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Fuzzy logic model for the categorization of manual lighting control behaviour patterns based on daylight illuminance and interior layout

Arzu Cılasun Kunduracı[1] and Z. Tuğçe Kazanasmaz[2]

Abstract

In considering total building energy consumption, lighting plays an important role in shaping energy consumption and use. Although key strategies (such as energy efficient lighting products, lighting control systems and energy simulation software) are developed so far, such attempts may be unsuccessful unless users are not taken into consideration. Users' behaviours and their manual lighting control actions depend on various factors, though within the scope of this study manual lighting control behaviour was analysed only in terms of interior layout and daylight illuminance. Three private offices in Izmir Institute of Technology were monitored using illuminance metres and occupancy/light detectors under eight different interior layout conditions. In relation to change of interior layout and daylight penetrations, users' manual lighting control behaviours were monitored. The obtained data were then used to construct a fuzzy logic model in MATLAB FIS editor. A fuzzy logic algorithm was applied to classify behaviour patterns about the tendency to turn on the lights. This kind of prediction of the light usage tendency regarding the occupancy is aimed to foresee the 'possible' manual lighting control behaviour within given conditions. The gathered classification can be used further in future studies of manual lighting control behaviour and energy-saving estimations/simulations.

Keywords

Manual lighting control, Fuzzy logic model, Behaviour pattern, Interior layout, Daylight illuminance

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Introduction [AQ1]

Energy consumption has always been a major concern for architects and users. Primarily, energy consumption is affected by the presence and activities of users in a building and their control actions undertaken with the intent of improving indoor environmental conditions (thermal, air quality, lighting and noise).[1] Therefore, energy use in buildings is closely linked to space utilization characteristics and the behaviour of each building's occupants. Energy consumption can be reduced further by understanding the occupants' needs and behaviours.

The world has been facing environmental problems due to excessive energy consumption. Thus, developing new methods to minimize energy waste is becoming increasingly important. Lighting has become one of the main factors in energy consumption since the 1970s.[2] So far, all key strategies developed to reduce the energy use of lighting have involved energy-efficient lighting products, lighting control systems and energy simulation software. However, such attempts may be

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unsuccessful unless users' requirements are taken into consideration.

The measures to reduce energy consumption would need data and it is desirable for such data to be used in making predictions regarding lighting energy usage. One of the biggest challenges in the prediction of building energy consumption is accurately quantifying users' behaviour and their manual control actions, which depend on various (triggering or inhibiting) factors. As Yan et al.[3] mention, occupants' behaviour is influenced by physical, physiological and psychological factors and other social factors such as age and gender. Also, when a user controls a specific indoor condition, other environmental conditions can be influenced, which may lead to unintended results. For example, to obtain higher daylight penetration and reduce artificial lighting energy consumption, a user may open the shading. This action could enhance the heat gain due to solar radiation from the outside and, thus, would require an increase in the cooling load. Therefore, manual control should be investigated in order to foresee any possible energy consumption.

Manual lighting control refers to an user's activation of a lighting system without any involvement of the automatic control system. Before the invention of building automation and energy management systems, manual lighting control was the only way to control lighting. Today, due to technological innovations, various types of lighting control systems are available. Despite these automatic control systems, users' behaviour still has a significant effect on the energy performance of a building.

Visual comfort and luminance expectations diverge among users. Some users prefer illuminance lower than the predetermined values, which may lead to the manual dimming or turning off lights. For example, according to Maniccia et al.,[4] over 50% of occupants studied indicated they would prefer a dimmer luminaire for their workstation. As a result, visual comfort expectations can vary among users, depending on their tasks they are undertaking.[5]

To realistically take into account manual lighting control behaviour, it should be analysed in relation to affecting factors (such as daylight, occupancy, blinds, space type, different control systems and energy consumption) that have already been discussed in previous works.[6–12] However, the influence of interior architectural arrangements on manual lighting control has not been previously analysed. Interior design of a building can influence users' actions or can even change their habits. For instance, a well-organized interior space may attract customers to shop or occupants to work more efficiently. As Tabak[10] mentioned, with the help of design, users can change their physical environment to satisfy their needs. Illuminance upon entrance is another significant factor, which could affect users' manual lighting control behaviour. The initial study by Hunt[6,11] reported that this correlation is based on switch-on probabilities derived from monitoring case studies, i.e., when the illuminance was higher than 100 lx, the switch-on probability in the majority of case studies was lower than 0.4. When it was lower than 100 lx, the probability rose dramatically from 0.5 to 1. In addition, by measuring the energy consumption, Yun et al.[13] showed that occupants are more likely to turn lights on upon their entrance if the room is relatively dark and to keep lighting on until their departure. Therefore, analysing interior layout design and daylight illuminance could reveal behaviour patterns, which may enable researchers and designers to classify and predict manual lighting control behaviour.

Fuzzy logic is an alternative methodology for predicting the manual lighting control behaviour because it can explain facts and knowledge through simple verbal rules using human-like logic. Several studies applied machine-learning techniques in various research fields. In architecture, Kazanasmaz and Tayfur[14] employed a fuzzy logic model to classify the planimetric effectiveness of nursing unit floor plans in hospitals. The daylight illuminance was successfully predicted (with 87% of accuracy) in a study of an office with a movable blind system.[15] Fuzzy logic modelling has an even wider application in the field of engineering.[14,16–18] In the view of recent knowledge and existing studies as mentioned above, the fuzzy model was used to develop the initial users' behaviour model as proposed by Hunt[6,11] by relating them to interior design parameters such as desk layouts and the distance from desk to window in identical private offices.[19] This research design was intended to define classes of users' behaviour, which could shed light on general and detailed estimation about how a user might interact with lighting systems.

Despite all aforementioned studies and proposals about users' behaviour models, there has been inconsistency in their findings. New studies are needed to broaden our knowledge and deepen our understanding. Additionally, simulation techniques/tools remain the most common and convenient way to define users' behaviour. As described below, fuzzy logic, one of the artificial intelligence techniques, is a novel and promising option. Thus, the aim of this paper is to develop a fuzzy model to determine users' behaviour patterns in terms of illuminance and interior layout. During the early phase of design when the interior design drawings are ready, such categorization of users' behaviour can be a practical and useful tool for predicting possible manual lighting behavioural attempts.

Fuzzy logic concept

Fuzzy logic (is a form of non-linear mapping of the input data to obtain scalar output data.[17] It is a type of machine learning technique which abstracts and classifies real case issues into simple tasks. This approach is based on both verbal statements and algorithms. There is a direct conversion from the former to the latter during the whole process. It is a powerful technique, which formulates approximate reasoning. A real-world event is categorized through variables into graded subsets and is defined through relative memberships. It dates back to 1965, when Lofti A. Zadeh[20,21] proposed the 'Fuzzy Set Theory'. When the data are either unavailable or incomplete, or whenever the process is highly complex, the fuzzy logic computational paradigm can be used.[22] Fuzzy logic basically provides partial truths and multivalued truths. Therefore, it is generally used for problems, which cannot be simply expressed by mathematical modelling.

