An indoor illuminance prediction model based on Neural Networks for visual comfort and energy efficiency optimization purposes*

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Abstract. Energy and comfort management are becoming increasingly relevant topics into buildings operation, for example, looking for trade-off solutions to maintain adequate comfort conditions within an efficient energy use framework by means of appropriate control and optimization techniques. Moreover, these strategies can take advantage from predictions of the involved variables. In this regard, visual comfort conditions are a key aspect to consider. Hence, in this paper an indoor illuminance prediction model based on a divide-and-rule strategy which makes use of Artificial Neural Networks and polynomial interpolation is proposed. This model has been trained, validated and tested using real data gathered in a bioclimatic building. As a result, an acceptable forecast of indoor illuminance level was obtained with a mean absolute error equals to 8.9 *lux* and a relative error lower than 2%.

Keywords: Indoor illuminance prediction · Neural Networks · Prediction model · System identification · Comfort control

1 Introduction

From the beginning, human beings have been bounded to the necessity of energy both to survive and to satisfy their own needs. This trend has been increasing according to world population growth and the discovery of new technologies. Nevertheless, as non-renewable energy sources, such as oil and coal, are more and more exhausted [4] the integration and use of different energy sources, just as renewable and non-renewable ones, is taking on special relevance. Furthermore, a model can be defined as *sustainable* if it is able "to satisfy the actual needs without compromising the ability of future generations to satisfy their own needs" [12]. Hence, it can be stated that, at present, the global energetic model is unsustainable from social, economic and environmental points of view [10]. Therefore, energy efficiency is becoming an increasingly relevant topic which

* This work has been funded by the National R+D+i Plan Project DPI2017-85007-R of the Spanish Ministry of Science, Innovation and Universities and ERDF funds.

has caused the appearance of several regulations which try to reduce global energy consumption and non-renewable energy sources dependency within main economic sectors [13].

Buildings sector is currently a major energy consumer. According to the information provided by Eurostat [14], energy consumption of building sector represents 38% of global energy consumption. Besides, the most part of it is originated fundamentally by the use of HVAC (Heating, Ventilation and Air-Conditioning) and lighting systems. The use of those systems allows to guarantee users' comfort from thermal and visual points of view [3]. Moreover, assuring a certain comfort degree has a direct impact on performance, productivity and users' health. Thus, energy efficiency and users' comfort management are raising great interest in researchers and companies. In fact, some control architectures are able to manage both objectives [3]. For that reason, it is needed to predict environmental conditions, that is, indoor temperature, illuminance level, air quality, etc.

This paper is focused on the development of an indoor illuminance prediction model for an office-room located inside a bioclimatic building, the CIESOL building. Multiple approaches have been presented in literature for this purpose. Moreover, it is worthy to highlight these ones: (i) based on scale models; (ii) based on computer simulations and (iii) based on analytical equations. However, illuminance level in a room is difficult to be modelled either by analytical equations, since a lot of variables are involved, or by a scale model mainly due to the fact that some elements cannot be identically reproduced, such as the main characteristics of construction materials. In addition, model integration into a control architecture is a relevant factor to take into account. In this regard, software for illuminance level simulation is not feasible, and thus, those methods become unattractive for addressing this problem.

More in detail, the indoor illuminance prediction model presented in this paper has been developed following a divide-and-rule strategy, and thus, a prediction model based on Artificial Neural Networks (ANN) has been developed [7, 8] to counteract the contributions of daylight into indoor illuminance. In addition, a polynomial interpolation has been implemented in order to consider the contribution of adjustable artificial lights into indoor illuminance. Besides, this prediction model has been used to support the upper layer, that is a set-points optimizer, of a multilevel hierarchical control system [9]. The complete illuminance prediction model has been tested using real data from a bioclimatic building and promising results have been obtained with a relative error lower than 2%.

The rest of the paper is organised as follows. In Section 2, a description of visual comfort concept and the facilities where the study has been conducted are presented. In Section 3, a model for illuminance level estimation is defined, while in Section 4, results for model validation are shown and discussed. Lastly, in Section 5, main conclusions and future works are summarised.

2 Scope of the Research: Visual comfort and CIESOL

Visual comfort can be defined as *"A subjective condition of visual well-being induced by the visual environment"* [6]. Therefore, to reach an appropriate visual comfort sensation it is needed to consider the properties of the visual environment, such as: illuminance level and its distribution, colour of light, glare, etc. The most recommendable values for these properties can be determined from international standards [6]. In this paper, it has been considered that a visual comfort condition can be achieved by means of an appropriate indoor illuminance level. Therefore, three key elements must be taken into account: natural light, artificial lighting and shading devices.

