

Application of teletraffic engineering modeling techniques for studying smart lighting systems for energy saving

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Limited natural energy resources compel humankind to search for efficient utilization of energy, and thus increasing number of fluorescent lamps are adopted for lighting systems. However, previous study showed that there exists a tradeoff between energy-saving and lifespan for fluorescent lamps. Consequently, it becomes an important topic on how to design an efficient and effective automatic control algorithm in illuminating engineering. The problem was traditionally studied by conducting surveys and experiments, which were unavoidably costly and rather time-consuming. This paper presents a novel application of teletraffic engineering modeling techniques in studying automatic lighting control systems. A queueing model is proposed to study typical lighting systems and a simple close-loop algorithm is illustrated to effectively adapt the system control parameters. Through computer simulation, we show that the proposed method provides an alternative way of studying lighting systems in a cost-effective manner, while providing adequate accuracy.

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1. Introduction

Limited natural energy resources remain a major concern all over the world due to the ever-increasing energy consumption with continuous growth of the global economy. Despite the fast development of renewable and clean energy, such as solar power and biofuels, generation of electricity still relies on coal and oil resources, which are not renewable and cause major environmental problems such as greenhouse gases and acid rain pollution. Statistics showed that commercial buildings account for over one-third of the total primary energy consumption. In particular, a quarter of total energy consumption by commercial buildings is contributed by electric lighting¹. Consequently, it becomes an important interior design strategy to improve the utilization efficiency of lighting systems.

Two types of widely-deployed lamps are incandescent and fluorescent lamps². The former make light by heating a metal filament wire to a high temperature until it glows. The hot filament is usually protected from air by a glass bulb, which is filled with inert gas or evacuated. The latter uses electricity to excite mercury atoms to generate short-wave ultraviolet light, which is in turn used to produce visible light by making a phosphor fluoresce. Compared to an incandescent lamp, a fluorescent lamp converts electrical power into useful light with much higher energy efficiency, and this makes fluorescent lamps more appealing as compared to incandescent for commercial buildings. Nevertheless, fluorescent lamps come with a relatively costlier lamp fixture due to their need for ballasts to regulate the electric current flowing through the lamps. Recent development of compact fluorescent lamps (CFLs) have dramatically reduced the cost of lamp fixtures and CFLs have become popular for residential lighting systems³. Many countries have started campaigns aimed at replacing incandescent lamps with CFLs to improve the energy efficiency so as to reduce electricity consumption.

Besides replacing lamps with low energy-efficiency by ones with high energy-efficiency, automatic lighting control can be applied to reduce energy consumption. For example, Rubinstein *et al.* have shown that up to 50% of lighting energy saving can be

achieved with lighting control systems⁴. Current automatic lighting control is usually realized by the application of timers and/or sensors⁵. For example, one may use light detection sensors to measure the illuminance and turn a lamp on whenever the detected illuminance is below a certain threshold values. Of course, we can also use timers to set the time for a lamp to be turned on/off.

In the literature, several papers discussed the application of occupancy sensors in automatic lighting control^{6,7}, which can be used for either dimming control (i.e., to vary the light output of the lamps) and switching control (i.e., to turn the lamps on/off)⁸. Dimming control considers different levels of light output¹ but is seldom applied to fluorescent lamps⁹. As such, we only consider switching control hereafter. For switching control, lamps will be automatically switched off after a certain amount of time has elapsed since the occupancy sensor detects the last movement in the space (e.g. a function room). This time is usually called the timeout setting, a typical factory setting being between 12 to 15 minutes¹⁰. As pointed out in reference 10, calibrating the timeout setting of occupancy sensors is not a trivial job. If it is set to a large value, less energy saving can be achieved; if it is set to a small value, the lighting system may result in false-offs when no motion is detected during periods of occupancy. Furthermore, as mentioned in reference 11, lamps with a longer burning cycle (i.e., lamp-on interval) will have longer average lifespan and shorter burning cycles will shorten lamp life. For example, lamps that are operated 24 hours a day could have an average lifespan of nearly 38,000 hours. Interested readers are referred to an introductory article on the lifespan of fluorescent lamps¹². In addition, studies have shown that savings from lighting operations are affected by the work function and the number of occupants¹³.

Garg and Bansal proposed to use a model to learn “human movement” patterns and change the timeout setting of lighting control accordingly. Experimental results showed about 5% more energy saving could be achieved by using smart occupancy sensors to adapt the timeout setting as compared to non-adapting sensors¹⁴. However, their work

only considered a single user and the results may not be pervasive. Next, a research group from Rensselaer Polytechnic Institute and US Environmental Protection Agency studied the effects of changing timeout settings of occupancy sensors on energy saving, lamp cycling and maintenance cost¹⁵. In particular, they investigated the energy and cost saving potential of using occupancy sensors for commercial lighting systems. Discrete values of timeout settings were adopted and they were varied from 5 to 20 minutes at 5 minutes increments. Although the studies in references 15 and 16 contained extensive numerical details, their method is costly in terms of data collection duration, used hardware and statistical analysis. For example, in reference 15, the researchers spent about 8 months and used a lot of data loggers to collect the statistics from 180 spaces in 24 States in the United States.

