# Modeling of Lighting Load in Residential Buildings

**M. Naveed Iqbal, Lauri Kütt, Noman Shabbir**

***Abstract— Energy and electricity consumption models are critical for effective decision making to improve the supply and demand system. On-site electricity generation using PV, energy efficiency strategies, and smart grid technologies have shaped the need for detailed electricity demand modeling. Lighting in the residential buildings is a significant part of total electricity consumption. High variability of the lighting load makes it a complex modeling problem as lighting usage depends on many variables. Occupant behavior, building structure, and environmental conditions have made it more challenging to model electrical lighting consumption patterns. This paper presents a strategy to model lighting load using occupancy and measurement data of total lighting demand in the residential buildings.***

***Keywords:lighting modeling; occupant behavior; electricity demand modeling; lighting usage;***

## 1. INTRODUCTION

Detail modeling of electricity consumption patterns in the residential buildings is vital to study the impact of distributed generation, demand-side management, and energy conservation policies. Integration of zero energy regulation, on-site electricity generation, and smart grid technologies make electricity demand model more critical [1], [2]. These models can help us to relate occupant behavior, their cultural background and socioeconomic status with the patterns in which they consume electricity.

Lighting in Europe and other regions of the world contributes to 20 % of the total end-user residential electricity consumption. It is highly variable and one of many reasons for variation in residential electricity demand. High variability of lighting load is due to its dependence on the solar cycle, irradiance factor, building design, number of dwellers and their preference of using electrical lighting. Building an indoor environment, aesthetics, number, and size of the windows play a vital role in the amount of lighting used. Therefore, the lighting load of different apartments in the same building can be very different from each other. An efficient lighting model must be capable of tackle daily and annual variations in the lighting demand with the seasonal and solar cycle variation. A lighting demand model, developed by Stokes, is based on the data of 30-minutes averaged lighting demand in 100 houses from different parts of the UK. The author has observed the relation between annual lighting demand trends and solar cycles. Another observation is about the morning and evening curves shifts due to the sunrise and sunset time variations annually [3]. Occupancy and occupant behavior affects lighting demand severely. It is reported in a study that up to 71 % of the variation in the residential electricity demand is due to the occupant behavior.

Accurate modeling of lighting demand depends on the measurement data, accurate occupancy profiles, and demographic information. These considerations make it a complex problem, and a compromise is required at some level due to lack of data availability and limited resources. Therefore, many current models lack some of these variables. Stokes model converted half hourly measured data into maximum, minimum demand and sinusoidal component [4]. The sinusoids change phase yearly due to the solar cycle variation. Standard deviation, maximum and minimum levels are used to construct a lighting model that can provide 30-minutes averaged lighting demand. It is then further converted into a 1-minute interval by estimating how lighting demand can vary between these half hourly intervals.

In another model for residential lighting demand Markov-chain approach is used. First, a three-state occupancy model is constructed [1]. Transition probabilities are used to determine the state of the occupants in the building using Markov-chain process. These occupancy states are then converted into lighting demand. Unoccupied or inactive states are translated into a constant lighting demand. This constant demand is a result of lights left in the ON-state during night time or daytime when dwellers are sleeping or absent in the building. Lighting demand during active occupancy state is determined using maximum and minimum demand level concerning solar irradiance level. In another lighting model, solar irradiance model and active occupancy models are used to predict the lighting demand. Light sharing phenomena between multiple active occupants in the same room is also taken into account [5]. Furthermore, switching events are considered to estimate the duration when a particular light is turned ON.

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Researchers also developed lighting demand models for commercial buildings. A similar model developed using measurement data from 15 office building. It is noted that lighting demand depends more on occupant activities rather than outdoor irradiance level [6]. A lighting switching model

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based on occupant behavior used stochastic approach using measurement and survey data for commercial offices. An interesting observation by the author is the effect of high occupancy on lighting demand. When the building is occupied with more people, lighting demand became almost constant and termed as crowd effect [7].

Although, all these models have used large datasets, however, the lighting demand has been generalized based on input parameters. The standard deviation from the maximum and minimum lighting demand is used in many existing lighting models. Other models used the relation between solar irradiance and occupancy level with the lighting demand variation. These models may provide excellent results when averaged over an extended period. A variation in the real-time demand to 1-minute level may provide different results from the simulated demand in the building. A high resolution of 1-minute lighting demand close to the real-time measurements can provide several advantages. It can be used with power quality data to access how different electrical appliances are interacting with each other and the network. It can provide valuable information about determining network parameters like transformer sizing, installation capacity of PV in the distribution network and power quality indexes [8].

