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An ANN-based model for the prediction of internal lighting conditions and user actions in non-residential buildings

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This paper presents an Artificial Neural Network (ANN) based approach able to predict the internal lighting conditions in a working environment, taking into account the daylight entering the respective space as well as the special requirements of each user. The model training procedure is based both on real illuminance and occupancy data (measurements throughout a year) and on simulations, in order to integrate all possible conditions. User preferences in respect to lighting and blinds are expressed through probability curves. Illuminance due to the external daylight is calculated and predicted throughout the whole year, depending on the weather conditions, the time of the day, the location and the office orientation. The work plane distance from the window and the usage of blinds are also considered. The proposed model is further implemented for the prediction and evaluation of energy consumption for lighting in a working space based on the user preferences.

Keywords: lighting preferences; ANN; lighting consumption; illuminance prediction; user behaviour; illuminance measurements

1. Introduction

There has been a constant attempt over the last decades to reduce the global human ecological footprint so as to ensure the sustainability of human existence. With respect to the utilization of electrical energy, this attempt has been largely correlated to the transformation of the human behaviour towards energy efficiency. Yet, there are aspects of the electrical energy related human behaviour that are difficult to confront in an individual manner, usually due to their collective nature. Such aspects are strongly associated with the electrical energy consumption in non-residential environments. In this context, the electrical energy demand for lighting usually stands out as an issue, as it represents a significant amount of the global electrical energy consumption.

This work aims to address this challenge in the field of office lighting. The obvious aim in this respect is to decrease the energy consumption needed for office lighting, preserving at the same time the user visual comfort. The contemporary lighting control systems attempt to regulate energy consumption through the combined control of artificial lighting and daylight entering a working space. Thus, a need arises for decision making algorithms that will achieve this goal, taking also into account the needs of the respective users. Today, the users tend to be addressed not individually, but rather in a collective manner, through design standards and established practices. This tendency however comes in contrast with the different perception of utility and comfort among different people, characteristics that also reflect on the use of lighting. In this context, studies have shown that automated lighting control systems aiming towards energy efficiency may not achieve the desired results when the user preferences are ignored (Dounis and Caraiscos 2009; Yang and Wang 2012).

Furthermore, the recent outspread of the demand side management paradigm, as a means to further rationalize energy consumption, requires the estimation of a building's electrical load profiles. Thus, the necessity becomes evident regarding models that will reliably predict the energy consumption according to the actual utilization of a building (Popoola 2018). Reliable estimation is of utmost importance due to the inconsistence of the results regarding the potential savings in a building through behavioural change. More specifically these savings have been reported to reach 20%, yet values differ up to 100% between various studies (Page, Robinson, and Scartezzini 2007). The issue of reliable estimation regarding the energy consumption becomes even trickier in lighting systems. In this case, it requires the comprehension of the connection between the user needs and desires (related to space occupancy, tolerable light levels, utilization of blinds, etc.) and external parameters (such as office orientation, weather conditions, etc.). This connection needs to be introduced in software tools that will be used to extract conclusions regarding energy consumption focusing on the user and combining his preferences with different external conditions.

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Relevant methodologies have been proposed in the literature (Acosta, Campano, and Molina 2016; Goia 2016; Mangkuto, Rohmah, and Asri 2016), however, they do not take user preferences directly into account.

The scope of this paper is to take into consideration the substantial respective work in the literature, and take it one step further. The basic objective is the development of an ANN-based model that will predict the internal lighting conditions in a working environment, taking into account the daylight entering the respective space and the special requirements of each user. The illuminance due to the external daylight is predicted for each day of the year, depending on the sky type (clear-overcast), the time of the day, the office location and orientation. The prediction also takes into account the distance from the windows and the usage of blinds. The user behaviour is illustrated with probability curves of using the lights or the blinds in respect to the illuminance levels on the work plane. Thus, the desired prediction does not merely correspond to the internal lighting conditions, but rather encompasses the user activities based on his behaviour. It is worth mentioning that the behaviour models examined correspond to both single-user and multi-user offices, aiming to also study the concept of consensus lighting.

The proposed model can be used to predict the energy consumption for lighting in a studied working space based on the user preferences and the investigation of possible energy savings through behavioural change. The model training procedure was based both on real data (measurements throughout a year) and on simulations, in order to integrate all possible cases, e.g. different office orientations, distances from window, weather conditions, etc. The basic advantages of the proposed model are its simplified nature (as it only takes into account the essential inputs, thus minimizing the need for input data) and its adaptability (as it can be implemented in different locations, for users with different preferences, and in offices with different lighting sources). The authors essentially strive to offer a generic model that can be easily adapted and tested under different conditions, comprising a readily available tool for the estimation of the lighting usage in a working environment even at early stage design, taking into account the user preferences.

The rest of the paper is structured so as to present all the different aspects that are taken into account in the proposed model. More specifically, in Section 2 a detailed analysis of the theoretical background is provided, in order to explain the different areas of interest that have been combined in this work. After that, in Section 3 the daylight measurements are described for the building under study, and subsequently the daylight simulation methodology is analyzed. In Section 4 the methodology is presented for the extraction of user behaviour patterns based on measurements. In Section 5 analytical expressions are provided concerning the calculation of solar radiation components. In Section 6, an ANN-based model that predicts illuminance and user actions is developed and evaluated. The model is further implemented to estimate lighting energy consumption for a variety of cases and to depict the impact of user preferences, office orientation and season. Finally, in Section 7 the main conclusions of this paper are summarized.

2. Theoretical background

The first step towards the implementation of the required tools is the understanding of the user perception and preferences regarding the daylight. Daylight comprises a factor that can contribute to substantial energy savings, as shown in several studies in literature. For example, using behavioural models by Lightswitch (Reinhart 2004), Bourgeois, Reinhart, and Macdonald (2006) showed that building occupants that actively seek day lighting rather than systematically relying on artificial lighting can reduce the respective primary energy consumption by more than 40%, as compared to occupants who rely on constant artificial lighting. However, even though it makes more sense in terms of energy efficiency, it is still not always possible to utilize the daylight in an internal space, due to unwanted factors such as daylight glare or temperature rise.

Regarding the utilization of daylight in internal spaces, there are two main issues to be addressed:

(1) There are difficulties in the prediction of daylight in an internal space, due to its non-linear nature. The respective prediction models have to manage a number of parameters, such as the climate conditions, the daylight transmission through fenestration systems, the user's position (related to the windows), etc. All these parameters need to be carefully determined and correlated with the possible resulting energy savings (Li 2010) and with the different daylight distribution within each space (Li et al. 2017). In any case, the respective user preferences should be thoroughly considered.

(2) It is rather difficult to introduce clear discomfort limits for all users. The concept of visual discomfort comprises a number of subjective characteristics. It is common practice to monitor the users and their actions along with the respective lighting conditions (external and internal) aiming to comprehend their needs (da Silva, Leal, and Andersen 2013). Among the conclusions in da Silva, Leal, and Andersen (2013), it is stated that there is a large degree of variability between occupants and/or offices. Other researchers have developed stochastic models for the simulation of the nature of occupant behaviour, based on the existence of probabilistic relationship between a user and a respective lighting system, or between environmental conditions and the usage of blinds

(Inkarojrit 2008; Gunay et al. 2014; Wang et al. 2016; Sadeghi et al. 2017; Stazi, Naspi, and D'Orazio 2017; Gilani and O'Brien 2018; Naspi et al. 2018).

Lighting in working spaces is subject to different requirements than lighting for other purposes, and it is strongly related to the respective type of work. There are many benefits for the user in a lighting system designed in such a way that he will be able to manage both the artificial lights and the blinds (Yao 2014). However, the manual lights can be combined with an automatic lighting control system (user adjusted) so as to achieve both desired and efficient lighting conditions. The potential energy savings and the respective user acceptance are closely interlinked with the control strategy they follow (Konstantoglou and Tsangrassoulis 2016). In the work of Iwata, Taniguchi, and Sakuma (2017), a system is proposed for the management of blinds and dimmable artificial lighting in office spaces utilizing an algorithm for glare prevention. Moreover, Xiong and Tzempelikos (2016) have proposed a model-based control for shading and lighting operation, aiming to reduce the energy consumption, preserving at the same time the visual comfort. However, this algorithm has not been implemented yet in occupied offices so as to be evaluated.

In order to consider the user preferences in a lighting system, these must initially be extracted and comprehended. For each individual user, the personal behavioural information has to be utilized, while for multi-user offices an apparent user behaviour curve is required. Gunay et al. (2017) have proposed a system that combines automated management of artificial lighting with information regarding the user behaviour. However, in the offices used to test and evaluate the model, the windows were not within the visual field of the occupants.

The ultimate objective of all this work is the balance between the user satisfaction and the estimation of the potential energy savings. In this respect, Sun and Hong (2017) have proposed a framework to quantify the impact of occupant behaviour on energy savings, showing that savings can vary up to 20% due to occupant behaviour. The effect of working hours and user habits on the energy consumption in an office is further studied by Delgoshaei et al. (2017). However, no clear metrics exist as yet to determine an occupant-centric building performance (O'Brien et al. 2017). The achievement of potential energy savings, while respecting the limits of user comfort in terms of lighting, needs to be further investigated.

