Predictive models of electrical energy use in office buildings due to plug loads

Ardeshir Mahdavi, Farhang Tahmasebi

Department of Building Physics and Building Ecology
TU Wien, Vienna, Austria

Abstract

This paper explores the relationship between inhabitants' presence, the installed power for office equipment, and the resulting electrical energy use. This exploration is based on long-term observational data obtained from a continuously monitored office area in Vienna, Austria. The findings facilitate the formulation of both simplified and probabilistic models to estimate annual and peak office plug loads. Aside from a general comparison of the performance of simple and stochastic models, the present contribution focuses on the question if and to which extent consideration of the diversity of the inhabitants influences the reliability of plug load predictions.

Introduction

The operation of office buildings requires energy for both indoor environment control (e.g., heating, cooling, ventilation, lighting) and office equipment. The latter category pertains primarily to plug loads due to computers, peripheral devices, telephones, etc. Plug loads are suggested to account for more than 20% of primary energy used in office buildings, and this ratio has been suggested to increase by 40% in the next 20 years (Roth et al. 2008).

Building performance simulation tools geared toward assessing buildings' energy and indoor environmental performance would benefit from reliable methods to estimate the magnitude of plug loads magnitude. Toward this end, the current state of knowledge (including both available information in standards and typical simulation input assumptions) with regard to the prevailing plug loads in office buildings is not sufficiently developed. Recently, a number of efforts have been initiated to investigate occupants' presence modelling approaches and their impact on building performance simulation (see, for example, Wang et al. 2016; Tahmasebi & Mahdavi 2016; Feng et al. 2015). However, only few recent studies have gone beyond the use of typical profiles of plug loads, trying to provide a deeper understanding or models of plug loads for building simulation (e.g., Gunay et al. 2016; Gandhi & Brager, 2016; Menezes et al. 2014).

Given this context, we have been working on developing methods to estimate office buildings' plug loads using a number of basic input assumptions. These methods are expected to facilitate the computation of both aggregated annual electrical energy use values and detailed time-dependent high resolution electrical energy use patterns. Starting from a brief description of our previous studies in this area, we move on to address, in the current contribution, a related and important research question, namely the diversity of the inhabitants (Mahdavi & Tahmasebi 2015) and its implications for plug loads modelling efforts.

Method

Overview

In previous publications (see, for example, Mahdavi et al. 2016), we have explored the potential for predicting plug loads in office buildings based on information regarding the: *a)* installed equipment power; *b)* presence patterns of inhabitants. To examine this potential, we selected an office area in a University building in Vienna, Austria that includes both single-occupancy and open-plan office zones. The office area is equipped with a monitoring infrastructure, which includes, amongst others, sensors for presence detection and plug loads. For the purposes of this paper, high-resolution data collected over a three-year period (2013 to 2015) were used to develop and evaluate the plug loads models. Table 1 gives an overview of selected office spaces with information regarding inhabitants, areas, and installed power.

The simplified approach

We hypothesised that plug load fraction *F* (ratio of actual plug load to the installed equipment power) of occupant *j* at time interval *i* is a function of presence probability *p*:

$$F_{j,i} = f(p_{j,i}) \qquad (1)$$

Table 1: Overview of the selected office zones with information on inhabitants (denoted as U1 to U7), areas, and installed equipment power

SPACE	INHABITANTS	EFFECTIVE INSTALLED POWER [W]	AREA [m^2]
Open-plan	U1, U2, U3, U4	640	43
Office 1	U5	180	19
Office 2	U6	90	34
Office 3	U7	130	17

https://doi.org/10.26868/25222708.2017.036

A linear version of this relationship could be formulated as follows (with a and b as empirically grounded coefficients):

$$F_{j,i} = a.P_{j,i} + b \quad (2)$$

We thus stipulated that the energy use E associated with plug loads for an office with m inhabitants over a time period consisting of n interval with a total length of T can be estimated as follows:

$$E = T \times \sum_{i=1}^{n} \sum_{j=1}^{m} \left(F_{j,i} \times Q_{e,j}\right) \quad (3)$$

Note that the coefficients a and b in equation 2 may be specified in an aggregated manner (i.e., for the entire population), or – in case sufficient empirical data is available – for individual office inhabitants.

