A Reinforcement Learning–Based Approach for Smart Lighting and Shading in Buildings

Fadwa Lachhab
LabSIV, Department of Computer Science, Faculty of Sciences
Ibn Zohr University, Agadir, Morocco
and
InterDisciplinary Applied Research Laboratory-LIDRA
International University of Agadir-Universiapolis, Agadir, Morocco

Mohamed Bakhouya
LERMALab, College of Engineering and Architecture
International University of Rabat
Sala El Jadida, Morocco

Lighting systems in commercial and residential buildings constitute a major source of the world energy consumption. Optimizing energy efficiency through lighting management requires an optimal control strategy in order to balance daylighting requirements while maintaining visual comfort in illuminated spaces. This paper introduces a reinforcement learning (RL)–based approach using the Q-learning algorithm to optimize lighting and shading control, maintaining constant illuminance with maximum visual comfort. A prototype was developed in a laboratory to test the scenario, using internet of things (IoT) and artificial intelligence (AI) technologies, for lighting and shading control. AI techniques are integrated to enable a smart conversation between lighting and shading systems in order to maintain the required light level. A real-time chatbot based on natural language processing (NLP) is integrated with IoT techniques in order to provide a user-friendly building automation system. Experiments have been conducted for validation purposes and obtained results show the effectiveness of the proposed solution by maintaining the ideal level of lighting with efficient consumption. In fact, the proposed control is capable of optimizing energy consumption by more than 45% against a normal lighting operation while maintaining occupants' visual comfort within a suitable illuminance.

Keywords: lighting control; shading control; energy efficiency; Internet of Things; artificial intelligence; visual comfort

1. Introduction

Lighting systems account for more than 20% of the world's total energy consumption [1]. They also become one of the important factors in maintaining visual comfort by taking into consideration the

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context-dependent occupant's perception and activity. Therefore, an energy-efficient lighting control is required for balancing the compromise between energy saving and occupant satisfaction. In fact, the lighting system is related to many other metrics that could significantly decrease the energy consumption, such as the shading system. The shading system allows a natural lighting, which is considered as a renewable energy by substituting for artificial light [2, 3]. Incoming illuminance from daylight also enhances wellbeing and the occupants' productivity. Thus, developing intelligent lighting control should take into consideration the shading system control in order to provide maximum visual comfort and minimum energy consumption.

With recent information and communication technologies (ICT) techniques, building automation is advancing nowadays and it can be considered as a complex system, which is composed of different entities (e.g., sensors, actuators, electrical appliances, computers). These might interact in a collective manner for efficient balance between energy efficiency and occupants' comfort [4]. The IoT is considered as an enabler for developing a worldwide network of interconnected objects or things that cooperate with other services to reach common goals. Currently, sensing, actuation, processing and control become a daily life need in many context-aware applications in agriculture, transportation, healthcare, building automation and energy efficiency [5]. In parallel to these advances, artificial intelligence (AI) chatbots are widely approved nowadays as a smart conversation between devices and users in order to provide a user-friendly building automation system [6]. The goal of using a chatbot is to understand the context of a conversation and process information from their environment in order to learn from it and improve the context. Based on natural language processing (NLP), the chatbot can provide many features to users, such as tokenization, classification, matching actions and a lot of other techniques in order to derive meaning from it.

This paper focuses on optimizing the tradeoff between energy efficiency and visual comfort in the management of lighting and shading systems. An optimal control strategy, integrating recent AI techniques, is introduced in order to balance between shading and lighting operations while regulating the light intensity. This approach was operated and implemented using a platform that combines IoT and AI technologies for real-time monitoring, processing and control for building services. The proposed control was evaluated using two metrics: the visual comfort (i.e., the level of the illuminance, comfort mode) and the energy metrics (i.e., the lighting level, shading level, the power consumption). Experiment results have been reported to demonstrate that the proposed control is capable of optimizing energy consumption by more than 45% against a normal lighting operation while maintaining occupants' visual comfort within a constant illuminance. In addition, the proposed system offers an AI chatbot that provides an intermediary between users and devices. The chatbot allows users to check the status of their systems and even control them accordingly. In summary, the main contributions of this paper are as follows. An energy-efficient lighting control strategy is developed and deployed in real scenarios. This strategy combines shading systems and lighting devices using IoT and AI algorithms, learns from a contextual change and adjusts between the shading and lighting devices to meet the maximum visual comfort. An AI-based chatbot based on NLP techniques is then deployed in order to understand context and remotely control the lighting and shading systems.

The organization of the rest of this paper is as follows. Section 2 presents an overview of the major aspects, which have been proposed for reducing energy consumption in buildings together with existing control strategies of lighting and shading systems. In Section 3, the proposed control strategy is introduced and implements the Q-learning algorithm in order to achieve maximum visual comfort. Section 4 presents the monitoring and processing platform prototype for gathering and processing data sensors and actuators of the real-lab scenario. Experimental setup and results of a lighting/shading system are presented in Section 5, together with the obtained AI-based chatbot performing automatic control of both lighting and shading. Conclusions and perspectives are given in Section 6.

2. Background and Related Work

Recent studies showed that buildings require energy-efficient control approaches in order to balance between energy efficiency and occupants' comfort [7, 8]. These approaches need to include the actual context of the building's envelope and the occupants' behavior. Generally, three major aspects can be considered for reducing energy consumption as depicted in Figure 1.

Passive strategies have been developed for reducing energy consumption by developing less-energy-consuming equipment and materials in buildings. Natural lighting, room relocation, natural ventilation and increased building insulation are examples of emerging techniques, which use natural forces to minimize electricity consumption [9]. In fact, the architecture design, building envelope and orientations can influence energy reduction. Therefore, the passive design of the building must be considered in the phase of construction in order to reduce the final energy usage during its operation.

Active strategies have been developed for reducing energy consumption in all building applications and services by integrating ICT concepts [10, 11]. The active strategy came after the construction of the building by controlling its services with the aim to improve energy saving. Efficient control strategies (e.g., heating, ventilation and air conditioning (HVAC) control, lighting control) are required by using advanced analytics and real-time data monitoring and processing (e.g., IoT and Big Data technologies).

The third aspect is related to renewable energy sources and storage devices (i.e., solar, wind and fuel cell) integration by developing new demand/response solutions in order to reduce energy dependency from the utility grid [12].

