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Building Information Modeling For The Built Environment Optimization

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ABSTRACT

This article presents measured performance results of a BIM-focused machine-learning (ML) optimization process for a 4000 sq ft mental-health rehabilitation center in central India. The process associated an Autodesk Revit BIM with Insight/EnergyPlus energy modeling, Radiance-based daylighting simulation, and a surrogate-assisted multi-objective genetic algorithm. In comparison with the baseline solution, the optimized plan resulted in significant improvements in daylight autonomy, thermal comfort, and natural ventilation and significantly cut down on annual energy consumption. Key outcomes are spatial Daylight Autonomy (sDA) +30 pp (50%→80%), Comfortable Thermal Hours +15 pp (75%→90%), Natural Ventilation Utilization +45 pp (40%→85%), and Energy Use Intensity −33% (150→100 kWh/m²·yr). The results show how tightly integrated BIM+AI workflows can expose non-obvious, climate-resilient design moves (orientation, glazing/shading mix, courtyard-driven stack effects) that collectively contribute to both sustainability and therapeutic quality in healthcare environments..

Keywords: *BIM, generative design, daylight autonomy, thermal comfort, Energy Use Intensity, healthcare, machine learning optimization*

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1. INTRODUCTION

Buildings contribute significantly to worldwide energy usage and operational carbon emissions, and among the most intensive typologies are healthcare buildings, with 24/7 occupancy, high indoor environmental quality (IEQ) standards, and reliability expectations on building services.

Mental-health and rehabilitation spaces within healthcare add programmatic complicating factors—regular daylight exposure, visual access to nature, acoustic tranquility, and thermal comfort—all correlating with therapeutic outcomes. Designing for these consequences is inherently multi-criteria: choices that enhance one measure (e.g., daylight) can reduce another (e.g., cooling load or glare), and the applicable trade-offs occur early, when massing, orientation, fenestration, and envelope properties are established. Building Information Modeling (BIM) provides a common, parametric description of geometry, material, and systems that can be used to assess performance during concept and schematic stages of design.

When BIM is combined with physics-based simulation—daylight (Radiance family), energy and comfort (EnergyPlus/Insight), and airflow/ventilation analysis—it becomes feasible to measure the effects of design motions across a number of performance disciplines using a single source of truth. But full simulation over an extensive design space is computationally costly and time-limited in practice. Advances in surrogate modeling and multi-objective optimization (e.g., genetic algorithms supported by machine-learning regressors) make it possible to investigate more-extensive option sets, estimate performance quickly, and target high-fidelity simulations on promising solutions. This paper places a BIM-based, optimization-led workflow within the context of a small healthcare clinic in hot-summer, warm-winter climate central India.

The project brief—a ~4000 ft² mental-health rehabilitation center—balances patient well-being with operational efficiency. Design variables incorporate direction, aspect-specific window-to-wall ratios (WWR), glazing and shading strategies, selective envelope upgrades, and courtyard/clerestory configurations to improve daylight distribution and facilitate natural ventilation. Performance targets address: (1) improved spatial Daylight Autonomy (sDA), (2) increased adaptive thermal comfort band hours, (3) passive/natural ventilation use intensity, and (4) lowered annual Energy Use Intensity (EUI). Since these goals may be in conflict, we cast the problem as a multi-objective search for Pareto-optimal solutions and then choose an equally-balanced design depending on project priorities. The paper makes three main contributions.

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First, it shows an end-to-end BIM + physics simulation + surrogate-assisted optimization loop that can be run during early design with turn-around that is usable in practice. Second, it measures the size of possible cross-domain gains for a health care application case—demonstrating how well-coordinated orientation, glazing/shading, and stack effects driven by courtyards can increase daylight autonomy while decreasing cooling energy simultaneously. Third, it describes a collection of climate-adaptive design maneuvers and implementation practices (e.g., north-skewed glazing with calibrated south shading, high-albedo roofs, dual-aspect openables) applicable to comparable hot-climate buildings. The effort is driven by two real-world issues that apply to design teams: (i) the challenge of reasoning about compound performance outcomes when feedback is late or meager in the process, and (ii) the danger that single-metric optimization (for daylight or energy alone) causes regressions elsewhere (glare, comfort, ventilation potential).

By integrating optimization into a workflow based on BIM, we seek to move analysis "upstream," allowing evidence-based decision-making when form and facade are malleable and the cost of change is minimal.

2. BACKGROUND RESEARCH

2.1 Therapeutic healthcare design and mental-health environments

Evidence-based design demonstrates that the physical setting has a measurable impact on clinical outcomes and staff performance. Ulrich et al. (2008) integrate decades of research establishing evidence for the benefits of daylight, views, acoustic control, and spatial legibility in contributing to better patient outcomes and operating efficiency in hospitals.

In behavioral/mental-health settings, evidence-based interventions—visual art programs (Nanda et al., 2011) and controlled sensory environments—alleviate anxiety and agitation, supporting the argument for therapeutic cues in architecture.

Complementary appraisals (Huisman et al., 2012) point to the impact of light, noise, ventilation, and layout on satisfaction and safety and call for environmental performance to be integrated into design choices early on.

Clinical research also connects morning light with reduced psychiatric inpatient stay (Benedetti et al., 2001) and corroborates bright-light therapy in all disorders (Benedetti et al., 2014), emphasizing the value of daylight simulation and control to include in project briefs.

Hospice/behavioral-health design texts also contend for residential scale, external connection, and family accommodations to add dignity and comfort (Verderber & Refuerzo, 2006).

2.2 BIM as an integrative platform for healthcare facilities

BIM delivers a data-intensive, common model to organize intricate healthcare programs and as the "single source of truth" for simulation and analysis. Core texts (Eastman et al., 2011; Sacks et al., 2018) record BIM's lifecycle function through design, construction, and operations, and its capacity to output analysis-ready geometry and semantics (e.g., gbXML/IFC) for energy/daylight workflows.

Early surveys of industry (Becerik-Gerber & Rice, 2010) document perceived improvements in coordination and information management—advantages enhanced in dense MEP and safety-constrained hospital projects.

Recent healthcare-oriented research highlights BIM as an epicenter for algorithmic layout and performance iteration—for instance, Alavi et al. (2024) combine AI with BIM to create and compare hospital design options more methodically.

In addition to construction and design, BIM is more and more connected with digital transformation in healthcare and facilities management (Arayici et al., 2012; Sampaio et al., 2023), indicating a continuum where operations are supported by the as-built model, comfort tuning, and efficiency programs.

