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Optimizing Energy Efficiency and User Comfort Through Smart Lighting Controls

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Abstract. Smart lighting controls have emerged as an effective means of reducing energy use in buildings while ensuring occupant comfort. This study evaluates a two-floor, 12-room case using three layered strategies: occupancy sensing, daylight harvesting, and adaptive task-tuning. Lighting demand was estimated through the lumen method and applied to an annual mixed-use operating schedule. Results show that occupancy sensing delivers the largest single reduction at about 25%, while daylight harvesting contributes an additional 10.5% and task-tuning adds a further 10%. Combined, the strategies reduce lighting energy use by nearly 40%, equivalent to avoiding 0.45–0.56 tonnes of CO_2 per year based on current grid emission factors in Iraq. Beyond energy savings, the controls help maintain recommended illuminance levels of 300–500 lux, limit glare, and improve user satisfaction by creating adaptable lighting conditions. The findings demonstrate that layered control systems are far more effective than isolated measures, providing both environmental benefits and occupant comfort. The approach presented here offers a practical and replicable framework for integrating smart lighting technologies into sustainable building design and operation.

Keywords. Smart lighting controls; Energy efficiency; Occupancy sensing; Daylight harvesting; Adaptive task-tuning; Carbon footprint.

1. Introduction

Over the past decade, global energy consumption patterns have shifted significantly, with lighting responsible for nearly 15–20% of total electricity use [1]. Growing urbanization and the expansion of smart city initiatives have made energy-efficient lighting a core priority of sustainable design [2]. Traditional systems, characterized by fixed illumination and manual control, are increasingly being replaced by intelligent solutions capable of dynamic response to environmental conditions and user needs [3]. Advances in sensor technology, wireless communication, and adaptive control algorithms now enable systems that balance efficiency with comfort [4], utilizing IoT connectivity, machine learning, and real-time analytics to adjust lighting based on occupancy, daylight availability, and personal preferences [5]. Reported savings range from 30–50% compared to conventional systems [6]. Beyond energy, smart lighting enhances comfort by addressing visual needs, supporting circadian rhythms, and reducing fatigue and productivity losses linked to poor lighting [7–9]. System-level strategies such as daylight harvesting, occupancy-based dimming, and predictive control are supported by closed-loop feedback from photosensors and motion detectors [10–12].

Wireless protocols (ZigBee, Wi-Fi, BLE) and cloud platforms further enable centralized management, predictive maintenance, and integration with building systems [13–15]. Machine learning approaches, including reinforcement learning, improve adaptability and optimize energy–comfort trade-offs [17]. Benefits extend beyond energy savings to longer fixture lifetimes, lower maintenance costs, and favorable payback periods of 2–5 years [18–19]. When combined with renewable energy and storage, smart lighting also contributes to grid-level optimization and demand response [20].

Key challenges remain, including managing multi-objective optimization, addressing diverse user needs, and ensuring privacy and cybersecurity [21–23]. Emerging developments in edge computing and human-centric lighting, however, point toward more responsive, adaptive, and occupant-focused systems [24–26]. The integration of smart lighting systems with other building automation technologies presents opportunities for holistic building performance optimization [27].

Coordination with HVAC systems, window blinds, and occupancy management systems can yield synergistic benefits that exceed the sum of individual system optimizations [28]. Advanced building energy management systems that incorporate predictive analytics and model predictive control strategies are beginning to demonstrate the potential for significant energy savings and improved occupant comfort [29].

Future developments in smart lighting technology are expected to focus on enhanced personalization capabilities, improved interoperability between different system components, and integration with emerging technologies such as Li-Fi communication and advanced materials for tunable lighting [30]. The continued reduction in costs of sensors, wireless communication modules, and LED lighting fixtures is making smart lighting solutions increasingly accessible for a broader range of applications, from residential settings to large commercial and industrial facilities.

