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The Impact of People Flow on Summer Energy Consumption in a Tokyo Office Building Using a State Space Model#

Ryuta Tsurumi[1,2*], Takahiro Yoshida[2]
1 NIKKEN SEKKEI Research Institute
2 Center for Spatial Information Science, the University of Tokyo
(Corresponding Author: tsurumi.ryuta@nikken.jp)

ABSTRACT

We investigated the relationship between people flow and building energy consumption during the summer using a state-space model for an office building in Tokyo. We estimated the elasticity of people flow for the cooling heat load and the power consumption of outlets, water supply and drainage pumps, and air conditioning fans. The results provide insights that will be valuable for spatial downscaling to accurately understand the dynamics of energy consumption in individual buildings when the use of electricity data.

Keywords: Electricity data, Smart meter, People flow data, State space model, Building Energy Management System, Carbon neutral

NONMENCLATURE

Abbreviations	
HVAC	Heating, Ventilation, and Air Conditioning
BEMS	Building Energy Management System
RMSE	Root-Mean-Square Error
S.E.	Standard error
Symbols	
y	dependent variable
α	state
β	regression coefficient
ε	observation error
η	state disturbance
t	time (hourly data)
D	dummy variable
H	variances of ε
Q	variances of η
$\ln(\cdot)$	natural logarithm
$N(\cdot)$	normal distribution

1. INTRODUCTION

To achieve carbon neutrality, it is crucial to reduce the energy consumption of cities, as a significant portion of urban energy consumption is attributed to buildings. For buildings to become carbon neutral, it is first essential to understand the energy consumption of individual buildings. However, this is not an easy task.

In Japan, due to legal revisions, private companies other than power utilities will be able to utilize smart meter electricity data starting in October 2023. This will allow the use of electricity consumption data at 30-minute intervals. However, due to privacy protection, the electricity usage of individual buildings cannot be used, and it is generally available as aggregate values by municipality or grid area.

On the other hand, with the recent widely spread of smartphones, it has become possible to use people flow data with latitude and longitude information. Electricity consumption in buildings is related to human movements[1–4]. Its observation or getting data, however, is usually difficult due to the building security. If it is possible to estimate the population in buildings from widely available GPS data, it will be strongly useful to determine the schedule in buildings, and thereby to estimate the energy consumption more accurately.

Therefore, this study aims to clarify the relationship between people flow and building energy consumption during the summer, a period of high energy usage, using an office building in Tokyo as a case study.

2. MATERIAL AND METHODS

2.1 Characteristics of the target building

We focused on the company's own building located in Chiyoda, Tokyo (Table.1). This building was chosen because it has a Building Energy Management System (BEMS) installed, allowing us to obtain detailed data on energy consumption by different uses within the building.

HVAC is crucial for the building's energy consumption. This building uses ice thermal storage for cooling. The ice thermal storage system makes ice at night using electricity and uses this ice for cooling during the day. Therefore, the people flow data does not directly

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correlate with the power data for HVAC. Instead, we analyzed the relationship with the heat load for HVAC. In buildings with typical electric heat sources that do not use thermal storage, there is a strong correlation between heat load and power consumption of HVAC.

In addition to the heat load, we analyzed the power consumption of (a)outlets, (b)lighting, (c)water supply and drainage pumps, and (d)air conditioning fans. It should be noted that the water supply and drainage pumps are mainly used for facilities such as toilets and do not include pumps related to HVAC.

Table. 1 Building information

Total floor area	20,581 m^2
Building use	Office
Completion year	2003
Building area	1498 m^2
Address	Chiyoda-ku, Tokyo
Story	Above ground: 14, below ground: 1
Heat storage system for HVAC	Ice heat storage system
Heat source for HVAC	Absorption water cooling/heating machine Brine heat pump (air source)
Lighting	Fluorescent light (high frequency)
Company cafeteria	Not exist

2.2 Data

We analyzed the summer period from August 7, 2018, to September 3, 2018. All data used in the analysis are at one-hour intervals.

