# Sensorless Illumination Control of a Networked LED-Lighting System Using Feedforward Neural Network

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***Abstract*—In order to resolve the problem of energy hunger nowadays, saving lighting energy in buildings contributes an important part. In this paper, a sensorless illumination control scheme for smart networked LED lighting has been investigated. The scheme is based on a feedforward neural network to model all the nonlinear and linear relationships inside the lighting system as the controlled plant. Because the scheme does not rely on lighting simulation software, it is flexible to be implemented on microcontrollers. The scheme, moreover, can provide not only high accuracy in modeling but also global optimum in energy saving. Without using light sensors in its control loop, the approach can save significant cost and provide ease of installation as well. In addition, it also has the strength of fast response owing to feedforward control based on neural networks. The experimental results show that the approach can easily attain more than 95% modeling accuracy and also improve more than 28% energy saving with its optimal nonlinear multiple-input multiple-output control.**

***Index Terms*—Energy saving, feedforward, illumination control, LED-lighting system, neural network, sensorless.**

## I. Introduction

With rapidly increasing energy demand all over the world, saving lighting energy in building environments has become increasingly important since lighting accounts for a considerable portion, typically more than 20% of energy consumption in buildings [1], [2]. This has led to the exploration of not only new lighting technologies such as solid-state lighting (SSL) [3] but also a smarter approach to utilize these SSL systems. In the aforementioned smart lighting systems, it is the illumination control that plays a crucial role in reducing the energy consumption of the building lights. At present, there are already some forms of illumination controllers generally used to turn on/off lighting luminaires or adjust dimming levels of luminaires such that the consumed power reduces while the visual comfort of users is well kept [4]–[11].

It is common in the lighting industry nowadays to design the lighting system using a zoning approach. While trying to achieve energy saving and human preference at the same time, traditional control approaches encounter the problem of complexity in deciding which luminaire should light up which area. To soften this problem, a zoning approach [2], [12] groups several luminaires in one zone together to be adjusted by one controller and with the corresponding sensors. The approach then transforms the control problem to become multiple single-input single-output (SISO). The first disadvantage of the approach, however, is that designers have to manually preset the zoning for luminaires, lit area, and sensors. Moreover, the interactions among the zones still exist, and thus, either the control response is low or energy saving is lost because these interactions are neglected during the design phase.

In lighting applications such as in a common shared-space office with multiple LED luminaires, the smart illumination control problem can be formulated as to automatically adjust dimming levels of the LED luminaires to ensure sufficient illuminance at users' tables at minimized energy consumption. In this problem, on the one side, information on occupancy of users at their working tables which is detected by occupancy sensors is essentially necessary. On the other side, information on illuminance at their tables is optional owing to the following reasons. The first reason is that this type of information can be evaluated based on illumination modeling. The second reason is that illuminance sensors placed on the office tables may affect the working users and, *vice versa*, users may affect the function of these sensors accidentally. Without using illuminance sensors, several researchers [2], [13]–[16] have used simulation software to conduct the lighting configuration and establish the relationship between luminaires and illuminance. The major drawback of this published state-of-the-art approach is that, for different buildings, the lighting setting for networked lighting system has to be manually changed. Moreover, in many cases, the simulation software could not accurately imitate the real environment. In addition, it is difficult to set up the simulation software in microcontrollers (MCUs) and digital signal processors, and thus, the use of a personal computer (PC) is compulsory.

To overcome the drawbacks of the aforementioned approaches, in this paper, we propose the use of a neural network technique to establish the relationship among dimming levels of luminaires and illuminance at the user tables. The neural network then will be included in sensorless feedforward illumination control for the smart networked LED-lighting system. The accuracy of the model depending on the configuration of the neural network and characteristics of the LED-lighting system will be examined. The daylight effect is beyond the scope of this research and will be investigated in future work.

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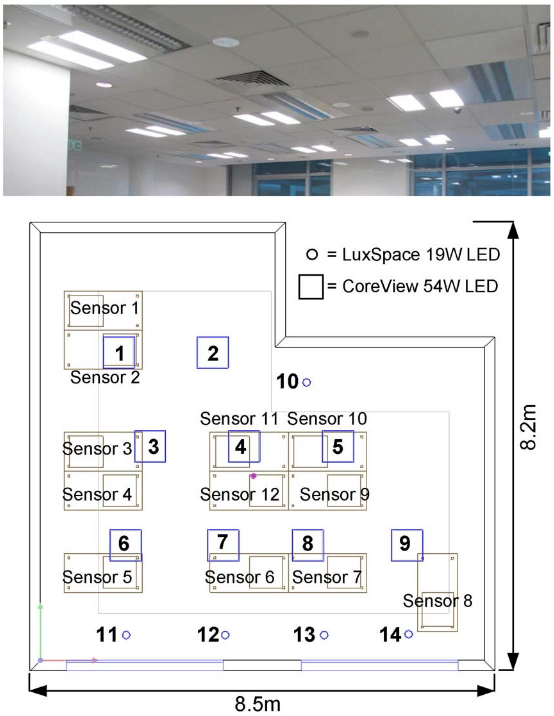


Fig. 1. Layout of two types of LED luminaires in the test bed.

