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A state-of-the-art artificial intelligent techniques in daylighting controller: models and performance

Sheryl Grace Colaco[1], Susan G Varghese[2,*], Ciji Pearl Kurian[2], and Sanjeev Kumar TM[2]

[1] Department of Electrical and Electronics Engineering, St. Joseph Engineering College, Mangalore, Karnataka, India
[2] Department of Electrical and Electronics Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, India

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Abstract. Lighting designers are always on the quest to develop a lighting control strategy that is aesthetically pleasing, comfortable, and energy-efficient. In an indoor context, electric lighting blended with daylighting controls forms a quintessential component for improving the occupant's comfort and energy efficiency. Application of soft computing techniques, adaptive predictive control theory, machine learning, HDR photography, and wireless networking have facilitated recent advances in intelligent building automation systems. The evolution and revolution from the 19th to the 21st century in developing daylighting control schemes and their outcomes are investigated. This review summarizes the state-of-the-art artificial intelligence techniques in daylighting controllers to optimize the performance of conventional photosensor-based control and camera-based control in commercial buildings. The past, current, and future trends are investigated and analyzed to determine the key factors influencing the controller design. This article intends to serve as a comprehensive literature review that would aid in creating promising new concepts in daylighting controllers.

Keywords: Daylight-Artificial Light Integrated Scheme, Energy, Automation, Soft computing Techniques, High dynamic range imaging, Window shading.

1 Introduction

As the world grapples with an energy crisis, substantial reductions in energy consumption in all areas, including lighting, have become imperative. In the last decades, the global lighting market underwent substantial changes (Huovila *et al.*, 2017; Varghese *et al.*, 2019a). According to studies, artificial lighting accounts for about 20% of global electricity usage in commercial buildings (Carletti *et al.*, 2017). The energy used for lighting is determined by the type of building and how it is used (ul Haq *et al.*, 2014; US Department of Energy, 2015). As a result of technological breakthroughs, lighting professionals have seen technological developments in energy-efficient light sources and lighting controls (Füchtenhans *et al.*, 2021). Because of Light-Emitting Diode (LED) technology, lighting energy consumption has decreased lately.

Furthermore, incorporating efficient lighting controllers would drastically reduce energy consumption in commercial buildings (Füchtenhans *et al.*, 2021). Intelligent building management systems emphasize daylighting and encourage artificial lighting control as an integral part of intelligent energy management in intelligent buildings, smart cities, green building designs, and LEED certifications (Varghese *et al.*, 2019b). Lighting researchers are now concentrating on developing unique, intelligent daylight-artificial lighting control systems that cut lighting energy consumption by maximizing daylight use (Pandharipande and Newsham, 2018). Several countries mandate energy conservation building codes for automatic light dimming/shut-off using pre-programmed photosensor/occupancy sensor controllers to reduce commercial building lighting energy use (Colaco *et al.*, 2008; Fernandes *et al.*, 2014). Lighting and window blind controllers are a great way to improve occupant comfort while simultaneously saving energy (Bakker *et al.*, 2017).

Because of daylight fluctuations, designers face a significant challenge when creating effective daylight-artificial-light integrated controllers (Kubba, 2017). Soft computing approaches efficiently characterize the dynamic, non-linear variations in daylight, contributing to the development of intelligent lighting controls that balance user comfort and energy efficiency (Belany *et al.*, 2021). These strategies benefit computer or embedded system algorithm development

* Corresponding author: susan.varghese@manipal.edu

to solve illuminance prediction and control problems (Wagiman *et al.,* 2020). Based on occupant usage patterns and comfort settings, AI-based lighting controllers with window blind controllers often report energy savings over conventional lighting control (Bughin *et al.,* 2017).

The Daylight-Artificial Light Integrated Scheme (DALIS) research team of the authors of this publication has been working on lighting controllers since 2005 at the Manipal Institute of Technology (MIT) for developing artificial intelligent lighting controllers. Kurian *et al.* (2008) developed a simulation-based multistage fuzzy-based methodology that included: (i) system identification of daylight illuminance, (ii) ANFIS controller for artificial light dimming, and (iii) window blind controller based on fuzzy logic to reduce daylight glare and increase uniformity. Later, Colaco *et al.* (2012) developed a computer-based real-time operation of the adaptive predictive control technique for the robust control of light dimming and window blind control in an actual test room. Sudheer Kumar *et al.* (2018) developed a camera-based fuzzy model to generate window blind control signals using the High Dynamic Range Imaging (HDRI) technique to improve occupant visual comfort, thermal comfort, and energy conservation. Varghese *et al.* (2019b) devised a wireless sensor network for daylight-artificial light integration using digital camera technology. The machine learning-based predictive model for the integrated daylight-artificial light system was developed by Sanjeev Kumar *et al.* (2020a). Mathew *et al.* (2022) depict a performance analysis of the Polymer Dispersed Liquid Crystal (PDLC) glazing effect on spectral, visual, thermal, and circadian characteristics in a daylight-artificial light integrated scheme. It is worth noting that a recurring theme in all these DALIS research projects is the development of a multistage fuzzy algorithm to generate a window blind control signal for occupant visual and thermal comfort. The Department of Science and Technology, Government of India supported these works, under the grant numbers WOS-A/ET-06/2008 and TMD/CERI/BEE/2016/083(G).

2 Aim and scope of the study

Daylight harvesting technologies are slowly being embraced in commercial buildings (Magno *et al.,* 2015). In this context, through a review of the literature in this area, the present paper addresses the following research questions (RQ): RQ1: What are the current barriers to existing conventional control approaches and identifying the need for AI-based lighting control strategies? RQ2: How can AI-based lighting control strategies in office buildings optimize the criteria of visual comfort and energy efficiency in a Daylighting scheme? RQ3: What are the benefits and drawbacks of the systems and concepts employed? This paper aims to address research queries. RQ1, RQ2 and RQ3. As a result, 100 papers have been compiled to shed light on [i] traditional photosensor-based artificial intelligent lighting controls and [ii] camera-based automated lighting controls, as shown in Figure 1. The goal is to direct readers' attention to the development of automated intelligent lighting controllers to help them understand application challenges, mitigation approaches and foster the creation of sophisticated future innovative lighting controllers.

