UDC: 551.5:31 (512.317) Keywords: Building energy simulation; Statistics; Typical meteorological year; Weather data.

Architectural Science Review
Volume 39, pp 201-209

A Statistical Approach to the Development of a Typical Meteorological Year for Hong Kong

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Measured hourly weather data for the 16-year period from 1979 to 1994 were analysed. Statistics techniques were used to develop a typical meteorological year (TMY) for building energy simulation. We used the Finkelstein-Schafer (FS) and the Kolmogrov-Smirnov (KS) two-sample statistics to analyse and select representative weather data for the formulation of a TMY for Hong Kong. Building energy computer simulations using DOE-2 were carried out. It was found that the monthly electricity consumption profile from the TMY was close to that from the 16-year long-term weather data. The root-mean-square error was 27.7MWh, 3.9% of the long-term mean monthly consumption. On an annual basis, TMY predicted 1.5% more consumption than the long-term.

Introduction

Buildings, energy and the environment are some of the key issues that the building professions have to consider in building project developments. There is a growing concern about energy consumption in buildings, particularly commercial buildings, and its likely adverse effect on the environment. There is increasing public pressure on the architects and engineers to design more energy-efficient buildings and building services systems. It is believed that building energy simulation technique is a useful design and analysis tool in the building design and planning process. Such technique enables architects and engineers to compare and assess the thermal and energy performance of different building forms and building services design schemes, and to estimate the likely energy consumption.

All energy simulation computer programs require weather data input to drive the thermal models within the simulation tools. The purpose and end-use of the building energy simulation must be considered when choosing the weather data. For an analysis to check the design performance in a specific year (as in an energy audit), the weather data of the year concerned should be considered. For comparative studies and long-term energy estimation, a yearly representative of the average climatic conditions is often used. Keeble [Ref.1] has classified three types of hourly weather data for building energy simulation:

i) Multi-year datasets - They are the fundamental set of weather data and include a substantial amount of information for a number of years.

ii) Typical years - A typical or reference year is a single year of 8,760 hourly data selected to represent the range of weather patterns that would typically be found in a multi-year dataset. Definition of a typical year depends on its satisfying a set of statistical tests concerning the multi-year parent dataset.

iii) Representative days - They are hourly data for some average days developed to represent the typical climatic conditions. Representative days are economical for small-scale analysis and are often found in simplified simulation and design tools.

For detailed simulation, typical years are most commonly used since analysis using a multi-year dataset is often not feasible and economical for the common design and analysis problems, whereas representative days are too limited and sometimes not accurate enough for a specific design and analysis problem. The typical year approach can reduce the computational efforts in simulation and weather data handling by using one year instead of multiple years. Also, a consistent form of weather data is ensured so that results from different studies can be compared. Provided that the long-term climatic data exist and are of sufficient quality, typical year weather data can be established from the multi-year dataset using suitable method.

The objectives of this study are :

i) To develop a typical meteorological year (TMY) for building energy simulation using statistics techniques.

ii) To carry out building energy simulation exercise to investigate how close the selected TMY can resemble the 16-year (1979-1994) long-term weather data in terms of monthly and annual energy consumption predictions.

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Basic Typical Meteorological Year Concept

The TMY method, developed by Sandia National Laboratories in the United States [Ref.2] is one of the most widely accepted methods for determining typical years. A TMY consists of twelve typical meteorological months (TMMs) selected from various calendar months in a multi-year weather database. For example, the January of 1980 may be selected as the first TMM, the February of 1989 as the second TMM, and so on. All the twelve selected months will then be combined to form the TMY. Smoothing of data for discontinuities is usually required to avoid abrupt changes at the boundary between two adjacent months coming from different years. Selection of a TMM is based on the statistical analysis and evaluation of four weather parameters, namely dry bulb temperature (DBT), dew-point temperature (DPT), wind speed (WSP) and global solar radiation (GSR). Nine indices are considered, including the daily maxima, minima and means of DBT, DPT and WSP and the daily total GSR. The nine daily indices and their respective weightings are shown in Table 1.

Table 1

Weather indices and weighting factors for TMY method

Weather parameter	Daily index	Weighting factors
Dry-bulb	Daily maximum	1/24
temperature	Daily minimum	1/24
(DBT)	Daily mean	2/24
Dew-point	Daily maximum	1/24
temperature	Daily minimum	1/24
(DPT)	Daily mean	2/24
Wind speed	Daily maximum	2/24
(WSP)	Daily mean	2/24
Global solar radiation (GSR)	Daily total	12/24

TMM selection involves minimising the difference from the long-term distributions, means and daily persistence of the weather indices. To determine a TMM, three basic properties are considered, namely frequency distributions (climatic elements should have frequency distributions close to the long-term ones), sequences (the sequences of daily measurements should be similar to the sequence often registered at that location) and correlations (the relationships among different climatic elements should be similar to the relationships observed in nature). The procedures assumes that a TMY consisting of the twelve TMMs, which meet all these criteria, would have weather patterns and system performances close to the long-term climatic conditions.

