LIGHTING OPTIMISATION CONTROL OF FLUO/LED SYSTEMS USING NEURAL NETWORK AND MATHEMATICAL MODEL

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ABSTRACT

This article proposes a comparison of different approaches in the lighting optimization process. Beginning with the dual Fluo/LED luminaires, a neural network model is designed to represent the relationship between dimming levels of luminaires and illumination. A similar model is built with a mathematical approach and the obtained results from all these models are compared with DIALux simulation. The proposed models, implemented in a specific room, show significant energy savings according to users preference illumination. The error generated by the models is low compared to the experimental one. The proposed approach is easy to implement in a microcontroller system and is applicable in all interior building.

Keywords: Illumination, Mathematical model, Neural network model, Dimming level, Energy savings

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1. INTRODUCTION

The increase of population is in phase with energy demand. In building, lighting is energy intensive since the energy demand for lighting represents a percentage of 25-35% of the total energy consumption of a building [1]. In Africa, this percentage is larger, about 56% [2]. Such statistics invites us to revisit our consumption patterns or, to rethink the way in which buildings, schools and homes are built. Clearly, a novel mindset on our daily habits in consuming energy should be defined.

Various studies about energy savings have been performed. In [3,4], a simple analysis method is used to evaluate the potential energy savings associated with electrical lighting when it is combined with daylight use. A fuzzy controller was developed in [5] to maintain the lighting illuminance level suitable for robotic manipulation in specific environments. The

same approach was developed in [6], where a fuzzy controller was designed to save lighting energy based on user displacements. In [7], the authors have implemented neural networks to find an optimal position of some luminaires. In [8], lighting control has been modeled as a linear programming problem to accomplish energy efficiency and satisfy occupants' lighting preferences. In [9], a feed-forward neural network model was proposed to describe the relationship between the dimming level of LED luminaires and the illumination on a table without using simulation software. The actuation command to the luminaires was generated by a feed forward neural network control strategy. Some researchers in [10], use simulation software to carry out the lighting configuration in the test room to establish the relationship between lights and table illuminance. However, to the best of our knowledge, there is no work in the literature taking into account the mathematical model relationship between illumination and dimming level of luminaire compared to other methods such as software simulation and neural network model.

In this article, a comparison of different approach in lighting optimization process is proposed. This study considers two different models built mathematically and with a trained neural network, in other to show a relevant reduction in percentage of dimming level of the luminaires. The article is organized as follows: in section 2, the test room in initial form with fluorescent luminaire and final form with LED luminaire is presented, followed by a mathematical model and neural network model. Also, implementations of the proposed optimization method are provided. Section 3 presents a case study where the methods explained in the previous section are implemented to have the desired levels of illumination. The lighting optimization solution is shown in section 4 while conclusions are drawn in section 5.

2. METHODOLOGY

2.1. Fluo/LED lighting test room

The test room is an office room with dimensions of 5.5 x 4.5 x 2.8 m. The fluorescent luminaire installed have the characteristics shows in Table 1. The Fluo test room and the visual arrangement of the luminaires insides the office room are shown respectively in Figure 1a and Figure 1b.

Table 1 Fluorescent luminaire TBS 165 G 4xTL5-14W HFS C6 specifications.

Visual form
Light Output Ratio	0.70
Total luminaire power	61W
Total lamp flux	4800lm
Luminous flux	3360lm
Technology	FLUO
Manufacturer code	TBS 165

Figure 1: (a) Fluo test room. (b) Visual form of the office and arrangement of the luminaires inside the room.

The objective is to design the relationship between the dimming level of the luminaire and the illuminance. In the installed room, we note that the luminaire is fluorescent technologies and to have a better result we will choose a LED luminaire with are more interesting because of their low power consumption and the fact that there are easily dimmable.

The LED luminaire RC480 W60L60 PCV 1x LED35S/840 AC-MLO of constructor PHILIPS are chosen for experimentation. Their specifications are shown in Table 2, while Figure 2 shows its image on the market. These luminaires are DALI controlled. The Digital Addressable Lighting Interface (DALI) is a standardized protocol (IEC 62386) for digital communication between lighting fixtures being addressed individually [11]. All the LED luminaire used are dimmable and can be controlled by a central controlling computer. The dimming level of a luminaire is proportional to its power consumption. The implantation principle of the luminaire in an office room is the same as in Figure 1b.

