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Optimizing Public Indoor Lighting System with Daylight-Based Illumination Control

Nur Hafizah ‘Aliyah Binti Shahrul Nizam[a], Nurulafiqah Nadzirah Mansor[a, *], Denny Haryanto Sinaga[b,c] and Muhammad Aliff Jamaluddin [a]

[a] *Universiti Malaya Power and Energy System Group (UMPES), Department of Electrical Engineering, Faculty of Engineering, Universiti Malaya, Kuala Lumpur, Malaysia*
[b] *Study Program of Electrical Engineering, Universitas Negeri Medan, Medan, Indonesia*
[c] *Innovation Centre of Renewable Sources and Waste Integration for Sustainable Energy (INNERWISE), Medan, Indonesia*
[*]*E-mail: afiqah.mansor@um.edu.my*
E-mails: fizah.liya@gmail.com, denny.sinaga@unimed.ac.id, aliffizham1660@gmail.com.

Abstract. This paper presents an optimization framework for public indoor lighting system using metaheuristic algorithms to determine the optimal lighting layout, select energy-efficient lamp combinations, and minimize energy consumption through daylight-based ON/OFF illumination control. The framework is applied to a multipurpose hall, aiming to ensure adequate lighting illuminance while reducing electricity usage and installation costs. The process begins with optimizing lamp layouts and positions using Evolutionary Programming (EP), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The best-performing algorithm is then adopted as the base model for further optimization. Different lamp types—10 W and 12 W light-emitting diodes (LEDs), 25 W compact fluorescent lamps (CFLs), and 36 W fluorescent lamps—are optimally combined to achieve additional cost and energy savings. A daylight-responsive control system is incorporated, utilizing hourly daylight data to switch lamps ON or OFF when required. Results show that the mixed-lamp configuration lowers both power consumption and initial installation costs, while the daylight-based control significantly reduces overall energy consumption. The optimized system complies with Malaysia Standards 1525 (MS 1525) and supports energy efficiency and sustainability in public buildings.

Keywords. Lighting system optimization, daylight-based illumination, public indoor lighting system, energy efficiency, metaheuristic algorithm.

1. Introduction

Lighting system, especially in public spaces, play a crucial role in ensuring safety, productivity, and visual comfort. Public spaces are areas accessible to all members of the community regardless of ownership, designed to enhance interaction, safety, and usability. In facilities such as multipurpose halls and hospitals, lighting systems often operate continuously, contributing significantly to energy consumption. For example, in hospitals, lighting alone accounts for up to 16% of total electricity use (Ghazali et al., 2023).

Daylight harvesting offers up to 47% reduction reliance on artificial lighting though many public buildings still operate without daylight-responsive strategies, leading to energy waste and higher operational costs (Qiao et al., 2023). Angelaki, Besenecker, and Danielsson (2022) reviewed lighting system in educational settings, while other studies have examined artificial–natural lighting integration in classrooms, showing that optimized window-to-wall ratios and skylight configurations can lower energy use by up to 27%. However, such approaches are often limited to static architectural elements, lacking adaptability to changing spatial conditions, which results in inefficient lighting use (Nur et al., 2024; Çelik, Didikoğlu et al., 2024; Ayoosu et al., 2021).

Velásquez et al. (2024) explored the potential of advanced indoor lighting technologies such as LEDs, highlighting significant energy savings but also noting a lack of adaptability to complex public environments like hospitals, offices, and halls. Similarly, Odiyur et al. (2021) and Galatanu (2020) demonstrated that well-designed daylighting systems can cut total building energy use by up to one-third, while enhancing occupant comfort.

Field studies in Malaysian public buildings reveal further challenges. Wan Abdullah et al. (2022) reported that most spaces fail to meet MS 1525 (2019) requirements, citing poor spatial orientation, limited glazing, and low-reflectance surfaces as key issues. Nur et al. (2024) suggested that illuminance levels of 300–500 lux is generally sufficient for visibility and comfort, yet few studies address how compliance with these standards can be dynamically modeled in multifunctional spaces with fluctuating daylight. Angelaki et al. (2022) also noted that rigid adherence to standards may result in contextually inappropriate designs, advocating instead for flexible, user-driven approaches that consider daylight availability and usage patterns.

Effective ON/OFF illumination control mechanisms are equally vital for reducing unnecessary energy use while maintaining appropriate lighting levels. Such systems, often guided by daylight and occupancy data, allow lights to operate only when needed, improving both energy performance and user comfort. Lin et al. (2024) introduced a human-centric lighting management framework for libraries, promoting smart switching systems that deliver "the right light at the right time." However, their case studies were largely conceptual or lab-based, lacking large-scale implementation and algorithmic optimization. Similarly, Caicedo and Pandharipande (2015) developed an adaptive lighting control system that combined occupancy and daylight sensing with iterative optimization, successfully reducing energy use while maintaining comfort. Yet, their model was limited to small spaces and did not incorporate advanced metaheuristic techniques, which could enhance scalability and performance in dynamic public settings.

Other studies highlight similar gaps. Parise et al. (2022) proposed a centralized control system with luminaire-integrated sensors that improved energy savings through distributed sensing but did not optimize switching schedules or luminaire placement. Pandharipande and Caicedo (2015) emphasized real-time control using daylight and occupancy data but did not extend their model to optimize broader parameters such as lamp type, placement, or threshold settings. Lin et al. (2024) further pointed out that despite many facilities being "smart-ready," the lack of intelligent switching algorithms leads to suboptimal performance and frequent manual overrides.

Overcoming these limitations, metaheuristic optimization techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Evolutionary Programming (EP) have been applied to lighting layout design (Panska et al., 2024; Allam et al., 2019; Krisam et al., 2023). These studies demonstrated that unconventional lamp arrangements can reduce the number of fixtures required while still meeting lighting standards. However, most remain restricted to static layouts and fixed lamp types, without integrating lamp selection, daylight variation, and real-time switching into a unified optimization framework. Skandali and Lambiri (2018) further showed the benefits of metaheuristic optimization in urban lighting systems, suggesting its wider applicability to complex indoor environments.

