Australian Journal of Science and Technology

ISSN Number (2208-6404)
Volume 6; Issue 1; March 2022

Original Article

Radial basis function network for smart lighting of residential buildings

Abul Kalam Azad[1]*, A. H. M Saadat[2], Obaidur Rahman[1]

[1]Department of Physics, Jahangirnagar University, Dhaka, Bangladesh, [2]Department of Environmental Sciences, Jahangirnagar University, Dhaka, Bangladesh

ABSTRACT

Building energy management systems is a centralized platform for managing building energy usage. They can detect and remove waste and ensure the efficient use of electricity resources. The use of widely dispersed sensors enables monitoring ambient temperature, lighting, room occupancy, and other inputs required to manage climate control (heating, ventilation, and air conditioning), security, and lighting systems. The three main goals of building energy management are proper management of building energy usage, reducing electricity bills, and environmental stewardship improvement without adversely affecting living standards. We focus on the largest electricity consumers in residential buildings, i.e., lighting in this paper. The efficient management of load categories will result in substantial savings in electricity expenditure and energy use.

Keywords: Artificial, energy, lighting, sensors, smart

Submitted: 18-01-2022, **Accepted:** 26-01-2022, **Published:** 30-03-2022

INTRODUCTION

Smart buildings are categorized by three lineaments[1] i.e., automatically controlled, the embodiments of occupant preferences and feedback, and learning ability. This environment is distinguished by a tight coupling of HVAC, security, lighting, and fire protection systems. They are sensor-rich and produce large amounts of data that can be analyzed to predict occupant behavior and detect equipment faults. This intelligence is convenient as it lessens the complexity of supervising and computing the vast numbers of agents; it facilitates the agents to adapt to changing occupant needs or environments; and it frees occupants from requiring an in-depth understanding of the system or having to make complex decisions.[2] Automation systems for buildings serve centralized management of climate control, lighting, and security systems to enhance energy efficiency and provide serenity. These techniques minimize energy misuse and costs while boosting output.[3,4] They also serve remote building management as well as improved occupant safety and security.[5,6] Sensors and actuators are an essential part of the building-automation network. These devices act such as the eyes, ears of the system. Unfortunately, wiring costs frequently overshoot sensor cost[7] so, Zigbee- the low-cost wireless communication schemes[8] is cost-effective wireless sensors and actuators throughout a building. Wireless sensor and actuator networks (WSAN)[9] have these features: battery-powered, low-cost; low-energy consumption (EC); short-range communication facilities; limited sensing, and computation capabilities.

Objective

The study's objective was to assess the Radial Basis Function Network (RBFN) for Smart Lighting of Residential Buildings.

SMART LIGHTING SYSTEM

Lighting absolves 28% of all commercial building electricity spending (US Department of Energy) and denotes a probable energy reserves source. These systems also unswervingly affect workplace coziness and occupant efficiency.[10,11] Developments to lighting systems promise substantial energy and cost savings and better occupant coziness. A significant amount of research has been steered on energy-efficient illumination. The goal is to lessen energy convention. WSAN's addition to lighting systems

Address for correspondence: Md. Abul Kalam Azad, Department of Physics, Jahangirnagar University, Dhaka, Bangladesh.
E-mail: azad58@eub.edu.bd

licenses granular control of lighting, letting modified control of residential lighting. A lighting control system's purposes are the living room's illumination, ambiance, and security.[12] The system diagram of the smart lighting control system is provided in Figure 1. Lighting systems consist of bulks and luminaires or lighting fittings. Ballasts deliver the start-up voltages essential for lamp ignition and control current flow through the bulb. Newer ballasts permit fluorescent dimming using analog or digital approaches, controlling illumination production. It has been revealed that the human eye is oblivious to the dimming of lights by 20%. In contrast, the dimming is performed at slow rate, thereby allowing substantial energy usage savings.[13]

Sensors

Sensors serving as the intelligent environmental control system's eyes and ears let the system sense and retort to actions in its environment. The most usually utilized sensors are occupancy and photosensors, though some systems include smart tags to detect and path occupants. So far, these smart tag-based systems are yet to increase extensive acceptance due to privacy concerns. Ultrasonic and Passive Infra-Red sensors used sensors occupancy primarily. Photosensors distinguish the amount of ambient light and use this information to find out the amount of artificial lighting essential to uphold total ambient lighting at a distinct value. Therefore, photosensors are a vital component of daylight systems.[14,15]