In this paper, 110 articles on smart lighting controllers from 1977 to 2022 are reviewed. These articles either directly or indirectly incorporated the idea of sustainability in BMS. Reviews highlighting the importance and variety of intelligent lighting controllers can be regarded as a valuable contribution when examining the published literature because researchers can use this work as a starting point for their studies. As the context for this study, this paper integrates soft computing techniques and sensor-based strategies to explain various aspects of smart lighting technologies. This study identifies intervention strategies (like AI-based strategies and lighting/blind control technologies) and value generation strategies (like specific adoption and implementation mechanisms for intelligent lighting controls), and it analyses the results in terms of the performances, user comfort, and energy efficiency attained through the use of different intervention strategies. Specifically, research questions have been developed to systematically guide the literature review. This paper also outlines the limitations in the existing literature, research challenges, and future research directions in the research area mentioned above. For the research community, the paper identifies some underexplored but promising future research avenues. The significant contribution of this work is to promote and give a better understanding of the current status of the technology and its challenges. The review discussed by Ngarambe J *et al.,* 2022 provides an overview of recent studies that are limited to only machine learning techniques to optimize daylighting in the early design stages and during the operation stage of buildings. Additionally, many papers are not available, that discuss the evolution of the daylight-artificial light integrated scheme from conventional models to ensemble models, photosensors to HDR sensors and controllers. To that end, the current paper aims to present a thorough review of conventional to artificially intelligent systems (consisting of all the soft computing techniques like fuzzy control, adaptive neuro-fuzzy inference systems, model predictive control, data-driven models), controllers based on conventional sensors to HDR sensors for the control of artificial light and window blind in buildings for achieving visual comfort and energy efficiency. Furthermore, gaps and challenges of aforementioned schemes and promising lines of a research inquiry into the building lighting controller domain are presented. The paper is organized as follows: Section 2: presents an overview of the concepts of conventional controllers, AI, Machine learning-based controllers, and Camera-based Lighting controllers including existing methods, merits, and limitations. Section 3 specifies the discussion on the results of the literature referred to. The research gaps and prospects for creating future intelligent controllers for diverse building applications and occupant comfort are discussed in Section 4. Section 5 presents the conclusion. It is anticipated that this literature review will serve as a useful resource for researchers intending to develop promising AI solutions for intelligent building design and occupant comfort.

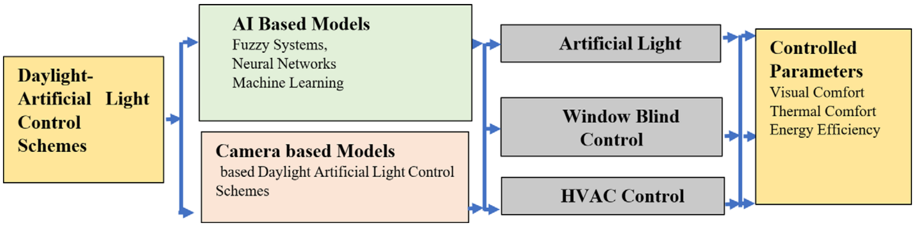

Fig. 1. Keywords used for review on intelligent models for daylighting control scheme.

3 Methodology

This study attempts to review and identify the most recent advancements in the use of artificial intelligence techniques for daylighting controller design and performance, with a focus on photosensor-based and camera-based intelligent lighting/window blind control techniques to promote occupant visual comfort and energy efficiency in office buildings.

Multiple databases were used to find sources to answer the research questions for this article. According to several criteria, the sources that described the methods used in the research to address the research questions were analyzed. In the beginning, Google Scholar was used to gather preliminary samples of the different kinds of articles that were available. The other databases used later include IEEE explore, Scopus, Web of Science, Sage Database, ACM, conference papers, and book chapters. The chosen articles are automatically analyzed for keywords as part of the bottom-up strategy. On the basis of the authors' opinions, a framework for a systematic literature review was developed using a top–down approach. The search terms chosen for this literary analysis included some of the most frequently occurring co-occurring terms such as intelligent lighting control, smart lighting, adaptive predictive lighting control, artificial light control scheme, HDR imaging, camera as a sensor, photosensor, occupancy, soft computing, fuzzy technique, ANFIS, ensemble models, data-driven models, and predictive models. To find the specifically tailored and pertinent articles, these search terms were variously combined with the query string boolean AND command. The resulting framework for a systematic review of the literature was created based on co-occurrence word analysis that has two research perspectives: Machine Learning perspectives and HDR imaging perspectives. The quantitative data analysis that relates to the research questions was examined. Information gathered from a few papers includes - Reference information in full, including the article's title, the author, the year it was published, the journal name, Research questions and objectives, Research topics/subtopics, Research techniques- Data employed, System Performance, models and algorithms, Technical performances, merits, drawbacks, and suggestions. Tabular forms were created in order to extract and map data from the chosen article, and the findings of the in-depth analyses are discussed in the following sections. Therefore, an interdisciplinary perspective on the published research that includes technical perspectives on the research questions could reveal avenues for the readers in the intelligent lighting control domain for Building Automation and Research.

4 Intelligent models for daylight- artificial light integrated scheme

4.1 Conventional photoelectric systems

The role of a daylight-responsive dimming system is to keep the task illuminance at or near the desired illuminance level by combining both daylight and artificial light (Wagiman *et al.*, 2020). Figure 2 shows the control of integrating daylight and artificial light integrated schemes (Kurian *et al.*, 2008). The control problem is in maintaining interior task illumination near a reference level while ensuring visual comfort, uniformity, and energy efficiency (Colaco *et al.*, 2012). Traditional lighting control techniques use multiple sensors such as a photosensor, occupancy sensor, and pyranometer to monitor illuminance, occupancy, and irradiance, respectively (Pandharipande and Caicedo 2015).