Building on these insights, this paper proposes a complete optimization framework that integrates mixed lamp type selection for an optimized lighting layout with daylight-based ON/OFF control, utilizing metaheuristic algorithms. The objective is to identify optimal lamp placement, reduce installation costs and power usage, and ensure compliance with MS 1525 standards, ultimately advancing energy efficiency and sustainability in public buildings.

2. Methodology

Lighting design methods have evolved from simple manual calculations to simulation-based systems capable of analyzing complex spatial and energy interactions. Manual approaches such as the Lumen Method and Point-to-Point Method are often used for early-stage calculations in standard spaces (Ismail et al.,2021). While using advanced software such as DIALux might be more-user friendly and interpretable, the Dialux-based work was typically used for design assessment without incorporating programmable or iterative optimization techniques, limiting its usefulness in scenarios where lamp layouts or controls must be dynamically (Eltaweel et. al, 2023)

2.1. Problem Formulation and Modelling

Public spaces are not defined only by their size or physical features but also by their intended purpose, function, and level of accessibility. Since the layout and use of such spaces are typically finalized during the planning phase, it becomes difficult to modify or adjust the lighting system afterward. Therefore, an effective and efficient lighting design must be considered early in the development process.

In this work, a multipurpose hall is selected and modelled as a rectangular room measuring 6 meters in length, 4 meters in width, and 4 meters in height. The floor is divided into a 6 by 4 uniform grid with 1-meter spacing, resulting in 24 calculation points. Each grid point represents a location where illuminance is evaluated. Lamps are mounted at 3.2 meters above the working plane, and their positions are restricted to these grid points. Illuminance at each point is computed using the inverse square law and Lambert's cosine law, which account for both distance and angle between each lamp and the corresponding point as described by Eq. (1).

$$E_i = \frac{I_i \cos\theta_j}{d_i^2} \tag{1}$$

The cosine factor in Eq. (1) is calculated using Eq. (2) where the distance between the lamp and the evaluated grid point is derived using Eq. (3)

$$\cos\theta_j = \frac{h}{d_i} \tag{2}$$

$$d_i = \sqrt{\left(x_{lamp} - x_{pt}\right)^2 + \left(y_{lamp} - y_{pt}\right)^2 + h^2} \tag{3}$$

The total illuminance at a grid point is then determined using the superposition principle, where contributions from all active lamps within the beam angle are summed. Ensuring compliancy with lighting standards, each grid point must receive illuminance between the specified 300 and 500 lux. In addition, the uniformity index U_0, defined as the ratio of minimum to average illuminance, must be at least 0.7, calculated using Eq. (4).

$$U_0 = \frac{E_{min}}{E_{avg}} \tag{4}$$

These design criteria are used as constraints in the optimization process to ensure lighting comfort and energy efficiency.

2.2. Layout Optimization using Metaheuristic Techniques

The candidate solution is represented as a binary vector of 24 elements corresponding to the 6 × 4 grid layout. A value of 1 indicates that a lamp is placed at the respective position, while 0 denotes an empty position. The optimization process searches for the best combination of lamp positions that satisfies the lighting constraints while minimizing power usage. The objective is then to ensure that all points are illuminated with 300 to 500 lux illuminance, minimizing deviation between the target illuminance at the evaluated points while reducing overall power consumption (Department of Standards Malaysia, 2019). A penalty is applied if the layout fails to meet the minimum uniformity index of 0.7.

The deviation from the target illuminance is calculated as in Eq. (5) while the total power consumption is calculated using Eq. (6).

$$f_1(x) = \sum_{i=1}^{n} \left(E_i - E_{target}\right)^2 \tag{5}$$

$$f_2(x) = n \times P_{lamp} \tag{6}$$

The overall fitness function used for MATLAB-based optimization is then calculated using Eq. (7) where the weight factors w_1 and w_2 are tuned to balance between minimizing deviation and power consumption. Penalty terms are applied if any point receives less than 300 lux or more than 500 lux, or if the uniformity ratio U_0 is below 0.7.

$$f(x) = w_1 * f_1(x) + w_2 * f_2(x) + Penalty \tag{7}$$

2.2.1 Evolutionary Programming (EP)

EP is a mutation-based evolutionary algorithm that operates without crossover. Each individual in the population is encoded as a binary string of 24 bits. In every generation, offspring are generated by applying bit-flip mutations to randomly selected bits in each parent. The number of bits flipped per mutation is randomized for each offspring. Both parent and offspring populations are merged, and the top 500 solutions based on fitness are selected using the (μ + λ) strategy ensuring strong selection pressure toward feasible and energy-efficient layouts. EP is suitable for this discrete optimization problem as it promotes diverse exploration without relying on complex recombination mechanisms. EP algorithm flowchart to obtain the optimal solution is shown in Fig. (1).