Lighting Control Approaches

On/off control, setting up, occupancy detection, and dimming are basic lighting control modes. More innovative schemes include daylight harvesting, task tuning, and demand response. Daylight harvesting involves measuring the amount of ambient light and harnessing ambient light to reduce the amount of artificial lighting obligatory to preserve light at a pre-set level. Task tuning involves adjusting the light output according to the tasks performed.[16,17] Demand response is dimming output according to utility signals. Smart lighting control systems gather digital control system with computation and communications systems. The result is cost-friendly but highly suitable lighting system. These systems were plotted and the terminology of the systems is provided in Figure 2.

Centralized smart lighting schemes carry faster performance and lower convergence times than decentralized arrangements, but this faces single-point failure issues. A summary of the various systems is provided in Table 1.

Prioritization

This is the most basic smart lighting method, where incompatible occupant lighting requirements are set by identifying user urgencies. In this method, area-based lighting arrangements are fixed by the highest status. WSAN-based lighting monitoring and control testbed was used with pre-defined user priorities.

Influence diagram

An influence diagram is a graphical illustration of the relationship between decision variables. The relationship between decision variables is marginal and conditional probabilities, permitting the Bayes rule for decision-making. Influence diagrams have three nodes, i.e., state, value, and decision node. Decision nodes are noted by rectangles and represent the control actions available to controllers of the system. State nodes are symbolized by ellipses and represent uncontrollable and uncertain events.

These nodes rank the different choices available to the system controller based on the current system. The optimal decision is the choice that maximizes (or minimizes) the selected cost function. Arcs denote the interrelations among nodes of the system. Input arcs from state nodes to decision nodes represent the information available to decision nodes or controllers at decision time. In contrast, arcs from decision nodes to state nodes point to causal affairs. An influence diagram for smart lighting control is shown in Figure 3 and shows the numerous states, decision nodes, and the system's input.[18,19] utilize influence diagrams to offer smart decision-making skills for WSAN-based lighting systems.