On the other hand, The CIESOL (http://www.ciesol.es) is a research centre on solar energy located inside the Campus of University of Almería, in the South East of Spain. Furthermore, this centre was built under some bioclimatic criteria (such as specific insulation depending on the orientation or HVAC systems based on solar cooling). The building itself has a total surface of 1071.91 m^2 distributed into two floors. Moreover, every room is monitored by a network of sensors, whose data is stored through an acquisition system, and controlled by means of some actuators, e.g HVAC systems, automated windows or shading devices. Data related to meteorological conditions, such as solar radiation, temperature or humidity, is collected and stored as well.

The model proposed in this paper has been obtained for a characteristic room of CIESOL building, where all the data were gathered, henceforth called L6. This room, with a total surface of 76.8 m^3 (4.96 $m \times$ 5.53 $m \times$ 2.8 m), is located in the first floor of the building and faces north, a moreover, it is delimited by two similar laboratories. It has a single window located at north wall covering 4.49 m^2 (2.15 $m \times$ 2.09 m). L6 is fully equipped with sensors and actuators which make possible an effective comfort control [3]. More in detail, L6 is equipped with automatic window and blind which can be operated from a remote computer. In addition, as artificial lights it counts with fluorescent lamps whose intensity can be regulated by applying a voltage between $[0, 10]$ V.

3 A Neural Network Model for indoor illuminance of an office-room

To estimate users' visual comfort inside a room, it is required to use a prediction model of indoor illuminance. To do that, it is worthy to mention that indoor illuminance is influenced by two main factors: (i) Natural light through window, which depends on global, diffuse or direct radiation, outdoor illuminance and window's parameters, and (ii) Artificial lighting which can be obtained as a function of indoor lights and lamps. Furthermore, to obtain an accurate illuminance prediction model, it is needed to take into account the geometry of the room and its main constructive characteristics. Nevertheless, the procedure to determine these parameters is a very complex task and, sometimes, even impossible. Therefore, an indoor illuminance prediction model in a room could be highly inaccurate if those parameters are not well characterised. For this reason, in this paper a black-box prediction model based on ANN has been obtained. The election of ANN approach has been motivated by the complexity of the problem and the principal features of ANNs: self-adaptive, fault tolerance, learning, flexibility and real time response [1, 2, 5].

More in detail, the black-box model presented in this paper has been defined using a divide-and-rule strategy by considering that artificial and natural lighting are unrelated, but an additive phenomena. Besides, artificial lighting can easily be modelled by means of a polynomial interpolation since they depend only from the input voltage applied to the regulate their intensity. On the contrary, contributions due to natural light depends on a huge variety of factors that can handily be managed by an ANN. The architecture proposed for the black-box model can be observed in Fig. 1.

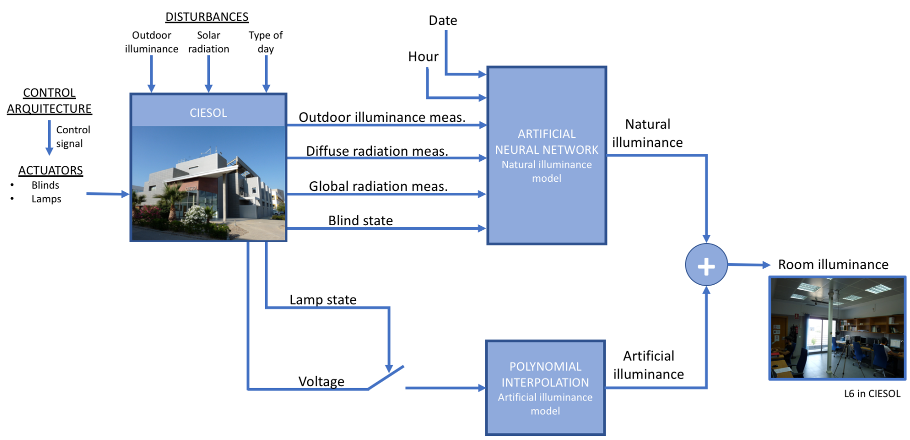

Fig. 1. Model architecture based on a divide-and-rule strategy.

The procedure to obtain the ANN forecasting model could be summarized as follows: (i) selection of inputs for the indoor illuminance prediction model; (ii) construction of the training, validation and testing data sets; (iii) establishment of ANN paradigms, that is, its architecture and structure; and (iv) training, implementation and evaluation of the indoor illuminance prediction model.