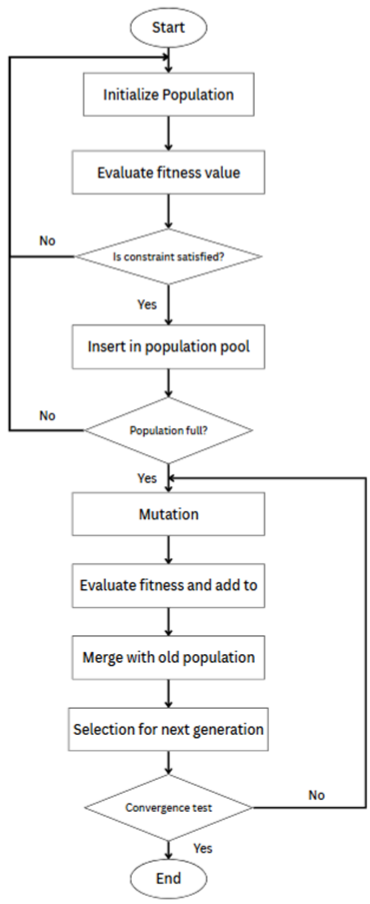

Figure 1. Evolutionary Programming Algorithm Flowchart

2.2.2. Genetic Algorithm (GA)

GA on the other hand is inspired by natural evolution and uses three core operators: selection, crossover, and mutation. Each solution is represented by a binary chromosome of 24 bits. A population of 500 individuals is initialized randomly. The algorithm retains a portion of the best performing individuals through elitism. The remaining solutions are generated through single-point crossover between parents, followed by random bit-flip mutations (typically affecting 1 to 4 bits). This balances between inheritance and random variation helps guide the population toward optimal lamp placements that reduce power usage while achieving the required illuminance. GA algorithm flowchart to obtain the optimal solution is shown in Fig. (2).

2.2.3. Particle Swarm Optimization (PSO)

PSO treats each candidate solution as a particle with a binary position vector and a continuous velocity vector. The position determines the lamp layout, while the velocity reflects the particle's movement tendency based on its previous performance and that of its neighbors. In each iteration, the particle updates its velocity using Eqs. (8) and (9).

$$v_i^{(t+1)} = wv_i^{(t)} + c_1r_1(p_i^{best} - x_i^t) + c_2r_2(g^{best} - x_i^t) \tag{8}$$

$$x_i^{(t+1)} = x_i^t + v_i^{(t+1)} \tag{9}$$

PSO's swarm-based search makes it capable of rapid convergence, especially effective when the fitness landscape is complex or contains multiple local optima. PSO algorithm flowchart to obtain the optimal solution is shown in Fig. (2).

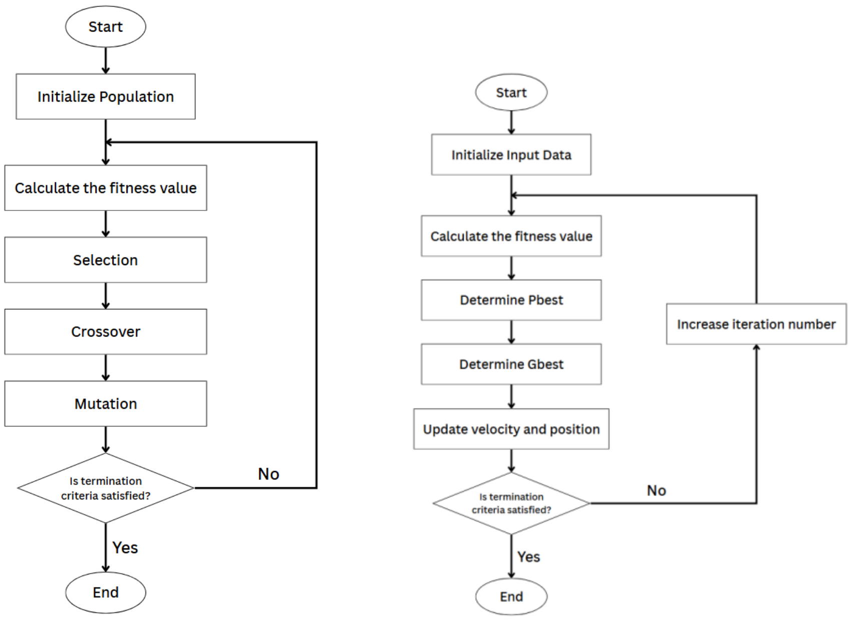

Figure 2. (left) Genetic Algorithm Flowchart (right) Particle Swarm Optimization Algorithm Flowchart

2.3. Mixed Lam Type Configuration

Lamp model selection is central to achieving both energy efficiency and illumination quality in public spaces. LEDs, CFLs, and traditional fluorescent lamps differ considerably in luminous efficacy, energy consumption, and operational cost, making data-driven decision-making essential in lighting optimization. An important aspect of effective lighting design is the strategic integration of different lamp technologies. Light Emitting Diodes (LEDs) are widely recognized for their superior performance, delivering over 200 lumens per watt and lifespans exceeding 50,000 hours (Aly et al., 2022). In contrast, fluorescent tubes and CFLs, though commonly used in institutional spaces, are less efficient (50–100 lm/W), contain toxic materials, and exhibit shorter operational lifetimes (Rajkumar et al., 2021).

Research has consistently shown that replacing CFLs and fluorescents with LEDs, or adopting a hybrid lamp configuration, can significantly improve lighting efficiency while reducing both power demand and operating costs (Kassaye et al., 2022; Faiz et al., 2017; Khaliq et al., 2017; Oluseyi et al., 2020; Adeleke et al., 2020). While these studies confirm the benefits of LED retrofitting, they often overlook the optimization of lamp placement and model combinations across diverse spatial contexts, as well as the potential role of daylight integration. Nonetheless, the literature highlights that installation cost remains a major barrier to widespread LED adoption. In addition, Akinradewo, Obiyemi, and Oyelami (2018) assessed the performance of various lighting installations within the context of renewable energy integration, further emphasizing the importance of holistic system-level approaches in lighting design.

In this work, the layout selected from the best-performing metaheuristic technique is further optimized to reduce both power consumption and installation cost. Four different lamp models are considered, each offering different luminous flux, power consumption, and initial purchase cost. These specifications are summarized in Table 1.

Table 1. Lamp Specifications

Type	Index	Flux (lm)	Power (W)	Cost (RM)
LED-Standard	1	2100	10	25
LED-High	2	2400	12	35
CFL	3	1800	25	17
Fluorescent	4	2000	36	15

Each possible solution assigns a lamp type to each of the predefined positions in the selected layout, using integer encoding from 0 to 4. A value of 0 indicates no lamp is installed, 1 represents a 10W LED lamp, 2 corresponds to a 12W LED lamp, 3 denotes a compact fluorescent lamp (CFL), and 4 indicates a fluorescent lamp. This index-based representation allows the optimization algorithm to select the most efficient combination of lamp types that meets the required illuminance and uniformity constraints.