As shown above, many factors have to be combined in the development of predictive algorithms for smart lighting systems (user oriented or occupancy based), or for the respective estimation of user activity and energy consumption. Intelligent systems, especially Artificial Neural Networks (ANNs), have been successfully used to simulate specific aspects of the problem as it is defined in the following analysis. These systems tend to present satisfactory results, mainly due to their ability to solve non-linear problems.

Several studies use ANNs for the prediction of the overall energy consumption in a building (Neto and Fiorelli 2008; Wong, Wan, and Lam 2010; Li et al. 2015; Chae et al. 2016; Safa et al. 2017). In the work of Wong, Wan, and Lam (2010) it is reported that the best energy predictions and minimum errors were achieved in the study of lighting comparing to cooling or heating. However, there is no mention of the user habits and preferences or of the usage of blinds for the mitigation of daylight. da Fonseca, Didoné, and Pereira (2013) have studied the effects of daylight on the overall building consumption. In this work, user comfort is taken into account through constant values proposed by regulations, rather than determined for each different user.

ANNs have been used for the prediction of solar radiation, be it in terms of global radiation or as solar irradiance on the building surface, and its correlation with different sky types (Janjai and Plaon 2011; Li, Chau, and Wan 2013; Loutfi et al. 2017). Moreover, ANNs have been utilized to calculate the natural and artificial illuminance distribution in an office using daylight simulations and a limited number of sensors (Si et al. 2014). However, there is no mention in the work regarding the usage of blinds, nor are the individual preferences of each user taken into account. Wang and Tan (2013) and Tran and Tan (2014) have developed predictive algorithms for the efficient control of LED lighting systems aiming to achieve energy savings, without however considering daylight. Finally, Kazanasmaz, Günaydin, and Binol (2009) have utilized an ANN for the prediction of daylight illuminance in office spaces, utilizing limited field measurements for 3 months. However, the usage of blinds and the user preferences are also not taken into account.

The user decision making process regarding the possible utilization of artificial lighting in an office is studied by Cılasun Kunduracı and Kazanasmaz (2017), through the development of a fuzzy logic algorithm that uses interior layout and daylight illuminance as inputs. Three single-user offices are investigated, and the user activities are monitored. However, even though the daylight entering the office is taken into account, the respective observations are conducted during winter months with limited daylight. Moreover, the usage of blinds is not monitored, and the user was asked not to interfere with them during the research.

3. Illuminance measurement and daylight simulation

The proposed model requires data (measurements and simulations) of illuminance within the working space under study. In this Section, the illuminance measurement set up that was implemented in the context of this work will be presented, along with details concerning the daylight

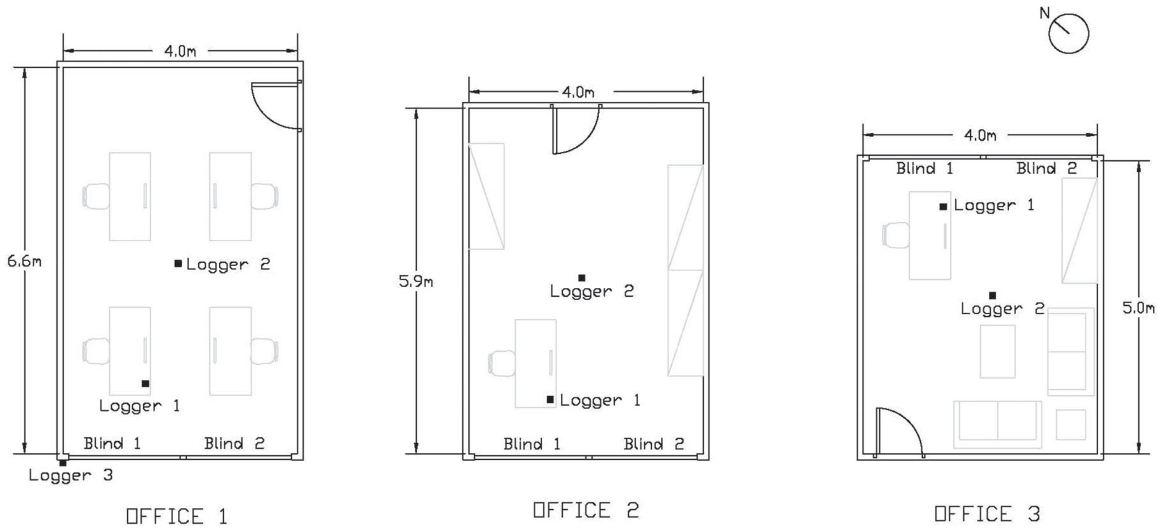

Figure 1. Floor plan schematic drawing for the examined offices.

simulations. Both will be showcased on a study involving three offices located in the same university building.

3.1. Description of the building under study

The case study of this paper is conducted in three different working environments (offices) in the building of the School of Electrical and Computer Engineering of Aristotle University of Thessaloniki, in Northern Greece (40°37’N 22°57’E). The examined offices are located on the 4th floor of the building and have unobstructed penetration of daylight. The three offices are almost identical in area size and they have the same size of windows (they present the same window to wall ratio, equal to 39%, while the window to floor ratio is between 18% and 24%). Offices 1 and 2 share the same orientation (South- West), while the Office 3 has a different orientation (North- East). Moreover, Office 1 is a multi-user office while the other two are single user offices. The offices are not equipped with automated lighting system and the users control both their artificial lighting and the blinds manually. In Figure 1, a schematic drawing of the floor plan of the examined offices is provided. The geometrical characteristics of the offices, the measurement points and the number of users can also be seen.

3.2. Measurement setup

For the purposes of this work, the horizontal illuminance (E) inside these offices has been monitored over a year, along with the occupancy and the usage of the manual blinds, using three data loggers.

The first logger is a light data logger (ONSET – HOBO Temperature/Light 64K Data Logger). This logger was placed on the working plane in order to record the respective horizontal illuminance (both artificial lighting and daylight). Its measurement range is 0–320 klux, and the respective sampling rate was set to one measurement per 5 min. In the single user offices, the loggers were placed on the users work plane. In the multi-user office the logger was placed on the desk closest to the windows, as the respective user is the first who feels the daylight discomfort. The position of the monitored desks is close to the windows in all the offices under study; this is a deliberate choice, but at the same time it creates a significant challenge, as it results to an extraordinary range of measured illuminance levels. However, this case is often encountered and has to be analyzed as it is missing currently in the respective literature.

The second logger is an Occupancy/ Light Data Logger (ONSET – HOBO UX90-006 Occupancy/ Light Data Logger). This logger was mounted on the ceiling of the offices under study, near a centrally located luminaire. This logger can monitor both room occupancy and changes regarding on and off switching of the lights, providing useful information about the lighting behaviour of the users.

In addition to these sensors, a third logger was mounted on the building exterior, outside the examined offices. This was a Data Logging Wireless Weather Station (ProWeather Station, Tycon systems) and it was used in order to monitor the weather on site for the testing period. External illuminance, outside the windows of the first monitored office, was recorded. In addition to these data, horizontal irradiance data for the duration of the measurements were collected from an urban photovoltaic station in the region.

Finally, the usage of blinds was monitored manually by the users, as they were kindly asked to note their daily actions (opening/closing the blinds and respective time of action). Also, the users were asked not to rotate the blinds, but only to use them as fully open or fully closed. This decision inserts a limitation in our modelling. However, it was taken after asking the users about their habits concerning the usage of blinds. All the users answered that they seldom rotate the blinds as they prefer to close them fully when the daylight becomes annoying. The fact that the users prefer to generally keep their blinds either fully open or fully lowered is also stated in other works (Foster and Oreszczyn 2001; Sutter, Dumortier, and Fontoynont 2006). Using the measurement based methodology described in Katsanou, Bouhouras, and Labridis (2017) the lighting preferences of the users were derived, and this will be analyzed in Section 4.

3.3. Daylight simulations

The development of a model that predicts the internal lighting conditions has to take into account the daylight entering the respective space and thus requires the ability to simulate all the possible cases regarding the actual daylight. For the offices under study this was achieved, additionally to measurements, through simulations. More specifically, hourly daylight penetration simulations were carried out, covering all possible orientations of the building, sky conditions (clear, overcast and mixed sky, as described in CIE 110) over 12 months, and different locations of the work plane inside the office (with the respective distance from the window set to be 0.5, 1.0, 3.3 and 5.5 m). The effect of the blinds usage in the internal illuminance was also simulated.

