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Smart lighting system using ANN-IMC for personalized lighting control and daylight harvesting

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ABSTRACT

Lighting contributes a significant portion to the overall energy consumption in an office building. It is thus important to reduce the energy consumption of lighting systems especially for Net Zero Energy Buildings (NZEB). Maximizing daylight harvesting can significantly increase the energy savings. With increase in demand for satisfying occupant preferences in visual comfort, the need for personalized lighting in the office space is also rising. In this paper, a novel lighting control system for Net Zero Energy Buildings (NZEB) is proposed which models the lighting system using Artificial Neural Network (ANN) and utilizes this model with the Internal Model Control (IMC) principle for controller design. Modeling the lighting system using ANN reduces the challenge of modeling a large and complex system with inherent process variability without the need to analyze extensive data-sets. The proposed ANN-IMC controller uses feedback from sensors on the task table to maintain desired illuminance, is easy to tune with just one parameter and is robust to process variability. The proposed control design is applicable to square systems where the number of lights and number of sensors are equal. However, the proposed architecture can also be extended for controlling other lighting accessories such as roller blinds. The performance of the proposed lighting control system to harvest the daylight effectively is demonstrated using both simulation results and an experimental setup in test-bed environment. The versatility of the proposed system will allow an operator to deploy personalized lighting in an office space.

1. Introduction

With energy consumption rising across the world, many countries including Singapore have embarked on various green building concepts for achieving sustainable growth. For instance, the ambitious target of ’The Inter-Ministerial Committee on Sustainable Development’ in Singapore is to achieve 80% Green Mark Certification for all buildings by the year 2030 [1]. Artificial lighting contributes a significant portion (around 29%) in overall energy consumption in office buildings [2]. In Singapore, the Green Mark Certification includes points for ’Use of better efficient lighting to minimize energy consumption from lighting usage while maintaining proper lighting level’ and ’Use of daylighting and glare simulation analysis to verify the adequacy of ambient lighting levels in all normally occupied areas'. Net Zero Energy Buildings (NZEB) which include on-site renewable energy sources are also brought to focus as part of sustainable growth in Singapore [3]. There are various initiatives taken by the Building and Construction Authority of Singapore for reducing the energy consumption of lighting systems (as well as the overall energy consumption). The introduction of low-powered LED lights and the use of low voltage DC distribution system has increased the potential for higher energy savings due to a higher system level efficiency as compared to AC distribution system [4]. This is in addition to the energy savings that can be achieved from occupancy detection and daylight harvesting [5]. Furthermore, the need for having personalized lighting to increase the occupantsâ€™ comfort is also becoming critical [6].

In this paper, a closed loop smart lighting control is proposed which satisfies the personalized lighting levels of occupants while simultaneously harvesting daylight to reduce energy consumption. The lighting control system design utilizes Artificial Neural Network based Internal Model Controller (ANN-IMC) for controlling illuminance using feedback from sensors placed at the desk level and by manipulating the ceiling lights and automatic roller blinds. Despite the advantages of the ANN, a closed loop system using ANN for smart lighting has not been

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reported in any of the methods available in literature. Implementation of a closed loop ANN based lighting control will eliminate the drawbacks identified by the authors in Ref. [7]. The proposed controller was implemented in a test-bed environment at the SinBerBEST laboratory in BEARS (Berkeley Educational Alliance for Research in Singapore). The experimental results from that implementation (presented in Section5) demonstrate the performance of the proposed controller in harvesting daylight effectively. The proposed controller also robustly maintains the illuminance levels at the setpoint despite moderate changes in the position of the sensors at the desks. The main contributions of the paper are the presented novel ANN-IMC controller which can achieve dynamic personalized lighting in the office space with daylight harvesting, a unified architecture for controlling luminaires as well as other auxiliaries such as blinds.

2. Related work

The use of artificial intelligence for lighting prediction and lighting control in an office space is at least two decades old [8]. The simplicity, versatility and ability to adapt to the changes have aided such systems to remain useful. The authors in Ref. [9] have used ANN based intelligent lighting control with on-line learning for smart homes which has the capability to adapt to the residents′ behavioral patterns. The authors used â€˜learning event-actions of the resident related to lighting adjustments to derive the ANN based intelligent control algorithm. The authors have stated that the algorithm cannot be applied for residents with conflicting behavior which prohibits its application to office spaces. In Ref. [10], the authors proposed a method based on ANN for satisfying the illumination preference of each office user on their table. The method also minimized the overall energy consumption of lighting system with distributed luminaires. The model presented was holistic and scalable, and represented the complex interactions between the intensity of each luminaires and the measured illuminance on each table. However, the authors did not include daylight interaction and daylight harvesting in the study. Based on the literature survey conducted in Ref. [11], it was observed that building occupants prefer natural over artificial light and that daylight achieved higher occupant productivity. Hence, it is important to consider daylighting in any lighting control system. The authors in Ref. [7] proposed a sensor less control strategy based on ANN, however daylight harvesting was not included as no closed loop control was involved. Furthermore, the desired illuminance (*lux*) was considered uniform across all task tables in Refs. [10] [7], which indicates that user preferences were not considered.

The authors of [12] developed an ANN model to represent the illuminance distribution in a room with different luminaires to estimate the time-dependent energy loss in lighting systems. An experimental survey on state-of the-art lighting control strategies, namely, Illumination Balancing Algorithm, Daylight and occupancy adaptive lighting, Spectral optimization for polychromatic lighting and Hierarchical optimization for spectrally tunable LEDs was presented in Ref. [13]. The authors concluded that each method has its own merits and drawbacks, and that selecting a method should depend on the control problem and application. A decision tree was presented to match a particular application to an appropriate algorithm. It is to be noted that the method proposed in this paper falls under the category of Daylight and occupancy adaptive lighting. The application of artificial intelligence is not just limited to office spaces and it has been used for public lighting as well [14].

A Fuzzy logic controller for lighting comfort that also considered daylighting was proposed in Ref. [15]. Simulation and experimental results for various desired illuminance (*lux*) levels on the table and their corresponding energy savings was presented. The results demonstrated that the potential for energy savings increased with increase in the number of occupants whose visual comfort required lower illuminance. In this method, the daylight contribution was obtained based on pre-measured values, which would make the control inaccurate in many cases. Also, the implementation necessitates detailed knowledge of the fuzzy rules. In Ref. [16], the authors proposed a Competition Over Resource algorithm for control of artificial lights in an office space and evaluated the method with a scale model. The algorithm is based on a bio-inspired meta-heuristic approach. However, impact of daylight is not considered in the evaluation. A smart phone based intelligent lighting control for smart homes was presented in Ref. [17] in which the authors used the standard PI controller for achieving the task. The above method cannot be extended to office space lighting owing to the complex interaction between different luminaires and target table sensors. The disadvantages of the above method was addressed in Refs. [18] and [19], however, the authors did not validate the method with neighbouring occupants having different desired settings. The authors in Refs. [20] [21], investigated the occupant behavior and preference in detail for Occupant centered lighting control for comfort and energy efficient building operation. The authors emphasize the necessity of an adaptive lighting control model. The method primarily focuses on ON and OFF control rather than dimming control which could drastically increase the robustness and performance of such algorithms.

