25	9.1	0.99980	0.368	1.42	4	8
AHU	1.5	14	12	2/4/3/3	2.95	12.6	0.99989	0.547	1.34	5	3
CT	1.6	12	24	1/4/3/2	2.45	10.8	0.99975	0.474	1.29	6	5
CH	1.9	18	72	2/5/5/5	3.95	16.0	0.99949	0.721	1.10	7	1
VAV	1.2	11	2	1/2/3/1	1.70	10.3	0.99998	0.410	1.00	8	11
BLR	2.0	20	36	4/4/4/4	4.00	17.7	0.99977	0.779	0.88	9	2
FP	1.5	25	24	5/2/1/3	3.00	22.6	0.99988	0.776	0.67	10	10
CC	2.4	20	20	1/3/4/3	2.50	17.7	0.99987	0.827	0.43	11	9
LVSBS	2.8	35	48	5/5/2/5	4.40	31.2	0.99982	0.970	0.13	12	12

Note. ID key: DWB domestic water booster pump; CHWP chilled water pump; BMS BMS field controller; CWP condenser water pump; AHU air handling unit supply fan and motor; CT cooling tower fan assembly; CH centrifugal chiller; VAV variable air volume terminal actuator; BLR gas-fired condensing boiler; FP fire pump; CC AHU cooling coil; LVSBS main low-voltage switchboard. Weights: S 0.35, D 0.30, E 0.20, R 0.15.

6.2 Reliability Curves and Risk Ranking

Figure 2(a) shows the domestic water booster pump and chilled water pumps falling to about 26 and 31 per cent survival at ten years, while the switchboard stays above 97 per cent; the early drop and flat tail of the BMS controller argue for functional testing rather than time-based replacement (Moubray, 1997). In the ten-year LRI ranking (Figure 3), the booster pump leads (1.77), followed by the chilled water pumps

(1.54), the BMS controller (1.44) and the condenser water pump (1.42). The chiller, despite a consequence score of 3.95, ranks only seventh because its 18-year characteristic life keeps its ten-year failure probability at 0.28, and the switchboard ranks last (consequence 4.40, failure probability 0.03). Consequence-only prioritisation, common in FM practice (Becerik-Gerber et al., 2012), would therefore misallocate early-life maintenance attention.

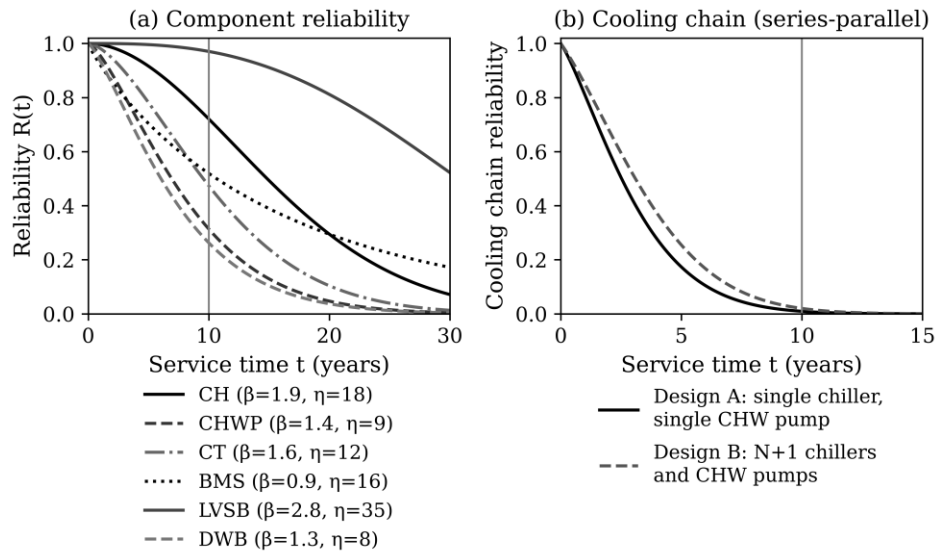


Figure 2. Illustrative reliability curves: (a) Weibull reliability of selected components; (b) cooling chain reliability for Design A and Design B (synthetic data)

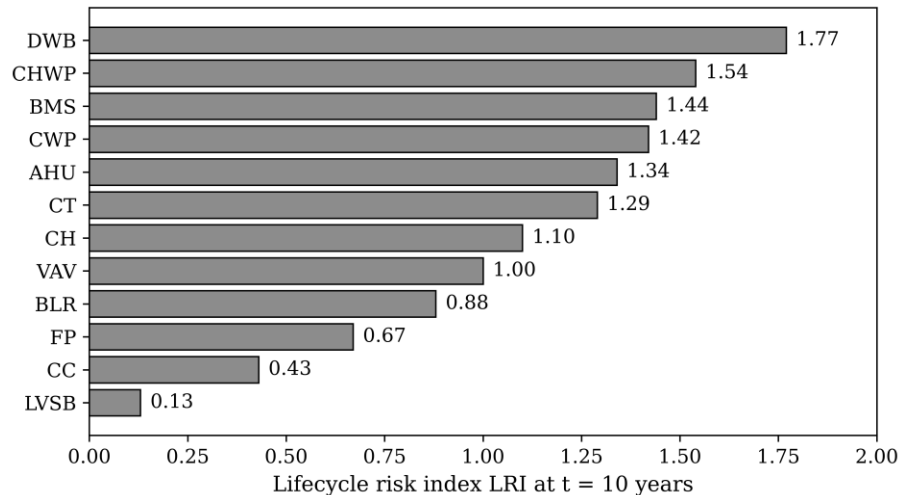


Figure 3. Lifecycle risk index ranking of MEP components at a ten-year horizon (synthetic data)