Table 2 LED Luminaire specifications.

Light Output Ratio	1.00
Total luminaire power	30W
Total luminaire flux	3500lm
Technology	LED
Dimmable	DALI
Manufacturer code	RC 480

Figure 2 LED luminaire RC480 W60L60 PCV 1x LED35S/840 AC-MLO.

2.2. Model formulation

2.2.1. Mathematical problem formulation

There are two main characteristics in an interior lighting namely illuminance and uniformity of the lighting. Both characteristics are normalized using EN 12464 standard [12] henceforth, turns all optimization efforts to lie within the specifications of the corresponding norm. It is worth to recall that our goal is to minimize energy consumption by reducing the dimming level of the luminaires in an interior building. Based on the superposition theory in physics, the illuminance at a specific point of the work plane level (E_i), is equal to the contribution of each luminaire on that measurement point (ω_{ij}) and the corresponding dimming level of that luminaire (α_j) [13, 14, 15, 16]. Representing the illuminance on each measurement point, the dimming of the luminaires also as a vector (α) and the contribution of each luminaire to each measurement point as a matrix (ω), the model can be formulated as shown below :

$$E = \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_M \end{bmatrix} = \begin{bmatrix} \omega_{11} & \cdots & \omega_{1N} \\ \vdots & \ddots & \vdots \\ \omega_{M1} & \cdots & \omega_{MN} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} = \omega \times \alpha \quad (1)$$

We can also rewrite equation 1 as follow :

$$E_i = \sum_{j=1}^N \alpha_j \omega_{ij} \quad (2)$$

Where N is the number of luminaire and i depend on the number of measurements points M.

The mean illuminance, according to equation (2) is :

$$E_m = \frac{\sum_{i=1}^M E_i}{M} = \frac{\sum_{i=1}^M \sum_{j=1}^N \alpha_j \omega_{ij}}{M} \quad (3)$$

To find the contribution of each luminaire, a simulation tool is used, but another method was to used a luxmeter at different choice point [13]. The luminaire needs to be already installed when the second method is used. To have the dimming level, we can modify equation 1 as :

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \omega_{11} & \cdots & \omega_{1m} \\ \vdots & \ddots & \vdots \\ \omega_{n1} & \cdots & \omega_{nm} \end{bmatrix}^{-1} \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_n \end{bmatrix} = \omega^{-1} \times E \quad (4)$$

Computing the pseudo matrix ω^{-1} , we can rewrite equation 4 as :

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} c_{11} & \cdots & c_{1N} \\ \vdots & \ddots & \vdots \\ c_{1M} & \cdots & c_{NM} \end{bmatrix} \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_N \end{bmatrix} = c \times E \quad (5)$$

Where $c = \omega^{-1}$ and $0 \leq \alpha \leq 1$

Equation 5 represents the mathematical representation of the dimming level of the luminaire in function of illuminance E.

The uniformity g_0 is defined as :

$$g_0 = \frac{E_{min}}{E_m} \quad (6)$$

Where E_{min} is the minimum value of illumination.

2.2.2. Neural Network model

Artificial neural networks (ANN) are computing systems that are inspired by, the biological neural networks that constitute animal brains. Theses types of systems "learn" to perform

tasks by considering examples, generally without being programmed with any task-specific rules. Figure 3 shows the principle/specification of our model.

Figure 3 ANN model principle.

There are many algorithms (gradient descent, quasi-Newton method, Levenberg-Marquardt, just to name few) used to design a neural network system according to the dimension of train data. In our model, we have many neural networks to train with just a few thousands of instances and a few hundreds of parameters, the best choice might be the Levenberg-Marquardt algorithm.

The Levenberg-Marquardt algorithm is a method tailored for functions of the type sum-of-squared-error. That makes it to be very fast when training neural networks measured on that kind of errors. The Levenberg-Marquardt algorithm, also known as the damped least-squares method, has been designed to work specifically with loss functions which take the form of a sum of squared errors. It works without computing the exact Hessian matrix. Instead, it works with the gradient vector and the Jacobian matrix. [17]

Figure 4 represents a state diagram for the training process of an artificial neural network with the Levenberg-Marquardt algorithm. The first step is to calculate the loss, the gradient and the Hessian approximation. Then the damping parameter is adjusted so as to reduce the loss at each iteration.

Figure 4 State diagram for the training process of a neural network with the Levenberg-Marquardt algorithm.