In Ref. [22], a review for answering major research questions on individual occupancy-based lighting control was carried out. The authors assert that only 24 research studies were eligible based on various factors. Out of these, only one applied the methods for an open office plan (the proposed method is also developed and tested in open office type testbed). Other studies presented in the review focused on personalized lighting. The authors in Ref. [23] justify the need to offer lighting that serves the preferences of individuals, and they assert that ”by offering illuminances close to peoples' own preferences a significant improvement in ratings of mood, lighting satisfaction, and environmental satisfaction can be established”. In Ref. [23], it was observed from an experimental study that consensus control improved user appreciation of office lighting in an open office. It was also emphasized in Ref. [24] that optimized systems for personalized environment is essential for improved health and well being. To enable the occupants to receive illuminances close to their own preferences without affecting the neighbours, there is a need for one sensor/light.

Personalized lighting in office space was achieved using an optimal lighting control algorithm in Ref. [25] where the authors used an illuminance generator model with optimization for generating dimming signals. However, the impact of daylight is not considered in the above research. Theoretical personalized lighting control based on space model and space model queries was discussed in Ref. [26]. The authors of [27] proposed a satisfaction based Q-learning control system for improving the performance of traditional automated lighting systems. A comfort model was proposed and a holistic control of lights and blinds was studied with a human-centric approach. The algorithm could provide valuable insight on human preferences based on q-factor. A luminaire based sensing approach for intelligent control of indoor lighting was proposed in Ref. [28]. A linear mapping approach and stand-alone PI controller for controlling the desired illuminance (*lux*) on table was proposed (other approaches are also presented and compared).

Luminarie based occupancy detection and counting [29] is increasingly becoming popular as the method has the notable advantage of minimal interference from external noises and can harvest daylight without any limitations. Even the effect of degradation of luminaires could be overcome by adjusting the desired set point through a user feedback system. In Ref. [30], the authors used a wireless sensor network based lighting system for achieving personalized lighting. However, the above method was not evaluated with daylight settings and control of blinds based on the model used was not considered. A comprehensive analysis was carried out for a centralized controller and distributed controller based personalized lighting control in Refs. [31] and [32]. The authors in Ref. [32] presented a distributed lighting control system which considered the daylight and occupancy profile.

The authors also presented a stability analysis for the proposed control system. However, the methods were not validated using experiments and also application to blinds control was not discussed. It was observed in Ref. [33] that the user satisfaction improved with actual usage of an automated blinds system with an expressive interface. It was observed that a medium automation with feedback from the users was more agreeable. A comprehensive review on 'Dynamic operation of daylighting and shading systems' was presented in Ref. [34] and a comprehensive review on different type of shading devices and type of studies used for analysis (simulation or experimental or both) was presented in Refs. [35,36]. It can be observed that none of the studies reviewed in the paper discussed about personalized lighting and automatic control of blinds.

There are many efficient methods of daylight harvesting such as redirecting the natural light to deeper regions of the room than the perimeter [37–41]. Transferring useful daylight into the core of the building can increase lighting energy savings but it can increase cooling loads as quantified in Ref. [38]. The decision to use such technologies would depend on the overall energy reduction strategy. The proposed control system can work in conjunction with louver technologies that actively redirect sunlight in the room without the need for any modifications. The authors in Ref. [42] presented an exhaustive survey on open loop control strategies for the control of shades, blinds and integrated lighting systems. The authors show that available methods depend on the an external photo sensor/camera for control strategies. The authors in Ref. [43] carried out a detailed analysis on the reasons why daylight linked control of lighting systems are not wide spread. One of the main reasons identified is the difficulty in design, installation and calibration of outdoor photo sensors. For the method proposed in this paper, the input from an external photo sensor/camera is not required and can operate with just indoor sensors.

In this paper, a comprehensive model that can cater for both achieving personalized light settings along with daylight harvesting and blinds control is proposed. Furthermore, the proposed technique was validated in a test-bed (with real day light emulator) further than high-fidelity simulations presented in the literature. The features of the proposed system in comparison with the existing methods in literature are presented in Table 1. It is to be noted that only methods applicable to office spaces are included in the comparison. The table shows that the proposed method can combine the advantages of all of the other methods.

3. Modeling and controller design

3.1. ANN model of the lighting system

ANN has been successfully applied for identification and control of many dynamic systems and with three typically networks being model predictive control, NARMA-L2 control, and model reference control [44]. As described by the authors [44,45], there are two stages in ANN based control, namely, system identification and control design. The advantages of ANN based control is that the undesirable or uncertain parts of any system dynamics can be cancelled or compensated easily and it has exceptional capability of approximating complex systems [46].

Table 1
Comparison of the proposed method with existing methods.

Features	Proposed Method	[10] [7],	[15]	[16]	[25]	[27]	[28]
Daylight harvesting	Yes	No	Yes	No	No	Yes	Yes
Complex interaction of distributed luminaires	Yes	Yes	Yes	Yes	Yes	No	No
Adaptive to luminaire degradation	Yes	Yes	Yes	Yes	No	Yes	Yes
Control of blinds	Yes	No	No	No	No	Yes	No
Occupant preference included	Yes	No	Yes	No	No	Yes	Yes
Closed loop control	Yes	No	Yes	Yes	No	Yes	Yes

An ANN based fitting model consisting of one input layer, hidden layer and output layer (feed-forward network) can be used for modeling the behavior of any $n \times n$ lighting system, with n lights and n task tables. A feed-forward network is used for the application and the network is designed to have sigmoid activation function for hidden neurons and linear activation function for output neurons. This is a standard network which has the capability to fit multi-dimensional mapping problems arbitrarily well. However, consistency of the data and sufficient neurons in hidden layer plays a critical role [7]. In this paper, the network is trained using the Bayesian Regularization back-propagation algorithm.

The equations governing the ANN model of the lighting system are given by,

$$H_f = Sig(W_h \times U + b_h) \tag{1}$$

$$\overline{Y}_p = Lin(W_o \times H_f + b_o) \tag{2}$$

where, $\overline{Y}_p$ is the measured illuminance vector of dimension n (minus the ambient or daylight contribution) and U is the luminaire power vector of dimension n. H_f is the output of hidden layer (of dimension h), W_h represents the weights of hidden neurons (of dimension $h \times n$) and b_h is its corresponding bias (of dimension h). W_o is a $n \times h$ matrix with 'h' with a corresponding bias b_o (of dimension n).

Equations (1) and (2) are together represented as,

$$\overline{Y}_p(t) = M_f(U) \tag{3}$$

where, the static non-linear function $M_f: \mathbb{R}^n \to \mathbb{R}^n$ represents the input-output behavior of the lighting system.