2.2.1 Weather data

We used the nearest weather data from the Japan Meteorological Agency's automatic weather station (AMeDAS). During the period, the average air temperature was 27.2 °C, the maximum temperature was 35.4 °C, and the minimum temperature was 18.7 °C (Fig. 1).

2.2.2 People in the building data

We used GPS data to capture the number of people in the building. The GPS data were collected as point-type floating data (Blogwatcher, Inc., 2018). Blogwatcher obtained smartphone location data from users who downloaded applications signed and consented to their terns of use with Blogwatcher. The collected data were anonymized, and no information was recorded during overnight hours. The users' IDs were randomized every morning to secure privacy. Therefore, we can capture trajectories and destinations of the users in a day.

To capture the number of people in the building by hour, we counted the number of users whose trajectories were contained within the 7.5 m buffer of the building(Fig. 2).

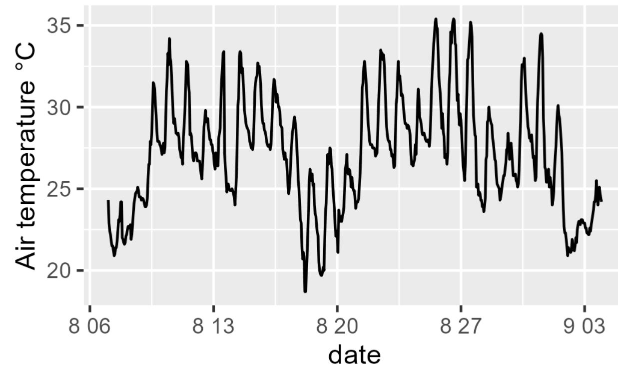

Fig. 1 Outside air temperature

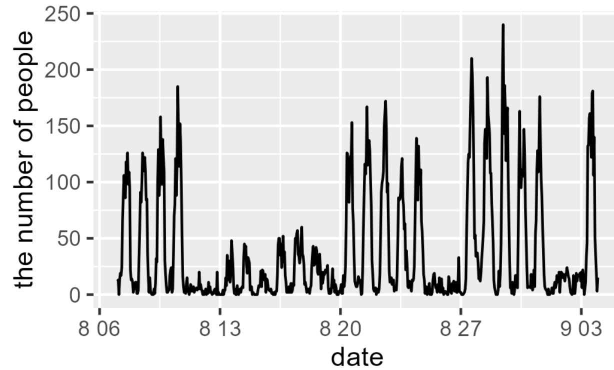

Fig. 2 The number of people in the building

2.2.3 Building energy consumption data

The heat load data and power consumption data by different uses in the target building are shown in Fig.3 to 7. These data are used as dependent variables.