For each TMM, a screening process is first performed to select five candidate years. A nonparametric method, known as Finkelstein-Schafer (FS) statistics [Ref.3] is used to determine the candidates by comparing the yearly cumulative distribution function (CDF) with the long-term CDF in the month concerned. An empirical CDF, which is a monotonic increasing function, is defined as follows [Ref.4] :

$$S_n(x) = \begin{cases} 0 & for\ x < x_{(1)} \\ (k-0.5)/n & for\ x_{(k)} \le x \le x_{(k+1)} \\ 1 & for\ x > x_{(n)} \end{cases} \quad where\ k = 1,\ldots,n-1 \qquad (1)$$

where $S_n(x)$ = value of the cumulative distribution function at x

n = total number of elements

k = rank order number

Values of the FS statistics are calculated for each of the daily indices using the following equation :

$$FS = \frac{1}{N}\sum_{i=1}^{n} \delta_i \qquad (2)$$

where FS = value of FS test statistics

δ_i = absolute difference between the long-term CDF and the yearly CDF at $x_{(i)}$ value

n = the number of daily readings for that month (e.g. for January, n = 31)

A weighted-sum average (WS) or composite index is then computed for each year and the five years with the smallest WS values are selected as the candidate years for the final selection. The WS values is given by:

$$WS = \sum_{i=1}^{9} WF_i \times FS_i \qquad (3)$$

where WS = weighted-sum average

WF_i = weighting factor for the i^{th} parameter (see Table 1)

FS_i = FS test statistics calculated for the i^{th} parameter

The final selection involves two steps. The first step checks the statistics associated with the mean daily DBT and daily total GSR, including the FS statistics and the deviations of the monthly mean and median from the long-term mean and median. The second step looks at the persistence in the mean daily DBT and daily total GSR by examining their run structure. Persistence is considered important for the design and analysis of solar systems since in some cases the distribution of a given year can be quite close to that of the long-term, yet there can still be atypically long runs of cloudy or warm or cool days. The general principle is to select years with small FS values, small deviations, and typical run structures. But there is no universal procedure or criteria. Various methods for the final selection have been proposed and used by different researchers. Some of them look at the root-mean-square difference of GSR [Ref.5]; some assess the persistence and the monthly mean and median [Ref.6]; some take the year with the lowest WS value as the TMM [Ref.7].

TMY Selection for Hong Kong

The basic TMY concept was expanded in the present study. In meteorological science, it is generally believed that at least 30 years of weather data are required to study the prevailing long-term climate patterns of a particular location. However, hourly solar radiation data prior to 1979 have not been measured. Therefore, only weather data for the 16-year period from 1979 to 1994 were studied. Both daily and hourly weather data were analysed. The hourly analysis can take the influence of hourly variations into consideration. Apart from the FS statistics, another nonparametric test statistics, known as the Kolmogrov-Smirnov (KS) two-sample statistics, was also used for the analysis [Ref.8]. While the FS statistics is based on the magnitude of the CDF difference, the KS statistics is based on the maximum deviation and is defined as follows :

$$KS = \max \left| \delta_i \right| \tag{4}$$

In order to select a TMY for Hong Kong, the basic process on frequency distributions was performed to determine the values of the nonparametric statistics. The assessment on persistence and run structure as suggested in the *TMY User's Manual* [Ref.9] was not followed since there was no evidence that it could provide useful information for relating building energy performance. To simplify the process in the final selection, the year with the lowest weighted-sum average of the test statistics (FS and KS statistics) was selected as the TMM (this approach was also used by Said and Kadry [Ref.7]).

Since cooling requirements are the most important energy use in fully air-conditioned commercial buildings in Hong Kong, the four essential weather parameters (namely DBT, DPT, WSP and GSR) for building cooling loads were considered. The relative importance of the weather parameters represented by the weighting factors is difficult to determine since different building designs and applications may result in some weather parameters becoming more influential. For example, extensive use of windows and skylights may make solar radiation a dominating factor for building energy consumption; whereas buildings with exceptionally high fresh air cooling load, humidity level may become more critical. The individual values of the test statistics calculated for each index can be used to work out a different set of weighted-sum values for the typical year selection if a particular application requires. For example, a typical wind year, a typical solar year and a typical humidity year may be constructed by putting more emphasis on the wind, solar and humidity data, respectively.