In the fuzzy system, the key idea is 'the allowance of partial belongings of any object to different subsets of a universal set instead of belonging to a single set completely'.[14] For this purpose, the fuzzy system have four basic steps: Fuzzification, Decision Making Unit, Rule Base and Defuzzification (Figure 1).

This structure informs us that membership functions of a fuzzy set convert inputs into ranks of membership in which fuzzy variables are matched to a number between 0 and 1 in the first step, known as Fuzzification. The membership function sets the conversion process using a linguistic term such as 'high', 'medium' or 'low'. Triangular or Trapezoidal membership functions are commonly applied because of their simplicity and linearity. Rule Base, as the second step, describes the fuzzy inference application using the mathematical interpretation of linguistic expressions. These rules are created to determine a relation between input (x_1, x_2,…) and output data (y_1). Non-linear relationships or uncertainties are described with IF-THEN or AND/OR rules but without any numerical equations or models.[23] This is the basis of fuzzy model application. In example below, Mamdani rule system is applied.[17] IF defines the antecedent part of the rule statement with the AND/OR connectors, while the consequent part is composed of THEN. The researcher constructs these rules by analyzing the input data[17,24] or by intuition due to norms regarding the subject matter in literature. The following rules are given as examples:

R1: IF x_1 is LOW and x_2 is LARGE; THEN y_1 is MEDIUM
R2: IF x_1 is LOW and x_2 is SMALL; THEN y_1 is LOW
R3: IF x_1 is HIGH and x_2 is LARGE; THEN y_1 is HIGH
R4: IF x_1 is HIGH and x_2 is SMALL; THEN y_1 is MEDIUM

The rules are set to define the relationship between x_1, x_2 and y_1 in the above example. Applying these rules to indoor illuminance, we can say that if the exterior horizontal illumination is low and the window area is small, then the interior workplane illuminance is low. Either one of the two rule systems, Mamdani or

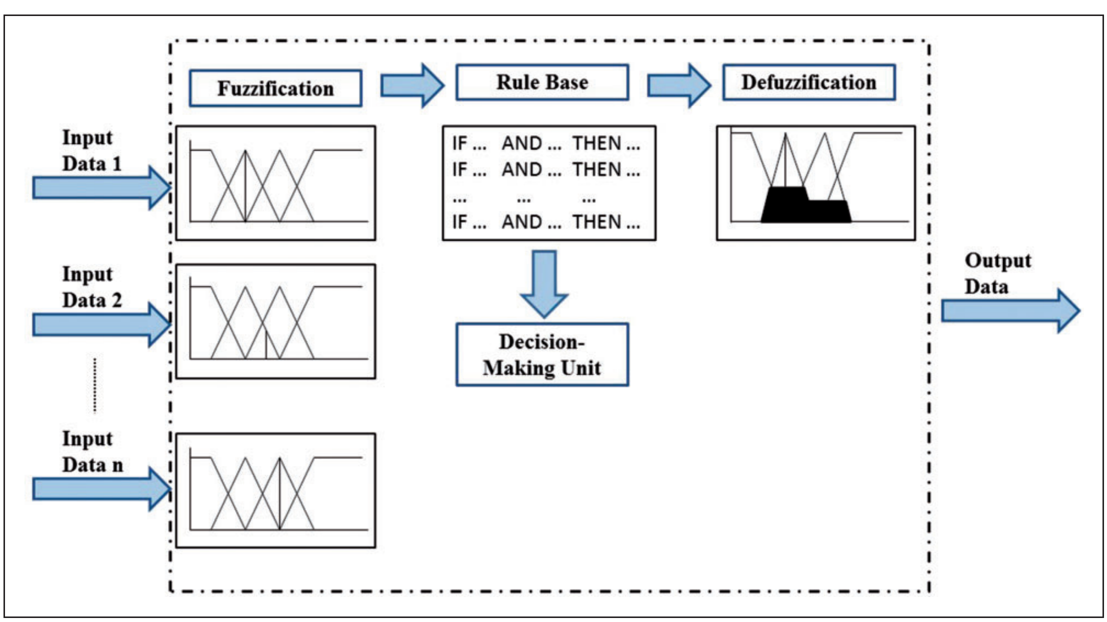

Figure 1. Structure of fuzzy system process.

Sugeno,[25] can be chosen depending on the subject matter. The consequent part of the fuzzy rule is expressed as a mathematical function of the input variable in the Sugeno system, while this is composed of verbal statements in the Mamdani system.[25,26] As the former is much more appropriate for neuro-fuzzy models, the latter was chosen for this study. *The fuzzy inference engine* utilizes all the fuzzy rules and trains how to alter inputs to corresponding outputs using activation operators in Decision Making Unit. Defuzzification presents these fuzzified outputs. Methodologies of defuzzification are available in literature.[25–27] Maximum membership principle and mean of maxima, for instance, are two types of methods which disregard the shape of the fuzzy set and are employed in certain problems.[28] The weighted average method, on the other hand, can only be implemented for symmetrical output membership functions. The bisector of area method 'picks the abscissa of the vertical line that divides the area of the combined output fuzzy subset in two equal halves'.[27] The centroid (COG) method is the most common one in which the output value is calculated as the 'abscissa under the centre of gravity of the combined output fuzzy subset'.[14] This is regarded as the basic general distribution method which provides a highly practical characterization of continuity.[29] Thus, the COG method is chosen for this study. Alternatively, one of the maxima methods, middle of maxima (MOM), was applied to compare results in validation procedure. Literature cites about their good behaviour as compared with the more basic defuzzication criteria.[29]Two subsequent phases – Rule Base and Defuzzification – involve more computations after the verbally structured relations turn into single numerical values.

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Methodology

Monitoring process. The monitoring procedure mainly included obtaining realistic (actual) manual lighting control data in private occupied offices in a university building. The reason to choose private offices as the subject case is as follows. Occupants in either open-plan or shared offices are often forced to put up with the preset comfort conditions even if they do not match their preferences. However, 'occupants in private offices were more likely to make environmental or behavioural changes to regain comfort, whereas occupants in open-plan spaces rely more on psychological coping mechanisms'.[30] Thus, monitoring private offices can give clearer outputs on the users' decisions. As users of offices in universities do not use their offices for a whole day due to lectures, seminars and meetings that happen frequently and they go in and out more often when compared to many other office types, observing their manual lighting control with frequent ins/outs and choosing a university building has been found to be more reasonable. This monitoring process involved measurements of illuminance on desk surface, occupancy and light on/off detections and interior layout arrangements. The overall monitoring phase took place in seasons when daylight was limited between November 2014 and February 2015; and in which users' manual lighting control could be triggered by this limitation.