## II. Illumination Control of Networked LED-Lighting System

The networked LED-lighting system consists of several LED luminaires for illumination of a given space, for example, a working space in an office. For configuration of the lighting controller, wireless sensor nodes can be used one time to collect necessary data and then discarded later on.

### *A. Test Bed of Networked LED-Lighting System as Controlled Plant*

The test bed of the smart LED-lighting system is an 8.5 m × 8.2 m office with 12 working tables. The office is located on the fifth level of the Research Techno Plaza (RTP) building and is the workplace for Energy Research Institute administration staff. The office is 2.8 m high with a working plane of 0.8-m height. Because the office has no direct access to the outdoor environment, the effect of daylight is almost zero and negligible. In the office, there is installation of 9 × 54 W LED luminaires and 5 × 19 W LED luminaires on the ceiling. Each 54-W LED luminaire is a modular lamp (CoreView) with a large beam angle, while each 19-W luminaire is a downlight lamp (LuxSpace) with a small beam angle, as shown in Fig. 1.

All installed LED luminaires are dimmable and controlled through a Digital Addressable Lighting Interface (DALI) control box. Since there are no high partitions among the working tables, each luminaire can affect the illuminance of more than one table. This then poses the difficulty to control the networked lighting system. For example, in the test bed, luminaire 1 affects tables 2 and 3, while luminaire 2 affects tables 1, 2, and 4. A manually preset solution is then using sensors 2 and 3 together for lighting control of luminaire 1 while using sensors 1, 2, and 4 together for lighting control of luminaire 2. This predefined solution for the complex networked lighting system is not only nonoptimal in energy saving but also time consuming and inconvenient. The interactions inside the lighting control system, furthermore, are not dealt by a multiple-input multiple-output (MIMO) approach. Hence, the control performance in terms of response and accuracy is poor. To illustrate the illuminance distribution, the test bed is simulated in DIALux lighting simulation software, as shown in Fig. 2.

Fig. 2. Test bed at RTP simulated in DIALux software.

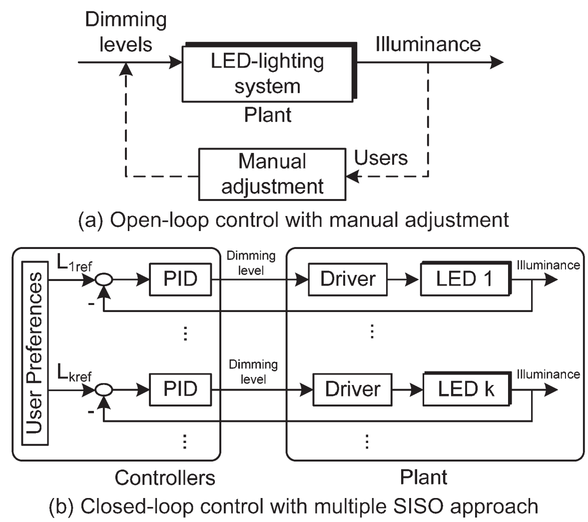


Fig. 3. Two conventional illumination control approaches. (a) Open-loop control with manual adjustment by users. (b) Closed-loop control following multiple-SISO approach.

### *B. Conventional Illumination Control Approaches*

In industrial practice, the most traditional illumination control approach is open-loop control, i.e., without light sensor feedback, as illustrated in Fig. 3(a). Following this approach, the users have to manually adjust the dimming levels of the luminaires until they are satisfied. The first drawback of this approach is that it is subjective, with no feedback lux measurement information, and, thus, inaccurate. The considerable inaccuracy then leads to loss of potential energy savings by 10%–20%. Moreover, the approach also has the other disadvantage of inconvenience caused, particularly when the number of luminaires is large which would confuse the users and when the different users have conflicting lighting interests.

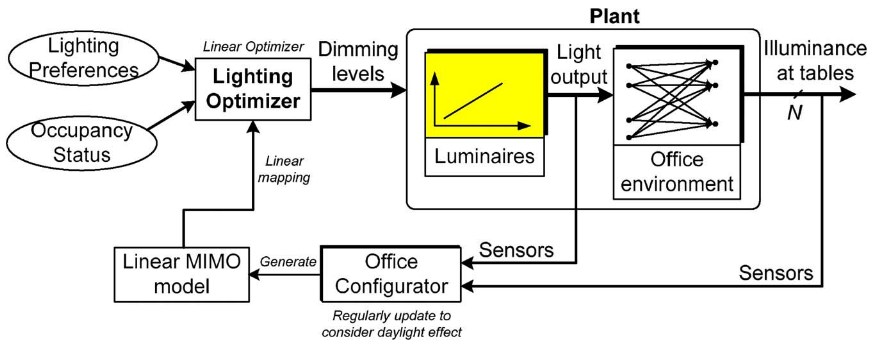


Fig. 4. Framework of the linear MIMO control approach in [25].