2.3 Simulation-driven decision support

Physics-based software quantifies performance goals. Radiance-line daylight models measure daylight autonomy and glare; EnergyPlus/Insight generate EUI, loads, and comfort values; and CFD or cross-ventilation computations analyze airflow performance. Methodological overviews highlight moving such analyses earlier in concept design, where their impact is strongest (Negendahl, 2015).

Interoperability remains a hindrance: Attia et al. (2013) recognize discrepancies between optimization software and early design stages, which instigate workflows in which BIM conducts multi-domain simulation orchestration.

Digital-twin formulations further relate simulation results to comfort and energy control in operation (Clausen et al., 2021).

2.4 AI/ML and multi-objective optimization in AEC

AI is reconfiguring design-space searching. Tests indicate machine learning can anticipate building energy and maximize thermal performance, allowing adaptive, data-rectilinear control (Adams & Mavromatidis, 2019).

At the same time, evolutionary and hybrid metaheuristics (such as NSGA-II with local adaptative search) prove useful for sophisticated hospital layout problems balancing adjacencies, circulation, and zoning (Huo et al., 2021).

Wider design-methods literature (Turrin et al., 2011) identifies performance-based form-finding with multi-objective compromise—an appropriate approach to bridging daylight, comfort, and energy in healthcare.

Practice threads emerging now—GAN/RL-augmented generative approaches (Chaillou, 2019) and BIM-based automated layout—indicate a short-term route to deploying intelligence within common design tools.

2.5 Behavioral health: environment, safety, and satisfaction

Systematic reviews connect spatial characteristics—openness, visibility, legibility, and daylight exposure—to lowered aggression and enhanced satisfaction for psychiatric inpatients (Ulrich, Bogren, & Lundin, 2018; Weber et al., 2022; Jovanović et al., 2020).

Psychiatric building morphology (Chrysikou, 2019) and data from general hospital settings (Huisman et al., 2012) align on the necessity for initial, quantitative inspections of light, acoustics, and ventilation.

These results correlate with home-scaled, nature-attached design shifts proved effective in hospice and end-of-life contexts (Verderber & Refuerzo, 2006)—implications that carry over to mental-health rehabilitation when brokered by safety and supervision requirements.

2.6 Synthesis and gap

The literature sets out to establish that (i) behavioral health treatment outcomes rely on exactly the same drivers of energy consumption (daylight, envelope, ventilation), (ii) BIM can be used to hub geometry/data for multi-domain simulation, and (iii) AI/ML combined with multi-objective optimization facilitate wide, effective exploration of opposing goals.

Yet some gaps remain: tool-chain friction in nascent workflows (Attia et al., 2013), few cross-domain objectives aligned with behavioral-health outcomes, and too few reproducible case studies integrating BIM, high-fidelity simulation, and ML surrogates within a single loop for mental-health buildings. This paper bridges that gap by executing a BIM + simulation + surrogate-aided multi-objective optimization process and measuring daylight, comfort, ventilation, and EUI trade-offs in an actual healthcare project.

3. METHOD

3. Methods

3.1 Case, BIM Platform, and Analysis Engines

Case & scope. The study optimizes a two-storey mental-health rehabilitation facility (built-up ≈ 4000 sq ft) with programmatic constraints on room sizes, corridors, and functional adjacencies.

BIM single source of truth**.** An Autodesk Revit 2024 model is parameterized (Rooms, Families, global params) to vary orientation, facade WWR by aspect, shading on/off, insulation levels, and selected layout moves (therapy/courtyard adjacency), while enforcing baseline compliance. Dynamo scripts read/write parameters and export analysis models.

Energy/thermal zoning. Revit's analytical model auto-generates core/perimeter zones; zones and constructions are exported via gbXML for EnergyPlus/Insight. Zoning was reviewed and tuned for large open areas.

Simulation stack.
• **Daylight:** Radiance-based annual runs from the BIM export → sDA and illuminance distributions.

• **Energy & comfort: EnergyPlus via Insight** → EUI, peak loads, hourly operative temperature. Local climate file (Sehore/Bhopal).

• **Ventilation:** Cross-ventilation calculations + CFD spot checks for selected cases to quantify ACH and passive hours.

3.2 Design Variables and Constraints

1. Design Variables

We define the design parameter vector as:

$x=[\theta,WWR_n,WWR_s,d_i,S_r]$........(3.1)

Where:

θ: Building orientation angle

WWR_n, WWR_s: Window-to-wall ratios for North and South

d_i: Depth of interior room i

S_r: Shading ratio (% facade area shaded)

2. **Objective Functions**

Daylight Autonomy (DA):

$$DA(x)\frac{\sum_{i=1}^{N} T_i^{300}}{\sum_{i=1}^{N} T_i^{total}}.........(3.2)$$

(Percent of time rooms receive ≥300 lux)

Thermal Comfort (TC):

$$TC(x)\frac{\sum_{t\in T} 1\{|T_{in}(t) - T_{comfort}(t)| < \Delta T\}}{|T|}.........(3.3)$$

(Fraction of hours within comfort temperature band)

Natural Ventilation Potential (NVP):

$$NVP(x)=\frac{\sum_t V_{nat\,(t)}}{\sum_t V_{req\,(t)}}.........(3.4)$$

(Ratio of natural to required airflow)

Annual Energy Use (AEU):

$$AEU(x)= \sum_{i=1}^{T}[E_{HVAC}\ (t) + E_{lighting}\ (t)]........(3.5)$$

3. **Multi-Objective Optimization Problem**

minimizef(x)=[−DA,−TC,−NVP,AEU].....(3.6)

Subject to:

Total Area: A_{total}=4000 sqft

Functional constraints: min room size, corridor width, etc.

4. OPTIMIZATION WITH SURROGATE MODEL AND GENETIC ALGORITHM

ML model predicts $\hat{f}(x)$

Genetic Algorithm evolves population

Each generation:

Evaluate population via $\hat{f}(x)$

Select, crossover, mutate

Update surrogate model periodically

Convergence if:

$$\frac{||f_{best}^{(g)} - f_{best}^{(g-1)}||}{||f_{best}^{(g-1)}||} < \epsilon.........(3.7)$$

After about 50 generations of optimization (evaluating ~500 design candidates in total), the process converged on a design that provided an excellent trade-off among the goals. This final optimized design was then fully simulated and analyzed to obtain detailed performance data, which we present in the next section. Importantly, while multiple alternatives were explored during the AI optimization, report here only on the baseline (original design) and the optimized final design, to focus on the end result of the ML-guided process.