Site description. To observe users' manual lighting control behaviour individually, three private offices were chosen for the monitoring stage of this study. They are located in a two-storey building in Izmir Institute of Technology (İYTE) Faculty of Architecture (38° 18′ 53.6940″ and 26° 38′ 16.7460″). Two of the rooms are on the first floor (Rooms 111 and 110) while the third one was located on the ground floor (Room Z06). Each room has two identical windows facing north, and the room height is 3.25 m (Figure 2). To provide artificial lighting, two surface-mounted luminaires operating with 2×35 W T5 fluorescent lamps with a total of lighting load of 140 W were installed. The windows were equipped with non-automated interior blinds. To minimize their lighting differences among the three rooms, blinds were positioned to achieve 500 l~~u~~x at a point 1 m away from the window on the same day in all three rooms. Users were asked not to interfere with the blinds' position during measurements. [AQ2] i agree with editor Prof. Chuck Yu's comments, lx (instead of lux)

Horizontal illuminance measurement. ONSET wireless illuminance data loggers (Model HOBO U12-O12, Bourne, USA) were used to record the horizontal illuminance on the desk. They were placed on the desk to record the total amount of light (both daylight and artificial lighting) that falls on the workplane. The sensors can record the illuminance both numerically and graphically every minute. Thus, any sudden significant change in the illuminance can be interpreted as a change of the artificial lighting condition.

Occupancy and light detection in the room. When dealing with the manual lighting control behaviour, monitoring the interior illuminance alone is not enough. Occupancy intervals is one of the important key aspects as 'several researchers reported that the duration of absence followed by the departure as the primary predictor for light switch-off action'.[30] Occupancy and light data loggers have been used in various lighting and energy consumption research.[31]

ONSET Occupancy and Light Data Loggers (Model: HOBO UX90-006, Bourne, USA) were chosen to record both occupancy and light on-off

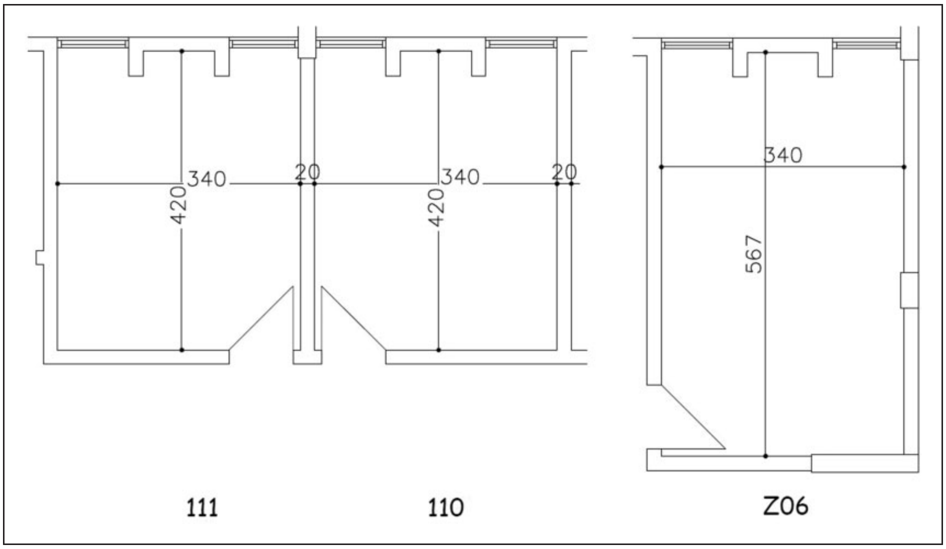

Figure 2. Geometry of test rooms.

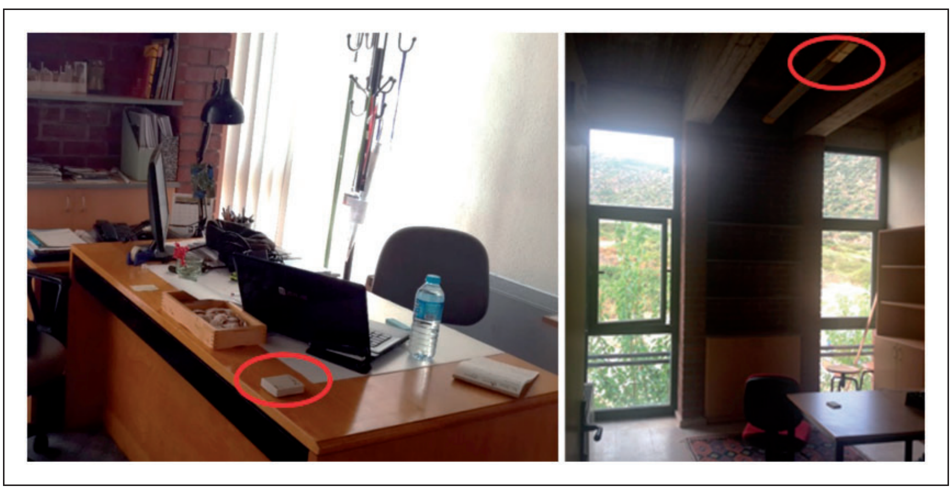

Figure 3. Location of the occupancy/light sensor.

conditions and to understand the connection between manual lighting control and the occupancy intervals. These devices perform in a large detection area (41° horizontally and 47° vertically). They can monitor room occupancy up to 5 m away as well as indoor lighting level changes with its integrated sensors. The devices are set to capture any change in occupancy or lighting level every second. For occupancy detection, the sensor was activated when there was any rapid/sudden change in its thermal sensation. For the light on-off records, two methods can be followed. Either the default value of 65 lx can be used as a threshold value or a new threshold value can be defined with calibration. By turning lights on and off, the sensor can be calibrated. After the calibration, the sensor can easily detect whether the lights are ON or OFF within the room. These sensors were mounted near the lighting fixture in each sample room (Figure 3).

Matching and comparing these two sensors for illuminance data and occupancy and light ON/OFF data helped better understand the user's manual lighting control behaviour. For instance, during entrance, if the user does not turn on lights over certain amount of illuminance, then this can be used to interpret the user's expectation for interior illuminance.

Interior layout arrangements. The monitoring procedure mainly involved obtaining realistic (actual) manual lighting control data in sample offices. Four basic directions of getting daylight penetration (from left, right, back and front) were the variants. To understand the effect of distance from the desk to the window on the manual lighting control, each direction was tested with two different distances: one was 1.45 m away from the window (named as direction-A) and the other is 2.45 m away (named as direction-B) (Figure 4). Consequently, variation in layout and distance would lead to eight sets of measurements for each sequence. Each interior layout was monitored for 10 days.

