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# An analysis of climatic influences on chiller plant electricity consumption

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ABSTRACT

Principal component analysis of dry-bulb temperature, wet-bulb temperature, global solar radiation, clearness index and wind speed was conducted, and a two-component solution obtained which could explain 80% of the variance in the original weather data. Clustering analysis of these two principal components resulted in a total of 18 typical day types being identified. A year long monitoring of the daily chiller plant electricity consumption in a fully air-conditioned office building was conducted. It was found that the typical day types exhibited daily and seasonal variations similar to the daily and monthly electricity consumption recorded. Three regression models were developed to correlate the daily chiller plant electricity consumption and the corresponding day types. The coefficient of determination ($R^2$) was 0.86–0.99 showing strong correlation. It is proposed that the day type approach can be used as a tool for weather normalisation and inter-year comparisons in the analysis of energy savings due to building retrofits. It was also found that the typical day types identified appeared to show a slight increasing trend during the 28-year period (1979–2006) indicating a subtle, but gradual change of climatic conditions that might affect chiller plant electricity consumption in future years.



## 1. Introduction

Buildings, energy and the environment are issues facing the building professions, researchers and energy policy makers worldwide. Hong Kong has no indigenous energy of her own and relies entirely on imported fuels. Over the past 30 years or so, Hong Kong has seen significant increase in energy-consumption, especially during economic expansion in the 1980s and early 1990s. Primary energy requirements (PER) rose from 195,405 TJ in 1979 to 566,685 TJ in 2006, representing an average annual growth rate of just over 4% [1]. Most of the PER (imported coal, natural gas and oil products) was used for electricity generation, which accounted for 66% of the total PER in 2006. The local building stocks accounted for about 80% of the total electricity use and over half of the imported PER [2]. There is a growing concern about energy use in buildings, especially those in the commercial sector, and its likely adverse effects on the environment. Annual electricity consumption in the commercial sector rose from 3823 GWh in 1979 to 26,491 GWh in 2006, representing an average rate of increase of about 7.4% per year, a few percents higher than the PER growth rate. Rising demands for electricity in the commercial sector continued unabated, even during the economic downturn (the Asian financial crisis) in the late 1990s and early 2000s. A significant proportion of this consumption was for air-conditioning during the hot, humid summer months. The recent report by the Inter-governmental Panel on Climate Change (IPCC) [3] has raised public awareness of energy use and the environmental implications, and generated a lot of interests in having a better understanding of the energy use characteristics of fully air-conditioned office buildings in Hong Kong, especially their correlations with the prevailing weather conditions. There had been a number of studies on energy signatures of buildings for energy savings analysis of pre- and post-building retrofits using mean outdoor temperatures or degree-days data [4–7]. Earlier works on cooling-dominated office buildings in subtropical Hong Kong also concentrated largely on the mean monthly outdoor dry-bulb temperature and degree-days data using simple two-parameter regression analysis techniques [8–10]. While these empirical or regression-based models show good correlations between energy use and the prevailing weather conditions, most of them either consider only one weather variable (dry-bulb temperature), or do not adequately remove the bias in the weather variables during the multiple linear regression analysis [11]. Our earlier work on fully air-conditioned office buildings in subtropical climates had shown that regressions models based on principal component analysis of key climatic variables could give a good indication of the monthly and annual electricity use [12], and heating, ventilation and air-conditioning (HVAC) was the single largest energy end-user in cooling-dominated commercial buildings [10,13,14]. The objectives of the present work were (i) to expand the principal component analysis to develop typical day types for subtropical Hong Kong using clustering technique, (ii) to examine (through a case study) the daily variations of energy use for space cooling in office buildings in response to different weather conditions as a function of the day types, and (iii) to investigate whether there was any underlying trend of changes in the

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local climates in terms of the typical day types identified. Five major weather parameters directly affecting the cooling requirements – dry-bulb temperature, wet-bulb temperature, global solar radiation, clearness index and wind speed – were considered.

## 2. Development of typical day types

In the analysis of long-term meteorological variables, it is often advantageous to group days based on the prevailing weather conditions and to assign them to specific weather day types. This technique can be used to assess the influences of climate on building performance and energy use. Because of its ability to categorise the complex and highly inter-correlated set of meteorological variables as a single cohesive index, the day-type approach tends to give a better understanding of the cause/effect relationship [11]. The development of typical day types involves three aspects – selection of key weather variables, principal components analysis (PCA) of long-term weather data and clustering analysis of the principal components.