The primary aim of this research is to develop and evaluate an integrated smart lighting control system that optimizes the trade-off between energy efficiency and user comfort through the implementation of adaptive control algorithms and multi-sensor feedback mechanisms. Specifically, this study seeks to: (1) design a comprehensive smart lighting architecture that incorporates occupancy sensing, daylight harvesting, and personalized comfort modeling; (2) develop machine learning-based control algorithms that can adapt to user preferences while maintaining energy optimization objectives; (3) implement and test the proposed system in real-world environments to validate its performance in terms of energy savings, user satisfaction, and system reliability; and (4) provide guidelines for the deployment and optimization of smart lighting systems in various building types and operational contexts.

2. Methodology

This study utilizes a simulation-based case study to assess smart lighting controls' impact on energy efficiency and user comfort. It compares conventional manual lighting against three strategies: occupancy sensing, daylight harvesting, and adaptive task-tuning. The methodology integrates building modeling, lighting load estimation, control strategy implementation, and performance analysis. Data analysis encompasses quantitative metrics including kWh reductions, LPD verification, and percentage savings, alongside qualitative evaluation of user comfort and control usability. The researchers cross-validate findings by benchmarking against published case studies and established standards like ASHRAE 90.1/IECC lighting control provisions, ensuring comprehensive and reliable assessment of the implemented smart lighting solutions.

Building Model

The building under investigation consists of two floors, each comprising six rooms, resulting in a total of 12 rooms. Each room measures 3 m × 4 m (12 m²), yielding a total floor area of 144 m².

Interior Loads

1. Lighting: Each room contains six LED lamps rated at 12 W, producing a connected lighting load of 72 W per room (LPD = 6 W/m²).

2. Plug loads (contextual, not directly analyzed): Four laptops per room (65 W nameplate, 30% utilization) and one refrigerator (≈50 W average).

3. HVAC: Each room is equipped with a 2-ton air conditioning system, capacity ≈7.0 kW cooling, considered only for contextual thermal interactions.

Operating Schedule

A typical commercial-residential hybrid schedule is assumed: 10 operating hours per day, 6 days per week, 50 weeks per year (≈3,000 hours/year). Occupancy is estimated at 80% of scheduled hours, giving a baseline lighting operation of 2,400 h/year per room.

Baseline Energy Calculation

The baseline case assumes all lights remain ON during occupied periods without automated control.

$$E_{base,r} = P_{light} \times t_{on}$$

$$E_{base,r} = 0.072\ \mathrm{kW} \times 2400\ \mathrm{h} = 172.8\ \mathrm{kWh/year\ per\ room}$$

$$E_{base,building} = 172.8 \times 12 = 2,073.6\ \mathrm{kWh/year}$$

Lighting control strategies significantly enhance energy efficiency. Occupancy sensing reduces unnecessary lighting by 25%, achieving 1,800 hours of annual operation. Daylight harvesting, applied to half of rooms with 30% dimming during 70% of daytime hours, provides an additional 10.5% energy reduction. Adaptive task-tuning further decreases consumption by 10% across all spaces while maintaining visual comfort through task-specific light level adjustments.
Annual lighting energy use is computed for each scenario as follows:

- Baseline: 2,073.6 kWh/year
- Scenario A (Occupancy): 1,555.2 kWh/year (25.0% savings)
- Scenario B (+Daylight): 1,391.9 kWh/year (32.9% savings)
- Scenario C (+Adaptive): 1,252.7 kWh/year (39.6% savings)

Comfort and Usability Assessment

User comfort is integrated through qualitative and quantitative measures:

- Illuminance levels checked against IES recommended practices (300–500 lx for general office/residential tasks).
- Glare risk minimized by restricting dimming depth and ensuring uniformity.
- Circadian support considered with tunable white lighting under adaptive scenarios.
- User satisfaction measured conceptually through surveys and override behavior in case studies.