The probabilistic model

To explore the potential of a probabilistic approach in predicting plug loads, we formulated a model, which utilizes three specific Weibull distributions to capture:

1) Plug load fractions during occupied periods or intermediate absences shorter than one hour;
2) Plug load fractions during intermediate absences longer than one hour;
3) Plug load fractions outside working hours.

The general formulation of a Weibull distribution is as follows, where λ is the scale parameter and k is known as the shape parameter:

$$f(x|\lambda, k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}} \quad (4)$$

Weibull distribution is widely applied in various statistical modelling efforts. Specifically, formalisms based on Weibull distribution are also used in the occupancy-related modelling studies (see, for example, Hong et al. 2016).

In order to obtain the parameters of the Weibull distributions, we used the monitored data pertaining to occupancy and plug loads at the studied office area in year 2014 using the maximum likelihood estimation method. Thereby, plug load fractions are picked randomly via inverse transform sampling method, whenever the occupancy state falls within one of the above possibilities. Note that, in the current implementation, the correlations between successive plug load fractions in different occupancy states is not taken into account.

It should be also noted that, to use this model, the occupancy states (occupied or vacant) at each time interval should be provided as input. For the purpose of current study, we used the stochastic occupancy model developed by Page et al. (2008). This model uses as input a profile of presence probability and average parameter of mobility (μ), which is defined as the ratio of state change probability to state persistence probability. The model output is a set of randomly generated non-repeating Boolean occupancy profiles resulting from the input occupancy schedules.

Similar to the implementation of the linear regression model, we provided the stochastic model with presence profiles for weekdays and weekends, either averaged across all occupants or for individual inhabitants, depending on the diversity representation approach (see the following section). Based on our experience in a previous study (O'Brien et al. 2016), the mobility factor was set to 0.1.

As with the simplified representation, the stochastic representation can be also realised both for the whole population and separately for individual inhabitants.

Diversity representation

To explore the implications of representing the diversity among occupants for models' predictive performance, we constructed the models based on empirical data (from the year 2014) in two different ways, namely using: *i)* occupancy and plug load profiles averaged across all occupants, and *ii)* individual occupancy and plug load profiles. For the office area investigated in the present study and using the empirical 2014 data, Table 2 gives the resulting simple plug load model's coefficients (slope and intercept) for the individual inhabitants as well as in aggregate. Table 3 provides the coefficients (scale and shape) of the stochastic model's Weibull distributions derived based on individual and aggregate presence and plug load data. Note that the computed values of the standard errors associated with the coefficient estimates are in the range of 0.0004 to 0.05.

Simulated alternatives and their verification

As alluded to earlier, our previous studies revealed a remarkable relationship between inhabitants' presence, their respective installed equipment power, and the resulting electrical energy use (see Figure 1). However, a significantly closer fit could be achieved, if this relationship is established for individual inhabitants as opposed to the population as a whole (see Figure 2). Obviously, this can be seen as the consequence of considering inhabitants' diversity with regard to electrical energy use for equipment.

Table 2: The linear function parameters of the simple plug loads model

Inhabitants	Slope (a)	Intercept (b)
U1	0.55	0.05
U2	0.76	0.06
U3	0.25	0.21
U4	0.33	0.07
U5	0.73	0.13
U6	0.72	0.04
U7	0.36	0.08
All	0.53	0.09

Table 3: The parameters of the Stochastic plug load model's Weibull distributions

Inhabitants	Weibull 1		Weibull 2		Weibull 3	
	λ	k	λ	k	λ	k
U1	0.50	2.05	0.29	1.20	0.07	1.30
U2	0.46	2.52	0.30	1.24	0.07	1.28
U3	0.35	1.62	0.24	1.51	0.18	1.45
U4	0.35	1.67	0.27	1.60	0.22	2.48
U5	0.51	1.80	0.41	1.12	0.12	0.99
U6	0.57	4.62	0.42	1.95	0.20	1.07
U7	0.41	2.00	0.21	1.09	0.09	1.14
All	0.56	1.89	0.38	1.32	0.14	1.07

Given the difficulties associated with obtaining necessary large-scale observational data on inhabitants' diversity, the relevance of the initially addressed research question becomes clear: To which extent is capturing inhabitants' diversity influences the outcome of pertinent standard performance indicators such as annual and peak office plug loads?

