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LETTER

Incorporating residual temperature and specific humidity in predicting weather-dependent warm-season electricity consumption

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Abstract

Climate warming and increasing variability challenges the electricity supply in warm seasons. A good quantitative representation of the relationship between warm-season electricity consumption and weather condition provides necessary information for long-term electricity planning and short-term electricity management. In this study, an extended version of cooling degree days (ECDD) is proposed for better characterisation of this relationship. The ECDD includes temperature, residual temperature and specific humidity effects. The residual temperature is introduced for the first time to reflect the building thermal inertia effect on electricity consumption. The study is based on the electricity consumption data of four multiple-street city blocks and three office buildings.

It is found that the residual temperature effect is about 20% of the current-day temperature effect at the block scale, and increases with a large variation at the building scale. Investigation of this residual temperature effect provides insight to the influence of building designs and structures on electricity consumption. The specific humidity effect appears to be more important at the building scale than at the block scale. A building with high energy performance does not necessarily have low specific humidity dependence. The new ECDD better reflects the weather dependence of electricity consumption than the conventional CDD method.

1. Introduction

Electricity consumption responds to weather conditions and thus to climate change (Eskeland and Mideksa 2010, Mirasgedis *et al* 2007, Sailor 2001, Sailor and Pavlova 2003, Semmler *et al* 2010, Wang *et al* 2010, Zhou *et al* 2013). Currently climate warming results in an increasing demand for cooling energy consumption (Ahmed *et al* 2012, Franco and Sanstad 2008, Howden and Crimp 2001, Sailor and Pavlova 2003). The increased interannual variability in climate conditions particularly during summer periods also has a significant negative impact on electricity demand (Mirasgedis *et al* 2007).

Urban areas house 54% of the world's population and consume 75% of global energy resources (Gago *et al* 2013). Urban heat island (UHI) effects further increase energy demand for electricity in warm climate areas and in warm seasons (Gago *et al* 2013, Li *et al* 2014, Lowe 2016, Santamouris 2014), particularly in city centres where high-rise commercial buildings are concentrated (Hirano and Fujita 2012).

A better prediction of the impacts of climate change on electricity consumption depends on an improved understanding and modelling of the weather dependence of electricity consumption. This weather sensitivity is also important for the short-term prediction of electricity consumption (Beccali *et al* 2008). Numerical models have been developed to investigate the effects of future changes of climate and/or urban development on energy consumption, including building energy performance modelling

(Ahn *et al* 2016, Soebarto and Guan 2013, Stavrakakis *et al* 2016), coupled climate and energy consumption modelling (Salamanca *et al* 2015), and coupled climate, energy consumption, and economic modelling (Labriet *et al* 2015). These models provide useful tools to investigate the complex and dynamic relationship between energy consumption and other relevant factors. However, they often have extensive data requirements, and thus are costly in terms of both time and resources. Alternatively, simple methods, such as those based on regression or empirical indices, provide parsimonious and inexpensive tools for urban managers and policy makers (Walter and Sohn 2016).

Potential meteorological factors influencing electricity consumption include temperature, humidity, wind and solar exposure (Huang *et al* 1987), of which air temperature and humidity are commonly reported as significant factors (Chen *et al* 2012, Guan *et al* 2014, Ihara *et al* 2008). In warm seasons, electricity consumption increases with air temperature when daily temperature rises above a certain threshold. This threshold is referred to as the base temperature for cooling energy demand. This is commonly used to calculate cooling degree days (CDD) to estimate the electricity consumption (Ahmed *et al* 2012, Al-Hadhrami 2013, Beccali *et al* 2008, Huang *et al* 1987, Kadioglu and Sen 1999, Krese *et al* 2011, Lee *et al* 2014, Mirasgedis *et al* 2007, Tselepidaki *et al* 1994, Valor *et al* 2001), although using direct meteorological data is often recommended in the first instance (Hekkenberg *et al* 2009).

However, it is found that the base temperatures (as daily mean temperatures) reported in the literature vary over a range from as low as 12.9 °C (Krese *et al* 2011) to as high as 22 °C (Beccali *et al* 2008) (table 1). A large proportion of this range is beyond the common-sense temperature threshold for cooling requirements. We certainly do not need any cooling air conditioning for a day with mean temperature at say 15 °C. Multiple factors may have led to such a large range of the apparent base temperature, including: (1) an industry-sector electricity consumption component with a low base temperature (e.g. refrigerators); (2) anthropogenic heat releases in buildings; (3) building heat inertia; (4) adaptive human comfort levels, and (5) local outdoor cooling sources (e.g. green infrastructures). These factors are explained in more detail in the following paragraphs.

Certain industries operate electrical appliances (refrigerators) with low base temperatures. Using the electricity data aggregated from different sectors can lead to a lower base temperature, than commonly seen in commercial, office and residential buildings. This problem can be addressed when electricity data from different sectors are analysed separately.

Heat release from building occupants, electrical appliances and lighting can increase indoor temperatures above the outdoor ambient temperature, and this in turn can trigger air conditioning operation when the outdoor temperature is still low. To include this effect, information of detailed building occupants and their activities are required, which is often difficult to obtain.

