

Mathematical Optimisation of Classroom Lighting Energy Consumption Using Occupancy and Illumination Constraints

Aishani Bajaj

Student, Class 12, Modern High School International, Kolkata

Abstract

Classroom lighting constitutes a substantial portion of energy consumption in educational buildings, with lighting accounting for approximately 23–42% of total energy use in educational facilities. Traditional lighting systems typically operate at full capacity regardless of human presence, leading to considerable energy waste during unoccupied periods. This paper reviews the literature on classroom lighting energy consumption, occupancy-based control strategies, sensor technologies and placement optimisation, daylight harvesting, and mathematical optimisation approaches, and on the basis of that review proposes a linear programming framework for classroom lighting control that treats occupancy and illumination requirements as explicit constraints. The studies reviewed report lighting operating time reductions of 48–52% and energy savings of 43–63% for occupancy- and daylight-responsive systems, together with reductions exceeding 60% where lighting is switched off during vacancy. The proposed framework is presented as a formulation rather than as an implemented and validated system; its purpose is to unify the occupancy-based control and daylight-responsive strategies that the reviewed literature has largely treated separately. The findings highlight the potential for occupancy- and daylight-responsive lighting models to significantly reduce energy consumption in educational buildings, with particular relevance for developing country contexts such as India.

Keywords: classroom lighting; energy optimisation; occupancy sensors; daylight harvesting; linear programming; sustainable buildings; smart lighting

1. Introduction

The building sector consumes approximately 20–40% of global energy, and CO₂ emissions from building operations account for roughly 10% of global greenhouse gas emissions [1]. Within buildings, lighting represents a significant portion of energy consumption, accounting for about 18–60% of total energy used in building operations. In educational buildings specifically, lighting accounts for approximately 23–42% of total energy consumption. This makes classroom lighting a critical target for energy efficiency interventions [1].

Classroom lighting is particularly important because it directly impacts student performance, productivity, mood, and visual health [2]. Numerous studies highlight prevalent suboptimal lighting in educational settings, with close to 50% of participants in some studies indicating that lighting conditions were suboptimal for task performance. In one study conducted in architecture studios in Cairo, 49% of participants reported experiencing visual discomfort issues [2]. These findings underscore the dual

challenge facing classroom lighting design: meeting illuminance requirements for occupant comfort and learning while minimising energy consumption.

In many educational facilities, luminaires remain switched on during vacant periods because lighting operation depends primarily on manual switching or fixed schedules [3]. Traditional lighting systems in campuses typically operate at full capacity regardless of human presence, leading to high electricity usage and increased operational costs [4]. Common phenomena include fully turning on lights during daytime, turning on all lights when few people are present, and failing to turn off lights when spaces are unoccupied [5].

This situation creates a significant opportunity for control-oriented sustainability measures that can improve building performance through intelligent operation rather than through major construction or replacement interventions. However, the effectiveness of such strategies depends not only on the control rule itself but also on the spatial placement of occupancy sensors, sensing radius, classroom geometry, and operating schedules [3].

This paper aims to review existing literature on classroom lighting energy consumption, occupancy-based control strategies, sensor technologies, and mathematical optimisation approaches, evaluate the potential energy savings of an occupancy- and daylight-responsive lighting model relative to conventional continuous lighting use, investigate the relationship between classroom occupancy patterns and electricity consumption from artificial lighting, and examine the role of daylight availability in reducing artificial lighting demand while maintaining recommended illumination levels. Section 2 presents the review. Section 3 draws on the reviewed literature to set out a proposed linear programming framework in which occupancy and illuminance requirements enter the same optimisation problem. Section 4 concludes and identifies directions for further work.

2. Literature Review

2.1. Classroom Lighting Energy Consumption: Magnitude and Significance

Lighting energy consumption in educational buildings has been the subject of extensive research. Seo and Yun developed a digital twin-based assessment framework for energy savings in university classroom lighting, analysing 55 classrooms across nine university buildings [1]. Their study revealed that in the classrooms examined, lighting was turned on in the absence of occupants for an average of 10.7 hours per day. This finding highlights the substantial waste inherent in conventional lighting management practices. The magnitude of this waste is considerable. Tipán and Igllón note that lighting systems represent an important component of electricity consumption in educational buildings, particularly in classrooms with long daily operating periods and intermittent occupancy [3]. Operating schedules in university classrooms often extend throughout the academic day, from 07:00 to 21:00, increasing the relevance of control-oriented energy-saving measures [3].