The inverse model (with input and output interchanged) is used for controller design and its equations are given by,

$$H'_f = Sig'(W'_h \times \overline{Y}_p + b'_h) \tag{4}$$

$$U = Lin'(W'_o \times H'_f + b'_o) \tag{5}$$

where, W'_h and W'_o are $h \times n$ matrices and b'_o and b'_o are the corresponding biases.

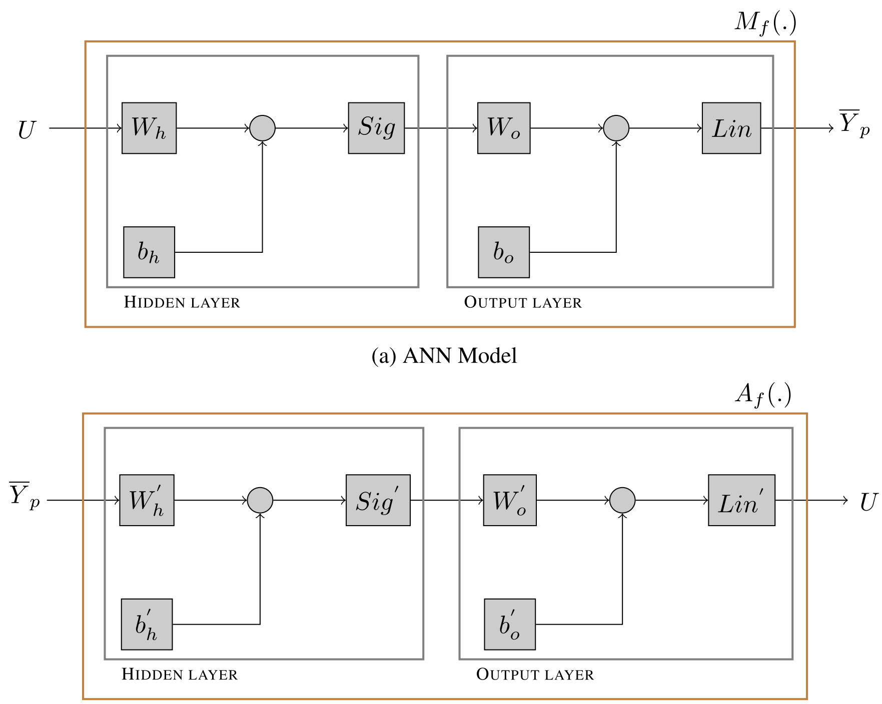
Equations (4) and (5) are together represented as,

$$U(t) = A_f(\overline{Y}_p) \tag{6}$$

where, the non-linear static function, $A_f: \mathbb{R}^n \to \mathbb{R}^n$ captures the inverse-plant behavior.

The structure of the networks used with their corresponding inputs and outputs are shown in Fig. 1. The training data to develop both A_f and M_f was obtained from the experimental measurements in the test-bed (described in Section 4). The training data consisted of illuminance (*lux*) levels measured at the tables with power setting for the lights ranging from 0 to 100% in steps of 5%. To gather the data for training the neural network, three parameters of the system were varied: the number of active lights (2, 4 or all active at a time), dimming % of active lights (in steps of 5, from 0 to 100) and the daylight intensity. Over 20,000 data points (resulting from combinations of the three parameters) were collected using the experimental setup described in Section 4. No human subjects were present during the data collection process. The ANN model as well as the ANN inverse-model are designed with 10 neurons in the hidden layer which reduces the overall data required for modeling.

It is to be noted that choosing the power levels and the combination of the luminaries for data collection would be a complex problem with the increase in the dimension of the system i.e., when n is large in a nxn system. However, with group control being a common aspect of any lighting control system, a system with large nxn could be conveniently split it into multiple subsets of mxm non-overlapping systems ($m < n$).



(a) ANN Model

(b) ANN Inverse-Model

Fig. 1. The structure of ANN inverse-model and ANN model with corresponding inputs and outputs.

In such cases the impact of lights in the neighbouring groups will be treated similar to the daylight disturbance. Hence, the proposed could be extended easily to any type of room. The authors trained the ANNs with the complete set as well as a subset consisting of the power setting for the lights ranging from 0 to 100% in steps of 5%, 253 data points (applicable only for the test-bed). It was observed that though the accuracy of ANN models was affected, the performance of the closed loop was not.

3.2. Design of ANN-IMC controller

For the purposes of control development, the lighting system is described as,

$$Y_p(s) = P(s)U(s) + D(s) \equiv \overline{Y}_p(s) + D(s) \tag{7}$$

where, $Y_p(s)$ is the measured output (illuminance in *lux*) of the actual-system, $\overline{Y}_p(s)$ is the measured output (in *lux*) in the absence of daylight or ambient light, $U(s)$ is the input (light power in %), $D(s)$ represents the unmeasured disturbance due to daylight and ambient light, and $P(s)$ is the unknown actual-system transfer function.The model of the lighting system is:

$$Y_m(s) = M(s) \times U(s) \tag{8}$$

where, Y_m is the model output (illuminance in *lux*), and $M(s)$ is the model transfer function. M can be considered the linear approximation of Eq. (3): $\overline{Y}_p(t) = M_f(U(t)) \approx M \times U(t)$.

The following assumptions and constraints for controller design are noted:

1. The dynamics between the $U(s)$ and $Y_p(s)$ are negligible. So, both $P(s)$ and $M(s)$ are static transfer functions. Thus, $M(s)$ is of the form,

$$M(s) \equiv M = \begin{bmatrix} k_{11} & k_{12} & \dots & k_{1j} \\ k_{21} & k_{22} & \dots & k_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ k_{i1} & k_{i2} & \dots & k_{nn} \end{bmatrix} \tag{9}$$

where, element k_{ij} represents the gain between illuminance output i (or lux sensor i) and power input of light j. The system P is a square matrix, ie. the number of lights and the number of sensors is equal.

2. The mismatch between plant and model can arise from non-linearities at the top end of the power input range. Mismatch can also be introduced if sensor locations are changed slightly.
3. The power input $U(t) \in \mathbb{R}^n$ has elements $0 \leqslant u_j \leqslant 100\ \forall\ j = 1,2\ldots n$, where, n is the number of lights as well as the number of illuminance sensors.
4. The daylight/ambient disturbance $D(t) \in \mathbb{R}^n$ has elements $300 \leqslant d_j \leqslant 2000\ \forall\ j = 1,2\ldots n$. Daylight is a slow varying and additive disturbance.

The control system is designed with the simple IMC approach [47] and is shown in Figs. 2, 3 and 4.