6.3 Horizon Sensitivity and Design Option Comparison

At $T = 20$ years the order changes substantially (final column of Table 4): the chiller rises from seventh to first (LRI 2.79), the boiler from ninth to second (2.53) and the air handling unit (AHU) fan from fifth to third (2.42), while the booster pump falls to fourth and the BMS controller to seventh. This is the horizon dependence stated in P4, arising because high-consequence wear-out components accumulate failure probability late in life (Rausand & Høyland, 2004). Two cooling chain options were then compared: Design A, a single chiller and chilled water pump in series with five other components, and Design B, which adds N+1 redundancy for the chiller and chilled water pump at an added capital cost of 458,000 currency units. Table 5 reports results over a 25-year study period at a 3 per cent real discount rate, with outage valued at 1,500 currency units per hour, following ISO 15686-5 (ISO, 2017).

Table 5. Comparison of cooling chain design options over a 25-year study period (synthetic data, 3 per cent real discount rate, outage valued at 1,500 currency units per hour)

Metric	Design A (single chiller and CHW pump)	Design B (N+1 chillers and CHW pumps)
Chain reliability $R(1)$	0.810	0.850
Chain reliability $R(5)$	0.173	0.255
Steady-state chain availability	0.99852	0.99925
Expected annual downtime (hours)	13.0	6.5
Expected outage hours over 25 years	261	134
Initial capital cost C_0	1.00 million	1.46 million
PV of energy, corrective and planned maintenance	3.54 million	3.60 million
PV of outage cost	0.39 million	0.20 million
Lifecycle cost (NPV)	4.93 million	5.26 million
Break-even outage cost (per hour)	4,061	4,061

Redundancy raises cooling chain reliability from 0.81 to 0.85 at one year and from 0.17 to 0.25 at five years (Figure 2(b)), and steady-state availability from 0.99852 to 0.99925, halving expected annual downtime from 13.0 to 6.5 hours (Table 5). Because failed components are repaired, availability rather than chain reliability is the relevant metric (IEEE, 2007). Expected outage hours over 25 years fall from 261 to 134, but the present value of lifecycle cost is 4.93 million for Design A and 5.26 million for Design B, with break-even at an outage cost of about 4,060 currency units per hour. Owners above that threshold, such as laboratories or data-intensive tenants, should select Design B, which is the decision rule of P6 and consistent with the criticality-based maintenance strategy of Horner et al. (1997).

7. Validation Protocol

Empirical validation is required before the propositions can be accepted. The staged protocol in Table 6 moves from construct validity to predictive validity and decision utility, following case-based evaluation of BIM-for-FM implementations (Kassem et al., 2015; Q. Lu et al., 2020) and validation of reliability models against field failure records (Abernethy, 2006). Stage 1 tests whether practitioners can populate and interpret the attributes in Table 3, with a target weighted kappa of at least 0.6 for consequence scores (Liu et al., 2013). Stage 2 compares design-stage Weibull parameters with values fitted to maintenance records. Stage 3 compares predicted failure counts and degradation-adjusted energy with at least three years of observations using mean absolute percentage error (Gerrish et al., 2017). Stage 4 compares buildings managed with and without LRI-based prioritisation on the ratio of corrective to planned maintenance and on unplanned downtime, testing P1 and P4 (Gao & Pishdad-Bozorgi, 2019).

Table 6. Staged validation protocol for the framework and its propositions

Stage	Data source	Metric	Acceptance criterion
1. Construct validity	Practitioner workshops using a sample model	Attribute completeness; weighted kappa for consequence scores	Completeness of at least 90 per cent for critical types; kappa of at least 0.6
2. Parameter validity	CMMS failure records from comparable buildings	Maximum likelihood Weibull fit with censoring; confidence interval on η	Design-stage η within the 90 per cent interval for most critical types
3. Predictive validity	Three or more years of work orders and metered energy	MAPE of predicted failures (Eq. 10) and energy (Eq. 9)	Lower error than constant-efficiency and fixed-schedule baselines (P5)
4. Decision utility	Matched buildings with and without LRI prioritisation	Corrective to planned maintenance ratio; unplanned downtime; LCC outcome	Statistically significant improvement supporting P1, P4 and P6

8. Discussion

8.1 Interpretation of Findings

Three findings stand out. Risk rankings depend on the planning horizon, so asset information models should store distributions rather than fixed priority classes, which qualifies the static criticality fields of BIM-based maintenance systems (Motawa & Almarshad, 2013). The economic case for redundancy is conditional: N+1 cooling halved downtime but was justified only above about 4,060 currency units per outage hour, turning a rule of thumb into an owner-specific decision consistent with lifecycle costing principles (Fuller & Petersen, 1996; ISO, 2017). Mission reliability and availability are easily confused,

since near-zero ten-year chain reliability coexists with availability above 0.998, and communicating these metrics correctly is a practical condition for adoption (Becerik-Gerber et al., 2012).