The issue is equally pertinent in the Indian context. India's peak electricity demand in 2023 reached approximately 243 GW, of which the lighting load has been estimated at approximately 18.6 GW [9]. This underscores the importance of lighting efficiency improvements for national energy conservation efforts. A lighting audit conducted in a higher educational institute in Gujarat, India, reviewed existing literature on lighting audit methodologies and energy conservation measures including daylight harvesting, LED retrofitting, and smart lighting controls [9].

2.2. Occupancy-Based Lighting Control Strategies

Occupancy-based lighting control is a well-established strategy for reducing unnecessary lighting operat-

ion. This approach links lighting operation to actual or assumed room use, reducing unnecessary operating time [3]. Several control strategies have been explored in the literature.

2.2.1. Binary ON/OFF Control

The simplest form of occupancy-based control involves turning lights on when occupancy is detected and off when the space becomes vacant. Seo and Yun found that it is possible to reduce power consumption by more than 60% by employing an off strategy involving a passive infrared sensor or manual management [1].

2.2.2. Dimming Control

More sophisticated approaches use continuous dimming rather than binary switching. Divya and Pai employed a linear programming approach to optimise energy consumption with respect to illuminance at particular locations in a classroom, demonstrating the effectiveness of this methodology for satisfying individual preferred illuminance [7].

2.2.3. Multi-State Control

A distributed multi-state LED lighting control system operating in a three-state configuration—active, dim, and idle—has been proposed for academic campus environments. This system dynamically modulates lighting states based on real-time human occupancy detection, with integrated sensor arrays continuously monitoring and relaying occupancy data to enable seamless state transitions [4].

2.2.4. Dynamic Retention Time Optimisation

Conventional occupancy-based lighting systems often rely on fixed retention times, leading to unnecessary lighting of unoccupied areas or premature deactivation that degrades user comfort. Recent research has proposed algorithms that optimise both dimming levels and retention times based on real-time occupant positioning, with retention times dynamically adjusted according to occupant–luminaire distance and its rate of change [8].

2.3. Sensor Technologies and Placement Optimisation

2.3.1. Sensor Types

Various sensor technologies have been employed for occupancy-based lighting control. PIR (passive infrared) sensors are the most common, with reported energy savings of 20–93% from introducing PIR-based occupancy control systems [1]. Machine vision-based systems using deep learning algorithms can accurately determine the presence, quantity, and activity area of indoor personnel, offering richer occupancy information than binary presence detection [5].

2.3.2. Sensor Placement Optimisation

The effectiveness of occupancy-based control depends critically on sensor placement. Tipán and Iglón developed a reproducible methodology integrating Voronoi-based spatial analysis, genetic algorithm optimisation, and dynamic occupancy-based lighting control simulation [3]. Their optimisation process evaluated candidate sensor positions according to spatial coverage, geometric regularisation, and an indirect energy-related penalty associated with uncovered zones.

For a representative classroom, the optimised sensor position was located near the geometric centre of the room, achieving an estimated spatial coverage of 94.7% under the adopted sampling-based geometric model with an effective detection radius of 6 metres [3]. Multi-classroom analysis showed that the required number of sensors depends on classroom geometry and the adopted sensing radius.

2.3.3. Comparison with Existing Approaches

Table 1 summarises key studies on sensor placement and lighting control in educational settings.

Study	Main Focus	Sensor Placement	Control/Energy Assessment
Tipán & Iglón (2026) [3]	Occupancy sensor placement optimisation + energy assessment	Yes (Voronoi + GA)	Yes (48–52% operating time reduction)
Seo & Yun (2022) [1]	Classroom lighting energy savings using digital twins	Not optimised	Yes (>60% power consumption reduction)
Divya & Pai (2019) [7]	Linear programming for individualised lighting	Not main focus	Yes (energy consumption optimisation)
Doulos et al. (2019) [10]	LED DC luminaires + daylight harvesting for near-ZEB	Photosensor placement	Yes (90.5 → 0.55 kWhp/m ²)
Delvaeye et al. (2016) [11]	Daylight control systems in school buildings	Not main focus	Yes (18–46% annual energy savings)
Nolé et al. (2022) [12]	Multi-objective ILP for classroom cognitive optimisation	Not applicable	Not applicable (cognitive outcomes)

Table 1: Comparison of Existing Approaches

2.4. Mathematical Optimisation Approaches for Lighting Control

2.4.1. Linear Programming

Linear programming has been widely applied to lighting optimisation problems. Divya and Pai formulated a linear programming problem to optimise energy consumption with respect to illuminance at particular locations in a classroom with multiple locations and different combinations of four luminaires [7]. Their study depicted the relationship between energy consumption and the number of luminaires at certain locations, considering individual satisfaction as a dynamic factor.