Unlike the statistical data analysis method, Chung and Burnett proposed to use an occupancy probability model to predict the energy savings that could be achieved by occupancy sensors with different timeout settings¹⁷. However, their study focused on the occupancy probability model and did not discuss the effect of timeout setting values on the lifespan of lamps.

Guo *et al.* presented a review of the performance of occupancy-based lighting control systems. They highlighted that significant uncertainty exists in lighting systems using single measurement points, which may cause lighting to shut off inadvertently or turn on due to the detection of passersby in adjoining hallways¹⁸. For example, the National Lighting Product Information Program (NLPIP) pointed out that half of a small sample of motion sensor detectors did not respond to a movement occurring within the coverage area claimed for the device⁷. In order to improve the accuracy of occupancy detection, Dodier *et al.* proposed using sensor belief networks based on Bayesian probability theory to determine occupancy¹⁹ and a similar work was presented in reference 20. However, the effect of timeout settings on energy saving was not

mentioned. Guo *et al.* proposed a data processing and evaluation framework for application to a lighting control sensor network^{21,22}.

A field study conducted by Floyd *et al.* pointed out the importance of proper installation and configuration of occupancy sensors in order to achieve and maximize energy saving^{23,24}. Their study showed that about 10% energy saving could be achieved with the proper use of occupancy sensors in open offices, which was further confirmed by the results based on a two-year lighting data²⁵. Furthermore, the energy saving could be up to 46% for private offices with occupancy sensors that were properly installed and commissioned.

Enlightened by previous studies on lighting control systems, in this paper we first apply teletraffic engineering modeling techniques to model a restroom and their users as a queueing system. Then, we investigate the effect of timeout settings on energy-saving and lifespan of fluorescent lamps. Next, instead of using fixed timeout settings as in conventional occupancy-sensors-controlled lighting systems, we propose a simple algorithm to adapt the timeout settings according to the real-time occupancy statistics. To the authors' best knowledge, this is the first time that teletraffic engineering modeling techniques have been introduced to lighting system modeling and simulation, which is expected to play an important role on the study of the energy saving of smart lighting systems.

The rest of this paper is organized as follows. Section 2 introduces the teletraffic engineering modeling technique, presents a queueing system model for a restroom and discusses the rationale behind. Section 3 presents a simple algorithm to adaptively change the setting of timeout values. In Section 4, the proposed queueing model is validated through computer simulation results, and effects of different parameter settings are discussed and analyzed. Finally, Section 5 concludes the paper and discusses our future work.

2. Queuing model for smart lighting systems

Historically, teletraffic engineering is related to traffic engineering, which is a branch of civil engineering. In brief, traffic engineering uses engineering techniques to achieve safe, efficient and reliable movement of people and goods on roadways. In terms of research areas, traffic engineering focuses on traffic rules (or protocols), infrastructure and vehicle design for safe and efficient traffic flow. Teletraffic engineering is the application of traffic engineering in telecommunications. Specifically, teletraffic engineers apply statistics including queueing theory²⁶, traffic patterns, practical models, measurements and simulations to plan telecommunication networks. This field was created by the work of a Danish mathematician, Agner Krarup Erlang. Later in 1946, the *Comité Consultatif International Téléphonique et Télégraphique* (CCIT) named the international unit of telephone traffic Erlangs in honour of this great mathematician.

The unit Erlang is dimensionless. For example, a single cord circuit has the capacity to be used for 60 minutes in one hour. If 100 six-minutes calls are received in one hour by the telephone switching network then the total traffic load in that hour is 600 minutes or 10 Erlangs. In simple mathematics, we have

$$E = \lambda h \quad (1)$$

where λ is the call arrival rate (number of call arrivals per hour) and h is the average call-holding time (in hours per call). $\lambda = 100$ calls/hour and $h = 0.1$ hours/call for the aforementioned example.

Queueing theory provides the mathematical analysis of property of waiting line or queues. In this paper, we consider an M/M/c queueing model for a restroom, where we assume that user arrivals follow a Poisson process (i.e., the inter-arrival time is

exponentially distributed) and service time (i.e., how long a user stays in the restroom) is also exponentially distributed.

Previous studies on occupancy sensors have revealed that (a) how often users enter / leave a room and (b) how long they stay inside the room are two important factors related to smart lighting control. For example, during peak office hours on weekdays, recorded data proved that it is of high probability a room will be occupied with lamps on, while during weekends, it is of high probability a room will be empty with lamps off. From a teletraffic engineering point of view, these two factors (a) and (b) exactly determine inter-arrival time and service time for a queueing model. This motivates us to examine a smart light system with occupancy sensors using a teletraffic engineering queueing model. In the following paragraphs, we describe each entity of the queueing model in details. For emphasis, those terms from queueing theory were purposely put in italics.

2.1 Server and customer

The facilities available in a restroom are modeled as *servers*. Those users have access to facilities are modeled as *customers*. By default, each *server* can only serve one *customer* at a time. For example, the number of servers in a restroom can be considered as three. Furthermore, we are taking the liberty of assuming infinite consumers.

