Building and Environment 44 (2009) 1751–1757

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Artificial neural networks to predict daylight illuminance in office buildings

Tuğçe Kazanasmaz*, Murat Günaydin, Selcen Binol

Department of Architecture, Izmir Institute of Technology, Gulbahce Kampus, Urla, Izmir 35430, Turkey

ARTICLE INFO

Article history:
Received 24 September 2008
Received in revised form
20 November 2008
Accepted 21 November 2008

Keywords:
Modeling
Building
Daylighting
Artificial neural networks

ABSTRACT

A prediction model was developed to determine daylight illuminance for the office buildings by using artificial neural networks (ANNs). Illuminance data were collected for 3 months by applying a field measuring method. Utilizing weather data from the local weather station and building parameters from the architectural drawings, a three-layer ANN model of feed-forward type (with one output node) was constructed. Two variables for time (date, hour), 5 weather determinants (outdoor temperature, solar radiation, humidity, UV index and UV dose) and 6 building parameters (distance to windows, number of windows, orientation of rooms, floor identification, room dimensions and point identification) were considered as input variables. Illuminance was used as the output variable. In ANN modeling, the data were divided into two groups; the first 80 of these data sets were used for training and the remaining 20 for testing. Microsoft Excel Solver used simplex optimization method for the optimal weights. The model's performance was then measured by using the illuminance percentage error. As the prediction power of the model was almost 98%, predicted data had close matches with the measured data. The prediction results were successful within the sample measurements. The model was then subjected to sensitivity analysis to determine the relationship between the input and output variables. NeuroSolutions Software by NeuroDimensions Inc., was adopted for this application. Researchers and designers will benefit from this model in daylighting performance assessment of buildings by making predictions and comparisons and in the daylighting design process by determining illuminance.

1. Introduction

Daylight is a primary light source for the office buildings. It should provide a comfortable and an efficient working environment mostly during daytime. Appropriate daylighting supported (supplemented) by artificial lighting systems satisfy the visual and psychological comfort conditions. In that case, its presence enhances human visual response, increases motivation and leads to high user performance and worker productivity [1–4]. In addition, properly designed daylighting reduces energy consumption and balances heating and cooling loads of buildings as well as supports human health and activities [5–7].

Adequate indoor illuminance is then a basic factor in daylight design and research for buildings [8]. It is clear in literature that daylighting performance research for lighting control systems based on indoor daylight illuminance and work plane illuminance [2,9,10] and daylight design in buildings based on distribution of daylight levels [11]. It is also necessary to estimate the amount of daylight and its distribution inside the buildings in order to evaluate visual comfort and energy efficiency [12]. To design good day-lit buildings, several design tools have been offered (guidelines, manual calculation formulae, computer software programs and models) to determine the illuminance of daylight at certain points [7].

Since a large variety of daylighting design have been applied over the years, prediction and determination of illuminance levels are necessary as a key stage in daylight design process as well as in daylighting performance assessment of buildings. In view of these recent research and knowledge, an investigation was constructed for the office building of the Faculty of Architecture in Izmir Institute of Technology (İYTE) to predict daylight illuminance in offices.

Several methods have been used to estimate daylight illuminance levels over the years. Three techniques basically were introduced including scale model studies, computer simulations and analytical formula [11,13,14]. Designers benefit from scale model method both to predict and evaluate the appearance of interior and to measure illuminance. Model ratios change from 1:8 to 1:32 and a large variety of finishing materials are applied to represent real ones to cover interior surfaces in buildings [11,13]. Since physical models require close matches of both geometry and building details, certain guidelines should be followed. All building surfaces must be constructed with correct reflectance. All

* Corresponding author. Tel.: +90 232 7507063; fax: +90 232 7507012.
E-mail addresses: tugcekazanasmaz@iyte.edu.tr (T. Kazanasmaz), muratgunaydin@iyte.edu.tr (M. Günaydin), selcenbinol@hotmail.com (S. Binol).

0360-1323/$ – see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.buildenv.2008.11.012

window details including glazing transmittance should be applied as much as possible. The scale and measurement locations should be chosen correctly. All unwanted light penetration should be avoided [11,15]. However, several studies showed that discrepancies would occur between buildings and their scale models related to these guidelines mentioned above. As a result of this, the physical model overvalued the daylighting performance of the building [10]. This example declares a doubt about how the models are reliable.

Computer lighting simulations, on the other hand, have been commonly used for illuminance calculations and interior visualization. Such programs are Radiance, Superlite, Adeline, Beem, LightCAD, Luxicon and Lumen Micro [11,16]. Although a high number of computer-based tools have been applied for daylighting design and studies, they vary according to two basic illuminance calculation methods which are radiosity and ray-tracing techniques. Radiosity algorithm based on modeling simple surfaces including perfectly diffused elements. While ray-tracing technique dealt with complex surfaces with specular reflections [16]. However, users still try to imagine the error range to be expected while using these programs [17]. Reinhart and Fitz identified weaknesses of existing daylighting design software programs by surveying occupants' satisfaction [18].