In addition, buildings store heat during the daytime and release it slowly during the night, with residual heat being retained, quite often for several days. Therefore, for a given day, indoor temperature is influenced by outdoor temperature and the residual heat stored in the building from previous days. This storage of heat can contribute to increasing air conditioning requirements even when the current outdoor temperature is low. The effect of residual heat in electricity consumption can be examined using the temperature difference between the present and previous days.

This temperature difference is referred to as the residual temperature. It can be calculated as:

$$\Delta T_{i,j} = T_{i-j} - T_i \tag{1}$$

where $\Delta T_{i,j}$ is the residual temperature in the ith day resulting from the $(i-j)$th day. If the residual temperature effect on electricity consumption is significant, it should be examined to understand the variation of its effect across different building sectors, urban forms, climates, building materials and designs. This effect can be readily incorporated into weather-dependent electricity demand modelling without requiring additional data.

Water vapour in the air may condense to liquid water and release heat when air conditioning is in operation to cool indoor temperatures. Thus, electricity consumption can increase with specific humidity (or water vapour concentration) in warm seasons when cooling air conditioning is applied. Theoretically, the amount of heat release from this condensation can be calculated from the latent enthalpy of the air. Thus, latent enthalpy has been used to quantify the specific humidity effect (Huang *et al* 1987, Krese *et al* 2011, Sailor 2001). Given a fixed specific humidity, latent enthalpy does not vary much (less than 5%) for a normal air temperature range. Thus, specific humidity has been associated directly with electricity consumption in warm seasons (Guan *et al* 2014, Ihara *et al* 2008).

Outdoor cooling sources, such as sea breezes and parkland irrigation, may lead to a higher apparent base temperature locally if a weather station beyond such a cooling influence is used as the reference. Meanwhile, these cooling sources often occur in company with an increase in specific humidity. In terms of the effect on electricity consumption, this increased specific humidity counteracts the cooling effect. To better estimate the benefit of these cooling sources in summer, the specific humidity effect should be considered in common weather dependent indicators, such as CDD.

Adaptive human comfort refers to how the human body adapts to its outdoor and indoor climate

Table 1. Summary of selected published studies showing a range of base temperatures.

Area	Electricity data	Predictor variables under consideration	Base temperature	Relationship	Reference
USA	Weekly, for the whole country	Population-weighted CDD	18.3 °C	Linear with CDD	Le Comte and Warren (1981)
USA	Monthly	Population-weighted CDD	18.3 °C	Nonlinear, due to market saturation	Sailor and Pavlova (2003)
Spain	Daily, for the whole country, 1983–1999	Population-weighted daily mean temperature	18 °C	Nonlinear, HDD and CDD are used	Valor *et al* (2001)
Greece	Daily, 1993–2003	HDD, CDD, GDP, population, energy intensity	18.5 °C	Linear	Mirasgedis *et al* (2007)
Palermo, Italy	Hourly, for a district, June 2002-Sept 2003	Daily mean temperature	22 °C for CDD and 18.7 °C for HDD	Linear with HDD and CDD; Neural network modelling with weather variables	Beccali *et al* (2008)
Athens and London	Hourly, 1997–2001	Daily mean temperature	20 °C for Athens 16 °C for London	HDD and CDD are used	Psiloglou *et al* (2009)
Slovenia	15-min, two buildings (office A and hotel B), a few time intervals in 2007 and 2010	CDD Enthalpy latent days	A: 5.14 g/kg, 12.9 °C B: 7.14 g/kg, 16.1 °C	Linear with CDD and ELD	Krese *et al* (2011)
Lebanon	Monthly, 1992–1999	Monthly average temperature, relative humidity, clearness index		Humidity and clearness index are not significant. Rationing changes the temperature dependence	Badr and Nasr (2001)
South Korea	Monthly in different regions, 2001–2010	Daily mean temperature	Varied between areas, 16.2 °C–19.4 °C, base temperature increases with annual mean temperature	Linear with HDD and CDD	Lee *et al* (2014)
Tokyo	Hourly, three business blocks, 2002	Daily mean temperature, specific humidity	Base temperature 15.0 °C and 21.3 °C Base humidity 9.9 g/kg	Piece-wise linear regression with T and q	Ihara *et al* (2008)
Tokyo	Office building energy consumption at 14:00h	Instantaneous temperature	17.25 °C	Piece-wise linear regression with T	Hirano and Fujita (2012)
Brisbane, Sydney, Melbourne and Adelaide Australia	Half-hourly electricity demand for 1999 and 2000, aggregated to weekly values	Daily data aggregated to weekly for analysis	Brisbane: 18.6 °C Sydney: 17.5 °C Melbourne: 16.9 °C Adelaide: 16.8 °C	Linear with CDD, HDD, THI and VPD depending on locations	Howden and Crimp (2001)
New South Wales	Daily data for the whole state, 1999–2010	HDD, CDD, price, population, Gross State Product	14.3 °C		Ahmed *et al* (2012)
Adelaide, South Australia	Hourly, three buildings for one year	Daytime temperature and specific humidity	17 °C daytime temperature	Linear	Guan *et al* 2014
Adelaide, South Australia	Hourly, multiple street blocks, five years	Daily temperature, specific humidity and residual temperature	Base temperature 15.0 °C, base humidity 7.5 g/kg	Linear	This study

(Taleghani *et al* 2013). Thus, the human comfort temperature may vary spatially, which may be reflected in the spatial variation of base temperature for cooling demand. For example, Lee *et al* (2014) reports that the base temperature for cooling demand within South Korea increases with mean annual temperature (table 1). Adaptive human comfort may vary seasonally (Kumar *et al* 2016, Yang *et al* 2015, Yun *et al* 2016), leading to seasonally varying base temperatures for cooling demand. However, this apparent temporally varying base temperature can be a result of seasonal effects of other climate variables (e.g. humidity and wind). In buildings with central air conditioning systems in the study area (and probably many other areas), the effect of this temporal adaptive comfort has not yet been incorporated in air conditioning operations. Given this complexity and the lack of a well-defined effective seasonal base temperature for cooling in the study area, the possible effect of seasonal varying base temperature is not considered in this study.