## 2. METHODOLOGY

Modeling of lighting demand in the residential sector is a challenging problem and requires a compromise between accuracy and considering all parameters affecting the final demand [9]. Therefore, we are proposing a strategy that can provide a high-resolution model based on measurement data of a residential building. It is based upon the active occupancy and individual switching events for each light in the building. Usage patterns of light switches are modeled instead of lighting power demand.

Occupancy and occupant activities are the primary reasons for the high variation in electricity demand. They will affect the lighting demand actively or passively. The lighting demand changes immediately when a building is occupied. Therefore, it is a passive effect of the occupancy. While the active effect involves tenant interaction with electrical appliances or indoor environment, like the opening of a window or window blind [10]. Sharing of lights in a room among dwellers involved in different activities makes it even more complicated. The researchers have used different approaches to model occupant behavior. Data from sensors and surveys are used to construct occupancy profiles. Radio-frequency identification sensors (RFID), infrared sensors, and cameras are used to record tenants behavior [11], [12]. The questionnaire-based survey is another technique to get information about the habitant's behavior and socioeconomic status [13]. Studies have shown that the measurement of electricity consumption also indicates the occupancy, and therefore electricity meter data can be used for this purpose [14]. In a similar approach, electricity meter data from three houses is used with the survey information from the tenants about their activity and time of different appliance usage. This information is used to construct an occupancy model [15]. Electricity consumption data of Swiss houses are used to create the occupancy information using machine learning approach [14].

Researchers have used a stochastic approach to convert data into occupancy profiles. The Markov-chain method is used to generate a 3-state occupancy model. Transition profiles are used to change from one state of occupancy to another state. These states include absent, present but inactive occupants and actively present occupants [1]. A similar approach is used to make a four-state occupancy model based on probability transitions. The additional state "active and absent" is also included [16].

We have used a similar transition-probability based approach to determine the active and present state of occupancy. We measured a house for 4-weeks using sub-meters at the appliance level. This data provides better insight as compared to the previous models based on aggregate power consumption data. With a short survey of occupant's routine, a clear relationship between occupancy and appliance usage is established. The electrical appliance like media devices, washing machine, coffee machine, tea heater, vacuumed cleaners and lighting usage is converted into "actively present" and "inactive or absent states." Fig. 1 shows the occupancy information obtained from sub-meter data at the appliance level.

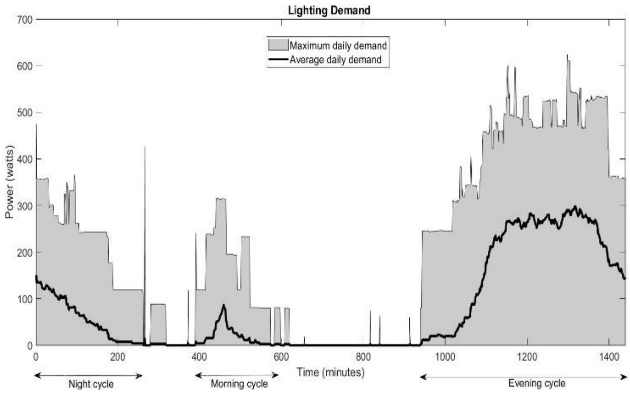


**Fig. 1. Active occupancy data generated by monitoring of electrical appliance**

Occupancy information, extracted from measurement data as shown in Fig. 1, is used to generate Empirical cumulative distribution functions (ECDF). Since weekdays and weekends occupancy shows different trends, separate ECDF's are required. Days 6, 7, 13, 14, 20, 21, 27, and 28 are weekends and show different occupancy trends in comparison to the weekdays. Random numbers are generated and compared with transition probabilities to generate morning, evening, and daytime active occupancy status.

Different lighting technologies are used in residential buildings, and the popularity of LED lamps are increasing because of the reduced prices and improving efficiency. Other lamps may include halogen, fluorescent, compact fluorescent, and incandescent. An Australian study shows an average number of lamps and their types in each house. It is reported that usage of incandescent lamps decreased significantly after 2008-09. LED lamps, on the other hand, are becoming more significant in numbers from a 1% share in 2010 to 15% in 2016 [17]. A lighting model used a similar database of lighting technology usage in the UK. Lights and their types in each house are generated randomly using this database [5].