The other traditional illumination control solution with more lighting automation is using a multiple-SISO control approach with lux sensor feedback to adjust the dimming levels of the luminaires, as illustrated in Fig. 3(b). As opposed to the open-loop lighting control, this closed-loop control is introduced to overcome the inaccuracy problem. Following this closed-loop approach, the SISO controller of each luminaire uses its corresponding light sensor to measure the actual illuminance at the user table and then feeds back the information to compare with its own reference in the control loop. The error between the illuminance reference and the actual value will then generate an appropriate dimming control action. An example of this multiple-SISO approach is the lighting controller in [17] and [18].

Even as the accuracy problem is being taken care of by the closed-loop lighting control, this lighting control approach is only useful when the luminaires do not affect one another, for example, when the luminaires are located far away from one another, or there are partitions among the luminaires. Otherwise, when the illumination correlation of the luminaires is not negligible, it becomes difficult to identify which sensors should accompany which controller and its corresponding luminaire for closed-loop control. For more complex lighting systems, this approach is slightly improved by using grouping technique, in which a group of luminaires is preset to control the lighting of a specific zone. The major drawback of this individual lighting control approach for a networked lighting system is that it bears the interactions between the lighting controllers, particularly the integral elements. For example, when lighting group A increases its light output, it also increases the illuminance at the nearby zone B. The controller of lighting group B then has its response by reducing its light output which consequently affects the illuminance at zone A. When the integral elements contribute the major part in lighting control actions, because of these interactions, the overall lighting system has to spend considerably large transient time to reach its stable state. Another limitation of this individual control approach is that it requires light sensors to facilitate the lighting adjustment [19]. Otherwise, either the illumination preferences are not met or energy conservation is not maximized or both.

### C. *State-of-the-Art Illumination Control Approaches*

According to the authors in [15], [20], and [21], correlation between light output and power input of a luminaire for ideal dimming operation is linear, except at low power (less than 20% of power rating). Based on the assumption that this correlation is linear by avoiding the less than 5% dimming region and knowing that correlation between light outputs of LED luminaires and illuminance at any point is also linear [22]–[24], the final correlation between ideal dimming levels of LED luminaires and illuminance at working tables is approximated to be linear. This approximated linearity has been used by researchers in [25]–[27] to formulate the lighting energy minimization problem as a linear programming problem which is easy to solve, for example, by using the simplex method. In detail, the approach in [25], as depicted in Fig. 4, considers the networked lighting control problem as a linear MIMO model owing to the use of sensors for measurement of light output and sensors for measurement of illuminance at user tables. A salient advantage of this approach is that it can incorporate the daylight effect by using the data from the sensors to configure/reconfigure the linear MIMO model of the office lighting system. On the other side, the approach in [26] uses no light sensors but simulation software to attain the illuminance model. This approach has the merit of low cost and ease of installation owing to no light sensors being used. The tradeoff, nonetheless, is the possibly large inaccuracy.

## III. Insights Into Networked LED-Lighting System Test Bed

### A. *Invalidation of Linear MIMO Model*

Following the ideal linearization approach suggested in [15] and [20]–[25], we can formulate the illumination modeling problem for the investigated test bed as a linear MIMO relation as follows. Let

$$\mathbf{d} = [d_1, d_2, \ldots, d_M]^T \tag{1}$$

be the $M \times 1$ vector of the dimming levels of the LED luminaires, where $M$ is the number of LED luminaires in the test bed. Let

$$\mathbf{t} = [t_1, t_2, \ldots, t_N]^T \tag{2}$$

be the $N \times 1$ vector of illuminance at working tables, where $N$ is the number of tables in the test bed. The dimming level $d_i$ of the $i$th LED luminaire is in the range of 0% (dark) to 100% (fully bright). Assuming linear relation between dimming levels of LED luminaires and illuminance at tables as mentioned earlier, we have

$$\mathbf{A} \times \mathbf{d} = \mathbf{t} \tag{3}$$

where $\mathbf{A}$ is the coefficient matrix of the linear MIMO relation of the system

$$\mathbf{A} = \begin{bmatrix} a_{1,1} & a_{2,1} & \cdots & a_{M,1} \\ a_{1,2} & a_{2,2} & \cdots & a_{M,2} \\ \cdots & \cdots & \cdots & \cdots \\ a_{1,N} & a_{2,N} & \cdots & a_{M,N} \end{bmatrix}_{N\times M}. \tag{4}$$

Considering that one set of input–output data includes one dimming level setting $\mathbf{d}$ as input and one resulted illuminance $\mathbf{t}$ as output, $M$ sets of data will be needed to obtain matrix $\mathbf{A}$, given that the input vectors are independent. It can be expressed in mathematical form as

$$\mathbf{A}\,[\,\mathbf{d}_1 \quad \mathbf{d}_2 \quad \cdots \quad \mathbf{d}_M\,] = [\,\mathbf{t}_1 \quad \mathbf{t}_2 \quad \cdots \quad \mathbf{t}_M\,]. \tag{5}$$