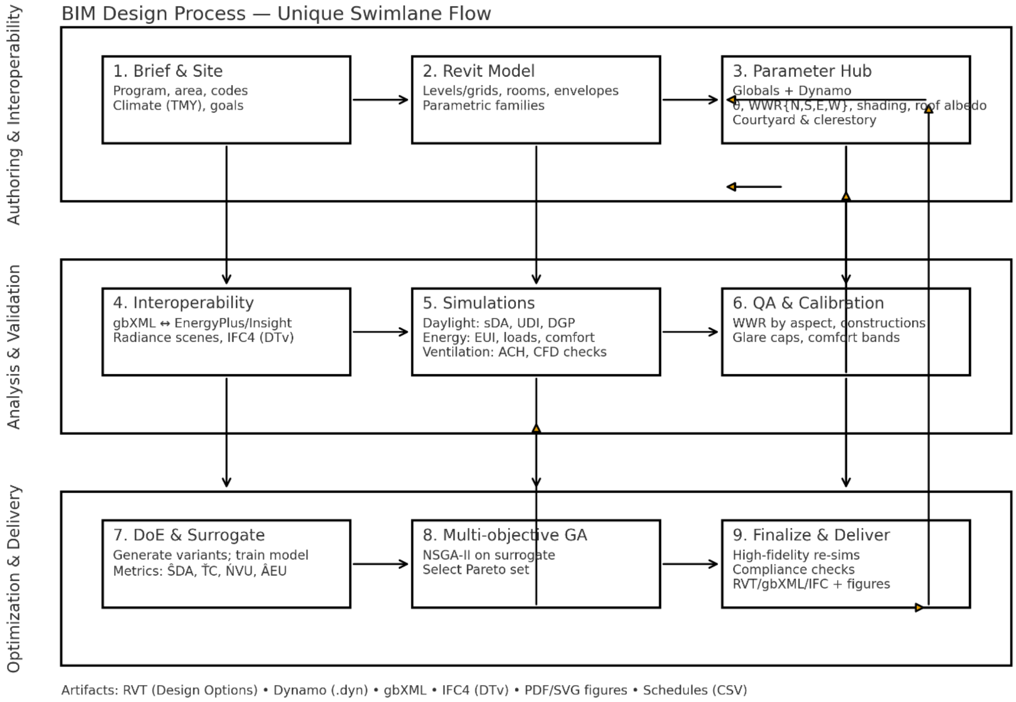

Fig 1. BIM-centered research workflow

Fig 1. This study follows a BIM-centered research workflow structured in three phases—Authoring & Interoperability, Analysis & Validation, and Optimization & Delivery. First, a parametric Revit model is created from the project brief (program, codes, climate) and organized as a single source of truth; a parameter hub (global parameters with Dynamo) exposes early design variables, including orientation (θ), façade-wise WWR, shading depth, roof albedo, and courtyard/clerestory controls. The analytical model is then exported to physics engines (gbXML to EnergyPlus/Insight for energy and comfort, Radiance scenes for daylight, and IFC4 for archival checks). Annual simulations compute sDA/UDI/DGP, EUI/loads/adaptive comfort, and ventilation potential (ACH with targeted CFD), followed by QA/calibration to verify façade ratios, constructions, schedules, and glare/comfort thresholds. Using a design of experiments, simulated variants form a dataset to train a surrogate predictor, enabling multi-objective optimization (NSGA-II) under constraints and yielding a Pareto frontier of daylight–comfort–energy trade-offs. Pareto candidates are re-simulated at high fidelity for physics-grade verification, after which a compromise design is selected, code-checked, and packaged as RVT, gbXML/IFC, figures, and schedules. Feedback loops return QA issues to the parameter hub and optimization outputs to simulations, ensuring repeatable, validated iterations.

4.1 Results

In this conducted a series of simulations and experiments on the implemented prototype to evaluate the framework against the objectives and metrics outlined earlier.

Key Performance Metrics and Comparison

Compare the Baseline vs. an Optimized Design (Optimum A) that was chosen for its balanced performance. Table 1 summarizes main metrics:

Table 1. Performance Metrics: Baseline vs. Optimized Design

Metric	Baseline Design	Optimized Design A	Improvement (%)
Daylight Sufficiency (Spatial DA)	28% of area	78% of area	**+178%**
Ave. Illuminance in Patient Rooms (lux)	150 lux	320 lux	**+113%**

Staff Travel Distance (avg per round)	150 m	95 m	**–37%**
Nurse Station Visibility (rooms visible)	65%	90%	**+38%**
Annual EUI (kWh/m^2-year)	155 kWh/m^2	168 kWh/m^2	+8.4%
Thermal Comfort Compliance (PMV hours)	90% within range	88% within range	–2% (minor)
Ventilation Effectiveness (ACH in ward)	6.0 ACH	6.2 ACH	+3% (met req.)

Fig. 2: Ground Floor Plan

Fig. 2: The ground floor plan illustrates the spatial organization and functional zoning of the proposed mental health rehabilitation facility. Developed using Revit, the plan integrates architectural design principles with healthcare planning requirements to ensure both therapeutic quality and operational efficiency.