Fuzzy logic model construction

A fuzzy logic model was developed to interpret the manual lighting control of users employing three changing factors; in other words, independent variables: desk layout, distance to window and illuminance (Figure 5). A fuzzy algorithm was needed to recognize behaviour patterns about the occupants' tendency to turn on lights by using these factors and to interpret relations among the non-linear input data. Employing this model would make it possible to predict and classify users' control behaviour patterns. The construction of such an algorithm relies on the monitoring data obtained from the previous step and consideration of the recommended illuminance mentioned in CIBSE standards.[32]

MATLAB Version R2009b FIS toolbox (MathWorks, Natick, USA)[33] was used to employ the fuzzy logic model by using observational data obtained during the onsite measurement phase.[28] In the FIS editor, each input data group was defined by the name, range, method, implication and aggregations. The fuzzy rules and their membership functions were built in accordance with the illuminance data set obtained from actual rooms and desk arrangements. Intuition together with the existing knowledge on lighting research and the nature of data which cover the occupancy/light on/off conditions gathered from the onsite measurements were considered to construct the subdivisions of output variable and behaviour pattern.

Onsite measurement data were analysed for each combination of user, layout and control action. Comprehensive evaluation method was used to analyse the occupancy, light usage and illuminance on desks, and this information was later used in the fuzzy model. For each layout, the illuminance prior to occupancy was noted and so was the light behaviour of the user. For example, for the Left A layout, User C entered the room on 03.11.2014 at 09:04, and the illuminance upon entrance was 4 lux (Table 1). The user turned on lights during occupancy and stayed in the room for 43 minutes (09:04–09:47). During his stay, the average illuminance (with daylight and artificial lighting) was 365 lux. While on 10.11.2014, the illuminance upon entrance was 209 lux, and the user did not switch on lights. Only daylight penetration supplied 138 lux during his occupancy (13:06–15:22). For each layout, the average lights on and average lights off illuminance were calculated to find the tendency and threshold of a user to turn on lights.

For this study, three input variables, namely layout, illuminance and distance, and one output variable, namely behaviour, were fuzzified in fuzzy subsets in MATLAB FIS editor, as a part of this study. Measurements covered a total of 374 data sets, each of which was composed of layout, distance, average illuminance and occupancy/light on-off data. A set of 320 of them was determined as meaningful. The remaining 54 data sets were eliminated because of uncertainties associated with class schedule, holidays and daylight penetration. The number of meaningful readings of each user was different. Only the occupied hours were taken into consideration. Therefore, there were several occupancy and light usage data on some days and none on some other days. The numbers of the onsite observations were used: average illuminance, occupancy and light on/off for each room and layout; these are summarized in Table 2.

Layout

Four basic layouts were tested in the sample offices. For the fuzzy logic model, each desk layout was expressed in terms of angular degree. For example, the right layout where the window is located on the right side of the desk corresponds to 90°; the back layout corresponds to 180°; the left layout, 270° and the front layout, 360°. The initial desk position was set to face the window (0°) and was then rotated counterclockwise. So, the layout range was 0°–360°, and five subsets were formed: very low (VL), low (L), medium (M), high (H) and very high (VH). These were formed to establish the triangular membership functions as shown in Figure 6.

Illuminance

As an input variable, the average illuminance records defining the horizontal illuminance on desk surface were grouped into three ranges and given lux values on Table 2. The triangular membership functions were set in three subsets, namely low (L), medium (M) and high (H), as shown in Figure 7. Although the optimum workplane illuminance was 500 lux, as recommended by the CIBSE standards,[32] the maximum threshold value was defined to be 300 lux due to the records of actual measurements. These three subsets, especially involving lower illuminance values, represent basic classifications that capture detailed deviations in any illuminance distribution.