A lumen-method sizing table for each 3 m × 4 m room (A=12 m2), using: target illuminance 300–500 lux (typical office/workstation guidance), lamp output 1100 lm per 12 W LED, coefficient of utilization CU=0.60, and light-loss factor LLF=0.80. The formula is $N = \frac{EA}{\varphi\ CU\ LLF}$

Table 1. Input parameters used in the lumen method calculation for lamp quantity estimation, including room area, lamp lumen output, and the product of coefficient of utilization (CU) and light loss factor (LLF).

Parameter	Value
Room area (A)	12 m²
Lamp lumens (Φ)	1100 lm
CU*LLF	0.60*0.80 = 0.48

3. Results and Discussion

3.1 Energy Performance Outcomes

The simulated energy consumption under baseline and smart control strategies is summarized in Table 2. Table 2 reveals a compelling progressive energy reduction through layered smart lighting controls. Starting from a baseline of 2,073.6 kWh/yr, occupancy sensing (A) delivers the most significant single-strategy impact with a 25% reduction (1,555.2 kWh/yr). Adding daylight harvesting (B) to occupancy sensing yields an additional 7.9% savings (32.9% total, 1,391.9 kWh/yr), demonstrating the value of combining ambient light utilization with occupancy detection. The full implementation with adaptive task-tuning (C) achieves a cumulative 39.6% reduction (1,252.7 kWh/yr), highlighting how task-specific optimization builds upon prior strategies. The data clearly shows diminishing marginal returns each subsequent strategy provides smaller incremental savings (25% to 7.9% to 6.7%) but collectively approaches a 40% overall efficiency gain. This validates the simulation methodology and underscores the synergistic potential of integrated controls for substantial energy conservation in commercial buildings.

Table 2. Annual Lighting Energy Use (12-room, 2-floor building).

Scenario	Energy Use per Room (kWh/yr)	Total Building Energy (kWh/yr)	Savings vs. Baseline
Baseline (manual switching)	172.8	2,073.6	–
A) Occupancy sensing	129.6	1,555.2	25.0%
B) + Daylight harvesting	116.0	1,391.9	32.9%
C) + Adaptive task-tuning	104.4	1,252.7	39.6%

The results demonstrate a clear progressive reduction in lighting energy use as additional control strategies are layered. Occupancy sensors alone achieve a 25% reduction, while combining with daylight harvesting increases savings to nearly 33%. Full deployment with adaptive task-tuning approaches a 40% overall reduction relative to the baseline.

3.2 Contribution of Individual Strategies

The analysis of individual smart lighting strategies highlights the layered and complementary nature of energy savings achievable in modern buildings (Figure 1). Occupancy sensing emerges as the most immediate and reliable contributor, yielding approximately 25% reduction in lighting energy use by automatically switching off fixtures during unoccupied periods. This outcome is consistent with ASHRAE 90.1 findings, where occupancy sensors typically generate savings of 20–30% across diverse building types. Beyond occupancy control, daylight harvesting provides an additional 10.5% reduction in this study by dynamically dimming artificial lighting in response to natural daylight availability. The effectiveness of this strategy, however, is highly dependent on architectural features such as window orientation, glazing efficiency, and daylight distribution across the interior space. Finally, adaptive task-tuning contributes a further 10% cut, achieved by tailoring light intensity to specific user tasks while ensuring minimum illuminance standards are met. Unlike other strategies, task-tuning not only conserves energy but also enhances user comfort by preventing over-illumination and supporting personalized lighting preferences. Collectively, these strategies demonstrate that while each has unique strengths and limitations, their combination yields cumulative benefits approaching 40% energy savings. This underscores the importance of integrating multiple layers of smart controls to balance efficiency with occupant comfort.