2.2 Inter-arrival time

As we consider the Poisson arrival of customers, the inter-arrival time is exponentially distributed with a well-known probability distribution function (PDF)

$$f_T(t) = \begin{cases} \lambda e^{-\lambda t}, & t \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where λ is the arrival rate. For a homogeneous Poisson arrival process, the probability of having k arrivals in time interval $(t, t+\tau]$ is given by,

$$P\{N(t+\tau) - N(t) = k\} = \frac{e^{-\lambda\tau} (\lambda\tau)^k}{k!} \quad (3)$$

2.3 Service time

Facility-occupancy time is modeled as *service time*, which is considered as a truncated Gaussian distributed with a known PDF,

$$f_T(t; \mu, \sigma, a, b) = \frac{\frac{1}{\sigma} \phi\left(\frac{t-\mu}{\sigma}\right)}{\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)} \quad (4)$$

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x^2\right) \quad (5)$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt = \frac{1}{2} \left[1 + \operatorname{erf}\left(\frac{x}{\sqrt{2}}\right) \right] \quad (6)$$

where μ and σ^2 are the mean and the variance of *service time*, respectively. With $a = 0$ and $b = \infty$, Equation 4 can be further simplified as

$$f_T(t; \mu, \sigma, 0, \infty) = \frac{\frac{1}{\sigma} \phi\left(\frac{t-\mu}{\sigma}\right)}{1 - \frac{1}{2} \left[1 + \operatorname{erf}\left(-\frac{\mu}{\sigma\sqrt{2}}\right) \right]} \quad (7)$$

For brevity, we use $\mathcal{N}_{(0,\infty)}(\mu,\sigma^2)$ to denote a truncated Gaussian distributed variable with $a = 0$ and $b = \infty$. From probability theory, if X and Y are independent, random variables that are Gaussian distributed, i.e., $X \square \mathcal{N}(\mu_x,\sigma_x^2)$ and $Y \square \mathcal{N}(\mu_y,\sigma_y^2)$, then $X+Y$ is also Gaussian distributed:

$$Z = X + Y \square \mathcal{N}(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2) \quad (8)$$

However, Equation 7 does not hold for truncated Gaussian distributed variables. Through simple simulation, we can show that summation of truncated Gaussian distributed variables can be better approximated by a Rayleigh distributed variable with certain offset. For example, as shown in Figure 1, we can see that a slight discrepancy exists between the cumulative distribution function (CDF) of summation of truncated Gaussian distributed variables and that of a Rayleigh distributed variable with offset.

In this paper, we consider two types of activities, and their respective server-occupancy time is Gaussian distributed. The related parameters are $\mathcal{N}_{(0,\infty)}(2,2^2)$ and $\mathcal{N}_{(0,\infty)}(10,6^2)$ minutes. Notice that these parameters are chosen in order to match the baseline case provided in reference 16 after a number of preliminary simulation runs. For the purpose of simulation study, we may use Rayleigh distribution to generate the random variables, especially when there are more than three types of activities to be considered.

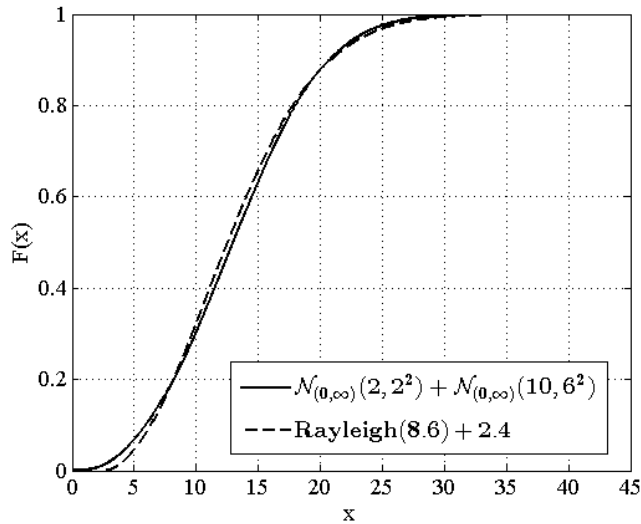


Figure 1. Comparison of the sum of two truncated normal distributed variables and a Rayleigh distributed variable.

2.4 Service model

The service model follows a *first-in-first-out (FIFO)* service discipline. A customer will leave the restroom immediately when he / she found all the facilities are occupied upon arrival. In other words, we assume customers will not wait to use the restroom facilities.

2.5 Computer simulation

Computer simulation was performed based on the flowchart shown in Figure 2. Inter-arrival time and service time were generated using random number generators.

