Determination of Illuminance Level Using ANN Model

Vedat Topuz[1], Selcuk Atis[2], Sureyya Kocabey[3], and Mehmet Tektas[4]

[1, 2, 4] Marmara University, Vocational School of Technical Sciences,
34722 Istanbul, Turkey
[3] Marmara University, Technical Education Faculty,
34722 Istanbul, Turkey
{vtopuz,satis,sureyyakocabey,tektas}@marmara.edu.tr

Abstract. In this study, an illuminance determining method, using an artificial neural network (ANN) model, has been designed. The model was realized as an alternative to existing simulation programs to determine the illuminance of a working place. In the model, maintenance factor (MF), working plane (WP), suspension height (SH) of luminaries were selected as input parameters. average illuminance (Eav), minimum illuminance (Emin) and maximum illuminance (Emax) of working plane were selected as output parameters that are the effective parameters in establishment and maintenance of luminance. Comparison between the real time measurements, illuminance simulation program (ISP) and ANN model results has shown that designed ANN model is satisfied.

Keywords: Illuminance Level, ANN Model.

1 Introduction

Illumination affects the mood and motivation level of people. Its systemic effect on mood has been expressed through experimental studies [1]. In this context, many studies have been made to research suitable illumination conditions, particularly for working places. While some of these studies have used classical model approaches, the others have used artificial intelligence modeling approaches [2-10].

One of the most important criteria implemented in these studies is to ensure that the illuminance must be in desired level depending on the tasks in working places. For this aim, illuminance level can be determined either by real time measurements or illumination simulator programs (ISP).

An alternative illuminance determining method using an ANN model has been designed in this study. The ANN model has been implemented by ANN simulator developed by research team. Illuminance data related to a working plane has been obtained by designed ANN model as well as the real time measurements and a commercial ISP. The obtained illuminance results have been compared with real time measurements both for ISP results and ANN model results.

In the following sections, mathematical and ANN modeling of illuminance have been outlined and result of the studies have been explained.

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2 Mathematical Model

Illuminance (E) is defined in SI system as follows

$$E = \frac{d\Phi}{dA} \tag{1}$$

where, E is illuminance (lux), A is area receiving the flux (m2), Φ is luminous flux (lumen). It can be treated as a vector quantity. It can be calculated as at a specific point (point-by-point method) illuminance or in an average uniform horizontal illuminance (lumen method) across the working plane.Consider a point source illuminating a surface at an angle θ to the normal as in Fig. 1

$$E_p = \frac{I_\theta.Cos\theta}{r^2} = E_{max}.\cos\theta \tag{2}$$

where Ep is illuminance value at point P (lux) Emax is the maximum illuminance that the source could produce at point P, when θ=00 (lux), Iθ is the luminous intensity of the source in the direction of the illuminated point (Iθ =dΦ/dω) (candela [cd]), r is distance of the light source to the object (meter), θ is angle of light source as to normal.

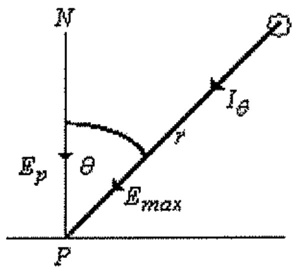

Fig. 1. A point source illuminating a surface at an angle θ to the normal

Specifications often require the lighting professional to know or design for average uniform horizontal illuminance. To do this with the Inverse Square Law for a large number of points would be both tedious and expensive. In addition, a second set of calculations would have to be made to determine the interreflected components. The lumen method is used to calculate the number of luminaries required for a uniform or general lighting layout. The lumen method calculates the average, uniform, horizontal maintained illuminance throughout a room. The average surface illuminance is calculated from the following equation

$$E_{av} = \frac{N \times \Phi_{in} \times n \times UF \times MF}{A} \tag{3}$$

where Eav is average illuminance(lux), N is the number of luminaries, Φin is initial luminous flux of the light source (lumen), n is number of lamps per luminaire, UF is utilisation factor. UF is the ratio of the total flux received by surface to the total lamp flux of the installation. It depends on the dimensions of room, the ceiling colour, the wall colour and the floor colour, A is area to be illuminated (m2), MF is the maintenance factor [11-12].

3 ANN Model

There are multitudes of different types of ANN models. Some of the more popular of them include the multilayer perceptron, which is generally trained with the back-propagation algorithm. Realized three layers perceptrons is shown in Fig.2.