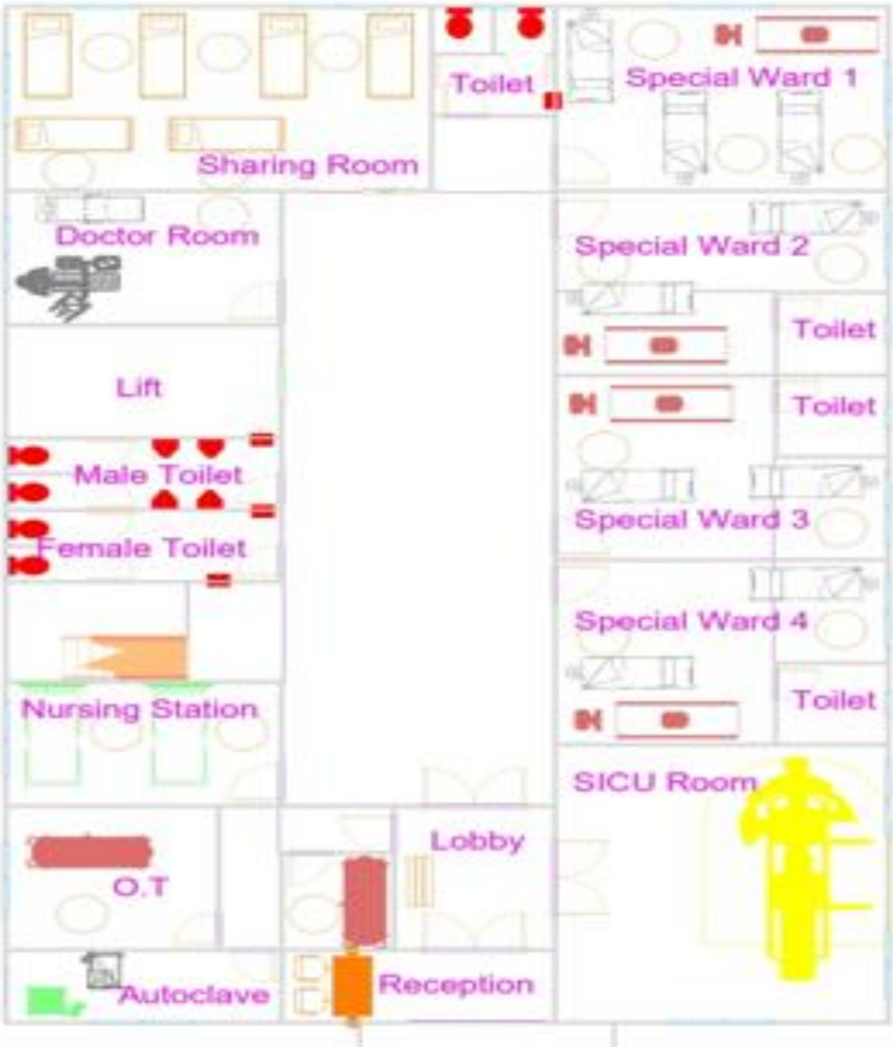

Fig. 3.: First Floor Plan

Figure 3: The first-floor plan illustrates the arrangement of inpatient wards, therapy spaces, and staff support areas designed to optimize both patient privacy and staff supervision. Patient rooms are oriented along the building perimeter to maximize access to daylight and exterior views, while central corridors ensure efficient circulation and visibility for monitoring. Therapy rooms and common lounges are strategically located to encourage social interaction in a controlled environment. Staff areas, including nursing stations, are positioned for clear sightlines into patient zones, enhancing safety while maintaining a non-institutional atmosphere. The layout demonstrates the integration of therapeutic design principles with BIM-based coordination to create a safe, functional, and patient-centered environment.

