



**ARTIFICIAL INTELLIGENCE AND GENERATIVE DESIGN FOR
PERFORMANCE-DRIVEN SUSTAINABLE RETROFITTING OF EXISTING
INSTITUTIONAL BUILDINGS: A MULTI-OBJECTIVE FRAMEWORK WITH A
CASE-STUDY VALIDATION ON A UNIVERSITY ACADEMIC BUILDING**

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Abstract

The existing building stock is one of the largest single contributors to global energy use and carbon emissions, yet most retrofit practice remains fragmented: individual measures are sized in isolation, trade-offs between energy, daylight, water and cost are rarely resolved simultaneously, and decisions seldom exploit the parametric and data-driven capabilities now available through building information modelling (BIM). This paper develops and validates a five-layer framework that couples a parametric BIM digital twin with artificial-intelligence (AI) surrogate models and a generative, multi-objective optimization engine to drive *performance-driven* retrofitting of existing institutional buildings. The framework is demonstrated on a three-story academic building the Department of Architectural Engineering and Design (AED) at the University of Engineering and Technology (UET), Lahore, Pakistan using a BIM-based and standards-referenced retrofit assessment as the empirical baseline. Envelope upgrades reduced wall, roof and window thermal transmittance to within IECC 2021 limits (for example, roof U-value from 0.1019 to 0.0394 BTU/h·ft²·°F); a light-emitting-diode (LED) retrofit lowered lighting demand by about 60%; ultrasonic occupancy sensors saved a further 42%; a roof-constrained rooftop photovoltaic (PV) array of roughly 100.7 kW offset about 44% of the peak electrical load; and combined rainwater harvesting and greywater reuse recovered a rooftop collection potential near 73,200 ft³ and displaced about 53% of potable water used for flushing. These measured potentials are then re-expressed as objectives, variables and constraints for the proposed generative engine, showing how a



single integrated search can reconcile competing performance goals that the conventional, measure-by-measure workflow handles only sequentially. The contribution is a transferable, standards-aware decision-support framework that bridges the gap between manual retrofit auditing and automated, generative, performance-based design for institutional buildings in rapidly urbanising, climate-stressed regions.

Keywords: Sustainable retrofitting; building performance; generative design; artificial intelligence; building information modelling (BIM); digital twin; multi-objective optimisation; institutional buildings; energy efficiency; performance-driven architecture

1. Introduction

Buildings are central to the global decarbonization agenda. The construction and operation of the built environment is responsible for a major share of worldwide final energy demand and energy-related carbon-dioxide emissions, and the overwhelming majority of the floor area that will exist in the coming decades has *already* been built [1], [2]. Because new, high-performance construction can influence only a small fraction of the stock in any given year, improving the performance of *existing* buildings retrofitting is the single most consequential level available to architects and engineers seeking to reduce operational energy, water consumption and greenhouse-gas emissions in the near term [3].

Retrofitting denotes the targeted upgrading of the operational, energy, environmental and functional characteristics of a building that is already in use. Existing buildings frequently combine outdated systems, inadequate insulation, inefficient lighting and poor water management, which together raise running costs, depress indoor environmental quality and shorten useful life. Well-conceived retrofits reverse these effects: they lower energy and water demand, improve thermal and visual comfort, raise asset value and extend service life, while contributing directly to climate-change mitigation and resource conservation [3], [4].

Institutional buildings, universities, schools, laboratories and administrative facilities are a particularly important and tractable segment of this stock. They are typically publicly owned, intensively occupied on predictable schedules, and visible to large communities of students and staff, which makes them



both high-impact and exemplary candidates for demonstrating sustainable practice. Yet, as a class, they are often operated with legacy envelopes, conventional fixtures and little renewable generation, leaving large performance gaps relative to contemporary codes and rating systems such as IECC, ASHRAE 90.1, LEED and BREEAM.

Two technological shifts now make a more ambitious approach possible. First, building information modelling (BIM) and the emerging practice of the building *digital twin* allow an existing building to be represented as a rich, queryable, parametric model whose energy, daylight and thermal behaviour can be simulated and continually reconciled against measured data [5], [6]. Second, advances in artificial intelligence (AI) in particular data-driven surrogate modelling and *generative design*, in which an algorithm autonomously explores large spaces of design alternatives against explicit objectives make it feasible to optimise many interacting retrofit decisions simultaneously rather than one at a time [7], [8], [9]. The convergence of these capabilities motivates a shift from *prescriptive*, measure-by-measure retrofitting toward *performance-driven* retrofitting, in which the design intent is expressed as quantitative performance targets and the computer is used to search for the configurations that best satisfy them.

This article responds to that opportunity. It proposes a structured framework that couples a parametric BIM digital twin with AI surrogate models and a generative, multi-objective optimisation engine, and it grounds the proposal in a detailed, standards-referenced retrofit assessment of a real institutional building. The case building is the Department of Architectural Engineering and Design (AED) at the University of Engineering and Technology (UET), Lahore, Pakistan: a three-storey academic block in a hot, water-stressed, rapidly urbanising context that is broadly representative of institutional stock across South Asia, the Middle East and North Africa.

1.1. Problem statement

Despite the maturity of individual retrofit technologies, three structural weaknesses persist in everyday practice. First, measures are usually evaluated *in isolation*: insulation thickness, glazing specification, lighting power, sensor placement, PV array size and water-reuse strategy are each sized against their own code clause, with little attempt to capture the interactions and trade-offs



between them. Second, the workflow is *single-objective and manual*: an engineer typically checks one quantity (a U-value, a lighting power density, a flush volume) against one threshold, so the design that emerges is feasible but rarely optimal across energy, comfort, water and cost together. Third, the rich parametric and data-handling capacity of BIM is *under-used*: models are built for documentation rather than for automated, iterative performance search. The result is fragmented decision-making, missed synergies and outcomes that fall short of what the same building, budget and codes could achieve.

