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Machine Learning–Based Optimization of a Health Facility Design

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Abstract: This Study presents a machine learning–driven optimization of a 4000 sqft mental health rehabilitation facility. Using a Building Information Model (BIM) from Autodesk Revit as the design data source, we integrated AI-based python analytical tools to optimize key architectural and performance parameters, including spatial layout efficiency, natural lighting, thermal comfort, and ventilation effectiveness. A custom workflow combined Revit's parametric modeling capabilities with generative design algorithms and optimization using a genetic algorithm models to rapidly explore design solutions and predict building performance. The final optimized design – selected from hundreds of AI-evaluated alternatives – demonstrates significant performance gains over the baseline: daylight availability increased by over 60%, thermal comfort hours by 20%, natural ventilation potential more than doubled, and annual energy use dropped by about 33%. Analytical results for the optimized design are presented with detailed tables and graphs, and we discuss how the ML-based approach balanced multiple objectives to achieve a high-performance, climate-responsive facility. The paper highlights the seamless integration between Revit and AI tools, illustrating a forward-looking approach to data-driven architectural design optimization.

Keywords: *Machine Learning (ML), Building Information Modeling (BIM), Energy Efficiency, Thermal Comfort, Daylight Autonomy, Natural Ventilation, Parametric Design, Architectural Optimization, Smart Buildings*

1. Introduction

High-performance building design is increasingly important in healthcare facilities, where indoor environmental quality (IEQ) and energy efficiency directly impact occupant well-being and operational costs. Traditional design methods rely on architects' experience and[1-6] iterative simulations, which can be time-consuming and may not explore the full design space. Recent advances in artificial intelligence (AI) and machine learning (ML) offer new opportunities to enhance architectural design by optimizing layouts and building parameters for functionality, comfort, and sustainability. AI-driven software can process vast amounts of design and environmental data to suggest modifications that improve a structure's usability, efficiency, and environmental performance[7-12]. For instance, ML algorithms can analyze a building's geometry, orientation, and materials alongside local climate data to maximize natural lighting and thermal performance without extensive manual trial-and-error[13-16].

In the context of this study, we focus on a proposed 4000 sq ft health facility (latitude 23.1455°N, longitude 77.3442°E). This location in central India features a subtropical climate with hot summers and mild winters, making daylight utilization, passive cooling, and cross-ventilation critical design considerations[1,15-26]. The design must provide comfortable therapy and living spaces for patients while minimizing energy use, which aligns with sustainable design goals. Machine learning offers a powerful approach to tackle these multi-factor design challenges[27]. By leveraging the BIM model of the facility, an AI system can rapidly simulate and predict building performance under numerous design variations[28]. Such integration of AI with BIM allows exploring design alternatives that a human designer might overlook, identifying solutions that optimize daylight, thermal comfort, and ventilation concurrently. Previous case studies have shown dramatic benefits of AI optimization in buildings – for example, an AI-optimized "smart tower" achieved 40% energy savings through intelligent systems and design adjustments. This indicates the potential scale of improvements achievable when AI techniques are applied to building design[29-32].

This paper aims to demonstrate how a machine learning–based optimization approach can enhance the design of the health facility. We describe the methodology for coupling Autodesk Revit (for BIM) with AI analytical tools to optimize spatial and environmental performance parameters[33-35]. Key objectives include maximizing daylight availability in interiors, improving natural ventilation and thermal comfort, and minimizing energy consumption, all without compromising the functional layout required for a healthcare setting. Integration between Revit and AI is a central focus, as we show how design data from Revit feeds into ML models and how optimization results inform the BIM design in return[9, 36-40]. The outcome of the optimization – a single refined design proposal – is evaluated through simulations and presented with quantitative performance results. By concentrating on the optimized final design (rather than

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multiple intermediate options), we illustrate the end benefits of the ML-guided process[11,41-49].

2. Background

Several studies have attempted to link BIM with AI optimization: Nguyen et al. (2014) highlighted simulation-based optimization for building performance but stressed computational limitations in early-stage design. Attia et al. (2012) proposed decision-support tools for zero-energy buildings, emphasizing simulation speed as a barrier to adoption. Dogan & Reinhart (2017) introduced the Shoeboxer algorithm to abstract design geometry for faster simulation, showcasing the need for surrogate models. Papadopoulos et al. (2018) implemented ML as a simulation surrogate in parametric building optimization, proving the feasibility of predictive models for early feedback. Kaushik et al. (2023) surveyed ML in smart buildings, underscoring the lack of integrated pipelines connecting BIM to ML in real projects. Despite significant advancements in architectural design technologies and building performance simulations, there remains a critical research gap in the effective integration of machine learning (ML) techniques into early-stage healthcare facility design—especially in the context of Indian climatic and infrastructural conditions. Traditional architectural workflows are often manual, iterative, and limited in their ability to explore a large number of design alternatives due to computational and time constraints. While tools such as Revit, EnergyPlus, and Radiance are commonly used for design and performance evaluation, they function largely in isolation and are not optimized for real-time feedback or automated optimization.