Analytical formula is another method, even a traditional one, used to estimate daylight in buildings. Due to the variation in sky conditions, daylight factor which is expressed as the ratio of interior horizontal illuminance to exterior horizontal illuminance is a very known and simple calculation formula. Such parameters included in the side lighting calculation are window dimensions, distance from window wall, glass area and wall reflectance. Others for top lighting calculation are such as sky factors, coefficient of utilization, glass area and floor area [14]. Lumen method, on the other hand, offered by the Illuminating Engineering Society of North America includes a detailed calculation process with the inclusion of sky contributed and ground contributed coefficient of utilizations [19]. Detailed information, calculation examples and related studies are available in literature [13,14,19].

In this study, however, an intelligence method, artificial neural network (ANN) was developed as a tool to predict daylight illuminance in office buildings. This is a recently developed alternative technique in the modeling of several research processes for various fields. Akkurt et al., in the field of mechanical engineering, applied ANNs to predict compressive strength of cement mortar. The model estimated favorable results within their sample range [20]. Sofuoğlu used ANN in the modeling of prevalence of building-related symptoms in office buildings. The model resulted in a high prediction performance when compared with those obtained by regression analysis [21]. In another example, Tayfur, in the field of civil engineering, employed ANN to predict longitudinal dispersion coefficient in natural streams. The model resulted satisfactorily since predicted values were in high agreement with the measured data [22]. Günaydin and Doğan estimated the cost of the structural systems of reinforced concrete structural skeleton buildings in the early architectural design phase by an ANN model in the field of construction management [23]. Another study in the field of energy conservation, solar radiation modeling was constructed for different climates and the ANN model was satisfactorily applied to predict daily global radiation using sunshine duration [24]. Despite these studies in engineering fields, there was no real evidence in literature for ANN models' recent use in the field of architecture.

The objective of this study is to develop ANN model to predict the daylight illuminance in office buildings and to offer a new methodology as an alternative to the existing illuminance calculation and prediction techniques. The performance of the model was quantitatively investigated by measurements in order to explore its applicability in architecture.

2. Overview of artificial neural networks

The inspiration of neural networks comes from basic functioning mechanisms of human brain. The network gathers information through a learning process. The inter-neuron connection strengths known as synaptic weights are used to store the knowledge [25]. This adaptive learning ability of neural networks gives an advantage in solving complex problems whose analytic or numerical solutions are difficult to obtain [26]. Estimating daylight illuminance is one of those problems.

The problem presented in this paper is based on optimum design and prediction utilizing a feed-forward neural network architecture and back-propagation learning technique. An ANN