### 2.1. Selection of key weather variables

A total of five climatic variables were considered, namely dry-bulb temperature (DBT, in °C), wet-bulb temperature (WBT, in °C), global solar radiation (GSR, in MJ/m$^2$), clearness index ($K_t$, dimensionless) and wind speed (WSP, in m/s). These five variables tend to have direct influences on the thermal performance of buildings and the corresponding energy use. They are indeed the key weather parameters used in the development of typical meteorological year (TMY) for building energy efficiency studies [15,16]. DBT affects the thermal response of a building and the amount of heat gain/loss through its envelope and hence energy use for the corresponding sensible cooling/heating requirements, whereas WBT dictates the amount of humidification required during dry winter days and latent cooling under humid summer conditions. These two most definitive weather variables provide complimentary information on the heat and moisture of the atmosphere. Information on solar radiation is crucial to cooling load determination and the corresponding design and analysis of air-conditioning systems, especially in tropical and subtropical climates where solar heat gain through fenestrations is often the largest component of the building envelope cooling load [14]. In addition to global solar radiation, $K_t$ (ratio of the GSR to the corresponding extraterrestrial radiation) is a measure of the cloudiness or attenuation of the incoming solar radiation during daylight hours, and helps identify the prevailing sky conditions. Wind data, in terms of speed and prevailing direction during different seasons, are important in natural ventilation design and analysis. These data would also, to some extent, affect the external surface resistance and hence *U*-values of the building envelope [17]. The longer the period of records and the more recent the weather data are, the more representative the analysis will be (since shorter periods may exhibit variations from the long-term average and considering only very early period of data may not reflect the present weather condition). Twenty-eight-year long-term (1979–2006) weather data from the local observatory were gathered for the analysis. To keep the analysis manageable, only daily values (a total of 10,220 × 5 data, 29 February was excluded) were considered in the PCA.

### 2.2. Principal component analysis (PCA) of long-term weather data

PCA is a multivariate statistical technique which can help get a better understanding of the dependencies existing among a set of inter-correlated variables [18,19]. PCA is conducted on centred data or anomalies, and is used to identify patterns of simultaneous variations. Its purpose is to reduce a data set containing a large number of inter-correlated variables to a data set containing fewer hypothetical and uncorrelated components, which nevertheless represent a large fraction of the variability contained in the original data. These components are simply linear combinations of the original variables with coefficients given by the eigenvector. A property of the components is that each contributes to the total explained variance of the original variables. The analysis scheme requires that the component contributions occur in descending order of magnitude, such that the largest amount of variance of the first component explains the largest amount of variance of the original variables, the second the next largest, and so on.

Table 1 shows a summary of the coefficients of the five principal components and the relevant statistics from the PCA. The eigenvalue is a measure of the variance accounted for by the corresponding principal component. The first and largest eigenvalue accounts for most of the variance, and the second the second largest amounts of variance, and so on. The percentage is given by the ratio of the individual eigenvalue to the trace of the correlation matrix, and calculation of all possible eigenvalues (i.e. considering all principal components) would account for all of the variance of the original variables. Principal components can be ranked according to their ability to explain variance in the original data set. A common approach is to select only those with eigenvalues equal to or greater than one (eigenvalues greater than one implies that the new principal components contain at least as much information as any one of the original climatic variables [20]) or with at least 80% cumulative explained variance [21]. In this study, a principal component was considered to be significant if the eigenvalue was greater than one or the cumulative explained variance reached 80%. It can be seen that the first two principal components have eigenvalues greater than one with a cumulative explained variance of 80% (i.e. this 2-component solution accounts for 80% of the variance in the original climatic variables). These two principal components were, therefore, retained. It is worth pointing out that the third principal component $Z_3$ has an eigenvalue of 0.97, slightly smaller than the customary threshold of one. In our earlier work on sector-wide (both commercial and residential) electricity use, however, it was found that including the third principal component in any subsequent energy analysis would only have marginal effect [22]. A new set of daily variables ($Z_1$ and $Z_2$) for each of the two significant principal components was, therefore, calculated as linear combinations of the original five climatic variables as follows:

$$Z_1 = 0.851 \times \mathrm{DBT} + 0.763 \times \mathrm{WBT} + 0.855 \times \mathrm{GSR} + 0.678 \times K_t - 0.169 \times \mathrm{WSP} \quad (1)$$

$$Z_2 = 0.516 \times \mathrm{DBT} + 0.639 \times \mathrm{WBT} - 0.48 \times \mathrm{GSR} - 0.708 \times K_t + 0.213 \times \mathrm{WSP} \quad (2)$$

Measured data for the five climatic variables were analysed and the daily values of $Z_1$ and $Z_2$ determined for the 28-year period from 1979 to 2006 using Eqs. (1) and (2). Fig. 1 shows the daily variations of the two principal components for 1979, 1988, 1997 and 2006. Both $Z_1$ and $Z_2$ profiles show appreciable daily variations. $Z_1$ tends to be at its lowest during the winter months (December, January and February) and peak in the summer (June–August). $Z_2$ shows similar but less distinct seasonal variations. It is interesting to note that the values of $Z_1$ are about two and a half times $Z_2$. Similar characteristics were observed for the other 24 years.