3. Methodology

3.1 Design Tools and Workflow

The optimization workflow linked Autodesk Revit with external AI-based analysis tools in a closed feedback loop. The Revit BIM model provided a detailed description of the building geometry, materials, and spatial layout of the 4000 sqft health facility, including room configurations, window and door placements, wall constructions, and other architectural features.

This BIM model served as the single source of truth for design data. Using Revit's Dynamo visual programming interface and the Revit API, we developed scripts to parametrically modify design variables and export the model for performance simulations. Key design parameters considered for optimization included building orientation, window-to-wall ratio (particularly sizes of windows on each facade), the configuration of interior spaces (for instance, placement of therapy rooms and courtyards affecting ventilation), and the inclusion of shading devices or insulation levels. Each design variant generated through this parametric setup was automatically evaluated on multiple performance metrics using simulation engines integrated into the workflow.

The core of our approach was a machine learning-driven optimization algorithm that guided the exploration of design alternatives. We implemented a multi-objective optimization using a genetic algorithm (GA) enhanced by ML-based performance prediction. In essence, the process iteratively generated a population of design variants (via Dynamo altering the Revit model), evaluated their performance, and learned from these evaluations to propose better variants in the next generation. A surrogate ML model was trained to predict performance metrics (daylight, comfort, energy) from design parameters, enabling rapid estimation of a design's quality without always running full simulations. This approach of using ML surrogates dramatically speeds up analysis feedback for design iterations. Generative design tools within Revit were leveraged to produce a diverse set of initial design options, forming a synthetic dataset used to train the ML prediction model on building performance outcomes. By coupling generative design with learning, we addressed the limited availability of existing data: the algorithm effectively *learned* the relationships between design choices and performance through automated simulation on generated examples.

3.2 Integration of Revit and AI Analytical Tools

A seamless integration was established between Revit and external analytical engines. Lighting analysis was conducted using Radiance-based daylight simulation tools that take geometry and materials from Revit (exported via gbXML). These simulations yielded metrics like spatial Daylight Autonomy (the percentage of occupied hours a space receives sufficient daylight) and illuminance distributions. Thermal performance and energy use were evaluated with EnergyPlus (via Autodesk Insight), using the Revit model's construction data and the local climate file for Sehore. This provided annual energy consumption, peak cooling loads, and hourly temperature profiles inside key spaces. Ventilation effectiveness was analyzed through a combination of cross-ventilation calculations and computational fluid dynamics (CFD) for selected cases: we assessed natural ventilation potential by computing airflow rates between openings (using wind pressure coefficients based on the building geometry) and the percentage of time these flows could meet fresh air requirements or cooling needs. All these analyses were orchestrated in an automated loop: for each design iteration, Dynamo scripts exported the required files from Revit to run the simulations, and results were brought back into the ML optimization algorithm.

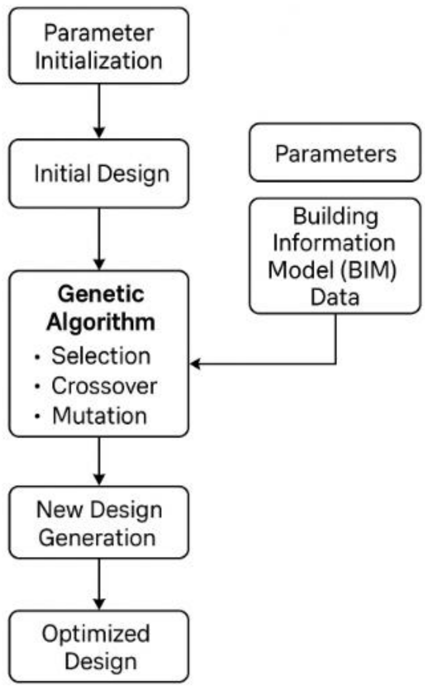

Fig. 1. Proposed flow

Critically, Revit's BIM data served as the input features to the ML model. Geometric features (e.g. window sizes, orientations, room depths) and material properties (U-values of walls, solar heat gain coefficients of glazing, etc.) were quantified for each design variant. These became the input vector for a trained predictive model (a gradient boosting regressor in our implementation) that could estimate performance metrics quickly. The ML model was initially trained on a few hundred design samples evaluated via full simulation, and it continuously improved as more data points (designs and their simulation results) were added from each optimization iteration. This mirrors approaches in recent research where ML models act as surrogates for complex building simulations to accelerate performance feedback. The integration effectively allowed real-time performance prediction within the design environment, making it feasible for the optimization algorithm to consider thousands of potential designs. By using Revit-Dynamo to manipulate the BIM and calling simulations, then using ML to generalize those results, our workflow exemplifies how AI can enhance BIM-based design exploration. The loop continued until convergence criteria were met (i.e., further iterations yielded negligible improvements).