Recent work has extended this approach to occupant-aware lighting control. An influence-based illuminance model incorporating luminous intensity, incidence angle, and the inverse-square law has been proposed to determine each luminaire's contribution to an occupant's illuminance [8]. Optimal dimming levels are obtained via linear programming to minimise total energy consumption under task lighting constraints.

2.4.2. Genetic Algorithms

Genetic algorithms have been employed for sensor placement optimisation. Tipán and Iglón [3] implemented a genetic algorithm formulated as a constrained two-dimensional search problem in which each individual represents a candidate occupancy sensor position within classroom boundaries. The optimisation process was guided by a multi-criteria fitness function that prioritised spatial coverage.

2.4.3. Multi-Objective Optimisation

Multi-objective integer linear programming has been applied to classroom optimisation problems, balancing multiple objectives such as maximising learning outcomes (represented by attention, memory, and preference) against constraints including illuminance [12].

2.5. Daylight Harvesting and Hybrid Lighting Systems

Daylight harvesting—the practice of using natural light to reduce artificial lighting demand—offers substantial energy savings potential. Doulos et al. demonstrated that annual lighting primary energy consumption in a typical classroom could be reduced from 90.5 kWhp/m² to 0.55 kWhp/m² through the use of LED DC luminaires together with daylight harvesting systems, measured against a baseline installation using legacy fluorescent luminaires [10]. This represents a reduction of over 99%, although it should be noted that a substantial share of this saving derives from the luminaire replacement itself rather than from daylight-responsive control alone.

Analysis of enhanced classroom daylighting utilisation showed that a classroom design incorporating a shed roof with an additional ceiling window (with window-to-wall ratios of 41% on the north face and 56% on the south face) was expected to achieve 27% energy savings using daylighting [13]. Compared with a typical model, the energy savings in the enhanced daylighting utilisation model could be 10 percentage points higher [13].

Analysis of three daylight control systems in school buildings found that total annual energy savings varied from 18% to 46% [11]. Daylight control systems that automatically adjust artificial light levels depending on daylight penetration can result in substantial energy savings.

Smart lighting integration in educational buildings addresses the limitation of passive daylighting by linking electric lighting operation to daylight availability and classroom occupancy [9]. Daylight-responsive dimming and occupancy-based controls can reduce unnecessary operation and over-illumination, particularly when daylight contribution varies across the room or throughout the day.

2.6. Occupant Comfort and Illumination Constraints

Classroom lighting significantly influences students' performance and productivity, as well as building energy consumption [2]. Numerous studies highlight prevalent suboptimal lighting in education, with almost half of students expressing discomfort, emphasising the need to enhance lighting environments. Research using HDRi surveillance lighting control systems demonstrated that energy savings of approximately 43–63% could be achieved while still ensuring visual comfort for the majority of students. Over 70% of students expressed satisfaction even when classroom brightness was reduced by 30%. Notably, perceived brightness was found to be more crucial than illuminance in evaluating visual comfort [2].

Evaluation of candidate lighting solutions for a model medical college classroom found that LED- and fluorescent tubular lamp-based lighting solutions were preferable for lower energy and maintenance costs (<US\$167/year), higher vertical illuminance levels (157–305 lx), satisfactory power factor (≥ 0.93), and good colour rendering index (CRI: 74–81) [6].

2.7. Optimisation Results from a Reported Case Study

Using the experimental setup of Tipán and Iglón as a case study, through analysis of classroom description, occupancy patterns, lighting system parameters, and simulation tools such as MATLAB, DIALux, and EnergyPlus, the optimised sensor position was located near the geometric centre of the room, achieving an estimated spatial coverage of 94.7% [3]. For classrooms with similar geometry, one sensor satisfied the 90% coverage criterion, while the largest classroom required two sensors.

The dynamic simulation showed reductions in lighting operating time of 48% for the 10-hour daily scenario and 52% for the 12-hour daily scenario [3]. These reductions were translated into lower daily and monthly energy consumption across different lighting configurations.