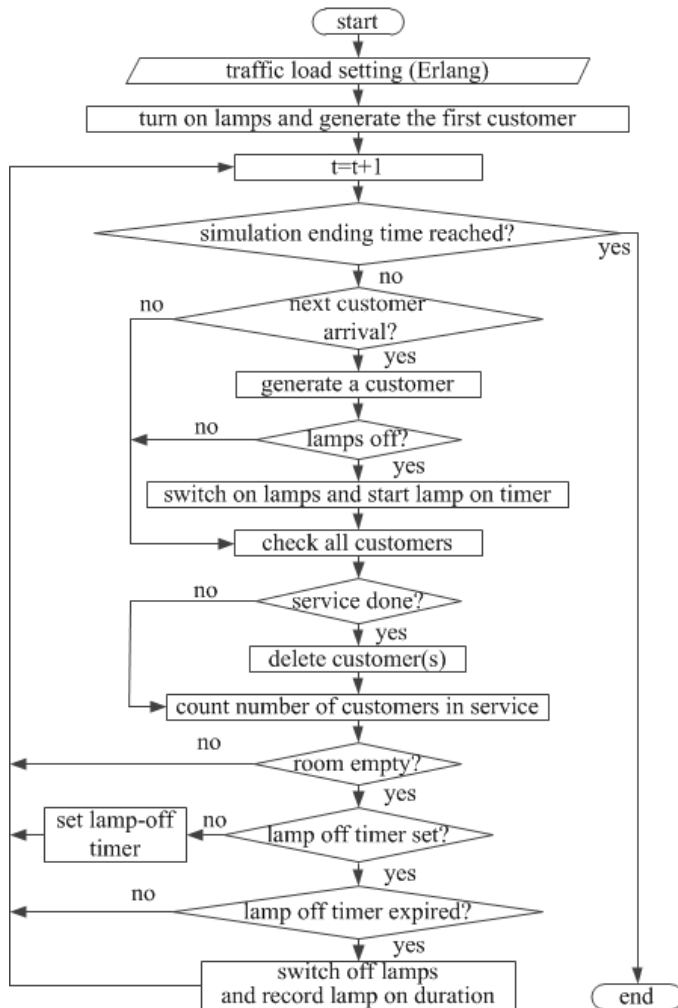


Figure 2. Flowchart for the proposed teletraffic queuing model.

3. Automatic lighting control algorithm

We consider a restroom with three facilities and the restroom is illuminated by fluorescent lamps controlled by manual switches and automatic occupancy-sensors, e.g., passive infrared (PIR) sensors²⁷. PIR sensors work by responding to temperature

differences, for example, when an infrared source with one temperature, such as a human body, passes in front of an infrared source with another temperature, such as a wall. Ideal PIR occupancy sensors are assumed and the lamps will not be turned off falsely when the facility is occupied.

Let us further assume that the lamps are switched on manually during the test period of studying the effectiveness of automatic lighting control.

3.1 Minimum lamp-on time

As we know, the lifespan of fluorescent lamps is adversely affected by the burning cycle, which is usually set to 3 hours on and 20 minutes off during a quality test. Under controlled testing conditions with a particular setting of burning cycle, the hours of operation after which half the lamps under test (usually in a large group) fail to produce light are conventionally referred to as the *average lamp life*. The average lamp life for a burning cycle of 3 hours/start is defined as the *rated lamp life*. An empirical formula²⁸ describes the relationship among average lamp life, rated lamp life and burning cycle, which is given as follows,

$$L = L_r \times M \times 1.71 \times \left(1 - \exp \left(- \left(\frac{u}{3.89} \right)^{0.505} \right) \right) \quad (9)$$

where L and L_r are the average lamp life and the rated lamp life, respectively. M is the mortality ratio and u the burn cycle in hours/start. Notice that M is dependent on survival criterion.

From the above, we can see that the longer the burning cycle, the longer the average lamp life. To increase the burning cycle, we should avoid frequent on/off switching. Therefore, we may have a minimum lamp-on time, $T_{on,min}$, whose nominal

value is 15 minutes¹⁰. In this paper, we will study the different effects of using fixed $T_{on,min}$ and adaptive $T_{on,min}$.

3.2 Timeout setting

As aforementioned, *timeout setting* is required when the lamps are automatically controlled using occupancy sensors. Let us denote the amount of time that a room is occupied as T_o , and the timeout setting as T_d . Furthermore, the amount of time for which a lamp is on is denoted as T_{on} . Therefore,

$$T_{on} = T_o + T_d \quad (10)$$

It is not difficult to deduce that

$$T_d = \begin{cases} T_{d,min} + T_{on,min} - T_o, & \text{if } T_o \leq T_{on,min} \\ T_{d,min}, & \text{otherwise} \end{cases} \quad (11)$$

where $T_{d,min}$ is a constant value.

3.3 Adaptation algorithm

Previous studies have shown that the lighting condition profile for the same facility (e.g., a classroom, an office or a restroom) exhibits salient difference between weekdays and weekends. As such, if fixed parameter settings optimized for one scenario (e.g., with high traffic load) were to be adopted for a smart lighting control system, they would result in inefficient energy saving for another scenario (e.g., with low traffic load). For example, during daytime on weekdays $T_{on,min}$ can be set to a larger value while during nighttime at weekends $T_{on,min}$ should be set to a smaller value. Therefore, we should

adapt the system parameter settings according to the traffic load at different times of a day or even periods of a year.