The objectives of this study are (1) to examine and quantify the residual temperature effect on electricity consumption in warm days, (2) to quantify the specific humidity effect on the electricity consumption at both the street-block and building levels, and (3) to incorporate the residual temperature and specific humidity into defining the cooling degree days for modelling weather-dependent electricity consumption.

The analysis is primarily based on daily electricity consumption of multiple street blocks in the central business district (CBD) of Adelaide, South Australia, with individual buildings being investigated for comparison. This comparison is particularly important for examining the specific humidity effect. Condensation from cooling air conditioners inside buildings may evaporate and absorb heat from the environment. It is hypothesized that the specific humidity effect is smaller at the street-block scale than at the building scale.

2. Methodology

2.1. Data

Half-hourly electricity consumption data were obtained from South Australia Power Networks for four subzones in the Adelaide CBD for 2010–2015. Each subzone covers an area of multiple street blocks (figure 1). The four subzones are shown in figure 1 as Whitmore Square 66/11 kV (WS), Coromandel Place 66/11 kV (CP), East Terrace 66/11 kV (ET) and Hindley Street 66/11 kV (HS). Because of the spatial overlap of the electricity supply subzones, it is difficult to describe the accurate building composition for each subzone. In general, the WS and ET subzones include a significant portion of private residential buildings, while the HS and CP subzones are primarily composed of commercial, education, non-private residential, and public institution buildings. The WS subzone includes a few high-rise office buildings and some commercial building blocks (figure 1).

Sub-hourly electricity consumption data from three office buildings in the Adelaide CBD were obtained from the relevant building owners/managers. These data have been used to examine temperature and humidity effects on electricity consumption in a previous study (Guan *et al* 2014), which includes details of the building descriptions. Here, the data are used to examine the residual temperature effects and to investigate the difference in weather dependence between the building and block levels. The three buildings (denoted as A, B and C, which is the same as in (Guan *et al* 2014)) are located within an area of 600 m (north–south) by 250 m (east–west). Building A is a 10-storey structure, constructed within the last 10 years. Building B has nine storeys and was constructed in the 1970s, with a few floors being retrofitted to improve energy performance in the early 2000s. Building C has 18 storeys and was constructed in the 1960s. The combination of buildings A, B and C is estimated to be a close approximation of the average office building stock in Adelaide (Guan *et al* 2014).

Hourly weather data was obtained from the Kent Town Bureau of Meteorology station, located approximately two kilometres from the CBD.

2.2. Method

As cooling electricity consumption is investigated in this study, the analysis is performed on the days warmer than the base temperature for cooling, using:

$$E = \beta_0 + \beta_1 T + \beta_2 q + \sum_{j=1}^{k} \beta_{2+j} \Delta T_j \text{ for } T > T_b \quad (2)$$

where E is the daily electricity consumption, T (°C) is the outdoor air temperature, ΔT_j is the temperature difference between two days as defined in equation (1), q (g/kg) is the specific humidity, T_b (°C) is the outdoor air temperature threshold beyond which building electricity consumption varies with air temperature. The daily electricity consumption includes two portions. The first, which is dependent on the weather conditions, is related to achieving indoor human comfort and in some cases maintaining specific materials at low temperatures. The other portion is associated with powering office equipment and lighting, and is not dependent on the weather conditions. The weather-independent component will be included in β_0, while the weather-dependent component will be reflected in the other terms in the regression equation.

The base temperature is usually determined from the scatter plot of electricity consumption vs mean daily temperature. Stepwise regression is applied to determine the number of residual temperature terms to be included in equation (2). Conventionally, the

