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Developing neural networks to investigate relationships between lighting quality and lighting glare indices

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Abstract

The present work compares the ability of the two most used glare indices, the Daylight Glare Probability (DGP) and the International Commission on Illumination (CIE) Glare Index (CGI), using Multiple Correspondence Analysis (MCA) and Artificial Neural Networks (ANN). The research investigates the efficiency of indexes in predictive indoor lighting quality. This study was carried out by analyzing data from a survey administered to ninety students in real design classrooms in the city of Biskra, Algeria. The experiment was conducted using three different lighting indoor conditions: natural and artificial lighting and mixed lighting. The true prediction of the Daylight Glare Probability for the variable Comfortable was 60.60%, and for (CIE) Glare Index the prediction values were equal to 44.60% for the same variable.

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Keywords: Design classrooms; Survey; Multiple Correspondence Analysis; Glare index; Artificial Neural Network.

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1. Introduction

In modern societies, as a result of urbanization and industrialization, people spend more time indoors than ever before. It is estimated that on average people spend more than ninety percent of their time indoors [1, 2]. Indoor comfort, such as thermal and visual comfort, plays accordingly a significant role and has a large impact on the working efficiency and satisfaction. The indoor environments, including university study environments, should, therefore, be studied since their design and configuration does not only influence an individual's perception of work-related tasks but also affects its general emotional-motivational state, well-being, and productivity of users[3,4,5]. The impact of building simulation tools in quantifying issues, such as visual comfort and energy savings, continues to be seen as significant; lighting analysis trends and interest towards computationally generated models simulations and visualization increased with the availability of powerful and accurate software. These can rigorously simulate buildings and urban spaces for thermal, acoustic, lighting conditions there are different tools and methods for glare assessment, but the most used are glare indices including DGP (Daylight Glare Probability), DGI (Daylight Glare Index), UGR (Unified Glare Rating) and CGI (CIE Glare Index).In the present paper, authors describe a comparative analysis between DGP, the most used glare metrics for the prediction of glare in indoor spaces using artificial lighting and CGI the most recommended glare index used to predict glare in spaces illuminates by natural lighting [6].The tow glare index was compared with the real glare experienced by users in the computer design classrooms. The data were collected using survey administrated to ninety students (users of design classroom). The data was analyzed using Multiple Correspondence Analysis (MCA) and Artificial Neural Networks (ANN), in order to determine which of these glare indexes is the most efficient for glare assessment, in the design classroom in highly luminous climate.

2. Methodology

2.1. Case study

The experimentation was carried out in the real computer design classroom at the University of Biskra, which is located in the south EST. of Algeria, and characterized by a specific local luminous climate [7, 8]. The classroom has a quarter of circle chip, with a radius equal to 10.05 m, 3.87 m height. It receives daylight from North-EST facing unilateral windows 3 by 10 m, daylighting is supplemented by electric lighting from ceiling mounted fluorescent fixtures. In the classroom, there are five tables with six workspaces for each one, hence 30 workspaces in total. As illustrated in (Fig. 1).

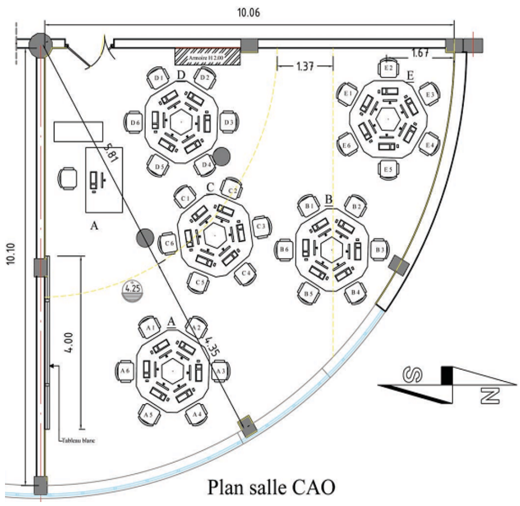

Fig. 1. Plan of the design computer class room

2.2. Processes

In order to assess the glare level in three different lighting class conditions, three different configurations of the design classroom were developed using exclusively: daylighting, electric lighting from the ceiling and the both of them, as illustrated in (Fig. 2).

Fig. 2. The same workplace under three different lighting configurations of class room.