1.2. Research gap

The literature contains extensive work on retrofit technologies, on simulation-based optimisation of *new* buildings, and, separately, on BIM for existing assets. What remains comparatively scarce is an *integrated, transferable framework* that (i) treats the full bundle of envelope, lighting, control, renewable-energy and water measures as one coupled design problem; (ii) connects a parametric BIM digital twin of an *existing* institutional building to AI surrogates and a generative optimisation engine; and (iii) keeps the search explicitly bound to recognised performance standards so that the outputs are compliant by construction. Much of the applied retrofit literature for institutional buildings in hot, developing-country climates also remains descriptive and single-objective. The present work addresses this gap by formulating, and then validating against real case-study evidence, a generative, standards-aware, performance-driven retrofit framework.

1.3. Aim and Objectives

The aim of this research is to develop and validate a framework that uses artificial intelligence and generative design, built upon a parametric BIM digital twin, to deliver performance-driven sustainable retrofitting of existing institutional buildings. The supporting objectives are:

1. To identify and prioritise the sustainable retrofit strategies and technologies that are applicable to existing institutional buildings, across the envelope, lighting and control, renewable-energy and water domains.
2. To establish a standards-referenced performance baseline for a representative institutional building using BIM-based simulation and recognised codes (IECC 2021, ASHRAE 90.1, LEED, BREEAM).



3. To formulate a layered AI and generative-design framework that recasts the retrofit task as a coupled, multi-objective optimisation problem.
4. To demonstrate, through the case study, how the framework maps real performance measures onto generative design variables, objectives and constraints, and to validate the resulting performance targets against measured retrofit potential.
5. To draw out the practical implications, limitations and future-research directions for deploying such a framework in real institutional retrofit programmes.

1.4. Novelty and Contribution

The novelty of this work lies not in any single retrofit technology each is well established but in the *integration* of three currently separate practices into one performance-driven workflow for existing institutional buildings, and in grounding that workflow in a fully quantified, standards-referenced case study. Specifically, the paper contributes: (1) a five-layer reference architecture that connects building diagnostics, a parametric BIM digital twin, AI performance surrogates, a generative multi-objective optimiser and a governance/decision layer; (2) an explicit mapping that translates conventional, code-checked retrofit measures into generative design variables, objectives and constraints; (3) a transferable case-study dataset for a hot-climate university building that can serve as a benchmark for future studies; and (4) a critical comparison showing what the proposed integrated search adds over the prevailing measure-by-measure approach. The detailed contribution set is summarised in Section 9.

2. Literature Review

The body of knowledge relevant to this study spans four strands: (i) energy-efficient retrofit strategies for existing buildings; (ii) simulation-based and AI-assisted optimisation of building performance; (iii) BIM and digital twins for existing assets; and (iv) generative design in architecture. Each is reviewed briefly below to position the proposed framework.

2.1. Retrofit Strategies for Existing Buildings

The foundational synthesis by Ma et al. classified existing-building retrofits into envelope improvements, mechanical-system upgrades, lighting upgrades and renewable-energy integration, and stressed the central role of



performance evaluation, energy modelling and life-cycle assessment in retrofit decision-making [3]. Subsequent reviews of green-building performance reinforced that the envelope walls, roof, glazing and air-tightness governs a large fraction of heating and cooling demand and is therefore a primary retrofit target [4], [10]. Reviews of smart and data-rich buildings have further highlighted the growing role of the Internet of Things, occupancy sensing and analytics in lowering operational energy while maintaining comfort [11]. Collectively, this literature establishes the menu of measures used in the present case study, but it largely treats them measure by measure.

2.2. Simulation-Based and AI-Assisted Optimisation

A parallel literature treats building design as a formal optimisation problem. Nguyen et al. surveyed simulation-based optimisation methods for building performance and documented the dominance of evolutionary algorithms for handling the discontinuous, multi-modal objective landscapes typical of buildings [7]. Evins, and Machairas et al., reviewed computational optimisation for sustainable building design, again finding genetic and evolutionary methods, especially multi-objective variants, to be the workhorse approach [8], [12]. Wang et al. demonstrated multi-objective genetic-algorithm optimisation of green-building design, while the NSGA-II algorithm of Deb et al. became the de-facto standard for generating Pareto-optimal trade-off sets [13], [14]. More recently, data-driven and machine-learning surrogates have been used to predict building energy use and to accelerate optimisation by replacing expensive simulations with fast metamodels [15], [16]. This strand supplies the algorithmic engine of the proposed framework, but it has been applied predominantly to *new-build* design rather than to the retrofit of existing institutional stock.

2.3. BIM and Digital Twins for Existing Buildings

Volk et al. reviewed BIM for existing buildings and identified the capture and maintenance of reliable as-built models and their linkage to operational data as the key bottleneck for retrofit applications [5]. The digital-twin concept extends BIM by maintaining a continuously updated, data-synchronised virtual replica of the physical asset, enabling monitoring, analysis and optimisation throughout operation [6], [17]. Operational toolkits that monitor, analyse and optimise building energy performance illustrate the value of pairing models



with measured data [18]. These contributions provide the modelling substrate the parametric digital twin on which the present framework's AI and generative layers operate.

