Optimizing Photosensor Placement for Energy-Efficient Lighting in Sustainable Building Design based on Multivariate Long Short-Term Memory Models

Giacomo Potenza[1,*,†], Cristina Baglivo[2,†], Marina Bonomolo[3,†] and Patrizia Ribino[1,*,†]

[1]National Research Council (CNR), Institute for High-Performance Computing and Networking (ICAR), Palermo, Italy
[2]Department of Engineering for Innovation, University of Salento, Lecce, Italy
[3]Department of Engineering, University of Palermo, Palermo, Italy

Abstract

In sustainable building design, optimizing lighting systems is essential to reducing energy consumption while maintaining occupant comfort. Photosensors, which guide the lighting control system in adjusting illumination based on ambient light levels, are critical in achieving energy efficiency and visual comfort. However, the optimal placement of these sensors is a complex task due to the dynamic and multidimensional nature of lighting conditions within a building. This study presents a novel approach for optimizing photosensor placement using multivariate Long Short-Term Memory (LSTM) models. Unlike conventional methods, LSTM models leverage historical data on indoor light patterns from photosensors and sunlight factors to capture long-term dependencies in time-series data. The proposed method is distinguished by its capacity to anticipate future lighting conditions, thereby enabling the system to adopt a proactive approach to environmental variations, representing a notable advancement over traditional reactive models. This approach allows for more accurate forecasts by accounting for past fluctuations in light conditions and associated environmental variables. The proposed method seeks to determine the optimal sensor placement, maximizing energy savings by ensuring efficient use of natural light while minimizing artificial lighting and maintaining visual comfort. Simulation results demonstrate significant improvements in energy efficiency compared to traditional sensor placement strategies, making this approach a promising solution for sustainable building design. The study highlights the importance of integrating advanced machine learning techniques like LSTM to enhance energy performance and sustainability in modern buildings, also looking at user satisfaction regarding visual comfort.

Keywords

Long Short-Term Memory (LSTM), Indoor Lighting Control, Visual Comfort, Smart Lighting Systems

1. Introduction

Buildings account for a large share of global energy consumption, around 40% of the overall energy demand. Moreover, they account for approximately 30% of carbon dioxide (CO2) emissions [1], contributing substantially to greenhouse gas effects, including climate change and global warming. Mitigating or eradicating adverse environmental impacts while simultaneously enhancing positive ecological outcomes through the building's design, construction, and operational processes is essential to promoting the development of sustainable buildings. In light of the ongoing urbanization process and the concomitant rise in expectations regarding occupant comfort, it becomes imperative to develop energy-efficient lighting systems that adapt to the daily dynamics of living spaces.

Energy-efficient lighting represents a fundamental aspect of sustainable building design, profoundly impacting both environmental sustainability and operational costs. To address this challenge, it is essential to investigate the potential of emerging technologies, such as photosensors, to enhance the efficiency of lighting management. Photosensors are critical in optimizing lighting systems in modern

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*Corresponding author.
†These authors contributed equally.
giacomo.potenza@icar.cnr.it (G. Potenza); cristina.baglivo@unisalento.it (C. Baglivo); marina.bonomolo@deim.unipa.it (M. Bonomolo); patrizia.ribino@icar.cnr.it (P. Ribino)
0009-0002-1502-4446 (G. Potenza); 0000-0001-9553-6382 (C. Baglivo); 0000-0001-6084-1205 (M. Bonomolo); 0000-0003-3266-9617 (P. Ribino)

buildings by adjusting artificial lighting based on ambient light levels. Proper sensor placement ensures that natural light is effectively utilized, reducing the reliance on artificial lighting and thus lowering energy consumption. However, determining the optimal placement of these photosensors is a complex challenge, as lighting conditions within a building fluctuate throughout the day due to changes in sunlight, room usage, and weather conditions.