Choosing $\mathbf{A}$ to be unknown, we have the standard linear equation

$$\begin{bmatrix} \mathbf{d}_1^T \\ \mathbf{d}_2^T \\ \cdots \\ \mathbf{d}_M^T \end{bmatrix} \mathbf{A}^T = \begin{bmatrix} \mathbf{t}_1^T \\ \mathbf{t}_2^T \\ \cdots \\ \mathbf{t}_M^T \end{bmatrix}. \tag{6}$$

*Normalization of Dimming Level as Input:* Because the actual dimming level of each LED luminaire is discretized and binary coded in the DALI controller using 1 B for each LED, a conversion is necessary to normalize back the input. Since the actual dimming level varying from 0% (dark) to 100% (fully bright) is equivalent to the discretized and binary-coded dimming level varying from 255 to 0, the conversion equation for normalization is then

$$d = \frac{255 - b}{255} = 1 - \frac{b}{255} \tag{7}$$

where $d$ is the actual dimming level and $b$ is the discretized binary-coded dimming level.

*Collection of Data:* The input set of the illumination model includes the $M$ dimming levels of $M$ LED luminaires. The corresponding output set of the illumination model then includes the $N$ measured table illuminance values. Each input set and its corresponding output set constitute a sample set. For the test bed with $M = 14$ and $N = 12$ 600 sample sets are collected by using either illumination meters or a wireless light sensor network. The input sets in the 600 sample sets are generated randomly without any repetition. During the data collection process, human interference and any effect of surrounding light sources are kept as little as possible.

*Result of Validation:* By selecting any $M = 14$ sample sets such that the formed matrix of dimming levels has full rank, which implies that it is invertible, coefficient matrix $\mathbf{A}$ can be easily obtained. However, during validation, the model bears an unacceptable inaccuracy as high as $10^5$ lx$^2$ in terms of mean square error (mse). In addition, while most of the coefficients in matrix $\mathbf{A}$ are positive, some of them are negative. This presence of negative coefficients is unacceptable because its practical meaning is that, when a luminaire related to the negative coefficient increases its light output, the corresponding table would have less illumination. The validation result therefore suggests that the use of a linear model is inadequate and another modeling approach should be examined.

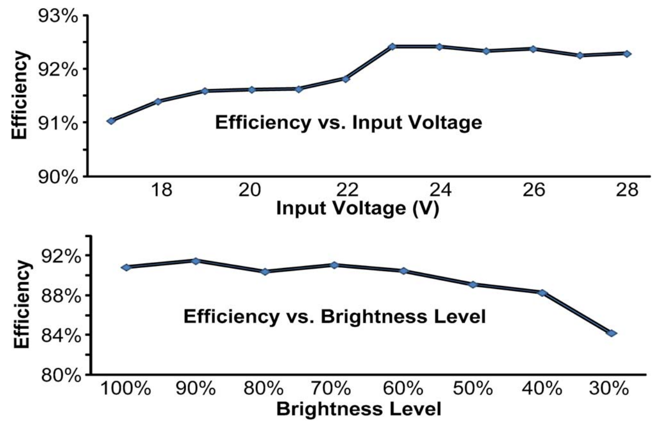


Fig. 5. Efficiency performance of a Phillips light driver.

## B. Nonlinearity of LED-Lighting System

For the unexpected invalidation of the linear model, the major reason is probably that the assumption of linear correlation between dimming levels and light outputs is wrong. After thorough investigation, the problems are found to be attributed to internal discretization in the DALI controller and power control in the light driver in the test bed that cause the nonlinearity. It is unfortunate that the datasheet of the DALI controller does not provide the internal discretization scheme, which can be often encountered in real-world lighting controller design. The dimming control scheme inside the DALI controller, nevertheless, is known to be open loop. In addition, efficiency performance of the Philips light driver used in the test bed clearly shows the nonlinearity for different input voltages and different brightness levels, as illustrated in Fig. 5. The efficiency curves of the light driver are expected ideally to be constant. However, the efficiency in practice always drops at low power range represented by low brightness level in this case and at low input voltage. In short, the internal discretization and the open-loop dimming control in the DALI controller, together with the nonconstant efficiency performance of the light driver, are the causes of nonlinearity in the relation between dimming levels of LED luminaires and illuminance at the user tables.

Inside the LED-lighting system as depicted in Fig. 6, from each dimming level to each corresponding light output, the relation is independently nonlinear SISO. Therefore, up to light output of luminaires, the system is multiple nonlinear SISO. The cross-relation, which is linear MIMO, only occurs between light output and illuminance at tables. This then turns the overall system into a nonlinear MIMO model.

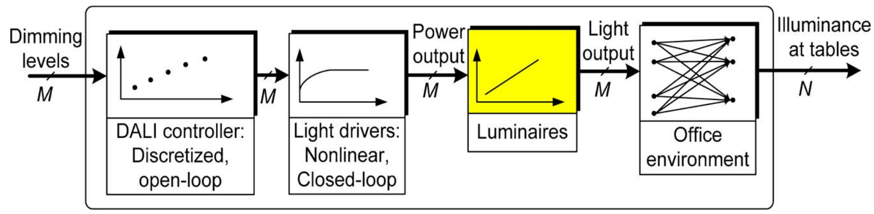


Fig. 6. Insights into the LED-lighting system.