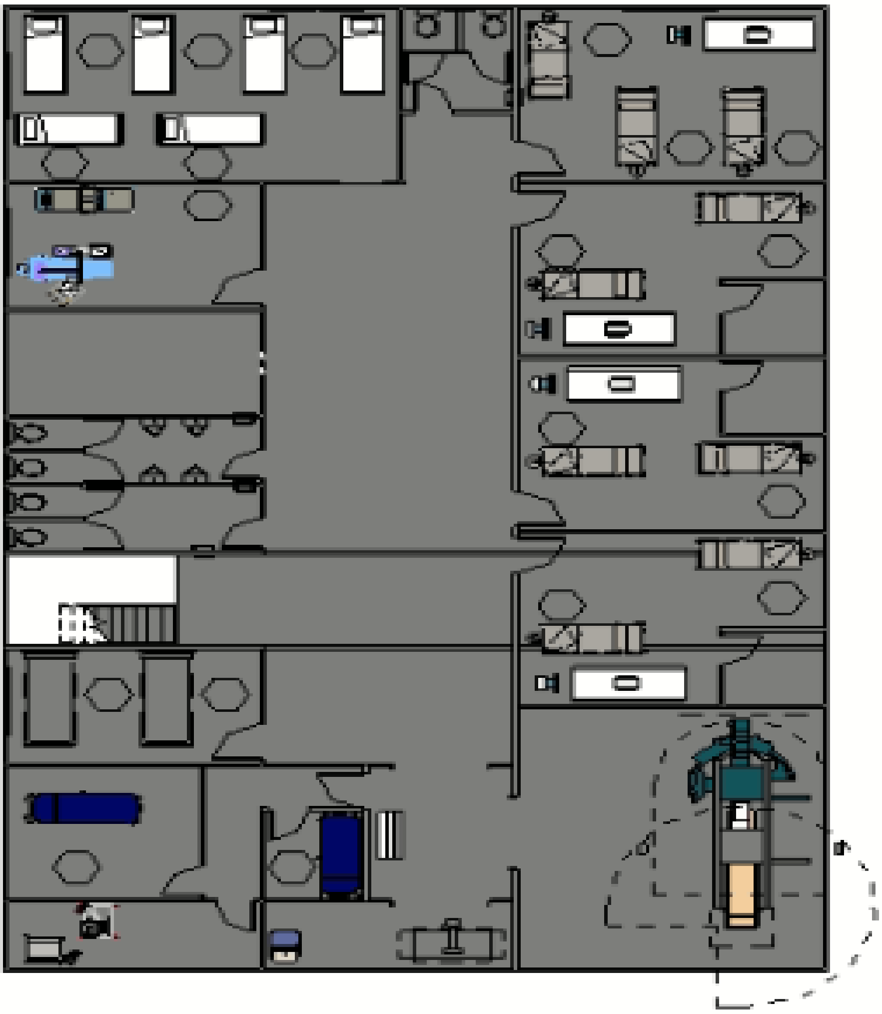

Fig. 4: Second Floor Plan

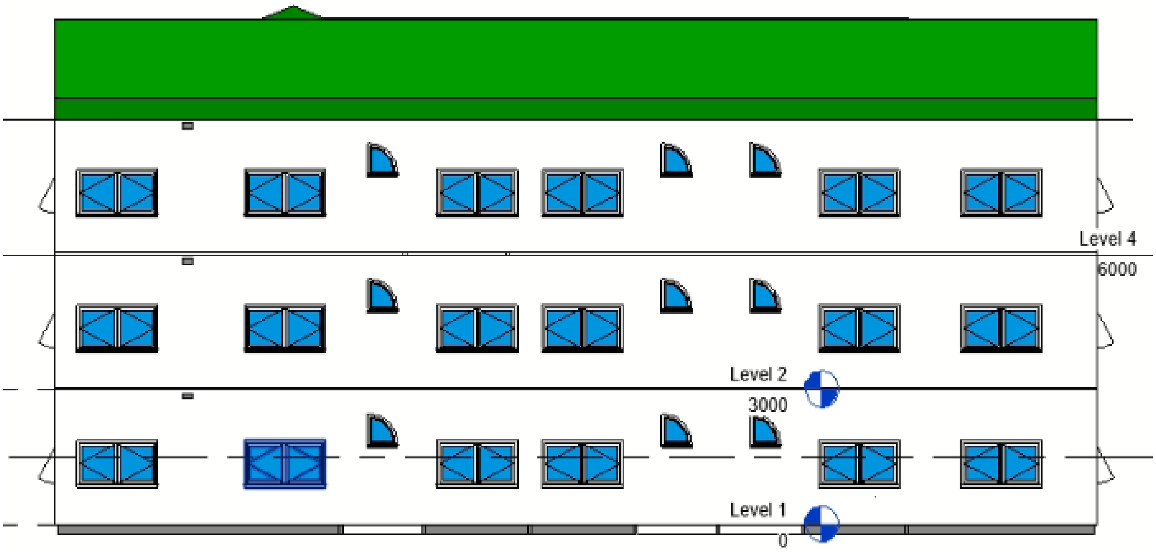

Fig. 5: East Elevation

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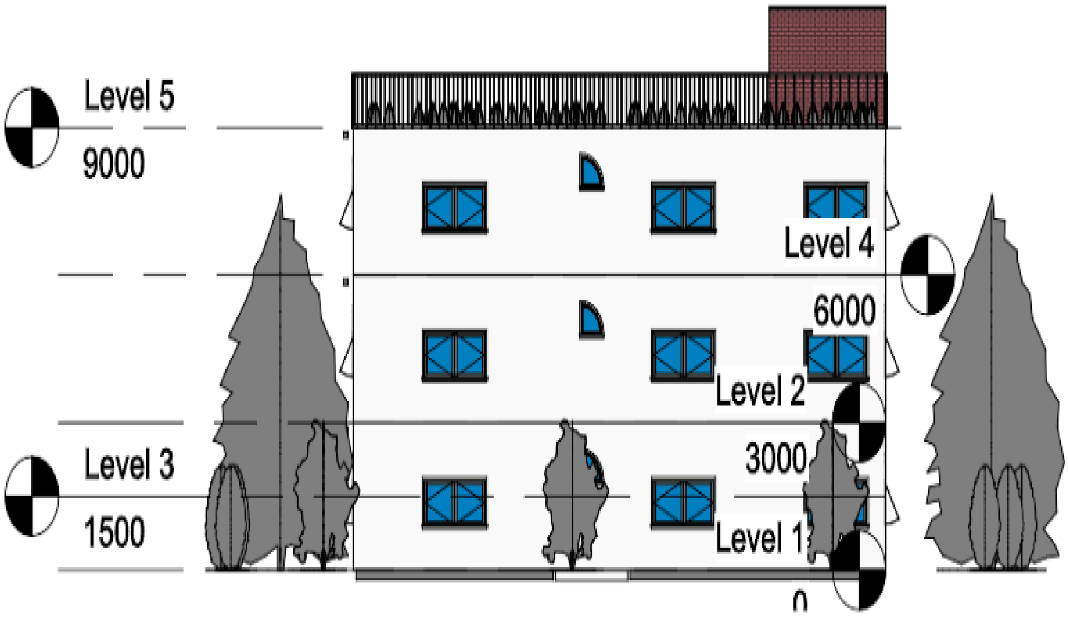