The closed loop equation of the general IMC structure is:

$$Y_p(s) = \underbrace{[I + PG_c]^{-1}PG_c}_{G_T(s)}R(s) + \underbrace{[I + PG_c]^{-1}}_{G_D(s)}D(s) \tag{10}$$

where, the controller $G_c(s)$ is,

$$G_c(s) = [I - QM]^{-1}Q \tag{11}$$

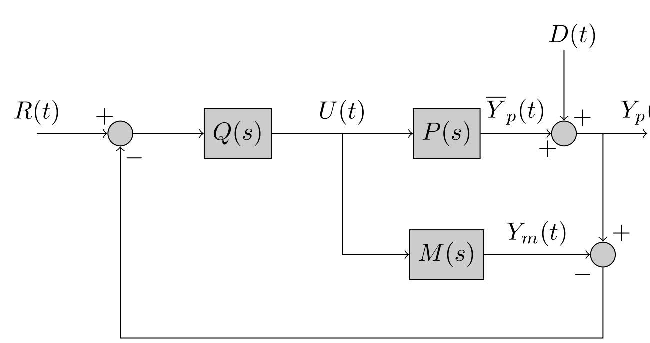


Fig. 2. Design structure of the IMC.

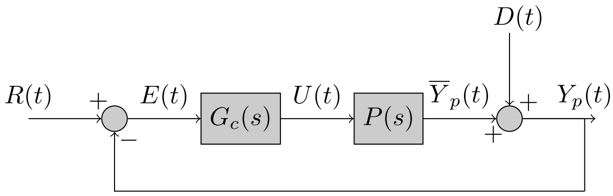


Fig. 3. Implementation structure of the IMC.

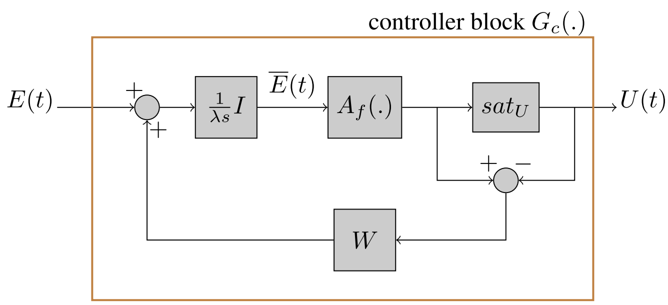


Fig. 4. Controller block for implementation.

and $G_T(s)$ is the tracking transfer function and $G_D(s)$ is the disturbance rejection transfer function.

If Q is selected as $Q(s) = M^{-1}f(s)$, the controller $G_c(s)$ in equation (11) reduces to,

$$G_c(s) = M^{-1} \times \frac{f}{1-f} = \frac{M^{-1}}{\lambda s} \tag{12}$$

where, $f(s) = \frac{1}{\lambda s + 1}$ and λ is a tuning parameter.

With the $G_c(s)$ in equation (12), the closed loop equation in equation (10) becomes,

$$Y_p(s) = [\lambda sI + PM^{-1}]^{-1}PM^{-1} \times R(s) + [\lambda sI + PM^{-1}]^{-1}|(\lambda s) \times D(s) \tag{13}$$

Applying FVT (Final Value Theorem) to equation (13) will show that tracking and disturbance rejection are successful even when $P \neq M$. In the ideal case, $P = M$, and the closed loop equation in equation (13) reduces to,

$$Y_p(s) = fI \times R(s) + (1-f)I \times D(s) \tag{14}$$

Thus, the control law is,

$$U(s) = M^{-1}\left(\frac{1}{\lambda s}E(s)\right) \equiv M^{-1} \times \overline{E}(s) \tag{15}$$

where, $E(t)$ is the error signal and $\overline{E}(t)$ is the *integrated* error.

At this step of the controller design, the ANN block A_f (Eq. (6)) trained to accept illuminance input and provide the corresponding power output is substituted for M^{-1} in Eq. (15). This is because the ANN function A_f better represents the inverse-plant than M^{-1} does because A_f captures non-linear behaviors.Therefore, in the actual implementation, the control law is,

$$U(t) = A_f(\overline{E}(t)) = A_f\left(\int_0^t \frac{1}{\lambda}I\, E(\tau)d\tau\right) \tag{16}$$

Thus, the ANN block together with integrator $\left(\frac{1}{\lambda s}I\right)$ is a non-linear controller.

For the sake of analysis, we allow the linear approximation of Eq. (6) as $U(t) = A_f(\overline{E}(t)) \approx A \times \overline{E}(t)$ which enables us to visualize the closed loop equation as,

$$Y_p(s) = [\lambda sI + PA]^{-1}PA \times R(s) + [\lambda sI + PA]^{-1}(\lambda s) \times D(s) \tag{17}$$

Equation (17) implies that, for nominal stability, If PAI (where P and A are static systems linearized around an operating point), then the condition for stability is simply determined by $(\lambda s + 1) < 0$.

3.2.1. Anti-windup reset

1. The integrator $\left(\frac{1}{\lambda s}\right)I$ can windup when the error $E(t)$ is sustained at a large value for a long time. For instance, such a situation can occur if the daylight is very strong, or if the setpoints are unattainable, and as a result, $\overline{E}(t)$ will grow indefinitely.
2. So, an Anti-Windup Reset scheme is used as shown in figure where $W = wI$ is the windup gain. This will drive the input of the integrator to 0 whenever the control action $U(t)$ reaches the saturation limits $[0 \quad 100]$.

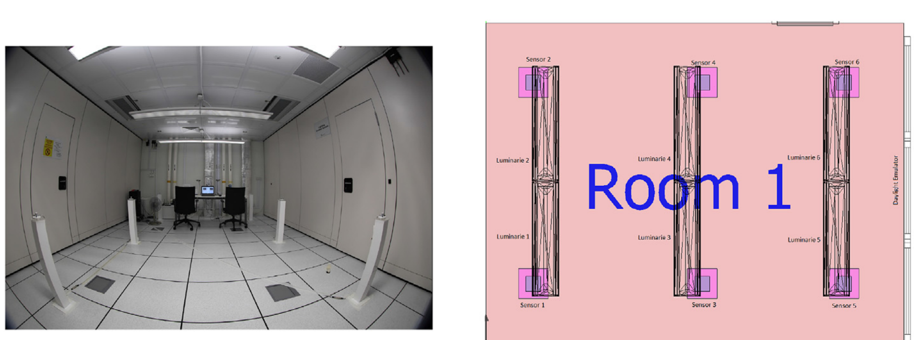
3.2.2. Discrete-time controller

Only the discrete-time version of the integrator $\left(\frac{1}{\lambda s}\right)I$ is implemented. The integrator is discretized using the forward-rectangular method. That is,

$$\frac{\overline{E}(z)}{E(z)} = \left[\frac{T}{\lambda(1-z^{-1})}\right] \times I \tag{18}$$

4. The experimental setup and model validation

The lighting arrangement and the room layout of the test-bed set up is shown in Fig. 5a and b. Zumtobel pendant lamps of type AERO 2 (9880 lumen) were used in the test-bed. EKO light sensors (ML-020S0) were used for measuring the illuminance at the desk level. The sensors used have a hemispherical field of view and the surrounding light sources have impact on the measurements. The impact of the different light sources on different sensors are represented by the gains shown in Equation (9). The dimensions of the test-bed are 5.6 m in length, 4.4 m



(a) Photograph of the Test-bed room

(b) Top-down layout of the Test-bed room

Fig. 5. The lighting Test-bed at the SinBerBest Laboratory.