The daylight simulations were conducted using Dialux Evo software. This software has been used also by other researchers in order to simulate daylight penetration or internal illuminance (Parise and Martirano 2013; van de Meugheuvel et al. 2014; Mavromatidis, Marsault, and Lequay 2014). Dialux Evo implements the photon mapping algorithm (Jensen 2001) in its calculation method, in contrast to the previous versions (Dialux), where radiosity method was used instead. A comparative testing between these two versions had indicated that the photon mapping algorithm may predict more accurate illuminance values under area light sources compared to radiosity algorithm (Mangkuto 2016). The monitored offices were accurately designed in the software, and the reflectance factors of the surfaces were set equal to 0.7 for ceiling, 0.5 for walls and 0.2 for the floor. In addition, the Maintenance Factor was set to 0.8 and the task area was considered at 0.8 m above the floor.

A sensitivity analysis was conducted as well (Katsanou et al. 2018), to provide understanding regarding the different cases of daylight penetration in an office and the effect of each parameter. In the above work, a comparison between measured data and respective simulations had been also conducted to verify simulation results and to ensure that these simulations can be used to handle missing data in the model building process.

4. Modelling of user discomfort

The scope of the proposed model is to predict the personalized lighting levels in a working space based on the daylight penetration and the usage of lights and blinds, therefore it needs to incorporate the user preferences. The model results in a targeted prediction of the actions made by the users in order to restore comfort and in a subsequent estimation of energy consumption. To achieve this, the respective user actions must be monitored and correlated to the lighting conditions.

Several mathematical models have been proposed in the literature, describing the relationship between the user behaviour and different environmental conditions. These behavioural models are mainly divided into "threshold models" and "regression formulas models". In the first type of models, the user will definitely perform an action if a parameter (e.g. internal illuminance) exceeds a certain value, while in the second type of models the user's action is expressed as a function of the aforementioned parameter. Stazi, Naspi, and D'Orazio (2017) have reviewed the driving factors that trigger user actions, including work plane illuminance and room illuminance for lights, as well as illuminance, solar radiation, glare and indoor/outdoor temperature for blinds. It is concluded that work plane illuminance is the major trigger variable, while the other aforementioned variables are either difficult to record or are in fact related to the illuminance.

In general, the lighting behaviour of each user is expected to be stochastic; the actions of different users in identical offices are found to differ significantly. Yet, the actions of each individual may be considered consistent and thus predictable. That is the main reason of using personalized probability curves based on the actual measurements in this work, instead of generalized behaviour models (Hunt 1980; Reinhart 2004; Haldi and Robinson 2010). An example underlining differences in monitored use of lights and blinds in the two adjacent offices (Office 1 and 2) was presented in Katsanou, Bouhouras, and Labridis (2017).

4.1. Description and evaluation of methodology

In this work, data driven probability functions connecting the user actions (regarding artificial lights or manual blinds) to the internal illuminance were formulated. To this end, our study is restricted to the intervals of office occupancy and focuses on the "intermediate" user actions. This means that actions on arrival or before departure were not considered, as they do not represent the discomfort thresholds. In fact, only the intermediate actions of switching the lights on (in a dark environment) and the actions of closing the blinds (in a very bright environment) were taken into account. On the contrary, intermediate events of turning the lights off or opening the blinds are rarely spotted; when this occurs, the specific action is not directly related to the comfort lighting levels, as it is affected by several circumstantial factors. Users may delay to act because of laziness, concentration to work, other non-physical stimuli, etc. (Reinhart 2004; Boyce et al. 2006; Haldi and

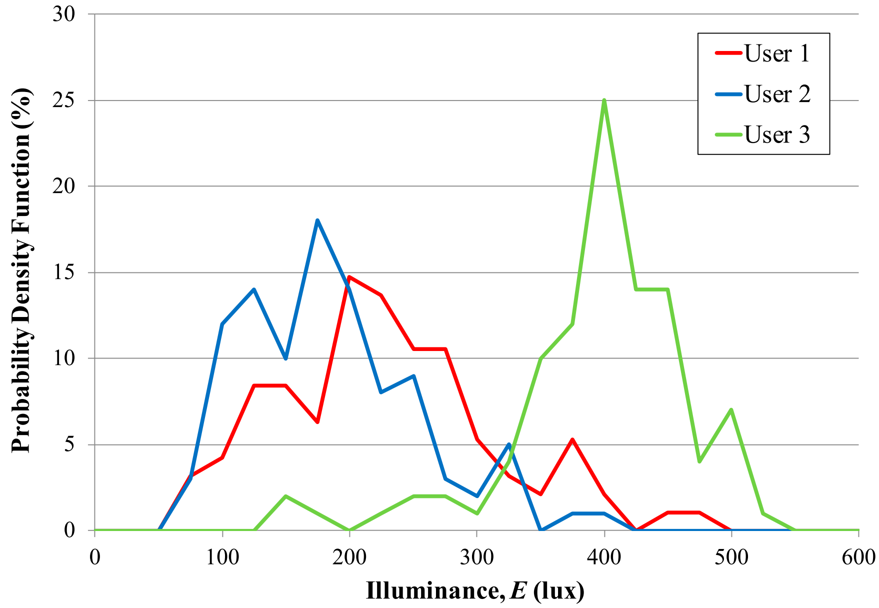

Figure 2. Probability density functions of illuminance values of the M_1, M_2, M_3 sets.

Robinson 2010; O'Brien, Kapsis, and Athienitis 2013). In addition, the probability functions that will be formulated are based solely on the monitoring of the action events, without taking into consideration the possible cases of non-action in the same illuminance values. This decision was taken in order to accurately assess the actions caused due to lighting discomfort, and accordingly to implement these actions in the ANN Model that is described in Section 6. As reviewed by D'Oca et al. (2019), there are numerous methodologies proposed in the literature that aim to represent the adaptive behaviour of a user, taking into account both cases of action and non-action in a certain illuminance level, averaged for a fixed time-step. However, for the scopes of this work, the following methodology was found to be more appropriate.

Two probability distributions are used to capture the preferences of each user. They model the probability of the user to act (to turn on the light or to close the blinds), when he feels discomfort, as a function of the overall illuminance on the work plane. In this work, these probability distributions were estimated using measurements of internal illuminance and data on the use of blinds, based on the set up of Section 3. It is assumed that there is a range of illuminance values within which each user feels comfort and consequently he takes no action. Also, there are critical values (thresholds), beyond which the user begins to feel discomfort and decides to act. Therefore, this behaviour needs to be parameterized.

Regarding the intermediate events under consideration, the following process was implemented. The illuminance value (E) at the timestamp of the event was sampled and two sets of M_i and N_i illuminance values (one for light switch and one for blinds) were formed for each user i. Each set contains all the illuminance values that caused discomfort to the user, so that the minimum and maximum values determine the limits of the discomfort zone. The values of each set present a certain distribution; the Probability Density Functions (PDFs) peak at different illuminance values and have a different width, revealing the differences among the three users (Figures 2 and 3).

The respective Cumulative Distribution Functions (CDFs) were derived for each user using the previous datasets (one for the use of lights and one for the use of blinds). These CDFs can be simulated using the logistic function, since the associated PDFs present a shape resembling the logistic distribution. The logistic function is a well-known S-shaped function and consists of two parameters a and b, describing the growth rate of the curve (parameter a) and the midpoint of the curve (parameter b).

For each user, $p(L = 1|E)$ is the probability that he switches on the light ($L = 1$) at an illuminance level higher than E and it is given by Equation (1):

$$p(L = 1|E) = \frac{1}{1 + e^{-a(E-b)}} \tag{1}$$

in which the parameters a and b are different for each user. Likewise, $p(BL = 1|E)$ is the probability that the user closes the blinds ($BL = 1$) for an illuminance level lower than E and is derived by Equation (2):

$$p(BL = 1|E) = \frac{1}{1 + e^{-c(E-d)}} \tag{2}$$

where parameters c and d differ again for each user.

Finally, there's a case of turning on the lights with the blinds closed. When the blinds close, the internal illuminance E turns to a much lower value E_{BL}. Equation (1) is

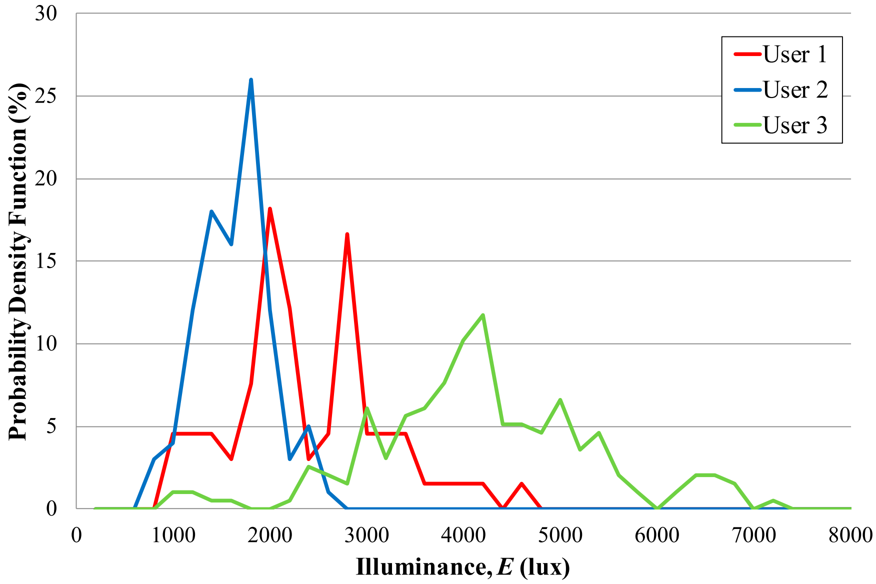

Figure 3. Probability density functions of illuminance values of the N_1, N_2, N_3 sets.