### 2.3. Clustering analysis of the principal components $Z_1$ and $Z_2$

The next step in the methodology is to apply an objective clustering scheme to the principal components $Z_1$ and $Z_2$. This process

**Table 1**
Coefficients of the five principle components and relevant statistics

| | | Principle component coefficient | | | | |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 |
| Climatic variable | Dry-bulb temperature | 0.851 | 0.516 | −0.024 | 0.050 | −0.084 |
| | Wet-bulb temperature | 0.763 | 0.639 | −0.038 | −0.007 | 0.086 |
| | Global solar radiation | 0.855 | −0.480 | 0.132 | −0.146 | −0.012 |
| | Clearness index | 0.678 | −0.708 | 0.147 | 0.129 | 0.024 |
| | Wind speed | −0.169 | 0.213 | 0.962 | 0.001 | −0.001 |
| Relevant statistics | Eigenvalue | 2.53 | 1.45 | 0.97 | 0.04 | 0.02 |
| | Explained variance | 50.5 | 29.1 | 19.3 | 0.8 | 0.3 |
| | Cumulative explained variance | 50.5 | 79.6 | 98.9 | 99.7 | 100.0 |

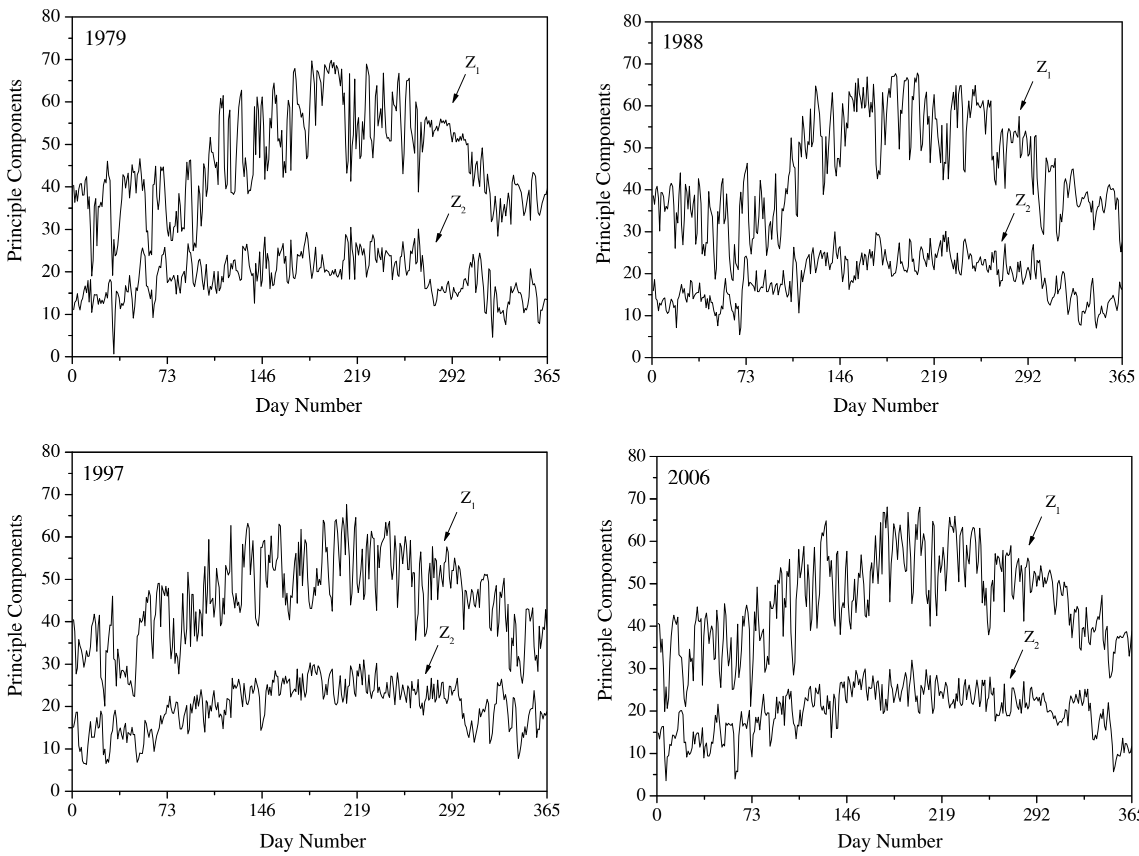


**Fig. 1.** Daily variations of the two principal components $Z_1$ and $Z_2$.

groups days with similar daily values into clusters that are meteorologically homogeneous. A group of days are considered homogeneous if all members in the group are similar, but differ substantially from members in other groups. The daily $Z_1$ and $Z_2$ for the 28 years were arranged in a data matrix. One of the most commonly used distance measure, the Square Euclidean distance was chosen as a criterion for the assessing the dissimilarity in $Z_1$ and $Z_2$. This distance was the summation of the square of the differences between each pair of daily $Z_1$ and $Z_2$. Hierarchical cluster tree was then formed using the Ward's algorithm [23] to determine any possible combination of two data or clusters. This algorithm merged the two days that were the nearest (i.e. those having the smallest distance between each other). A new cluster was formed after merging, and the distance between this cluster and all the other days were re-calculated. This process was done in an iterative way, until there was a unique cluster.