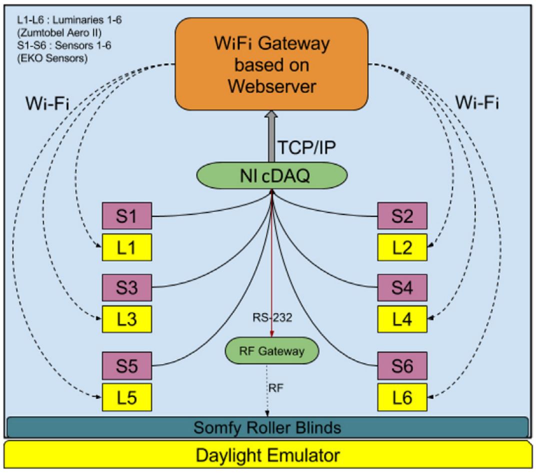
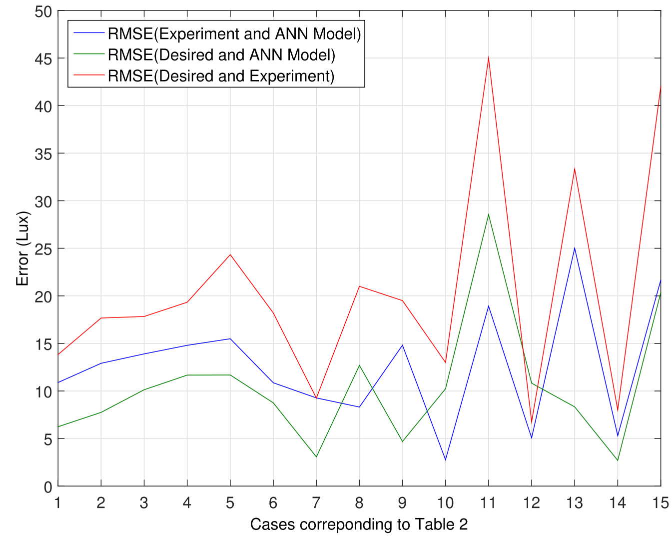
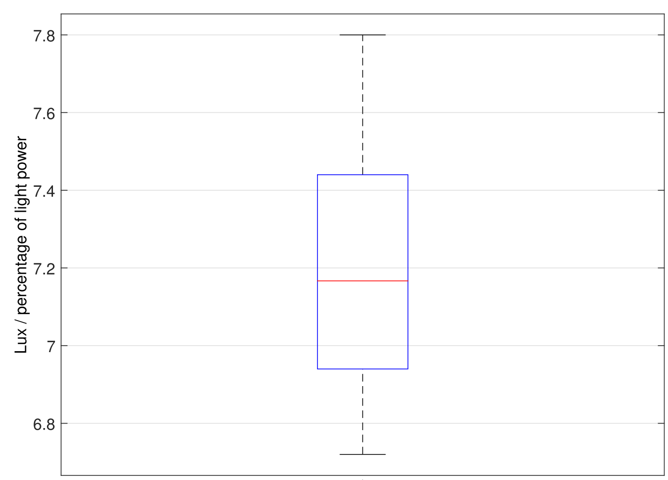


Fig. 6. Hardware architecture.



(a) RMSE of different parameters



(b) Box-plot of the RMSE

Fig. 7. RMSE plots.

in breadth and 3 m in height. The luminaires are mounted such way that it is located in the center of the room i.e., equidistant from the walls. The sensors are placed in the tentative seating locations for the occupants. The test-bed uses a National Instruments Data Acquisition platform (NI cDAQ) to acquire signals from the sensors as well as to actuate the lights through a web-server based WiFi gateway. A WiFi to DALI gateway at each light interprets the command signals. This hardware architecture, shown in Fig. 6, is used for both for system identification and for controller implementation. The performance of the ANN model and ANN inverse-model trained using data obtained from the experimental setup is presented in Table 2 for few of the cases.

Fig. 7a shows the Root Mean Square Error (RMSE) between desired illuminance and actual measurements, RMSE between the desired illuminance and predicted illuminance from ANN Model, and RMSE between the actual measurements and predicted illuminance from ANN Model. It can be observed that the RMSE of experimental value and the predicted illuminance from ANN Model is mostly lower than 25 *lux* with a maximum at 45 *lux*. Fig. 7b shows the box plot for *lux*/percentage of all the luminaires based on the experimental results. The mean *lux*/percentage of light power is approximately 7.2, from which the maximum RMSE is 6.25% and RMSE of experimental value and predicted *lux* from ANN Model is always lower than 3.47%. '100 *lux*' in the desired illuminance column in Table 2 is used to indicate the absence of a particular occupant. These values have not been considered in the RMSE calculations.

Table 2
Performance of the ANN model and ANN controller.

Desired Illuminance (*lux*)						Light power (%) predicted by ANN Inverse-Model						Actual Output for the light power predicted by ANN Inverse-Model						ANN Model Output for the light power predicted by ANN Inverse-Model					
300	300	300	300	300	300	15	23	11	19	13	26	290	325	283	313	291	309	298	295	278	299	294	303
350	350	350	350	350	350	18	27	12	22	15	31	360	385	330	364	335	362	351	348	323	354	346	358
400	400	400	400	400	400	21	31	14	26	18	37	406	429	384	419	410	427	405	400	369	408	397	414
450	450	450	450	450	450	24	36	16	30	20	42	451	494	431	476	446	472	455	449	415	458	447	467
500	500	500	500	500	500	26	40	17	33	22	47	489	534	458	517	486	528	502	493	462	501	493	515
100	300	300	300	300	300	0	28	13	19	12	26	168	338	275	310	288	306	162	310	288	298	287	306
100	100	300	300	300	300	0	0	17	25	13	25	106	112	297	314	288	308	104	103	305	299	295	301
100	100	100	300	300	300	2	1	0	30	17	27	106	125	176	325	313	325	109	109	178	316	312	310
100	100	100	100	300	300	3	7	0	0	18	32	108	128	118	119	317	322	95	99	118	107	301	309
100	100	100	100	100	300	4	6	1	0	0	37	95	98	97	104	132	313	96	89	93	101	132	310
100	500	500	500	500	500	0	48	19	34	21	45	265	545	435	516	417	516	265	525	434	499	470	519
100	100	500	500	500	500	0	0	33	44	24	43	162	176	514	510	498	501	178	180	522	515	501	506
100	100	100	500	500	500	0	0	0	54	32	46	130	173	280	540	540	520	118	150	224	505	516	504
100	100	100	100	500	500	1	5	1	0	32	54	110	125	183	166	508	508	96	106	95	156	501	505
100	100	100	100	100	500	4	5	1	0	0	65	112	117	131	153	213	542	106	97	122	146	204	520