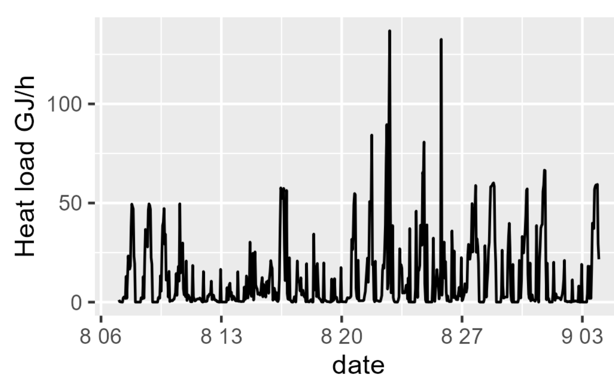

Fig. 3 Heat load

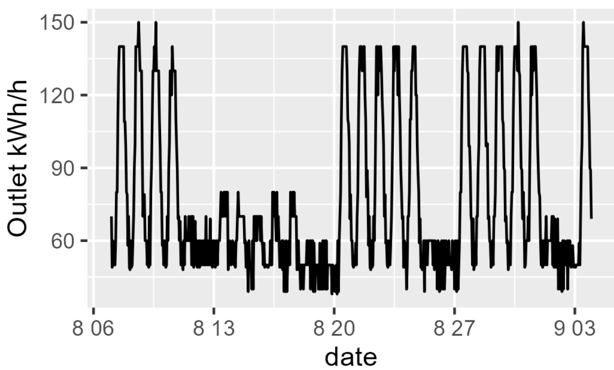

Fig. 4 Outlet power consumption

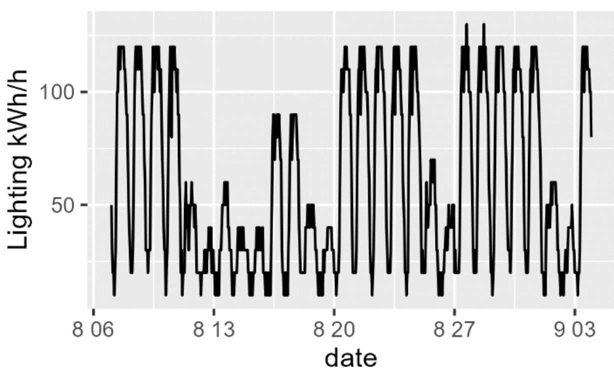

Fig. 5 Lighting power consumption

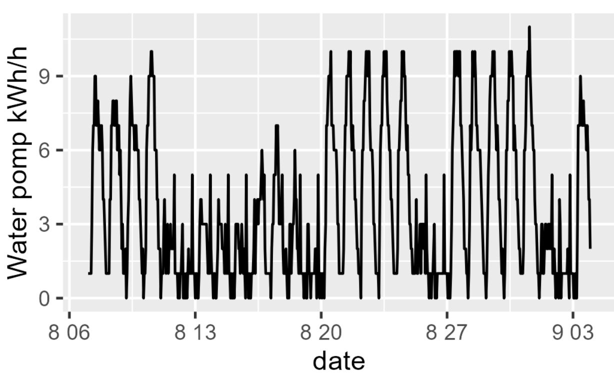

Fig. 6 Water supply and drainage pump power consumption

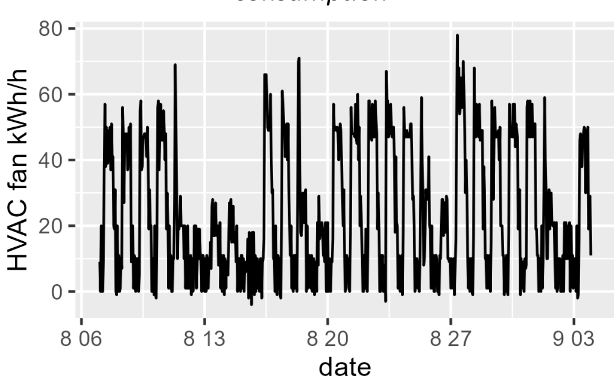

Fig. 7 HVAC fan power consumption

2.3 Statistical model

Since the heat load and power consumption are time series data at one-hour intervals, we used a state-space model to appropriately represent the time series. The advantages of the state-space model include the ability to separate state variations (such as changes in the level of power consumption) from observational errors, high flexibility in modeling, including extensions to non-linear models, and ease of handling missing observations.

In this study, we used the local level model, a type of state-space model, with people flow data and temperature data set as time-invariant regression components. Temperature was used as a control variable because it significantly affects building energy consumption, especially HVAC.

We compared statistical models targeting heat load. The observation equations compared are shown in Equations (1-1) to (1-6).

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_2 x_{2t} + \varepsilon_t, \quad (1\text{-}1)$$

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_3 \ln(x_{2t}) + \varepsilon_t, \quad (1\text{-}2)$$

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_3 \ln(x_{2t}) + \beta_4 D_{1t} \ln(x_{2t}) + \varepsilon_t \quad (1\text{-}3)$$

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_3 \ln(x_{2t}) + \beta_5 D_{2t} \ln(x_{2t}) + \varepsilon_t, \quad (1\text{-}4)$$

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_3 \ln(x_{2t}) + \beta_4 D_{1t} \ln(x_{2t}) + \beta_5 D_{2t} \ln(x_{2t}) + \varepsilon_t, \quad (1\text{-}5)$$

$$\ln(y_t) = \alpha_t + \beta_1 x_{1t} + \beta_3 \ln(x_{2t}) + \beta_6 x_{1t} \ln(x_{2t}) + \varepsilon_t, \quad (1\text{-}6)$$