In order to find out the final number of clusters, the overall heterogeneity within the clusters as a function of the number of clusters was considered. This function is a weighted sum of the distances within a cluster and is similar to an intra-cluster variance. It reaches its minimum when the number of clusters is equal to the total number of days (i.e. 10,220), but attains its maximum when the number of cluster is one. It increases gradually as the combination of clusters proceeds, and the number of clusters decreases. If a marked increase at a given number of clusters is observed, it represents the forming of a heterogeneous cluster from two homogeneous clusters and indicates the end of the merging process. At each merging step (agglomeration), the two clusters that merged are those that resulted in the smallest increase in the overall sum of the within-cluster distances. The within-cluster sum of squares is the coefficient in the agglomeration schedule [24]. In theory, there is a distinct breakpoint in the iterative process at which dissimilar day types begin to be merged, indicating the correct number of naturally occurring day types. In practice, more often than not, this point cannot be easily identified. It is a matter of striking a balance between achieving small number of clusters and maintaining acceptable similarity or homogeneity within each cluster. In our study, the selection of the number of typical day type was based on intuition and hence somewhat subjective. The number of clusters and the corresponding coefficients generated during the clustering process was analysed. Fig. 2 shows the coefficient as a function of the number of groups. It can be seen that the gradient of the curve begins to level off around 16–20. In this study 18 was selected.

The frequency of occurrence of these 18 day types was determined and a summary is shown in Table 2. The "U-shape" frequency of occurrence indicates clearly the distinct features of the local subtropical climates (i.e. hot summer and warm winter). Mean DBT varied from 12.1 °C for day type 1 (DT1) to 29.4 °C for DT2. If 18 and 25 °C were assumed to be the demarcations for winter and summer, then winter (DT1-DT5), mid-season (DT6-DT11) and summer (DT12-DT18) accounted for 18.1, 33.9 and 48%, respectively, of the total occurrence during the 28-year period, indicating short winters and long summers.

## 3. Case study – chiller plant electricity consumption

An office building with a centralised HVAC system was selected for this study. It was a 14-storey, purpose-built owner-occupied building with a gross floor area of 17,400 $m^2$. It had a typical operating schedule of 10-h (08:00–18:00) working day and 5½-day week with an energy utilisation index (i.e. annual total building electricity consumption divided by the corresponding GFA) of 180 kWh/$m^2$ in 2006. In the investigation and evaluation of building energy use, two different categories of loads are usually considered. The first category is the base load, which is defined as the non-weather-related energy use. Typical examples are artificial lighting, office equipment, other electrical appliances and the vertical transportation (i.e. lifts and escalators). The second category is energy consumed in the HVAC system. This is weather-sensitive and requires the determination of how much energy is used for heating and cooling (both latent and sensible) and electricity use for the associated equipment such as fans and pumps. In this particular case study, the centralised HVAC system had four major electricity end-use components – chillers, electric heating batteries, fans and pumps. Because of the short, mild winter in subtropical Hong Kong, heating requirement is usually insignificant, especially in cooling-dominated commercial buildings with large internal heat gains due to people, electric lighting and office equipment. Among the four components, electricity consumption in the chiller plant (which consisted of two water-cooled centrifugal chillers) was most sensitive to daily changes in the local weather conditions. Chiller plant electricity consumption data metered dur-