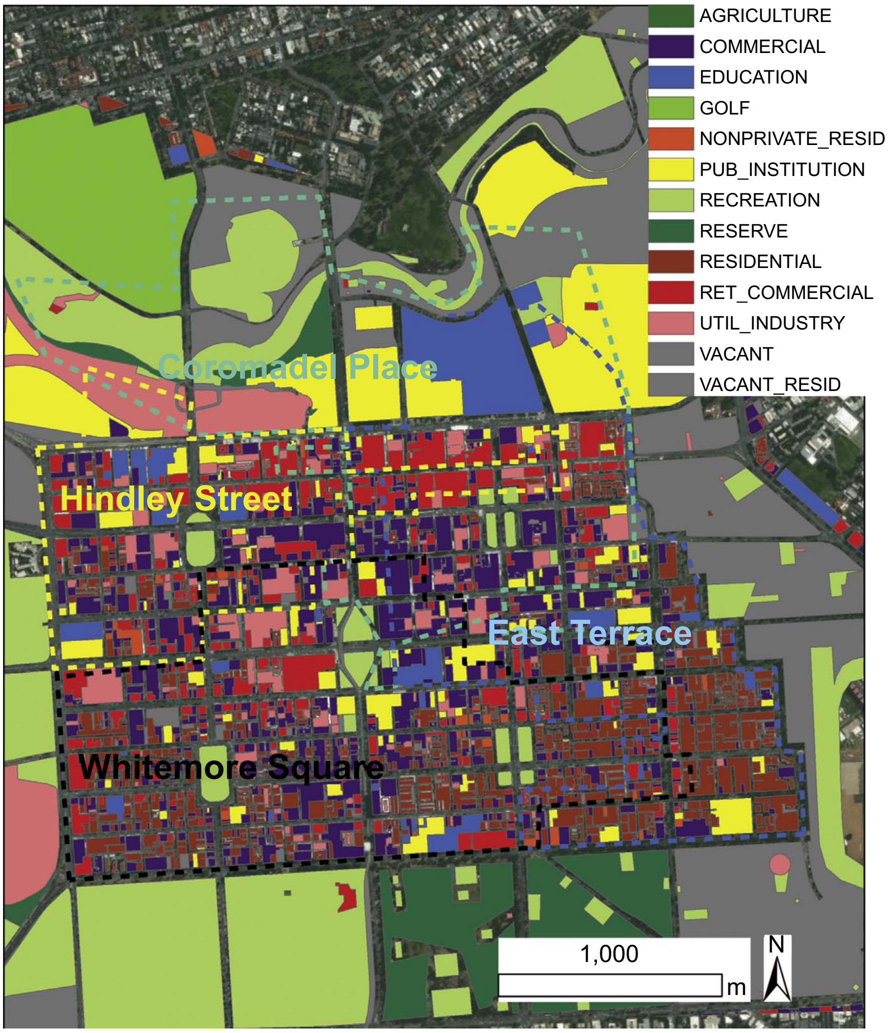

Figure 1. Estimated coverage of the four electricity supply subzones in the Adelaide central business district (adapted from South Australia Power Networks) and the building and land-use types (provided by Data SA).

cooling degree days is calculated according to:

$$\mathrm{CDD} = \sum_{i=1}^{n} (T_i - T_b) \qquad \text{for } T > T_b \tag{3}$$

where n is the number of days in the time interval of interest. In this study, we propose to include the residual temperature and specific humidity effects in the cooling degree days calculation, referred to as the extended cooling degree days (ECDD), which is calculated as:

$$\mathrm{ECDD} = \sum_{i=1}^{n} \left[(T_i - T_b) + \max \left[\frac{\beta_2}{\beta_1}(q - q_b), 0 \right] + \sum_{j=1}^{k} \frac{\beta_{2+j}}{\beta_1} \Delta T_j \right] \qquad \text{for } T > T_b \tag{4}$$

where q_b (g/kg) is the base specific humidity, above which the specific humidity affects electricity consumption. All other symbols are explained in equation (2).

It has previously been found that weather dependence is better reflected by the daytime (7:00–18:00) temperature than by daily temperature for office buildings (Guan *et al* 2014). Both daily average and daytime average weather conditions (temperature and specific humidity) are used in the analysis. Residual temperature is calculated based on daily temperatures for either case.

3. Results

3.1. Patterns of electricity consumption at the street-block scale

The buildings in the Adelaide CBD are mixed for office, commercial, public use and residential use. The electricity consumption differs between working days and non-working days. For example, at the street-block scale, the daytime electricity consumption in working days is about twice that of non-working days (figure 2). A mix of electricity consumption of two groups of days may weaken the weather dependence. Thus, in the following data analysis, only electricity consumption of working days is used.

The relationship between daily electricity consumption data vs daily temperature is shown for the four sub-zones in figure 3. All four subzones share a

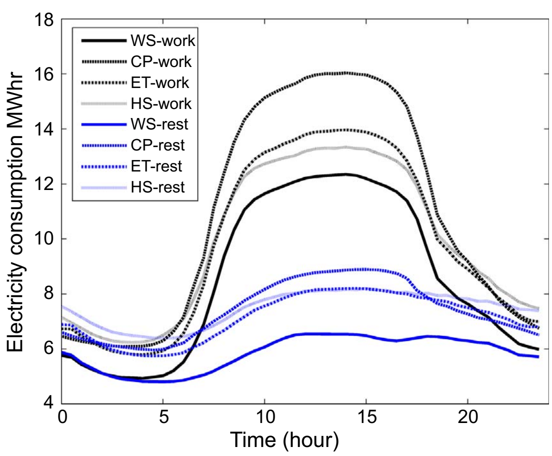

Figure 2. Mean diurnal hourly electricity consumption of four subzones in the Adelaide CBD for two groups of days (working days vs weekends and holidays), based on data in five consecutive financial years (2010/11–2014/15).

common pattern that electricity consumption increases with temperature for days with daily mean temperatures above 15 °C. The responses to temperature slightly vary among the subzones for days of mean temperature below 15 °C. The two subzones in the northern CBD have no or very weak temperature dependence for cold days, while the two subzones in the southern CBD show clear temperature dependence. This difference between northern and southern CBD sections is likely to be related to different building compositions. The northern section is concentrated with office and public buildings, in which winter heating is primarily powered by gas. While in the southern section, residential dwellings are mixed with other types of buildings. This explains the observed significant temperature dependence of the electricity consumption for cold days. However, the electricity consumption of warm days is the focus of this study.