3. IMPLEMENTATION OF THE METHODOLOGY

3.1. Office simulation

DIALux [18] which is a simulation tool that is used for electric lighting design practice and energy research is used for lighting simulation and the illumination and uniformity are fixed by the norm 12464 [12]. In these case, the recommend plage of variation of illumination is around $E_m = 300lx$ and $E_m = 500lx$ and uniformity will be up to $g_0 = 0.6$. The Light loss factor is choice 0.8 and the Height of working plane around 0.800 m. Figure 5 shows the illumination isolines without specific optimization and the result obtain give $E_m = 542lx$ and $g_0 = 0.669$.

Figure 5 Illumination isoline of the office.

3.2. Optimization procedure using mathematical model

The first step is to define the quantity of point of the table of illuminance and then find the corresponding illuminance using a luxmeter integrated into a DIALux software. Table 4 gives the parameter used in our modelization. The mathematical formulation of the proposed model which is adapted to the arrangement of the above mentioned office room is presented in equation 6.

$$\alpha = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \end{bmatrix} = c \times E = \begin{bmatrix} c_{11} & \cdots & c_{631} \\ \vdots & \ddots & \vdots \\ c_{16} & \cdots & c_{636} \end{bmatrix} \begin{bmatrix} E_1 \\ E_2 \\ \vdots \\ E_{63} \end{bmatrix} \quad (6)$$

With $0 \leq \alpha \leq 1$

Table 4 Model parameter

Number of luminaires (M)	6
Dimming level number	6
Number of measurement points in x axis	9
Number of measurement points in y axis	6
Total Number of measurement points (N)	63

The office room is divided into 63 zones representing by a measured point « E_i ». The repartition of the measured illuminance point is shown in Figure 6.

E1	E2	E3	E4	E5	E6	E7	E8	E9
E10	E11	E12	E13	E14	E15	E16	E17	E18
E19	E20	E21	E22	E23	E24	E25	E26	E27
E28	E29	E30	E31	E32	E33	E34	E35	E36
E37	E38	E39	E40	E41	E42	E43	E44	E45
E46	E47	E48	E49	E50	E51	E52	E53	E54
E55	E56	E57	E58	E59	E60	E61	E62	E63

Figure 6 Table of illuminance

3.3. Optimization procedure using neural network model

A Two-layer feed-forward neural network, developed in Matlab 2014a [19], is used for mapping between a data set of numeric inputs, dimming levels of 6 luminaires and a set of numeric targets, the corresponding illuminance of 63 points given the dimming setting. Thus, the network is with 63 inputs and 6 outputs, shown in Figure 7.

Figure 7 The two-layer feed-forward network.

After defining the input and output of our neural network model, the design process can be done. The first step is to collect the data. In this phase, we use about a hundred random set of input data. These samples points are obtained with DIALux simulation. The dimming level of the luminaire is taken between 50% and 100% and as parameter of the hidden layer, we use a hyperbolic tangent sigmoid transfer function.

The second step is the division of data. With these settings, the input vectors and target vectors will be randomly divided into three sets as follows:

- 70% will be used for training.
- 15% will be used to validate that the network is generalizing and to stop training before overfitting.
- The last 15% will be used as a completely independent test of network generalization.

The third step is the train of the network. The training process requires a set of examples of proper network behavior – network inputs c and target outputs t . The process of training a neural network involves tuning the values of the weights W and biases b of the network to optimize network performance. The performance function for feedforward networks is mean

square error (MSE) – the average squared error between the network outputs α and the target outputs t . The curve of the calculated MSE during the training process is shown in Figure 8. The MSE is defined in equation 7.

$$MSE = \frac{1}{N} \sum_{i=1}^N (t_i - \alpha_i)^2 \quad (7)$$

The last step is to create and initialize the network. A two-layer feed-forward neural network with M neurons in the hidden layer is created. The weights and biases of the network are also initialized. The regression of the network is shown in Figure 9.

Figure 8 The best validation performance of the trained network

Figure 9 The regression result of the trained network.