2.8. Energy Saving Analysis

The energy savings potential from various control strategies is summarised in Table 2.

Control Strategy	Energy Savings	Source
Occupancy-based ON/OFF control	48–52% operating time reduction	Tipán and Iglón (2026) [3]
PIR sensor-based off strategy	>60% power consumption reduction	Seo and Yun (2022) [1]
HDRi surveillance lighting control	43–63% energy savings	Budhiyanto and Chiou (2024) [2]
Enhanced daylighting utilisation	27% energy savings	Nur et al. (2024) [13]
LED DC luminaires + daylight harvesting	90.5 → 0.55 kWhp/m ² (vs. fluorescent baseline)	Doulos et al. (2019) [10]
Multi-state LED lighting control	Significant reduction reported	Sarkar et al. (2025) [4]

Table 2: Summary of Energy Saving Analysis

These findings indicate that optimised occupancy-based control can support sustainability-oriented energy management in educational buildings by reducing unnecessary electricity use while preserving the existing lighting infrastructure.

3. Proposed Linear Programming Framework

The review in Section 2 shows that occupancy-based control [1, 3, 4, 8] and daylight-responsive control [10, 11, 13] have largely been studied as separate strategies. That's where linear programming has been applied to classroom lighting it has been used to satisfy illuminance requirements at fixed locations without an explicit occupancy term [7, 8]. This section sets out a formulation in which both appear as constraints on the same optimisation problem. This framework has not been implemented yet, and it is just a proposal ; no numerical results are claimed for it here, and Section 4 identifies its validation as the principal item of further work.

3.1. Scope and Assumptions

The framework applies to a single classroom fitted with individually dimmable luminaires, an occupancy sensing system of the kind reviewed in Section 2.3, and a daylight measurement or estimation capability. The 4 assumptions that are adopted into this framework are:

- Illuminance at a point is the sum of the contributions of the individual luminaires and of daylight. This superposition property is what the influence-based illuminance model of [8] relies upon, and it is the reason the problem can be written as a linear program.
- The illuminance contributed by a luminaire is proportional to its dimming level. This is an idealisation; measured dimming curves for DC LED luminaires are monotonic but not exactly linear [10], and Section 3.7 notes how a piecewise-linear approximation preserves the structure of the problem.
- Electrical power drawn by a luminaire is proportional to its dimming level, so that minimising power is equivalent to minimising the sum of dimming levels weighted by rated power.

- Occupancy is known for each control interval, either from sensors or from timetable data, and is treated as a parameter of the problem rather than a decision variable.

3.2. Notation

Symbol	Meaning	Type
$J = \{1, \dots, n\}$	Set of dimmable luminaires in the classroom	Set
$I = \{1, \dots, m\}$	Set of task points on the working plane (e.g. desk positions)	Set
$T = \{1, \dots, T\}$	Set of control intervals, each of duration Δt	Set
a_{ij}	Illuminance (lx) delivered at point i by luminaire j at full output	Parameter
D_{it}	Daylight illuminance (lx) at point i during interval t	Parameter
$o_{it} \in \{0, 1\}$	Occupancy indicator: 1 if point i is occupied during interval t	Parameter
$\omega_t \in \{0, 1\}$	Room occupancy indicator: 1 if any point is occupied during t	Parameter
P_j	Rated electrical power (W) of luminaire j at full output	Parameter
E^T	Required maintained illuminance (lx) at an occupied task point	Parameter
E^M	Minimum illuminance (lx) required anywhere in an occupied room	Parameter
E^U	Upper illuminance limit (lx) guarding against over-illumination	Parameter
$\rho \in (0, 1)$	Required uniformity ratio on the working plane	Parameter
$\delta \in (0, 1]$	Maximum permitted change in dimming level between intervals	Parameter
$d_{jt} \in [0, 1]$	Dimming level of luminaire j during interval t	Decision variable

Table 3: Notation used in the proposed framework

3.3. Illuminance Model

The coefficient a_{ij} expresses how much illuminance luminaire j delivers at task point i when operating at full output. Following the influence-based model of [8], which combines luminous intensity, incidence angle, and the inverse-square law, the direct component may be written as:

$$a_{ij} = (I_j(\gamma_{ij}) \cdot \cos \theta_{ij}) / r_{ij}^2 \cdot MF \quad (1)$$

where $I_j(\gamma_{ij})$ is the luminous intensity (cd) of luminaire j in the direction of point i , θ_{ij} is the angle of incidence at the working plane, r_{ij} is the distance from luminaire to point (m), and MF is the maintenance factor accounting for lamp depreciation and dirt accumulation. Equation (1) captures the direct component. the interreflected component may be added either as a constant term or by obtaining a_{ij} from photometric

simulation software of the kind used in [3]. In either case superposition is preserved, and the coefficients remain constants of the optimisation problem.