3.2. Regression of weather dependence at the block and building scales

Regression analysis is performed to examine the weather dependence of daily electricity consumption at both the street-block and building scales, using daytime (office hours) and daily average weather conditions (temperature and specific humidity). It is found that at the street-block scale, there is not much difference when using either daytime average or daily average weather conditions (figure 4). However, at the building scale, using daytime weather conditions significantly improves the regression performance in explaining the temporal variability of daily electricity consumption for Building A, but not for Buildings B and C. Building A is a recently constructed office building, with high energy-use efficiency, while Buildings B and C are around 50 years old. This difference in building age (thus different designs and materials) may explain the differences shown in figure 4. In this study, daily average weather condition is used for analysing street-block daily electricity consumption, to be consistent with most published studies, particularly those involving the CDD concept. While at the building scale, daytime average weather condition is applied, given the significant differences shown in figure 4 for Building A.

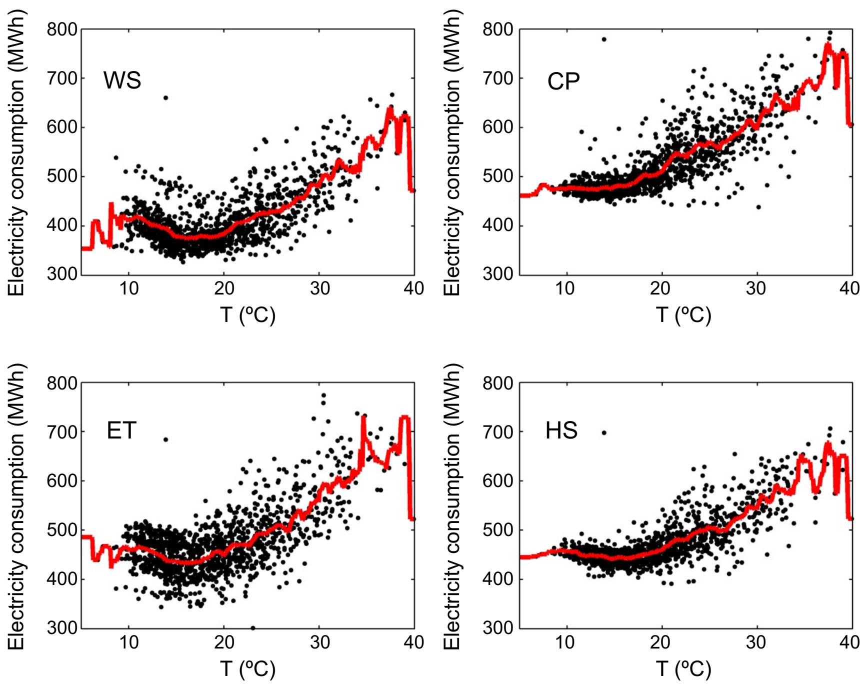

Figure 3. Daily electricity consumption of four subzones in the Adelaide CBD vs daily mean temperature for working days in five consecutive financial years (2010/11–2014/15). The red line is the average daily electricity consumption data averaged over a 1-degree window with the centre points propagating at a 0.1-degree step.

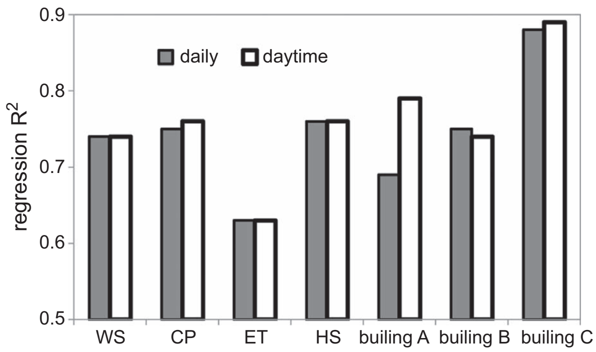

Figure 4. Regression performance using daytime average temperature and specific humidity vs daily average temperature and specific humidity for the four subzones and three office buildings.

Table 2. Linear regression results for daily electricity consumption (MWh) vs three predictor variables (daily temperature, specific humidity and residual temperature) for the electricity supply subzones in the Adelaide CBD (2010/11–2014/15)

Subzones		Variables			Statistics			
		T (°C)	q (g/kg)	dT (°C)	R^2	Standard error[a]	$\beta_{(dT)}/\beta_{(T)}$	$\beta_{(q)}/\beta_{(T)}$ (°C)/(g/kg)
Whitmore Square	β	12.09	5.28	2.31				
	p value	8.0E–184	4.0E–13	1.1E–08	0.74	0.075	0.19	0.44
Coromandel Place	β	12.90	5.82	3.11				
	p value	3.5E–188	2.3E–14	2.7E–13	0.75	0.060	0.24	0.45
East Terrace	β	13.01	6.65	1.69				
	p value	5.6E–132	6.3E–11	2.6E–03	0.63	0.090	0.13	0.51
Hindley Street	β	10.85	4.73	2.23				
	p value	1.2E–192	3.2E–14	1.1E–10	0.76	0.055	0.21	0.44

[a] The standard error is normalized by mean daily electricity consumption.