4.2 Artificial intelligence models in lighting controller design

Developing an integrated and adaptive lighting concept is a crucial aspect of the lighting design process. The primary integration challenges are: maximizing daylight utilization while reducing lighting energy consumption, and (iv) improving occupant comfort (Colaco *et al.*, 2012; Guillemin and Morel, 2001). The use of data-driven modeling techniques could be beneficial in identifying and predicting the behavior of the underlying dynamic illuminance process (Colaco *et al.*, 2012). The models are designed to solve real-time measurement, prediction, and control issues in a daylight-artificial light system. Several scholars and international energy agency programs have used soft computing approaches to illustrate the use of adaptive control theory in the building domain (Wagiman and Abdullah, 2018). Side-lit windows help allow daylight into a building. Electric lighting and window blinds can be controlled manually, automatically, or both (Reinhart and Voss, 2003). On the other hand, automated control of electric lights and window blinds is a cost-effective and promising method for overcoming human inertia, increasing energy efficiency, and improving visual/thermal comfort (Galasiu *et al.*, 2004; Lolli *et al.*, 2019). The application of fuzzy logic control to the building domain dates back to the 1990s (Dounis and Caraiscos, 2009). Lighting researchers have found that fuzzy logic control is a preferable alternative for designing lighting control systems due to the nonlinearity of the process and the lack of a formal mathematical model for daylighting (Ghadi *et al.*, 2016). Different buildings like residential or

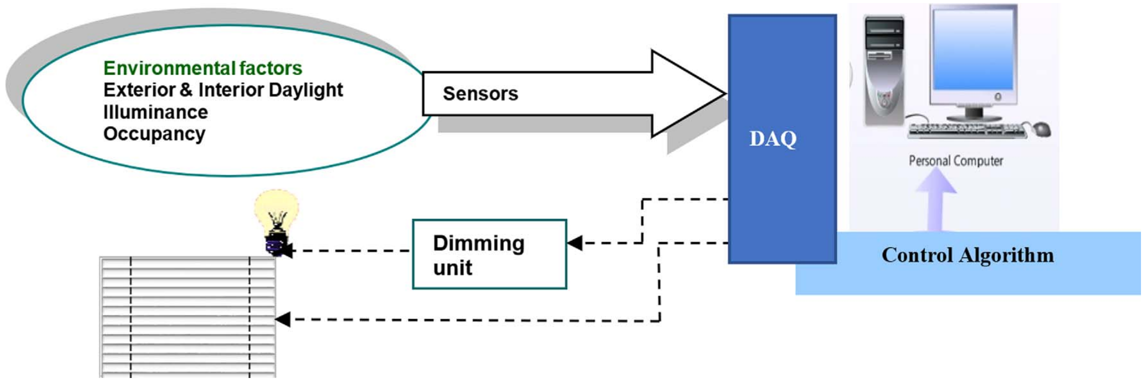

Fig. 2. Basic control scheme for daylight artificial light integration (C.P. Kurian *et al.*, 2008).

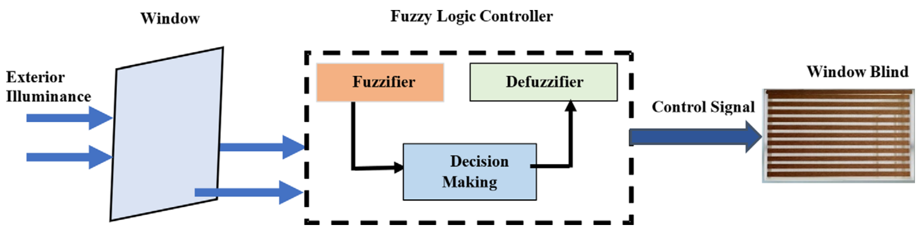

Fig. 3. Block diagram for a window blind controller based on fuzzy logic.

commercial have been monitored and controlled by a centralized building automation system. The studies show that the fuzzy automated control of shadings helps in improving energy efficiency and occupant comfort (Iwata *et al.*, 2017). A fuzzy system for daylighting control, as illustrated in Figure 3, consists of a fuzzy logic circuit with an input stage, a processing stage, and an output stage (Panjaitan and Hartoyo, 2011). The input stage converts the inputs from switches and sensors into non-linear membership functions. The processing stage includes fuzzification and rules processing, and the output stage sends a control signal value to fluorescent dimming ballasts/LED drivers.

4.3 Predictive models based on machine learning

Figure 4 details the input and output details of the machine learning control scheme. The bulk of window blind control research uses fuzzy logic (Trobec Lah *et al.*, 2006) techniques to control the entire opening/closing/slat angle using various control parameters such as irradiance, temperature, illuminance, brightness, and other associated qualities. The primary problem is to apply the fuzzy rule-based technique to industrial items with limited calculation capacity (Sanjeev Kumar *et al.*, 2020a). As a result, the data-driven method has received much attention in recent years in building automation, and it is swiftly becoming the preferred choice of academics (Sadeghi *et al.*, 2017; Yeon *et al.*, 2019).

4.4 Digital camera as a luminance detection device for lighting control

Image sensors/digital cameras are perceived to replace conventional sensors such as photosensors and occupancy

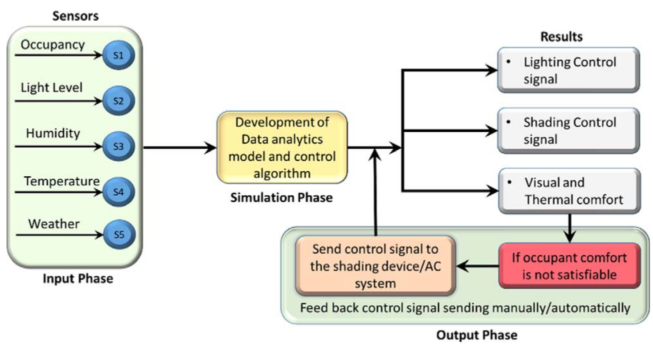

Fig. 4. Process flow diagram for providing visual and thermal comfort using data-driven controllers.

sensors to control window blinds and lighting (Newsham and Arsenault, 2009). The basic block diagram of the image sensor-based lighting control scheme is shown in Figure 5.