Numerous studies have chosen to install illuminance sensors either at the top of the desk or at a predetermined location that accurately represents the desk's position [2, 3, 4]. However, the work plane is not an appropriate location to directly install reference photosensors, as they can be easily shaded or interrupted by activities such as reading or movement. Numerous design guidelines and manufacturers, such as [5, 6, 7][1], have identified the ceiling as the primary location for sensor installation. Even if sensors can be positioned on light fixtures or walls, it is contingent upon the specific type of sensor employed and the room's configuration. However, such traditional sensor placement methods that rely on static strategies fail to account for the dynamic nature of lighting environments. These factors lead to suboptimal energy savings and comfort levels.

To address this issue, this study proposes an advanced approach using Multivariate Long-Short-Term Memory (LSTM) models [9, 10], a recurrent neural network (RNN) well-suited for handling time-series data and predicting complex patterns. LSTM is designed to memorize long-term temporal dependencies through memory cells containing several types of gates and to learn nonlinearity. By leveraging LSTM models, which can process multiple variables over time, optimal lighting conditions can be predicted based on historical data, environmental factors, and building usage patterns. This research aims to optimize the placement of photosensors in buildings by modeling lighting conditions with multivariate LSTM models. The approach allows for a dynamic, data-driven solution that maximizes energy efficiency while maintaining optimal lighting conditions for occupants. Integrating advanced machine learning techniques into building design can significantly enhance the sustainability of modern structures, reducing their carbon footprint and operational costs.

The rest of the paper is organized as follows. Section 2 introduces related works. Section 3 presents the LSTM model. Results and conclusions are presented in Sections 4 and 5.

2. Related works

Recent research has extensively explored the optimization of light sensor placement for indoor lighting control, revealing various advanced methodologies to enhance energy efficiency and visual comfort. One notable study employed Artificial Neural Networks (ANNs) to determine the optimal positioning of light sensors, achieving highly accurate predictions with a Mean Squared Error (MSE) of 2.20×10^{-3} and a correlation coefficient (R^2) of 0.9583. This approach demonstrated the capability of ANNs to significantly improve the effectiveness of daylight-linked lighting control systems by accurately predicting sensor positions, which in turn enhances energy efficiency in buildings [11]. In parallel, another study introduced a novel method for optimal sensor placement by integrating the inverse square law and Lambert's cosine law to calculate illumination levels. This method utilized the k-medoids clustering algorithm to identify the best sensor positions by grouping room coordinates based on light levels. The approach was validated through extensive field measurements and simulations, proving its high accuracy in determining the optimal sensor locations and demonstrating its practical applicability in real-world scenarios [12]. Furthermore, research focusing on spaces equipped with dynamic shading devices developed spatial sensitivity curves to address the challenges of varying daylight conditions. The study tested different sensor placements to identify locations that ensure consistent light control despite dynamic shading variations. The results highlighted the necessity of carefully selecting sensor positions to maintain optimal illuminance levels on the work plane and achieve the highest correlation between sensor measurements and actual light conditions [13]. Additionally, advancements in optimization techniques have been explored, such as the Battle Royale Optimization (BRO) algorithm combined with a fuzzy logic controller. This approach was shown to improve energy efficiency by up to 30.8%,

[1] A more exhaustive list can be found at [8]