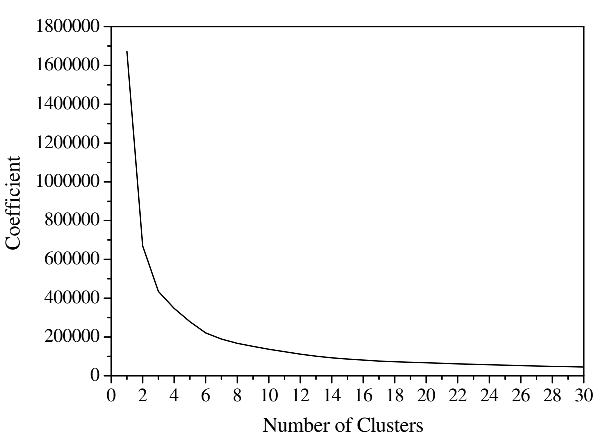


**Fig. 2.** Overall heterogeneity as a function of the number of clusters.

**Table 2**
Summary of typical day type occurrence and relevant weather statistics

| Day-type | Number of days of occurrence | | | | | | | | | | | | | Mean values of weather variables | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | January | February | March | April | May | June | July | August | September | October | November | December | Total | DBT | WBT | GSR | $K_t$ | WSP |
| 1 | 102 | 98 | 38 | 3 | | | | | | | 4 | 36 | 281 | 12.1 | 10.0 | 4.14 | 0.15 | 2.1 |
| 2 | 98 | 37 | 14 | 0 | | | | | | | 7 | 97 | 253 | 13.6 | 9.4 | 13.72 | 0.53 | 2.4 |
| 3 | 149 | 204 | 166 | 32 | | | | | | 4 | 15 | 82 | 652 | 16.0 | 14.2 | 4.40 | 0.15 | 3.5 |
| 4 | 144 | 78 | 24 | 3 | | | | | | 0 | 29 | 139 | 417 | 16.3 | 12.6 | 14.10 | 0.53 | 2.8 |
| 5 | 45 | 67 | 44 | 1 | | | | | | 2 | 49 | 48 | 256 | 17.9 | 14.2 | 16.18 | 0.58 | 3.0 |
| 6 | 126 | 103 | 154 | 98 | 6 | | | | | 4 | 43 | 112 | 646 | 18.7 | 16.9 | 6.23 | 0.21 | 3.6 |
| 7 | 164 | 88 | 92 | 40 | 0 | | | | | 7 | 80 | 246 | 717 | 19.4 | 16.7 | 12.16 | 0.45 | 3.1 |
| 8 | 36 | 82 | 139 | 89 | 14 | | | | 1 | 54 | 280 | 61 | 756 | 21.4 | 18.3 | 15.06 | 0.51 | 2.9 |
| 9 | 4 | 12 | 44 | 104 | 35 | 1 | | | 5 | 16 | 69 | 19 | 309 | 21.6 | 20.0 | 4.77 | 0.15 | 3.5 |
| 10 | | 10 | 67 | 103 | 96 | 16 | 1 | | 17 | 52 | 91 | 22 | 475 | 23.6 | 21.5 | 8.56 | 0.26 | 3.0 |
| 11 | | 2 | 42 | 123 | 52 | 13 | 0 | | 21 | 252 | 57 | 0 | 562 | 24.5 | 21.1 | 18.03 | 0.54 | 2.9 |
| 12 | | 1 | 21 | 74 | 72 | 18 | 1 | | 42 | 155 | 83 | 5 | 472 | 25.1 | 22.5 | 13.37 | 0.41 | 2.9 |
| 13 | | 2 | 18 | 39 | 112 | 137 | 90 | 104 | 95 | 71 | 23 | 1 | 692 | 25.8 | 24.4 | 4.07 | 0.11 | 3.5 |
| 14 | | | 1 | 77 | 195 | 71 | 30 | 50 | 179 | 80 | 0 | | 683 | 27.1 | 24.0 | 20.03 | 0.54 | 2.7 |
| 15 | | | 4 | 24 | 93 | 149 | 109 | 131 | 122 | 49 | 5 | | 686 | 27.3 | 25.3 | 8.98 | 0.24 | 3.0 |
| 16 | | | | 26 | 108 | 163 | 165 | 191 | 206 | 115 | 5 | | 979 | 28.2 | 25.6 | 14.32 | 0.38 | 2.8 |
| 17 | | | | 4 | 44 | 136 | 194 | 198 | 110 | 7 | | | 693 | 29.3 | 26.3 | 19.37 | 0.50 | 2.7 |
| 18 | | | | | 41 | 136 | 278 | 194 | 42 | | | | 691 | 29.4 | 26.2 | 23.63 | 0.60 | 2.6 |

*Note:* DBT (°C), WBT (°C), GSR (MJ/$m^2$), $K_t$ (dimensionless), WSP (m/s).