Table 3. Linear regression results for daily electricity consumption (KWh) with daytime average temperature, daytime average specific humidity and daily residual temperature for three office buildings

Building floor area (m^2)		Variables			Statistics			
		T (°C)	q (g/kg)	dT (°C)	R^2	Standard error[a]	$\beta_{(dT)}/\beta_{(T)}$	$\beta_{(q)}/\beta_{(T)}$ (°C)/(g/kg)
A	β	159.27	121.35	41.96				
20000	p value	8.0E–33	4.8E–11	2.5E–03	0.79	0.100	0.26	0.76
B	β	78.51	73.45	54.50				
8460	p value	2.2E–23	4.0E–06	1.0E–06	0.74	0.068	0.69	0.94
C	β	439.62	198.08	131.36				
20600	p value	7.4E–89	2.7E–12	3.1E–09	0.89	0.056	0.30	0.45

[a] The standard error is normalized by the average daily electricity consumption.

The initial stepwise regression analysis with residual temperatures from multiple preceding days suggests that the significant influence on daily electricity consumption mainly comes from one preceding day (not shown). The regression results for the four subzones are included in table 2. The three predictor variables (daily temperature, specific humidity and one-day residual temperature) explain about 75% of the subzone electricity consumption for WS, CP, and HS, and 63% for ET. The residual temperature dependence is about 20% of the temperature dependence (column 8 in table 2). The dependence on specific humidity appears to be related to the temperature dependence, being fairly uniform across subzones (column 9 in table 2).

A similar analysis is performed for the three buildings (table 3). Again, the residual temperature appears to be a significant influence on warm-day daily electricity consumption. The three variables (daytime temperature, specific humidity and one-day residual temperature) explain 74%–89% of the variability of daily electricity consumption in warm days. This is on average higher than that at the street-block scale, which indicates that office buildings (perhaps other buildings as well) are more weather-dependent than other electricity-users in the Adelaide CBD. The residual-temperature sensitivity is larger at the building level than at the street-block scale, particularly for Building B, which represents 69% of the temperature dependence of this building. The dependence of electricity consumption on specific humidity is also larger at the building scale, particularly for Buildings A and B (column 9 in table 3).

3.3. Extended cooling degree days

To incorporate residual temperature and specific humidity effects in the extended CDD (equation 3), the coefficient ratios need to be relatively stable temporally and spatially (over the area in which the electricity consumption is estimated or simulated). Based on the results shown in section 3.2, the coefficient ratios vary over a relatively large range (0.26–0.69 for residual temperature and 0.45 – 0.94 for specific humidity) between the three office buildings (table 3). This variation may be related to the differences in building ages, energy performance and occupant density. It is therefore difficult to transfer the ratios from one building to another.

Nevertheless, at the street-block scale, the coefficient ratios show more stability across subzones (table 2). For each subzone, the stability of the coefficient ratios is examined for both residual temperature (figure 5) and specific humidity (figure 6). The interannual variability is relatively large; but the standard deviation is still either about 50% or smaller than the mean for most cases shown in figures 5 and 6.

To make the extended CDD concept easily applicable, it is desirable to use uniform (across space) and constant (over time) coefficient ratios to relate the residual temperature and specific humidity effects on electricity consumption to the temperature dependence. For this study, fixed values of the coefficient ratios (0.2 for the residual temperature from figure 5, and 0.45 for the specific humidity from figure 6) are used in calculating the extended CDD.

To calculate the extended CDD, the base specific humidity is required. A plot of daily electricity consumption vs specific humidity does not show as a clear relationship for a base specific humidity value (not shown), as that for temperature (figure 3). This is because the dominant temperature effect overshadows the effect of specific humidity. After the temperature and residual temperature effects are removed, the specific humidity effect becomes clearer (figure 7). A base specific humidity of 7.5 g/kg is estimated for the Adelaide CBD.

Now we are ready to calculate the extended CDD for each warm working day. The correlation between the daily electricity consumption and the conventional CDD and the extended CDD is shown in figure 8. The extended CDD sharpens the correlation between the electricity consumption and weather condition. This result indicates that the extended CDD, based on fixed values of relative residual temperature dependence and specific humidity dependence, can improve simulation of daily electricity consumption.

4. Discussion

4.1. Residual temperature effect

Although it would seem obvious that residual heat would affect indoor temperatures, this effect has not been previously included in estimating/predicting the

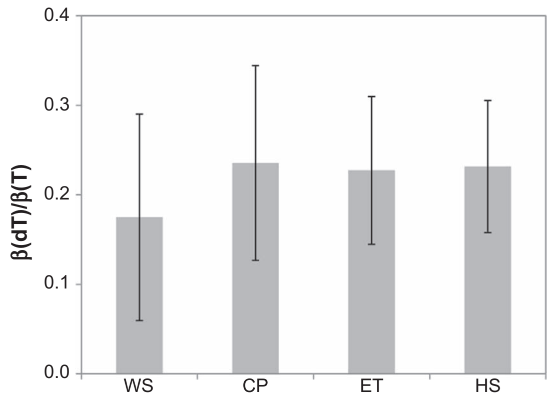

Figure 5. Mean and standard deviation of the ratios of residual temperature and temperature coefficients from the regression with data for warm working days in each individual year for the four subzones, showing the temporal (error bars) and spatial (between the four subzones) stability of residual temperature effects.