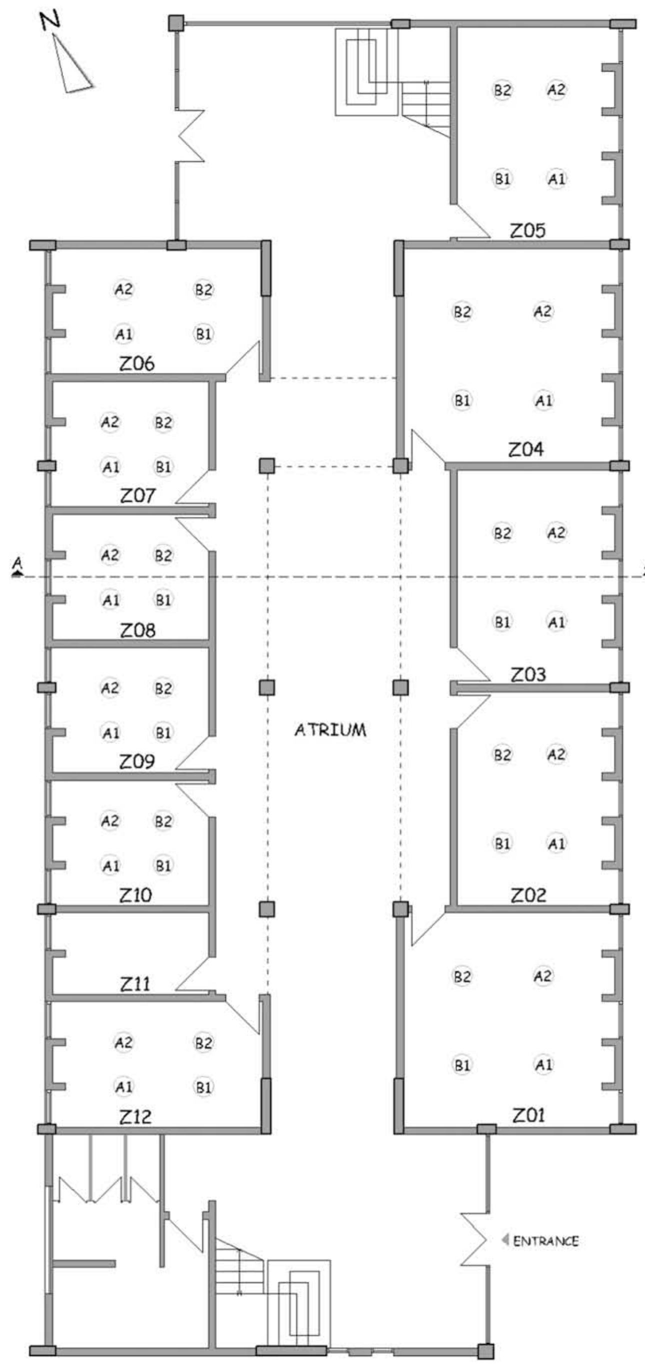

Fig. 1. A schematical drawing of ground floor plan displaying illuminance measurement points.

software as well as a spreadsheet was used for modeling. The software adopted in this application was NeuroSolutions by NeuroDimensions Inc. [27]. Hegazy and Ayed's [28] spreadsheet was also modified and used for comparison.

The model has been developed in three phases: the modeling phase, the training phase, and the testing phase. The modeling phase involves the analysis of data, the identification of illumination estimation parameters and the selection of the network architecture and of the internal rules. The training phase requires the preparation of data and the adoption of learning algorithm for the training. The testing phase evaluates the prediction accuracy of the model. The actual illumination levels are compared with the estimated ones and the illumination percentage error is then calculated.

3. Description of the physical facility

The subject building is associated with the Faculty of Architecture of Izmir Institute of Technology (İYTE) in Izmir, Turkey. This office building is situated in the northern part of the campus on a hilly site (latitude 38°19′; longitude 26°37′). Offices are located in a 2-story building (Block C) which is approximately 1072 m^2 as the schematical expression of the basic layout is shown in Fig. 1. The story height for all rooms is 3.50 m. The surface area of a typical window in a room is almost 2.00 m^2. All windows are identical for all rooms; however, there were 10 rooms having three typical windows, another 10 rooms having two windows and only 4 rooms having one typical window. So, there are a total of 24 rooms occupied by instructors and professors. Each floor contains 12 rooms of which 7 are facing west, 5 are facing east and an atrium located in the centre of the building with a large skylight (17.00×3.50 m). A circulation corridor connects all rooms to the atrium. The schematical expression of the section including illuminance measurement points is shown in Fig. 2.

4. Method

The study was designed and constructed in accordance with due artificial neural networks algorithm. By utilizing certain building parameters, weather data related to daylight and illuminance levels by field measurements, an ANN model was developed. Daylighting measurements were then compared according to this model.

By following certain key factors related daylighting prediction and calculations an ANN model was developed. As the movements of sun as a light source create variations and patterns of available daylight, latitude of the building, the conditions for its immediate surrounding, climate conditions, ambient temperatures and sunshine availability all have direct impact on strategies in the process of daylight design. While daylight availability, thus daylight penetration to the building, is higher in relation to seasonal variations at certain latitudes, several buildings and vegetation at the surrounding area may obstruct daylight entering the building. To determine the building orientation is even another basic stage in daylighting availability [4,16,29].

Solar radiation (energy from the sun) which is partly converted to visible radiation is an indicator for the amount of daylight on the surface of the earth. It changes according to the depth and condition of the atmosphere. While traveling through atmosphere, sunlight is diffused [scattered] by particles, dust and water vapor. The diffusion process produces sky luminance [19]. Thus humidity as a function of the amount of water vapor in atmosphere and solar radiation as a function of the amount of visible radiation were included as key variables in the ANNs model construction. IESNA Handbook (2000) depicts that to determine position of sun, time is necessary and a 24 h clock is used to express it. In the model construction, date was included as well [19].

Apart from climate conditions, location, atmospheric conditions and time, building parameters such as vertical apertures (windows), horizontal apertures (skylights) and glazing type determine the amount of light penetration in buildings. As a general rule, illuminance level decreases as the distance from window wall to reference point is increasing [13,14]. On the other hand, the surface area of a typical window is identified in previous section and only the number of identical windows changes for each room. So the number of windows rather than surface area was used as a building parameter for the sake of simplicity. As the model was constructed for one single building, factors such as latitude, surrounding building and vegetation, glazing options and surface reflectance were eliminated.