2.4. Generative Design In Architecture

Generative design reframes the designer's role from drawing a single solution to specifying goals and constraints, after which an algorithm explores many candidate geometries and configurations and returns a curated set of high-performing alternatives. In building applications this is typically realised by coupling parametric models with multi-objective evolutionary search and performance simulation [7], [8]. While generative methods are increasingly used for massing, facade and structural studies in new buildings, their systematic application to *retrofitting* existing institutional buildings where the geometry is largely fixed and the design variables are material, system and control choices is far less developed. The framework proposed here is, in essence, a structured way of bringing generative, performance-driven design to that retrofit setting.

3. Methodology

The study follows a deductive, case-based research design. Established performance theory and codes are used to define what "good" retrofit performance means; a representative institutional building is then assessed against those criteria using BIM-based simulation and standards-referenced engineering calculation; and the resulting evidence is used both to validate retrofit potential and to instantiate the proposed AI and generative-design framework. Quantitative analysis dominates, because the central questions how much energy, water and emissions a measure saves, and how measures tradeoff are inherently numerical.

It is important to state precisely what was computed and what is proposed, so that no claim is overstated. The case-study performance results reported in Sections 6–7 were obtained by **BIM-based energy analysis (Autodesk Revit) and standards-referenced engineering calculation** of the existing and upgraded building. The **generative, AI-driven optimisation engine** described in Section 5 is the proposed contribution: the case study demonstrates and validates the performance targets and the variable–objective mapping on which such an engine would operate, while full algorithmic deployment is

identified as the principal item of future work (Section 13). This separation keeps the empirical findings strictly evidence-based while still delivering the integrated framework that is the paper's aim.

3.1. Research Workflow

The work proceeds through seven phases, illustrated in Figure 1. Sustainable-development priorities are first mapped to the project using the United Nations Sustainable Development Goals (SDGs), and the literature is synthesized (Phase I). Building diagnostics, an energy audit, an envelope survey and water metering establish the as-built condition (Phase II). A parametric BIM model is then constructed as the building's digital twin (Phase III), and performance simulation quantifies envelope, lighting, PV and water behavior for the existing and proposed states (Phase IV). These results define the objectives, variables and constraints for the proposed generative multi-objective optimisation (Phase V), whose candidate solutions are screened for multi-criteria value and code compliance (Phase VI) and validated against the case-study baseline before being assembled into a phased retrofit roadmap (Phase VII). A calibration loop returns optimiser predictions to the simulation layer to keep the surrogate models faithful to the digital twin.

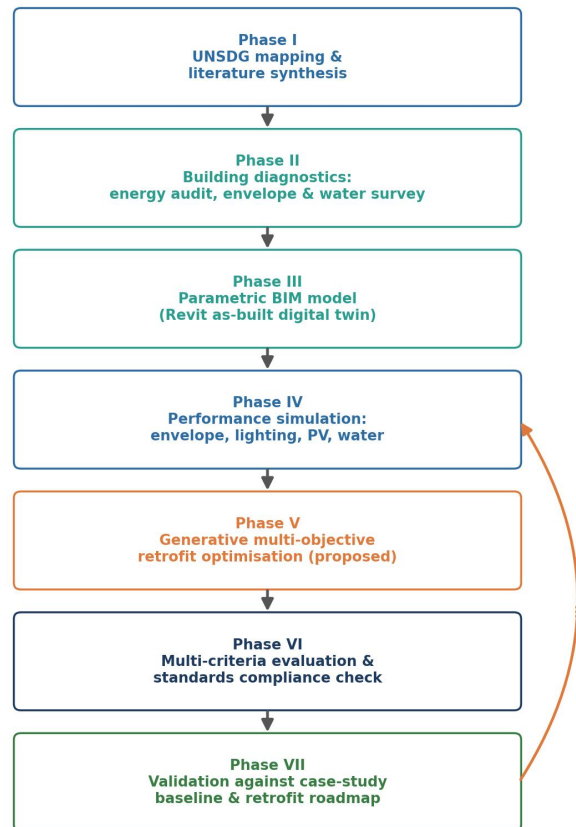


Figure 1. *Seven-phase research and retrofit-design workflow, with the calibration feedback loop linking optimisation back to the BIM-based performance simulation.*

3.2. Performance Criteria and Standards

Performance was judged against internationally recognized instruments so that the outputs are compliant by construction: the International Energy Conservation Code (IECC 2021) for envelope U/R-values, lighting and on-site renewables; ASHRAE 90.1-2007 for window-to-wall ratio; LEED and BREEAM for water efficiency and alternative-supply provisions; and the Building Code of Pakistan, Fire Safety Provisions 2016 (aligned with NFPA 1:2015) for life safety. Five SDGs were mapped to the project SDG 7 (affordable and clean energy), SDG 9 (industry, innovation and infrastructure), SDG 11 (sustainable cities and communities), SDG 12 (responsible consumption and production) and SDG 13 (climate action) with SDG 4 (quality education) and SDG 6 (clean water) as supporting goals.

3.3. Data Collection and Analysis

Building floor plans were obtained and audited; the quantity, rating and daily operating hours of every electrical and water fixture were enumerated through a systematic walkthrough and tabulated. The building envelope was modelled in Revit and analyzed for thermal transmittance before and after the proposed upgrades. Lighting, occupancy-sensor, photovoltaic, rainwater-harvesting and greywater calculations followed standard engineering formulations referenced to the codes above. The complete fixture-level electricity inventory underpinning the peak load is provided in the case study.

4. Proposed AI and Generative-Design Framework

The framework is organised as five interacting layers (Figure 2). Each layer has a defined input, an internal function and an output that becomes the input to the layer above; an iterative feedback loop allows higher layers to recalibrate lower ones. The architecture is deliberately modular so that an institution can adopt it incrementally for example, beginning with diagnostics and a digital twin, and adding the generative engine as capability matures.