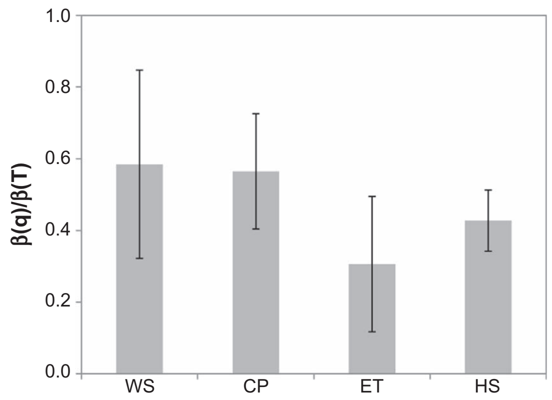

Figure 6. Mean and standard deviation of the ratios of specific humidity and temperature coefficients from the regression with data for warm working days in each individual year for the four subzones, showing the temporal (error bars) and spatial (between the four subzones) stability of specific humidity effects.

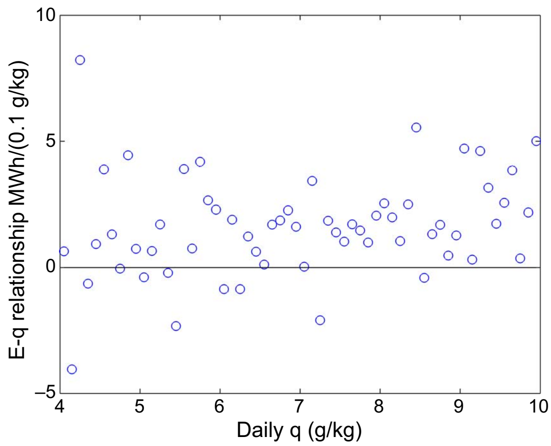

Figure 7. Response of daily electricity consumption for four subzones in the Adelaide CBD to daily specific humidity, using a step of 0.1 g/kg and a window of +/− 1.5 g/kg. In this analysis the T and dT effects have been removed.

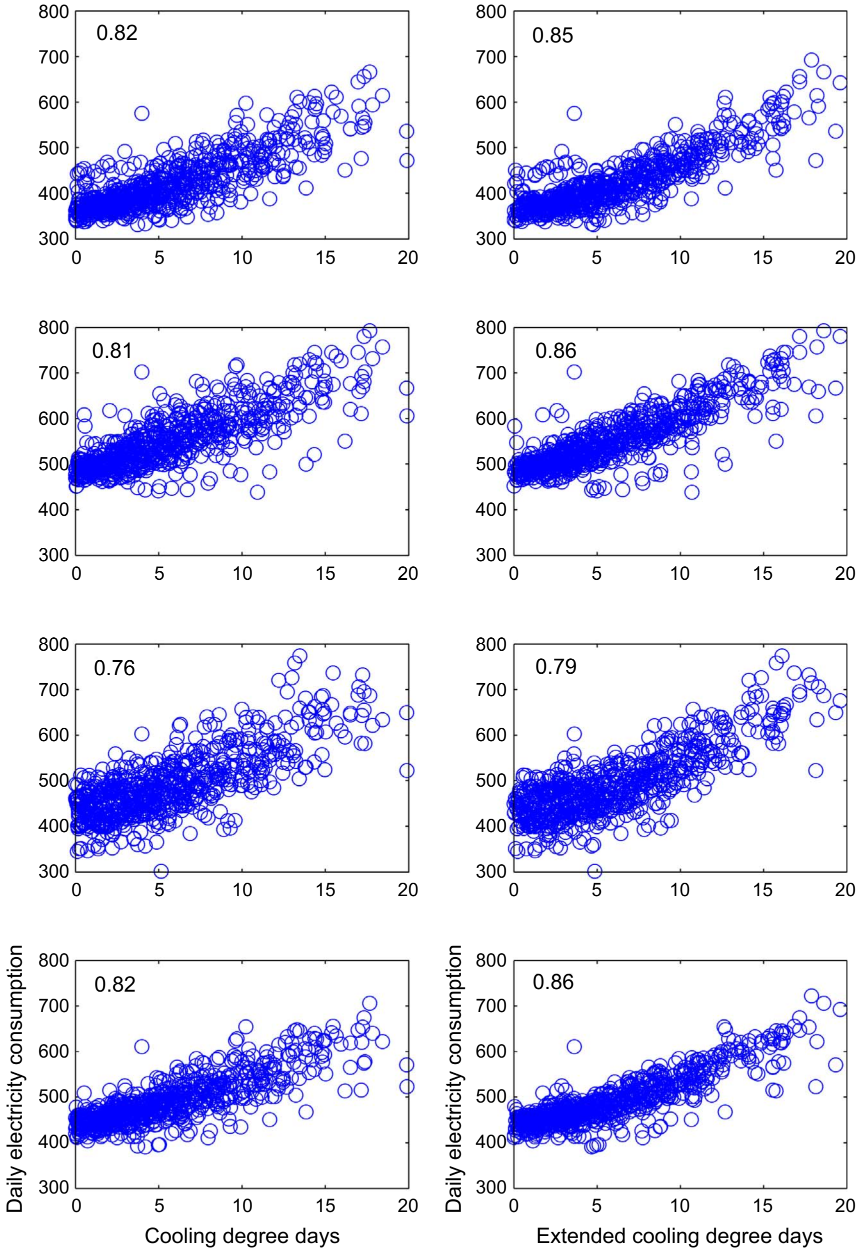

Figure 8. Relationship of daily electricity consumption (MWh) for four subzones (from top to bottom: WS, CP, ET and HS) vs daily cooling degree days (left) and extended cooling degree days (right). The numbers in the top left-hand corners of the panels are Pearson correlation coefficients.