The fitness function, extended from Eq. (7), is modified by including installation cost and lamp type selection as described through Eqs. (10) – (11).

$$f(x) = w_1 * f_1(x) + w_2 * \ f_2(x) + f_3(x) + Penalty \tag{10}$$

$$total\ power\ consumption = f_2(x) = \sum_{t=1}^{T} n_t \cdot p_t \tag{11}$$

$$total\ installation\ cost = f_3(x) = \sum_{t=1}^{T} n_t \cdot c_t \tag{12}$$

n_t, p_t, c_t are the number, wattage, and unit cost of lamp type t, respectively. The weighs w_1 and w_2 are determined based on the relative importance and range of each objective. This formulation penalizes solutions that are too costly, consume excessive power, or fail to meet visual comfort standards.

The Genetic Algorithm (GA) is used for this optimization process. Each individual in the population represents the lamp types assigned to fixed positions. The GA operates with a population size of 100, using single-point crossover and random mutation. Each mutation randomly assigns values from 0 to 4 at selected positions with a 50% mutation probability per individual. The goal is to minimize the fitness function by selecting energy efficient and cost-effective lamp combinations that comply with all lighting performance criteria.

2.4. Daylight-Based ON/OFF Control

The lamp positions and types used are derived from the optimized layout and configuration obtained previously. The control system operates by switching off unnecessary lamps when sufficient daylight is available, while maintaining compliance with MS 1525 lighting standards.

A south-facing window configuration is used to ensure maximum and consistent daylight entry (Bagheri et al., 2024). The total glazing area is approximately 14.77 m², distributed across two windows on the southern wall as shown in Fig. 3. In Malaysia, daylight is abundant throughout the year, indicating high penetration of natural lighting (Abdullah et al., 2022). Thus, hourly daylight data are obtained using DIALux simulation software for a typical day in Kuala Lumpur and mapped onto each grid point on an hourly basis.

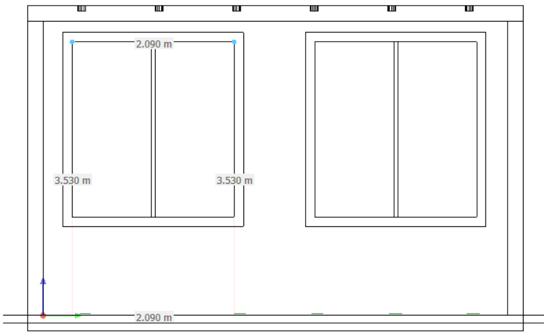

Figure 3. Elevation Plan of Windows

At any time t, the total illuminance at grid point (x, y) is the sum of daylight and artificial contributions as described in Eq. (13), evaluated on an hourly basis to determine whether a lamp should remain ON or be turned OFF depending on the contribution of daylight at that time.

$$E_{total}(x, y, t) = E_{day}(x, y, t) + \sum_{i=1}^{N_{active}} E_{lamp,i}(x, y) \tag{13}$$

A greedy algorithm is implemented for lamp switching. Initially, all lamps are turned ON to ensure compliance. Then, for each lamp, the algorithm temporarily switches it OFF and recalculates the total illuminance at all grid points. If any point falls below the 300 lux threshold, the lamp remains ON; otherwise, it is permanently switched OFF for that hour. This iterative process ensures that only the minimum number of lamps remain active, thus reducing energy usage while maintaining proper lighting performance.

Two key metrics are used to assess the effectiveness of the daylight-based control system:

- Compliance Rate: This is the percentage of grid points that meet the minimum illuminance requirement (300 lux) at a given hour, as described through Eq. (14).

$$Compliance\ (t) = \frac{|\{(x, y)|\ E_{total}\ (x, y, t)\ \geq\ 300\}|}{24} \times 100\% \tag{14}$$

- Average Daylight Illuminance: This metric describes the overall daylight contribution at a given hour, as shown in Eq. (15).

$$\bar{E}_{daylight} = \frac{1}{24}\sum_{x=1}^{6}\sum_{y=1}^{4} E_{daylight}(x,y,t) \tag{15}$$

Furthermore, the monthly lighting operational cost is computed and compared between systems with and without daylight control. The commercial tariff B from Tenaga Nasional Berhad (TNB) is used where higher kWh cost is applied for total energy consumption of more than 200kWh. This cost analysis highlights the economic benefit of incorporating daylight-based control, particularly in commercial or institutional buildings with significant daytime lighting demand.

3. Results and Discussion

This section presents the outcomes of the three-stage optimization: lamp layout, lamp type configuration, and daylight-based ON/OFF control. Results are evaluated based on compliance, energy savings, and cost efficiency.

3.1. Layout Optimization

Three different algorithms; EP, GA and PSO were evaluated in MATLAB for their performance in optimizing lamp layout across a 6 x 4 grid space. The objectives were to minimize the deviation between actual and target illuminance, reduce power consumption by minimizing the number of lamps used, and ensure all grid points receive illumination between 300 and 500 lux with a minimum uniformity of 0.7.

As shown in Fig. 4, all techniques successfully converged, with GA achieving the fastest convergence and lowest fitness function value. PSO exhibited slower convergence and slightly lower uniformity, while EP produced comparable results to GA but required significantly more computational time. The computational times and final fitness values are summarized in Table 2. Considering both performance and efficiency, GA was selected as the preferred technique for subsequent optimization involving lamp type selection and daylight-based control.