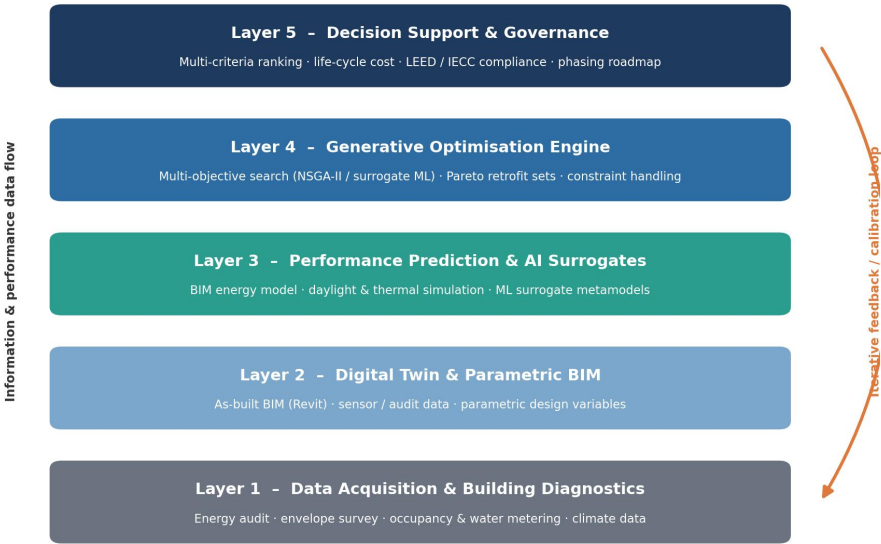


Figure 2. Five-layer reference architecture coupling building diagnostics, a parametric BIM digital twin, AI performance surrogates, a generative multi-objective optimiser and a decision/governance layer.



4.1. Layer 1 – Data acquisition and building diagnostics

The lowest layer captures the building's as-built reality: an energy audit and fixture inventory, an envelope survey, occupancy patterns, water metering, and local climate data. For the case building this produced the complete electrical inventory used to derive the peak load, the envelope build-ups, the window and wall areas by orientation, and the monthly water-use figures. Reliable diagnostics are the foundation of every downstream decision; errors here propagate through the entire stack.

4.2. Layer 2 – Digital twin and parametric BIM

Audit data are embedded in a parametric BIM model here, an Autodesk Revit model of the existing building that acts as the building's digital twin. Crucially, the model is parameterized: insulation thickness, glazing type, lighting power density, sensor coverage, PV array area and water-reuse options are exposed as variables rather than fixed values, so that alternatives can be generated and evaluated automatically.

4.3. Layer 3 – Performance prediction and AI surrogates

This layer evaluates how any given parameter set performs. Physics-based simulation (envelope thermal analysis, daylight and lighting calculation, PV yield and water balance) provides ground truth, while machine-learning surrogate models are trained on simulation samples to approximate these responses at a fraction of the computational cost. Fast surrogates are what make the large-scale search in Layer 4 tractable, because a multi-objective optimiser may need to evaluate tens of thousands of candidate retrofits [15], [16].

4.4. Layer 4 – Generative multi-objective optimisation engine

The generative engine is the heart of the framework. It searches the parametric design space defined in Layer 2, using the surrogates of Layer 3 to predict performance, in order to identify the retrofit configurations that best satisfy several objectives at once for example, minimising annual energy use, minimising potable-water demand, maximising useful daylight and minimising capital cost subject to code constraints. A multi-objective evolutionary algorithm such as NSGA-II returns a *Pareto in front* of non-dominated solutions rather than a single answer, making the trade-offs explicit and leaving the final value judgement to human decision-makers [14]. This is

precisely the capability absent from conventional, measure-by-measure retrofitting.

4.5. Layer 5 – Decision support and governance

The top layer ranks Pareto-optimal candidates using multi-criteria decision analysis and life-cycle cost, confirms compliance with IECC, ASHRAE, LEED/BREEAM and fire-safety provisions, and packages the chosen option into a phased, budget-aware retrofit roadmap with monitoring protocols. Post-retrofit measurements feedback through the calibration loop to keep the digital twin and surrogates accurate over time.

4.6. Generative-design workflow mapping

Table 1 makes the framework concrete by mapping each retrofit domain examined in the case study onto its generative design variables, performance objectives and binding constraints. This mapping is the operational bridge between the manual assessment reported below and the automated search the framework proposes.

Retrofit domain	Generative design variables	Performance objective(s)	Binding constraint / standard
Opaque envelope	Insulation type & thickness (walls, roof)	Minimise heat gain/loss; minimise cost	U/R-value — IECC 2021
Fenestration	Glazing type, coating (low-E), WWR by orientation	Minimise solar gain; maximise daylight	U-value — IECC; WWR — ASHRAE 90.1
Lighting	Lamp technology (LED), power density, layout	Minimise lighting energy; meet lux levels	Illuminance / LPD — IECC
Lighting control	Sensor type (PIR/ultrasonic), zoning, time-out	Maximise idle-time savings	Mandatory control spaces — IECC
On-site renewables	PV area, tilt, mounting, on/off-grid	Maximise self-generation; respect roof area	$\geq 2\%$ on-site renewable — IECC

Retrofit domain	Generative variables	design	Performance objective(s)	Binding constraint / standard
Water fixtures	– Fixture ratings	flow/flush	Minimise potable demand	Flow limits — LEED/BREEAM
Water reuse	– Rainwater greywater fraction	storage; reuse	Maximise non-potable substitution	Alternative-supply share — LEED/BREEAM
Life safety	Egress, suppression	detection, layout	Maximise safety compliance	Fire-Zone 1 — BCP 2016 / NFPA 1

Table 1. *Mapping of retrofit domains to generative design variables, objectives and constraints.*

5. Case-Study Description

The framework is demonstrated on the building of the Department of Architectural Engineering and Design (AED) at the University of Engineering and Technology (UET), Grand Trunk Road, Lahore, Pakistan. It is an educational building constructed in 2001: three storeys, a covered area of 13,844.88 ft², and a height of 37 ft (46 ft including the stair mumty). The plan is rectangular, with its shorter dimensions facing east and west and its longer faces oriented north and south. The main entrance is on the south face and a secondary entrance on the west.