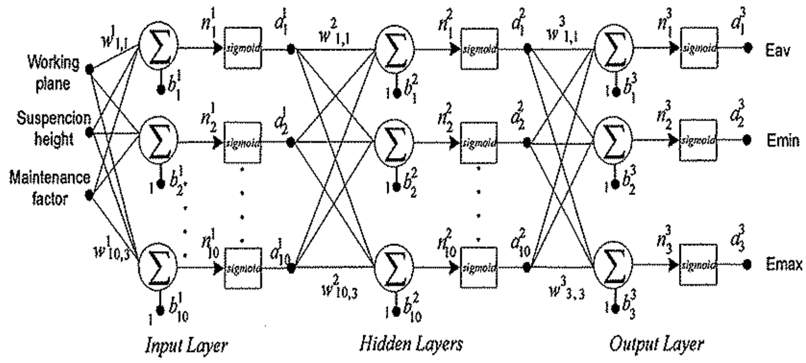

Fig. 2. Three-layer feedforward network

ANN must be trained before it becomes useful.. The training method tries to minimize the current errors for all processing elements. The training continues until the ANN reaches user defined performance level. Test is critical to insure that the network has not simply memorized a given set of data, but has learned the general patterns involved within an application. For train to multilayer perceptron with backpropagation, the first step is propagating the inputs towards the forward layers through the network. For a three-layer feedforward network, training process is initiated from the input layer [13]:

$$\begin{aligned} &a^0 = p \\ &a^{m+1} = f^{m+1}(W^{m+1}a^m + b^{m+1}), \qquad m = 0,1,2 \\ &a = a^3 \end{aligned} \tag{4}$$

where a output vector, p is input vector, f(.) is the activation function, W is weighting coefficients matrices, b is bias factor vector and m is the layer index.

Second step is propagating the sensibilities (s) from the last layer to the first layer through the network: s^3, s^2, s^1. The error calculated for output neurons is propagated to the backward through the weighting factors of the network. It can be expressed in matrix form as follows:

$$\begin{aligned} &s^3 = -2\dot{F}^3(n^3)(t-a) \\ &s^m = \dot{F}^m(n^m)(W^{m+1})^T s^{m+1}, \quad \text{for } m = 2,1 \end{aligned} \tag{5}$$

where t is target vector and $\dot{F}^m(n^m)$ is Jacobian matrix. The last step in backpropagation is updating the weighting coefficients. The state of the network always changes in such a way that the output follows the error curve of the network towards down.

$$W^m(k+1) = W^m(k) - \alpha s^m (a^{m-1})^T \quad (6)$$

where α represents the training rate, k represents the epoch number. By the algorithmic approach known as gradient descent algorithm using approximate steepest descent rule, the error is decreased repeatedly.

In this study, ANN designing process involves four steps. These are gathering the data, selecting the ANN architecture, training the network, and testing the network. We gather all the training and testing data from experiment described below. These data sets consist of two part which are inputs (WP, SH, MF) and target (Eav, Emin and Emax). From these experiments 60 of them used as ANN learning data set and 30 of them test data set. The number of layers and the number of processing elements in per layer are important decisions for selecting the ANN architecture. Choosing these parameters to a feedforward backpropagation topology is the art of the ANN designer. There is no quantifiable best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems.The optimal numbers of neurons in the first and second layers have been chosen as 10. Also, the activation function has been chosen as a sigmoid function for all of the layers. Realized ANN model is shown in Fig. 2.

4 Results

The experimental space is a classroom in sizes of 10.33 x 6.98 x 3.72 m at the University of Marmara, Technical Education Faculty. The classroom is illuminated by six without reflector luminaires which have 2x36W T8 fluorescent lamp and each lamp luminous flux is 3350 lumen. The values of wall, ceiling and floor reflectance are respectively 60%, 83% and 33%. In Real time measurement, Lutron LX-1102 luxmeter is used.The experimental measures were made in September at night. Firstly, while luminaires were mounted on ceiling, illuminance measurement was made at 150 points on the working plane in height of 0.5, 0.6, 0.7, 0.8, 0.83 meters. Then, suspension height of luminaire was changed. 0, 0.3, 0.5, 0.6, 0.7, 0.9 meters and every measurements were repeated for each suspension height as shown in Fig. 3.