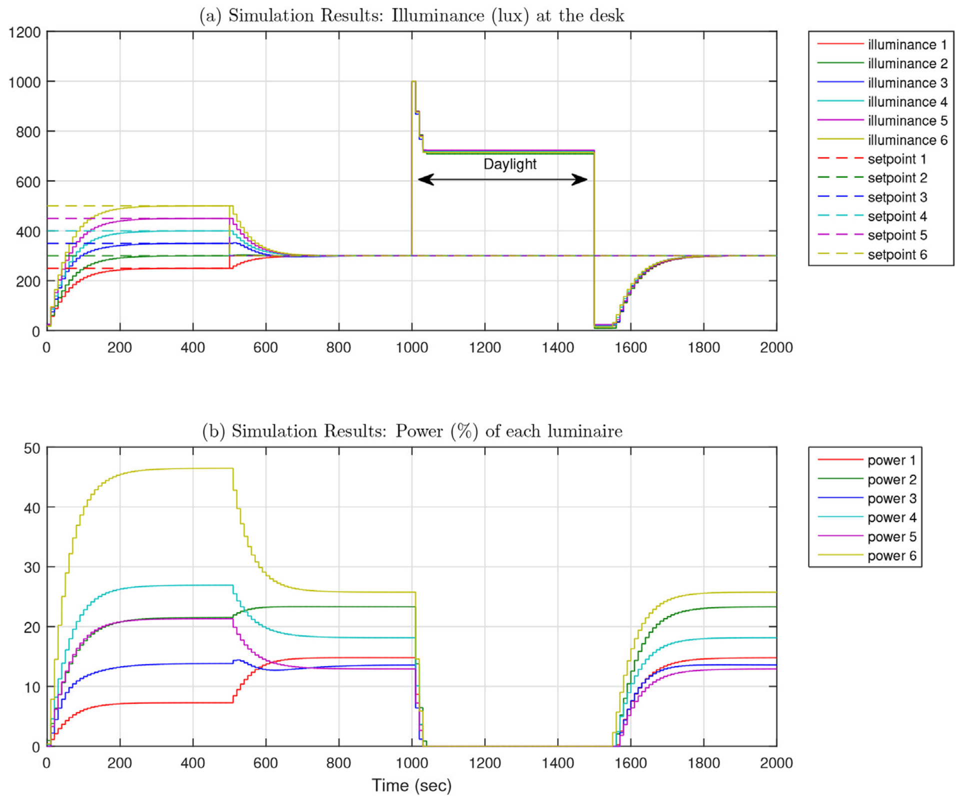


Fig. 8. Performance of ANN-IMC control (simulations).

5. ANN-IMC closed loop illuminance control

5.1. Simulation results

The controller and model developed in Section 3 were used in Matlab-Simulink to demonstrate closed loop illuminance control at the desk level (6 points) similar to Table 2. These simulations (shown in Figs. 8 and 9) were carried out with following conditions.

1. Desired illuminance at each desk was 250, 300, 350, 400, 450 and 500 *lux* respectively. This setting is chosen to show the capability of the control system to track combinations of setpoint values.
2. At $t = 500s$, the desired illuminance is changed to 300 *lux* on all desks. This setting is chosen to show the response of the system to step input.
3. At $t = 1000s$, a daylight disturbance of constant 700 *lux* on all desks is introduced. This setting is chosen to show the response of the system to daylight.
4. At $t = 1500s$, the daylight disturbance is removed. This setting is chosen to demonstrate the anti-windup reset function.
5. The response time of the closed loop system to step changes in setpoints and disturbances depends on the choice of λ and $\lambda = 60$ was selected for the simulation.

Fig. 8 shows that even with different desired illuminances on the desks, the control system is able to drive the lighting system to the setpoints. In the presence of daylight disturbance, the set points are not achieved owing to physical input constraints. That is, a negative power value was necessary to compensate for the large daylight which is not possible. It can also be observed that the control system quickly drives the system back to the setpoints once the daylight disturbance is removed. This highlights the anti-windup behavior.

Fig. 9 shows the simulation results for a case when three of the occupants suddenly leave their desk and their corresponding desired illuminances (300, 400 and 500 *lux* respectively) are defaulted to 100*lux* (step change). Even with extreme difference in setpoints on adjacent desks, the control system is able to achieve its targets. A constant daylight disturbance is used once again for a short duration.

5.2. Experimental results

The proposed controller was implemented in the test-bed to control the illuminance (*lux*) at the desk level. The experiment was carried out for various cases and the results are presented in Figs. 10 and 11. The controller parameter λ was set to 60 for the closed loop experiment. Fig. 10 shows the closed loop response of the system with varying setpoints, with no daylight. Up to time $t = 800s$, all combinations of illuminance setpoints are achieved by the control system. After time $t = 800s$, extreme setpoint combinations are tested that drives a few of the control inputs to 0. In that condition, some of the setpoints will not be reached because that can happen only if negative control actions can be applied. For example, between $t = 1100s$ and $t = 1300s$, when the setpoint to desk 6 is stepped up from 100 to 500, the illuminance at desk 5 becomes higher than its setpoint (because luminaire 6 influences desk 5's illuminance). The controller does its best to bring down the illuiminance at desk 5 by setting the power input to luminaire 5 to 0.

Fig. 11 explores the case with fixed setpoints of 300 *lux* on all desks with the influence of daylight. Emulated daylight was switched on for short duration (using the daylight emulator of the testbed). The impact of the daylight on the illuminance at a given desk will depend on its distance from the emulator. So, the additive disturbance is not the same at all the desks. The controller tries to compensate for this disturbance by moving all the power inputs but one to zero. Two of the desks are maintained at desired illuminance while the others are overpowered by bright daylight even if the corresponding lights are fully off.