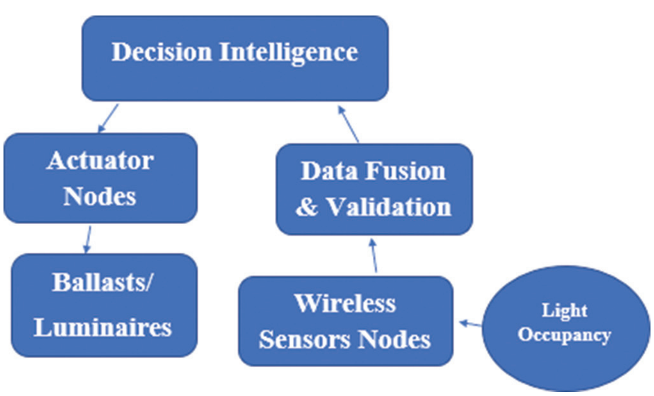

Figure 1: Smart lighting system

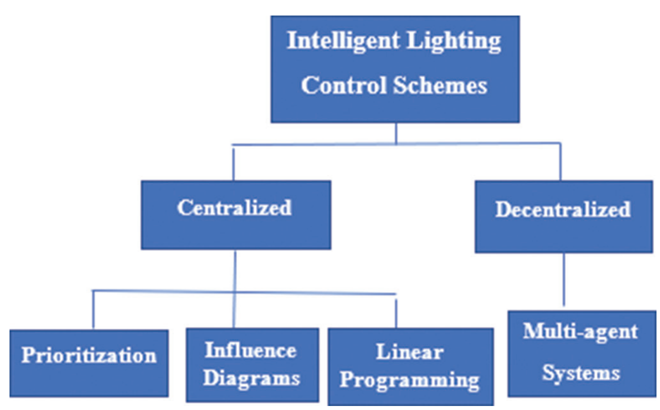

Figure 2: Smart wireless lighting control

Table 1: Comparison of smart lighting control systems

Index	Prioritization	Influence diagrams	Linear programming	Multi-agent systems
Overview	Conflicts resolved by deferring to the highest priority user present	Complex interrelationships Formulated using simple graphs, Non-deterministic decision-making	Effective optimization system for modeling and sufficient competing objectives	Idyllic for environments where learning and prediction are essential while interrelationships between system parameters are either unknown or not well-defined
Approach	Node prioritization	Bayesian probabilities	Linear optimization, scalarization	Artificial Intelligence, Neural networks, expert systems
Response time	Fastest	Quick response	Quick response	Average
Scalability	Centralized architecture which bounds scalability	Centralized architecture which bounds scalability and produces single-point failures	Centralized architecture which bounds scalability and produces single-point failures	Very scalable because of distributed construction
Weaknesses	Can guarantee ease for a single occupant	Probability need to have resulted via experimentation	Optimization issue formulation is a non-trivial task	Not any wireless system presently deployed due to the complexity of the problem

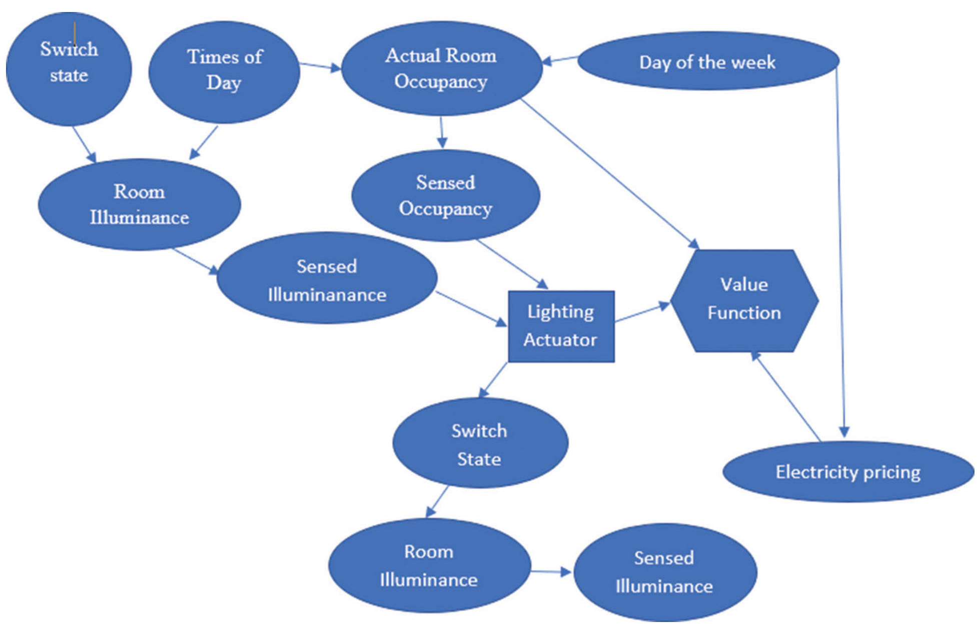

Figure 3: Influence diagram for smart lighting control

Their systems operated dimmable ballasts and were able to satisfy conflicting occupant preferences in shared workspaces.

Linear programming

This is the most common outline for lessening lighting EC, subject to the limitation of satisfying user necessities. It maximizes or minimizes an objective function subject to restraints, and there is a huge collection of experiments in this zone. For instance,[20,21] formed an illuminance model of the room to be lighted. This model captured the effect of each luminaire on work surface lighting. Their objective was to minimize work surface illuminance levels subject to the satisfaction of current room occupants' lighting preferences.

Their system computes the optimal linear combination of individual illuminance models and lighting levels, minimizing energy usage.

Multi-agent Systems

Multi-agent systems utilize huge numbers of autonomous smart agents that cooperate in providing decentralized control of complex tasks. These schemes incorporate the advantages of influence diagram-based lighting control schemes without requiring centralized control. Their advantages include scalability, self-configuration, and adaptation utilizing machine learning techniques-a theoretical framework for such a system was proposed by.[22,23] RBFN is included in the evolutionary multi-agent system.