In order to quantify the values of luminance and glare index DGP and CGI, at the eye level of users, a calibrated camera 1200D canon EOS was mounted on a tripod at 1.20 m high, equipped with a circular Fisheye lens Sigma (4.5mm f/2.8 EX DC Circular Fisheye HSM); this type of lens is recommended since it better resembles the human visual field [9, 10] suggests modified human visual field according to the total field of [11].The fisheye HDR photography was analyzed with using Eva glare software for measuring DGI and CGI [12] in the different workplace spaces of a classroom. In the same time, a survey was administrated to ninety students, in order to assess their real discomfort glare during the task to ask the students: design using computer tool. Refer to the literature review seven questions [13, 14] were asked to the students. Seen table 1:

Table 1. A part of questionnaire asked to the students

Question A							
Is there a discomfort caused by the presence of light in your workplace space?							
Yes				No			
Question B							
How do you qualify the general atmosphere created by the light in workplace space?							
Lighting Factors	**Unser's feeling affirmations**						
1- Light level	Very Dark	-2	-1	0	+1	+2	Very Bright
2- Visual comfort	Very boring	-2	-1	0	+1	+2	Very Stimulating
3- Naturality	Very Artificial	-2	-1	0	+1	+2	Very Natural
4- Visual comfort	Very Glaring	-2	-1	0	+1	+2	Very Comfortable
5- Precision	Blurry	-2	-1	0	+1	+2	Precise
	Not defined	-2	-1	0	+1	+2	Well defined
6-Pleasantness	Unpleasant	-2	-1	0	+1	+2	Pleasant

2.3. Statistical and Neural Network analysis

The data collected in the ninety students' workplaces have been analyzed using statistic tool in order to compare the survey results with glare assessment using different glare indexes. Therefore, in the first step a Multiple

Correspondence Analysis was used in order to study the degree the correlation results between the seven variables of the questionnaire to relationships of several ordinal dependent variables.

To determine a reliable prediction DGP and CGI, an ANN model based on Pleasant and Comfortable variables selected in the first MCA study with significant correlation (p-value <0.05) was used. In the ANN modeling process, we divided the data in tow subsets: nearly 35% of the student for constructing the models (training subset) and the remaining 65 % for testing the model (as the validation subset). After evaluating the model, we applied Multiple Layer Perceptron (MLP) networks to determine relevant relationships and to determine which is the best glare index. In terms of reliable prediction performance of the DGP and CGI glare index. With ANN we used a three-layer MLP network with 4 variables (15 nodes) in the input layer, 3 nodes in the middle layer and 8 nodes in the output layer. The hidden layer had 3 neurons, determined as the optimal configuration giving the lowest error in the training and testing sets of data with minimal computing time [15, 16].

3. Results and discussion

3.1. Multiple correspondence analysis

Data collected from (Fig. 3) shows some pitfalls, which may exist when developing Multiple Correspondence Analysis models. Three of the seven variables tested (were not significant), these variables are: Naturality (r 0.20, P-value 0.65), Stimulating ((r 0.15, P-value 0.82), Precise ((r 0.15, P-value 0.82). Overall, we obtained a significant correlation between the remaining variables. In addition, we note that tow variables ‘Comfortable’, ‘Pleasantness ‘(see Fig. 3) show much higher significant correlation than the others, with the p-value less than 0.01 and (r more than 0.85). So these two variables are the most representative of real discomfort sensation of the users.

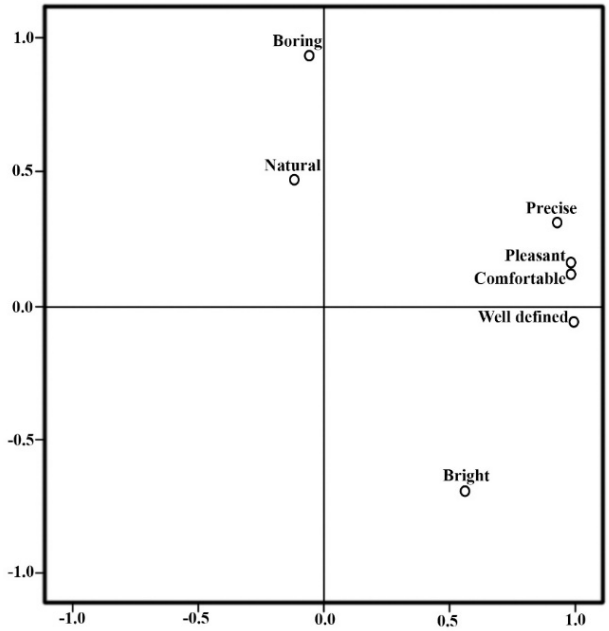

Fig. 3. Multiple correspondence analysis for design using computer.

3.2 Artificial neural network model

As regards the ANN network the architecture that was developed, included fourteen neurons for CGI and twelve neurons for DGP in the hidden layer. For DGP: the overall average of the relative errors are fairly constant across training 40.20%, with a value for Unpleasant/Pleasant equal to 43.10%, and 39.20% for Glaring/Comfortable, a percentage of 46.54 % was reached testing model with a value for Unpleasant /Pleasant equal to 43.10% and 39.20%, Glaring/Comfortable.