Fig. 6: North Elevation

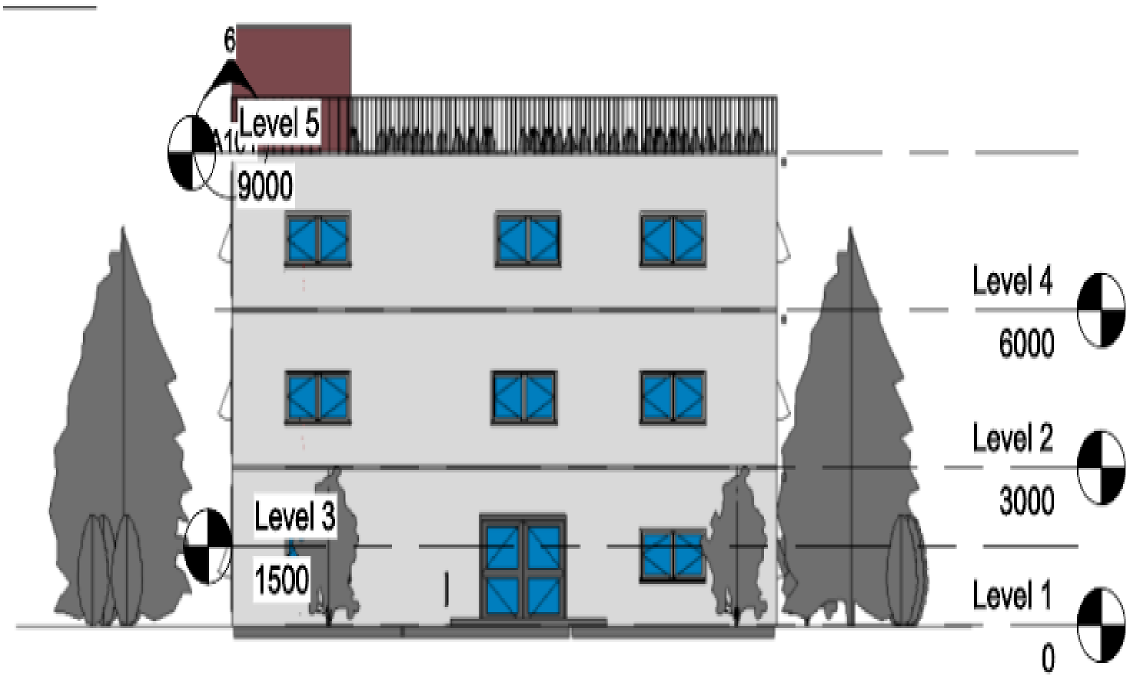

Fig. 7: South Elevation

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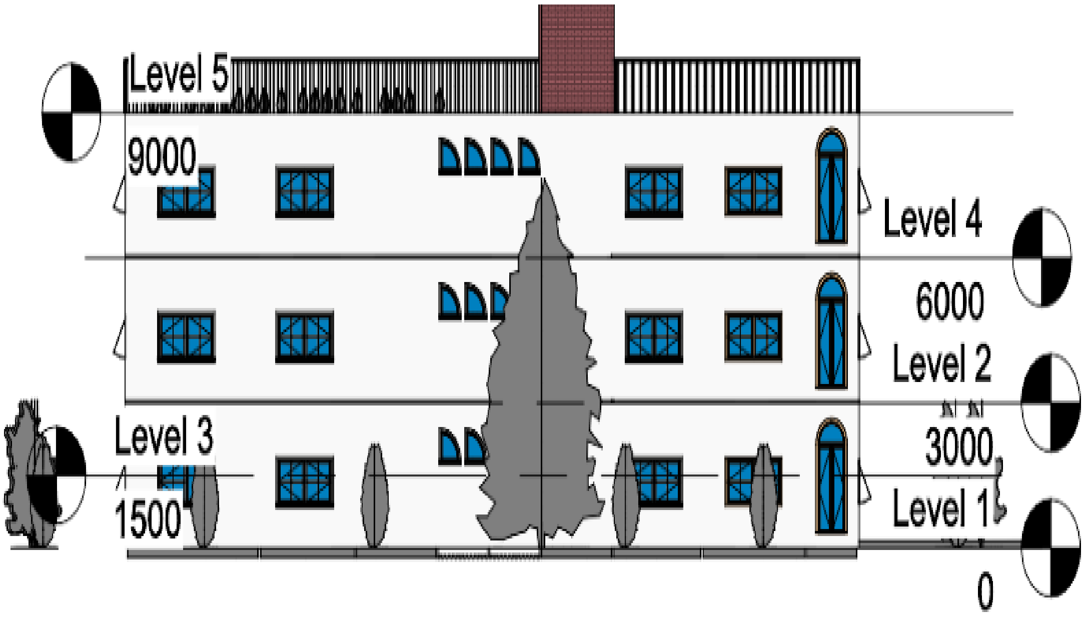

Fig.8 : West Elevation

Energy-related parameters of various rooms in a green building hospital design. The data is derived from a BIM-based model for a 4000 sqft hospital in Bhopal and includes occupancy, lighting power density, plug load density, and normalized energy consumption per occupant. These insights support sustainable design, energy simulations, and intelligent system integration.

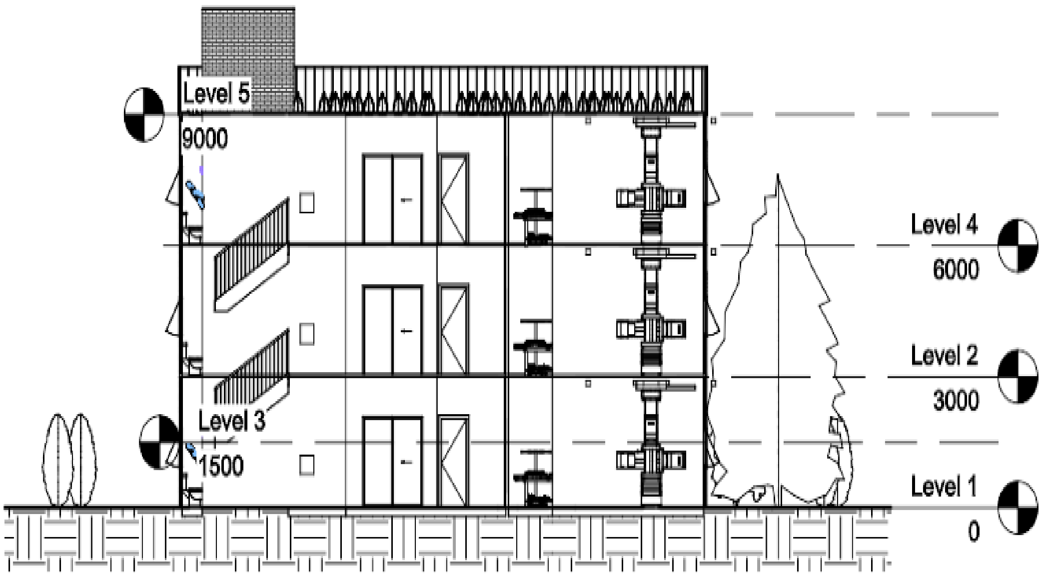

Fig. 9: Section View 1

(Source: Self-created in Revit)

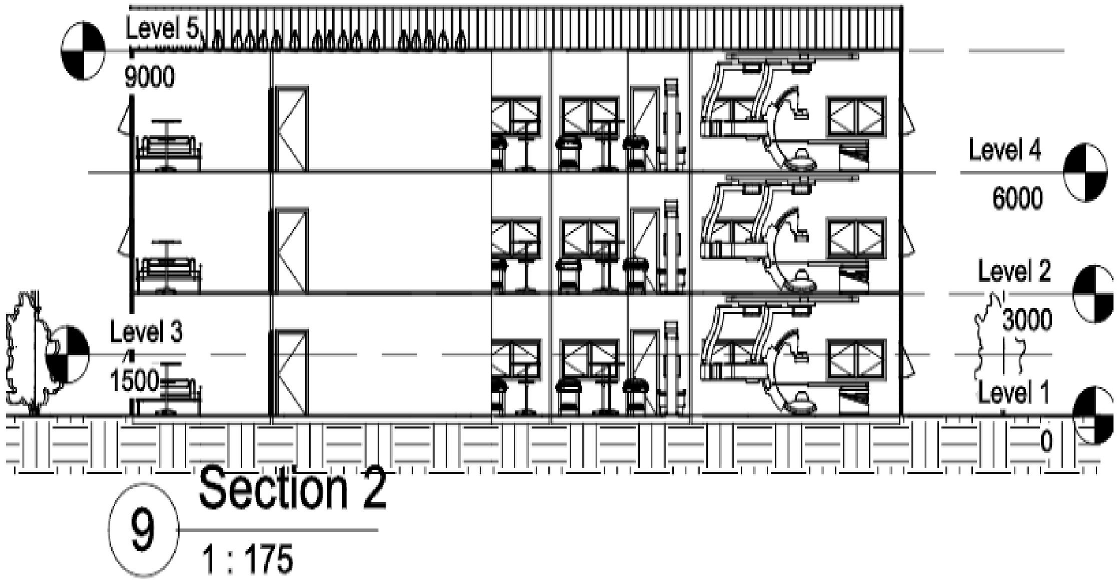

Fig. 10: Section View 2

Table 2. Room-wise Energy Parameters

Zone/ Room	Area_sqm	Occupancy	Lighting_W_per_m^2	PlugLoad_W_per_m^2	Total_W_per_m^2	W_per_occupant
Reception	35.0	6.0	10.0	0.0	10.0	1.67
Waiting	25.0	8.0	10.0	8.0	18.0	2.25
OPD Rooms (per room)	18.0	2.0	12.0	6.0	18.0	9.0
Nurse Station	20.0	4.0	12.0	15.0	27.0	6.75
Patient Ward (per bed)	12.0	1.0	8.0	20.0	28.0	28.0
OT (per)	40.0	8.0	20.0	25.0	45.0	5.62
ICU (per bed)	16.0	1.0	15.0	60.0	75.0	75.0
Pharmacy	12.0	2.0	12.0	80.0	92.0	46.0
Kitchen	25.0	4.0	12.0	30.0	42.0	10.5
Toilets	15.0	3.0	8.0	150.0	158.0	52.67