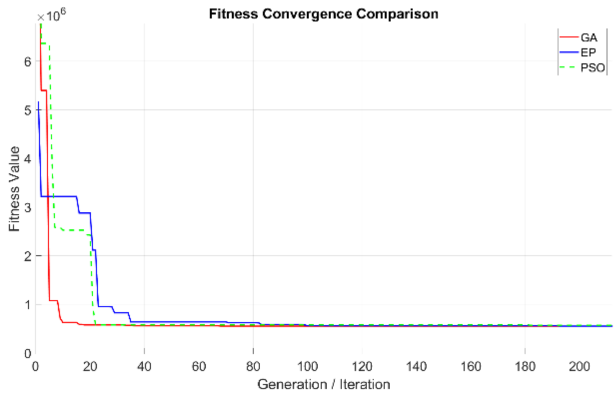

Figure 4. Convergence trends of EP, GA, and PSO in layout optimization.

Table 2. Comparison of Optimization Techniques for Lamp Layouts

Item.	Technique		
	EP	GA	PSO
Best fitness value	559864	554541	571632
Computational time (to converged)	107	68	81
Number of lamps	22	22	22
Power consumption	440W	440W	440W
Uniformity	0.81	0.81	0.79

The selected layout using GA is shown in Fig. 5, demonstrating a well-distributed illuminance pattern across space without extreme underlit or overlit regions. This confirms GA's effectiveness in balancing spatial coverage, visual comfort, and energy efficiency.

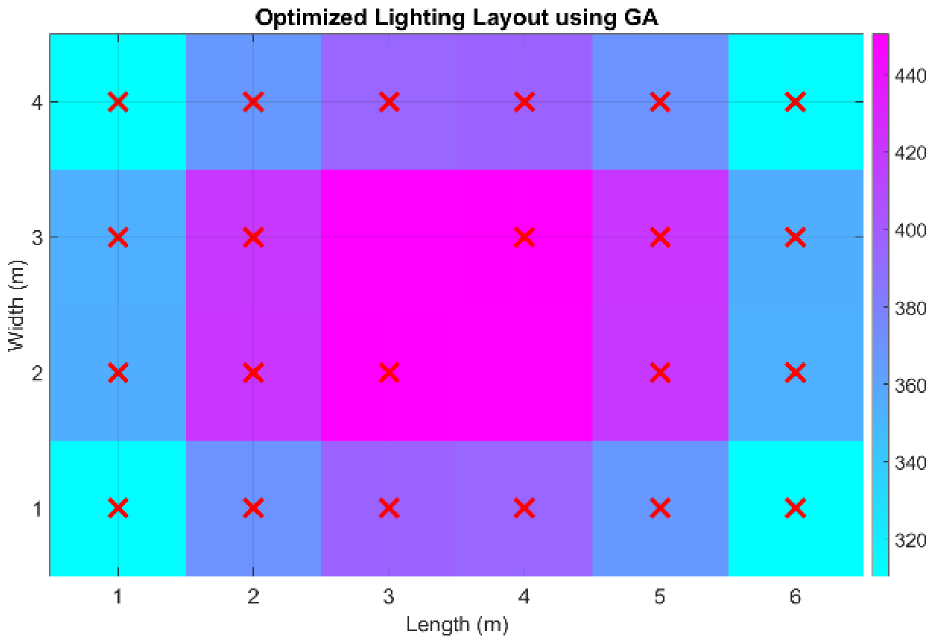

Figure 5. Final optimized lighting layout using GA.

3.2 Light Intensity (lumen) vs Number of Lamp

Light intensity of the lamp plays crucial effect on number of lamps installed. Three lighting scenarios are tested using the GA approach with the same setup as the previous process. The effect of lamp luminous flux on system efficiency and lighting distribution is observed and recorded in Table 3. Increasing lamp intensity significantly reduces the number of lamps required. The 3500 lumens LED lamp achieved compliance using 15 lamps, while a composite 3 x 2200 lumens lamp configuration required only 8 lamps to maintain illuminance within the desired range of 300 to 500 lux.

While higher light intensity helps reduce the number of lamps and improves coverage uniformity across the space, high-lumen lamps typically require higher wattage. Thus, leading to increased energy consumption per lamp. Additionally, high-output lamps and clustered configurations may incur higher initial installation costs due to greater unit price and energy demands.

Table 3. Comparison of Different Light Intensity

Item.	Light Intensity (lumens)		
	2200	**3500**	**3 x 2200**
Quantity	22	15	8
Lux range (lux)	310.5-450.5	336.46-435.48	339.1-428.96
Uniformity	0.81	0.86	0.87

3.3 Mixed Type Lamp Optimization

Further reducing energy consumption and initial installation cost, the selection of optimal lamp types for each fixed position was conducted. The optimization algorithm evaluated various combinations of lamp models with differing luminous flux, power ratings, and unit costs.

The final lamp configuration obtained after type selection is illustrated in Fig. 6. The results show a diverse mix of lamp models strategically assigned to balance illumination levels, cost, and power usage. Lamps with higher luminous flux were placed in underlit areas, while lower-power models were concentrated in regions already receiving sufficient light.