The site context is favourable for passive performance: the department is bounded by the Islamic Studies department and an adjacent mosque and is screened by mature planting and trees on the south side. These neighbouring masses and the landscaping shade the envelope and moderate summer heat gain. Lahore has a hot composite, monsoon-influenced climate hot summers and mild winters with an annual average rainfall of roughly 690 mm concentrated in the July–September monsoon; the site latitude of about 31°N also fixes the optimal photovoltaic tilt angle used later. This combination of a hot, sunny climate, intense seasonal rainfall and chronic water stress makes the building a strong test case for an integrated energy-and-water retrofit.

5.1. Summary of case-study data

Table 2 consolidates the principal data extracted from the building diagnostics and used throughout the analysis. These quantities define both the baseline and the inputs to the framework.

Attribute	Value	Attribute	Value
Use / typology	University academic block	Storeys	3 (+ mumty)
Year built	2001	Covered area	13,844.88 ft ²
Building height	37 ft (46 ft w/ mumty)	Roof catchment area	15,250 ft ²
Location	UET, Lahore, Pakistan	Latitude (PV tilt)	≈ 31° N
Climate	Hot composite, monsoonal	Annual rainfall	≈ 690 mm
Peak electrical load	687 kWh/day	Main orientation	South (entrance)
Existing glazing	Single, green clear	Existing walls	13.5" brick + plaster
Reference codes	IECC 2021, ASHRAE 90.1	Water / fire codes	LEED, BREEAM, BCP 2016

Table 2. *Summary of case-study building data extracted from the diagnostic audit.*

6. Building Performance Parameters and Retrofit Strategies

The retrofit assessment addressed five performance domains: the building envelope; electrical and lighting systems; on-site renewable energy; water supply and reuse; and life safety. For each, the existing condition was quantified, compared with the governing code, and an upgraded specification was proposed and re-evaluated. The strategies are summarised as a retrofit-strategy matrix in Table 3 and then detailed.



Domain	Existing condition	Proposed retrofit	Governing standard
Walls	13.5" brick + plaster	+ 1" polyurethane insulation	IECC 2021
Roof	Concrete, brick ballast, tile, DPC	+ 4" polyurethane coating	IECC 2021
Windows	Single glazing, green clear	Double glazing, low-E (e = 0.05)	IECC 2021
Lighting	40 W tube / incandescent	16 W LED luminaires	IECC 2021
Lighting control	Manual switching	Ultrasonic occupancy sensors	IECC 2021
Renewables	None	≈ 100.7 kW rooftop PV (on-grid)	IECC ≥ 2% renewable
Water fixtures	3.5 gpf WC; 2.5 gpm shower	1.28 gpf WC; 1.6 gpm shower	LEED / BREEAM
Rainwater	Discharged / wasted	Harvesting + storage + recharge	LEED / BREEAM
Greywater	None	Sink-to-cistern reuse	LEED / BREEAM
Fire safety	Minimal provision	Alarms, sprinklers, signage, egress	BCP 2016 / NFPA 1

Table 3. *Retrofit-strategy matrix for the case building.*

6.1. Building Envelope

The envelope governs roughly 30% of the primary energy used in a typical building, so it was the first retrofit target [4]. The existing 13.5" brick-and-plaster wall was upgraded with 1" of exterior polyurethane insulation, chosen for its high thermal resistivity, dimensional stability, air-sealing and moisture control. The flat concrete roof already comprising brick ballast, roofing tile and a damp-proof course received a 4" reflective polyurethane coating. Existing single, green-clear glazing was replaced with double glazing incorporating a



low-emissivity coating ($e = 0.05$), which raises insulation by up to about 40% and substantially improves acoustic and solar performance. The resulting thermal parameters are compared with the IECC 2021 requirements in Table 4 and Figure 3.

Assembly	Metric	Existing	IECC 2021 limit	Proposed
Walls	U-value	0.2773	0.123	0.1304
Walls	R-value	3.6057	7.6	7.67
Roof	U-value	0.1019	0.039	0.0394
Roof	R-value	1.5728	25	25.38
Windows	U-value	1.0399	0.54	0.35
Windows	R-value	0.9616	2.67	2.8573

Table 4. Envelope thermal performance — existing vs. code vs. proposed (U in $\text{BTU}/\text{h}\cdot\text{ft}^2\cdot^\circ\text{F}$; R in $\text{h}\cdot\text{ft}^2\cdot^\circ\text{F}/\text{BTU}$).