The artificial illuminance at point i during interval t is then the sum over all luminaires of their contributions at the chosen dimming levels:

$$E_{it}^{\text{art}} = \sum_{j \in J} a_{ij} d_{jt} \quad (2)$$

3.4. Daylight Contribution

Daylight enters the formulation as a known quantity for each interval. Where measured values are unavailable, the daylight factor method gives:

$$D_{it} = DF_i \cdot E_t^{\text{ext}} \quad (3)$$

where DF_i is the daylight factor at point i , determined by classroom geometry and window-to-wall ratio, and E_t^{ext} is the external horizontal illuminance during interval t . The sensitivity of DF_i to glazing configuration is precisely what [13] examines. Because equation (3) scales a constant by a known quantity, the daylight term remains a parameter and the linearity of the problem is unaffected. Total illuminance at a point is therefore:

$$E_{it} = \sum_{j \in J} a_{ij} d_{jt} + D_{it} \quad (4)$$

3.5. Objective Function

The objective is to minimise the total electrical energy consumed by the lighting installation over the scheduling horizon:

$$\min Z = \Delta t \cdot \sum_{t \in T} \sum_{j \in J} P_j d_{jt} \quad (5)$$

This is a linear function of the decision variables, since Δt and P_j are constants. Here, all luminaires are identical, and the objective reduces to minimising the sum of the dimming levels.

3.6. Constraints

Task illuminance

Every occupied task point must receive at least the maintained illuminance recommended for classroom work. This is where a point is unoccupied. The constraint is relaxed automatically, because the right-hand side becomes zero:

$$\sum_{j \in J} a_{ij} d_{jt} + D_{it} \geq E^T o_{it} \quad \forall i \in I, t \in T \quad (6)$$

This single inequality showcases where occupancy and illumination meet. The occupancy term o_{it} switches the illuminance requirement on and off, so the solver is free to leave regions of the classroom dark whenever nobody is working in them. Through this, the operating time reduces by 48–52% reported in [3] exploit.

Background illuminance in an occupied room

An occupied room requires a minimum ambient level throughout for safe circulation, even at points where no task is being performed:

$$\sum_{j \in J} a_{ij} d_{jt} + D_{it} \geq E^M \omega_t \quad \forall i \in I, t \in T \quad (7)$$

Upper illuminance limit

Over-illumination wastes energy and is associated with visual discomfort. The finding in [2] states that perceived brightness matters more than illuminance, since over 70% of students remained satisfied at 30% reduced brightness, motivates an explicit ceiling:

$$\sum_{j \in J} a_{ij} d_{jt} + D_{it} \leq E^U \quad \forall i \in I, t \in T \quad (8)$$

Uniformity

Selectively dimming luminaires over unoccupied areas can produce an uneven luminous environment. Requiring each point to reach a fixed proportion of the mean level of the working plane bounds this effect,

and remains linear because the mean is itself a linear function of the decision variables:

$$E_{it} \geq \rho \cdot (1/m) \sum_{k \in I} E_{kt} \quad \forall i \in I, t \in T \quad (9)$$

Vacancy and bounds

Dimming levels are bounded below by zero and above by the room occupancy indicator, so that all luminaires are driven to zero output whenever the room is vacant. This reproduces the switch-off strategy that [1] associates with power consumption reductions exceeding 60%:

$$0 \leq d_{jt} \leq \omega_t \quad \forall j \in J, t \in T \quad (10)$$

Temporal smoothness

Large changes in output between consecutive intervals are perceptible and distracting. Bounding the rate of change addresses the comfort concern that motivates the dynamic retention time work of [8], and is linear once written as a pair of inequalities:

$$-\delta \leq d_{jt} - d_{j,t-1} \leq \delta \quad \forall j \in J, t \in T \setminus \{1\} \quad (11)$$

3.7. Complete Formulation and Properties

After considering all the constraints and limitation of classroom lighting, here is the proposed model which can be used to solve this problem:

$$\min Z = \Delta t \sum_t \sum_j P_j d_{jt}$$

The objective and all constraints are linear in the decision variables d_{jt} , and the variables are continuous. The model is therefore a linear program, solvable to global optimality by the simplex or interior-point methods. This matters practically: the problem has nT decision variables and of the order of $(3m + 2n)T$ constraints, so a classroom with 12 luminaires, 30 task points and 120 control intervals over a school day yields 1,440 variables and roughly 13,000 constraints — a problem size that is solved in well under a second by standard solvers, and small enough to run on the embedded hardware of the kind of distributed control system described in [4].