4.1. Data compilation

The data obtained from the field measurements were used in this work. In the compilation procedure, first, data sheets were designed to record illuminance measurements at specific points for each sample rooms. Thus recording information were also room/space designations, point labeling, actual room dimensions, dates for measurements, time (actual hours for measurements) and measurement readings (Table 1). In order to denote the grid spacing for measurement locations, existing floor drawings were obtained. In order to use for the application of the model, meteorological data were obtained from the Weather Station in the

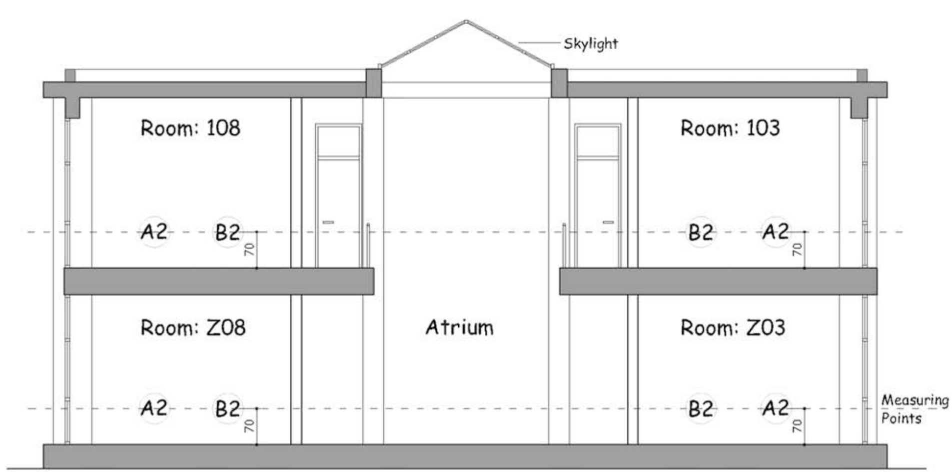

Fig. 2. A schematical drawing of the section A–A with location heights of measurement points.

Table 1
An example of a record sheet for illuminance measurements.

Date					Time				
28 February 2008					09:00 a.m.				
Ground floor (illuminance-lux)					First floor (illuminance-lux)				
Z1	A1	A2	B1	B2	101	A1	A2	B1	B2
	222	603	207	193		308	379	120	205
Z2	A1	A2	B1	B2	102	A1	A2	B1	B2
	555	669	385	369		235	683	463	405
Z3	A1	A2	B1	B2	103	A1	A2	B1	B2
	472	718	610	900		423	726	576	399
Z4	A1	A2	B1	B2	104	A1	A2	B1	B2
	236	518	297	266		277	428	221	223
Z5	A1	A2	B1	B2	105	A1	A2	B1	B2
	594	878	403	573		416	768	557	478
Z6	A1	A2	B1	B2	106	A1	A2	B1	B2
	268	371	53.5	60.8		950	480	111	83.6
Z7	A1	A2	B1	B2	107	A1	A2	B1	B2
	1146	617	102	87.5		224	253	42.6	46
Z8	A1	A2	B1	B2	108	A1	A2	B1	B2
	476	860	42.4	58.1		258	314	80.2	71.5
Z9	A1	A2	B1	B2	109	A1	A2	B1	B2
	432	743	206	288		569	1032	162	228
Z10	A1	A2	B1	B2	110	A1	A2	B1	B2
	312	320	112	115		484	478	229	218
Z11					111	A1	A2	B1	B2
X						497	489	166	185
Z12	A1	A2	B1	B2	112	A1	A2	B1	B2
	408	488	64.1	65.2		743	456	175	246

Department of Mechanical Engineering in İYTE. Field measurements were then conducted through a detailed procedure which is explained in the next section.

4.2. Field measurements

By following certain practical guidance offered by Chartered Institution of Building Services Engineers (CIBSE), a survey was carried out for the measurement of daylight illuminance in sample rooms. The number of measurement points and their locations were also determined according to recommendations of the CIBSE Code 1994. The number of points is related with the Room Index (ratio between room size and height) and the locations should be at the centre of equal small areas (divisions of the floor area of the room) each of which are square if possible. The measurement is taken at the centre of each small area which is defined by grid points [30].

In this study, the survey was carried out on the ground and first floors of the office building in İYTE in the period between the months of November 2007 and January 2008. It covered all prevailing conditions including clear sky, partly cloudy sky and overcast sky. A portable PeakTech® digital lightmeter with a silicon photo diode detector attached to the amplifier by a flexible cable was used for the field measurement. A portable stand made of metal was used to locate the measuring cell at a constant height for each reading. The height was 0.7 m from the floor level. Measurements were taken 0.5 m away from walls/columns/partitions and grid points were positioned with equal spacing (Fig. 1). Drawings displaying the spacing of grid points for illuminance measurements (A_1, A_2, B_1, B_2) for two sample rooms and their heights from the floor level are shown in Figs. 2 and 3.

4.3. ANN model construction

This study constructed a three-layer ANN model of feed-forward type (with one output node) on Microsoft Excel (Fig. 4). The process followed the back-propagation formulation and simplex optimization applying Excel spreadsheet method as defined by Hegazy and Ayed [28]. The spreadsheet process represents a template for one-hidden-layer ANN model. There were 13 neurons in the input layer for the 13 input variables in the model. The middle layer had 7 neurons although different numbers of neurons were also tested for best performance. For example, the model including 5 and 6 hidden neurons resulted, respectively, 35.87% and 20.62% error. On the other hand, increased numbers of neurons (8, 9 and 11 hidden neurons) were also tested with errors very close to 2.20%. Thus, optimum number of neurons was found to be 7 with an average error of 2.20%. In the output layer, one neuron was used for the output variable of the illuminance level. These 13 input variables, their maximum and minimum values are listed in Table 2. Two variables for time (date, hour), 5 weather determinants (outdoor temperature, solar radiation, humidity, UV index and UV dose) and 6 building parameters (distance to windows, number of windows, orientation of rooms, floor identification, room dimensions and point identification) were considered as input variables. Illuminance was used as the output variable.