Since the luminance value matching the pixel value obtained from the image and scene luminance is not identical, it is critical to calibrate the camera to derive absolute luminance for general lighting applications (Varghese *et al.*, 2018; Sudheer Kumar *et al.*, 2015). Raw HDR images can be calibrated by: (i) Photometric calibration with a Calibration Factor (CF) and (ii) vignetting correction (Cai and Chung, 2011). The CF was calculated using the color checker chart method by selecting a calibration curve with the minimum error. By multiplying the calibrated luminance value with the conversion factor, the luminance value at space can be calculated (Varghese *et al.*, 2019b; Newsham and Arsenault, 2009; Pierson *et al.*, 2021). A significant advantage of using a digital camera for luminance measurement is quantifying the luminance of a scene

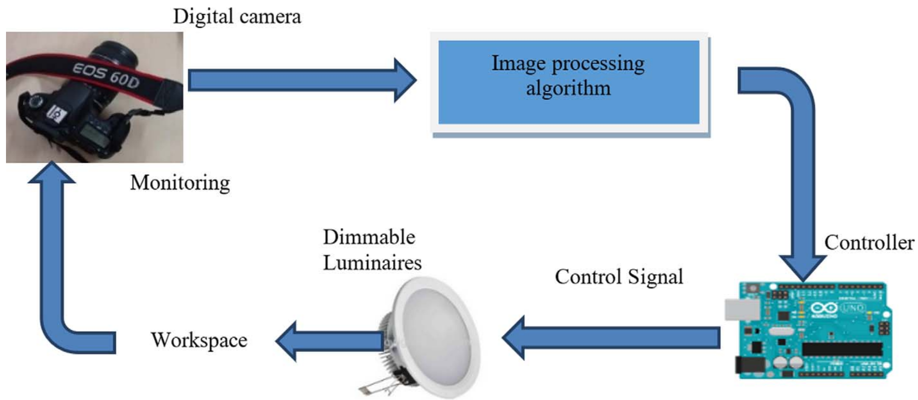

Fig. 5. Block diagram of a camera-based control scheme.

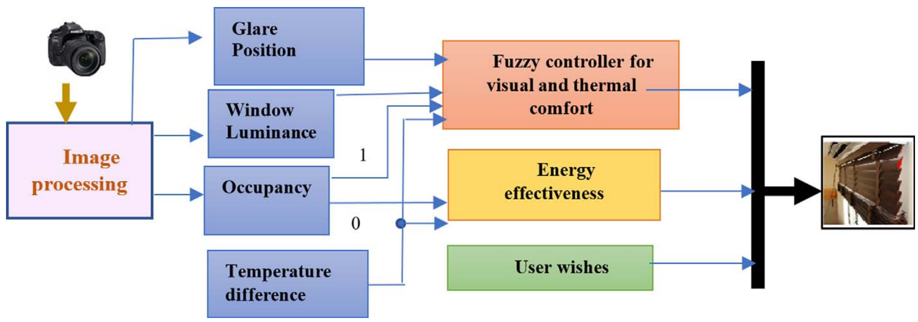

Fig. 6. Generalized block diagram of image-based lighting and window blind control scheme.

(Wuller and Gabele, 2007). Luminance distribution measured in the user's Field of View (FOV) could be used as an input for lighting control systems to achieve a comfortable daylight-linked indoor environment (Kruisselbrink *et al.*, 2019).

Photo sensors, occupancy sensors, and other sensors that control window blinds and lighting can all be replaced with digital cameras (Newsham and Arsenault, 2009). Moeck and Anaokar (2006) and Mead and Mosalam (2017) discussed about work plane illuminance-based control. Jain and Garg (2018) specify that digital camera-based analysis is more affordable than sky scanners for climate-based daylight modeling. Varghese *et al.* (2019b) demonstrated a wireless networked daylight artificial light integrated scheme with Venetian window blinds and dimmable LED luminaires using a DSLR camera as the input measurement (occupancy, window luminance, and interior glare). Figure 6 illustrates a block diagram of image-based lighting and window blind control scheme.

5 Application of intelligent models for daylight – artificial light integrated scheme

This section answers the research question RQ1 "What are the current barriers to existing conventional control approaches". Crisp (1977) published the first study on an automatic daylight artificial light integration control strategy for energy savings while maintaining optimal task illuminance levels. Later, Coley and Crabb (1994) introduced the notion of real-time interior illuminance prediction and computerized artificial light control utilizing a self-commissioning adaptive algorithm, which is considered the foundation for the model-based lighting control scheme. Subsequently, Rubinstein *et al.* (1993) presented the first demonstration of the closed-loop photocell control system. Their experimental setup consisted of a unique two-part photosensor and electronic dimming ballast with a 100% to 20% dimming range. Their experiment on integrating daylighting, lumen maintenance, and scheduling demonstrates lighting energy saving of approximately 50%. In real-time environments, daylight fluctuations pose a substantial hurdle to the successful operation of photosensor-based lighting controls and the general acceptance of daylight dimming controls in commercial buildings (Ehrlich *et al.*, 2002). One of the methods to address the shortcomings of existing commercial controllers is developing control algorithms to predict the interior daylight illuminance and produce control decisions/actions at the desired time step interval (Guillemin and Morel, 2001). The open-loop, closed-loop, and integral reset control algorithms are the most common control algorithms used in commercial lighting controllers (Colaco *et al.*, 2008; Doulos *et al.*, 2008).

A new generation of connected lighting systems driven by data and enabling data is emerging. For connected lighting, commercial users can increase the significant energy savings of LEDs by tying luminaires to the internet.

Basic artificial lighting design principles include uniformity, avoiding glare, and light source color appearance. Lighting scenarios through color tuning and ignition of luminaire grouping should contribute towards this direction (Samiou *et al.*, 2022). Recent progress in the photoelectric system includes:

(i) Automated self-calibrating lighting control system which minimizes power consumption.
(ii) IoT-based intelligent LED lighting with sensors.
(iii) Cloud-based smart lighting control system focused on fatigue regulation of the human circadian rhythm by utilizing photopic illuminance sensors.