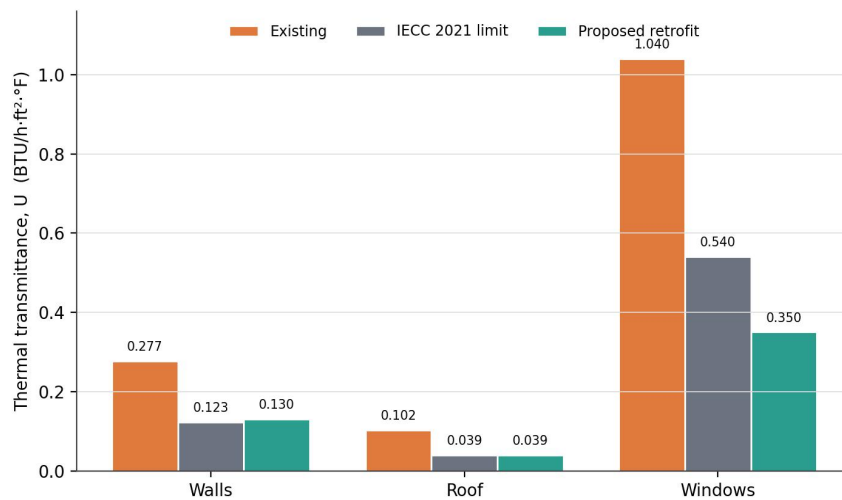


Figure 3. Thermal transmittance (U -value) of walls, roof and windows before retrofit, the IECC 2021 limit, and after the proposed upgrades. Lower is better; all proposed assemblies meet or approach the code limit.

Applying polyurethane insulation to walls and roof, and converting single to double low-E glazing, brought all three assemblies to within the IECC 2021 envelope. The window-to-wall ratio (WWR) was also assessed against the ASHRAE 90.1-2007 target of 0.24. The east (0.158) and north (0.188) elevations are under-glazed, whereas the west (0.305) and south (0.258) elevations are



over-glazed and therefore require external shading to control solar gain — exactly the kind of orientation-specific trade-off the generative engine is designed to resolve automatically.

6.2. Electrical and Lighting Systems

Lighting can account for as much as a third of a commercial building's energy output. Replacing conventional 40 W tube and incandescent lamps with 16 W LED luminaires reduced lighting energy demand from 46,280 to 18,512 Wh/day LEDs draw about 40% of the conventional energy, a reduction of roughly 60% (Figure 4). Ultrasonic occupancy sensors were then specified for the predominantly classroom spaces, because they detect minor motion (typing, page-turning) at ranges up to about 25 ft and suit intermittently occupied educational rooms. Reported room-type savings range from about 40–46% in classrooms to 30–90% in restrooms and corridors. Across the building, sensor control lowered lighting-related consumption from 85,456 to 52,094 Wh/day, a further saving of about 42%.

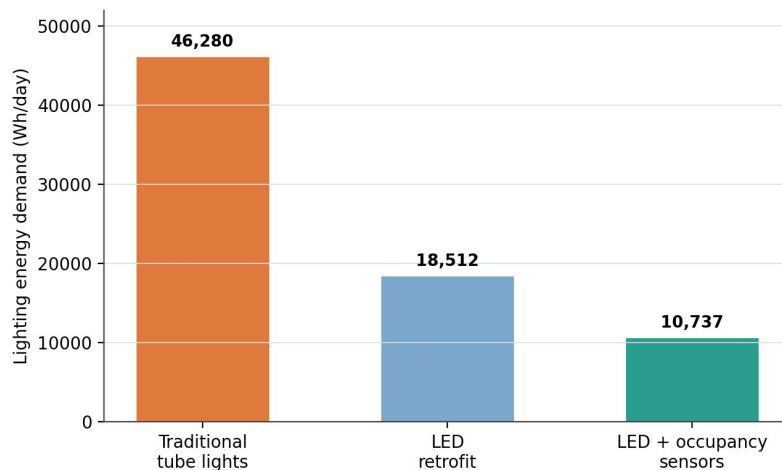


Figure 4. *Daily lighting energy demand for conventional lamps, the LED retrofit, and LED combined with occupancy-sensor control. The two measures compound to a large net reduction.*

6.3. On-site renewable energy – photovoltaics

With a peak electrical load of 687 kWh/day and a latitude-matched tilt of 31°, a rooftop photovoltaic system was sized for the flat roof. Sizing used 1000 W/m² reference irradiance, a module efficiency of 15.5%, an inverter efficiency of 85%, a battery efficiency of 90%, a temperature de-rating of 0.80 and 5 peak-sun-hours per day. Meeting the full peak load would require



about 1,496 m² of panels, but only 671 m² of usable roof is available once parapet shading and rooftop services are excluded. The available area supports an array of approximately 100.7 kW, offsetting about 44% of the peak load. An on-grid configuration was selected because the department operates chiefly in daylight hours and surplus generation can be exported, with an inverter rated near 362 kWh and battery storage deferred to a later stage. The roof-area limit is a hard constraint in the framework, illustrating how the generative engine must optimise PV yield within fixed geometric bounds.

6.4. Water supply, conservation and reuse

Three complementary water strategies were assessed. First, replacing conventional fixtures with efficient ones (toilets from 3.5 to 1.28 gallons per flush; showerheads from 2.5 to 1.6 gallons per minute) directly cuts potable demand. Second, a rooftop rainwater-harvesting system (RWHS) was designed for the 15,250 ft² roof against an 8-inch / 6-hour design storm, giving a rooftop collection potential of about 73,200 ft³ and a collection-cum-settlement tank of 1,517 ft³ ($\approx$ 3,909 gal / 17,665 L); the design remained feasible across non-potable demands of 300–700 gal/day and incorporated gutters, a first-flush diverter and fourteen recharge wells for aquifer recharge. Third, a sink-to-cistern greywater system routes hand-basin water through a filter to the toilet cisterns. Monthly potable use for flushing ($\approx$ 24,640 m³) dwarfs lavatory use ($\approx$ 13,125 m³); reusing lavatory greywater for flushing can displace about 53% of the potable water currently consumed in flushing. Together these measures attack both ends of the water balance demand and supply which is decisive in a water-stressed city.