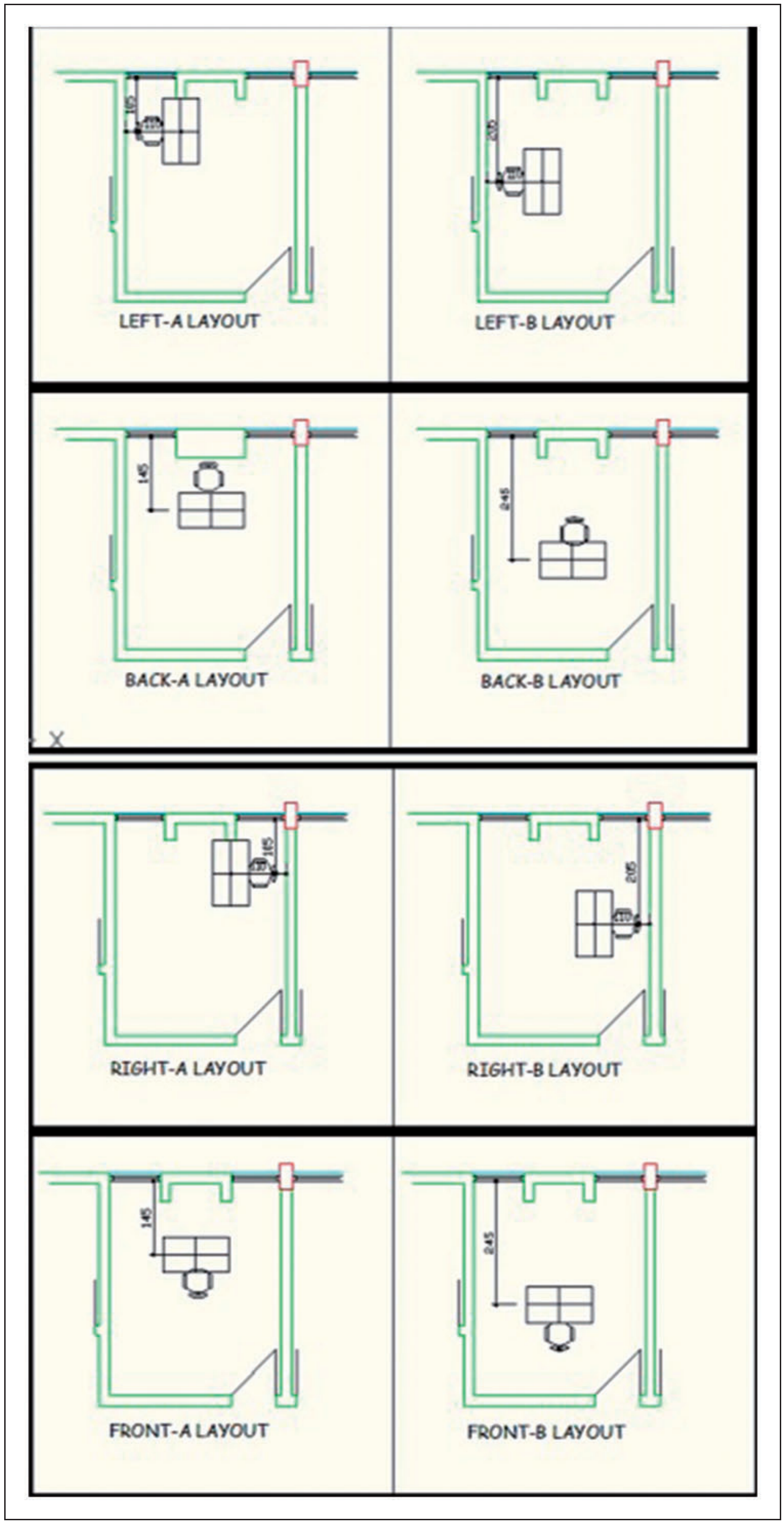

Figure 4. Interior layout arrangements in monitoring phase.

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Distance

The distance between the desk and window has a significant effect on manual control habit. Because each test room had only one occupant and is small in dimension, two subsets low (L) and high (H) were considered to have triangular membership functions, as presented in Figure 8. The minimum value was 1 m from the window and the maximum value was 2 m.

Behaviour pattern

Inputs were fuzzified in the above fuzzy subsets in order to cover the degree of behaviour patterns that corresponds to users' attempt to turn on lights. The subsets of fuzzy changes in behaviour patterns present basic classification and these could be applied to any type of single occupied office. Thus, the behaviour was considered to have a maximum value of 1 and was subdivided into three subsets as low (L), medium (M), and high (H) and to have triangular membership functions as represented in Figure 9.

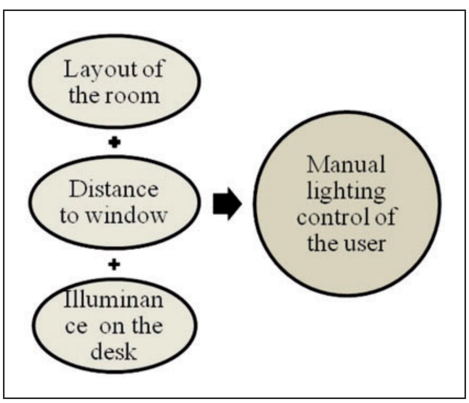

Figure 5. Input variables (on the left) and output variable (on the right) for the fuzzy logic model.

The fuzzy Rule Base, representing the relationships between the inputs (i.e., layout, illuminance and distance) and the output (i.e., behaviour pattern) was then applied. Fuzzy rules were intuitively employed by taking into account the monitoring data. They were also inferred from general knowledge presented in literature, in particular the commonly used Mamdani rule system.[17] The system was used to relate the input variables to the output variable verbally by constructing fuzzy rules.[14,16,34] The antecedent part of a rule – the part beginning with IF, up to THEN, was included a statement on layout, illuminance and distance; whereas the consequent part – the part beginning with THEN, up to the end, was included a statement on behaviour. For example,

> 'IF the layout is 'Low', the illuminance is 'Low' and the distance is 'High', THEN the behaviour is 'High'.

There were a total of 30 fuzzy rule sets, which are presented in Table 3. The following fuzzy inferencing engine operators were used. The min operator was applied to define the firing strength of each rule. The max composition operator combined fuzzy output sets from each fired rule into a single fuzzy output set. The COG method was employed for defuzzification.

As workplane illuminance on the desks was a dominant factor for the switching on/off behaviour, all possible fuzzy rules in the fuzzy set were to be employed to transform these inputs to corresponding output by taking the importance of this input into consideration.

Results

Validation

Simulations were done using MATLAB to check the accuracy of predictions of different fuzzy models.

Table 1. Analysis of monitoring data of lights usage and illuminance.

Left A User C					
Date	Time	Occupancy	Light	Illuminance upon entrance	Average Illuminance during occupancy
03-11-2014	09:04	0	0	4	
03-11-2014	09:04–09:47	1	1		365
10-11-2014	13:06	0	0	209	
10-11-2014	13:06–16:22	1	0		138
11-11-2014	10:52	0	0	138	
11-11-2014	10:52–11:55	1	1		423
11-11-2014	14:48	0	0	128	
11-11-2014	14:48–16:12	1	0		254

Table 2. Description of data sets.

Data set	Room 1			Room 2			Room 3			
Number of readings for	occupancy	light on	light off	occupancy	light on	light off	occupancy	light on	light off	Total
Left A Oct 31–Nov 14 08:30–17:30	23	5	18	20	8	12	4	1	3	94
Left B Nov 17–Nov 28 08:30–17:30	6	5	1	17	6	11	8	2	6	62
Right A Dec 01–Dec 11 08:30–17:30	4	2	2	5	2	3	2	1	1	22
Right B Dec 12–Dec 25 08:30–17:30	9	8	1	3	1	2	11	5	6	47
Back A Dec 26–Jan 06 08:30–17:30	3	2	1	6	2	4	2	2	0	22
Back B Jan 07–Jan 18 08:30–17:30	14	11	3	6	1	5	3	3	0	46
Front A Jan 19–Jan 30 08:30–17:30	5	4	1	14	9	5	5	3	2	48
Front B Feb 02–Feb 16 08:30–17:30	7	5	2	8	2	6	2	0	2	34
Total										374

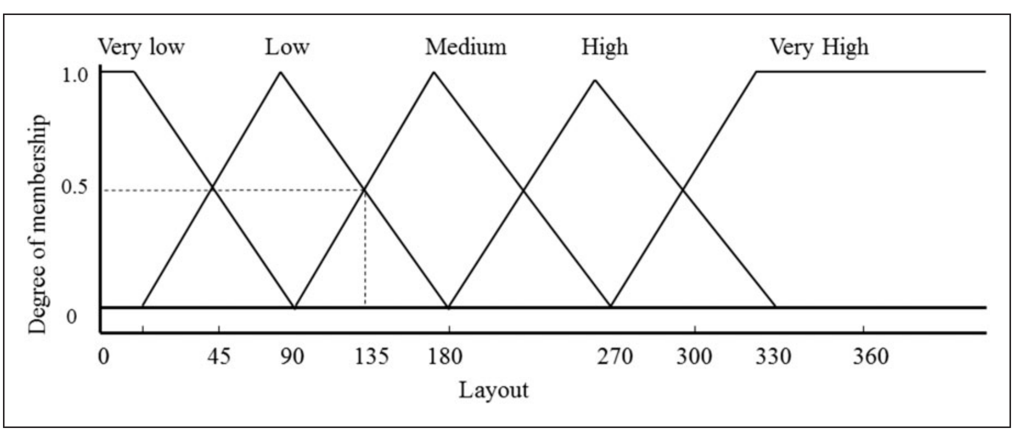

Figure 6. Membership functions of layout in the fuzzy logic model.