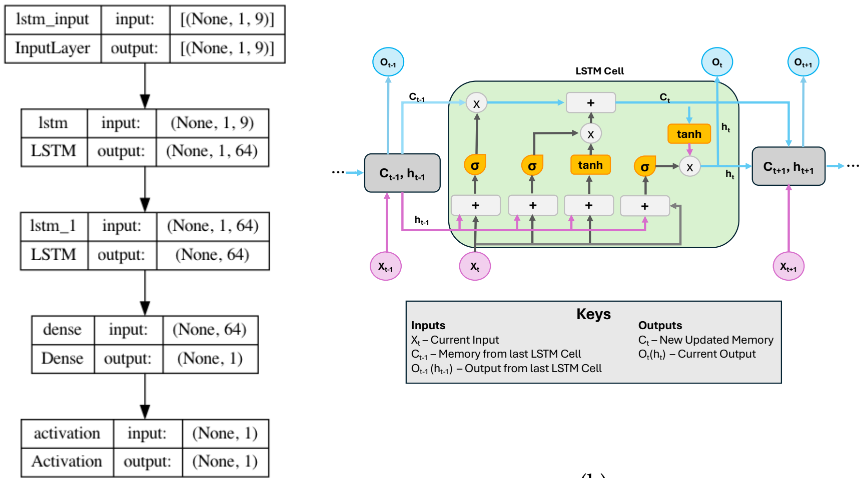
alongside reducing initial costs and energy demand, while ensuring compliance with the EN12464-1 standards [14]. Another innovative method, Particle Swarm Optimization (PSO), was used to develop a new optimal light sensor placement technique known as OLSPM-PSO. This method shows a reduction in the required sensors and energy consumption, exhibiting superior accuracy in light distribution compared to other methods [15]. These studies emphasize the increasing complexity of lighting systems, highlighting the importance of advanced methodologies for optimizing energy efficiency and visual comfort within smart buildings.

Innovations proposed by our study LSTMs are an advanced class of neural networks designed to handle and predict sequential data, making them particularly well-suited for analyzing and interpreting time-series data collected from sensors. The aforementioned approaches are typically static and lack the capacity to adapt to environmental variations. Thus, they cannot respond effectively to real-time changes, such as daytime fluctuations in sunlight or alterations in occupants' activities. Our study focuses on developing an LSTM-based approach to analyzing data collected from light sensors installed in an office. This approach can predict future illumination levels by learning from historical data to create accurate predictive models. The generated forecasts enable a deeper understanding of future lighting trends, promoting more proactive and informed management. Our approach differs from the previous ones in several points. While earlier research employed various methods, such as ANN and clustering algorithms, to optimize sensor placement and improve lighting control, our approach introduces a novel predictive element. Previous studies primarily focused on optimizing sensor locations or enhancing control systems based on current or historical data. In contrast, our method leverages LSTM networks to provide future-oriented predictions, allowing for dynamic lighting system adjustments based on anticipated conditions. In contrast to conventional methodologies, which depend on fixed data sets, our LSTM model incorporates a diverse array of variables, encompassing historical data and real-time environmental conditions. This integration markedly enhances the precision of lighting predictions. Moreover, previous works required extensive validation through field measurements and simulations to confirm their effectiveness. Our LSTM-based approach aims to streamline this process by providing real-time forecasts, thus enabling more immediate and adaptive responses to changing lighting conditions. This advancement enhances the accuracy of lighting predictions and contributes to a more efficient and sustainable energy management strategy in both office and residential settings.

3. LSTM Conceptual Scheme for Optimal Lighting Sensor Placement

In this study, we propose a novel method for optimizing the placement of lighting sensors in smart buildings using Long Short-Term Memory networks [9, 10]. LSTMs, a type of neural network well-suited for handling time-varying data, enable the model to capture complex temporal patterns and accurately predict lighting conditions. The LSTM model is specifically designed to identify temporal dependencies in lighting data, with layers dedicated to learning from historical patterns and making informed predictions. By leveraging this predictive approach, we aim to improve lighting management in smart buildings, offering a data-driven sensor placement and validation solution. The following are the main steps for developing the proposed LSTM neural network. Accurate data collection enables the model to capture comprehensive information, while feature engineering facilitates the extraction of meaningful patterns. Normalization ensures that measurement scales do not affect learning, and the LSTM architecture optimizes the storage of relevant information. Collectively, these steps enhance prediction accuracy and improve lighting management performance.

Data Collection It represents a fundamental stage in generating forecasts, as it determines the quality of the resulting predictions. The data required for our LSTM model can be broken down as follows: (i) *Illuminance [lux]* is a key factor for our objectives. It is measured by light sensors positioned at various points within the building. These sensors provide brightness readings that fluctuate over time, so collecting these readings over an extended period is essential to obtain a comprehensive representation.