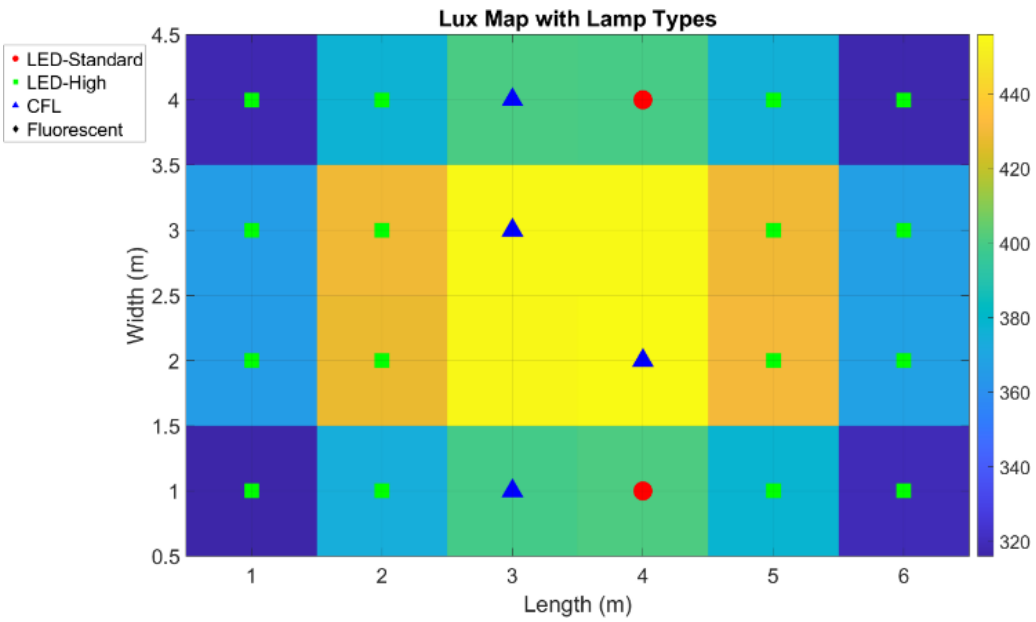

Figure 6. Final optimized mixed lamp layout using GA.

This configuration enhanced lighting uniformity and significantly reduced total energy consumption, while still complying with required standards. As shown in Fig. 8, energy usage decreased by 29.1%, while installation costs dropped by 11.9%, primarily due to the algorithm's tendency to assign cost-efficient models such as CFLs and LED lamps in suitable areas. Although the use of multiple lamp types may introduce slight complexity in installation and future maintenance, the overall improvements in energy efficiency and cost effectiveness affirm the practical potential of mixed-type configurations when implemented with professional planning and control as shown in Fig. 7.

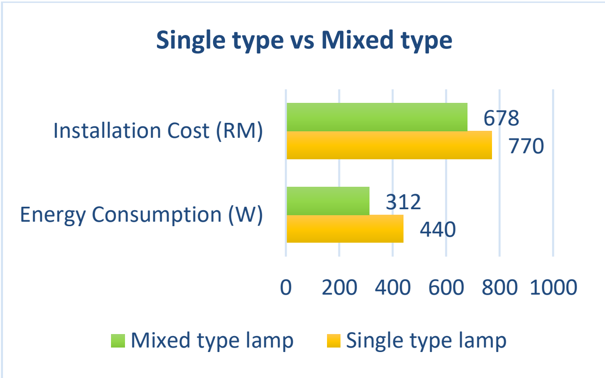

Figure 7. Comparative bar chart of total installation cost in RM (top) and.total energy consumption in Watt (bottom) for mixed and single type lamp

3.4 Daylight Based Control

The daylight-based ON/OFF control strategy was implemented using optimized layout and lamp configuration to minimize unnecessary lamp operation during daylight peak hours. Fig. 8 and Fig. 9 illustrate the hourly switching status for single and mixed lamp types respectively. During peak daylight hours, most lamps were turned off without violating the minimum illuminance requirement. Hence, validating the effectiveness of control algorithm.

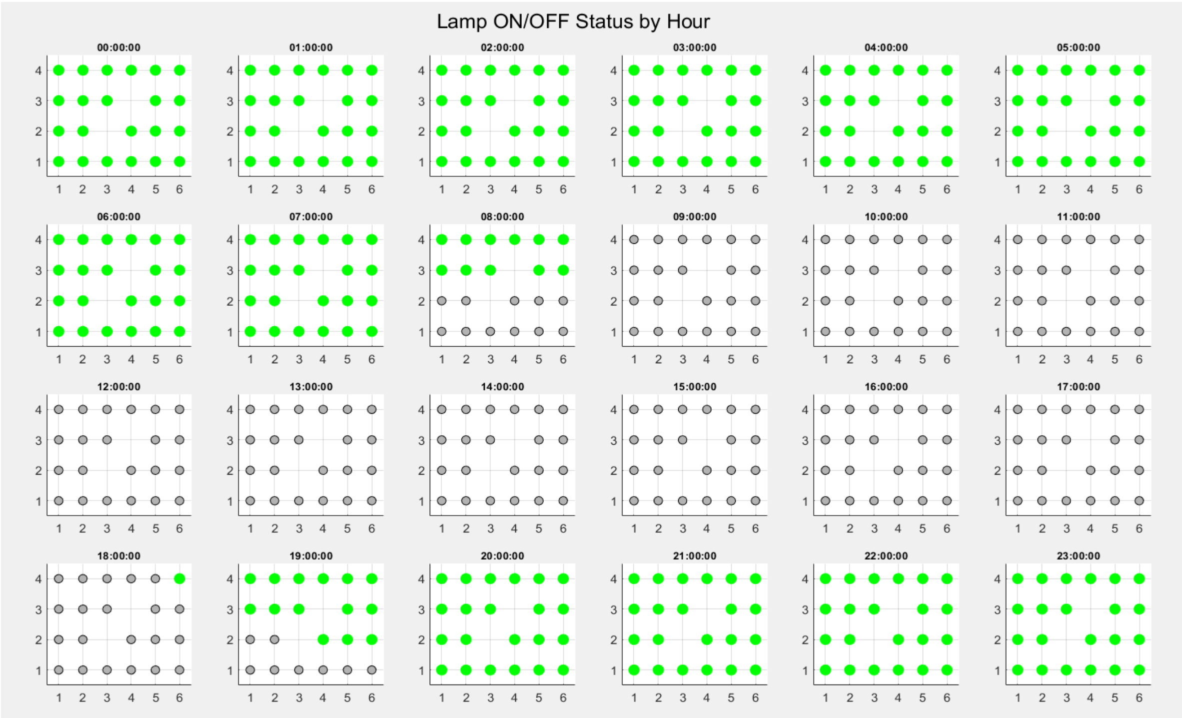

Figure 8. Single-type configuration hourly lighting operation.

