Accounting for the Diversity of Use Patterns in Representations of Office Plug Loads in Building Performance Simulation

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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.

1. Introduction

Plug loads denote office buildings' energy requirements due to computers, peripheral devices, telephones, etc. Plug loads can constitute more than 20 % of primary energy used in office buildings, and this ratio has been suggested to further increase in the future (Roth et al., 2008). Hence, simulation tools need reliable methods to estimate the magnitude of plug loads. Compared to a relatively broad range of research efforts regarding inhabitants' presence models (Wang et al., 2016; Tahmasebi and Mahdavi, 2017; Feng et al., 2015), only few studies have gone beyond the use of typical profiles of plug loads to provide more advanced models of plug loads for building simulation (e.g. Gunay et al., 2016; Gandhi and Brager, 2016; Menezes et al., 2014).

Given this context, we have been working on developing methods to compute both aggregated annual and detailed time-dependent electrical energy use patterns. In the present contribution, we specifically focus on the problem of the diversity of the inhabitants (Mahdavi and Tahmasebi, 2015) and its implications for plug loads modelling.

2. Method

Previously, we have suggested that plug loads in office buildings could be estimated based on the knowledge of: i) installed equipment power and ii) presence patterns of inhabitants (Mahdavi et al., 2016). The corresponding findings are based on data from an office area (with both single-occupancy and open-plan office zones) in a University building in Vienna, Austria (see Table 1). For the purposes of this paper, high-resolution data (monitored presence and plug loads) collected over a three-year period (2013 to 2015) were used to develop and evaluate the plug loads models.

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

$$F_{j,i} = a.p_{j,i} + b \qquad (1)$$

Consequently, plug loads *E* for an office with *m* inhabitants over *n* intervals with a total length of *T* could be computed using Equation 2. Note that the coefficients *a* and *b* in equation 1 may be specified in an aggregated manner (i.e. for the entire population), or – given that sufficient empirical data is available – for individual office inhabitants.

$$E = T \times \sum_{i=1}^{n} \sum_{j=1}^{m} \left(F_{j,i} \times Q_{e,j}\right) \qquad (2)$$

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Table 1 – Selected office zones with information on inhabitants (denoted as U1 to U7), areas, and installed equipment power.

Space	Inhabitants	Installed power [W]	Area [m²]
Open-plan	U1, U2, U3, U4	640	43
Office 1	U5	180	19
Office 2	U6	90	34
Office 3	U7	130	17

2.2 Stochastic Approach

To compute plug loads stochastically, we utilized 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.

A Weibull distribution is generally formulated as using Equation 3, where λ is the scale parameter and k is known as the shape parameter. Plug load fractions are picked randomly via inverse transform sampling method, whenever the occupancy state falls within one of the above possibilities.

$$f(x|\lambda,k) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-\left(\frac{x}{\lambda}\right)^{k}} \quad (3)$$

Electrical energy use can thus be calculated in a manner similar to the aforementioned simplified model (see Equation 2). Note that, to use this model, the occupancy states (occupied or vacant) at each time interval need to be provided as input. In the current study, we used a presence model (Page et al., 2008) that uses a profile of presence probability and average parameter of mobility (μ: the ratio of state change probability to state persistence probability). The latter was set to 0.1 (O'Brien et al., 2016). As output, the model produces a set of randomly generated non-repeating Boolean occupancy profiles.

As with 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. In this case, too, the stochastic representation can be realised both for the whole population and for individual inhabitants.

2.3 Representation of Diversity

To address diversity representation among inhabitants, we used empirical data (from the year 2014) to generate models in two different ways: i) occupancy and plug load profiles averaged across all occupants, and ii) individual occupancy and plug load profiles. Using 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 based on individual and aggregate presence and plug load data.