In ANN modeling, the data were divided into two groups; the first one was used for training and the rest was for the testing of the model. As to have statistically balanced data, the training and testing data set had approximately the same minimum to maximum ranges and average illuminance values as in the main data set. There were a total of 100 data sets each with 14

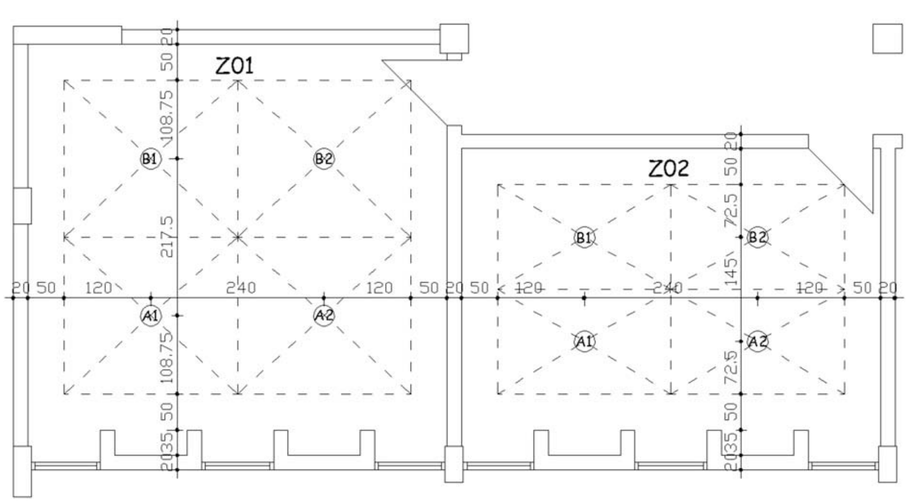

Fig. 3. A representative drawing displaying the spacing of grid points for illuminance measurements.

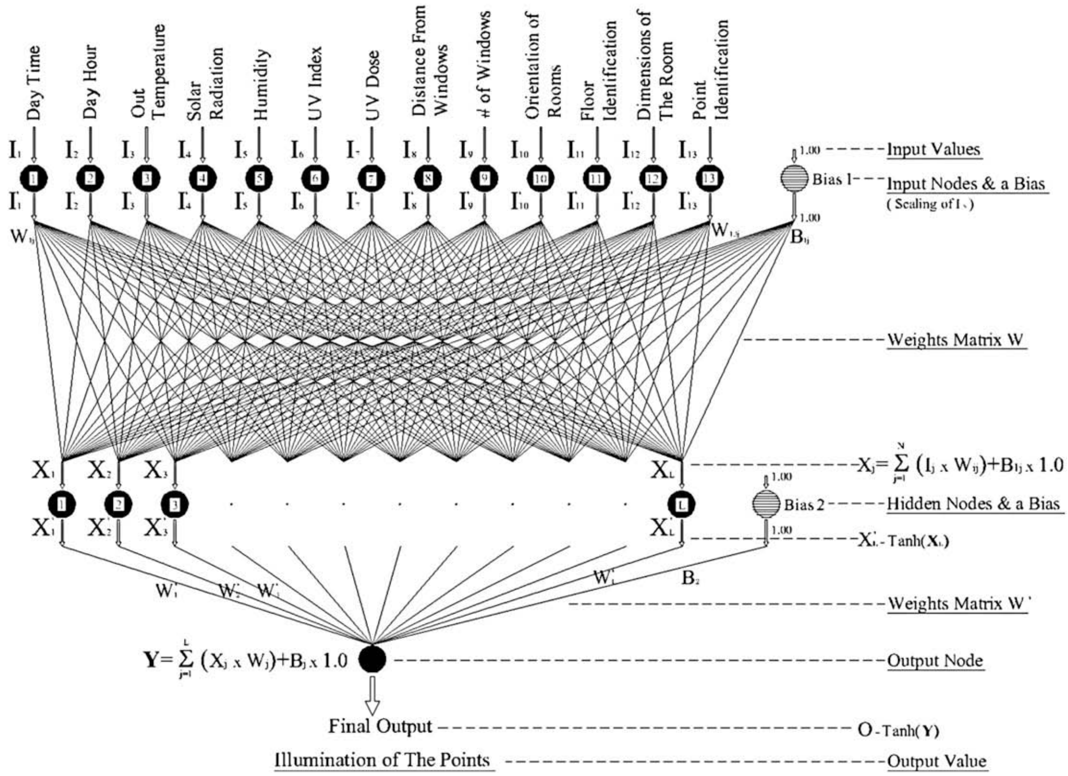

Fig. 4. Structure of the best performing network.