5.2 Artificial intelligence models in lighting controller design

This section answers research query RQ1 "identifying the need for AI-based lighting control strategies". Several approaches for estimating and predicting interior daylight illuminances have been proposed in the literature, including: (i) Models based on analytical formulas that are typically employed in conjunction with climate-based studies, and (ii) Computer lighting simulation tools for computing illuminance and visualizing interiors. However, the methods described above provide only a limited understanding of the full process dynamics and may be helpful in the simulation environment during the planning/design phase (Ahmad *et al.*, 2020; Brembilla and Mardaljevic, 2019; Kim and Kim, 2019; Harish and Kumar, 2016). Bauer *et al.* (1996) from the Technical University of Vienna were the first to create a fuzzy logic-based control system for reducing energy demand for artificial lighting in a building. The results of their research suggest an 11% reduction in lighting energy use. Furthermore, they claim that the intelligent controller could save 8% of artificial lighting energy compared to a user who kept the blind half-open all the time. Guillemin and Morel (2002) devised an adaptive controller for the control of window blinds, lights, and HVAC. The designed automated shading device controller adjusts the maximum blind aperture to avoid glare while staying below the maximum to match the user-defined set point illuminance. Genetic algorithms were developed to maximize the parameters of fuzzy logic for self-adaptation. Trobec Lah *et al.* (2006) proposed a contemporary method for managing interior illuminance using a fully automated fuzzy system for altering window blinds that constantly respond to available solar radiation changes and make decisions in the same way as humans do. The control technique uses a cascade control strategy, with the Sugeno-style fuzzy controller acting as the primary controller and a typical Proportional-Integral-Derivative (PID) controller acting as the secondary. The authors Tran and Tan (2014) demonstrated a sensorless illumination control approach using a feedforward neural network for a networked LED lighting system. The experimental method was effective in addressing non-linear and linear relationships within the lighting system, which was used as the controlled plant. Their experiments revealed that their method could reach 95% modeling accuracy while saving 28% energy. Jin and Ho (2009) developed a fuzzy logic controller that maximizes energy savings while maintaining lighting comfort. Their experimental results demonstrate a lighting energy efficiency of 56%, with intelligent lighting output adjustment depending on occupant movements and lighting preferences.

For Net-Zero Energy Buildings (NZEB), Kandasamy *et al.* (2018) designed a novel lighting control system. The Artificial Neural Network (ANN) and Internal Model Control (IMC) principles are used for lighting controller design. A roller blind control system was fitted to limit the glare and maintain desired task illuminance. Their simulation and experimental results show a 40% to 50% energy efficiency. Wagiman and Abdullah (2018) presented an intelligent lighting control system in an office building using an ANN model. The results showed that the Radial Basis Function Network (RBFN) controller could achieve target illuminance levels with 34% energy savings. In their research, Seyedolhosseini *et al.* (2020) classified light sources as controlled or uncontrollable. A combination of linear optimization, artificial neural network, and bias calculation elements was used to achieve the required illumination situation. The study results demonstrate that the method could obtain a significant accuracy between the desired and sensed illuminance levels/values. The PROMETHEE II multicriteria decision aid methodology was used in a case study by Madias *et al.* (2022) to determine the best position for the installation of a light sensor in order to maximize the performance of a daylight harvesting system in a typical office environment. The study had two shortcomings. There cannot be (i) many photosensors independently controlling various light zones, and (ii) image sensors like CMOS and CCD cannot be employed to carry out the investigation. Tan *et al.* (2022b) in their research presented a digital twin-based intelligent lighting system that adaptively provides lighting quality and minimizes energy consumption. Their results report an energy saving of 79.66% and 79.86% because the proposed system had to be ON only for 4 h a day compared to the traditional lighting system that was ON for 16 h a day. However, this paper does not report the optimization of intelligent decision-making control of the lighting system using advanced models.

5.3 Predictive models based on machine learning

This section tries to provide the answer regarding research queries RQ2 and RQ3. Model-based adaptive predictive-based control systems for shading devices using real-time data and robust control methods are becoming increasingly popular to improve occupant visual/thermal comfort and energy economy (Gunay *et al.*, 2017; Huchuk *et al.*, 2016; Sanjeev Kumar *et al.*, 2020b). Xiong and Tzempelikos (2016) and Shen and Tzempelikos (2017) proposed a model-based predictive control for shading devices with real-time data and demonstrated robust control schemes with the potential to improve the indoor environment while reducing lighting energy consumption. IoT-based architecture of model predictive control of lighting control systems may be researched in this context. The recent research in model-based systems includes an Occupancy detection framework. The work combines sensor data from different data modalities, including time series environmental data (temperature, humidity, and illuminance), image data, and acoustic energy data using the ensemble method (Tan *et al.*, 2022a).

5.4 Digital camera as a luminance detection device for lighting control

This section also answers to research query RQ2 in conjunction with RQ3. Compared to conventional sensor-based control, a breakthrough in intelligent technologies has introduced new generation control approaches in intelligent buildings. Camera-based control and its applications in lighting control systems are currently popular (Liu *et al.*, 2016). The authors Inanici (2006) and Sarkar *et al.* (2008), used high dynamic range photography as a luminance mapping tool. A luminance-based lighting and shading control system is described by Newsham and Arsenault (2009). Research into camera-based lighting controls dates back to 1992 when Glennie *et al.* (1992) reported on their new lighting control system labeled ImCon, which included a Charge-Coupled Device (CCD) camera for acquiring surface luminance and spatial information. Sarkar and Mistrick (2006) developed a prototype called Camsensor that employs an HDR imaging technique coupled with a Complementary Metal-Oxide-Semiconductor (CMOS) image sensor to control an electric lighting system using Digital Addressable Lighting Interface (DALI) ballast. The paper discussed the calibration procedure for illuminance measurement involving: (i) conversion of pixel radiance to luminance (factory calibration) and (ii) conversion of luminance to illuminance (site calibration). The same authors, Sarkar *et al.* (2008), continued their research and developed a prototype light-dimming model that was compatible with DALI ballast. Moeck and Anaokar (2006) presented a method for calculating and analyzing illuminance contributions from high-resolution luminance maps, which can be used to determine the amount of light emitted by specific objects, colors, and features.