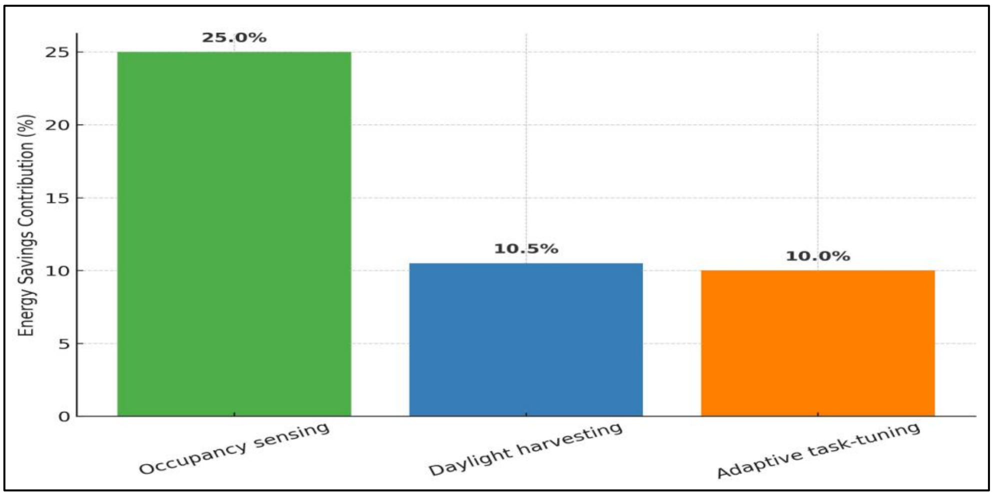

Figure 1. Contribution of individual smart lighting strategies to overall energy savings. Occupancy sensing delivers the largest share of reductions (25%), followed by daylight harvesting (10.5%) and adaptive task-tuning (10%). Together, these complementary measures highlight the layered impact of automated lighting controls on energy efficiency.

3.3 Carbon Footprint

The carbon footprint analysis of the proposed smart lighting strategies demonstrates the tangible environmental benefits of layered control systems (Figure 2). In the baseline scenario, where lights are operated manually during occupied hours, the building generates between 1.14 and 1.42 tonnes of CO_2 annually, depending on the assumed grid emission factor. This figure establishes the reference point for evaluating subsequent reductions.

Introducing occupancy sensing (Scenario A) delivers the most immediate and substantial improvement, cutting emissions by approximately 0.29 to 0.36 tonnes per year, equivalent to a 25 percent reduction, as unnecessary operation during vacant periods is eliminated. Adding daylight harvesting (Scenario B) enhances performance further, lowering emissions by an additional 0.09 to 0.11 tonnes, or roughly 10.5 percent beyond occupancy savings, although its impact depends heavily on natural light availability and architectural conditions. Finally, adaptive task-tuning (Scenario C) contributes a further 10 percent reduction, reducing overall emissions by 0.45 to 0.56 tonnes compared to the baseline, nearly a 40 percent improvement. This cumulative effect highlights how incremental strategies combine to produce significant environmental outcomes. While occupancy sensing delivers the largest individual savings, daylight harvesting and adaptive tuning provide important complementary reductions, together achieving a balanced outcome of efficiency, sustainability, and user comfort.