components (x_1, x_2,…,x_{13}; y) 13 of which are input variables whereas the 14th one is the output variable. The actual number of input data used is 13 per input variable. Thus one data set involves 100 data each of which has 13 parameters. The first 80 of these data sets were used for training of the model and the remaining 20 for testing. Microsoft Excel Solver used simplex optimization method for the optimal weights. The program then instructed to run for 10,000 iterations. The model employed in this study was trained by a back-propagation learning algorithm. The training of all cases in a training set is named iteration. The error was measured for each run of the iteration number. Training should be stopped when the error remains unchanged for a given number of iterations. This is done in order to avoid overtraining, in which case the model memorizes the training values and is unable to make predictions when an unknown example is presented to it. In this model, 10,000 iterations were found adequate for the final training process. The performance of the model deteriorated for less iteration than 10,000, while the model starts to memorize the output values for iterations more than 10,000. The model's performance was then measured by using the illuminance percentage error (IPE):

$$\mathrm{IPE} = \frac{E(i) - T(i)}{T(i)} 100\% \tag{1}$$

Table 2
The input variables used in the model construction.

Code	Input variable	Data used in ANNs model	
		Minimum	Maximum
x_1	Date (1,2,…,100)	1	114
x_2	Hour (9.00, 12.00, 15.00)	9.00	15.00
x_3	Outdoor temperature (°C)	5.70	22.00
x_4	Solar radiation	12.00	700.00
x_5	Humidity	29.00	89.00
x_6	UV index	0.00	3.50
x_7	UV dose	0.00	0.19
x_8	Distance to window (m)	1	2
x_9	# of Windows (1,2,3)	1	3
x_{10}	Orientation of rooms (1 = east; 2 = west)	1	2
x_{11}	Floor ID (1 = ground floor; 2 = first floor)	1	2
x_{12}	Room aspect ratio (length/width)	0.58	1.30
x_{13}	Point ID (1 = A_1; 2 = A_2; 3 = B_1; 4 = B_2)	1	4
y_1	Illuminance (lux)	9.40	1679.00

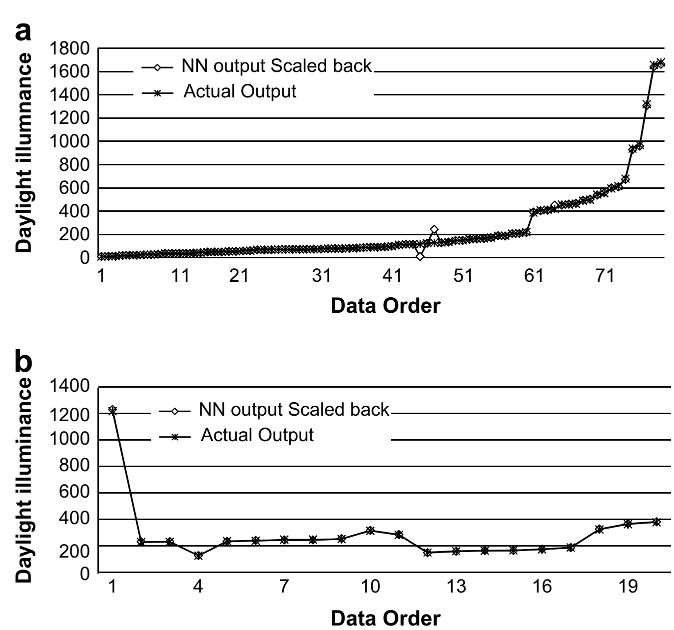

Fig. 5. Observed vs. predicted illumination levels for (a) training and (b) testing data sets.

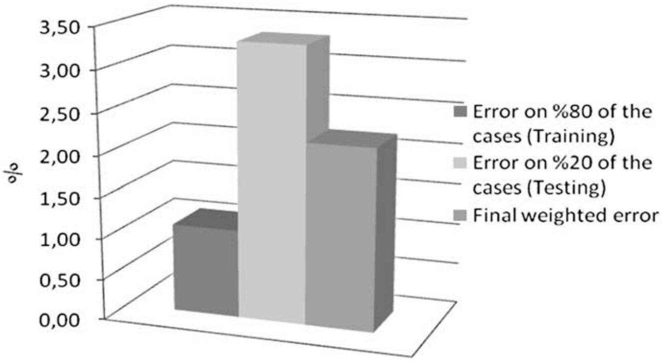

Fig. 6. Comparison of the training and testing performance of the model.

where $E(i)$ is the estimated illuminance level, $T(i)$ is the actual measured illuminance level and IPE is illuminance percentage error.