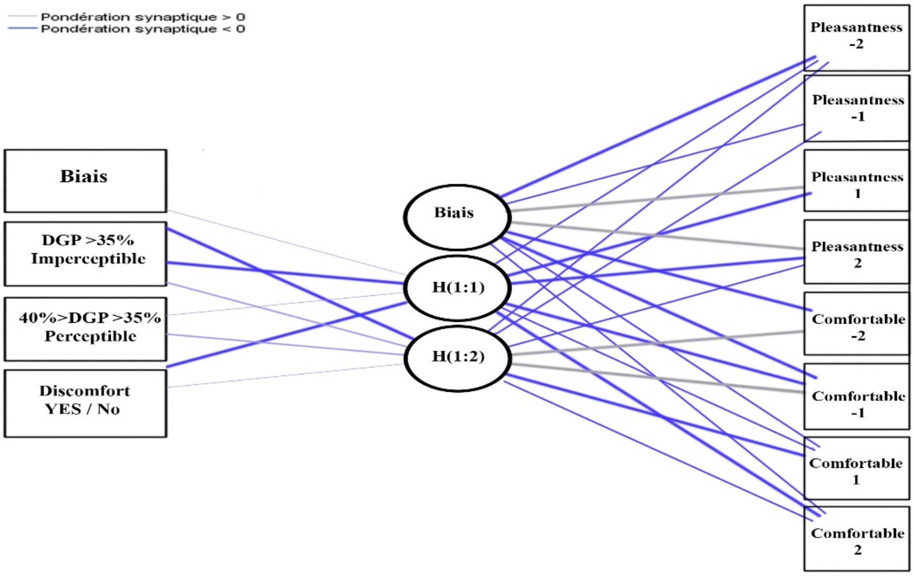

Fig. 4. Multi-layer perceptron network structure for DGP glare

However, we have obtained a different result with the CGI, so the percentage average overall relative error for training model was 65.10 %, with percentages of 55.60 % for Unpleasant /Pleasant, and 69.60 % for variables Glaring/Comfortable, In addition, referred to (see Fig. 4) average overall relative error for Testing model was 50.36 %, with percentages of 43.80 %for Unpleasant /Pleasant, and 56.30 % for variables Glaring/Comfortable. Both ANN model reasonable prediction which gives us some confidence that the model is not overtrained, and that the error in future cases, scored by the network will be close to the error reported in (Tab 2).

Tab 2. Summary training testing (MLP) Model for the DGP and CGI Glare index, model with ninety Students

	DGP index		
Training	Sum of Squares Error		110.032
	Average Overall Relative Error		41.20%
	Relative Error for scale dependents	Unpleasant /Pleasant	43.10%
		Glaring / Comfortable	39.20%
Testing	Sum of Squares Error		46.546
	Average Overall Relative Error		43.20%
	Relative Error for scale dependents	Unpleasant /Pleasant	43.80%
		Glaring / Comfortable	39.50%
	CGI index		
Training	Sum of Squares Error		109.382
	Average Overall Relative Error		65.10%
	Relative Error for scale dependents	Unpleasant /Pleasant	55.60%
		Glaring / Comfortable	69.60%
Testing	Average Overall Relative Error		35.518
	Average Overall Relative Error		50.36%
	Relative Error for scale dependents	Unpleasant /Pleasant	43.80%
		Glaring / Comfortable	56.30%

4. Conclusions

Multi-Layer Perceptron (MLP) and Neural Network Models, that were used to predict which is the closest glare index (DGP, CGI) to the real perception of the students, using glare indicators and survey in the computer design classrooms, under highly luminous climate. The model developed appears to perform reasonably well. Unlike traditional statistical methods, such as quantitative and categorical approach base on simple linear regression and correlation. The Neural Network Models provides the dynamic output as further data (lighting environment, users) is fed to it, while the ANN do not require performing and analyzing sophisticated statistical methods [17].So based on the results from ANN and MLP models developed in the previous sections, the predictive value of the ANN model developed based on DGP is most robust, than the ANN model developed using CGI index, under the local luminous sky conditions in the city of Biskra, the DGP model predicts discomfort glare with a higher probabilities performance assessment of the real glare, with relative error for scale for variables Glaring/Comfortable equal to 39.20 % and percentage of 43.80% for variables Unpleasant/Pleasant. The authors recommend the use of the ANN model developed based on DGP, for the assessment of light quality indoor spaces under the local luminous climate. Finally, these results on the use of ANN for population analyses open new fields for their applications to architecture specifically for the assessment of the comfort and well-being indoors spaces.

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