In our model, we have decided to use halogen lamps before taking measurements. Since halogen lamps have a sizeable power rating (45 watts in our study), it will be easy to distinguish each lighting events compared to the LED lamps as their power consumption is very low. The switching events can be populated with different types of lighting technology at a later stage. Table I shows the number of lights controlled by every switch in the building. The total power rating of lighting controlled by each switch is also mentioned in the table. The occupancy patterns and the number of lighting switches are the input of our switching-event based lighting demand model.

**Table .1: Lighting switches in the building**

| Switch | Controlled lights by the switch | Total lighting power |
|---|---|---|
| 1 | 3 x halogen lamps | 120 watts |
| 2 | 3 x halogen lamps | 120 watts |
| 3 | 3 x halogen lamps | 120 watts |
| 4 | 3 x halogen lamps | 120 watts |
| 5 | 2 x fluorescent lamps | 60 watts |

## 3. MODEL DESCRIPTION

The 4-week measurement data from the residential building is recorded using sub-meters at the appliance level. Each electrical appliance usage is recorded over this period. A single sub-meter measures total lighting load in the house. Therefore, the data gives us an aggregated power consumption by all lights used at any time instant. Fig. 2 shows the daily average lighting demand load curve and the maximum demand recorded in this residential building.

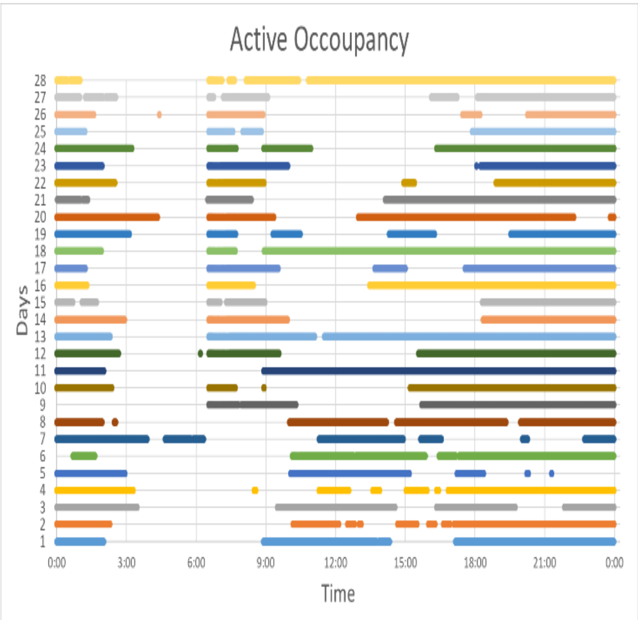


**Fig. 2. Lighting demand variation**

High variability of lighting demand is evident from Fig. 2. Variation in solar irradiance values, occupant activities and their desire to control the indoor environment are the significant reasons for this variation [18]. Solar radiance and weather conditions can be treated as global variables as all the buildings in the same region have similar values of these parameters [5]. However, building architecture plays an important role. The number of windows facing directly towards the sun may generate different results in comparison to the apartments with windows on the opposite side in the same building. It is also valid for the houses with different design at the same location. Relative usage of the lighting is also essential. Some of the lights in a house are less frequently used compared to the others. Studies show that lights in the bedroom, living room and kitchen are more frequently used. It is, therefore, a challenging task to relate all the variables with each other and with the lighting demand. Since we aim to develop a lighting model with a high resolution of 1-minute intervals and compare it with power quality data of different lamps, we decided to use switching events patterns.

Lighting demand, shown in Fig. 2, is divided into three intervals; morning interval, evening interval and the day interval. Measurement results indicate a similar lighting usage pattern during these three intervals. However, there is a difference during the same intervals on weekdays when compared with weekends. Weekends occupancy trends are different from weekdays as seen in the Fig. 1. For example, on weekends the occupancy and lighting demand during day interval is more when compared with weekdays. Each interval is converted into the switching events. All the switching events less than 10-minute duration are considered as noise and treated as a separate entity. Time periods with no switching or noise event, are treated as gaps. Switching intervals may also overlap. For example, if one switch is in the ON-sate for 30 minutes and another switch is also turned on during this interval. The number of switches in the ON-sate depends upon the time during the interval. During evening interval more switches are in the ON-sate because sunlight is not available and occupants are more active regarding appliance usage. Cooking appliances, media, and entertainment devices are more frequently used during the middle part of the evening interval between 19:00 and 22:00. High lighting demand can be observed during this interval as shown in the Fig. 2.