Newsham and Arsenault (2009) demonstrated that for daylight harvesting, window blind control, and presence detection, a single CMOS camera chip could replace the multiple sensors required by conventional lighting schemes. They devised a proof-of-concept scheme that they tested in a single space. Bellia *et al.* (2011) conducted a comparison study of horizontal illuminance measurement using a traditional lux meter and the HDR imaging method in a school setting. They devised a method for extracting illuminance measurements from luminance maps using a digital camera calibrated to function as a photometer. Their findings revealed that using HDR instead of a lux meter to measure illuminance resulted in a 20% reduction in error. In terms of human vision, luminance-based interpretation (Cai, 2016) replaces conventional illuminance-based metrics. When it comes to assessing glare metrics and spatial distribution of light levels, the luminance measurement system outperforms illuminance sensors (Tyukhova, 2014). Sky luminance distribution is derived from sky images for daylight simulations (Humann and McNei, 2017; Inanici, 2006; Spasojevic and Mahdavi, 2007). To control blinds and lighting, photosensors, luminance meters, pyranometers, and occupancy sensors can all be replaced with digital cameras (Jain and Garg, 2018).

Lighting levels are frequently measured in terms of illuminance or luminance (Suk, 2019). The distribution of indoor luminance impacts the occupants' visual comfort (Kruisselbrink *et al.*, 2020). Adam *et al.* (2019) proposed a microcontroller-based light-dimming system and developed a Matlab algorithm to identify and calculate the luminance of dark/light areas for this purpose. The authors compared their system's installed power and energy performance with a typical photosensor-based system for total light output and 50% light output from fluorescent and LED lamps. Their findings show that while both systems have the same energy performance, the microcontroller-based system requires slightly more installed power than a traditional photosensor-based system. Kruisselbrink *et al.* (2020) proposed ceiling-based luminance measurements to collect relevant data without interfering with occupants' actions. Pierson *et al.* (2021) described the step-by-step process to create a 180° luminance map from different exposures of the same daylit scene. (Wuller and Gabele, 2007) described a method for using digital still cameras as luminance meters that are independent of exposure settings. Adam *et al.* (2019) presented a microcontroller-based CCD camera controller for DALI digital dimming. The image was sent over Ethernet, and image processing using Matlab enabled the detection of dark areas and the calculation of luminance. For testing, a DALI photosensor was also used. Using a photosensor and microcontroller with a CCD camera, they were able to save about 49% energy in fluorescent and LED lamp systems. Kim and Tzempelikos (2021) developed a method for non-intrusive luminance monitoring integrated with daylighting control applications. Modeling discomfort due to glare by evaluating luminance uniformity metrics and incorporating wireless networking is a new development in HDR imaging in lighting (Abboushi *et al.*, 2022).

6 Results and discussion

This section offers results of prevailing research in artificial intelligence methods and camera-based models for daylighting control to improve occupant visual comfort and energy efficiency in the building sector.

6.1. Data-driven models

Machine Learning models have proven to provide a practical approach to interior daylighting prediction for occupant visual comfort, thermal comfort, and energy efficiency (Luo *et al.*, 2022). Table 1 offers a review of the performance of developed data-driven models and Table 2 offers prediction model-based DALIS.

6.1.1 Data

A substantial amount of indoor and outdoor daylight data is needed to create daylight forecasting models. Machine learning approaches use input data to identify patterns or correlations between the input response and output

Table 1. Summary of the related works based on the data-driven model.

Work source	Key findings	Performance
Mavromatidis *et al.* (2014)	For the estimation of the daylight factor, a polynomial-based regression model was proposed.	Prediction of daylight factor with root mean square levels 0.99 by a set of independent variables
Borile *et al.* (2017)	Light sensors on luminaires and a workplace reference point were used to collect experimental data.	Adjustable dimming levels; Minimized energy use
Le *et al.* (2014)	Developed using a Support Vector Machine (SVM)-based Machine Learning (ML) method.	Thermal discomfort reduction through blind control with SVM technique
Caicedo and Pandharipande (2016)	Support Vector Regression (SVR)-based energy consumption model	Energy savings
Xiong and Tzempelikos (2016)	Model-based control (MBC) techniques for lighting and shading controls were developed; Minimum sensor inputs (irradiation, indoor/outdoor illuminance) were considered.	Satisfies the visual comfort criteria; Maximize daylight utilization, Minimize lighting energy use. DGP values remained below 0.35; lighting energy use was reduced
Sadeghi *et al.* (2017)	Predict electric light dimming and roller shade lowering/raising actions. The intermediate operational states of electric lighting and shading systems were predicted with Bayesian regression models.	Data on environmental parameters, individual characteristics and human attributes governing human-shading and – electric lighting interactions
Gunay *et al.* (2017)	"Discrete-time Markov logistic regression models from the light-on and blind-closing behaviours in recursion" were developed.	Modest electricity energy reductions of 0.9 kWh/m^2 only with adaptive lighting controls and 1.2 kWh/m^2 with both adaptive lighting and blind controls
Sanjeev Kumar *et al.* (2020b)	Real-time data driven predictive models for thermal and visual comfort. Luminaire dimming and ensemble learning based window blind position prediction; Daylight glare assessment models using SVM, decision tree, ensemble tree, and ANN	The model consumes 17% less power than the uncontrolled system and 15% less power than the baseline system

predictor variables for anticipating the response variable under specific conditions.

For comprehension purposes, a few parameters of daylight data sources, response variables, and predictor variables mentioned in the literature are:

Daylight data source: a) data collected from laboratory/Field studies with outdoor/indoor sensors and cameras, b) weather input-based daylight simulation tools, c) subjective survey;
Predictors: Interior and Exterior irradiance/illuminance, work plane/ceiling illuminance, building factors, Climate and Sky parameters, work plane height, Window orientations, Exterior Daylight on Window (EDW), Visual Daylight Glare Probability (DGP), Useful Daylight Illuminance (UDI), Daylight Glare Index (DGI), Glare Sensation (GS)
Responses: light/window blind position control, daylight metrics, subjective responses with respect to glare

It is a common practice to use window blind slat angle controls with up/down/intermediate positions to reduce daylight glare, and promote visual and thermal comfort and energy efficiency (Papinutto *et al.,* 2022). The performance of the controller is assessed in comparison to the baseline case, which uses traditional manual control, in terms of light control, window blind control, visual comfort, and energy savings (Bakker *et al.,* 2017).