(a) (b)

Figure 1: The architecture of the adopted stacked LSTM neural networks and the related LSTM cell schema

(ii) *Environmental Conditions:* Factors such as direct sunlight, cloud cover, time of day, and season influence daylight. This data can be obtained through external sources. The data was acquired with a frequency of five minutes.

Feature Engineering and Data Preprocessing Before training an LSTM model, preparing and transforming data into a format that the model can utilize effectively is essential. This process is crucial for ensuring the model's optimal performance. In particular, *Feature extraction* involves identifying salient characteristics within a given data set and deriving meaningful information from the raw data. Temporal features pertain to the order or sequence of events, such as the time of day, the day of the week, and the season. Spatial characteristics include the distance to windows and the position in relation to light sources. Historical light levels refer to previously recorded readings at specified time intervals. Extracting pertinent features enhances the model's capacity to discern meaningful patterns within the data set, thereby facilitating more precise and pertinent forecasts of lighting conditions. On the other hand, *Normalization and Scaling* allows data to be transformed into a uniform scale to ensure effective learning by the model. Min-Max normalization scales the data to a range between 0 and 1. For instance, if a sensor reads values between 100 and 500, min-max normalization transforms these values into a range between 0 and 1. Z-score standardization transforms the data to have a mean of 0 and a standard deviation of 1, facilitating comparison by scaling the data so that values can be compared more easily. In this study, the Min Max normalization technique was employed to ensure that the model could learn effectively and accurately interpret the variations in the sensor readings.

LSTM Model Design The architecture of the adopted deep neural network is shown in Figure 1a, where the LSTM cells are used as basic building blocks in the hidden layers. The input layer mainly processes the data, receiving temporal data organized in time windows. In our model, the inputs are the current illuminance values of a given photosensor to be examined, solar elevation and azimuth values, and the illuminance value on the work plane at previous time steps. LSTM layers store long-term information due to their gating mechanisms, which allow the model to retain or discard information, which is beneficial for identifying complex patterns over time. Dense layers process the output of the LSTM layers and provide the final prediction, such as the future illumination level on the work plane. Figure 1b shows the architectural scheme of the LSTM cells [2]. For each LSTM cell, inputs are the current feature vector x_t, the memory from the last LSTM cell C_{t-1}, and the output of the last LSTM cell h_{t-1}. On the other hand, the outputs are the new updates memory C_t and the current output h_t.

[2]Figure is adapted from the literature.

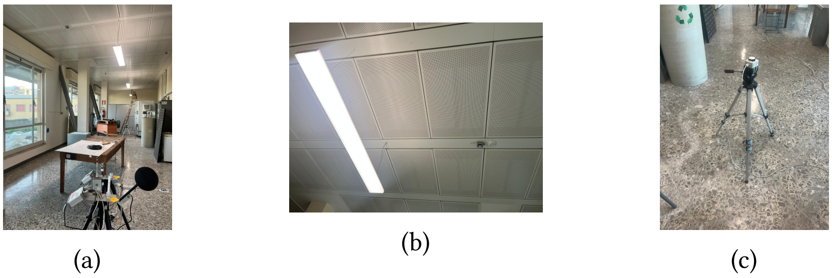


Figure 2: Data acquisition was conducted in a lab of the Department of Energy, Information Engineering and Mathematical Models (DEIM) at the University of Palermo (Fig.2a). A photosensor on the ceiling (Fig.2b). The apparatus emulates the position of a sensor on a work surface, situated at the typical height of a desk (Fig.2c).