Where $\varepsilon_t \sim N(0, H_t)$, y : Heat load for air conditioning, x_1:outside air temperature, x_2:people in the building, D_1:Outside air temperature is 26 °C or higher Dummy, D_2:Outside air temperature is 30 °C or higher Dummy,

In Equations (1-4) to (1-6), cross terms with dummy variables were introduced to account for the possibility that the impact of people flow on energy consumption might differ between high and low temperatures.

the common state equation for all models is shown below. The initial state was initialized using a diffuse prior.

$$\alpha_{t+1} = \alpha_t + \eta_t, t = 1, \ldots, 671 \quad (2)$$

Where $\eta_t \sim N(0, Q_t)$

We used the best model from the heat load model comparison for outlets, lighting, water supply and drainage pumps, and air conditioning fans. Calculations were performed using the R package KFAS (version 1.5.1) [5–6]. Since we applied logarithmic transformation, variables containing zeros had a small constant added to the entire variable (0.01 GJ/h for heat load, 0.1 people for people flow, and 0.1 kWh/h for other power consumption). Using a logarithmic model is convenient because the estimated β can be applied regardless of building size. For example, in the log-log model (1-2), a 1% increase in the number of people would result in β% increase in y.

3. RESULTS

The parameter estimation of the model comparison using cooling heat load as the dependent variable are shown in Table 2. As an evaluation metric, we display the RMSE of the one-step ahead prediction error and the maximum log-likelihood. RMSE is calculated for t = 3, ..., 671, excluding the initial state where errors are very large due to diffuse initialization. The model with the smallest RMSE and largest maximum log-likelihood is Model (2). The smoothed state of Model (2) is shown in Fig. 8.

Using the independent variables of Model (2), the parameter estimation for models with outlets, lighting, water supply and drainage pumps, and air conditioning fans as dependent variables are shown in Table 3. As a representative example, the smoothed state for outlets is shown in Fig. 9.

4. DISCUSSION

4.1 The impact of people flow on heat load and energy consumption

We used a state-space model to explain the relationship between energy consumption and people flow in the office building in Tokyo during the summer. We used temperature and people flow as time-invariant regression components. Initially, we compared statistical models based on log-transformed heat load, exploring log-transformed terms cross terms in the explanatory variables. As a result, Model (2), which included log-transformed people flow and did not include cross terms, achieved the highest Maximum log-likelihood and was considered the best model. While there was a tendency for the impact of people flow to decrease as temperature down, the results were not statistically significant (in Models (4) and (5), the β of the dummy variable representing temperature above 30 °C was estimated to be negative.).

Using Model (2) for interpretation, it was observed that when people flow inside the building increased by 1%, there was a tendency for the cooling heat load to increase by 0.114 ± 0.051% (mean ± S.E.). Additionally, it was observed that when temperature increased by 1 °C, there was a tendency for the cooling heat load increase by 25.2 ± 5.8%.

Using the same independent variables as Model (2), we estimated (a)outlets, (b)lighting, (c)water supply and drainage pump, and (d)air conditioning fans. It was estimated that when people flow increased by 1%, there was a tendency for outlets to increase by 0.020 ± 0.005%, Lighting by 0.032 ± 0.010%, Water supply and drainage pump by 0.236 ± 0.024%, and Air conditioning fans by 0.218 ± 0.032%.

The elasticity of people flow was found to be largest for water supply and drainage pump, due to the direct relationship between water usage, such as toilet facilities, and the number of occupants in the building. Additionally, air conditioning fans showed second largest elasticity, possibly because the building incorporates CO_2 control for ventilation, adjusting the ventilation volume according to the number of occupants present. Cooling heat load not only deals with heat load generated from occupants but also needs to handle heat load from the building envelope unrelated to occupancy, which explain why the elasticity is relatively small. Furthermore, the majority of this building's office areas feature open-plan layouts without walls, leading to a tendency to turn on lighting for an entire floor when even one person is present, resulting in relatively lower correlation with people flow. Lastly, outlets, which are associated with individual activities such as charging personal laptops, exhibited lowest elasticity due to the presence of many appliances, such as internal network servers, refrigerators, which operate independently of human occupancy.