By following the outcomes of this calculation, the model arrived at the optimum solution with an average percentage training error of 3.32% for the output variable The data used for testing have been separated before the training phase in order to use for testing. That is to say, the testing cases have not been introduced in the model at any phase before testing. Thus, the training of the model was successfully accomplished since the model was in accordance with the actual data (Fig. 5a). The trained model was tested with the group of 20 data sets after the application of optimization (Fig. 5b). The performance of the model was successful with an average error of 2.20%. Training performance of the model was 1.08%, while testing performance was 3.32%. Thus the prediction power of the model was 97.80% (Fig. 6). The predicted values in the model had close matches with the actual data.

4.4. Sensitivity analysis

The effect that each of the model inputs have on the model output can be investigated via sensitivity analysis. Sensitivity analysis is a method to investigate relationships between the inputs and outputs of the model. It explores the model response and evaluates the accuracy of model. It is performed by feeding input variables at varying levels into the developed model and producing prediction outputs. By doing this one can get a feedback about the most significant input parameters. It also provides irrelevant inputs which can be eliminated from the model for the sake of simplicity. So it may improve the model's performance. During sensitivity analysis, the model learning is disabled; therefore network weights are not affected. Sensitivity is employed to find the rate of change in a model output due to changes in the model inputs. The unit for sensitivity is percentage and results are finally reported in a figure. In this model four parameters namely, hour, number of windows, orientation, and identification point are found to be the most effective illuminance parameters (i.e., each one has more than 40% sensitivity). On the other hand dimensions of the room, outdoor temperature, and UV day are found to be least effective parameters (Fig. 7). However, the usage of only the most effective four parameters decreases the average prediction accuracy of the model, since the remaining parameters have a comparable power additively. This finding may support that even the small clues (i.e., parameters) may improve the models prediction capability as in the case of the problems solved by Adeli and Wu, and Günaydin and Doğan [23,31].

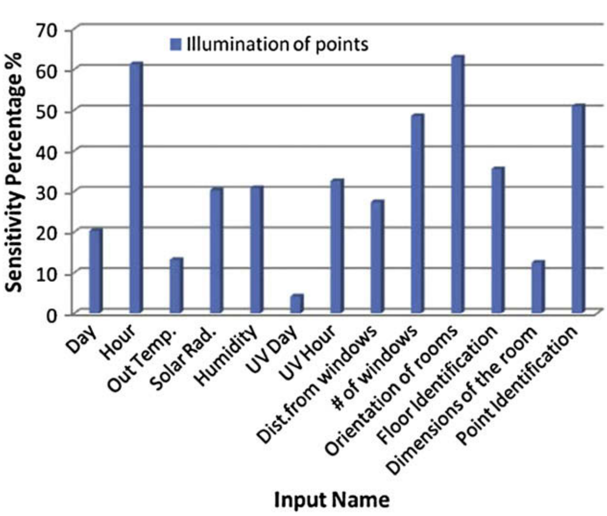

Fig. 7. Results of the sensitivity analysis.

5. Conclusions

In this study, a three-layer ANN model was developed to predict daylighting levels in office buildings. Input parameters used in the model included date, hour, outdoor temperature, solar radiation, humidity, UV index and UV dose, distance to windows, number of windows, orientation of rooms, floor identification, room dimensions and point identification. The model was constructed for the office building of the Faculty of Architecture in İYTE. It was resulted satisfactorily in terms of predicting daylighting levels.

Sensitivity analysis was performed on the model to determine the effect of each input variable on the model output variable. It depicted the relationship between the input and output. The effect of hour, number of windows, orientation, and identification point were found to produce higher impact on illuminance values. While UV day had the lowest effect. A similar interaction was observed for the impact of dimensions of the room and outdoor temperature on lighting levels. The field measurement was made during a 3-month period. Although it covered all prevailing sky conditions, it excluded seasonal variations. Another investigation may be conducted during a 12-month period to include seasonal parameters such as month or 3-month period. Thus the impact of seasonal parameters on illuminations might be evaluated.

Conclusions derived from the study mainly dealt with methodology. The main purpose was to construct a new methodology for the investigation by using an intelligence method called artificial neural networks. As this algorithm has been widely used in engineering researches [20–23] and not commonly used in architecture, this study aimed to offer this methodology in the field of architectural studies. Since one trial application for such a model in the field of architecture [24] shows such a clue that it may be applicable also in problems related to the field of building design.

Tough guidelines, scale models, computer programs and analytical formula referred by literature [7,13–19] have been common design tools to determine daylight illuminance, it is now expected that this investigation will guide researchers and designers for the application of ANN model as a new design assist tool. Researchers would be aware of this model as the utilization of ANN model has not been commonly used in the field of architecture and they apply this model in daylighting evaluation studies. They will then benefit from this model in daylighting performance assessment of buildings by making predictions and comparisons. Architects and lighting designers would benefit from this model by using it as a design assist tool to determine illuminance and light distributions. Even they might improve it with the inclusion of more spatial parameters and climatic and geological aspects to determine the location characteristics of any type of building.