In general, existing lighting control circuits using PIR sensors adopt one or a combination of three basic control algorithms: integral (reset) control, open-loop control and close-loop control. We investigate the performance of an intelligent close-loop algorithm that is used to adapt the system setting parameters of a lighting system. In particular, we assume that the average value of time duration that a room is occupied, $T_{o,avg}$, is estimated at a fixed sampling interval, T_s , e.g., 20 minutes. Then, $T_{o,avg}$ is used to generate new $T_{on,min}$ and $T_{d,min}$ values of the system setting for the next T_s . The following adaptation algorithm is used,

$$\begin{cases} T_{on,min} = T_{o,avg} \\ T_{d,min} = T_{o,avg} (1 - \alpha), \text{ where } \alpha \in [0, 1] \end{cases} \quad (12)$$

where α is an index indicating a user's preference on energy saving. On the one hand, if α is larger than 0.5, the user prefers to save energy rather than to prolong the life of the lamps; on the other hand, if α is smaller than 0.5, the user prefers to prolong the life of the lamps rather than to save energy.

4. Results

The simulation imitates a restroom with three facilities and automatic lighting control, which can be realized by a combination of PIR occupancy sensor and microphone sensors to improve control accuracy. Let us suppose the total power rating of CFLs installed in this restroom is 60 watts and the electricity price is 8 cents/kWh. For simplicity, we take the liberty of considering only the electricity consumption by the

CFLs and ignore that by the lighting control gear and sensors. As such, the cost for the restroom to be occupied and the lamps to be on for one hour is

$$60 \times 1 \times 8 / 1000 = 0.48 \text{ cents} \quad (13)$$

In order to perform fair comparisons with previous studies using data collection and a statistical analysis method, we use the same baseline scenario found in references 15 and 16. We may take that baseline as the *Manual Control Scheme*, i.e., without automatic lighting control. Users will switch on the lamps when they enter the restroom and find the lamps are off. However, one may not compulsorily switch off the lamps when he / she is the last one who leaves the restroom.

Without loss of generality, $T_{d,min}$ takes a nominal value of 0 minutes, and $T_{on,min}$ takes discrete values from 0 minutes to 20 minutes, with a 5 minute interval. We are interested in the following performance criteria related to the smart lighting control: (a) percentage of time when the restroom is lighted during occupied periods; (b) percentage of time when the restroom is lighted during unoccupied periods; (c) electricity cost for the restroom during a particular time period; and (d) average number of off to on switching per hour for the CFLs in the restroom. For each traffic load, we keep it constant for one hour and run computer simulation for a period of 30 days (machine time). The 95% confidence intervals are within $\pm 10\%$ of the average values shown for each data point presented in the figures.

4.1 Effect of traffic load

Let us first examine the effect of varying traffic load on performance criteria (a) and (b). The traffic load is varied from 0.025 Erlangs to 0.60 Erlangs. Figure 3 shows the lighting condition profile for the percentage of time when the restroom was lighted while

occupied. As expected, it increases as the traffic load increases. Furthermore, it is regardless of the $T_{on,min}$ settings. This exactly reflects how often and how long the restroom occupied by users is solely determined by the traffic load.

Next, Figure 4 shows the lighting condition profile for the percentage of time when the restroom was lighted while unoccupied. When $T_{on,min}$ was set to zero, this percentage was close to zero because no delay was required for the lamps to be switched off. When the restroom became unoccupied, the lamps were switched off immediately. As $T_{on,min}$ increases, the amount of extra time for the restroom to remain lighted increases.

4.2 Validation of queueing model

Based on Figure 3, we have estimated the traffic load for different time intervals for the queueing model of the restroom corresponding to the measurement results of a restroom provided in Figure 5 in reference 16. For a particular time interval of day, e.g., from 2:30pm to 3:30pm, the amount of traffic load is estimated, which corresponds to the average percent of time when the restroom was lit while occupied. For the sake of readability, we have plotted the baseline lighting condition profile in Figure 5. The estimated traffic load for respective time intervals are shown in Table I.

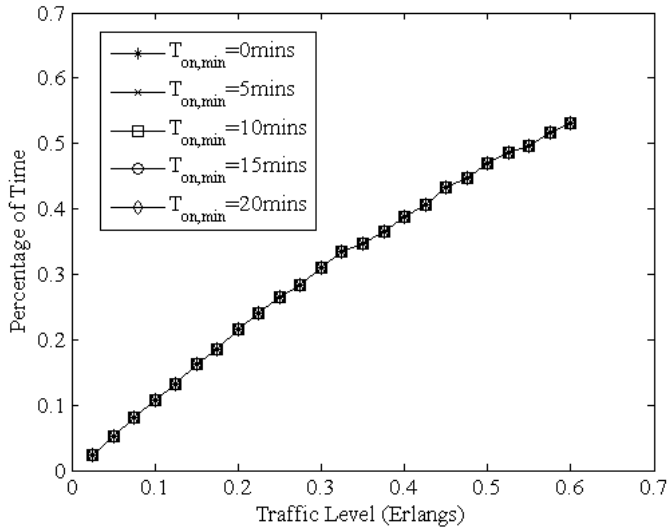


Figure 3. Lighting condition profile for the percentage of time when the restroom was lit while occupied.