4.2 Limitation

In this study, we used data based on smartphone location information as people flow data. It’s important to note that we don’t capture 100% of people inside the building. Additionally, there’s a possibility that people walking near the building, such as on sidewalks, are also included in the data. A rough estimate based on company’s attendance records etc. suggests that this data captures around 30 to 50 percent of office-workers in the building. However, our statistical model estimates elasticity, so if the capture rate remains constant throughout the period, the impact of capture rate on elasticity is likely small.

This study specifically focuses on the summer period. Winter or intermediate periods may be different behaviors, so accumulating data over the entire year will allow us to assess long-term effects.

Due to data constraints, our study examined a single office building located in Tokyo. To improve external validity, we plan to expand our analysis to include other buildings in the future.

Notable energy consumption we couldn't address in this study is elevators. Elevators consumed up to 30 kWh/h during the study period. Unfortunately, the coarse pulse detection of elevator power meters (with a minimum detectable amount of 10 kWh/h) prevented us from including them in our estimation.

5. CONCLUSIONS

In this study, we investigated the relationship between energy consumption by major end-uses in a office building in Tokyo and people flow during the summer. Using state-space model and controlling for outside air temperature, we estimated that a 1% increase in people flow in the building led to the following trends in heat load or energy consumption: cooling heat load increased by 0.114±0.051%(mean ± S.E.), outlets by 0.020±0.005%, lighting by 0.032±0.010%, water supply and drainage pump by 0.236±0.024%, and air conditioning fans by 0.218±0.032%. These findings contribute valuable insights for spatial downscaling to accurately monitor energy consumption dynamics in individual buildings when electricity data from smart meter utilization becomes more widespread.

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*Table. 2 Parameter estimation results (*heat load model*)*

Dependent variable: ln(heat load for air conditioning)	(1)	(2)	(3)	(4)	(5)	(6)
Outside air temperature	0.226*	0.252*	0.238*	0.306*	0.292*	0.359*
(Standard error)	(0.061)	(0.058)	(0.062)	(0.068)	(0.071)	(0.084)
People in the building	0.007*					
(Standard error)	(0.003)					
ln(People in the building)		0.114*	0.085	0.123*	0.097	0.914*
(Standard error)		(0.051)	(0.066)	(0.051)	(0.066)	(0.465)
Outside air temperature is 26 °C or higher Dummy × ln(People in the building)			0.051		0.046	
(Standard error)			(0.075)		(0.075)	
Outside air temperature is 30 °C or higher Dummy × ln(People in the building)				-0.120	-0.117	
(Standard error)				(0.080)	(0.080)	
Outside Air temperature × ln(People in the building)						-0.030
(Standard error)						(0.018)
RMSE	1.72	1.90	1.91	1.90	1.91	3.01
exp(RMSE)	5.57	6.69	6.75	6.69	6.74	20.31
Maximum log-likelihood	-1304.8	-1302.6	-1305.0	-1304.0	-1306.4	-1305.2
R^2 (squared correlation coefficient between dependent variable and smoothed state)	0.88	0.88	0.88	0.88	0.88	0.88

*The 95% confidence interval does not include zero.

Table.3 Parameter estimation results. (other model)

	Dependent variable:			
	(a) ln(Outlet)	(b) ln(Lighting)	(c) ln(Water supply and drainage pump)	(d) ln(Air conditioning fans)
Outside air temperature	0.051*	0.100*	0.132*	0.205*
(Standard error)	(0.006)	(0.014)	(0.023)	(0.023)
ln(People in the building)	0.020*	0.032*	0.236*	0.218*
(Standard error)	(0.005)	(0.010)	(0.024)	(0.032)
RMSE	0.19	0.41	0.91	1.92
exp(RMSE)	1.21	1.51	2.47	6.83
Maximum log-likelihood	205.2	-223.8	-889.2	-1112.9
R^2(squared correlation coefficient between dependent variable and smoothed state)	0.96	0.99	0.56	0.38

*The 95% confidence interval does not include zero.