2.4 Simulated Alternatives

A non-random relationship can be shown to exist between inhabitants' presence, their respective installed equipment power, and the resulting electrical energy use (Fig. 1). A stronger correlation can be revealed considering individual inhabitants as opposed to the population as a whole (Fig. 2). This may be interpreted as the consequence of considering inhabitants' diversity with regard to the electrical energy used for equipment. The difficulties associated with obtaining necessary observational data on inhabitants' diversity highlight the relevance of the initially addressed research question: To which extent can the calculated values of standard performance indicators such as annual and peak office plug loads be influenced by inter-inhabitant diversity?

To systematically explore this question, we used data from the year 2014 to calibrate models of annual and peak plug loads for the aforementioned office area. The calibrated model was used to predict plug loads for the years 2013 and 2015. Thereby, both simplified and stochastic models were generated with and without consideration of diversity (Table 4). Moreover, to put the model's performance in a more familiar context, we provided, for the same office area, the electrical energy use estimations based on plug load profiles from ASHRAE 90.1.

Table 2 – Coefficients 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 – Parameters of the stochastic model's Weibull distributions

Inhab-itants	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

Table 4 – Explored modelling scenarios with 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

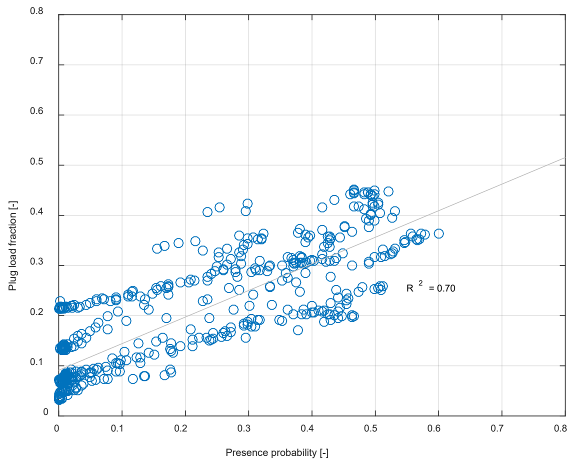

Fig. 1 – The relationship between plug load fraction and presence probability for all office inhabitants

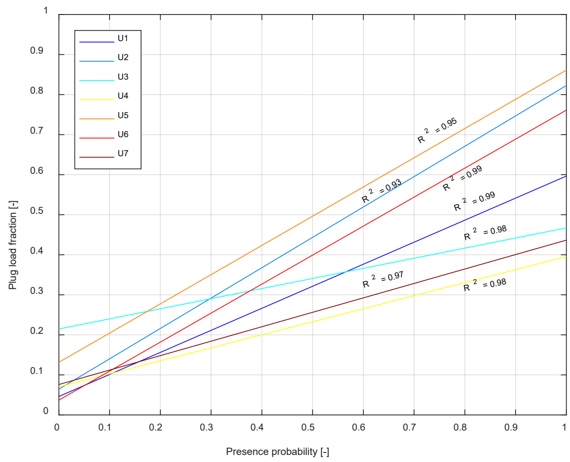

Fig. 2 – The relationship between plug load fraction and presence probability for individual office inhabitants

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

3. Results and Discussion

Table 5 provides a summary of the monitored and calculated total and peak equipment-related electrical energy use in the selected office area for the years 2014, 2013, and 2015, together with the values of the aforementioned error statistics.

The simplified method provides reasonable predictions of annual plug loads (Fig. 3). However, the probabilistic plug load model performs better than the simplified model in terms of peak load (Fig. 4) and the distribution of predictions. The latter conclusion can be inferred from the lower values of JSD for the probabilistic model (Table 5). Independently of the diversity treatment, the non-stochastic model displays a slightly better performance in predicting time interval plug loads (see MBE, RMSE, and NRMSE values in Table 5).

As to the primary question of the present treatment, namely the diversity consideration, the results may be interpreted as follows. Inclusion of diversity does not improve the predictive performance of the models with regard to annual and peak plug loads (see Fig. 3 and 4, as well as Table 5). Indeed, the inclusion of diversity has either very little impact on the predicted value of the energy use indicators or it even slightly worsens the prediction performance.