The original TMY methodology was developed for solar systems and hence a large weighting factor of 0.5 for the global solar radiation. For building designs in Hong Kong, one can argue that the relative importance of the weather parameters and hence the weighting factors may be different from those used in the original TMY method for solar system design and analysis. However, the same weighting factors were used for this study because :

i) Solar heat gain accounts for a significant proportion of the total building cooling load, nearly 50% for residential buildings in subtropical Hong Kong [Ref.10]. For commercial buildings, the percentage is lower but still substantial.

ii) Although latent cooling is important, there is no clear evidence that a larger weighting factor for DPT would improve the selection of representative weather data and the subsequent building energy simulation.

The nine indices and their respective weighting factors shown in Table 1 were used for the daily weather data in the present study. For the hourly data, only hourly means were considered. The weighting factors used for these four hourly indices are shown in Table 2.

Table 3 shows the results of the TMY selection using the daily indices, five candidate years are shown to illustrate the selection patterns. For instance, the five candidate years for January (in ascending order of their weighted-sum averages) are 1980, 1994, 1985, 1991 and 1982. It can be seen that TMY selections using the FS and KS statistics often give similar results, eight out of the twelve TMMs are the same. When the FS and KS statistics for each individual index are examined, it is found that the statistics often differ from one index to another, and from month to month. Years considered typical for a certain index (e.g. DBT) may not be necessarily typical for GSR. The temperatures (i.e. DBT and DPT) tend to agree more often with each others whereas GSR and WSP exhibit very different patterns.

By extending the original TMY concept to hourly data, TMY selection for Hong Kong was performed based on four hourly indices and the results are shown in Table 4. Many of the years selected from hourly indices are the same as those from the daily indices, ten TMMs in the FS statistics and five TMMs in the KS statistics are the same. When comparing the results from the FS and KS statistics for the hourly indices, six of the twelve TMMs selected are the same.

The patterns shown in Tables 3 and 4 indicate that the CDF differences as detected by the two nonparametric methods have similar properties. If the two distributions have no significant difference statistically at the hourly level, they should also be close at the daily level. Since the hourly data contain more information, TMY selection based on the hourly indices would be a better choice if hourly data are required for the end use. It should be noted that comparison of CDFs and the results of the nonparametric statistics depends only on the rank order of the variables, not on their actual values. The relative positions, not the magnitude, are important for determining the closeness of the distributions. This is an essential properties of nonparametric methods. In general, the larger the sample size for the test statistics, the higher the probability that any real differences will be detected. In statistical terms, the

Table 2

Proposed weighting factors and indices for TMY selection

Weather parameter	Hourly Index	Weighting factors
Dry-bulb temperature (DBT)	Hourly mean	1/6
Dew-point temperature (DPT)	Hourly mean	1/6
Wind speed (WSP)	Hourly mean	1/6
Global solar radiation (GSR)	Hourly mean	1/2

Table 3
TMY selection for Hong Kong using daily indices

Ranks	Year selected (such as 80 stands for 1980)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	Five candidate years selected from FS statistic using daily indices											
1st	80	90	93	80	89=	86	86	86=	82	84	89	93
2nd	94	88	84	93	93=	87	90	93=	93	86	84	85
3rd	85	82	80	79	86	90	92	89	89	93	91	89
4th	91	86	86	86	82	91	80	82	90	89	86	82
5th	82	81	92	92	84	92	83	85	87	91	85	86
	Five candidate years selected from KS statistic using daily indices											
1st	85	90	93	93	93	86	89	86	82	84	89	93
2nd	80	88	92	79	89	87	86	93	93	86	86	89
3rd	94	82	86	80	84	91=	92	89	87=	93	84	85
4th	82	86	84	87	86	92=	80	82	90=	89	91	82
5th	93	80	80	89/92	87	90	83	91	89	81	85	90

Note: **If two figures are given or the figure is followed by '=', there are equal scores (ties) at three decimal places during the selection.**

critical region within which the result of the test statistics is considered significant will be larger if more data are analysed. If only a limited amount of data is used for testing the goodness-of-fit, then it is likely that the test will give non-significant results. The uncertainty band within which the true population lies will be wider in the case of daily indices (fewer data) than the hourly ones (24 times more data).