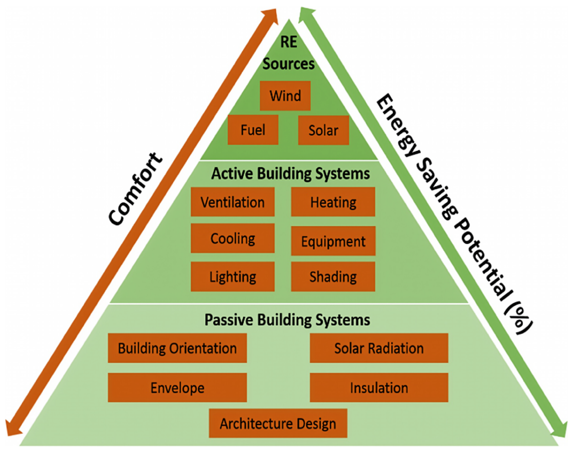

Figure 1. The three major aspects for reducing energy consumption.

This paper targets the second aspect by controlling lighting and shading systems. It aims to integrate advanced ICT techniques, which are required to develop context-driven control approaches taking into consideration occupants' needs and behaviors. In previous work [13, 14], we have developed context-driven approaches for HVAC and ventilation systems and compared them against conventional controls, such as ON/OFF and proportional-integral-derivation (PID) strategies. The aim was to show their effectiveness for maintaining occupants' comfort and energy savings. Since ventilation systems [13] are the most studied building system, we focused on them to further reduce energy consumption while keeping occupants' comfort within acceptable limits. We then developed an intelligent control approach for heating and air conditioning systems [14] by optimizing temperature set points and operation modes while providing the desired indoor environment's quality at minimum energy consumption.

Most control approaches used in lighting control are based on predefined rules or time-triggered approaches [15, 16]. In fact, various research around the word uses centralized methods to switch ON or

OFF buildings' services (i.e., HVAC, ventilation, lighting) according to fixed schedules [17]. For example, lighting services are generally controlled based on a time-triggered approach or automatic lighting based on occupancy. The lighting systems depend initially on the control approach used to adjust the intensity illuminance manually or automatically through context awareness, such as the perception and the activities of occupants. Considering the large number of studies regarding lighting control, only a few research projects have considered the comfort and environmental aspects. In fact, visual comfort is related to the indoor lighting conditions of the building. Adjusting the light based on the occupant's activity is highly recommended in order to allow a good view in illuminated spaces. Several models were developed to predict the visual comfort, for instance, the proposed daylight glare probability (DGP) method [18]. This computes the discomfort glare metric, taking into consideration the daylight conditions in order to enhance a good indoor illuminance.

Q-learning is a widely used reinforcement learning (RL) algorithm that enables an intelligent system to make optimal decisions by interacting with its environment [19]. Unlike rule-based approaches, Q-learning can adapt over time by learning the best actions to take in different situations without requiring a predefined model [20]. This approach is particularly effective for dynamic systems like lighting and shading control, where conditions change frequently due to daylight variations, occupancy and energy demands.

IoT technologies have progressed from the convergence of wireless and wired infrastructures. The IoT is considered as an enabler for developing a worldwide network of interconnected objects or things that cooperate with other services to reach common goals [21]. Currently, sensing, actuation, processing and control become a daily life need in building automation and energy efficiency [22]. These applications could react to the environment's changes and users' preferences with the aim to make their life more comfortable according to their situation. For example, data generated from the metric-based sensors in buildings could be used to predict the activity of the user in real time and control a service accordingly by turning on/off or even adjusting the equipment in order to save energy and to maintain occupants' comfort.

In fact, many research projects aim to integrate an intelligent conversational software agent (i.e., chatbots) with IoT scenarios in applications, which collect, process and act in real time according to the context changing [23]. There are two types of chatbots that perform as intelligent conversational agents: the rule-based chatbots operating under predefined rules that give a matching response to users and the AI-based chatbots that use NLP in order to analyze users' requests.

AI-based chatbots offer users a simple way to interact with the devices of a building and make requests by sending a simple message, which is processed by NLP techniques.

In this paper, we aim to combine the AI-based approach and IoT techniques for lighting and shading control in order to maintain the required light level and occupants' visual comfort. However, gathering and real-time processing of generated data is still a challenging task. Several wireless technologies have been implemented in building automation, such as ZigBee, Z-Wave, Bluetooth and Wi-Fi [24]. These technologies differ in range and data bandwidth, thereby affecting the reliability and performance of the signals employed in controlling building devices. It is worth noting that Wi-Fi is the latest technology used in building and home automation, which runs with higher range and data bandwidth [25]. Many IoT devices currently make use of Wi-Fi in order to transmit and receive information wirelessly.

In summary, with recent ICT techniques, approaches to the control of building systems are advancing and could integrate IoT, Big Data, context-driven strategies and AI technologies. These control strategies leverage collected data using different wearable sensors and devices in order to perform hybrid control for building services through a high context awareness [26, 27]. While several studies in the literature have addressed lighting control, to the best of our knowledge, few have intelligently integrated both shading and lighting systems to adjust illuminance levels for optimal visual comfort.

3. Optimal Lighting Control Approach

This section presents the proposed control approach for lighting and shading systems in order to balance energy efficiency and the user's wellbeing. The lighting and the shading controls are introduced separately, taking into consideration the comfort level of illuminance. The proposed controls are performed by an AI agent with the Q-learning algorithm that balances between the lighting and shading operations in order to reach the maximum visual comfort. Regarding the energy efficiency, the daylight coming from shading devices as natural light may decrease significantly the operation and the intensity of artificial light and thus can save energy.

The recommended lighting illuminance depends on the workspace and the occupant's activity according to the National Optical Astronomy Observatory (NOAO) [28]. For instance, the ideal lighting illuminance in a home is between 400 and 500 lux with a normal activity, such as reading, watching TV or cooking [29].

The illuminance is quantified in lux (i.e., the luminous flux per unit area), which is the unit of light level. It can be computed by the following relation:

$$I = \frac{L_{\mathrm{I}} C_{\mathrm{u}} L_{\mathrm{LF}}}{A_{\mathrm{I}}}. \quad (1)$$

The parameters are as follows: I is the illumination (lux, lumen/m^2), L_I is the lumen per lamp (lumen), C_u is the coefficient of utilization, L_{LF} is the light loss factor, and A_I is the area per lamp (m^2). To obtain the illuminance in lux, our AI agent gathers the photoresistor's value in ohms and converts it based on the data provided in Table 1 [29].