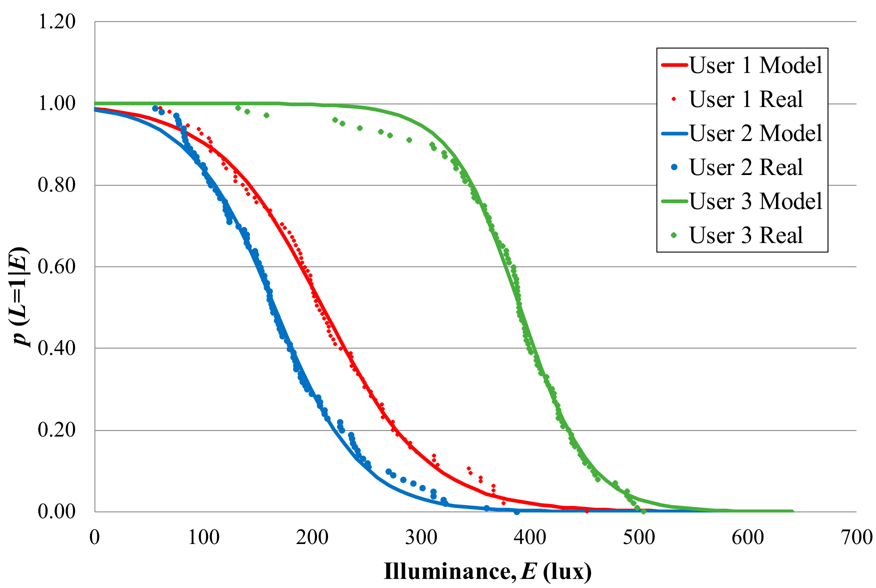

Figure 4. Probability to switch on the artificial lighting in relation to the illuminance level on the work plane, for three users.

still considered valid, meaning that the user reacts in the same way concerning the illuminance of his environment regardless the state of the blinds. As a result, for this case, Equation (3) is implemented having the same parameters a and b and E_{BL} instead of E:

$$p(L = 1|E_{BL}) = \frac{1}{1 + e^{-a(E_{BL} - b)}} \tag{3}$$

The combination of Equations (1) to (3) can lead to the calculation of the total probability of switching the light on (with or without blinds). This probability is directly coupled to the energy consumption for lighting in a room and is derived by the following Equation:

$$p(L = 1|E, E_{BL}) = (1 - p(BL = 1|E)) \cdot p(L = 1|E) + p(BL = 1|E) \cdot p(L = 1|E_{BL}) \tag{4}$$

In Figures 4 and 5, the modelled probability curves (Equations 1 and 2) and the real CDFs of the user actions in the three monitored offices are provided. It should be noted that the User IDs refer to the monitored offices IDs.

In Table 1, the parameters a, b, c and d along with the fitting errors for all cases are presented. In order to examine the goodness of fit, the Kolmogorov–Smirnov two-sample test was implemented. The two-sample K–S test is one of the most useful and general nonparametric methods for

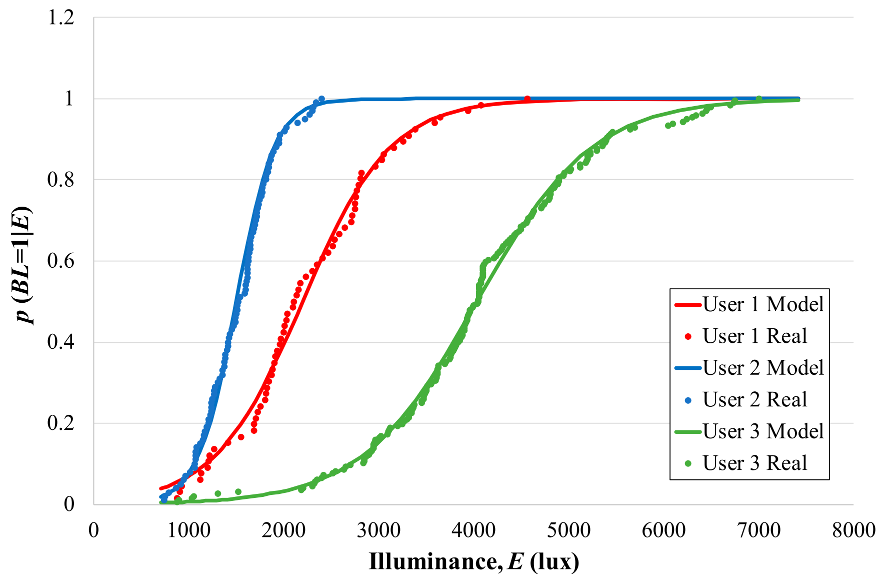

Figure 5. Probability to close the blinds in relation to the illuminance level on the work plane, for three users.

Table 1. Parameters and fitting errors for user actions probabilities of Equations (1) to (3).

Parameters and goodness of fit for $p(L=1\|E)$					
User ID	*a*	*b*	K-S, *Z*	*p-value*	RMSE
1	– 0.02045	209.8	0.363	0.998	0.01878
2	– 0.02528	165.5	0.495	0.967	0.02203
3	– 0.03151	390.8	0.424	0.994	0.02242
Parameters and goodness of fit for $p(BL=1\|E)$					
User ID	*c*	*d*	K-S, *Z*	*p-value*	RMSE
1	0.002153	2198.8	0.435	0.991	0.02978
2	0.00512	1500.2	0.636	0.813	0.03193
3	0.001656	4035.4	0.657	0.782	0.01844

comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples. Kolmogorov–Smirnov Z, the p- value at the level of significance of 0.05 and the Root Mean Square Error (RMSE) between the observed and the estimated curves are provided.

4.2. Comparison of users' behaviour

The resulting probability curves for the offices under study exhibit clear differences among the respective users. Offices 1 and 2 share the same orientation and windows configuration. The user of Office 2 generally exhibits much less tolerance to external lighting conditions; thus, he tends to close the blinds starting from an illuminance value (E) of 750 lux, with the respective probability reaching 0.9 at the value of 2200 lux. At the same time, he also requires less utilization of the artificial lighting, with a 0.5 probability to turn the lights on when the respective work plane illuminance is lower than 150 lux.

The users of Office 1 are more tolerant to the daylight, and start closing the blinds when the work plane illuminance exceeds 1000 lux, whereas the respective probability becomes 0.5 for illuminance values over 2300 lux. In addition, they require more artificial lighting, as they tend to use it with a probability of 0.9 for illuminance below 120 lux and with a probability of 0.5 for values below 200 lux.

The user of Office 3 exhibits different behaviour. More specifically, Office 3 has a northeast orientation, meaning that the highest daylight values occur during the early morning hours and last for a short interval. Due to this fact, the user seldom closes the blinds and presents higher tolerance to external light. He also tends to utilize the artificial lights more, presenting a probability equal to 0.9 to turn the lights on for illuminance lower than 330 lux, which is significantly higher than the other users. However, this value is still lower than 500 lux, which is the minimum work plane illuminance value proposed by (ECS 2011), indicating that energy efficiency can be obtained by all users.

The analysis of the measured data also shows that the three examined offices have different working schedules. That was within the intentions of the original case planning, as it offers the ability to monitor the user actions at different times and different lighting conditions. Figure 6 depicts the mean annual occupancy schedules (with the respective variations) for the offices under study.

All the previously mentioned behavioural data will be used in the proposed predictive model in order to accurately describe the discomfort thresholds of each user, to underline the differences between them concerning the use of lights and blinds and consequently to estimate their respective energy consumption for lighting. It should be noted that this is not a wide demographic research of user preferences, or a deep study of user perception

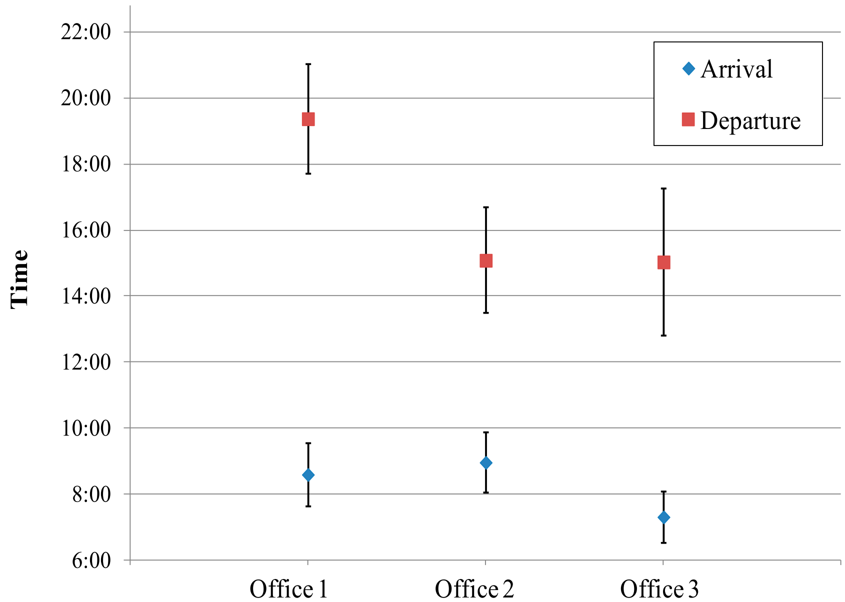

Figure 6. Mean occupancy schedules and respective variations for the three offices.

regarding daylight based on social or psychological variables. The scope of the proposed model was to show that any monitored user in an office can be represented by probability curves of action triggered from lighting discomfort depending on illuminance.