Critical Value Test for the Selected TMY

Estimation of the critical values for test statistics can provide a conditional measure of uncertainty. However, the critical values for many nonparametric methods are difficult to compute even for a small sample since recursive formulae and complicated probability derivations are involved. The KS two-sample statistics is the one that has its critical values defined in statistical references, such as Gibbons and Chakraborti [Ref.8]. The two-sided critical region of the KS statistics at a significant level is given by:

$$KS_{m,n} \geq C_a \tag{5}$$

where $KS_{m,n}$ = KS test statistics calculated for the two samples of sizes m and n

C_a = critical value of KS statistics at significant level

If the calculated statistics is larger than the critical value, then the null hypothesis that the two CDFs are different can be rejected. For large sample sizes, the two-sided critical value of the KS statistics can be approximated by an asymptotic distribution of the following form :

$$C_a = K\sqrt{\frac{m+n}{m \times n}} \tag{6}$$

where K = coefficient relating to the significant level

In the TMY selection, KS statistics is used for comparing the long-term and yearly CDFs. The size of the long-term CDF will be equal to the number of years multiplied by the total number of data in each yearly CDF. Let N_y be the number of years and n be the size of each yearly CDF, then m will be equal to $N_y \times n$ and the critical value of the KS statistic can be written as:

$$C_a = K\sqrt{\frac{N_y \times n + n}{N_y \times n \times n}} = K\sqrt{\frac{N_y + 1}{N_y \times n}} \tag{7}$$

Equation (7) was used to calculate the critical values of the KS statistic for the significant levels from 1% to 5% for the sixteen years of weather data. To check the selected TMY for Hong Kong, the critical values for the KS statistics were compared with the values of the KS statistics calculated in the TMY selection. A comparison was made with a critical value of 2.5% (i.e. a significant level of 0.025) and the results are shown in Table 5. The

Table 4

TMY selection for Hong Kong using hourly indices

Ranks	Year selected (such as 80 stands for 1980)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	Five candidate years selected from FS statistic using hourly indices											
1st	80	88	93	80	82	86=	86=	86	82	84	89	93
2nd	94	90	80	87=	93	87=	90=	93	87	86=	84=	85
3rd	85	91	84	93=	86	90	89	89	89=	89=	91=	86
4th	89	82=	86	79	89	92	80	82	90=	85	86	82=
5th	82	92=	92	86	83	91	91	91	93	93	90	83=
	Five candidate years selected from KS statistic using hourly indices											
1st	80	88	93	87	86	90	89	86	87	84	89	85
2nd	89	90	86	93	82	86	86=	93	82	86	84	93
3rd	94	82	92	80	89	87	90=	91	93	80	91	86
4th	82	89	90	89	93	92	91	89	90	89	86	89
5th	87	91	82	79	87	91	92	82	89	81	90	79

Note: **If two figures are given or the figure is followed by '=', there are equal scores (ties) at three decimal places during the selection.**

2.5% level was chosen since the same significant level is usually used for the outdoor design temperatures and it is a common significant level for general HVAC applications [Ref.11]. It can be seen that all the weighted-sum averages of the KS statistics calculated for the TMMs using daily indices are smaller than the 2.5% critical values. This implies that there is not enough evidence that the TMMs are different from the long-term weather conditions under this test. For the hourly indices, however, five TMMs have the weighted-sum averages above the 2.5% critical values. This means that these candidates can be different from the long-term weather conditions under the 2.5% significant level criteria. The critical values proposed here can be used to quantify and assess the reliability of TMY selection in a way similar to how the outdoor design temperatures are defined using the significant frequency level. As weather files for the typical years will be used for building energy simulation, the degree of uncertainty of the weather input in the building energy analysis can be further assessed by examining the simulated energy performance from different weather years.

Energy Prediction Test for the Selected TMY

To get some idea about the effects of weather data from different years and to assess how close the monthly and annual energy consumption predicted from the developed TMY would be to that predicted from the long-term weather data, a series of computer simulation was performed. The twelve TMMs based on the hourly KS statistics (shown in Table 4) were selected to form the TMY for the energy simulation. Smoothing of weather data for discontinuities was carried out using the cubic spline function to avoid abrupt changes at the boundary between two adjacent months from different years. The last six hours of the preceding day and the first six hours of the following day were adjusted accordingly.

The simulation tool used was the DOE-2.1E building energy simulation computer program [Ref.12]. A generic office building was developed for the comparative energy studies. A survey of the existing commercial buildings in Hong Kong was conducted to find out the design characteristics common to most commercial buildings in Hong Kong [Ref.13]. Descriptions of a generic base-case model building were then established for use in the building energy simulation. The generic building developed was a 40-storey office building (35m by 35m) with curtain-wall design and a centralised heating, ventilating and air-conditioning (HVAC) system. The floor-to-floor and window heights are 3.4 and 1.5m, respectively. This represents a window-to-wall ratio (WWR) of 44%. The building and the HVAC plant operate on a 10-hour day (08:00 to 18:00) and a 5½-day week basis. Details have been reported elsewhere [Ref.14].