Symbol	Quantity	Conversion/Value
V_{in}	supply voltage	5v
R	constant	10000
R_{aw}	sensor output value	sensor value
V_{out}	analog value of the sensor	$V_{\mathrm{out}} \to R_{\mathrm{aw}} \times \left(\frac{V_{\mathrm{in}}}{1024}\right)$
RLDR	resistance	$\mathrm{RLDR} \to \left(R \times \frac{V_{\mathrm{in}} - V_{\mathrm{out}}}{V_{\mathrm{out}}}\right)$
lux	resistance	$\mathrm{lux} \to \frac{500}{\frac{\mathrm{RLDR}}{1000}}$

Table 1. Illuminance properties.

3.1 Artificial Intelligence–Based Agent

The proposed control, which is illustrated in Algorithm 1, ensures that occupants receive the recommended illuminance level, offering the flexibility to configure their preferred comfort mode. Users can select from predefined modes, such as watching TV, reading or cooking, or create a personalized mode by setting their desired lighting level. The AI agent, based on Q-learning, balances the operation of lighting and shading systems by setting an automatic default mode of 500 lux. However, occupants have the option to increase the lighting intensity through the existing preset modes. In addition, they can define a new personalized mode with specific lighting preferences. The AI agent prioritizes achieving the ideal illuminance level by first adjusting the shading system. If natural daylight is insufficient, it then regulates the artificial lighting to meet the required lux level, ensuring both energy efficiency and visual comfort.

The environment is modeled using three state variables that represent the dynamic conditions under which the lighting control system operates. First, the current lux level, which ranges from 0 to 900 lux, reflects the ambient light intensity available in the room. Second, the shading position corresponds to the percentage of window coverage and is continuously adjusted to regulate the amount of natural light entering the space. Finally, the lighting level represents the artificial light intensity, which can be varied from 0% to 100% in increments of 5%, allowing fine-tuned control based on the desired illumination and comfort level.

Algorithm 1. AI agent for lighting and shading control.

Input: User Mode (Auto or Manual), Database of modes and lux values
Output: Adjusted shading and lighting levels

1. Initialize AI_Agent
2. **if** Mode = Auto **then**
3. Set IdealLux ← 500
4. **else**
5. **if** User chooses an existing mode **then**
6. Retrieve IdealLux from Database for selected mode
7. **else**
8. Add a new mode with user-defined lux value to Database
9. Retrieve IdealLux from newly added mode
10. Perform Shading_Adjustment_Algorithm based on IdealLux
11. Perform Lighting_Adjustment_Algorithm based on IdealLux

The system's action space consists of two primary operations: shading control, which adjusts the shading position by modifying the angle of openness based on calculated percentages; and lighting control, which increases, decreases or maintains the current lighting level. Indeed, to optimize learning, the system employs a reward mechanism that encourages efficient energy use while maintaining user comfort. A reward of +10 points is granted when the illuminance remains within the ideal range of 480–520 lux, while a −1 penalty is applied if the lighting level is close to but slightly outside this range. A −5 penalty is imposed for significant deviations from the target illuminance, and additional penalties are assigned for unnecessary shading or lighting adjustments, to prevent energy wastage. These values were empirically determined based on iterative testing in the real-lab environment to ensure fast convergence of the learning process. The +10 reward strongly reinforces the goal state, while −1 and −5 enable differentiation between minor and major deviations. Penalties on unnecessary actions further reduce energy consumption and promote stable decisions. The learning process consists of two phases: exploration, where the agent initially takes random actions to assess their effects; and exploitation, where it leverages previously learned Q-values to make optimal decisions that enhance lighting efficiency.

The proposed control integrates a movable shading system to maximize the incoming daylight in order to decrease the use of artificial lighting. As presented in Algorithm 2, the shading control can automatically move the blind to a calculated angle in order to increase the indoor lighting based on the occupant's preference. In cases where the blind is opened completely and there is a need of lighting, then the lighting control is activated.

Algorithm 2. Shading adjustment algorithm.

Input: IndoorLux, OutdoorLux, BlindLevel, IdealLux
Output: Lighting or shading control action

1. **if** OutdoorLux < 30 ***and*** BlindLevel > 0 **then**
2. Close the blind;
3. **else if** IndoorLux < IdealLux ***and*** BlindLevel < 100 **then**
4. Increase shading level;
5. **else if** IndoorLux < IdealLux **then**
6. Perform lighting adjustment;
7. **else**
8. Maintain current state;

The lighting control technique, as shown in Algorithm 3, is performed by an AI agent, which controls the intensity of light by adjusting the lighting devices. The aim is to achieve the desired mode or the automatic mode of lighting. It takes into consideration the recommended level of illuminance. The lighting control is activated after checking the operation of the shading control in order to allow maximum daylight for energy saving and occupant wellbeing. It also allows the occupant to go over the lighting standards (i.e., between 400 and 500 lux) by choosing or creating personalized modes. The lighting control is performed by a dimmer (i.e., using pulse-width modulation) in a values range between 0 and 255 converted into a percentage in order to get the lighting level.

Algorithm 3. Lighting adjustment algorithm.

Input: IndoorLux, IdealLux, Occupancy
Output: Lighting control action

1. **if** Occupancy is ***false*** **then**
2. Turn light off
3. **else**
4. **if** IndoorLux < IdealLux **then**
5. Increase light level;