5. Sky modelling and solar radiation components

The understanding and estimation of solar radiation is also necessary for the determination of the daylight into a room. The solar radiation depends greatly on the day of the year and the geographic location of the building. The shape and the maximum values of the diurnal radiation curve also differ significantly, according to the declination and orientation of the examined surface. In addition, the solar radiation that reaches a surface depends on the respective sky conditions. Different models have been introduced (Liu and Jordan 1960; Orgill and Hollands 1977; Erbs, Klein, and Duffie 1982; Perez et al. 1990; Reindl, Beckman, and Duffie 1990; Lam and Li 1996), in order to decouple the total horizontal irradiance into its components (direct and diffuse irradiance).

In this work, the model introduced by Reindl, Beckman, and Duffie (1990) was incorporated into the proposed predictive model for the assessment of the internal illuminance according to the external solar radiation components. Reindl's model provides an estimation of the diffuse fraction k_d based on measured global horizontal irradiance data. This fraction depends on the clearness index (k_t) value and the solar altitude α, Equation (5). The diffuse fraction (k_d) is defined as the ratio of diffuse horizontal irradiance to the global horizontal irradiance, Equation (6). The clearness index (k_t) is defined as the ratio of global horizontal irradiance to the respective extraterrestrial solar irradiance, Equation (7). Low k_t values correspond to overcast skies, when only the diffuse fraction exists, while high k_t values correspond to clear sky when the diffuse component decreases to a minimum value and the direct fraction presents its highest value.

To implement this approach, hourly data of global horizontal irradiance measured at a small urban PV station located near the monitored building that matched our study period were utilized. The respective extraterrestrial irradiance was calculated and using Reindl's model the hourly components of direct and diffuse irradiance were estimated.

$$\begin{aligned}
&\text{Interval: } 0 \le k_t \le 0.3\\
&k_d = 1.020 - 0.254k_t + 0.0123\sin(\alpha)\\
&\text{Interval: } 0.3 < k_t < 0.78\\
&k_d = 1.400 - 1.749k_t + 0.177\sin(\alpha)\\
&\text{Interval: } k_t \ge 0.78\\
&k_d = 0.486k_t - 0.182\sin(\alpha)
\end{aligned} \tag{5}$$

$$k_d = \frac{I_{dif}}{I_{glo,hor}} \tag{6}$$

$$k_t = \frac{I_{glo,hor}}{I_0 \cdot \cos\theta_z} \tag{7}$$

where:

I_0 is the extraterrestrial irradiance

$$I_0 = I_{sc}\left(1 + 0.033\cos\frac{2\pi \times n}{365.25}\right) \quad \mathrm{W/m^2} \tag{8}$$

depending on the day of the year n and on the Solar Constant $I_{sc} = 1373\ \mathrm{W/m^2}$, and

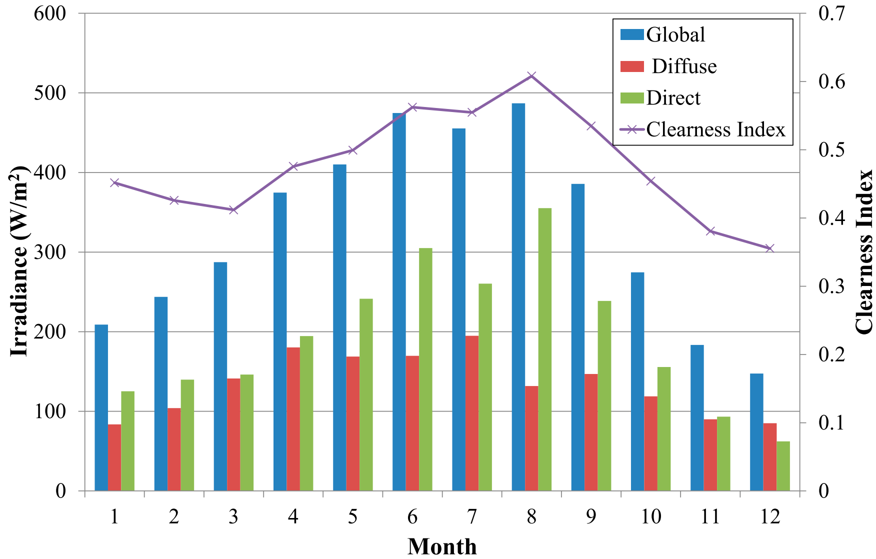

Figure 7. Mean monthly global, diffuse, direct irradiances and clearness index for the measured period.

θ_z is the zenith angle of the sun:

$$\theta_z = \cos^{-1}[\cos\varphi\cos\delta\cos\omega + \sin\varphi\sin\delta] \tag{9}$$

Zenith angle θ_z depends on declination angle δ, latitude φ and solar hour angle ω. Declination angle δ varies seasonally due to the tilt of the Earth on its axis of rotation and the respective rotation of the Earth around the sun. Equation (10) is used here for the calculation of the declination angle, as proposed by Cooper (Duffie and Beckman 1980):

$$\delta = \frac{23.45\,\pi}{180}\sin\left(\frac{2\pi(n+284)}{365}\right) \quad \text{(rad)} \tag{10}$$

Solar hour angle ω specifies the angular divergence of the position of the sun with respect to the solar noon for each hour of the day. It can be calculated using Equation (11):

$$\omega = 15^\circ(t_{sol} - 12\text{h}) \tag{11}$$

The solar time t_{sol} is calculated for the building time zone using Equation (12):

$$t_{sol} = t_{std} + \frac{L_{std} - L_{loc}}{15^\circ/\text{h}} + \frac{E_t}{60\,\text{min}/\text{h}} \tag{12}$$

where:

t_{sol} is the solar time (hours), t_{std} is the standard time (hours), and

L_{std} and L_{loc} designate the longitudes (degrees) of the time zone and the location respectively.

The parameter E_t is the well-known Equation of Time and it can be approximated using Equation (13):

$$E_t = 9.87\sin 2B - 7.53\cos B - 1.5\sin B \quad \text{(min)} \tag{13}$$

with

$$B = 360^\circ \times \frac{n-81}{364} \tag{14}$$

where n stands for the day of the year (with $n = 1$ for 1 January).

In Figure 7, the mean monthly Global, Diffuse and Direct Irradiances (W/m^2) along with the mean monthly clearness index (k_t) for the measured period are presented.

After estimating the components of direct and diffuse irradiance on a horizontal surface, the respective values for tilted surfaces can be calculated using Equation (15). It should be mentioned that for a tilted surface, solar radiation contains three components corresponding to the direct irradiance, the diffuse irradiance from the sky and the reflected irradiance from the ground (Kreider, Curtiss, and Heating 2002).

$$I_{glo,til} = I_{dir}\cos\theta_i + I_{dif}F_{sky} + I_{glo,hor}\rho_g F_{grd} \tag{15}$$

where:

I_{dir} is the direct irradiance

F_{sky} is the fraction of the isotropic radiation from the sky as seen from a flat surface tilted at an angle θ_p, given by Equation (16):

$$F_{sky} = \frac{1+\cos\theta_p}{2} \tag{16}$$

F_{grd} is the fraction of the isotropic radiation from the ground as seen from the titled surface, given by Equation

(17):

$$F_{grd} = \frac{1 - \cos\theta_p}{2} \tag{17}$$

and parameter ρ_g is the reflectivity of the ground, set in our case equal to 0.6. The parameter θ_i is the incidence angle of the sun on the plane which can be calculated using Equation (18):

$$\cos\theta_i = \sin\theta_z \cdot \sin\theta_p \cdot \cos(\gamma - orien) + \cos\theta_z \cos\theta_p \tag{18}$$

where: θ_z is the zenith angle, θ_p is tilt of the surface, *orien* is the orientation of the tilted surface and γ is the solar azimuth, Equation (19):

$$\sin\gamma = \frac{\cos\delta \cdot \sin\omega}{\sin\theta_z} \tag{19}$$

Finally, in the case of vertical surfaces (walls), where $\theta_p = 90^\circ$, the global irradiance on the surface $I_{glo,vert}$ is calculated using Equation (15) as:

$$I_{glo,vert} = I_{dir}\cos\theta_i + \frac{I_{dif}}{2} + \frac{I_{glo,hor}\rho_g}{2} \tag{20}$$

As it will be analytically discussed in Section 6, the three components of Equation (20) are used as different inputs in the proposed ANN model as they were found to be essential for its accuracy.