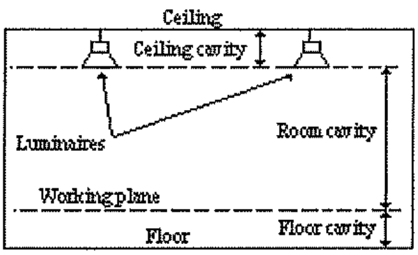

Fig. 3. Working plane height (floor cavity) and luminaries suspension height (ceiling cavity)

According to EN12464-1:2002 standard, the maintenance coefficient of measurement class is determined as 0.81. Besides, by considering the different maintenance conditions of environment, 0.7, 0.6, 0.5, 0.4 maintenance factor coefficients were determined. As you seen in equation (3) maintenance factor (MF) is direct proportional to illuminance (E). For this reason, the Eav, Emin and Emax for 0.7, 0.6, 0.5, 0.4 maintenance coefficients were calculated.

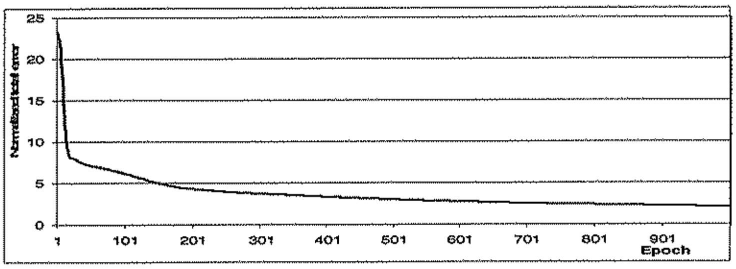

Fig. 4. Variation of the total training error through the one thousand epochs

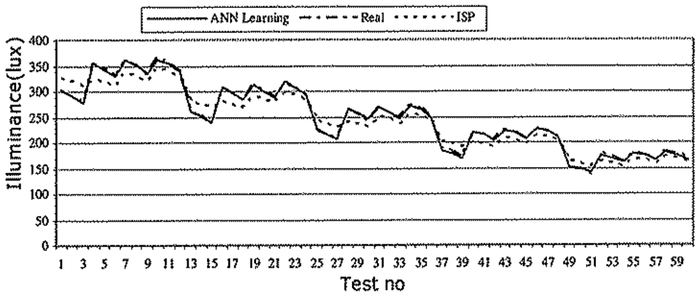

Fig. 5. Results of the learning step; ANN, real and ISP output values of average illuminance

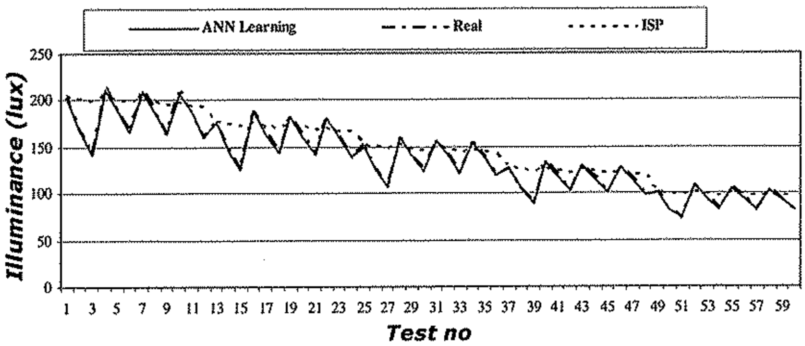

Fig. 6. Results of the learning step; ANN, real and ISP output values of minimum illuminance

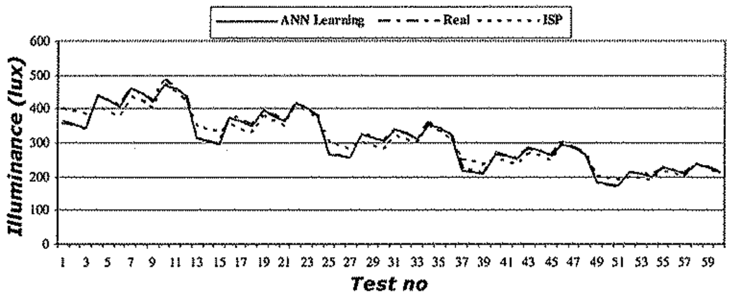

Fig. 7. Results of the learning step; ANN, real and ISP output values of maximum illuminance

The ISP was used to determine whether the model created by making a prediction with ANN could be used as a simulator in prediction of illuminance in the classroom. In the ISP a real time measurements condition was established and Eav, Emin, Emax values were recorded. Then ANN simulator has been trained through the one thousand epochs. The training process has been stopped when the error has become stable. Variation of the total absolute error through the epochs is shown in Figure 4. End of the training step, founded Eav, Emin and Emax values are shown in Fig. 5, 6, 7. Each figure also shows the real measurement values, ANN and ISP output data.