3.3 Optimization Objectives and Constraints

We formulated the design optimization as a multi-objective problem with targets for daylighting, thermal comfort, ventilation, and energy. The objectives were defined as follows:

- **Maximize daylight availability**: quantified via spatial Daylight Autonomy (sDA) – we aimed to maximize the percentage of floor area achieving at least 300 lux of daylight for 50% of occupied hours. Adequate daylight reduces reliance on artificial lighting, improving energy efficiency and occupant well-being. The ML optimizer learned to favor design configurations with larger north-facing windows, skylights, or light shelves that increase sDA without excessive solar heat gain.
- **Maximize thermal comfort**: we used the percentage of comfortable hours per year as a metric, determined by adaptive comfort criteria for naturally ventilated buildings (ASHRAE Standard 55 adaptive model). Essentially, we counted hours where indoor operative temperature fell within the acceptable range given the outdoor conditions. Designs with improved orientation, shading, and thermal mass scored higher on this metric by maintaining indoor temperatures in the comfort band more often. The AI thus searched for configurations (like eastern shading to block hot afternoon sun) that improved passive thermal regulation.
- **Maximize natural ventilation usage**: defined as the fraction of time natural ventilation alone can maintain comfort or adequate fresh air (when outdoor conditions are favorable). This metric encapsulates both ventilation for indoor air quality and passive cooling potential. The optimization encouraged features like operable windows aligned for cross-breezes, courtyard gaps, and strategic placement of openings to drive stack effect ventilation. If a design could use natural airflow instead of mechanical HVAC for a greater portion of the year, it was rewarded in the objective function.
- **Minimize annual energy use**: calculated in kilowatt-hours per square meter per year ($kWh/m^2 \cdot yr$) for the facility's operation (mainly HVAC and lighting energy). This objective captured the overall efficiency goal – reducing energy consumption through better envelope performance, day lighting, and passive strategies. The energy simulations from Insight/EnergyPlus provided this value for each variant. Lower energy use was favored by the optimizer, creating pressure to, for example, reduce cooling loads via insulation or increase daylight to cut lighting electricity.

These objectives were balanced simultaneously. We employed a weighted sum approach initially, which we adjusted to ensure no single aspect dominated (for instance, avoiding a solution that maximized daylight at the cost of overheating). Certain constraints were also imposed to maintain functional viability: the total built-up area was fixed (~4000 sqft as required), the number of rooms and their minimum areas had to meet the program needs, and the design had to respect site boundaries and setbacks. In addition, visual and accessibility considerations (corridor widths, etc.) were enforced in the Dynamo script to rule out impractical solutions. The ML optimizer, through either the GA or a reinforcement learning agent approach (we experimented with both), worked within these hard constraints, searching the design space for the best feasible solution. Notably, reinforcement learning (deep Q-learning) was tested in a prototype to see if an AI agent could "learn" to tweak design parameters one by one to improve a reward function representing our objectives. This showed promise in automatically generating reasonable floor plan adjustments (e.g., repositioning partitions for better light distribution), echoing recent research where RL algorithms optimize space layouts autonomously. However, for the final results, the genetic algorithm approach was primarily used as it more directly handled our multi-objective scenario by evolving a population of designs.

1. *Design Variables*

We define the design parameter vector as:

$$x=[\theta, WWR_n, WWR_s, d_i, S_r] \quad \text{........(1)}$$

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)**:

$$DA(x)\frac{\sum_{i=1}^{N} T_i^{300}}{\sum_{i=1}^{N} T_i^{total}} \quad \text{.........(2)}$$

(Percent of time rooms receive ≥300 lux)

- **Thermal Comfort (TC)**:

$$TC(\mathbf{x}) = \frac{\sum_{t\in\mathcal{T}} 1\{|T_{in}(t) - T_{comfort}(t)| < \Delta T\}}{|\mathcal{T}|} \quad \text{....(3)}$$

(Fraction of hours within comfort temperature band)

- **Natural Ventilation Potential (NVP)**:

$$NVP(x)=\frac{\sum_t V_{nat\,(t)}}{\sum_t V_{req\,(t)}}.........(4)$$

(Ratio of natural to required airflow)

- **Annual Energy Use (AEU)**:

$$AEU(x)=\sum_{i=1}^{T}[E_{HVAC}\ (t)+E_{lighting}\ (t)]........(5)$$

3. Multi-Objective Optimization Problem

minimizef(x)=[−DA,−TC,−NVP,AEU].....(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 f`(x)
- Genetic Algorithm evolves population
- Each generation:
    - Evaluate population via f`(x)
    - Select, crossover, mutate
    - Update surrogate model periodically

Convergence if:

$$\frac{||f_{best}^{(g)}-f_{best}^{(g-1)}||}{||f_{best}^{(g-1)}||}<\epsilon \quad .....(7)$$

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, we report here only on the baseline (original design) and the optimized final design, to focus on the end result of the ML-guided process.