6.1.2. Machine Learning Algorithms and model evaluation

Data-driven daylighting models presented in this review study utilized regression, classification, and clustering techniques for predicting daylighting parameters. The type of algorithm depends on application type, data size, the complexity of the task, computational time, and output accuracy (Alanne and Sierla, 2022). Ayoub (2020) present a detailed review of the literature on machine-learning approaches to predict daylighting performance inside buildings, with an emphasis on prediction, various algorithms, data representation, and evaluation metrics. Regression and classification-based predictive models prominently used in the literature are based on algorithms like ANN, Support Vector Machine (SVM), Decision Tree (DT), Ensemble

Table 2. Summary of the related works based on the prediction model for daylight artificial light integration.

Literature	Data	Window blind control	Algorithm Details	Model Evaluation	Performance
Xie and Sawyer (2021)	**Predictors:** Irradiance, sky ratio, glare; **Response:** Window Blind Position; **Data Source:** Experimental real-time field data	**Type:** Venetian Blind; **Position:** East, West, North, and South; **Control:** Up–down, intermediate position with static slat angle of 45°	**Algorithms:** KNN, SVM, and RF; **Parameter Tuning:** Hyperparameter Optimization	**Statistical:** NA**Real-time: window venetian blind Slat angle** control 0°, 15°, 30°, and 45°for glare prediction below 0°, 15°, and 30°	Could prevent 86.5%–96.9% of the glare and potentially reduce lighting energy use by 80.8%
Sanjeev Kumar *et al.* (2020a)	**Predictors:** Indoor and outdoor window illuminance, work plane/ceiling illuminance, vertical illuminance; **Response:** Window Blind Position DGI, DGP, and GS; Field data collected from test room	**Type:** Venetian Blind; **Position:** East; **Control:** Up–down and intermediate position with static slat angle of 45°.	**Algorithms:** ET, ANN, GPR, and SVM; **Parameter Tuning:** Bayesian Hyperparameter Optimization; **Feature Selection:** DT; **Type:** Regression for DGP/DGI and classification for GS	**Regression:** MSE, RMSE, MAE, MAPE, and R^2; **Classification:** Accuracy, PE, AUC-RoC, Precision, and Recall; **Hypothesis:** Friedman's ranking test for model selection	ET model performs better than other models. The accuracy of DGP, DGI and GS are 99.84%, 99.39% and 94.4%; Total energy Consumes 17% less power than the uncontrolled system and 15% less power than the baseline system.
Chiesa *et al.* (2020)	**Predictors:** Illuminance (indoor/outdoor) and temperature **Response:** Blind Control, and LED; **Data Source:** Experimental (50 × 50 × 50 cm) Set up	**Type:** Venetian Blind; **Position:** East, and West; **Control:** Slat Angle Control (No up-down control)	**Algorithms:** Fuzzy Logic; **Parameter Tuning:** NA; **Feature Selection:** NA; **Type:** NA	**Real-time:** Indoor illuminance (300 lux), outdoor illuminance (1000 lux), and Lighting Energy.	When illumination is controlled by zones, Zones 1 and 2 consume power of 0.7 W and 0.69 W respectively compared to 4 W and 1 W without control
Yeon *et al.* (2019)	**Predictors:** Outdoor temperature, Relative Humidity, Solar Altitude, Solar Radiation, zone people occupant count; **Response:** Blind Slat angle (0 to 180°);	**Type:** Venetian Blind; **Position:** South; **Control:** Slat angle control (no up and down control)	**Algorithms:** ANN; **Parameter Tuning:** N/S; **Feature Selection:** N/S; **Type:** Regression	**Statistical:** RMSE;	The overall energy consumption was 9.1% lower than the baseline scenario of blind angle set at 50°.
Sadeghi *et al.* (2017)	**Predictors:** environmental variables, human attributes**;** **Response:** Blind up and down position; Data **Source:** Field study conducted in private offices	**Type:** motorized roller shades; **Position:** South; **Control:** Raising and lowering (25%, 50%, 75%, and 100%)	**Algorithms:** Bayesian modeling and BR models; **Parameter Tuning:** N/S; **Feature Selection:** N/S; **Type:** Regression	**Statistical:** RMSE	BMBCL models predicted shade raising/lowering and electric light dimming actions. BR models predicted the intermediate operating states of the systems.

Table 3. Summary of the related works based on the camera-based models for daylight artificial light integration.

Literature	System and control strategy	Photometric measurement	Performance
Budhiyanto and Chiou (2022)	System: LCS uses LabVIEW with real-time high dynamic range images and a digital multiplex controller to brighten lamps sequentially to provide visual comfort.	The prototype works well with both schemes and provides different combinations of lamp brightness levels, starting from 10% to 60%, based on the activities and required luminance	Save 73–82% of electricity; The presence of daylight does not always result in more energy savings, since visual comfort needs to be considered
Varghese *et al.* (2019b, 2022)	**System:** Daylight Artificial light integrated scheme with Venetian window blind and dimmable LED luminaires; **Control**: maximize daylight, reduce glare, and maintain desired illuminance; fuzzy control algorithm (tuned for real-time) taking inputs from image	**Calibration:** curve for photometric measurement derived in the range of 50 lx to 2000 lx.; Level of Significance higher than 0.05 in the luminance measurement for 15 days; Luminance measurement with maximum 13% error	Maintained illuminance (lux) in the workplace with 5% with uniformity of 0.94; Seasonal energy savings, in comparison with uncontrolled lighting scheme
Kim *et al.* (2020)	**System:** Window Shading control based on exterior Luminance; **Sensor**: HDRI-based camera sensor for Window, occupant positioned HDRI sensor in the interior, photometers (2) to measure vertical illuminance; **Control:** Automation of the roller shades using sun position and exterior Luminance data. Uniformity in interior illuminance with DGP index less than 0.3.	HDRI sensor as a luminance measuring device; calibration factor not addressed; DGP index-based glare source detection; Determining a practical luminance threshold for HDRI-based control is suggested as future work; A sensor with a wider dynamic range is suggested to capture high luminance	Successful in detecting location, size, and brightness of glare source; Exterior Luminance used for control; Not used for lighting control with specific luminance value and glare position identification
Mead and Mosalam (2017)	**System:** Automated full luminance distribution measurement; **Sensor:** RPiCM ; **Control:** Not Addressed	Luminance measurement with 20% error; RPi camera requires vignetting correction; Range of luminance variation is measured to identify the luminance distribution	To improve the quality of HDR image, exposure sequence needs to be specified individually for each test case.
Caicedo and Pandharipande (2016)	**System:** Daylight –Artificial Light scheme; **Sensors:** Conventional Photosensors and occupancy sensor; **Control:** Inner loop with PI controller for ceiling sensors and outer loop to recalibrate the controller setpoints.	Multiple Ceiling sensors, work plane sensors at each zone; **Calibration** –the ratio of measured illuminance at ceiling and workspace sensor	Provided net illuminance above desired level; Out of the 8 workspaces considered 4 could achieve above target illuminance
Liu *et al.* (2016)	**System:** Artificial light control; **Sensor:** Light sensors and motion sensors; **Control:** Fuzzy logic control, integrated with PI control for lighting comfort and minimizing energy consumption.	Light sensors located on the working table; Glare not addressed	With 300 lx illuminance level; 3% difference between measured and reference illuminance; 57% energy saving is estimated