Each model took values of workplane illuminance, desk position and distance to window as input and was interrogated to predict the manual lighting control behaviour. First, the COG method was applied with a threshold of 0.5 since this has been widely used. To check the tendency to turn on/off lights, the value below or equal to 0.5 would correspond to the possibility of not switching on lights, while the value above 0.5

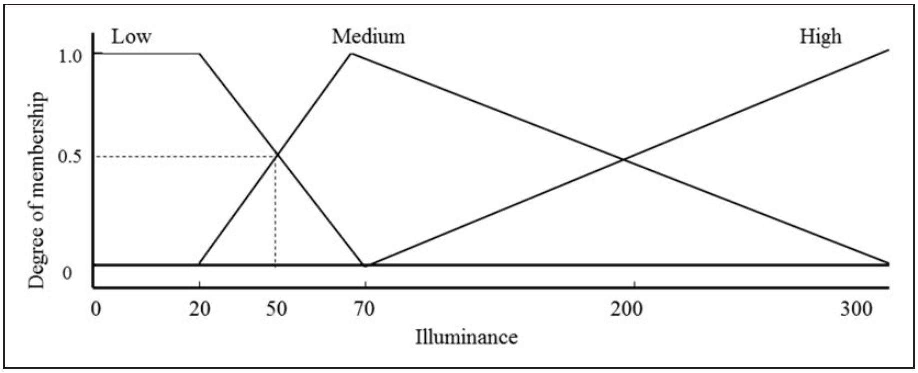

Figure 7. Membership functions of illuminance in the fuzzy logic model.

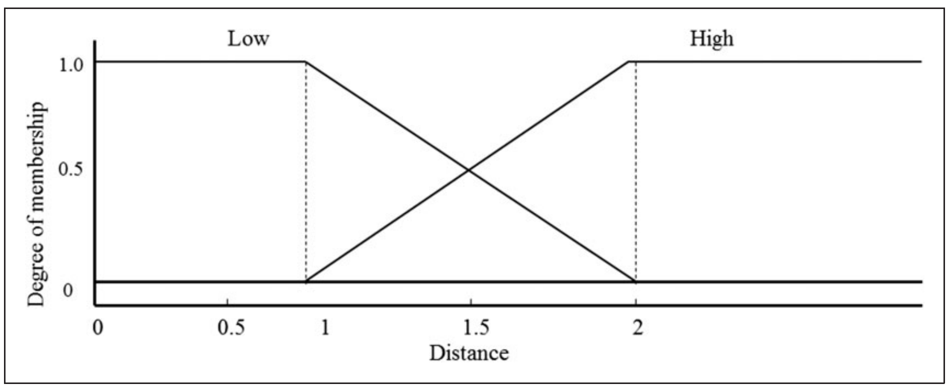

Figure 8. Membership functions of distance in the fuzzy logic model.

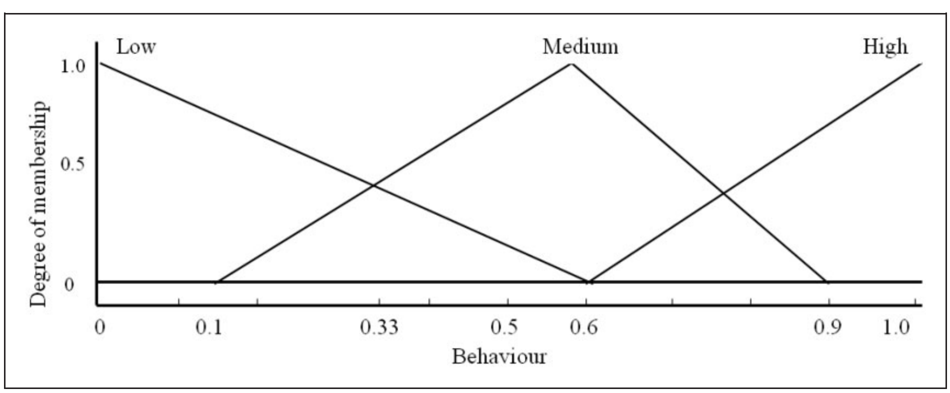

Figure 9. Membership functions of behaviour pattern in the fuzzy logic model.

corresponds to the possibility of switching on lights. This assumption was deduced from the general and basic knowledge of possibility theory. Second, the MOM method was employed to consider how the outputs were distributed. The outputs should be close to certain values. That is, high values of outputs would reach their peak, low values outputs would hit the bottom, and sub-values would disappear. Third, when mis-predictions were mostly observed in values around 0.5 and the MOM method would break the distribution of output values, the COG method computed these outputs with a threshold of 0.6, and subsequent testing predictions and discussions were based on the COG method and the threshold of 0.6 and results are given in Table 4.

A total of 50 sample sets were randomly chosen from the 320 sample sets collected to construct the fuzzy model and to compare observed outputs (turning on/

Table 3. Examples of fuzzy rule sets.

Situation	IF desk layout is	AND illuminance level is	AND distance to window is	THEN manual lighting behaviour	COMMENT
1	VLOW	LOW	LOW	MEDIUM	Would expect medium probability, to turn on lights
2	VLOW	LOW	HIGH	HIGH	Would expect high probability, to turn on lights
3	VLOW	MEDIUM	LOW	LOW	Would expect low probability, to turn on lights
4	VLOW	MEDIUM	HIGH	LOW	Would expect low probability, to turn on lights
5	VLOW	HIGH	LOW	LOW	Would expect low probability, to turn on lights
6	VLOW	HIGH	HIGH	LOW	Would expect low probability, to turn on lights
7	LOW	LOW	LOW	MEDIUM	Would expect medium probability, to turn on lights
8	LOW	LOW	HIGH	HIGH	Would expect high probability, to turn on lights
9	LOW	MEDIUM	LOW	MEDIUM	Would expect medium probability, to turn on lights
10	LOW	MEDIUM	HIGH	MEDIUM	Would expect medium probability, to turn on lights
11	LOW	HIGH	LOW	LOW	Would expect low probability, to turn on lights
12	LOW	HIGH	HIGH	LOW	Would expect low probability, to turn on lights
13	MEDIUM	LOW	LOW	MEDIUM	Would expect medium probability, to turn on lights
14	MEDIUM	LOW	HIGH	HIGH	Would expect high probability, to turn on lights
15	MEDIUM	MEDIUM	LOW	HIGH	Would expect high probability, to turn on lights
16	MEDIUM	MEDIUM	HIGH	HIGH	Would expect high probability, to turn on lights
17	MEDIUM	HIGH	LOW	LOW	Would expect low probability, to turn on lights
18	MEDIUM	HIGH	HIGH	MEDIUM	Would expect medium probability, to turn on lights
19	HIGH	LOW	LOW	MEDIUM	Would expect medium probability, to turn on lights
20	HIGH	LOW	HIGH	HIGH	Would expect high probability, to turn on lights
21	HIGH	MEDIUM	LOW	LOW	Would expect low probability, to turn on lights
22	HIGH	MEDIUM	HIGH	MEDIUM	Would expect medium probability, to turn on lights
23	HIGH	HIGH	LOW	LOW	Would expect low probability, to turn on lights
24	HIGH	HIGH	HIGH	LOW	Would expect low probability, to turn on lights
25	VHIGH	LOW	LOW	MEDIUM	Would expect medium probability, to turn on lights
26	VHIGH	LOW	HIGH	HIGH	Would expect high probability, to turn on lights
27	VHIGH	MEDIUM	LOW	LOW	Would expect low probability, to turn on lights
28	VHIGH	MEDIUM	HIGH	LOW	Would expect low probability, to turn on lights
29	VHIGH	HIGH	LOW	LOW	Would expect low probability, to turn on lights
30	VHIGH	HIGH	HIGH	LOW	Would expect low probability, to turn on lights