4. RESULTS AND DISCUSSIONS

The simulation of the lighting levels is carried out in DIALux. The different models designed allow us to conduct our experiment. Since the initial value of the overall illumination of the part is $E_m = 542\text{lx}$, users lighting preferences are set to have the corresponding coefficients of variation for each of the implemented models. These preferences are chosen in the range from 300lx to 500lx , accepted by the standard EN12464 and tested on the models developed in the implementation part of the methodology. The isolines curves obtained for each case are shown in Figure 10. For each set illumination value, the illumination table is obtained by subtracting for each level of illumination E_{ij} the value to be removed from the initial illumination for having the desired illumination. Thus, for the reference 500lx for example, we must subtract from each of the 63 measuring points the excess amount of illumination ie about 42lx . The same procedure is applied for the different other references. The introduction of these illuminance values in our models gives the coefficients of variation presented in Table 5. We can already see that the dimming level values obtained by each model are close. The actual illumination values given by these coefficients of variation calculated by our models are then verified by DIALux simulation. The values obtained by simulation are recorded in Table 6. By calculating the error between the different models, it is found that it is very small, a few lux more or less than the reference value. We can therefore conclude that the values that the users would set using the models designed will be very close to reality and therefore the models can be used in practice. Moreover, we see that the results of the mathematical model are closer to those obtained by simulation than those of the neural network model. This can be explained by the not very large number of points used to train the network.

The ultimate objective sought is the reduction of energy consumption, Table 7 presents for the desired illumination references and the range of variation of this economy in power consumed which ranges from about 8% to 45%. It can therefore be concluded that according to users needs, energy savings can be very high.

These two models are interesting because they can be easily implemented in a microcontroller and therefore with a graphical interface on a computer. The user following these needs can set levels of illumination as he wishes. Given that these levels of illumination will be lower than the level for which the illumination is maximum, a reduction in the consumption of electrical energy will necessarily be achieved. The only constraint of the system is the knowledge beforehand of the different lighting points when all the levels of illumination are set to 100% for the mathematical model and to have a number of test points for the training of the system by neural network.

Table 5 User preference illumination and corresponding dimming level of luminaires

	MATHEMATICAL MODEL					NEURAL NETWORK MODEL				
Users preference illuminance (lux)	300	350	400	425	500	300	350	400	425	500
α_1	0.44	0.55	0.67	0.72	0.89	0.34	0.42	0.52	0.59	0.86
α_2	0.44	0.56	0.67	0.72	0.89	0.45	0.56	0.68	0.73	0.90
α_3	0.78	0.83	0.88	0.90	0.98	0.69	0.77	0.85	0.89	0.98
α_4	0.78	0.83	0.88	0.90	0.98	0.96	1	1	1	1
α_5	0.44	0.55	0.67	0.72	0.89	0.45	0.52	0.60	0.87	0.87
α_6	0.45	0.56	0.67	0.72	0.89	0.48	0.60	0.72	0.91	0.91

(a)

(b)

(c)

(d)

(e)

(f)

(g)

(h)

Figure 10 Isoline under user preference illuminance (a) target of 500lx with Neural Network model (b) target of 500lx with Mathematical model (c) target of 425lx with Neural Network model (d) target of 425lx with Mathematical model (e) target of 400lx with Neural Network model (f) target of 400lx with Mathematical model (g) target of 350lx with Neural Network model (h) target of 350lx with Mathematical model (i) target of 300lx with Neural Network model (j) target of 300lx with Mathematical model.

Table 6 Parameter value after optimization and corresponding light simulation

	MATHEMATICAL MODEL					NEURAL NETWORK MODEL				
Users preference of illuminance (lux)	300	350	400	425	500	300	350	400	425	500
Experiments values of illuminance (lux)	306	355	404	426	500	311	356	400	424	500
Gap	6	5	4	1	0	11	6	0	-1	0

Table 7 Optimal lighting power consumption

Users' preference (lux)	Approximate Percentage of energy saved
300	45%
350	36%
400	26%
425	22%
500	8%

5. CONCLUSION

Starting from the problem of reducing the consumption of lighting in buildings, this article highlights a comparison of different approaches in lighting optimization process. Beginning with the dual Fluo/LED luminaires, a neural network model is designed to represent the complex relationship between the coefficient of variation of luminaires and illumination. A similar model is built with a mathematical approach and the result given by all these models are compared with DIALux simulation with satisfactory results. The evaluation of error shows that the mathematical model is better than the neural network model but the two allow us to optimize lighting consumption in a specific building. The proposed model, implemented in a specific room, show significant energy savings according to user preference illumination. The gap generated by the models is low compared to the experimental one. The proposed

approach is easy to implement in a microcontroller system and is applicable in all interior building.

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