Two properties are worth noting. First, because the feasible region is defined by the illuminance constraints alone, infeasibility has a direct physical interpretation: it indicates that the installed luminaires cannot meet the required illuminance at some occupied point even at full output, which is a design fault rather than a control failure. Second, the energy saving achieved by the model is measured against the conventional practice described in Section 2, in which all luminaires run at full output for the whole schedule:

$$Z_{\text{base}} = \Delta t \cdot T \cdot \sum_{j \in J} P_j \quad S = 1 - Z^* / Z_{\text{base}} \quad (12)$$

where Z^* is the optimal objective value and S the fractional energy saving. Expressing the saving this way makes the framework's output directly comparable with the figures collected in Table 2.

3.8. Applying the Framework

Instantiating the model for a particular classroom requires four inputs: the geometry and photometric data needed to compute the coefficients a_{ij} from equation (1); an illuminance target E^T taken from the applicable standard; an occupancy profile o_{it} , obtained either from sensor logs or from the timetable; and a daylight profile D_{it} . Once assembled, the linear program can be solved for a representative day and the saving computed from equation (12). Because the coefficients depend only on the physical installation, they need to be computed once for a given classroom and reused across scenarios.

4. Conclusion and Future Work

This paper has reviewed the literature on classroom lighting energy consumption and, on that basis, proposed a linear programming framework that treats occupancy and illumination as constraints on a sin-

gle optimisation problem. The key findings of the review are:

- **Significant energy waste exists in conventional classroom lighting:** Lighting remains on during unoccupied periods for an average of 10.7 hours per day in university classrooms, representing a substantial opportunity for energy savings [1].
- **Occupancy-based control is highly effective:** Optimised occupancy-based control can reduce lighting operating time by 48–52% [3], with power consumption reductions exceeding 60% reported where lighting is switched off during vacancy [1].
- **Sensor placement is critical:** The effectiveness of occupancy-based control depends on sensor placement, with genetic algorithm-based optimisation achieving spatial coverage of up to 94.7% [3].
- **Daylight harvesting offers substantial additional savings:** Replacing legacy fluorescent luminaires with LED DC luminaires operated under daylight harvesting control reduced annual lighting primary energy consumption from 90.5 kWhp/m² to 0.55 kWhp/m² in a reported classroom study [10], while daylight control systems alone have been found to deliver 18–46% annual savings [11].
- **A unified mathematical framework is feasible:** The framework set out in Section 3 shows that dimming levels can be optimised under occupancy-dependent illuminance constraints within a linear program, which is solvable to global optimality at classroom scale.

Despite the substantial body of research on classroom lighting optimisation, several gaps remain:

- **Limited integration of occupancy and illumination constraints:** While individual studies have addressed occupancy-based control or daylight harvesting separately, few have developed unified mathematical frameworks that simultaneously optimise both. The framework proposed in Section 3 is intended as a step toward such an integration, but it has not yet been validated.
- **Limited focus on retrofit-oriented strategies:** Many studies assume new construction or complete lighting system replacement, whereas retrofit strategies for existing buildings are more practically relevant.
- **Geographic limitations:** Most studies have been conducted in developed country contexts, with limited research on classroom lighting in developing countries such as India, where energy efficiency improvements could have significant impact.
- **Economic analysis:** Complete economic payback assessments for occupancy- and daylight-responsive lighting systems in classroom settings remain limited.
- **Photometric validation:** Many optimisation studies lack photometric validation of their results. Based on the identified gaps, future research should focus on:
 - **Numerical validation of the proposed framework:** Instantiate the model of Section 3 for a real classroom using measured photometric and occupancy data, solve it for a representative schedule, and compare the resulting saving against the figures summarised in Table 2.
 - **Integrated occupancy-daylight optimisation:** Develop mathematical frameworks that simultaneously optimise occupancy-based control and daylight harvesting.
 - **Economic feasibility analysis:** Conduct comprehensive cost-benefit analyses for occupancy- and daylight-responsive lighting systems in classroom settings, particularly in developing country contexts like India.
 - **Photometric validation:** Validate optimisation results with actual photometric measurements in real classroom environments.
 - **IoT-based implementation:** Develop and test IoT-based adaptive control modes that integrate real-time user input, daylight harvesting, and occupancy mapping.