The proposed control loop has robustness to variations in sensor locations and so occupants can move the desk sensor locations to suit their needs (moderate changes). Even without any modifications to the

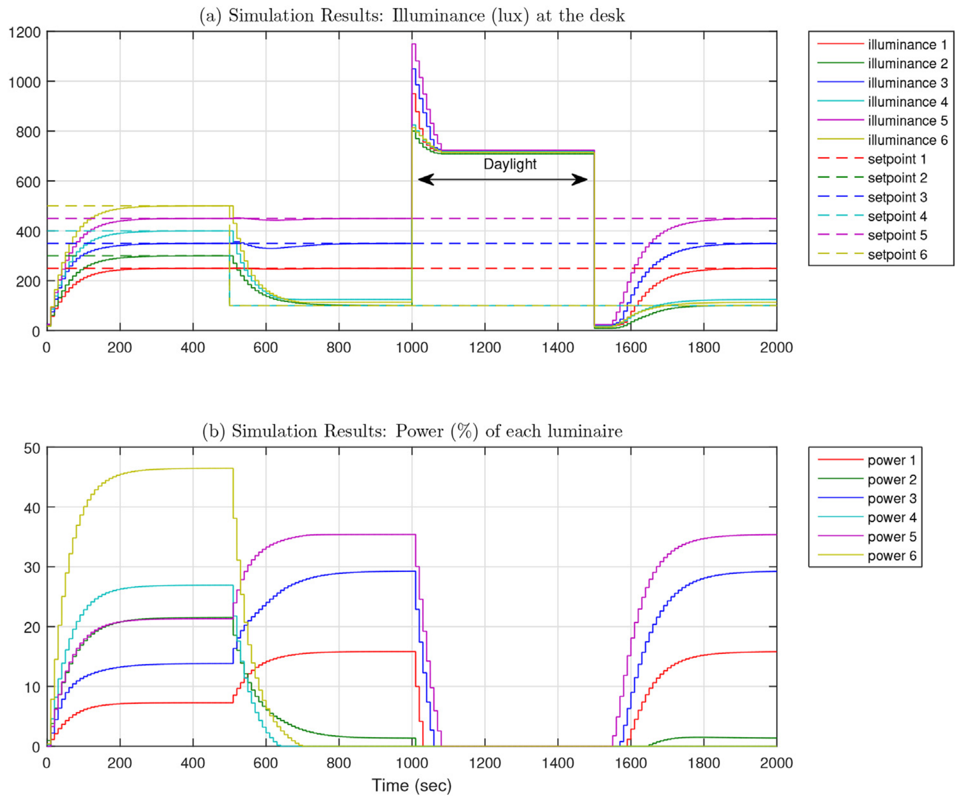


Fig. 9. Performance of ANN-IMC control (simulations).

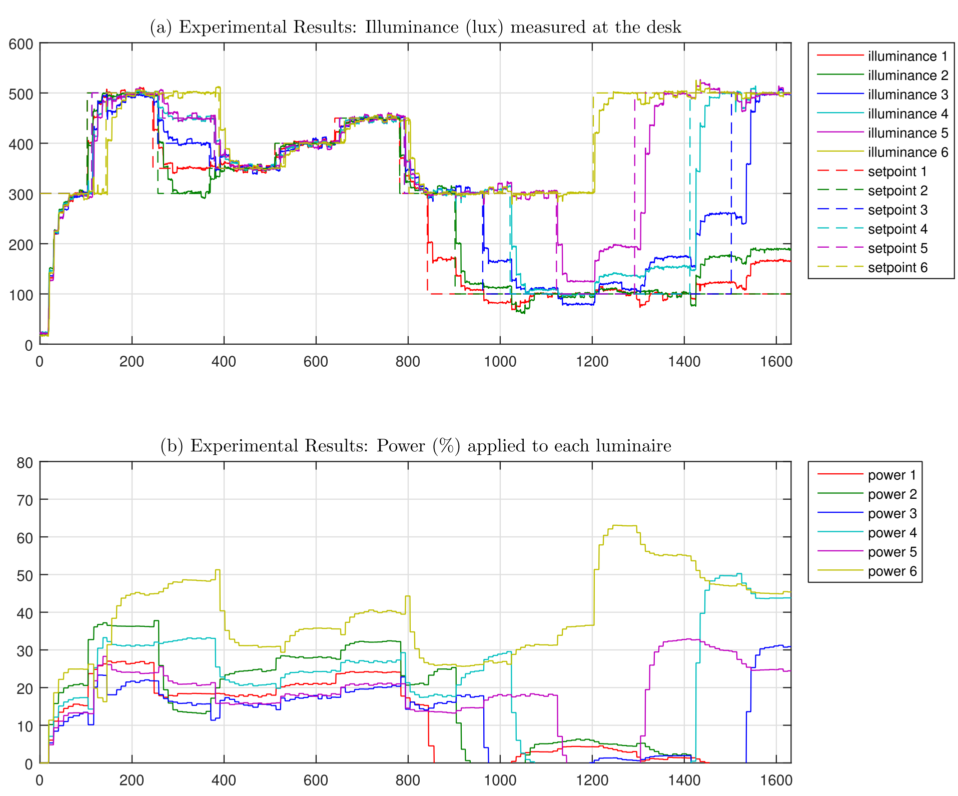


Fig. 10. Performance of ANN-IMC Control with zero daylight and varying setpoint.

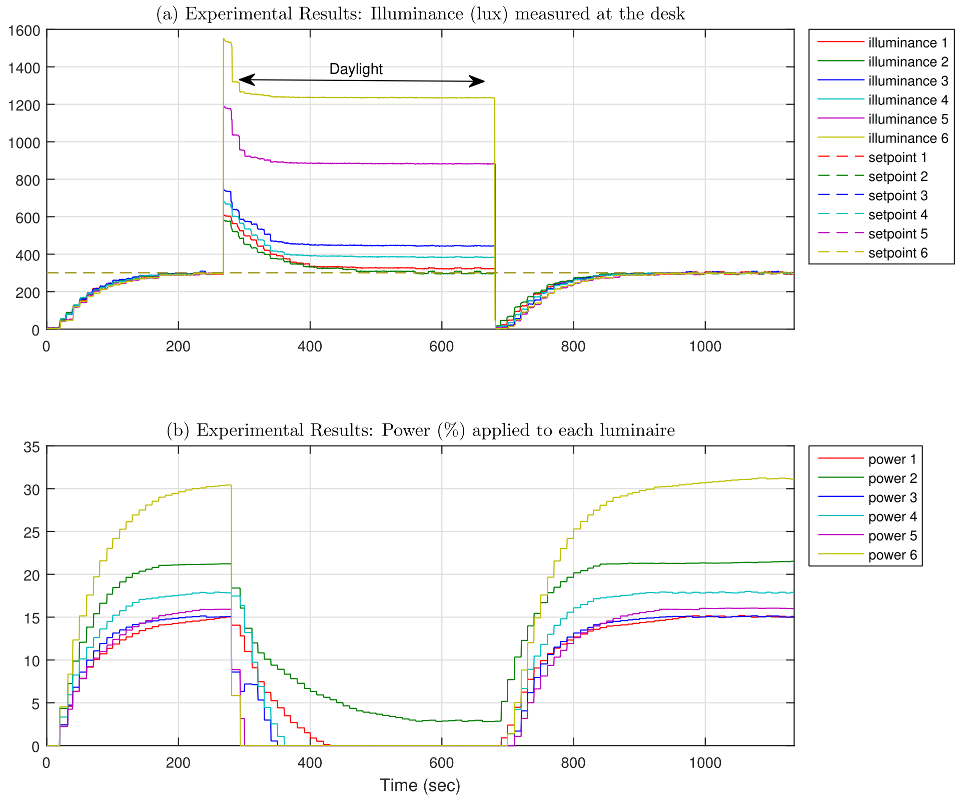


Fig. 11. Performance of ANN-IMC Control with fixed setpoint and daylight disturbances.

controller, tracking is still achieved. The effect of changes in sensor locations were observed in the values of power % applied to the luminaires by the controller to compensate for plant-model mismatch.