The summary representation of Table 6 illustrates this observation in simple terms. It indicates if the inclusion of diversity in plug load modelling improves the results or not. Thereby, the values of the statistics RE_a (Relative Error of annual load predictions), RE_p (Relative Error of peak load predictions), JSD, MBE, RMSE, and NRMSE were taken into consideration. Aside from rather small improvements for simplified model's results for 2013, the inclusion of diversity seems 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.

4. Conclusion

This contribution explored the performance of simple and stochastic office plug loads models. Thereby, the focus was on the implications of inhabitants' diversity. The results suggest the following:

- Plug load fractions strongly correlate with the inhabitants' presence probability.
- Both simple and probabilistic can exploit this correlation to provide reasonable predictions of annual peak plug loads. The stochastic model however, more reliably predicts peak plug loads.

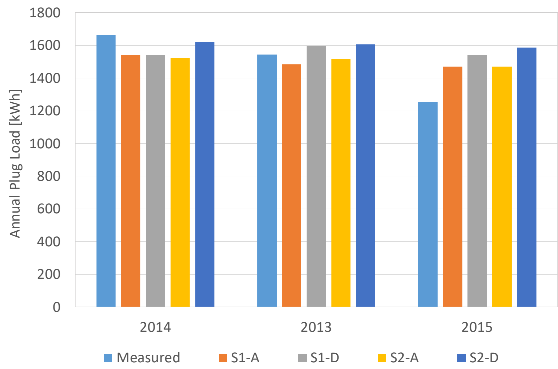

Fig. 3 – Annual plug load obtained via different modelling approaches, along with the respective monitored values

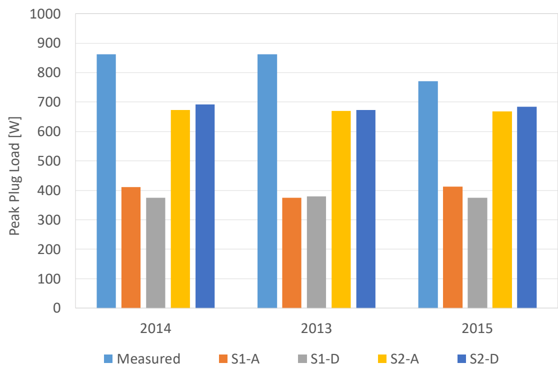

Fig. 4 – Peak plug load obtained via different modelling approaches, along with the respective monitored values

Table 5 – Statistical comparison of the monitored 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	-	3025.7	141.1	936.0	21.5	0.42	202.1	352.3	47.8

- In the present case study, 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 did not improve model predictions.
- The performance differences between simple and stochastic plug loads was found to be much less important for the quality of predictions when compared to the availability of reliable information on inhabitants' presence and installed plug loads. This circumstance, which is independent of the diversity inclusion issue, can be inferred from the very large deviations of standard-based plug load estimations (see Table 5, last row).

Table 6 – Improvement test of the values of the statistical indicators REa (Relative Error of annual load predictions), REp (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 [%]	Yes	No	No	No
RE_p [%]	Yes	No	Yes	Yes
JSD [-]	-	No	No	No
MBE [W]	Yes	No	No	No
RMSE [W]	Yes	No	No	No
NRMSE [%]	-	No	No	No

Needless to say, we do not suggest that the above observations generally apply, given various shortcomings of our case study – particularly in view of the limited magnitude of available data and the small number of inhabitants. Nonetheless, we believe the study does provide valuable initial observations and insights: independently of the choice of specific mathematical formalisms, the observed significant correlation between plug load fractions and presence patters has the potential to offer a solid basis for developing plug load prediction models. Our study also suggests that, to support simulation-based design processes, it is important to obtain dependable basic information regarding the nature of occupancy and the technical specification of the office equipment: The sole reliance on standard-based procedures could be misleading.

As to the implications of the diversity consideration for the prediction of annual and peak plug loads, the case study did not show that the inclusion of inhabitants' diversity is beneficial in principle. However, this matter, too, requires further in-depth studies before ultimate conclusions can be formulated.

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