Each of the three intervals is further divided into small sub-intervals depending on the demand variation. The probability of the number of switches in the ON-sate is calculated during each small sub-interval. ECDF's are estimated for each sub-interval using these probabilities.



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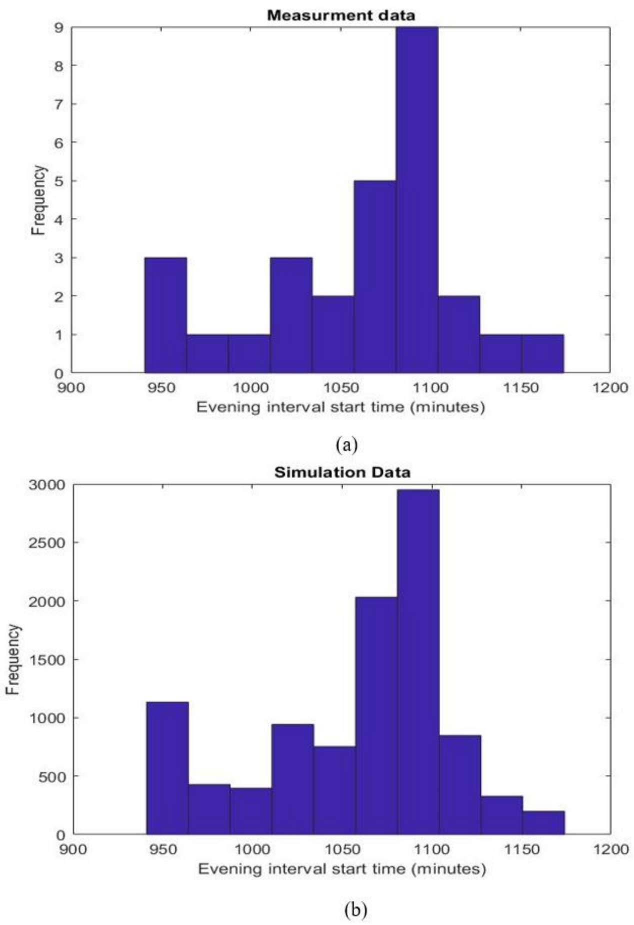


**Fig. 3. Evening interval start time histograms (a) measurement data (b) Simulated data**

For each interval, the start time of the first switching event is estimated from the measurement database using ESDF of the start times. Fig. 3 shows the histogram of the start times of evening cycles for both measurement and simulated data. The number of light switches in the ON-sate is estimated by generating the random number and comparing it with the sub-interval ECDF in which the start time falls. Duration of each switching interval is calculated using the same approach. After each switching interval noise and gaps are added. The second switching event start time is the sum of the previous switching end time, noise and gap intervals. Fig. 4 shows the block diagram of the lighting model.

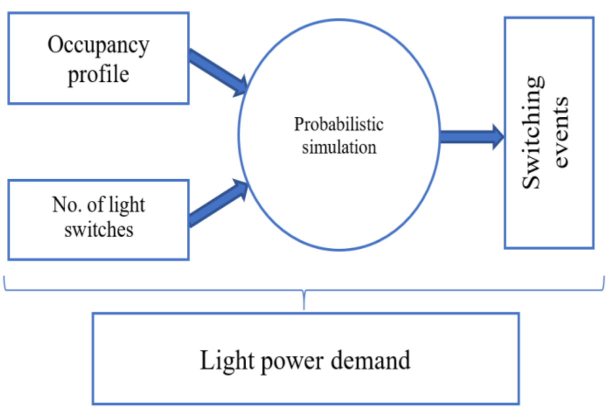


**Fig. 4. Lighting model description diagram**

## 4. RESULTS AND DISCUSSION

We have used the transition probability-based approach for creating an individual light switching model. For every new step, the decision is made by comparing random numbers with the corresponding ECDF. Morning, evening and daytime intervals are calculated for each day. The outputs of the model are switching events and their durations. These switching events are converted into lighting power demand by comparing the number of lights in the ON-state with the power consumption data recorded during the 4-week measurement. The average lighting demand of the measurement data is compared with the average lighting demand of the simulated data for 5 years.