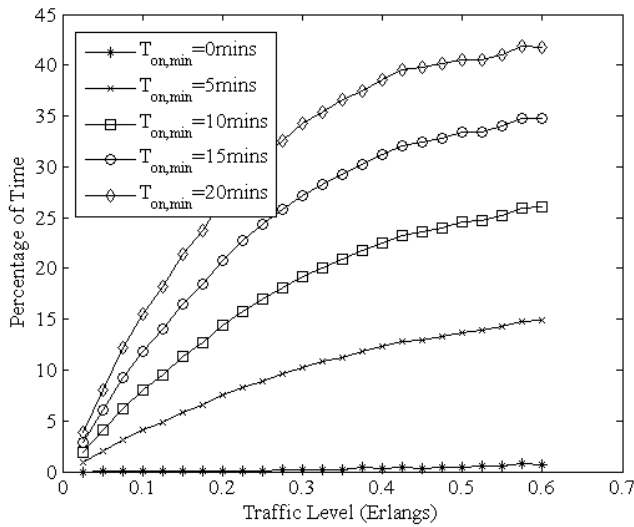


Figure 4. Lighting condition profile for the percentage of time when the restroom was lit while unoccupied.

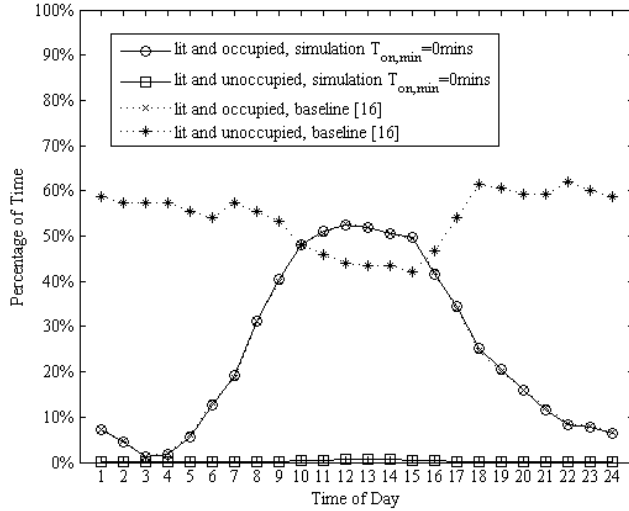


Figure 5. Lighting condition profile for the percentage of time when the restroom was lit during occupied / unoccupied periods for baseline and simulation with $T_{on,min} = 0$ minutes.

4.3 Smart lighting control with fixed system settings

From now on, simulations are performed based on the traffic loads in Table I without specific notations. Computer simulation studies were performed to investigate how various parameters of smart lighting control systems affect energy saving and life of lamps in terms of electricity cost and average number of off-to-on switching per hour, respectively.

Figure 6 shows the electricity cost per hour for the restroom during different times of day for the baseline and the simulation study with different $T_{on,min}$ settings. From Figure 6, we can clearly see that smart lighting control will help us save cost. With a $T_{on,min}$ setting of 0 minutes, which largely imitates the situation where all users are disciplined and they always switch off the lights when they are the last one who leave the

restroom. This indicates the minimum cost we can have when using an automatic lighting control system although it is important to remember that we have not taken into account the electricity cost due to the control gear and sensors. With an increasing value of $T_{on,min}$, the cost increases. During the peak time of day, the percentage of savings as compared to the baseline scenario is smaller as compared to that during the off-peak hours. This result is consistent with an important finding in reference 16. The peak saving contribution from smart lighting control does not fall within the typical peak utility billing periods, e.g., from 10am to 4pm.

Besides electricity cost, we are also interested in the life of the lamps, which is closely related to the average number of off-to-on switching per hour. This is particularly true for CFLs because filaments of CFLs need to be heated before they can excite mercury atoms, although a slight portion of the filaments will also be vapourized during this warm up process. As such, a filament will degrade after each off-to-on switching and eventually fail. Figure 7 shows the lamp switching profile as affected by the $T_{on,min}$ setting. A larger value of $T_{on,min}$ setting will lead to a lower average number of off-to-on switching per hour and consequently a longer life for the lamps. For example, at peak hour, e.g., 12pm-1pm in Figure 7, we may reduce the average number of off-to-on switching per hour by 57.8% by increasing $T_{on,min}$ from 0 minutes to 20 minutes. From Figure 6, we noticed that this happened at the expense of electricity cost increased by 80%.

If we may model life of CFLs by a finite number of off-to-on switching, from the average number of switching per hour at different times of day, as shown in Figure 7, we can calculate how many lamps should be replaced during a study period, thus we are able to include the cost of replacing lamps in our study of smart lighting systems. This forms part of our future work.

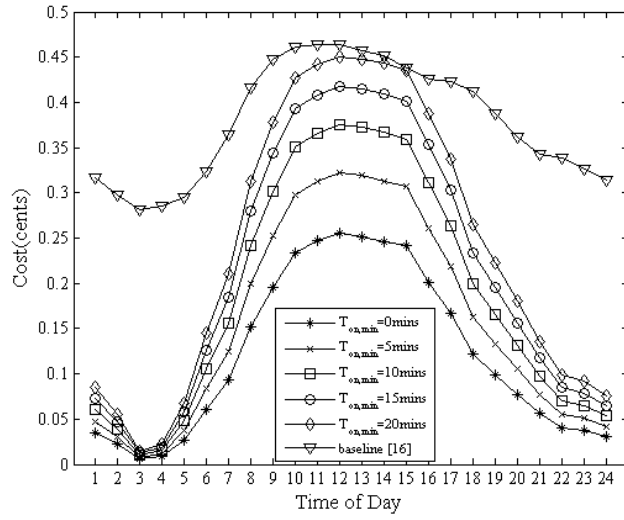


Figure 6. Electricity cost profile for the baseline and simulation with different $T_{on,min}$ settings.