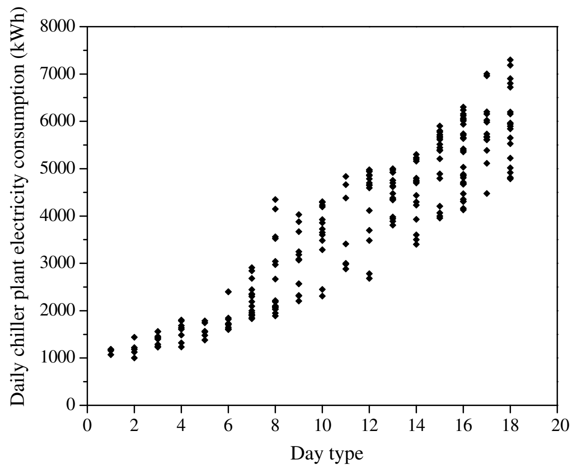


**Fig. 3.** Daily chiller plant electricity consumption and the corresponding day types.

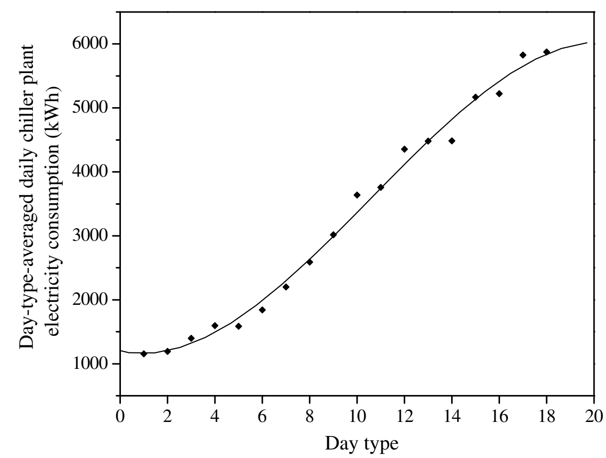


**Fig. 4.** Day-type-averaged electricity use and the corresponding day types.

ing 2006 were gathered and analysed. The chiller plant consumed 58 kWh/m$^2$, accounting for about one-third of the annual total building electricity use. Daily chiller plant electricity consumption was compared with the corresponding day types. Since the building operated on a 5½-day week and was closed during the public holidays, all Saturdays, Sundays and public holidays were excluded in the analysis. There were altogether 247 days of data and a summary is shown in Fig. 3. It can be seen that, though daily consumption varies quite a lot for the same day type, a general increasing trend can be observed. Electricity consumption varies from 1157 kWh in DT1 to 7300 kWh in DT18.

To investigate the strength of correlation between consumption and day type, regression analysis was conducted for the 247 daily electricity consumption data and the corresponding day types. A third order polynomial (i.e. $Y = a + b_1X + b_2X^2 + b_3X^3$, where $Y$ is the daily electricity consumption and $X$ the day type) was obtained and a summary of the regression statistics is shown in Table 3. It can be seen that the regression have a rather high coefficient of determination ($R^2$) of 0.86, indicating reasonably strong correlation between the electricity use and day type (i.e. 86% of the changes in daily electricity consumption can be explained by variations in the corresponding day types). An error analysis was also conducted by comparing the 2006 measured consumption data with those calculated from the regression equations using the corresponding day types. To quantify the differences, mean bias error (MBE) and root mean square error (RMSR) were determined as follows:

$$\mathrm{MBE} = \frac{\sum_{i=1}^{247}(Y_i - M_i)}{247} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{247}(Y_i - M_i)^2}{247}} \tag{4}$$

where $Y_i$ is the predicted daily chiller plant electricity consumption (kWh), $M_i$ is the measured daily chiller plant electricity consumption (kWh).

The MBE provides information on the long-term performance of the modelled regression equation. A positive MBE indicates that the predicted annual electricity consumption is higher than the actual consumption and vice versa. It is worth noting that overestimation in an individual observation can be offset by underestimation in a separate observation. The RMSE is a measure of how close the predicted daily data are to the actual ones based on the measured daily chiller plant electricity consumption. Normalised mean bias error (NMBE) and coefficient of variation of the root mean square error (CVRMSE) were also determined by dividing the MBE and RMSE by the mean daily electricity consumption, and a summary is shown in Table 3. It can be seen that the MBE is very small (an overestimation of 0.15 kWh, 0.004% of the mean daily consumption). This small MBE is probably a result of fortuitous cancellation between overestimation and underestimation among the 247 daily consumption data. The RMSE is quite large, 615 kWh which is 16.3% of the mean daily consumption. This suggests that while prediction of chiller plant electricity use on an

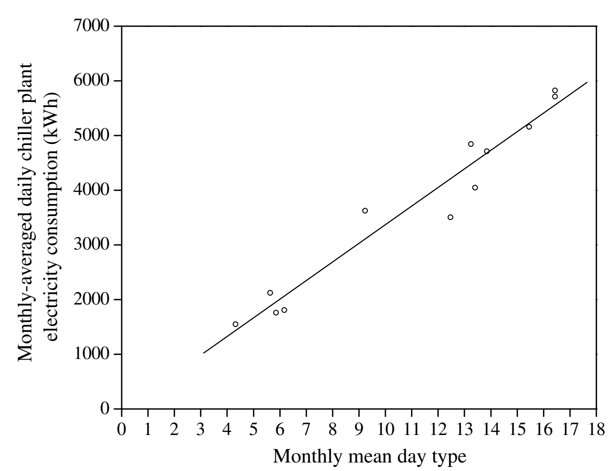


**Fig. 5.** Monthly-averaged electricity use and the corresponding monthly mean day types.

**Table 3**
Summary of regression analysis

| | $a$ | $b_1$ | $b_2$ | $b_3$ | $R^2$ | MBE (kWh) | NMBE (%) | RMSE (kWh) | CVRMSE (%) |
|---|---|---|---|---|---|---|---|---|---|
| Daily chiller plant electricity consumption | 1154 | −57.5 | 40.6 | −1.28 | 0.86 | 0.153 | 0.004 | 615 | 16.3 |
| Day-type-averaged daily chiller plant electricity consumption | 1195 | −76.0 | 42.8 | −1.34 | 0.99 | −0.056 | −0.002 | 146 | 3.9 |
| Monthly-averaged daily chiller plant electricity consumption | −53.5 | 342.9 | – | – | 0.95 | 0.044 | 0.001 | 348 | 9.3 |

annual basis could be very accurate, individual daily consumption could differ from the measured data by up to 16.3%.