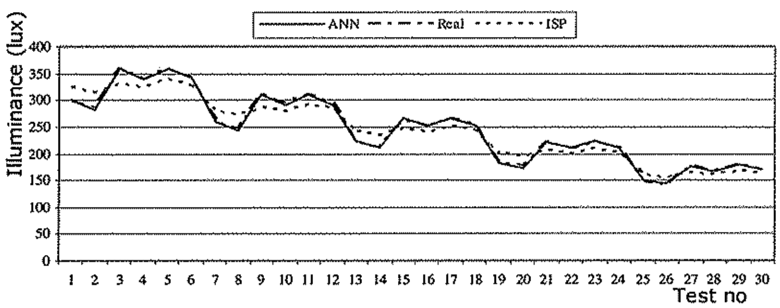

Fig. 8. Results of the testing step; ANN, real and ISP output values of average illuminance

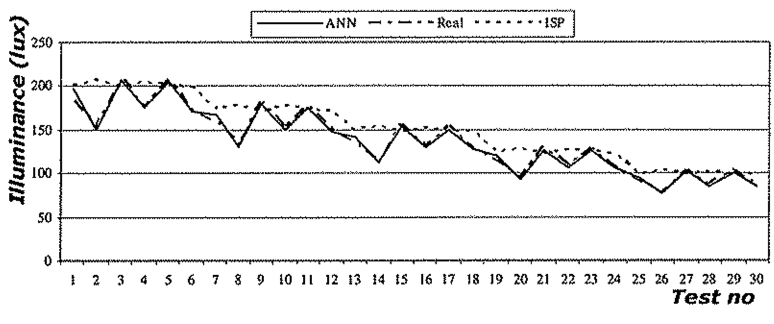

Fig. 9. Results of the testing step; ANN, real and ISP output values of minimum illuminance

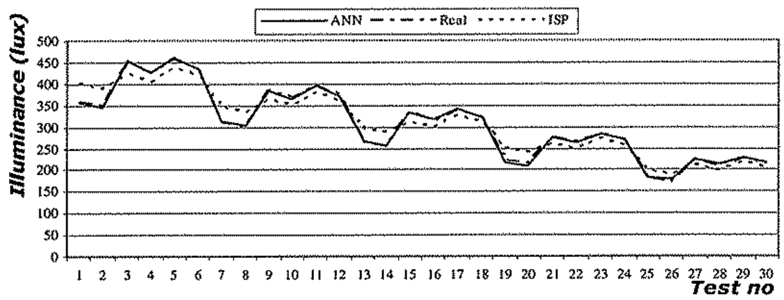

Fig. 10. Results of the testing step; ANN, real and ISP output values of maximum illuminance

After the training step testing step was realized. In the testing step, the data which were not used in learning step were applied to ANN, to prove the performance of realized ANN. model. Also end of the testing step, founded Eav, Emin and Emax values are shown in Fig. 8, 9, 10. Each figure also shows the real measurement values, ANN and ISP output data.

5 Conclusion

In this study, an illuminance determining method using an ANN model has been designed. This model was realized as an alternative to existing ISP to determine the illuminance of a working place.

The root mean square error (RMS) between the real time measurements and ANN model results are shown in Table.1. The RMS errors between the real time measurements and ISP results are also shown in Table.1, depending on both the learning data and test data.

Table 1. RMS error obtained by ANN and ISP

	Eav		Emin		Emax	
	ANN	ISP	ANN	ISP	ANN	ISP
Learning Data	0,21	2,31	0,14	2,51	0,44	2,75
Test Data	0,16	1,61	0,31	1,96	0,25	2,05

Referring to Table 1, Eav error obtained by ANN model has been reduced comparing to error obtained by ISP, both learning and test step. In the same manner, Emin and Emax error obtained by ANN model have been reduced comparing to ISP. So, the designed model can be used to develop an illumination control system reducing the operation and maintenance cost. Such a control system study will be planned in the future.

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