6. Development and implementation of ANN models

Two distinct ANN models were developed assigned to predict the internal illuminance (E) and the user actions in an office. The models were intended to be generic, adaptable to the user preferences and applicable for a work plane at any distance from windows, for any office orientation, for any day of the year, for different sky conditions and blinds state.

ANNs are broadly applied in the areas of the energy modelling, such as load and renewables forecasting, demand side management, operation of building management systems, etc. An advantage of an ANN model is that it does not require detailed building information and could train itself to adapt to complicated surroundings, thus it is preferable for data driven models like the one proposed in this work. Besides that, it has capabilities in pattern recognition and pattern classification.

An ANN model of Feed-Forward type (FFNN) consists of neurons structured in layers; an input layer, an output layer and between them one or more hidden layers. In each neuron the inputs applied are biased and then filtered via a hyperbolic tangent sigmoid function. In typical fully connected ANN each neuron is linked with the neurons of the previous layer and each link has its' own weight factor. The middle layer of the ANN holds a filtering role for the inputs especially in complicated problems with non-similar inputs and outputs. The ANN parameters, i.e. weights and biases, are determined using the Levenberg-Marquardt back propagation algorithm. This is an iterative process that is considered complete when a fitting error is minimized.

Vectors of input-output data (patterns) were formed and divided into three data sets, called Training, Validation and Testing data sets. These three sets were carefully formed in order to be statistically balanced. Samples were utilized from a wide data base that includes both simulated and real-data covering all aforementioned conditions (a total number of 512 daily sets, i.e. 12288 hourly patterns). 50% of data were used for training, 17% for validation and 33% for testing purposes. The training process is terminated using the loss function of Mean Squared Error (MSE) for the validation set; consequently, the trained model is applied on test data and forecasting errors are calculated.

6.1. *Model 1*

The aim of this model is to forecast for the same hour of the day two different illuminance values (E) and (E_{BL}) on the work plane referring to the respective states of blinds (open and closed). These illuminance values are then translated into possible user actions based on the formulated probability functions of the user (Section 4). The inputs and the outputs selected for Model 1 (shown in Table 2) are presented and described as follows:

Two different sinusoidal indices (inputs 1–2) were used to represent the day of the year, so that each day is described by a unique vector. This is a common option for several similar simulation problems that present a seasonal effect (e.g. load forecasting) (Bakirtzis et al. 1996).

As analyzed in Section 3, the season of the year and the office orientation (input 3), are both critical for the diurnal curve of the daylight illuminance. Sky condition, described via the clearness index k_t (input 4), has an obvious increasing effect on the outputs, while work plane distance from windows (input 5) has a decreasing one (Katsanou et al. 2018).

Inputs 6–9 are four distinct irradiance values on the window plane calculated on an hourly basis as described in Section 5. The direct irradiance (Input 6), the diffuse (Input 7), the reflected (input 8) and total irradiance (input 9) are all incorporated in the model. Each value is calculated for the vertical window surface considering the time of the day, the day of the year, the orientation of the office, the sky condition and the reflectivity of the surrounding environment. However, some of the latter parameters are also used as separate inputs (1–4) as several tests proved they are essential for the model efficiency.

Regarding the outputs of Model 1, illuminance values presented a wide range from 0 to 50 klux. Since ANN optimization algorithms perform better for data sets with a normal distribution, it was decided that a logarithmic transformation of illuminance values should be implemented.

Table 2. Inputs and outputs of the two ANN models.

Inputs	Description	Range of Values
1–2	Day of the year indices, cos $(2\pi n/365)$, $\sin(2\pi n/365)$, $n = 1, 2, \ldots, 365$	$[-1, 1]$
3	Office orientation (rad, 0 for South, π for North)	$[0, 2\pi)$
4	Clearness index k_t	[0, 1]
5	Work plane distance from window	0.5, 1, 3.3, 5.5 m
6	$I_{dir}\cos\theta_i$	[0, 613] W/m^2
7	I_{dif} /2	[0, 227] W/m^2
8	$I_{glo,hor}\,\rho_g$ /2	[0, 294] W/m^2
9	$I_{glo,vert}$ (from Equation 20)	[0, 824] W/m^2
Model 1 Outputs	Description	
1	Illuminance, (E) with open blinds	[0, 4.7] log$_{10}$lux
2	Illuminance, (E_{BL}) with closed blinds	[0, 3.4] log$_{10}$lux
Model 2 Outputs	Description	
1	Probability to switch on the lights (with open blinds), $p(L = 1\|E)$	[0, 1]
2	Probability to close the manual blinds, $p(BL = 1\|E)$	[0, 1]
3	Probability to switch on the lights (with closed blinds), $p(L = 1\|E_{BL})$	[0, 1]

The architecture of the ANN depends on various factors: the number and type of inputs and outputs, the correlation between inputs and outputs, the size of the dataset, etc. Since a variety of heterogeneous inputs (indices, distances, irradiances, etc.) and outputs (illuminances, probabilities, etc.) exists, there is no strong linear correlation between them, thus at least one hidden layer is essential as presented in Figure 8. The hidden layer acts as filter or classifier of input signals. The number of neurons in the hidden layer and the possible addition of a second or third hidden layer were determined though tests. The addition of a second hidden layer brought a modest improvement in the results (8%). However, when a third hidden layer was added, the ANN did not perform better. The optimal ANN structure for Model 1 was found to be 9:18:9:2, meaning 9 inputs, 18 neurons in the first hidden layer, 9 neurons in the second hidden layer and 2 neurons in the output layer (2 outputs).

In Figure 9 some indicative results of the model performance for different circumstances are illustrated. This Figure presents 8 days of real and forecasted internal illuminance values with open blinds (E) and closed blinds (E_{BL}) for 8 different office orientations. A variety of diurnal patterns is noted however the proposed model provides satisfying accuracy for all cases.

In order to depict how the model adapts in a wide variety of cases a scatter diagram of all forecasts (4096 hourly samples) versus real values is presented in Figure 10. The overall performance is highly acceptable, as suggested by the R-squared coefficient; evident weaknesses usually appear during sunrise-sunset transient intervals as a result of the hourly-based simulation of illuminance.

Both real and forecasted values of internal illuminance have to be transformed into possible user actions through Equations (1) to (4), which indicate if the user will switch on the lights or close the blinds. In Table 3, Mean Absolute Errors (MAE) between real and forecasted user action probabilities for the three monitored users are provided for Model 1.

The proposed model should be evaluated based on the probability errors of Table 3, as the aforementioned probabilities, especially $p(L = 1|E, E_{BL})$, are directly related to electrical load for lighting (per unit) or in kW after multiplying $p(L = 1|E, E_{BL})$ with the respective installed lighting capacity. It should be noted that this error for Model 1 (3.2–4.2%) is referring to forecasting hourly lighting loads of the dataset which includes different office orientations, work plane's distance from windows, it covers all seasons and weather conditions, it is irrespective of working hours and it is based on the preferences of the average user. Regarding total light energy consumption (in kWh) for the studied period, the model can provide accurate results with a slight overestimation (+0.0722%).

6.2. *Model 2*

A second model was developed (Model 2) where the ANN directly forecasts the three probabilities of user to act ($p(L = 1|E)$, $p(BL = 1|E)$and $p(L = 1|E_{BL})$). In this model the same inputs (as in Model 1) were used. The inputs and the outputs of Model 2 are presented in Table 2. In this model, there are different patterns for each one of the three Users under study. Specifically, the patterns have the same inputs and different outputs. Thus, three different ANN models were trained and optimized, one for each user.

The optimum structures of these ANNs were also investigated and the respective Mean Absolute Errors are presented in Figure 11. It was found out that there are slight differences in the results among the three users, but in general the best performing configurations have three or four hidden layers. However, this improved performance comes with a disproportional increase of model complexity and computational time.

The results of Table 3 indicate that Model 1 is more accurate than Model 2, proving that the correlation between external irradiance and internal illuminance is more effective. Nevertheless, Model 2 provides also

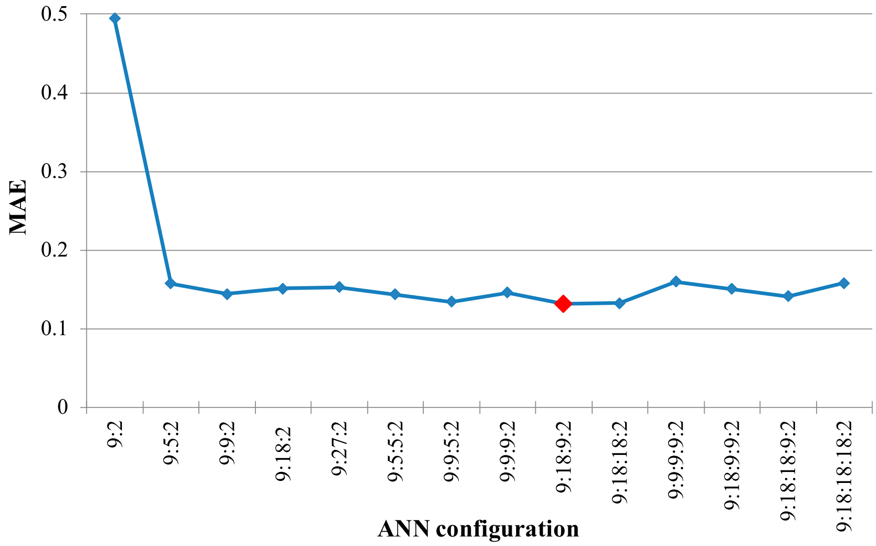

Figure 8. Mean absolute errors of different ANN configurations for Model 1. Forecasting error refers to logarithmic values of illuminance.