To have a better idea about the underlying trend of the seasonal and monthly variations in chiller plant electricity consumption, two more regressions were conducted using day-type-averaged and monthly-averaged daily consumption data. Fig. 4 shows the 18 day-type-averaged consumption data plotted against the corresponding day types. Again, a third order polynomial was found to fit the consumption data well. The regression model shows excellent correlation with 0.99 $R^2$, −0.002% NMBE and 3.9% CVRMSE (see Table 3). Likewise, the 12 monthly-averaged consumption data were regressed against the corresponding monthly mean day types (see Fig. 5). A linear two-parameter regression equation (i.e. $Y = a + b_1X$) was developed and a summary of the relevant statistics is shown in Table 3. Again, the correlation is considered strong – 0.95 $R^2$, 0.001% NMBE and 9.3% CVRMSE. It is interesting to note that both the low (winter months) and high (summer months) monthly mean day types tend to be closer to the linear regression line. This suggests that there could be larger diversity in chiller plant electricity consumption during the mid-season in subtropical climates. In terms of the root mean square error, regression model based on day-type-averaged consumption appears to be far better than the other two.

The regression results enable the chiller energy-consumption signature to be established. This in turn allows the influences of external weather conditions on the energy use to be estimated and any sudden changes of energy use assessed on a daily basis. Another possible application of these regression results is that the day type approach can be used as a tool for weather normalisation and inter-year comparisons in the analysis of energy savings due to building retrofits (i.e. energy conservation measures). Energy-consumption can be grouped together by the day type. Similar weather day types during the pre- and post-retrofit periods can then be identified and energy-consumption signature compared. We believe this technique could also be applied to other climates. For instance, in severe cold climates (e.g. Harbin) where winter heating is the primary energy use in buildings, heating energy requirements could be correlated with the local day types. Likewise, in cold winter and hot summer climates (e.g. Shanghai), both cooling and heating are essential and could therefore be correlated either separately or together (as total HVAC loads) with the prevailing day type identified. Given the growing demand for energy use in Mainland China and its diverse climates [25], this could have implications for energy efficiency programmes involving any building retrofits.

## 4. Changes in the local climates during the 28-year period (1979–2006)

It had been shown that the periods of record could affect the selection of prevailing weather conditions for air-conditioning requirement analysis and helped detect any underlying trend of changing climatic characteristics [26]. Earlier works on long-term (1961–2000) ambient temperature in Hong Kong [27] and seasonal variations in building energy use [12] revealed a slight increase in the annual cooling degree-days and principal components, and suggested that cooling requirements, hence energy use for air-conditioning could be significantly affected if such trend persisted. In this study, an attempt was made to ascertain whether there was any underlying trend of changes in the climatic indicators (i.e. the typical day types) during the 1979–2006. For each of the 28 years the frequency of occurrence of the 18 day types identified