Several parameters must be optimized to train the LSTM neural network: (i) The optimizer adjusts the model weights to minimize the error. Adam has been chosen as it combines gradient descent with moving averages of gradients to improve convergence. (ii) The Loss Function quantifies the discrepancy between the model's predictions and the actual values. The Root Mean Squared Error (RMSE) is chosen, it is calculated as the mean of the squares of the differences between predictions $\hat{y}_i$ and actual values y_i.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Model Evaluation and Validation The model's evaluation is conducted using a subset of the dataset, thereby ensuring that it demonstrates data generalization that has not been previously encountered. It is crucial to highlight that the validation is based exclusively on the predicted data, as opposed to the data collected by the photosensors on the desk. This methodology permits the examination of the model's efficacy in predicting lighting conditions instead of merely comparing predicted values with actual measurements. The coefficient of determination (R^2) is a number between 0 and 1 that quantifies the degree to which a model's output can be explained by its input. In other words, it measures how well a statistical model predicts an outcome. It is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{2}$$

where y_i are the observed values, $\hat{y}_i$ are the expected values, $\bar{y}$ is the average of the observed values, and n is the total number of observations. As reported in [16], the prediction performance is considered: Excellent for $R^2 \geq 0.9$, Good for $0.7 \leq R^2 \leq 0.9$, Fair for $0.3 \leq R^2 \leq 0.7$ and Poor for $0 \leq R^2 \leq 0.3$.

4. Experimental Evaluation

4.1. Scenario description

Data acquisition was performed within a laboratory on the rooftop of the Department of Engineering at the University of Palermo (see Fig.2a). The total area of the space is $106m^2$, while its overall height measures $4.4m$, including a false ceiling. The room has four windows, each measuring $2.4m$ in width and $2.9m$ in height. These windows are positioned in a southeast orientation. Adjacent to the windows is a balcony distinguished by its lush green roofing system. The windows are partially obscured by a solar shelter measuring $2.7mx19m$ [17]. Furthermore, vegetation on green roofs can significantly impact the indoor daylight contribution, influencing the surface's color and reflectance properties. The variation in albedo can occur throughout the annual cycle and over extended timeframes, particularly in response to changes in vegetation type or as vegetation matures, leading to additional shading effects. Figures 2b and 2c show a photosensor located on the ceiling and the sensor that emulates a sensor placed on a work plane located at the same height as the classical height from the ground of a desk.

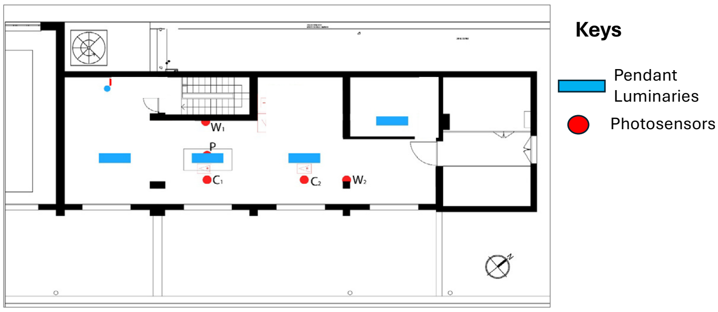


Figure 3: Sensors are located in distinct areas of the office: ceiling (C1, C2), wall (W1, W2), and work plane (P).

4.2. Experimental results

A series of experiments was conducted to evaluate the effectiveness of the proposed approach for optimizing photosensor placement using Multivariate LSTM models. The experimental setup [17] involved a typical office building environment equipped with five photosensors collecting different light exposure levels (see Figure 3). Among them, one is positioned on the work plane to capture the real light illuminance levels. The remaining are located in different office points, two on the ceiling and two on the lateral walls. Hence, four tests have been conducted to determine the best photosensor showing the best correlation with the illuminance levels on the work plane and the best-predicted light levels.

The LSTM model was trained for each test using historical data collected over 18 days from the photosensor on the work plane and other photosensors, including illuminance and energy consumption records and sunlight conditions. During such a period, some environmental conditions changed (e.g., solar radiation). The model's performance was assessed based on its ability to predict future work plane lighting levels and optimize sensor placement accordingly. Tables 1 and 2 show the evaluation results.