RBFN

RBFN offer a striking substitute to BP networks.[24] They accomplish admirable approximations for curve fitting problems and can be trained easily and quickly.RBFN generally exhibits a slow response in the recall phase due to the large number of neurons associated with the second coating.[25,26] Linear weights with the output layer can be treated separately from the hidden layer neurons in RBFN. As the secreted layer weights are adjusted through a nonlinear optimization, output layer weights are adjusted by linear optimization. RBFN accuracy and speed may be further upgraded by selecting the proper centers and widths of the interesting fields. The reallocation of centers to locations where input training data are meaningful can lead to more effective RBFN.[27]

Meanwhile, the hidden layer contains nonlinear transformation and linear combiner functions. However, suppose the following pair of Gaussian hidden functions are defined:

$$h_1(x) = e^{-|x-u_1|^2} \quad u_1 = (1,1)$$

$$h_2(x) = e^{-|x-u_2|^2} \quad u_2 = (0,0)$$

If we calculate h_1 (x), h_2 (x) for the above input shapes, we will have Table 2. Figure 4 shows the graph of the outputs in the h_1–h_2 space.

The XOR problem in h_1–h_2 space is drawing to a new problem, which is linearly detachable. Therefore, Gaussian functions can be used to solve the above interpolation problem with a one-layer network. Suppose there exist N points (X_1., XN) and N set's real values (d_1, d_2, d_3.................., d_1); find a function that pleases the following condition:

$$F(x_i)=d_i; i=1, 2, \ldots, N \tag{1}$$

Figure 5 shows a simple radial basis network. This network is a feed forward network similar to back propagation, but it has a different performance. The first difference is the initial weights. The initial weights are not chosen randomly despite the random initial selection of the weights in back propagation. Hidden layer weights are set to values that produce the chosen response. Such weights are allocated so that the network offers the maximum output equal to its weights. The activation functions h_i can be:

$$h_i = e^{\frac{D_i^2}{2\sigma^2}} \tag{2}$$

D_i is notated as the cente's input distance recognized by the weight vector of hidden layer neuron i.

$$D_i^2 = (x-u_i)^T (x-u_i)$$
$$x : \text{input vector} \tag{3}$$
$$u_i : \text{Wieght vector of hidden layer neuron i}$$

Hence, the Neuron's final influence will decrease for the inputs far from the center. It is practical to offer the values of each input of the training set to a neuron, which will be the network's faster training. The key part of the training of the system is fine-tuning the weights of the output layer. Figure 6 shows a single neuron.

Table 2: Mapping of XY to h_1–h_2

Input pattern: X	$h_1(x)$	$h_2(x)$
(1.1)	1	0.1353
(0.1)	0.3678	0.3678
(0.0)	0.1353	1
(1.0)	0.3678	0.3678

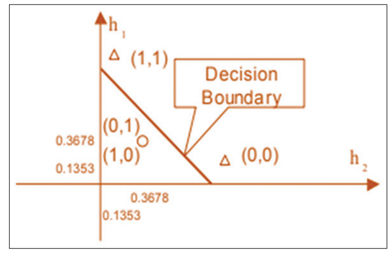

Figure 4: XOR Problem in h_1–h_2 Space.

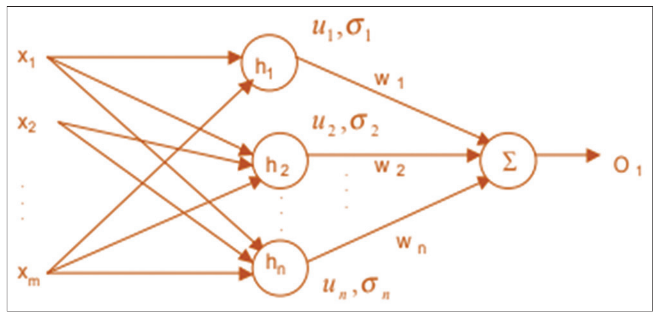

Figure 5: A simple radial basis network

Function $h(x)$, as shown in Figure 7, can be defined as follows:

$$h_x = e^{\frac{(x-u)^2}{2\sigma^2}} \tag{4}$$

As both graph and formula show-

$$\begin{cases} h(x) = 1 & x = u \\ h(x) = 0 & |x-u| > 3\sigma \\ 0 < h(x) < 1 & |x-u| < 3\sigma \end{cases} \tag{5}$$

The above formula specifies that each Neuron only owns contributions from the inputs near the center. For additional values of x, the Neuron will have zero output value without any contribution to the network's final output. Figure 8 shows a radial basis neuron with two inputs, X_1 and X_2.