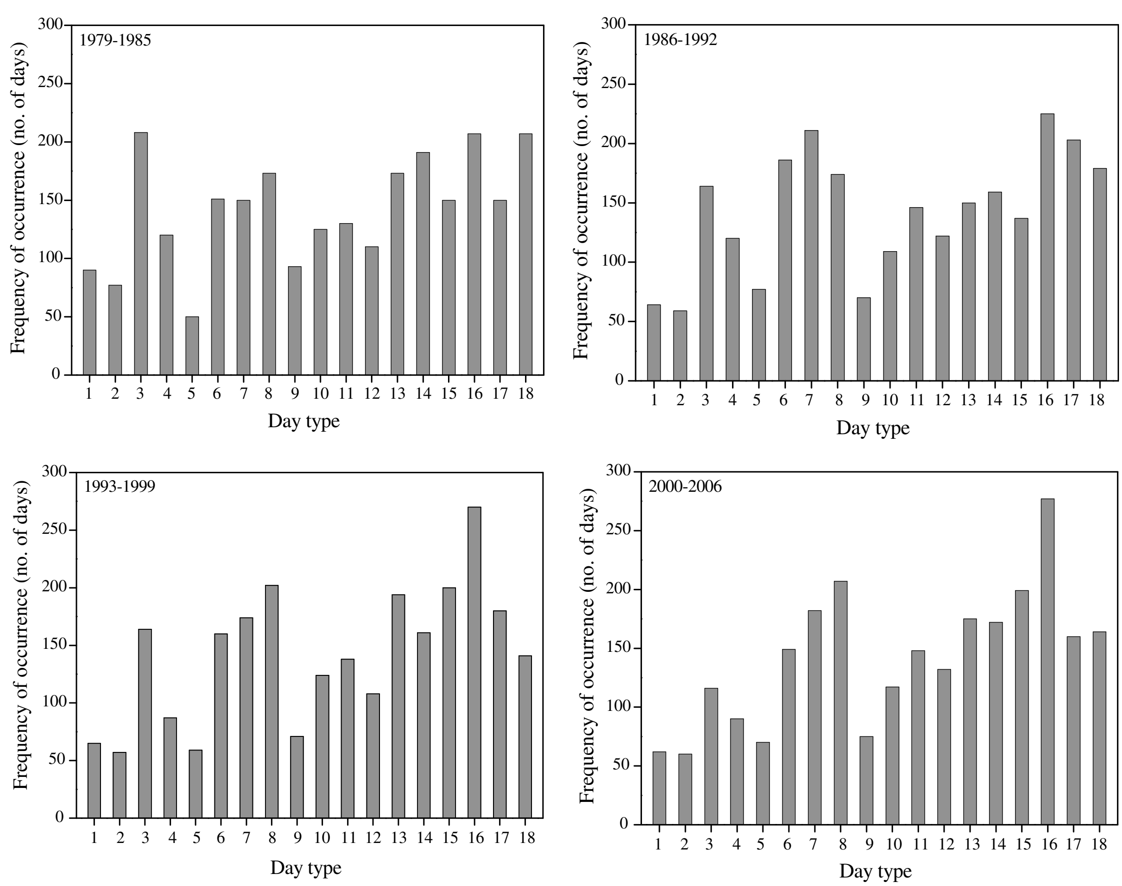


**Fig. 6.** Frequency of occurrence of the 18 typical day types during the four periods (1979–1985, 1986–1992, 1993–1999 and 2000–2006).

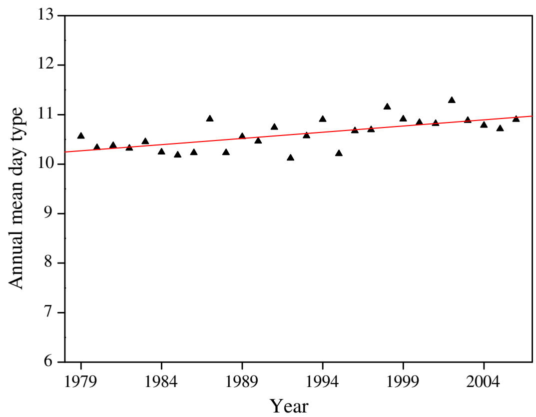


**Fig. 7.** Variations of the annual mean day type during 1979–2006.

were analysed. Four periods were considered namely, 1979–1985, 1986–1992, 1993–2000 and 2000–2006, and a summary of the frequency of occurrence during these periods is shown in Fig. 6. It can be seen that during 1979–1985, DT3 had the highest frequency of 208. In the subsequent periods DT16 had the highest frequency, well above 250 in 1993–1999 and 2000–2006, indicating warmer weather conditions during the more recent periods. To have a better understanding of the overall long-term trend, annual mean day types were determined and a summary of the yearly variations during the 28-year period is shown in Fig. 7. A small but gradual increasing trend can be observed. Mean day type varied from 10.1 in 1992 to 11.3 in 2002 with a mean of 10.6. The annual mean day type did not vary a great deal from one year to another (a standard deviation of 0.62, 6% of the corresponding mean value). The slightly increasing trend had a slope of 0.03. Although the increase was small, if this trend persists it could affect future chiller plant electricity use. Given the growing concern about climate change, this might have some energy and environmental implications.

## 5. Conclusions

Principal component analysis of prevailing weather conditions in subtropical Hong Kong was conducted. Five major climatic variables – dry-bulb temperature, wet-bulb temperature, global solar radiation, clearness index and wind speed – were considered. It was found that a two-component solution would contain as much information as the original five variables and could explain 80% of the corresponding variance. Clustering technique was applied to the two principal components to develop typical day types for building energy study. A total of 18 day types were identified. A year long monitoring of the daily chiller plant electricity consumption in a fully air-conditioned office building was conducted. Through this case study, it was found that the typical day types exhibited daily and seasonal variations similar to the daily and monthly electricity consumption recorded. Three regression models were developed to correlate (i) the daily chiller plant electricity consumption and the corresponding day types, (ii) day-type-averaged daily chiller plant electricity consumption and the corresponding day types and (iii) monthly-averaged daily chiller plant electricity consumption and the corresponding monthly mean day types. The coefficient of determination ($R^2$) was 0.86, 0.99 and 0.95 for the daily, day-type-averaged and monthly-averaged regressions, respectively. One possible application of these regression results is that the day type approach can be used as a tool for weather normalisation and inter-year comparisons in the analysis of energy savings due to building retrofits (i.e. energy conservation measures). Energy-consumption can be grouped together by the day type. Similar weather day types during the pre- and post-retrofit periods can then be identified and energy-consumption signature compared. It was also found that the typical day types identified appeared to show a slight increasing trend during the 28-year period indicating a subtle, but gradual change of climatic conditions that might affect chiller plant electricity consumption in future years. Given the growing concerns about climate change and its impact on energy use in the built environment, it might have energy and environmental implications if this trend persists. Although the work was conducted for subtropical climates, it is envisaged that the approach could be applied to other climates.

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