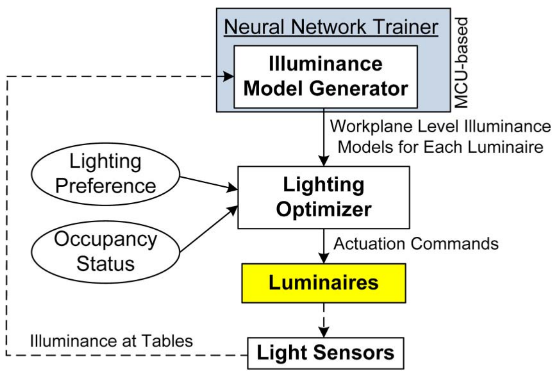


Fig. 7. Framework of lighting system using neural network for illuminance modeling.

## IV. Sensorless Illumination Control of Networked LED-Lighting System Using Feedforward Neural Network

### A. Proposed Approach Using Feedforward Neural Network

In order to control the lighting system, the researchers in [25] had to use photosensors arranged on the ceiling to capture the luminance of the LED luminaires. The researchers in [26] used no light sensors but simulation software to generate the illuminance model, which is different from this approach. Both approaches, however, have not considered the nonlinearity characteristics caused by power electronic devices inside the system. To tackle this problem, we propose the use of neural networks to attain the nonlinear MIMO model of the studied lighting system. The framework of the proposed approach is depicted in Fig. 7. In the proposed approach, light sensors for illuminance at tables are not regularly used in real-time control. They are used to update the nonlinear MIMO model only when office configuration changes. This approach is suitable for the studied office lighting test bed since little daylight effect exists.

Compared with the approach in [26], the proposed approach does not require office configuration knowledge and, thus, avoids the inaccuracy caused by insufficient or incorrect data in the simulation software approach, which is its first advantage. Second, it has the feedback channel for illuminance, and therefore, it is easy and convenient to accurately update the illuminance model whenever the office configuration changes. Third, the approach is flexible because the implementation can be MCU based but neither PC based nor dependent on simulation software. Finally, the light sensors for illuminance at user tables, which are based on wireless communication, are used only once for any model updating and then can be removed.

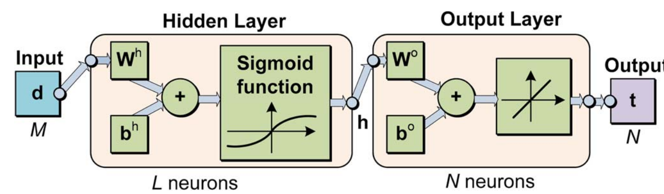


Fig. 8. Two-layer feedforward neural network.

Therefore, not only the wiring problem of the wired sensors but also the maintenance problems, e.g., owing to batteries, of the wireless sensors are avoided. Moreover, compared to the approach in [25], the proposed approach has the strengths of cheap cost and ease of installation attributed to less usage of light sensors.

Similar to the two state-of-the-art approaches presented, the proposed approach helps overcome the difficulty of controlling networked lighting system by viewing the system as a MIMO model with all the complex nonlinear relationship among power supply grid, power electronic devices, luminaires, and human with their working tables. Additionally, in terms of feedforward control with fast response, it eliminates the drawback of inaccuracy that the approach in [26] suffers from. Achieving fast response and high accuracy at the same time is crucial in nighttime scenarios. For example, when one person walks into the dark room after office hours, the illumination controller has to quickly and accurately turn on the correct luminaire(s) with appropriate dimming level(s) to provide sufficient lighting to the user at minimal energy consumption.

### B. Configuration of Neural Network

The objective of the illumination modeling is to attain the relationship among dimming level setting of LED luminaires and illuminance at tables. Because there are no meters or sensors used to obtain the data of power output and light output inside, the examined LED-lighting system can be viewed as a black box with inputs of dimming levels and outputs of illuminance at the tables. A neural network is selected to map the relation between the inputs and outputs of this black box.

Considering the two-layer neural network with $M$ inputs, $L$ hidden neurons, and $N$ outputs, as illustrated in Fig. 8, the vector of hidden neurons is

$$\mathbf{h} = [h_1, h_2, \ldots, h_L]^T. \tag{8}$$

Denoting $w^h_{j,k}$ as the weight that connects hidden neuron $j$ with input neuron $k$, weight matrix $\mathbf{W}^h$ in the hidden layer is

$$\mathbf{W}^h = \begin{bmatrix} w_{1,1}^h & w_{1,2}^h & \cdots & w_{1,M}^h \\ w_{2,1}^h & w_{2,2}^h & \cdots & w_{2,M}^h \\ \vdots & \vdots & \ddots & \vdots \\ w_{L,1}^h & w_{L,2}^h & \cdots & w_{L,M}^h \end{bmatrix}. \tag{9}$$