Figure 9 displays the three-dimensional graph of this Neuron. As seen, the fundamental idea is similar. As Figure 8 displays, the function is radially symmetrical around the center U.

Training of the radial basis network includes two stages. In the first stage, the centerU_i and diameter of receptive σ_i of each Neuron will be assigned. At the second stage of the training, the weight vector W will be adjusted accordingly. After the training phase is completed, the next step is the recall phase in which the outputs are applied, and the actual outputs of the network are produced.

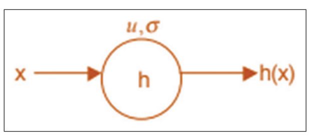

Figure 6: A simple radial basis neuron

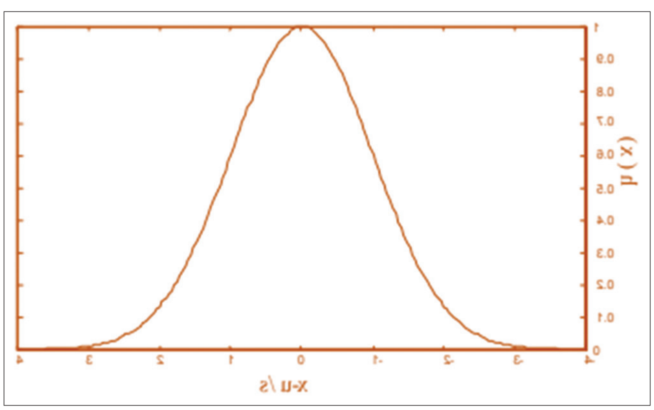

Figure 7: The Graph of *h* (*x*)

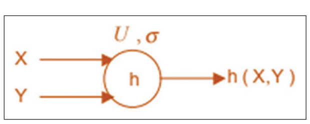

Figure 8: A simple radial basis neuron with two inputs

Finding the Center U_i

One of the most popular approaches to locate the centers U_i is to divide the input vector into some clusters and then find the center of each cluster and locate a hidden layer neuron at that point.

Finding the Diameter of the Receptive Region

The value of σ can have a striking effect on the act of the network. There are different approaches to find this value. One of the popular methods is based on the similarity of the clustering of the input data. For each hidden layer neuron, each Neuron's RMS distance and its nearest neighbor will be considered; this value is denoted as σ. The training phase of RBFN can be briefed as follows:

1. Apply an input vector X from the training set.
2. Calculate the output of the hidden layer.
3. Calculate the output Y and compare it to the chosen value. Adjust each weight W accordingly:
   $w_{ij}(n+1) = w_{ij}(n) + \eta.(x_j - y_j)x_i$ (6)
4. Repeat 1–3 for each vector in the training set.
5. Again, repeat 1–4 till error is lesser than a maximum tolerable amount.

The advantage of a radial basis network is faster training. Backpropagation's main problem is its lengthy training; therefore, radial basis networks have caught a lot of attention lately.

IMPLEMENTATION

The daylight illuminance model matrix is created by illuminance contribution from daylight. According to the standard, the plane is designed with measurement points, where the maximum distance between points can be calculated based on EN12464-1. The illuminance values on points will form

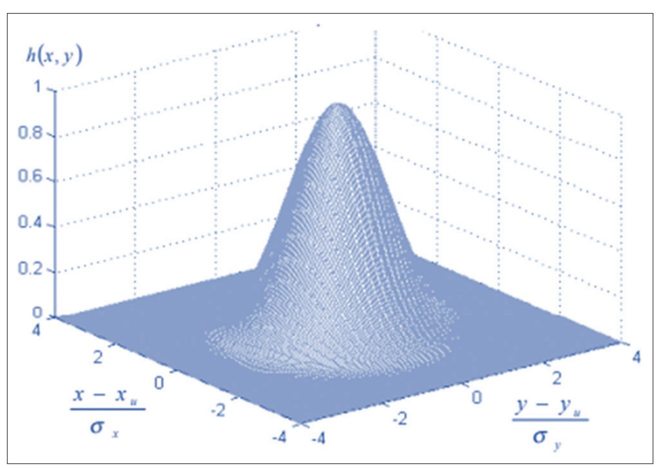

Figure 9: Graph of h (x,y) for the neuron having two inputs

the daylight illuminance matrix ($E_{daylight}$) and can be stated as follows:

$$E_{daylight} = \begin{bmatrix} E_{1,1} & L & E_{1,N} \\ M & o & M \\ E_{M,1} & L & E_{M,N} \end{bmatrix} \quad (7)$$

Here, $E_{m,n}$ is the illuminance level contributed from daylight for each measurement point.