3.1 ANN Inputs and Size

Firstly, it is required to determine which are the key parameters that affect the model distinguishing between daylight and artificial lighting contributions. More concretely, the inputs selected for the model which represent the natural light contribution have been: date, hour, outdoor illuminance, diffuse and global radiation, blind state (open/close). Date and hour variables are significant since they provide to the ANN information about how solar path changes along the year. In addition, outdoor illuminance and diffuse and global radiation also provide information about the outdoor environmental conditions. To simplify the ANN model, an static model is assumed, that is, the current output does not depend on past outputs. In addition, the geometrical characteristics of the room have been also neglected, so an average workplace in L6 has been selected for data gathering. Finally, in order to achieve an appropriate performance, some limits have been established over these inputs, see Table 1.

Table 1. List of input variables for the ANN model

Variable	**Unit**	**Measurement range**
Date	–	$[1, 366]$
Hour	–	$[0, 1]$
Outdoor illuminance	$[lux]$	$[0, 56977]$
Diffuse radiation	$\left[W/m^2\right]$	$[0, 758]$
Global radiation	$\left[W/m^2\right]$	$[0, 1281]$
Blind state	–	$\{0, 1\}$

In addition, the inputs chosen to model the artificial lighting contribution have been the lamp state (on/off) and the voltage applied to regulate them.

3.2 Data-Sets Construction

To estimate an accurate ANN model to predict the influence of daylight into indoor illuminance, it is required the availability of an appropriate set of historic data. In this paper, a data set composed by 57000 measurements which encompasses from March to July has been used. To obtain this data set, several tests using the available actuators in L6 have been performed in order to gather all the dynamics needed to determine an ANN with a good performance. More information about the instrumentation used to acquire them can be found in [3]. Furthermore, this data set has been divided into three different data subsets which have been used to train, validate and test the ANN model. The first data subset which can be denoted as *Training Data Set* encompasses 75% of total measurements and it is used to estimate ANN parameters through the Levenberg-Marquardt optimization algorithm [11]. The second data subset, *Validation Data Set*, includes 20% of total data points and it is employed to measure ANN generalization, and thus, to prevent *over-training*. Finally, the *Testing Data Set* utilizes 5% of total measurements and it is an independent data subset used to determine the ANN performance after training process. Concretely, the *Testing Data Set* is composed of data selected in order to encompass different types of environmental conditions and situations which can appear in an office room, see Table 2.

3.3 Architecture and Structure Selection

As it has been mentioned previously, an ANN model acts as a black-box model, and thus, it is not necessary to acquire a deep knowledge about the modelled

Table 2. Description of the Testing Data Set

Samples	Date	Type of day	Test
$1 - 650$	March, 31st	Clear day	Blind test
$651 - 825$	April, 5th	Clear day	Blind test
$826 - 1080$	April, 11th	Clear day	Blind and variable lamps' voltage test
$1081 - 1220$	July, 10th	Clear day	Variable lamps' voltage test
$1221 - 1420$	July, 14th	Clear day	Constant lamps' voltage test

system since ANN approach is able to determine the existing relationship among inputs and outputs by using historical data. As it is well known, an ANN is composed of an input layer, one or more hidden layers and one output layer [10].

In this paper, to establish the appropriate number of hidden layers and neurons a sensitivity analysis and an optimization process considering time of training and results accurateness have been performed. At the end, this paper proposes an ANN indoor illuminance prediction model based on daylight contribution with two hidden layers, each of which is composed by 12 neurons and a sigmoid activation function.

4 Results and Discussion

The proposed indoor illuminance prediction model has been validated using real data from L6 room in CIESOL building. As it was emphasized before, this model is composed of an ANN used to predict the contribution of natural light and a polynomial interpolation in order to deal with artificial lighting contribution. Firstly, an overview of the results obtained for the ANN illuminance prediction model is presented. Afterwards, the validation of the polynomial interpolation developed to counteract the effect of artificial lights into indoor illuminance model has been included. At the end, reader can find validation results for the complete illuminance prediction model presented in Section 3. For goodness-of-fit evaluation, Mean Absolute Error (MAE) index has been used, see Eq. (1), where y_i represents the real data gathered at L6 and $\hat{y}_i$ shows the results provided by the ANN model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{1}$$

Figure 2 presents the results obtained for the ANN illuminance prediction model to counteract daylight effect using the *Validation Data Set*. As it can be observed, error is primarily distributed on a range of ± 2 lux with an average of 0.2 lux, revealing a good behaviour of the ANN. Besides, a MAE index equals to 1.2 lux, that is 0.4%, and a standard deviation of 2.1 lux have been obtained. In addition, Fig. 3 depicts a regression analysis, that is, a representation of the existing relation between real and estimated data. Ideally, a $y = x$ line represents the best performance of the ANN (regression coefficient, $R = 1$).