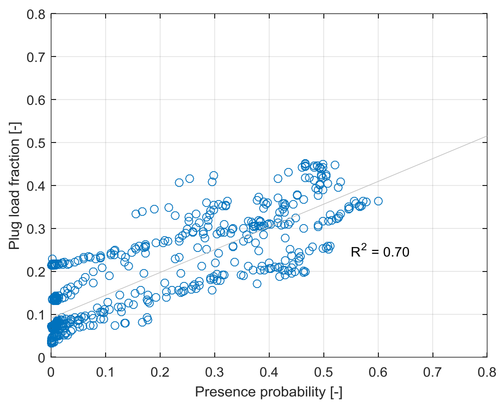

Figure 1. Linear regression analysis of the relationship between plug load fraction and presence probability for all office inhabitants

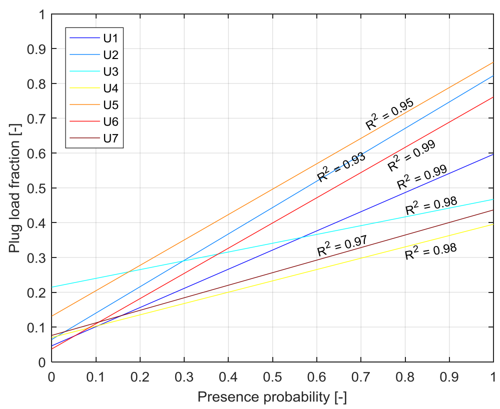

Figure 2. Linear regression analysis of the relationship between plug load fraction and presence probability for individual office inhabitants

To explore this question in a systematic manner, we used detailed data from the year 2014 to calibrate models of annual and peak plug loads for the aforementioned office area. The calibrated model was subsequently used to predict plug loads for the years 2013 and 2015. Toward this end, both simplified and stochastic models were generated with and without consideration of diversity (see Table 4). In addition, to put the model's performance in a context more familiar to practitioners, we provided, for the same office area, the electrical energy use estimations resulting from the use of ASHRAE 90.1 plug load profiles for office buildings.

The computed annual and peak plug load values were compared with observational data based on Relative Error. For interval by interval comparison of the monitored and calculated energy use, we considered the standard statistical indicators, namely Root Mean Square error (RMSE), Normalised Root Mean Square Error (NRMSE), and Mean Bias Error (MBE). Moreover, to compare the distribution of predicted and monitored plug loads, we utilized the Jensen–Shannon divergence (JSD) metric (for details, see Mahdavi et al. 2016). This metric is used to compute distances between two probability distributions and it is bounded between 0 and ln (2).

Table 4: Explored modelling scenarios with respective information regarding the modelling technique (simplified versus stochastic) and inhabitants' representation (aggregate versus diverse).

Modelling scenario	Modelling technique	Diversity
S1_A	Simplified	No
S1_D	Simplified	Yes
S2_A	Stochastic	No
S2_D	Stochastic	Yes
S3_A	ASHRAE profile	No

Results and discussion

Table 5 provides a summary of the monitored and calculated total and peak electrical energy use (due to office equipment) in the selected office area for the years 2014, 2013, and 2015. The table includes also the values of the aforementioned error statistics. Predicted and measured annual and peak plug loads (for modelling scenarios specified in Table 4) are also depicted in Figure 3 and Figure 4 respectively.

The comparison of model predictions with observed data facilitates a number of conclusions. The simplified method provides fairly reasonable predictions of annual energy use associated with plug loads (see Figure 3). However, the probabilistic plug load model outperforms the simplified model in terms of peak load (see Figure 4) and the distribution of predictions. The latter finding can be inferred from the lower values of JSD in case of the

Table 5: Statistical comparison of the monitored electrical energy use associated with plug loads for the years 2013 to 2015 with the respective calculations according to various modelling scenarios: S1_A (simple model, average occupant); S1_D (simple model, individual occupants); S2_A (stochastic model, average occupant); S2_D (stochastic model, individual occupants)