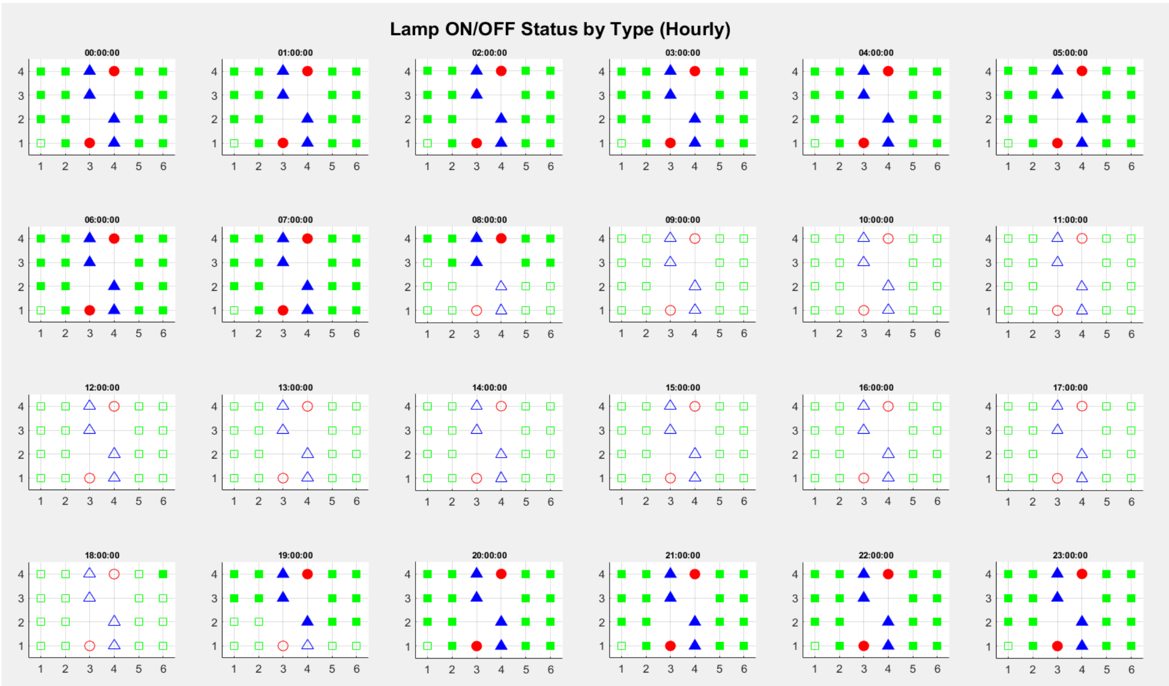

Figure 9. Mixed-type configuration hourly lighting operation.

Comparing both approaches, turning lamps off from 8 a.m. to 6 p.m. and on during remaining hours achieved significant savings without relying on daylight data. As shown in Table 4, it reduced energy consumption to 5.4 kWh for the single-type configuration and 4.0 kWh for mixed-type configuration, resulting in monthly cost reductions of 49.2% and 47.1% respectively compared to lamp only.

Integrating real-time daylight responsiveness further improved efficiency, especially in the mixed-type configuration and can be seen in Fig. 10. It maintained low energy use throughout the day while sustaining full compliance with lighting standards. Since both fixed schedule and daylight-based control achieved the same minimal energy usage, it highlights the value of optimized lamp configuration paired with smart control strategies.

Table 4. Comparison of Operation Cost and Daily Energy Consumption for Different Cases

Type	Case	Operational Cost, 30d (RM)	kWh (24hours)
Single	Lamp only	137.81	10.6
	6pm-8am ON 8am-6pm OFF	69.95	5.4
	Lamp + Daylight	75.69	5.8
Mixed	Lamp only	97.79	7.5
	6pm-8am ON 8am-6pm OFF	51.72	4.0
	Lamp + Daylight	51.72	4.0

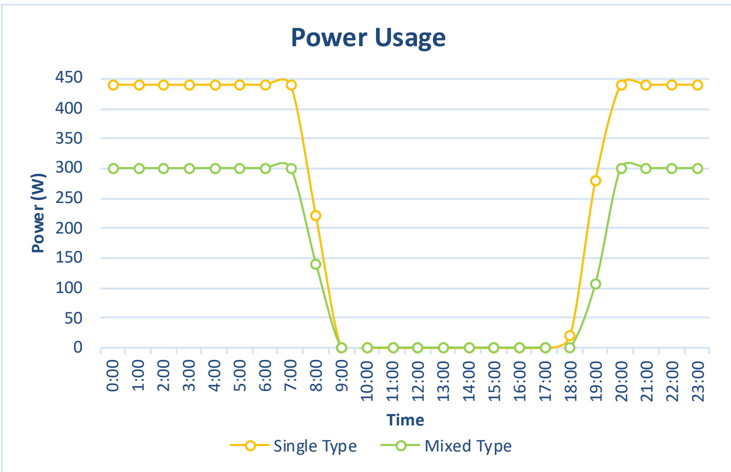

Figure 10. Hourly energy consumption for both configurations.

The daylight-based control approach demonstrates significant potential for reducing operational costs and energy consumption in public indoor spaces, particularly in Malaysia due to high availability of daylight penetration. It offers a scalable and cost-effective solution that complements energy efficient lamp selection.