Consequently, the utility of this model is the capability to depict satisfactory predictions of daylight illuminances and it is a less time consuming process in providing feedback information for existing buildings.

References

[1] Manav B. An experimental study on the appraisal of the visual environment at offices in relation to colour temperature and illuminances. Build Environ 1993;42:979–83.
[2] Park KW, Athienitis AK. Workplane illuminance prediction method for daylighting control systems. Sol Energ 2003;75:277–84.
[3] Fontoynont M. Perceived performance of daylighting systems: lighting efficacy and agreeableness. Sol Energ 2002;73:83–94.
[4] Ruck NC. International Energy Agency's solar heating and cooling task 31. IEA; 2006.
[5] Capeluto IG. The influence of the urban environment on the availability of daylighting in office buildings in Israel. Build Environ 2003;38:745–52.
[6] Miyazaki T, Akisawa A, Kashiwagi T. Energy savings of office buildings by the use of semi-transparent solar cells for windows. Renew Energ 2005; 30:281–304.
[7] Leslie RP. Capturing the daylight dividend in buildings: why and how? Build Environ 2003;38:381–5.
[8] Li DHW, Tsang EKW. An analysis of measured and simulated daylight illuminance and lighting savings in a daylit corridor. Build Environ 2005;40:973–82.
[9] Atif MR, Galasiu AD. Energy performance of daylight-linked automatic lighting control systems in large atrium spaces: report on two field-monitored case studies. Energ Build 2003;35:441–61.
[10] Thanachareonkit A, Scartezzini JL, Andersen M. Comparing daylighting performance assessment of buildings in scale models and test modules. Sol Energ 2005;79:168–82.
[11] Littlefair P. Daylight prediction in atrium buildings. Sol Energ 2002;73:105–9.
[12] Li DHW, Cheung GHW, Lau CCS. A simplified procedure for determining indoor daylight illuminance using daylight coefficient concept. Build Environ 2006;41:578–89.
[13] Egan MD. Concepts in architectural lighting. New York: Mc Graw-Hill; 2002.
[14] Moore F. Environmental control systems heating cooling lighting. New York: Mc Graw-Hill; 1993.
[15] Baker N, Fanchiotti A, Steemers K. Daylighting in architecture – a European reference book. Commission of the European communities Directorate-General XII for science, research and development. Brussels and Luxembourg: James and James; 1993.
[16] International Energy Agency (IEA). Daylight in buildings, a source book on daylighting systems and components. International Energy Agency (IEA) Solar Heating and Cooling Programme, Energy Conservation in Buildings & Community Systems. Berkeley, CA: The Lawrence Berkeley National Laboratory; 2000.
[17] Maamari F, Fontoynont M, Adra N. Application of the CIE test cases to assess the accuracy of lighting computer programs. Energ Build 2006;38:869–77.
[18] Reinhart C, Fitz A. Findings from a survey on the current use of daylight simulations in building design. Energ Build 2006;38:824–35.
[19] Rea MS. The IESNA lighting handbook. New York: Illuminating Engineering Society of North America; 2000.
[20] Akkurt S, Tayfur G, Can S. Fuzzy logic model for the prediction of cement compressive strength. Cement Concr Res 2004;34(8):1429–33.
[21] Sofuoğlu S. Application of artificial neural networks to predict prevalence of building-related symptoms in office buildings. Build Environ 2008;43:1121–6.
[22] Tayfur G. Fuzzy, ANN, and regression models to predict longitudinal dispersion coefficient in natural streams. Nord Hydrol 2006;37(2):143–64.
[23] Günaydın M, Doğan SZ. A neural network approach for early cost estimation of structural systems of buildings. Int J Proj Manag 2004;22:595–602.
[24] Lam JC, Wan KKW, Yang L. Solar radiation using ANNs for different climates China. Energ Convers Manag 2008;49:1080–90.
[25] Haykin S. Neural networks: a comprehensive foundation. New York: Macmillan; 1994.
[26] Rafiq MY, Bugmann G, Easterbrook DJ. Neural network design for engineering applications. Comput Struct 2001;79:1541–52.
[27] NeuroSolutions tool for Excel. The NeuroDimensions Inc.; 2002.
[28] Hegazy T, Ayed A. Neural network model for parametric cost estimation of highway projects. J Construct Eng Manag 1998 May/June:210–8.
[29] Kim G, Kim JT. Projecting performance of reintroduced direct sunlight based on the local meteorological features. Sol Energ Mater Solar Cells 2003; 80:85–94.
[30] Chartered Institution of Building Services Engineers (CIBSE). Working plane illuminance in electrically lit spaces. Available from: http//www.cibse.org/pdfs/factfile3.pdf; 1996.
[31] Adeli H, Wu M. Regularization neural network for construction cost estimation. J Construct Eng Manag 1998;124(1):18–24.