Model	Run period	Run period sum		Run period peak		Distribution	Time interval values		
		Value [kWh]	RE [%]	Value [W]	RE [%]	JSD [-]	MBE [W]	RMSE [W]	NRMSE [%]
Measured	2014	1662.7	0.0	861.7	0.0	0.00	0.0	0.0	0.0
S1_A	2014	1540.8	-7.3	411.6	-52.2	0.43	-13.9	119.6	14.7
S1_D	2014	1541.2	-7.3	374.3	-56.6	0.46	-13.9	120.6	14.8
S2_A	2014	1524.5	-8.3	672.5	-22.0	0.30	-15.8	131.3	16.1
S2_D	2014	1620.5	-2.5	691.9	-19.7	0.36	-4.8	131.7	16.2
Measured	2013	1543.4	0.0	861.9	0.0	0.00	0.0	0.0	0.0
S1_A	2013	1484.7	-3.8	374.7	-56.5	0.53	-6.7	99.8	12.5
S1_D	2013	1596.5	3.4	380.3	-55.9	0.52	6.1	99.7	12.5
S2_A	2013	1514.2	-1.9	669.4	-22.3	0.32	-3.3	121.2	15.2
S2_D	2013	1606.8	4.1	673.6	-21.8	0.39	7.2	122.4	15.3
Measured	2015	1255.0	0.0	770.6	0.0	0.00	0.0	0.0	0.0
S1_A	2015	1470.5	17.2	412.2	-46.5	0.41	24.6	102.6	13.9
S1_D	2015	1541.2	22.8	374.3	-51.4	0.46	32.7	123.1	16.7
S2_A	2015	1469.8	17.1	667.7	-13.4	0.28	24.5	120.2	16.3
S2_D	2015	1587.5	26.5	684.6	-11.2	0.33	38.0	124.6	16.9
ASHRAE 90.1 plug load profiles	-	3025.7	141.1	936.0	21.5	0.42	202.1	352.3	47.8

probabilistic model (see Table 5). As for the time interval plug loads, regardless of diversity treatment, the non-stochastic model reveals a slightly better performance (see MBE, RMSE, and NRMSE values in Table 5).

With regard to the main question of the present treatment, namely the diversity consideration, the results may be interpreted as follows. Inclusion of diversity does not improve the performance of the models with regard to annual and peak plug load predictions (see Figures 3 and 4 as well as Table 5). Indeed, for all statistics considered, the inclusion of diversity has either very little impact on the predicted value of the energy use indicators or it even slightly degrades the prediction performance.

To explicitly illustrate this observation, consider the summary representation in Table 6. Thereby, the net magnitude of improvement (positive values) or degradation (negative values) of the considered statistics are shown as the result of the inclusion of diversity in modelling. Aside from rather small improvements for simplified model's results for 2013, inclusion of diversity appears to worsen, rather than improve the results. Notably, the intuitively expected positive effect of such inclusion on RE_p and JSD values is not supported by the results.

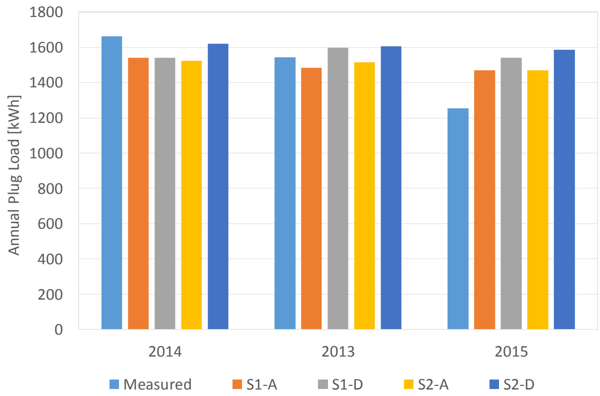

Figure 3: Annual plug load obtained via different modelling approaches, along with the respective monitored values

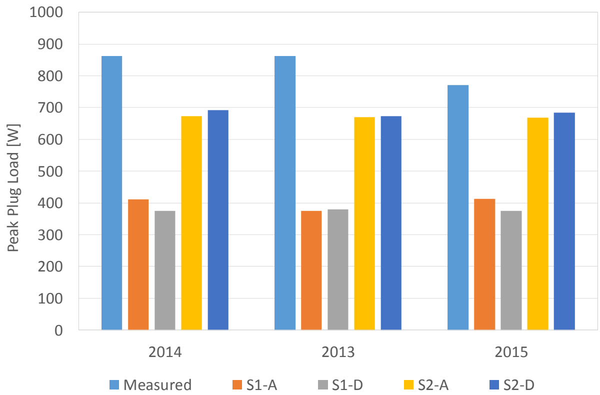

Figure 4: Peak plug load obtained via different modelling approaches, along with the respective monitored values