The illuminance vector (E) can be obtained as follows:

$$E = E_{daylight} \times d \quad (8)$$

Where, $E = [E_1 \; L \; E_N]^T$ s the vector of illuminance is measured on the working plane and$d$ = $[d_1 \; L \; d_k]^T$ is a vector of the dimming levels of luminaires, and K is the number of K^{th} luminaires. The study's main objective is to minimize luminaires' dimming levels while maintaining the visual performance and comfort of occupants in the building. The visual performance refers to average illuminance levels (E). The objective function can be formulated using equation.[9] In this case, the lighting control system was divided into several controlling zones. The zones are determined by the number of light sensors installed in the room,[28] It means, practically, a sensor will control several numbers of luminaires in the room. This concept is similar to lighting control by manual switches. The smaller number of light sensors installed will minimize the initial cost. The locations of the sensors were place based on the light sensor placement guide in.[29,30] The objective function, which is the dimming levels of luminaires, can be expressed as follows:

$$d_k = (E_{FB} - E_{FOV,k})/E_{FB,} \; k = 1, 2, 3\ldots K \quad (9)$$

Where E_{FB} is maximum illuminance levels when a luminaire is "on"and $E_{FOV,k}$ is the average illuminance value within the field of view of K^{th} sensor. Based on the result calculated in the equation, the average illuminance levels (E) can be determined using equations (10) as follows:

$$\bar{E} = \frac{1}{N}\sum_{j=1}^{N} E_j \quad (10)$$

The value of dimming levels is in the range of 0 to 1. 0 refers to the 'off' condition, while 1 refers to the lamp's highest brightness level. The dimming level of luminaire capabilities relies on the type of luminaire and can be referred to as the luminaire datasheet provided by luminaire manufacturers.[31,32] The control signal has a linear relation with the LED luminaire's energy consumed. As a result, the total EC of lighting concerning the luminaires dimming levels can be defined as follows:

$$EC = \sum_{k=1}^{k} P_k d_k \quad (11)$$

P_k is the total rated power of luminaires in the K^{th} zone, and d_k is dimming luminaires in the K^{th} zone.

The objective function and its constraints of the proposed RBFN controller are presented in the equation.

The proposed RBFN model was developed using the MATLAB platform.

$$\min f(D) = \sum_{k=1}^{k} d_k \quad (12)$$

Where, $D_{min} < d < D_{max}$

$E > E_m$

Where, f (d) is an objective function: the average dimming levels of all the luminaires, D_{min}, and D_{max} are luminaire's dimming capability lower and upper bounds, respectively, E is average illuminance levels measured on working plane and E_m is averagely maintained illuminance levels set point.

RESULTS AND DISCUSSION

The case study is an actual living room of my apartment. The room dimensions are 20 m (length), 8 m (width), and 2.7 m (ceiling height). The room is illuminated by 24 T8 recessed luminaires arranged in the grid of 8 by 3. Each luminaire consists of 2 × 38W T8 lamps. The total lighting power density (LPD) and average illuminance levels (E) are 11.4 W/m^2 and 514 lux, respectively.

The lighting system was retrofitted with the LED luminaires to benefit LED lamps' advantages: Dimming control capabilities and energy-efficient. The luminaire specifications are as follows: the total luminous flux of 3500 lm, the total power of 34 W, and recessed type. The retrofit lighting contributed 35.

LED luminaires (5 by 7 grid). As a result, the LPD and (E) were 7.4 W/m2 and 625 lux, respectively. It showed that the retrofit with LED luminaires had contributed to reducing luminaires' power in room space and reduced the lighting system's EC.

Moreover, it also increased the illuminance levels that would also provide visual performance in the room. The luminaires' layout in living room is illustrated in Figure 10; the black squares represent the luminaires, and the blue circles represent the light sensors. In this paper, six-light sensors were placed on the ceiling of the room, and the sensor field of view was considered half opening of 60°. The sensors' arrangement and their indexing are shown in Figure 10.