As we can see, the model achieved high prediction accuracy with a coefficient of determination (R^2) of 0.986 and a mean RMSE of 0.024. This indicates that the LSTM model effectively captures the complex relationships between the illuminance level on the work plane and the illuminance level on a different location over time. To confirm such a result, Figure 4 shows the trend of the predicted values on the work plane from the lighting levels collected on the optimal sensor.

R^2

Sensor	**Min**	**Max**	**Mean**	**Standard Deviation**
$C1$	0.959	0.967	0.964	0.003
$C2$	0.955	0.970	0.963	0.004
$W1$	0.963	0.980	0.973	0.005
$W2$	0.981	0.989	0.986	0.003

Table 1
The Min, Max, mean, and standard deviation of R^2 related to different photosensors are presented. The $W2$ sensor shows the most favorable overall performance, exhibiting a higher average R^2 and a low standard deviation.

RMSE

Sensor	Min	Max	Mean	Deviation Standard
$C1$	0.035	0.041	0.037	0.002
$C2$	0.034	0.043	0.038	0.002
$W1$	0.028	0.039	0.032	0.003
$W2$	0.021	0.028	0.024	0.002

Table 2
The Min, Max, mean, and standard deviation of RMSE values related to different photosensors are presented. Sensor $W2$ has the lowest RMSE, indicating superior prediction accuracy compared to the other sensors.

4.3. Evaluation of energy saving and visual comfort

The proposed approach was compared to traditional static placement methods by considering the optimal sensors W2 and a photosensor C_test placed on the ceiling as photosensors for separately controlling a lighting system. We mainly evaluated the energy savings and visual comfort obtained using such photosensors. To better understand, we introduce the concepts of lumen, lux, power, and visual comfort. Lux measures illuminance (E) at any moment, and it is closely related to the concept of lumen (lm). While lumens quantify the total amount of light emitted by a source, lux accounts for the spatial distribution of luminous flux (Φ_v) by considering the area over which this light is spread [18]. It indicates how much light is falling on a surface. Then, one lux is defined as one lumen per square meter. When concentrated within one square meter, a luminous flux of 1000 lumens results in an illuminance of 1000 lux for that area. The distribution of 1000 lm over an area of $10m^2$ results in a significantly reduced illuminance level of merely 100 lux. The following equation expresses this relationship:

$$\Phi_v(lm) = E(lux) * A(m^2) \tag{3}$$

However, lux doesn't directly tell us about energy consumption; instead, it relates to how much light is produced and distributed over a space. On the contrary, power (P), measured in watts (W), is the rate at which electrical energy is used by the light source instantaneously. Depending on their efficacy, different light sources require different amounts of power to produce the same lux level.

Luminous efficacy [19] measures how efficiently a light source converts electrical power into visible light and quantifies the amount of light output per unit of power consumed expressed in lumens per watt (lm/W). It indicates how effectively a light source produces light for a given amount of energy input. Hence, the power P in watts (W) is equal to the luminous flux Φ_v in lumens (lm), divided by the luminous efficacy η in lumens per watt (lm/W) according to the following equation:

$$P(W) = \frac{\Phi_v(lm)}{\eta(lm/W)} \tag{4}$$

Hence, the power required to maintain a certain lux level in an area depends on (i) the total lumens needed to achieve the desired lux level and (ii) the efficacy of the light source.

On the other hand, visual comfort is a subjective measure of how comfortable and effective a lighting environment is for human vision, especially in workplaces. It can be influenced by a range of factors. Among them, illuminance plays a crucial role. While visual comfort is often subjective, quantitative ways exist to compute visual comfort based on specific metrics. In this paper, we use the VC_{index} [20] that is a measure based on the amount of light falling on the working plane defined as follows:

$$VC_{index} = 100 - PD_L \tag{5}$$

where PD_L is the Percentage of Dissatisfied with lighting in relation to lux. It evaluates visual discomfort that arises when the illuminance is too low or too high for a specific task or environment. The function of daylight illuminance $E_{min}[lux]$ and the predicted PD was calculated with the following equation:

$$PD_L = \frac{(-0.0175 + 1.0361)}{1 + exp[4.0835 \times (log(E_{min}) - 1.8223)} \times 100 \tag{6}$$