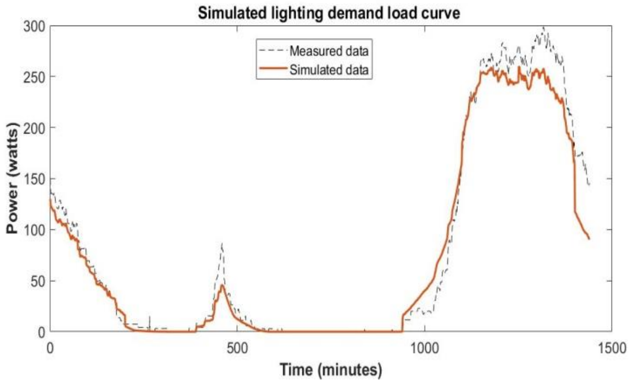


**Fig. 5. Average lighting demand of measurement and simulated data**

Fig. 5 shows that simulated data is following the same trends as of measurement data. The simulated data exhibits the same properties regarding occupancy, occupant activities and other parameters responsible for lighting demand variation. The results can be improved by taking measurement data over a more extended period including all season. This model can be used to estimate regional demand by extended the measurement for more buildings with different architecture, occupants, and demographics. However, it is beyond the scope of our project. We will use this high-resolution model with power quality measurement data of electrical appliances to create another model. It will help us to understand the behavior of non-linear loads including lightings when they interact with each other and the network. It will also help us to establish the limits on maximum PV integration in the distribution network in the presence of nonlinear loads, electric vehicles, and smart grid technologies.

## 5. CONCLUSION

A lighting demand model for residential buildings is presented in this paper. Individual switching-events based approach is used. Switching events for each interval during the day are generated and populated with power consumption data to verify the model. This model will be extended to a total electricity consumption model for the residential building with 1-minute resolution. The power quality database for all electrical appliances, PV inverters, and the network will be added afterward. It will help us to understand the non-linear load behavior under the influence of on-site PV generation, smart grid technologies, electric vehicles adoption and energy management strategies in the domestic buildings.

## REFERENCES


1. J. Widén, A. M. Nilsson, and E. Wäckelgård, "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand," Energy Build., vol. 41, no. 10, pp. 1001–1012, 2009.
2. EU, "Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings (recast)," Off. J. Eur. Union, pp. 13–35, 2010.
3. IAEA, "Model for Analysis of Energy Demand (MAED-2) User's Manual," Int. At. Energy Agency, Vienna, p. 196 pp., 2006.
4. M. Stokes, M. Rylatt, and K. Lomas, "A simple model of domestic lighting demand," Energy Build., vol. 36, no. 2, pp. 103–116, 2004.
5. I. Richardson, M. Thomson, D. Infield, and A. Delahunty, "Domestic lighting: A high-resolution energy demand model," Energy Build., vol. 41, no. 7, pp. 781–789, 2009.
6. X. Zhou, D. Yan, T. Hong, and X. Ren, "Data analysis and stochastic modeling of lighting energy use in large office buildings in China," Energy Build., vol. 86, pp. 275–287, 2015.
7. C. Wang, D. Yan, and X. Ren, "Modeling individual's light switching behavior to understand lighting energy use of office building," Energy Procedia, vol. 88, pp. 781–787, 2016.
8. M. N. Iqbal and L. Kütt, "End-user electricity consumption modelling for power quality analysis in residential building," 2018.
9. M. N. Iqbal, L. Kütt, and A. Rosin, "Complexities associated with modeling of residential electricity consumption," in IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University, 2018, p. 6.
10. D. Aerts, J. Minnen, I. Glorieux, I. Wouters, and F. Descamps, "A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison," Build. Environ., vol. 75, pp. 67–78, 2014.
11. N. Li, G. Calis, and B. Becerik-Gerber, "Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations," Autom. Constr., 2012.
12. M. S. Gul and S. Patidar, "Understanding the energy consumption and occupancy of a multi-purpose academic building," Energy Build., 2015.
13. J. Yang, M. Santamouris, and S. E. Lee, "Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings," Energy Build., vol. 121, pp. 344–349, 2016.
14. W. Kleiminger, C. Beckel, and S. Santini, "Household occupancy monitoring using electricity meters," in Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '15, 2015.
15. A. Molina-Markham, P. Shenoy, K. Fu, E. Cecchet, and D. Irwin, "Private memoirs of a smart meter," in Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building - BuildSys '10, 2010.
16. E. McKenna, M. Krawczynski, and M. Thomson, "Four-state domestic building occupancy model for energy demand simulations," Energy Build., vol. 96, pp. 30–39, 2015.
17. N. Z. Governments, "2016 Residential Lighting Report," 2016.
18. D. R. G. Hunt, "The use of artificial lighting in relation to daylight levels and occupancy," Build. Environ., 1979




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