- **Machine vision integration:** Explore the use of machine vision and deep learning algorithms for more accurate indoor environment perception and intelligent lighting design.
- **Indian context studies:** Conduct studies specifically focused on Indian classroom environments, considering local building practices, occupancy patterns, and economic conditions.

References

1. Seo, H., & Yun, W. (2022). Digital twin-based assessment framework for energy savings in university classroom lighting. *Buildings*, 12(5), 544. <https://doi.org/10.3390/buildings12050544>
2. Budhiyanto, A., & Chiou, Y. (2024). Visual comfort and energy savings in classrooms using surveillance camera derived HDR images for lighting and daylighting control system. *Journal of Building Engineering*, 86, 108841. <https://doi.org/10.1016/j.jobbe.2024.108841>
3. Tipán, L., & Iglón, J. (2026). Sustainable energy performance optimization of occupancy sensor placement in smart lighting systems for university classrooms. *Sustainability*, 18(11), 5772. <https://doi.org/10.3390/su18115772>
4. Sarkar, S., Das, S., Pal, B., Rahaman, M. M., & Ghosal, P. (2025). A distributed multi-state LED lighting control system for energy optimization in academic campuses. In *2025 IEEE International Symposium on Smart Electronic Systems (iSES)*, Jaipur, India (pp. 104–109). <https://doi.org/10.1109/iSES67504.2025.00030>
5. Xu, W. (2025). Machine vision algorithm for indoor environment perception and intelligent lighting design. In *2025 International Conference on Electrical Drives, Power Electronics & Engineering (EDPEE)*, Athens, Greece (pp. 1107–1111). <https://doi.org/10.1109/EDPEE65754.2025.00200>
6. Bhattacharya, S., Bhattacharya, S., Das, A., Mahata, S., & Biswas, S. (2025). Evaluation of candidate lighting solutions for a model medical college classroom and insights for lighting system design in educational institutions. *Facilities*, 43(5/6), 397–415. <https://doi.org/10.1108/F-10-2024-0146>
7. Divya, C., & Pai, N. (2019). A linear programming approach towards individuation lighting system with optimal energy consumption. *Materials Today: Proceedings*, 17, 168–175. <https://doi.org/10.1016/j.matpr.2019.06.415>
8. Lee, J., & Kim, D. H. (2025). Occupant-aware lighting control algorithm with dynamic retention time. In *2025 16th International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju, Republic of Korea (pp. 348–351). <https://doi.org/10.1109/ICTC66702.2025.11388847>
9. Vachhani, S. V., Pandya, D. J., & Changela, C. (2026). Energy conservation through lighting audit and automated control strategies for a higher educational institute. *Interdisciplinary Journal of Research and Development*, 13(2), 95. <https://doi.org/10.56345/ijrdv13n208>
10. Doulos, L., Kontadakis, A., Madias, E., Sinou, M., & Tsangrassoulis, A. (2019). Minimizing energy consumption for artificial lighting in a typical classroom of a Hellenic public school aiming for near Zero Energy Building using LED DC luminaires and daylight harvesting systems. *Energy and Buildings*, 194, 201–217. <https://doi.org/10.1016/j.enbuild.2019.04.033>
11. Delvaeye, R., Ryckaert, W., Stroobant, L., Hanselaer, P., Klein, R., & Breesch, H. (2016). Analysis of energy savings of three daylight control systems in a school building by means of monitoring. *Energy and Buildings*, 127, 969–979. <https://doi.org/10.1016/j.enbuild.2016.06.033>
12. Nolé, M. L., Soler, D., Higuera-Trujillo, J. L., & Llinares, C. (2022). Optimization of the cognitive processes in a virtual classroom: A multi-objective integer linear programming approach. *Mathematics*, 10(7), 1184. <https://doi.org/10.3390/math10071184>

13. Nur, Y. A., Yoon, G., & Sato, T. (2024). Energy savings evaluation of enhanced classroom daylighting utilization. *Energy and Buildings*, 312, 114179. <https://doi.org/10.1016/j.enbuild.2024.114179>