Similarly, denoting $w_{i,j}^o$ as the weight that connects hidden neuron $j$ with output neuron $i$, then the weight matrix $\mathbf{W}^o$ in the output layer is

$$\mathbf{W}^o = \begin{bmatrix} w_{1,1}^o & w_{1,2}^o & \cdots & w_{1,L}^o \\ w_{2,1}^o & w_{2,2}^o & \cdots & w_{2,L}^o \\ \vdots & \vdots & \ddots & \vdots \\ w_{N,1}^o & w_{N,2}^o & \cdots & w_{N,L}^o \end{bmatrix}. \tag{10}$$

The bias vectors in the hidden layer and output layer are respectively

$$\mathbf{b}^h = [b_1^h, b_2^h, \ldots, b_L^h]^T \tag{11}$$
$$\mathbf{b}^o = [b_1^o, b_2^o, \ldots, b_N^o]^T. \tag{12}$$

Using transfer function tansig for the hidden layer and linear transfer function purelin for the output layer, the output vector $\mathbf{t}$ can be calculated as

$$\mathbf{h} = \mathrm{tansig}(\mathbf{W}^h\mathbf{d} + \mathbf{b}^h) = \frac{2}{1 + \exp\left[-2(\mathbf{W}^h\mathbf{d} + \mathbf{b}^h)\right]} - \mathbf{I} \tag{13}$$

$$\mathbf{t} = \mathbf{W}^o\mathbf{h} + \mathbf{b}^o = \frac{2\mathbf{W}^o}{1 + \exp\left[-2(\mathbf{W}^h\mathbf{d} + \mathbf{b}^h)\right]} - \mathbf{W}^o + \mathbf{b}^o. \tag{14}$$

The key research questions in configuring the neural network are as follows: 1) how to select the number of hidden neurons $(L)$ and 2) how many data sets are needed to train the neural network. For the first question, from the analysis viewpoint, because the nonlinearity in the system is introduced by energy performance at drivers and of SISO type, there are mainly $M$ nonlinear characteristics inside the system that can be represented by using $L = M$ hidden neurons. Because the cross-relations between light outputs of luminaires and illuminance at the tables are constant, they can be represented accurately by $N$ output neurons.

For the second question on the number of data sets needed, it is obvious that the number of data required depends on the number of hidden neurons $(L)$. In general, as previously mentioned, the shape of the sigmoid function in hidden neurons, as illustrated in Fig. 8, is similar to that of efficiency performance of the light driver, as illustrated in Fig. 9. Hence, three to four operating points can be used for the hidden neuron to capture that efficiency curve.

### C. Optimal MIMO Control Approach

Similar to other lighting approaches, the goals of the examined sensorless lighting control scheme are as follows:

1) to satisfy user preferences of illuminance at their working tables;
2) to minimize the overall lighting power consumption.

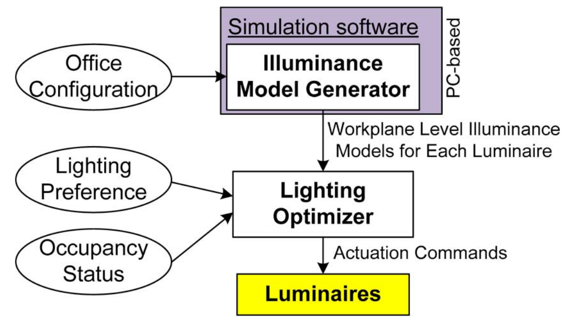


Fig. 9. Framework of the lighting system using simulation software for illuminance modeling in [26].

Considering the system as a whole and following the MIMO control approach, global optimization can be derived while illumination preferences are all satisfied, as obtained in [25] and [26]. By assuming that the dimming level of a luminaire is proportional to its power consumption, the total power consumed by all the luminaires in the system can be calculated as

$$P_\Sigma = \sum_{i=1}^{M} p_i(d_i) = \sum_{i=1}^{M} P_i d_i \tag{15}$$

where $P_\Sigma$ is the overall power consumption, $p_i$ is the instantaneous power consumed by the $i$th luminaire, $P_i$ is the rated power of the $i$th luminaire with full brightness, $d_i$ is the current dimming level of the $i$th luminaire ranging from zero (dark) to one (fully bright), and $M$ is the number of luminaires. The optimal control problem then can be formulated as

$$\min P_\Sigma = \min \sum_{i=1}^{M} P_i d_i \tag{16}$$

subject to

$$0 \le \mathbf{d} \le 1 \tag{17}$$
$$\mathbf{t} = \text{“NeuralNetwork”}(\mathbf{d}) \ge \mathbf{r} \tag{18}$$

where $\mathbf{r} = [r_1, r_2, \ldots, r_N]^T$ is the $N \times 1$ vector of illuminance preference and “NeuralNetwork” is the neural network model built earlier to map the relationship among dimming levels of luminaires and illuminance at the tables. It should be noted that the constraint (18) is nonlinear. Because the optimization problem is discretized and nonlinear constrained, either nonlinear constrained optimization algorithm or mixed integer programming algorithm can be used. In this research, the first optimization algorithm is chosen since the resolution of the discretization in dimming levels is rather fine.