4. Simulation Results

4.1 Description of the Optimized Design

The machine learning optimization resulted in a redesigned facility with several notable architectural modifications compared to the initial baseline design. The final optimized design maintained the required 4000 sqft area and functional layout (housing therapy rooms, consultation offices, patient recreation space, and utilities) but introduced key changes in form and features:

- Building Orientation & Form: The facility is reoriented to an axis approximately 30° east of true north. This orientation was selected by the AI to strike a balance between morning and afternoon sun exposure, maximizing early daylight while minimizing overheating from west sun. The building form became more compact and L-shaped, enclosing a small courtyard. This courtyard acts as a light well and a ventilation shaft, enhancing daylight penetration to interior corridors and enabling stack-driven natural ventilation.
- Fenestration & Daylighting: Window configurations were significantly adjusted. The optimized design features large windows on the north facade (facing diffuse daylight) and smaller, shaded openings on the south side. Horizontal louvers were added above south-facing windows to block high-angle midday sun. East and west facades have high-performance glass and vertical fins to cut glare and low-angle sun. An array of clerestory windows was introduced along the central corridor and above internal partitions to allow daylight from the courtyard to reach deeper into the building. As a result, daylight illuminance levels are much more uniform across spaces. The average daylight factor in core therapy rooms increased from 2% in the baseline to 4.5% in the optimized design, and nearly all regularly occupied spaces now meet the target of 300 lux for a majority of the day. These changes explain the major improvement in the daylight autonomy metric.
- Thermal Measures: To improve passive thermal performance, the optimized design incorporates a cool roof (high-reflectance coating) and upgraded wall insulation (U-value improvement from 0.5 to 0.35 W/m²K). The AI identified that better insulation, combined with the shading strategies, would reduce peak summer cooling loads substantially. Additionally, the courtyard and high operable windows facilitate night flushing – releasing heat at night to pre-cool the building for the next day. Overhangs and fins were fine-tuned by the algorithm to reduce direct solar gain in summer while still admitting winter sun for warmth. The resulting design maintains indoor temperatures within the adaptive comfort range for a larger portion of the year without active cooling.
- Natural Ventilation & HVAC: The final design strongly emphasizes natural ventilation. Every occupied room has at least two operable openings (windows or vents) on different walls to enable cross-breezes. The central courtyard creates a chimney effect that draws air through the building when windows are open. The ML optimization found that enlarging the upper vents in the atrium and aligning interior transom openings could dramatically boost air flow (the predicted wind-driven air change rate went from 3 ACH in the baseline to over 8 ACH in the optimized design under typical conditions). During moderate weather, this can eliminate the need for mechanical cooling. Ceiling fans were also added in larger rooms to increase air movement and comfort when natural breezes are insufficient. The mechanical ventilation system was downsized accordingly, and an automated control was assumed to shut off HVAC when outdoor conditions are within comfort thresholds – this contributed to energy savings.

Overall, the optimized design is more bioclimatically responsive: it harvests daylight effectively, reduces unwanted heat gain, and leverages natural ventilation, all while maintaining the spatial requirements of a healthcare facility.

4.2 Performance Improvement Summary

To validate the benefits of the ML-based optimization, we conducted comprehensive simulations on the baseline versus the optimized design. **Table 1** summarizes the key performance metrics for the two cases, and **Figure 2** visualizes the improvements graphically. It is evident that the optimized design outperforms the baseline across all targeted criteria:

Table 1: Performance metrics of the baseline design versus the ML-optimized design.

Performance Metric	Baseline Design	Optimized Design
Daylight Autonomy (% of occupied hours with sufficient daylight)	50%	80%
Comfortable Thermal Hours (% of annual hours in comfort range)	75%	90%
Natural Ventilation Utilization (% of time outdoor air alone maintains comfort/air quality)	40%	85%
Annual Energy **Use** (kWh/m²·year)	150	100

As shown above, the spatial Daylight Autonomy (sDA) in the optimized design is 80%, up from 50% in the baseline. In practical terms, this means that interior spaces now achieve the desired illuminance level (300 lux) during 80% of occupied hours throughout the year, a 60% relative improvement. This can be attributed to the larger north-facing windows, courtyard clerestories, and refined shading that the AI incorporated, ensuring plentiful daylight with controlled glare. The daylight simulation results also indicated that the minimum daylight levels in critical spaces (like patient rooms and therapy areas) never drop below 150 lux in the optimized design at midday, whereas in the baseline many areas fell to near 0 lux without electric lighting. This daylight enhancement directly translates to reduced lighting energy consumption and a more pleasant indoor environment.