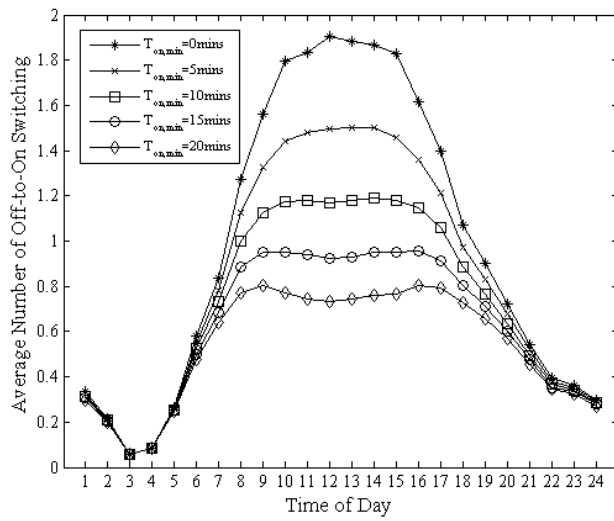


Figure 7. Lamp switching profile for simulation with different $T_{on,min}$ settings.

4.4 Smart lighting control with adaptive system settings

Next, we investigate the performance of the proposed adaptive algorithm in equation (12) to change the $T_{on,min}$ and $T_{d,min}$ in a real-time manner. In order to determine an appropriate sampling interval, T_s , we first set α to 0 and vary the sampling interval from 15 to 60 minutes with an increment of 15 minutes. The performance of the adaptive algorithm was compared with that of the case with fixed parameter settings, which can be treated as an adaptive case with $T_s=\infty$ (no adaptive feedback). From Figure 8 and Figure 9, we can see that T_s has a trivial effect on the adaptive algorithm. We also notice that the initial values of $T_{on,min}$ and $T_{d,min}$ would not affect the system performance because they were adapted according to the traffic load. Thus, for simplicity, we choose 60 minutes as the sampling interval. In practice, the longer the value of T_s , the less the power drawn by the central processor of the smart lighting control circuits because of reduced sampling and processing efforts.

Finally, we study the effect of α , which emulates an index to reflect the user's preference on energy saving. In particular, the value of α can be adjusted using a potentiometer in a practical implementation of smart lighting control circuits. This would allow users to easily set their preference. In computer simulations, we vary α from 0 to 1 with an increment of 0.25. From Figure 10 and Figure 11, we can see that the setting of preference index α significantly affects the system performance, especially when the traffic load is high. For example, under high traffic load (e.g. from 10am to 4pm), electricity cost can be reduced by 29% at the expense of increasing average number of off-to-on switching per hour by 100% if the user prefers to save energy ($\alpha=1$) than to prolong the life of the lamps ($\alpha=0$).

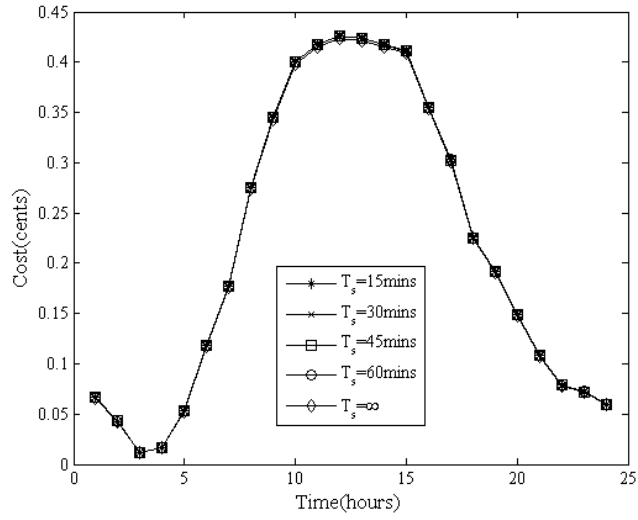


Figure 8. Electricity cost profile for baseline and simulation with different T_s settings.

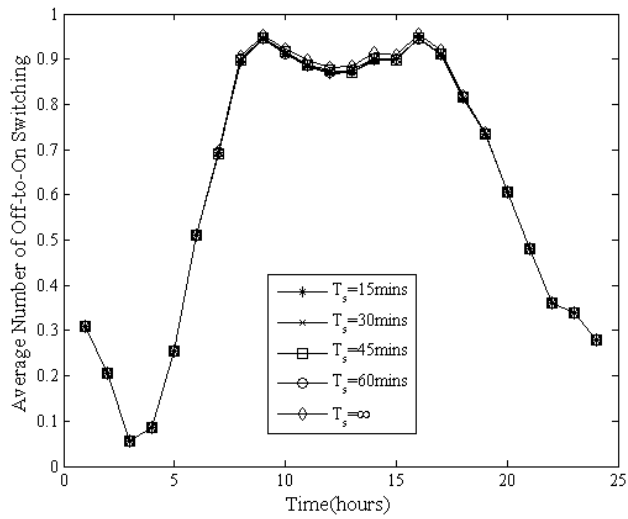


Figure 9. Lamp switching profile for simulation with different T_s settings.