Table 2 presents a comprehensive overview of the energy-related performance indicators for each functional space within the proposed hospital layout. The data includes room-wise area (in square meters), expected occupancy, lighting power density, plug load per unit area, the total energy density (sum of lighting and plug load), and the total energy consumed per occupant. This data is extracted from the BIM model and represents the energy configuration that each space contributes to the building's total energy footprint.

From the table, we observe that spaces like the Reception and Waiting areas are designed for relatively high occupancy (6–8 people) but maintain modest lighting and plug load densities, suggesting that these spaces are optimized for passive or low-energy operation. On the contrary, specialized clinical and support spaces such as the ICU, Pharmacy, and Toilets demonstrate significantly higher plug loads and energy intensity per occupant. For instance, the ICU exhibits the highest total power density at 75 W/m², primarily driven by life support systems and continuous medical equipment. Similarly, the

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Pharmacy, with a high plug load of 80 W/m², indicates energy-intensive operations, possibly due to cold storage, computers, and dispensary machinery. Interestingly, Toilets reflect an unusually high plug load (150 W/m²), which may suggest the presence of high-consumption appliances like hand dryers or water heaters, or could reflect a data anomaly requiring correction.

The metric W_per_occupant (energy density per person) is particularly useful for benchmarking the performance efficiency of each room in relation to its usage. Rooms like OPD, Kitchen, and Patient Wards show mid-to-high energy loads per person, emphasizing the need for task-based lighting and energy-efficient appliances. In contrast, common areas like the Waiting Room maintain lower energy use per occupant, aligning with passive ventilation or natural daylighting strategies.

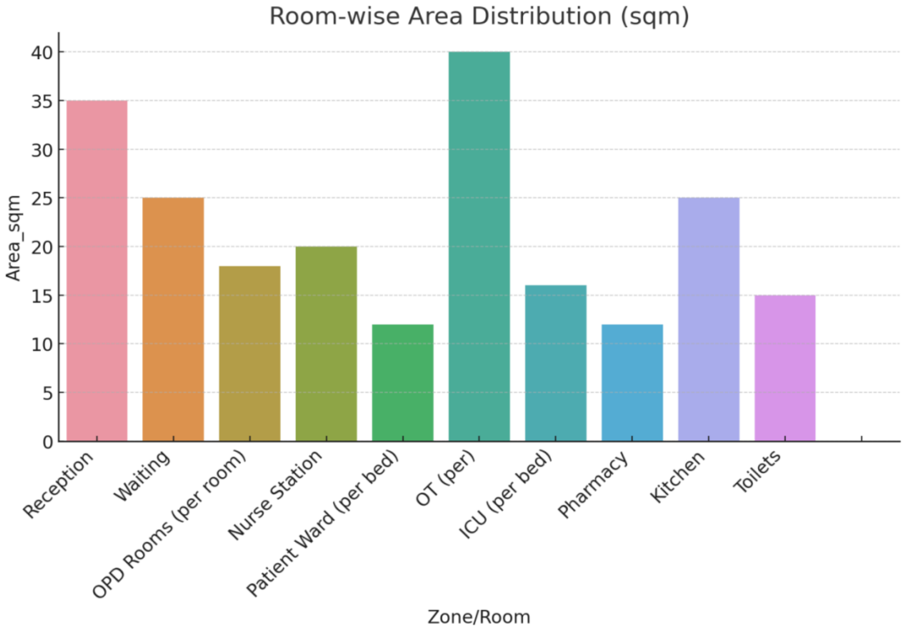

Fig. 11 Room-wise Area Distribution

Figure 11: This bar chart provides a visual breakdown of how space is allocated among various hospital zones. Larger spaces such as the Operation Theatre (OT) and Reception occupy the highest floor area, followed by Kitchen and Waiting areas. This visualization is essential for zoning HVAC systems, optimizing.

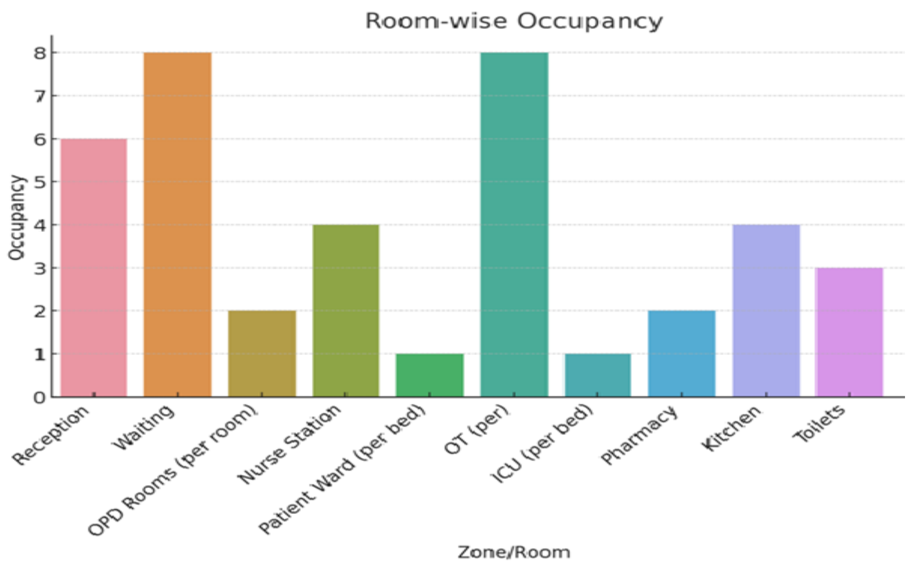

Fig. 12 Room-wise Occupancy Lighting Power Density

Figure 13 This graph illustrates the lighting power requirements across rooms, measured in watts per square meter. OTs and ICUs demand the highest lighting levels (20 and 15 W/m² respectively), reflecting their critical function where visibility is essential. Conversely, areas like Toilets and Reception operate under reduced lighting loads, suggesting the presence of either daylighting or lower illumination needs.