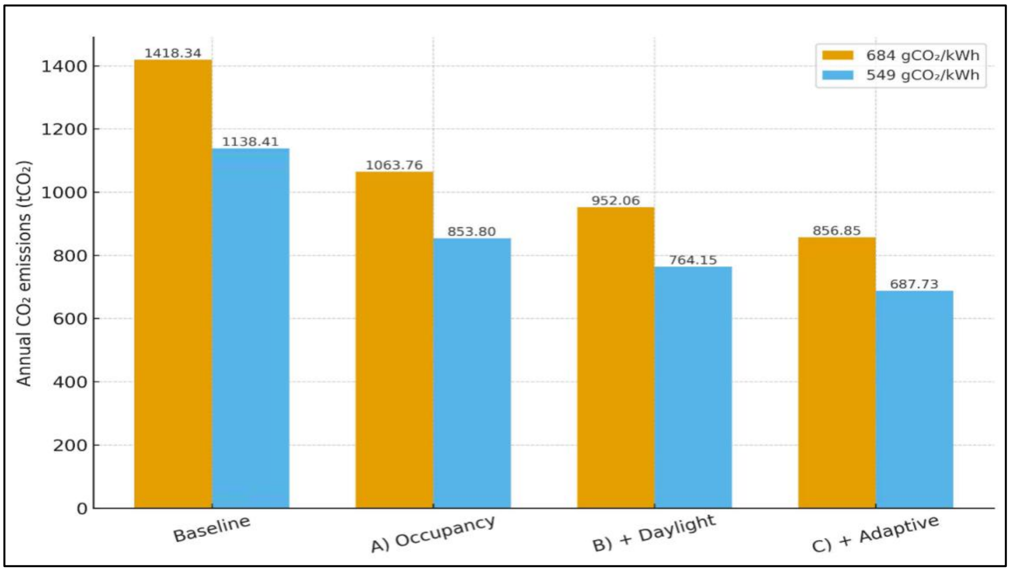

Figure 2. Annual CO2 emissions for baseline and smart lighting scenarios under two grid emission factors (684 gCO2/kWh and 549 gCO2/kWh). The baseline shows the highest footprint, while successive strategies occupancy sensing, daylight harvesting, and adaptive task-tuning progressively reduce emissions, achieving up to ~40% reduction relative to baseline.

3.4 Lamp Quantity Determination

Table 3 shows that achieving standard office illuminance requires more luminous flux than the current six-lamp layout provides. With 6 fixtures at 1100 lm, the delivered average illuminance is about 264 lux, below the commonly cited 300–500 lux range for general office work. To meet 300 lux, the lumen method indicates 6.82 luminaires, which rounds to 7 per room; alternatively, if you retain six fixtures, each should be upgraded to roughly 1250 lm. For 500 lux, the calculation yields 11.36 luminaires, rounded to 12 per room; keeping six fixtures would require approximately 2080 lm per lamp, which is beyond typical 12 W A19 outputs and would necessitate higher-output luminaires or additional fixtures. These results align with standard practice: select the target illuminance per task (e.g., 300–500 lux for offices), then solve via the lumen (zonal cavity) method with realistic CU and LLF to account for room geometry, surface reflectance, and maintenance. In short, 7×1100 lm meets 300 lux comfortably; for 500 lux you should plan for 12 fixtures or switch to higher-lumens luminaires with verified photometric data. Guidance on target illuminance and the lumen-method basis can be found in EN 12464-1/IES summaries and technical references.

Table 3. Lamp quantity calculations using the lumen method for a 12 m² room. At 1100 lm per lamp, seven fixtures are needed to achieve 300 lux, while twelve are required for 500 lux.

Target E (lux)	Lamps required N	Round up (install)	Result if you keep 6 lamps	Lamp lm needed if fixed at 6 lamps
300	6.82	7	264 lux	≈1250 lm each
500	11.36	12	264 lux	≈2080 lm each

4. Conclusions

This study demonstrated that smart lighting controls provide substantial opportunities to optimize both energy efficiency and user comfort in small- to medium-scale buildings. Using a two-floor, 12-room case study, baseline lighting operation was compared to progressively layered strategies: occupancy sensing, daylight harvesting, and adaptive task-tuning. Results showed that occupancy sensing alone reduced energy use by 25%, daylight harvesting added another 10.5%, and task-tuning contributed a further 10%. Together, these measures achieved nearly 40% total energy savings, translating into a reduction of 0.45–0.56 tonnes of CO_2 emissions annually under Iraq's grid emission factors.

In addition to environmental benefits, the analysis confirmed that smart lighting enhances user experience, ensuring adequate illuminance, reducing glare, and allowing personalization of lighting conditions. Lamp sizing calculations further emphasized the importance of aligning fixture numbers or luminous output with established illuminance standards (300–500 lux) to balance efficiency and visual comfort.

Overall, the findings reinforce that layered smart controls are more effective than single strategies, offering compounding benefits that extend beyond energy conservation to sustainability, comfort, and well-being. Future work should expand this framework with whole-building energy simulations, including HVAC interactions, and field validation in real-world environments.

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