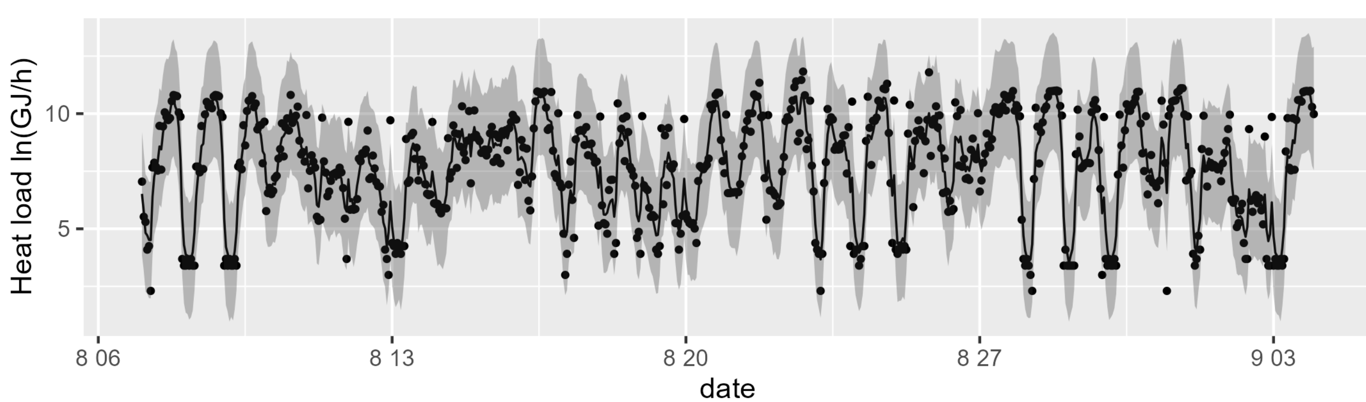

Fig. 8 Smoothed state of heat load mode (2). Line: Smoothed state, Dot: observed value, Shadow: 95% prediction interval

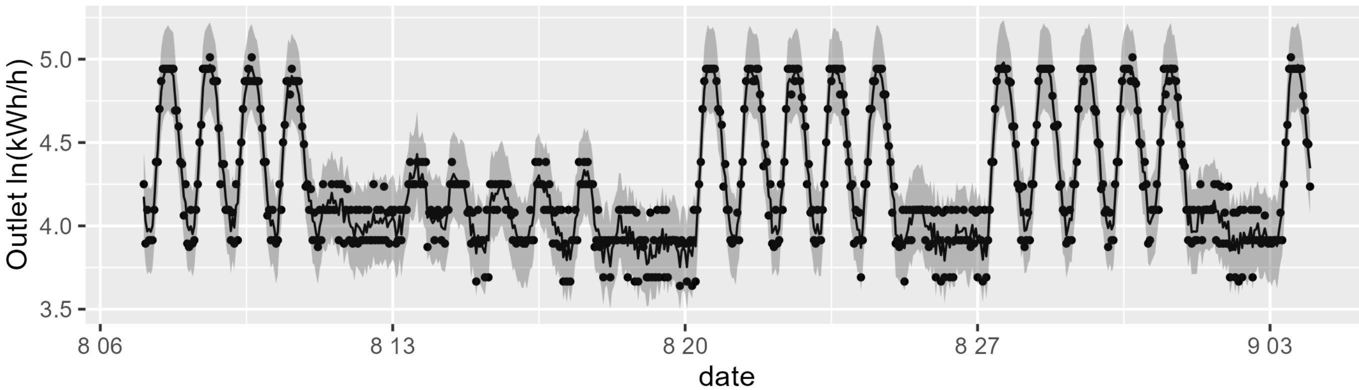

Fig. 9 Smoothed state of outlet mode. Line: Smoothed state, Dot: observed value, Shadow: 95% prediction interval