4. Conclusion

This study presented an optimized indoor lighting system for public spaces using metaheuristic algorithms and daylight-based control. The proposed approach successfully reduced power consumption, installation cost, and daily energy use while maintaining illuminance compliance and high lighting uniformity. Mixed lamp configurations and adaptive ON/OFF control using daylight data contributed to overall energy savings of up to 47.10%. Optimizing lighting in public indoor spaces is crucial due to their high occupancy, operational hours, and visual comfort requirements. The outcomes demonstrate the potential for practical, energy-efficient, and environmentally responsible lighting solutions in facilities such as hospitals, schools, and community halls. Future works should consider larger or multi-room scenarios to confirm the robustness of the proposed method.

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References

Adeleke, A. Q., Bahaudin, A. Y., Kamaruddeen, A. M., & Bamgbade, J. A. (2020). Renewable energy adoption in the construction industry: Barriers and drivers. Renewable and Sustainable Energy Reviews, 132, 110040. https://doi.org/10.1016/j.rser.2020.110040

Akinradewo, O. F., Obiyemi, O. O., & Oyelami, S. O. (2018). Performance evaluation of lighting installations for renewable energy integration. International Journal of Renewable Energy Research, 8(3), 1294–1302.

Allam, M., Abdelalim, A., & Hasan, A. (2019). Daylight optimization using genetic and particle swarm algorithms with EnergyPlus and DIVA. International Journal of Sustainable Built Environment, 8(1), 177–192. https://doi.org/10.1016/j.ijsbe.2019.01.003

Aly, S., Ibrahim, M., & Hassan, A. (2022). Advances in LED lighting technology for energy-efficient buildings. Energy and Buildings, 261, 111982. https://doi.org/10.1016/j.enbuild.2022.111982

Angelaki, S., Besenecker, U., & Danielsson, C. B. (2022). A review of lighting research in educational spaces. IOP Conference Series: Earth and Environmental Science, 1099(1), 012032. https://doi.org/10.1088/1755-1315/1099/1/012032

Bagheri, S., Moradinasab, H., & Yeganeh, M. (2024). The effect of window proportions in low-rise residential buildings on annual energy consumption in humid temperate climate (Case study: Rasht city in Iran). Frontiers in Energy Research, 12, 1463678. https://doi.org/10.3389/fenrg.2024.1463678

Caicedo, D., & Pandharipande, A. (2015). Daylight-adaptive lighting control using occupancy sensing. Lighting Research & Technology, 47(3), 296–311. https://doi.org/10.1177/1477153513516452

Eltaweel, A., & Su, Y. (2023). An integrated DIALux-based framework for lighting design assessment in architectural spaces. Journal of Building Engineering, 74, 106825. https://doi.org/10.1016/j.jobe.2023.106825

Faiz, A., Yusoff, M. A. M., & Rijal, H. B. (2017). Energy saving potential of LED lighting in institutional buildings. Energy Procedia, 105, 139–144. https://doi.org/10.1016/j.egypro.2017.03.303

Ghazali, M. F., et al. (2023). Energy consumption analysis in Malaysian hospitals. Energy Reports, 9, 4567–4579. https://doi.org/10.1016/j.egyr.2023.07.132

Ismail, A. R., Rahman, H. A., & Hashim, N. A. (2021). Evaluation of point-to-point method and lumen method in early-stage lighting calculations. Journal of Advanced Research in Applied Sciences and Engineering Technology, 24(1), 1–9. https://doi.org/10.37934/araset.24.1.19

Kassaye, A., Mengesha, T., & Dadi, G. (2022). Hybrid lighting systems for improved energy efficiency in institutional buildings. Sustainable Energy Technologies and Assessments, 52, 102043. https://doi.org/10.1016/j.seta.2022.102043

Khaliq, M. A., Riffat, S. B., & Omer, S. A. (2017). Energy-efficient lighting systems: A review of technologies and applications. Renewable and Sustainable Energy Reviews, 78, 1050–1067. https://doi.org/10.1016/j.rser.2017.04.102

Krisam, P., Zhang, Y., & Müller, D. (2023). Comparative performance of metaheuristic and mathematical optimization for building energy systems. Energy and Buildings, 277, 112587. https://doi.org/10.1016/j.enbuild.2023.112587

MS 1525:2019. (2019). Code of practice on energy efficiency and use of renewable energy for non-residential buildings. Department of Standards Malaysia.

Oluseyi, P. O., Akinbulire, T. O., & Babatunde, O. M. (2020). Energy efficiency analysis of lighting retrofits in public institutions. Journal of Cleaner Production, 276, 124169. https://doi.org/10.1016/j.jclepro.2020.124169

Panska, D., Stevanovic, M., & Barozzi, M. (2024). Genetic algorithm for lighting layout optimization in enclosed spaces. Applied Energy, 355, 121983. https://doi.org/10.1016/j.apenergy.2023.121983

Pandharipande, A., & Caicedo, D. (2015). Smart indoor lighting systems with luminaire-based sensing: A review. IEEE Sensors Journal, 15(5), 2773–2786. https://doi.org/10.1109/JSEN.2014.2381875

Qiao, H., Wang, M., & Liu, F. (2023). Energy savings with daylight responsive lighting systems. Building and Environment, 226, 110638. https://doi.org/10.1016/j.buildenv.2022.110638

Rajkumar, M., Devi, L., & Kumar, P. (2021). Comparative analysis of CFL, fluorescent, and LED lighting technologies. Energy and Ecology, 37(2), 101–112. https://doi.org/10.1016/j.energyeco.2021.01.008

Skandali, C., & Lambiri, Y. S. (2018). Optimization of urban street lighting conditions focusing on energy saving, safety and users' needs. Journal of Contemporary Urban Affairs, 2(3), 112–121. https://doi.org/10.25034/ijcua.2018.4726

Wan Abdullah, W. N. H., Tharim, A. H. A., Ismail, A., & Ahmad, A. C. (2022). Determination of design solutions to overcome daylighting design failure in existing educational buildings. International Journal of Sustainable Construction Engineering and Technology, 13(2), 152–160. https://doi.org/10.30880/ijscet.2022.13.02.