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else if IndoorLux > IdealLux + 5 then
    Decrease light level;
else
    Maintain current lighting;
```

3.2 Artificial Intelligence–Based Chatbot

The proposed AI-based control is mainly based on the processing of users' needs, particularly for the adjustment of lighting and blinds. The proposed algorithm, based on NLP techniques (i.e., classification, sentiment analysis, matching actions), leads to the processing of the textual inputs in order to derive meaning from them and efficiently perform the systems' control. We have proposed a general architecture for implementing the proposed chatbot, as shown in Figure 2. The proposed chatbot has been implemented using open source software and frameworks based on novel AI and IoT technologies that include the NTLK toolkit [30], an open source platform for natural language processing. The NodeJS server hosts the web application and the chatbot algorithm. Our chatbot is capable of understanding natural language through the occupant's request in order to identify the actions and the keywords.

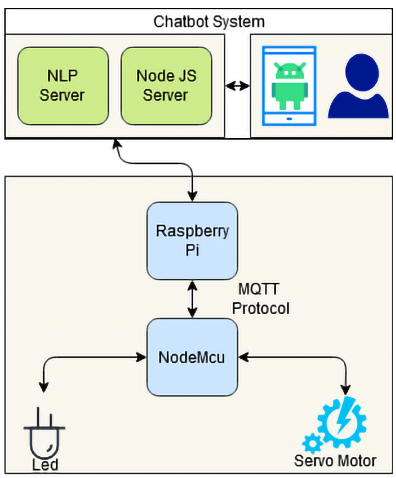


Figure 2. The architecture of the proposed chatbot.

We first receive the occupant's instructions from his/her device, which is connected to a local network through a web application designed as a conversational agent. Then the occupant's request is transmitted to the NodeJS server (non-blocking server) in order to process the sentence by our algorithm based on NLP. In our solution, we have used our knowledge database in order to adjust and adapt the results to the occupant's environment. The AI-based chatbot is capable of expanding the response to the same action through a well-provided knowledge database (i.e., JSON file). This latter integrates an algorithm that uses a sentiment analysis technique that classifies the users' requests into overall negative and positive sentiments.

After the processing, the result is transferred over the gateway (Raspberry Pi) to the actuators with the intention of performing the control tasks (i.e., adjusting the illuminance of lighting or regulating the shading percentage). In fact, the process retrieves the confirmation from the actuators in order to generate a suitable response (processed or not) to the occupant.

Our NLP chatbot algorithm is distributed in two phases to optimize and sharpen the results in order to meet the users' need with precision as shown in Figure 3.

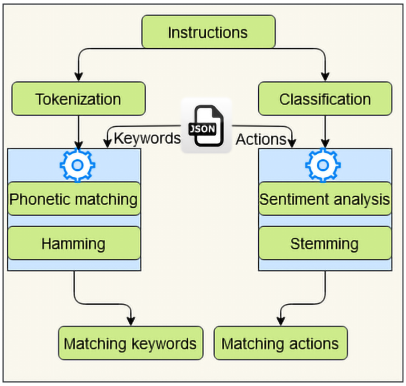


Figure 3. The proposed algorithm.

The first step is to classify the sentence to get the matching actions and at the same time use tokenization. In this step, we parse the input string to find the matching keywords. The second step uses the knowledge database that contains both the keywords and the actions. The keywords list contains all the tokens that refer to our system, such as light, shading, kitchen, temperature, status and so on. The actions list covers all the functions that should be performed by the IoT system, such as ON, OFF, increase, decrease, turn, put and so on. The tokens generated from the tokenization process are passed to the phonetic matching, in which each word is analyzed based on the knowledge database.

The output of the tokenization process is passed to the phonetic matching stage, where each input word is compared with the knowledge-base keywords. The top-rated words resulting from the tokenization and phonetic matching are then processed using the Hamming distance method to select the most accurate matching keywords. However, for the classification technique, we used the sentiment analysis method as the most common use case for automatic text classification.

This technique determines the nature of the action and then prepares the corresponding response after what the stemming derives to contextualize the actions. The goal of this process summarizes the algorithm that will produce keywords and actions of an actual context to operate.

4. Platform Architecture

This section presents the platform architecture and its hardware and software components. This platform implements the real-time monitoring, processing and the above-mentioned control techniques. The developed platform is composed of three main layers, which are illustrated in Figure 4 as follows: data collection, data processing and data storage/visualization.

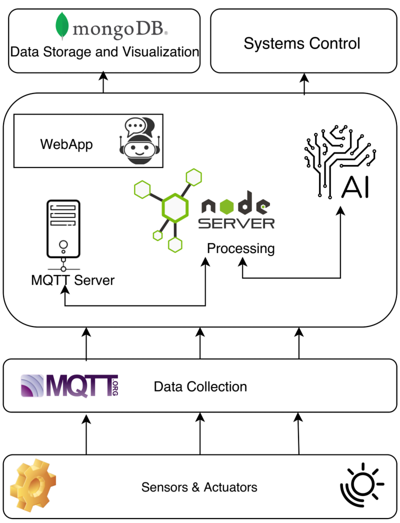


Figure 4. The platform architecture layers.

For handling data coming from the lighting and shading systems, the platform is composed of hardware and software components that are presented in the following subsections: hardware components are mainly composed of sensors and actuators (i.e., LDR and PIR sensors and servomotors), and software components are provided by the two main layers of the platform as illustrated in Figure 5.

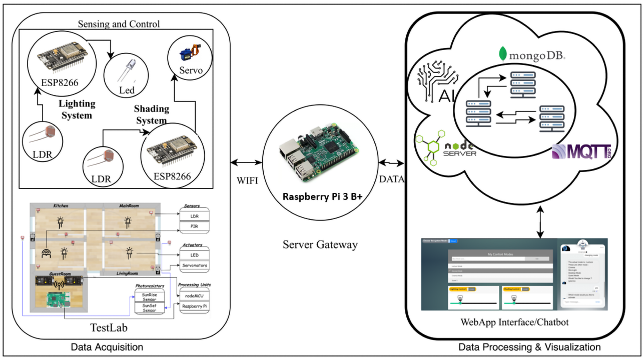


Figure 5. The representation of the developed prototype.

4.1 Sensing and Control Modules