Table 6: Net changes in the values of the statistical indicators RE_a (Relative Error of annual load predictions), RE_p (Relative Error of peak load predictions), JSD, MBE, RMSE, and NRMSE as a result of inclusion of diversity in plug load modelling

Statistics	Simplified model		Stochastic model	
	2013	2015	2013	2015
RE_a [%]	+0.4	-5.6	-2.2	-9.4
RE_p [%]	+0.6	-4.9	+0.5	+2.2
JSD [-]	+0.01	-0.05	-0.07	-0.05
MBE [W]	+0.6	-8.1	-3.9	-13.5
RMSE [W]	+0.1	-20.5	-1.2	-4.4
NRMSE [%]	0	-2.8	-0.1	-0.6

Conclusion

This paper addressed the performance of simple and stochastic models, for the prediction of plug loads in office buildings. Specifically, we explored the potential implications of including the diversity of inhabitants for the predictions. The observed tendencies of the results appear to imply the following conclusions:

- Plug load fractions display a statistically significance dependency on the inhabitants' presence probability.
- Both simplified and stochastic formulations of the above mentioned dependency can support reasonable predictions of annual peak plug loads. However, peak plug loads are more reliably predicted by the stochastic model.
- In the present case, the inclusion of diversity (i.e., implementation of individual functions for individual occupants) in the course of simple and stochastic prediction of annual and plug loads could not be shown to improve the quality of model predictions.
- Independent of diversity inclusion, the performance differences between simple and stochastic plug loads appear to be much less important for the quality of predictions as compared to the availability of basic reliable information on inhabitants' presence and installed plug loads. This circumstance can be clearly inferred from the very large deviations of standard-based plug load estimations (see last row of Table 5).

Note that the above conclusions are by no means definitive. Multiple limitations of the present study would falsify any such claim. We were greatly constrained with the data availability. While the (temporal and spatial) resolution of the collected is very high, it pertains only to one office area. Likewise, the treatment of diversity is greatly limited by the small number of inhabitants: As such, the office area is used by a variable number of 10 to 20 individuals. But we decided to apply high data quality standards (specifically, long-term continuity and numeric plausibility of data, certainty with regard to correspondence of specific sensor data to individual inhabitants), focusing thus on a small number of inhabitants.

Despite these limitations, we believe the study not only offers a model character for further in-depth studies in the field, but the results provide valuable initial observations and insights. Independent of the choice of specific mathematical formalisms, the observed strong correspondence between plug load fractions and presence patters appear to offer a fundamental opportunity for developing plug load prediction models. Moreover, to support simulation-based design processes, it is important to obtain some dependable basic information regarding the nature of occupancy and the technical specification of the office equipment: Sole reliance on standard-based procedures may result in major misestimations. As to the implications of diversity consideration for prediction of annual and peak plug loads, we of course cannot suggest that the inclusion of inhabitants' diversity is generally futile. However, the present study does not support a corresponding counter claim.

Acknowledgement

The research presented in this paper benefited from the authors' participation in the ongoing efforts of the IEA-EBC Annex 66 (Definition and Simulation of Occupant Behaviour in Buildings) and the associated discussions.

Nomenclature

$F_{j,i}$	Inhabitant j's plug load fraction at time interval t_i ($F_{j,i} = q_{j,i}/Q_{e,j}$)
$P_{j,i}$	Inhabitant j's presence probability (at the workplace) at time interval ti
Q_j	Installed (name-tag) plug loads at Inhabitant j's workplace
$Q_{e,j}$	Effective installed plug loads at Inhabitant j's workplace
$q_{j,i}$	Inhabitant j's actual plug load at time ti
T	Length of time interval
JSD	Jensen–Shannon Divergence
MBE	Mean Bias Error
NRMSE	Normalised Root Mean Square Error
RE_a	Relative Error of annual load predictions
RE_p	Relative Error of peak load predictions
RMSE	Root Mean Square Error

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