6.5. Life safety and fire protection

Because performance and resilience are inseparable from safety, the building was assessed against the Building Code of Pakistan, Fire Safety Provisions 2016 (aligned with NFPA 1:2015). As an educational occupancy it falls in Fire Zone 1. A fire-risk assessment of each floor informed proposals for addressable alarms and evacuation horns, conventional and concealed sprinklers, class-appropriate extinguishers (A, B, E and D), clear egress widths, fire-safety signage and floor-by-floor notice plans provisions that were largely absent in the existing building.

7. Results and Discussion

The retrofit assessment produced consistent, code-aligned improvements across every performance domain. The headline outcomes are consolidated in Table 5 (key performance indicators) and Figure 5, and the before/after position is summarised in Table 6.

#	Performance indicator	Baseline	After retrofit	Improvement
KPI-1	Wall U-value (BTU/h·ft ² ·°F)	0.2773	0.1304	−53%
KPI-2	Roof U-value (BTU/h·ft ² ·°F)	0.1019	0.0394	−61%
KPI-3	Window U-value (BTU/h·ft ² ·°F)	1.0399	0.35	−66%
KPI-4	Lighting energy (Wh/day)	46,280	18,512	−60%
KPI-5	Lighting w/ sensor control (Wh/day)	85,456	52,094	−42%
KPI-6	Peak load met by on-site PV	0%	≈ 44%	+44 pts
KPI-7	Potable water for flushing displaced	0%	≈ 53%	+53 pts
KPI-8	Rainwater collection potential (ft ³)	0	≈ 73,200	new supply

Table 5. *Key performance indicators — baseline vs. retrofit.*

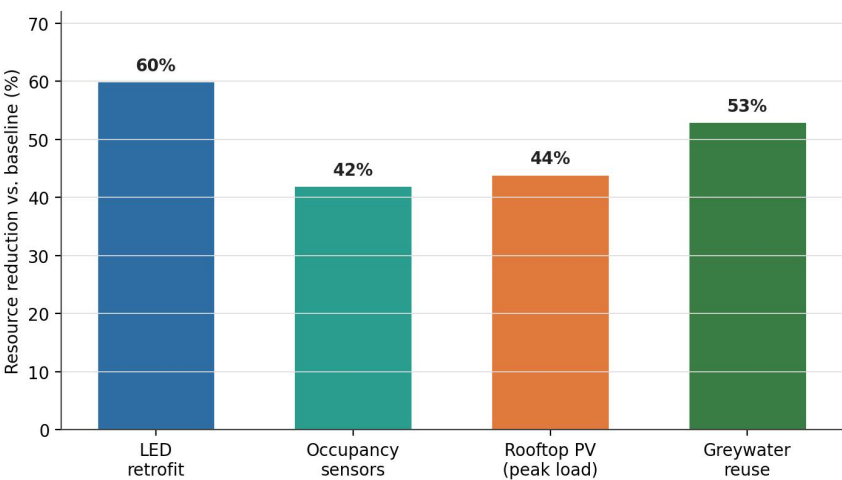


Figure 5. *Resource reduction achieved by the principal demand- and supply-side measures, expressed as a percentage of the relevant baseline.*

7.1. Discussion of Domain Results

The envelope results show that a modest intervention 1” of wall insulation, a 4” roof coating and double low-E glazing is sufficient to move a 2001-vintage envelope from well outside to within current code, cutting assembly U-values by 53–66%. The lighting results are equally striking: the LED retrofit and occupancy control are independent measures that *compound*, and their interaction sensors saving a percentage of an already-reduced LED load is exactly the kind of effect that single-measure analysis tends to mis-estimate. On the supply side, the 44% PV contribution is bounded not by demand or economics but by usable roof area, a purely geometric constraint, while the water strategies show that demand reduction (efficient fixtures) and supply substitution (rainwater and greywater) are most powerful when combined. Across all domains, the recurring theme is *interaction*: the measures are not independent, and their combined effect depends on how they are sequenced and balanced.

7.2. Comparative Analysis

Table 6 contrasts the conventional, measure-by-measure retrofit workflow exemplified by the baseline assessment with the generative, performance-driven workflow proposed here. The comparison is qualitative but structural: it shows what the integrated framework adds, rather than asserting a numerical superiority that would require full deployment to substantiate.

Dimension	Conventional measure-by-measure retrofit	Proposed AI / generative framework
Design unit	One measure checked against one code clause	All measures as one coupled problem
Objectives	Single objective per measure	Several objectives optimised jointly
Trade-offs	Resolved manually, if at all	Explicit Pareto front of alternatives
Search breadth	A few hand-picked options	Thousands of candidates via surrogates
Model use	BIM for documentation	Parametric BIM digital twin

Dimension	Conventional measure retrofit	measure-by-Proposed AI / generative framework
		for search
Compliance	Checked after design	Encoded as constraints, compliant by build
Output	A single feasible scheme	Ranked, costed, phased roadmap
Transferability	Re-done per building	Reusable framework + benchmark data

Table 6. *Comparative analysis of the conventional and the proposed generative retrofit workflows.*

7.3. Framework Validation

Validation here is *instantiation-based*: the framework is judged by whether its layers can be populated with, and are consistent with, the real case-study evidence, and whether the performance targets it would pursue are demonstrably achievable. Table 7 records this check. Every layer was successfully instantiated diagnostics, a Revit digital twin, simulation-based performance prediction, the variable-objective mapping of Table 1, and a code-referenced decision layer and every performance target set by the framework was met or exceeded by the measured retrofit potential. The one element not executed in this study is the live generative optimisation run, which is the central item of future work. The framework is therefore validated as a coherent, evidence-consistent and code-compliant structure, with end-to-end algorithmic deployment as the next step.