### D. Practical Implementation

The proposed approach can be easily implemented on PC with common programming softwares (e.g., C, Python, and MATLAB) that support coding of neural networks and optimization. Moreover, this control system can be implemented on MCUs or DSPs as well. For instance, a 24-b TMS320 DSP with extra EEPROM or Flash memory can be used. The purpose

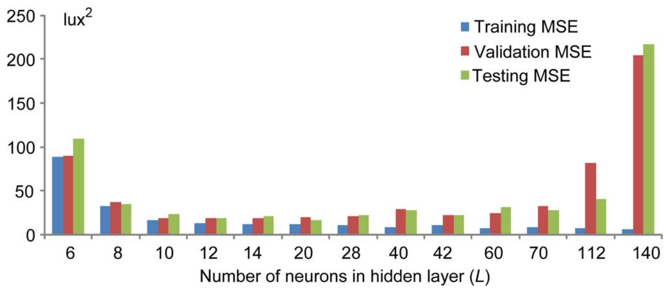


Fig. 10. MSEs for different numbers of hidden neurons ($L$).


Fig. 11. MSE for different numbers of data sets for training and $L = M = 14$.

of the extra EEPROM or Flash memory is to store the updated data of the neural network.

## V. Experimental Results

### A. Performance of Neural Network in Modeling

To validate the estimation of the number of hidden neurons $(L)$ needed in the neural network, 600 data sets are used and divided into three different groups of training (70%), validation (15%), and testing (15%). During the training of the neural network, the training data group is used to adjust the coefficients in the network, while the validation data group is used to measure the network generalization and indicate when the training can stop. The testing data group is used to independently measure the network performance after training. From Fig. 10, it can be seen that, for values of $L$ from 8 to $5M = 70$, the network modeling accuracy is high with all the three mses less than 50 lx$^2$. The best results are with $L = 10$ up to $L = 2M = 28$. This verifies that the selection of $L = M$ is acceptable and also recommended.

For the case of $L = M$, the validation results in Fig. 11 show that all the three mses are less than 80 lx$^2$ when more than $4M = 56$ data sets for training are used. For the case of $L = 5M$, the results in Fig. 12 show that about $20M = 280$ data sets for training are needed to ensure that all the three mses are less than 100 lx$^2$. These results verify that using $4L$ data sets for training is sufficient to obtain an acceptable modeling accuracy. A substantial modeling accuracy is necessary because a poor accuracy in modeling results in either more energy being wasted or sacrificed visual comfort. Also, it may significantly reduce the convergence speed of the optimizer.

To collect the data sets from the office to train the neural network, illumination meters can be used manually to measure illuminance at the user tables. However, this task requires a considerably large amount of time. Hence, in our research project, an automated wireless mesh sensor network has been developed to accomplish this task.

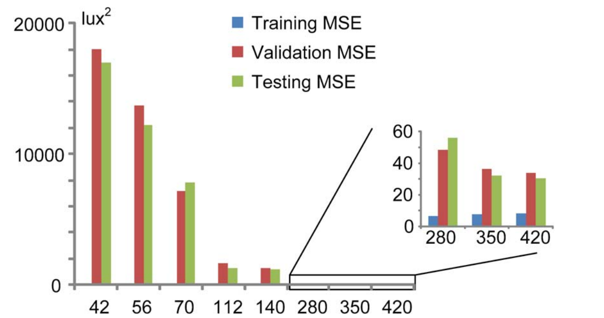


Fig. 12. MSE for different numbers of data sets for training and $L = 5M = 70$.

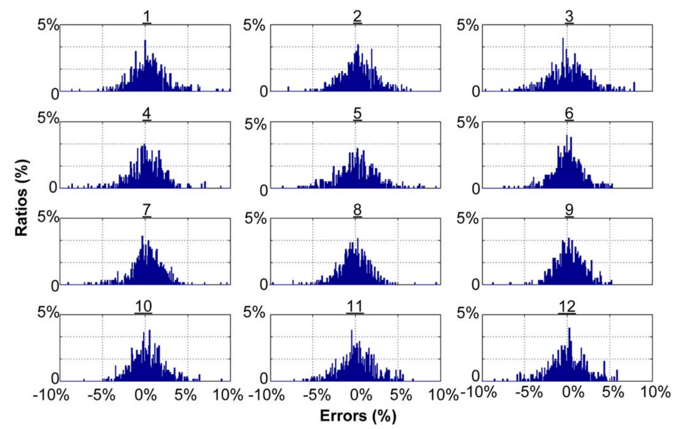


Fig. 13. Histograms of percentage errors between neural-network-based model and actual system at 12 tables.

For the accuracy of the modeling, the histograms of percentage errors between the model and the actual system are derived and shown in Fig. 13. With 50 lx$^2$ mse overall, it can be seen that the model obtains more than 95% accuracy. Nonetheless, it should be noted that the data sets used to train the neural network must cover the important lower bounds and upper bounds of all combinations of the dimming levels to avoid inaccurate extrapolation. Again, the inaccuracy is the cause of either loss of energy saving or visual discomfort.