8.2 Relation to Digital Twins and Sustainability

The framework complements digital twins rather than replacing them: design-stage parameters act as priors that a twin updates as sensor and work order data accumulate, turning assumed reliability into evidenced reliability (Q. Lu et al., 2020; Cheng et al., 2020) and addressing the cold-start problem of predictive maintenance in new buildings. Because degraded components raise operational energy use and emissions, linking failure probability to energy penalty extends green BIM from design compliance to lifecycle performance (Wong & Zhou, 2015; Y. Lu et al., 2017). Replacement events from Equation (10) can also replace the fixed service lives that BIM-based LCA often assumes for the embodied impacts of maintenance (Soust-Verdaguer et al., 2017).

8.3 Theoretical Contribution

The contribution is not a new reliability method, since Equations (1) to (6) and (10) are standard (Rausand & Høyland, 2004), but a specification of where reliability data reside in BIM, how they propagate to risk, energy and cost, and how decisions return to design. The study reframes the BIM-for-FM information problem as one of computable lifecycle quantities, extending the nD perspective of Ding et al. (2014) and responding to the observation of Volk et al. (2014) and Pärn et al. (2017) that operational value depends on computable information. It maps reliability constructs onto COBie and IFC property sets without schema change (Laakso & Kiviniemi, 2012; National Institute of Building Sciences, 2015), and it replaces deterministic replacement schedules in ISO 15686-5 costing with expected failure counts (ISO, 2017). Its propositions make the framework predictive rather than classificatory, unlike maturity models such as that of Succar (2009).

9. Implications for Practice and Policy

Designers should give MEP families reliability attributes and report availability and lifecycle cost in plant option studies, using shared parameters mapped to COBie and IFC export (Laakso & Kiviniemi, 2012; Eastman et al., 2011). Owners should specify reliability fields, consequence weights and an outage cost per hour in their ISO 19650 information requirements (ISO, 2018). COBie guidance could add optional type-level reliability properties to the fields Patacas et al. (2015) found underspecified. Public procurement could require expected failure counts in ISO 15686-5 lifecycle cost evaluation, making bids that differ in redundancy and equipment quality comparable (ISO, 2017). Maintenance contractors could use LRI

rankings to justify condition-based tasks for wear-out components and run-to-failure policies for low-consequence random-failure items (Moubray, 1997).

10. Limitations and Future Research

The review relied on targeted searching and citation tracking of English-language, peer-reviewed or standardised sources, and theme formation involves interpretive judgement (Whittemore & Knafl, 2005). The application uses synthetic parameters, whereas real Weibull parameters for building equipment are scarce, heterogeneous and often based on small samples, so field calibration is essential (Abernethy, 2006). The model assumes independent failures and minimal repair, although common-cause failures and imperfect repair are frequent in practice (Rausand & Høyland, 2004), and maintenance itself alters failure behaviour (Endrenyi et al., 2001). Consequence scores are ordinal and weight-dependent (Liu et al., 2013), and the energy penalties in Equation (9) need empirical estimation. Future research should fit building-specific failure distributions from maintenance records, add Bayesian updating within digital twins (Q. Lu et al., 2020), model imperfect repair and common-cause failure, test the propositions through the protocol in Section 7, and develop open property set definitions for exchanging reliability data across tools (Ahmad & Kamaruddin, 2012; Tang et al., 2019).

11. Conclusion

This study connected building information modeling with lifecycle reliability assessment so that design decisions for building services can be judged by their consequences for maintenance, energy and lifecycle risk. The review found that research on model-based facility management, information exchange, digital twins, energy simulation and lifecycle costing rarely treats component failure as a quantity the model can compute. The five-layer framework closes that gap: design objects carry reliability parameters, information standards host them, reliability functions convert them into probability, availability and risk, energy and cost functions translate them into whole-life outcomes, and decisions return to design before documentation is finalised. In a synthetic mid-rise building, risk rankings shifted with the planning horizon, redundancy halved downtime but was justified only above an identifiable outage cost, and availability rather than mission reliability proved the appropriate service metric. Six propositions and a staged validation protocol make the framework testable against field data.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data generated for the illustrative application are synthetic and are reported in full in Tables 4 and 5 of this article.

Author contributions

Susan Ochi Makut: conceptualization, reliability and maintenance framing, writing (original draft).
Adedoyin Oluwatoyin Olutimehin: methodology, formal analysis, visualization, writing (original draft).
Adeshola Oladunni Bankole: literature review, validation, writing (review and editing).

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