Hence, a regression coefficient $R = 0.999$ proves a reasonably acceptable ANN prediction model.

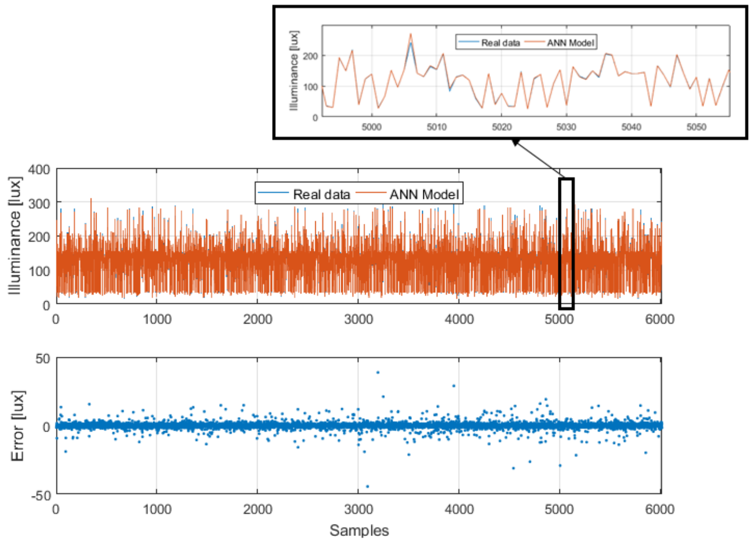

Fig. 2. Validation of the ANN model to counteract natural light effect

In Fig. 4, a validation of the polynomial interpolation for artificial illuminance and its maximum absolute error for voltages comprised between $[0, 10]\,V$ is shown. As can be observed, error becomes bigger at lower voltages as there are some non-linearities. Even so, these errors can be considered tolerable mainly due to the following reasons: (i) normal operating conditions imply high voltages as an input because of selected set-points; (ii) MAE index is equal to 6.2 lux (2.2%) with a standard deviation of 3.7 lux.

Finally, regarding the validation of the complete illuminance prediction model, the model's output has been calculated as an aggregation of natural and artificial illuminance predictions. Figure 5 shows the validation results obtained by using the *Testing Data Set* presented in Section 3.2. The upper graph in Fig. 5 depicts the evolution of indoor illuminance for both real data gathered in L6 (in blue) and the results provided by the complete model (in red). Besides, the lower graph shows the error. It can be observed that the error is primarily concentrated in a ± 20 lux range with an average error equals to -4.1 lux is observed, pointing out some negative trend. In addition, MAE index is equal to 8.9 lux and standard deviation of 7.6 lux. These values can be considered negligible since the total range of the *Testing Data Set* is equal to 513 lux, that is, a relative error equals to 1.73%. In this concern, the performance of the proposed prediction model is considered to be suitable for the addressed problem, as two main phenomena were neglected and have become the main source of error: (i) non-linearities observed for low voltages operating conditions in artificial illuminance model, (ii) settling time in artificial illuminance model, as dynamics are not instantaneous.