The sensing/actuating modules are embedded in an ESP8266 NodeMCU microcontroller as an IoT unit for gathering illuminance values and the operation's state of the system. This incoming data is intercepted by the message queuing telemetry transport (MQTT) broker server that performs some preprocessing functions, such as parsing and aggregation, before transmitting them to the NodeJS server, which constantly waits for incoming data. The main hardware modules that have been deployed are as follows:

- Light-depending resistance (LDR) sensor/photoresistor: made of high-resistance semiconductor, it is used in circuits for lighting intensity detection. The value returned by the sensor is in ohms and can be converted to lux.
- Passive infrared sensor (PIR): a motion sensor that detects infrared light radiation from moving things or people in order to activate or not the lighting system.
- SG90 servomotor: a 5v motor controller that rotates with 180 degrees. It is used in our case for controlling the shading system in order to allow incoming daylight into the test-lab prototype.
- 5mm LED: a light-emitting diode used as artificial lighting. It is controlled via a pulse-width modulated (PWM) signal in order to adjust the intensity of illuminance.
- ESP8266 NodeMCU: an open source IoT component that includes the ESP8266 Wi-Fi module, which could be integrated with various sensors and actuators through its GPIOS [31]. In our case, we used two NodeMCU boards for lighting and shading systems.
- Raspberry Pi 3 B+: used as a broker server and the preprocessing unit that transmits and receives data from the processing server (i.e., NodeJS server [32]).

4.2 Data Collection, Processing and Visualization

In the proposed platform, we have chosen NodeJS, which works with an NLP module [33] in order to perform AI actions. The platform layers are composed of three main services:

- Data collection is represented by a MQTT broker to gather the incoming data from sensors and actuators in order to transmit these values to the processing layer for more analysis and control.
- Data processing is performed by the NodeJS server, which integrates the AI agents presented in the third section. It allows the communication of the shading and lighting systems in order to achieve the desired illuminance based on the occupant's perception. Occupant perception in this context refers to the individual's subjective comfort regarding light intensity. It is modeled indirectly through selected activity modes (e.g., reading, watching TV, eating), which correspond to predefined illuminance thresholds. The proposed control allows the occupant to interact with the systems and choose the mode of operation based on ongoing activities. It also includes a user interface that enables the occupant to select preferred modes of operation, which serve as input to the AI decision process.
- Data visualization is a web application based on JavaScript and the ChartJs plugin to generate charts of different metrics of the system. It also integrates an AI interface that allows the occupant to control the lighting intensity by choosing a lighting mode. The occupant can also add his/her preferences into the system. The data storage is managed by MongoDB, which collects the values every two seconds during the data capture of the experiment.

5. Experimental Setup and Results

The main purpose of these experiments is to control the lighting system combined with the shading system in order to improve maximum visual comfort and minimum energy consumption. During these experiments, we realized several series of tests with varied weather conditions in order to highlight the performance of the system. We then considered only one day in this paper for easy visualization of the results. In this case study, we have set up a laboratory test to measure and control the lighting and the shading systems.

As shown in Figure 6, the prototype includes four rooms: a kitchen, a main room, a guest room and a living room. In each room, two LDR sensors were deployed at different angles to capture varying light conditions and compute the average illuminance level. We have designed the prototype with a window in each room to perform shading control. For comparison purposes, we have used the proposed control in three rooms (i.e., kitchen, main room and living room) and a natural control with no shading in the guest room.

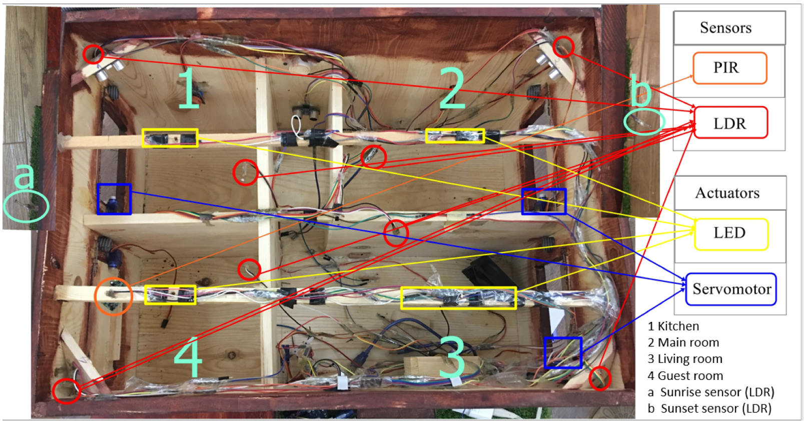


Figure 6. The laboratory test prototype.

We have evaluated four main metrics for the proposed control against the natural control:

1. the outdoor illuminance for the two sides of the prototype (i.e., the sunrise and sunset sides) in order to get the amount of daylight
2. the indoor illuminance, which directly affects the occupants' wellbeing
3. the artificial lighting rate and the blind position
4. the total energy consumption during the PWM operation periods