The numbers of sensors determine the number of zones. As a result, the number of zones was 6. The details of luminaire indexing based on their zones are presented in Table 3.

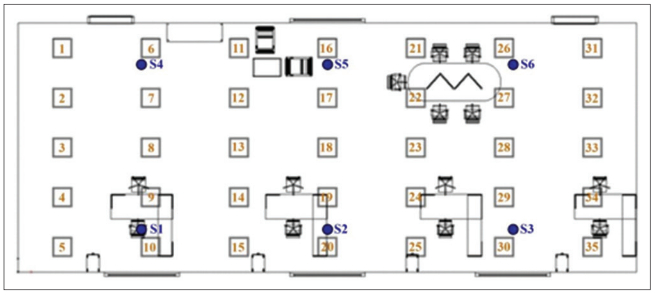

Figure 10: Top view of a living room

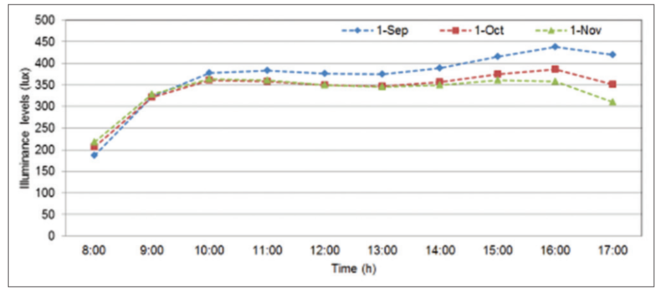

Figure 11: Average daylight illuminance in my room

Table 3: The luminaire numbers based on their zone

Zone	Luminaire
1	3–5, 8–10
2	13–15, 18–20, 23–25
3	28–30, 33–35
4	1,2,6,7
5	11,12,16,17,21,22
6	26,27,31,32

In this study, daylight simulation was carried out using DIALux under the clear sky condition, from 08:00 to 17:00 per 1 h of interval time on March 1, April, and May in 2020. The simulated data was recorded for the training process purpose. The data was divided into two parts, which were input data and target data. The inputs represent the average illuminance values [Figure 11] within the sensor field of view (E_{FOV}) vector, while the outputs represent the dimming levels of the luminaires (d) vector.

Figure 12 shows the architecture of the proposed RBFN as a controller in the lighting system. It can be seen the number of neurons for input and output layers is 6. Meanwhile, the hidden layer consists of a radial basis and linear layers containing 30 and 6 neurons.

To test and validate the proposed RBFN model, the light sensor output data were obtained from the DIALux simulation on April 25, 2020, under clear sky condition. The light sensor output data are the input vector of the controller (RBFN model). The controller processes the sensor data and generates the dimming levels for luminaires. The dimming levels of luminaires' results under the proposed RBFN controller for selected zones and their mean are presented in Figure 13. Based on Figure 13, the highest dimming levels of luminaires for the whole zones at time 8:00 due to at that time, the illuminance distribution from daylight across the room was the lowest compared to other times. The mean dimming levels of luminaires for the whole working hours was 0.35. The dimming levels of luminaires at Zone 4 showed the highest dimming value due to the zone was the lowest illuminance distribution contribution from daylight.

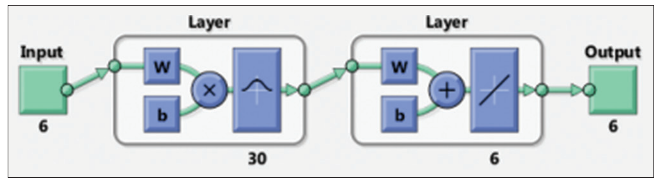

Figure 12: Architecture of proposed RBFN

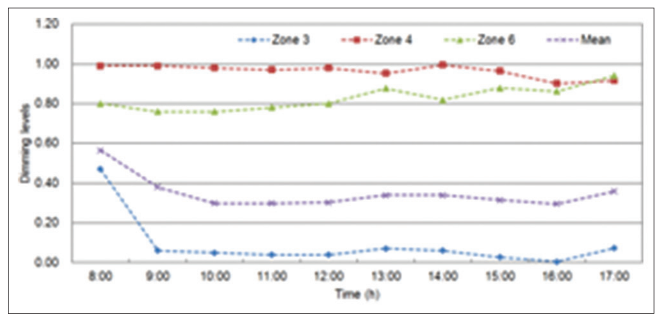

Figure 13: Dimming levels of luminaires results for selected zones and their mean