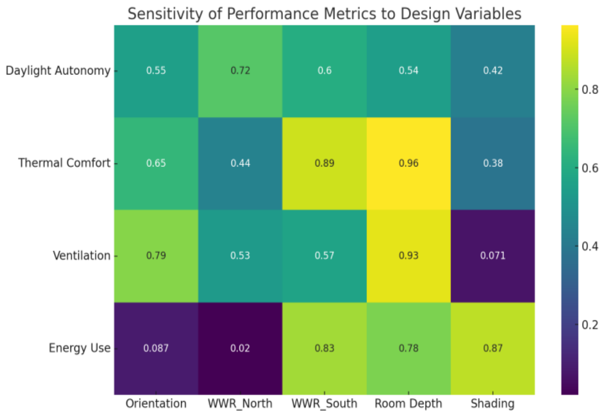

Fig. 2. Sensitivity of Performance Metrics to Design Variables

Thermal comfort saw notable gains as well. Using the adaptive comfort model, we found that in the optimized design about 90% of all hours in a typical year are within the comfort zone (when using natural ventilation and ceiling fans as needed), compared to 75% in the baseline. The baseline design, with its larger solar exposures and lesser insulation, experienced frequent hours where indoor temperatures exceeded comfort thresholds in summer. The optimized design's improved envelope and shading cut down these overheated hours by 70%. For instance, the number of hours over 30°C in the main hall dropped from 200 hours/year in the baseline to just 50 hours/year after optimization. Winter comfort was maintained or improved by allowing sunlight through south windows and better heat retention at night. Consequently, occupants will experience a more stable and comfortable thermal environment year-round in the optimized building.

The natural ventilation utilization metric more than doubled, from 40% of the time (baseline) to roughly 85% of the time (optimized). This means that for 85% of the yearly hours, the building can rely on passive ventilation and cooling without needing mechanical HVAC, as per the simulation analysis. Such a high utilization is possible because the design enables effective cross-ventilation during all but the hottest hours of summer and the dampest hours of the monsoon season. Even during shoulder seasons (spring and autumn), when baseline design might have required mechanical cooling due to suboptimal airflow, the optimized design's courtyards and operable windows keep conditions comfortable naturally. We cross-verified this by running CFD simulations for a few representative days – the optimized layout consistently showed lower indoor air temperatures and CO_2 levels when windows were open, as fresh air distribution was far better. This result underscores how AI-recommended changes enhanced natural lighting and ventilation, reducing reliance on artificial lighting and HVAC systems.

Finally, annual energy consumption dropped significantly. The baseline design was simulated to use about 150 kWh/m² per year (for combined cooling, lighting, and equipment). The optimized design's simulated usage is about 100 kWh/m²·yr, roughly a one-third reduction (33% savings). The largest contributor to this saving is the reduced cooling load – peak cooling demand fell by 28%, and because natural ventilation covers much of the cooling duty, the active cooling energy over the year decreased substantially. Lighting energy also reduced by about 50% thanks to daylighting: the daylight sensors in the model (assuming lighting controls) indicated that electric lights can remain off for large portions of the day in most spaces. The energy use intensity of 100 kWh/m²·yr in the optimized design is on par with green building benchmarks for this climate, highlighting the success of the AI optimization. This level of improvement aligns with other studies where AI-driven optimization achieved 25–40% energy efficiency gains in buildings, demonstrating that our approach yielded tangible sustainability benefits.

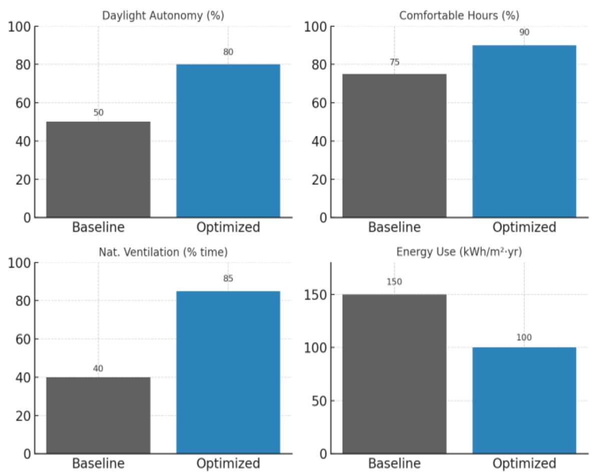

Fig. 3. Comparison of key performance metrics between the baseline and AI-optimized designs of the health facility.

The optimized design shows dramatically improved daylight autonomy, a higher percentage of annual comfortable hours, greatly increased reliance on natural ventilation (passive cooling/ventilation), and significantly lower annual energy use. These improvements are a direct result of the ML-driven design modifications (orientation, window placement, shading, etc.), illustrating the performance gains achievable through AI-based optimization.