off) with the fuzzy model outputs. As fuzzy model construction was based on measured data and inputs could not be mathematically formulized. The fuzzy linguistic control rules defined by Mamdani[17,24] would become more appropriate than those defined by Sugeno.[25] A total of 24 sets of data, including every possible variation with a highest illuminance ranged from 4 lx to 301 lx, were used in this validation process. According to randomly chosen sample sets, the possibility of switching on lights was 58%. Furthermore, the output of the fuzzy model agreed with experimental observations in 21 out of the 24 randomly selected cases. This result shows a high rate of accuracy of 87.5%. The rest of sample sets were implemented in the model for the subsequent predictions with an accuracy of 77%. The frequency for occupants turning on lights was 64% in this data set. Thus, fuzzy model predictions were shown to fit measurement results reasonably well. Lower prediction accuracy (77%) was expected due to the unpredictable behaviour of some occupants. Most discrepancies were observed when the possibility of switching on lights was calculated as 0.5 or when the front layout was active. Following this validation process, the classifications were set and discussed as below.

Fuzzy classifications

The fuzzy model presents three classifications of manual lighting control behaviour patterns. Constructing these classifications were initially based on two options for the possibility of turning on lights

Table 4. Data sets of fuzzy model. [AQ5] it is correct, thank you

Data sets for validation						Data sets for testing predictions			
			Behaviour pattern						Behaviour pattern
Layout	Distance to window	Illuminance	0.5 (COG)	0.6 (COG)	(MOM)	Layout	Distance to window	Illuminance	0.6 (COG)
Left	A	209	0.188	0.224	0.110	Left	A	78.6	0.195
Back	A	4	0.600	0.533	0.500	Left	A	20	0.533
Right	A	290	0.188	0.219	0.010	Left	B	4	0.870
Front	A	4	0.600	0.611	0.500	Left	B	77	0.533
Left	B	209	0.188	0.386	0.110	Left	B	68	0.538
Left	A	4	0.500	0.533	0.500	Right	A	4	0.533
Back	A	4	0.600	0.511	0.500	Right	A	42	0.524
Front	A	28	0.572	0.580	0.500	Right	B	5	0.870
Front	B	51	0.438	0.468	0.095	Right	B	12	0.870
Left	A	290	0.164	0.195	0.010	Right	B	42	0.624
Left	B	265	0.188	0.275	0.040	Back	A	99	0.847
Right	A	290	0.188	0.219	0.010	Back	A	35	0.611
Left	A	301	0.164	0.195	0.000	Back	B	12	0.870
Right	B	4	0.837	0.870	1.000	Back	B	43	0.850
Right	B	28	0.729	0.730	0.960	Back	B	36	0.859
Back	B	37	0.438	0.858	0.915	Back	B	20	0.870
Left	A	4	0.5	0.533	0.500	Back	B	91	0.869
Front	B	67	0.438	0.240	0.015	Front	A	59	0.399
Left	B	16	0.729	0.870	1.000	Front	A	67	0.286
Right	A	275	0.164	0.253	0.030	Front	A	146	0.228
Right	B	27	0.74	0.743	0.965	Front	B	91	0.196
Left	B	7	0.837	0.870	1.000	Front	B	51	0.419
Right	A	234	0.164	0.195	0.080	Front	B	195	0.231
Left	B	36	0.74	0.658	0.925	Left	A	209	0.224
						Left	A	128	0.205
						Left	B	114	0.561

COG: centroid; MOM: middle of maxima.

due to a regular/nominal judgement and the possibility of switching on lights and the possibility of not switching on lights. This analysis provides the rating on users' tendency to turn on lights, setting up the classes of their behaviour patterns. Thus, we can classify the tendency of behaviour values predicted by this fuzzy application into three groups as: the Low tendency class where the rate is less than 0.33, the Normal tendency class where the rate ranges from 0.33 to 0.77; and High tendency class where the rate is greater than 0.77. Additionally, we can divide the Normal Tendency Class into three subsets as Low-Medium, Medium and Medium-High when commenting further on the individual findings. Prediction results are summarized in Figure 10 and Table 5.

Regarding Figure 10, 9 out of 24 observations are in the Low tendency, meaning that users would not switch on lights in those situations. Users in only one observation (S09) with a value of 0.468 are in the Low-Medium tendency class. While 5 observations (S4, S7, S15, S21 and S24) are in the Medium-High tendency class with values between 0.600 and 0.770; and 4 cases are in high tendency class, with values above 0.77. Data sets S2, S6, S8 and S17 are in the Medium tendency class (between 0.500 and 0.600), meaning that there is an equal chance for occupants to either switch on or not switch on lights. We believe that such observations are the cause of discrepancies in model predictions.