6. Blinds actuation when daylight causes glare

The automatic actuation of roller blinds is tied to the useful daylight index [48]. That is, the roller blinds are automatically deployed when the maximum daylight contribution at any sensor location is greater than 2000 *lux*. The blinds are later retracted when the maximum daylight contribution at any sensor location is less than $2000 \times \frac{tf}{100}$ *lux*, where tf% is the transmission factor of the blinds. (In the test-bed, roller blinds with 5 % fabric were used.) This behavior can be represented by equation (19).

$$Blinds = \begin{cases} close \;\; if \;\; \|Y_p(t) - Y_m(t)\|_\infty \geq 2000 \\ open \;\; if \;\; \|Y_p(t) - Y_m(t)\|_\infty < 2000 \times tf\% \end{cases} \tag{19}$$

where, $Y_p(t)$ is the measured illuminance (which includes $D(t)$, the daylight disturbance), $Y_m(t)$ is the model output (which does not incorporate daylight) and $\|.\|_\infty$ is the $\infty - norm$ which captures the maximum value element of the vector. Hysteresis can be introduced to avoid the oscillation that might occur if the daylight contribution at any sensor fluctuates.

The block diagram for deploying/retracting the roller blinds is shown in Fig. 12. An advantage of the proposed method to actuate the blinds is that the ANN Model from Section 3 is used to calculate the daylight contribution without the need for separate daylight sensors. Figs. 13 and 14show the blinds in open and closed positions

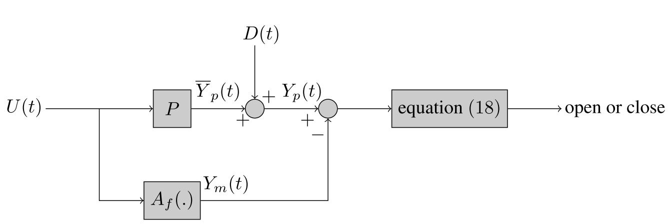


Fig. 12. Roller Blinds actuation logic.

Fig. 13. Blinds open for.$\|Y_p(t) - Y_m(t)\|_\infty \geq 2000$.

Fig. 14. Blinds closed for.$\|Y_p(t) - Y_m(t)\|_\infty < 2000 \times \frac{tf}{100}$.

Table 3
Base LPD calculation for the Test-bed.

Desired Lighting Intensity	Total Power (W)	Baseline LPD (W/m^2)
300 lux	98.61	4.00
500 lux	177.43	7.20

Table 4
Average daylight at S6.

Time	8:30am-11:30am	11:30am-02:00pm	02:00pm-18:00pm
Average daylight at S6 (lux)	1050	2120	3070

Table 5
Potential energy savings.

Desired Lighting Intensity	Average Power consumption with the proposed method (W)	Actual LPD (W/m^2)	Savings from baseline (%)
300 lux	44.59	1.81	54
500 lux	106.07	4.30	40

respectively where the sensors located closest to the windows were the ones that saw the maximum contribution from the emulated daylight.

7. Analysis on potential energy savings

An analysis on the potential energy savings with proposed method is presented in this section. The Test-bed described in Section 4 is used for the analysis. The base 'Lighting Power Density (LPD)' with the available lighting system is presented in Table 3.

It is to be noted that the LPD of the lighting system is high as the system is designed to cater multiple experiments and not optimized for the space. Hence, the LPD cannot be compared to market standards and should only be used as baseline or a guideline for determining the performance of the control system. The Test-bed uses a daylight emulator and not actual daylight, hence the desired daylight settings for a typical day is derived using the geographical location of the Test-bed and DAILux software. Corresponding daylight settings are emulated using daylight emulator and daylight at all six sensors are determined, which is further used in the simulation platform (Matlab-Simulink) to carry out numerical analysis on energy savings with the proposed method.

A complete data-set containing the light intensity of the daylight emulator and corresponding light intensity at all six sensors is presented in the supplementary data. The average daylight for a typical day in Singapore at the sensor *'S6'* is presented in Table 4. The results for energy savings with the above data (i.e., daylight from DIALux and light intensity for the given daylight at *'S6'*) obtained from simulation platform (Matlab-Simulink), is presented in Table 5.

With non-personalized lighting system, the opportunity to increase the savings from 40% to 54% does not exist. This is due to the reason that, once the system is designed for 500*lux* even if some of the occupants desire lower light intensity at the desk, the energy savings cannot be increased. Hence, the proposed method increases the range of energy savings that could be achieved. However, the energy savings depends on the profile of the preferences from occupants even though the proposed method can facilitate the feasibility.

It is to be noted that the interplay of occupancy controls and daylight/personal controls is also crucial in the lighting control system. Proposed lighting control system leverages on a centralized occupancy detection and localization system (ODLS). The above ODLS serves many subsystems in the building energy management such as lighting control, HVAC, demand response etc. The ODLS will feed the desired light settings to the lighting control system. ODLS is virtual occupancy sensing technique and is based on smart phones and wifi [49,50]. The control system is robust to moderate changes in the position of the sensor especially when it only shifts along the task plane (and not along its perpendicular). The setpoint to the control loop is determined from occupants' feedback which is based on their personal visual comfort. Obviously, the occupant feedback will depend on the current illuminance at the desk. If the position of the sensor is shifted and the lights react to this change perceptibly, a user still has the ability to readjust their personal visual comfort. This adds a second layer of robustness. The translation from occupants' qualitative preference to quantitative setpoint values is only possible with an ODLS and occupant feedback system. However, these two systems are beyond the scope of the paper and so, only the capability of the proposed system to track the setpoint is evaluated.

8. Summary

This paper presented a closed loop controller for smart lighting systems (with equal number of lights and sensors) using ANN models and IMC-based control design. The features of the proposed method are.

1. Simplified ANN based modeling of the lighting system using limited number of data points (with real data gathered from illuminance sensors on the task table).
2. The proposed control system fully harvests daylight while maintaining desired illuminance on individual task tables for personalized light settings.
3. The proposed method is robust to the plant-model mismatch that occurs due to natural variation (moderate) in the position of task table sensors.
4. The proposed method has the capability to control other smart light accessories such as roller blinds (unified model). The blinds are activated based on the useful daylight index to avoid glare and maintain visual comfort.

The method proposed in this paper could be effectively used in NZEB where personalized light settings are required as it incorporates daylight harvesting without compromising on user preferences.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.buildenv.2018.05.005.

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