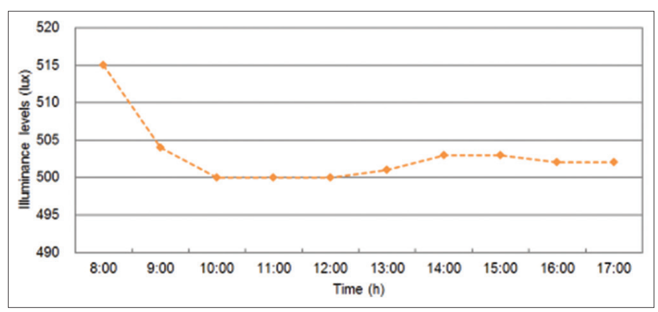

Figure 14: Average illuminance levels under the proposed RBFN controller

The DIALux software simulation was carried out to validate the illuminance levels fully satisfied with the EN12464-1 based on the dimming levels generated from the proposed controller.[33] Figure 14 shows the average illuminance levels under the proposed RBFN controller. The average illuminance levels under the proposed RBFN controller were archived above the threshold of E that was specified in the EN12464-1, which is 500 lux. From the simulation results, the isoline from both daylight and artificial light at time 13:00 is depicted in Figure 15.

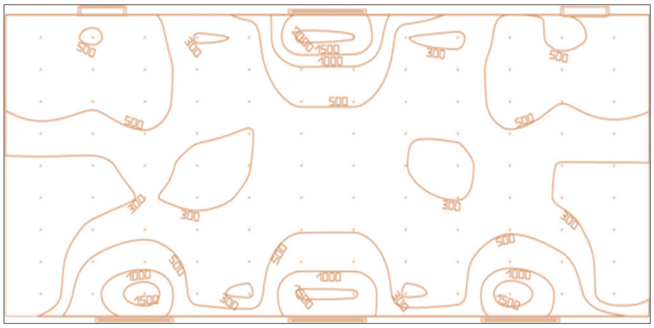

Figure 15: Isoline from both daylight and artificial light at time 13:00

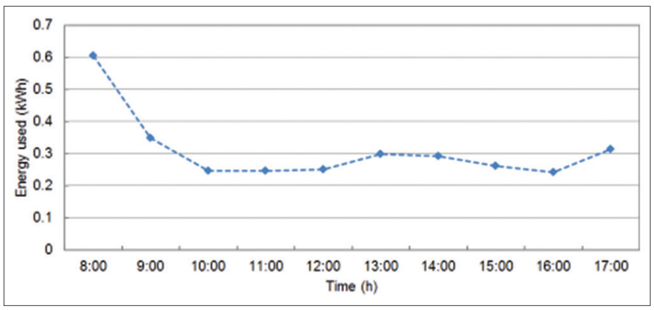

Figure 16: Energy Used under the Proposed RBFN Controller

According to the equation, the total EC of all luminaires under the proposed RBFN controller was calculated.[11] Figure 16 presents the energy used under the proposed RBFN controller during day hours by considering the electricity tariff for the low voltage commercial buildings (tariff B) from the electricity utility of Bangladesh, 20,000MW.[34] The total electricity cost was BDT 5.614/day. Energy-saving (ES) can be described as the difference between existing and proposed systems' EC and is divided by the existing system's EC. ES is the most widely used to evaluate energy performance, and most studies have been expressed in percentage (%). As a result, the ES of the proposed RBFN controller was 34%.

CONCLUSION

This paper is offering a smart lighting control system using the RBFN model in a resident. The controller's objective function is to minimize the dimming levels of luminaires that satisfy the minimum of E stated in the EN12464-1. The light sensor field of view was considered to calculate the dimming levels of luminaires for the proposed RBFN controller. The proposed controller was tested and validated at an actual office room and was simulated using DIALux software. The results showed that the proposed RBFN controller showed great performance in achieving dimming level targets and satisfied the EN12464-1. Furthermore, the energy savings recorded from the proposed RBFN controller was 34%.

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