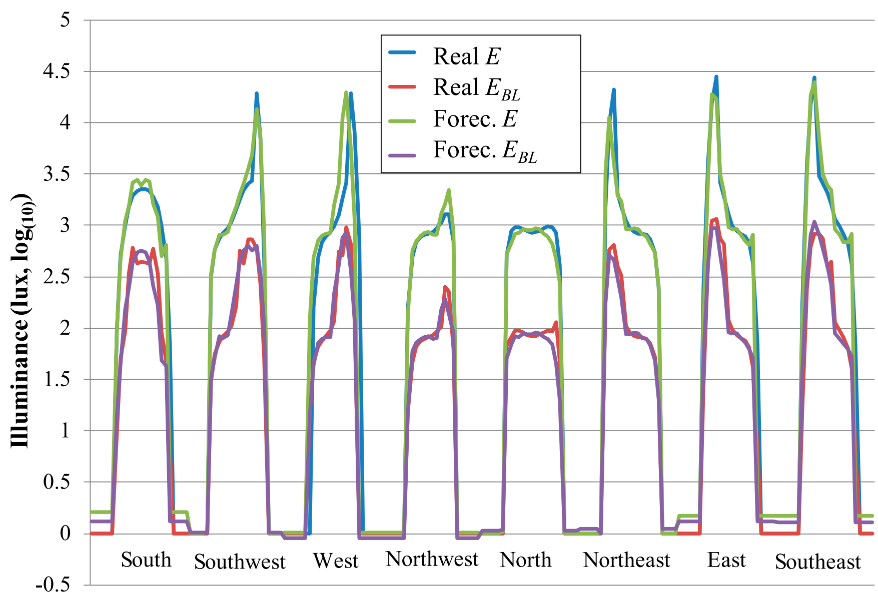

Figure 9. Daily real and forecasted internal illuminance values with open blinds (E) and closed blinds (E_{BL}) for 8 different office orientations.

satisfying results as the average error in the prediction of $p(L=1|E, E_{BL})$ ranges from 4.1% to 5.1%. Regarding the total lighting consumption, as in Model 1, it also presents accurate results with a negligible overestimation (+0.0778%).

6.3. Implementation of Model 1 for energy consumption

In the previous subsections, two models were presented. The first one can forecast internal illuminance on a work plane, while the second one directly estimates the possible user actions. The superiority of Model 1 is clear as (a) it is a tool providing illuminance values useful for a wide range of applications, (b) it was found to perform better than Model 2 when these illuminance outputs are transformed into user-action probabilities, and (c) it is even more efficient when estimating total lighting consumption over a period of time.

This tool can be further implemented, in order to investigate the effect of user behaviour patterns on the corresponding energy consumption for lighting. A case study follows, concerning the three monitored users described in Section 4 for the duration of a year. The probability curves for each user were presented in Figures 4 and 5. The annual period was fully simulated on an hourly basis, using weather data for the city of Thessaloniki, Greece, from EnergyPlus database, providing 8760 values for input

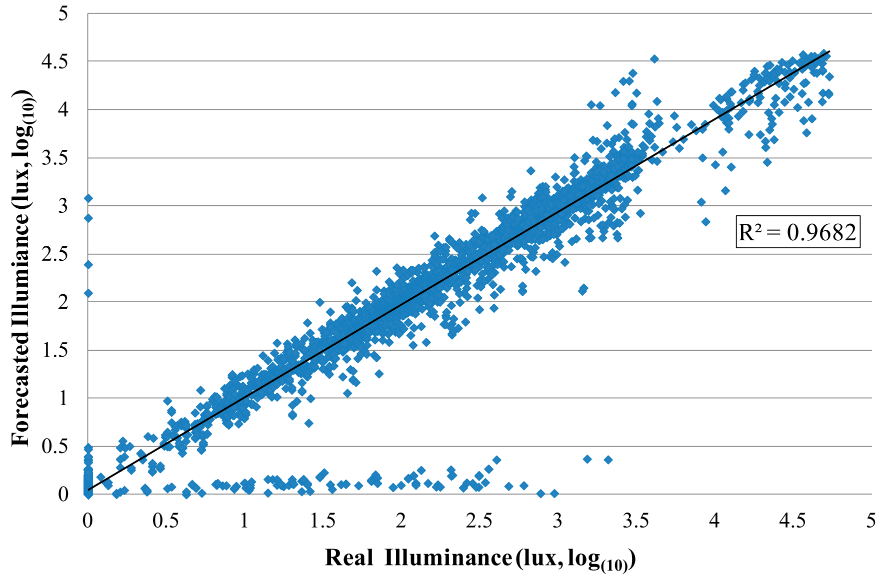

Figure 10. Scatter diagram of the overall performance of the ANN, presenting real vs forecasted illuminance values.

Table 3. Comparison of the two models based on MAE of user action probabilities.

	Error for Model 1			Error for Model 2		
Probability	User 1	User 2	User 3	User 1	User 2	User 3
$p(L = 1\|E)$	0.0273	0.0279	0.0263	0.0376	0.0394	0.0344
$p(BL = 1\|E)$	0.0210	0.0235	0.0150	0.0183	0.0227	0.0101
$p(L = 1\|E_{BL})$	0.0146	0.0182	0.0082	0.0144	0.0172	0.0080
$p(L = 1\|E, E_{BL})$	0.0373	0.0423	0.0326	0.0461	0.0514	0.0411

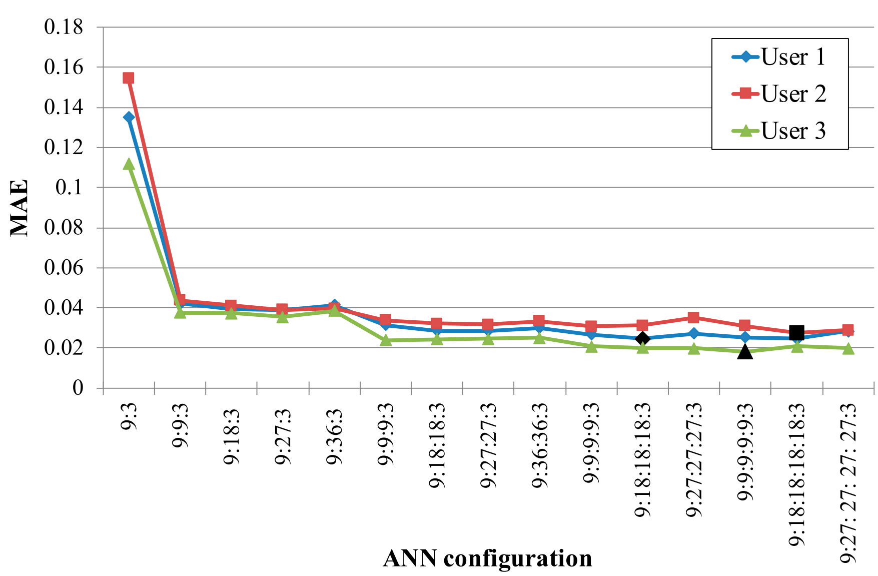

Figure 11. Mean absolute errors of different ANN configurations for the three users for Model 2. Outputs and errors refer to user action probabilities.

4 (Table 2). It should be noted, that these values do not correspond to a specific year, but they describe a typical meteorological year for the specific region. Input 5 (distance from window) was set equal to 1 m. The rest of the inputs were calculated as described in Section 5 for each hour of the year, depending on the office orientation.

The proposed Model 1 produced the hourly illuminance time series which were accordingly transformed into

Table 4. Forecasted energy consumption for lighting for 24 different cases.