As illustrated in Figure 7, the outdoor illuminance depends primarily on the position of the sunlight. We have captured the daylight on two sides of the test lab (i.e., the sunrise illuminance was the right side and the sunset was the left side of the test lab). The chart shows for each side an exponential curve at some period of the day and a decreasing on the other side. For instance, the sunrise sensor collects values from 8am to 4pm and the sunset sensor from 12am to 9pm. By considering these values, the AI agent can balance between the different blinds in each corresponding side and choose which angle operates to satisfy the desired level of lighting.

The indoor illuminance was captured for each room as shown in Figure 8. An automatic mode (i.e., maintaining 500 lux) is performed by the three rooms described previously, and artificial lighting is performed in the guest room with a blind completely open. Regarding the shading operation, we observe in Figure 9 that the blinds are adjusted according to the available daylight by the corresponding side. The opening level of these blinds depends on the sun position. For example, the kitchen blind changes from 100% during the

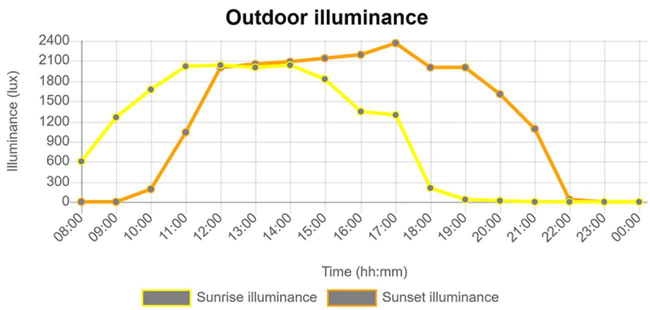


Figure 7. The outdoor illuminance (sunrise/sunset).

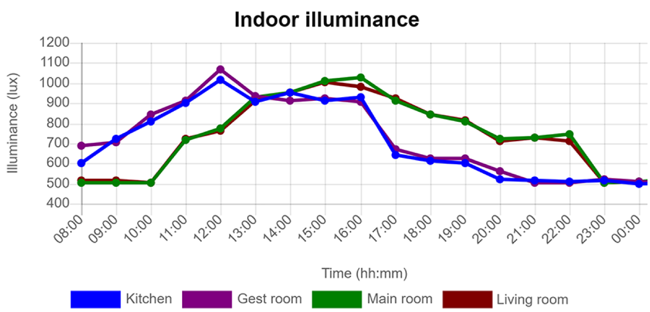


Figure 8. The indoor illuminance per room.

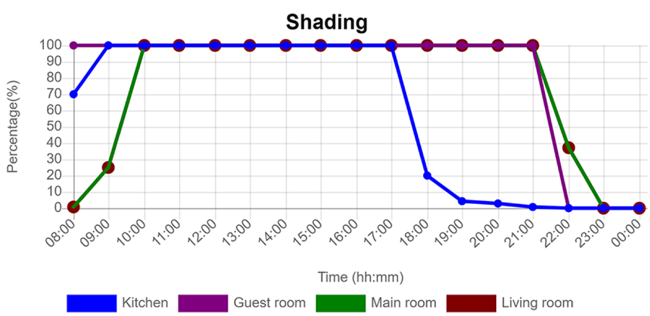


Figure 9. The shading operation (%) per room.

journey because it is oriented to the sunrise direction and starts closing in the afternoon since there is a decreasing of the sunlight on this side. Through the shading control, the proposed control maximizes the entrance of sunlight in order to minimize the use of artificial lighting. In correspondence with these results, the lighting control is activated when the desired level of lighting is not satisfied by only the incoming sunlight. As shown in Figure 10, the guest room simulated a normal control with 100% of lighting in contrast to the proposed control in other rooms, in which the lighting operation is reduced through the use of an AI agent that balances between sunlight and artificial lighting.

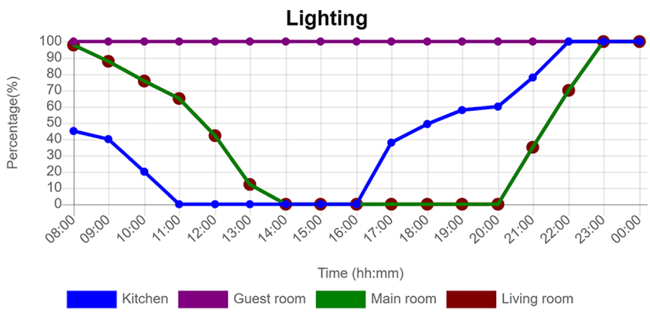


Figure 10. The lighting operation (%) per room.

Finally, we have measured the daily total energy consumption of each room as shown in Figure 11. The total energy spent within one day is 3.5 WH by a normal control and varies between 0.8 WH and 1.2 WH by the proposed control for the other rooms. So compared to the natural control, the proposed control is able to maintain the ideal level of lighting with efficient power consumption. By applying Q-learning, the system continuously refines its decision-making process, ensuring a self-adaptive control strategy that effectively balances natural and artificial lighting. Experiment results confirm that this approach reduces energy consumption by over 45% while consistently maintaining visual comfort within the required illuminance range.

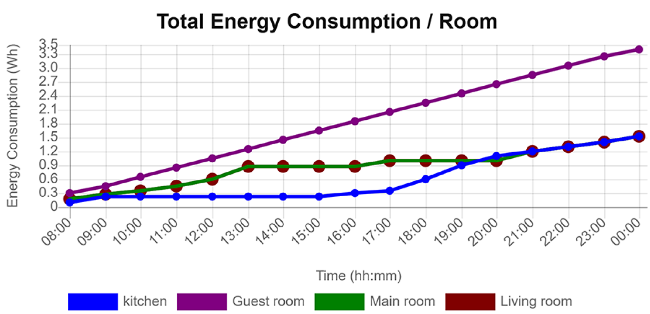


Figure 11. The total energy consumption during a day per room.

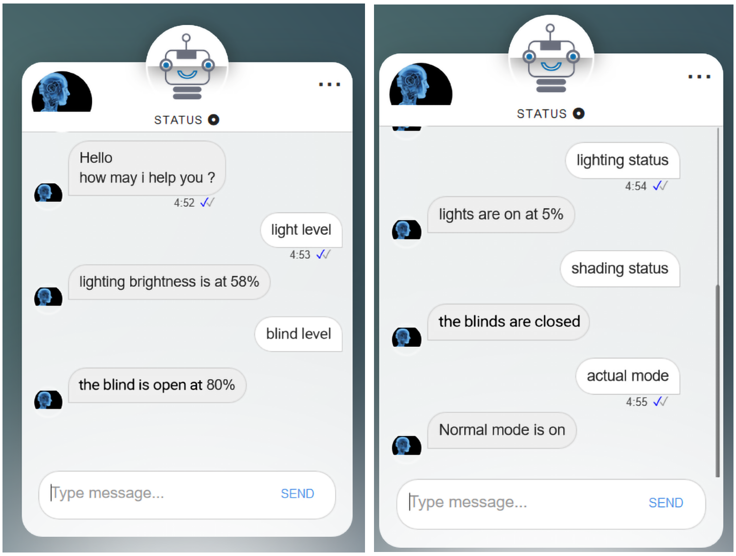
5.1 Artificial Intelligence–Based Chatbot Results

The main aim of these experiments is to control the lighting and shading devices with an AI-based chatbot application hosted on a web server in our local network. Using this chatbot, we can control all the implemented prototypes for lighting, shading and smart plugs. The proposed chatbot processes the textual input of the user to derive meaning from it and controls the system. The goal of this chatbot is to overcome interfaces with menus and buttons to perform some actions. The chatbot offers a chat interface as a simple conversation, which makes the interaction easier.

From our experiments, we can identify three scenarios:

1. The context extraction, where the user requests the status of the IoT devices and the lighting metrics.
2. The lighting control, where the user requests to turn on/off LEDs or adjust illuminance.
3. The training mode, which the system performs over what is defined in the knowledge database.

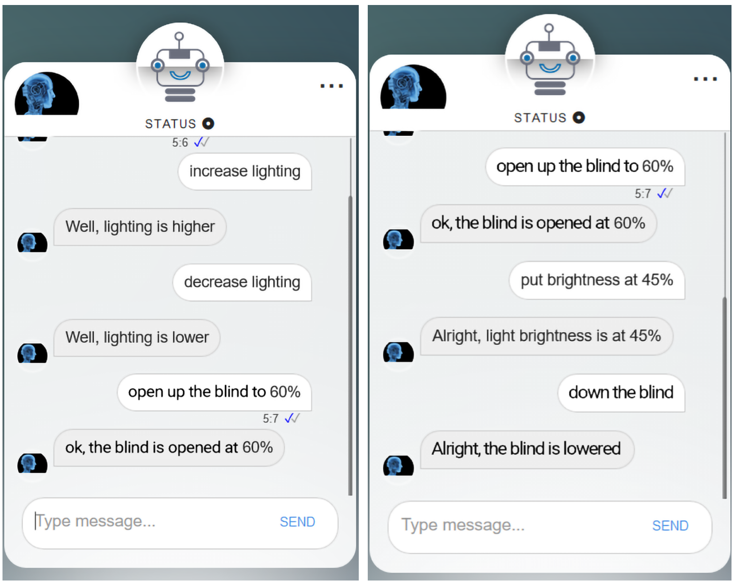
The main aim of these experiments is to control the lighting and shading devices with an AI-based chatbot application hosted on a web server in our local network. The proposed algorithm is capable of understanding the context of a given request in order to identify the keywords and actions. As illustrated in Figure 12, the proposed chatbot retrieves information in real time from the deployed systems, which can extract the level and the status of both lighting and shading systems.



(a) (b)

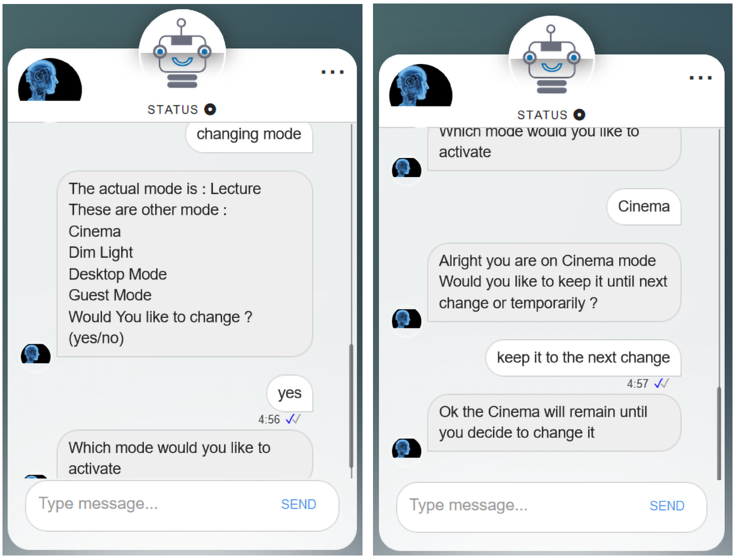
Figure 12. The proposed chatbot.