Figure 1 shows the sixteen monthly electricity consumption profiles for the individual years from 1979 to 1994. It can be seen that all the years show similar seasonal variations in the electricity use. Electricity consumption peaks during the six hot summer months from May to October,

Table 5
Comparison of KS statistics and their 2.5% critical values

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
	Year selected (such as 80 stands for 1980)												
	TMM's selected from KS statistics using daily indices												
TMM	85	90	93	93	93	86	89	86	82	84	89	93	89
WS	0.193	0.165	0.156	0.116	0.146	0.136	0.144	0.119	0.125	0.116	0.115	0.132	0.040
c_α (2.5%)	0.278	0.292	0.278	0.282	0.278	0.282	0.278	0.278	0.282	0.278	0.282	0.278	0.081
Reject? [2]	No	No	No	No	No	No	No	No	No	No	No	No	No
	TMM's selected from KS statistics using hourly indices												
TMM	80	88	93	87	86	90	89	86	87	84	89	85	89
WS	0.060	0.065	0.064	0.048	0.065	0.058	0.048	0.040	0.058	0.036	0.050	0.068	0.019
c_α (2.5%)	0.057	0.060	0.057	0.058	0.057	0.058	0.057	0.057	0.058	0.057	0.058	0.057	0.017
Reject? [2]	Yes	Yes	Yes	No	Yes	No	No	No	No	No	No	Yes	Yes

Notes: 1. TMM is the typical meteorological month, WS is the weighted-sum average of the KS statistic and $c_\alpha(2.5\%)$ is the critical value at 0.025 significant level.

2. No = null hypothesis cannot be rejected; Yes = null hypothesis is rejected (i.e. not identical distributions)

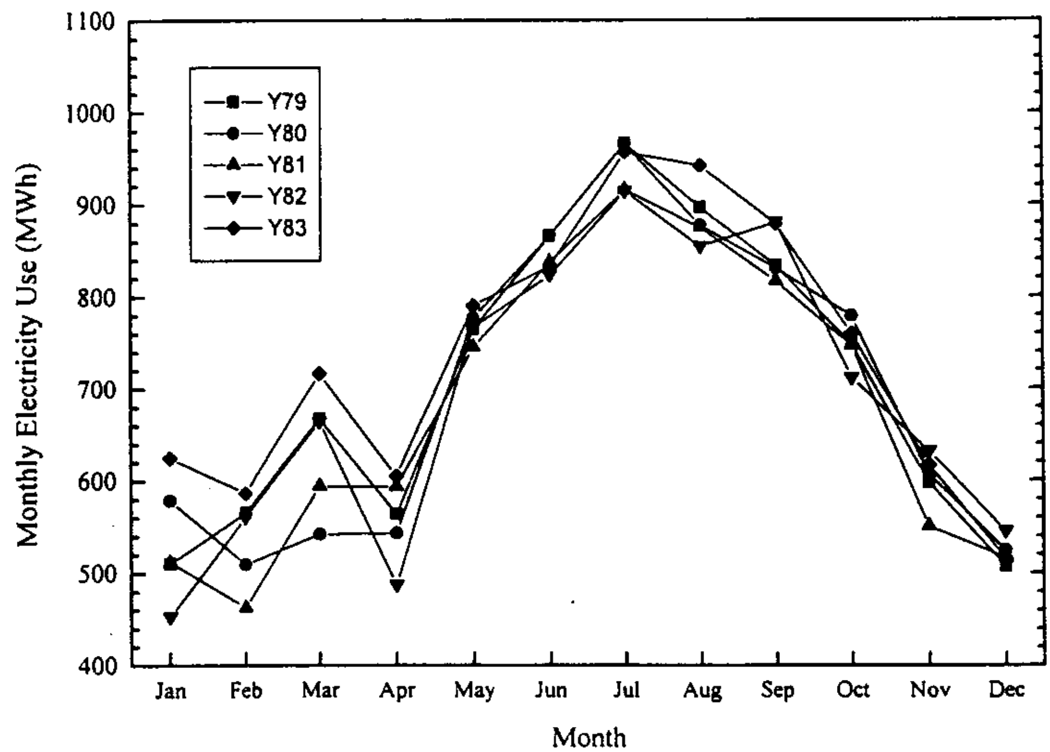

Figure 1a. Predicted monthly electricity use from the five individual years (1979-1983).