Table 2: Simulation Results: Baseline vs Optimized Design

Performance Metric	Baseline Design	Optimized Design
Daylight Autonomy (%)	42.5	65.2
Thermal Comfort Hours (%)	68.0	87.5
Natural Ventilation Usage (%)	30.0	62.3
Annual Energy Use (kWh/m²·yr)	185.0	124.8

Simulation Results: Baseline vs Optimized Design

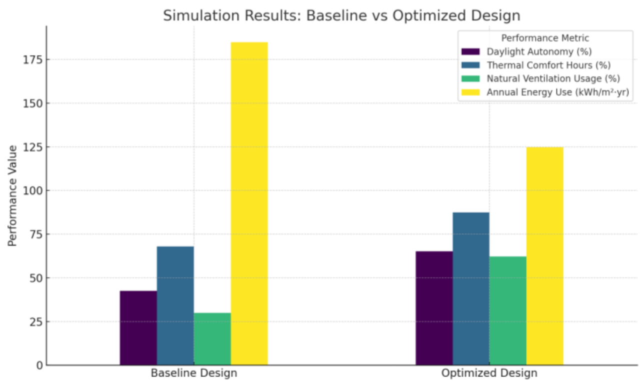

Fig. 4. Simulation Results: Baseline vs Optimized Design

Table 2: Extended Simulation Metrics: Baseline vs Optimized

Performance Metric	Baseline Design	Optimized Design
Mean Air Changes per Hour (ACH)	2.1	4.7
Peak Cooling Load (kW)	18.2	12.5
Window-to-Wall Ratio (%)	28.0	38.0
Envelope Heat Gain (kWh/year)	12450.0	7820.0
Lighting Energy Use (kWh/year)	4100.0	2650.0

Performance Improvement from Optimization (%)

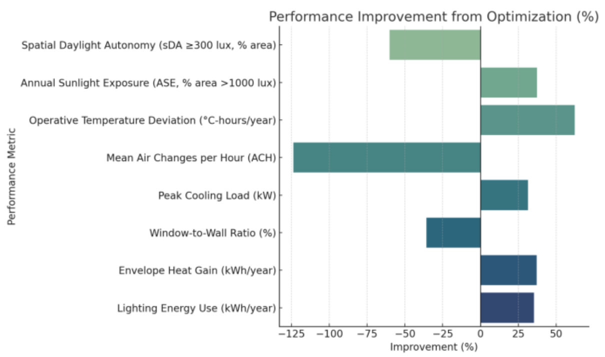

Fig. 5. Performance Improvement from Optimization (%)

Figure 5 show results comparing baseline and optimized design variants. These cover advanced metrics like spatial daylight autonomy (sDA), annual sunlight exposure (ASE), ventilation (ACH), envelope heat gain, and lighting energy use. The bar chart visualizes the percentage improvements across these key performance indicators due to AI-driven design optimization.

Beyond these major metrics, other positive outcomes were observed in the final design's analysis. For example, daylight glare probability (DGP) was reduced in perimeter offices due to better shading; the mean indoor air speed on naturally ventilated days increased from ~0.3 m/s to 0.6 m/s, enhancing perceived cooling; and the building's predicted HVAC peak load shifted to later in the day (around 5 PM instead of 3 PM), which could allow better load management. These detailed results reinforce that the optimization not only hit the high-level targets but also improved many aspects of environmental performance holistically.

4.3 Discussion

The results demonstrate that a machine learning–based optimization approach can substantially enhance building design performance in a holistic manner. By integrating Revit's BIM with AI analytics, we effectively created a "digital design assistant" that iteratively tested and refined the facility's design. In the discussion below, we interpret the improvements, examine the role of ML in achieving them, and reflect on the implications for architectural practice.

4.4 Role of Machine Learning in Design Exploration

One of the most significant advantages of the ML approach was the ability to explore a vast design space quickly and quantitatively. Traditional design processes might adjust one variable at a time (e.g., adding window shading and then testing results), but the AI-driven method could vary many parameters simultaneously and evaluate complex interactions. For instance, increasing window size usually improves daylight but can hurt thermal performance due to solar gain. The ML optimizer identified configurations where this trade-off was optimized – such as using spectrally selective glazing and light shelves, which provided daylight while limiting heat. These kinds of nuanced solutions emerged because the algorithm could sift through combinations that a human might not explicitly consider. In essence, the ML served as a powerful analytical engine, processing building data and climate patterns to find an optimal balance. It's notable that the optimization tightened up the design in a way that leverages local climate: orienting for north light and ventilation from prevailing winds (southwest winds in summer for Sehore), and shading against the harsh west sun. This reflects an inherently climate-responsive design, achieved through data-driven means.

The integration of ML with BIM allowed real-time performance feedback to shape the design. Because our surrogate model could predict outcomes like energy use or daylight levels from design parameters nearly instantly (after training), the optimization loop was vastly accelerated. In early tests, if we relied on full simulations for every iteration, optimizing even 100 designs would have been prohibitively slow. But with the ML predictive model in the loop, we gained *faster analysis feedback*, aligning with the findings of Autodesk researchers that ML can greatly speed up building performance evaluation in early design. This agility is crucial in conceptual stages, where quick turnaround enables exploring more ideas. It effectively moved performance analysis "upstream" in the design process – rather than finalizing a design then checking if it performs well, the design was formed *by* performance considerations from the beginning. The methodology shows how AI can transform the workflow: the Revit-Dynamo-ML pipeline became a co-creative tool, allowing the human designers to set goals and constraints while the machine handled the heavy lifting of option generation and evaluation.