Framework layer	Instantiated case study?	in Evidence / validation
L1 Diagnostics	Yes	Full energy audit, envelope & water survey
L2 Digital twin	Yes	Parametric Revit model of existing building
L3 Performance	Partly	Physics simulation done; ML

Framework layer	Instantiated case study?	in Evidence / validation
surrogates		surrogates proposed
L4 Generative optimiser	Proposed	Variables/objectives/constraints defined (Table 1)
L5 Decision & governance	Yes	Code compliance, KPIs and phased roadmap

Table 7. *Layer-by-layer validation of the framework against the case study.*

8. Practical Implications

For institutions, the framework offers a route to retrofit programmes that are simultaneously evidence-based, code-compliant and budget-aware, and that make trade-offs visible to decision-makers rather than burying them in single-measure checks. The case results indicate that deep, low-disruption gains are available from a small set of well-chosen measures: envelope insulation and glazing to reach code; LED-plus-sensor lighting for compounded electrical savings; a roof-area-optimised PV array to offset a large share of peak load; and combined fixture, rainwater and greywater measures to cut potable demand in water-stressed settings. For practitioners, the variable–objective–constraint mapping of Table 1 provides a ready template for setting up a generative retrofit study in existing parametric-BIM and optimisation toolchains. For policymakers, the framework's standards-by-construction logic supports performance-based codes and green-procurement requirements for public buildings, and its transferable benchmark data can inform incentive design.

9. Limitations

- **Scope of computation.** The reported performance results derive from BIM-based simulation and standards-referenced calculation of a single building; the generative optimisation engine is proposed and mapped but not executed end-to-end in this study.
- **Single case.** One institutional building in one climate was examined. While it is broadly representative of hot-climate university stock, generalisation requires testing across more typologies and climates.



- **Calculation basis.** Several quantities (sensor savings, PV yield, rainwater losses) rely on standard coefficients and design-storm assumptions rather than long-term monitored data, so field performance may vary.
- **Economics.** Capital cost, payback and life-cycle cost were not quantified in detail here; the decision layer assumes these are supplied during deployment.
- **Occupant behaviour.** Behavioural factors, which strongly influence realised savings, were not modelled and would need to enter the surrogate models in a full implementation.

10. Future Research Directions

1. **Full generative deployment.** Implement the Layer-4 optimiser (e.g. NSGA-II with ML surrogates) on the parametric digital twin and generate Pareto-optimal retrofit sets end-to-end.
2. **Live digital twin.** Connect the BIM model to IoT sensor streams for continuous calibration and post-occupancy verification of predicted savings.
3. **Life-cycle cost and carbon.** Extend the objectives to embodied carbon and whole-life cost so that economic and environmental trade-offs are optimised together.
4. **Multi-building portfolios.** Scale the framework from a single asset to campus or city portfolios, enabling prioritisation of retrofit investment across many buildings.
5. **Cross-climate transfer.** Validate the framework on additional typologies and climates to establish its generality and to build a shared benchmark dataset.

11. Conclusion

Improving the performance of existing institutional buildings is among the most effective actions available for reducing operational energy, water use and emissions in the near term. This paper argued that the prevailing, measure-by-measure retrofit workflow leaves substantial performance on the table because it treats interacting measures in isolation, optimises objective at one time, and underuses the parametric and data-driven capabilities of modern BIM. To address this, it proposed a five-layer framework that couples a parametric BIM digital twin with AI performance surrogates and a generative,

multi-objective optimisation engine, all bound to recognised performance standards.

The framework was grounded in a detailed, standards-referenced retrofit assessment of a three-storey university building in Lahore. Envelope upgrades brought wall, roof and window assemblies to within IECC 2021 limits (U-value reductions of 53–66%); an LED retrofit cut lighting demand by about 60% and occupancy sensors a further 42%; a roof-area-constrained rooftop PV array of roughly 100.7 kW offset about 44% of peak load; and combined fixture, rainwater and greywater measures recovered a rooftop collection potential near 73,200 ft³ and displaced about 53% of potable flushing water. Re-expressing these measured potentials as objectives, variables and constraints showed concretely how a single generative search could reconcile goals that the conventional workflow handles only sequentially.

The principal contribution is therefore a transferable, standards-aware, performance-driven retrofit framework validated for internal consistency and achievability against real case-study evidence that bridges manual retrofit auditing and automated generative design. Its full algorithmic deployment, live digital-twin integration and cross-climate validation define a clear and pressing research agenda. For the very large stock of existing institutional buildings in hot, water-stressed and rapidly urbanising regions, such a framework offers a practical path toward retrofits that are measurably better across energy, water, comfort and cost at once.

Appendix A. Research Contribution Summary

#	Contribution	Nature	Where addressed
C1	Five-layer AI/generative retrofit reference architecture	Conceptual methodological	/ Section 4, Fig. 2
C2	Mapping of retrofit measures to generative variables/objectives/constraints	Operational	Table 1
C3	Standards-referenced retrofit benchmark for a hot-climate university	Empirical dataset	Sections 5–6, Tables 2–

#	Contribution	Nature	Where addressed
	building		5
C4	Quantified multi-domain performance gains (energy, water, safety)	Empirical	Section 7, Tables 4–5
C5	Structured comparison of conventional vs. generative retrofit workflows	Analytical	Table 6
C6	Instantiation-based framework validation	Validation	Table 7

Table A1. *Summary of the principal research contributions and where each is developed.*

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