It is worth noting that visual comfort is greatly influenced by ensuring that illuminance levels are suitable for the task at hand; for general office work, the threshold of 500 lux is considered comfortable. Under-lighting (below optimal lux) and over-lighting (above optimal lux) both cause discomfort, too much light can cause glare, while too little light can lead to eye strain [21].

Let's assume light sources with $100lm/W$ illuminate a work plane with a surface area of $10m^2$. Let's assume two lighting control systems to regulate the luminous flux to have a standard level of 500 lux on the office work plane. Let's assume the first works with a sensor C_test placed on the ceiling according to static strategy and the second one with the optimal sensor W2 found with the proposed approach.

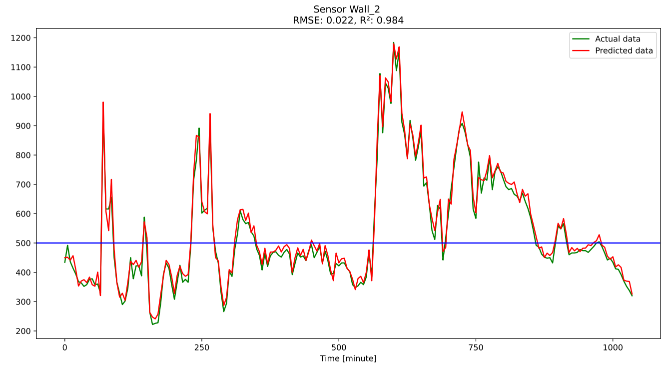


Figure 4: Actual data and predicted data on work plane by using the optimal sensor W2.

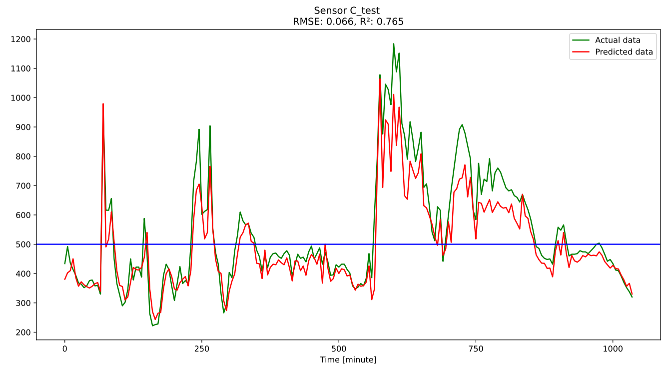


Figure 5: Actual data and predicted data on work plane by using Sensor C_test.

Figures 4 and 5 show the trend of actual data and predicted data using the C_test sensors and the $W2$ sensor, respectively. Observing Figure 4, it becomes apparent that the trend of predicted illuminance on the work plane, when employing the optimal sensor, demonstrates a close correlation with the actual illuminance measurements. This is not the case with the test sensor.

The graphs depicted in Fig.6 show the amount of power waste by using the first sensor and the optimal one with respect to the real illuminance level of the work plane. It is worth noting that, using the *C_test* sensor, there are periods of time for which the lighting control system doesn't work efficiently, thus wasting energy. Conversely, the lighting control system working with the optimal sensors works very efficiently with the predicted values by producing a very limited amount of energy waste.