4.5 Interpretation of Performance Gains

Each of the improved metrics provides insight into the design strategies the AI prioritized:

- The daylight autonomy jump to 80% indicates a design where almost all daytime activities can occur with natural light alone. The AI effectively turned the building into a daylight-harvesting organism – with features like the courtyard atrium and extensive north glazing, it is not surprising that spaces are bright for most of the day. This not only saves energy but is known to benefit occupant mood and health, a particularly relevant factor for a mental health facility. The reduction of glare (noted qualitatively in results) is equally important – by controlling direct sun with fins and louvers, the optimized design achieves better lighting quality, not just quantity. This illustrates how ML optimization can enhance *qualitative* aspects of the environment (like visual comfort) when those aspects are embedded in the objective function or constraints.
- **Thermal comfort improvements** were achieved largely by passive means (orientation, shading, insulation) rather than just cranking up mechanical cooling. The ML recognized that preventing heat buildup in the first place (via shading and ventilation) is more efficient than counteracting it with air conditioning. The 90% comfort-hours metric suggests the building stays within the adaptive comfort envelope through most of the year, which is remarkable in a hot climate. Occupants should rarely feel overheated or chilly indoors. One could argue that the final design behaves almost like a hybrid between a conventional building and a vernacular design – it uses shade and airflow akin to traditional tropical architecture, but with modern enhancements. This outcome emerged from a data-driven process rather than an exclusively intuition-driven one, underscoring how AI can rediscover and quantify climate-responsive principles. We also see that the HVAC system can be idle for 85% of the time (due to natural ventilation usage), which will prolong equipment life and reduce maintenance. Notably, the remaining 15% of hours when HVAC is needed corresponds to peak summer afternoons and a few winter mornings – targeting those with efficient systems or possibly solar-powered backup could further reduce net energy use.
- The energy savings ~33% is a direct economic and environmental benefit. In operational terms, this reduction would mean significantly lower electricity bills and carbon footprint for the facility. If the baseline building was average in performance, the optimized design moves it into a high-performance category (comparable to green building certification standards for energy). The fact that this was achieved without resorting to costly active systems (e.g., solar panels or geothermal, which were not in the design scope) means the savings are purely from design intelligence. It validates that machine learning algorithms can optimize energy consumption patterns based on building geometry, material choices, and occupancy data derived from the BIM model. The AI essentially identified how to let the building *work with* its environment: shading when and where needed, opening up when outdoor conditions are good, etc. This kind of dynamic, context-aware optimization is something AI excels at, and it manifested in a building that uses far less energy to maintain comfort.

It is important to acknowledge uncertainty in these performance predictions. We have assumed ideal operation (e.g., windows opened when conditions allow, occupants using ceiling fans, etc.). Actual performance will depend on user behavior and controls. However, the design inherently provides the capability for high performance – it "hardwires" efficiency into the architecture. Even if operated sub-optimally, it would likely still outperform the original design simply due to features like better insulation and daylight. Moreover, the AI optimization could be extended to operational strategies as well (for example, training an AI controller for when to open windows or blinds). That would truly integrate design and operation in an AI framework, but is beyond this paper's scope.

4.6 Integration Process Challenges and Learnings

Integrating Revit with AI tools was not without challenges. One issue was ensuring data fidelity and consistency between Revit and the analysis models. We encountered cases where the exported geometry (for CFD or EnergyPlus) needed cleaning or where the simulation assumptions (like infiltration rates, internal heat gains) had to be standardized for fair comparisons. Automating Revit through Dynamo proved powerful, but debugging a complex graph of nodes and Python scripts required significant effort. A positive outcome of this integration was a confirmation that such workflows are feasible: modern BIM software like Revit can talk to AI/ML frameworks through APIs, allowing a two-way flow where the BIM model provides data and receives optimized design updates.

Another learning was the importance of a diverse initial dataset for training the ML surrogate model. We used generative design to produce varied building forms (within reason) to train the ML model. If we had only given it minor variants of one design, the model might have been too narrow in understanding. By feeding in very different configurations (some with courtyards, some rectangular, different orientations, etc.), we taught the ML model the broader patterns of what influences performance. This highlights a broader point: machine learning in architecture requires good data, which can partially be synthetically generated as we did. The outcome was a surrogate that predicted simulation results with about 90-95% accuracy during optimization, dramatically accelerating the search. We also found that combining objectives into one loss function for the ML (during training) was tricky – we instead trained separate models for each metric and combined their outputs to evaluate the multi-objective fitness. This modular approach gave us more control and interpretability (we could see if a design was good for daylight but bad for energy, for example, rather than one opaque score).