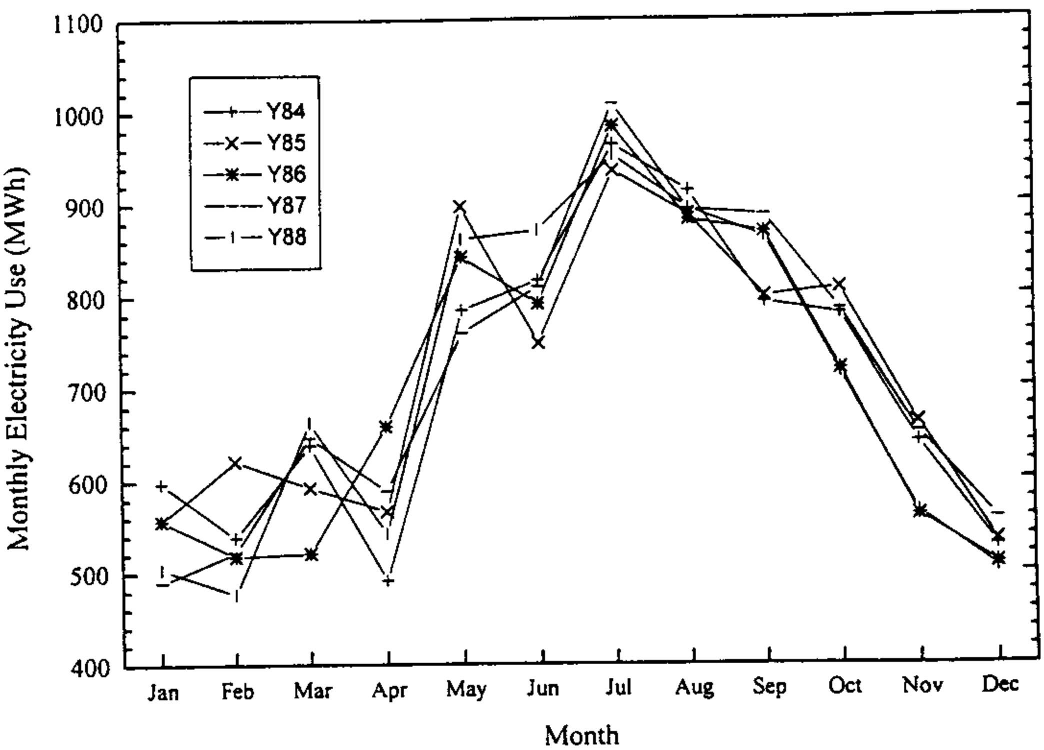

Figure 1b. Predicted monthly electricity use from the five individual years (1984-1988).

when the average outdoor air temperature exceeds 25°C. The minimum and maximum monthly differences between the sixteen years are 87 and 196MWh, respectively. These represent 12.3 and 27.7% of the long-term mean monthly electricity use of 707MWh. On an annual basis, the largest difference between the sixteen year is 661MWh, 7.8% of the long-term mean annual electricity consumption. Predictions from the TMY were analysed and compared with those from the sixteen individual years. Figure 2 shows that predictions from the TMY lie within the maximum and minimum range of predictions from the sixteen individual years, and follow quite closely the 16-year long-term mean.