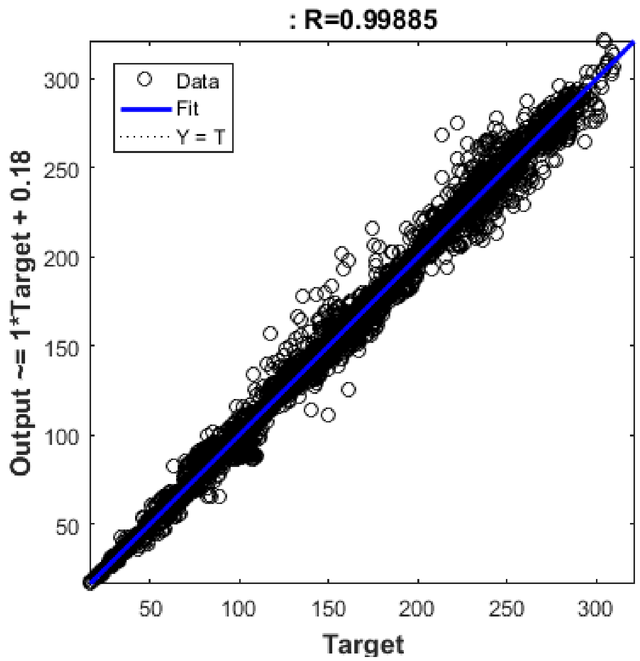

Fig. 3. Regression analysis for ANN model

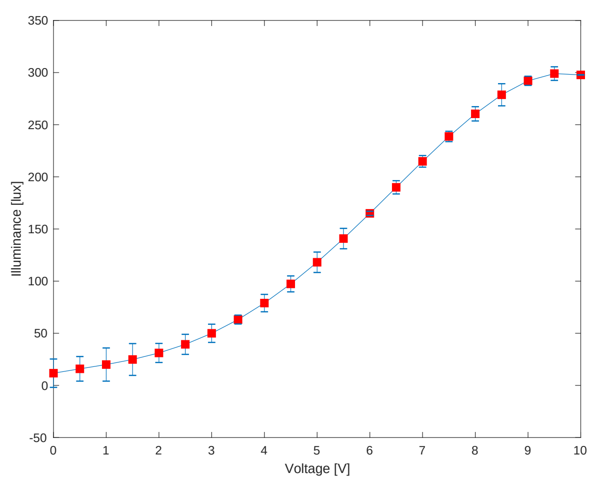

Fig. 4. Validation of the polynomial interpolation to counteract artificial lights effect

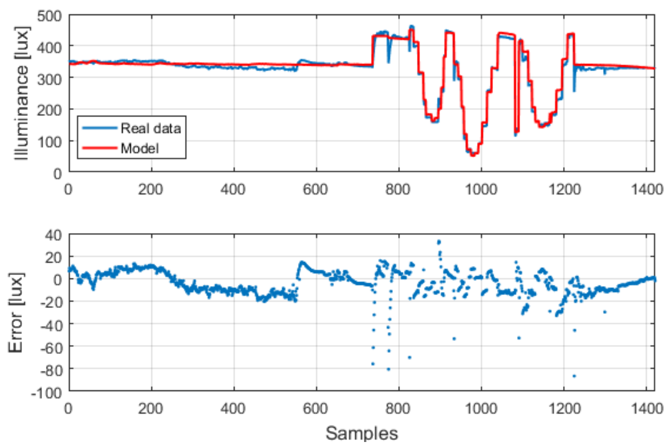

Fig. 5. Results provided by the complete illuminance prediction model for the Testing Data Set

Thus, this approach supposes a trade-off solution combining simplicity and speed for modelling. Table 3 shows a summary of the results obtained and discussed in this section.

Table 3. Summary results obtained for the Testing Data Set

Model	**Range [lux]**	**MAE [lux]**	**Rel. error [%]**	**Std. dev. [lux]**
ANN model	$[0, 310]$	1.2	0.4	2.1
Polyn. interpolation	$[10, 298]$	8.2	2.2	3.7
Complete model	$[0, 513]$	8.9	1.7	7.6

5 Conclusions and Future Works

In this paper, an illuminance prediction model for an office room has been developed, so that it could be integrated into the upper layer (set-points optimizer) of a multilevel hierarchical control system. A quick and accurate implementation of such estimator was needed. For that, an innovative approach - following divide-and-rule strategy - has been presented as a methodology for constructing an illuminance model composed by two main inputs: natural light model, based on ANN, and artificial lighting model, based on polynomial interpolation. This approach enables to simplify ANN inputs, in order to optimize ANN training, both from time and necessary data points of view.

Illuminance modelling can become a huge challenge as lots of variables are involved. In this regard, this paper presents a simple, fast and potentially adaptable methodology, that allows to work from a black-box model perspective, making these variables transparent for the user. However, some information is missed, concretely differences between workplaces in the office, as geometrical parameters are neglected.

The performance of the proposed model has been tested along different days from March to July and, as it was shown within Section 4, the obtained results are promising. More in detail, the model is able to estimate illuminance level with a relative error of 1.7% for the studied range ([0,513] lux). These results show that ANN models are flexible and versatile options to consider when dealing with such kind of dynamics.

However, the model is currently able to accurately estimate illuminance for the period of the year from March to July, it should be capable to make whole-year predictions though. As future works, a 12-month period training has to be accomplished.

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