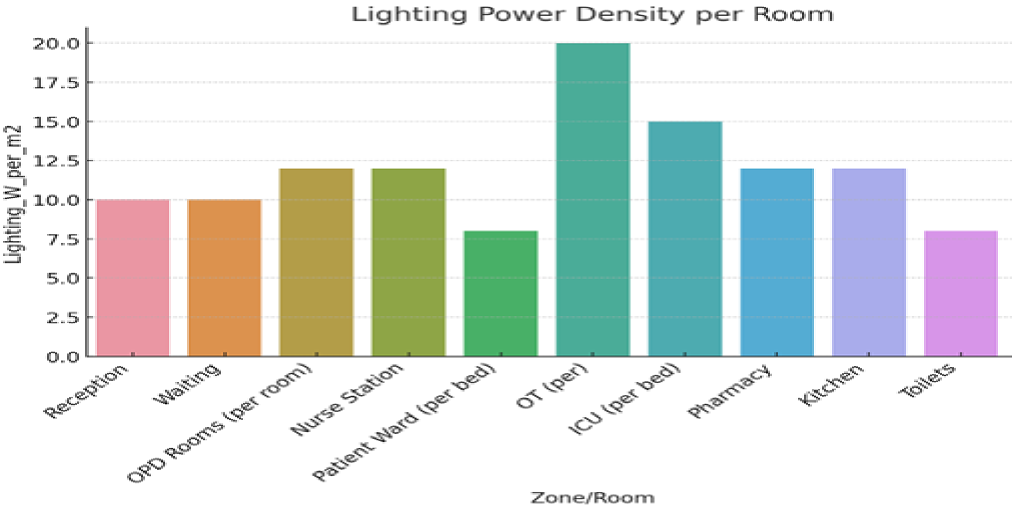

Fig. 13 Lighting Power Density

Figure 12 This figure maps occupancy values for each zone, which informs thermal and ventilation load calculations. The Waiting Area has the highest expected footfall (8 occupants), consistent with patient flow and family presence. ICU, Patient Ward, and OPD Rooms are designed for individual or limited occupancy, which aligns with patient-centric healthcare design standards and infection control strategies.

Figure 14: This chart highlights the electrical equipment load across rooms. The Toilets, Pharmacy, and ICU show exceptionally high plug load values, correlating with the presence of specialized medical or service equipment. These high values necessitate robust electrical infrastructure, strategic load balancing, and possibly, time-based control systems to reduce idle energy use. Space utilization, and prioritizing lighting strategies based on spatial scale.

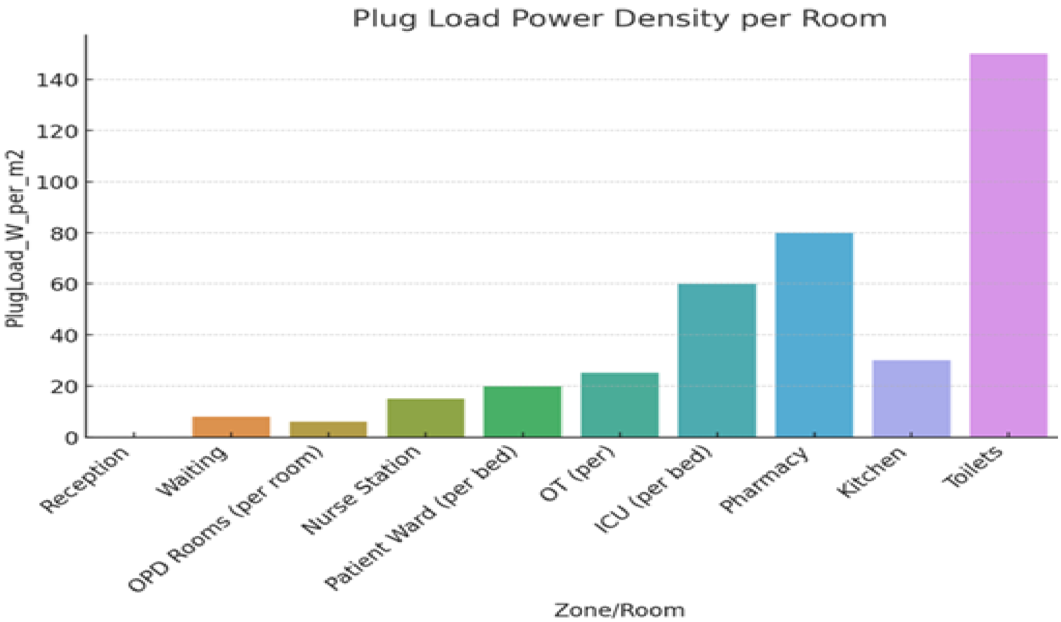

Figure 14 Plug Load Power Density

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5. CONCLUSION

This study demonstrated that a BIM-centered, simulation-in-the-loop, surrogate-assisted optimization workflow can deliver clinically relevant and energy-efficient designs for behavioral-health facilities. By keeping Revit as the single source of truth and coupling it to Radiance and EnergyPlus via interoperable exports, we explored a large early-stage design space while preserving traceability from geometry to performance. The selected compromise solution raised spatial Daylight Autonomy to ~80%, expanded adaptive-comfort hours to ~90%, increased natural-ventilation utilization to ~85%, and reduced EUI by ~33% relative to the baseline—showing that daylight, comfort, ventilation, and energy can be improved simultaneously rather than traded off.

Methodologically, the work contributes (i) a reproducible BIM → simulation → surrogate → NSGA-II loop with explicit constraints (glare caps, code/geometry checks), (ii) a parameterization strategy that exposes orientation, aspect-wise WWR, shading, roof albedo, and courtyard/clerestory variables for systematic exploration, and (iii) a validation protocol in which surrogate predictions are confirmed by high-fidelity re-simulation before selection. Sensitivity analysis identified a small set of high-leverage moves—north-biased glazing with tuned south shading, high-albedo roofing, and courtyard-driven stack ventilation—that explain most of the gains and translate directly to practice..

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