### B. Optimization Results and Energy Saving

As illustrated in Fig. 14, the examined LED-lighting system was designed to fully illuminate the whole space of the office, i.e., high illuminance (in lux) at most of the points inside the office. When all the LED luminaires are at their full brightness, the total power consumption is 581 W. This operating point of the lighting system is favored during office hours when intensive administration actions are conducted. However, before and/or after office hours, when the administration staff only focus on their work at their tables, for example, preparing documents, it is not required to have the full illumination for the whole office space. Instead, illumination can concentrate on the user tables, as encouraged in [28]. In addition, it also often happens that only a few and not all administration staff have to work overtime to complete their tasks before deadlines. In such

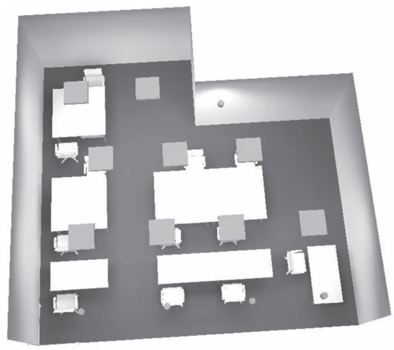

Fig. 14. Illustration of the office test bed illuminated with full brightness of all the LED luminaires.

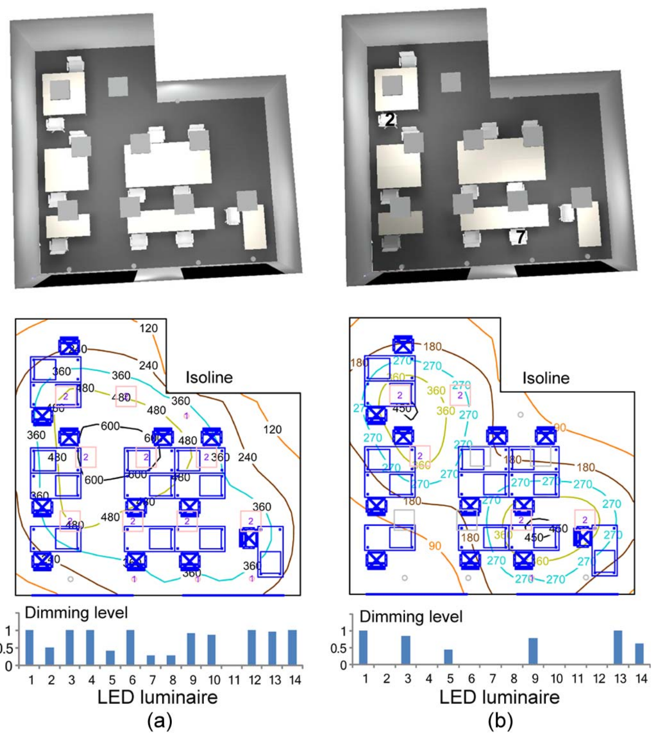


Fig. 15. Illustration of the experimental results with optimal control for nighttime scenarios. (a) All 12 tables have the preferences of 350 lx each. (b) Only two tables have the preferences of 350 lx each.

a case, not all the tables need to have sufficient illuminance of more than 350 lx.

Owing to the optimizer operating based on the proposed sensorless illumination control approach, during nonoffice scenarios, to accomplish the requirement of illumination for only user tables, the total power consumption can be decreased down to 418 W, i.e., 28% power saving. The optimization result is illustrated in Fig. 15(a) with all the 12 tables each having 350 lx or above. As previously mentioned, the light power is saved by concentrating on the illumination for the user tables, not the whole office space.

For the other scenario when only two administration staff members work during nonoffice hours, the total power consumption is further decreased down to 196 W, i.e., 66% power saving. This saving is achieved by taking the occupancy status of the users at their tables into the illumination control. It should be noted again that this energy saving can be attained without regular use of light sensors. By using only occupancy sensors and neural networks to represent the nonlinear MIMO system, the optimizer can effectively reduce the lighting power consumption. As illustrated in Fig. 15(b), the two tables, number 2 and number 7, with administration staff working during nonoffice hours have sufficient illuminance of 350 lx as their preferences.

The distinguished merits of the sensorless illumination control presented are that not only can it be performed with 100% automation but also it requires less use of light sensors and, thus, low installation cost and low maintenance cost. Given the LED-lighting system already installed, after placing the user tables inside the office and using light sensors only one time for autoconfiguration, the proposed approach can significantly improve the lighting power saving automatically while satisfying user comfort. During regular real-time control process, the light sensors are not used. This is because the model of the lighting system as controlled plant that has been already generated and stored inside the neural network is used instead to evaluate the outputs as illuminance at user tables.

## VI. Conclusion

In this paper, a sensorless illumination control approach of a networked LED-lighting system using a feedforward neural network has been presented. The approach has shown its effectiveness in tackling the nonlinearity characteristics of the networked LED-lighting system in the office test bed. With the merits of low cost, ease of installation, flexibility, high accuracy, and fast response, it proves to be a promising candidate for the control of the future smart and energy-efficient networked LED-lighting system. Experimental results have been shown to validate the guidelines on how to configure the neural network as well as the energy saving functionality.

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