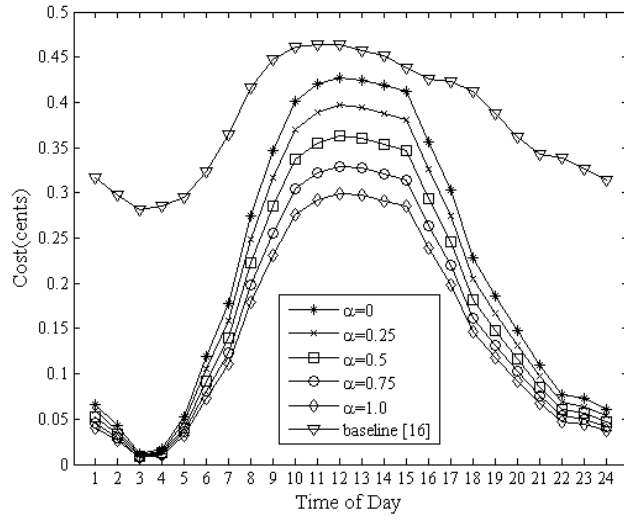


Figure 10. Electricity cost profile for baseline and simulation with different α settings.

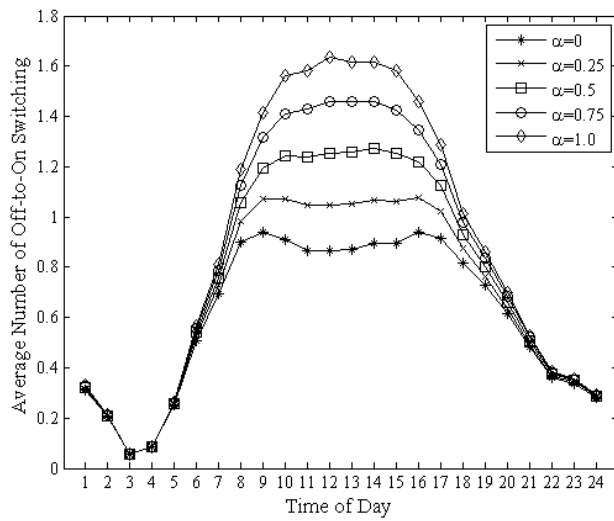


Figure 11. Lamp switching profile for simulation with different α settings.

5. Conclusion and future work

Lighting becomes important because people are very interested in the efficient utilization of scarce energy resources. This paper proposes to apply teletraffic engineering modeling techniques to study the performance of smart lighting control systems with fluorescent lamps. The salient feature of this queueing model is that it only requires data on *how often* and *how long* users will occupy a facility or space. Furthermore, a simple adaptation algorithm is proposed to make the smart lighting control system change its system parameter settings according to the real-time traffic load. Computer simulation showed that it was able to effectively control the system performance according to the user preference, which can be done by simply setting one system parameter.

Our future work includes conducting a traffic load data collection study on the proposed queueing model and lighting control algorithm. In addition, as a complement to the smart lighting control system, intelligent algorithms can be designed to control the ballasts of fluorescent lamps to reduce transient current and then further improve the energy efficiency, which is particularly useful during the utility's peak hour of the day and would ease the relationship between electricity consumption and electricity generation as highlighted in smart power grids.

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Figure captions

Figure 1. Comparison of the sum of two truncated normal distributed variables and a Rayleigh distributed variable.

Figure 2. Flowchart for the proposed teletraffic queueing model.

Figure 3. Lighting condition profile for the percentage of time when the restroom was lit while occupied.

Figure 4. Lighting condition profile for the percentage of time when the restroom was lit while unoccupied.

Figure 5. Lighting condition profile for the percentage of time when the restroom was lit during occupied / unoccupied periods for baseline and simulation with $T_{on,min} = 0$ minutes.

Figure 6. Electricity cost profile for the baseline and simulation with different $T_{on,min}$ settings.

Figure 7. Lamp switching profile for simulation with different $T_{on,min}$ settings.

Figure 8. Electricity cost profile for for baseline and simulation with different T_s settings.

Figure 9. Lamp switching profile for simulation with different T_s settings.

Figure 10. Electricity cost profile for baseline and simulation with different α settings.

Figure 11. Lamp switching profile for simulation with different α settings.

Table I. Traffic load at different time intervals

Time Intervals	Traffic load (Erlangs)	Time Intervals	Traffic load (Erlangs)
1*	0.075	13	0.579
2	0.033	14	0.554
3	0.005	15	0.535
4	0.015	16	0.404
5	0.056	17	0.316
6	0.130	18	0.215
7	0.183	19	0.176
8	0.333	20	0.136
9	0.428	21	0.096
10	0.540	22	0.066
11	0.555	23	0.064
12	0.590	24	0.052

* i^{th} time interval denotes (i-1):30 to i:30 hour of the day¹⁶.