Tree (ET), Random Forest (RF), Bayesian Multivariate Binary-Choice Logit (BMBCL), and Bayesian Regression (BR) models, K-Nearest Neighbor (KNN). Similar reviews on data-driven approaches relevant to building energy consumption prediction are presented by Amasyali and El-Gohary (2018) and Wei *et al.* (2018).

6.2 Camera-based models

Study characteristics of camera-based lighting control models, for the analysis, are divided into system and control strategy, photometric measurement, and observations for HDRI-based lighting control with AI techniques as shown in Table 3.

7 Limitations and recommendations for future research

The majority of recently developed controller models as discussed in Section 4 have predictive models and the accuracy of dynamic responses depends on the computational ability of the algorithms. A parametric study is further essential for different participants, building geometries, geographical locations, sensor positions, and components of lighting comfort such as glare, sky conditions (Mardaljevic, 2012, 2015), color rendering index, light color, and flicker in order to verify the generalizability and adaptability of control schemes for any environmental conditions. A life cycle cost analysis of system performance, cost differences, initial investment information, and energy implications of lighting control solutions has received little attention from current research. Therefore, case studies with different building types, luminaires, and individual solutions would be needed.

The following few cutting-edge methods are gaining attention in light of the status of the study and the proposed framework for the advancement of the technologies:

- The occupants of the building experience discomfort as a result of uncontrolled solar radiation penetration through the glazing, also raising the building's overall energy consumption (Oh *et al.*, 2018). The majority of the studies examined in this literature do not take occupant behavior for window glazing variations into account (Paone and Bacher, 2018). Various current research is in progress regarding the modeling and control of switchable glasses through climate-responsive machine learning algorithms, and smart glass integration with spectrally tunable LED luminaires for circadian entrainment and visual comfort (Mathew *et al.*, 2022; Colaco *et al.*, 2018).

The direction of further research would be smart lighting in smart buildings utilizing IoT and Cloud computing which is still in its early stages when applied to energy efficiency and user comfort. Intelligent lighting services are implemented using techniques and technologies that fully integrate multiple sensors and controllers, drivers, network protocols, and communication platforms. Research could emphasize developing flexible wireless lighting control in large buildings to integrate the latest sensors and overcome communication traffic, bandwidth, latency issues, network failure, *etc* (Adu-Manu *et al.*, 2018). Developing building cybersecurity approaches and technical strategies with an emphasis on lighting systems, energy efficiency, and user comfort presents a study opportunity. Putrada *et al.* (2022) in their review present an extensive analysis of new machine-learning methods for achieving user comfort and energy efficiency in a smart lighting system including implementation challenges, technical solutions, and future possibilities. Recent emerging research on smart lighting emphasizes maximizing occupant comfort and individual preferences rather than just building energy conservation. A personal lifelog-based lighting curation system was developed by Seo *et al.* (2021) that employs Big Data analysis to recommend minimal illuminance and CCT for a personalized luminous environment associated with the task, fatigue level, and mood class (Boyce, 2010).

- Another avenue for research is the application of digital twin technology for developing and analysis of adaptive daylighting schemes using lighting and shading control. Akimov *et al.* (2022) applied the idea of digital twin technology to energy-efficient building design using passive control of static shading systems to achieve thermal and visual comfort conditions. The emphasis is on the data exchange between the physical and virtual environments for the most accurate representation of the real environment while minimizing the error factor in the sensing device and measurement technique that can cause a deviation from real life.
- Application of ML-based models for different workplace luminance-illuminance mapping with image sensor can be carried out to design a lighting control system with adaptive illuminance setting.

8 Conclusion

The objective of this literature review was to provide a comprehensive investigation to: (1)Identify the current barriers to existing conventional control approaches and the need for AI-based lighting control strategies; (2) Summarize the most effective techniques in AI-based lighting control methods in office buildings to maximize the criteria of visual comfort and energy efficiency in daylight artificial light integrated schemes; (3) To evaluate the advantages and limitations of the concepts. Although the use of intelligent control and comfort metric evaluation techniques in the building automation domain is not a new topic, recent research demonstrates their viability in the control and comfort evaluation process, leading to improvements in building energy efficiency and occupant comfort in a real-time environment. Given this, the lighting control in the open-plan office is a significant and challenging problem while regulating both the occupant's comfort and energy conservation. The main impediment to the widespread use of building lighting controllers is the occupants' disapproval of controller behavior (light on/off/dim/window blind movements/delays). This calls for the need to pay more attention to research and design of human-building interaction interfaces to increase occupant acceptance of the system. Despite the potential use of machine learning in daylighting studies, the development of artificial intelligent controllers is still in its early stages. This implies that there is a lot of scope for expanding the breadth of the presented reviewed studies on actual buildings to address the practical limitations of the intelligent controllers, boundaries of occupant acceptability, and energy conservation.

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