electricity consumption of buildings. Based on meteorological data for Adelaide, which has a Mediterranean climate, it is found that the residual heat effect is statistically significant in influencing daily electricity consumption at both the building and block scales. At the block scale, the residual temperature effect is about 20% of the temperature dependence, while at the building scale, the effect appears to be larger. Whether or not similar relationships occur in other climate zones is yet to be determined.

Of the four subzones, the residual temperature effect is strongest in the Coromandel Place subzone, and is weakest in the East Terrace subzone. This may be associated with the different building compositions. In Coromandel Place, the primary type of buildings is commercial, public institution, and non-private residential (figure 1). They are large in size, and generally hold more residual heat. In East Terrace, particularly in the southeast corner, private residential buildings are dominant (figure 1). The ventilation level is likely to be high in such buildings, leading to relative weak but still significant residual heat effects, in comparison to the other three subzones. The humidity effect is largest in the East Terrace subzone, which can be relevant to the fact that the building composition of this subzone is different from the other three subzones.

The residual temperature effect varies over a fairly large range among the three examined buildings. This variation may reflect the effect of building design, structure, and construction materials. Building B, with the strongest residual heat effect, happens to be a building with fewer windows. The design was to reduce solar radiation input to the building. To reduce the residual temperature effect in summer, night-time ventilation using natural winds may be a potential solution. Thus, the concept of residual temperature effect on electricity consumption can be used as a quantitative indicator for some aspects of building energy performance, and may provide useful information to guide building design and operation management.

4.2. Specific humidity effect

It is well known that specific humidity can increase cooling energy consumption. At the block scale, the effect is relatively stable (table 2), while at the building scale, the specific humidity effect varies over a large range (table 3). It is worth noting that the sensitivity of electricity consumption to specific humidity does not seem to be correlated to building age. Building A has the highest energy performance ranking, while its specific humidity dependency is about 50% larger than that at the block scale (comparing the numbers in Column 9 of tables 2 and 3). Building C is an old building, but has a specific humidity dependency similar to that at the block scale.

From an energy balance point of view, the amount of heat released from vapour condensation in the cooling system roughly equates to that absorbed when the condensation evaporates in the environment. Thus, it is likely that the specific humidity effect on electricity consumption becomes weaker when moving from the building to block scales. This hypothesis is supported by the results of this study (tables 2 and 3).

Environmental cooling often comes with an increase in specific humidity. One typical example is sea breezes, which while decreasing temperature by a few degrees depending on the distance to the coast, also increase specific humidity (Gharib and Guan 2015). Therefore, from a cooling energy consumption point of view, sea breezes may not produce much benefit. Nevertheless, their value on outdoor comfort is significant, but this is beyond the scope of this study. Another example is large-scale parkland irrigation. Irrigation may reduce temperatures in summer, but at the same time it can increase specific humidity in the surrounding area. To evaluate the benefit of irrigation cooling on energy consumption, it is therefore important to include the specific humidity effect.

4.3. Extended cooling degree days

The ECDD concept proposed in this study considers the effects of air temperature, specific humidity, and residual temperature on electricity consumption in warm seasons. It has a form similar to CDD, and only requires readily available meteorological data (temperature and humidity). As demonstrated in this study, ECDD better reflects than CDD the temporal variability of electricity consumption in warm working days.

It is worth noting that the electricity consumption of office buildings in warm working days seems to be better associated with daytime weather conditions, while at the block scale (with mixed electricity users), the association with daytime and daily weather condition is similar. Thus, for the office building sector, it might be a good option to use daytime weather data, instead of daily data, to calculate the ECDDs. This may be particularly useful for high-energy performance office buildings in which the night-time electricity consumption is reduced to a very low level (Guan *et al* 2014).

5. Conclusions

In this study, we examined the association between warm-day electricity consumption and weather condition for four electricity-supply subzones and three office buildings in the Adelaide CBD. In addition to temperature and specific humidity, it was found that the residual temperature, which is a new concept proposed in this study to reflect the building thermal inertia effect on electricity consumption, is statistically significant in explaining temporal variation of daily electricity consumption of warm working days in the study area. The residual temperature effect is about 20% of the current-day temperature effect at the block scale, and increases with a large variation at the building scale. Investigation of this residual temperature effect provides some insight into the influence of building design and structure on electricity consumption.

The specific humidity effect appears to be important at both the block and building scales. The base specific humidity is estimated to be 7.5 g/kg in the study area. This effect, when normalized by the temperature effect, is quite stable across the subzones (blocks), but varies over a large range among the three examined office buildings. A building with high energy performance does not necessarily have low specific humidity dependence.

The new ECDD concept better reflects the weather dependence of electricity consumption than the conventional CDD method. Given its simple form, it is suggested that ECDD be used to predict electricity demand in response to climate variability and change.

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