Regarding visual comfort, Fig.7 reports that the graph related to how the visual comfort index deviates from the ideal comfort index at 500 lux. Using the test sensor, the lighting control system tends to underestimate, on average, the lux level on the work plane with respect to the real one. This behavior causes the light control system to adjust the light source to a higher level to reach the optimal level of 500 lux. This means there will be too much light on the working plane with respect to the optimal one. This can cause discomfort due to the glare effect on the working plane. Conversely, using the optimal sensor, the trend of the predicted illuminance values on the working plane is very similar to the actual one. However, their trend over time is slightly lower than the real one. In this case, the behavior of the lighting control system regulates the illuminance at the optimal one, but it may occur that the real illuminance on the working plane is slightly lower than the optimal one. Since the difference is very low, the effect on eye strain is limited since the comfort level is comparable to the optimal one.

In summary, results showed an improvement in energy efficiency. These savings were primarily due to the model's ability to dynamically adjust light levels based on optimized predicted light conditions, allowing for more efficient use of daylight throughout the day. Moreover, because the LSTM-optimized sensor placement can maintain optimal lighting conditions, illuminance levels can be kept within the recommended threshold of 500 lux for office environments, thus maintaining occupant comfort.

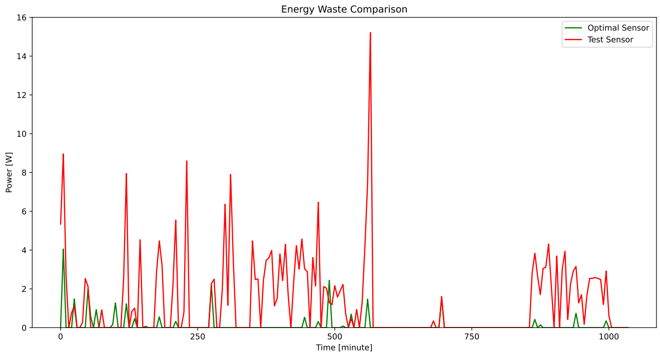


Figure 6: Energy waste comparison by using the optimal sensor or the test sensor to control a lighting system.

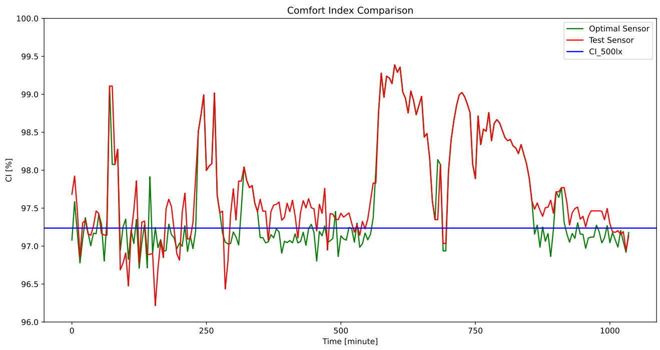


Figure 7: Deviation of the visual comfort index from the ideal one using the test sensor and the optimal one.

5. Conclusion and Future works

Using an LSTM for optimal lighting sensor placement leverages its strength in handling sequential data and temporal dependencies. By training an LSTM on historical light level data and other relevant features, the model can learn to predict optimal sensor placements that maximize energy efficiency and visual comfort dynamically. This approach allows for adaptive, data-driven decision-making in smart building management. The experimental results demonstrate that the proposed approach improves energy efficiency in lighting systems while maintaining occupant comfort compared to traditional methods. They can be used as a foundation for developing more efficient energy management systems, which will enhance the quality of life for occupants and reduce the environmental impact of buildings. These findings highlight the potential of advanced machine learning techniques, such as LSTM, to enhance sustainability in building design. However, since the accuracy of LSTM predictions is contingent upon the quality and quantity of the historical data collected, the model's performance could be suboptimal in scenarios where data are insufficient or unrepresentative. Additionally, the variability of environmental conditions and human interactions may present a significant challenge in predicting future scenarios.

We plan to deploy the trained LSTM model on Building Management Systems to make real-time decisions. Moreover, we are working on implementing a continuous feedback loop in which the system monitors its performance and provides data back to the model for periodic retraining to ensure it remains effective under evolving conditions. Finally, we are studying how to incorporate feedback from building occupants about comfort and adjust the model and sensor placements based on this feedback.

Acknowledgments

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