Discussion

I agree with Prof. Chuck Yu's comment

[AQ3]Our finding ~~that~~ the relationship between daylight levels and switch-on possibilities is quite compatible with cases reported by Hunt.[6] That is, an

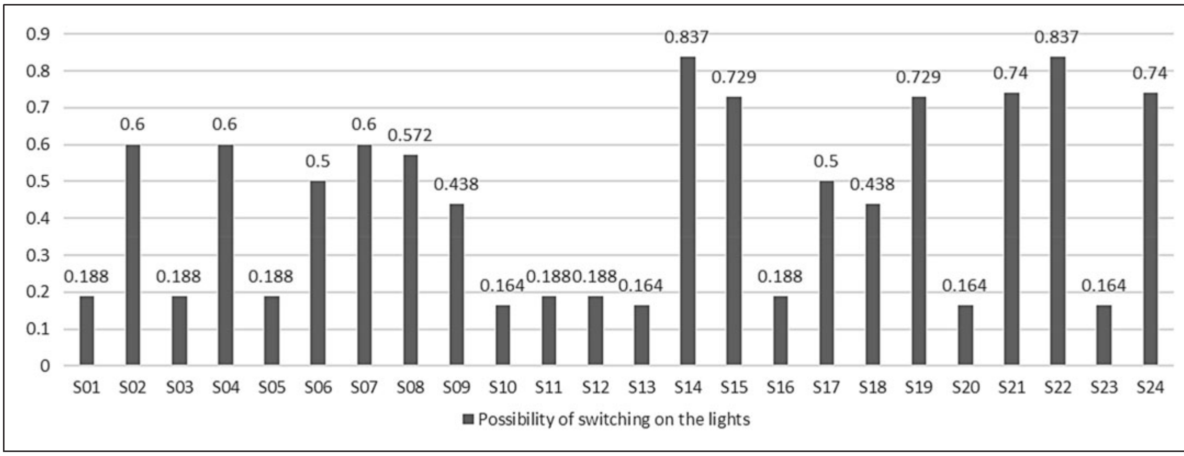

Figure 10. Distribution of tendency of behaviour pattern to switch on lights (S: sample).

Table 5. Prediction results for the behaviour pattern values.

	Layout	Position	Illuminance	Monitoring behaviour	Tendency of behaviour pattern value	Comment
1	Back	A	4	Turned on the lights	0.611	Back layout blocks some amount of daylight which is directed to the back of the user. The desk is in the perimeter zone close to window. Daylight illuminance on the desk is strongly low. (User in the Medium-High class. can probably switch on the lights).
2	Back	B	36	Turned on the lights	0.858	Back layout blocks some amount of daylight, which is directed to the back of the user. The desk is at the edge of the perimeter zone. Daylight illuminance on the desk is strongly low. (User in the High class. can probably switch on the lights)
3	Front	A	28	Turned on the lights	0.580	Front layout provides the highest possible amount of daylight which is directed to the face of the user. The desk is in the perimeter zone close to window. Daylight illuminance on the desk is strongly low. (User in the Medium class. take the same chance either to switch on the lights or not).
4	Front	B	91	Not turned on the lights	0.196	Front layout provides the highest possible amount of daylight which is directed to the face of the user. The desk is at the edge of the perimeter zone. Daylight illuminance on the desk is low. (User in the Low class. can probably not switch on the lights).

(continued)

Table 5. Continued

	Layout	Position	Illuminance	Monitoring behaviour	Tendency of behaviour pattern value	Comment
5	Left	B	209	Not turned on the lights	0.386	Left layout provides the impact of sidelighting fully. The desk is at the edge of the perimeter zone. Daylight illuminance on the desk is strongly high. (User in the Low-Medium class can probably not switch on the lights).
6	Left	A	4	Turned on the lights	0.533	Left layout provides the impact of sidelighting fully. The desk is in the perimeter zone close to window. Daylight illuminance on the desk is strongly low. (User in the Medium class. take the same chance either to switch on the lights or not)
7	Right	B	28	Turned on the lights	0.730	Right layout provides the impact of sidelighting. The desk is in the edge of the perimeter zone. Daylight illuminance on the desk is strongly low. (User in the Medium-High class. can probably switch on the lights)
8	Right	B	4	Turned on the lights	0.870	Right layout provides the impact of sidelighting. The desk is in the edge of the perimeter zone. Daylight illuminance on the desk is strongly low. (User in the High class. can probably switch on the lights)

illuminance of 100 lx is a threshold value for the occupant to turn on lights. However, the effect of the office layout and the distance between the desk and window are noticeable. For example, despite identical and very low desk illuminance, receiving daylight from left direction close to the window or right direction away from the window would lead to a difference in behaviour pattern value: 0.533 (Medium tendency class) for the former case and 0.870 (High tendency class) for the latter case (Table 4).

This methodology is based on fuzzy model construction using observational and measurement data in a real indoor space. The Mamdani fuzzy inference system together with collected data has become a strong concept pairing in that sense as field measurements covered four winter months. The model was developed using data sets of activities observed during this time. Thus, the developed fuzzy model can be defined as 'data driven'. Although two inputs of the model, distance and layout, are independent of geographic and seasonal climatic variations, the other input, which was daylight illuminance on desks, has dependency on seasonality and location. Thus, further research should collect year-round data sets to test the fuzzy model so that the data include higher level of illuminance on desks. Similar studies can be conducted at different geographical locations. These can enhance the universal capability of the fuzzy model in predicting the user's behaviour. The universal capability of the present model is limited to the observational data collected only for one location and during one specific time period. The validation procedure is specific to this study. The blinds of these test rooms were set as static with adjustable slats that blocked the direct sunlight in each room. We also set identical illuminance of 500 lx at a point on the desk in each room. These settings had provided the consistency of daylight conditions regardless of the outdoor daylight illuminance at the beginning of measurements. The model takes into consideration the indoor daylight illuminance on these desks, however.

Conclusion

This study analysed manual lighting control in relation to the various factors, especially interior architectural factors, to obtain realistic manual lighting control behaviour of occupants in offices. Our findings have provided certain significant possibility values and classification for manual lighting control, which can be used in both energy simulation and research.

Despite the passive user assumption in existing standards and simulation software, the findings of this study have suggested that, in the absence of an automatic lighting control system, users do not use artificial lighting throughout their working hours. Therefore, one cannot define all occupants as passive users. The suggested classification generated from the fuzzy model would offer a detailed manual lighting control possibilities, which can be used in future studies and can be implemented in simulations. Recently, the value of manual control factor (occupancy dependency factor) is implemented as 1 in The European Standard EN 15193:2007,[35] which means the lights are switched on during working hours and users are passive. However, the possibility of switching on lights can be represented by constants 0.25, 0.50 or 0.75 in the calculation instead of using 1. This would provide alternatives of choosing different behaviour patterns and could reduce the switch-on time (less than 9.6 h) per day.

Previous manual lighting control studies have ignored the contribution of interior layout. However, our findings have illustrated that providing higher illuminance over the desk (either relocating them near a window area or changing the layout) could increase manual lighting control and therefore reduce artificial lighting usage. Since the main decision on whether to turn on lights is given upon entrance when looking at the luminance on the desk, the focus of the design should be on providing well-lit desk areas.

Authors' contributions

[AQ4] All authors contributed equally in the preparation of this manuscript.

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