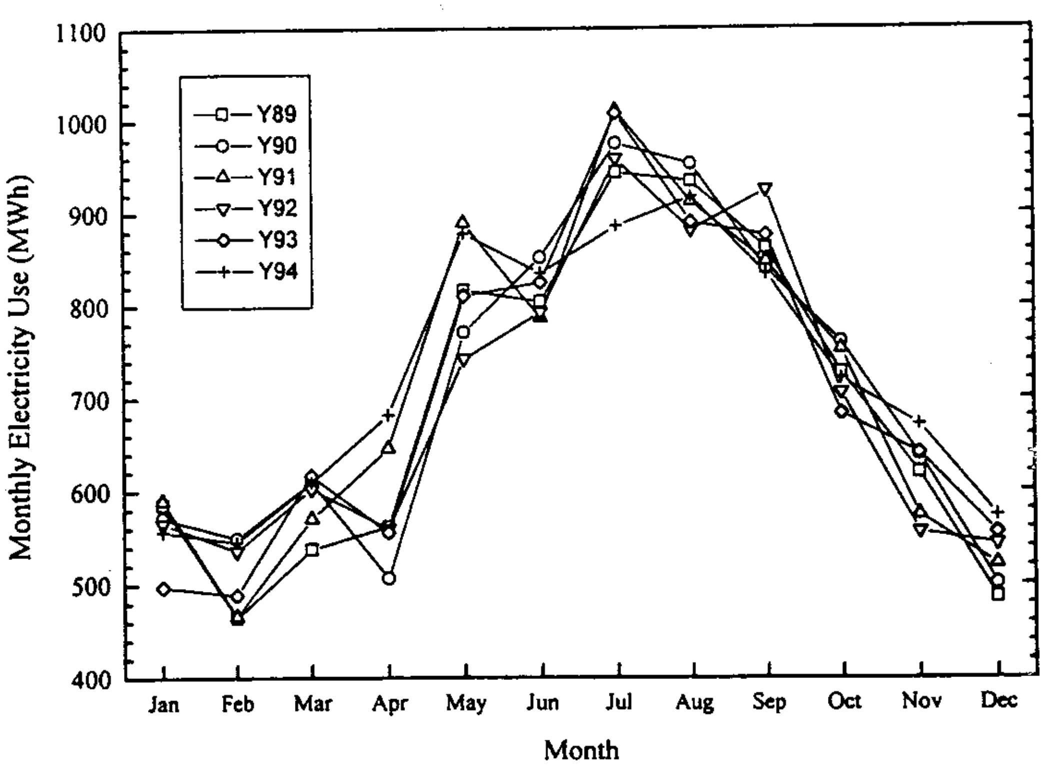

Figure 1c. Predicted monthly electricity use from the six individual years (1989-1994).

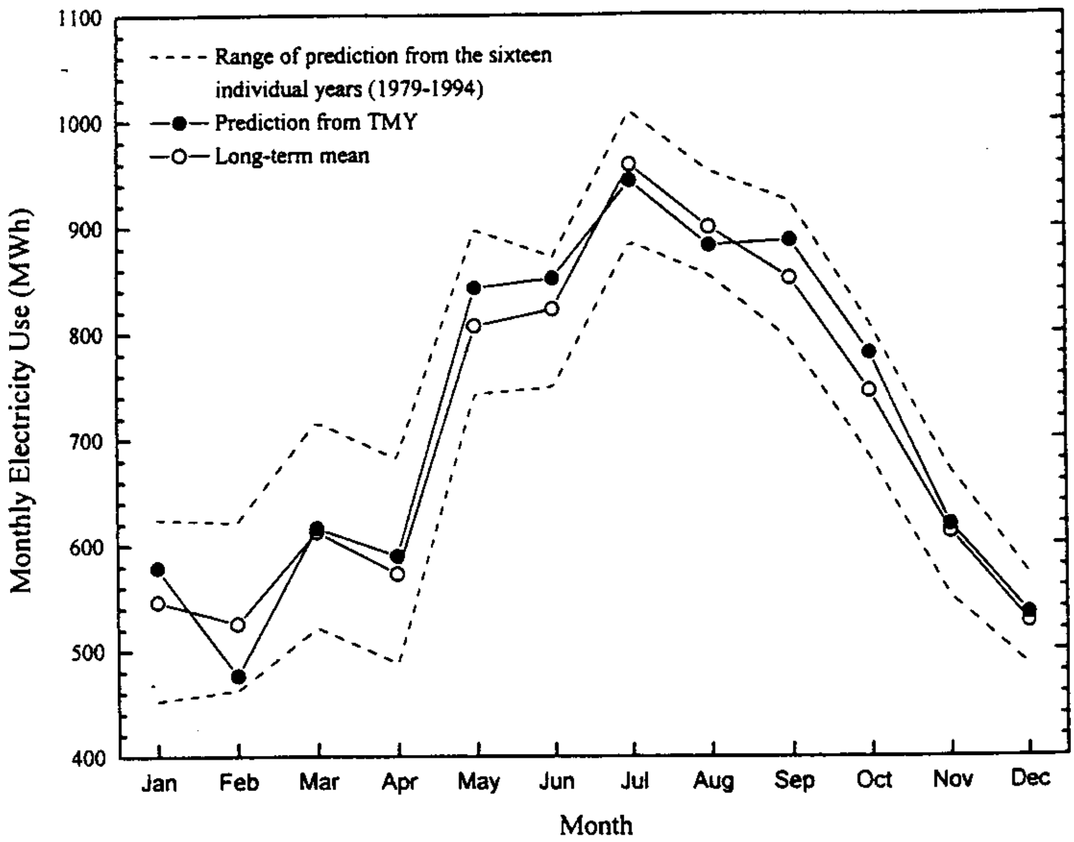

Figure 2. Predicted monthly electricity use from the TMY.