Based on the keywords and the actions identified in the user's request, the system performs the suitable action, as shown in Figure 13, such as adjusting the illuminance, selecting some of the presented modes of lighting or adjusting shading over the different rooms. For example, if the keyword is blind, and the action word is open with parameter of 60%, then the system will open the blind of the desired room to 60%. In fact, the intelligent chatbot understands the intent of the user request in order to learn from it and improve the context. As depicted in Figure 13, we have proposed to the user to create a new mode of lighting so that the system can save it and perform it. The user gives the desired illuminance and the suitable name of the new mode.



(a) (b)

Figure 13. (*continues*).



(c) (d)

Figure 13. The lighting control: adjusting (a) the level; (b) the brightness; and (c, d) changing the mode of illuminance.

6. Conclusions and Perspectives

In this paper, we presented an intelligent approach for lighting control through artificial intelligence (AI) and internet of things (IoT) techniques. The proposed control proved its ability to maintain visual comfort while minimizing energy consumption. The lighting system is performed by an AI agent that balances between lighting and shading operations in order to reach maximum visual comfort (i.e., between 400 and 500 lux). To enable real-time monitoring and control, an IoT- and AI-based platform was developed. Q-learning, a reinforcement learning (RL) algorithm, was integrated into the system to optimize decision-making by continuously learning from previous states and adjusting shading angles and lighting intensity accordingly. Experiments have been conducted in our laboratory test to measure and control the lighting and shading systems. The results are reported to highlight the efficiency of the proposed control; it maintains the ideal level of lighting compared to the conventional control. An AI-based chatbot was developed and integrated into our system in order to provide a user-friendly application. The chatbot processes the textual input of the user to derive meaning from it and operate the control system. As part of our ongoing work, the system will be coupled to the HVAC system in order to maintain thermal comfort while using sunlight to avoid glare. We will then upgrade our chatbot with voice recognition capabilities in order to facilitate intuitive control over building services and provide better assistance to users.

References

[1] M. A. Ul Haq, M. Y. Hassan, H. Abdullah, H. A. Rahman, M. P. Abdullah, F. Hussin and D. M. Said, "A Review on Lighting Control Technologies in Commercial Buildings, Their Performance and Affecting Factors," *Renewable and Sustainable Energy Reviews*, **33**, 2014 pp. 268–279. doi:10.1016/j.rser.2014.01.090.

[2] A. Mahdavi, A. Mohammadi, E. Kabir and L. Lambeva, "Occupants' Operation of Lighting and Shading Systems in Office Buildings," *Journal of Building Performance Simulation*, **1**(1), 2008 pp. 57–65. doi:10.1080/19401490801906502.

[3] A. Tzempelikos and A. K. Athienitis, "The Impact of Shading Design and Control on Building Cooling and Lighting Demand," *Solar Energy*, **81**(3), 2007 pp. 369–382. doi:10.1016/j.solener.2006.06.015.

[4] F. Lachhab, M. Bakhouya, R. Ouladsine and M. Essaaidi, "Energy-Efficient Buildings as Complex Socio-technical Systems: Approaches and Challenges," *Advances in Complex Societal, Environmental and Engineered Systems* (M. Nemiche and M. Essaaidi, eds.), Cham: Springer, 2017 pp. 247–265.

[5] P. Temdee and R. Prasad, *Context-Aware Communication and Computing: Applications for Smart Environment*, Cham: Springer, 2018.

[6] T. Parthornratt, D. Kitsawat, P. Putthapipat and P. Koronjaruwat, "A Smart Home Automation via Facebook Chatbot and Raspberry Pi," in *2018 2nd International Conference on Engineering Innovation (ICEI)*, Bangkok, Thailand, Piscataway, NJ: IEEE, 2018 pp. 52–56. doi:10.1109/ICEI18.2018.8448761.

[7] E. M. Wells, M. Berges, M. Metcalf, A. Kinsella, K. Foreman, D. G. Dearborn and S. Greenberg, "Indoor Air Quality and Occupant Comfort in Homes with Deep versus Conventional Energy Efficiency Renovations," *Building and Environment*, **93**(2), 2015 pp. 331–338. doi:10.1016/j.buildenv.2015.06.021.

[8] A. Martínez-Molina, I. Tort-Ausina, S. Cho and J.-L. Vivancos, "Energy Efficiency and Thermal Comfort in Historic Buildings: A Review," *Renewable and Sustainable Energy Reviews*, **61**, 2016 pp. 70–85. doi:10.1016/j.rser.2016.03.018.

[9] S. B. Sadineni, S. Madala and R. F. Boehm, "Passive Building Energy Savings: A Review of Building Envelope Components," *Renewable and Sustainable Energy Reviews*, **15**(8), 2011 pp. 3617–3631. doi:10.1016/j.rser.2011.07.014.

[10] B. Morvaj, L. Lugaric and S. Krajcar, "Demonstrating Smart Buildings and Smart Grid Features in a Smart Energy City," in *Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE)*, Leiria, Portugal, Piscataway, NJ: IEEE, 2011 pp. 1–8. ieeexplore.ieee.org/document/6028313.

[11] T. Karlessi, N. Kampelis, D. Kolokotsa, M. Santamouris, L. Standardi, D. Isidori and C. Cristalli, "The Concept of Smart and NZEB Buildings and the Integrated Design Approach," *Procedia Engineering*, **180**, 2017 pp. 1316–1325. doi:10.1016/j.proeng.2017.04.294.