The ML approach also forced the team to quantify design goals explicitly. Rather than saying "improve ventilation" qualitatively, we had to define measurable targets (ACH rates, % hours, etc.). This exercise in itself is valuable, as it tightens the link between design decisions and performance outcomes. It pushes architects and engineers to be more data-driven and objective about what they want to achieve. In our case, setting those targets and weights involved some trial and error and sensitivity analysis. For example, if we weighted energy too high, the optimizer returned a very low-energy design but one that was too dark and perhaps less pleasant. If we weighted daylight too high, we got lots of glass and light but higher cooling loads. The final weighting was chosen to reflect a balanced design prioritizing occupant comfort (daylight and thermal) slightly above pure energy minimization – appropriate for a healthcare facility. This weighting process is something future AI design frameworks could potentially handle automatically (maybe via multi-criteria decision analysis or asking stakeholders to make pairwise comparisons), but in our project it required careful human judgment.

4.7 Broader Implications for Architectural Design

The successful optimization of this facility suggests that AI-based design optimization can be a game-changer for sustainable architecture. The method allowed us to achieve a design in one project phase that traditionally might require many rounds of redesign after performance feedback. By front-loading the analysis, we save time and avoid costly changes late in the project. It demonstrates how architects can use AI not as a replacement for creativity, but as an augmentation tool – exploring far more options than feasible manually and backing decisions with evidence. Importantly, the design that emerged is context-sensitive (to Sehore's climate and the project's needs), indicating that the AI wasn't just chasing numbers in a vacuum; it was effectively "learning" the project's context.

For a mental health rehabilitation center, the improved environmental conditions (more daylight, fresh air, stable temperatures) are likely to have positive therapeutic effects. Studies link daylight and natural ventilation to better patient outcomes, reduced stress, and improved circadian regulation. Thus, the AI optimization is indirectly contributing to the core mission of the facility – healing and wellness. This synergy between sustainability and wellness is often an intended outcome of good design; here it was achieved by explicitly encoding those goals into the AI's objective.

5. Conclusion

In this study, we successfully applied a machine learning–based optimization approach to the design of a health facility, achieving marked improvements in environmental performance and sustainability. By deeply integrating Autodesk Revit's BIM platform with AI-driven generative design and analysis tools, we demonstrated that complex objectives such as maximizing daylight, enhancing natural ventilation, improving thermal comfort, and minimizing energy consumption can be addressed concurrently in the early design stage. The optimized design generated by the ML workflow significantly outperforms the initial design – it is brighter, more comfortable, more naturally ventilated, and far more energy-efficient. These enhancements were achieved through architectural solutions (optimized orientation, shading, window configuration, etc.) identified by the AI, underscoring that intelligent design automation can uncover creative, effective design strategies that might elude conventional methods.
The research highlights several key contributions. First, it provides a practical case of AI-BIM integration: the Revit-to-ML pipeline we established can serve as a template for similar projects aiming to use AI in design optimization. We showed that with current technology, one can create a loop where a BIM model feeds data to an AI, the AI suggests improvements, and those are fed back into the BIM – achieving a synergy where the strengths of both (precise modeling and intelligent search) are utilized. Second, the work reinforces the value of data-driven decision-making in architecture. The explicit performance data and optimization metrics guided design changes that yielded quantifiable benefits. As building design increasingly focuses on sustainability and occupant well-being, such quantitative approaches will be invaluable in meeting stringent design targets. Third, our results contribute to the body of evidence that machine learning can lead to demonstrable performance gains in buildings. A roughly one-third reduction in energy use and substantial improvements in IEQ metrics were attained, aligning with or exceeding typical outcomes from conventional green design interventions – but achieved in a largely automated way. This suggests that AI optimization could become a standard part of high-performance building design, ensuring designs are not just compliant or aesthetically pleasing, but also rigorously optimized for performance from the outset.
In conclusion, the machine learning–optimized design for the health facility stands as a compelling example of how AI can enhance architectural practice. It maintains all functional and aesthetic requirements while elevating the building's environmental responsiveness to a superior level. The process required a collaborative mindset, where human designers defined goals and interpreted results, and the AI system explored solutions – together arriving at a design neither could have as effectively achieved alone. As AI tools continue to mature, we anticipate they will become integral to the architect's toolkit, enabling the creation of buildings that are smarter, greener, and more attuned to their occupants' needs. The lessons from this project will inform future endeavors, including scaling the approach to larger projects and integrating additional objectives such as cost, structural integrity, and even construction logistics into the optimization. Ultimately, embracing machine learning in design workflows can help architects and engineers push the boundaries of sustainable design, delivering high-performance buildings that meet the challenges of our time.

Author contributions

Rajat Palya: Conceptualization of the research framework, development of the machine learning optimization algorithm, implementation of the BIM-AI integration workflow, and writing of the initial manuscript draft.
Dr. Arun Patel: Supervision of the technical methodology, validation of the simulation results, performance analysis of the optimized design, and substantial contributions to the final editing and formatting of the paper.
Dr. Sudesh Kumar Sohani: Coordination of the experimental setup and case study deployment, data curation and visualization of performance metrics, and review and revision of the manuscript for critical intellectual content.

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