To compare the representativeness of different weather years, mean bias errors (MBE) and root-mean-square errors (RMSE) were calculated. Mean bias errors and root-mean-square errors are defined as follows :

$$MBE_j = \frac{\sum_{i=1}^{12} \left(x_{ij} - y_i\right)}{12} \quad (8)$$

where x_{ij} = monthly electricity consumption for individual year (j = 1 to 16)

y_i = monthly electricity consumption for the 16-year long-term mean

$$= \frac{\sum_{j=1}^{16} x_{ij}}{16}$$

$$RMSE_j = \sqrt{\frac{\sum_{i=1}^{12} \left(x_{ij} - y_i\right)^2}{12}} \quad (9)$$

A positive MBE indicates that the annual electricity consumption is higher than the long-term annual prediction and vice versa, and the RMSE is a measure of how close the monthly profile is to the long-term. Figure 3 shows the MBE and the RMSE for the sixteen individual years and the TMY. It can be seen that MBE ranges from -26MWh for 1981 to 29.1MWh for 1983. In other words, the annual electricity use from 1981 is 312MWh less than the long-term value of 8,483MWh and the annual consumption from 1983 is 349.2MWh more. The year 1984 has the smallest MBE of 0.75MWh, and its annual electricity use is only 0.1% more than that of the long-term. It is interesting to observe that the MBE for the TMY is 10.4MWh, somewhere between the smallest MBE of 0.75MWh and the largest MBE of 29.1MWh. Annual electricity use from the TMY is 8,608MWh, 1.5% more than that of the long-term. Although the year 1984 has the smallest MBE, its monthly profile is not the closest to that of the long-term. The small MBE is a result of a fortuitous cancellation between over- and under-estimation. The closest monthly profile is the TMY which has the smallest RMSE of 27.7MWh, representing 3.9% of the long-term monthly mean consumption.

Conclusion

Statistics techniques were used to develop a typical meteorological year (TMY) for building energy simulations in Hong Kong. It was found that the monthly electricity consumption profile predicted from the selected TMY was close to the 16-year (1979-1994) long-term prediction, with a root-mean-square error of 3.9%. In terms of annual electricity use, TMY had 1.5% more than the long-term. Despite the limited period of measured weather data (only sixteen years), it is envisaged that the TMY can give a good indication of the long-term energy performance in building energy simulation exercise in Hong Kong. Furthermore, although this study is specific to weather data and a generic office building in Hong Kong, it is believed that the methodology developed and procedures demonstrated can be applied to other locations with similar building developments and climates, particularly in Southern China.

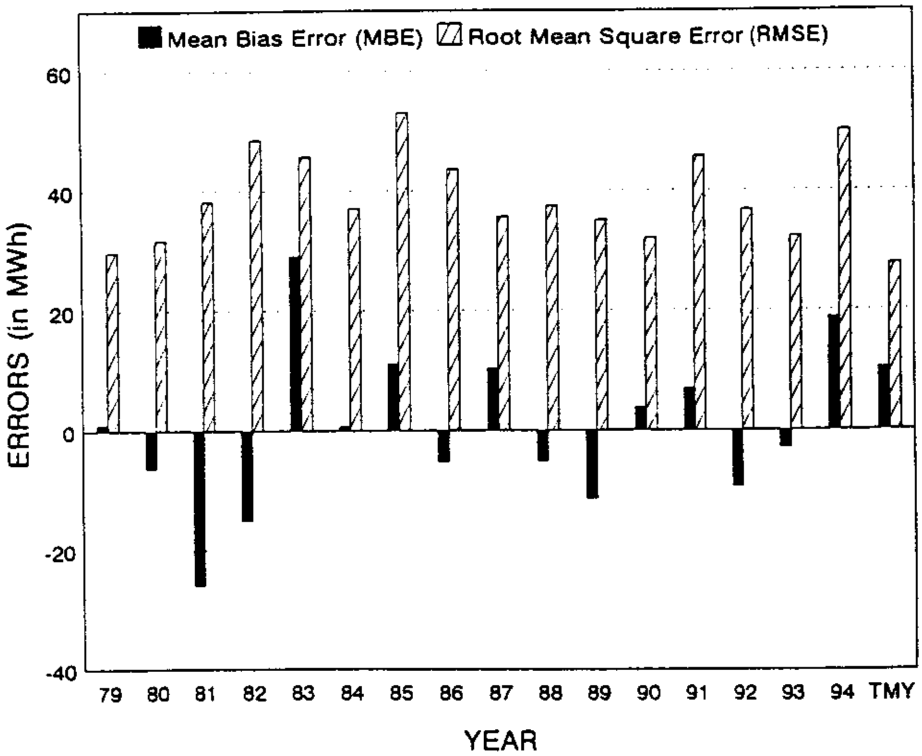

Figure 3. Mean-bias errors and root-mean-square errors for the different years

Acknowledgements

The hourly weather data were obtained from the Royal Observatory Hong Kong. Work was funded by a UGC Competitive Earmarked Grant (Project No. 9040139). S C M Hui is supported by a City University of Hong Kong studentship.

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