	Energy Consumption for Lighting (pu-hours/semester)					
	User 1		User 2		User 3	
Office Orientation	Winter	Summer	Winter	Summer	Winter	Summer
North	268.3	26.4	270.7	58.4	310.4	9.9
East	284.9	47.2	296.7	92.3	319.6	45.7
South	268.5	78.6	254.3	117.4	321.0	23.1
West	270.3	27.9	265.8	42.4	297.9	17.3

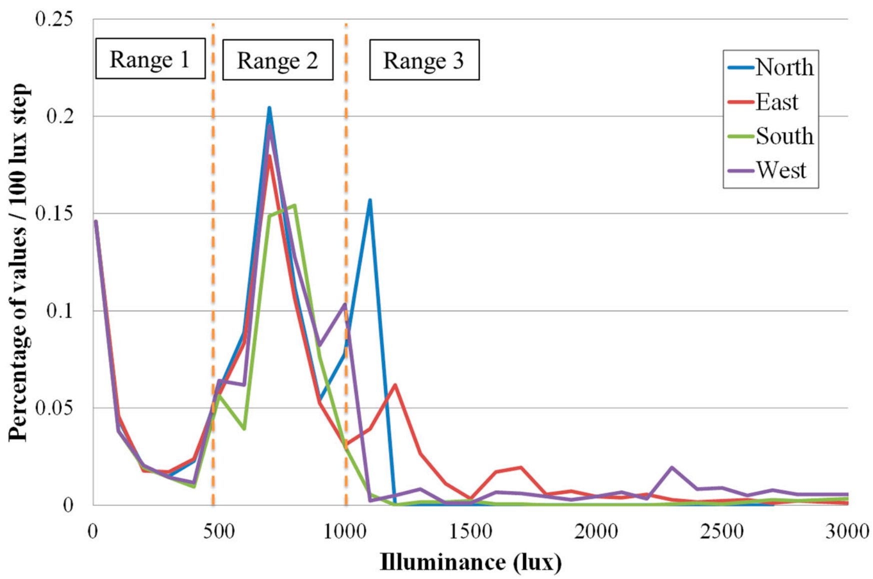

Figure 12. Distribution of illuminance values for Winter Semester, depending on the office orientation.

$p(L=1|E,E_{BL})$values using the probability functions for each user. In this case, a realistic working schedule was implemented assuming five days per week and working hours from 8:00 to 18:00. If an installed lighting capacity equal to $P_{inst,i}$ in W is considered, the total energy consumption E_{ij} for each user can be estimated using Equation (21):

$$E_{ij} = P_{inst,i} \cdot \sum_{k=1}^{M} p_{Lon,tot,ijk} \tag{21}$$

where:
i is the user,
j is the office orientation,
k is the hourly step, and
M is the total number of hours considering the working schedule.

For comparison reasons, the total installed capacity of the luminaires is considered 1 pu for each user and the working schedules are identical. Table 4 presents 24 values of total lighting consumption depending on

(1) the user, as each user has different action probability curves
(2) the office orientation, to demonstrate its effect for the same user, and
(3) the season. To this end, the annual period is divided in two semesters, "Winter" (October to March) and "Summer" (April to September) showing the impact of external lighting.

Figures 12 and 13 present the distribution of illuminance values produced by Model 1, for each semester and orientation restricted for the working hours. The vertical lines approximately indicate three distinct ranges of illuminance values; within Range 1 (0–500 lux) the user most probably switches on the light, Range 2 (500–1000 lux) represents the lighting comfort zone and within Range 3 (above 1000 lux) the user may close the blinds. These Figures can be used to interpret the numerous results of Table 4. For instance, consumption during Summer Semester is always lower comparing to Winter Semester (2–30 times depending on the case), as there are no illuminance values in Range 1 (Figure 13). User 3 has the highest consumption during the Winter Semester, because he switches the light on for higher illuminances (see$p(L=1|E)$, Figure 4). User 2 has the highest consumption in Summer Semester, because he is the first who

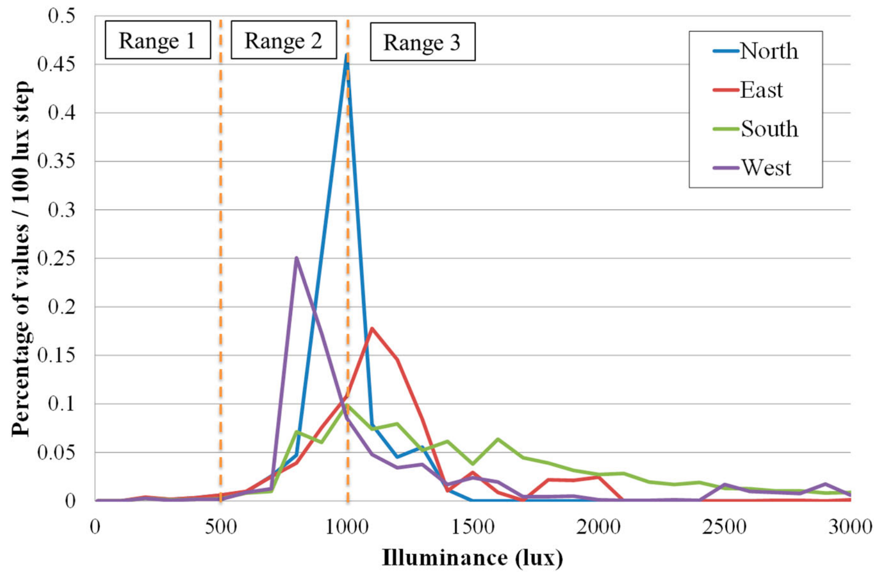

Figure 13. Distribution of illuminance values for Summer Semester, depending on the office orientation. A considerable percentage of values (20% of East, 20% of West and 9% of South) lies above 3000 lux.

closes the blinds (see $p(BL = 1|E)$, Figure 5) and probably switches the light on (see $p(L = 1|E_{BL})$, Equation 3).

The effect of orientation for each user has been also investigated. During Winter, East office orientation usually presents the highest consumption. As shown in Figure 12 for Winter, all orientations present the same distribution pattern in Range 1, while East Orientation has a number of values in Range 3. During Summer, West and North office orientation present the lowest consumption, as most values appear in comfort zone (Range 2).

It is consequently shown in Figures 12 and 13 that the User preferences affect lighting consumption in a unique manner. Also, it is confirmed how essential it was to connect these preferences with parameters as orientation, distance from window, etc., in order to build an adaptable and efficient predictive tool.

6.4. *Applications of the proposed models*

The trained generic Model 1 is user-independent and can be applied to test the performance of any similar office in a different site or country. For instance, the methodology of Section 6.3 could have been used to extract the consumption for a building in London instead of Thessaloniki by changing the weather input data. Since it mostly relates external radiation to internal illuminance, it can be easily applied anywhere as long as the window-to-wall ratio is the same. Furthermore, the outputs of Model 1 (illuminance on task area for open/closed blinds) can be coupled with generalized occupant-behaviour-models.

Model 2 is trained and formed based on the data of a specific user and thus it is more restricted. Still, the trained model can be applied, for instance, to estimate and compare the user actions and consumption in different conditions (distance of task area from windows, office orientation, country, etc.).

For a completely different building (different window to wall ratio, obstacles to the outside environment, etc.), the proposed process would have to be followed step by step utilizing calculations, measured data and simulations. This is needed in order to develop a generic model, applicable to different orientations, locations, task area distances from windows, etc. However, if the intention is to build an ANN model for a specific office and user, in order for example to use it in a real time application inside the office, the training of the model would be rather simpler, requiring basically illuminance data (gathered from an illuminance data logger on task area) for Model 1 and the user preferences for Model 2.

7. Conclusions

In this work, a novel ANN-based model for the prediction of internal illuminance and user actions in a working environment has been presented. The proposed model takes into account the daylight entering the respective space, the usage of blinds and incorporates the requirements of each user. In this context, the model leads to a targeted prediction of the users' actions regarding their lighting conditions, as well as to the corresponding energy consumption.

In order to simulate the behaviour of the users under study, data driven probability functions connecting the user actions to the internal illuminance were formulated. Among the monitored users' actions, only the intermediate events of switching the lights on or closing the blinds were considered. This approach was followed to distinguish the user actions triggered by internal illuminance discomfort from actions related to other factors. It was found that the probability curves for the offices under study exhibit clear differences among the respective users.

The hourly daylight conditions are essential for the accuracy of the model. To this end, a validated sky model was incorporated in order to extract the components of direct and diffuse irradiance from the horizontal irradiance data and use them as inputs to the model.

Two versions of the model (Model 1 and Model 2) were developed, tested and evaluated. Model 1 forecasts the internal illuminance on a work plane, which is then translated into user actions through the user probability functions. Model 2 directly estimates the possible user actions. The overall performance of the two models is highly acceptable, as the forecasted hourly lighting load errors are in the order of 3.2–4.2% (for Model 1) and 4.1–5.1% (for Model 2). Also, regarding the total lighting consumption, the two versions present accurate results with only a negligible overestimation.

Model 1 was additionally implemented for an annual period, in order to study the impact of various parameters in the overall lighting consumption. It was found that user preferences, orientation, distance from window, etc. affect the annual lighting consumption causing deviations up to 25% for the examined case study.

The proposed model comprises a predictive tool that can be utilized for various purposes, e.g. a real-time adaptive control application or a greater scheme able to predict user oriented total energy consumption (thermal, air-conditioning, etc.). Also it can classify users in order to estimate the potential savings in a building through behavioural change and it can be further applied to formulate personalized incentives in a demand side management programme.

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