[12] K. Lo, "A Critical Review of China's Rapidly Developing Renewable Energy and Energy Efficiency Policies," *Renewable and Sustainable Energy Reviews*, **29**, 2014 pp. 508–516. doi:10.1016/j.rser.2013.09.006.

[13] F. Lachhab, M. Bakhouya, R. Ouladsine and M. Essaaidi, "Context-Driven Monitoring and Control of Buildings Centilation Systems Using Big Data and Internet of Things–Based Technologies," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, **233**(3), 2019 pp. 276–288. doi:10.1177/0959651818791406.

[14] F. Lachhab, M. Bakhouya, R. Ouladsine and M. Essaaidi, "A Context-Driven Platform Using Internet of Things and Data Stream Processing for Heating, Ventilation and Air Conditioning Systems Control," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, **233**(7), 2019 pp. 877–888. doi:10.1177/0959651819841534.

[15] B. D. Hahnlen and J. W. Yon. Simplified Lighting Control System. US Patent 8,148,851, filed May 27, 2009, and issued Apr 3, 2012. patents.justia.com/patent/8148851.

[16] A. I. Dounis, P. Tiropanis, A. Argiriou and A. Diamantis, "Intelligent Control System for Reconciliation of the Energy Savings with Comfort in Buildings Using Soft Computing Techniques," *Energy and Buildings*, **43**(1), 2011 pp. 66–74. doi:10.1016/j.enbuild.2010.08.014.

[17] I. Wojnicki, S. Ernst, L. Kotulski and A. Sezdziwy, "Advanced Street Lighting Control," *Expert Systems with Applications*, **41**(4, Part 1), 2014 pp. 999–1005. doi:10.1016/j.eswa.2013.07.044.

[18] J. Wienold, "Dynamic Simulation of Blind Control Strategies for Visual Comfort and Energy Balance Analysis," in *Proceedings of Building Simulation 2007: 10th Conference of IBPSA*, Beijing, China, Britton, SD: International Building Performance Simulation Association, 2007 pp. 1197–1204. publications.ibpsa.org/conference/paper/?id=bs2007_231.

[19] A. Haydari and Y. Yilmaz, "Deep Reinforcement Learning for Intelligent Transportation Systems: A Survey," *IEEE Transactions on Intelligent Transportation Systems*, **23**(1), 2022 pp. 11–32. doi:10.1109/TITS.2020.3008612.

[20] J. Clifton, and E. Laber, "Q-Learning: Theory and Applications," *Annual Review of Statistics and Its Application*, **7**(1), 2020 pp. 279–301. doi:10.1146/annurev-statistics-031219-041220.

[21] L. R. Suzuki, "Smart Cities IoT: Enablers and Technology Road Map," *Smart City Networks* (S. Rassia and P. Pardalos, eds.), Cham: Springer, 2017 pp. 167–190. doi:10.1007/978-3-319-61313-0_10.

[22] N. Aste, M. Manfren and G. Marenzi, "Building Automation and Control Systems and Performance Optimization: A Framework for Analysis," *Renewable and Sustainable Energy Reviews*, **75**, 2017 pp. 313–330. doi:10.1016/j.rser.2016.10.072.

[23] N. M. Radziwill and M. C. Benton, "Evaluating Quality of Chatbots and Intelligent Conversational Agents." arxiv.org/abs/1704.04579.

[24] T. Sauter, "The Three Generations of Field-Level Networks—Evolution and Compatibility Issues," *IEEE Transactions on Industrial Electronics*, **57**(11), 2010 pp. 3585–3595. doi:10.1109/TIE.2010.2062473.

[25] A. M. ElShafee and K. A. Hamed, "Design and Implementation of a WiFi Based Home Automation System," *World Academy of Science, Engineering and Technology*, **6**(8), 2012 pp. 2177–2183. doi:10.5281/zenodo.1060319.

[26] Z. A. Almusaylim and N. Zaman, "A Review on Smart Home Present State and Challenges: Linked to Context-Awareness Internet of Things (IoT)," *Wireless Networks*, **25**(6), 2019 pp. 3193–3204. doi:10.1007/s11276-018-1712-5.

[27] M. Donohoe, B. Jennings and S. Balasubramaniam, "Context-Awareness and the Smart Grid: Requirements and Challenges," *Computer Networks*, **79**, 2015 pp. 263–282. doi:10.1016/j.comnet.2015.01.007.

[28] National Optical Astronomy Observatory (NOAO), *Recommended Light Levels (Illuminance) for Outdoor and Indoor Venues*. (Dec 15, 2025) cdn.hackaday.io/files/1804277719388768/LightLevels_outdoor-indoor.pdf.

[29] J. Vanus, T. Novak, J. Koziorek, J. Konecny and R. Hrbac, "The Proposal Model of Energy Savings of Lighting Systems in the Smart Home Care," *IFAC Proceedings Volumes*, **46**(28), 2013 pp. 411–415. doi:10.3182/20130925-3-CZ-3023.00014.

[30] S. E. Bird, "NLTK: The Natural Language Toolkit," in *Proceedings of the COLING/ACL 2006 Interactive Presentation Sessions (COLING-ACL'06)*, Sydney, Australia, Stroudsburg, PA: Association for Computational Linguistics, 2006 pp. 69–72. doi:10.3115/1225403.1225421.

[31] M. Kashyap, V. Sharma and N. Gupta, "Taking MQTT and NodeMcu to IOT: Communication in Internet of Things," *Procedia Computer Science*, **132**, 2018 pp. 1611–1618. doi:10.1016/j.procs.2018.05.126.

[32] S. Tilkov and S. Vinoski, "Node.js: Using JavaScript to Build High-Performance Network Programs," *IEEE Internet Computing*, **14**(6), 2010 pp. 80–83. doi:10.1109/MIC.2010.145.

[33] P. M. Nadkarni, L. Ohno-Machado and W. W. Chapman, "Natural Language Processing: An Introduction," *Journal of the American Medical Informatics Association*, **18**(5), 2011 pp. 544–551. doi:10.1136/amiajnl-2011-000464.